Computers & Industrial Engineering 198 (2024) 110670

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

Enhancing internal supply chain management in manufacturing through a simulation-based digital twin platform

Antonio Cimino [a], Francesco Longo [b,*], Giovanni Mirabelli [b], Vittorio Solina [b], Pierpaolo Veltri [b]

[a] University of Salento – Department of Innovation Engineering
[b] University of Calabria – Department of Mechanical, Energy and Management Engineering

ARTICLE INFO

Keywords:
Digital twin
Internal supply chain
Simulation
Manufacturing industry
Automated simulation modelling
Production planning

ABSTRACT

Digital Twin (DT) technology is profoundly changing the manufacturing landscape and supply chain management with its ability to create real-time digital replicas of physical processes, allowing for enhanced monitoring and optimized decision-making. However, the analysis of scientific literature reveals that further efforts are needed to spread the use of Industry 4.0 technologies, in the specific context of Internal Supply Chains (ISCs). The main aim of this study is to design, develop test and validate a multi-plant Simulation-Based DT production planning platform for ISCs management. A modular architecture is adopted, and the focus is on a Simulation-Based Digital Twin module, which uses an object-oriented structure and enables what-if analyses, involving several scheduling rules and ISC configurations. The proposed solution ensures flexibility and scalability, two crucial features in a constantly evolving market environment. The platform is tested and validated through a case study, involving a corporate group in the Oil & Gas manufacturing sector, which needs to improve the ISC performance, under a Make-To-Order production strategy. The comparison with a baseline scenario, where the platform is not adopted, shows that the proposed approach can significantly reduce the average flow time, the average tardiness, the number of late orders. This study has important practical implications because enables proactive and smart decision-making, aimed at resource optimization and continuous improvement, through predictive analytics and scenario analysis.

1. Introduction

The Fourth Industrial Revolution has transformed traditional manufacturing practices through the integration of disruptive technologies such as the Industrial Internet of Things (IIoT) (Pivoto et al., 2021), Blockchains (Lim et al., 2021), Digital Twins (DTs) (Semeraro et al., 2021), Cloud Computing (Nguyen et al., 2021), Cyber-Physical Systems (CPS) (Lee et al., 2020), and advanced Data Analytics (Wang et al., 2022). These technologies enable the creation of smart, interconnected ecosystems that facilitate real-time decision-making and enhance operational efficiency (Oztemel and Gursev, 2020). The focus of this paper is on DTs, that are virtual replicas of physical systems, processes, or products that continuously collect real-time data from their physical counterparts via sensors (Tao et al., 2022). This data is then used for simulations and analytics to optimize performance, predict production needs, and identify potential issues (Lu et al., 2020). In the context of Supply Chain Management, DTs represent a dynamic tool for monitoring, simulating, and optimizing supply chain processes, leading to improved coordination and efficiency (Kamble et al., 2022). More specifically, when referring to activities that occur within the boundaries of a single organization, the scientific literature speaks of Internal Supply Chain (ISC) Management. Unlike traditional SC management, which involves coordination among various external entities, ISC management focuses on optimizing the flow of materials, information, and processes across different departments, divisions, or plants within the same company or corporate group (Prakash, 2014; Turkulainen et al., 2017). Integrating DTs in ISC management can offer significant benefits, such as the ability to perform "what-if" analyses to test different production scenarios and strategies without necessarily disrupting actual operations (Ivanov and Dolgui, 2021; Le and Fan, 2023). For instance, they can simulate the impact of a machine breakdown on production schedules and propose optimal reallocations of resources to minimize downtime (Aivaliotis et al., 2019). Digital twins also enable real-time visibility and synchronization across multiple plants, enhancing decision-making and collaboration throughout the supply chain (Moshood et al., 2021). The adoption of DTs for ISC management is not without challenges.

* Corresponding author at: Via Pietro Bucci 45C, Rende, (CS) 87036, Italy.
E-mail address: f.longo@unical.it (F. Longo).

https://doi.org/10.1016/j.cie.2024.110670

Available online 21 October 2024

Implementation costs, data integration issues, and the need for specialized skills can hinder their deployment (Kamble et al., 2022). These complexities highlight the need for developing flexible, scalable, and user-friendly digital twin-based platforms. Such platforms can enable seamless data flow and decision-making across different functional areas, supporting real-time optimization and adaptability in production planning and ISC management (Nakagawa et al., 2021; Longo et al., 2022; Cimino et al., 2023; Han and Trimi, 2022). For example, cloud-based platforms can leverage DTs and CPS to provide real-time insights into production processes and supply chain logistics, allowing companies to respond promptly to market dynamics and operational disruptions (Pisching et al., 2018; van Dinter et al., 2023). The primary objective of this paper is to propose a digital platform that leverages the DT concept to support production planning within a multi-plant environment of an ISC. The platform is designed to enable enhanced decision-making, flexibility, and improvement of production processes across different plants within the same corporate group. To demonstrate its effectiveness, the proposed platform is tested and validated through a real-world case study involving a specific corporate group in the oil and gas sector.

The rest of this paper is structured as follows. Section 2 explores the current state of the art about simulation-based digital twins in the manufacturing context and relevant approaches for internal supply chain management. The identified research gaps are described, with the aim of making the innovative contribution of the paper as clear as possible. Section 3 describes the Multi Plant Digital Twin Production Planning Platform, while Section 4 is focused on its main module, which concerns the adoption of the simulation-based digital twin paradigm. Section 5 proposes a case study in the Oil & Gas sector, with the aim of testing and validating the conceptual proposal. Conclusions are reported in Section 6.

2. Literature review

2.1. Simulation-Based digital twins in production planning and supply chain management

The use of the concept of "twin" has spread significantly in recent years, with the advent of the Fourth Industrial Revolution (Tao et al., 2022). However, it dates back at least to the 1960s, when the National Aeronautics and Space Administration (NASA) built two identical space vehicles, with the aim of using one of them to simulate and replicate the conditions of the other in flight, as part of the Apollo program. Nowadays, this concept is extremely broad and applied to multiple domains (Zhuang et al., 2018; Mandolla et al., 2019; Catalano et al., 2022). In the manufacturing field, a DT can be seen as a virtual representation of processes, personnel, products, assets, which are updated in real time as the physical counterpart changes (Lu et al., 2020). More generally, Qi and Tao (2018) highlight the coexistence of 3 concepts in defining a DT: "virtualization of physical entities", "materialization of virtual process", "integration between virtual and reality".

Within the manufacturing field, DT technology offers significant utility and efficiency across several key practices such as product design (Lo et al., 2021), production planning (Park et al., 2020), and even maintenance (Errandonea et al., 2020). The most relevant simulation-based digital twins, with specific reference to production planning, are briefly discussed below. Ma et al. (2020) have recently proposed a DT-driven production management system to dynamically simulate and optimize manufacturing processes, with good results especially in terms of reduction of defective rate of products. Park et al. (2020) proposed and applied to a micro smart factory, a digital twin-based cyber physical production system (CPPS), observing an improvement in the makespan. Negri et al. (2021) presented, with promising results, a simheuristics framework for robust scheduling in Flow Shop Scheduling Problems, leveraging real-time field data via DT and Equipment Prognostics and Health Management. To gain a broader understanding of the use of DT-oriented approaches for production planning, the reader is addressed to some recent and comprehensive literature reviews (Lim et al., 2020; Lu et al., 2020; Leng et al., 2021). Overall, it is possible to state that scientific interest in DT is growing enormously in recent years: by entering the keyword "Digital Twin" on Scopus (a well-recognized scientific database) in the field "Article title, Abstract, Keywords", it is possible to see that almost 7,000 documents were published in 2023, compared to approximately 5,000 and 3,000 respectively in the years 2022 and 2021. This number was less than 100 in 2011, when the Fourth Industrial Revolution started. However, some barriers remain with respect to its definitive success and widespread diffusion, especially among companies. According to Liu et al. (2023), though the application field of the DT is very extensive, most of the documents concern only theoretical concepts, and there is still a certain research gap about the prediction of the working state of physical entities through DT-based virtual models. According to Liu et al. (2021), there are still data integration issues to be solved so that DT can improve manufacturing processes in an efficient, dynamic and intelligent way. Essentially, significant research efforts are still needed to make this paradigm fully mature. For completeness, it is necessary to discuss also the application of DT-based approaches for Supply chain management (SCM), which has always been one of the most debated disciplines in the scientific panorama, given the numerous challenges that decision-makers must face in this field such as production planning, inventory management, shipping management, demand forecasting. SCM is critical for businesses as it can ensure cost efficiency, customer satisfaction, risk mitigation, quality control, and strategic alignment. By streamlining processes, managing risks, and fostering collaboration, it enables companies to operate efficiently, adapt to changing market conditions, and meet customer demands effectively, ultimately driving long-term success and competitiveness (Rebelo et al., 2022; Altekar, 2023). Within such a discipline, the new technologies of the Fourth Industrial Revolution are offering new opportunities, which if properly exploited, can bring countless benefits. Specifically, in the last few years, the concept of Supply Chain DT is emerging (Ivanov and Dolgui, 2021; Le and Fan, 2023; Singh et al., 2023), as through simulation it is possible to test different scenarios without risk, therefore determining the best work configuration from both a strategic and operational point of view. Basically, such a concept involves creating a virtual replica or representation of a physical supply chain network, using real-time data and advanced analytics. It integrates data from various sources such as sensors, IoT devices, Enterprise Resource Planning (ERP) systems, and external data streams to simulate and visualize the entire supply chain process. This digital replica enables actors to monitor, analyze, and optimize the performance of the supply chain in a virtual environment. By providing insights into potential disruptions, bottlenecks, and opportunities for improvement, Digital Twins facilitate smart decision-making and enhance the resilience and efficiency of the supply chain itself (Nguyen et al., 2022; Kamble et al., 2022; Longo et al., 2023). Table 1 summarizes the main contributions in terms of the use of simulation-based DTs in the context of SCM.

As it can be noted, the application of DTs to supply chains is a completely new trend, which has developed especially after the advent of the COVID-19 pandemic, in order to improve the resilience of supply chains and efficiently face disruptions (Burgos and Ivanov, 2021; Ivanov, 2022; Cimino et al., 2024). An important line of research concerns agri-food supply chains, considering that significant challenges must be faced in this sector, such as quality and safety of goods as well as shelf-life (Binsfeld and Gerlach, 2022; Maheshwari et al., 2023; Hu et al., 2023; Guidani et al., 2024; Cimino et al., 2024). What is clear is that so far there are no approaches, which propose to use platforms based on simulation-based DTs to improve the management of ISCs, that is the main focus of the present paper.

2.2. Approaches for internal supply chain management

In the broad spectrum of SCM, there is an extremely relevant branch

Table 1
Relevant research on Simulation-Based DTs for Supply Chain Management.

Reference	Main Goal	Proposed Approach
Burgos and Ivanov (2021)	To assess the resilience of food retail supply chains during the COVID-19 pandemic and identify factors influencing their performance.	A digital supply chain twin, enabled by discrete-event simulation model, to analyze the effects of pandemic intensity, inventory dynamics, and customer behavior on supply chain operations.
Ivanov (2022)	To predict and mitigate the impacts of blackouts on supply chains by analyzing their effects on SC performance, resilience, and viability.	Simulation analysis with a digital supply chain twin to assess blackout scenarios, and development strategies for mitigation and recovery based on the dynamics of power loss and disruption propagation.
Marmolejo-Saucedo (2022)	To enhance decision-making in supply chains by integrating large-scale optimization problems into a digital twin platform.	Utilize discrete event simulation and heuristic algorithms within a commercial supply chain management platform to solve Bin-Packing and Vehicle Routing problems in real time.
Binsfeld and Gerlach (2022)	To provide a method for quantifying the benefits of using digital supply chain twins (DSCTs) in logistics and supply chain management.	Extensive simulations of a food supply chain under various scenarios and development a new method to quantify DSCT benefits for inventory management and performance evaluation.
Perez et al. (2022)	To optimize supply chain processes by accurately modeling and managing task dynamics, lead times, and disruptions.	An integrated digital twin framework using queueing networks and real-time data for offline and online optimization of supply chain operations.
Badakhshan and Ball (2023)	To enhance supply chain performance during disruptions by optimizing inventory and cash replenishment policies.	A supply chain digital twin framework that integrates machine learning and simulation to identify optimal inventory and cash management strategies under disruption.
Hu et al. (2023)	To improve food quality, safety, and operational efficiency in cold chain logistics warehouses by reducing product loss and optimizing temperature control.	A five-dimensional digital twin model integrating real-time data for visualization, monitoring, and intelligent decision-making to optimize warehouse operations.
Maheshwari et al. (2023)	To optimize procurement, production, and distribution strategies (PPDs) in a food processing company to enhance supply chain productivity and flexibility.	A digital twin model using mixed-integer linear programming (MILP) and agent-based simulation (ABS) improves makespan, lead time, and resource utilization through real-time data and decision-making.
Guidani et al. (2024)	To enhance sustainability in Agri-Food Supply Chains (AFSC) by increasing transparency and enabling informed decision-making across all operational levels.	An AFSC digital twin provides a holistic virtual model, acting as a control tower with multi-dimensional dashboards for monitoring and optimizing economic, logistic, environmental, safety, and nutritional indicators.
Corsini et al. (2024)	To optimize the replenishment strategy of a manufacturer by dynamically adjusting parameters to improve resilience against unpredictable supply disruptions.	A digital twin integrates data analytics, simulation, machine learning (ANN), and metaheuristic optimization (PSO) to self-adjust replenishment parameters based on real-time data.
Cimino et al. (2024)	Increasing sustainability and resilience of supply chains	A cyclic and holistic Methodology, based on Simulation, for exploiting the concept of Supply Chain Digital Twin
This paper	Supporting production planning activities of multi-plants belonging to the same ISC, with reference to a specific corporate group	Digital platform, enabling Simulation-Based Digital Twin

The references contained in this table were collected through a search conducted on the scientific database Scopus in August 2024. The query consisted of the use of the keywords “Digital Twin” AND “Supply Chain” AND “Simulation” in the field “Article title, Abstract, Keywords”. 204 documents were identified in a first step. Subsequently, all papers with one or more of the following characteristics were excluded: non-English language, full-text not available, literature reviews, lack of supply chain view, lack of implementation of a Digital Twin, only theoretical documents.

of research which concerns the management of internal supply chains. An ISC focuses on the activities and processes that occur within the corporate group itself, from raw material acquisition to the delivery of the final product or service. An efficient ISC is crucial to reduce costs and deliver high-quality products or services to customers, and therefore remain competitive in an increasingly globalized world. The main scientific contributions that propose solutions to improve the management of ISCs, with a focus on the manufacturing sector, are listed and briefly discussed below. Starting from the importance of data and information availability, Schmidt et al. (2019) have recently proposed a data-driven framework to identify the factors that influence logistics Key Performance Indicators (KPIs) in an ISC of an injection molding tool manufacturer. Ivanov and Jaff (2017) have recently presented a conceptual framework, with the aim of providing a set of strategies to reduce manufacturing lead time, in the context of ISCs. Chibba and Rundquist (2009), through case studies concerning Swedish multinational organizations, demonstrated the importance of an integrated information system to streamline the flow of materials of ISCs. A quite debated topic regards the integration of ISCs, which refers to the degree of collaboration and coordination between the different entities within the boundaries of the same corporation group. According to Turkulainen et al. (2017), goal alignment, knowledge sharing, and management of interdependencies, are among the main factors for a good ISC integration, while standardization and centralization are considered as significant integration mechanisms. This is the result of interviews with several managers of manufacturing firms.

Table 2 summarizes the most relevant approaches in the scientific literature for internal supply chain management, with a focus on the manufacturing sector.

As it can be noted from Table 2, the number of scientific works that focus on ISCs, with reference to the manufacturing sector, is still extremely limited. Most of the contributions are based on interviews with ISC actors, with the aim of collecting qualitative insights to understand integration mechanisms, but also information and/or material flows (Chibba and Rundquist, 2009; Ivanov and Jaff, 2017; Turkulainen et al., 2017; Alansaari et al., 2019). To date, there is a clear lack of approaches able to exploit the potential of simulation-based digital twins to support ISC management.

3. Research gaps and our contribution

The analysis of the current state of the art regarding the use of DTs in manufacturing and supply chain management, with a focus on ISCs, reveals some important research gaps, which need to be addressed:

- Although Industry 4.0 paradigms are significantly spreading (Oztemel and Gursev, 2020), little has been done to improve the management of ISCs. Most of the scientific works are currently based

Table 2
Relevant research on ISC management with a focus on the manufacturing sector.

Reference	Main goal	Proposed Approach
Chibba and Rundquist (2009)	Mapping and describing information and physical material flows in ISCs	Interview-based and process-oriented mapping tool
Prakash (2014)	Identifying the relationship between Quality of Service (QoS) and organizational performance in ISCs	A model, which links QoS with organisational performance through intermediate variables of satisfaction, loyalty and competitive advantage
Basnet (2013)	Building a consensus among practitioners and researchers in defining and measuring the concept of ISC integration	Measurement tool for ISC integration
Ivanov and Jaff (2017)	Reducing manufacturing lead time	Conceptual framework, driven by survey questionnaire
Turkulainen et al. (2017)	Understanding how managers integrate ISC activities	Information Processing View based on qualitative interview data
Kailash et al. (2018)	Evaluation and optimization of Return on Investment (ROI)	Benchmarking framework for comparative analyses
Schmidt et al. (2019)	Identification of cause-effect relationships for improving logistics KPIs	Systematic framework for root cause analysis
Kailash et al. (2021)	Identification of interrelationships among performance measures of ISCs	Weighted interpretive structural modelling approach
Alansaari et al. (2019)	Identification of the impact of employee commitments and recruitment process on internal supply chains of manufacturing firms	Structural equation modelling for analyzing data collected from managers
Giera et al. (2023)	Ensuring quality and safety of goods	Qualitative risk management method, able to identify the risk factors with the greatest impact on quality and safety of goods
This paper	Supporting production planning activities of multi-plants belonging to the same ISC, with reference to a specific corporate group	Digital platform, enabling Simulation-Based Digital Twin

The references contained in this table were collected through a search conducted on the scientific database Scopus in August 2024. The query consisted of the use of the keywords "Internal Supply Chain" AND "Manufacturing" in the field "Article title, Abstract, Keywords". 1307 documents were identified in a first step. Subsequently, all papers with one or more of the following characteristics were excluded: non-English language, full-text not available, no proposed approach regarding the management of internal supply chains, no focus on the manufacturing sector.

on qualitative questionnaires aimed at identifying performance indicators in the various stages of ISCs (Chibba and Rundquist, 2009; Ivanov and Jaff, 2017; Turkulainen et al., 2017). To date, there are no DT-oriented approaches to support ISCs. More specifically, while there are interesting approaches on using DTs to support production planning in manufacturing or improve the management of material flows in supply chains, there are no DT-oriented models to support the production activities of multiple plants in ISCs.

- Although DT is a topic of great interest, some barriers remain regarding its large-scale diffusion among companies. Data integration & standardization is still an open issue (Liu et al., 2021).
- According to Liu et al. (2023), many DT-based research works are only theoretical then case studies are really needed to demonstrate practically the goodness of this technology.

Based on the research gaps highlighted, the innovative contribution of this paper can be summarized as follows:

Our innovative contribution can be summarized as follows:

- A novel digital platform is designed and developed to support production planning across multiple plants within the same corporate group. It allows users to perform what-if scenario analyses and adjust manufacturing parameters for individual plants or the entire ISC, with an impact on key performance indicators assessed through a simulation-based DT.
- The platform offers a unified tool for consistent data integration and standardization across plants. Moreover, flexibility in simulating various production processes with standardized data and scalability in adapting to different ISC tiers, are ensured.
- A case study in the Oil&Gas sector is proposed, with the aim to test and validate the proposed Multi-Plant DT Production Planning Platform in a real-life environment.

4. Multi plant digital twin production planning platform

In this section, the authors introduce the developed multi-plant production planning platform designed to support the manufacturing activities among various plants belonging the same corporate group. For the purposes of this work, a corporate group is defined as a set of production plants within the same company. These plants are interconnected, forming a supply chain that operates collectively to support the company's manufacturing activities. Within this framework, the platform provides end-users with the capability to conduct what-if scenario analysis for efficient manufacturing production planning. Furthermore, end-users can select and modify manufacturing parameters either for a selected plant or the overall internal supply chain, prompting the platform to quantitatively assess the impact of these changes on designated manufacturing KPIs. This quantitative analysis is executed by the platform's core module, a simulation-based digital twin, which replicates each plant's manufacturing production, utilizing a set of standardized and structured input data.

To leverage the platform's capabilities, specific technical prerequisites must be satisfied: (1) plants must share a unified information system, ensuring consistent data integration and standardization; (2) plants actively contribute to various production stages of the same company's end-products, thus establishing reciprocal flow of materials and orders (this collaborative interaction can significantly influence the production plans of each plant).

The platform is characterized by two key features: flexibility and scalability. Its flexibility is evident in its capacity to simulate any type of production process when provided with structured input data, regardless of the specific context of individual production systems. This flexibility is achieved through a data-driven approach, where simulation models are generated based on structured input data. Essentially, the platform views any production system as a network of resources working together in a specific sequence to complete production orders. Here, a resource refers to any plant machinery, tool, or equipment needed for carrying out production operations. Each simulation model is developed as a set of resource objects, each performing a specific production operation, and arranged in a sequence reflecting the operations flow needed to manufacture a product specified in a customer order. Therefore, as long as the platform is provided with the key data characterizing the resources, the operations they need to perform, the sequence of these operations, and the customer orders detailing the products to be manufactured, it can simulate any production system independently of its specific context. The list of the necessary data required to enable this functionality is detailed in Table 3 (see section 4.1). Furthermore, the platform is inherently scalable, accommodating usage across different supply chain tiers as well as accurately reflecting the complexity of each plant, regardless of the number of resources, production operations, or customer orders it manages. This adaptability is enabled through object-oriented programming, which allows the platform to dynamically generate simulation models tailored to each plant's specific characteristics. Fig. 1 illustrates an example of the code used within the module to create workstation objects corresponding to each available resource in

Table 3
DS Input data.

Data Group	Data Element	Description	Data Type
Resources	Resource ID*	Unique identifier for a production resource (machine, tool, equipment)	String
	Capacity*	Maximum number of products that can be concurrently processed within the resource	Int
	Workers*	Numbers of operators actively working on that resource	Int
	Energy Working	Electric power consumption [kW] of the resource during its operational state	Double
	Energy Waiting	Electric power consumption [kW] of the resource when it is in a standby or inactive state, i.e., not actively performing any work	Double
	Plant ID*	Specific corporate group plant where the resource is situated	String
	Mean Time To Repair (MTTR)	Average time [min] required to repair the resource in the event of a failure	Int
	Mean Time Between Failure (MTBF)	Average duration [min] between two instances of failures for the resource	Int
	Maintenance Date	Most recent maintenance date for the resource	Date
Orders	Order ID	Unique identifier for the production order	String
	Plant ID	Specific corporate group plant where the order has been placed (identical to the data element Plant ID within the Resources data group)	String
	Start Date	Planned start date for that order production	Date
	Due Date	Expected end date for that order production	Date
Bill of process	Order ID	Unique identifier for a production order (identical to the data element Order ID within the Orders data group)	String
	WIP ID	Code assigned to an individual semi-finished product, which may undergo multiple production operations	String
	Next WIP ID	Code assigned to the next semi-finished product to start once the current WIP ID is completed	String
	WIP operation	Code used to identify the position of a specific operation in the sequence of the process for fulfilling the order	String
	Pre-processing time	Time [min] required to set up a resource before the start of the operation	Int
	Processing time	Time [min] that a resource needs to complete a specific operation	Int
	Resource ID	Unique identifier for a production resource assigned to execute a specific operation (identical to the data element Name ID within the Resources data group)	String
	Process description	Description of the individual operation	String
	Processed time	Total time [min] already spent on an operation currently in progress	String

*Subset of information to be specified for a fully manual operation.

the plant. As shown, the resource creation process is driven by a *for-next* loop, which iterates through the available resources in the database until all workstation objects have been generated. This loop is not bound to a fixed number of resources; instead, it adapts based on the variable *Resources.ydim*, which can be updated as needed to reflect changes in the plant's resource configuration. This approach ensures that the simulation models are always aligned with the current state of the plant. As a result, the simulation models can be generated for plants with either a high number of resources or just a few, demonstrating the platform's scalability in accommodating varying levels of plant complexity. It is important to remark that the scalability can be achieved only if the input data follow the structure reported in Table 3 (see section 4.1).

4.1. Supply chain dynamics

The designed platform is developed to support the production planning activities across multiple plants belonging to the same corporate group. In this section, the authors describe the intricate dynamics of a generalized supply chain, presenting all the possible relationships among plants that can leverage the capabilities of the platform. Fig. 2 provides a visual overview of the supply chain. This latter may be organized into *n* tiers, where each tier refers to the position of a plant within the hierarchy of the supply chain network and consists of a varying number of nodes. Nodes represent plants belonging to the same corporate group. Nodes at lower tiers can produce subcomponents, supplying them to nodes at higher tiers for the assembly of other products subcomponents and/or end customers products. The first tier primarily supplies to external customers, while lower tiers have the flexibility, in general, to serve both external customers (e.g., providing subcomponents as spare parts or for alternate purposes) and higher-tier nodes within the corporate group. Nodes at upper tiers can place orders for subcomponents to lower-tier plants within the company. Nodes at the same tier level can engage in mutual orders to enable lateral collaboration. End customers can place orders both for final products to the first-tier plants as well as for subcomponents directly to lower-tier plants, introducing a dynamic purchasing option.

In this complex context, the effectiveness of a production plan is contingent upon a multitude of factors. Among the others, the number of orders to be processed, the timeframe in which orders are received and need to be processed, the availability of subcomponents from other plants, and fluctuations in customer demands significantly impact manufacturing activities. These factors introduce a level of complexity that requires a technological solution capable of supporting production planning within these intricate dynamics. Such a tool must not only accommodate the diverse relationships among nodes and their production capacities but also possess the agility to adapt to changing production scenarios of each plant in real-time.

4.2. The platform overall architecture

Within this section, the authors present an overall overview of the platform's architecture, defining the structures and interactions inherent to its primary components. Fig. 3 serves as a visual representation, depicting the essence of the platform's architectural design. The platform consists of three key components: the Data Set module (DS), the Simulation-Based Digital Twin module (SBDT), and the End-Users module (EU). The DS module is a crucial part of the platform. It holds a Microsoft access database filled with standardized data from manufacturing plants. Basically, all plants, operating under the same corporate informative system, regularly upload their manufacturing process data to an internal database hosted on a corporate group server. In this regard, two python modules, along with FIWARE, orchestrate the transfer of updated data from the internal corporate group database to the DS module database, which is a key component of the platform. The first python module, installed on the corporate group informative system, is responsible for extracting predefined set of data from the corporate group database, validating them, and sending them to FIWARE. If the data fails validation, this module triggers an alert email to the designated operator (to be assigned by the corporate group) for data correction, integrity and validation. If the data is valid, the module converts them into the NGSVi2 format, which is compatible with

```
for var i := 1 to Resources.ydim      -- ydim is the number of resources listed in the database
    -- Create a new object in the System model for each resource
      .Models.WorkstationClass.createObject(.Models.SystemClass, y, x, "RESOURCE" + Resources["Name ID", i])

    -- Create a reference to the newly created object using its Name ID
    var str: string
    str := "~.System.RESOURCE" + Resources["Name ID", i]
    var obj: object
    obj := str_to_obj(str)

    -- Assign properties to the resource object
    obj.nome := Resources["Name ID", i]  -- Name ID: Unique identifier for the resource
    obj.Capacity := str_to_num(Resources["Capacity", i])  -- Capacity: Maximum products processed concurrently
    obj.Workers := str_to_num(Resources["Workers", i])  -- Workers: Number of operators working on the resource
    obj.EnergyWorking := Resources["Energy Working", i]  -- Energy Working: Power consumption during operation
    obj.EnergyWaiting := Resources["Energy Waiting", i]  -- Energy Waiting: Power consumption in standby
    obj.PlantID := Resources["Plant ID", i]  -- Plant ID: Identifier for the plant location
    obj.MTTR := str_to_num(Resources["Mean Time To Repair (MTTR)", i])  -- MTTR: Average repair time
    obj.MTBF := str_to_num(Resources["Mean Time Between Failure (MTBF)", i])  -- MTBF: Average time between failures
    obj.MaintenanceDate := Resources["Maintenance Date", i]  -- Maintenance Date: Most recent maintenance date


    -- Set the buffer property for the resource object
    var stbu: string
    stbu := "~.System.B" + Resources["Name ID", i]
    var obb: object
    obb := str_to_obj(stbu)
    obj.buffer := obb

next
```

Fig. 1. Object-oriented programming code for resources creation.

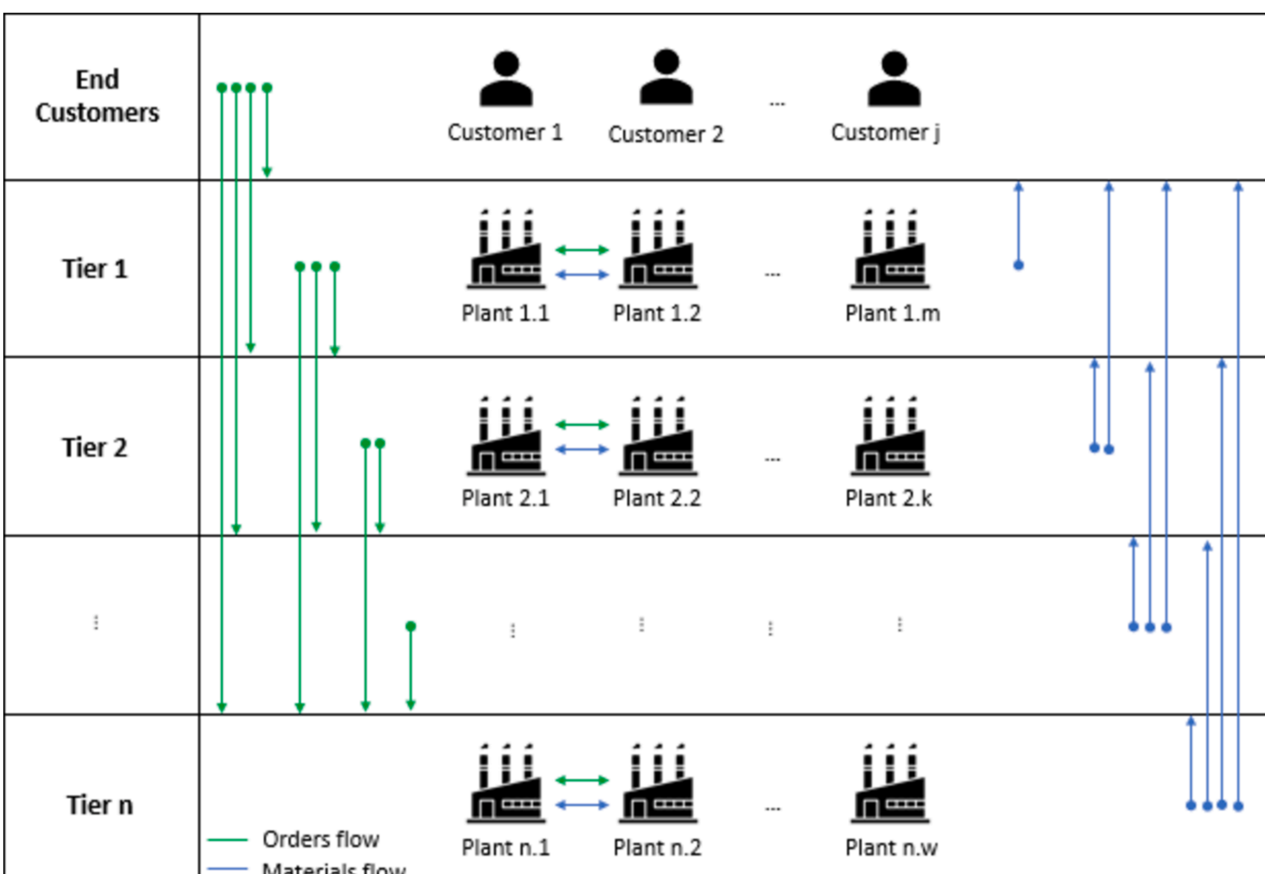

Fig. 2. Supply chain dynamics.

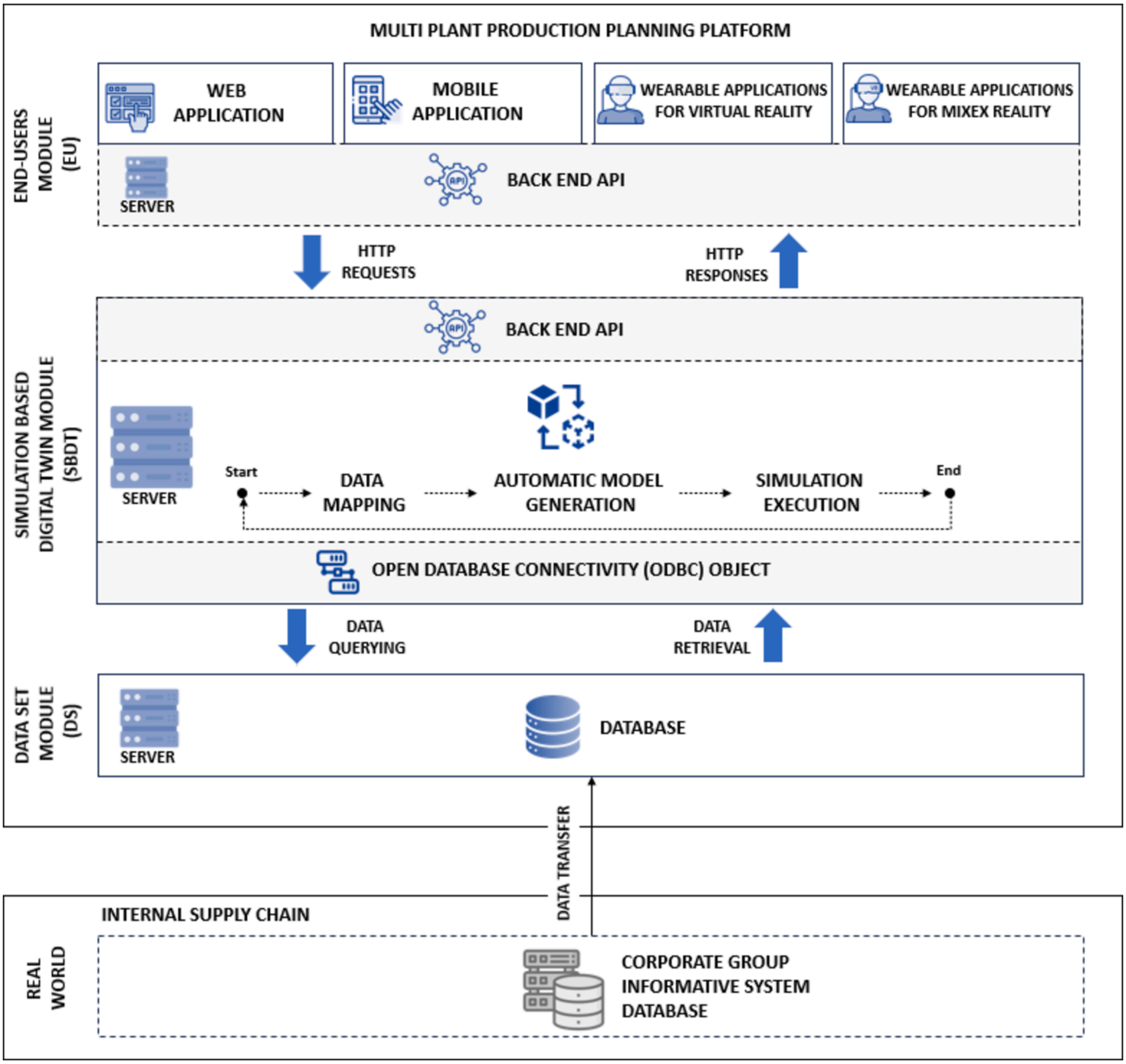

Fig. 3. Platform overall architecture.

FIWARE, and transmits it. FIWARE is an open-source framework for IoT platforms that facilitates data exchange across different applications (more information on FIWARE is available at https://www.fiware.org/). It enables data exchange through a publish/subscribe mechanism that utilizes Hypertext Transfer Protocol Secure (HTTPS) (Cimino et al., 2023). In this setup, the first python module sends/publishes data directly to FIWARE, which serves as a centralized hub for data distribution. The second python module, specifically developed and installed on a platform's server, requests subscribed/predefined data from FIWARE, converts them from the NGSVi2 format to a format readable by the DS database, and stores it within this latter. This data transfer mechanism is built upon data models that define the list of data to be published and subscribed as well as data formats and semantics used by the different applications (Cimino et al., 2023).

The data stored in the DS database serve as input for the SBDT module, which represents the key component of the platform. Developed using Tecnomatix's Plant Simulation software (further information on Plant Simulation software can be found at https://www.dex.siemens.com/plm/tecnomatix/plant-simulation), this module automatically generates simulation models of the manufacturing plants production processes and run simulations. The SBDT module gets the connection with the DS module database through its Open Database Connectivity (ODBC) object, which acts as a bridge between the SBDT module and the DS database. ODBC is a standard Application Programming Interface (API) that allows applications to access and interact with various database management systems (Elmasri and Navathe, 2016). The module uses Structured Query Language (SQL) to execute queries that request and retrieve the necessary input data from the DS database. Subsequently, these data are, firstly, classified and stored in Plant Simulation tables (data mapping) and, secondly, this structured information is utilized for the automatic generation of simulation models (automatic model generation) and the execution of simulations (simulation execution). The SBDT module is able to replicate any type of manufacturing process, if the input data adhere to a specific standardization. The intricate logics and operational functioning of the SBDT module represent the core of this research work, and as such, Section 4 is entirely dedicated to its description. Once the SBDT module completes the development of simulation models, end-users can access the SBDT module through the EU module, which consists of diverse user-friendly interfaces including web, mobile, and wearable applications for virtual and mixed reality. By accessing the platform via these interfaces, end-users can select and vary several manufacturing parameters, thus setting up different manufacturing scenarios. Then, SBDT module runs simulations for each scenario in order to assess their performance based on predefined set of KPIs (the complete list of the available platform manufacturing parameters and KPIs are presented in Section 4). These assessments allow the end-user to select the most suitable manufacturing scenario. The interaction between the EU module and the SBDT module is facilitated through their respective back-end APIs, which are a set of tools and rules that allows different software applications to communicate with each other. The back-end APIs leverage on Hypertext Transfer Protocol (HTTP), which is communication protocol for transferring data. The HTTP communication protocol operates on a request-response model. Basically, the back-end APIs of the EU module can initiate HTTP requests directed to the SBDT module's back-end APIs to request information, and in response, the SBDT module's back-end API respond with the requested information via HTTP responses. All data exchanged between the modules is formatted in JSON (JavaScript Object Notation), a widely used data format that makes it easy to organize and share information clearly and efficiently.

Additionally, to ensure secure data transfer, a Virtual Private Network (VPN) is used. A VPN creates a private, encrypted connection over the internet, which means that the data exchanged between the SBDT and DS modules, as well as between the corporate group's information system database and the DS module, is protected from unauthorized access. This encrypted connection helps to safeguard sensitive information and ensures that it cannot be easily intercepted or accessed by anyone outside the intended network.

5. The simulation based digital twin module

In this section, the authors present the SBDT module operational functioning. The primary objective of this module is to create a virtual replica of any kind of manufacturing process, consisting of one or more operations, leveraging on standardized data taken as input. Upon the automatic generation of manufacturing processes simulation models, the SBDT module becomes a dynamic tool for conducting what-if analyses across different manufacturing scenarios. This capability enables end users to make decisions by assessing the impacts of several manufacturing parameters on different KPIs within the domain of multi plant production planning activities. Section 4.1 presents the input data groups necessary for initializing the simulation model. In Section 4.2, the authors describe the simulation modeling approach employed by the SBDT module by presenting its main components, their functionalities and interaction. Finally, Section 4.3 is dedicated to simulation runs and what-if analysis scenarios. Here, the manufacturing parameters that can be selected and modified, along with the associated KPIs, which allows the evaluation of each manufacturing scenario's performance, are presented.

5.1. Data input

To leverage the full potentialities of the platform, it is necessary to ensure the availability of several manufacturing data, categorized into the three following groups:

1) *Resources data*: it consists of information related to each plant resource, including machines, tools, and various equipment necessary for carrying out a production operation. Please note that, for a fully manual operation, it is essential to list a fictitious resource, specifying only a subset of information, the specifics of which are detailed in Table 3;
2) *Orders data*: this category includes the list of ongoing and planned orders within each manufacturing plant, providing detailed information for each order;
3) *Bill of process data*: these data specify, for each production order, the list of operations along with the associated resources required for its completion.

Table 3 summarizes, for each of the aforementioned data groups, a list of the data element with their descriptions and type definition, which serves as input to the SBDT module.

5.2. Simulation modelling approach

This section describes the simulation modeling approach enabling the SBDT module to generate simulation models of any kind of production processes. As highlighted in Section 3.2, the module utilizes Tecnomatix's Plant Simulation software, built upon the principles of object-oriented modeling. Therefore, Plant Simulation is organized around *objects*, instances of *classes* that specify the attributes and behaviors shared by these objects. In the context of SBDT, three key classes have been defined (input class, workstation class and system class), whose instances and their interaction allows to automatically reproduce the production process of the manufacturing plants. Following, the authors begin by introducing the key classes of the SBDT module and then detail the main steps followed by the SBDT module to develop the simulation models.

Input Class

The input class establishes the connection between the SBDT and the DS modules to get input data as well as generate the simulation models virtual resources representing real plants resources, referred to as *objects workstation* within the platform. The class consists of several *objects method* and *objects table*, where *objects method* are lines of code that define the operational logic of the class and *objects table* are used to structure and classify the platform's input data. Specifically, the input class includes an *object method* to establish a connection with the DS module via ODBC. Upon establishing the connection, three distinct *objects method* – one for each data group outlined in Table 3 – execute SQL queries requesting input data from the DS module. The DS module responds with the requested data which are then organized into its internal *objects table*, categorizing them into the data group related to the resources, orders, and the bill of process. Once the data are stored within the SBDT module, the input class uses them to customize generic instances of the workstation class, creating a corresponding *object workstation* for each resource listed in its resource data table. This customization is achieved through the programming code which has been already presented in Fig. 1.

Workstation Class

The workstation class defines the attributes and behaviors of a generic virtual resource (*object workstation*) which can be customized by the input class to reproduce the behavior of any kind of real resource. This class has been designed to replicate behaviors, interactions, and functionalities of real-world resources within the SBDT module. Fig. 4 provides an overview of all the objects developed within this class. Utilizing various *objects method*, this class is designed to manage the operations which *objects workstation* have to carry out taking into account scheduling rules and maintenance activities. It's important to highlight that the coordination and interaction between the different objects of this class are managed by the system class, which will be discussed in detail later in this research.

The operational logic of each *object workstation* can be summarized as follows: a start method is implemented to initialize each *object workstation* within the simulation. This method prompts the *object workstation* to begin processing when the system class requests its involvement. Upon initialization, the *object workstation* first checks its current state, which can be either "available" or "busy". An *object workstation* is considered "available" if it is not currently engaged in any operation,

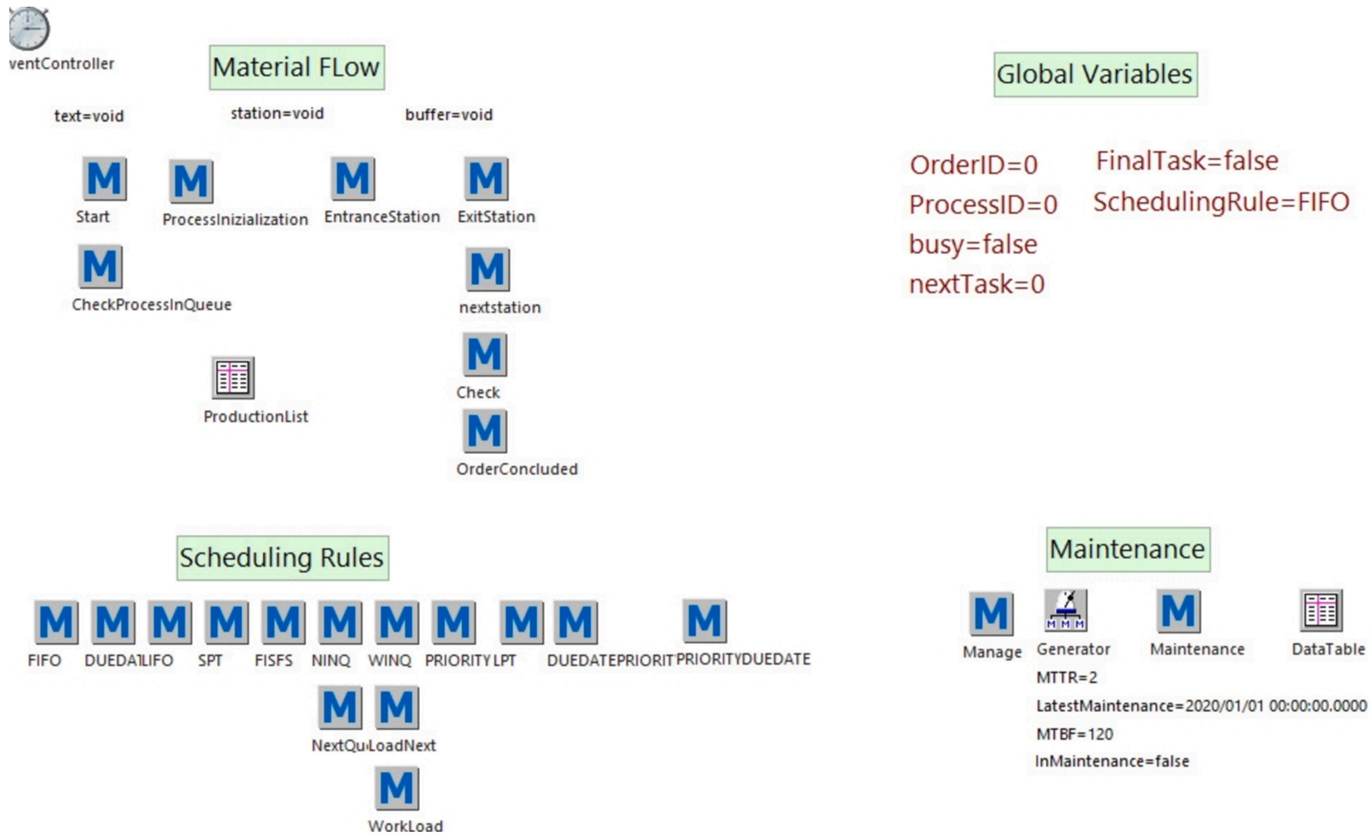

Fig. 4. Workstation class overview.

and "busy" if it is actively performing a task. If the *object workstation* is "busy", any incoming items are placed in an *object queue*, where they wait for the next available slot according to the selected scheduling rule. If the *object workstation* is "available", it immediately begins the operation, updating its state to "busy". After completing an operation, the *object workstation* marks the current operation, as identified by the WIP operation data for that order, as completed. It then checks if there are any items in the *object queue* awaiting processing. If no items are in the *object queue*, the workstation sets its status to "available" and waits for further initialization from the system class. If there are items in the *object queue*, it begins processing the next item. Fig. 5 depicts visually the aforementioned operational logic.

System Clas

The system class manages the *objects workstation* (virtual resources) and their interactions to replicate the entire production process necessary to complete the manufacturing orders. This class is highly complex, consisting of 905 distinct *objects method* defined through several thousand lines of programming code. At the start of each working day, the class accesses the order data table within the input class to identify orders that have not yet been initialized and are scheduled to start on that specific day. Once the relevant orders are identified, for each of them an *object method* retrieves the bill of process data by matching the order ID from the orders data table with the corresponding entries in the bill of process data table. For each operation to be performed for completing that order, the class assigns the appropriate *object workstation* by linking the resource ID from the bill of process data table with the entries in the resources data table. This approach enables the system class to determine which operations are needed for each order and which resources execute them. Additionally, the class determines the sequence in which the operations will be performed (based on the WIP ID and next WIP ID data), coordinating the flow of operations and it initialize the *objects workstation* in accordance with the operational logic of the workstation class. Furthermore, the system class includes all the objects developed

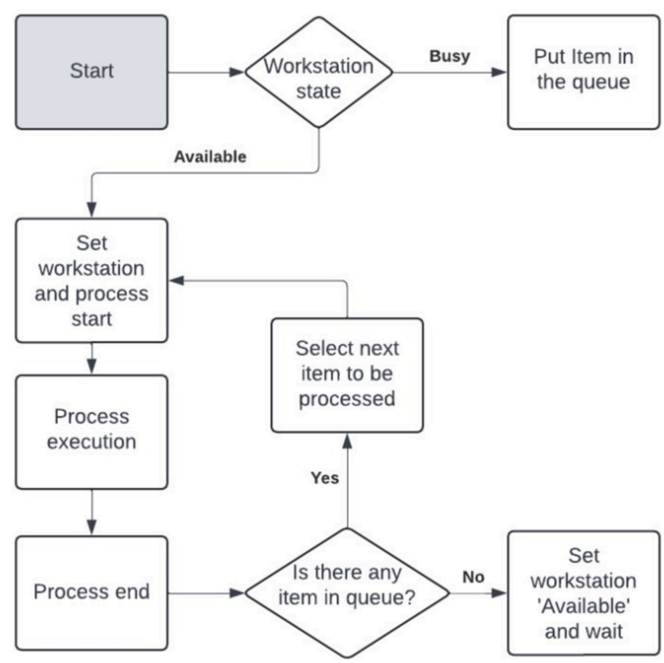

Fig. 5. Operational logic of *objects workstation.*

for calculation the KPIs, which will be discussed in detail in Section 4.3.

Simulation modeling steps

Following, the authors report the main steps run by the SBDT module for the simulation modelling.

STEP 1 – DATA EXTRACTION

The first step involves getting input data from the DS module.

Leveraging on its ODBC object, the SBDT module through its input class executes data queries to request and retrieve the necessary input data from the DS database.

STEP 2 – DATA MAPPING

The obtained data are imported within the input class and systematically organized into three distinct data table objects (resources data table, orders data table and bill of processes data table), aligning with the predefined input data groups (resources, orders, and bill of process), as presented in section 4.1.

STEP 3 – PRODUCTION RESOURCES REPLICATION

The input class customizes generic instances of the workstation class, generating as many *objects workstation* as the number of resources listed in its resource data table. These objects, reproducing virtually all the manufacturing plants available resources and faithfully replicating their behaviors, are subsequently stored within the system class.

STEP 4 – PRODUCTION PROCESSES REPLICATION

The system class identifies the orders to be fulfilled, determine the required operations for each order, and assign the corresponding resources to execute these operations in the correct sequence. By managing the interactions between the different resources, the system class replicates the entire production process needed to complete the manufacturing orders.

Fig. 6 provides a visual representation of the systematic step-by-step simulation modeling approach.

5.3. Simulation and what-if analysis

Once the SBDT successfully maps the internal supply chain, including production resources, orders, and associated processes for each plant, the platform becomes a dynamic tool available to end users (i.e. overall internal supply chain production planner, plant production planner, production director, etc.) to support production planning activities. The initial step involves (1) simulating the current state of production orders and processes for each plant, and assessing them based on predefined KPIs. Subsequently, end users can vary several manufacturing parameters (2) in order to generate alternative manufacturing scenarios (3). The impact of these changes on the selected KPIs is then evaluated (4). This iterative cycle (2 to 4) continues until the end users decide for the final manufacturing scenario (5), based on improved KPIs values. The implementation of the assigned manufacturing parameters values and the calculation of KPIs within the platform are orchestrated by the programmed methods embedded within the system class of the SBDT. Fig. 7 visually represents this iterative cycle.

Table 4 reports the list of changeable manufacturing parameters, providing details for each of them, the name, a brief description, a predefined set of options (if applicable) to be selected, and the data type

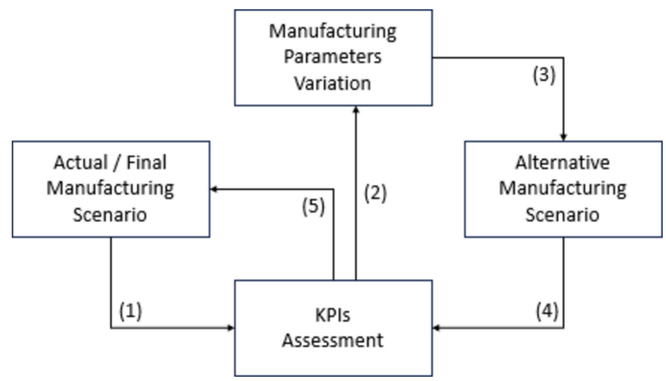

Fig. 7. Iterative decision-making cycle.

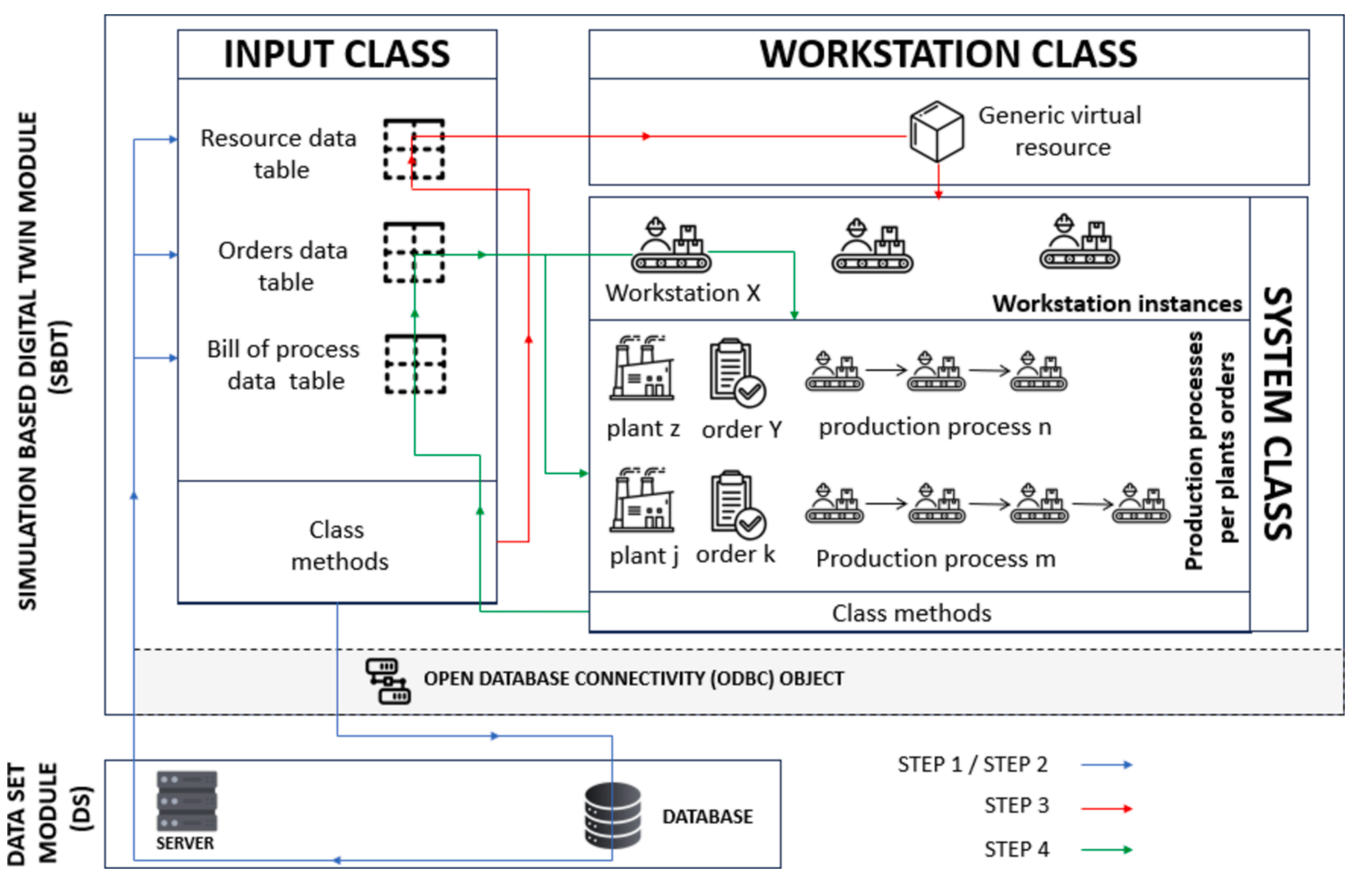

Fig. 6. Simulation modeling steps.

Table 4
Manufacturing parameters.

Manufacturing parameter name	Description	Multiple Options Selection	Data Type	Resource	Process	Order	Plant	Supply Chain
Supply Chain Configuration*	Setup of the supply chain, delineating the list of plants capable of fulfilling a particular order	Conf. 1 Conf. 2 Conf. n	N/A	–	–	–	–	✓
Scheduling Rule**	Load rule applied to either a single resource or all resources within a plant. It determines the prioritization of items in the queue, favoring those with higher priority when multiple pieces are waiting to be processed	FIFO LIFO SPT LPT EDD NINQ WINQ LWKR	N/A	✓	–	–	✓	–
Process Time Variability	Variability of the process time given as input for each resource. It reflects the real-world scenario where actual process times may vary within a certain range due several dynamic factors	0 % 5 % 10 % 15 % 20 %	N/A	✓	–	–	–	–
Order Start Date***	Planned production start date for a specific order	N/A	Date	–	–	✓	–	–
Order Due Date	Latest due date to complete a specific order	N/A	Date	–	–	✓	–	–
Working Shift***	Number of designated working shifts for a specific plant	1 shift 2 shifts 3 shifts	N/A	–	–	–	✓	–
Maintenance Date	Next scheduled date for routine maintenance of a specific resource	N/A	Date	✓	–	–	–	–

*The set of available configurations differ based on the specific supply chain under examination.
**FIFO = First In First Out; LIFP = Last In First Out; SPT = Shortest Processing Time; LPT = Longest Processing Time; EDD = Earliest Due Date; NINQ = Number In Next Queue; WINQ = Work In Next Queue; LWKR = Last Workload Remaining.
***This manufacturing parameter can be changed only for orders not yet in production.
***One working shift is currently configured with a duration of 8 h. It can be customized according to the plant's requirements.

that end users can input within the platform. Additionally, it specifies the elements to which these design parameters are associated, such as resources, plants, processes, orders, and the overall internal supply chain. Furthermore, when a parameter lacks predefined options, end-users have the flexibility to input any value following the specified data type format. On the other hand, in instances where a predefined set of options is available, the data type column is denoted as not applicable (N/A). This is because users are not required to adhere to any specific data type, as it is already defined by the implemented option, and they can only select one of them.

As concern what-if analysis, a manufacturing scenario is defined by the specific combination of manufacturing parameters values that end-user's input into the platform. After accessing the platform, end-users can customize these parameters based on the options and data types outlined in Table 4. By adjusting values for the manufacturing parameters, end-users create different potential manufacturing configurations to be assessed against the set of pre-defined KPIs. Once the manufacturing parameter values have been set and the scenario is determined, before launching the simulation, end-users need to configure the simulation settings, according to their specific needs. Specifically, there are two key settings to be adjusted:

1. Simulation span: this setting specifies the number of working days to be simulated, starting from the simulation start date
2. Simulation speed: this setting determines the pace at which the simulation will run. End-users can choose from three options:
   a. Realtime simulation speed: the simulation runs in real-time, mirroring actual time progression
   b. Fast simulation speed: in this mode, 8 working hours are simulated in just 1 s
   c. Virtual simulation speed: this mode runs the simulation as quickly as the hardware allows, maximizing speed based on the platform's computational capabilities

Following the definition of the manufacturing scenario and the configuration of the simulation settings, the SBDT module initiates the simulation and computes the values of a predefined set of KPIs. These KPIs offer a quantitative evaluation of the scenario's performance, allowing end-users to compare alternative scenarios and choose the most suitable one. Table 5 summarizes the implemented KPIs within the platform, presenting their names and descriptions, along with the presentation format through which end users can acquire the information. Additionally, it specifies the elements to which these KPIs are associated, such as resources, plants, processes, orders, and the overall internal supply chain.

The KPIs are calculated using *objects method* implemented within the system class of the SBDT module. As examples, following the authors present the *object method* developed to calculate the KPIs average flow time and average tardiness at plant level. The method employs a *for-next* loop to calculate the total flow time and total tardiness. Specifically, it navigates through the order data table, iterating over each order to check its status. For completed orders, it increments the total flow time variable with the flow time of that specific order. Next, for each completed order, it checks whether the order was completed late. If an order was delayed, it increments a variable by the amount of tardiness of that specific order to compute the total tardiness. At the end of the *for-next* loop, it calculates the KPIs average flow time and average tardiness by using an *if-end* loop. If at least one order is completed, the average flow time and tardiness are computed by dividing the total values of flow time and tardiness, computed within the aforementioned *for next* loop, by the number of completed orders. Fig. 8 illustrates the programming code of the *object method* implemented to calculate the KPIs for average flow time and average tardiness.

Figs. 9 to 11 illustrate examples of graphs generated by the platform to visualize KPIs such as utilization levels, average and peak queue levels, and energy consumption for each resource.

The utilization level graph (Fig. 9) displays the usage of each plant resource throughout the simulation period (simulation span) chosen by the end-users. Specifically, for each resource, the graph indicates the percentage of time spent working, waiting for tasks, setup time, downtime due to failures, mandatory breaks, and stops for regular maintenance, thus providing an overall summary of the resource's

Table 5
KPIs.

KPI name	Description	Presentation Format	Resource	Process	Order	Plant	Supply Chain
Utilization Level	Level of usage of either a specific resource or the entire production plant within a predefined period set by the end-user	Graph	✓	–	–	✓	–
Average Queue Level	Average number of items to be processed and in queue either for a specific resource or at plant level within a predefined period set by the end-user	Graph	✓	–	–	✓	–
Peak Queue Level	Peak number of items to be processed and in queue either for a specific resource or at plant level within a predefined period set by the end-user	Graph	✓	–	–	✓	–
Energy Consumption	Amount of energy consumed at the resource, process, order, plant, and supply chain levels within a pre-defined period set by the end-user	Graph	✓	✓	✓	✓	✓
Gantt	Production schedule displaying the start and end times of orders at singe plant and overall supply chain level	Graph	–	–	–	✓	✓
Tardiness	Delay in fulfilling a customer order in comparison to the initially scheduled delivery date	Numerical values [days]	–	–	✓	–	–
Average Tardiness	Average delay in fulfilling customer orders compared to the initially scheduled delivery date, evaluated at both the plant and supply chain levels and within a pre-defined period set by the end-user	Numerical values [days]	–	–	–	✓	✓
Flow Time	Total duration required to complete a specific order	Numerical values [days]	–	–	✓	–	–
Average Flow Time	Average total duration required to complete customers' orders at both the plant and supply chain levels and within a pre-defined period set by the end-user	Numerical values [days]	–	–	–	✓	✓
Number of late orders	Total number of delayed orders in fulfilling the customer due date at plant and supply chain level	Numerical values [# orders]	–	–	–	✓	✓
Number of orders not completed	Total number of orders not yet completed at plant and supply chain level	Numerical values [# orders]	–	–	–	✓	✓
Number of completed orders	Total number of completed orders at plant and supply chain level	Numerical values [# orders]	–	–	–	✓	✓

```
-- Initialize counters for completed orders and late orders
count: integer
late_count: integer
late_count := 0
count := 0

-- Initialize variables to store total Flow Time and total Tardiness
var TotalFT, TotalTD: time

for var i := 1 to orders.ydim          -- Start a loop that iterates through all orders
    if orders["Status", i] = "Completed"      -- Check if the current order is completed
        count += 1                    -- Increment the count of completed orders
        TotalFT += orders["Flow Time", i]           -- Add the Flow Time of this order to the total
        TotalTD += orders["Tardiness", i]              -- Add the Tardiness of this order to the total
        if orders["Tardiness", i] > 0                -- Check if the order is late
           late_count += 1                          -- Increment the count of late orders
        end
    end
next

-- KPIs calculation
if count != 0                -- Check if any orders were completed
    AverageFlowTime := TotalFT / count              -- Calculate the Average Flow Time
    AverageTardiness := TotalTD / count                -- Calculate the Average Tardiness
end

NumberOfLateOrders := late_count                -- Assign the number of late orders to a variable
NotCompletedOrders := orders.ydim - count                -- Calculate the number of not completed orders
CompletedOrders := count                -- Assign the number of completed orders to a variable
```

Fig. 8. Average flow time and average tardiness *object method.*

performance.

The graph (Fig. 10) depicting the average and peak queue levels KPIs illustrates the number of items waiting in queue for each resource during the simulated period. This visualization helps identify bottlenecks and resource constraints by highlighting how often and how severely queues build up at different stages of the production process. Additionally, the energy consumption graph (Fig. 11) displays the energy usage of each resource, measured in kilowatt-hours (kWh), throughout the simulated working days. This graph allows end-users to evaluate the energy efficiency of resources, offering a clear understanding of how each resource contributes to the overall energy footprint of the production system.

It is noteworthy to note that this paper focuses on introducing the platform, providing an overview of its architecture, and detailing the specifics of the SBDT module through a case study to demonstrate its

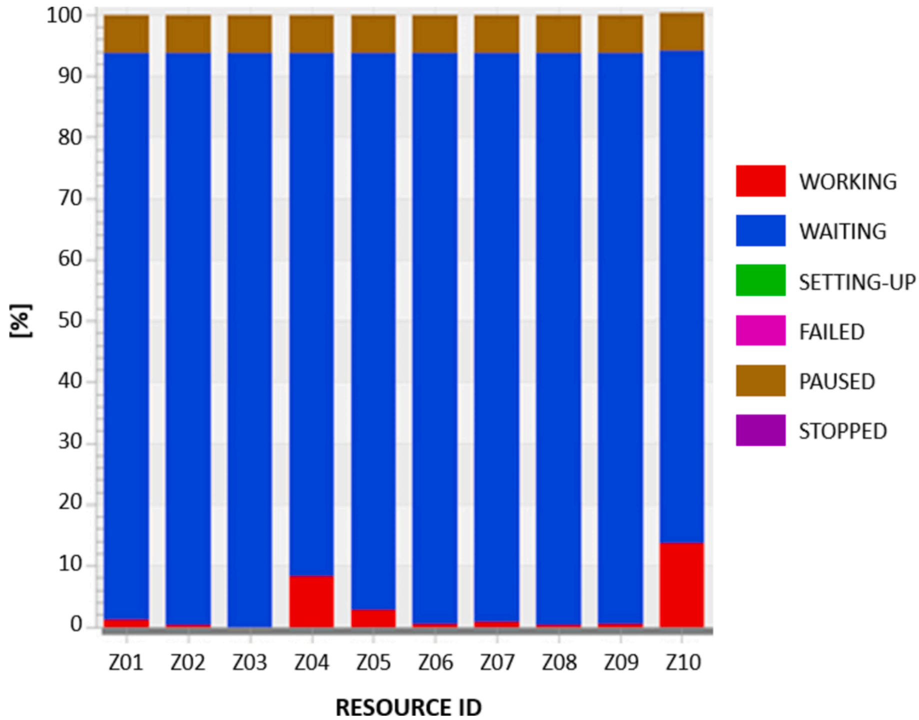

Fig. 9. Example of graph showing the resources utilization level.

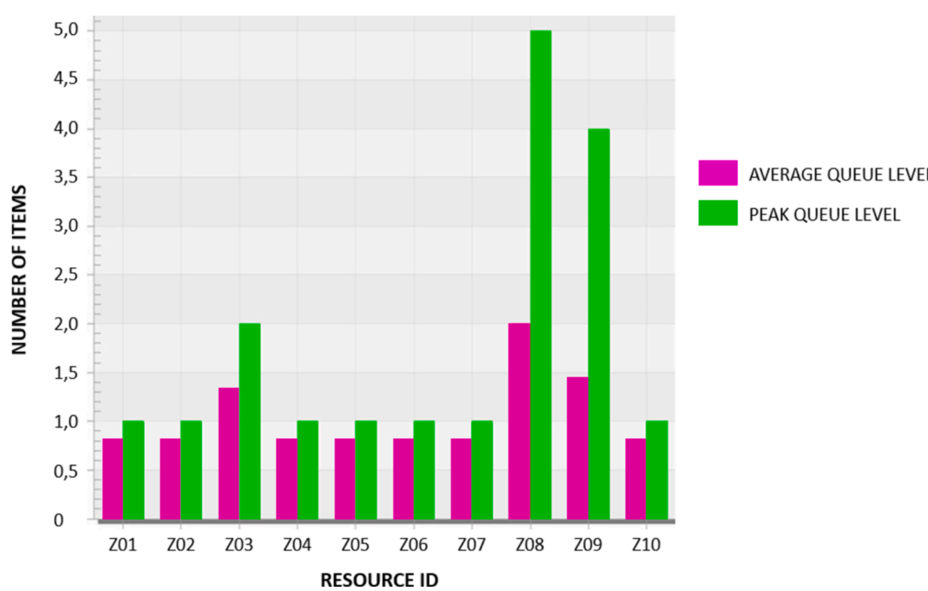

Fig. 10. Example of graph showing resources average and peak queue levels.

practical use. The detailed exploration of other platform modules, especially those associated with the EU one, including graphic user interfaces to input manufacturing parameters and display KPIs are deferred to a future research work.

6. Calculation

This section is aimed at explaining and discussing the application of the Multi Plant Digital Twin Production Planning Platform to a real case study. Practically, it is shown how the tool proposed in this paper can support corporate groups in improving their performance at two levels: (i) plant and (ii) ISC.

6.1. Case study: reference context

The case study addressed in this paper refers to a corporate group that operates in the Oil&Gas sector and manufactures different types of energy-oriented products. For privacy reasons, the name of the group it is not revealed. With a strong presence in the Italian market, it is a leading corporate group specialized in developing innovative solutions for energy production, transformation, and sustainability, leveraging its extensive expertise in engineering and technology to address the evolving needs of the customers. The Oil&Gas industry presents unique challenges for supply chain management due to the complex nature of its projects, the high degree of customization required, and the global scale of operations. This corporate group faces the critical challenge of

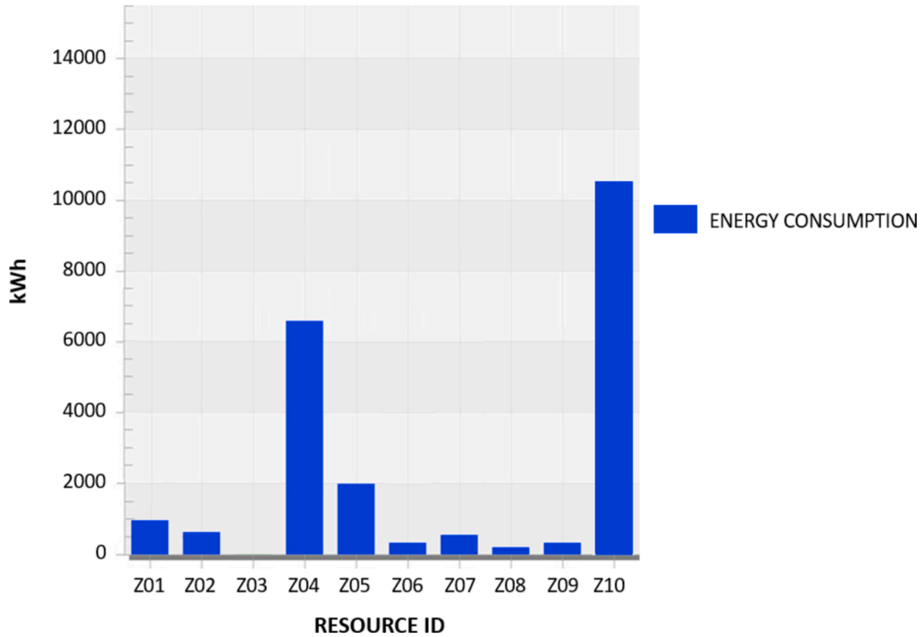

Fig. 11. Example of graph showing the resources energy consumption.

reducing lead times for orders that traverse multiple nodes in its ISC, while simultaneously striving to gain a more precise overview of their entire production process (i.e., supply chain visibility). The corporate group works according to a make-to-order (MTO) policy, and product customization is one of its main strengths.

6.2. *Case study: platform implementation*

This section details how the developed solution was implemented at the corporate group.

Definition of the goals

The authors of this manuscript conducted a period of research at the corporate group, during which they carried out structured interviews with the management team. Through these interviews, they identified the primary objectives to be achieved by implementing the platform previously introduced and described. The interviewed workers highlighted a significant challenge in effectively planning orders due to the complexity of the process. Each time a new customer order is received, there are existing orders already in progress, making it necessary to determine whether to uphold the current decisions or to reschedule entirely. These decisions become particularly difficult in the absence of a supportive planning tool. In this context, the need to improve KPIs such as Flow Time, Tardiness, and the total number of late orders was underscored. Given that these are high-value customized products, any delay in delivery incurs substantial penalties, related to each day of delay, as stipulated in the customer contracts.

Data collection, mapping of the production process and implementation

The corporate group produces different types of products. The focus

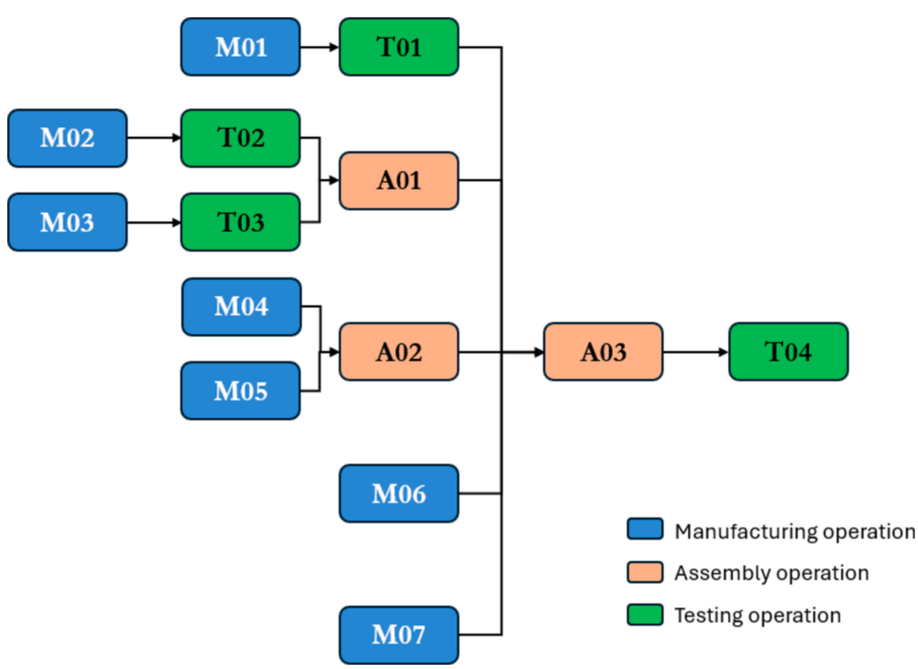

Fig. 12. Sequence of operations for turbine manufacturing.

of this paper is on a customizable turbine. After a series of visits to the corporate group, the data needed to model the entire production process were collected through specific interviews and company documents. As detailed in Fig. 12, some manufacturing, assembly, and testing operations are necessary to create the finished product. The customization opportunity granted to the customer does not influence whether to carry out the operations nor their sequence, but only their duration, which is determined by the product's technical specifications.

To perform all the aforementioned operations, the corporate group utilizes a network of five production plants (P), each capable of executing specific operations as outlined in Fig. 13. This figure illustrates the internal supply chain, which is organized into three tiers. It is important to underline that all plants can carry out also other operations, based on the available resources. However, those indicated are the only ones related to the product of interest.

As it can be noted, some operations can be conducted by one or more plants (i.e., A01 and A02 can be carried out by P3 or P4; M06 an M07 can be carried out by P1 or P2). Therefore, given a new order, the decision maker can choose which operations to assign to which plants, according to the 16 Supply Chain Configurations (SCCs) indicated in Table 6.

Once the objectives were defined, the company data collected, and the production process mapped, the authors proceeded with the implementation of the SBDT, following the simulation modelling approach presented in section 4.

6.3. Case study: results and discussion

This section presents and discusses the results obtained. The reference period, encompassing the entire year of 2023, was particularly intense for the corporate group, which had to manage over 50 new orders related to the turbine featured in this case study. Additionally, several orders received in the prior year were already scheduled across various plants. To support decision-making as effectively as possible, a dashboard with a set of indicators, was made available to the production planner. As an example, the Flow Time value for order O_030 according to the different SCCs is shown in Table 7, considering the FIFO load rule. Table 8 instead shows the Tardiness value for order O_022 based on the different SCCs, under the SPT rule.

Basically, every time a new order is received and accepted by the corporate group, SDBT simulates the assignment to all 16 supply chain configurations for 3 different load rules: FIFO, SPT, EDD. Therefore, 48 different scenarios are simulated. In this context, two KPIs are evaluated: Flow Time and Tardiness. Given this dashboard, the planner can choose the SCC for each order.

The platform also provides information about what happens to the rest of the orders already in progress, in case a new order is assigned to a certain supply chain configuration. In this way, the planner has two types of information. On the one hand, he/she has a view on the single new order and can evaluate the benefits of assigning it to one SCC rather than another. On the other hand, for each possible SCC, he/she can evaluate the impact that assigning the new order to a SCC has on all the other orders already in progress. Experimentation on the use of the platform continued throughout 2023. At the end of the year, to prove the validity of the proposed solution, the results obtained were compared with those that would have been obtained if the corporate group had continued to process orders as usual, i.e. view on the single plant more than the entire ISC and systematic use of the EDD rule. Table 9 shows that using the Simulation-Based DT platform has allowed to reduce the average Flow Time value by 7–8 % and average Tardiness by 30 %. In addition, a lower number of late orders has been recorded, which is an extremely significant aspect, considering that it could be necessary to pay expensive penalties in case of late delivery of the product.

In summary, the proposed platform provides significant support to effectively solve the problem of assigning new orders to the multiple plants of the ISC. This solution enables the simulation of numerous scenarios, whose goodness can be evaluated in a safe and controlled environment before making decisions in the real world.

7. Conclusions

The research activities begin with a review of the literature on the use of SBDTs in production planning and supply chain management, with a particular focus on the primary research approaches proposed for ISC management. This analysis reveals that, while several promising methodologies exist for using digital twins to support production planning in manufacturing and enhance material flow management in supply chains, there is a lack of digital twin-oriented models designed to support production activities across multiple plants within an ISC. To address this gap, the authors introduce a multi-plant production planning platform specifically developed to support production planning activities in ISCs. The platform allows end-users to evaluate alternative manufacturing scenarios, with each scenario defined by a unique combination of manufacturing parameter values which can be given in input to the platform. Upon accessing the platform, end-users can customize these parameters at both the plant and ISC levels, creating various potential configurations. These configurations are then simulated by the platform and assessed against a set of pre-defined KPIs, enabling users to identify and select the most suitable scenario. In this research, the authors first introduce the platform's overall architecture, including a brief description of its main modules. The focus then shifts to detailing the platform's core component, the SBDT module. Developed using Tecnomatix's Plant Simulation software, the module consists of three key

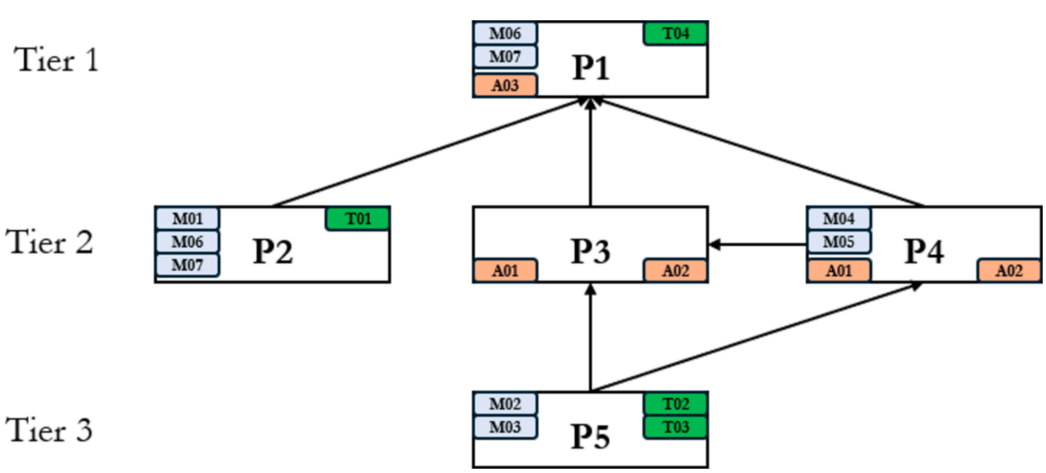

Fig. 13. Corporate group ISC.

Table 6
Possible SCCs, based on the operations assigned to the different plants.

SCC	M02	M03	T02	T03	M01	M06	M07	T01	A01	A02	M04	M05	A03	T04
SCC1	P5	P5	P5	P5	P2	P1	P1	P2	P3	P3	P4	P4	P1	P1
SCC2	P5	P5	P5	P5	P2	P1	P1	P2	P3	P4	P4	P4	P1	P1
SCC3	P5	P5	P5	P5	P2	P1	P1	P2	P4	P3	P4	P4	P1	P1
SCC4	P5	P5	P5	P5	P2	P1	P1	P2	P4	P4	P4	P4	P1	P1
SCC5	P5	P5	P5	P5	P2	P1	P2	P2	P3	P3	P4	P4	P1	P1
SCC6	P5	P5	P5	P5	P2	P1	P2	P2	P3	P4	P4	P4	P1	P1
SCC7	P5	P5	P5	P5	P2	P1	P2	P2	P4	P3	P4	P4	P1	P1
SCC8	P5	P5	P5	P5	P2	P1	P2	P2	P4	P4	P4	P4	P1	P1
SCC9	P5	P5	P5	P5	P2	P2	P1	P2	P3	P3	P4	P4	P1	P1
SCC10	P5	P5	P5	P5	P2	P2	P1	P2	P3	P4	P4	P4	P1	P1
SCC11	P5	P5	P5	P5	P2	P2	P1	P2	P4	P3	P4	P4	P1	P1
SCC12	P5	P5	P5	P5	P2	P2	P1	P2	P4	P4	P4	P4	P1	P1
SCC13	P5	P5	P5	P5	P2	P2	P2	P2	P3	P3	P4	P4	P1	P1
SCC14	P5	P5	P5	P5	P2	P2	P2	P2	P3	P4	P4	P4	P1	P1
SCC15	P5	P5	P5	P5	P2	P2	P2	P2	P4	P3	P4	P4	P1	P1
SCC16	P5	P5	P5	P5	P2	P2	P2	P2	P4	P4	P4	P4	P1	P1

Table 7
Flow Time value for order O_030, based on the different SCCs, under the FIFO load rule.

SCC	Flow Time [days]
SCC1	152
SCC2	156
SCC3	148
SCC4	147
SCC5	150
SCC6	140
SCC7	165
SCC8	142
SCC9	158
SCC10	150
SCC11	152
SCC12	152
SCC13	152
SCC14	153
SCC15	155
SCC16	160

Table 8
Tardiness value for order O_022, based on the different SCCs, under the SPT rule.

SCC	Tardiness [days]
SCC1	0
SCC2	0
SCC3	12
SCC4	8
SCC5	5
SCC6	4
SCC7	0
SCC8	0
SCC9	2
SCC10	3
SCC11	4
SCC12	5
SCC13	0
SCC14	0
SCC15	2
SCC16	11

classes (input class, workstation class, and system class). The interaction of these classes allows for the automatic reproduction of the production processes of the manufacturing plants. The paper details the main operational logic of each class, as well as how they interact with each other. Moreover, the authors also outline the key manufacturing parameters and the KPIs, explaining how the platform enables the generation and assessment of different manufacturing scenarios. The platform's effectiveness is demonstrated through a case study in the Oil & Gas manufacturing sector, illustrating how end-users can optimize ISC production planning. The study shows how the platform helped the corporate group to select a manufacturing scenario that resulted in improved average flow time and tardiness compared to a baseline scenario chosen without using the platform.

Table 9
Comparison between the two settings: use of the platform vs. non-use of the platform in 2023.

KPI	Use of the Platform	Non-use of the platform (baseline)
Average Flow Time [days]	145	157
Average Tardiness [days]	7	10
Number of Late Orders [units]	4	13

Regarding the implications of this research, the work has a significant impact on the ISC management framework, particularly in improving decision-making processes for production planning. By presenting a flexible and dynamic tool for analyzing the effects of various manufacturing parameters, this research provides several key benefits. The ability to simulate different manufacturing scenarios allows managers to allocate resources more effectively across multiple plants, improving overall efficiency in terms of under- or over-utilized resources. The platform enables real-time assessment of various production strategies, allowing corporate groups to quickly adapt to changes in market conditions, supply chain disruptions, or operational constraints. In addition, the platform's use of simulation-based digital twins enhances predictive analytics, allowing managers to anticipate potential bottlenecks, resource shortages, or inefficiencies before they occur, leading to proactive decision-making. Furthermore, by regularly evaluating different scenarios and their outcomes, best practices and areas for improvement can be identified, promoting a culture of continuous improvement and operational excellence. Finally, by providing a clear view of the potential impacts of different manufacturing scenarios, the platform minimizes the risk of costly errors or miscalculations, ensuring that decisions are data-driven and evidence-based.

However, despite its contributions and relevant implications, the platform also has some limitations that point to future research directions. Currently, the choice of the most suitable manufacturing scenario is left discretionarily to the end-user based on the KPI values, rather than being driven by automated optimization. Future research efforts are therefore needed for implementing optimization algorithm or artificial intelligence techniques for automating and optimizing the decision-making process. Additionally, the platform functioning depends on the use of the same corporate group information system by all the plants of the ISC. However, in a large corporate group, this is not always the case (e.g., following acquisitions of plants belonging to different groups). Therefore, further research efforts are required to enable communication between the platform and plants, regardless of the information systems they use. Furthermore, the platform's effective functioning depends on a well-defined, standardized, and structured data framework. This may limit its applicability in environments where data sources are heterogeneous or not standardized. Therefore, future developments could focus on incorporating capabilities that allow it to handle diverse data structures and formats. Finally, when multiple plants are capable of performing the same production step, the allocation of orders or multiple orders to these plants, which is currently determined by the end-users, evolves into a complex allocation problem. This challenge represents a key area for further investigation in future research studies.

CRediT authorship contribution statement

Antonio Cimino: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Francesco Longo:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Giovanni Mirabelli:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Vittorio Solina:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Pierpaolo Veltri:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

References

Aivaliotis, P., Georgoulias, K., & Chryssolouris, G. (2019). The use of Digital Twin for predictive maintenance in manufacturing. *International Journal of Computer Integrated Manufacturing, 32*(11), 1067–1080.

Alansaari, O., Yusoff, R., & Ismail, F. (2019). Exploring the link between employee commitment, recruitment process, and performance of internal supply chain of manufacturing firms in UAE. *Uncertain Supply Chain Management, 7*(2), 237–250. https://doi.org/10.5267/j.uscm.2018.10.002

Altekar, R. V. (2023). *Supply chain management: Concepts and cases* (2nd ed.). PHI Learning Pvt. Ltd.

Badakhshan, E., & Ball, P. (2023). Applying digital twins for inventory and cash management in supply chains under physical and financial disruptions. *International Journal of Production Research, 61*(15), 5094–5116. https://doi.org/10.1080/00207543.2022.2093682

Basnet, C. (2013). The measurement of internal supply chain integration. *Management Research Review, 36*(2), 153–172. https://doi.org/10.1108/01409171311292252

Binsfeld, T., & Gerlach, B. (2022). Quantifying the benefits of digital supply chain twins—A simulation study in organic food supply chains. *Logistics, 6*(3), 46. https://doi.org/10.3390/logistics6030046

Burgos, D., & Ivanov, D. (2021). Food retail supply chain resilience and the COVID-19 pandemic: A digital twin-based impact analysis and improvement directions. *Transportation Research Part E: Logistics and Transportation Review, 152*, Article 102412. https://doi.org/10.1016/j.tre.2021.102412

Catalano, M., Chiurco, A., Fusto, C., Gazzaneo, L., Longo, F., Mirabelli, G., Nicoletti, L., Solina, V., & Talarico, S. (2022). A digital twin-driven and conceptual framework for enabling extended reality applications: A case study of a brake discs manufacturer. *Procedia Computer Science, 200*, 1885–1893. https://doi.org/10.1016/j.procs.2022.01.389

Chibba, A., & Rundquist, J. (2009). Effective information flow in the internal supply chain: Results from a snowball method to map information flows. *Journal of Information & Knowledge Management, 8*(04), 331–343. https://doi.org/10.1142/S0219649209002439

Cimino, A., Gnoni, M. G., Longo, F., & Solina, V. (2023). Integrating multiple industry 4.0 approaches and tools in an interoperable platform for manufacturing SMEs. *Computers & Industrial Engineering, 186*, Article 109732. https://doi.org/10.1016/j.cie.2023.109732

Cimino, A., Longo, F., Mirabelli, G., & Solina, V. (2024). A cyclic and holistic methodology to exploit the Supply Chain Digital Twin concept towards a more resilient and sustainable future. *Cleaner Logistics and Supply Chain, 11*, Article 100154. https://doi.org/10.1016/j.clscn.2024.100154

Corsini, R. R., Costa, A., Fichera, S., & Framinan, J. M. (2024). Digital twin model with machine learning and optimization for resilient production–distribution systems under disruptions. *Computers & Industrial Engineering, 191*, Article 110145. https://doi.org/10.1016/j.cie.2024.110145

Elmasri, R., & Navathe, S. B. (2016). *Fundamentals of Database Systems* (7th ed.). Pearson.

Errandonea, I., Beltrán, S., & Arrizabalaga, S. (2020). Digital Twin for maintenance: A literature review. *Computers in Industry, 123*, Article 103316. https://doi.org/10.1016/j.compind.2020.103316

Giera, J., Kulińska, E., & Dendera-Gruszka, M. (2023). Analysis safety and quality of products for internal supply chains. In *International Conference on Intelligent Systems in Production Engineering and Maintenance* (pp. 380–392). Cham: Springer Nature Switzerland.

Guidani, B., Ronzoni, M., & Accorsi, R. (2024). Virtual agri-food supply chains: A holistic digital twin for sustainable food ecosystem design, control and transparency. *Sustainable Production and Consumption, 46*, 161–179.

Han, H., & Trimi, S. (2022). Towards a data science platform for improving SME collaboration through Industry 4.0 technologies. *Technological Forecasting and Social Change, 174*, Article 121242. https://doi.org/10.1016/j.techfore.2021.121242

Hu, B., Guo, H., Tao, X., & Zhang, Y. (2023). Construction of digital twin system for cold chain logistics stereo warehouse. *IEEE Access*. https://doi.org/10.1109/ACCESS.2023.3295819

Ivanov, A., & Jaff, T. (2017). Manufacturing lead time reduction and its effect on internal supply chain. In *Sustainable Design and Manufacturing 2017: Selected papers on Sustainable Design and Manufacturing* (pp. 398–407). Springer International Publishing.

Ivanov, D., & Dolgui, A. (2021). A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. *Production Planning & Control, 32*(9), 775–788. https://doi.org/10.1080/09537287.2020.1768450

Ivanov, D. (2022). Blackout and supply chains: Cross-structural ripple effect, performance, resilience and viability impact analysis. *Annals of Operations Research, 1–17*. https://doi.org/10.1007/s10479-022-04754-9

Kailash, S. H., R.K., & Goyal, S. (2018). Benchmarking framework for internal supply chain management: A case study for comparative analysis. *International Journal of Manufacturing Technology and Management, 32*(4–5), 412–429. https://doi.org/10.1504/IJMTM.2018.093357

Kailash, S.h., R.K., & Goyal, S. (2021). Weighted interpretive structural modelling approach for exploration of performance measures of benchmarking of internal supply chain management. *International journal of agile systems and management, 14*(1), 119–139. https://doi.org/10.1504/IJASM.2021.114911

Kamble, S. S., Gunasekaran, A., Parekh, H., Mani, V., Belhadi, A., & Sharma, R. (2022). Digital twin for sustainable manufacturing supply chains: Current trends, future perspectives, and an implementation framework. *Technological Forecasting and Social Change, 176*, Article 121448. https://doi.org/10.1016/j.techfore.2021.121448

Le, T. V., & Fan, R. (2023). Digital twins for logistics and supply chain systems: Literature review, conceptual framework, research potential, and practical challenges. *Computers & Industrial Engineering, 187*, Article 109768. https://doi.org/10.1016/j.cie.2023.109768

Lee, J., Azamfar, M., Singh, J., & Siahpour, S. (2020). Integration of digital twin and deep learning in cyber-physical systems: towards smart manufacturing. *IET Collaborative Intelligent Manufacturing, 2*(1), 34–36.

Leng, J., Wang, D., Shen, W., Li, X., Liu, Q., & Chen, X. (2021). Digital twins-based smart manufacturing system design in Industry 4.0: A review. *Journal of Manufacturing Systems, 60*, 119–137. https://doi.org/10.1016/j.jmsy.2021.05.011

Lim, K. Y. H., Zheng, P., & Chen, C. H. (2020). A state-of-the-art survey of Digital Twin: Techniques, engineering product lifecycle management and business innovation perspectives. *Journal of Intelligent Manufacturing, 31*, 1313–1337. https://doi.org/10.1007/s10845-019-01512-w

Lim, M. K., Li, Y., Wang, C., & Tseng, M. L. (2021). A literature review of blockchain technology applications in supply chains: A comprehensive analysis of themes, methodologies and industries. *Computers & industrial engineering, 154*, Article 107133. https://doi.org/10.1016/j.cie.2021.107133

Liu, X., Jiang, D., Tao, B., Xiang, F., Jiang, G., Sun, Y., & Li, G. (2023). A systematic review of digital twin about physical entities, virtual models, twin data, and applications. *Advanced Engineering Informatics, 55*, Article 101876. https://doi.org/10.1016/j.aei.2023.101876

Lo, C. K., Chen, C. H., & Zhong, R. Y. (2021). A review of digital twin in product design and development. *Advanced Engineering Informatics, 48*, Article 101297. https://doi.org/10.1016/j.aei.2021.101297

Longo, F., Mirabelli, G., Nicoletti, L., & Solina, V. (2022). An ontology-based, general-purpose and Industry 4.0-ready architecture for supporting the smart operator (Part I-Mixed reality case). *Journal of Manufacturing Systems, 64*, 594–612. https://doi.org/10.1016/j.jmsy.2022.08.002

Longo, F., Mirabelli, G., Padovano, A., & Solina, V. (2023). The Digital Supply Chain Twin paradigm for enhancing resilience and sustainability against COVID-like crises.

Procedia Computer Science, 217, 1940–1947. https://doi.org/10.1016/j.procs.2022.12.394

Lu, Y., Liu, C., Kevin, I., Wang, K., Huang, H., & Xu, X. (2020). Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues. *Robotics And Computer-Integrated Manufacturing, 61*, Article 101837. https://doi.org/10.1016/j.rcim.2019.101837

Liu, M., Fang, S., Dong, H., & Xu, C. (2021). Review of digital twin about concepts, technologies, and industrial applications. *Journal of Manufacturing Systems, 58*(Part B), 346–361. https://doi.org/10.1016/j.jmsy.2020.06.017

Ma, J., Chen, H., Zhang, Y., Guo, H., Ren, Y., Mo, R., & Liu, L. (2020). A digital twin-driven production management system for production workshop. *The International Journal of Advanced Manufacturing Technology, 110*, 1385–1397. https://doi.org/10.1007/s00170-020-05977-5

Maheshwari, P., Kamble, S., Belhadi, A., Venkatesh, M., & Abedin, M. Z. (2023). Digital twin-driven real-time planning, monitoring, and controlling in food supply chains. *Technological Forecasting and Social Change, 195*, 122799.

Mandolla, C., Petruzzelli, A. M., Percoco, G., & Urbinati, A. (2019). Building a digital twin for additive manufacturing through the exploitation of blockchain: A case analysis of the aircraft industry. *Computers in industry, 109*, 134–152. https://doi.org/10.1016/j.compind.2019.04.011

Marmolejo-Saucedo, J. A. (2022). Digital twin framework for large-scale optimization problems in supply chains: A case of packing problem. *Mobile Networks and Applications, 27*(5), 2198–2214. https://doi.org/10.1007/s11036-021-01856-9

Moshood, T. D., Nawanir, G., Sorooshian, S., & Okfalisa, O. (2021). Digital twins driven supply chain visibility within logistics: A new paradigm for future logistics. *Applied System Innovation, 4*(2), 29. https://doi.org/10.3390/asi4020029

Nakagawa, E. Y., Antonino, P. O., Schnicke, F., Capilla, R., Kuhn, T., & Liggesmeyer, P. (2021). Industry 4.0 reference architectures: State of the art and future trends. *Computers & Industrial Engineering, 156*, Article 107241. https://doi.org/10.1016/j.cie.2021.107241

Negri, E., Pandhare, V., Cattaneo, L., Singh, J., Macchi, M., & Lee, J. (2021). Field-synchronized Digital Twin framework for production scheduling with uncertainty. *Journal of Intelligent Manufacturing, 32*(4), 1207–1228. https://doi.org/10.1007/s10845-020-01685-9

Nguyen, T. N., Zeadally, S., & Vuduthala, A. B. (2021). Cyber-physical cloud manufacturing systems with digital twins. *IEEE Internet Computing, 26*(3), 15–21. https://doi.org/10.1109/MIC.2021.3058921

Nguyen, T., Duong, Q. H., Van Nguyen, T., Zhu, Y., & Zhou, L. (2022). Knowledge mapping of digital twin and physical internet in Supply Chain Management: A systematic literature review. *International Journal of Production Economics, 244*, Article 108381. https://doi.org/10.1016/j.ijpe.2021.108381

Oztemel, E., & Gursev, S. (2020). Literature review of Industry 4.0 and related technologies. *Journal of intelligent manufacturing, 31*(1), 127–182. https://doi.org/10.1007/s10845-018-1433-8

Park, K. T., Lee, J., Kim, H. J., & Noh, S. D. (2020). Digital twin-based cyber physical production system architectural framework for personalized production. *The International Journal of Advanced Manufacturing Technology, 106*, 1787–1810. https://doi.org/10.1007/s00170-019-04653-7

Perez, H. D., Wassick, J. M., & Grossmann, I. E. (2022). A digital twin framework for online optimization of supply chain business processes. *Computers & Chemical Engineering, 166*, Article 107972. https://doi.org/10.1016/j.compchemeng.2022.107972

Pisching, M. A., Pessoa, M. A., Junqueira, F., dos Santos Filho, D. J., & Miyagi, P. E. (2018). An architecture based on RAMI 4.0 to discover equipment to process operations required by products. *Computers & Industrial Engineering, 125*, 574–591. https://doi.org/10.1016/j.cie.2017.12.029

Pivoto, D. G., de Almeida, L. F., da Rosa Righi, R., Rodrigues, J. J., Lugli, A. B., & Alberti, A. M. (2021). Cyber-physical systems architectures for industrial internet of things applications in Industry 4.0: A literature review. *Journal of Manufacturing Systems, 58*(Part A), 176–192. https://doi.org/10.1016/j.jmsy.2020.11.017

Prakash, G. (2014). QoS in the internal supply chain: The next lever of competitive advantage and organisational performance. *Production Planning & Control, 25*(7), 572–591. https://doi.org/10.1080/09537287.2012.729101

Qi, Q., & Tao, F. (2018). Digital twin and big data towards smart manufacturing and industry 4.0: 360 degree comparison. *IEEE Access, 6*, 3585–3593. https://doi.org/10.1109/ACCESS.2018.2793265

Rebelo, R. M. L., Pereira, S. C. F., & Queiroz, M. M. (2022). The interplay between the Internet of things and supply chain management: Challenges and opportunities based on a systematic literature review. *Benchmarking: An International Journal, 29*(2), 683–711. https://doi.org/10.1108/BIJ-02-2021-0085

Schmidt, M., Maier, J. T., & Härtel, L. (2019). Data based root cause analysis for improving logistic key performance indicators of a company's internal supply chain. *Procedia CIRP, 86*, 276–281. https://doi.org/10.1016/j.procir.2020.01.023

Semeraro, C., Lezoche, M., Panetto, H., & Dassisti, M. (2021). Digital twin paradigm: A systematic literature review. *Computers in Industry, 130*, Article 103469. https://doi.org/10.1016/j.compind.2021.103469

Singh, G., Singh, S., Daultani, Y., & Chouhan, M. (2023). Measuring the influence of digital twins on the sustainability of manufacturing supply chain: A mediating role of supply chain resilience and performance. *Computers & Industrial Engineering, 186*, Article 109711. https://doi.org/10.1016/j.cie.2023.109711

Tao, F., Xiao, B., Qi, Q., Cheng, J., & Ji, P. (2022). Digital twin modeling. *Journal of Manufacturing Systems, 64*, 372–389. https://doi.org/10.1016/j.jmsy.2022.06.015

Turkulainen, V., Roh, J., Whipple, J. M., & Swink, M. (2017). Managing internal supply chain integration: Integration mechanisms and requirements. *Journal of Business Logistics, 38*(4), 290–309. https://doi.org/10.1111/jbl.12165

van Dinter, R., Tekinerdogan, B., & Catal, C. (2023). Reference architecture for digital twin-based predictive maintenance systems. *Computers & Industrial Engineering, 177*, Article 109099. https://doi.org/10.1016/j.cie.2023.109099

Wang, J., Xu, C., Zhang, J., & Zhong, R. (2022). Big data analytics for intelligent manufacturing systems: A review. *Journal of Manufacturing Systems, 62*, 738–752. https://doi.org/10.1016/j.jmsy.2021.03.005

Zhuang, C., Liu, J., & Xiong, H. (2018). Digital twin-based smart production management and control framework for the complex product assembly shop-floor. *The International Journal Of Advanced Manufacturing Technology, 96*, 1149–1163. https://doi.org/10.1007/s00170-018-1617-6