Computers & Industrial Engineering 198 (2024) 110616

Contents lists available at ScienceDirect

Computers & Industrial Engineering

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

Transitioning trends into action: A simulation-based Digital Twin architecture for enhanced strategic and operational decision-making

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ARTICLE INFO

Keywords:
Simulation
Digital Twin
Manufacturing trending technologies
Strategic and operational decision-making
Robotics

ABSTRACT

In the dynamic realm of nowadays manufacturing, integrating digital technologies has become paramount for enhancing operational efficiency and decision-making processes. This article presents a novel system architecture that integrates a Simulation-based Digital Twin (DT) with emerging trends in manufacturing to enhance decision-making, accompanied by a detailed technical approach encompassing protocols and technologies for each component. The DT leverages advanced simulation techniques to model, monitor, and optimize production processes in real time, facilitating both strategic and operational decision-making. Complementing the DT, trending technologies such as artificial intelligence, additive manufacturing, collaborative robots, autonomous vehicles, and connectivity advancements are strategically integrated to enhance operational efficiency and facilitate the adoption of the Manufacturing as a Service (MaaS) paradigm. A case study within a MaaS supplier context, deployed in an industrial laboratory with advanced robotic systems, demonstrates the practical application of optimizing dynamic job-shop configurations using Simulation-based DT, showcasing strategies to improve operational efficiency and resource utilization. The results of the industrial experiment were highly encouraging, underscoring the potential for extension to more intricate industrial systems, with particular emphasis on incorporating sustainability and remanufacturing principles.

1. Introduction

Over the past few years, there has been a surge of interest in Digital Twins (DTs), recognized as a revolutionary method for modelling, supervising, and enhancing intricate systems spanning diverse sectors such as manufacturing, healthcare, transportation, and urban development. Fundamentally, a DT embodies a virtual rendition of a tangible system or entity, integrated with sensors, data analysis tools, and simulation functionalities to replicate its real-world counterpart within a digital realm (Attaran et al., 2023). In navigating the landscape of digital replication, it is crucial to delineate between three fundamental concepts: the Digital Model (DM), the Digital Shadow (DS), and the DT. The DM is a foundational framework, offering a virtual representation of physical entities for visualization and analysis. Contrarily, the DS encompasses the comprehensive data footprint generated by the interaction of these entities in the digital realm, enabling real-time insights and predictive analytics. Finally, the DT merges the DM with the dynamic data streams of the DS, creating a synchronized, real-time replica that facilitates decision-making processes and optimization strategies across various domains (Attaran et al., 2023; Bogdán et al., 2023). By harnessing data from sensors, Internet of Things (IoT) devices, and other sources, DTs replicate the behaviour and performance of their physical counterparts with unprecedented fidelity. This synchronization empowers stakeholders with actionable insights, predictive analytics, and scenario simulations, facilitating informed decision-making and proactive operational strategies. Moreover, DTs facilitate the integration of disparate data sources and enable cross-functional collaboration, fostering agility and innovation throughout the product lifecycle. In essence, DTs serve as enablers of efficiency, agility, and intelligence in the Industry 4.0 landscape, driving transformative changes across manufacturing, supply chain management, and beyond (Shao et al., 2019; Stavropoulos, 2022).

1.1. Simulation-based digital twins

Under the scope of Industry 4.0, simulation plays a pivotal role within DT frameworks, serving as the bridge between the physical and digital domains. Through simulation, the behaviour and performance of the physical system can be accurately replicated and analysed within the DT environment. This enables stakeholders to conduct virtual experiments, test alternative scenarios, and optimize parameters without disrupting the actual operations of the physical system (Phanden et al.,

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https://doi.org/10.1016/j.cie.2024.110616

2021). Simulation techniques encompass various methodologies, including discrete event simulation, agent-based modelling, and system dynamics, each tailored to specific types of systems and phenomena (Sumari et al., 2013). By leveraging simulation within DT architectures, organizations can gain valuable insights into the behaviour of complex systems, identify inefficiencies or bottlenecks, and devise strategies for improvement and optimization. Related to simulation and for strategic and operational decision-making, optimization techniques stand as indispensable for driving efficiency, adaptability, and competitiveness in modern manufacturing environments. In the era of interconnectedness and digitalization, the need for optimization techniques has become more pronounced than ever before. Optimization methodologies, ranging from traditional mathematical programming to advanced evolutionary algorithms (heuristics and metaheuristics), are pivotal in orchestrating the intricate interplay of factors within manufacturing systems, optimizing production processes, and maximizing resource utilization (Ansari & Daxini, 2022; Mital & Mohan, 1995). By harnessing the power of optimization within the framework of Industry 4.0, manufacturers can leverage intelligence-driven insights to drive continuous improvement, enhance operational efficiency, and adapt to dynamic market demands with agility and precision.

1.2. The role of new emerging technologies

Complementary to manufacturing systems optimization, new technologies (hardware and software) and methods appear to empower DTs regarding customization, connectivity, interaction with humans, and interoperability. Related to these, trend topics such as Artificial Intelligence (AI), Collaborative and Mobile Robots, and Additive Manufacturing (AM) appear. Several examples of DTs appear in the literature, incorporating and studying the advantages of these new technologies (Yao et al., 2023).

Kumar and Agrawal also depict these and other technological advances (Cloud Computing, Big Data Analysis, Cybersecurity, Augmented Reality) related to industrial DTs and summarize their role, benefits, and challenges of each of them (Kumar & Agrawal, 2024). Baratta et al. examine the potential of DTs to enhance Human-Robot Collaboration (HRC) in manufacturing systems, with a particular focus on how DTs can provide a realistic simulation environment for testing and optimizing collaboration strategies (Baratta et al., 2024). Also, the emergence of manufacturing services, like Manufacturing-as-a-Service (MaaS), has become increasingly popular. These paradigms aim to revolutionize product development and workstation setups by introducing pay-as-you-use models while maintaining product quality and production speed. By integrating with DT systems, shop floor workstations can adapt to produce multiple products efficiently, and existing layouts can be optimized or reconfigured as needed. Researchers can explore decision support algorithms and methodologies, such as knowledge graphs and reasoning software, to improve recommendations. Additionally, incorporating HRC techniques into DT systems can enhance workforce monitoring and allow operators to work alongside versatile machines like Cobots, boosting efficiency and flexibility. As these techniques evolve to ensure effective and safe working environments, DT systems play a crucial role in enhancing connectivity and providing decision support for workstation configuration and resource allocation to mitigate disruptions (Lim et al., 2021). The incorporation of circular and sustainable factors in this scope is also fundamental. Reliable information is crucial for the circular flow of materials and products, impacting processes like reconditioning and supply chain management. Concepts like DTs facilitate decentralized access to relevant information, ensuring it reaches the appropriate parties when needed. Digital Twins are anticipated to become increasingly significant, aiding in effectively executing circular economy strategies (Preut et al., 2021).

The present work introduces a novel approach that leverages a Simulation-based Digital Twin architecture to enhance strategic and operational decision-making in manufacturing environments. The proposed solution uses a simulation model developed with the FlexSim simulation engine to simulate and retrieve performance indicators based on optimized decisions. The model is also connected to an IoT platform in real-time, permitting start simulating with a snapshot of the current system.

The remainder of the article is organized as follows. Section 2 discusses the existing literature on industrial applications of Digital Twins systems. Section 3 presents the Simulation-based Digital Twin architecture describing the relation with trending topics and a technical approach regarding protocols and technology. Section 4 describes the industrial experiment, comprising the hardware related to the industry case study, used for the methodology feasibility analysis. Later in this chapter, the simulation–optimization results are also presented and analysed. Finally, Section 5 outlines the findings, comprising functionalities that may be useful to add to the system.

2. Related work

This chapter aims to provide a comprehensive overview of related work in the field of coupling emerging technologies for improving dynamic systems, with a particular focus on manufacturing applications. By examining existing literature, methodologies, and technological advancements, this chapter seeks to identify key trends, gaps, and opportunities in integrating simulation techniques within DT architectures. Through an in-depth analysis of relevant research contributions, theoretical frameworks, and practical implementations, this chapter sets the stage for exploring novel approaches and methodologies for enhancing decision-making, operational efficiency, and adaptability in dynamic manufacturing environments.

2.1. Architectures and simulation-based digital twins

Regarding DTs, new architectures arise very often in the literature. Van Dinter et al. contribute with their architecture modelling of DT-based predictive maintenance systems using multiple architecture views and applied to three industrial cases (van Dinter et al., 2023). Another research work conducted by Qian et al. (2022) demonstrates the role of DT architectures for Smart Transportation, Smart Grid, Smart Cities and Smart Manufacturing. They also describe the main challenges of integrating DTs into Cyber-Physical Systems (CPS) related to Data Science, Optimization and Security and Privacy. In this work, a reference to Čolaković and Hadžialić work (Čolaković & Hadžialić, 2018) regarding the challenges for the IoT systems architecture was made. The detailed technical description and explanation of the data representation and communication protocols were fundamental for the present research. Related to the production field of DTs in CPS, Talkhestani et al. (2019) explored three key characteristics: synchronization with the physical asset, co-simulation capability, and active data acquisition. Based on these characteristics, the authors proposed distinct architectures for DTs and Intelligent DTs, in this last case incorporating AI as a central feature to enable autonomy.

Redelinghuys et al. present a six-layer architecture and a manufacturing case study implementation. The six-layer DT architecture serves as a comprehensive framework for facilitating communication between the physical and the virtual systems, as well as between the DT and external entities. This architecture was designed to accommodate diverse vendor products within the physical twin while minimizing the use of proprietary or custom-developed elements to reduce development and support costs. It emphasizes using open or vendor-neutral communication formats across the layers to ensure interoperability. The architecture has six layers, each serving a specific function in the DT ecosystem. Layers 1 and 2 represent the physical twin, while Layer 3 comprises a local data repository for obtaining sensor values from controllers in Layer 2. Layer 4 functions as a custom-developed IoT Gateway or data-to-information converter. Layers 5 and 6 encompass a cloud repository and emulation and simulation tools, respectively. The flow of data and information between the layers illustrates data transmission from the physical system to the cloud repository, where it is stored and made accessible in cyberspace. The research also showed how to use an IoT Gateway and deploy the DT in an industrial experiment using OPC-UA servers and cloud-based database services (Redelinghuys et al., 2020).

The importance of simulation on DTs' architecture is evident. Several studies have been presented to explore simulation-based DTs applied to different industrial contexts and related problems. Coelho et al. explored the foundation for implementing a DT for in-house logistics systems, integrating real-time information, intelligent autonomous vehicles, and flexible operational environments. Leveraging simulation software Simio, a decision support tool for in-house logistics was developed, validated, and applied in real-world company settings (Coelho et al., 2021). Another research work, presented by Krenczyk and Paprocka, proposes the integration of discrete simulations, AI methods, and probability theory to enhance flexibility in production systems, mainly focusing on smart factory operations. It introduces a comprehensive framework including data exchange architecture, simulation creation, performance optimization, and predictive analysis of production processes. A DT approach is applied to a hybrid flow shop in the automotive industry, with a case study demonstrating the effectiveness of the Ant Colony Optimization (ACO) algorithm for multi-criteria scheduling problems using the simulation software FlexSim. ACO is compared to other optimization methods, such as the immune and genetic algorithms, showing superior performance in achieving production plans with minimal delays and maximum resource utilization. Additionally, the paper emphasizes predicting reliability parameters for limited resources within the DT, ensuring stable deadlines for production tasks (Krenczyk & Paprocka, 2023).

2.2. The influence of new machine learning methods

Machine Learning (ML) also appears more and more for industrial applications. For example, Ferreira et al. compare supervised and unsupervised ML methods using images for defect detection in the context of industrial textile production (Ferreira et al., 2024). Applied to DTs, Santos et al. present a Deep Reinforcement Learning (DRL) based approach to balance multi-manned assembly lines dynamically. By embedding DRL in a close-to-reality training environment simulated using discrete event simulation and FlexSim, the proposed methodology offers a more effective decision-making process for assembly line management. Preliminary results from testing the approach on a real-world instance demonstrate comparable solutions to those obtained using optimization-based strategies (Santos et al., 2024a).

2.3. Research gaps and challenges

Building upon the related work conducted in the field of integrating emerging technologies and simulation within DT architectures for manufacturing, it is vital to identify potential gaps in the existing literature. Liu et al. highlight that there are various ways to implement DTs, and not all of them may be recognized as genuine DTs by certain experts. The main limitation is that the requirements and design choices depend heavily on the specific use case. Additionally, the choice of functionalities is closely tied to the technical setup, as some features require others to work effectively. For example, an automatic decision-making module would be ineffective without automated integration between the virtual and physical components (Liu et al., 2021).

A research work conducted by Kritzinger et al. (2018) highlights the following gaps related with DTs:

1. Limited exploration of specific manufacturing sectors;
2. Insufficient coverage of emerging technologies such as AI or IoT and their integration with simulation;
3. Lack of real-world case studies showing successful applications of simulation and DT in manufacturing;
4. Scarcity of research on decision-making methodologies within DT architectures, like optimization algorithms or predictive analytics.

Kumar and Agrawal (2024) also enumerate the existing challenges related to industrial DTs. Among them, four are highly related to the context of our work, namely:

- **Uniform synchronization** - Two-way synchronization requires significant resources and fast IoT connections to ensure reliable data exchange, maintaining data integrity and smooth communication between IoT devices and backend systems.
- **Global optimization** - Joint optimization of several sources contributes to accurate changes in the physical system. The challenge is related to the development of advanced modelling and optimization techniques in specific contexts.
- **Scalability** - Sectors like logistics and supply chain networks need DT solutions that can scale effectively to handle expansive and constantly changing environments. Managing and processing massive volumes of data, supporting various use cases, and responding to shifting business demands present significant scalability challenges.
- **Interoperability** - Integrating DT with various systems, such as inventory management, product lifecycle management, and enterprise resource planning, involves overcoming compatibility issues and ensuring smooth data exchange.

Among the advancements in manufacturing technology, integrating simulation tools with IoT platforms emerges as a critical frontier. However, despite notable progress, a significant gap persists in seamlessly incorporating real-time data from IoT sources into simulation models (Tan et al., 2019). This gap underscores the need for further research and innovation to address the challenges associated with data acquisition, conversion, and integration in this context.

Addressing the aforementioned gaps could enhance the authors' understanding of how these technologies improve decision-making and manufacturing efficiency, particularly by using simulation connected in real-time with promising advanced technologies.

The authors of the presented work previously created a DT-based solution for real-time monitoring and optimization of processes, including AM technologies and automated vehicles. The work involved a detailed simulation model and an industrial experiment focusing on an AM cell. The results validated the strategy of integration, communication, and data exchange. The current work suggests an improved approach for production sequencing and balancing using recent systems (Santos et al., 2024b).

To the best of the authors' knowledge and based on the literature reviewed, the proposed work introduces a multi-level DT architecture incorporating new technologies (advanced software and hardware), taking advantage of different data sources, controlling and synchronizing different solutions such as simulation, robotics, humans, AM cells and permitting scalability and improving systems performance in each level of decision-making. An industrial experiment with the aforementioned equipment and functionalities was designed to confirm and validate the novelty of the proposed approach.

3. System architecture

This chapter delves into the details of a comprehensive system architecture that leverages the power of simulation within DT frameworks to enhance decision-making, operational efficiency, and adaptability across dynamic systems, particularly within the domains of manufacturing and logistics. Through the integration of emerging technologies and advanced methodologies, this architecture not only provides real-time support for operational decision-making but also fosters innovation and resilience in the face of evolving demands and uncertainties. After the system architecture description, technical details on the main components are provided.

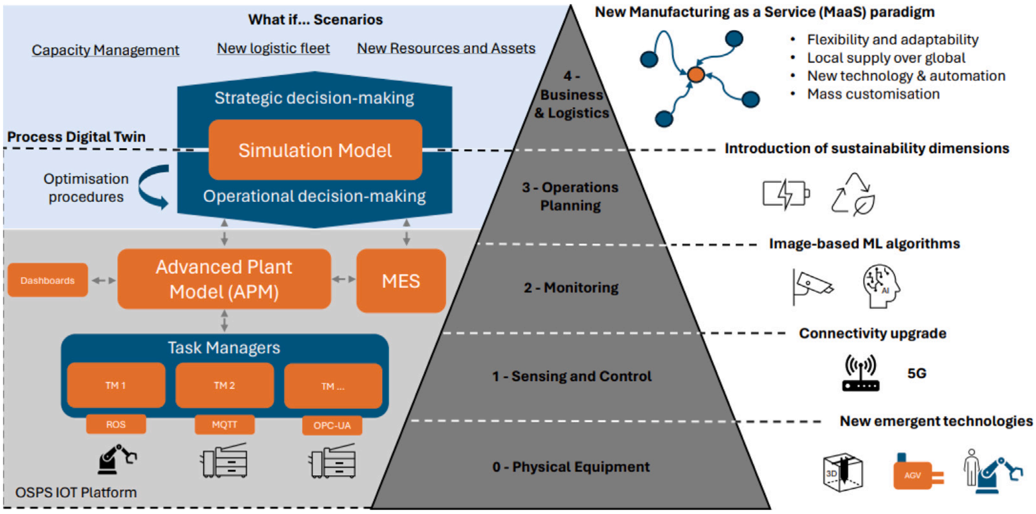

Fig. 1. System architecture diagram.

3.1. Integration of trending technologies in a simulation-based digital twin architecture

The system architecture of the proposed work is presented in Fig. 1. This novel architecture illustrates two key sides: Simulation-based DT architecture components and the trending technologies from the shop floor to organization business and logistics. Positioned at the centre, the ISA-95 pyramid (based on Scholten, 2007) serves as a framework for integrating enterprise and control systems, encompassing various levels of manufacturing operations. On the right side, trending technologies are incorporated, reflecting the latest advancements in areas such as ML, AM, collaborative robots, autonomous vehicles, connectivity advances (5G), and new updates on operation and business strategies related with the circular economy, sustainability and the adoption of MaaS paradigm. These technologies are strategically aligned with the ISA-95 pyramid to enhance operational efficiency and connectivity across different levels of the manufacturing hierarchy. On the left side, the I4.0 Simulation-based DT architecture is depicted, representing a virtual replica of the physical manufacturing environment. This DT leverages simulation techniques to model, monitor, and optimize manufacturing processes in real-time, facilitating resource optimization and decision support.

3.1.1. Strategic decision-making

At the cornerstone of dynamic systems optimization lies the ability to make informed strategic decisions. Simulation is a formidable tool in this regard, offering stakeholders invaluable insights into potential outcomes and trade-offs associated with various strategic choices. By simulating different scenarios and analysing key performance indicators (KPIs), decision-makers can effectively evaluate the impact of different investment strategies on equipment, technology, and processes. For instance, simulation can elucidate the implications of investing in advanced manufacturing technologies versus traditional methods, thereby guiding strategic investments to maximize long-term competitiveness and performance. Embracing the paradigm of MaaS, the DT architecture enables dynamic adaptation and customization of production processes to meet diverse local Supply Chain (SC) needs. Leveraging plug-and-play functionality and in relation to lower levels of the pyramid, the architecture dynamically orchestrates production activities, optimizing resource utilization and minimizing lead times. Furthermore, seamless integration with automated warehouses and logistics systems ensures efficient material flow and inventory management, thereby enhancing overall supply chain performance and resilience. Despite not being represented in the architecture, the Simulation Model component could also be integrated with an Enterprise Resource Planning (ERP) solution to connect, exchange data, and translate business and MaaS strategies to the simulation of what-if scenarios.

3.1.2. Operational decision-making

The proposed architecture also integrates simulation seamlessly into DT frameworks to provide real-time support for operational decision-making. Embedded or external optimization procedures (based on AI or mathematical exact methods) are also fundamental to obtaining an intelligent and automatic decision-making system. The architecture leverages AI and optimization methodologies to enhance decision-making and resource allocation. By integrating optimization techniques into the simulation model, organizations can optimize production schedules, minimize production costs, and maximize resource utilization. Towards fostering sustainability and circularity, the architecture also incorporates provisions for monitoring and defect detection using AI image-based algorithms. By leveraging AI-powered vision systems, organizations can detect and rectify defects in real-time, thereby minimizing waste and optimizing resource utilization. Furthermore, integrating remanufacturing principles into the production process enables a waste minimization strategy, promoting a closed-loop approach to manufacturing and enhancing sustainability. The proposed simulation model component was developed to further consider remanufacturing strategies and is essential to calculate the cost-benefit trade-off to the decision planner.

One of the most critical components to achieving efficient operational decision-making is the Advanced Plant Model (APM), a dynamic representation of the physical production environment augmented with simulation capabilities. The APM continuously monitors and controls human-operated and robotic production systems, enabling proactive decision-making and optimization. Leveraging an IoT platform based on the Open Scalable Production System (OSPS) framework, the architecture facilitates data exchange and communication between heterogeneous systems, ensuring interoperability and real-time decision support across the entire production ecosystem (Arrais et al., 2019; Santos et al., 2021). The integration with the Manufacturing Execution System (MES) is also fundamental to support APM in monitoring and tracking the real-time execution of production orders of a generated production schedule.

3.1.3. Introducing new technology in the shop floor

The architecture embraces the integration of cutting-edge technologies to enhance operational efficiency and agility. Mobile Autonomous Robotic systems, including Autonomous Mobile Robots (AMRs) and

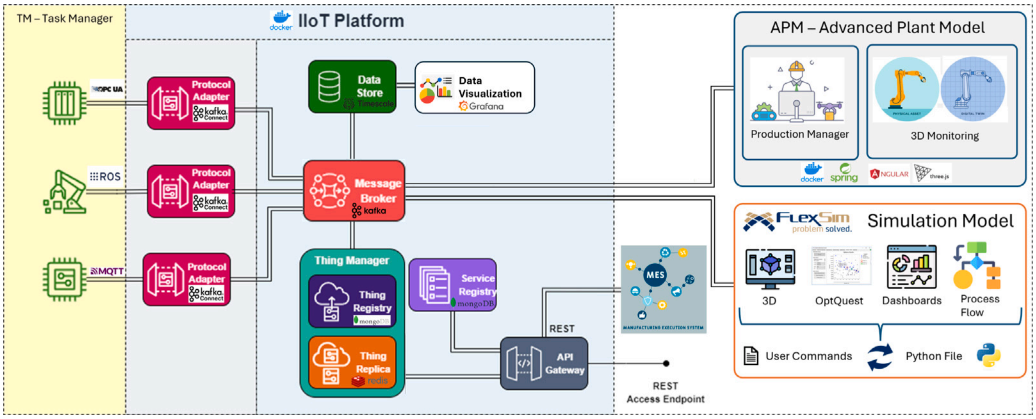

Fig. 2. Digital Twin main components.

Automated Guided Vehicles (AGVs), which can be coupled with a robotic manipulator, play a pivotal role in streamlining material handling and logistics operations. These systems have advanced sensors and control mechanisms, enabling autonomous navigation and task execution within dynamic production environments. By seamlessly integrating these technologies into the DT architecture, organizations can achieve higher levels of flexibility, responsiveness, and productivity in their operations. Recognizing the transformative potential of AM, the architecture incorporates capabilities such as 3D printing to enable on-demand production and customization. By integrating 3D printers into the production workflow, organizations can rapidly prototype new designs, produce complex geometries, and respond swiftly to changing market demands. The architecture considers the Task Manager module for all these new technologies, which incorporates several task managers for each component and correspondent connectors and protocols (ROS, OPC-UA, MQTT, among others). New connectivity systems and technologies related to 5G are also fundamental to guarantee faster data transfer and real-time communication to enhance automation, robotics, and overall manufacturing efficiency.

In summary, the proposed system architecture represents a holistic approach to leveraging simulation within DT frameworks for enhancing decision-making, operational efficiency, and adaptability across dynamic systems. By integrating emerging technologies, AI, and optimization methodologies, organizations can unlock new opportunities for innovation and competitiveness while simultaneously fostering sustainability and resilience in an ever-evolving business landscape. Next, technical explanations of each component of the system architecture are provided.

3.2. Technical approach

Following the gaps identified in the related work chapter, Fig. 2 presents the leading software, technologies and detailed information of each service of the DT architecture, serving as a basis for other research studies.

3.2.1. IOT platform

The IoT platform is a software solution that facilitates device connectivity and data management. It acts as a mediator, enabling devices from various manufacturers to communicate with each other and share data securely. This ensures interoperability, which is a key factor for the success of IoT implementations. The majority of information flow goes through the IoT platform, limiting direct interaction between systems and applications. A microservices-based architecture was utilized to implement the solution. This architectural style involves developing an application structured as a set of services that run independently and are easily scalable. Microservices are instantiated using Docker containers, where each microservice runs in isolation from the others.

Among the various microservices, the Message Broker stands out as it acts as an intermediary that processes communication between two or more applications. It is responsible for receiving messages from multiple sources (Publishers), determining their destination, and directing them to the correct channel (Subscribers). The Protocol Adapter is a component that supports devices (Task Manager) lacking connectivity with the protocols natively supported by the Message Broker. In this manner, devices utilizing other protocols communicate with this gateway, which in turn performs a bi-directional translation of requests to one of the protocols supported by the Message Broker. Each Protocol Adapter ensures interoperability between the protocols natively supported by the message broker and an additional protocol such as OPC-UA or ROS. It was developed using a connector system to facilitate the implementation of additional protocols, requiring only the implementation of a connector for the desired protocol.

Before accessing the IoT platform, resources (sensors, industrial equipment) need to be registered. The Thing Registry is responsible for managing and characterizing the information associated with each resource. The Thing Replica maintains a digital copy of all devices registered on the platform. The information stored includes the current values of readings from various sensors, the device's status, and other relevant information that the devices wish to make available on the platform. Additionally, a REST API (API Gateway) is provided, allowing external systems to interact with the various devices through their digital replicas, thereby avoiding direct connections to the physical devices.

Through the Service Registry, it is possible to register external services within the platform, making them available in the service catalogue and capable of being invoked as if they were an integral part of it. In a microservices architecture, an API Gateway enables microservices to be easily consumed by applications or other services by exposing a single endpoint for these applications. In the case of the IoT platform, this concept extends to external services registered in the Service Registry. Thus, the gateway centralizes the invocation not only of the microservices that are part of the platform but also of all externally registered services through the Service Registry.

The Data Store contains the historical database that stores all events published on the message broker. It provides a centralized repository for storing and managing historical data, enabling various operational and analytical functionalities crucial for the efficient operation and management of industrial systems. For instance, the data visualization component enables the intuitive creation of dashboards based on the information available in the platform. It allows, for example, the creation of dashboards for monitoring sensors or production indicators.

3.2.2. Advanced plant model

The APM provides a real-time digital representation of the current state of the factory floor, encompassing semantic and geometric information. Manufacturing operators can leverage the information held in the APM, which includes representations of workers, resources such as mobile robots, and equipment such as workstations and logistics supermarkets. The dynamic relationships among all objects can be depicted by the production schedule generated by the MES. To ensure the digital model remains synchronized with physical reality, real-time data is captured from the shop floor. This allows the APM to maintain and continuously enhance its digital representation using data generated by active objects in the manufacturing area.

The APM also incorporates a module called the Production Manager, responsible for overseeing a fleet of robotic manipulators and other industrial equipment. It ensures control over the allocation and execution of tasks on resources while monitoring the production plan.

3.2.3. *Simulation model and integration with optimization*

Focusing on the simulation model and optimization procedures, tools such as FlexSim,[1] and OptQuest,[2] provide powerful capabilities for simulating complex production environments and optimizing operational workflows, enabling organizations to achieve higher levels of efficiency and competitiveness. The adopted simulation model will be used to show the potential of dealing with uncertainties and defects on the production line, loading real-time data and assisting in making decisions about using new technologies to address any bottlenecks or unwanted KPIs.

The model was implemented using the FlexSim software 2023. It provides a Graphical User Interface (GUI) for building simulation models. Users may drag and drop items into the desired location to establish the behaviours and interactions of humans, machines, conveyors, robots, and resources. It uses Discrete Event Simulation (DES) approaches, in which the simulated system alters at discrete times, usually in reaction to events like arrivals, departures, or status changes. FlexSim's 3D visualization tools are one of its best qualities. Users can build intricate 3D models of their systems, enabling immersive research and analysis. Using multiple dashboards facilitates efficient communication of findings and the understanding of complicated processes.

Users can conduct experiments by running simulations with different scenarios and parameters to evaluate the impact of changes or test alternative strategies. FlexSim supports optimization techniques to help users find the best configurations or policies for their systems. Furthermore, the model seamlessly integrates real-time connections with external data sources, enabling dynamic decision-making in response to environmental changes. It was specifically developed to incorporate strategic and operational decisions. It can be used not only to evaluate the advantages of acquiring new equipment but also to take a data snapshot (Work-In-Process) of the current real-time production and adapt a production integrated with APM and MES for the actual case. In addition, Optquest is also integrated to efficiently reorganize the order sequence in job scheduling problems, with the main objective of minimizing the makespan.

Simulation model main components

The essential components of the suggested architecture for a simulation base model are shown in Fig. 2, along with how it links to a wrapper service developed using Python programming language. The purpose of each of the parts of the system that make up the simulation model can be described as follows:

- **Main dashboard** controls the entire simulation model, capable of displaying information in real-time and internally simulated information and graphics that function as analysis tools. Multiple buttons were configured using FlexSim's internal programming language (FlexScript) to request the Work-In-Process (WIP), start and reset the model, define the number of production orders and equipment (for example, AGVs on top of a job-shop cell named MPCs), send priority orders and schedules, optimize production plans, and create production plans with random products to evaluate the impact of possible variability of the system.
- **User commands** - Custom user coding functions developed in order to send instructions or adjust the simulation model. Many possibilities are available such as modifying model parameters, starting or stopping a process, or changing the model state. Furthermore, external services can send user commands to the simulation model, triggering specific actions or changing the model's behaviour. Particularly, five user commands are essential in this process:
  - "GetWIP()" - establish a connection to the Python wrapper (connector to IoT platform) and allow real-time data collection and return as output a JSON string with complex data structure embedded.
  - "SetupWIP(WIP)" and "SetupMPCs(WIP)" - receives the output of the previous user command and converts JSON data into FlexSim objects and data tables information. As output, it completes source data tables of process flow, triggers processes and creates 3D objects corresponding to a snapshot from the real-time data. Also, it changes the positions, routings, and time of processing and setup of the resources and assets accordingly.
  - "CreateProductionPlan()" - based on optimizing the planned production orders, chooses the configuration with the lowest makespan and builds a JSON message with a new production schedule with the orders organized to be sent to the APM.
  - "SendProductionPlan()" - establish a connection to a Python wrapper (IoT connector) to send the optimized production schedule to the APM.
- **Data tables** - to quickly access fundamental model information, access data produced by the model that may be exported for further analysis, and compile all WIP data necessary to initially build up the simulation model.
- **3D model** - a nearly realistic 3D model to help visualize the production process. The simulation model may represent real-time data and events prior to the simulation start, which makes it simpler to visualize, provided by a continuous connection to the APM via the IoT platform (Kafka connector).
- **Process flow** - It is the brain module of FlexSim for modelling the production system's corresponding rules and complex stochastic characteristics. By creating a visual representation of the workflow or sequence of operations that entities or resources will follow as they move through the system, the process flow allows for real-time optimization and adaptation based on the information it receives. Additionally, customized FlexSim blocks and logic can be utilized to create heuristics that may be written in various languages, including Python, and run as part of the process flow.

The Python wrapper is a vital link between the FlexSim simulation model and external systems within the simulation base model architecture. The aiokafka,[3] library enables asynchronous message exchange with a Kafka broker, employing methods like "consume_messages" and "Send_producer_request" to handle message consumption and production. The data transmitted via these messages are in JSON format, allowing easy processing and analysis by the simulation model. Leveraging asyncio,[4] and aiokafka, the Python script achieves non-blocking message transmission, which is crucial for real-time manufacturing

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[1] https://www.flexsim.com/ accessed on 02.01.2024.

[2] https://www.flexsim.com/optquest/ accessed on 02.01.2024.

[3] https://aiokafka.readthedocs.io/en/stable/ accessed on 02.01.2024.

[4] https://docs.python.org/3/library/asyncio.html accessed on 02.01.2024.

systems, ensuring high-performance communication without primary thread interference. Overall, the Python wrapper is a critical component in the simulation base model, enabling seamless communication and integration with the IoT platform.

This subsection outlines an approach for creating a DT and optimizing manufacturing processes in real-time utilizing FlexSim, external connections, and heuristics.

4. Industrial experiment

In this case study, the authors explore the application of optimizing a dynamic job-shop configuration (Mohan et al., 2019) within a MaaS supplier context. This supplier specializes in providing assembly services for a diverse mix of products across various industries, requiring flexibility and adaptability in production processes to accommodate varying product specifications and demand fluctuations.

At the heart of the MaaS assembly operations lies the dynamic job-shop configuration, a versatile manufacturing layout where jobs move through multiple workstations in non-fixed sequences. Each workstation is equipped to handle a specific set of tasks, and the sequence of operations may vary depending on the product being assembled. Additionally, setup times between tasks are sequence-dependent, meaning the time required to prepare a workstation for a specific job is influenced by the preceding and succeeding tasks.

The optimization of this dynamic job-shop configuration poses a significant challenge, known as the job-shop scheduling problem with sequence-dependent setups. This problem involves determining the optimal sequence of tasks and allocation of resources to minimize production time and maximize throughput while considering the sequence-dependent setup times.

Within this context, the presented case study aims to investigate how leveraging advanced technologies, such as dynamic workstations and Mobile Programmable Cobots (MPCs) in a flexible assembly cell, can enhance the efficiency and adaptability of the MaaS assembly operations. By addressing the complexities of the job-shop scheduling problem with sequence-dependent setups, the authors seek to uncover strategies to improve operational efficiency, optimize resource utilization, and meet the diverse assembly requirements of different industries served by the MaaS supplier.

In terms of hardware, assets, and equipment available for the experiment case study, the system is comprised of an automatic vertical storage system (Fig. 3(a)), an INESC TEC AGV (Fig. 3(b)), an LD-250 OMRON,[5] AMR integrated with a roller conveyor (Fig. 3(c)), a Prolynk,[6] adaptive production platform and a 5-metre belt conveyor system integrated with an ABB IRB2600 industrial manipulator (Fig. 3(d)). The adaptive production platform comprises five frames with four positions, each with an index unit and a frame with one position for the automatic battery changer. Additionally, the system has three MPCs with a maximum payload of 15 kg and a maximum speed of 400 mm/s.

The 3D Raise3D Pro2 Plus,[7] printer with a build volume of 305 × 305 × 605 mm and a wireless compatibility functionality was the equipment used to produce the thermoplastics materials.

4.1. Application of the proposed digital twin architecture to case study

The developed solution includes the creation of a DT representation model presented in Fig. 4. Fig. 5 presents the FlexSim 3D model and the main dashboard of the conducted industrial experiment. The main components described above are the Prolynk system with the MPCs routes, the collaborative robotic arm, both AGVs, and their routes also on the ground, and the complete representation of the real system.

The DT represents the current production WIP, serving as the main point for analysis by the decision support system. This enables the simulation of various production scenarios and the ability to respond to issues such as defects or delays in the assembly line. After a setup phase and taking into account the details described above, a sequence of procedures is performed between the main components of the system and illustrated as follows:

1 DT setup and preparation

  1.1 Regarding **strategic decision-making**, the simulation model creates a random production plan that connects resources to products based on a predefined demand and tests it for multiple replications and a variable number of MPCs — this would permit the KPIs analysis and understanding the impact of having different number of MPCs available;
  1.2 Once it is validated the strategic phase, the **operational decision-making** is described. Simulation model validates under uncertainty the generated production schedule and sends the message containing the approved plan (JSON format) to APM through the IoT platform;
  1.3 The APM guarantees the implementation of the production schedule, initiating the allocation of tasks to resources, workstations, and MPCs over time. The APM will adjust the MPC routes according to the different types of products in each order;

2 Process execution and response to unforeseen events

  2.1 The assembly MaaS system starts performing with three different products and correspondent sequence-dependent setups, and all the resources on the system constantly send their status and relevant information to APM;
  2.2 The omnidirectional AGV moves autonomously without human intervention until reaching the automatic vertical storage system. The AGV resorts to data collected from two LIDAR sensors, based on natural landmarks, for the tasks of localization (using the Perfect Match algorithm) and navigation (Rocha et al., 2020; Sobreira et al., 2019);
  2.3 The system segments the stored injected parts in a cluttered scenario using the image provided by a 3D structured light sensor from Photoneo called Phoxi S. Following this, a two-finger gripper from Robotiq attached on a collaborative robotic manipulator UR10 performs the bin-picking action to grasp the required parts (Cordeiro et al., 2023; de Souza et al., 2021);
  2.4 The AGV carries the parts to the adaptive production platform. There, the operator manually picks the material from the AGV and inserts it into the dynamic MaaS assembly line;
  2.5 In parallel (after detecting a defect) and using the simulation model to support user decision-making, a new order is automatically sent to APM to activate the AM cell. This cell consists of a 3D printer that prints the product and an automatic process for storing the product in the vertical warehouse is performed to avoid stockouts;
  2.6 After completing a batch of products, the operator places the finished products in a box on top of the AIV;

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[5] https://automation.omron.com/en/us/promotions/omron-ld250-mobile-robot-launch accessed on 02.01.2024.

[6] https://www.prolynk.eu/en/acceuil/ accessed on 02.01.2024.

[7] https://www.raise3d.com/products/raise3d-pro2-plus-3d-printer/ accessed on 02.01.2024.

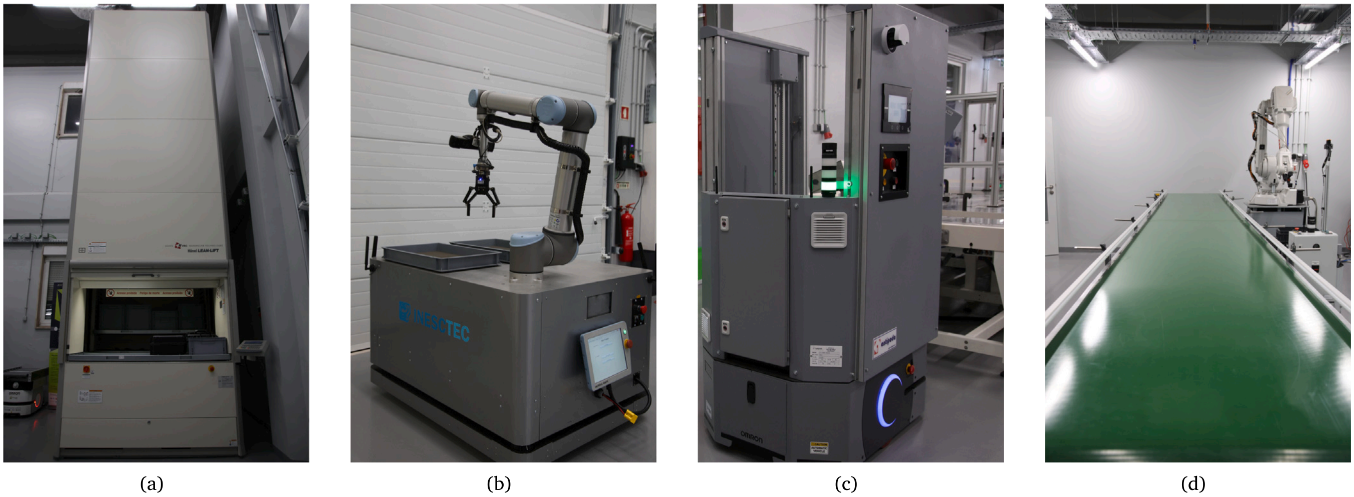

(a) (b) (c) (d)

Fig. 3. Case study components: (a) HÄNEL Lean-Lift automatic vertical storage system; (b) omnidirectional AGV; (c) LD-250 AIV; and (d) belt conveyor system and an industrial manipulator.

2.7 The LD-250 AMR moves until the belt conveyor system and, on the way to pass through the doors, requires communication autonomously via wireless to send the request;
2.8 The AMR roller conveyor sends the box to the belt conveyor that is stopped closer to the ABB industrial manipulator, and returns to its waiting point;
2.9 The ABB has attached a PN-025-2 pneumatic gripper responsible for picking the boxes and following with its palletization.

3 Predictive and prescriptive simulation–optimization

3.1 When a defect occurs in any of the final products or components, the simulation model requests the WIP to the APM from that moment onward to support decision-making on adding new production orders or changing current production orders in order to continue minimizing makespan but also accomplishing the production of all demanded products;
3.2 The simulation model loads real-time WIP and updates the 3D model positioning the MPCs in the correct place, adding the products in the correct position and calculating the current status of task execution (considering stochastic times of human performing assembly processes). After simulating the impact of the current scenario, simulation retrieves KPIs of not changing the predefined production schedule;
3.3 Then, the user can run the optimization to understand if there are better alternatives in terms of production scheduling or utilization of available resources and technology. In this case, the vertical warehouse provides an alternative for the product component detected with a defect, the optimization is used to calculate a production re-scheduling, which calculates the involvement of the omnidirectional AGV transporting the product to the assembly line, and send the updated schedule again to the APM;

To obtain a visualization of this research and the correspondent DT architecture applied to the case study, a video of the main interaction steps is provided in the supplementary material.

4.2. Analysis of simulation–optimization results

Following tests conducted in this setting, evaluations were made regarding communication effectiveness, evaluation of production plans, integration capabilities, and performance improvements, all of which were subsequently validated. Initial findings indicated that the base model of the FlexSim simulation successfully communicated, loaded the existing manufacturing process, and executed changes to manufacturing orders within the actual system.

For the evaluation of the optimization in terms of strategic and operational decision-making, the main metric used to evaluate multiple scenarios was the makespan, and the results are presented next. Regarding strategic decision-making, as mentioned above, an evaluation of a number of MPCs utilized was conducted. Fig. 6 presents the makespan results of using 2 or 3 MPCs. Once the assembly tasks were operated by humans, statistical distributions were included in the tasks' processing time. To achieve a sufficient confidence level, experiments with 20 replications were conducted in the simulation model experimenter. As expected, as the number of MPCs increases, the makespan decreases, and the expected gain of 30% of the makespan is highlighted.

On the other hand, the simulation model with optimization procedures performed by Optquest was used to optimize job-shop production scheduling scenarios. Fig. 7 illustrates the evolution of the optimizer for a total of 50 production orders. In terms of stoppage conditions, a wall time of 10000 s and a total of 1000 iterations were defined in Optquest. As expected, Optquest is capable of calculating new optimized solutions each iteration and the makespan minimization is also clear.

The makespan helped to prove that the simulation model was correctly applied and also that the communications between the APM and the model were correctly validated. In addition, the APM was also validated by checking communication with all the components, whether MPCs or mobile robotics. The APM and the simulation model also allowed multiple KPIs of the case study components to be visualized, such as the utilization rate of robots and operators and their status. After analysing and demonstrating the DT application to the case study, the next chapter presents the main conclusions and future work.

4.3. Limitations of the presented work

The DT architecture developed and explained in this work is a virtual model of a physical object, system, or process designed to simulate, analyse, and predict the behaviour of its real-world counterpart. While DTs offer numerous benefits, they also have certain limitations. In this research, the following topics can be discussed:

- **Data quality and availability:** The effectiveness of a DT depends on the quality and availability of data. As explained in the previous chapter, the OSPS data architecture was used to

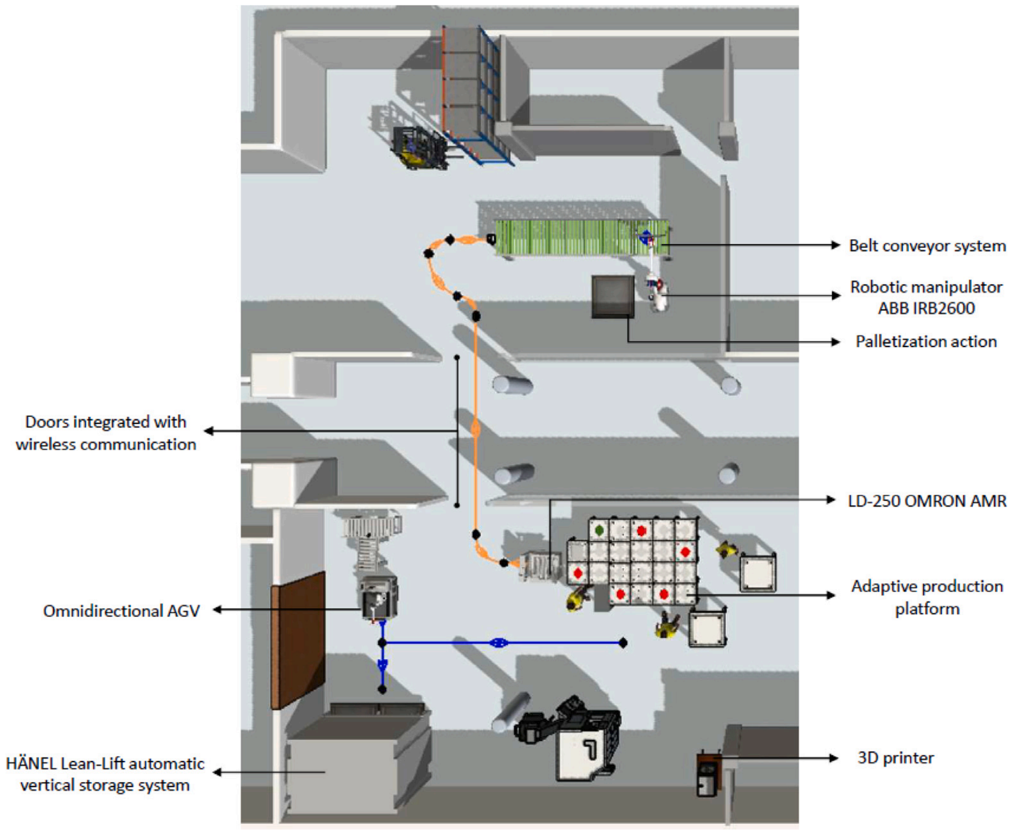
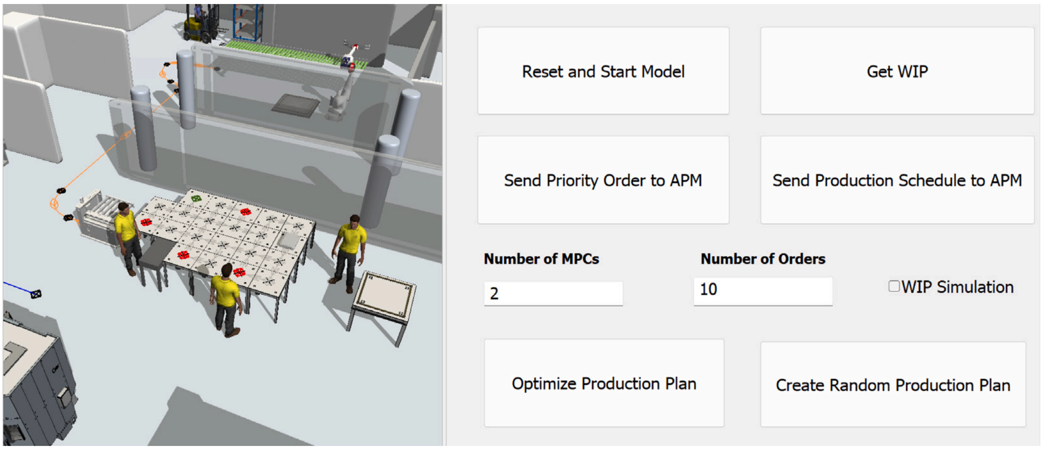


Fig. 4. Case study simulated environment: the blue lines depict the AGV trajectory, and the orange ones illustrate the AMR path.



Number of MPCs 2

Number of Orders 10

☐WIP Simulation

Fig. 5. Main dashboard of the simulation model.

deal with large amounts of data. Using reference data models and structures, the OSPS defines UML class diagrams and services sequence diagrams to set which data and events are relevant and filtered to specific contexts. Regarding availability, the APM can get relevant real-time information from IOT sensors, robotics, and other services, such as simulation. However, on certain occasions, the information coming from the shop floor is insufficient to fully guarantee the virtual-real system correspondence in every aspect. In this case, approximations are made. It is planned to implement cameras and object recognition ML methods and integrate them with the DT to understand and access the system's state. This will increase the data available and quality to monitor and support decision-making.

- **Security and privacy:** DTs often rely on real-time data streams, making them vulnerable to cyberattacks. Ensuring the security and privacy of sensitive data is crucial but can be difficult to guarantee. The APM ensures security and safe data treatment. Also, it includes a login system that is required to enter and access the DT. Nevertheless, despite not being the main topic of this research, more cybersecurity strategies could be included.
- **Maintenance and updating:** To remain accurate and useful, DTs need regular updates and maintenance as their physical counterparts evolve. This ongoing requirement adds to the cost and effort needed to keep the DT relevant and up-to-date with the system updates. The APM needs to be updated every time a big change is detected in the production line (new production flows, machines, resources, etc.), but following the same principles of

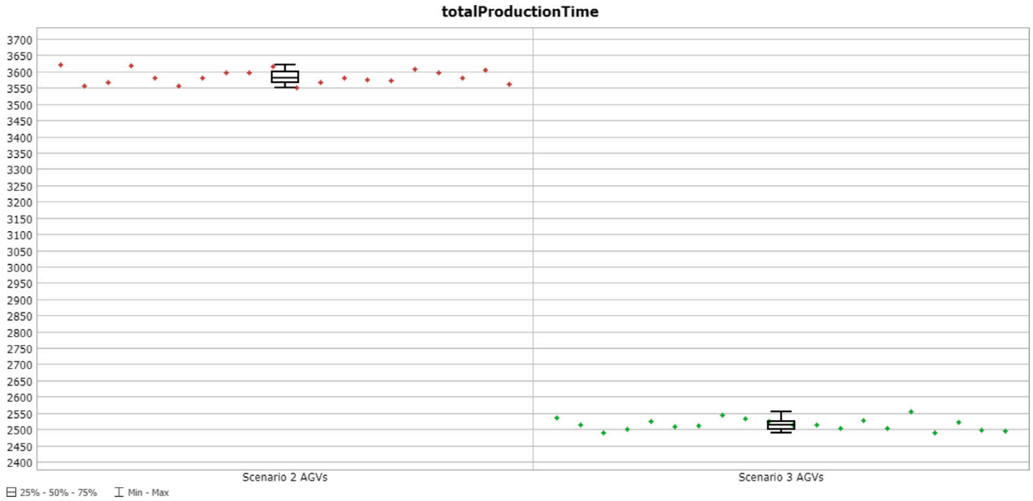


Fig. 6. Makespan results of the simulation model varying the number of MPCs.

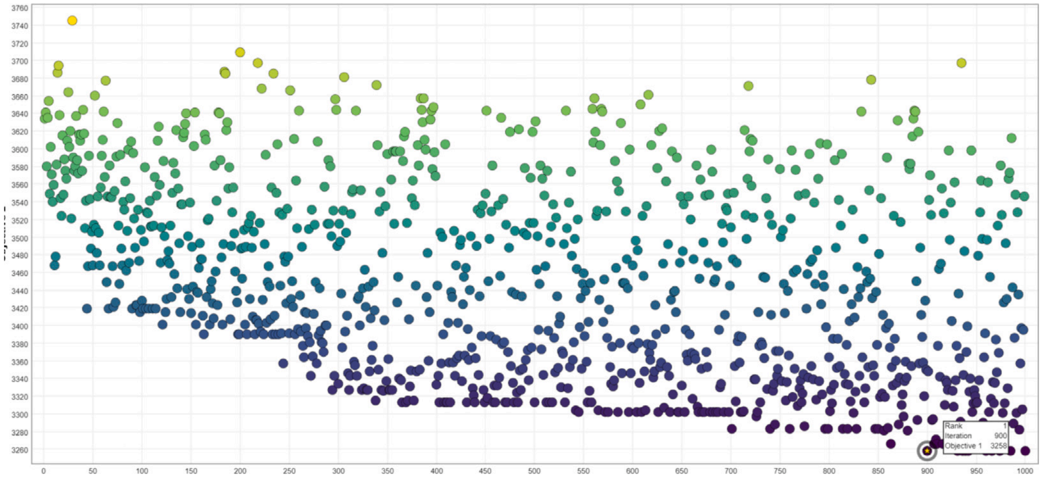


Fig. 7. Optquest iterations and makespan results — production schedule with 50 orders.

the architecture here defined and in a short period of time. The simulation is also updated according to the APM state and in line with what happens in reality. As the next steps, with the support of cameras and more data processing units, some changes could be automatically incorporated into the APM and simulation, permitting faster system updates.

5. Conclusions and future work

As industries continue to navigate the evolving landscape of manufacturing, the integration of advanced technologies has become increasingly imperative for staying competitive. Among these technologies, Simulation-based Digital Twin stands out as a powerful tool for enhancing decision-making, operational efficiency, and adaptability across dynamic manufacturing systems. Positioned as the cornerstone of new manufacturing strategies, DT architectures offer a virtual window into the intricacies of production processes, enabling real-time monitoring, modelling, and optimization.

Building upon this foundation, a novel system architecture was introduced, seamlessly integrating trending technologies with DTs to enhance manufacturing operations. Positioned at the forefront of this architecture is the DT, serving as a virtual replica of the physical manufacturing environment. This DT leverages advanced simulation techniques to model, monitor, and optimize production processes in real-time, enabling informed decision-making at both strategic and operational levels.

The technical description of the DT highlights its capabilities in providing a set of tools, protocols, databases, and services to implement the DT efficiently in real systems. By leveraging data from sensors, IoT devices, and other sources, the DT accurately models the behaviour of the physical system.

The presented case study delves into the practical application of Digital Twin-based simulation in optimizing dynamic job-shop configurations within a MaaS supplier context. By tackling the complexities of production scheduling with sequence-dependent setups, this work aims to uncover strategies to enhance operational efficiency, optimize resource utilization, and address the diverse assembly requirements of different industries. Overall, this novel system architecture represents a comprehensive approach to leveraging DTs and emerging technologies in manufacturing. By combining the power of simulation with cutting-edge technologies, organizations can unlock new opportunities for innovation, competitiveness, and sustainability in the ever-evolving manufacturing landscape.

Future work is planned to enhance the proposed DT framework and case study by incorporating sustainability and remanufacturing principles, with a focus on disassembly processes. This extension will involve integrating sustainability metrics into the DT simulation to assess environmental impact and identify opportunities for improvement. Modelling remanufacturing operations within the DT is also aimed at, particularly focusing on disassembly efficiency and component reuse. The case study will serve as a practical testbed for implementing these enhancements, allowing the authors to evaluate their impact on resource utilization, waste reduction, and overall environmental performance within a Manufacturing-as-a-Service supplier context. Additionally, an analysis of the economic implications of sustainability and remanufacturing initiatives will be made to provide insights for decision-makers and stakeholders, fostering the adoption of environmentally responsible manufacturing practices.

CRediT authorship contribution statement

Romão Santos: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Henrique Piqueiro:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Rui Dias:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Cláudia D. Rocha:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Data availability

No data was used for the research described in the article.

Acknowledgements

This work was supported by the European Union's Horizon Europe research and innovation program through the RENÉE project (grant no. 101138415).

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.cie.2024.110616.

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