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Towards Developing a Digital Twin Implementation Framework for Manufacturing Systems

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THE UNIVERSITY OF SOUTH ALABAMA
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TOWARDS DEVELOPING A DIGITAL TWIN IMPLEMENTATION FRAMEWORK FOR MANUFACTURING SYSTEMS

BY

Jonatan H. Loaiza

A Dissertation

Submitted to the Graduate Faculty of the
University of South Alabama
in partial fulfillment of the
requirements for the degree of

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in

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To my amazing family and friends for their unconditional love and support throughout my life that motivate me to be better.

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LIST OF ABBREVIATIONS

Abbreviation	Description
AM	Additive Manufacturing
AIA	Aerospace Industries Association
AIAA	American Institute Of Aeronautics And Astronautics
API	Application Programming Interface
AI	Artificial Intelligence
AR	Augmented Reality
BDD	Block Definition Diagrams
CDBB	Centre For Digital Built Britain
C2PS	Cloud-Based Cyber-Physical System Architecture
CAD	Computer Aided Design
CONOPS	Concept Of Operations
CRM	Customer Relationship Management
CATWOE	Customers, Actors, Transformation, Worldview, Owner, Environment
CPS	Cyber Physical System
DMS	Database Management System
DOS	Denial-Of-Service attack
DT	Digital Twin
DCS	Distributed Control System

Dr.	Doctor
ERP	Enterprise Resource Planning
FHWA	Federal Highway Administration
GE	General Electric
IFR	Ideal Final Result
ID	Identification
IIoT	Industrial Internet of Things
IT	Information Technology
IEEE	Institute Of Electrical And Electronics Engineers
IBM	International Business Machines Corporation
IEC	International Electrotechnical Commission
ISO	International Organization For Standardization
IOT	Internet Of Things
IPv6	Internet Protocol Version 6
LoRa	Long Range Radio
MitM	Man-In-The-Middle attack
MES	Manufacturing Execution System
MS	Manufacturing Systems
MEMS	Microelectromechanical Systems
MSM	Mirroring Spaces Model
MSM	Mirroring Spaces Model
MBSE	Model-Based Systems Engineering
MDPI	Multidisciplinary Digital Publishing Institute
NASA	National Aeronautics And Space Administration

NFC	Near Field Communication
OT	Operations Technology
PDM	Product Data Management
PLM	Product Lifecycle Management
PLC	Programmable Logic Controller
RFID	Radio-Frequency Identification
ROI	Return On Investment
STS	Socio Technical Systems
SCM	Supply Chain Management
SOI	System Of Interest
SRL	System Readiness Level
SysML	Systems Modelling Language
SoS	Systems Of Systems
TRIZ	Theory Of Inventive Problem Solving (Russian Acronym)
3D	Three-Dimensional Space
2D	Two-Dimensional Space
UK	United Kingdom
US	United States
UPC	Universal Product Code

ABSTRACT

Loaiza, Jonatan, H., Ph.D., University of South Alabama, May 2023. Towards Developing a Digital Twin Implementation Framework for Manufacturing Systems. Chair of Committee: Robert, Cloutier, Ph.D.

This research studies the implementation of digital twins in manufacturing systems. Digital transformation is relevant due to changing manufacturing techniques and user demands. It brings new business opportunities, changes organizations, and allows factories to compete in the digital era. Nevertheless, digital transformation presents many uncertainties that could bring problems to a manufacturing system. Some potential problems are loss of data, cybersecurity threats, unpredictable behavior, and so on. For instance, there are doubts about how to integrate the physical and virtual spaces.

Digital twin (DT) is a modern technology that can enable the digital transformation of manufacturing companies. DT works by collecting real-time data of machines, products, and processes. DT monitors and controls operations in real-time helping in the identification of problems. It performs simulations to improve manufacturing processes and end-products. DT presents several benefits for manufacturing systems. It gives feedback to the physical system, increases the system's reliability and availability, reduces operational risks, helps to achieve organizational goals, reduces operations and maintenance costs, predicts machine failures, etc. DT presents all these benefits without affecting the system's operation.

This dissertation analyzes the implementation of digital twins in manufacturing systems. It uses systems thinking methods and tools to study the problem space and define the solution space. Some of these methods are the conceptagon, systemigram, and the theory of inventive problem solving (TRIZ in Russian acronym). It also uses systems thinking tools such as the CATWOE, the 9-windows tool, and the ideal final result (IFR). This analysis gives some insights into the digital twin implementation issues and potential solutions. One of these solutions is to build a digital twin implementation framework

Next, this study proposes the development of a small-scale digital twin implementation framework. This framework could help users to create digital twins in manufacturing systems. The method to build this framework uses a Model-Based Systems Engineering approach and the systems engineering "Vee" model. This framework encompasses many concepts from the digital twin literature. The framework divides these concepts along three spaces: physical, virtual, and information. It also includes other concepts such as digital thread, data, ontology, and enabling technologies.

Finally, this dissertation verifies the correctness of the proposed framework. The verification process shows that the proposed framework can develop digital twins for manufacturing systems. For that purpose, this study creates a process digital twin simulation using the proposed framework. This study presents a mapping and a workflow diagram to help users use the proposed framework. Then, it compares the digital twin simulation with the digital twin user and system requirements. The comparison finds that the proposed framework was built right.

CHAPTER I - INTRODUCTION

Digital transformation can change the way organizations and economies work. It gives organizations the opportunity to change their business models by implementing modern technologies. These technologies change the regular operations of companies. It affects the business structure, processes and products. Hence, businesses must restructure the whole organization to compete in the digital era. Nowadays, even more organizations turn their companies to the digital world making them fierce competitors to beat in the market. However, this digital transformation could bring more problems to the actual system lifecycle. The integration and digitization of system processes is a complex task (Ziyadin et al., 2020).

There are many technologies that help organizations throughout their digital transformation. One of these technologies is Digital twin (DT) which transforms physical objects into live virtual objects. These DT can perform diagnostics, prognostics, and predictions of business operations. Digital twin's goal is to provide real time image and information of objects, processes, and services. All these images can add value to system processes to improve business performance. This was not possible before due to constraints in technology such as big data analysis, implementation cost, complex processes, data storage, accessibility, and so on. Nowadays, a digital twin is available due to innovative, inexpensive, and more powerful technology. Digital twin development uses the knowledge of information technology (IT) and operations technology (OT) to model system processes and fulfill its functions (Trauer et al., 2020).

Digital twin technology presents a lot of potential to be an important dominant asset in a manufacturing system. It gives information to manufacturing systems to improve production processes and create better products according to the customer needs. It contributes to the evolution of manufacturing by working in virtual twin environments with real-time data in a secure manner. Manufacturing systems can rely on real-time status of their processes and machines. Digital twin supplies feedback to the physical system showing its ability to learn. It uses Big Data to predict failure and improve the system performance. It helps factories to test potential products. Companies can also use digital twins as a duplicate, backup copy, of the entire system life cycle (R. He et al., 2019).

Several journal articles describe the application and impact of DT in manufacturing systems. Factories look for connectivity in their systems and with the outside world. Many technologies are growing and changing manufacturing systems (Xu et al., 2019). Some researchers called this impact the next Industrial revolution or Industry 4.0. This new industrial revolution embraces the idea of implementing DT all over the world. DT has the objective to make simulations with real-time data using high-detailed virtual models (Qi & Tao, 2018). Some DT models use low-level virtual models and accurate parameters. This could be a problem of fidelity for DT models. Hence, DT must learn through experience and make simulations to predict events. (Umeda et al., 2019).

Digital twin technology is an important ally to stay at the forefront of modern technology. Therefore, this research looks to define, characterize, and describe digital twins in complex systems. It looks to develop a framework to help factories implement digital twins in their systems.

1.1 Background

The implementation of digital twin is changing several organizations such as manufacturing, consulting, government, and construction. Each one has a slightly different definition of a DT. However, they have the same goal of understanding problems and developing solutions applied to businesses. DT improves organizations by developing new business opportunities and supporting plans in the future. It monitors the entire system and gives a better analysis of the organization's current situation. It finds undercover problems and solves them promptly. It also predicts future problems in the system.

According to Fuller et al. (2020), people misunderstand the definition of DT. Some people think it is just a 3D model or it is just a simulation software. Their study presents some common misconceptions of DT.

The first misconception is that DT are digital models. A digital model is the virtual representation of a physical object. However, the data exchange between the physical object and the virtual model is not automatic. Hence, any change in the physical object does not affect the virtual model. Some examples of digital models are computer designs of buildings, products, processes, and so on. These designs could carry on simulations, but they do not have any connection to the physical infrastructure.

The second misconception is that DT are digital shadows. This is also a virtual representation of a physical asset. It even has data flowing from the physical asset to the virtual model. Nevertheless, there is no data exchange from the virtual model to the physical object. This means that the virtual model resembles all changes of the physical object in real time, but it cannot provide feedback to the physical object. The virtual model's goal is limited to monitor a physical infrastructure. Therefore, a DT has data flowing between the physical object and the virtual model. The virtual model mirrors all the physical objects in real time. It mimics the changes of the physical object and gives feedback to it. The exchange of data is reciprocal. Figure 1.1 describes the comparison of the DT misconceptions based on data flow.

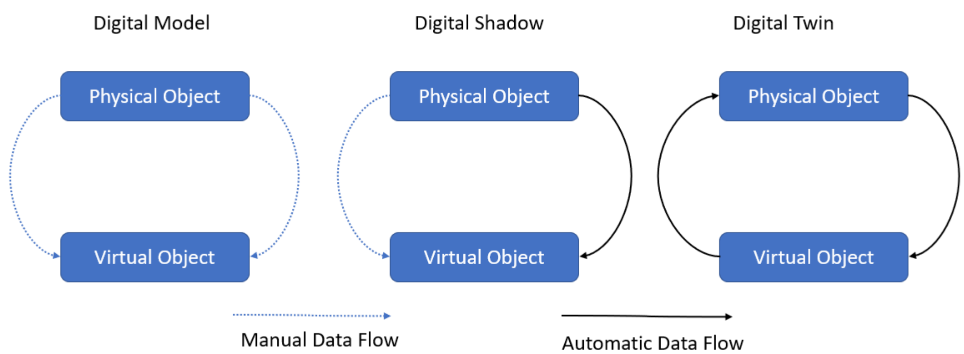

Figure 1.1. Digital Model, Shadow, and Twin. Modified and redrawn from Fuller et al. (2020).

It is important to differentiate digital twins from simulation software. Despite the fact that they share some capabilities to perform simulations, they are not the same. Digital Twin is more than a simulation software. Simulation software also uses computer aided design tools to produce digital models. However, they need to wait for the end-product or the finalization of a process to start modeling them. DT captures all the characteristics, behaviors, geometry, etc. of a physical object in a virtual model throughout its lifecycle. The DT uses IoT devices to capture real-time data that makes the simulation process automatic. It enables the user to see the live physical asset changes. As described before, the digital model becomes a digital twin due to the integration of IoT devices that creates a close loop between the physical and virtual objects. This link called Digital thread allows the integration of system components.

Digital twins find their niche and usability in several industries and organizations such as manufacturing, automotive, construction, health, agriculture, and so on. In terms of marketing, companies that develop digital twins sell it as a software solution. They market it as a software technology that brings many solutions to big companies that manage great quantities of data and have many processes. As for its application and suitability, most DT belong to manufacturing systems due to its complex system to produce raw materials into end-products. However, different industries started to implement DT because it offers solutions through predictions, and diagnostics. Most of the new industries that are using DT highlight it due to its simulation capability. Mature digital twins are present in the entire system's life cycle. They add value to organizations' business models. This makes possible the idea of more industries implementing and using DT in their entire business processes.

Governments are also adopting DT technology. For instance, the Centre for Digital Built Britain (CDBB) of the University of Cambridge designed the Gemini Principles as part of the United Kingdom (UK) Industrial Strategy planning. These principles show 9 guidelines to create DT for infrastructure in the UK. The goal is to integrate all DT around the country into a big national digital twin. This national digital twin is an ecosystem of digital twins connected via securely shared data (Bolton et al., 2018).

The creation of a national digital twin needs a refinement of requirements. Data is crucial for its development, but without management and security is useless and harmful. It is necessary to implement a set of principles and definitions to refine the requirements. These are broad definitions that every business or non-business sector could apply. Different stakeholders such as government, industry, academia, and so on created these principles called Gemini Principles. The first publication was in 2018 to help synchronize information management across different organizations. A framework with principles and definitions reduces the risk of sharing data to the environment. These principles provide strong values to guide organizations in this process. The goal is to ensure the creation of the national digital twin. Figure 1.2 presents the Gemini principles.

THE GEMINI PRINCIPLES

Purpose: Must have clear purpose	**Public good** Must be used to deliver genuine public benefit in perpetuity	**Value creation** Must enable value creation and performance improvement	**Insight** Must provide determinable insight into the built environment
Trust: Must be trustworthy	**Security** Must enable security and be secure itself	**Openness** Must be as open as possible	**Quality** Must be built on data of an appropriate quality
Function: Must function effectively	**Federation** Must be based on a standard connected environment	**Curation** Must have clear ownership, governance and regulation	**Evolution** Must be able to adapt as technology and society evolve

Figure 1.2. The Gemini Principles. Redrawn from Bolton et al. (2018).

As Figure 1.2 describes above, digital twins must have a clear purpose, must be trustworthy and must function effectively. The principles look simple but they have a deep connotation to apply it. They describe the goal but do not provide solutions. The CDBB wants organizations to innovate on the development of their DT. These principles will evolve along with new input from the different organizations part of the national digital twin.

DT presents several benefits to an organization. It increases the reliability and availability of a system. It manages a system by monitoring, simulating, and controlling. The idea is to improve the system performance. It reduces risks that are present in operations, employees, and the environment. It also helps to reduce the risk to achieve organizational goals. This is possible due to a reduction of incidents and downtimes in the system. Overall, this technology improves strategic planification. Moreover, it reduces operations and maintenance costs. DT can predict failure before it happens. It is capable of ordering parts and scheduling preventive or corrective maintenance. The best of all these benefits is that it does not affect the regular production of the system. Finally, it improves production performance and processes. It helps the system to produce quality products. DT provides the system with real time data of machines, products, and processes. This improves the customization of end-products and reduces failure along the supply chain (General Electric, 2021).

1.2 Problem Statement

Many researchers are studying digital transformation from different points of view. There is not an exact definition and method of how to conduct this transformation correctly. The problem of transforming a physical system to the digital world are the uncertainty and emergence behavior that this operation presents. It may bring problems such as loss of data, cybersecurity threats, unpredictable behavior, and so on. Other inquiries that digital transformation brings are the selection and use of tools and technologies, how to digitize the system processes and structure, and how to perform the integration of the physical and virtual spaces (Ziyadin et al., 2020).

Digital twin is a technology that can enable this digital transformation. However, there is uncertainty about the implementation and use of DT technology in production processes. Some companies still have doubts about the benefits of DT due to its novelty. Organizations are still testing and trying its impact in their daily activities. Other companies have not heard or known little about DT. There are also companies that do not have the infrastructure and means to implement it (Intelligent Software Engineering, 2020). According to Tommy Quek (2017), Digital Twins being part of the Internet of Things (IOT) present the following disadvantages: compatibility, complexity, privacy, safety and security, less employment, and dependability. It is important to clarify that these disadvantages may or may not happen to all systems that implement DT. Each DT model and domain technology has its own characteristics, behaviors, structure, and so on.

Nevertheless, performing a system’s digital transformation is not easy. It will face problems in the physical system such as silos block, and slow digital acceleration. These silos prevent the connection and flow of data of the system's components. On the other hand, digital twins connect data from different physical objects through the virtual space. It allows users to access the system's data of processes and products from any location in the world. Digital twin models are more than a computer-aided design. They look for the continuous communication between the virtual and physical space. This is possible through the identification and updating of a digital thread. The digital thread eases the creation of a system's digital twins. However, it presents emergent behavior such as the creation of new threads. The addition of threads creates a woven digital mesh that connects a system with other systems. The system can see the creation of new threads due to emergent behavior properties. This could be an advantage or disadvantage for the actual system.

Furthermore, it is not easy to perform the integration and synchronization of different system domains. This process could carry potential problems due to the uncertainty and risk of sharing essential information to the digital world. Hence, it is important to have a framework that assures a successful and secure digital transformation of manufacturing systems. The extension of this framework could contemplate the integration of the digital twin manufacturing system to other systems in a systems of systems (SoS) environment.

Consequently, the development of digital twin models needs a framework that supports the digital transformation of a manufacturing system in a secure and methodical way. This research gives a framework to create digital twin models of physical objects in a manufacturing system.

1.3 Research Questions

To address the problem statement, it is necessary to define the research questions. The answers to these questions give enough information to develop a digital twin implementation framework. This research intends to answer the following questions:

- How does a framework improve the creation of digital twin models in a manufacturing system?
- What are the processes to create digital twins of physical objects in a manufacturing system?
- What are the functionalities of digital twin models in manufacturing systems?
- What are the requirements, behavior, and structure of a digital twin manufacturing system?
- What tools/equipment/hardware/software are necessary to implement digital twins in a manufacturing system?

1.4 Research Hypothesis

The following hypothesis is based on the research questions lines above.

- A digital twin implementation framework can be defined that allows manufacturing systems to create digital twin models from their physical system.
    - Proposition: If factories apply the digital twin implementation framework, they will be able to create digital twin models.
    - Null Hypothesis: The proposed digital twin framework cannot allow factories to create digital twin models.

1.5 Research Objectives

The research objectives are the following:

- Developing a digital twin implementation framework that facilitates the creation of digital twin models in manufacturing systems.
- Defining the requirements, behavior, and structure of a digital twin manufacturing system.
- Deciding the processes to create digital twin models of physical objects in manufacturing systems.
- Deciding the functionalities of digital twin models in manufacturing systems.
- Deciding the tools/equipment/hardware/software necessary to implement digital twin models in manufacturing systems.
- Performing a verification process to certify the correctness of the framework.

1.6 Uniqueness of this Research

This research is unique in terms of scope and methodology. This research looks to study the meaning, characteristics, behaviors, and processes of digital twin models in manufacturing domains. This work develops a framework for digital twin implementation in manufacturing systems. There are few articles about the development of digital twins that focus on a specific use case. Some researchers describe the digital twin development for production, quality, or monitoring.

This research studies manufacturing from a high-level perspective. It studies the components, processes, requirements, structure, and subsystems working together as one single system. It studies the digital twin behavior and integration into a real manufacturing system. It uses systems thinking methods to study the development of digital twin models for the manufacturing sector. Systems thinking tools enrich the problem space and the solution space. Moreover, this work focuses on all manufacturing systems. It uses a holistic approach, considering and generalizing all types of manufacturing. Finally, this research presents a case study to verify the digital twin implementation framework.

Digital twins can help manufacturing companies to have a better understanding and perspective of the different business processes. Managing real time information will help factories create high-quality products, faster than competitors at a low-cost.

1.7 Research Contribution

This research presents several contributions to manufacturing systems in their attempt to transform their factories and be part of the digital world. This could motivate other researchers to study and develop digital twin models in manufacturing domains. The research contributions are the following:

- A systems thinking analysis to implement digital twins in manufacturing systems.
- A Model-Based Systems Engineering (MBSE) of a small-scale digital twin for manufacturing systems.
- A digital twin implementation framework to develop digital twin models of physical objects in manufacturing systems.
- The verification of the proposed small-scale digital twin implementation framework for manufacturing systems.

1.8 Dissertation Organization and Structure

This research presents the following structure. Chapter II presents the literature review of relevant topics for this dissertation. These topics are digital twin, digital thread, cyber-physical system, internet of things, manufacturing systems, and manufacturing systems as part of sociotechnical systems. Chapter III analyzes the implementation of a digital twin manufacturing system using a systems thinking approach. Chapter IV develops the digital twin implementation framework for manufacturing systems. This chapter shows the digital twin manufacturing system model in SysML. It shows the system's structure, behavior, and requirements. Chapter V presents the research verification of the digital twin implementation framework. It verifies the framework against the digital twin requirements. It shows the application of the proposed framework to the production of bolts. It develops a process digital twin simulation, analyzes the results, and gives key insights. Chapter VI presents the conclusions and future research. Finally, the summary of all references shows all the documents (journal articles, conferences, book sections, etc.) used in this doctoral research.

CHAPTER II - LITERATURE REVIEW

The literature review of the different topics is available in engineered magazines such as INSIGHT INCOSE and journal articles databases such as Scopus, Web of Science, and MDPI (Multidisciplinary Digital Publishing Institute). The topics presented in this literature review are digital twin, digital thread, cyber physical system, internet of things, framework, and manufacturing systems. This literature provides essential information to develop the DT implementation framework. Finally, the prospective data source will come from case studies in the literature review.

2.1 Digital Twin

2.1.1 Digital Twin Definition

According to Barricelli, et al. (2019), Digital Twins are computer-based models that simulate, mirror, emulate, or twin the behavior of a physical entity. A unique key identifies and links the DT with its physical twin. NASA claims “A Digital Twin is an integrated Multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin” (Glaessgen & Stargel, 2012).

IBM claims that "A digital twin is a virtual representation of an object or system that spans its lifecycle, is updated from real-time data, and uses simulation, machine learning and reasoning to help decision-making." In other words, DT is a highly complex virtual model that is 100% similar to a physical asset. Examples of physical things that a DT can resemble are cars, buildings, machines, engines, and so on. DT collects data through sensors implemented in the physical asset. This allows the creation of the virtual model that displays information of the physical thing in real time (Armstrong, 2020).

The Digital Twin Consortium proposed a DT definition for future purposes in 2020. It suggests that "A digital twin is a virtual representation of real-world entities and processes, synchronized at a specified frequency and fidelity." DT gives a holistic understanding of a system. It uses Internet of Things (IoT) devices and use cases to integrate different system components. It helps to transform and improve system processes to make better decisions. It uses current and historical data for simulations. The main goal is to improve the desired results of the system of interest (Object Management Group, 2021).

Table 2.1 gives other definitions of DT from different companies and sectors around the world. Most of these definitions fall into three categories such as modelling of systems or components, modelling assets across organization, and modelling processes and behaviors. Some of these companies think DT supports a 3D modelling simulation. Other companies think DT are just dashboards that show information about the physical object in real time (Slingshot Simulations, 2021).

Table 2.1. Some digital twin definitions.

	Sector	Digital Twin Definition
Boeing	Aerospace	An ultra-high-fidelity simulation that is a virtual working model of highly complex systems and components.
CDBB	Academia	A realistic digital representation of something physical.
Dassault Systémes	3D Simulation Software	A "Virtual Twin" is a virtual representation of what has been produced. We can compare a Virtual Twin to its engineering design to better understand what was produced versus what was designed, tightening the loop between design and execution.
Deloitte	Consulting	A near-real-time digital image of a physical object or process that helps optimize business performance.
General Electric	Multi-national conglomerate	A living model that drives a business outcome.
Microsoft	Software	A virtual model of a process, product, production asset or service. Sensor-enabled and IoT connected machines and devices, combined with machine learning and advanced analytics, can be used to view the device's state in real-time. When combined with both 2D and 3D design information, a digital twin can visualize the physical world and provide a method to simulate electronic, mechanical, and combined system outcomes
Siemens	Multi-national conglomerate	A virtual representation of a physical product or process, used to understand and predict the physical counterpart's performance characteristics.

Note. Reprinted from What are Digital Twins? By Slingshot Simulations, 2021, (https://www.slingshotsimulations.co.uk/news/digital-twins/what-are-digital-twins/).

Microsoft also agrees that IoT helps businesses to manage their assets better. Due to digitalization of businesses, companies are competing with each other to optimize their processes. DT could help to create models of their entire environment. This will give companies the ability to create better products, improve production, reduce overall costs, and improve customer needs. There are several examples of DT implementation in different sectors such as buildings, factories, farms, energy networks, railways, stadiums, and even entire cities.

It is important to consider the contribution of DT in manufacturing assets, people, factories, and production networks. DT models manufacturing assets and connect each other in the virtual world. It gives users a complete picture of their factory with real-time data. The benefits are the improvement of decision making, resilience and flexible operation and customization of products. DT helps people to perform their activities. It is also a means of communication between workers. Furthermore, it is possible to include virtual models of people that gather their characteristics and behaviors. Production Planning will be easier with current and reliable data. Even though some people do not consider this relevant, the understanding of human states can increase factory productivity. Virtual training is one example of the use of DT with people. Workers can have personalized practice sessions before working in the real factory. This application will improve the use of resources and the technical worker skills. Another contribution is the well-known DT capability of mirroring entire factories to create a live virtual replica. This capability gives factories the possibility to organize and plan automatically. It connects the factory with other systems in the supply chain tracking product through its lifecycle. Some upsides are the identification of failures, the production analysis, requirement of resources prediction, preventive maintenance. Finally, DT could connect the factory, people, and assets to a bigger network to make businesses. DT contributes to production networks using Big Data. This gives an advantage to factories to predict and test potential business ideas (Lu et al., 2020).

2.1.2 Digital Twin Framework in Manufacturing

There are some frameworks and architectural models in the literature review that describe the implementation of digital twin technology in manufacturing environments. These articles present different frameworks and architectural models based on scope, functionality, concepts, and attributes.

Zhuang et al. (2018) elaborated a framework to create digital twins for the management and control of production in a smart shop floor. Specifically, they created a framework for the assembly of satellites. The framework presents four parts. The first part is the physical assembly shop floor which shows all the physical objects. The second part is the assembly shop floor digital twin which transforms the physical assembly shop floor into a digital format. The shop floor digital twin allows workers to control and track the production processes in real time. It also helps perform simulations and analysis of the production activities. The third part is the assembly shop floor big data storage and management platform. This platform sets up bi-directional communication between the physical shop floor and digital twin. Finally, the last part is the digital twin and big data-driven assembly shop floor service/application platform. This platform gives functionalities to the DT such as monitoring, prediction, and optimization of the different production processes through the application of technologies. These technologies follow the functional and target requirements of the production management and control service platform, and the prediction service platform. The last two platforms are part of the digital twin and big data-driven assembly shop floor service/application platform.

Alam & El Saddik (2017) developed a Cloud-Based Cyber-Physical System Architecture (C2PS). They assume that several independent systems connect each other to achieve a major goal through an omnipresent communication network. This architecture model presents five layers: physical things, cyber things, peer-to-peer relation, intelligent service, and system usage and administration. The physical things have a digital twin or cyber things counterpart with a unique identification number. This ID number could be the IPv6, or a Universal Product Code (UPC), for instance. Cyber things are in the cloud which allow them and the physical things to store data. Sensors in the physical things layer update the cyber things to show the current state of physical things. The Intelligent Service or Middleware layer allows users to control the access to data collected by sensors. The peer-to-peer relation layer allows the creation of communication groups between the different physical things. The creation of these networking groups is based on the users' communication criteria. The Intelligent Service layer is where the digital twins, the peer-to-peer relations, and ontologies come together to create services. These services send data to the last layer, the system administration and usage. This layer supports many services such as data consumption, data visualization, service manager, and service integrator.

Zhang and Zhu (2019) developed a framework for the smart manufacturing of products using digital twin technology. This framework has four main layers: physical layer, model layer, system layer, and information processing layer. The physical layer contains the physical objects such as machines, tools, equipment to gather data, and so on. These objects receive and send data from manufacturing activities in the physical shop floor. This layer integrates all the physical objects which are around the shop floor. It creates an IoT network to perform processes, collect and pre-process data through different modules: control execution, perception, and network. The model layer has the digital twins of the physical entities, production processes, activities, and so on in cyberspace. A model-based definition technology creates the DT models. The DT models characteristics are interaction, computing, and control. They allow the simulation and analysis of physical objects in cyberspace. They allow users to control physical objects using a machining database and knowledge database from the information processing layer. The information processing layer holds information such as the digital twin data, manufacturing service, and product service. It allows communication between the physical and model layer. The system layer presents the manufacturing service platform and digital twin application subsystem. The manufacturing service platform encompasses functions such as SCM, CRM, ERP, MES, DCS, PLM, and PDM. The DT application subsystem presents functions to control the physical and model layer tasks.

2.2 Digital Thread

Digital Thread was born from the need of digital disruption to connect data from different areas and processes in complex systems. This is a framework that allows communication between the several areas of a company that are compared as silos. These silos do not share information outside of its boundaries. Therefore, digital thread looks to integrate all these silos throughout the system’s life cycle. It is a strategy to improve the communication in the different areas of the system (Hedberg et al., 2016).

It is part of the digital twin along with connected products and the IoT. It helps to connect the digital twin with the physical system and allows the exchange of data between these two. It provides data traceability in all phases of the system life cycle. Moreover, digital thread allows the integration of digital twin to Model Based Systems Engineering (MBSE) methodology. This thread will facilitate the modelling of a digital twin. It also helps to share data from one source to another. Digital twin and digital thread can accelerate the digital transformation of complex systems (A. Madni et al., 2019).

A digital thread presents the framework to connect data flows and produce a holistic view of an asset's data across its product lifecycle. Digital thread represents the lowest level design of a physical item into the digital world. It is part of the model-based systems engineering (MBSE). It helps in the creation and traceability of a digital twin. This term is capable of tracing the digital twin to the requirements and physical objects (Leiva, 2016).

According to Lang (2019), the final goal of digital thread is to facilitate the access and use of data in a system. It creates a unit that communicates with internal processes and the environment continuously. A system can create digital threads of different processes and products. For instance, the digital thread of a product goes over all the product life cycle phases. As a property of complex systems, digital thread also shows emergence threads due to new processes and influences from the environment.

Taber et al. (2020) states that the goals of digital threads are managing data, avoiding productivity bottlenecks, promoting collaboration between systems, increasing market agility, and adding business value to the organization. The implementation of digital threat requires a strategy to achieve the objectives mentioned before in four steps. The first one is to define digital thread use cases in the organization. This step looks to identify potential use cases related to digital thread. It will help decide on future technology and evaluate suppliers for future business opportunities. The second one is to categorize use cases according to their business added value. Use cases link data of the different system's components quickly in a cost-effective way. Use cases, customers' value, and requirements will help define business goals. The third one is to perform an audit to find critical data. This is an internal audit of the digital system. It will help the system identify available data, type of data, usable data, and so on that influence digital thread use cases. The last step is to show the importance of digital thread and expand its implementation to the rest of the organization. This step looks to validate use cases to demonstrate its importance with measurable value and ROI. This will help the system to continue developing existing and new digital thread use cases. However, the system will have to make some changes such as integrating people and data and adding new functions and roles. The system expects the thread to grow with more stakeholders, and behaviors in the digital space.

Digital thread presents benefits in five main categories based on products, processes and people. The main categories are engineering excellence, manufacturing efficiency, product and service innovation, service optimization, and sales and marketing experience. Engineering excellence encompasses quality improvement, reduction of work failures, and development of new products. Manufacturing efficiency looks to improve production efficiency and effectiveness, reduce production time, and improve productivity. Product and service innovation focus on customer satisfaction, and revenue-based business models. Service optimization intends to solve problems on time and give better technical solutions. Finally, sales and marketing experience can increase product sales, and better inform customers about products (Taber et al., 2020).

Digital thread allows the development of digital twins by connecting product or processes data with graphical objects. It also provides digital twins with several functionalities such as the prediction of maintenance and services. It connects data from all stages of the product life cycle ensuring its functionality and updating. All these give the system a holistic perspective to manage and analyze data. Hence, digital thread is a key element to develop a digital twin. Digital thread being part of complex systems grow fast due to new technologies. This expansion creates a woven of different processes, functions, and products. Moreover, a digital thread can relate to other digital threads creating a digital fabric. Nowadays, this happens in a globalized world that interconnects systems with other systems. Digital fabric or mesh will enable physical systems to create new digital experiences (Lang, 2019).

There are examples in industry that need a digital thread to perform their functions. One example is Additive Manufacturing (AM) that requires the integration of all stakeholders to share and access data in real time. It also helps in the design of automated systems and to differentiate the several stakeholders and subsystems. Digital tread implements a traceability from the system requirements to the design, production, distribution, and disposal stage. Bonham et al. design and integrate digital thread to AM to improve the communication and relationship of the stakeholders (Bonham et al., 2020).

2.3 Cyber Physical System (CPS)

The concept of CPS started in 2006 by Helen Gill. Tao et al. (2019) describes it as a complex system that increases constantly. That is why common IT concepts cannot define CPS easily. The implementation of CPS or DT requires sensors and actuators to allow data and control interaction between the physical and digital space. Nowadays, the implementation of CPS in factories is in pilot stages. Most research about CPS is theoretical and looks to satisfy more scientific inquiries than engineering practices. There are few cases of CPS in the real world. However, countries such as the U.S. and Germany consider CPS as a crucial concept to improve the current manufacturing industry and as a pillar of the new industrial revolution or Industry 4.0.

To Yang et al., CPS are the interaction between physical, digital processes and the environment. This interaction enables the system to work with other systems, subsystems, and components in real time. It uses data and modern IT to produce smart products. The authors suggest digital twin is part of the CPS because it gives capabilities to the physical and cyber space due to data twinning. One capability is the remote use of machines with software, sensors, and actuators. Another capability is the simulation and optimization of processes in the cyber world. All these bring systems fidelity, safety, and predictability to perform activities at a low cost. Yang et al. article cites other authors that collaborate in the development of CPS. Some authors define five architectural levels for CPS. These architectural levels are connection, conversion, cyber, cognition, and configure. Other articles present a framework to develop CPS with digital twin as the crucial point for managing and sharing data between the two spaces. Figure 2.1 shows this type of architectural framework of CPS. Finally, other articles study the digital twin capability to acquire data in a CPS (Yang et al., 2017).

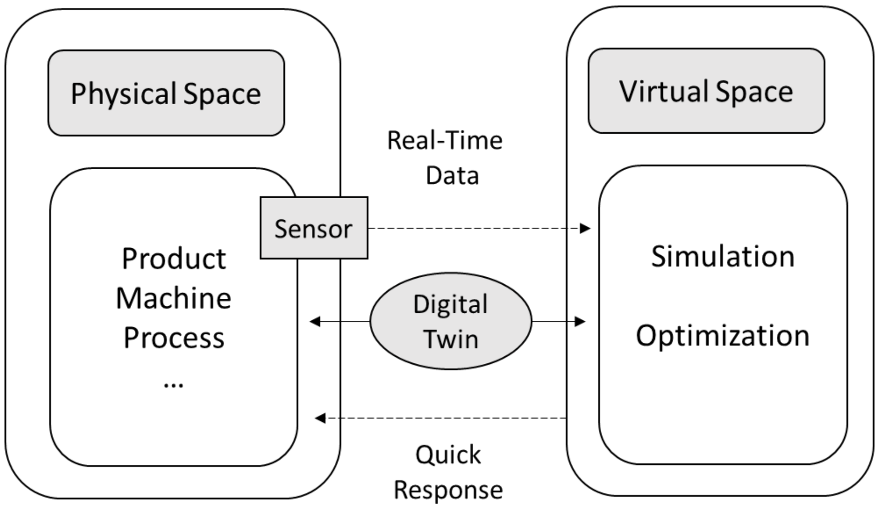

Figure 2.1. Composition and the modelling framework of the CPS. Modified and redrawn from Yang et al. (2017).

Another journal article made by Lee and Seshia (2011) explains that CPS was born from the concept of embedded systems. These systems have strongly connected software and physical processes to develop work in real time. The author describes CPS as the group of IT devices connected to the physical system to manage data. This connection between the physical and digital world is not a union of worlds such as the digital twin. However, it forms an interaction between them. It looks to monitor, control, and integrate the system operations with the collection of several software applications related to each IT device.

Lee and Seshia also present five maturity CPS levels that go from basic to complex. These levels are setting basics, creating transparency, increasing understanding, improving decision making, and self-optimizing. The first level establishes the general conditions for the implementation of CPS. The next level focuses on the generation of information. The increasing understanding level looks to process the generated information. The fourth level analyzes and links information in the system. Finally, the self-optimizing level decides the maturity of a system to use and manage knowledge. At this point, the system solves problems by itself. Hence, it is called a cyber-physical system.

According to Tao et al. (2019), cyber-physical systems and digital twins share many commonalities such as the integration of the physical world to the digital world. Both have the same goal of managing and improving the physical system from the cyber world. They are complex systems that make analysis in real time. They nurture the main system with feedback and present dynamic controls. However, CPS relies on the combination and interdependency work of embedded systems. CPS uses computing, communication, and control to perform its functionalities efficiently. Moreover, there are some differences between CPS and DT. One is that CPS is more oriented to scientific research and DT has more practical uses in engineering. Another difference is that the DT and the physical system present a one-to-one communication flow. CPS presents a one-to-many communication flow. The physical system communicates to other many embedded systems. The next difference is on the principal elements that make both concepts possible. DT presents models and data as main components. The main elements of a CPS are sensors and actuators that allow other embedded systems to work. Moreover, CPS and DT have different components in each system level which are unit, system, and system of systems.

Digital Twin is an example of a Cyber-physical system (CPS). Gunes, V. et al. (2014) describes CPS implementation challenges related to their attributes. These challenges are interoperability, security, dependability, sustainability, reliability, and predictability. Interoperability refers to the challenge of systems to work together. This is necessary to exchange information and perform functionalities. Interoperability's attributes are composability, scalability, and heterogeneity. The next challenge is security. This allows the safety interaction of a system with other systems. It gives users access to the various parts of a system. It protects the unauthorized release of crucial information. Security's attributes are integrity, confidentiality, and availability. The implementation of CPS should consider the dependability of many components to others without affecting its operations. Dependability is necessary to perform certain functionalities and achieve an outcome. It presents reliability, maintainability, availability, and safety as attributes. Sustainability demands CPS to use resources wisely and preserve them over time. It looks to create robust systems that do not compromise its requirements to operate. It presents the following attributes: adaptability, resilience, reconfigurability, and efficiency. Another CPS challenge is reliability. The attributes for this challenge are robustness, predictability, and maintainability. Reliability analyzes the way systems perform their functions. It is the degree of correctness in a system activity. Finally, predictability challenges a system to predict and achieve an outcome according to the system requirements. These challenges present the following attributes: accuracy and compositionality. Figure 2.2 shows the association of CPS challenges with their attributes.

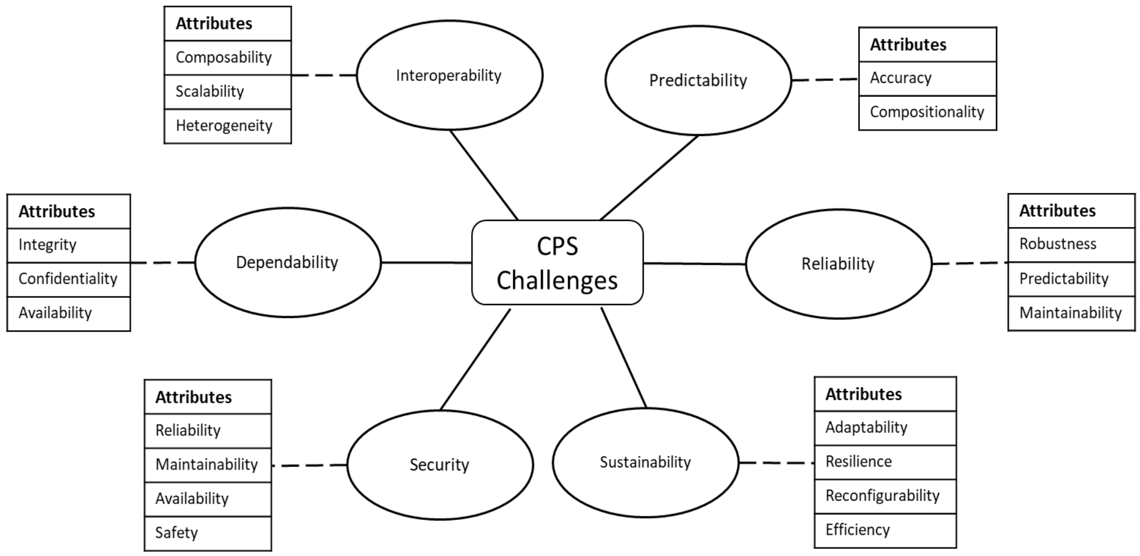

Figure 2.2. Cyber-Physical System Challenges. Modified and redrawn from Gunes et al. (2014).

2.4 Internet of Things

Internet of Things (IoT) is the collection of physical devices embedded by sensors, actuators, software, and other technologies over the Internet or another network. These devices communicate with each other sending and receiving data (Lin et al., 2017). In manufacturing, companies use the term Industrial Internet of Things (IIoT) which is the connection of industrial things through the web. IIoT gives factories the possibility to improve the business performance by modelling, monitoring, and controlling business processes (Lade et al., 2017).

The IoT presents the following characteristics: interconnectivity, smart sensing, intelligence, saving energy, expressing, and safety. The IoT systems must connect different devices in one central environment. It also has smart sensing capabilities to control devices in the physical space. It must be intelligent to learn and improve its capabilities. This is important to manage devices and distribute tasks. It must save and use power energy efficiently to control all devices connected to the IoT system. It must communicate the current state of a particular device to all devices around it. It facilitates the communication between machines and people. Finally, it must be safe to operate. It must protect people that use the devices by communicating the state of machines or preventing devices from being used if they are not in a good condition (S. Singh & Singh, 2016).

IIoT presents distinctive characteristics that come with several challenges. These challenges are complexity, heterogeneity, resource constraints, poor interoperability, security vulnerability, and privacy vulnerability. The IIoT architecture is complex because it uses different devices with several transmission protocols such as Bluetooth, NFC, LoRa, Sigfox, and so on. All these present different transmission coverage range. The IIoT architecture uses heterogeneous devices, types of data, and communication protocols. This heterogeneity brings more problems such as confidentiality, safety, and interoperability. Moreover, IIoT must overcome resource constraints. It must deal with limited battery energy, storage, computing capabilities, and so on. These constraints lead to security breaches in the IIoT architecture. Another challenge is the poor interoperability due to the heterogeneity of IIoT systems. This challenge makes it difficult to share data between systems. The next challenge of IIoT is the security vulnerability. The resource constraints prevent implementation of encryption, decryption, authentication methodologies, for instance. The last challenge is the privacy vulnerability. The IIoT system must protect the operational data of all devices. This is a challenge due to the complexity, heterogeneity, and decentralization of IIoT systems (Kumar et al., 2021). Nevertheless, recent advances in communication and information technology overcame some of these challenges. Now, it is possible that IIoT systems get more power and better computing capabilities. Recent works use blockchain along with IIoT systems to improve it and reduce these challenges (Zheng et al., 2017).

Lin et al. describes an IoT architecture model with three layers: application layer, network layer, and perception layer. The perception or sensor layer goes at the bottom of the IoT architecture. This layer groups different devices into the IoT network through sensors, actuators, etc. It collects, processes, and evaluates data from physical objects. Then, it sends the processed data to the application layer through the network layer. The next layer is the network or transmission layer. This is the middle layer that allows the continuous communication between the perception and application layer. It gets the physical devices data from the perception layer and decides to which application sends it in the IoT system. It allows communication between different physical components and applications. It is an important layer because it integrates heterogeneous components, applications, communication technologies and protocols in the IoT network. The top layer in the IoT architecture is the application or business layer. This layer uses the data from the network layer to perform tasks in the IoT system. Applications are based on the system requirements. This could be the data storage in a database or the data analysis to predict outcomes in the IoT system (2017).

2.5 Manufacturing Systems

Manufacturing systems (MS) are the combination of different components such as actors, tools, machines, and processes to transform raw materials into final products. Anbumalar (2014) presents four classic types of manufacturing systems such as job shop, flow shop, project shop, and continuous process. It is relevant to define measurable parameters to meet MS goals. These parameters are production rate, work in process inventory, percentage of defects, percentage on time delivery, production volume, and total cost. Figure 2.3 shows the typical function of a manufacturing system in general. When facing problems, the ideal MS should adjust itself to continue working properly.

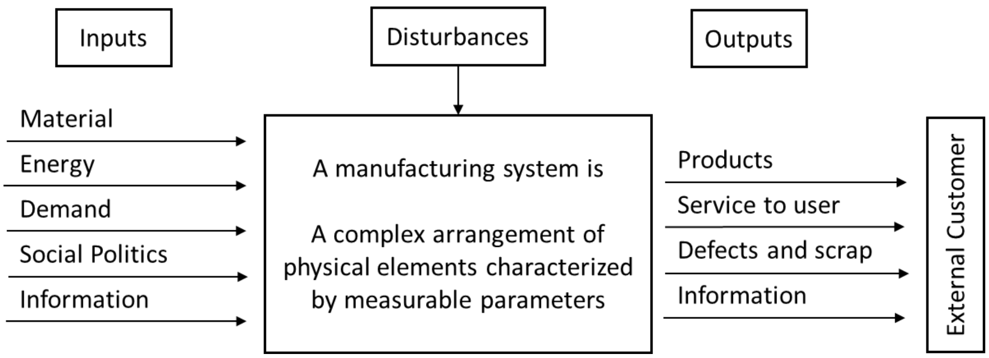

Figure 2.3. General definitions for any manufacturing system. Redrawn from Anbumalar (2014).

McCarthy et al. (2000) think that MS are complex adaptive systems that mix different elements working together for a common goal, transforming materials into a final product. The properties that distinguish a manufacturing system are assemblage, relationship, objectives, and adaptive. MS assemblage refers to the different components of a system, such as people, machines, information, sub-systems, and so on. The relationship is the connection between the components to get a result, the final product. The objectives are the results that the system wants to achieve. These goals should not be contradictory between each other. On the contrary, they should work together to meet them all. Some common objectives in MS are the product specifications, quality process and product, manufacturing time, and cost. Finally, the adaptive property is the condition that makes a system flexible to changes in its surrounding environment.

According to J.T. Black (2006), manufacturing is the activity to transform inputs, adding value to the raw materials, into an output product. The different processes are interconnected and linked to each other forming a system. MS needs another system, a production system, to perform other functions than manufacturing and send the product or service or both to the final customer. These functions are the design, analysis and control of business operations to meet the final goal, getting money. Manufacturing systems is a subsystem of a production system. MS have experienced evolution over time because of complexity. These systems present many parts to make a prediction and a few to forecast statistically. The number of activities, processes, components include in the system make it unpredictable and uncertain presenting emergent behaviors.

Moreover, MS has experienced changes in the system's architectural methods with focus on world-wide manufacturing. Factories that want to be more competitive in a globalized world must address innovations in finance, resources, technology, communication, and so on. These changes lead to modern approaches in MS that are ultra-quality systems, dynamic manufacturing, lean production and flexible manufacturing. All these changes have proved benefits, such as increasing profit and reduction of manufacturing costs (Rechtin & Maier, 2000).

Ultra-quality systems refer to the cost of quality adhere to manufacturing. There are two perspectives, the first one is the quality present in features that customers perceive as value added. The second one is the quality present in the absence of defects that avoid extra cost in maintenance, inventory, warranty, and so on. It gives confidence to customers and sellers that the product will not cause problems, but it has a cost. The system becomes more complex because there are more agents, methods, machines interacting. To keep quality in the system, one technique is the notion that everyone in the factory's processes is a seller and customer at the same time. Another is the five whys which helps to find the basic cause of a problem. These techniques aim to prevent a system failure, a combination of subsystems defects, at the same time.

Dynamic manufacturing systems are the configuration from static to real time dynamic systems. There are two design approaches, intersecting waterfall, and feedback systems. Intersecting waterfalls explains the intersection between the product's design and business processes in manufacturing. The feedback system suggests the idea of using feedback information to solve problems. These systems are non-linear and present features such as, higher risk than linear ones, changes can result in chaotic behavior, and different systems present different behavior and results.

Lean production is a mix between ultra-quality and dynamic feedback systems. It aims to be less complex than mass production, focusing on minimum waste. Waste are all the processes, activities, materials that do not add value to the MS. Transforming the mass production system into lean manufacturing involves more than just getting rid of the resources, inventory, documents, and processes. It requires a change in the system design to value distinct characteristics and interrelationships in lean manufacturing. The benefits are less delivery times, less manufacturing costs, and better quality.

Flexible manufacturing allows the system to produce distinct products on the same production line. In the past, this method was expensive for the system because it involved more resources, processes, and technology. Now, it focuses on one basic platform and many modules that add different values to products. This type of production is unique for each customer and works according to the demand that prefers more products than reliable and durable products over time. One example is the production of cellphones that releases more models every year than more units of one single model.

2.5.1 Manufacturing Systems as Part of Sociotechnical Systems

In McDermott et al. (2013) article, the author discusses the modelling of STS to solve problems. It is important to consider STS, such as Manufacturing Systems, as a complex adaptive system. This theory suggests that not all systems can decompose and recompose hierarchically to solve problems and create solutions. There are complex adaptive systems that consider hidden information, and interactions that create new behaviors. Manufacturing systems manage a lot of information and data that sometimes are not visible and create conflict to the processes. The interaction between the components creates emergent behaviors. Also, the level of complexity is so high that there may be no one in charge. In manufacturing, it means that engineers can only influence the entire system by managing their own departments. No one can manage all the interactions and processes between humans and machines. That is why MS presents complex adaptive systems characteristics. These characteristics are nonlinear, dynamic, random, chaotic, and out of equilibrium's point. They have agents independent from the system's dynamics. Each agent has their own purpose that results in a conflict of interest. The agents learn from experience to adapt to the system creating emergent behaviors. Finally, the most important characteristic is that no one can control the system, only influence it. Hence, it is unpredictable and uncontrollable.

According to complex systems theory, MS presents the following characteristics: agents, schemas, and predictions. Manufacturing agents are all the entities that interact with the system and produce a result. Manufacturing schemas are the defined interactions between the agents. These schemas are constraints applied to single agents or groups of agents. Manufacturing prediction is the attempt to foresee the future of the system with actual data. This prediction employs diagnostic, and analytical processes (McCarthy et al., 2000). Figure 2.4 shows an example of complex adaptive systems.

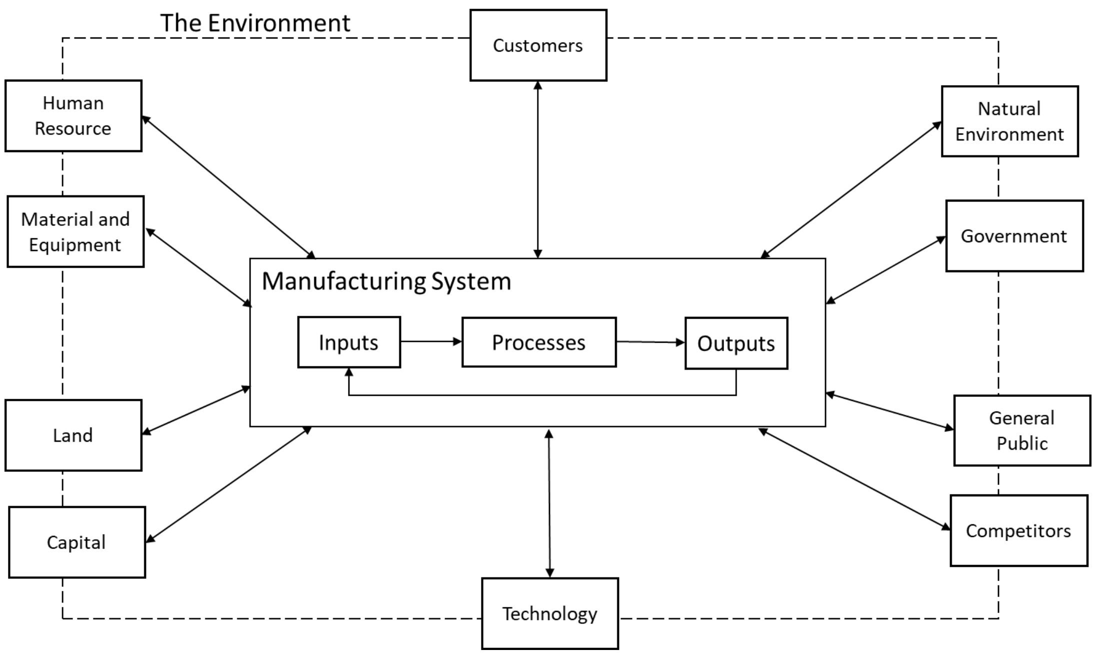

Figure 2.4. Manufacturing organizations as open systems. Modified and redrawn from McCarthy et al. (McCarthy et al., 2000).

Manufacturing systems are STS because of their complexity. They present the following complex systems properties. MS are open systems because of their interaction with the environment. As discussed in the earlier paragraph, MS are non-linear presenting more options, solutions, and consequences. MS is rich in components and interactions.

They also may work with small continuous energy, far from equilibrium. MS shows emergent behavior that changes between stable and unstable depending on the system's need. They show indirect and distributed information around the internal system. MS may use new or standard solutions because of uncertainty. MS components are easy to find but understanding their parts is useless. Finally, MS are the result of their past with complex interactions that are changing over time (Righi et al., 2012).

MS are an organized complex system because they have a complex model and a robust behavior. The MS performance requirements are the same as an STS. Manufacturing systems present boundaries of security and extendibility that allow the input of other systems or restrict the entrance of non-welcome elements. The reliability of MS controls the internal structure and oversees the operations to minimize failures. The flexibility encourages MS to change and adapt to an unfamiliar environment. The functionality requirement in MS is present in the use of resources to increase system effectors. The usability reduces system effectors in favor of the user. Finally, system receptors enable the system to communicate at all or at a certain level with other systems. This is part of the user's privacy and connectivity requirement of the MS. These requirements make MS complex and full of different behaviors.

CHAPTER III – ARTICLE 1: ANALYZING THE IMPLEMENTATION OF A DIGITAL TWIN MANUFACTURING SYSTEM: USING A SYSTEMS THINKING APPROACH[1]

3.1 Abstract

Digital twin (DT) is a technology that promises great benefits for the manufacturing industry. Nevertheless, DT implementation presents many challenges. This article looks to understand and study the problems associated with the implementation of DT models in a manufacturing domain. It applies systems thinking techniques to analyze and refine these problems. Systems thinking presents several methods and tools that help in studying a problem space and a solution space. The conceptagon framework describes the DT model as a system with several attributes and analyzes it in detail. A systemigram shows the relationship of manufacturing systems and the DT model. It maps the processes and components for DT implementation. The TRIZ method analyzes, and forecasts problems related to DT development and provides solutions based on patterns of invention. The CATWOE analysis allows identification of stakeholders and the study of the DT model from their perspectives. It provides a root

definition of the DT model to refine a problem and the problem's contradiction. The 9 windows tool helps to delimit the DT implementation problem, based on time and space. It gives eight more perspectives to solve the DT problem. Finally, the ideal final result (IFR) method provides the ideal DT model concept for manufacturing systems.

3.2 Background

Manufacturing systems have changed over the last decades due to user demands. The changes were due to rapid technological advances, more complex systems, and changing customer needs. Hence, manufacturing systems must be flexible, reliable, and focused on the user's customization. These changes brought new opportunities for businesses, but there is uncertainty about the implementation and use of modern technologies. One of these technologies is the digital twin (DT) method, which transforms physical spaces into virtual spaces. However, this digital transformation could bring more problems and affect a manufacturing system's life cycle (Ziyadin et al., 2020).

A digital twin (DT) is a virtual representation of a physical asset that is virtually indistinguishable from its physical counterpart. It includes design and engineering details that describe the asset's geometry, materials, components, and behavior or performance. In other words, it is the digital counterpart of a physical entity. DT is a model that shows the virtual and physical space of a system. The system uses sensors, actuators, controllers, and interaction models to integrate the physical and virtual space into one single system. The model's process connects data and information between the physical and virtual spaces. DT uses conceptualization, comparison, and collaboration tools to solve problems and to innovate. It can simulate and optimize three areas of a manufacturing system: production planning and control, maintenance, and layout planning (Trauer et al., 2020).

The digital twin method is relevant for factories in staying at the forefront of the next industrial revolution, Industry 4.0. It is a duplicate, backup copy of a system of interest. It provides digital solutions for manufacturing companies. These solutions will add business value to their processes and products. These companies will be able to simulate current and future processes and make better decisions. DT digitalizes the system, its process, and products. The DT advantages are operational improvement, quick development of products, fewer defects, easy access to data, and the creation of new businesses (Parrott & Warshaw, 2017).

The implementation of DT adds several values for businesses, in terms of quality, warranty, costs and services, operational costs, record retention and serialization, new product introduction costs and lead times, and revenue growth opportunities. Moreover, DT presents diverse models based on a system's maturity and complexity, such as digital visualization, digital development, digital twin enterprise, digital twin ecosystem, and digital twin orchestration. These models go from low-level maturity to high-level-maturity. Digital twin intends to provide real time images of objects, processes, and information. These images can add important value in improving business performance. The development of digital twins uses knowledge of information technology and operations technology to model business processes and fulfill business functions.

Nevertheless, there are many challenges in implementing DT in a manufacturing system. One challenge is the connection and integration of all Internet of Things (IoT) devices, machines, and objects. These connections allow data-sharing among physical and virtual spaces. It is also important to consider that DT works with real-time data, without requiring human-to-human interaction. Moreover, DT operations must be autonomous. Overcoming these challenges establish big milestones in the creation of digital twins. Moreover, costs and time are always challenging for new and big projects. The time and resources needed to carry out this work could be enormous. It is difficult to estimate the cost of implementing DT, due to its variety. Complex systems require a huge investment for developing and operating DT technology (Anderton, 2020).

3.2.1 Specific Contribution

This section focuses on studying the ambiguity of some problems with the DT concept and its implementation. There are problems related to the DT definition and/or the development of DT models in a manufacturing domain (Fuller et al., 2020). It is necessary to define, characterize, and describe the DT concept for manufacturing systems.

Previous articles have considered the use of systems theory or science to define digital twin technology. All of them supported DT and presented the benefits of implementing DT in manufacturing domains. Nevertheless, they presented different purposes and scopes of study. Mandi et al. (A. Madni et al., 2019) studied the integration of DT into model-based systems engineering (MBSE). They characterized different DT levels based on model sophistication. Bianconi et al. (Bianconi et al., 2020) used systems thinking principles to study the DT definitions in the literature. They presented a methodological reference that could help researchers propose a new DT definition. Dietz and Pernul (Dietz & Pernul, 2020) used a system-of-systems approach to describe DT technology. They presented future applications of DT in different fields, DT capabilities, and challenges from a business perspective.

This article analyzes the digital twin concept and its implementation in manufacturing systems through the application of systems thinking methods and tools. System thinking allows the DT implementation problem refinement, and the discovery of potential solutions. This is possible through the development of conceptual models that help define and refine a problem space. Moreover, system thinking provides tools to discover and explore a solution space. These tools include the conceptagon, the systemigram, and the theory of inventive problem solving (the TRIZ method, according to its Russian acronym) to study the DT implementation problem and its potential solutions. Systems thinking also uses the CATWOE analysis to define the DT problem from the stakeholder's perspective. The "CATWOE" mnemonic stands for Customer, Actor, Transformation, Worldview, Owner, and Environment. The CATWOE analysis uses the 9 windows tool to study the DT implementation problem, based on time and space. Finally, it uses the ideal final result (IFR) tool to propose the best practical solution for creating an exact digital twin of a manufacturing system. Each of these methods analyzes the implementation of a digital twin manufacturing using a systems approach.

3.2.2 Limitations

This study was limited in terms of scope and methodology. First, it used only a few systems thinking methods to study the idea of developing DT models for the manufacturing sector. Using more systems thinking tools would enrich the problem space and the solution space. Second, this work focused on all manufacturing systems. It used a holistic approach, considering and generalizing all types of manufacturing. Third, it studied the problem and solution spaces associated with DT implementation in manufacturing systems. It structured and analyzed these problems and proposed some potential solutions. It did not proceed further to solve these problems. This study did not present a particular case study or solution.

Finally, this paper studied the research problem from the managers' perspectives. It did not consider other points of view. Overall, this article is a good initial step in working on DT models for manufacturing domains. This study suggests further research to develop a framework for DT implementation in manufacturing systems. Also, it requires further research to study DT behavior and integration into a real system.

This article follows the following structure. Section 3.3 presents a literature review, including the most relevant topics for the development of this article. Section 3.4 sets out the systems thinking methods for analyzing the implementation of a digital twin model in a manufacturing domain. Section 3.5 presents a discussion of the results from the analysis performed with respect to the digital twin model. Section 3.6 presents the conclusions and proposes future research of digital twin technology in manufacturing systems.

3.3 Literature Review

This section discusses the most relevant topics related to this article's methodology.

3.3.1 Digital Twin

A digital twin is a virtual representation of a physical asset that is virtually indistinguishable from its physical counterpart. It includes design and engineering details that describe the asset's geometry, materials, components, and behavior or performance (Brennen & Kreiss, 2016). Dr. Grieves created the concept of digital twins in 2002 at the University of Michigan. However, at that time it was a concept without a name. In 2005, Dr. Grieves named it the mirroring spaces model (MSM), but the name changed again in 2006 to the information mirroring model. Finally, John Vickers of NASA named it digital twin in 2011. Despite the several names, the model and the basic concept have not changed (M. Grieves, 2014). Figure 3.1 shows a DT of a physical asset.

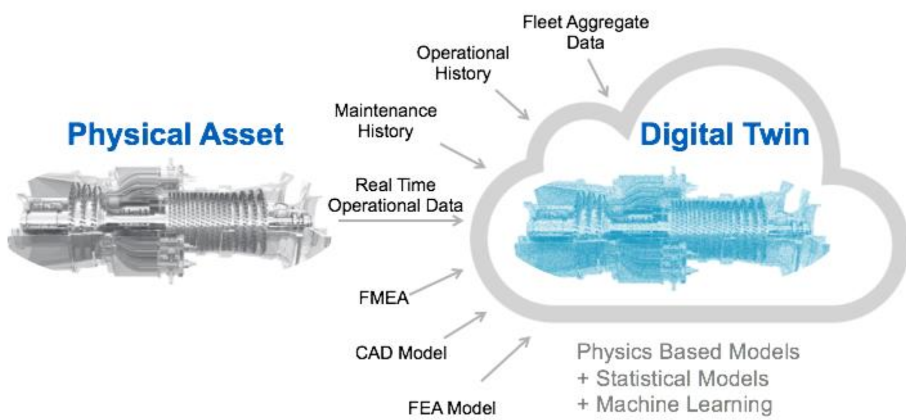

Figure 3.1. Digital Twin Model of a Physical Asset. Redrawn from Ibrahim et al. (2022)

Big companies like Microsoft Azure define DT as "a digital replica of real-world things, places, business processes, and people. A digital twin is designed to understand, control, simulate, analyze, and improve real-world business operations. Azure Digital

Twins is an Internet of Things (IoT) platform that enables the creation of next-generation IoT solutions that model the real world" (Microsoft, 2021).

Microsoft has a software package called Azure Digital Twins. This software models a customer's environment and provides security to the virtual copy. The customer chooses the size and boundaries of the DT. The DT connects the system with other systems, subsystems, and components. It allows access to block silos in a business that prevent the customer from seeing the whole picture of the business. DT provides businesses with a platform for creating dynamic business logic. Microsoft also provides a data management service, with software called Azure Data, Azure Analytics, and Azure AI. Azure Data integrates with Azure DT to keep records of past events and predict future events. This powerful software provides businesses with an advantage over competitors and with capabilities to face future challenges (Microsoft, 2021).

DT architecture links the physical object and the virtual model by establishing a communication between them. Three elements are part of high-level DT architecture: the information model, the communication mechanism, and data processing. The information model gathers the characteristics, behaviors, and information of the physical object. This is necessary to abstract the data that emerge from data processing. The communication mechanism allows interaction between the physical and virtual models. It establishes bidirectional communication. Data processing feeds the DT with data from several sources to mirror the physical object. This requires high performance to synchronize the data with the information model (Angrish et al., 2017; Lu et al., 2020).

IBM describes four types of DT: components twins, asset twins, system twins, and process twins. Each type is part of the production stage and focuses on different areas. An organization could present multiple digital twins integrated into a composite system of DT. Components twins resemble single parts of a manufacturing system. They are the smallest units of a DT. Several components' twins comprise asset twins. The interaction of different components provides functions that lead to the creation of data. System twins integrate asset twins, allowing the study of multiple assets in a system that work together to fulfill the system's goals. A system twin has more detailed levels of the characteristics, behaviors, functions, and structures of a system. It allows control of the work of DT components and DT assets. At this level, a DT can propose, for example, improvement solutions for factory productivity. Finally, process twins encompass all the system's parts in the supply chain of manufacturing. Process twins are the highest level of DTs, showing all the production stages of a product from suppliers to customers. This DT model provides a managerial perspective and looks to increase the processes efficiency in a factory (IBM, 2021).

Many industries apply DT to their daily activities, along with other IoT devices. These applications are due to the increased use of technology in businesses. DT fits perfectly with every organization that wishes to explore and obtain a complete picture of its physical assets in the virtual world. DT provides organizations with the possibility of evolving over time, including developing more technology along the way. There are some well-known companies, such as Siemens, ANSYS, and Dassault, that implement DT technology. The applications of DT within business organizations include manufacturing, electricity, automobiles, aerospace, healthcare, drilling platforms, vessels, construction, and urban applications (Qi et al., 2021).

3.3.2 Systems Thinking

Arnold and Wade (2015) define systems thinking as a methodical approach to understanding problems and finding solutions. It analyzes the interrelationship of a system's components and how they work together as one single system. It also analyzes the relationship of a system with other systems in a system-of-systems context. Systems thinking is different from traditional research analysis, which separates a system into components to study them individually. A systems thinking approach studies systems from a high-level perspective. The system thinking method is present in many different domains, such as politics, economics, human resources, education, and health. It defines a problem based on the following questions:

- What is the problem or need?
- Who has the problem or need?
- Why is it important to solve the problem?
- Who needs [what] because [why]?

Goodman (2019) states that systems thinking is a discipline for studying problems thoroughly, to solve the right problem. It helps in achieving a deeper understanding of the problem and formulating questions about it. It looks to find common variables and patterns in a system's structure, which can explain the system's behavior and, therefore, the problem's source. Finding faulty system structures creates the necessity to improve them and to propose several solutions.

System thinkers have creative minds that look beyond the problem and challenge themselves to develop solutions that are not common and that are sometimes unpopular. Systems thinking may not solve all kinds of problems. Problems that best suit the system thinking approach occur when the problem is relevant, repetitive, and causing other problems, and when the affected people know the problem very well and have tried to solve the problem unsuccessfully.

Kim (1999) explained that systems thinking allows people to see and talk about a problem in a unique way. Systems thinking introduces the concept of systems and how they affect people's lives. It provides a distinct perspective on daily behaviors. It also provides several tools for understanding problems visually and communicating about them. Kim believes that the first step in being a systems thinker is defining what a system is and how it behaves. In addition, systems thinkers consider the relationship of systems with other systems, forming a bigger system of systems. Finally, system thinkers must apply systems thinking to different life situations.

Sweeney and Sterman (2000) assumed that systems thinking studies a system's dynamics complexity. It analyzes and visualizes the complexity behavior of a system through graphics and concepts. Moreover, Sweeney and Sterman list specific systems thinking skills as including the ability to:

- Understand how the behavior of a system arises from the interaction of its agents over time (i.e., dynamic complexity).
- Discover and represent feedback processes (both positive and negative) hypothesized to underlie observed patterns of system behavior.
- Identify stock and flow relationships.
- Recognize delays and understand their impact.
- Identify nonlinearities.
- Recognize and challenge the boundaries of mental (and formal) models.

Systems thinking provides tools such as mind mapping, causal loop diagramming, CATWOE, conceptagon, TRIZ. These tools help in developing brainstorm solutions and choosing the best solution from different options. Systems thinking uses the solution space to better understand the problem space and to refine it (Gupta, 2019).

3.4 Methodology

This section describes the methodology used to analyze the problem of implementing a DT in a manufacturing system. This article uses non-traditional methods to analyze this research problem. It uses system thinking methods and tools to perform the analysis. It uses the conceptagon method to define a digital twin in a manufacturing system. Then, it uses the systemigram approach to examine a DT's relationship with other systems. Finally, it uses the TRIZ method to study the problem and solution space in implementing DT models in a manufacturing system.

3.4.1 Conceptagon

This article explores the DT manufacturing system model through the conceptagon framework, as shown in Figure 3.2. This framework provides system architectures a holistic understanding of a system and the systemic process. It is an analytic and powerful tool for defining the problem space and the solution space. It has 21 attributes divided into 7 triads. The conceptagon framework's purpose is to establish a broader understanding of the system of interest, its components, its relationships, and its processes. Conceptagon also establishes an intelligent discussion and collaboration between the domain or system researchers (Boardman et al., 2009).

This article uses the conceptagon framework to analyze DT development in a manufacturing system. It is important to clarify that there is not an official method for using the conceptagon framework. The authors applied the conceptagon in this way so that researchers could have the freedom to study the sets of triads as they wished. They will discover the linkages across the triads, which will guide them to new analyses for their system of interest.

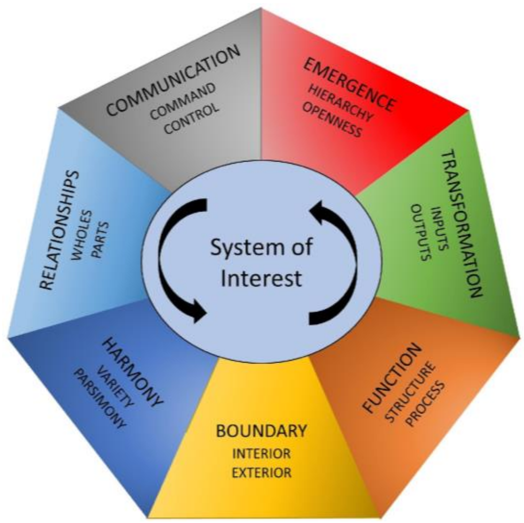

Figure 3.2. The Conceptagon. Redrawn from Boardman et al. (2009)

3.4.1.1 Boundaries, Interiors, and Exteriors

This triad discusses the design of a digital twin model for manufacturing systems. It explores the interior, exterior, and boundaries of a system. The definition of a system's boundary comes from the definition of the system's interior and exterior. A system's interior encompasses all the objects or components that are in the system. It shows the relationship between them. The system's exterior is the environment to which the system belongs. Here, the system interacts with other systems. Hence, the system's boundaries are what makes the system different from others. It delimits the interior and exterior of a system. It distinguishes a system from other systems and makes it unique. Also, it shows that the system has no control or authority beyond its boundaries.

The interior of a manufacturing DT system presents many components. Figure 3.3 shows the DT components. These are RFID readers, RFID tags, PLC, transducers, software, electric actuators, switches, MEMS sensors, and RFID transceivers. The exterior of the DT system model is the manufacturing system. This is a bigger domain or system holding the DT domain that becomes a subsystem of the manufacturing system. This domain incorporates stakeholders and other components, such as artificial intelligence, digital thread, cloud computing, and smart machines. The DT manufacturing system boundary is the DT physical counterpart that provides specific characteristics that limit the model (Židek et al., 2020).

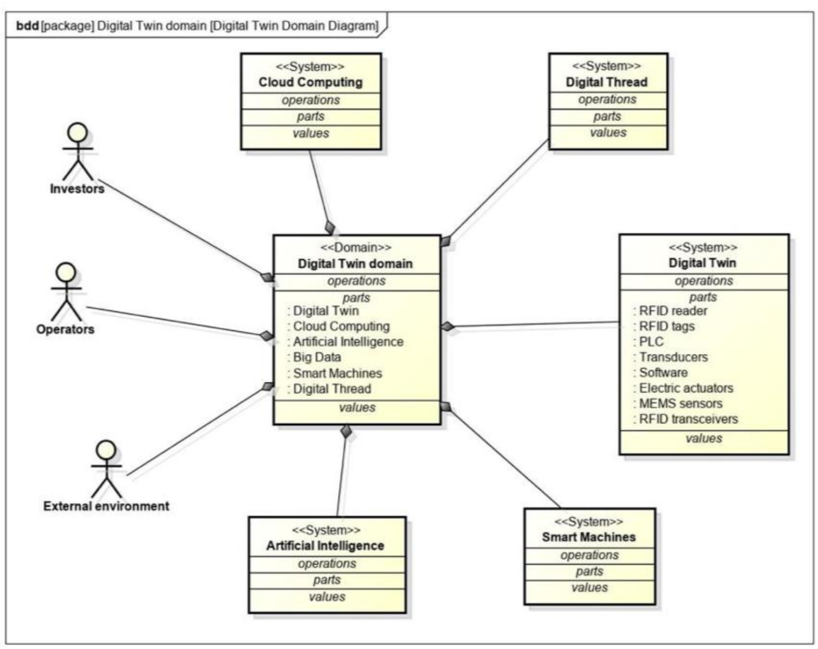

Figure 3.3. Digital Twin Domain Diagram.

This article used systems modelling language (SysML) to model the DT subsystem of a manufacturing system. It uses the “composition to association” arrows to connect objects as blocks and actors on the diagram. It connects stakeholders (investors and operators), the external environment, cloud computing, digital threads, artificial intelligence, and smart machines to the DT domain. This domain includes the DT model that controls other “systems” or components in performing the diagnostic and prognostic DT functions. These other “systems” are components from the manufacturing system’s viewpoint.

3.4.1.2 Input, Output, and Transformation

In this triad, the DT model shows a high-level description of its behavior and purpose. The DT processes transform inputs into outputs. Inputs are elements that enter a system to undergo a transformation. The DT inputs are images, procedures, data, algorithms, and energy. The transformation is the system process or processes that transform inputs into outputs. DT processes are the diagnostic, prognostic, and simulation of objects, data, and processes. The outputs are images, results, data, analysis, and energy. The DT goal is to provide information and data relevant to the operations of the manufacturing system to which it belongs. Figure 3.4 shows the DT components, inputs, and outputs.

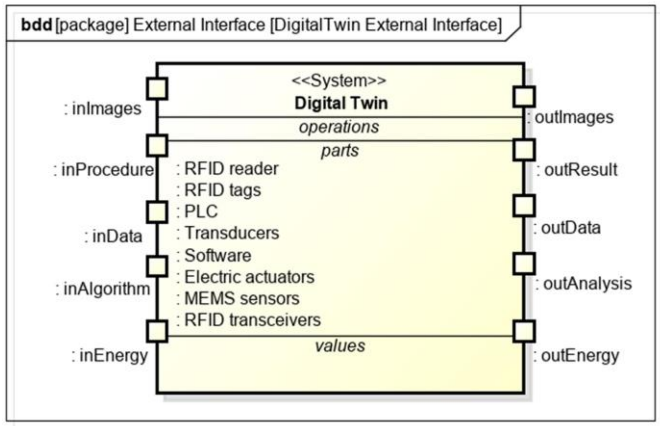

Figure 3.4. Digital Twin Subsystem Inputs and Outputs.

This article used SysML to model the inputs and outputs of the DT subsystem. SysML is an external interface that displays the DT parts in the block and shows ports as inputs and outputs, similar to a process model. The SysML model shows the DT technology that receives images, data, algorithms, energy, and procedures to use and transform them into outputs. These outputs go to the end user in the form of images, analysis, data, and results. These outputs help users to make informed decisions.

3.4.1.3 Relationships, Wholes, and Parts

This triad studies the relationship of the system's parts and the system as one single entity. In this case, the DT is an entire system that cannot exist without the parts. However, the DT is more than its parts in the sense that the single elements cannot perform the DT functions on their own. It is the collective behavior that arises from the part's relationships that enables DT functions. All parts of the DT work together as one entity to fulfill their collective functions. There are many relationships between the parts in the system's interior. These relationships affect the system as a whole and its environment. Hence, it is not possible to improve the parts without considering the entire system. However, sometimes degrading a system's parts may improve the performance of the system. Figure 3.5 shows the DT internal interface.

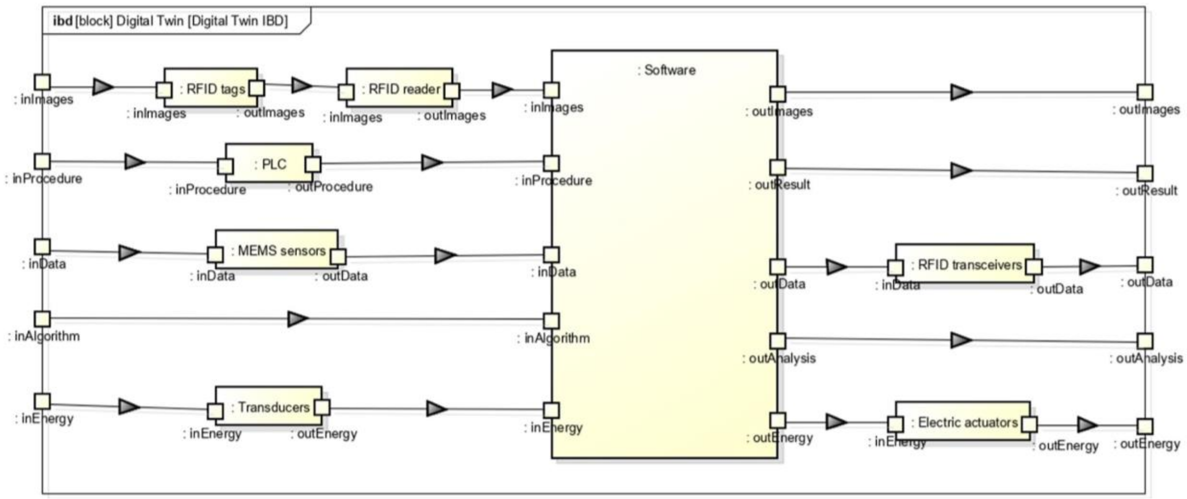

Figure 3.5. Digital Twin Internal Interface.

The interior of a DT shows the relationship of the system's components and how they transform the inputs into outputs. For instance, the object's data is an input to the DT. MEMS sensors collect data from the physical object. Then, the DT software performs the data analysis or operation. The user can see the results and use the RFID transceivers to send commands to the object.

The article used SysML to diagram the DT internal interface. SysML provides a block diagram that comes from the digital twin domain diagram. The digital twin subsystem allows the addition of an internal block diagram that shows inputs, outputs, and DT components. It uses "item flow" arrows and ports to diagram the relationship between components, which are blocks on the diagram.

3.4.1.4 Emergence, Hierarchy, and Openness

This triad underlines the presence of emergence behavior on systems, due to openness creating hierarchy levels in the system domain. The system experiences evolution due to its characteristic of openness that allows it to add components and make relationships with other systems. This happens due to the external relationships of the system with its environment. This exposure generates unexpected changes in the system, called emergent behaviors. The emergence attribute makes systems evolve, adopting new features and functions. It is here that the concept of hierarchy becomes relevant in the understanding of systems. The different hierarchy levels create new dynamics with specific structures (A. Madni et al., 2019).

As for the digital twin, being part of a bigger system makes it susceptible to changes. Adding new components to the manufacturing system will affect the digital twin's operations. It will expand the DT's resources and functions. These changes will create emergent behaviors in the DT that require organization, so that they do not disrupt the system within which the DT belongs or the other systems around it. The DT itself is an open system that will incorporate modern technologies, such as IoT devices and software. This openness causes an evolution in the DT model. As the literature review explains, a system could start developing a DT of components. Then, it could integrate these DT components into subsystems. Later, it could integrate different subsystems into a single system. The DT model evolution creates emergent behaviors, new structures, and new dynamics.

3.4.1.5 Structure, Process, and Function

Systems present structures and processes to perform their function. The structure allows a system to perform all its functions. This functional architecture includes requirements, resources, rules, people, materials, etc. These internal components are interrelated with each other, creating processes. The system processes are the series of activities that produce an outcome. This outcome is the main function of the system. Structures and processes are responsible for the system’s constraints. Therefore, the system’s design creates a robust model structure, with defined processes (McGee & Edson, 2011).

The DT does not have a physical structure, but as an operational tool it has a digital structure. However, the technology that enables the digital twin is composed of physical components. As this article mentions above, the digital twin model is the virtual representation of a physical object. However, the entire digital twin technology is more than the software that displays a virtual copy of the physical object. It has several components that work together to enable the DT functions. Figure 3.3 shows the DT components. The main function of a DT is to improve the processes of a system to perform diagnoses and prognoses. Moreover, a DT has several processes working together to perform its functions. Some of these functions are collecting and analyzing data in real time. It recognizes and inspects objects with RFID technology. It uses software to create a CAD model of the system of interest, its process, and/or its products. It runs simulations to provide forecasts about the system’s status.

3.4.1.6 Communication, Command, and Control

This triad studies the governance of a system. It focuses on the system's communication received from other systems and, in an ideal case, the system's answers. This triad discusses a system's means of communication, both internal and external. Communication is a key step in starting a system's processes, transforming inputs into outputs, and performing the system's functions. Systems that keep good internal and external communications acknowledge them through feedback and control. The system's structure provides the system with command-and-control functions. The system commands its internal elements to perform their functions. Moreover, subsystems are part of the manufacturing system's control of other subsystems, to enable them to work together for the main system's goals. These are system's characteristics, where one system gives and the other obeys (A. Madni et al., 2019).

The DT components maintain constant communication between the internal elements to enable them to use their relationships to perform their functions. It controls the system's internal components to fulfill its goal. It communicates with other systems to receive inputs and transform them into outputs. The means of communication are RFID technology, transducers, and PLCs. These components communicate internally with the software that performs the DT functions. Then, the DT sends the results, information, data, etc., to other systems that are part of the overall manufacturing system. Moreover, the external communications of the DT with other systems, such as IoT devices, are crucial in meeting the system's goals. The DT also receives commands from other systems, such as smart machines, cloud computing, etc., to perform activities that satisfy the other system's needs. Feedback from the internal components and the external systems enables the DT to control their parts effectively. Finally, this triad helps the digital twin to be dynamic, adapt to different environments, and evolve.

3.4.1.7 Harmony, Variety, and Parsimony

This triad discusses the best arrangements between a system's components. There is harmony when a system has the best arrangement or the ideal structure. However, harmony is not easy to achieve, due to the variety of components and the parsimony in systems. Systems have several parts with a variety of elements, features, types, etc. Parsimony is a system's constraint that keeps the system as simple as possible (McGee & Edson, 2011).

The DT and its components work together in perfect harmony to meet the major system's goals. The DT fulfills its function, although it has different components in quality, characteristics, and type. Moreover, the parsimony in a DT model prevents it from becoming complex and adding more components. It is normal to think that this restriction limits the DT's evolution. However, the DT could evolve and be more intelligent and autonomous with the actual components, or with the reduction of them. This accords with the statement of Madni et al. (2019) regarding distinct types of DT: predigital twins, digital twins, adaptive digital twins, and intelligent digital twins. These DT types were not required to incorporate additional components or technology to upgrade a DT model. Furthermore, since parsimony is a constraint, the DT limits itself to develop new features, abilities, and functions.

3.4.2 Systemigram

This article presents a systemigram for understanding the relationship between a DT model and a manufacturing system, for the implementation of a DT. This DT model considers as essential the use of concepts such as the system readiness level, systems engineering, and digital transformation for the DT implementation.

The systemigram describes and structures the problem of implementing digital twin models in manufacturing systems. Furthermore, it shows the relationship between the DT concept and systems engineering. The latter could help in DT modeling and developing in manufacturing domains. Figure 3.6 shows a systemigram for the conceptual analysis of DT manufacturing systems.

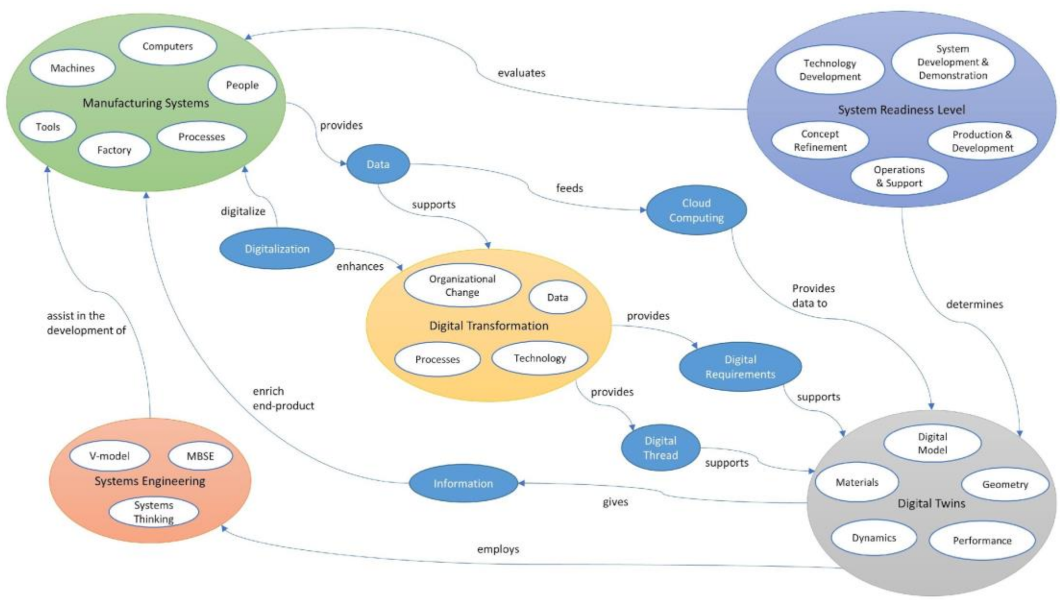

Figure 3.6. Systemigram for Conceptual Analysis of Digital Twin Manufacturing Systems.

Manufacturing systems encompass different components, such as production processes, machines, computers, people, etc. These elements and data undergo a transformation to the digital world. Digital transformation involves both digitization and the digitalization of objects, processes, and data to achieve the goal of transforming organizational systems into the digital world. Digitization is the transformation of non-digital objects into digital objects. Digitalization is a method of restructuring organizations from a system level perspective.

Digital transformation is the last phase in implementing IT technology in businesses, changing the business model with a new logic for doing business and creating value (Verhoef et al., 2021). It promotes data sharing with other systems to make impactful changes in the business world. The process of digital transformation is disruptive. Digital changes are disruptive because they have a significant impact on business operations. They can change an entire business model and create a revolution. Digital transformation creates a virtual space for analyzing data. It also allows the identification of requirements and threads that set the limits of the digital twin (Ziyadin et al., 2020).

In addition to digital transformation, manufacturing systems must consider the system readiness level (SRL). The SRL is an index that evaluates the maturity of a system in performing certain operations. Further, this index could determine the implementation of a digital twin. An SRL has five levels: concept refinement, technology development, system development and demonstration, production and development, and operations and support. Once the system is ready to implement a digital twin, it is time to consider the components of the system's twin. The components of a digital twin are materials, digital models, geometry, performance, and dynamics (Tetlay & John, 2010).

Finally, the DT provides relevant information to the manufacturing system to improve production processes and create better products according to customer needs. It also enhances the use of systems engineering for the development of manufacturing systems. Systems architectures could use model-based systems engineering (MBSE), system thinking methods, or the "Vee" model to create or improve systems. This last action closes a system's cycle of relationships.

3.4.3 TRIZ Method

The theory of inventive problem solving (TRIZ according to its Russian acronym) is a system thinking method for analyzing and forecasting problems. It is part of systems thinking because it uses a systemic approach to solve problems. It assumes that solutions to problems lie in the patterns of invention. It encompasses two main concepts: generalization of problems and solutions, and elimination of contradictions. According to this method, problems are contradictions that cannot exist together. TRIZ presents 40 principles of innovative thinking, 39 characteristics of technical parameters, and nine laws of systems evolution (MindTools, 2022).

There are three steps in using the TRIZ method. First, TRIZ defines the problem and the contradiction in a few words. Second, it studies the problems as if they were systems. Hence, it considers stakeholders, components, and system's interactions. The best tool for the second step is 9 windows. Finally, it decides on the principles of innovative thinking to solve the contradiction.

To define the problem, it is necessary to apply a technique before using the TRIZ method. This technique is the CATWOE analysis developed by Smyth and Checkland (Smyth & Checkland, 1976). They studied several historical definitions and created this technique to formulate a root definition for a proposed system. The CATWOE analysis considers the following elements: customers, actors, transformation, worldview, owner, and the environment. This article carried out a CATWOE analysis to support a holistic perspective of the research problem. This article decided to study the DT implementation problem in manufacturing from the managers' viewpoints. The CATWOE analysis for a potential DT manufacturing system is the following:

- Customers: The managers.
- Actors: The employees, investors, government, suppliers, and users.
- Transformation: The availability of a virtual system that interacts with the physical manufacturing system and other systems to help manage and keep track of manufacturing processes. Cloud storages save factory data and allow access from every point in the world with internet connection.
- Worldview: The digital twin system is a future investment. Managers expect to make profit in the long term. The manufacturing industry is evolving into the next stage, Industry 4.0.
- Owner: The CEO and shareholders of manufacturing systems that decide to implement a digital system corresponding to the business's actual physical manufacturing system.
- Environment: The constraints of every engineering project are the costs, the time, and the performance related to the implementation of the digital system.

After performing the CATWOE analysis, the root definition of a DT manufacturing system is the following: A manager-operated and -owned digital twin simplifies the interaction between the virtual space, the physical space, and surrounding systems that are part of supply chain management. It helps to manage different work processes. It works with cloud storage to save data and allow access from every point in the world, due to internet connectivity. This digital twin is a future investment from which managers expect to make profit in the long term. The constraints of every engineering project are the costs, the time, and the performance related to digital twin implementation.

Based on the system's root definition, this article defined the problem and the contradiction. The problem is how to develop accurate digital twin models of a manufacturing system. In other words, the problem is how to determine if a system has developed an accurate DT model or if the DT resembles its physical object. Hence, it is a problem of model fidelity and accuracy. The research problem's contradiction, based on the TRIZ technical parameters, is improving the digital twin's adaptability or versatility without decreasing its automation extension. Therefore, the problem could be in the design phase of the digital twin model. The TRIZ innovative solutions for this problem are identifying inexpensive short-living objects, discarding and recovering, and changing parameters (Altshuller et al., 2005). The digital twin model of the manufacturing system must be accurate in resembling the physical system's characteristics and attributes, to avoid problems such as system disruption.

After studying the problem from a high-level perspective, the problem was studied in detail. The 9 windows tool reduces the complexity of a problem (ASQ, 2022). It gives a system new perspectives on the problem, based on time and space. It assists in identifying the real problem to solve. It uses a 3 × 3 matrix that creates nine segments of "the world." The row labels are past, present, and future. The column labels are the super-system, the system, and the subsystem. The system's problem is placed in the center of the matrix. The subsystem presents the system's components that can solve the system's problem from the past, present, and future perspectives. The super-system is the environment where the system belongs, and it proposes solutions based on time. Table 3.1 shows the matrix that illustrates the use of the 9 windows tool for analyzing a DT implementation problem.

Table 3.1. Windows tool to solve a digital twin implementation problem.

	PAST	PRESENT	FUTURE
SUPER-SYSTEM	Incomplete digital transformation of the manufacturing supply chain	Lack of connection between systems to prevent a supply chain disruption	Create a digital thread that connects data and systems throughout the supply chain
SYSTEM	Non-autonomous operations or regulatory automation in manufacturing systems	No clear definition and inaccurate digital twin models of a manufacturing system	Develop a framework or method to create digital twin models of a manufacturing system
SUBSYSTEM	No integration or connectivity between IoT devices in a system.	No integration or connectivity of digital twin components and other devices in the system	Design an integration model for multiple and diverse components in the system

The problem is that there is not a clear definition of digital twins in manufacturing systems. Factories are developing inaccurate digital twin models. All of these could be detrimental to the regular operations of a manufacturing system. The subsystem solution is to design an integration model for digital twin components and other devices in the system. The super-system solution is to create a digital thread that connects data and systems throughout the supply chain. The system solution is developing a framework or method to create digital twin models of a manufacturing system. This framework must support autonomous operations and the assessment of accurate digital twin models of manufacturing systems.

Finally, the TRIZ step considers the development of the ideal final result (IFR). The IFR is one of the most powerful tools of the TRIZ method. This tool looks for the ideal condition or solution of a system, irrespective of the problem's constraints. The TRIZ method describes ideal systems as systems that do not exist until they perform all their functions (Mishra, 2013). This is a contradiction, in that this work found the problem lines above using the TRIZ technical parameters. Then, the TRIZ method applies a system thinking tool to transform the problem and find some solutions. To conclude, the TRIZ method selects the solution that presents a functional ideal model to solve the research problem and to achieve the IFR.

This work already defined the problem lines above. In this case, the research problem is the lack of a clear definition and an accurate digital twin model of a manufacturing system. The problem's contradiction is improving the digital twin's adaptability or versatility without decreasing its extent of automation. Then, this work used the 9 windows tool to transform the problem and present some potential solutions. Finally, this work selected the ideal solution to implement DT models in a manufacturing domain. The IFR technique creates digital twin models that expand the automation in the manufacturing system internally, and externally to other systems in the supply chain. The ideal digital twin model must show adaptability to new systems, subsystems, components, and environments to improve continuously over time.

3.5 Results and Discussion

The analysis of digital twin implementation for manufacturing systems presented several results. The article showed how important it is to use a systems approach, to achieve a higher perspective for consideration of the problem or system of interest. Implementing a DT is not easy. Some companies still have doubts about the benefits of DT, due to its novelty. Organizations are still testing and measuring the impact of a DT in their daily activities. Other companies have not heard of DT or know little about it. There are also companies that do not have the infrastructure or the means to implement a DT (Intelligent Software Engineering, 2020).

There is no common definition of a DT. This prevents an understanding of the DT concept. Hence, some factories do not realize its value, to the point of degrading it (Fuller et al., 2020; M. Singh et al., 2021). Moreover, the integration of data is a challenge for DT development. This integration gives users access to all data in a system's lifecycle from various locations. This is difficult, due to different data sources, formats, interfaces, and security protocols (Kuehn, 2018; Qi & Tao, 2018).

A DT also needs a standardized information model that integrates the different system components, to allow the DT to work across different components, subsystems, and systems. Standard technology, models, information, and APIs keep data flowing smoothly throughout a system. It is recommended that system designers try to standardize system components as much as possible (Barnstedt et al., 2021). Finally, a DT must resemble the physical system accurately and in real time. This involves the integration of several components that must work together to fulfill the DT’s diagnostic and prognostic functions (Bazaz et al., 2019).

Through the application of the conceptagon method, it is noticeable that a digital twin is a complex system (R. He et al., 2019; Jiang et al., 2020; Qi et al., 2021). It has distinct parts that are related to each other to fulfill their collective mission. Since the software is enabled by many components, the digital twin boundary could be unclear (Perno et al., 2022). This happens due to the extension of the digital twin in the manufacturing system (M. W. Grieves, 2019). Hence, it is important to consider the digital twin as a system, and to consider the relationships between its parts.

In addition, the digital twin processes are crucial in transforming inputs into outputs. The outputs are based on the digital twin’s structure and arranged functions (Lin et al., 2017). A DT has several processes in performing its functions. The main DT function is to perform diagnostics and prognostics for a system’s regular operations (Trauer et al., 2020). The DT tool has a virtual structure, but the technology that enables the digital twin is composed of physical components (Alam & El Saddik, 2017).

Moreover, it is important that a DT manufacturing system be open to other systems and environments, to enable upgrading and to remain important over time (Dietz & Pernul, 2020). However, this openness creates emergent behaviors in the system. A digital twin experiences new behaviors that arise from the constant relationship between the digital twin’s components, and the digital twin itself, with other systems in the supply chain. A DT incorporates new components, creates new processes, and creates new relationships. This forces a digital twin to establish order and determine the hierarchy within the system (M. Grieves & Vickers, 2017).

An open digital twin communicates with other systems to receive inputs and transform them into outputs (Qi et al., 2021). This creates two main functions in the digital twin: being in command and being in control of other systems in the supply chain.

Finally, the digital twin components must be harmonious with themselves and with other systems to work normally (Tuegel, 2012). However, a DT presents many constraints. The system's limitation attributes are parsimony and variety, which are contradictory. A DT has several components that differ in quality, characteristics, and type (Fuller et al., 2020). Each component performs the necessary work and obtains the resources to do it. However, a DT should find a balance and remain as simple as possible. In summary, a DT must be dynamic, adapt to different environments, and evolve (A. Madni et al., 2019).

The systemigram illustrates the relationship of a DT with other concepts and systems. It presented a picture of DT implementation. It showed the relationships between the manufacturing system and the DT. The manufacturing system needs to transform its components into the digital world. The transformation will make possible the implementation of a digital twin. The system needs to add cloud computing, a digital thread, artificial intelligence, and other requirements to satisfy the digital twin's needs (Židek et al., 2020). Nevertheless, a manufacturing system should evaluate its system readiness level, before implementing modern technology such as a DT (Sauser et al., 2006).

Based on the systemigram, it is possible to identify two benefits of implementing a DT. First, it will improve the manufacturing system's operations and create new business opportunities (Kuehn, 2018); second, it will increase the knowledge and use of systems' engineering in the academy and in industry (A. Madni et al., 2019).

The TRIZ method helped to refine the problem and the contradiction to find the best ideal solution to DT implementation. The problem is the lack of a single definition (Fuller et al., 2020; M. Singh et al., 2021), methodology (Barnstedt et al., 2021), and the indicators for developing accurate digital twin models of a manufacturing system (Bazaz et al., 2019). The research problem's contradiction is improving the digital twin's adaptability or versatility without decreasing the DT's extension of automation. The TRIZ innovative solutions for this problem are identifying inexpensive short-living objects, discarding and recovering, and changing parameters. The digital twin model of the manufacturing system should be accurate in resembling the physical system's operations and avoid problems such as system disruption. Then, the 9 windows tool showed some potential solutions to solve the DT implementation problem. The literature also studied these problems and solutions. These solutions are:

- Creating business models that include digital transformation (Urbach & Röglinger, 2019; Verhoef et al., 2021; Ziyadin et al., 2020);
- Connecting different manufacturing systems to prevent the supply chain disruption (Bolton et al., 2018; Ivanov, 2018);
- Creating a digital thread that connects data and systems throughout the supply chain (Bonham et al., 2020; Gerlach et al., 2021);

- Implementing technology such as IoT devices that support autonomous operations (Rosen et al., 2015; S. Singh & Singh, 2016);
- Designing an integration model for multiple and diverse components in the system (Bajaj et al., 2016; Vrabič et al., 2018);
- Developing a framework or method to create accurate digital twin models of a manufacturing system (Pang et al., 2021; X. Zhang & Zhu, 2019; Zhuang et al., 2018).

Finally, the IFR technique shows that the ideal DT model is one that expands its automation to all manufacturing system operations. It also expands its automation to the other systems in the supply chain. For instance, a digital twin should be capable of ordering supplies when there are not enough materials in stock (Bonham et al., 2020). The ideal DT model adapts to new systems, subsystems, components, and environments, without losing its functionality (A. Madni et al., 2019).

3.6 Conclusions

Systems thinking tools are useful in understanding the problem and finding potential solutions for DT implementation in a manufacturing domain. The methods and tools used in this article were the conceptagon, the systemigram, CATWOE analysis, 9 windows, the ideal final result technique, and the TRIZ method. All of these tools analyzed the problem of implementing digital twin models in manufacturing systems. Systems thinking allows researchers to learn more about the problem space and to find potential solutions. Moreover, systems thinking studies all the attributes of a digital twin model from a systems perspective. Finally, it presents potential solutions from different perspectives.

The analysis showed that a DT model is a complex system composed of many components that are interrelated with each other in performing diagnostic and prognostic functions. The ideal DT model for manufacturing domains must be an open system that improves continuously and adapts to different circumstances. DT implementation must consider the following attributes: communication, emergence, transformation, function, boundary, harmony, and relationships. These attributes could help to model the DT manufacturing system architecture.

The results and discussion section highlighted some challenges in the implementation of DT in manufacturing systems. Some organizations believe there are many uncertainties about DT, such as the definition, the benefits, the impact on daily activities, etc. Moreover, the development of DT presents challenges in the integration of components and data that are heterogeneous. The biggest challenge is to create DT models that resemble physical objects accurately. The implementation of a digital twin is challenging because of its complexity, novelty, and cost. It involves the integration of several components and systems, such as IoT devices.

After giving a description of a digital twin model and defining the problem of implementing a DT in a manufacturing system, a main conclusion was reached. It is necessary to develop a framework to create accurate DT models of a manufacturing system. This new DT system is a complex system that requires a holistic approach for its implementation to benefit the final products, the processes, and the entire system.

This section considered, as future research, the development of a framework or method to develop DT models for a manufacturing system. Such future research would help manufacturers evaluate the possibilities of implementing DT models in their factories. Moreover, it will provide them with a broad perspective for analyzing the current digital transformation of their factories. They could measure how far along their factories are in implementing modern technologies, such as DT models. For example, factories could measure their adaptability and flexibility to technological changes.

3.7 Chapter III – References

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CHAPTER IV - ARTICLE 2: PROPOSING A SMALL-SCALE DIGITAL TWIN IMPLEMENTATION FRAMEWORK FOR MANUFACTURING FROM A SYSTEMS PERSPECTIVE[2]

4.1 Abstract

Due to the fourth industrial revolution, manufacturing companies are looking to implement digital twins in their factories to be more competitive. However, the implementation of digital twins in manufacturing systems is a complex task. Factories need a framework that can guide them in the development of digital twins. Hence, this article proposes a small-scale digital twin implementation framework for manufacturing systems. To build this framework, the authors gathered several concepts from the literature and designed a digital twin subsystem model using a model-based systems engineering (MBSE) approach and the systems engineering "Vee" model. The systems modelling defines the digital twin components, functionalities, and structure. The authors distribute most of these concepts throughout the framework configuration and some concepts next to this general configuration. This configuration presents three spaces: physical, virtual, and information. The physical space presents a physical layer and a

perception layer. The information space has a single layer called middleware. Finally, the virtual space presents two layers: application and model. In addition to these layers, this framework includes other concepts such as digital thread, data, ontology, and enabling technologies. This framework could help researchers and practitioners to learn more about digital twins and apply it to different domains.

4.2 Introduction

Manufacturing companies must follow the Industry 4.0 trends to survive in a highly competitive market. The fourth industrial revolution uses modern technology to transform manufacturing and make it smart (Deloitte Development LLC., 2017; Frank et al., 2019). Smart factories digitize the physical layout, business processes, and products, and integrate them in the digital world (Lu et al., 2020; Tao, Qi, et al., 2019). This improves the efficiency of processes (Li et al., 2023), creates better products (Tao et al., 2018), and enables data-driven decisions (Kuehn, 2018). Smart manufacturing encompasses recent technologies such as the Internet of Things (IoT), artificial intelligence (AI), augmented reality (AR), big data analytics, and so on to enable the digital transformation of factories (B. He & Bai, 2021; Qi & Tao, 2018; Saad et al., 2020; Židek et al., 2020). The integration of some of these technologies result in the development of digital twins (Yang et al., 2017; Yildiz et al., 2020).

Digital twin (DT) is a tool of Industry 4.0 that helps factories achieve digital transformation. DT mirrors the physical system in the virtual world. It has a continuous communication with its counterpart in the real world through an information channel (M. Grieves, 2014). DT uses several components such as sensors, actuators, software, databases, etc. DT collects, transfers, and stores data (Kritzinger et al., 2018). Factories could use digital twins for monitoring, data analysis, product development, and so on. In manufacturing, DT finds its application in, for example, predictive maintenance, process planning, product design, and factory design (Martínez-Gutiérrez et al., 2021; Trauer et al., 2020).

Nevertheless, the implementation of DT brings challenges to factories. DT implementation represents a huge investment of physical and human resources. Some researchers believe that a digital twin must use sophisticated technologies such as artificial intelligence and machine learning to operate. Furthermore, DT is a complex system that includes many concepts and processes. Researchers have different definitions for a digital twin and their capabilities for manufacturing. Finally, there are not clear examples of a digital twin for manufacturing because of data property. Companies do not share their DT models to the public (Bordeleau et al., 2020; Identity Management Institute, 2021; Tao, Zhang, et al., 2019).

Therefore, factories need a framework that can guide them in the development of digital twins. Frameworks help to study a new concept or phenomena such as digital twins. Frameworks are an effective way to gather main concepts of the topic of interest and integrate them in a defined structure (Jabareen, 2009). Even though there are many concepts related to DT in the current literature review, a framework can help to explain and resolve conflict between DT concepts. Frameworks can have a specific application that differentiate it from other frameworks. A digital twin implementation framework could enable manufacturing systems to implement digital twins in a secure, easy, and fast manner.

Existing DT literature present frameworks and related works for different manufacturing processes, and types with distinct characteristics, methods, and objectives. For instance, there are frameworks that focus on simulation and optimization of digital twins. Guo et al. (Guo et al., 2019) proposed a DT framework to optimize factory layout designs and solve hidden design flaws. Zhang et al. (Z. Zhang et al., 2019) proposed a DT framework using discrete-event simulation models for production planning and layout design. Marmolejo-Saucedo (Marmolejo-Saucedo, 2022) developed a DT framework using optimization models for large-scale problems in supply chains. This framework considers the use of big data analytics but does not include artificial intelligence. Some focus on collecting and enabling data throughout the digital twin models. The Kumbhar et al. (Kumbhar et al., 2023) framework proposed a DT data-driven framework for detection and diagnostics of flaws. It executes a DT simulation to identify bottlenecks and improve bottlenecks throughput in complex manufacturing systems. Some frameworks do not focus on modelling the digital twin. Friederich et al. (Friederich et al., 2022) focused on developing a framework to improve the simulation functionality of DT using machine learning and process mining techniques. Some researchers suggest a standardized framework. Shao and Helu (Shao & Helu, 2020) developed the scope and requirements for a generalized DT framework. However, their proposed framework just focuses on the use of DT in factories, not on the implementation. The International Organization for Standardization (ISO) developed the ISO 23247 which presents an overview, definitions, principles, and requirements for a DT framework (STEP-NC AP238, n.d.). Nonetheless, a generalized framework may be incompatible for factories with different contexts or applications.

Consequently, after analyzing the digital twin (DT) concept in a previous article (Loaiza & Cloutier, 2022), the next research step is to propose a small-scale digital twin implementation framework for a manufacturing system. This framework aims to design a digital twin for discrete manufacturing processes. Discrete manufacturing puts together tangible components into a final product in an assembly line (Zhao et al., 2013). This work focuses on small size manufacturing companies that do not have resources such as sophisticated technology and skilled workers. It provides a comprehensible step-by-step implementation process. Furthermore, the authors used a methodology with a systems perspective to build this framework. This article gathers relevant digital twin concepts from the literature and models a digital twin for manufacturing systems. This model provides a high-level perspective about the development of digital twins and posterior implementation in factories. It defines essential digital twin functionalities, components, and structure. The system's modelling follows a model-based systems engineering (MBSE) approach and uses the "Vee" model developed by the U.S. Federal Highway Administration (Transportation, 2007), which are based on the ISO 15288 systems and software engineering - system life cycle processes (ISO/IEC/IEEE 15288, 2015).

This study presents some limitations and assumptions in terms of scope to build a digital twin implementation framework for manufacturing systems. This work looks to develop small-scale digital twins from a systems perspective. This study does not focus on a specific technology or functionality such as cloud computing or artificial intelligence, nor does this framework develop a digital twin for a specific task or activity such as model fidelity design or product development. This study generalizes the development of digital twin models in a manufacturing domain. The concepts presented in this article are not comprehensive. Nevertheless, they could help practitioners to implement digital twins in their factories.

This article has the following structure. Section 4.3 presents a literature review, including the most relevant topics for the development of this article. Section 4.4 models a digital twin subsystem of a manufacturing system. In Section 4.5, the authors propose a small-scale digital twin implementation framework for manufacturing systems. Section 4.6 presents a discussion about the digital twin model and proposed framework. Finally, Section 4.7 presents the conclusions and proposes future research on digital twin technology for manufacturing systems.

4.3 Literature Review

4.3.1 Digital Twin Components

Digital Twin has three main components: products in the physical space, products in the virtual space, and the connections of data and information that unifies both spaces (M. Grieves, 2014). Currently, a digital twin presents more behavioral characteristics due to the knowledge of information technology and operations technology. These technologies allow DT to model processes, machines, products, and so on, and perform specific functionalities such as testing a product's performance capabilities. Figure 4.1 shows the original concept of a digital twin as an information mirroring model that displays the product in the virtual space (AIAA & AIA, 2020).

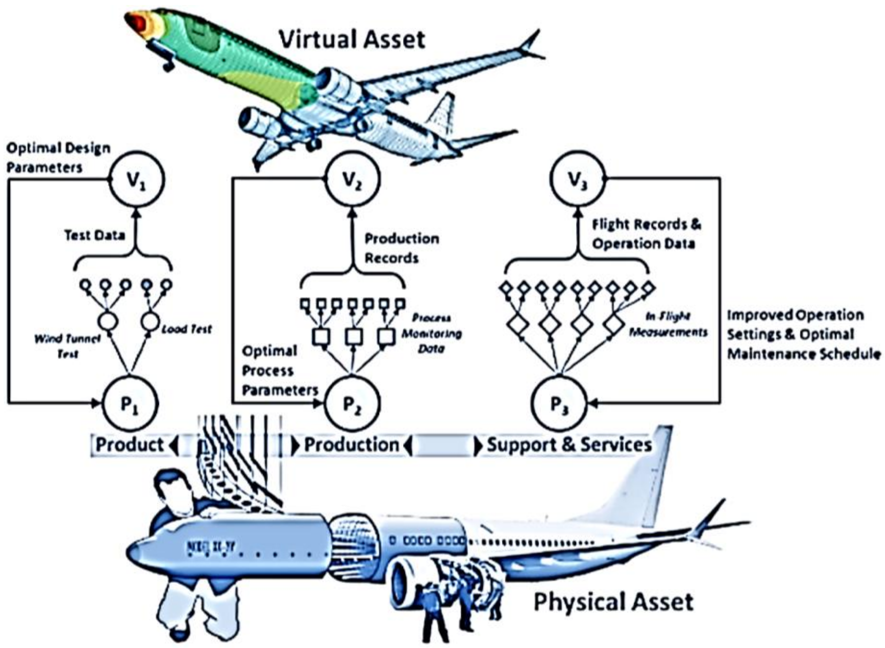

Figure 4.1. Representation of the Digital Twin Concept (AIAA & AIA, 2020). Reproduced with permission from AIAA Digital Engineering Integration Committee. "Digital Twin: Definition and Value—An AIAA and AIA Position Paper." American Institute of Aeronautics and Astronautics (AIAA & AIA), 2020.

Loaiza and Cloutier's article (2022) studied the selection of the digital twin components for a manufacturing system. Each digital twin configuration space presents different components or concepts. These components are necessary to enable the digital twin capabilities. The authors used the conceptagon to distribute them into internal and external components. The internal components belong to the digital twin system. These components are RFID readers, RFID tags, PLC, transducers, software, electric actuators, switches, MEMS sensors, and RFID transceivers. The external components belong to the manufacturing system. These components are artificial intelligence, digital thread, cloud computing, and smart machines. Moreover, the conceptagon describes the digital twin's behavior and functionalities such as data collection, data analysis in real-time, simulation of objects, and so on. Finally, it also considers the relationship between the system's components and how they transform inputs into outputs. Digital twin inputs are images, procedures, data, algorithms, and energy. The outputs are images, results, data, diagnosis, and energy. The authors concluded that the digital twin's goal is to give information and data that support manufacturing system's operations.

Loaiza and Cloutier's article (2022) also presents a systemigram, which is a systems thinking tool. This tool studies the relationship between a digital twin, manufacturing system, and other concepts such as system readiness level, systems engineering, and digital transformation for the DT implementation. It provides an insight to several components within different concepts. The systemigram shows how data flows from the physical system to the digital twin, which sends feedback to the system closing the loop.

4.3.2 Characteristics of Digital Twin Technology

According to DI SPRING (2019), a company that promotes Industry 4.0, DT presents the following characteristics: connectivity, homogenization, smart programmability, traceability, and modularity. These characteristics make DT different from other technologies. The connectivity of DT is one of its most distinguishing features. It is the foundation of DT to connect the real world with the virtual world. It is crucial for the development of DT functionalities. Connectivity is a feature that will change over time as DT evolves. Homogenization is a feature that allows DT to collect and share data with other digital platforms. DT gathers information from the physical source to mirror it into a virtual model. Homogenization brings benefits such as low-cost ways to manage data and enhances the user experience to collaborate on a single digital source. DT is a smart technology that can program its functions automatically. The characteristic of smart programmability makes it possible to control physical objects. DT uses sensors, actuators, and artificial intelligence. DT can manage factory's processes and program them according to learning experience. This gives an introduction to servitization in manufacturing. Smart programmability improves DT services to meet customer's needs. The DT characteristic of traceability enables it to perform functionalities such as simulation. DT can check past information of processes or products for diagnosis due to its digital thread. Digital tread implements traceability from the system requirements to the design, production, distribution, and disposal stage of a system of interest. It improves the communication and relationship of the DT with other systems. Finally, modularity is a system characteristic adopted by DT to separate and reorganize components. It gives flexibility and variety to DT models, reducing the complexity of systems by arranging a system in modules. The complexity of a system's components is not visible at this level of model abstraction. The benefit of modularity is to understand and look at the right problem.

Barricelli et al. (2019) believe that a DT has the following characteristics: connection with multiple devices, a high amount of data storage, and the ability to make smart decisions. The physical and virtual spaces should have a seamless connection to the Internet and other networking devices to allow data sharing. This connection sets up direct and indirect communication through physical devices and cloud computing. The DT process of communication links physical objects and the DT, the DT and other DTs in the surrounding environment, and the DT and domain experts. DT is also capable of gathering distinct kinds of data and organizing them in categories, concepts, areas, etc. It understands data sources through ontologies. It shows data properties and the relationship between them. A digital twin should implement a database or storage system to save historical data and current data. Data is key to the performance of DT functionalities. Finally, a digital twin has the characteristic of making predictions, prescriptions, and descriptions of situations, processes, tasks, status, etc. It uses artificial intelligence that allows DT to learn capabilities. This is possible due to algorithms that work as a virtual cognitive brain that collects data and makes intelligent decisions.

4.3.3 The "Vee" Model of the Systems Engineering Process

Systems engineering is a disciplined approach that focuses on the design, implementation, operation, and retirement of systems (Shea, 2017). The IEEE 15288, Systems and Software Engineering—System Life Cycle Processes, describe the processes to manage systems over their life cycles (ISO/IEC/IEEE 15288, 2015). The "Vee" model is one of several system models that describe these system processes. The "Vee" model has a V-shape describing a system's development from left to right. It is an iterative model that improves the system until its maturity. The left-side of the "Vee" starts in the abstraction level where the system is decomposed into several components. The right-side assembles these components to develop the final product (Forsberg et al., 2005).

Systems engineering literature presents different variants of the "Vee" Model with different terminology and levels of decomposition. However, these models have activities in common throughout the system's development (Firesmith, 2013). In general, the left-side of the "Vee" model presents the system's definition and planning stage, and the right-side the system's integration, test, and operational stage. The first activity on the left-side describes the system stakeholder's needs. The second activity transforms these needs into the system's requirements. The next activity decomposes the system in a lower level presenting a high-level architecture. The next step is a more detailed architecture of the system design. The bottom activity of the “Vee” model is the execution of the plan. It looks to create the system’s components. Then, going up to the right-side of the “Vee” model, the next activity aims to integrate the components and verify and validate that the system meets the stakeholder’s needs. Finally, the last activity is when users operate and maintain the developed system through several iterations of the “Vee” model. The following iterations use feedback such as data, tests, updates, and so on, to improve the system until its retirement or replacement (Khan & Mclucas, 2008).

4.3.4 Model-Based Systems Engineering

The model-based systems engineering (MBSE) approach is a graphical modelling language that enables the design of complex systems such as a digital twin system. This approach aims to create systems engineering domain models to save and exchange information different to the document-centric model. It uses computer modelling to define systems based on properties, specifications, and future behavior. Systems modelling is helpful for architectural design processes. It also supports the development and procurement of requirements in the system, subsystems, and components. The MBSE goal is to give precision, consistency, traceability, and integration to the entire system lifecycle (Selvy et al., 2014; SysML.org, 2005).

According to Delligatti (2014), MBSE looks for the integration, coherence, and consistency of system activities in one single model. This is an advantage over the traditional document-based approach. The MBSE approach aims to generate documents automatically based on the information provided to the system model. The benefits are noticeable when the designer wants to change a requirement or update it. Changes in requirements affect the entire system model. The MBSE approach keeps track of these changes and updates the system automatically. There is no need to examine and update all the models and documents that were affected by that change as in the traditional document-based approach. The MBSE approach supports the application of the systems engineering "Vee" model for project development. The "Vee" model presents the system requirements from the stakeholder's needs, the system design, analysis, integration and test, and the verification and validation process. The Vee model activities begin in the conceptual design and finish with the actual operation of the project.

4.3.5 Smart Manufacturing

The trend of manufacturing is to become smart due to IoT devices, and software that improves management decisions. Smart manufacturing (SM) involves and studies all the stages of production from suppliers to customers. Agencies such as the Department of Defense and the Department of Energy use this term to describe the use of intelligence to produce better products. Smart manufacturing implements intelligence along the supply chain manufacturing. It gives users a holistic perspective to study, plan, and manage manufacturing processes. This is possible through the implementation of IoT devices, and development of data analytics, modelling and simulation (Davis et al., 2012).

The National Institute of Standards and Technology definition of SM is that it integrates all the components of a manufacturing system. SM processes meet supply chain manufacturing needs in real-time such as factory conditions, customer needs, and supply networks (U.S. Department of Commerce, 2021). Digital twins are a part of smart manufacturing. It connects physical assets to an industrial network and models them in the virtual space. It provides SM with tools to simulate, improve models, and predict physical objects' status in real-time. DT is not the only technology that makes manufacturing smart. Big data, artificial intelligence, and cloud computing, along with DT, work together to enable automated processes and activities. This is the case of DT technology. It needs other IoT technologies to perform its functionalities.

There are three applications of smart manufacturing. The first one is smart production. This application describes production with augmented intelligence to manufacture smart end-products. SM are capable of making production more flexible and efficient. It improves the human–machine interface towards collaboration. The second application is the smart production network. It puts SM in a bigger system perspective. It considers the integration of other systems in the supply chain management. The goal is to create a big manufacturing network that helps each other to satisfy the constantly changing customer needs. This network will ease production planning and create automated processes at distinct levels in the SM. The upsides are more revenue, production processes that respect the environment, and a socially responsible factory. The last one is mass personalization, which means that SM will focus on customized production. This changes mass production for a personalized one that allows users to create their own end-product (Lu et al., 2020).

4.3.6 Conceptual Framework

A conceptual framework is an analytical tool that studies different concepts. It allows researchers to make comparisons and organize ideas. It not only gathers concepts, but also integrates them into one single structure. The goal is to find factors, attributes, variables, behavior, processes, and so on that describe the new concept. Some researchers could mistake conceptual frameworks with conceptual models. The second one considers concepts alone. The first one considers factors and variables. It presents an approach to interpret the real world. However, it does not study cause-and-effect relationships. It helps to understand new concepts (Miles & Huberman, 1994).

According to Levering (2002), conceptual frameworks are a good start to explain a concept or phenomena. They allow problems to be understood but cannot determine the specific outcome as quantitative models. Nevertheless, they can solve a problem based on external concepts or factors that are interrelated. Researchers follow a qualitative analysis process to develop conceptual frameworks. According to Jabareen (2009), conceptual frameworks connect several concepts in a network to investigate a phenomena. They simplify ideas and organize them in a way that is easy to apply. It is the product of a qualitative process that explores theorization. It gathers several theories to build a new concept. A concept presents components which define the concept itself. Hence, these components are not separable, heterogeneous, and endo consistent. These concepts have a background of other concepts. All these components and concepts form the conceptual framework of the new concept. Conceptual frameworks are ontology-, epistemology-, and methodology-based. Concepts that are part of a framework have an ontological and epistemological structure or nature. The ontological nature defines concepts or things in the real world. The epistemological nature describes these things or concepts in an abstract or ideal world. The methodology explains how to build the framework and evaluates its contribution to the real world.

The conceptual framework analysis technique involves the research and analysis of concepts relevant to the new topic. It is a grounded theory technique that looks to find phenomena or events, patterns, and relationships in theory. The selection of concepts is based on the number of occurrences in a text, their meaning, and importance. All of them are part of the new conceptual or theoretical framework. It is critical to evaluate and select data relevant to the new concept or phenomena. Data could come from several sources which are part of different disciplines. Hence, conceptual frameworks present a multidisciplinary approach to analyze data. The conceptual framework analysis is an interactive process that compares concepts and data, continuously. This process manages emerging theory based on the conceptual level and scope. The conceptual framework analysis presents the following process (Jabareen, 2009):

1. Mapping the selected data sources.
2. Extensive reading and categorizing of the selected data.
3. Identifying and naming concepts.
4. Deconstructing and categorizing the concepts.
5. Integrating concepts.
6. Synthesis, resynthesis, and making it all make sense.
7. Validating the conceptual framework.
8. Rethinking the conceptual framework.

4.4 Modelling a Digital Twin for Manufacturing Systems

This section uses the systems engineering "Vee" model and a model-based systems engineering (MBSE) approach to design complex systems such as a small-scale digital twin subsystem of a manufacturing system. The system of interest (SOI) for this study is a manufacturing system with the digital twin as a subsystem. The authors use a MBSE tool such as Astah SysML for the system modelling. They also use the "Vee" model activities presented by the Federal Highway Administration (FHWA) (Transportation, 2007) to develop the digital twin subsystem. Figure 4.2 shows the FHWA's "Vee" model.

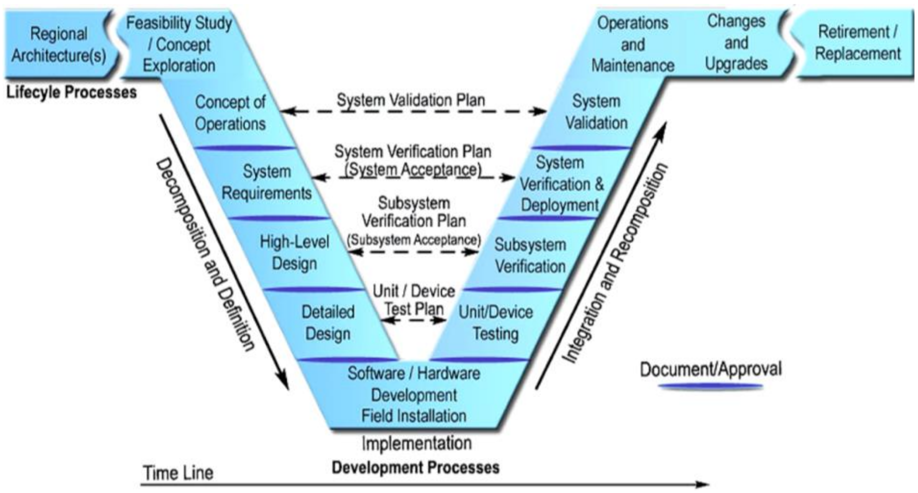

Figure 4.2. **"**Vee" model of the Systems Engineering Process (Transportation, 2007).

In this case, the only interest of this article is the left-side of the "Vee" model. This side presents some crucial activities for the digital twin planning and design. These activities or steps are the concept of operations, system requirements, high-level design, and detailed design. This article employs a MBSE approach to perform and integrate all these activities. MBSE allows the creation, visualization, and traceability of each activity throughout the entire system.

4.4.1 Concept of Operations

This section defines the system's concept of operations (CONOPS). The CONOPS is a document where stakeholders define the system needs and main operational goal from a high-level or systems perspective. This document helps to define the system requirements (Transportation, 2007). The system's modelling starts with the operational need or top-level use case. The manufacturing system (MS) operational need is the implementation of digital twin technology in the manufacturing processes. To meet this goal, the system's architects identify the MS stakeholders and develop a context diagram. These stakeholders interact with the MS as described in the use cases. Then, the system's architects describe the system's top-level use case which is the major usage scenario for the MS. Finally, it presents the concepts of operations and system domain which characterize the system needs.

4.4.1.1 Top-Level Use Case

Use cases are actions or events that define the interactions between an agent and a system to achieve a goal (Delligatti, 2014). The system of interest (SOI) considers the digital twin technology implementation as a top-level use case. The system interacts with operators and the physical factory. The system needs operators to implement digital twin technology in the factory. These operators could be programmers, engineers, data analysts, and so on. Figure 4.3 shows the system's top-level use case.

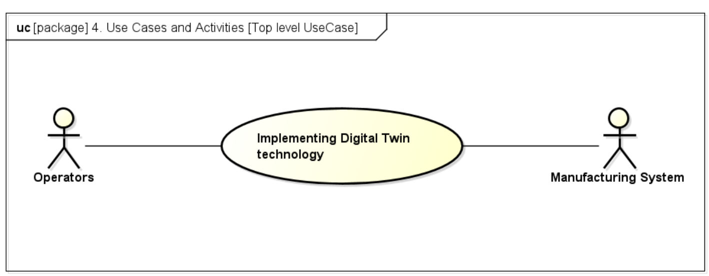

Figure 4.3. Top-Level Use Case.

4.4.1.2 Stakeholders

The MS stakeholders are all interested in the system because the system satisfies their operational need(s). The stakeholders' identification is important to define the system's requirements. The system's life cycle decides who the SOI stakeholders are (Delligatti, 2014; Transportation, 2007). This system presents two groups of stakeholders: active and passive. Figure 4.4 shows the stakeholder's diagram.

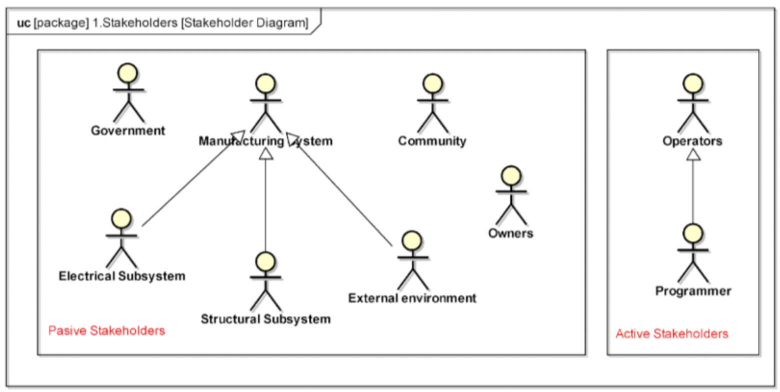

Figure 4.4. Stakeholder's Diagram.

Active stakeholders are those who have a continuous participation with the SOI. They provide inputs and get outputs from the SOI. The active stakeholder for the digital twin subsystem of a manufacturing system is the following:

Operators/Programmer: The MS needs operators to work on the DT subsystem and perform operational tasks such as simulating, monitoring, and controlling. Operators are key elements in the DT subsystem's life cycle from its conception to its retirement or replacement. In return, operators receive a salary for working hours.

Passive stakeholders do not have a continuous interaction with the system. This does not mean they are not interested in the system. They are just not active participants in the system's lifecycle. The passive stakeholders are the following:

Owners: The MS needs owners to put money or capital to develop new projects such as the digital twin implementation on the factory operations. Owners need to invest in the factory's structure, machines, equipment, material, labor costs, and so on.

External Environment: The MS shall be responsible with its environment because the system gets energy and natural resources from it. Therefore, the system must be careful with waste emissions to the environment.

Electrical Subsystem: The electrical energy allows the use of machines and other equipment, as well as the factory lighting.

Structural Subsystem: The MS uses the factory facilities as its infrastructure to manage the business from the materials reception to the delivery of products. This subsystem is the physical space of the digital twin subsystem.

Community: The community has similar interests in the SOI as the environment. Hence, the system shall be responsible to the community. The community shall accept the factory and support its operations. In return, the factory provides jobs, products, and services to the society.

Government: The government regulates the SOI development and operations. It defines and enforces laws, norms, incentives, rules, regulations, and so. The factory will retribute the government by obeying the law and paying taxes.

Figure 4.5 presents the system of interest context diagram that shows the interaction of stakeholders with the digital twin subsystem.

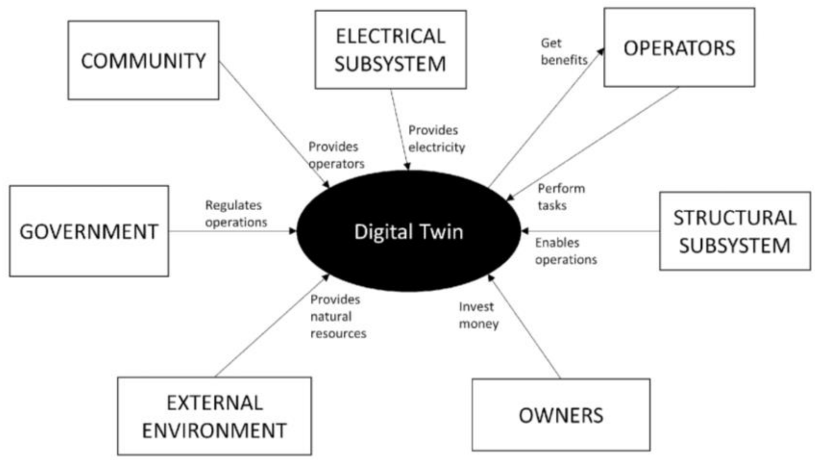

Figure 4.5. Context Diagram.

<u>4.4.1.3 CONOPS and System Domain</u>

The CONOPS and system domain describes the system's characteristics from a user perspective. A MS looks to implement digital twin technology in its regular operations. Digital twin is a smart technology that twin physical objects in the virtual world. DT simulates real-time data to make decisions. DT optimizes processes and objects in the virtual world and applies the results in the real world. DT capabilities are monitoring, simulating, and controlling manufacturing processes. DT monitors production processes in real time. DT simulates 'what-if' scenarios to prevent or reduce risks and improve processes. Finally, DT controls the physical system to apply the simulation results (M. Singh et al., 2021; Trauer et al., 2020). Figure 4.6 shows the digital twin's CONOPS diagram.

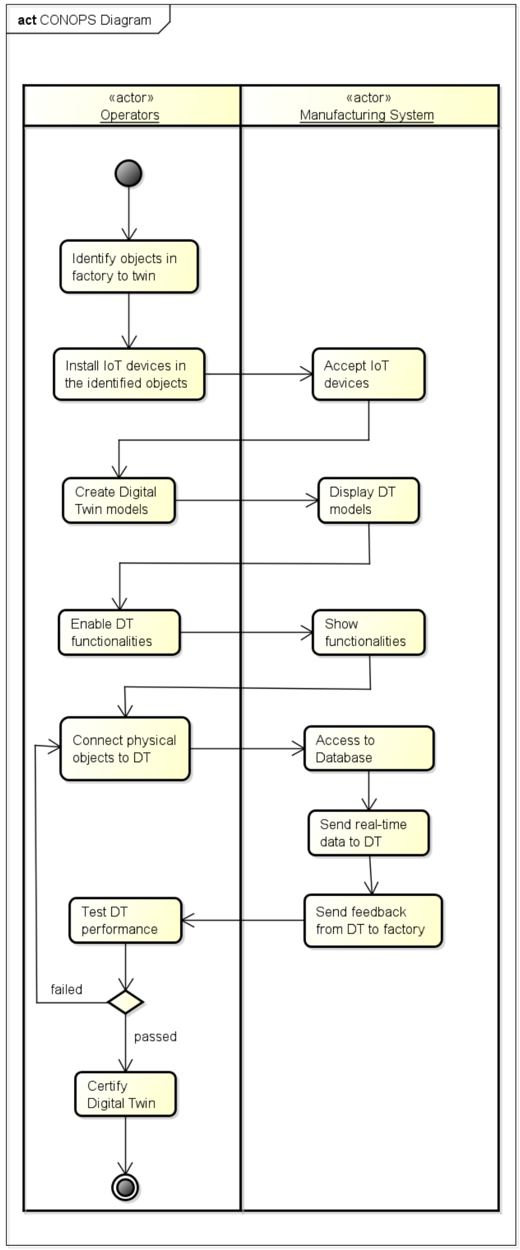

Figure 4.6. CONOPS Diagram.

The CONOPS diagram shows the activities to implement DT in a factory. First, MS operators identify physical objects in the factory to twin in the virtual world. Then, they install IoT devices, such as sensors and actuators, in the factory to collect data from and operate the objects. The third step is to create digital twin models in the virtual world.

The next step is to enable digital twin capabilities such as simulation, monitoring, and controlling objects. MS workers model the factory processes and add functionalities to the DT models. Then, the operators connect the DT models to the factory using real-time data. Finally, they test the DT performance, and certify it. Therefore, the high-level tasks involved in the CONOPS for the implementation of a digital twin for a manufacturing system are to install IoT devices, develop digital twin models, enable digital twin functionalities, and connect the factory to the digital twin. The authors describe these tasks in the use cases lines below.

4.4.2 System Requirements

Requirements describe the necessary operational outcomes to fulfill an operational need. They define the system's functions and features. From a high-level perspective, requirements focus more on what the system should do than how to do it. They do not get into details (Transportation, 2007). This is the case of this system of interest which needs requirements to fulfill its use cases. The SOI operational need is to implement digital twin technology in the manufacturing system. Therefore, the system of interest needs three high-level requirements such as resources, technology, and digital transformation. Figure 4.7 shows the system's high-level requirements in a SysML requirements diagram. Finally, this section divides the requirements into functional, non-functional, and interface requirements. Table 4.1 shows some of the digital twin requirements for a manufacturing system.

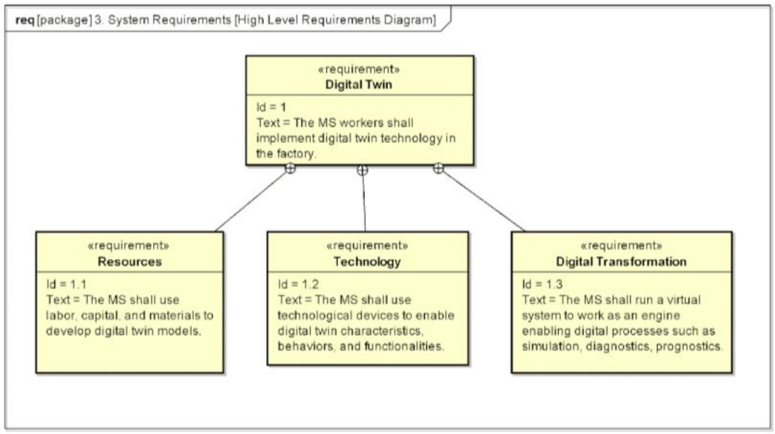

Figure 4.7. High-level Requirements.

Table 4.1. Some of the digital twin requirements for a manufacturing system.

ID Req.	Requirement	Description	Type of Requirement
1.1.1	Physical	The MS shall use physical resources to support the creation of digital twin models.	Non-Functional
1.1.1.1	Infrastructure	The MS shall use a physical infrastructure to operate the digital twin's "hardware."	Interface
1.1.2	Human	The MS owners shall hire employees to implement digital twins in the manufacturing system.	Non-Functional
1.2.1	Smart Machines	The operators shall install smart machines that work in a network setting and make automated decisions.	Functional
1.2.2.3	Data Visualization	The DT software should use maps, graphics, dashboards, and so on to represent data and information.	Functional
1.3.1.1	Digital Thread	The MS workers shall create a digital thread to connect the physical space to the virtual space.	Functional
1.3.2.3	Objects	The MS workers shall digitize physical objects in the system according to the DT scope.	Functional

4.4.3 High-Level Design

After defining the system requirements, the system's architects describe high-level use cases and design the system's logical architecture. This section shows use cases with several tasks that enable the realization of the system's top-level use case (Transportation, 2007). It also shows an overall system's architectural design to satisfy the system requirements. This architectural design decomposes the system into subsystems and components (Delligatti, 2014).

4.4.3.1 Use Cases

The system of interest considers the following use cases: install internet of things (IoT) devices, develop digital twin models, enable digital twin functionalities, and connect the factory to the digital twin. These use cases allow the top-level use case of implementing digital twin technology in the manufacturing system to be achieved. They are high-level tasks because they are composed of other tasks. Figure 4.8 shows the system's use cases.

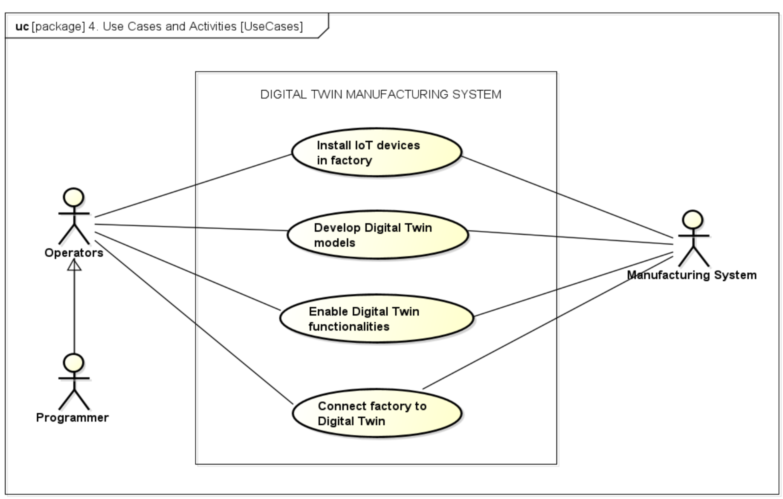

Figure 4.8. Use Cases.

1. Install IoT devices: This high-level task starts with the selection of IoT devices that are compatible with the manufacturing system. If they are not compatible, the factory must select other devices. If they are compatible, the operators proceed with installing the IoT devices to the factory. Then, the system operators must operate the IoT devices in the factory. Finally, the operators test the performance of these devices. If the IoT devices pass the test, they approve their installation. If not, they must be reinstalled.
2. Develop digital twin models: This high-level task starts with the installation of digital twin software. Then, the operators integrate the IoT devices to the digital twin software and set the configuration for their use. The next step is the digitization of the physical objects in the factory by creating computer-aided design (CAD) objects. The digital twin software must display these CAD objects. Finally, the operators must test and approve the virtual object's fidelity with respect to the real objects.
3. Enable digital twin functionalities: This high-level task starts with the operators mapping the factory processes to mirror them in the digital twin. Then, the operators define the digital twin functionalities and implement them to the digital twin software. The next step adds DT functionalities to the virtual models. Finally, operators display the digital twin functionalities and test their behavior. If the digital twin does not pass the test, operators must redefine the digital twin functionalities for the virtual models.
4. Connect factory to digital twin: This high-level task uses IoT devices to collect and centralize data in a database. Then, operators create the digital

thread to integrate the physical manufacturing system and the digital twin. The digital thread enables the flow of data between the physical and virtual spaces. Finally, operators test the digital twin performance by feeding data from the factory to the digital twin and vice versa. They also test the digital twin functionalities. If the digital twin does not pass the test, operators must check and correct the integration between the physical and virtual spaces. If the digital twin passes the test, it is ready to be released and used in the factory's regular operations.

4.4.3.2 System Logical Architecture

A logical architecture is an abstract representation of the requirements. It presents a structure design that defines functions, properties, and interfaces of logical components. It should be abstract and not give specific detail. Hence, it does not identify physical elements, but rather a baseline to start developing the physical system. In SysML, logical architecture uses block definition diagrams (BDD). These blocks or components are distinguished from other diagram's blocks by the stereotype "Logical." The logical architecture divides the components in three categories or platforms: physical, virtual, and information management. This architecture enables the creation of the system's physical architecture (Delligatti, 2014). The digital twin subsystem defines the logical components from the system's requirements in Figure 4.9.

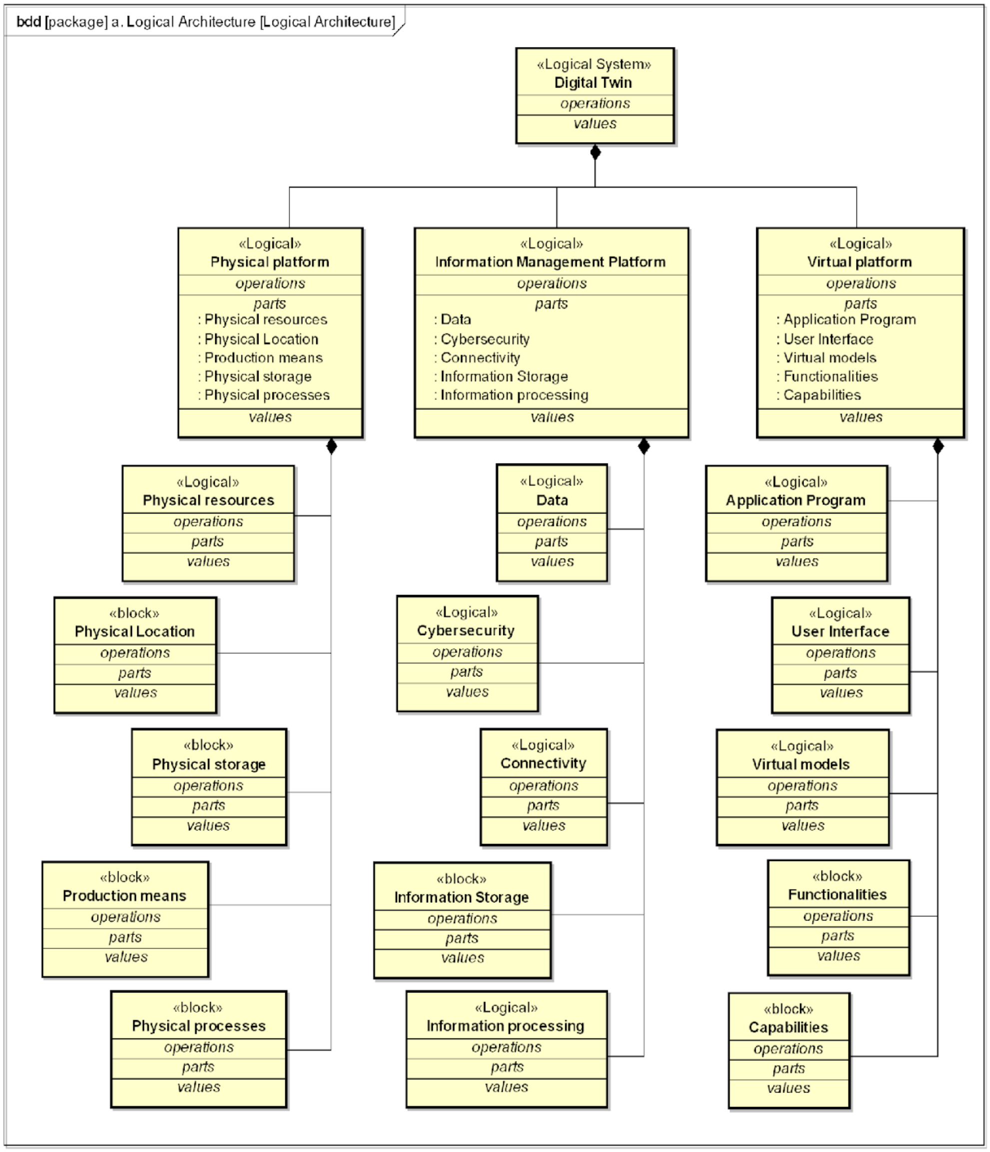

Figure 4.9. Logical Architecture.

4.4.4 Detailed Design

A detailed design shows the physical components that enable the realization of the system. It presents the system's physical architecture which derives from the system's logical architecture (Transportation, 2007). This section is the last activity of the system's planning and design.

4.4.4.1 System Physical Architecture

Physical architecture is a technical representation of the logical architecture. Physical architecture represents the structure design of the system's physical components. In SysML, physical architecture also uses block definition diagrams (BDD). The physical blocks or components are distinguished from other diagrams by the stereotype "Physical." The physical architecture divides the components in three main categories: factory, data management, and DT software. Physical components are actual devices or software objects that realize logical components (Delligatti, 2014). The "factory" physical components are the physical realization of the "physical platform" logical components. The "data management" components realize the "information management platform" logical component. Finally, the "DT software" realizes the "virtual platform" logical component. The digital twin subsystem model defines the physical components based on the previous logical architecture in Figure 4.10.

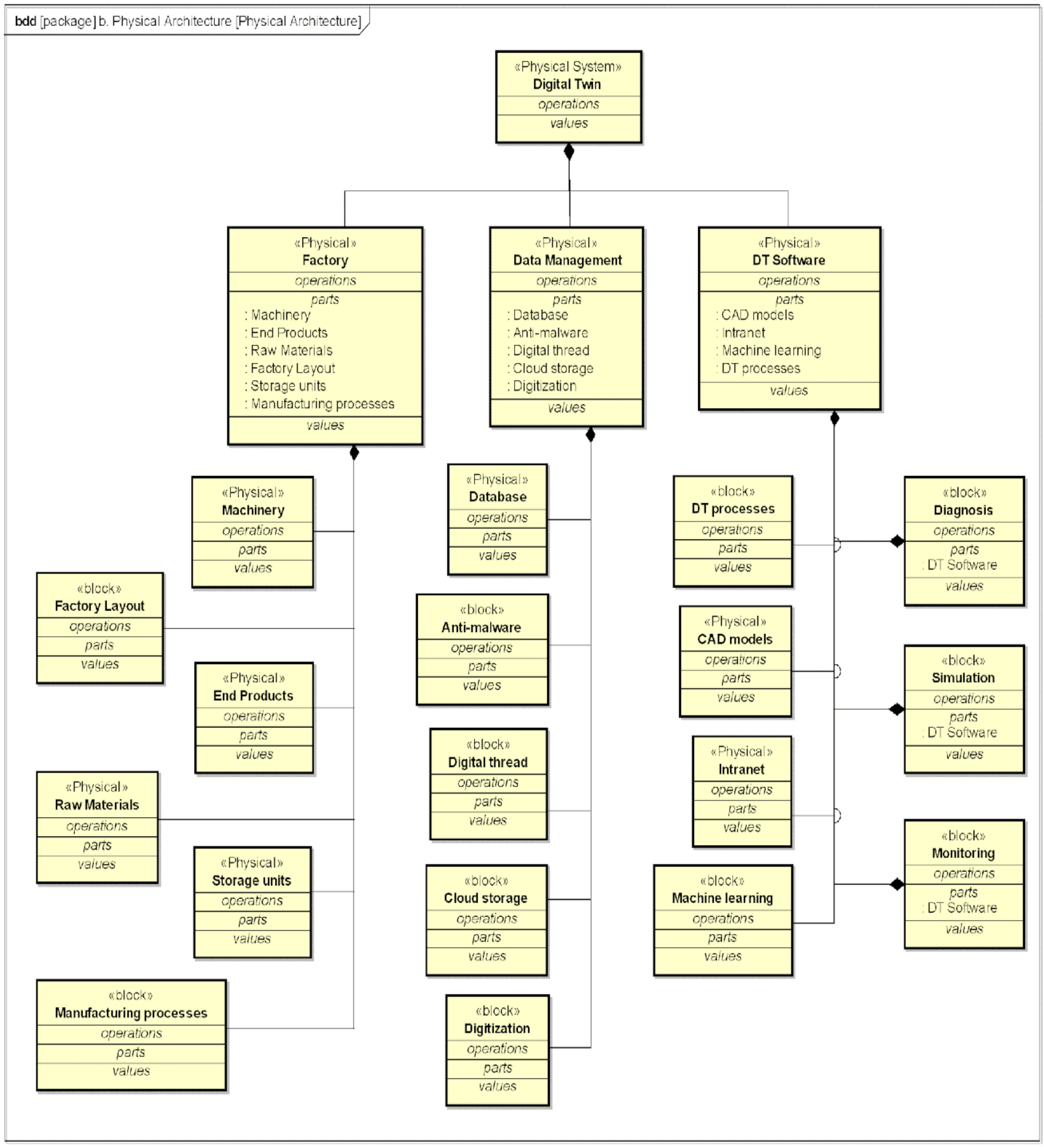

Figure 4.10. Physical Architecture.

4.5 Small-Scale Digital Twin Implementation Framework for Manufacturing Systems

This study proposes a framework to develop digital twins in manufacturing domains. This study considers the general configuration of digital twin technology and the digital twin components presented in the literature review. This configuration presents three main spaces or systems which are physical, virtual, and information. It allows continuous data flow through all spaces. It gives the digital twin updated information from the real world. It also helps to make better decisions and improve processes in the physical systems (M. Grieves, 2014; Lu et al., 2020; Yang et al., 2017). This framework also takes into consideration the system modelling presented above. It employs the use cases and system requirements to define the digital twin main goal, capabilities, and functionalities. It uses the system's logical and physical architecture to define some key concepts part of a digital twin design. Figure 4.11 presents a framework to implement the digital twin in manufacturing systems.

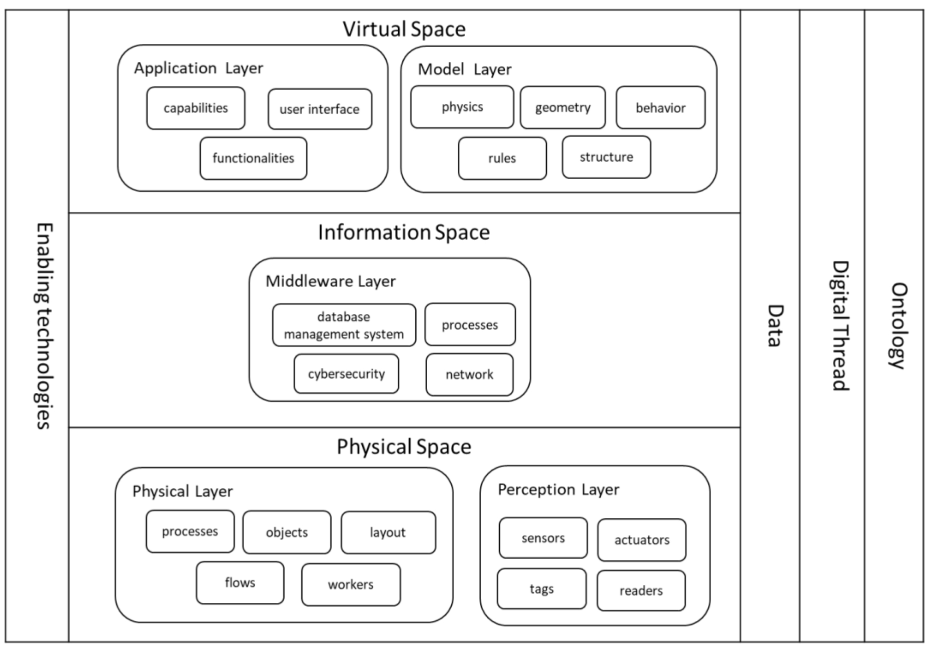

Figure 4.11. Small-Scale Digital Twin Implementation Framework.

This article develops a step-by-step process to use this framework and implement digital twins in a manufacturing system. The steps are the following:

1. Define what processes, products, or systems to twin in the virtual space.
2. Install perception devices such as sensors, actuators, tags, and readers in the physical layer.
3. Create a database management system that gives access to different types of databases.
4. Enable a digital thread that connects different types of data, devices, and systems.
5. Install a digital twin software that shows digital twin models and data and enables user's operation.
6. Create digital twin models with their properties in the DT software.
7. Enable digital twin functionalities such as feeding data to DT models.

There are some non-mandatory steps that users could follow to improve the digital twin maturity. One step is using a digital twin ontology to be familiar with DT concepts and relationships. Another step is integrating enabling technologies such as cloud computing, artificial intelligence, and so on to improve the system's digital twin.

After presenting the digital twin implementation framework for manufacturing systems, this study explains in detail the framework spaces, layers, and concepts lines below.

4.5.1 Physical Space

The physical space is a complex environment with many components interacting between each other. This article encompasses a discrete manufacturing system and its processes. It presents many processes such as product manufacturing, maintenance, logistics, product development, and so on. These processes have rules and a common physical constraint (Qin et al., 2016). The system must install sensors over the physical asset that they want to resemble in the virtual space. This data helps to resemble the behavior and structure of objects and create digital twin models.

The physical space provides real-time data to enable digital twin capabilities such as simulation, control, and monitoring. These capabilities allow the physical objects and predict potential outcomes to be analyzed. Digital twin technology allows the physical space to control its objects automatically. It uses sensors and actuators in the real world to automatize processes. It will capture all the physical objects' lifecycle in the virtual space through the information space (Agrawal et al., 2022). This space presents two layers: the physical layer and the perception layer, with their respective components. The physical layer contains several physical objects that collect and send data to the virtual space for its analysis. It creates a network of objects that collaborate with each other to perform processes. The perception layer collects data and executes commands in the physical space.

The physical layer components for this framework are processes, objects, layout, workers, and flows. Physical processes are manufacturing activities to develop products from raw materials. They are a set of statements that assign certain behavior to a product. These processes transform inputs into end-products. Production processes create a system that interacts with other systems to deliver products to customers (Black, 2006). Objects are entities such as machines, materials, parts, products, tools, and so on present in the physical space of the factory. These objects go through certain processes in a layout. Some of these objects (machines, parts, tools) are smart devices that connect to other devices creating a network or internet of things. They can provide real-time data about the manufacturing processes to the digital twin application and model layer. They can also receive feedback from these layers. The objects that are not smart need the perception layer components to send to and receive data from the virtual space. These objects share data such as position in the layout and status. Objects that use digital twins can enhance or develop an augmented perception of their physical environment (Chukhno et al., 2020; Yang et al., 2017). The layout is the factory's floor that distributes the different objects, modules, and stations. It is the physical space where the processes transform resources into end-products. Factories layouts could be complex due to the high amount and variability of parameters. This complexity is related to the selection and positioning of objects. Digital twin can solve this complexity and improve a layout structure (Kuehn, 2018; Pang et al., 2021). Workers are the human force that develop or assemble new products in a factory. Factories must match processes with skilled labor to fulfill production goals. This is a challenge that could decide a factory's productivity. Hence, productivity is related to the working layout and conditions in which workers perform their tasks. Workers are an essential component in the mechanical, physical, or chemical transformation of raw materials. Nevertheless, complex manufacturing systems such as additive manufacturing could replace workers with sophisticated but flexible machines (Levinson, 2017; Weller, 2015). Finally, flows are a sequence of processes which products follow in a manufacturing layout. They link different process parameters and organize them to finish at a certain time. They allow factories to design their work by defining the flow of people, materials, processes, and so on. This provides reliability and predictability to the factory's operations. They define the production lead time and capabilities that ensure the production of quality products (Boukas & Haurie, 1990; Dallery & Gershwin, 1992).

The perception layer is in charge of collecting data from the physical space. It presents the following components: actuators, sensors, readers, and tags. A digital twin uses sensors to collect data of changes in the real world such as images, motion, pressure, and so on. Data is relevant for feeding digital twin models constantly in the virtual space. Sensors, being part of the IoT, can monitor and control processes. They can also upgrade standard devices into smart devices with network connectivity (R. He et al., 2019; Kadlec et al., 2009). Actuators help machines, tools, or other devices to execute changes in the physical space. It uses electrical or hydraulic energy to command mechanical movements. Factories use them for opening doors, stop motions, execute motions, accelerate/decelerate, etc. Common types of actuators are pneumatic, electric, and electro-hydraulic (Gubbi et al., 2013; R. He et al., 2019; Tao, Qi, et al., 2019). Tags and readers are radio frequency identification (RFID) devices. Readers emit and receive signals from the tags. Tags communicate the location of the physical object (Pang et al., 2021).

4.5.2 Virtual Space

Digital twin uses the virtual space to show the physical objects in the virtual world. The virtual space is a copy of the physical space. It transforms physical objects into virtual objects. It resembles all characteristics of the physical counterpart. The virtual space displays the structure, behavior, information, and so on of the physical object (M. W. Grieves, 2019; Lai et al., 2020). It also displays diverse types of digital twin models based on components, assets, processes, and systems. IBM (Armstrong, 2020) explains that a digital twin for manufacturing systems could integrate different digital twin models into a composite digital twin system. The virtual models allow the analysis of data and the improvement of the physical system. The digital twin goal is to implement post-analysis solutions in the physical system.

Digital twin recognizes every change on the physical asset. The virtual space mirrors its counterpart in the real world. It has different capabilities such as control, diagnostics, and prognostics (Agrawal et al., 2022). It receives real-time data from the physical system to analyze it and give feedback to the physical system. It shows the system's current situation and potential cases. The virtual space allows the design and test of new models (Xie et al., 2020). The simulation capability plays with the physical objects to propose potential changes for the benefit of the system. It can simulate the system's physics and structure. This capability allows operators to make better informed decisions throughout the system's lifecycle (Kuehn, 2018). However, digital twins are more than a simulation tool (Exor International, 2020). Digital twin is a flexible and agile technology that works with real-time data under different use cases (Guo et al., 2019). The user can monitor the physical space changes through the virtual space. It updates the virtual objects in real time. It can control physical objects from the virtual space using actuators in the physical space. These capabilities analyze data and provide information about the objects, processes, and services. All these add value and improve the system's operations.

The proposed framework presents two layers in the virtual space: application and model. The application layer analyzes data and sends useful information to the physical space. This layer helps employees to make better informed decisions. It analyzes short, medium, and long-term data. The application layer concepts are user interface, capabilities, and functionalities. User interface is the software that enables a human–digital twin technology interface. It shows the digital twin models and data. It allows users to operate the digital twin functionalities and capabilities. It helps operators to make data-driven decisions. (Diehl, 2001; A. M. Madni et al., 2014). Digital twin presents main capabilities such as modelling, simulating, monitoring, and controlling. DT adds these capabilities to physical systems, improving their processes and functionalities. It also improves the efficiency and accuracy of physical objects. It makes physical systems smart with powerful communication and computing capabilities. DT capabilities enable a better simulation environment in terms of fidelity, speed, and granularity. A customized DT can choose the number and types of capabilities (Agrawal et al., 2022; AIAA & AIA, 2020; Tao, Qi, et al., 2019). Finally, DT presents some functionalities such as creating virtual models from physical objects, resembling the behavior of physical objects in the virtual space, using real-time data, providing feedback to the physical system, designing better products, solving complex problems, testing innovative ideas, and so on. These functionalities vary depending on the type of manufacturing system and the digital twin scope (Söderberg et al., 2017).

The model layer allows the DT to replicate physical objects in the virtual space. It presents all the characteristics of the physical objects. Based on the DT model level of fidelity, it could be indistinguishable from the physical object that it resembles. The model layer components are rules, physics, geometry, structure, and behavior. Digital twin rules are a group of triggers, conditions, and effects in the virtual models. These rules play an important role in deciding the digital twin system's architecture (Wu et al., 2020). Physics-based digital twins are models that resemble the governing laws of nature such as space, time, and so on. These types of DT models require a great computational resource and processes. Currently, engineers use physics-based models for finite element analysis. Engineers should also consider the physics of objects for developing DT models. Physics-based models present benefits such as reliability and predictability. (Kapteyn et al., 2020). Digital twin models must also consider geometry to design physical objects. Geometry describes the size, shape, position, and properties of physical objects. It could represent the digital twin in two-dimensional (2D) or three-dimensional (3D) form. Geometry elements are points, curves, lines, surfaces, bodies, patches, etc. These are necessary to form a solid geometric model. The collection of geometric objects leads to the creation of a mesh (Friedenthal et al., 2015; Söderberg et al., 2017). The structure concept organizes system components, elements, or parts, and presents its internal and external connections. It decomposes objects or classes into subcategories or subclasses. Then, it integrates them based on causal or correlational relationships. It describes value properties, interfaces, flows, and constraints. The user interface displays the DT model's structure hierarchy (SysML.org, 2005; Weilkiens, 2019). The last concept in the model layer is behavior. Behavior defines the interaction between DT models such as activities, state machines, and sequences. There are two types of behaviors based on functions and state. The function-oriented behavior studies DT model activities, connections, and compositions. It shows the execution of activities such as the transformation of inputs into outputs. The state-based behavior studies the changing of models before and after function execution. DT models can show the history of objects through different transitions. Behaviors enable or realize DT capabilities. It can change the DT model's property values and structure (Erickson, 2009; Weilkiens, 2005).

4.5.3 Information Space

The information space connects and enables a bi-directional communication between the physical and virtual space. This space supports the digital twin's internal and external communication in real time. It supports the system's network and internet connection. Connectivity helps in the development and evolution of digital twins (M. W. Grieves, 2019). It supports the creation of a digital thread which generates data traceability keeping operators informed. Digital twin uses a digital thread to send and receive data from the physical and virtual space. Moreover, a digital thread allows the digital twin to analyze a system's lifecycle and integrate the system's components. Finally, it connects the digital twin with external systems that belong to the manufacturing supply chain (A. Madni et al., 2019; Pang et al., 2021).

Information space supports a continuous exchange of data between the physical and virtual space. This interaction enables all digital twin functionalities. This space helps to model objects, processes, systems, and end-products. After analyzing data, the virtual space uses the information space to give feedback to the physical space. Dataflow is important to predict failures and improve the system. Database abstracts physical space data and shares it with the different system components. It collects, compiles, preprocess, and stores data from both spaces. Digital twin uses historical data to create better solutions such as predictions, prescriptions, and diagnosis of the physical system (R. He et al., 2019; Kapteyn et al., 2020; Lu et al., 2020). This makes digital twins a smart technology able to learn.

The proposed framework includes the middleware layer in the information space. The middleware layer is an intermediary between the physical space and virtual space (Angrish et al., 2017; IBM Cloud Education, 2021). It manages communication between the two spaces. It uses a wireless or wired connection for this purpose. It stores real-time data collected in the physical space. It processes data and sends it to the virtual space for analysis. This layer feeds data to the application layer in the virtual space. It has two main functions: networking and data management. The networking function aims to exchange information along the distributed network of applications and objects. It allows communication between the physical and model layer. The data management function stores data and supports the middleware to perform its processes (Alam & El Saddik, 2017; M. W. Grieves, 2019; Steinmetz et al., 2018).

The middleware layer components are network, cybersecurity, processes, and databases. Digital twin network connects objects from the physical space to the application layer. This network enables digital twin functionalities. A DT network focuses on communication technology and wireless communication. It allows continuous communication and transfers data between objects. It integrates several types of components with different communication protocols and technologies (Fuller et al., 2020; Lu et al., 2020). Cybersecurity looks to protect the virtual and physical space from threats such as malware, eavesdropping attacks, man-in-the-middle (MitM) attacks, denial-of-service (DOS) attacks, and so on. It defines policies, best practices, tools, guidelines, and technologies to assess risk, mitigate potential damage, and counterattack cybercriminals. It maintains the confidentiality and availability of information and data. An example of cybersecurity for digital twins are the authentication and authorization security processes.

The authentication process verifies the user's identity. It determines if they are true or valid users. Authorization checks the user's access rights. It authorizes or denies their access. Digital twins could be a tool to enhance the cybersecurity of a factory. It could help to recognize attacks in real-time. Moreover, it could simulate potential threats or damages to the system. DT can help to build a better security system (Craigen et al., 2014; Holmes et al., 2021). Middleware processes connect different software, physical components, and data to bring a single centralized service to users. It links new applications such as digital twins to the manufacturing system. It manages different devices in the physical layer, allowing communication between them. It manages applications, provides internet connection, and allows the sending and receiving of data between layers (Angrish et al., 2017; IBM Cloud Education, 2021). The last concept in the middleware layer is the database management system (DMS). A DMS is a software that allows users to create and manage databases. It has several databases with different types of data. Databases store data from physical objects, processes, products, and so on. DMS can give access to several apps and users at the same time. It also brings security to data due to its centralized storage capability. Digital twins process a great amount of data to analyze, perform functionalities, and make decisions (Derclaye, 2005; Gunjal, 2003).

4.6 Discussion

This article follows a methodological structure to build a DT implementation framework. Frameworks provide a guideline that makes the development of digital twins easier. This framework intends to be easy to learn and precise in terms of concepts. It collects many concepts under a defined structure. This study explains how to collect relevant concepts, and classify them in classes, spaces, or layers. It analyzes these concepts and their relationships, properties, and functions. It creates a structure based on their taxonomy. This framework could help small factories to build a digital twin of their products, processes, and systems. They are an effective tool to learn about digital twins and how to implement it in a manufacturing environment.

Before building the digital twin implementation framework, this article studies the complexities of digital twin in the literature review. The digital twin implementation framework uses data found in the literature review and digital twin subsystem model. This framework organizes the concepts in a general digital twin configuration with three spaces: physical, information, and virtual. Physical space presents two layers: physical and perception. Information space has a single layer: middleware. Virtual space presents two layers: application and model. In addition to these layers, users could use other concepts for the development and operation of a digital twin, such as ontology and enabling technologies. These concepts could help increase the maturity of a digital twin, but they are dispensable in its implementation.

Through the modelling of a digital twin subsystem, it is noticeable that DT is a complex system. It was necessary to use a MBSE approach to design it. MBSE provides consistency, traceability, and precision to the digital twin subsystem design. The systems modelling helped to build the digital twin implementation framework. It presents CONOPS, stakeholders, requirements, use cases, logical architecture, and physical architecture. It considers the implementation of digital twins in manufacturing as an operational need. It explains with use cases how to implement digital twins. It describes missions, requirements, activities, functions, objects, relationships between objects, and integration of spaces. It explores several devices and concepts for the physical and virtual spaces. It presents a logical and physical architecture that defines the abstract and technical components necessary for DT implementation.

This study presents a concise description of the DT implementation framework to help researchers and practitioners understand it. The digital twin implementation starts in the physical space. The physical space uses the perception layer components to get data from the physical layer. The physical layer components are the factory processes, machines, layout, tools, and every object that is physically there. The data travels through the information space to the virtual space. The information space saves all data in a database and digitizes it. It also enables the entire system to connect with other systems. The digitized data feeds the model and application layer in the virtual space. The application layer is the interface between the operator and the virtual world. It shows the digital twin software, capabilities, and functionalities. Digital twin software is a computer program designed for end-users. Digital twin capabilities are simulation, monitoring, and diagnosis. The digital twin system has many functionalities in a factory. The systems modelling presents some high-level functionalities. Finally, the model layer represents the physical objects in the virtual space with all its characteristics, behaviors, structure, geometry, level of fidelity, and rules.

Finally, this study proposes a new definition for digital twins. “Digital twins are virtual objects that mirror physical objects in the virtual world. Digital twins’ characteristics, behaviors, functionalities, and connectivity vary according to their level of maturity.” This definition uses the verb mirror which means to show a reflection of a physical object. This reflection shows the characteristics and data of the original object.

This new mirrored object is part of the virtual world. A channel or thread connects and allows communication between the physical and virtual object. Digital twins can be as complex as the system wants it to be. The system scope and desired functionalities decide the level of maturity of the digital twins.

4.7 Conclusions and Future Research

This article proposed a small-scale digital twin implementation framework for manufacturing systems. The authors used several concepts from the literature review and a digital twin model for manufacturing systems to build this framework. They developed a digital twin model using a MBSE approach. This model helped to define the DT concepts used later in the digital twin implementation framework. This framework uses a digital twin configuration with three spaces: physical, virtual, and information. These spaces have a continuous interaction to enable digital twin functionalities. These spaces present some layers with different concepts. This structure helps researchers and practitioners to learn about digital twins and apply it on their domains.

The development of a digital twin implementation framework highlights some digital twin characteristics. Digital twin is a modern technology that enables smart manufacturing, along with artificial intelligence, cloud computing, and so on. Digital twin looks to support different operations in the factory. It presents some functionalities such as collecting data, processing data, performing simulations, solving problems, and allowing communication between spaces. Digital twin provides feedback from predictions, prescriptions, and descriptions of current and potential situations to the physical space.

Moreover, this framework provides some conclusions for DT operations. DT must enable connection between different devices and applications. It must manage different devices and standardize them. It should help users to make data-driven decisions. It must define the traceability of data from the physical space, through the information space, and to the virtual space. It should be flexible to implement new functionalities and connect new devices and applications to the DT domain.

Finally, this article proposes future research for digital twin development. Future research needs to validate the proposed digital twin implementation framework. It must use the framework to create digital twin models of a factory. Manufacturing case studies are needed to apply the framework. This study could confirm that the proposed framework helps to create a small-scale digital twin for a manufacturing system. Future investigation could also refine the framework and include more concepts relevant to the DT development. This research could lead other researchers to work on DT implementation for manufacturing systems. For instance, researchers can use the proposed framework and compare it to other frameworks in the literature.

4.8 Chapter IV - References

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CHAPTER V - ARTICLE 3: VERIFICATION OF A DIGITAL TWIN IMPLEMENTATION FRAMEWORK FOR MANUFACTURING SYSTEMS

5.1 Abstract

Digital twins could help manufacturing systems in their digitization efforts. Continuing the digital twin research, this article looks to verify the correctness of the small-scale digital twin implementation framework previously developed by the same author. It presents a verification process to meet this objective. The author uses the proposed framework to create a process digital twin simulation of a bolt manufacturing system. Before creating this simulation, the author developed a digital twin mapping diagram and a digital twin implementation framework workflow diagram. These diagrams can make using the small-scale digital twin implementation framework easier. The digital twin mapping diagram helps users to identify the different concepts that are part of the proposed framework and relate these concepts to the manufacturing system of interest. The digital twin implementation framework workflow diagram presents a step by step instruction for the creation of digital twins. Finally, the author compares the process digital twin simulation to the digital twin user and system requirements. If the characteristics of the digital twin simulation follow the digital twin requirements, the small-scale digital twin implementation framework is completed and verified.

5.2 Introduction

Digital twins are a modern technology that enables the digitalization of manufacturing systems (Bauer et al., 2019; M. Singh et al., 2021). Researchers define digital twins as virtual models that mirror a factory in real-time (M. W. Grieves, 2019; Yang et al., 2017). They provide many advantages to manufacturing operations due to its three main capabilities: monitoring (Voigt et al., 2021), prognostics (Tao, Zhang, et al., 2019), and diagnostics (Magargle et al., 2017). These capabilities could help factories to improve their production processes (Li et al., 2023; Magomadov, 2020), redesign their layout system (Guo et al., 2019; Kuehn, 2018), or prevent machine failures (Aivaliotis et al., 2019; van Dinter et al., 2022). Nevertheless, the implementation of digital twins is a challenging and complex task. Factories need to define what objects to twin in the virtual space, the application of the digital twin, what capabilities to consider in the digital twin, among other decisions (Bordeleau et al., 2020; Boyes & Watson, 2022).

There is no single accepted method to implement digital twins in manufacturing systems. Researchers studied the digital twin concept from different perspectives and proposed some alternatives for the digital twin implementation such as digital twin frameworks (Guo et al., 2019; Marmolejo-Saucedo, 2022; Mokhtari & Imanpour, 2023; Onaji et al., 2022). These frameworks focus on some particular tasks or specific type of manufacturing. The problem with these frameworks is that the authors do not explain how to use them. Another problem is that there are not complete examples of digital twins in the real-world. The few examples in the literature do not provide much detail, perhaps due to a property rights issue. Therefore, Loaiza et al. (2023) developed a small-scale digital twin implementation framework in the article “Proposing a Small-Scale

Digital Twin Implementation Framework for Manufacturing from a Systems Perspective." This framework could help solve the problem of how to develop digital twin models for discrete manufacturing systems.

This article looks to expand this previous work by verifying the correctness of the small-scale digital twin implementation framework. Hence, this study developed a verification process to decide if the framework was built right based on a reference. The reference for this verification process is the digital twin literature which defines system requirements. The verification method used in this article is demonstrated by simulation and compliance with requirements. This study develops a process digital twin simulation for a bolt manufacturing system using the proposed framework. The process digital twin simulation intends to demonstrate that the digital twin implementation framework follows the digital twin system requirements and could help users develop digital twin models.

This study is limited in terms of scope and methodology. This study does not use a real-world manufacturing system to gather data and integrate real-time data to the digital twin. This study looks to model a process digital twin in Simio software and simulate digital twin capabilities. It assumes that the digital twin simulation has a physical counterpart in the real world. Moreover, this article does not intend to validate the proposed framework because that implies the use of a real-world manufacturing system. A validation process for a digital twin studies the relationship between the digital twin and the real system. The validation process is out of the scope of this study. However, the author suggests the validation of the digital twin implementation framework in a real-world scenario as further research.

This article presents the following structure. Section 5.3 presents a literature review on application fields of digital twin and challenges to implement a digital twin. Section 5.4 shows the methodology to verify the small-scale digital twin implementation framework. Section 5.5 presents the case study of a bolt manufacturing system. Section 5.6 shows the application of the proposed framework to the manufacturing case study. Section 5.7 shows the verification of the proposed framework against the digital twin system requirements. Finally, Section 5.8 presents the conclusions and proposes future research.

5.3 Literature Review

5.3.1 Application Fields of Digital Twin

In Manufacturing, several factories created their own DT software and used it in their daily production. General Electric created the "Predix" application that allows the development of DT models. This application checks and studies data (Magargle et al., 2017). DT brought the following improvements to GE due to the maintenance prediction. It increased its reliability to a range of 93-99.49% in less than 2 years. It reduced 40% of corrective maintenance in less than one year. It reduced 75% time to achieve outcomes. It saved $11M in lost production by detecting and preventing failures. Maintenance forecasting leads to reduction of costs. General Electric DT platform saved $1.5 billion in Operations and Maintenance costs of customers. It implemented solutions to their infrastructure assets due to the development of DT functions. GE along with other companies such as GIS, and AEMS technologies developed a Network DT that increases the connectivity of assets with real-time data. Also, it improves the communication and data sharing of associates. This network reduced operational costs up to 30% and planning time up to 20%. DT can help to reduce 75% of waste in a factory. DT simulation helps get the best solution for production processes. It improves the use of resources, quality, and cost of production (General Electric, 2021).

IBM is also in this list of industries that created DT platforms. IBM created the "Watson IoT platform" to manage IoT devices and data tools. It collects the following IoT devices such as cloud services, and data analytics. These devices make possible the development of Digital Twin (IBM, 2021). IBM has worked with DT for a long time. Recently, the company introduced Augmented Reality (AR) to its IoT platform. This IoT device allows the visualization of the virtual models in another dimension. It allows the interaction with these models through voice commands. IBM performed all these in its Maximo lab services. Moreover, IBM knows the importance of systems engineering and the DT impact in a system lifecycle. Hence, it introduced Model Based Systems Engineering (MBSE) to its IoT platform (Armstrong, 2020).

Siemens is another company that created the software "MindSphere" to deal with the new industrial revolution. It uses technology such as Cloud computing that links physical assets to the DT. The connection of physical objects with real-time data can change business processes and solutions (Petrik & Herzwurm, 2019). The industrial platform for innovation PTC created "Thingworx". This platform works with Industrial Internet of Things (IIoT) devices to support their connectivity, analysis, production, and other functions (Chen et al., 2018). Finally, there are open-source projects that created DT platforms. "Ditto" is the name of the first project. Eclipse developed this platform to manage and control the interface of DT. It can connect to other IoT devices (Ditto, 2021). Bentley Systems developed another project called "iModel.js" platform. It allows the creation, access, leverage, and integration of DT (Bentley Systems, 2021).

In the automotive industry, companies also implemented DT models to their infrastructure system. DT can resemble the parts or the behaviors of a vehicle. This is useful to make simulations, analyze data and test new product's capabilities. DT along with Artificial Intelligence simulate data in real-time, understand present behavior, and predict future events in an automobile. Tesla is just one example of the automotive companies that use DT (Fuller et al., 2020).

In the construction industry, companies can exploit several features of DT. The DT model of an infrastructure building is rich in detail. DT technology can develop many functionalities on this model. One DT function is to design new infrastructure and test it on virtual space. Moreover, it can monitor and predict behavior of physical assets such as smart cities. It supports decisions with reliable data. One benefit is simulating the construction of a facility. This improves and enriches the design stage (Din et al., 2019). Mohammadi & Taylor (2019) provided an example of digital twins in the construction industry. They developed a smart city digital twin of the city of Atlanta.

In the aircraft industry, there are many examples of digital twin models (General Electric, 2021). Digital twin helps this industry sector to make predictions and test the components of an airplane, for instance. The DT model can simulate the physics, structure, and hypersonic condition of a plane. Some examples are the modelling of an airplane to detect fatigue cracks, and deformations in the aluminum and steel materials. DT can perform simulations throughout the airplane lifecycle. This helps to reduce time and cost in the production and maintenance stages. Another example is the use of DT to model virtual multi-physical environments that could damage the aircraft's structure (Tuegel et al., 2011).

5.3.2 Challenges to Implement a Digital Twin

There are many challenges to implement a DT in a manufacturing system. One of them is the connection and integration of all IoT devices, machines, and objects. These connections allow data sharing among physical and virtual spaces. It is also important to consider that DT works with real-time data without requiring human to human interaction. Moreover, DT operations must be autonomous. Accomplishing these challenges are big milestones to create digital twins. Moreover, cost and time are always challenging for new and big projects. The time and resources needed to carry out this work could be enormous. It is hard to estimate the cost to implement DT due to its variety. Complex systems require a huge investment for developing and operating DT technology (Anderton, 2020).

Deloitte is a company that works developing DT for other companies. They proposed a white paper that explains the required collaboration, investment, and commitment to implement DT in an organization. DT will bring changes such as reorganization of the factory layout, processes improvement, technology acquisition, and so on. The paper also suggests that DT implementation needs a thorough planification. This will decide the DT benefits and the return on investment, for instance (Mussomeli et al., 2020).

According to Barnstedt et al. (2021), there are three main challenges to implement DT. The first one is the lack of a common definition of DT. This prevents users from understanding what the DT concept is about. Hence, some factories do not realize its value to the point of degrading it. The concept started in 2002 by Dr. Grieves without a name. In 2005, the concept was under the name of Mirroring Spaces Model (MSM), but the name changed again in 2006 to Information Mirroring Model. John Vickers of NASA proposed the name of Digital Twin to this concept in 2011. Some researchers believe that DT was in the industry before Dr. Grieves proposed it. The second challenge is the integration of data. This gives access to all data in the system's lifecycle from various locations. This is hard to do due to different data sources, formats, interfaces, and security protocols. It is necessary to design a system that contemplates the DT and its functionalities such as data sharing. The third challenge is the standardized information model. This allows DT to work across different components, sub-systems, and systems. Standard technology, models, information, and APIs keep data flowing smoothly through the system. System designers should try to standardize system components as much as possible.

5.4 Methodology

Verification looks that the system was built right based on system requirements. This study develops a verification process to confirm that the digital twin implementation framework has fulfilled the digital twin requirements. This process collects objective evidence to prove that the proposed framework is right or true. This process includes a series of actions to check the correctness of the framework (AcqNotes, 2021; Bouyssounouse & Sifa, 2005; The MITRE Corporation, 2020). Figure 5.1 shows the verification process of the digital twin implementation framework.

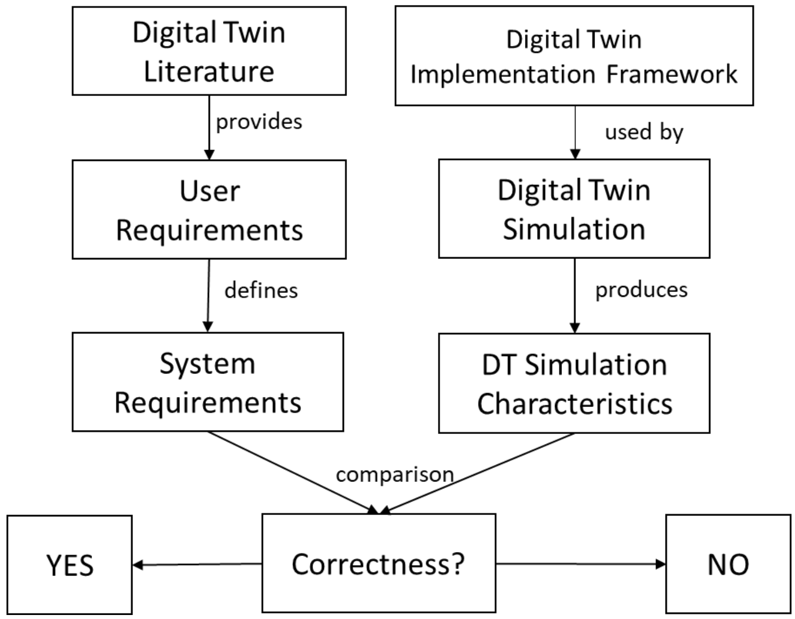


Figure 5.1. Verification Process for the Digital Twin Implementation Framework.

This verification process uses digital twin literature as a reference to verify elements such as the digital twin implementation framework. In order to perform this verification, the process needs to define a verification action. A verification action is a technique or method that looks to verify elements based on expected results. The verification action to verify the framework is the demonstration of the correctness of the proposed framework. So, the authors develop a digital twin simulation to demonstrate the proposed framework correctness. Simulations are purpose driven models that can help answer questions related to the concept of digital twin. Simulation produces performance measures and a behavior consistent with the hypothetical real-world manufacturing system presented in this study. The developed digital twin simulation uses the proposed framework for its development. This simulation presents characteristics that will be compared to the expected results. The expected results are digital twin system requirements which derived from the digital twin user requirements. Comparison between the system requirements and the simulation characteristics looks for the compliance of system requirements. This is a demonstration that the proposed framework can help users to implement digital twins. Therefore, this study assumes that if the obtained results match or comply with the expected results, the proposed digital twin implementation framework is correct and verified.

5.5 Case Study

This case study describes the production of bolts in a real-world assembly line. The bolts manufacturing process starts with the arrival of raw materials such as steel wire rods. The straightening process looks to straighten and treat the wire rod using a forming machine. The next process uses a cutting machine to cut the wire rod into the required size. Then, the cold heading machine makes the bolt’s hexagonal head. After this process, the trimming machine cuts the edge of the bolt, so the threading machine can make the dreads. The process terminates with the finished bolts that are stored in boxes. This process uses conveyor belts to transfer the material around the machines (Samanta & Dutta, 2012). Figure 5.2 presents the bolt manufacturing process flow diagram.

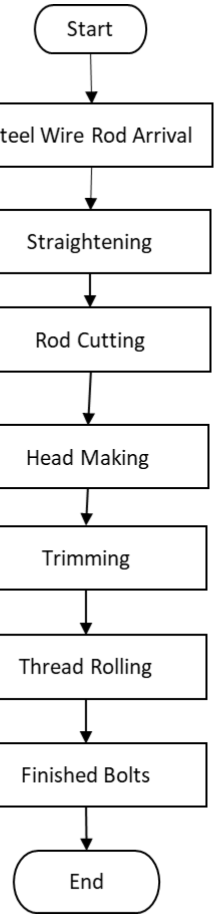


Figure 5.2. Bolt manufacturing process flow diagram. Modified and redrawn from Samanta & Dutta (2012).

This article uses SIMIO software to run a simulation and generate synthetic data. This is an alternative to real data of a physical system. The bolt manufacturing simulation model starts with the arrival of entities, such as steel wire rods, to the source. The source provides entities to the model with a random exponential interarrival time of fifteen minutes. Then, the entities go through each server that stands for a different machine of the bolt manufacturing system. The first server is the forming machine that performs the straightening process. This event lasts five minutes. The second server is the cutting machine with a processing time of five minutes. The third server stands for the head making process and lasts ten minutes. The fourth server represents the trimming event with a duration of five minutes. The last server is the threading machine which has a processing time of fifteen minutes. The simulation ends with the processed entities or finished bolts arriving at the sink or packing box. All events have a discrete processing time because a random distribution will not ease the construction of a digital twin simulation. Table 5.1 shows the events with their respective Simio objects and processing time. Table 5.2 presents the results of running the simulation for twenty-four hours.

Table 5.1. Bolt manufacturing events for simulation

Number	**Event**	**Physical Object**	**Simio Object**	**Processing time (minutes)**
1	Materials Arrival	Raw Materials Station	Source	Random.Exponential (15)
2	Straightening	Forming Machine	Server	5
3	Rod Cutting	Cutting Machine	Server	5
4	Head Making	Cold Heading Machine	Server	10
5	Trimming	Trimming Machine	Server	5
6	Thread Rolling	Threading Machine	Server	15
7	Finished Bolts	Packaging Box	Sink	-

Table 5.2. Bolt manufacturing final performance measures for 24 hours

Performance Measure	**Value**
Total Production	93 bolts
Average total time in system	150 minutes
Maximum total time in system	244 minutes
Average total number of parts in system	11 parts
Maximum total number of parts in system	21 parts
Forming Machine Utilization	38.88 %
Cutting Machine Utilization	77.11 %
Cold Heading Machine Utilization	76.38 %
Trimming Machine Utilization	38.19 %
Threading Machine Utilization	97.23 %

5.6 Application of Framework

This article applies the proposed framework to the bolt manufacturing system to create a process digital twin simulation. This digital twin simulation focuses on the manufacturing system processes. This article uses the framework developed by Loaiza et al. (2023) in a previous article. Figure 5.3 shows the digital twin implementation framework. Moreover, it uses the bolt manufacturing system synthetic data and characteristics as inputs for the process digital twin simulation.

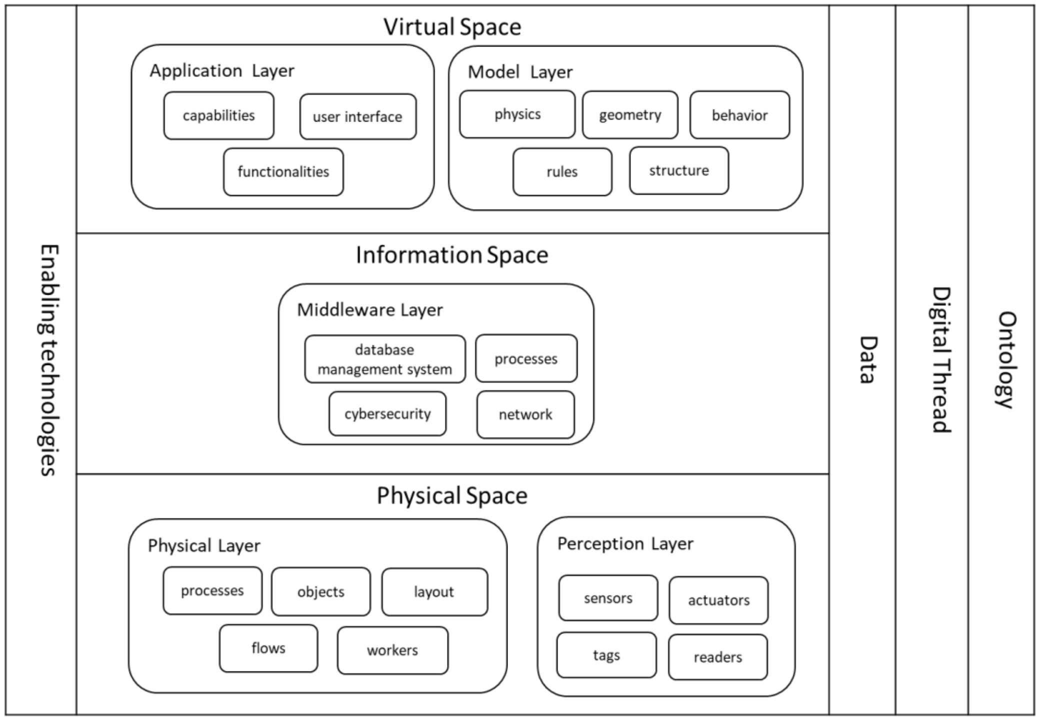


Figure 5.3. Digital Twin Implementation Framework (Loaiza et al., 2023).

Before using the proposed framework, the author developed a mapping diagram. This diagram maps each concept in the proposed framework and creates a structure with classes and subclasses. It maps the concepts that belong to the physical space, information space, and virtual space. These digital twin concepts become classes in this mapping diagram. It also provides a factory logical example as a reference for a real-world system. This could help researchers to use the proposed framework. Figure 5.4 shows the digital twin implementation framework mapping diagram.

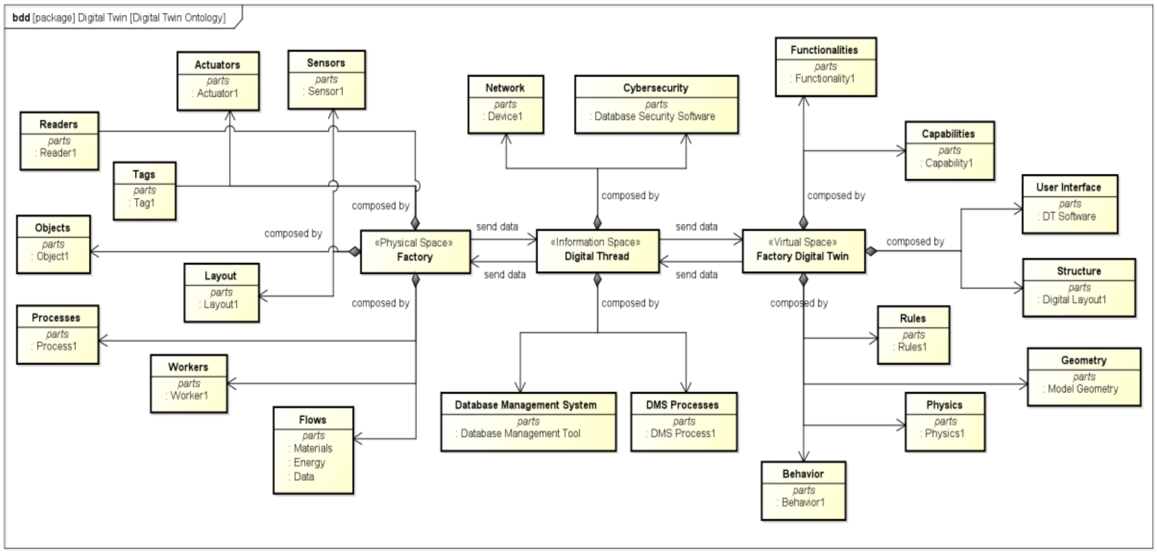


Figure 5.4. Digital Twin Implementation Framework Mapping Diagram.

Consequently, the author applies the map diagram to the bolt manufacturing case study. This map diagram allows to map the bolt manufacturing classes that belong to the physical space. These classes are machines, processes, sensors, actuators, layout, and flows. In this case study, the author does not consider workers, tags, and readers because they are not necessary to simulate a process digital twin. These classes are essential for other types of digital twins such as components, assets, and system digital twins. These classes help to mirror humans or objects that are moving constantly. Moreover, this article assumes that classes in the information space are part of the process digital twin simulation because the digital twin simulation cannot represent objects such as cybersecurity software, data management tool, digital processes, and network devices in Simio or any simulation software. These objects are essential for a real-world digital twin, but they are out of the scope of the process digital twin simulation. Finally, the author considers the functionalities, capabilities, user interface, structure, behavior, physics, and geometry classes as part of the virtual space. These virtual classes mirror the physical classes of the bolt manufacturing system. As for the geometry, this simulation only considers the type of machines for the process digital twin. It does not present the machines as dynamic computer aided design (CAD) models. It is not the scope of this simulation to focus on the machine's details as if it were a component digital twin. For the same reason, the author does not consider rules. Rules are important for types of digital twins that consider humans, machines, objects in motion. This is not the case for the process digital twin simulation. Figure 5.5 shows the mapping of a bolt manufacturing system in the digital twin implementation framework mapping diagram.

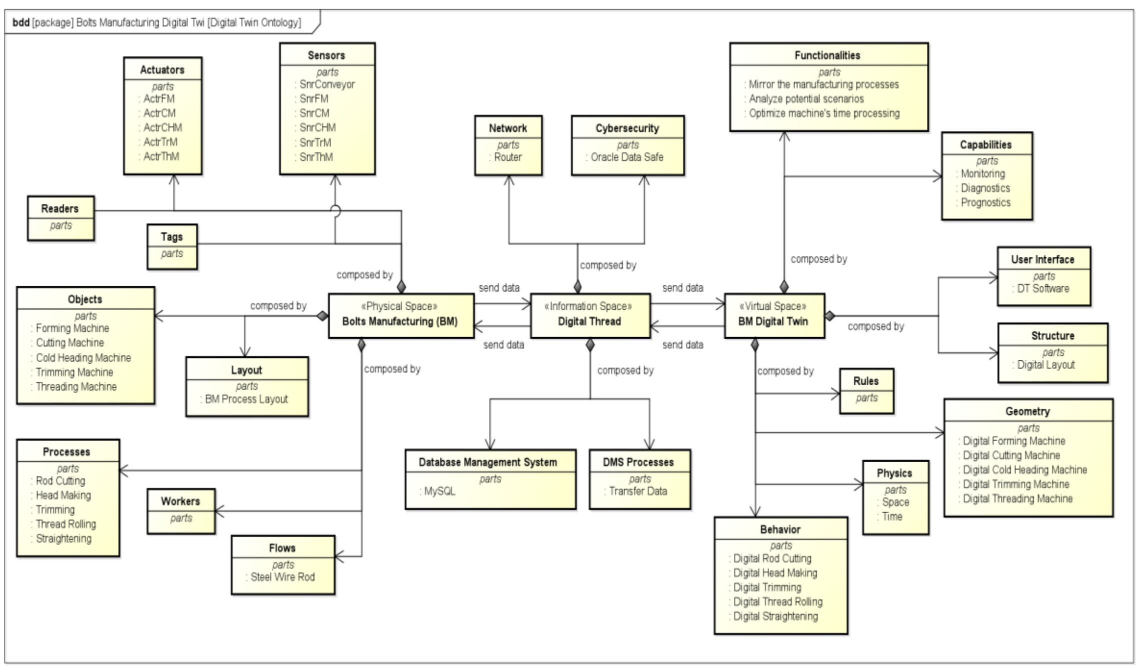


Figure 5.5. Digital Twin Implementation Framework Mapping diagram for a Bolt manufacturing system.

Once the classes and subclasses are mapped in the digital twin implementation framework mapping diagram, it is time to develop and simulate the process digital twin. In order to do this; the authors developed a workflow diagram to create a digital twin. Even though this diagram provides a step by step instruction for the creation of real-world digital twins, it helps develop the process digital twin simulation model. Figure 5.6 shows the digital twin implementation framework workflow diagram.

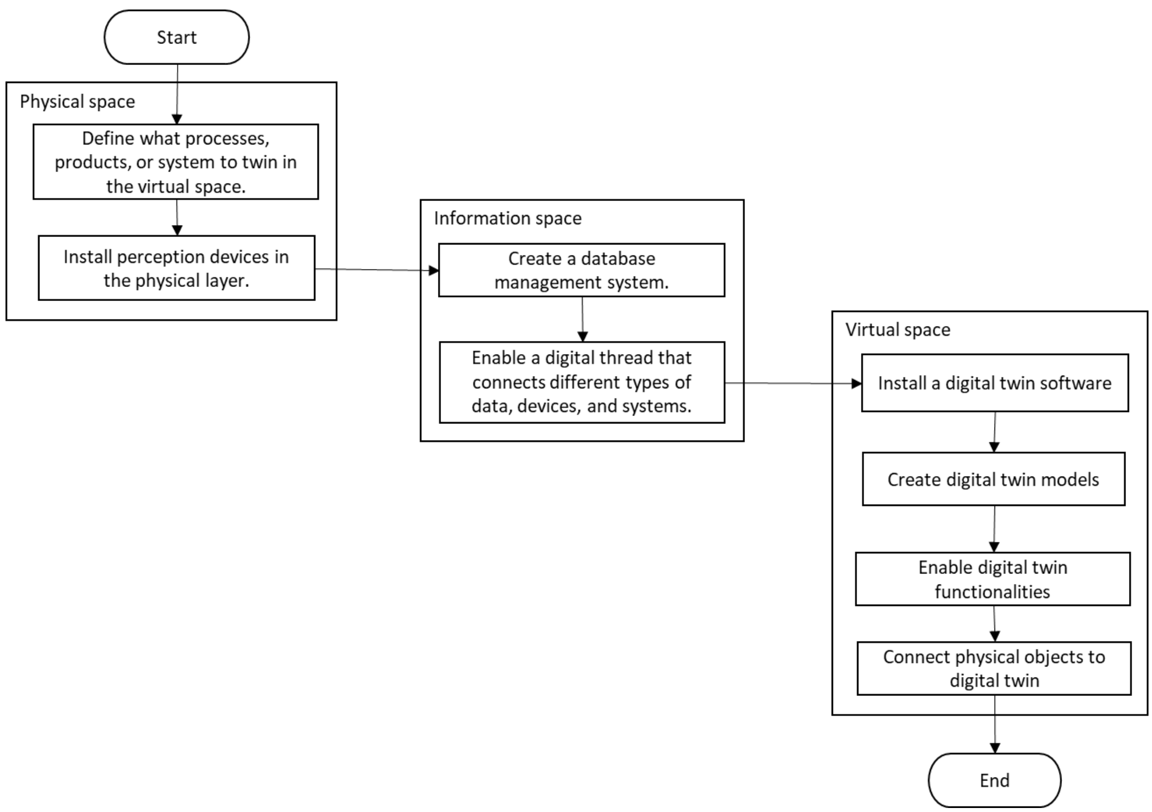


Figure 5.6. Digital Twin Implementation Framework Workflow Diagram.

This diagram starts with the definition of processes to twin in the virtual space. In this case study, the processes to twin are straightening, rod cutting, head making, trimming, and thread rolling. As part of these processes, this study considers the type of machines, flow, and layout of the bolt manufacturing system. Then, this study supposes the realization of the installation of perception devices in the physical layer, the creation of a database management system, and the enabling of a digital thread since the purpose of this study is the process digital twin simulation. These three steps are relevant steps in the development and validation of a real-world digital twin. In the virtual space, the first step is to install the digital twin software. For this study, the author selected Simio software as the digital twin software. The next step is the creation of digital twin models. Simio software allows users to create digital twin models based on the type of machines in the bolt manufacturing system. It also allows users to simulate the layout, processes, and flows. After creating the digital twin models, Simio software enables the simulation of digital twin capabilities such as monitoring, prognostics, and diagnostics. Finally, the last step in the workflow diagram is to connect the physical objects to the digital twin. Simio allows users to simulate the connection between the “physical” system and its digital twin.

5.6.1. Process Digital Twin Simulation in Simio software

Simo is a software that allows users to create dynamic models and run simulations to study the behavior of systems. This study uses Simio to make the process digital twin simulation of a bolt manufacturing system. This simulation focuses on studying digital twin capabilities, modeling, and optimization. It shows the digital twin capabilities such as monitoring, prognostics, and diagnostics of manufacturing processes. It shows the digital models of “physical” objects and helps study different scenarios to optimize the “physical” factory.

The creation of the process digital twin simulation starts by replicating the processes in the “physical” factory. This means that the digital twin processes share the same properties and behavior as the “physical” processes. Moreover, the digital twin replicates the types of machines, layout distribution, and flow of data and materials. The digital twin simulation presents three replications of the “physical” factory to simulate each digital twin capability. These replications can be considered as “assembly lines” in this simulation. For this study, only the monitoring “assembly line” mirror in the geometry of the “physical” factory. It is not necessary to mirror the geometry of the “physical” factory in the prognostics and diagnostics “assembly lines” since their purpose is to make predictions for the system’s optimization. The next step is to create different entities for each “assembly line.” The process digital twin simulation has four types of entities, so Simio software could provide a detailed and different result for each type of entity that goes through each “assembly line”. Then, the authors create a separator object at the beginning of the “physical assembly line” that simulates a sensor. This separator object makes copies of the “physical” entities enabling the creation of the digital thread. The digital thread sends “data” or entities to the digital twin. It also sends feedback to the “physical” factory through actuators. This simulation assumes that machines in the “physical” factory have actuators. Actuators can change an ongoing process manufacturing in real time. These actuators allow the process digital twin to make modifications such as the processing time. In complex manufacturing systems, actuators can perform tasks such as opening and closing gates to a different assembly line or locking doors; but that is not the case in this study. Figure 5.7 shows the process digital twin simulation of a bolt manufacturing system in a two-dimensional space. Figure 5.8

shows the process digital twin simulation of a bolt manufacturing system in a three-dimensional space.

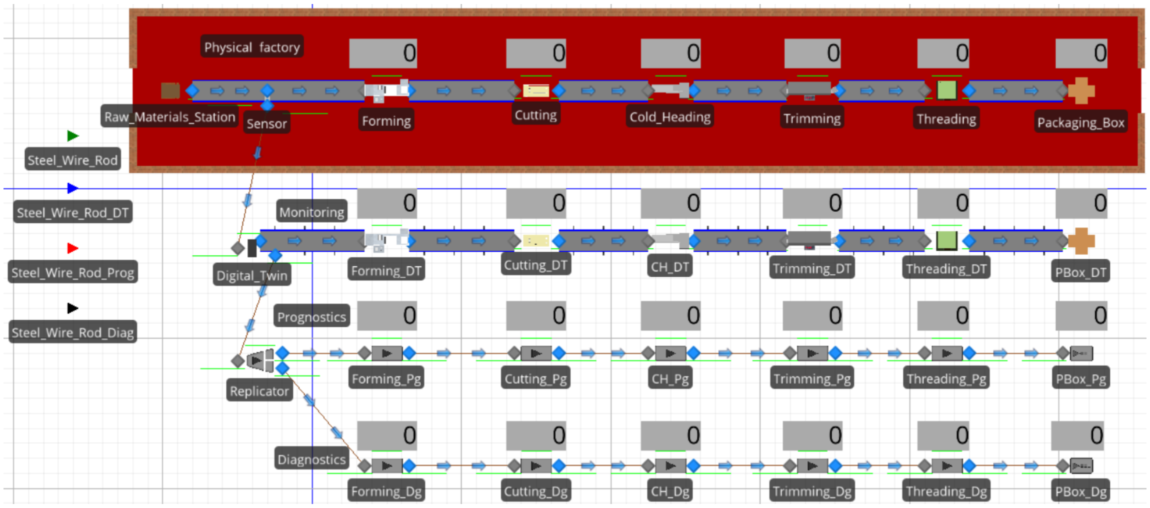


Figure 5.7. Process Digital Twin Simulation of a Bolt Manufacturing System - 2D model

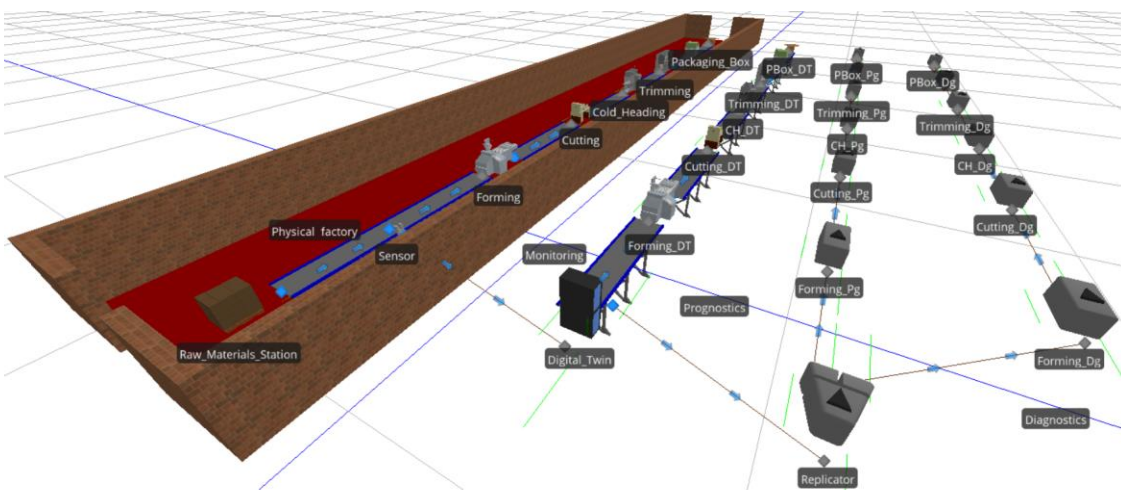


Figure 5.8. Process Digital Twin Simulation of a Bolt Manufacturing System – 3D model

To simulate the monitoring capability, the digital twin processes must have the same properties as the “physical” processes. These properties are processing time, initial capability, buffer capacity, reliability logics, and so on. Machines on the monitoring "assembly line" use attached animations, such as labels and graphics, to show the current state of the "physical" factory. Figure 5.9 shows the monitoring dashboard for the process digital twin of a bolt manufacturing system.

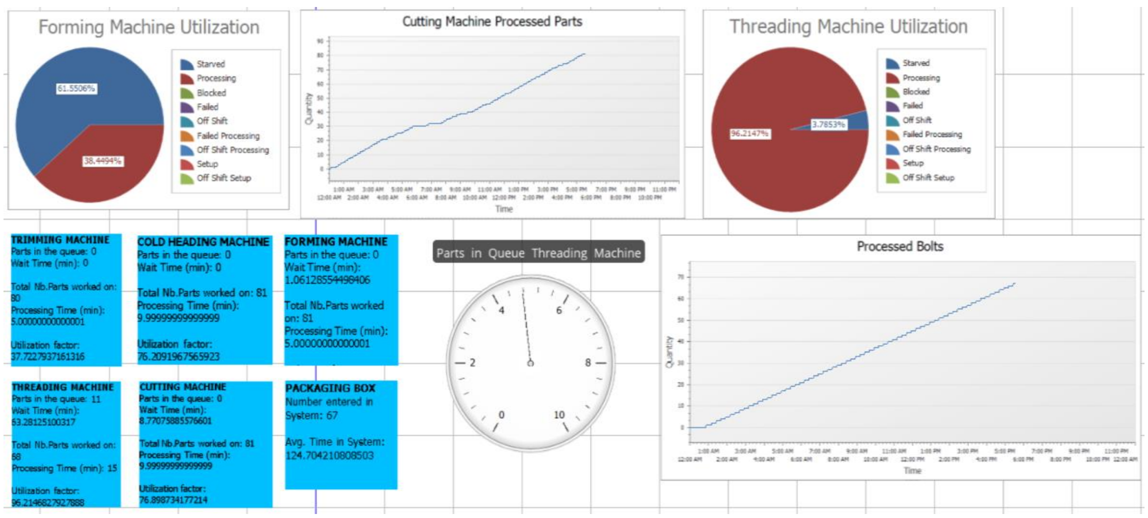
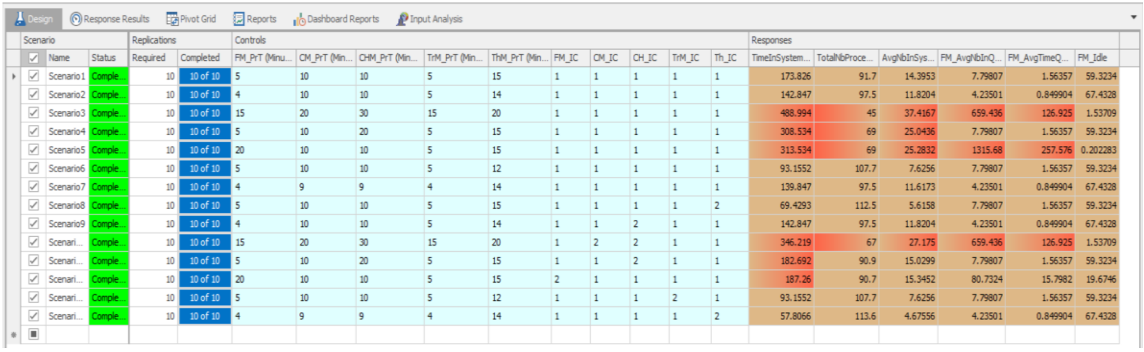


Figure 5.9. Monitoring dashboard for the process digital twin

For the diagnostics capability simulation, Simio software has an experiments tab to perform tests, compare several scenarios, and label results based on lower and upper bound goals. This simulation cannot give diagnosis in real time due to software limitations. However, this experimentation tab could stand for a digital twin diagnostics capability. Figure 5.10 shows the diagnostics capability of the process digital twin simulation.



Scenario		Replications		Controls										Responses					
Name	Status	Required	Completed	FM_PrT (Minu...	CM_PrT (Min...	CHM_PrT (Min...	TrM_PrT (Min...	ThM_PrT (Min...	FM_IC	CM_IC	CH_IC	TrM_IC	Th_IC	TimeInSystem...	TotalNbProce...	AvgNbInSys...	FM_AvgNbInQ...	FM_AvgTimeQ...	FM_Idle
Scenario1	Comple...	10	10 of 10	5	10	10	5	15	1	1	1	1	1	173.826	91.7	14.3953	7.79807	1.56357	59.3234
Scenario2	Comple...	10	10 of 10	4	10	10	5	14	1	1	1	1	1	142.847	97.5	11.8204	4.23501	0.849904	67.4328
Scenario3	Comple...	10	10 of 10	15	20	30	15	20	1	1	1	1	1	488.994	45	37.4167	659.436	126.925	1.53709
Scenario4	Comple...	10	10 of 10	5	10	20	5	15	1	1	1	1	1	308.534	69	25.0436	7.79807	1.56357	59.3234
Scenario5	Comple...	10	10 of 10	20	10	10	5	15	1	1	1	1	1	313.534	69	25.2832	1315.68	257.576	0.202283
Scenario6	Comple...	10	10 of 10	5	10	10	5	12	1	1	1	1	1	93.1552	107.7	7.6256	7.79807	1.56357	59.3234
Scenario7	Comple...	10	10 of 10	4	9	9	4	14	1	1	1	1	1	139.847	97.5	11.6173	4.23501	0.849904	67.4328
Scenario8	Comple...	10	10 of 10	5	10	10	5	15	1	1	1	1	2	69.4293	112.5	5.6158	7.79807	1.56357	59.3234
Scenario9	Comple...	10	10 of 10	4	10	10	5	14	1	1	2	1	1	142.847	97.5	11.8204	4.23501	0.849904	67.4328
Scenari...	Comple...	10	10 of 10	15	20	30	15	20	1	2	2	1	1	346.219	67	27.175	659.436	126.925	1.53709
Scenari...	Comple...	10	10 of 10	5	10	20	5	15	1	1	2	1	1	182.692	90.9	15.0299	7.79807	1.56357	59.3234
Scenari...	Comple...	10	10 of 10	20	10	10	5	15	2	1	1	1	1	187.26	90.7	15.3452	80.7324	15.7982	19.6746
Scenari...	Comple...	10	10 of 10	5	10	10	5	12	1	1	1	2	1	93.1552	107.7	7.6256	7.79807	1.56357	59.3234
Scenari...	Comple...	10	10 of 10	4	9	9	4	14	1	1	1	1	2	57.8066	113.6	4.67556	4.23501	0.849904	67.4328

Figure 5.10. Diagnostics Capability of the Process Digital Twin Simulation

The prognostics capability of a digital twin looks to perform simulations in real-time to optimize the system performance as the diagnostics capability. This capability allows users to play with different variables and observe different system behaviors. The main difference with the diagnostics capability is that the prognostics capability does not provide a final result or compare several scenarios at once. The prognostics capability is more like a sandbox which uses the digital twin to test the system environment and run simulations without affecting the "physical" factory. In this case study, the prognostics is a single "assembly line" which runs a parallel simulation to the "physical assembly line." This parallel simulation allows users to observe the bolt manufacturing system behavior and make changes in real-time. Simio has a table tab that allows users to change the "assembly lines" properties in real-time such as processing time. By changing properties in the prognostics "assembly line," users can see the immediate effects of the potential changes in the digital twin. Then, users can change the properties in the "physical" factory when the simulation is running. Figure 5.11 shows the prognostics capability of the process digital twin simulation.

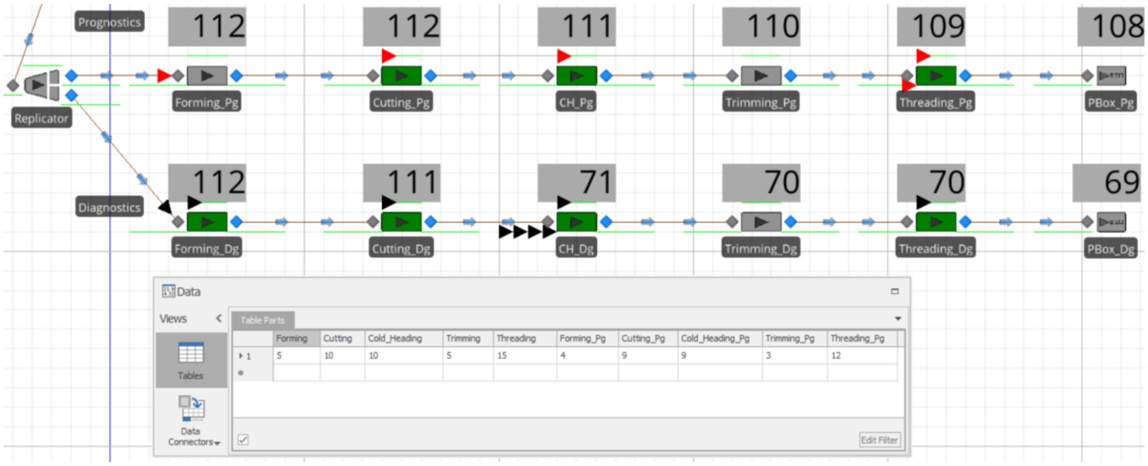


Figure 5.11. Prognostics Capability of the Process Digital Twin Simulation

The process digital twin simulation in Simio software was able to mirror the "physical" factory processes. Moreover, Simio software helped to develop the digital twin modelling and simulate the digital twin capabilities for the system's optimization. This digital twin simulation can compare different scenarios and make changes to the "physical" factory in real-time. This is just a simple example of how digital twins could be used as a performance improvement tool. Figure 5.12 shows the process digital twin simulation results for 24 hours. This article provides detailed results for each digital twin capability in Tables 5.3, 5.4 and 5.5. From these results, the author shows that the monitoring capability presents the same results as the "physical" factory since it mirrors all the "physical" factory processes, behavior, flows, and geometry. The results of the diagnostics and prognostics capabilities are different because they work with distinct properties such as processing time, initial capability, and so on.

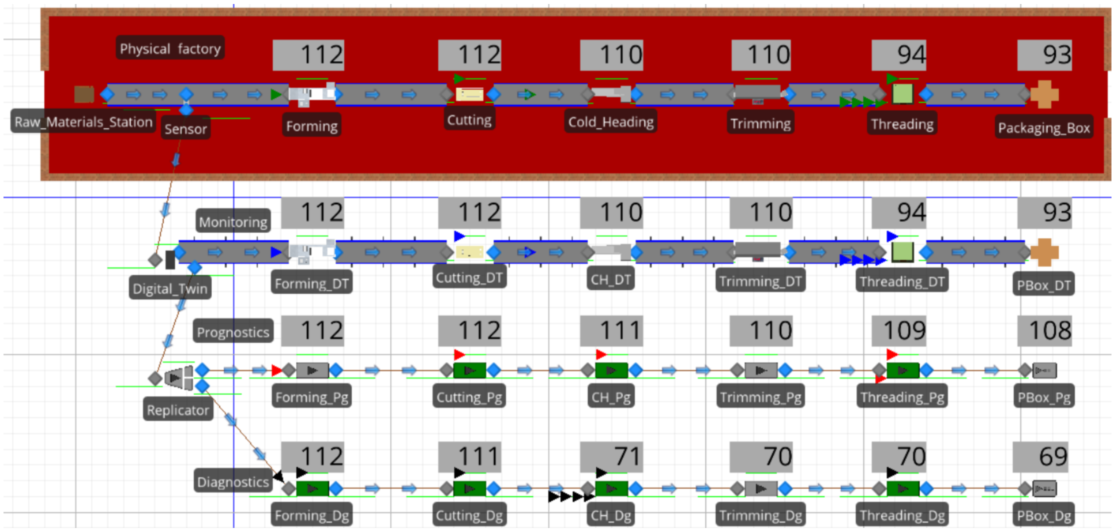


Figure 5.12. Process Digital Twin Simulation of a Bolt Manufacturing System – 24 Hours Results

Table 5.3. Bolt manufacturing monitoring capability measures for 24 hours

Performance Measure	**Value**
Total Production	93 bolts
Average total time in system	150 minutes
Maximum total time in system	244 minutes
Average total number of parts in system	11 parts
Maximum total number of parts in system	21 parts
Forming Machine Utilization	38.88 %
Cutting Machine Utilization	77.11 %
Cold Heading Machine Utilization	76.38 %
Trimming Machine Utilization	38.19 %
Threading Machine Utilization	97.23 %

Table 5.4. Bolt manufacturing diagnostics capability measures for 24 hours

Performance Measure	**Value**
Total Production	69 bolts
Average total time in system	318 minutes
Maximum total time in system	562 minutes
Average total number of parts in system	23 parts
Maximum total number of parts in system	44 parts
Forming Machine Utilization	77.53 %
Cutting Machine Utilization	76.76 %
Cold Heading Machine Utilization	98.33 %
Trimming Machine Utilization	48.61 %
Threading Machine Utilization	96.11 %

Table 5.5. Bolt manufacturing prognostics capability measures for 24 hours

Performance Measure	**Value**
Total Production	108 bolts
Average total time in system	68 minutes
Maximum total time in system	115 minutes
Average total number of parts in system	5 parts
Maximum total number of parts in system	10 parts
Forming Machine Utilization	31.11 %
Cutting Machine Utilization	69.54 %
Cold Heading Machine Utilization	68.85 %
Trimming Machine Utilization	22.91 %
Threading Machine Utilization	90.61 %

5.7 Verification of the Digital Twin Implementation Framework

After getting the results from the process digital twin simulation, this article compares the simulation characteristics with the digital twin system requirements. This is the last step in the verification process described in Section 5.3. The verification process looks to verify the correctness of the digital twin implementation framework. This study uses the digital twin user requirements found in the digital twin literature. Then, it derives system requirements from the user requirements. The digital twin system requirements describe what a digital twin must do, not how it does it. It describes a digital win based on definitions. It presents the digital twin structure, objects, operations, capabilities, and so on. This study concludes that the digital twin implementation framework elements presented in the simulation follow the digital twin user and system requirements. Table 5.6 shows that the digital implementation framework was verified against the digital twin system requirements. In the table, there are some requirements that do not apply to this study. A mature digital twin model complies with these requirements.

Table 5.6. Verification of the Digital Twin Implementation Framework.

No.	User Requirements	System Requirements	DT Simulation Characteristics	Framework Elements
1	The DT shall collect data from the physical factory	Collected data shall be stored in a database.	DataTable, WriteProcesses	Database management system
		Collected data shall be synchronized when adding a new object in the factory.	Separator, DataTables	Sensors, Actuators
		Collected data shall be used by the digital models	Server properties	Objects, Data
		Collected data shall use sensors, tags, and readers.	Separator	Sensors. Tags, Readers
2	The DT shall implement digital thread between the physical space and virtual space.	Digital thread shall establish a bidirectional communication	Separator, DataTable	Digital thread
		Digital thread shall create a closed loop between the physical and virtual space.	Separator, DataTable	Network, database processes
		Digital thread shall have a data management module.	Simulation properties	Database management system
3	The DT shall control objects in the physical factory.	Controlled objects shall use actuators	DataTable	Actuators
4	The DT shall allow a human-software interaction.	The human-software interaction shall use an electronic device.	Laptop	User interface
5	The DT shall have access to Internet at a high speed.	Internet connection shall use a Wi-Fi Hotspot.	-	Network

Table 5.6, cont.

No.	User Requirements	System Requirements	DT Simulation Characteristics	Framework Elements
6	The DT shall communicate to other systems within the factory's network.	Network Communication shall be enabled by a router	Separator	Network
		Real-time data shall feed digital models	Separator, Server properties	Functionalities
		Real-time data shall retrieve data from database	-	Database management system
7	The DT shall work with real-time data.	Real-time data shall be collected every second.	UserDefined Element, Timer Element	Capabilities, Data
		Objects Modelling shall allow users to create digital models.	Separator, Server properties, Sink	Functionalities
		Objects Modelling shall mirror physical objects processes.	Server properties	Processes
8	The DT shall mirror factory's physical objects.	Objects Modelling shall mirror physical objects behavior.	Server properties	Behavior, Rules, Flows
		Objects Modelling shall mirror physical objects features.	Server properties	Geometry, Rules
		Objects Modelling shall mirror the factory's layout.	Server properties, Paths	Layout, Structure, Physics
9	The DT shall monitor activities in the physical factory.	Objects Modelling could mirror human behavior.	Simio software	User interface
		Monitoring capability shall have a dashboard to represent the current state of the factory.	Server properties, Animation	Capabilities
		Monitoring capability shall have a control module.	Server properties, Data Table tab	Capabilities

Table 5.6, cont.

No.	User Requirements	System Requirements	DT Simulation Characteristics	Framework Elements
10	The DT shall make predictions of potential states of the factory.	Prognostics capability shall be used as an optimization tool	Server properties, Data Table tab	Capabilities
		Prognostics capability shall have a simulations module.	Server properties, Data Table tab	Capabilities
11	The DT shall provide a diagnosis of the current state of the physical factory.	Prognostics capability shall be able to evaluate different scenarios.	Server properties, Experiments tab	Capabilities
		Diagnostics capability shall have a data analytics module	Server properties, Experiments tab	Database management system
		Diagnostics capability shall make informed and verified decisions using data.	Server properties, Experiments tab	Workers
12	The DT shall have a security system to prevent data theft	The security system shall protect the database	-	Cybersecurity
13	The DT should learn from historical data to predict new outcomes.	Historical data shall be available to the user	-	Database processes
14	The DT shall manage high amount of data.	High amount of data shall be supported by the electronic devices	Laptop, Simio software	Database processes
15	The DT shall enable remote access to users	Remote access shall authenticate users	Laptop, Simio software	User interface

5.8 Conclusions and Future Research

This article looks to verify the small-scale digital twin implementation framework previously developed by the same author. The author develops a verification process to demonstrate that the proposed framework was built right and can help users to build a small-scale digital twin. The verification process starts with the development of a process digital twin simulation using the proposed framework. This study performs some activities to create the process digital twin simulation. First, it uses a bolt manufacturing system as a case study to simulate a real-world bolt manufacturing system and get synthetic data. This data helps create the digital twin in Simio which is a simulation software. Then, this article presents step by step instructions to use the proposed framework and develop the process digital twin simulation for the bolt manufacturing system. Moreover, it develops a mapping diagram for the proposed framework. This diagram helps in the identification of concepts in a manufacturing system in relation to the proposed framework. After this activity, the article finally simulates a process digital twin simulation in Simio software. To finish the verification process, this article compares the digital twin requirements found in the literature and the process digital twin simulation results that come from the proposed framework. The comparison shows that the simulation follows the digital twin system requirements. Therefore, the authors conclude that the digital twin implementation framework was verified and could develop digital twins of a manufacturing system.

Moreover, the process of digital twin simulation in Simio leaves some conclusions. The digital twin simulation shows that manufacturing digital twins can share some features, but they are unique in some ways. Users decide what they want to twin in the virtual space. It shows that it is not practical to put sensors everywhere on the assembly line. Based on the simulation, it is better to put sensors at the beginning of the assembly line to count the number of parts that are going to be processed. Similarly, actuators should be installed in the machines to change their configuration and not in the assembly line. Actuators cannot change the status or properties of a physical material that goes through the assembly line.

For future research, the author contemplates the validation of the small-scale digital twin implementation framework for manufacturing systems. In order to do this, it is necessary to have a real-world factory where to collect data and install the perception devices. Another study could be the integration of the digital twin and the physical factory. This is challenging because a digital twin relies on real-time data from the factory. This future research could study how to make this connectivity and feed both spaces with continuous data.

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CHAPTER VI - CONCLUSIONS AND FUTURE RESEARCH

6.1 Research Conclusions

Digital twins need a framework and a methodology that could guide users in their implementation in manufacturing systems. This research develops a small-scale digital twin implementation framework. This need arose from the analysis of the implementation of digital twins in a manufacturing domain presented in Chapter III. The analysis of the digital twin problem space showed many challenges that factories encounter. Factories do not want to invest a significant amount of money on digital twin implementation. Some companies have never heard or do not know much about digital twins. This could happen due to a lack of common definition of digital twins. Other companies do not have the technology to implement digital twins. This research concludes that digital twins are complex systems, and their implementation is not an easy task. Digital twin as a system has many components that are interrelated between each other. These components enable digital twin processes that transform inputs into outputs. Digital twin is an open system that embraces new components and creates emergent behavior.

This research accomplished the research objectives. It presented a digital twin implementation framework that guides the development of digital twin in manufacturing domains. Before proposing this framework, this research modeled a digital twin subsystem to describe the digital twin concept in a manufacturing domain. It defined the requirements, behavior, structure, functionalities, and capabilities of a digital twin. It also shows the components that are part of the digital twin technology. These components are hardware devices and software computer programs. Then, it presented a step-by step process to use the digital twin implementation framework and create digital twins of a physical manufacturing system. Finally, it shows the verification process of the digital twin implementation framework to certify its correctness against the digital twin requirements.

Chapter IV presents the small-scale digital twin implementation framework. The development of the proposed framework intends to clarify the digital twin issues and present a solution for users. This framework presents a step-by-step process for the digital twin implementation. This research gathered some concepts from the digital twin literature and the modelling of a digital twin subsystem to build the proposed framework. This framework presents a basic structure with a physical, information, and virtual space. It defines digital twin characteristics and allows the incorporation of new components to the digital twin domain. Chapter V complements the small-scale digital twin implementation framework. This research includes a digital twin mapping diagram and a digital twin implementation framework workflow diagram. The first diagram helps users to identify and categorize the physical elements that are part of their factories. The second diagram is a graphical representation of the digital twin implementation processes. This diagram shows the processes that enable the realization of the different spaces in the framework.

Chapter V also shows the verification of the small-scale digital twin implementation framework. This research presents a verification method to demonstrate that the proposed framework allows factories to implement digital twins. Hence, the author developed a process digital twin simulation using the proposed framework due to limitations on the research . The verification method indicates the comparison between the digital twin simulation and the digital twin requirements. This research shows that the digital twin simulation follows the digital twin user and system requirements. Consequently, this research assumes that the small-scale digital twin implementation framework was verified.

This research has a systems engineering approach to study digital twin technology from the problem formulation to the solution development. It uses systems thinking methods and tools, model-based systems engineering (MBSE) methodology, and the Systems Engineering “Vee” model. Chapter III uses systems thinking methods and tools to describe the problems of implementing digital twins in manufacturing systems and present some potential solutions to these problems. Chapter III and IV uses the MBSE methodology to model the digital twin as a subsystem part of a manufacturing system. MBSE helped describe the implementation of digital twins and gathered relevant concepts from the digital twin literature. Chapter IV uses the “Vee” model in the development of the small-scale digital twin implementation framework. Finally, Chapter V uses the verification process of the systems engineering “Vee” model to verify the proposed framework.

6.2 Future Research

This work suggests the following studies as future research: the validation of the small-scale digital twin implementation framework, the development of a digital twin readiness assessment index, and a practical study of some challenges in implementing digital twins in manufacturing systems.

The validation of the proposed framework in this dissertation must confirm that the developed digital win is what the user needs, and it is the right system for the user organization. This validation requires a real-world manufacturing system where to implement the digital twin and test its accuracy. The validation process goes beyond the verification process. It also uses an action to validate an element based on a reference. Then, it compares obtained results and expected results to determine the conformity of the element. After these activities, the validation process tests the conformed element based on stakeholders needs during the system's operation in the intended environment. If the element passes this test and satisfies the stakeholders needs, this study could conclude that the small-scale digital twin implementation framework is acceptable to the user (AcqNotes, 2021; The MITRE Corporation, 2020). As part of the validation of the digital twin implementation framework, it is important to describe the limitations of this framework. This future research must explain and demonstrate the limits of the proposed framework in a manufacturing context. Understanding the limitations of this framework will help determine its usability and validity. It might be possible that this framework will not be suitable for some types of manufacturing. For instance, the comparison of this framework with other frameworks could help to show the limitations of the proposed framework. Finally, the validation of the digital twin implementation framework may lead to other types of research studies. Researchers could expand the framework and include more concepts relevant to the digital twin (Anderton, 2020; Fuller et al., 2020; Identity Management Institute, 2021; Tao, Zhang, et al., 2019).

The second suggestion for future research is the development of a digital twin readiness assessment index. This future research could help users evaluate the possibility of implementing digital twins in their factories. This index will give users a measure of how far along their factories are in implementing digital twins. It will show a broader perspective of the digital transformation status in their factories. To build this index, the future research must select the most principal factors that decide the development of digital twins. The literature review helps define the key attributes and how to measure the selected attributes. Some of the potential attributes of a digital twin in a manufacturing domain are connectivity, complexity, digitalization level, modularity, manufacturing readiness level or manufacturability, technology maturity, system readiness level, accuracy or fidelity, compatibility, functionality, usability, adaptability, availability, and so on. The future study must define the attribute's ranking and weight based on relevance. It could use normalization techniques to adjust the calculated measures on different scales to a common scale. Finally, the study sums all results to calculate the digital twin readiness assessment index. The verification and validation of this future research must consider the application of the digital twin readiness assessment index to different manufacturing case studies. This future research could lead to deeper studies about the adaptability and flexibility of manufacturing systems to technological changes. Figure 6.1 shows the digital twin readiness assessment index development process.

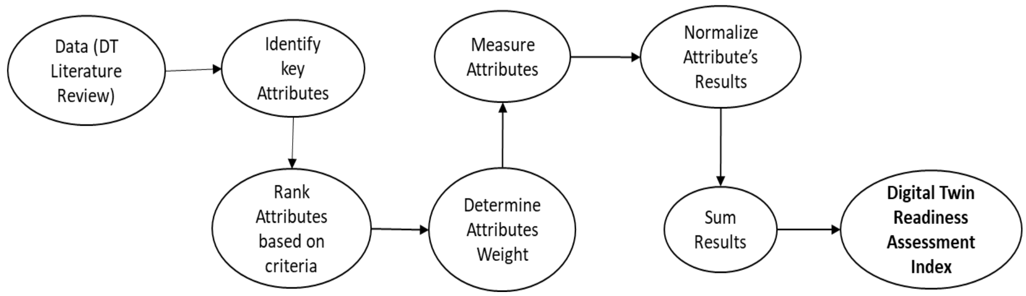

Figure 6.1. Digital twin readiness assessment index development process.

The last suggestion for future research is the practical study of some challenges in implementing digital twins in manufacturing systems. The digital twin implementation must consider the integration of real-physical components and the digital twin software. This is a challenging task that requires technical knowledge. Another digital twin implementation challenge is the collection of data in real-time. This could define the success of the digital twin operation since digital twins rely on real-time data to work. The last digital twin implementation challenge is the study of humans in digital twins or the sociotechnical study of digital twins. This challenge looks to upgrade the maturity of the digital twin. The integration of humans to the digital twin subsystem must consider the use of some components such as readers, tags, etc. It should also consider the study of new concepts such as rules, dynamics, human behavior, and so on.

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