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A SURVEY IN DIGITAL TWIN-ENABLED MANUFACTURING SYSTEMS: A LITERATURE REVIEW ABOUT DRIVERS, ENABLERS, BARRIERS, AND EXPLORATION OF DIGITAL TWIN-INTEGRATED SYSTEMS FRAMEWORKS FOR SCHEDULING PURPOSE

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SUMMARY

1. Glossary

Acronym	Concept
AI	Artificial Intelligence
AR	Augmented Reality
CMS	Content Management System
CPS	Cyber Physical System
CRM	Customer Relationship Management
DES	Discrete Event Simulation
DT	Digital Twin
EPHM	Equipment Prognostics and Health Management
ERP	Enterprise Resource Planning
GDPR	General Data Protection Regulation
IIoT	Industrial Internet of Things
IoT	Internet of Things
MES	Manufacturing Enterprise System
ML	Machine Learning
MTTR	Mean Time To Repair
OPC-UA	Open Platform Communication - Unified Architecture
PDM	Product Data Management
PLM	Product Lifecycle Management
RUL	Remaining Useful Life
VR	Virtual reality
VSM	Viable System Model

2. Introduction

The utilization of technology that promotes connectivity across organizational systems, processes, and products is critical in the current framework of Industry 4.0 and in the future adoption of Industry 5.0. Another factor to consider in this period is the ever-increasing amount of data accessible that gives full descriptions of the underlying industrial processes.

This thesis introduces the concept of the Digital Twin (DT), one of the technologies that will be at the forefront of Industry 4.0 and 5.0 since they promote the use of IoT-enabled systems, massive utilization of big data and collaboration between humans and robots:

> *"A digital twin can be defined, fundamentally, as an evolving digital profile of the historical and current behaviour of a physical object or process that helps optimize business performance. The digital twin is based on massive, cumulative, real-time, real-world data measurements across an array of dimensions. These measurements can create an evolving profile of the object or process in the digital world that may provide important insights on system performance"* [5].

It's a technology that is transforming the manufacturing context and, in general, the way complex systems are designed and managed. The key innovation is that process management via the DT enables the conception, development, and testing of processes, including performance evaluation, using a virtual representation first and subsequently implementing them in the real world.

According to a 2022 study [28], the number of papers related to the topic has grown exponentially in recent years; specifically, a search on one of the major database for scientific articles (Scopus) revealed that it went from about 30 articles published in 2016, the highest historical figure up to that time, to an average of 3000 articles in 2021 and statistically much more at the end of 2022. This research undoubtedly reveals how the DTs tool, along with all of the technologies and methodologies on which it is built, is constantly increasing and finding more and more space in the scientific literature in many fields.

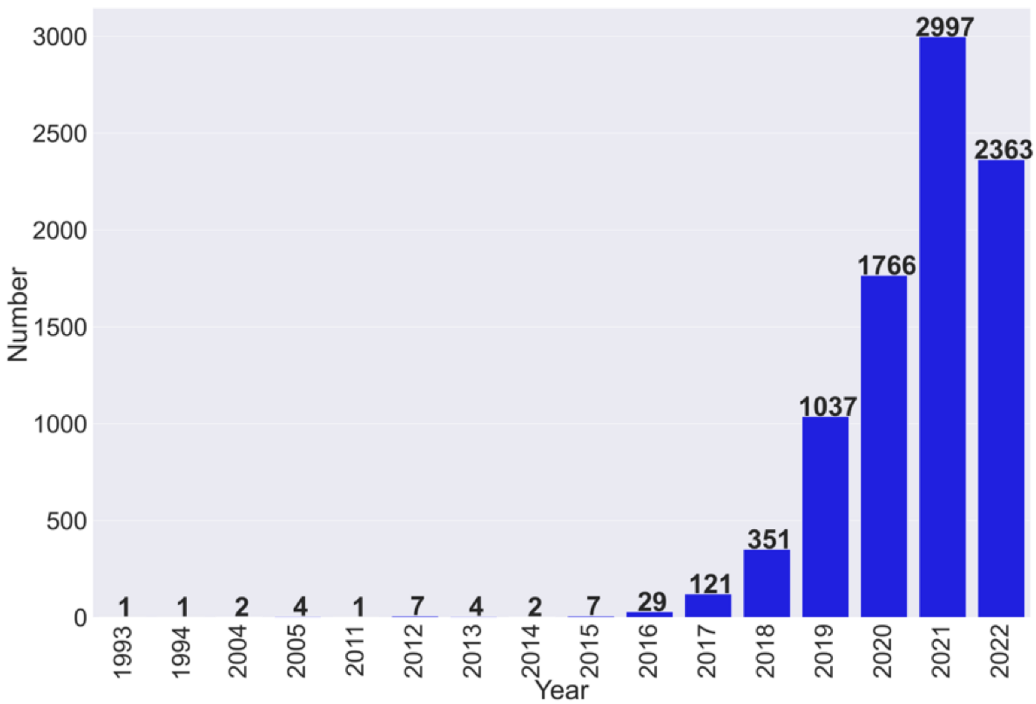

Figure 1 - The number of publications on digital twins (data taken from Scopus, records from January 2016 to March 2022) [28]

The purpose of this thesis is to highlight synergies and differences of the main DT frameworks regarding mainly scheduling activities described in the technical literature and link some of the main connected aspects by giving an in-depth study of existing research as well as review of the potentiality and problems that Digital Twins provide to the manufacturing industry.

Through literature research, this thesis investigates the world of DT-enabled systems. The study will concentrate on numerous key areas, such as the drivers that drive businesses to adopt this technology, the enablers that enable its effective implementation, and barriers that might obstacle its complete acceptance and integration. The methodologies and technologies utilized to successfully incorporate DTs into industrial systems will also be investigated. The review focuses on the application of DTs in several sectors and activities necessary in the manufacturing world, such as resource planning, material procurement, machinery maintenance, and real-time processing scheduling (key aspects for activities in the world of industry 4.0); in particular, the work will aim to revise the main logic architectures related to the last mentioned aspect (real-time processing scheduling) in order to identify a common logic infrastructure applicable to a variety of manufacturing contexts.

2.1 Approach, Methodology and Material Categorization

The approach used to explore the technical literature and prepare the thesis follows a well-defined logic described in the following steps:

1. An initial overview was conducted, through the main search engines for scientific papers (such as Google Scholar, IEEExplore, Clarivate Analytics' Web of Science, Archive Ovuerte HAL, Science Direct, Elsevier's Scopus, etc.) that allowed to map the main strands on which the scientific literature in the field of manufacturing and Industry 4.0 is developed and investigate regarding the application of DTs.
2. The second phase involves a review of the most cited articles (selected with the help of Connected Papers software, etc.) in order to identify the most credited papers in individual research chapters (the various levels on which DTs can enhance and make a positive contribution to manufacturing).
3. Then they were analysed by pre-dividing the articles into papers describing Industry 4.0 and future technologies, general reviews around DTs, specific reviews describing the possible adoption of DTs in the various levels of manufacturing, technical analyses of specific frameworks in the various levels of manufacturing. The purpose is to identify and subdivide the main branches of research.
4. Finally, they were categorized, on appropriate Excel file table, using the procedure outlined in the article [7] (enter in an Excel file bibliographic references to articles in which enablers, drivers, and barriers are described and identified references to papers that provide frameworks for the deployment of DT), according to the topics

covered in the thesis chapters, which are described in the dedicated section (number 2.2):

a. general Information
b. drivers, enablers, barriers, challenges and benefits linked to DT adoption.
c. supply chain planning and demand forecasting information
d. scheduling frameworks
e. predictive Maintenance information

The questions this research paper seeks to answer follow:

- What are the key features of DTs in manufacturing systems?
- What are the primary drivers, enablers, and barriers to DT adoption in manufacturing systems?
- What features should a DT's logical architecture have for scheduling operations within a production system?

According to the procedures outlined above, research was conducted using these questions in order to maintain the emphasis on the primary subjects addressed by the thesis.

2.2 Sections Description

The following thesis is structured into three main chapters:

- The introduction (Chapter 2) provides an initial concept of DT and its subsequent evolution over time and summarily describes the main areas and topics of analysis on which the thesis focuses; it also provides the approach that was followed to analyse all the scientific articles on which the analysis performed is based.
- Chapter 3 provides a classification and commentary of the main drivers, enablers and barriers to the implementation of DTs in manufacturing, particularly distinguishing between technological and "social" factors as well as attempting to make a connection between the main enablers and barriers to determine which aspects an organization should invest in to overcome such barriers.
- Chapter 4 focuses on a review of the main frameworks, mainly related to scheduling activities, looking for differences, evolutions and main common features, in order to define a pattern that can be followed to be able to implement a DT based on a reliable framework, for scheduling purpose, adaptable to various contexts.

2.3 Evolution of the Digital Twin concept through Industrial eras

Michael Grieves introduced, for the first time, the notion of Dt at the University of Michigan in 2003, in the context of Product Lifecycle Management Systems. [3].

He originally proposed the idea of producing a digital duplicate of assets and physical systems to protect them from harm or difficulties during analysis and diagnostic activities [1]. First reference to DT was as Mirrored Spaces Models. Grieves decided to change the definition of DT, during 2006, into Information Mirroring Model [3].

This definition was than evolved by the National Aeronautics and Space Administration (NASA) in 2010. They defined the DT as an ultra-realistic, high scaling simulation, which uses the best available physical models, sensor data and historical data for mirroring one or more real systems [2]. This new definition of DT concept coincided with the first practical implementation (due to technological restrictions, such as not developed system hardware power, lack of efficient and reliable connection mechanisms and protocols, data management, etc., DTs had no real-world application in a manufacturing system. [3]).

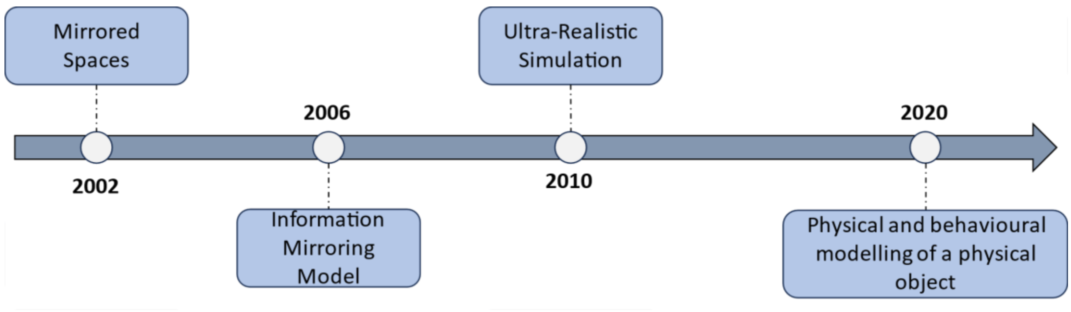

Figure 2 - DT concept evolution through time

the concept has continued to evolve simultaneously with the increase in the number of papers published on the subject. For example, John Vickers in [52], as reported by [28], redefined his conception of DT as:

> *"A set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level."*

Up to one of the most recent definitions offered by [39] and taken up by other experts in the field: DT viewed as a software representation of a physical object including its conditions and behaviour via models and data collected in the real world.

3. Drivers, Enablers and Barriers to DT implementation

3.1 Drivers

Commonly, a “driver" is a crucial factor or influential factor that hat convince someone to do something or causes something to happen [36, 37]. These considerations are typically reasons for businesses or individuals to invest time, and effort in developing and deploying innovative technologies.

As stated in [4] about the drivers in manufacturing DT world:

> “*In this case, Drivers can be understood as factors and forces that induce companies to initiate and fully-implement digital twin-related projects*.”

Below follows a list of the main drivers, described by various papers, that direct organizations to adopt Digital Twins for production, planning, maintenance, scheduling, etc.:

- the rising need to provide manufacturing flexibility: the word "flexibility" has been used to refer to the ability to develop a greater range of product variants as well as the ability to flexibly rearrange the manufacturing process in response to required modifications [4]. This point is the main focus of the DT for scheduling frameworks investigated in chapter 4.
- Competitiveness: as an exogenous variable, experts highlighted rising corporate competitiveness, which sets pressure on enterprises to find ways to cut costs while maintaining quality and efficiency. As digital twin drivers, experts cited benefits such as quality defect recognition,

failures forecasting, cost savings [4] (including the high costs associated with disruptive testing and cost linked with prototypes [3]). In research [52], the aspect relative to cost reduction becomes clearer due to the use of digital models rather than physical prototypes (figure 2). In particular, the physical cost rises linearly whereas the virtual cost decreases exponentially:

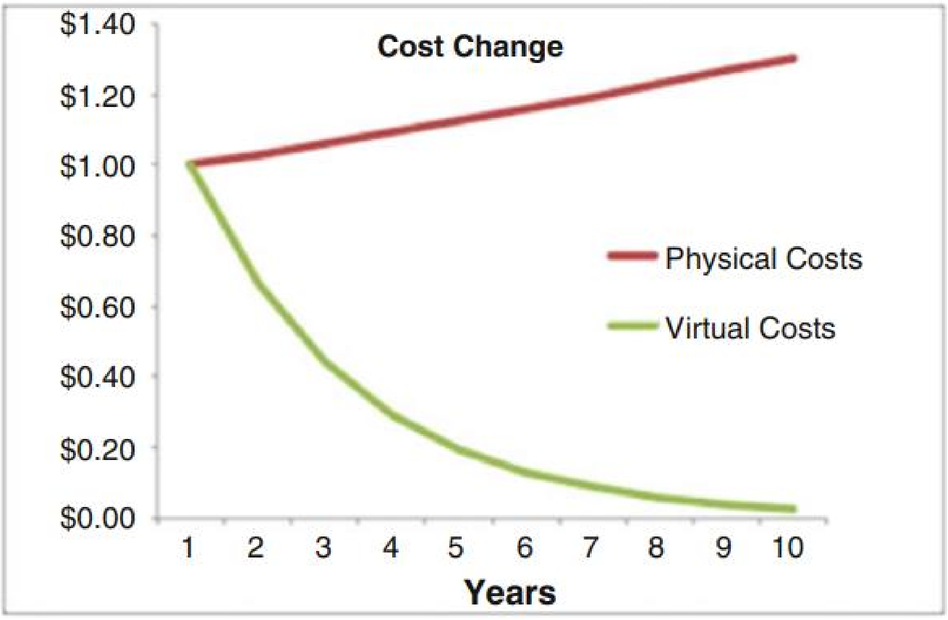

Figure 3 - Physical Costs vs Virtual Costs [52]

- Employee safety was noted in the literature as a driving force of digital twins. Workforce safety comes through an effective training and education phase that could be safer through the use of DTs and related tools such as AR and VR, especially in the case of risky environment, harmful equipment [3], so it is critical knowing how to deal with emergency mistakes from the moment the staff begins working [49].

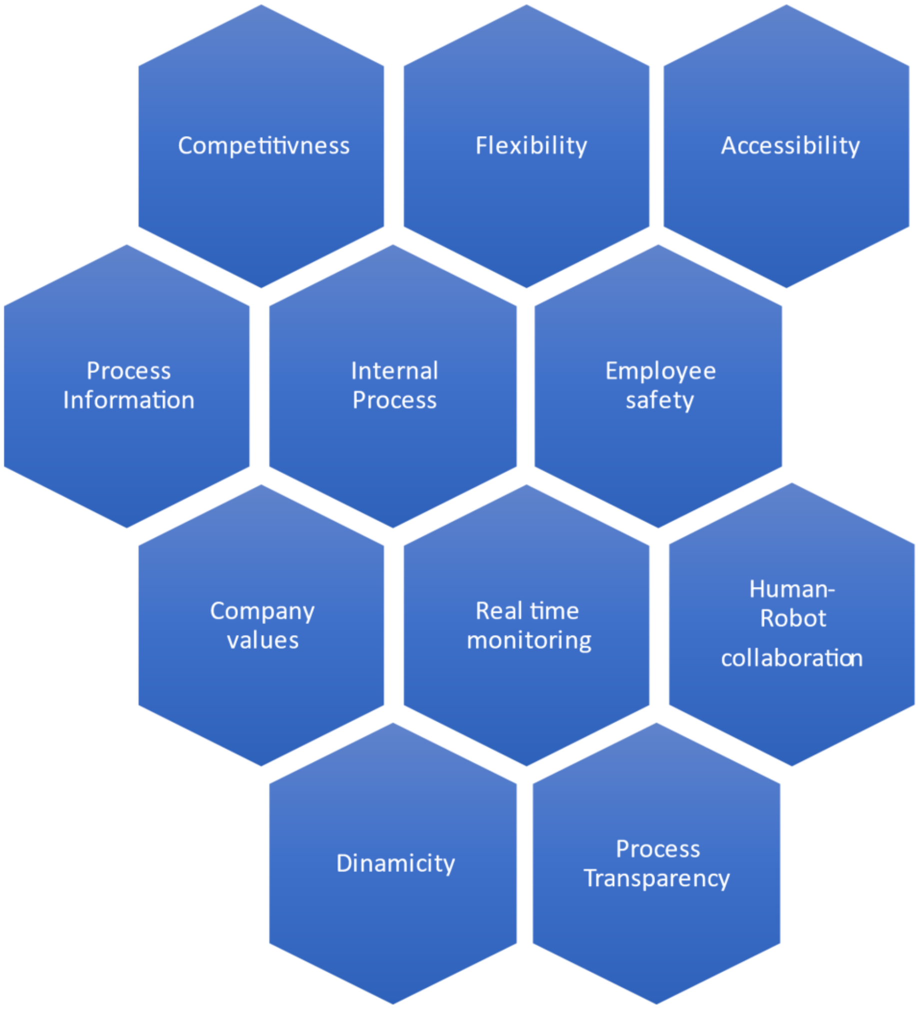

Figure 4 - DT Implementation Main Drivers

- Accessibility was also stated as a crucial drive for DT adoption. Indeed, without being bound to a specific geographic area allows the user to check the progress of production or communicate with the DT-enabled system remotely [52], which might be a significant benefit in scenarios such as the COVID-19 pandemic, as described by [3].
- The necessity of switching from traditional production systems in which activities like design, demand forecasting, scheduling, etc. of the production process take place concurrently with the evolution of

the system itself and thus takes into account all of the information of the environment of which it is a part. This requirement is identified by [3], which reports the dynamism feature, implying a constant flow of data between the virtual and physical portions of the system.

- Within the scope (analysed in the previous point) of modernizing and projecting manufacturing systems into the future, there is the need, at least for large global companies, to make Human-Robot collaboration (the main point of future Industry 5.0) concrete and increasingly constant [15].

  For example, [41] emphasizes this approach, reporting that the Human-robot job allocation, workstation layout optimization, human ergonomic analysis, and robot program testing are all possible with a digital twin of a human-robot collaborative work environment.
- The straightforward requirement for real-time monitoring of the physical system was also mentioned as a motivator for the installation of industrial digital twins [5]. In fact, it enables the producer to predict problems faster [50], to save expenses, eliminate resource waste [51], as well as improve other essential deliverables [50]. The high-quality digital twin model with real-time data also aids in understanding the situation and making better and more accurate optimization decisions [41], other than be more responsive to exogenous changes.
- Analysts claimed that internal process enhancement activities might result in digital twin projects as one of the most important drivers [4]. A further internal motivator cited by experts is an effort to increase stakeholder transparency in the whole manufacturing process [4]. As reported in [27], transparency in manufacturing context means *"full availability and access to information required for collaboration and collective management decision making. It means full disclosure of*

detailed historical records for root-cause investigation purposes to uncover areas for continuous improvement. DTs aim to collect information at every level of the production system, enabling for more accurate solutions and bringing a business-level perspective closer to operational-level choices.

The ability to obtain a full digital footprint of the production system has made it possible to gain exhaustive information about the entire process and product lifecycle, and that is an important driver identified by [5].

- Boosters that enhance company value: companies should assess the business benefit that the digital twin provides by taking into account factors that involve tactical effectiveness and marketplace. Among other things, these difficulties in strategy can be translated into particular solutions that could offer the wide commercial value that a digital twin could provide. Figure 4 lists a summary of such values by category [5].

Category of business value	Potential specific business values
Quality	• Improve overall quality • Predict and detect quality trend defects sooner • Control quality escapes and be able to determine when quality issue started
Warranty cost and services	• Understand current configuration of equipment in the field to be able to service more efficiently • Proactively and more accurately determine warranty and claims issues to reduce overall warranty cost and improve customer experiences
Operations cost	• Improve product design and engineering change execution • Improve performance of manufacturing equipment • Reduce operations and process variability
Record retention and serialization	• Create a digital record of serialized parts and raw materials to better manage recalls and warranty claims and meet mandated tracking requirements
New product introduction cost and lead time	• Reduce the time to market for a new product • Reduce overall cost to produce new product • Better recognize long-lead-time components and impact to supply chain
Revenue growth opportunities	• Identify products in the field that are ready for upgrade • Improve efficiency and cost to service product

Source: Deloitte analysis.

Figure 5 - DT Business Drivers reported in [5]

3.2 Enablers

3.2.1 Systems and Technologies enablers

The expression "Enabler" refers to the enabling aspects (organization, skills, network development, etc.) required to establish an atmosphere favourable to innovation in the business environment [6]. In the context of this thesis, the enablers comprehend the variables which make digital twins feasible.

Among the various enablers listed by the technical literature, they stand out as technological enablers the following ones:

- Artificial Intelligence (AI) and Machine Learning (ML): one of the primary innovations that enable for DTs at the moment is AI. As stated by [10], AI and ML are two of the main technical forces propelling DTs toward their truly potential.
  AI enables robots to acquire information from experience, adapt to new inputs, and carry out activities usually made by humans. It can observe the environment, evaluate the scenario, and choose the best course of action to achieve the set objective [8], even in uncertain circumstances and volatile environment.
- Hardware concerns and Data Storage: As DTs will produce significant amounts of data in real time to provide problem detection and more effective maintenance scheduling, the capacity to store this data efficiently is a key enabler for the effective adoption of DTs [7].
  Regarding hardware, as mentioned in research [9], reducing prices have made it substantially simpler for organizations acquire access to more powerful processing resources, enabling improved accuracy, depth, and resiliency in the DTs [9].

As a result, it is critical to create a data flow and a data platform capable of collecting an ever-increasing amount of data to support real-time analytics [33].

- Virtual reality (VR) and augmented reality (AR): can be considered among the key technologies that promise to add new perspectives in many sectors [10; 31], they enable a wide range of use cases for operators in a manufacturing plant, including virtual commissioning, remote assistance, and operator training systems, as well as simulations in a simulated setting [7], and provide to workforce improved and safer interaction frameworks and interface upgrades [21].

  > *"This enabler of Industry 4.0 ensures higher levels of awareness on the shop-floor and speedy information distribution due to enhanced technologies for communication […] "*[38].

  [22] reports the use of virtual reality alongside with a variety of wearable devices (e.g., tactical gloves, head-mounted accessories, etc.) for viewing a product's or environment's virtual model.

- The Industrial Internet of Things (IIoT) infrastructure is critical since it deals with the installation of certain industrial applications. [38].
  IoT facilitates interactions among devices across the same systems as well as the gathering of massive amounts of data from the manufacturing process. This allows a range of use cases, such as predictive maintenance and defect detection, to undertake maintenance operations just when needed, preventing unexpected shutdowns and breakdowns of the production infrastructure [7]. The Thus, data gathered by sensors within a production facility may be evaluated to yield useful insights. These insights can then be sent to

actuators to automate routine tasks along the production process, as previously outlined [7].

The reality of IoT devices and sensors is a very fast-growing market, as identified by [23], in which an annual growth of 24.70% (Figure XXX) between 2023 and 2032 is predicted; it sees growth in the world of manufacturing especially for activities concerning real-time analytics, security and data management solutions.

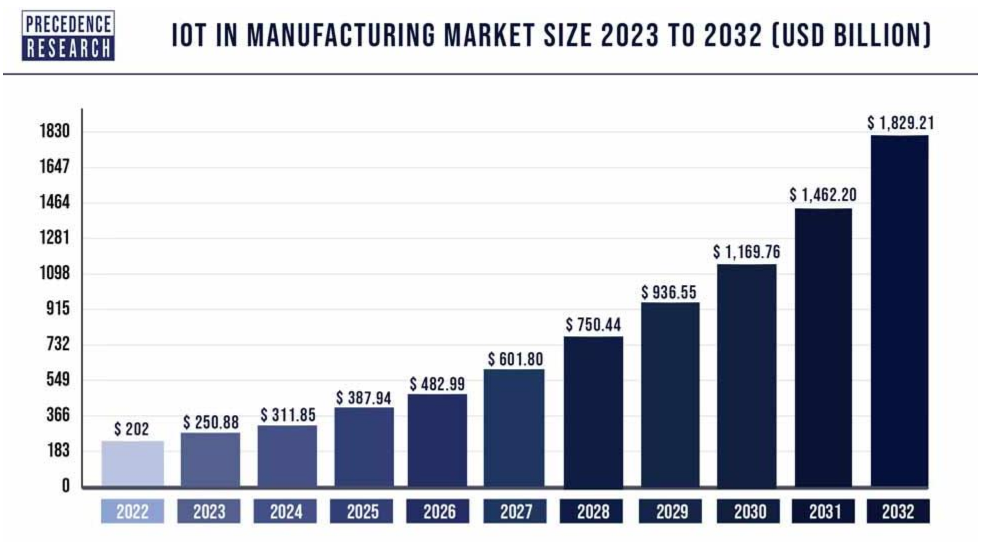

Figure 6 - IoT Market Growth projection (2022-2032) [23]

- Simulation models are seen as a necessary technology for the adoption of DT, since they enable the creation of a behavioural model that determines how the physical asset (like machinery, equipment, etc.) should react to external factors determined by the environment, contact with other objects [22], and simulate the working and dynamics of the production system and the methods it employs.
  They can also help in assessing risks and inventory analysis, so they can have a direct impact on the performance of many processes in an

organization [38], to the point of virtually mapping an entire factory design, as reported by [25].

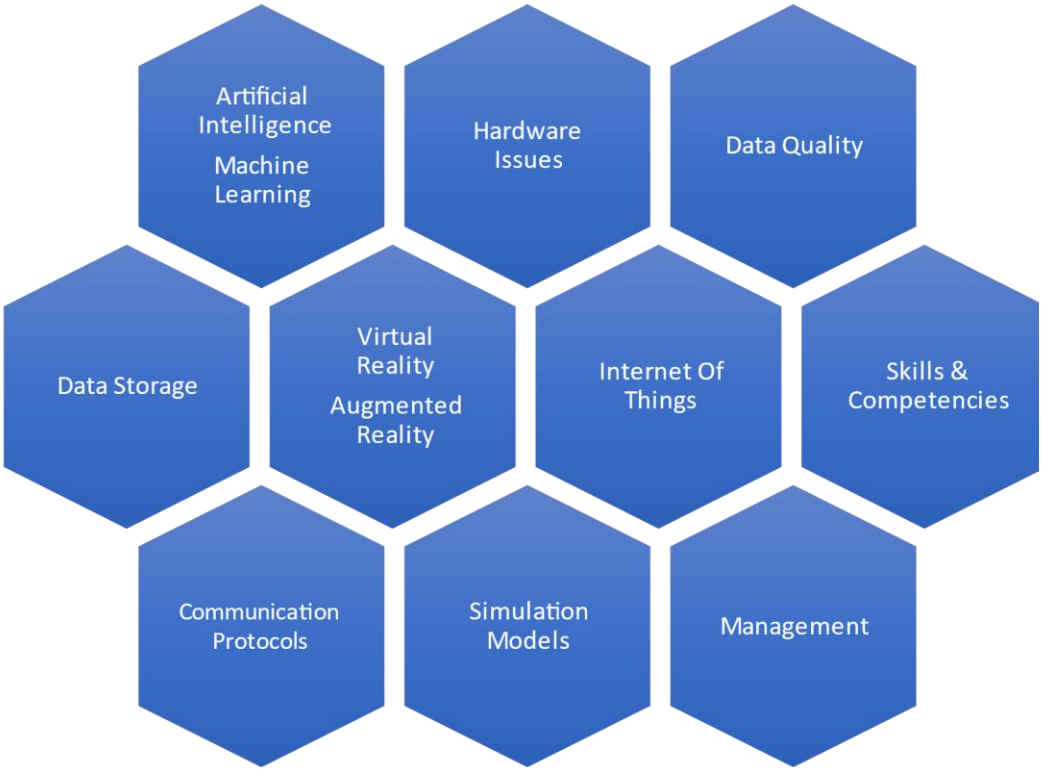

Figure 7 - DT Main Technological Enablers

Various research has been done or are underway in order to understand how to expand the use of these technologies in different fields of work.

- Communication protocols are a critical enabler for DTs in the industrial environment. They enable systems within the same IoT to communicate data and input signals in order to conduct particular actions based on DT input [7]. The goal of standardizing communication protocols inside an organization is to promote information exchange and synchronization. [25].

The networking domain has been identified as a key enabler since it is required for the collection, processing, and storage of raw data, as well as accurate visualization [50].
The reliable and efficient exchange of data is a crucial aspect of Digital Twin-based system as it’s highlighted in the frameworks for dynamic scheduling analysed in this thesis (chapter 4).

3.2.2 People-related and culture enablers

This brief section is dedicated to the enablers that concern the people who lead all the production activities, the skills and competences required in the field.

- Skills and Competencies: The exploration of force-labour training models and identification of key competencies that future workers must have in the field remains a keystone and a facilitator in the adoption of DTs [21], in order to guide workers toward the type of technology and business culture that provide DTs.
- Data Quality: as facilitators of the digital twin's use in manufacturing, experts emphasized process uniformity, a well-defined deployment plan, and correct data fills on enterprise management software [7] (e.g., ERP, CRM, CMS, etc.). DTs, in fact, need high-quality data characterised by a constant data stream [50] to be efficient and reliable.

  When an organization learns how to measure the quality of the data that collects and processes within its system, then such measures can be useful at the strategic level to analyse the state of the system and evaluate its performance in terms of improvement or adherence to established standards [26].
- Organization culture & Management: experts identified aspects that describe the crucial function of leadership within an organization when dealing with a digital twin project, in terms of organizational culture and strategy enablers [4]. In order to accelerate the DT introduction into the organization many employees-related features were identified, such as the importance of cultivating leadership qualities in employees and promoting collaboration among employees

coming from different department [54]. Experts also identified management willingness to support long-term initiatives, senior management backing, and the ability to make financial investments as enabling factors [4].

3.3 Barriers

Adoption and deployment of digital twin technology has the potential to transform companies by connecting the physical and digital areas improving operational efficiency and promoting informed decision-making. However, like with any profound innovation, integrating digital twins into established corporate structures comes with difficulties. This section dives into some of the key problems and obstacles identified by experts as possibly impeding the smooth integration and full success of potential digital twin adoption in the manufacturing contexts.

- Process and System Integration: experts identified challenges concerning process integration as a barrier to adoption. [4]. System integration involves the transfer from old and obsolete legacy systems and equipment to the most recent cutting-edge technology. This barrier category encompasses both the challenge of combining new systems into existing ones and the issue of integrating various elements of existing systems collectively [7].

  System integration issues include the need to create a new User Interface (UI) following the integration of more DTs and the difficulty of combining the technology with which they were realized, if different, and the distribution pattern [19].

  As an outcome, it appears that integration across different portions of the business is critical to the success of digital twin projects. This conclusion is not improbable given the significance of organizational integration in analogous digital transformation programs, such as Industry 4.0's integrations [4]. The high cost of new IT-environment is a point emphasized in the study [43].

- Scalability issues: making DTs scalable to millions of devices, as theorized, turns out to be a difficult problem to manage [18]. points out that, from a purely technical rather than organizational point of view as in the previous point, it could be complicated to integrate the numerous techniques used by equipment and sensors to gather, process, and format data.
- Assets and operational evolution: one of the primary obstacles, is the necessity to incorporate any new asset or operational changes into the present framework, which is often the product of a considerable investment and hence impossible to replace owing to the unsustainable costs involved. Because such systems have a lengthy lifespan, the issue of integration becomes more and more obvious with time [7]. Part of the challenge is the high cost of resources and equipment required to implement a system based on DTs (e.g., due to the large number of sensors and IoT systems), and part of the problem is the scarcity of these resources in some regions of the world [5].

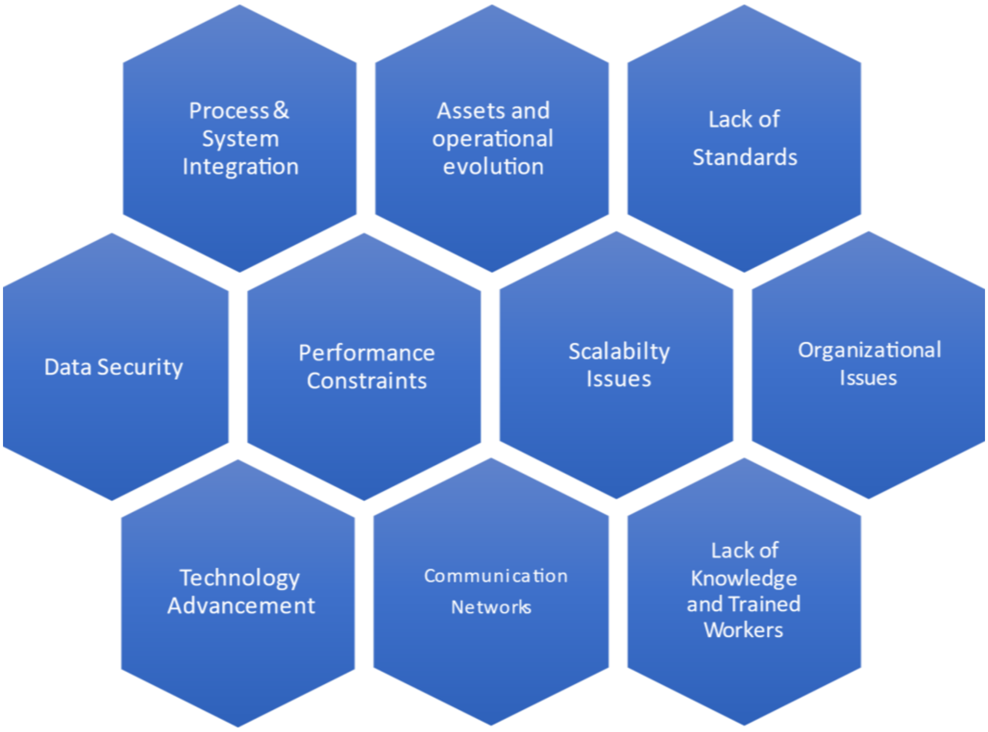

Figure 8 - Main Barriers for DT Implementation

- Data Security: All hazards related with data capture, exchange, archiving, and processing, along with the protection of intellectual property are covered by security concerns. The problem of data protection and the possible loss or leakage of data is described by [19], in which is highlighted how it should be the foreground especially in cases of integrating DTs within a pre-existing system and in the case of delivering a systems DT combined with the structure itself.

  DTs amass data and intellectual assets which grow in value over time [8].

  As pointed out in [8,] there is a need for data transparency and the use of methods to ensure data security, opening and preventing data loss or other potential harm.

When DT connect at different levels (as in [31]), it is necessary to consider data segregation and segmentation in accordance with the General Data Protection Regulation (GDPR), as illustrated in [19].

- Technological advancement: although this point may be seen as an advantage in the adoption and implementation of DTs in an increasingly easy way, it could lead to a mismatch between the different components that are supposed to form these systems. A number of articles including [50] highlight the possible technological advancement at different steps; particular is the example described in the cited article: the supporting systems or IoT devices may not be compatible with the DT.

  The same could be true for other technologies such as ML, AI, real-time technologies, etc. [3].
- One point related to technological advancement concerns the communications network, through which DTs can implement the exchange of data necessary for their operation; [50] and [7] reports how the lack of an efficient 5G network can be an impediment to being able to connect sensors and devices. As stated by [20], 5G has a much better latency and it allows 100 times more devices to be connected than 4G. So, the development of such a network is not an optional extra but something essential.
- Performance constraints: they are closely tied to hardware and software resource limits that provide an effective flow of data between physical and digital systems, allowing DTs to reach their full efficiency in industrial purposes.

  One of the most distinguishing features of DTs is their capacity to represent and track the status of their physical twins in real time [7], while they likewise are capable of delivering a variety of services, ranging from status monitoring to properly providing solutions, and even controlling the physical system autonomously [4].

Experts have attributed performance concerns to the lack of maturity of certain widely used technologies (particularly those used to enable decision assistance and driverless action) as potential impediments to deployment. As a result, the lack of maturity in predictive data analysis approaches could end up being a barrier to applications when unpredictability of such technologies is a danger [4].

Also, part of the problem is the difficulty of achieving a high level of modelling, a possible barrier identified by many articles dealing with the subject ([22; 26; 34; 25]).

- Lack of Standardization: the article [50] notes, as a barrier, the lack of standardization due to both the differences between the various definitions of DT provided in the scientific literature and the differences between DTs designs and frameworks.

  [43], on the other hand, identifies a certain lack of standardization in the data acquisition process that directly impacts the implementation of DTs, and [3] point out other roots for absence of uniformity like models, interfaces, protocols. Instead, in [21] is reported that there may be discrepancy between exchange data sources among various suppliers, producers and consumers that could lead to an interoperability problem.
- Organizational issues: the theme of the internal division of the organization in departments was first described by [52] and then reported by [13]. The first one states:

  > *"There is a natural siloing of information within [...] functional areas. Each of these informational silos has*

information about the systems. However, there may be very little sharing across functions".

Instead, in order to be implemented, the DT idea need a unified view of this information across all departments and functional boundaries [52].

- Lack of Knowledge and trained workers: an additional aspect, advocated by [21], that could affect the proper and effective use of DTs, is the lack of knowledge suitable for the use of DTs by the organization that decides to adopt them and of workers properly trained in managing such systems.

3.4 Mapping connections among enablers and barriers

Taking a cue from the exercise of mapping and create logical link between barriers and enablers that permit them to be overcome, propose in [7], the same notion is suggested again in this part, but this time based on the evaluation of barriers and enablers reviewed in the preceding sections. The arrows begin with an enabling element and terminate with a barrier, demonstrating which enabler categories have a favourable influence on which barrier categories (figure 9).

As discussed in the preceding paragraph, the technological barrier is possible to overcome through the advancement of the primary technologies on which DT-enabled systems are built: the development of AI, ML, and VR/AR representation technologies, simulation and modelling techniques that allow the system's physical and behavioural equipment to be represented, and the general development of hardware components.

In the past few years, VR and AR have been seen as technological catalysts for the development of DTs. The aforementioned technologies enable the construction of training tools for new operators and give users a more participatory method to utilize DTs [7].

Communication technologies and new improvements in IoT/IIoT have decreased system integration difficulties. A growing number of manufacturers are creating and delivering unified IoT/IIoT platforms and solutions that are backwards compatible with current systems ([10]; [12]). IoT systems would also make DT use scalable; in fact, an organization's ability to expand the number of devices and sensors tasked with tracking system status and collecting data allows it to use DT-enabled systems on a large scale.

Vendor-neutral communication methods like as OPC-UA are being utilized to overcome the issue of integrating previous systems and new IoT/IIoT systems for the implementation of DTs in industrial applications [7].

It is essential for a business to have an effective communication protocol in order to overcome problems at several levels: improving the whole network of business communication and thereby ensuring a certain standard. Although significant effort is necessary to guarantee that sensitive data may be communicated safely between physical assets and associated DTs, such procedures are acceptable for the creation of DTs in industrial contexts, as evidenced by the work of numerous researchers in the field.

Organizational issues are mitigated through increasing knowledge. The application of Industry 4.0 standards, in particular, helps businesses to build the groundwork for the successful growth of DTs through the creation of a comprehensive and integrated data infrastructure for exchanging data between a physical asset and its DT [12].

Personnel training, upgrading and reskilling will benefit the environment by contributing to the establishment of new processes, tools, and standards for the construction of DTs [13].

The organizational issues are primarily determined by high-level decisions and, as a result, by management: managers' ability to develop an organizational culture oriented toward the DT and, as a result, an appropriate vision from which they can formulate feasible financial decisions for system development and implementation.

Knowledge-building technologies and design methods help to alleviate organizational difficulties. Workforce upgrading and reskilling [14] and the application of Industry 4.0 standards [12] allow businesses to keep their workforces up to speed on the newest technology developments, overcome a shortage of DT specialists and experience, and eventually make educated judgments on the matter.

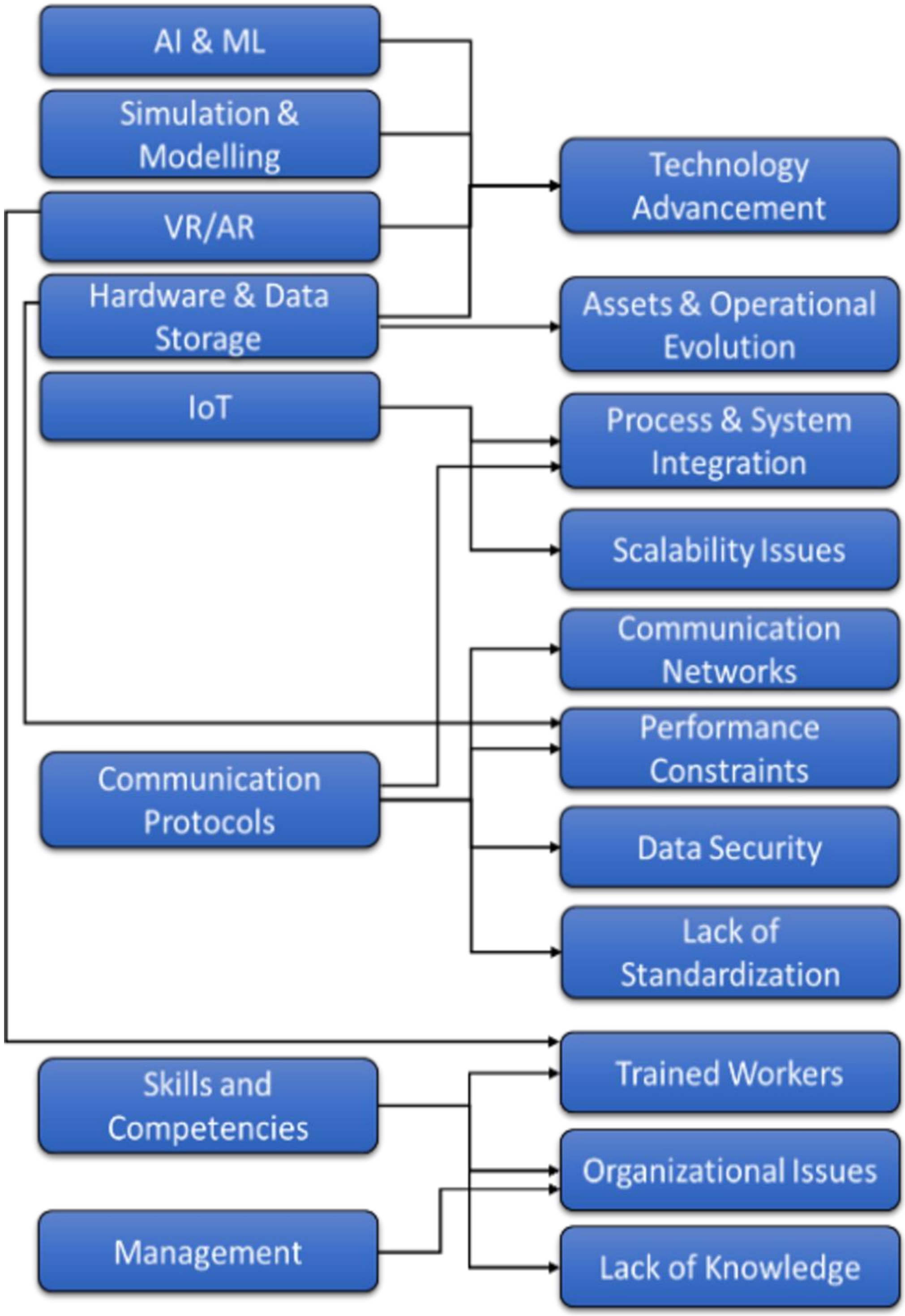

Figure 9 - DT Enablers and Barriers Connections

4. Digital Twin Frameworks in Flow-Shop Systems for Scheduling Purpose

Regardless of the adoption of dispatching rules, kanban cards, and other distributed production management systems (Panwalkar and Iskander, 1977; Green and Appel, 1981; Hopp and Spearman, 1996), many manufacturing facilities still develop and amend production schedules. Because of a lack of comprehensive global information [29], these strategies usually promote speed but lack long-term vision, leading in insufficient responsiveness to disruptive events.

Today's industries need to be more adaptable in order to respond to unexpected real-time occurrences and rapidly evolving market change [40].

The consequently, production plans must be adaptable for events such as increasing demand, varying delivery duration, supplier delays, machine faults, and external effects such as weather or accidents. In practice, delays and unexpected events result in pre-scheduling failures, forcing the business to rely on make-to-order manufacturing operations in the flow shop environment [30].

Real-time scheduling has been extensively studied and proven to considerably enhance scheduling decisions in an ever-changing context. Is also important to evolve production schedules using automated decision-making carried out while production is in progress [31].

Several studies indicate that using DTs on these systems provides significant benefits, like minimizing the medium makespan [e.g., 1; 31] in order to identify a solution to this challenge in the scheduling of flow shop systems, carrying out the advantages of real-time scheduling strategies.

4.1 Frameworks Review

The technical literature in the field of scheduling activities includes numerous approaches that integrate DTs in order to create a Cyber Physical System (CPS) able to make the scheduling activity increasingly effective and efficient. Many studies are concentrated in providing frameworks suitable for scope, which have common characteristics, therefore considered the basis for the realization of a highly compatible and flexible system in relation to each application case, but also the differences on which it is necessary to investigate thoroughly. This chapter aims to verify some examples of infrastructures that integrate the use of DT in order to make the scheduling activity more responsive to changes and identify the main characteristics and a main pattern that can be followed to theorize an efficient DT framework.

A basic framework of a real-time flow shop assembly DT system is proposed in the study [30].

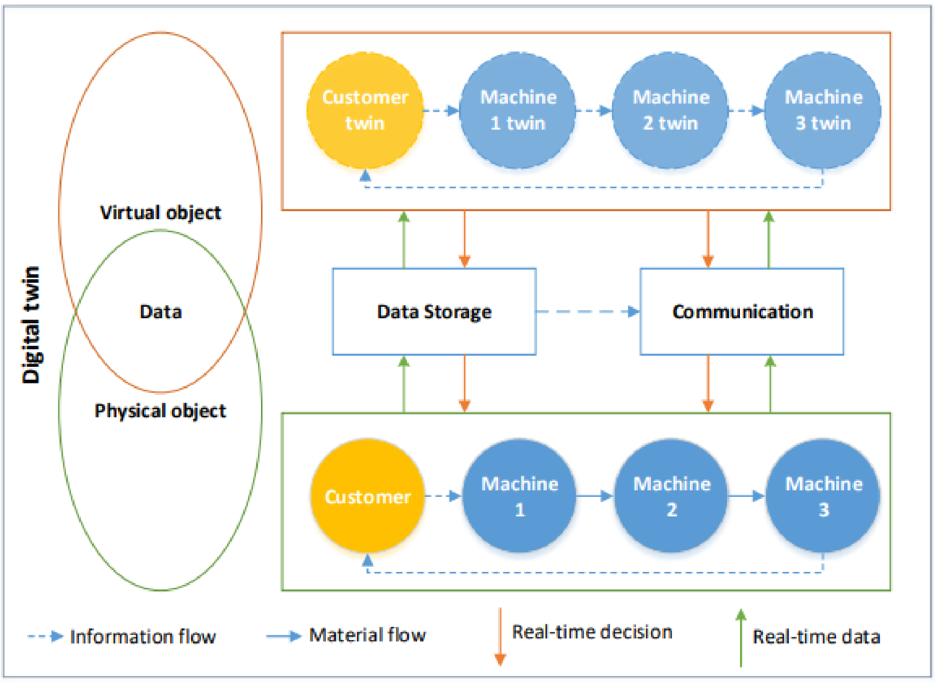

Figure 10 - DT Framework proposed by [30]

The proposed concept is based on the characteristics of dividing DTs into two main components, reported by [3], in physical object and virtual object where *"there is an automatic bidirectional flow of data between the physical and digital object"*.

In fact, one of the features that is repeated in this type of flow shop systems using DTs, is the development of a DT for each machine in order to map each individual unit that makes up the system.

The communication system adopted is based on a constant exchange of information about the status of the machinery: the physical object signals whether or not it is ready to process a job, the virtual object, on the other hand, keeps track of any disruptions and updates the scheduling sequence [30].

The framework concept proposed by [2], shown in figure 11, focuses on the joint implementation of a manufacturing system DT and a decision support system. Again, each machine is simulated via DT thanks to the data collected from the physical world, thus relying on real-time communication between physical and virtual object.

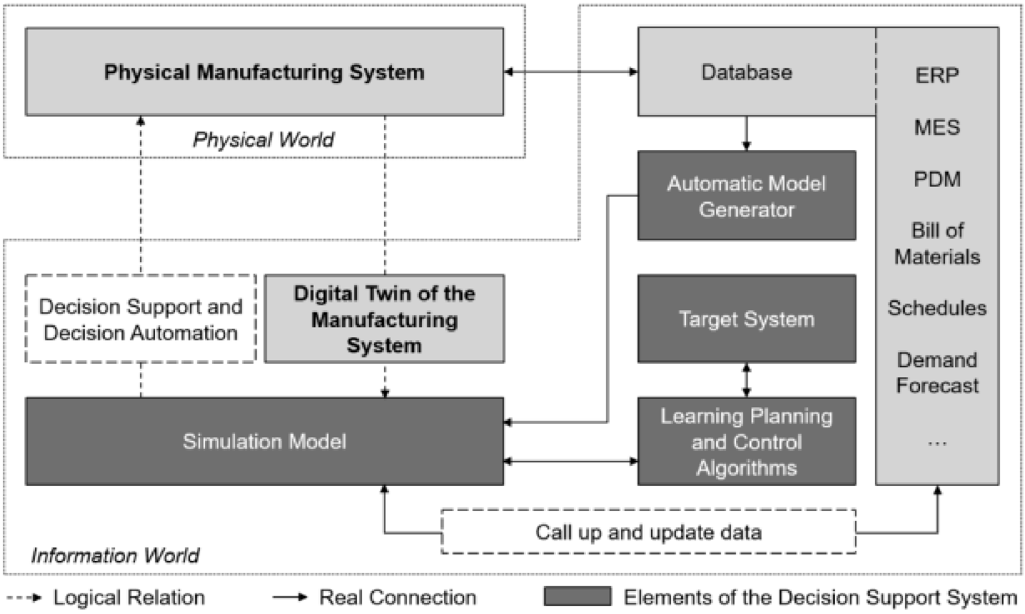

Figure 11 - DT Framework proposed in [2]

Through the use of a model generator and an optimization algorithm, solutions are chosen or generated and subsequently tested, then proposed to the decision maker to select the best possible option.

It should be pointed out that depending on the proposed framework, the measure (Job Flow Time, Job Lateness, Makespan, etc. [48]), as well as the dispatching rules (such as First Come First served, First In First Out, Shortest Processing Time, Earliest Due Date, Critical Ratio, Slack per Operation, etc.

[48]), through which the various proposed scheduling alternatives are evaluated and thus the result [42], may also change.

[43] highlights an important evolution in scheduling systems: through the use of DTs, simulation and optimization algorithms, we are moving from a purely statistics-based pre-scheduling approach to a dynamic approach based on real-time data analysis.

The module that deals with optimization also has common features, and it is therefore possible to develop a pattern to be used as a trail to follow for the implementation of future DTs. Specifically, in study [31] and [1] it is shown how the optimization module operates in detail. Starting with an initial job sequence that is tested through the simulation module, the performance is measured and if the sequence is the optimal one it is forwarded to the Manufacturing Enterprise System (MES) or scheduling system, otherwise the optimization mechanism is applied so that other options can be tested until the optimal one is found.

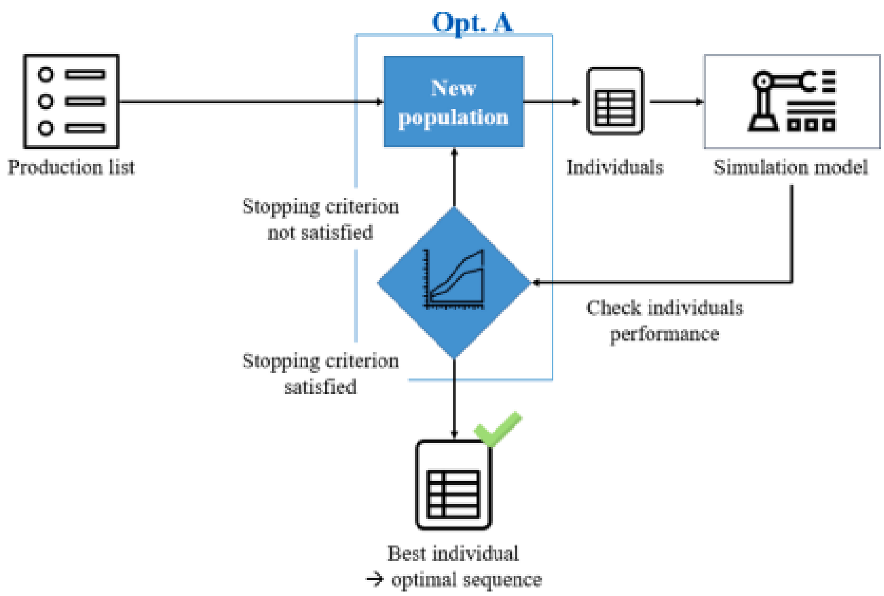

Figure 12 - Optimization module adopted in framework proposed in [31]

2021 research [1] identifies a framework, in figure 13, made for a flow shop system, similar to the two previously described in which, however, a difference and an evolution from the previous two is highlighted: in fact, in addition to the data input, optimization and physical system modules, the Discrete Event Simulation (DES) module and the Equipment Prognostics and Health Management (EPHM) module are introduced.

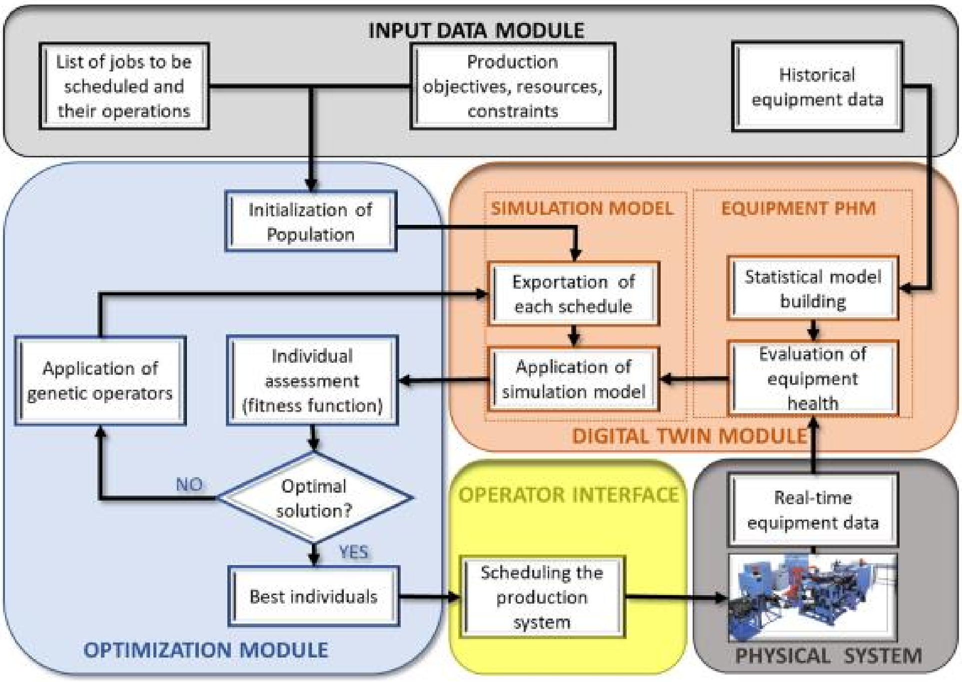

Figure 13 - DT framework proposed in study [1]

"A DES models the operation of a system as a (discrete) sequence of events in time. Each event occurs at a particular instant in time and marks a change of state in the system" [32]. This allows the system simulations to be tested.

The predictive maintenance field entails shifting maintenance approach away from traditional fail-and-fix techniques (diagnostics) and toward a predict-and-prevent approach (prognostics). Prognostics and Health Management (PHM) is an engineering subject that focuses on anticipating when a system or component may no longer operate properly [35].

The EPHM receives real-time input from the physical equipment and elaborates it to provide predictive data to the manufacturing system simulation model [1]. As explained in the case study attached to the research paper, the EPHM module calculates the failure probability and when a breakdown occurs it adds the Mean Time To Repair (MTTR) to the processing time.

The addition of the EPHM module succeeds in making an important contribution to the scheduling mechanism proposed by any framework that uses DTs; in fact, it allows the addition, in real time, of another important piece of information that the simulation module can take into account to develop a more accurate prediction: the state of the machinery, the probability of breakage related to it, and the additional time required for repair (MTTR).

Despite PHM is a very broad branch that considers various methods designed to offer early identification and isolation of a component's or sub-element's precursor and/or preliminary defect [35], one of the most studied branches is the estimation of Remaining Useful Life (RUL), as reported by [44].

> *"The Remaining useful life (RUL) is the length of time a machine is likely to operate before it requires repair or replacement"* [46].

One of the most cited studies in the field [34], provides a framework for estimating the RUL, which has already been identified as one of the most important data for the purpose of predictive maintenance of machinery and to have an estimation of the machinery's lifetime [47]. The aforementioned study shows how after an initial phase of physical modelling of the machinery and the use of physical data collected through IoT systems, the operation of the machinery itself can be simulated and then the RUL can be calculated. This operation should be repeated continuously in order to update the data [34].

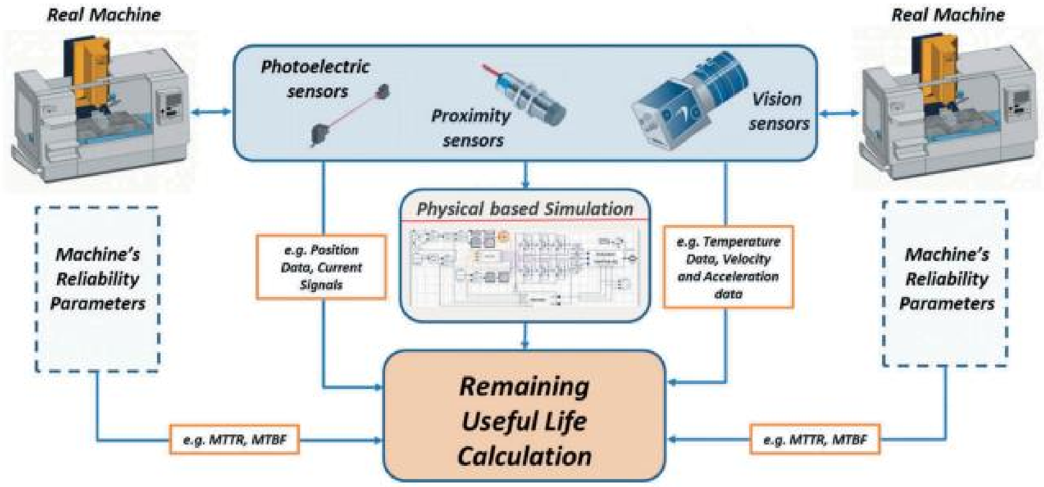

Figure 14 - RUL calculation method proposed in [34]

It can be pointed out that most of the frameworks analysed in the literature (and in all those analysed in this research) are based on the concept of Predictive-Reactive dynamic scheduling [45].

The predictive-reactive framework is a process of scheduling and rescheduling when the originally created schedule is modified in response to current occurrences [40].

Although the various studies show that all dynamic scheduling DTs rely mainly on real-time data to analyse the manufacturing physical system they control, all of them also use some source data such as production objectives [2; 9; 31], resources [2; 9; 40], constraints [2; 40], etc. This data is taken from the main management systems such as MES, ERP (which provides the info related to earliest start date, latest due date, job nominal processing time, etc. [40]), PDM, PLM, etc.

Most frameworks describe a DT infrastructure that manages the production of a single part or department of manufacturing. To date, however, manufacturing organizations are made up of a very vast and well-connected production and logistical network; therefore, it is necessary to have scalable DT-based infrastructures.

An example of such a framework has been studied by [31] (figure 15), in which a division and linkage between local DTs and global DTs is proposed; the former allow, as in other cases [2; 9; 30; 40], to mimic workstation and process activities while the latter allow to collect data and results of process optimizations managed by local DTs [31].

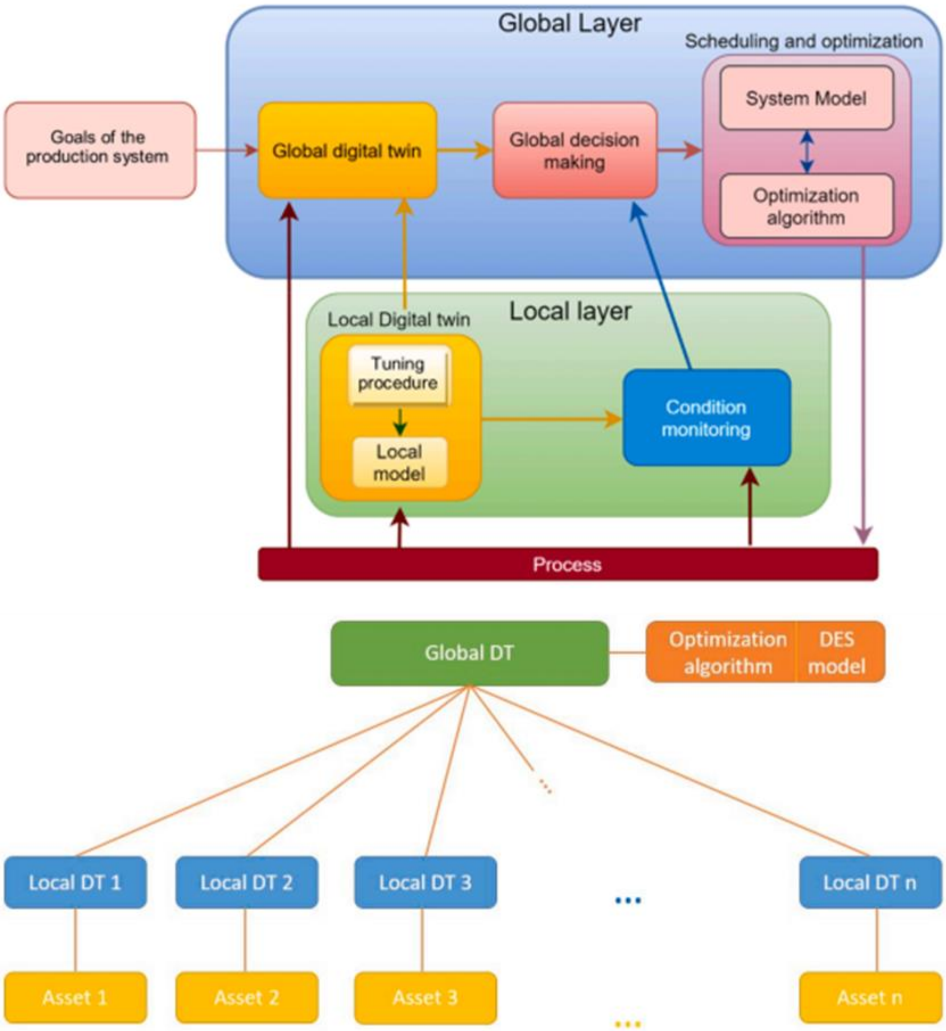

Figure 15 - DT framework and linkage between Global DT and Local DT studied in [31]

This infrastructure reflects the classification of hierarchical levels described by [24] and reported by analysis [3] in which the infrastructure of DTs is divided into three levels:

- Unit Level: refers to each unit-level physical twin.
- System Level: permits a *"Interconnectivity and collaboration among multiple unit-level DT"* [3]
- SoS Level: a connection of many system level DTs which can link different companies or departments.

Among the various modules that should compose a production system based on DTs dedicated to scheduling, in addition to the real-time information derived from the sensors and IoT systems that control the machinery and equipment, that make up the physical systems, all the reference data managed by the company's databases are essential: both what concerns the product, its production process and the information related to the quantities of product to be produced for each time bucket. Regarding the latter, demand forecasting is of great importance in order to avoid underproduction or overproduction scenarios.

In fact, demand prediction is the very first phase in planning. Forecast predictions define necessary products, quantity, and timelines. As stated by multiple researchers, demand forecasting in the age of the e-supply chain is transitioning from an empirical to an analytical approach [13].

Demand forecasting is a technique that is used for the estimation of what can be the demand for the upcoming product or services in the future. This type of forecasting involves analysing past demand, current market trends, and other data to make predictions as accurate as possible about future demand [16].

Among the various studies proposed by the scientific literature, [17] identifies a link between the simulation module and the organization's database: specifically, the use of data contained in the ERP administrative system represents the historical data base on which to base the analysis, which is connected to the simulation module, that will present the results (from the various simulation methods) to a decision maker via a dashboard. As a result, the final manual step is the process of decision-making.

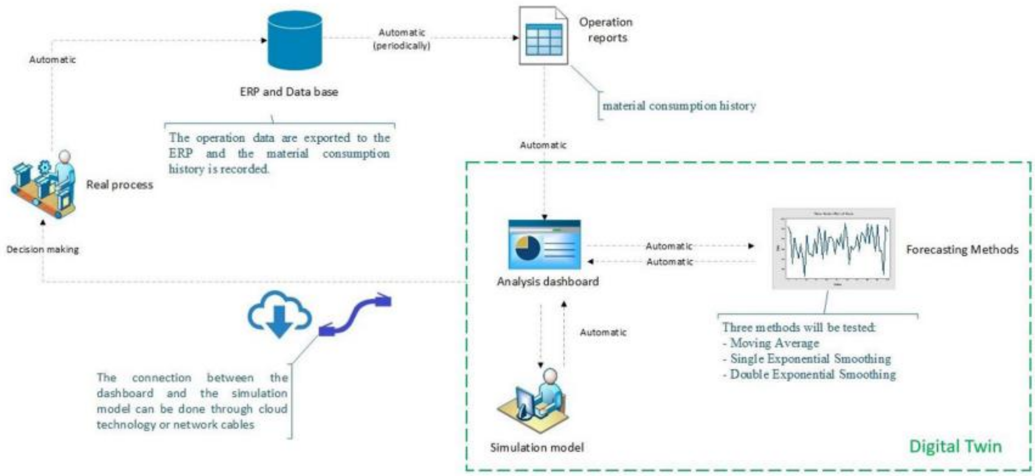

Figure 16 - Demand Forecast framework based on DT realized by [17]

Another requirement for demand forecasting algorithms is the ability to cope with different forms of demand (stationary, seasonal, and/or trending). To address this issue, the study [21] proposes implementing a Viable System Model (VSM), which employs a variable known as "demand reactivity" for measuring changes in demand between time periods and comparing them to statistical limits established a priori; in this way, the VSM can recognize demand patterns and use the most appropriate forecasting algorithm accordingly.

4.2 Pattern reassumption

To summarize all the considerations made in the preceding paragraphs, a list of the main points, useful in creating an adaptable and reliable framework for flow-shop production systems, is presented (figure 17).

A framework that uses DTs to make scheduling activities more responsive to changes in the environment and the very conditions of the system in which it operates should possess:

- Physical Assets: includes all the machinery and generally the physical part of the system.
- Data Module: which collects all the information related to the machinery and the process at the various production stations (mainly through IoT devices)
- Database: gathers and makes accessible to the system all available information and data in various organizations, process and resource management systems (ERP, MES, PLM, PDM, etc.)
- Predictive Maintenance Module: allows calculation of a number of parameters related to the state of machinery, including mainly RUL, in order to take into account, during simulation, the possibility of breakdowns and reduce the Mean Time To Repair (MTTR).
- Simulation Module: Allows the simulation process to be used to produce values on which to base the scheduling process's evaluation.
- Optimization Module: applies a series of iterations designed to find all possible scheduling options and choose the optimal solution based on the measures identified to make the choice. It must be linked cyclically with the Simulation Module.

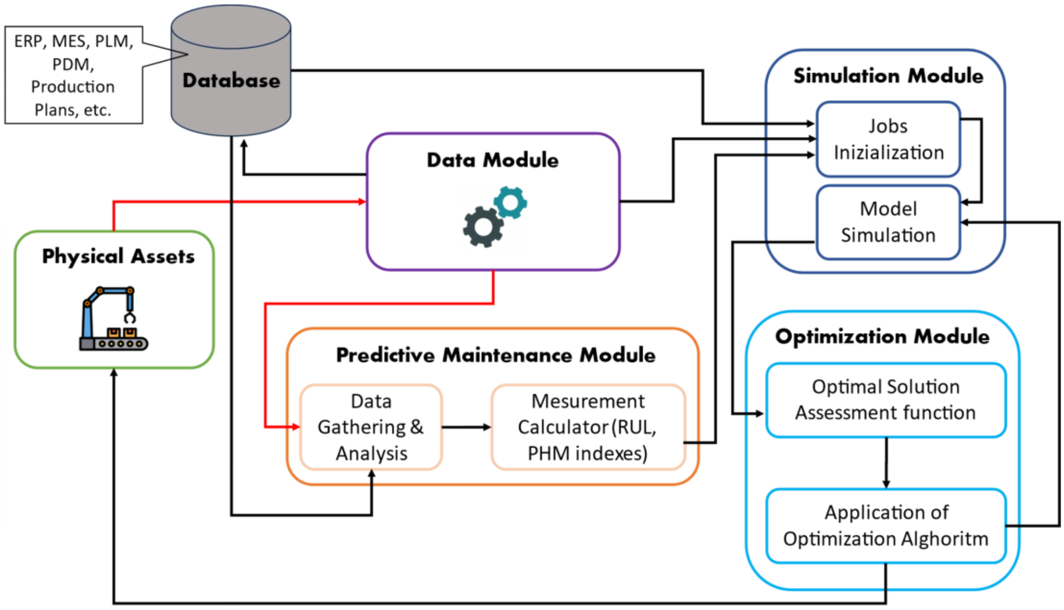

Figure 17 - DT-enabled pattern framework based on considerations made on frameworks studied by the technical literature

The pattern outlined emphasizes that the use of DTs within the system must be based both on historical data, provided by the various business management systems and saved in the company databases, and on real-time data collected through the IoT systems networked with the equipment and all the physical assets.

The framework must always be based on the iteration of a simulation mechanism, which has the task of initializing the jobs list and simulating performance through appropriate measurements, and on an optimization mechanism that, through an appropriate algorithm (which is not the subject of the thesis work), suited to the context in which it is to be implemented, has the task of proposing appropriate changes to the population subject to the scheduling activity.

One of the problems that can affect scheduling activities is the downtime and breakdown of the machinery making up the production line. Hence the need to be able to implement a forecasting algorithm that must estimate the main

PHM indices and forward this information to the simulation module. Taking this data into account tends to eliminate or at least reduce downtime and increase the performance of the system itself.

In this way, the simulation module is central as, using historical and real-time data, it has the entire wealth of information of the system at its disposal and can take into account the state of the machinery (current and historical) and information on the demand forecast in order to make the most efficient scheduling possible.

It is crucial to note that the proposed framework, which is based on studies of flow-shop systems, can achieve good results despite the fact that the task routing options are limited.

In fact, the characteristics of a flow-shop system, as opposed to job-shop and open-shop systems, allow for easier scheduling since they require a unidirectional flow and precedence of operations, resulting in a natural order of the machines [53].

The eventual presence of several work routing options implies the presence of an enhanced simulation and optimization module in order to test and identify the best choice.

5. Conclusion and Perspectives

The goal of this thesis was to examine numerous publications dealing with the issue of DTs and presenting potential frameworks for adoption that differ in idea and implementation concerns but share key characteristics. This leads to demonstrate that it is feasible to create a track or pattern that serves the same goal as the frameworks from which it is derived while also being adaptable in accordance with the requirements of the system in which the DT must operate, as well as the resources and technology available to the organization that want to use it. In fact, in order to make a technology accessible while simultaneously attracting consumers to use it, it must include qualities such as reliability, flexibility, and clarity of understanding and usage.

Obviously, the introduction of a new technology is always intended to improve the characteristics and performance compared to the technology in use at the time, but there may also be an advantage of another kind (economic, reliability, etc.); all the drivers described in this research, highlight all the reasons that may convince an organization to adopt the new technology, in this case DTs in production systems. Drivers were highlighted at all levels of a corporation, from the top (business/strategic) to the lowest (specific unit or machinery performance).

As technology advances, we may expect even more real-time data integration and AI-driven knowledge. Collaboration between researchers, businesses, and government is crucial for breaking through present barriers (technical, political, and legal concerns). Addressing data security issues, creating standard communication protocols, and building a digital transformation culture are all key stages toward digital twin adoption in regular manufacturing operations and phases. Manufacturers may position themselves at the forefront of innovation and efficiency in the industry 4.0 era by studying current case studies and forecasting future trends.

The revision of the main drivers, enablers and barriers raises some questions:

- will the time difference between the evolution of the primary DT technologies and the need to integrate DTs in the manufacturing industry have a negative impact on the industry 4.0, as well as the approach to industry 5.0?
- will be possible to identify a logical framework (and/or a technical architecture) that can be applied to any manufacturing system in the future?

As stated at the outset of this thesis, scientific literature is increasingly focusing on the topic of DT, both in the manufacturing and in other fields, and as with any new technology, the more research into it, the greater the development.

6. Table of Figures

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