machines

Article

Digital Twin for Flexible Manufacturing Systems and Optimization Through Simulation: A Case Study

Adriana Florescu

Department of Engineering and Industrial Management, Faculty of Technological Engineering and Industrial Management, Transilvania University of Brasov, Bd. Eroilor 29, 500036 Brasov, Romania; fota.a@unitbv.ro

Abstract: The research presented in this paper aligns with the advancement of Industry 4.0 by integrating intelligent machine tools and industrial robots within Flexible Manufacturing Systems (FMS). Primarily, a development approach for Digital Twin (DT) is presented, beginning from the design, sizing, and configuration stages of the system and extending through its implementation, commissioning, operation, and simulation-based optimization. The digitization of current industrial processes entails the development of applications based on modern technologies, utilizing state-of-the-art tools and software. The general objective was to create a digital replica of a process to propose optimization solutions through simulation and subsequently achieve virtual commissioning. The practical nature of the research is reflected in the design and implementation of a Digital Twin for a real physical system processing a family of cylindrical parts within an existing experimental FMS. A digital model of the system was created by defining each individual device and piece of equipment from the physical system, so the virtual model operates just like the real one. By implementing the Digital Twin, both time-based and event-based simulations were performed. Through the execution of multiple scenarios, it was possible to identify system errors and collisions, and propose optimization solutions by implementing complex, collaborative-robot equipment where multiple interactions occur simultaneously.

Keywords: flexible manufacturing systems; digital-twins; simulation; Industry 4.0

check for updates

Citation: Florescu, A. Digital Twin for Flexible Manufacturing Systems and Optimization Through Simulation: A Case Study. *Machines* **2024**, *12*, 785. https://doi.org/10.3390/machines12110785

Academic Editors: Raul D. S. G. Campilho and Dimitrios Manolakos

Received: 4 October 2024
Revised: 4 November 2024
Accepted: 5 November 2024
Published: 7 November 2024

1. Introduction

Human creativity, correlated with the desire for a permanent increase in the standard of living, constitutes the basis of societal development. Recognized as a new paradigm in the field of manufacturing, the concept of Industry 4.0 presents an opportunity to re-engineer and revitalize production through a new perspective focused on the digitization of current production systems. In order to effectively respond to new market demands, companies must rethink their entire production workflow by implementing digital technologies. This digital transformation will improve organizational competitiveness [1], while strengthening companies' ability to make optimal decisions.

With the rapid technological evolution driven by Industry 4.0, industrial companies need up-to-date strategies to respond to various challenges, including greater uncertainty and variability in global markets, heightened competition, pressures for innovation, and accelerated product launch times, leading to reduced delivery times. Additionally, customer behavior is shifting toward a demand for mass customized products.

The transformation to Industry 4.0 is grounded in three core directions: industrial–technological, economics in business models, and social [2].

The current stage of development is characterized by the transition from Industry 4.0 with new technologies already implemented in some companies, toward a sustainable and resilient society based on the new paradigm of Society 5.0 [3–5]. A new concept, "The Resilient Operator 5.0", integrated into smart manufacturing systems represents an alternative vision [6,7] for the development of Industry 5.0. Presently, we are seeing avant-garde studies and research focused on the development and implementation of artificial intelligence, human–intelligent machine collaboration, and the integration of biotechnologies, as well as quantum computers and quantum technologies—a stage some authors refer to as Industry 6.0 [8].

The implementation of flexibility and automation concepts, together with the rapid progress of information technology, has created the essential prerequisites for achieving the transition to the digitalization of production systems within the Industry 4.0 framework. The development of manufacturing systems capable of managing flexibility requirements in achieving a wide typological diversity of products, based on customer demand, is now a key competitive factor for companies across industrial sectors. Enhanced production system flexibility boosts manufacturing performance, leading to increased competitiveness. In the research study conducted by Brettel [9], relationships between flexibility and performance are analyzed, and a systematic, logical diagram of empirical reviews is developed to connect the model to advancements in Industry 4.0 technologies [10].

Production systems have undergone dynamic evolution, requiring increasing flexibility, the trend being towards complete automation and the development of flexible robotic systems [11,12]. Flexible production can be viewed from a strategic perspective as essential for the development of advanced production systems capable of offering customers high-quality, varied, and customized products. This justifies the need for greater process flexibility and versatile resources, to respond to the variability and uncertainties inherent in the operation of production systems [13]. The flexible production system has proven to be the foundation of Industry 4.0, capable of managing changes both in technology and in the adoption of new management methods. It has the agility to reconfigure operating instructions in order to introduce new products into manufacturing or modify existing ones within a specified time period at the request of customers. Practice has shown that the flexible automated manufacturing system [14] is a pivotal element in the ongoing industrial evolution.

Increasing the competitive advantage and performance of companies, especially in the industrial sector, requires continuous innovation and the adaptation of production systems and business processes to accommodate new customized products and services. By developing intelligent platforms that integrate all operations in the value-creating chain and interconnected systems, people, machines, and products, the industry enters a new stage of development characterized by "intelligent and autonomous production" [15].

The experience and development of large industrial companies [16–18] demonstrate the feasibility of gradually implementing advanced production systems characterized by flexibility and automation, to which new technologies in the field of digitization, connectivity, and artificial intelligence can be added today. Iterative and agile product development processes enable complex processes to be managed within flexible, intelligent systems under conditions of uncertainty. These conditions are generated by the variability in product demand in the market and the focus on diverse, mass-customized products, as well as variations in the internal production environment: rapid changes in manufacturing, the simultaneous production of several types of random items from the same family, and functional blockages that occur in the operation of dynamic systems like Flexible Manufacturing Systems (FMS). Along the way, companies have identified that optimization begins by simplifying existing processes, then continuing with the integration of modern technologies and the adoption of flexible automation [12] solutions to effectively respond to changing market demands.

An element of novelty in the development of smart manufacturing in recent years has been the introduction of the notion of the "Digital Twin" [19,20] as a software solution for the virtual creation and simulation of a real physical system, in order to analyze the performance and optimize the functioning of complex dynamic systems. The Digital Twin (DT), along with the technologies of Industry 4.0 (the Internet of Things, Big Data Analytics, and Cloud Computing), enables advanced analysis in the field of system optimization through the integration of monitoring and control functions. DT is an exceptionally useful tool in industrial practice, particularly in real-time monitoring and total predictive maintenance, with new data being constantly updated and facilitating accurate and immediate interventions in the system.

Current concepts, such as "Digital Twins" [21,22] and "virtual commissioning" [23], studied in specialized literature, are still in the early stages, as there is no general method for their design and implementation. Currently, there are studies and research focused on designing models and architectures of Digital Twins, as highlighted by authors [24–26]. Efforts are being made to standardize these approaches; however, practical application poses several challenges. Additionally, well-documented studies, such as [27–29], suggest that the use of a Digital Twin results in significant differences based on the fields of applicability, as noted by [30–33]. As a result, it is timely to initiate future research activities to establish relevant industrial applications and to investigate and demonstrate the wide range of applications and benefits of these new technologies.

The present scientific research contributes to the development of intelligent manufacturing systems by implementing and applying new knowledge, methodologies regarding the design and use of relatively new concepts such as "Digital Twins (DT)" and virtual commissioning and the optimization of DT simulation, based on the current state of the reviewed literature.

Even though classic simulation tools are still used in the design of production systems, working with static data, they do not capture the system in its dynamic evolution. Events asynchronous in time that cause interruptions in the production flow or delayed reactions from operators can only be captured by simulation in a real-time environment. To help overcome these limitations that the production field still faces and to reduce this gap, the paper aims to study and configure a digital model of the Digital Twin type in the manufacturing industry, with the goal of creating a dynamic and autonomous manufacturing system.

The use of advanced technologies like Digital Twins throughout the design, manufacturing, and maintenance phases, by developing technical solutions for collaboration between humans and smart machines, creating human–machine interface systems, and enabling remote maintenance, brings significant transformations in managing dynamic processes in real time. Expected results can only be achieved by using established, state-of-the-art simulation software.

These new approaches could become elements of resilience and flexibility for the physical production environment; "agility could be the key to the resilience of the manufacturing industry" [34], digital technologies being the main pillars. A manufacturer can virtually redesign a product, process or production system and even simulate its performance in the real world. DT creates a virtual representation of both the physical elements and the dynamics of how an IoT, Internet of Things, connected product functions and interacts in its environment throughout its entire life cycle.

Structured in four sections, the scientific article begins by presenting the current context of the development of advanced production systems and an analysis of the specialized literature on the Industry 4.0 and Digital Twins approach, highlighting the opportunity for application and their benefits (Section 1). The proposed research methodology and framework are presented in Section 2. The applied research (Section 3) aims to design and implement the "Digital Twin" of a Flexible Manufacturing System, conducted through physical experimentation, and to find optimization solutions within a company, through its virtual commissioning and dynamic simulation. In Section 4, conclusions and future research directions are discussed.

2. Materials and Methods

The main objective of the research consists in approaching a flexible manufacturing system from the perspective of implementing Industry 4.0 (I4.0) technologies and moving to Industry 5.0 (I5.0) by designing a Digital Twin and offering optimization solutions through simulation. Subsequently, the behavior of the real physical system was tested, by creating a virtual commissioning model (predictive maintenance).

In terms of simulation, the main contribution is represented by the correspondence between the real and the digital universe. The fact that physical objects can be transposed into computer objects through digitization is currently the most powerful concept for simulation, which allows new processes to be tested and studied before they are implemented.

The applied case study focused on the development of a company in the manufacturing industry, and a project to digitize a production system aligned with the management's requirements. Many companies that have taken the first step toward digitalizing their production systems see sustainable development as an opportunity by adding new dimensions of digitalization and connectivity. The goal is to streamline processes and increase competitive advantage, especially given the shortening of product life cycles and the demand for mass customization according to customer requirements.

2.1. Industry 4.0 Approaches

Initially perceived as an "industrial paradigm", the concept of Industry 4.0 (I4.0) first introduced in Germany in 2011 has revolutionized industries worldwide. It has since expanded globally under various names tailored to each country's specific context: France—"Industrie du Futur", UK—"Catapult", USA—"Smart Manufacturing", China—"Made in Chaina 2025", and Japan—"Industrial Value-Chain Initiative".

Currently, through advanced technologies, Industry 4.0 actively contributes to societal transformation by digitizing and connecting systems and incorporating elements of artificial intelligence. The technological advancements in Industry 4.0 are built upon key pillars: Cyber-Physical Systems (CPS), Big Data Analytics, the Internet of Things, Cloud Computing, Human–Machine Interaction (HMI), Robotics, and Artificial Intelligence.

A synthetic analysis of the transition from Industry 4.0 to Industry 5.0 within the current specialized literature—covering concepts, technologies, models, and areas of applicability—has led to the identification of several reference papers (Table 1).

Table 1. Summary of reviewed papers: transition from I4.0 to I 5.0 and Society 5.0.

Research Areas	Literature Review
Industry 4.0 initiative Industry 4.0 concept	Quin, J. et al. (2016) [1]; Ulrich, S. (2013) [35]; Bauernhansel, T. (2014) [36]; Berger, R. (2014) [37]; Burmeister, C. et al. (2016) [38].
Basic conceptual models in Industry 4.0	Dombrovski (2017) [39]; Sony (2018) [40]; Schumacher, A. (2019) [41]; Santos, R.C. et al. (2020) [42]; Amaral, A. (2021) [43]; Zoubek, M. et al. (2021) [44].
Industry 4.0 technologies	Ryalat, M. et al. (2023) [45]; Gupta, B.B. et al. (2021) [46]; Culot, G. et al. (2020) [47]; Pei, E. et al. (2020) [48]; Frank, A. G. et al. (2019) [49].
Industry 4.0 implementation in companies and SMEs	Vrchota, J. et al. (2019) [50]; Gajdzik, B. et al. (2021) [51]; Moeuf, A. et al. (2020) [52]; Lodgaard, E. et al. (2022) [53]; Grufman, N. et al. (2020) [54]; Vinodh, S. et al. (2020) [55]; Schönfuß, B. et al. (2021) [56].
Industry 4.0 sustainability	Ghobakhloo, M. (2020) [3]; De Sousa Jabbour, A.B.L et al. (2018) [57]; Fritzsche, K. et al. (2018) [58]; Leong, W.D. et al. (2020) [59]; Sharma, M. et al. (2023) [60].
Industry 5.0 Society 5.0	Mourtzis, D. et al. (2024) [4]; Pereira, A.G. et al. (2020) [5]; Romero, D., & Stahre, J. (2021) [6]; Lu, Y., et al. (2022) [7]; Adel, A. (2022) [61]; Aslam, F. et al. (2020) [62]; Polonara, M. et al. (2024) [63]; Borboni, A. et al. (2023) [64]; Li, C. et al. (2023) [65]; Prassida, G.F. et al. (2022) [66]; Kopp, T. et al. (2021) [67]; Vanderborght, B. (2020) [68].

If until now Industry 4.0 has provided tools for technological development, we are currently witnessing a transformation toward Industry 5.0, which emphasizes human and social development within Society 5.0 [61,62].

In this context, there is a need to develop new models of intelligent production, motivating and empowering people to work alongside intelligent machines in Industry 4.0. The innovative technologies of Industry 4.0 are driving an increasing number of industrial companies to transform into smart factories by reconfiguring and optimizing flexible manufacturing systems.

2.2. Digital Twin Concept

The concept of the Digital Twin (DT), closely associated with the development of Industry 4.0 and various fields of application, appears in the reviewed literature with multiple definitions and approaches [69,70]. A recent scientific study [71] highlights the development trends of this key technology for the industry in the coming years, emphasizing the digital transformation from "Industry 4.0—Smart Factory" to "Industry 5.0—Human Robot Interface" and eventually to "Industry 6.0—Cognitive Manufacturing". In accordance with the latest ideas on industrial development [28], Digital Twins (DTs) endowed with elements of Artificial Intelligence (AI) and utilizing machine learning algorithms are the foundation for the development of autonomous factories that can continuously and dynamically self-adapt.

The authors of the research presented in [72] believe that an essential characteristic of a "Digital Twin" is the "connection between digital and physical systems", with the ability to provide real-time information about the physical system. The key technologies underlying the configuration and modeling of a DT were also highlighted in [73], including modeling based on physical systems, data-based modeling, big data cybernetics, platform infrastructure, and human–machine interface (HMI). Table 2 presents some representative research tracing the concept of Digital Twins from its emergence to the present, covering its evolution, characteristics, implementation of digital models, and applicability.

Table 2. Summary of reviewed papers: "Digital Twins".

Research Areas	Literature Review
"Digital Twin" concept	Bilberg, A., & Malik, A. A. (2019) [74]; Kritzinger, W. et al. (2018) [75]; Wagg, D. et al. (2020) [76].
Methodologies, conceptual models, DT configurations	Psarommatis, F. et al. (2022) [22]; Kusiak, A. (2022) [23]; Heindl, W. et al. (2022) [24]; Perno, M. et al. (2022) [25]; Riedelsheimer, T. et al. (2021) [26]; Gupta, B.B. et al. (2021) [46]; Culot, G. et al. (2020) [47]; Segovia, M. et al. (2022) [62].
Research on the applicability of the DT	Semeraro, C. et al. (2023) [18]; Wang, K. J. et al. (2021) [19]; Yangguang L. et al. (2021) [20]; Kusiak, A. (2022) [21]; Singh, M. et al. (2020) [29]; Psarommatis, F. et al. (2022) [77]; Huang, H. et al. (2021) [78]; Piromalis, D. et al. (2022) [79]; Leng, J. et al. (2021) [80].
Research on the different effects of the DT in various fields of activity	Fett, M. et al. (2023) [28]; Singh, M. et al. (2022) [29]; Kousi, N. et al. (2021) [30]; Zohdi, T.I. (2021) [31]; Zandi, K. et al. (2019) [32]; Li, W. et al. (2020) [33]; Attaran, M. et al. (2023) [81]; Wang, K. et al. (2022) [82]; Agnusdei, G.P. et al. (2021) [27]; Fera, M. et al. (2020) [83]; Malik, A. A et al. (2020) [84].
DT integration in Flexible Manufacturing Systems and collaborative robots	Pereira, J.A.P. and Campilho, R.D.S.G. et al. (2022) [11]; Sousa, V.F.C. et al. (2022) [12]; Adel, A. et al. (2022) [61]; Polonara, M. et al. (2024) [63]; Makris, S. (2020) [85]; Koesters, A. et al. (2024) [86]; Resman, M. et al. (2021) [87]; Kaiser, J. et al. (2023) [88].

In practice, there are several software solutions for implementing Digital Twin models, with Siemens offering the most services for building a "Digital Twin" (Process Simulate module—Tecnomatix, Siemens PLM [89]) and including a Human–Machine Interface (Process Simulate Human). Considering the various existing approaches to the "Digital Twin" concept and the lack of a standard methodology for constructing Digital Twins, it is timely to initiate research in this direction, particularly focusing on applicability in Flexible Manufacturing Systems.

Digital Twin models applied to advanced production systems and cyber-physical systems can mirror their state and allow simulation in a specific environment, enabling real-time monitoring and control of processes. These models form the very basis for the development of total predictive maintenance by creating models for virtual commissioning [90].

By collecting relevant data from the analyzed system through simulation and predictions based on virtual models, a Digital Twin can act in all phases of the product life cycle, from design to manufacturing, testing, operation, exploitation, and maintenance (Figure 1).

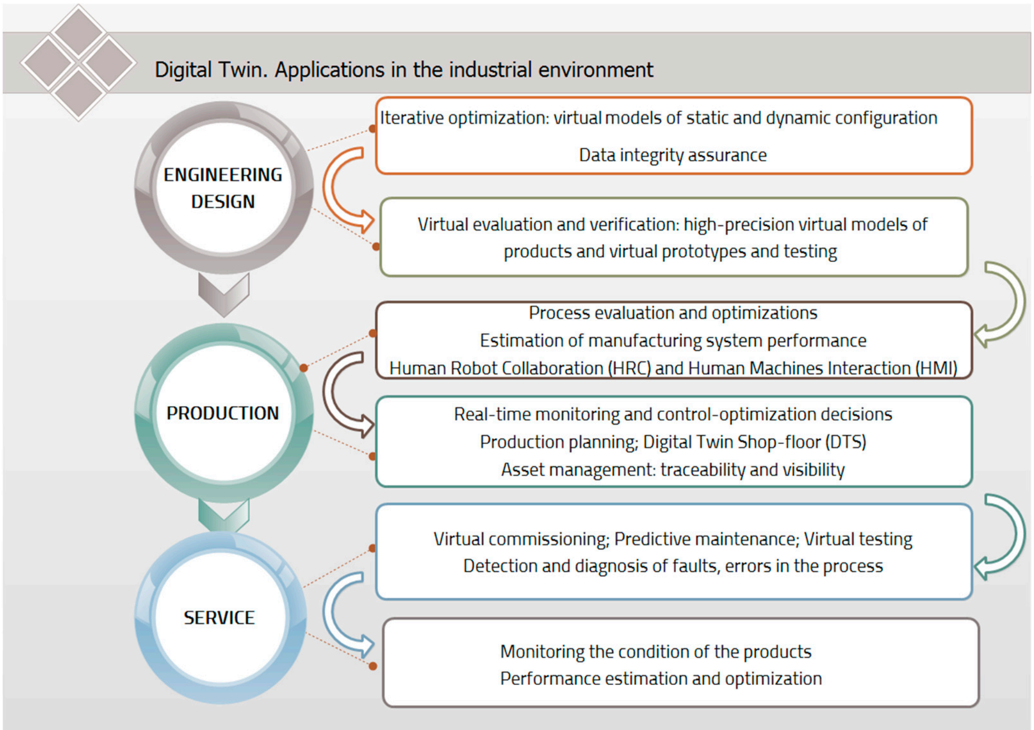


Figure 1. Digital Twin applications in industrial environment.

A Digital Twin can represent the real state of a manufacturing system as a 3D simulation model with real-time updates, requiring a suitable simulation model, such as the generic simulation model of the developed Flexible Manufacturing System.

3. Results of Digital Twin Design and Dynamic System Simulation

The DT simulation research method for the flexible manufacturing system involves replacing the real, dynamic, and complex system with its model or a simulator. This approach involves using simulation languages and/or software to perform experiments and obtain information on the evolution of the system's behavior over real time.

3.1. Process Description: Case Study

The sequential process carried out by the physical manufacturing system implements an automated flow of operations for cylindrical parts (discs, flanges, rings, and circular shafts of machine tool components). Figure 2 shows parts supply, transport, transfer, drilling, turning, inspection, grinding, the storage of good parts, and the transfer of scrap parts to rework stations [14]. The requirements for improving the cycle time and increasing the productivity in the processing of parts from this benchmark family were taken into account.

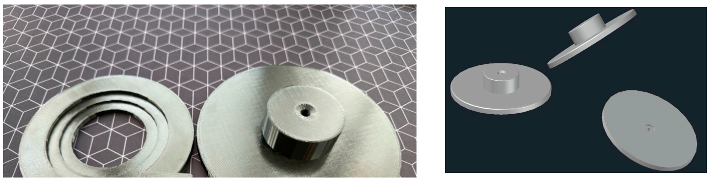


Figure 2. Examples of machined landmark types.

The phases of the processing process within the experimental FMS, physically existing in the laboratory, previously designed by the author [14], consist of the following:

- The automatic supply of cylindrical semi-finished products from a warehouse;
- Transporting the parts on the conveyor to the drilling station;
- The transfer of the piece to the machining station through drilling;
- The drilling processing of the semi-finished product, with the possibility of setting the drilling depth and advance speed on the computer;
- Transporting the drilled piece to the next station, for processing by turning;
- The turning of cylindrical semi-finished products;
- Processing by rectification and final control;
- The transportation of processed parts, with a conveyor, to the product warehouse;
- The final control and selection of good parts for delivery and their storage in the warehouse of finished products;
- The identification and evacuation of scrap parts, which do not fall within the allowed tolerances, using the SCADA (Supervisory Control and Data Acquisition) software application, CX–Supervisor (Release 3.1 by OMRON 2010);
- Controlling the process through a programmable logic controller (PLC) and process monitoring and control software;
- The actuation of equipment and devices in the system by using nine pneumatic actuation cylinders, the existence of a regulator filter and electrovalves, a stepper motor and related driver, three presence sensors (optical or inductive), and laser sensors.

The 3D model of the real system is shown in Figure 3. The original (Supervisory Control and Data Acquisition (SCADA) software application, previously developed by the author for the same system, was designed for production tracking by real-time monitoring and controlling of asynchronous events that may occur in the flexible manufacturing process.

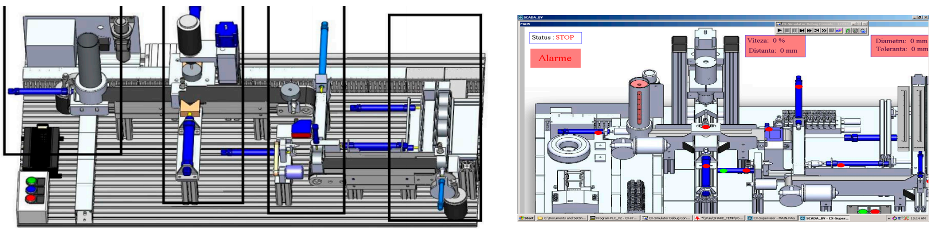


Figure 3. 3D model of the automated system—FMS and process monitoring and control application.

Creating a digital representation of the factory involves digitizing flexible lines, workstations, machine tools, devices, and individual equipment, resulting in a virtual model with similar functionality to the real system. Virtual commissioning, implemented with Process Simulate—version V15.1.2. by Siemens [89,90], is useful for reducing costs, product launch time, and other resources involved in the actual commissioning of certain processes or even the entire plant.

3.2. Digital Twin Design for an FMS: Case Study

The research conducted toward the integration of Flexible Manufacturing Systems into Industry 4.0 had the general objective of creating a digital copy of a process, aimed at proposing optimization solutions and subsequently implementing it in virtual operation.

A first step was to design a "Digital Twin" for an existing manufacturing system, taking into account process improvement requirements. The potential for applying the concept of virtual commissioning in the system studied, within a manufacturing company, was also analyzed.

Digital Twin Configuration Methodology for a Flexible Manufacturing System

The Digital Twin design methodology for the studied system follows the stages outlined in Figure 4.

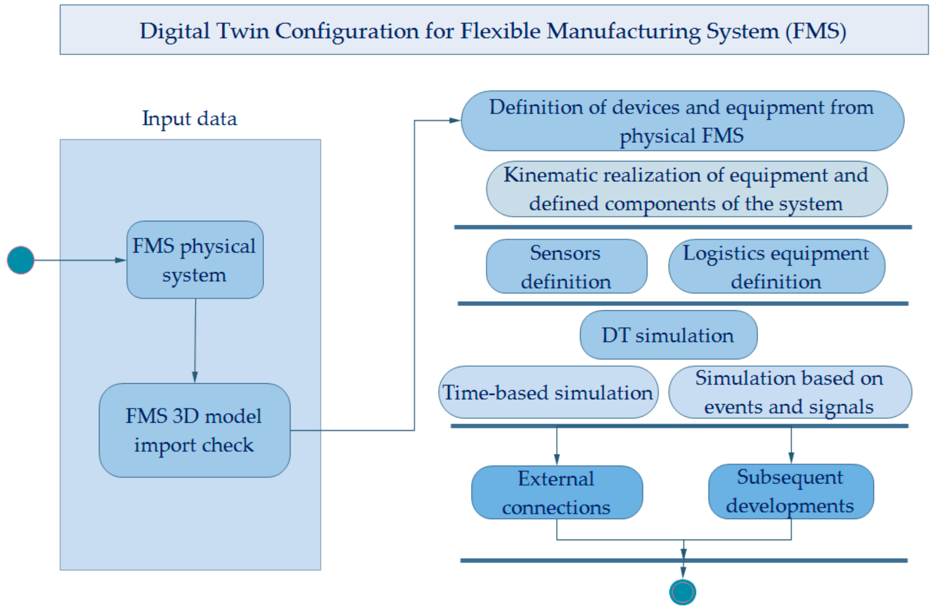


Figure 4. Digital Twin design stages for Flexible Manufacturing Systems (FMS).

Figure 5 summarizes some intermediate sequences from the Process Simulate application used in the Digital Twin design for the physical model of the existing FMS.

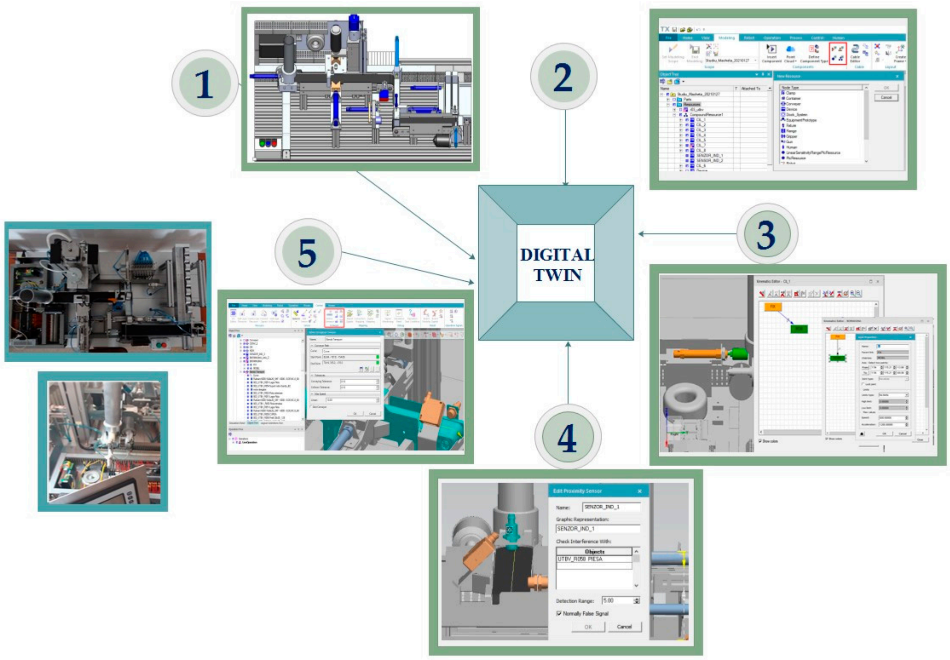


Figure 5. Digital Twin design sequences: case study application.

- Step 1—Importing the 3D model of the system. The CAD (3D) model of the automated system was taken in STEP format and imported into Process Simulate using the "Convert and Insert CAD Files" function.
  In this way, the original model was converted to JT format, the native format recognized by Process Simulate.
- Step 2—Defining devices and equipment based on the existing physical system model. After the conversion of the 3D model was completed, the stage followed where each piece of equipment was isolated into an individual device. In Process Simulate, new resources can be created to represent each piece of equipment as realistically as possible.
- Step 3—Kinematic realization for the defined equipment. Each piece of equipment defined in Process Simulate can have one or more kinematic torques defined. They make the connections between the moving elements, such as pneumatic cylinders for actuating the equipment and the devices integrated into the experimental physical system. Thus, the device can move in such a way as to reproduce the movements of real devices. The fixed and moving parts of the device were defined, as well as the types of motion: rotation, translation, or combined motion (Kinematics Editor Command). The parameters considered in the definition of these kinematic couples are the type of movement, the axis or vector of movement, the minimum and maximum limits of the movement, the velocity, and the acceleration (Joint Type Command). Except for the movement type, all mentioned parameters can be changed at any time. Predefined positions of the device (Pose Editor command) where the kinematic torque has a certain value have been set. Here, the name and value of the kinematic couple can be assigned for the respective position. Defining these elements is very important, as they will be used in all aspects of the project. For example, in Figure 6, the values set for a pneumatic actuation cylinder (pneumatic cylinder 7) from the experimental FMS system are presented in detail. Similarly, the positions for each kinematic couple of the system were defined.

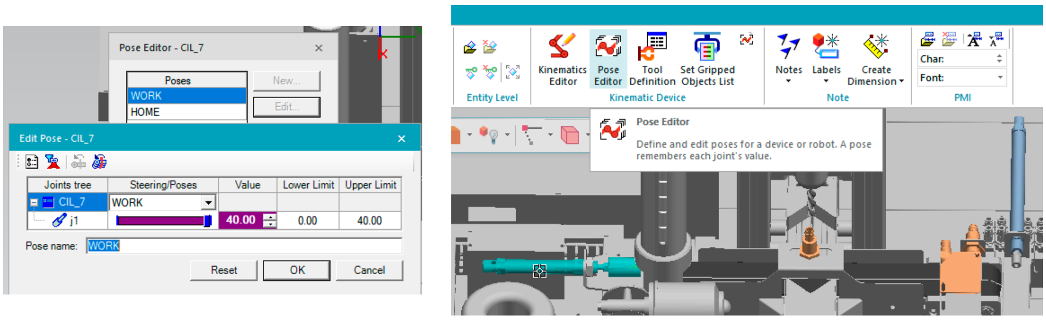


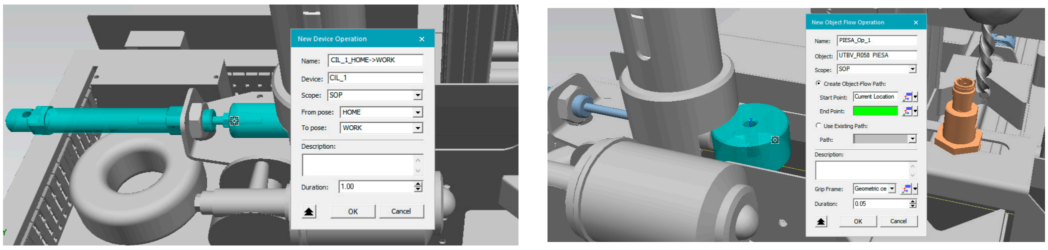
Figure 6. Kinematic implementation for the defined equipment: program sequence.

- Step 4—Defining the sensors. In Process Simulate, sensors are resources capable of detecting the presence of an object or a specific property of that object. The most commonly used types are proximity sensors and photoelectric sensors. Property sensors are used to detect certain characteristics assigned to the object, such as weight, color, type, barcode, etc. A real-life analogy would be RFID (Radio Frequency Identification) systems, where a special tag can be written or read by a device.
- Step 5—Conveyor belt definition. To create a conveyor belt in Process Simulate, the 3D resource was selected, and the "Define Conveyer" command was used. The conveyor belts of the system were defined, specifically a curve that dictates the direction and orientation of the transport, with the latter characteristic being reversible. The conveyor belt's characteristics were set as follows: tolerance refers to the precision required for placing objects on its surface, and feed speed is represented in units of [mm/s] and can be adjusted at any time depending on the process.

3.3. DT Simulation Results

Time-based simulation aims to perform a predefined sequence of operations to present the ideal process or solution. The operations used are simple and predefined, and their goal is to move the device from one position to another or to move parts along a predetermined trajectory. To carry out this simulation, commands such as "New Device Operation" or "New Object-Flow Operation" were used.

Sequences regarding the setting of the movement parameters and the trajectory are presented in Figure 7. "Device-type" operations allow the movement of a piece of equipment from one position (pose) to another within a predefined time, set in Figure 7a. The name is arbitrary, and the parameters of the operation can be changed at any time. "Object-Flow" operations are created in a similar way, the difference being that in this case, the operation is actually a path that the selected object will follow. The start and end points of the trajectories can be defined, or a predefined trajectory can be selected, as shown in Figure 7b.



(**a**) (**b**)

Figure 7. Settings: (**a**) movement parameter settings and (**b**) trajectory setting.

In the end, a Digital Twin for the analyzed system was created, as a complex sequence of operations that will identically reproduce the real process (Figure 8).

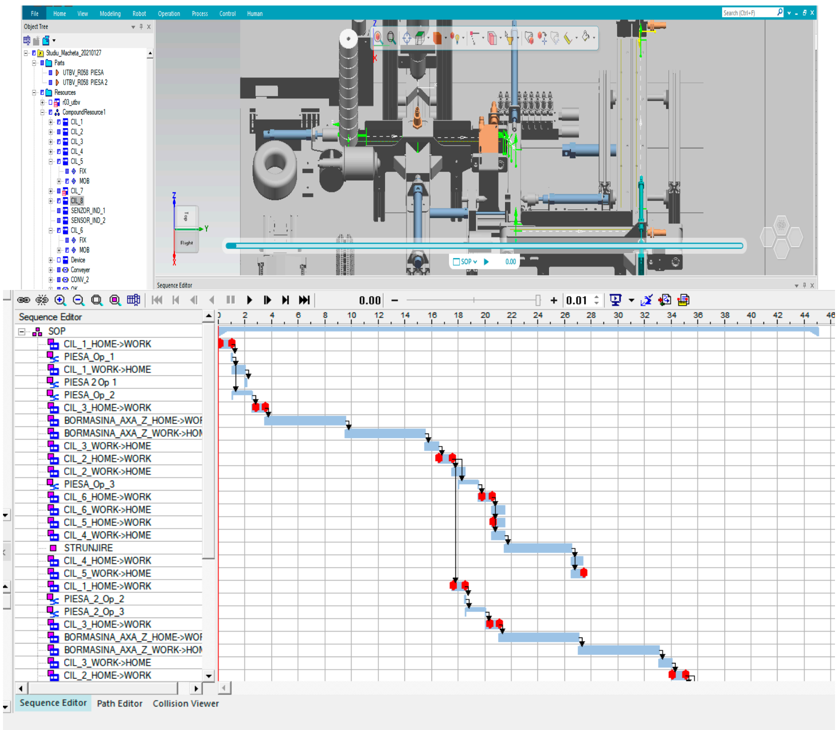


Figure 8. Digital Twin. Time-based simulation—Process Simulate.

Knowing and managing the parameters of each device is necessary to carry out the virtual commissioning phase of the project—experimental FMS.

The time-based simulation led to a number of significant results:

- Everyone involved in the project can have a visual representation of the production line. This results in a better understanding of the process.
- The simulation allowed for the identification of collisions in the system between the devices or equipment that compose it and the possibility of correcting them.
- Several process variants were simulated to choose the optimal solution.

These simulation variants took into account the identification of blockages, functional errors, the recording of production times in different process sequences, the load levels of the workstations, and even the interactions between man and machine or device. The simulation analysis allowed the visualization of statistical data for each workstation and equipment. The appearance of blockages (narrow places, waiting lines) was observed at the unloading workstation, at the exit from the system (Figure 9), the blockage time being very high (81.53%).

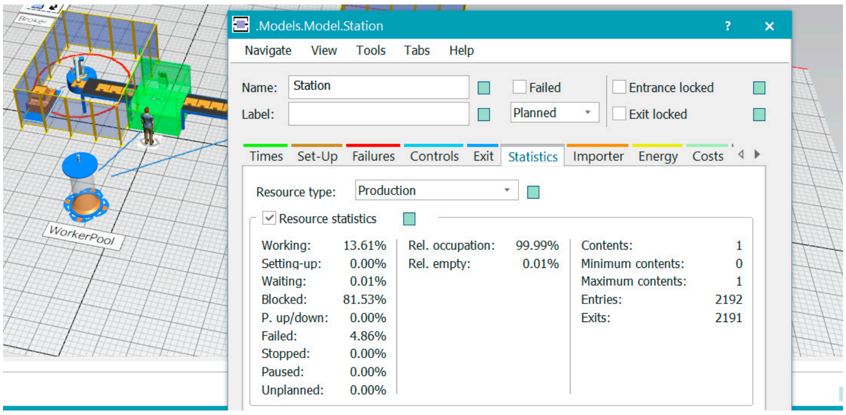


Figure 9. Simulation scenario. Analysis of bottlenecks.

In order to eliminate the asynchronies in the system, respectively the blockages, measures were taken to optimize the operation, for example, arranging a workstation in parallel and integrating a robot on the exit area. Thus, the working times of the system improved (to 95.03%) and it was possible to eliminate the malfunctions that appeared in the system (Figure 10).

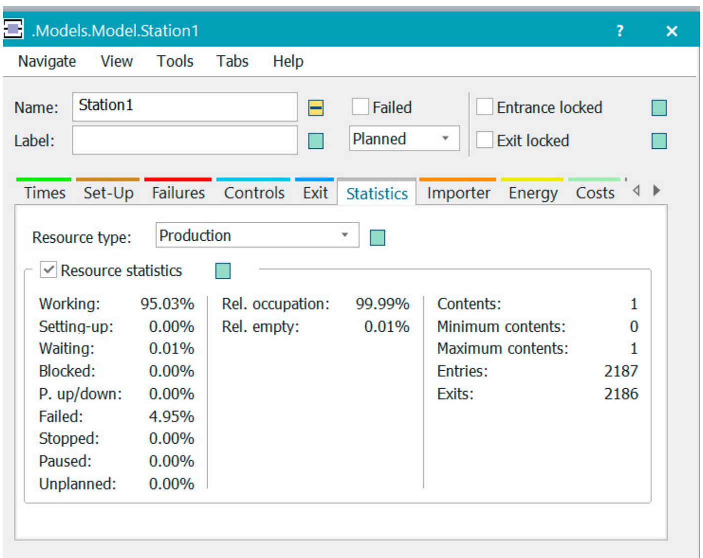


Figure 10. Simulation statistical resources.

Through the created model, the dynamic flows of the process were evaluated, including the manufacturing technological operations, but also the industrial logistics activities—the handling and transport/transfer of semi-finished products.

The grapho-analytical model (Figure 11) developed for the system analyzed by simulation and a digital twin contains a number of optimization parameters and criteria, objective functions, and performance indicators and offers the optimal synthesis in the environment and in real time.

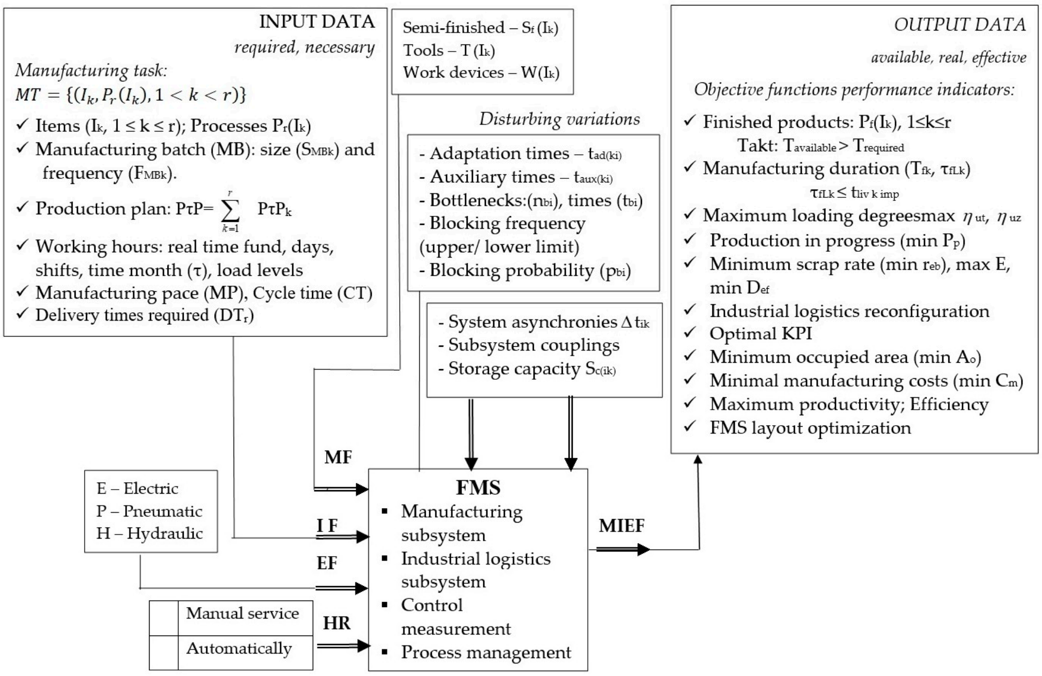


Figure 11. Graphical model of manufacturing system parameters.

In order to carry out the modeling and simulation used in the design and performance analysis of a manufacturing system, the developed manufacturing model [91] was used, which contains the input data, variables and output data, conditions, and restrictions imposed. The system is characterized by inputs–outputs and information links. Functional or organizational blockages, blockage times—t_{bi}, auxiliary times—$t_{aux(ki)}$, adaptation times—$t_{ad(ki)}$, the number of causes of blockages—n_{bi}, the frequency of occurrence of blockages—f_{bi}, the blocking probability—pi, and the size of the asynchronies—Δt_{ik}, have a major influence on the evolution of the system. According to the diagram in Figure 11, the three flows interact in the manufacturing system, material flow—MF, informational flow—IF, and energetic flow—EF, in order to create the finished product, under imposed economic conditions, the human resource—HR for servicing, control, and manufacturing.

3.4. Optimization Solutions

3.4.1. Correcting the Collisions Identified in the System

Following the previously performed time-based simulation analysis, the mechanical interactions between the equipment could be better observed. With the Digital Twin of the system, the ways to avoid and eliminate the identified collisions were analyzed. The DT simulation allowed the identification of the collision between the pneumatic actuation cylinder 4 and a device in the automated system (Figure 12). Procedurally, the correct solution was to reconfigure the 3D model and run the simulation again. Through the data provided by the Digital Twin in real time, constant monitoring was done during the simulation to check if the equipment was in proximity or in collision. When the equipment are at a very small distance from each other, they will be colored yellow (Figure 13), and when the distance reaches (0.00 mm), the equipment will be colored red (Figure 12).

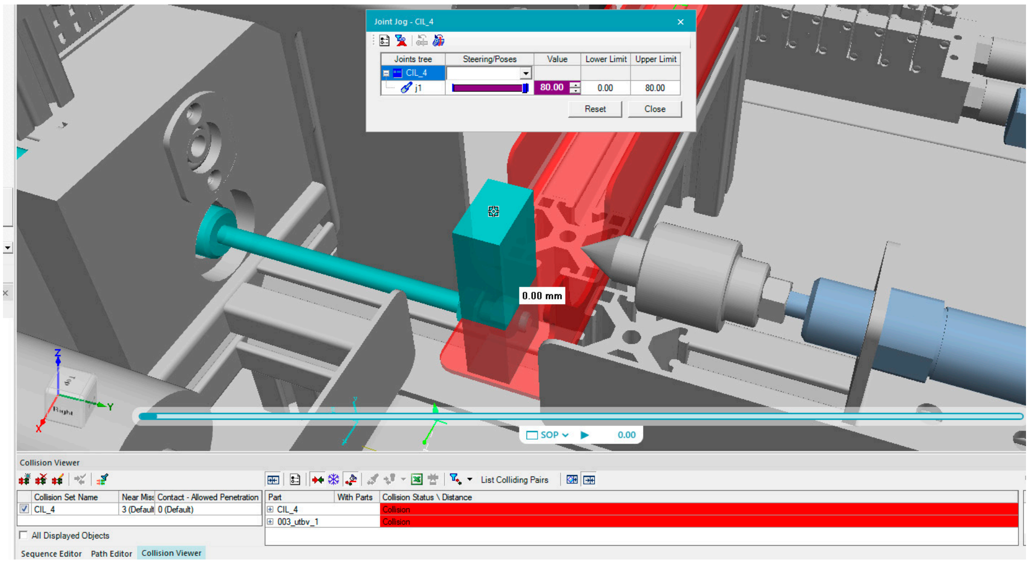


Figure 12. Identification of mechanical interactions: collisions in the system.

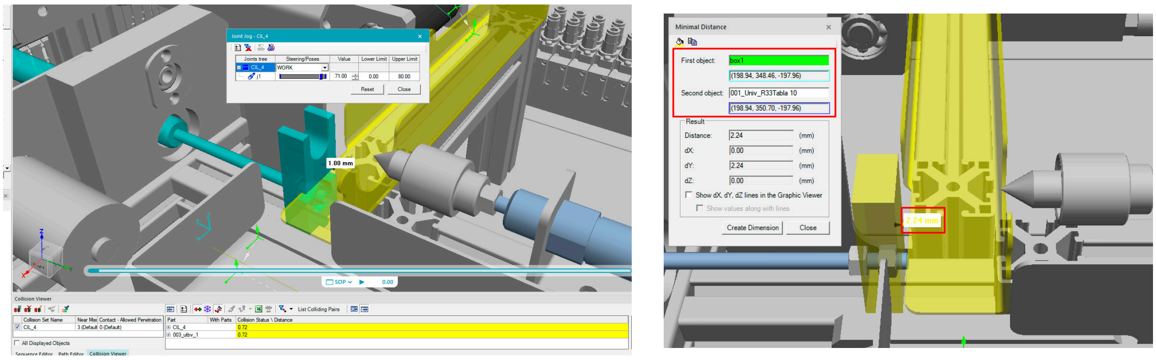


Figure 13. Optimization solution: correcting system collisions.

As an optimization solution for correcting operational errors, (Figure 12), it was possible to limit the stroke of the pneumatic cylinder and redesign the shape of the part at the end of the cylinder rod. At the same time, a validation of the equipment in terms of dimensions was carried out by performing the exact calculation of the minimum distance between the objects of the system.

3.4.2. Configuring the Virtual Commissioning Environment

Process Simulate offers several possibilities for connecting the system to an external control environment for the purpose of virtual commissioning (Virtual Commissioning) [73]: OPC DA/UA (data access/unified access); Siemens PLCSIM Classic; Siemens PLCSIM Advanced; Siemens SIMIT; Siemens Simulation Unit; and WinMod. The path to the OPC Server, the location of the signals on the server, and the type of mapping of the signals between Process Simulate and the PLC will be chosen (the mapping/association can be done according to its name and address). The images in Figure 14 show the sequences from the configuration application for the analyzed case study, the FMS—experimental system designed and built in the research laboratory.

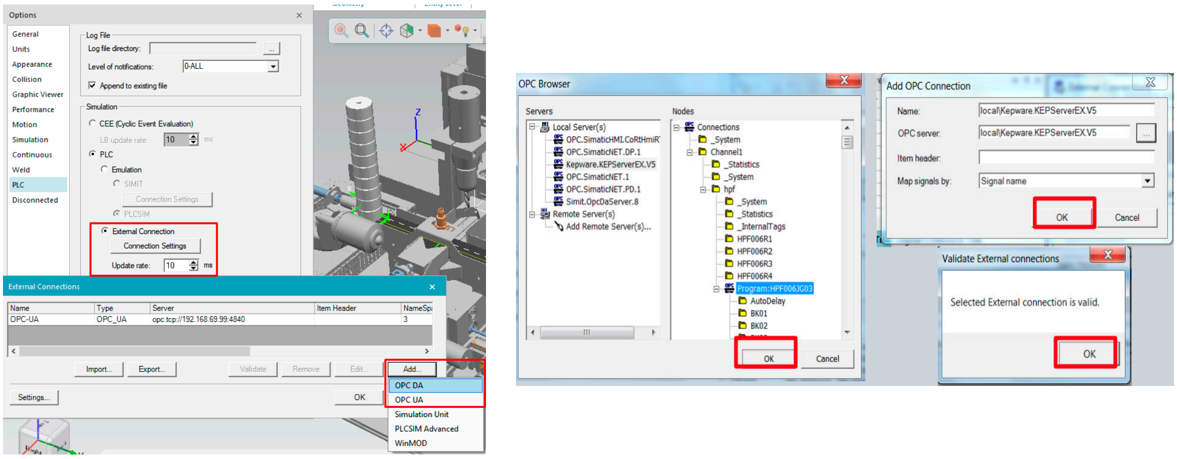


Figure 14. The configuration sequence for the virtual commissioning of the system.

A newly developed research direction has taken shape through the possibilities of adding new elements to an existing process, as well as other existing functionalities in Process Simulate that could become of interest in the future for the digitization of processes within certain companies in the industrial environment.

3.4.3. Integration of Collaborative Robotics

The proposed simulation optimization solutions describe the possibility of adding new elements to the existing process, as well as other existing functionalities in Process Simulate that may become of interest in the future. Several work scenarios were analyzed to determine if the process can be modified, extended, or optimized [74].

The solution to optimize the existing process by introducing the collaborative robot is presented in Figure 15. The interactions between the equipment and the possibility of inserting the robot at the entrance or exit of the FMS were tested. Several scenarios were tested by simulation.

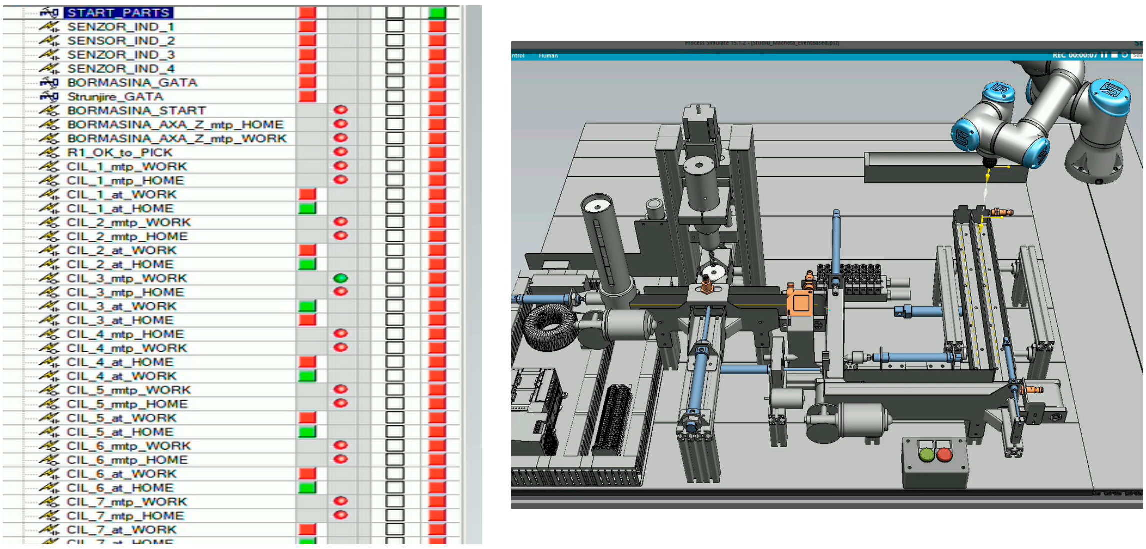


Figure 15. Proposed optimization solutions—collaborative robot.

Through discrete-event simulation, the state of the simulation resources was checked at predetermined intervals (between 10 and 100 ms) (Figure 13). The simulation then runs based on a predetermined sequence of operations, and the triggering events, signal, and state changes necessary to move from one operation to another were identified. Essentially, every 10 ms, the status of each device, each sensor, the position of objects on conveyor belts, the position of robots, etc., is checked, and all of this information is updated both visually and logically.

An important result of the research is the realization of the DT model, which enabled the development of a digital copy that mirrors reality, where we send commands to actuate the devices and receive constant, real-time information about their state. This is the major difference between regular simulation and DT simulation.

The designed digital model allowed for the testing of the interactions between the equipment and the possibility of introducing the robot at the entrance or exit of the FMS. Integrating the robot at the parts evacuation station at the exit was chosen based on previous simulation variants, which identified bottlenecks and long waiting times (Figure 10).

3.4.4. Human–Machine Interface (HMI)

The DT model, configured through the HMI solution, serves as a foundation for human–machine resource allocation and human operator assistance. Through the "Human" module in the Process Simulate application (Figure 16), several scenarios could be tested, resulting in optimization solutions for the process analyzed in FMS [91]:

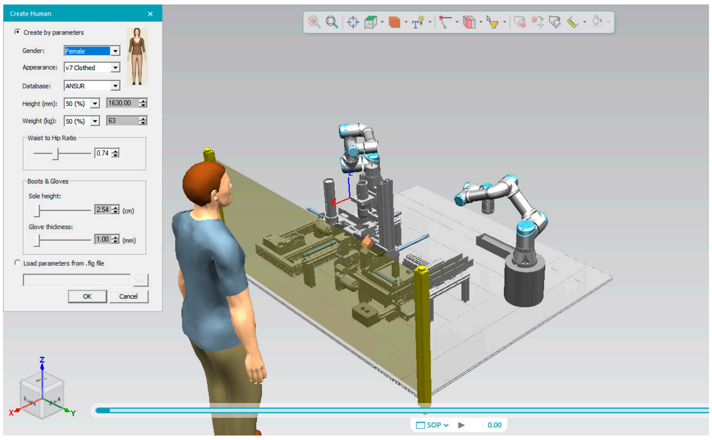


Figure 16. Human–machine interaction: simulation sequence [91].

- Cycle time validation for human operations;
- The testing of safety equipment: light barriers, laser scanners, emergency buttons, etc.;
- Carrying out studies on ergonomics, accessibility to equipment, and tools.

The main measurable indicators in the process relate to downtime during unplanned equipment shutdowns within the system and the frequency of their occurrence. Additionally, the created digital model, together with HMI development, enables real-time monitoring of process parameters, such as failure rates, operational errors, and human errors. Minimizing these factors positively impacts product quality and the safety of human operators.

The operator views the data in real time by connecting to the workstation in the industrial process through a user interface screen. This allows real-time monitoring of process parameters, such as equipment speed and the pressure variation in the pneumatic actuation cylinders, to ensure the correct system operation. The output data can be displayed in the form of reports diagrams, which are useful for operators in the supervision of, and intervention in, the process.

At the same time, the application of HMI technology identifies the training and development needs of operators. The HMI integration solution, as an advanced technology in Industry 4.0 that creates physical and cognitive connections between humans, machines, and intelligent devices, constitutes a future research direction.

3.4.5. Implementation of Automated Guided Vehicle Systems (AGVS)

Transport systems using AGVs serve manufacturing lines where a system based on conveyor belts or conveyors is not an optimal solution. Thus, it was possible to expand the functionality of the process by introducing several workstations and allowing the transport of parts between the stations to be carried out through a system of AGVs.

Figure 17 shows the sequence of the virtual model of the flexible manufacturing system—experimental FMS.

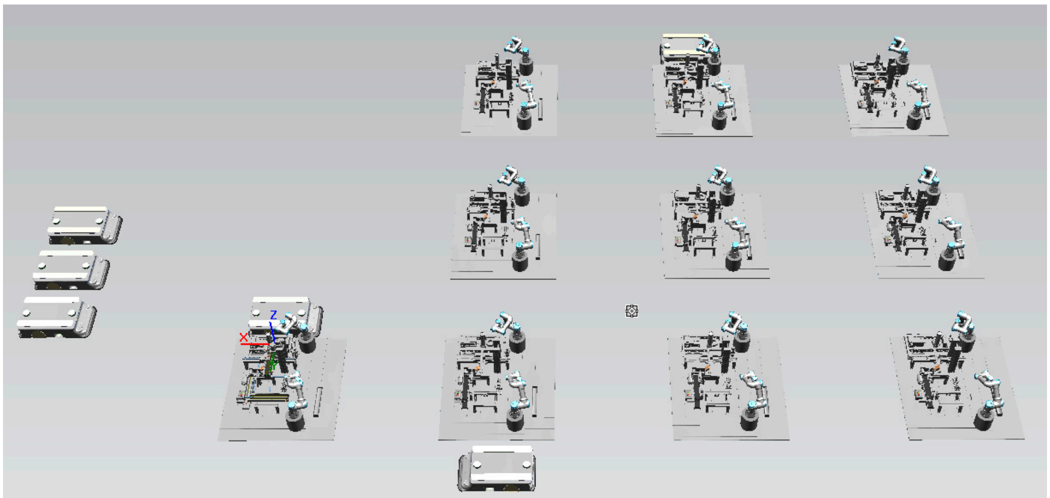


Figure 17. The AGV optimization solution. Simulation scenario sequence.

In this scenario, a series of AGVs supplying the facilities with parts and another series where the completed parts are stored were considered. Robots installed in the vicinity of the facility will be able to transfer parts between the work table and the AGV. Through the digital representation of the real process, it was possible to detect problems in operation and create scenarios through simulation to find the implementation solution, all in real time, thereby reducing the physical time of commissioning.

In this research, all of the resources and technologies needed to implement a new contemporary concept in Industry 4.0, virtual commissioning, have been detailed, resulting in an extended model that can be applied in a real factory and allows the detection of any anomalies in operation before connecting to any real equipment.

4. Conclusions

By integrating into the current flexible production systems, the components and technologies of Industry 4.0, collaborative robots, intelligent machines, additive manufacturing, Digital Twins, and simulation, a new qualitative leap can be made towards the mass customization of products at the request of customers. The direction of applied research on the integration of flexible production systems in Industry 4.0 is part of the current concerns at the international level and is associated with upward development in multinational companies in the country and has allowed the achievement of important results of an applicative nature. Through the analysis of the Digital Twin (DT) concept, a leading simulation concept for Industry 4.0, its applications in the industrial environment could be identified. This resulted in the possibility of applying DT starting from the design, dimensioning, and configuration stages of the system, all the way through to its implementation, commissioning, and operation. Production processes and operational efficiency have been optimized, and new opportunities have emerged for integration into the evolving paradigm of Industry 5.0. A novel element of this research is the realization of the Digital Twin of the analyzed Flexible Manufacturing System, using the Process Simulate software package from Tecnomatix/Siemens, version 15.1.2 [89], in a manufacturing company. An important step has been taken in human resources by training operators to acquire new skills in working with collaborative robots and human–machine interaction (HMI Concept), thus preparing the company for the transition to Industry 5.0.

Research in the field of implementing a "Digital Twin" in the manufacturing process began by digitizing the experimental system, obtaining results regarding the following:

- Proposing solutions to optimize the process through digitization using Industry 4.0-specific technologies with implications for production and management;
- The implementation of collaborative robots, simulation studies on interactions with the human operator (HMI—human–machine interface), and ergonomic studies;
- The implementation of the AGVS (automated guided vehicle system) concept.

The applied scientific research was carried out through concrete activities, with the final result being the software design of the digital copy: defining devices and equipment based on the experimental physical model and the kinematic realization; defining the sensors; performing time-based simulation; identifying mechanical interactions between equipment and highlighting potential collisions; the optimization solution for avoiding collisions by analyzing several scenarios; realizing the simulation based on discrete events, in which the event sequences validate both the equipment from a constructive point of view and the operation logic of the process; and utilizing the optimization solution by implementing complex, robot-type equipment, where many interactions occur simultaneously.

Expanding the research by disseminating the results and applying the studied concepts and designed models within a manufacturing company, through a scientific research contract, was an immediate priority. A future research direction resulting from the current study is the virtual commissioning of the existing physical experimental system by implementing the new virtual commissioning concept. The result will be an extended model that can be applied in a real factory, allowing for the detection of any anomalies in operation before connecting to any real equipment, as well as the reduction of physical commissioning time, with favorable implications in production management. Further developments were proposed for the short term, through other studies and implementations in several companies based on specific case studies. This research contributes to a technical advance and evolution in the way production systems interact with their economic and social environment, promoting interconnectivity and adaptability in a more applied way.

Funding: This research received no external funding.

Data Availability Statement: The data used to support the findings of the current study are available from the corresponding author upon request.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Qin, J.; Liua, Y.; Grosvenor, R. A Categorical Framework of Manufacturing for Industry 4.0 and Beyond. *Procedia CIRP* **2016**, *52*, 173–178. [CrossRef]
2. Chiarello, F.; Trivelli, L.; Bonaccorsi, A.; Fantoni, G. Extracting and mapping industry 4.0 technologies using Wikipedia. *Comput. Ind.* **2018**, *100*, 244–257. [CrossRef]
3. Ghobakhloo, M. Industry 4.0, digitization, and opportunities for sustainability. *J. Clean. Prod.* **2020**, *252*, 119869. [CrossRef]
4. Mourtzis, D.; Angelopoulos, J.; Panopoulos, N. A Literature Review of the Challenges and Opportunities of the Transition from Industry 4.0 to Society 5.0. *Energies* **2022**, *15*, 6276. [CrossRef]
5. Pereira, A.G.; Lima, T.M.; Charrua-Santos, F. Society 5.0 as a result of the technological evolution: Historical approach. *Adv. Intell. Syst. Comput.* **2020**, *1018*, 700–705.
6. Romero, D.; Stahre, J. Towards the resilient operator 5.0: The future of work in smart resilient manufacturing systems. *Procedia CIRP* **2021**, *104*, 1089–1094. [CrossRef]
7. Lu, Y.; Zheng, H.; Chand, S.; Xia, W.; Liu, Z.; Xu, X.; Wang, L.; Qin, Z.; Bao, J. Outlook on human-centric manufacturing towards Industry 5.0. *J. Manuf. Syst.* **2022**, *62*, 612–627. [CrossRef]
8. Almusaed, A.; Yitmen, I.; Almssad, A. Reviewing and Integrating AEC Practices into Industry 6.0: Strategies for Smart and Sustainable Future-Built Environments. *Sustainability* **2023**, *15*, 13464. [CrossRef]
9. Brettel, M.; Klein, K.; Friederichsen, N. The relevance of manufacturing flexibility in the context of Industrie 4.0. In Proceedings of the 48th CIRP Conference on Manufacturing Systems, Ljubljana, Slovenia, 12–14 June 2016; Elsevier: Amsterdam, The Netherlands, 2015; Volume 41, pp. 105–110. [CrossRef]

10. Schuh, G.; Potente, T.; Wesch-Potente, C.; Weber, A.R.; Prote, J. Collaboration Mechanisms to increase Productivity in the Context of Industrie 4.0. In Proceedings of the 2nd CIRP Robust Manufacturing Conference, Bremen, Germany, 7–9 July 2014; Volume 19, pp. 51–56.
11. Pereira, J.A.P.; Campilho, R.D.S.G.; Silva, F.J.G.; Sánchez-Arce, I.J. Robotized cell design for part assembly in the automotive industry. *Proc. Inst. Mech. Eng. Part C* **2022**, *236*, 8807–8822. [CrossRef]
12. Sousa, V.F.C.; Silva, F.J.G.d.; Campilho, R.D.S.G.; Pinto, A.G.; Ferreira, L.P.; Martins, N. Developing a novel fully automated concept to produce bowden cables for the automotive industry. *Machines* **2022**, *10*, 290. [CrossRef]
13. Mishra, R.; Pundir, A.K.; Ganapathy, L. Manufacturing Flexibility Research: A Review of Literature and Agenda for Future Research. *Glob. J. Flex. Syst. Manag.* **2014**, *15*, 101–112. [CrossRef]
14. Florescu, A.; Barabas, S.A. Modeling and Simulation of a Flexible Manufacturing System—A Basic Component of Industry 4.0. *Appl. Sci.* **2020**, *10*, 8300. [CrossRef]
15. Arnold, C.; Kiel, D.; Voigt, K.I. How the Industrial Internet of Things Changes Business Models in Different Manufacturing Industries. *Int. J. Innov. Manag.* **2016**, *20*, 1640015. [CrossRef]
16. Tao, F.; Zhang, H.; Liu, A.; Nee, A.Y.C. Digital Twin in Industry: State-of-the-Art. *IEEE Trans. Ind. Inform.* **2019**, *15*, 2405–2415. [CrossRef]
17. Zheng, T.; Ardolino, M.; Bacchetti, A.; Perona, M.; Zanardini, M. The impacts of Industry 4.0: A descriptive survey in the Italian manufacturing sector. *J. Manuf. Technol. Manag.* **2020**, *31*, 1085–1115. [CrossRef]
18. Veile, J.W.; Kiel, D.; Muller, J.M.; Voigt, K.-I. Lessons learned from Industry 4.0 implementation in the German manufacturing industry. *J. Manuf. Technol. Manag.* **2020**, *31*, 977–997. [CrossRef]
19. Semeraro, C.; Lezoche, M.; Panetto, H.; Dassisti, M. Digital twin paradigm: A systematic literature review. *Comput. Ind.* **2021**, *130*, 103469. [CrossRef]
20. Wang, K.J.; Lee, Y.H.; Angelica, S. Digital twin design for real-time monitoring—A case study of die cutting machine. *Int. J. Prod. Res.* **2021**, *59*, 6471–6485. [CrossRef]
21. Lu, Y.; Liu, Z.; Min, Q. A digital twin-enabled value stream mapping approach for production process reengineering in SMEs. *Int. J. Comput. Integr. Manuf.* **2021**, *34*, 764–782. [CrossRef]
22. Psarommatis, F.; May, G. A literature review and design methodology for digital twins in the era of zero defect manufacturing. *Int. J. Prod. Res.* **2022**, *61*, 5723–5743. [CrossRef]
23. Kusiak, A. Predictive models in digital manufacturing: Research, applications, and future outlook. *Int. J. Prod. Res.* **2022**, *61*, 6052–6062. [CrossRef]
24. Heindl, W.; Stary, C. Structured Development of Digital Twins—A Cross-Domain Analysis towards a Unified Approach. *Processes* **2022**, *10*, 1490. [CrossRef]
25. Perno, M.; Hvam, L. Developing a Framework for Scoping Digital Twins in the Process Manufacturing Industry. In *SPS2020*; Säfsten, K., Elgh, F., Eds.; IOS Press: Amsterdam, The Netherlands, 2020; ISBN 9781643681467.
26. Riedelsheimer, T.; Gogineni, S.; Stark, R. Methodology to develop Digital Twins for energy efficient customizable IoT-Products. *Procedia CIRP* **2021**, *98*, 258–263. [CrossRef]
27. Agnusdei, G.P.; Elia, V.; Gnoni, M.G. Is Digital Twin Technology Supporting Safety Management? A Bibliometric and Systematic Review. *Appl. Sci.* **2021**, *11*, 2767. [CrossRef]
28. Fett, M.; Wilking, F.; Goetz, S.; Kirchner, E.; Wartzack, S. A Literature Review on the Development and Creation of Digital Twins, Cyber-Physical Systems, and Product-Service Systems. *Sensors* **2023**, *23*, 9786. [CrossRef]
29. Singh, M.; Srivastava, R.; Fuenmayor, E.; Kuts, V.; Qiao, Y.; Murray, N.; Devine, D. Applications of Digital Twin across Industries: A Review. *Appl. Sci.* **2022**, *12*, 5727. [CrossRef]
30. Kousi, N.; Gkournelos, C.; Aivaliotis, S.; Lotsaris, K.; Bavelos, A.C.; Baris, P.; Michalos, G.; Makris, S. Digital Twin for Designing and Reconfiguring Human–Robot Collaborative Assembly Lines. *Appl. Sci.* **2021**, *11*, 4620. [CrossRef]
31. Zohdi, T.I. A digital twin framework for machine learning optimization of aerial firefighting and pilot safety. *Comput. Methods Appl. Mech. Eng.* **2021**, *373*, 113446. [CrossRef]
32. Zandi, K.; Ransom, E.H.; Topac, T.; Chen, R.; Beniwal, S.; Blomfors, M.; Shu, J.; Chang, F.-K. A Framework for Digital Twin of Civil Infrastructure—Challenges & Opportunities. *Struct. Health Monit.* **2019**. [CrossRef]
33. Li, W.; Rentemeister, M.; Badeda, J.; Jöst, D.; Schulte, D.; Sauer, D.U. Digital twin for battery systems: Cloud battery management system with online state-of-charge and state-of-health estimation. *J. Energy Storage* **2020**, *30*, 101557. [CrossRef]
34. Delollite Development LLC. 2021 Manufacturing Industry Outlook. Available online: https://www2.deloitte.com/us/en/pages/energy-and-resources/articles/manufacturing-industry-outlook.html (accessed on 18 January 2022).
35. Ulrich, S. *Industrie 4.0—Beherrschung der Industriellen Komplexität mit SysLM*; Springer-Vieweg: Berlin, Germany, 2013.
36. Bauernhansel, T.; ten Hompel, M.; Vogel-Heuser, B. *Industrie 4.0 in Produktion, Automatisierung, und Logistik*; Springer-Vieweg: Berlin, Germany, 2014.
37. Berger, R. *Industry 4.0 The New Industrial Revolution How Europe Will Succeed*; Roland Berger Strategy Consultants GmbH: München, Germany, 2014.
38. Burmeister, C.; Lüttgens, D.; Piller, F.T. Business Model Innovation for Industrie 4.0: Why the Industrial Internet Mandates a New Perspective on Innovation. *Die Unternehm.* **2016**, *70*, 124–152. [CrossRef]

39. Dombrowski, U.; Richter, T. The Lean Production System 4.00 Framework—Enhancing Lean Methods by Industrie 4.0. In *Advances in Production Management Systems. Smart Manufacturing for Industry 4.0, Proceedings of the IFIP International Federation for Information Processing 2018, Seoul, Republic of Korea, 26–30 August 2018*; Springer International Publishing: Basel, Switzerland, 2018; Volume 536, pp. 473–481; ISBN 978-3-319-99706-3.
40. Sony, M. Industry 4.0 and lean management: A proposed integration model and research propositions. *Prod. Manuf. Res.* **2018**, *6*, 416–432. [CrossRef]
41. Schumacher, A.; Nemeth, T.; Sihn, W. Roadmapping towards industrial digitalization based on an Industry 4.0 maturity model for manufacturing enterprises. *Procedia CIRP* **2019**, *79*, 409–414. [CrossRef]
42. Santos, R.C.; Martinho, J.L. An Industry 4.0 maturity model proposal. *J. Manuf. Technol. Manag.* **2020**, *31*, 1023–1043. [CrossRef]
43. Amaral, A. A Framework for Assessing Manufacturing SMEs Industry 4.0 Maturity. *Appl. Sci.* **2021**, *11*, 6127. [CrossRef]
44. Zoubek, M.; Poor, P.; Broum, T.; Basl, J.; Simon, M. Industry 4.0 Maturity Model Assessing Environmental Attributes of Manufacturing Company. *Appl. Sci.* **2021**, *11*, 5151. [CrossRef]
45. Ryalat, M.; ElMoaqet, H.; AlFaouri, M. Design of a Smart Factory Based on Cyber-Physical Systems and Internet of Things towards Industry 4.0. *Appl. Sci.* **2023**, *13*, 2156. [CrossRef]
46. Gupta, B.B.; Tewari, A.; Cvitić, I.; Peraković, D.; Chang, X. Artificial intelligence empowered emails classifier for Internet of Things based systems in Industry 4. *Wirel. Netw.* **2021**, *28*, 493–503. [CrossRef]
47. Culot, G.; Nassimbeni, G.; Orzes, G.; Sartor, M. Behind the definition of Industry 4.0: Analysis and open questions. *Int. J. Prod. Econ.* **2020**, *226*, 107617. [CrossRef]
48. Pei, E.; Loh, G.H.; Nam, S. Concepts and terminologies in 4D printing. *Appl. Sci.* **2020**, *10*, 4443. [CrossRef]
49. Frank, A.G.; Dalenogare, L.S.; Ayala, N.F. Industry 4.0 Technologies: Implementation Patterns in Manufacturing Companies. *Int. J. Prod. Econ.* **2019**, *210*, 15–26. [CrossRef]
50. Vrchota, J.; Volek, T.; Novotná, M. Factors Introducing Industry 4.0 to SMES. *Soc. Sci.* **2019**, *8*, 130. [CrossRef]
51. Gajdzik, B.; Grabowska, S.; Saniuk, S. A Theoretical Framework for Industry 4.0 and Its Implementation with Selected Practical Schedules. *Energies* **2021**, *14*, 940. [CrossRef]
52. Moeuf, A.; Lamouri, S.; Pellerin, R.; Tamayo-Giraldo, S.; Tobon-Valencia, E.; Eburdy, R. Identification of Critical Success Factors, Risks and Opportunities of Industry 4.0 in SMEs. *Int. J. Prod. Res.* **2020**, *58*, 1384–1400. [CrossRef]
53. Lodgaard, E.; Torvatn, H.; Sørumsbrenden, J. Future competence at shopfloor in the era of Industry 4.0—A case study in Norwegian industry. *Procedia CIRP* **2022**, *107*, 961–965. [CrossRef]
54. Grufman, N.; Lyons, S.; Sneiders, E. Exploring Readiness of SMEs for Industry 4.0. *Complex Syst. Inform. Model. Q. CSIMQ* **2020**, *25*, 54–86. [CrossRef]
55. Vinodh, S.; Antony, J.; Agrawal, R.; Douglas, J.A. Integration of continuous improvement strategies with Industry 4.0: A systematic review and agenda for further research. *TQM J.* **2020**, *33*, 441–472. [CrossRef]
56. Schönfuß, B.; McFarlane, D.; Hawkridge, G.; Salter, L.; Athanassopoulou, N.; de Silva, L. A catalogue of digital solution areas for prioritising the needs of manufacturing SMEs. *Comput. Ind.* **2021**, *133*, 103532. [CrossRef]
57. De Sousa Jabbour, A.B.L.; Jabbour, C.J.C.; Foropon, C.; Godinho Filho, M. When titans meet—Can industry 4.0 revolutionise the environmentally-sustainable manufacturing wave? The role of critical success factors. *Technol. Forecast. Soc. Chang.* **2018**, *132*, 18–25. [CrossRef]
58. Fritzsche, K.; Niehoff, S.; Beier, G. Industry 4.0 and Climate Change—Exploring the Science-Policy Gap. *Sustainability* **2018**, *10*, 4511. [CrossRef]
59. Leong, W.D.; Teng, S.Y.; How, B.S.; Ngan, S.L.; Rahman, A.A.; Tan, C.P.; Ponnambalam, S.; Lam, H.L. Enhancing the adaptability: Lean and green strategy towards the Industry Revolution 4.0. *J. Clean. Prod.* **2020**, *273*, 122870. [CrossRef]
60. Sharma, M.; Luthra, S.; Joshi, S.; Kumar, A.; Jain, A. Green logistics driven circular practices adoption in industry 4.0 Era: A moderating effect of institution pressure and supply chain flexibility. *J. Clean. Prod.* **2023**, *383*, 135284. [CrossRef]
61. Adel, A. Future of Industry 5.0 in society: Human-centric solutions, challenges and prospective research areas. *J. Cloud Comput.* **2022**, *11*, 40. [CrossRef]
62. Aslam, F.; Aimin, W.; Li, M.; Ur Rehman, K. Innovation in the era of IoT and industry 5.0: Absolute innovation management (AIM) framework. *Information* **2020**, *11*, 124. [CrossRef]
63. Polonara, M.; Romagnoli, A.; Biancini, G.; Carbonari, L. Introduction of Collaborative Robotics in the Production of Automotive Parts: A Case Study. *Machines* **2024**, *12*, 196. [CrossRef]
64. Borboni, A.; Reddy, K.V.V.; Elamvazuthi, I.; AL-Quraishi, M.S.; Natarajan, E.; Azhar Ali, S.S. The Expanding Role of Artificial Intelligence in Collaborative Robots for Industrial Applications: A Systematic Review of Recent Works. *Machines* **2023**, *11*, 111. [CrossRef]
65. Li, C.; Zheng, P.; Yin, Y.; Pang, Y.M.; Huo, S. An AR-assisted deep reinforcement learning-based approach towards mutual-cognitive safe human-robot interaction. *Robot. Comp. Integr. Manuf.* **2023**, *80*, 102471. [CrossRef]
66. Prassida, G.F.; Asfari, U. A conceptual model for the acceptance of collaborative robots in industry 5.0. *Procedia Comp. Sci.* **2022**, *197*, 61–67. [CrossRef]
67. Kopp, T.; Baumgartner, M.; Kinkel, S. Success factors for introducing industrial human-robot interaction in practice: An empirically driven framework. *Int. J. Adv. Manuf. Technol.* **2021**, *112*, 685–704. [CrossRef]

68. Vanderborght, B. *Unlocking the Potential of Industrial Human–Robot Collaboration: A Vision on Industrial Collaborative Robots for Economy and Society*; Publications Office of the European Union: Luxembourg, 2020.
69. Negri, E.; Fumagalli, L.; Macchi, M. A Review of the Roles of Digital Twin in CPS-based Production Systems. *Procedia Manuf.* **2017**, *11*, 939–948. [CrossRef]
70. Gejo-García, J.; Reschke, J.; Gallego-García, S.; García-García, M. Development of a System Dynamics Simulation for Assessing Manufacturing Systems Based on the Digital Twin Concept. *Appl. Sci.* **2022**, *12*, 2095. [CrossRef]
71. Rahmani, R.; Jesus, C.; Lopes, S.I. Implementations of Digital Transformation and Digital Twins: Exploring the Factory of the Future. *Processes* **2024**, *12*, 787. [CrossRef]
72. Segovia, M.; Garcia-Alfaro, J. Design, Modeling and Implementation of Digital Twins. *Sensors* **2022**, *22*, 5396. [CrossRef] [PubMed]
73. Rasheed, A.; San, O.; Kvamsdal, T. Digital Twin: Values, Challenges and Enablers from a Modeling Perspective. *IEEE Access* **2020**, *8*, 21980–22012. [CrossRef]
74. Bilberg, A.; Malik, A.A. Digital twin driven human–robot collaborative assembly. *CIRP Ann.* **2019**, *68*, 499–502. [CrossRef]
75. Kritzinger, W.; Karner, M.; Traar, G.; Henjes, J.; Sihn, W. Digital Twin in manufacturing: A categorical literature review and classification. *IFAC-PapersOnLine* **2018**, *51*, 1016–1022. [CrossRef]
76. Wagg, D.; Worden, K.; Barthorpe, R.; Gardner, P. Digital Twins: State-of-The-Art Future Directions for Modelling and Simulation in Engineering Dynamics Applications. *ASCE-ASME J. Risk Uncertain. Eng. Syst. Part B Mech. Eng.* **2020**, *6*, 030901. [CrossRef]
77. Psarommatis, F.; May, G. A standardized approach for measuring the performance and flexibility of twins. *Int. J. Prod. Res.* **2022**, *61*, 6923–6938. [CrossRef]
78. Huang, H.; Yang, L.; Wang, Y.; Xu, X.; Lu, Y. Digital Twin-driven online anomaly detection for an automation system based on edge intelligence. *J. Manuf. Syst.* **2021**, *59*, 138–150. [CrossRef]
79. Piromalis, D.; Kantaros, A. Digital Twins in the Automotive Industry: The Road toward Physical-Digital Convergence. *Appl. Syst. Innov.* **2022**, *5*, 65. [CrossRef]
80. Leng, J.; Wang, D.; Shen, W.; Li, X.; Liu, Q.; Chen, X. Digital twins-based smart manufacturing system design in Industry 4.0: A review. *J. Manuf. Syst.* **2021**, *60*, 119–137. [CrossRef]
81. Attaran, M.; Celik, B.G. Digital Twin: Benefits, use cases, challenges, and opportunities. *Decis. Anal. J.* **2023**, *6*, 100165. [CrossRef]
82. Wang, K.; Wang, Y.; Li, Y.; Fan, X.; Xiao, S.; Hu, L. A review of the technology standards for enabling digital twin. *Digit. Twin* **2022**, *2*, 4. [CrossRef]
83. Fera, M.; Greco, A.; Caterino, M.; Gerbino, S.; Caputo, F.; Macchiaroli, R.; D'Amato, E. Towards digital twin implementation for assessing production line performance and balancing. *Sensors* **2020**, *20*, 97. [CrossRef]
84. Malik, A.A.; Masood, T.; Bilberg, A. Virtual reality in manufacturing: Immersive and collaborative artificial-reality in design of human-robot workspace. *Int. J. Comput. Integr. Manuf.* **2020**, *33*, 22–37. [CrossRef]
85. Makris, S. *Cooperating Robots for Flexible Manufacturing*; Springer: Berlin/Heidelberg, Germany, 2020.
86. Koesters, A.; Koetz, F.; Bock, M.; Fett, M.; Breimann, R.; Kirchner, E. Methodical Development of a Digital Twin for an Industry Valve. *Machines* **2024**, *12*, 674. [CrossRef]
87. Resman, M.; Protner, J.; Simic, M.; Herakovic, N. A Five-Step Approach to Planning Data-Driven Digital Twins for Discret Manufacturing Systems. *Appl. Sci.* **2021**, *11*, 3639. [CrossRef]
88. Kaiser, J.; McFarlane, D.; Hawkridge, G.; André, P.; Leitão, P. A review of reference architectures for digital manufacturing: Classification, applicability and open issues. *Comput. Ind.* **2023**, *149*, 103923. [CrossRef]
89. Siemens Tecnomatix—Process Simulate V15.1.2. Available online: https://docs.plm.automation.siemens.com/tdoc/tecnomatix/15.1.2/tecnomatix_eMS/#uid:index (accessed on 7 February 2024).
90. Siemens PLM Virtual Commissioning. Web p. Available online: https://www.plm.automation.siemens.com/en/products/tecnomatix/launch-production/virtual-commissioning (accessed on 22 April 2024).
91. Florescu, A.; Barabas, S. Development Trends of Production Systems through the Integration of Lean Management and Industry 4.0. *Appl. Sci.* **2022**, *12*, 4885. [CrossRef]