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Doctoral Program in Management, Production and Design (37th cycle)

A Roadmap Towards a Digital Twin for Automated Storage and Retrieval Systems

By

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1. Introduction

Intralogistics is a term that refers to the management, control, and optimisation of material and information flows within a facility. It encompasses a wide range of activities, including storage, handling, internal distribution, and transportation of materials (Drissi Elbouzidi et al., 2023). In this context, the last decades have seen rapid advances in the field of automated warehouses. Automated warehouses play a pivotal role in supporting modern supply chain processes (Marolt et al., 2022). The current prevalence of these systems is evident across a range of industrial sectors, including manufacturing, large-scale distribution, e-commerce, and healthcare. An illustrative implementation of such automation can be found in automated storage and retrieval systems (AS/RSs), which are characterised by the storage and retrieval of unit loads (ULs) by means of automated and autonomous mechanical devices called handling machines (HMs) (Azadeh et al., 2019). Compared to traditional warehousing systems, AS/RSs offer significant benefits including reduced space utilisation, lower labour costs, faster retrieval, and improved inventory control (Boysen & Stephan, 2016). In the academic literature, special attention has been paid to the AS/RS configuration, both from a design and operational point of view (Gaku & Takakuwa, 2017). This because the system configuration greatly influences both the initial investment required and later the overall performance that the system can achieve (Gagliardi et al., 2012). Focusing on the systems studied by researchers, traditional stacker-crane based AS/RS (T-AS/RS) and shuttle-based S/RS (SBS/RS) are the most studied systems. Nevertheless, T-AS/RS have recently faced a decrease in interest from academics, probably demonstrating maturity of the technology, while SBS/RS, being a relatively new solution with improved performance, has gained a lot of attention in recent years (Ferrari & Mangano, 2023).

Due to recent global events and the subsequent heightened strain on supply chains, intralogistics processes have faced significant pressure to balance the growing demand-supply challenge both efficiently and effectively. As a result, AS/RS have had to become increasingly adaptable to manage daily operations (Kembro & Norrman, 2019). These systems are increasingly being tasked with handling the growing complexity brought on by the high levels of uncertainty resulting from the unpredictable and fluctuating product demand. Indeed, recent unpredictable events have been forcing companies to redesign entirely or partially their supply chain and the way inventory is managed. In this context, the implementation of automated warehouse systems that are capable of rapid adaptation to market fluctuations and responsive to evolving customer requirements could confer a competitive advantage. The attainment of enhanced flexibility may be achieved through the utilisation of innovative facility designs, technological advancements, or the incorporation of advanced simulation and optimisation methodologies. Specifically, in the context of Industry 4.0, the new paradigm called digital twin (DT) emerged, which is defined as simulation-based virtual counterparts of a physical system, exploiting real-time data synchronisation to optimise the actions undertaken by the physical system (Kritzinger et al., 2018). DTs are computerised models that represent the system state at any given moment in time (Ivanov & Dolgui, 2020). The core concept of a DT is therefore to create a highly accurate virtual replica of the physical asset it represents, while maintaining a real-time connection between the two (Coelho et al., 2021). The implementation of DTs offers a range of significant advantages. Through the use of DTs, various simulations can be exploited to determine the most efficient system setup. The ability to simulate what-if scenarios provides a powerful decision-making tool to evaluate the impact of different operational strategies and mitigate the risks associated with changes and actions taken in the physical system (Braglia et al., 2019). From the definition given above, it is clear how the capabilities of the DT are highly dependent on the level of integration between the physical system and its digital replica. Specifically, a digital model (DM) is a digital representation of an existing or planned physical object without any automated data exchange between the two. In contrast, a digital shadow (DS) features an automated one-way data flow from the physical object to its digital counterpart. Finally, a DT involves fully integrated, bidirectional data flows between the physical and digital objects (Kritzinger et al., 2018).

2. Theoretical background

2.1. Digital twin in intralogistics

Despite the clear benefits of DTs and the growing attention they have been receiving in recent years, their application to intralogistics processes and automated warehouses has been largely overlooked. Therefore, this study aims to explore the significance and potential applications of DT technology in AS/RSs. To evaluate the use of DT in the intralogistics sector, a literature review was conducted. The articles were selected based on the relevance of the publication to the intralogistics processes. In fact, the primary focus was on the use of DTs within warehouses, including also industrial production contexts, if the focus of the research was on the material handling within the facility. Only researches that clearly studied the DT implementation were considered as relevant and analysed. Additionally, only applications that clearly specified the presence of at least one data flow between the physical and the digital object were taken into

account. A total number of 37 papers was analysed.

The first step of the analysis was studying the trend of publications over the years. From Figure 1, it is easily noticeable that research on the topic of DT has been increasingly growing.

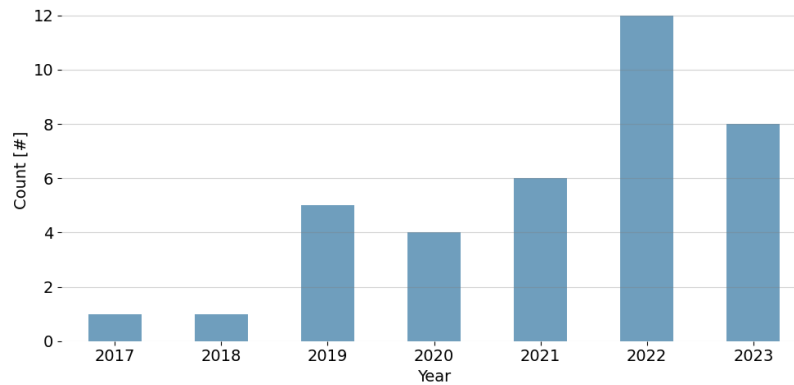


Figure 1 : Evolution of DT related publications

This is understandable, considering that the technology has only gained significant attention in recent years. However, it is important to highlight that in 2023, the number of articles decreased compared to 2022, signalling a shift in the previously upward trend. The lower publication count for 2024 can be attributed to the fact that the analysis did not include all papers from that year, as some were still in the publication process.

The subsequent analysis was conducted to identify the main warehousing systems studied with the application of a DT. Warehouses were differentiated into automated warehouses, e.g. AS/RS, traditional warehouses, e.g. served by forklifts or operators, and robotic warehouses with automated guided vehicles (AGVs), autonomous mobile robots (AMRs) or unmanned aerial vehicles (UAVs). The classification also included smart factory, as several publications holistically analysed systems encompassing production processes, material handling equipment (such as conveyors, AMRs, and robotic arms), as well as warehouses. The majority of publications referred to systems with autonomous robots (32.43%), followed by automated warehouses (27.03%), and traditional warehouses (21.62%). Smart factory is the system with fewer occurrences (18.92%).

One of the main elements of a DT is the virtual replica of the real system, that is the DM. The subsequent analysis focused on classifying the DM encountered in the publications. In analysing the 37 papers, the following types of DM were identified:

- Discrete event simulation (DES)
- Agent-based modelling (ABM)
- Hybrid modelling (HMO)
- Virtual environment (VE)
- Analytical Model (AM)
- Artifact-Centric Business Process Model (ACBPM)
- Markov decision process (MDP)
- Semi-physical simulation (SPS)

With the DT, it is possible to optimise and simulate different scenarios, assessing their feasibility, identifying potential issues, or advantages of changes made to the system. The

presence of an optimisation model within the DT is crucial, as it allows for the use of the extensive data collected from the physical object to optimise the system (Leng et al., 2021). Therefore, the use of optimisation models in the articles of the corpus was evaluated. The description and implementation of optimisation models were found in 22.5% of the cases. The types of optimisation observed are as follows.

- Joint optimisation model (JOM)
- Genetic algorithm (GA)
- Jonker–Volgenant algorithm (JVA)
- Non-dominated sorting genetic algorithm II (NDSGA-II)
- Scatter search (SS)
- Tabu search (TAS)
- Simulated annealing (SA)

Zhang et al. (2022) introduced the concept of cognitive DT, where DT are extended to cognitive capabilities and they are equipped with abilities of self-learning, reasoning, and adjusting decision-making rules using real-time data. Cognitive DTs use machine learning (ML) and artificial intelligence (AI) to support humans in decision-making by providing them with relevant information and recommendations. Cognitive DTs also use a variety of data sources, collate them, and process them to generate useful insights for analysts (Ivanov, 2023). Being the use of ML and AI so relevant in the DT development, their presence was tracked in the analysed articles. The use of ML or AI was found in 15% of the articles. The identified AI and ML models are the following:

- Reinforcement learning (RL)
- Adaptive network-based fuzzy inference system (ANFIS)
- Auto-encoder (AE)
- Deep reinforcement learning (DRL)
- Multiple linear regression and time series analysis (TSA)

Figure 2 shows the occurrences of each digital, optimisation and AI/ML model in the corpus of papers. Focusing on the DM, the majority of publications used the virtual environment (47.5%), mainly for ergonomics and learning objectives. The other main important DM are DES and ABM, or the combination of them, which account for a 22.5% of the total of publications. The papers using these approaches were focused mainly on the objective of optimising warehouse processes. Regarding the optimisation model, it is evident that only a small portion of the papers analysed introduced optimisation algorithm in their DT. The most common optimisation model was the JOM, present in 3 articles, as it allows for the optimisation of multiple decision variables in aggregate. GAs are the second most common optimisation model, appearing in 2 articles of the corpus. Similarly, the use of AI/ML is still scant. The most used method is RL, being present in 2 papers of the total.

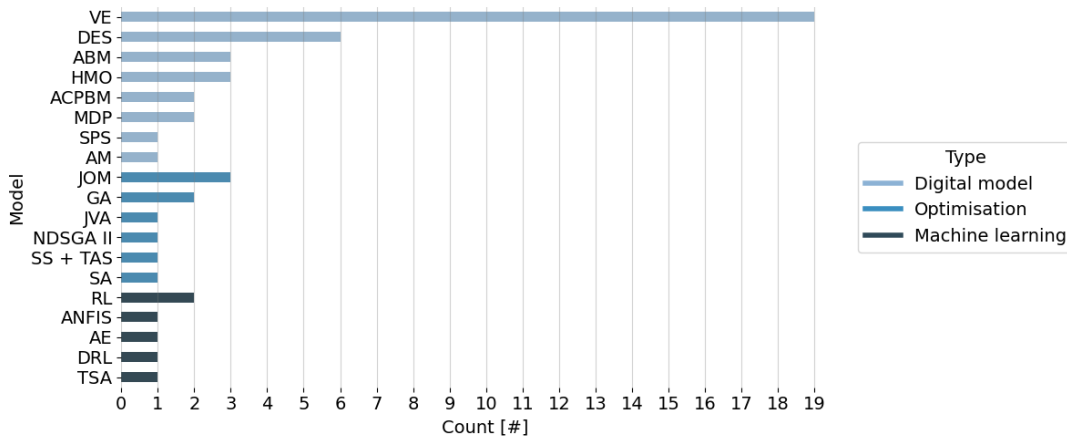


Figure 2 : Types of digital twin models

The following analysis focused on evaluating the presence of real-time communication between the physical and digital object. According to the inclusion and exclusion criteria, all the selected articles featured at least a unidirectional real-time communication between the two parts. The concept of real-time communication was also extended to articles where there was not a continuous flow of information between the two objects, provided that the communication occurred at fixed time intervals in the worst-case scenario. Focusing more specifically on the communication between the physical and digital twins, being the data flow present in all the papers analysed, bidirectional data exchange was found in 17 out of 37 articles (45.95%), which is just under half of the cases. This result highlights how integrating a DT into an existing system is particularly complex and how difficult is to directly control the physical object based on the results of the simulation and analysis conducted with the digital object. Data flows were also analysed based on the type of data shared between the two environments. The results of this analysis are presented in Table 1, which shows the type of flow and the data shared based on the type of DM. The values in the table correspond to the number of publications.

Table 1: Data flow

Type of flow	Data	VE	DES	ABM	HMO	Other	Total
Physical → digital	System state	5	2		3	4	14
	AGV/AMR/UAV position	3	1	2		1	7
	Operator position	6					6
	Operator input	3					3
	Object position	1	1				2
	Forklift position		2				2
	Environment parameters	1				1	2
	Resource availability and demand			1			1
	Total	19	6	3	3	6	37
Digital → physical	Routes	2	3	1	1	2	9
	Task sequence	1	1	1		3	6
	UAV command	2					2
	Total	5	4	2	1	5	17

2.2. Simulation modelling for AS/RS

Simulation models are the pillars of DTs (Ivanov & Dolgui, 2020). Creating a reliable DM is fundamental for successful DT implementation (Tao et al., 2018). The DM serves as the virtual counterpart of the physical warehouse, aiming to replicate its operations with a high level of fidelity and detail. Depending on the specific objectives of the DT application, different types of models can be developed (Assad Neto et al., 2021). In order to find the main trends in the application of simulation and modelling techniques in the field of AS/RSs, a systematic literature review was conducted (Ferrari & Mangano, 2023). The Scopus database was used for the analysis as it is recognised by the academic community as one of the most comprehensive scientific peer-reviewed literature databases. The time frame of the review was limited to 2012-2021. Papers focusing exclusively on optimisation techniques, i.e. research that merely proposes new optimisation, heuristic or scheduling algorithms, were not included, as the objective was to investigate the main simulation approaches in the design and evaluation of AS/RS systems, the main associated impacts and the potential drivers that determine the choice of a specific simulation method. Finally, academic papers that were not strictly focused on storage systems (e.g. automated guided vehicles and robotic fulfilment centres) were discarded. After carrying out a snowballing process, a final corpus of 87 papers was obtained.

The papers were classified according to the methodology used. As it can be observed in Figure 3, AM is one of the most used approaches to evaluate the performance of automated systems. This may be due to the fact that AMs are easily reconfigurable, computationally less expensive than other methods, and efficient for enumerating warehouse design parameters. DES is another frequently used method, being warehouse processes discrete in nature. Queuing models (QM) are less used, even though they allow determining the probability distributions of the performance parameters of the systems under study. Simulation modelling (SM) was the fourth methodology used in the corpus of papers. Generally speaking, it involves the use of a specific simulation paradigm, but in the papers falling into this category, this was not explicitly defined. As a consequence, the proposed models were not described in detail. Although the Scopus queries did not include keywords related to AM and QM, a significant number of articles using these approaches appeared in the results, often in combination with simulation methods for validation purposes.

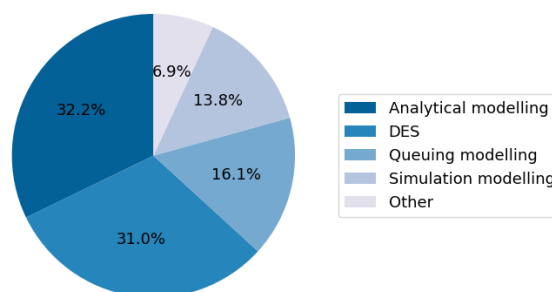


Figure 3 : Modelling methodologies

The analysis of the 87 articles in the corpus identified a prevailing methodological trend, with mathematical models being the most commonly employed approach for studying such systems, often validated through simulation techniques.

2.3. Research aim

The objective of this study is to investigate the significance and potential applications of the DT technology to AS/RSs. By conducting a comprehensive examination of the role of DTs in optimising and enhancing the efficiency of AS/RS, this study aims to answer the following research questions:

1. Which are the primary elements that compose a DT for AS/RS, with a particular focus on the essential components, their functionalities, and how they interact within the system?
This will involve proposing an architectural framework for a DT tailored to AS/RSs. The framework will emphasise the identification of key components, their specific functionalities, and the interrelationships between these components, ensuring a cohesive and integrated system.
2. How can the digital object of the AS/RS DT be designed, developed, and validated to maximise its reliability and effectiveness?
This will focus on the design of a DM that includes energy consumption aspects, combined with a structured approach for calibration and validation. The DM will be also associated with an AI module aimed at solving the order sequencing problem (OSP) in an AS/RS environment.
3. To what extent could the functionalities of the DT contribute to the optimisation of automated warehouse operations?
This will involve using DT technology to assess the performance of AS/RS, focusing on critical metrics such as time efficiency and energy consumption. In addition, the impact on specific warehouse processes, including order picking, will be thoroughly analysed and quantified.

By answering to these research questions, this study aims to explore the importance and potential uses of DT technology in AS/RSs. Ultimately, the study is intended to provide a comprehensive and practical roadmap for deploying DTs in AS/RSs, addressing both the underlying theoretical foundations and the real-world challenges of implementation. By doing so, the study aspires to contribute to the advancement of warehouse automation technology, allowing the creation of more efficient, flexible, and responsive AS/RS solutions.

3. Configuration design of a digital twin for automated warehouses

Figure 1 shows a high-level architecture, which aims to define the main elements constituting a DT of an AS/RS.

The first element is the physical warehouse, i.e. the physical object of a DT. The physical object is the cornerstone of a DT, serving as the real-world counterpart that the DM seeks to replicate in detail. The relevance of the physical system lies in its role as the data source and behavioural patterns that shape the functionality of the DT. In this work, the physical warehouse comprehend the entities that have a physical location inside the physical AS/RS, like HMs, aisles, storage racks, conveyors and ULs.

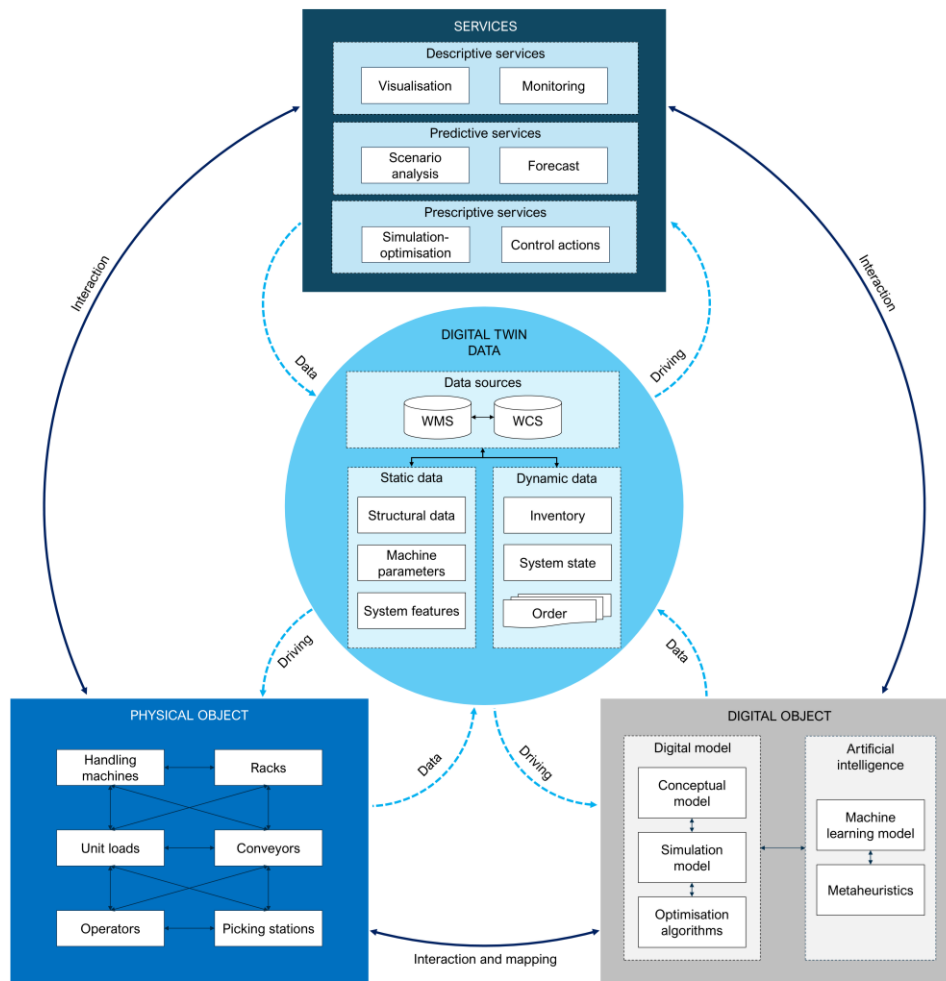


Figure 4: Digital twin architecture

Within the architecture, the digital object is crucial, acting as a detailed virtual representation of the physical system. It is composed of two main elements, namely the DM and AI. Creating a reliable DM is fundamental for a successful implementation of DT (Tao et al., 2018). The DM serves as the virtual counterpart of the physical warehouse, aimed to replicate its operations with a high level of fidelity and detail. The DM incorporates three main elements, that is a conceptual model, a DES model, and optimisation algorithms. The conceptual model outlines the key components, processes, and relationships within the physical warehouse. The DES model build on the conceptual model replicates the warehouse operations in a simulation platform. It can be used to simulate the behaviour of various elements under different conditions, such as inventory flow, equipment performance, and order processing. The optimisation algorithms then leverages data from these simulations to find the most efficient solutions for resource allocation, scheduling, and process improvements. By applying advanced algorithms, it can suggest strategies for optimising certain aspects within the DES model.

The integration of AI within the DT represents a significant advancement in enhancing the system capabilities and overall efficiency (Drissi Elbouzidi et al., 2023). The first step in integrating AI involves identifying the specific requirements and objectives that it needs to

address. This could include enhancing predictive maintenance, optimising inventory management, and improving order processing. Understanding these objectives helps in selecting the appropriate approach that aligns with the warehouse's operational goals. In the architecture proposed, AI is seen essentially as the combination of advanced ML models and sophisticated metaheuristics. By combining ML and metaheuristics, the DT becomes a powerful tool capable of processing and analysing large volumes of data produced by the AS/RS, and efficiently optimising short-term operational decisions, ultimately leading to enhanced performance in AS/RS.

The functions provided by DTs are organised into three interconnected categories of services, namely descriptive, predictive, and prescriptive (Ivanov, 2023). The primary role of DTs is to provide comprehensive information and insights about its corresponding physical entity. By maintaining alignment with the current state of the physical system, DTs unlock predictive capabilities, enabling them to simulate and forecast the system's behaviour and future conditions. Beyond prediction, DTs also offer prescriptive functionality, characterised by their ability to deliver automated feedback to the physical entity.

The data managed by the DT can be classified into two main categories, namely static and dynamic data (Tao et al., 2018). The first refers to information related to physical and structural aspects of the physical system that usually do not change among simulations, namely the structural data of the AS/RS, parameters of the HMs, and other system features such as characteristics of the various ULs or the coordinates and dimensions of the storage locations. On the other hand, the second one consists of dynamic and operational data that change over time, such as the level of stock for each SKU, the position of each UL within the system, the coordinates of the HMs, and the list of POs to be completed. These data originates from specific data sources. AS/RSs are usually supported by information technology (IT) systems, such as the warehouse management system (WMS) and the warehouse control system (WCS). These systems are integral to the seamless operation and coordination of warehouse activities (Ferrari et al., 2022). The WMS focuses on the day-to-day warehouse operations, including inventory tracking, order fulfilment, and shipment management, while the WCS handles the real-time control of material handling equipment and automation technologies within the warehouse. These systems are highly relevant as primary data sources for a DT of the warehouse, providing the necessary real-time and historical data to create an accurate and dynamic DT.

4. Physical object

Although stacker cranes are renowned for their reliability and efficiency, they do have limitations, especially when faced with high-volume tasks. As e-commerce and supply chain needs continue to evolve, the requirement for more agile and productive AS/RS solutions is becoming increasingly evident. This has sparked interest in multi-level shuttle (MLS) systems as a potential game-changer in warehouse automation (Ferrari et al., 2022). The MLS system is an AS/RS suitable for installation in limited spaces due to its remarkable adaptability. It is lightweight, and its small size enables it to fit perfectly into industrial environments where high storage racks are not an option and medium-low stock levels are the standard. The MLS system is designed to address the needs of automated warehouses that require higher performance than a traditional mini-load stacker crane system can provide (Ferrari et al., 2024).

From a design point of view, the HM of a MLS system is able to move small ULs such as plastic

totes along three axes. The horizontal and vertical movements occur simultaneously. The system is also able to manage four different types of ULs. In particular, type UL1 measures 600x400x220 mm, type UL2 measures 300x400x220 mm, type UL3 measures 600x400x120 mm, and type UL4 measures 300x400x120 mm. Therefore, UL1 and UL3 occupies double the space of UL2 and UL4 in a storage location, as well as on board of the HM. The HM is able to store two UL simultaneously. Moreover, two ULs of the same type can be loaded on board of the shuttle simultaneously or with sequential retrieval operations. A single UL can be also transferred from one side of the HM to the other one. The MLS is an aisle-captive system. The rack has a double front, with multi-deep storage locations. Specifically, two UL1/UL3 or four UL2/UL4 can be stored in the same storage location at the same time. The MLS system is also equipped with an input/output roller conveyor system located at one extremity of the rack. Figure 5 represents a possible layout configuration of the warehouse system under study.

From an operational point of view, the HM operates either on single command, dual command, or multi command type. The dwell policy is point-of-service-completion, meaning that the HM remains at the position of the last operation when it completes the backlog of storage/retrieval missions to be performed.

The MLS system is supported by an IT infrastructure based on a WMS and a WCS (Ferrari et al., 2022).

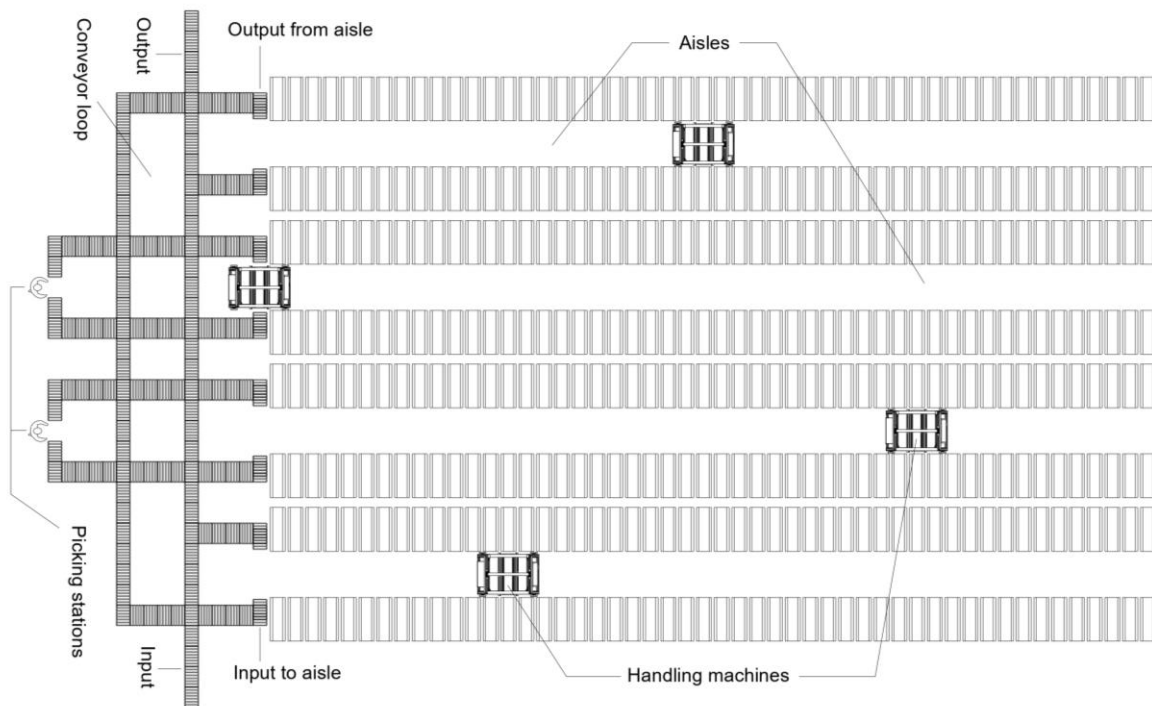


Figure 5 : Multi-level shuttle system

5. Digital model

5.1. Conceptual model

A conceptual model representing the MLS system was developed using the Unified Modelling Language (UML) class diagram. UML class diagram was chosen because it is a formal tool to graphically represent a system architecture showing the different classes of objects in the system, their attributes, and the relationships between them. In Figure 6 it is depicted the UML model developed. It is divided into three groups of classes, each of which is coloured differently. Blue classes refer to physical entities of the system, green classes represent the IT infrastructure of the system, and yellow classes include the logic entities of the system. From an operational point of view, the conceptual model allows also to understand the interaction between classes and the functioning of the DM.

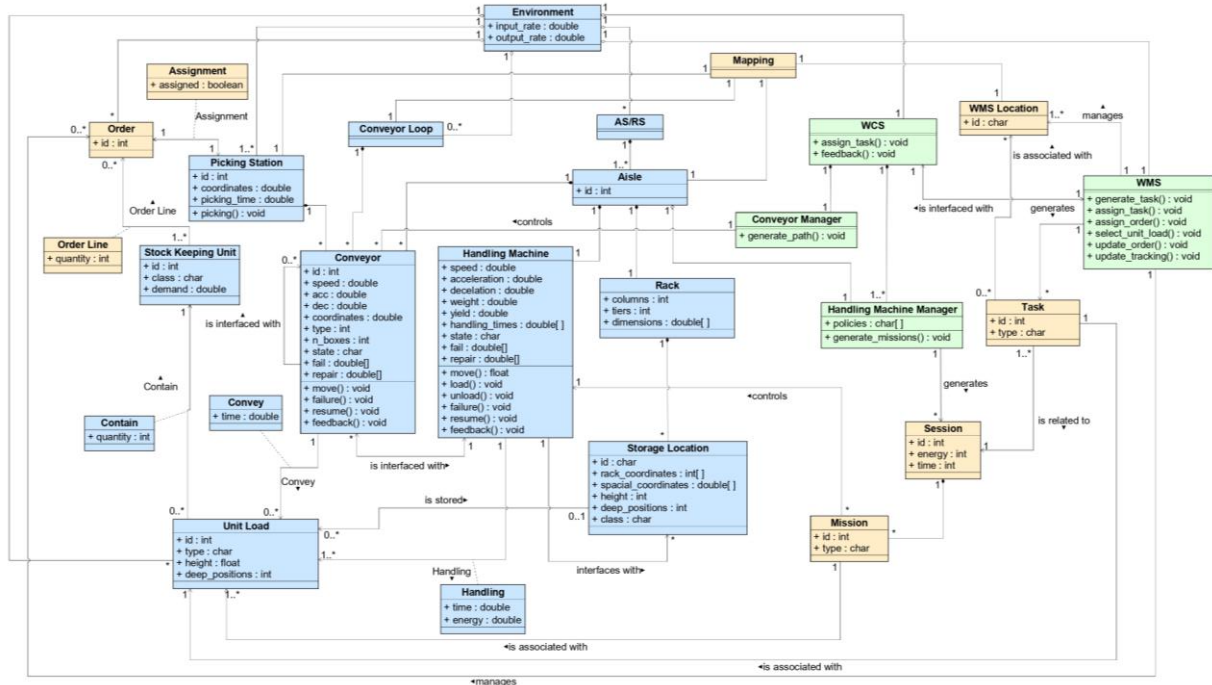


Figure 6 : Conceptual model

5.2. Discrete event simulation model

The conceptual model was translated in a DES model. A DES model allows for the examination of complex systems in detail and the development of virtual experiments to be performed. It is particularly useful when systems are too complex to be analysed directly through observation or mathematical analysis (Law, 2015). The modelling and simulation software used was AnyLogic™, which is designed to simulate diverse logistics and supply chain structures.

Within the DES model, time and energy consumption mathematical models were integrated. The models were taken from (Ekren, 2020; Lehmann & Hußmann, 2021; Lerher et al., 2014) and extend to integrate additional variables. Consider a mission $\phi = (i, j)$ where $i, j \in \{0,1\}$. i indicates the type of HM mission, with $i = 0$ indicating that the mission is a storage mission and $i = 1$

indicating that the mission is a retrieval mission. j indicates the destination of a mission and $j = 0$ indicates that the destination of the mission is a storage location, while $j = 1$ indicates that the destination of the mission is a conveyor. Therefore, the total time to complete a mission t can be calculated as:

$$t = \begin{cases} t_r + t_m + t_s + t_d & \text{if } \phi = (0,0) \\ t_r + t_m + t_s + t_{c_o} & \text{if } \phi = (0,1) \\ t_r + t_m + t_d + t_a & \text{if } \phi = (1,0) \\ t_r + t_m + t_s + t_{c_i} & \text{if } \phi = (1,1) \end{cases}$$

where t_r is the time to calculate the route, t_m is the time to travel, t_s is the time to start the storage or retrieval of a UL, t_d is the time to store or retrieve a UL, t_{c_i} is the time to load a UL from the input conveyor, t_{c_o} is the time to unload a UL onto the output conveyor, and t_a is the time to adjust the UL onboard the HM.

On the other hand, the total energy required to complete a mission e_t can be calculated as:

$$e_t = \begin{cases} e + e_d & \text{if } \phi(0,0) \vee (1,0) \\ e + e_{c_o} & \text{if } \phi = (0,1) \\ e + e_{c_i} & \text{if } \phi = (1,1) \end{cases}$$

where e is the energy consumed to travel, e_d is the energy to store or retrieve a UL, e_{c_i} is the energy required to load a UL from the input conveyor, and e_{c_o} is the energy consumed to unload a UL onto the output conveyor.

Figure 7 displays the DES model in the AnyLogic™ environment.

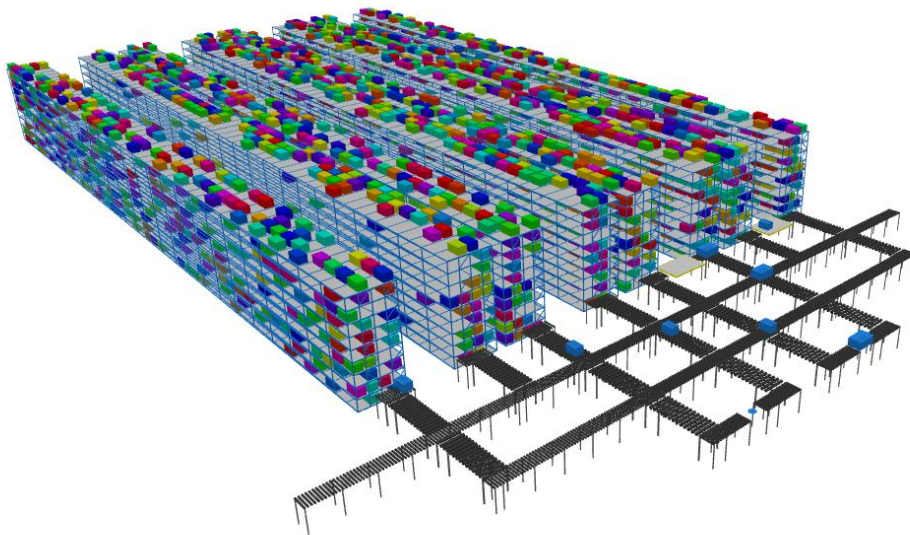


Figure 7 : AnyLogic™ discrete event simulation model

5.3. Optimisation-embedded simulation

In an optimisation-embedded simulation, the simulation model serves to drive the entire process, with the optimisation process being an intrinsic and integral part of it (Zhou et al., 2021).

Order processing in a multi-PS parts-to-picker system involves several critical decisions, including order sequencing, order allocation, ULs selection, ULs sequencing, conveyor path selection and aisle assignment (Wang et al., 2023). Each decision represents a sub-problem, many of which have been studied extensively in the literature. Notably, the majority of these sub-problems are recognised as NP-hard, requiring sophisticated methods for effective solutions and optimal results. Given the holistic approach adopted in this study, the primary focus is on the overall functionality of the system, rather than on the optimisation of individual sub-problems that typically characterise AS/RSSs. Consequently, the majority of these sub-problems were addressed using simple and efficient heuristics. ULs sequencing and conveyor path selection were instead solved using a graph-based approach.

As an example, the optimisation algorithm used to generate the sequence of storage and retrieval missions for the DES model is presented. Once one or more storage/retrieval tasks need to be completed, the WCS generates a list of missions that are grouped into a session. To generate this list of missions, an algorithm with the objective of finding the optimal list of missions required to complete the set of tasks was developed. The approach used was based on a dynamic programming (DP) model, which can be effectively described by defining a statuses transition graph (Ko & Han, 2022). In a statuses transition graph, each status corresponds to a node of the graph and in this problem each node was modelled as the set of the following information:

- The position of the HM within the warehouse, referred to as the last storage location visited.
- The list of ULs on board of the HM.
- The list of pending tasks to be completed.
- The list of storage locations that underwent a storage, retrieval or relocation operation.
- The depth to which the HM extends to perform the storage/retrieval operation during the current node.
- The list of child and parent nodes.

In a graph defined in this manner, each path from the initial node to the final node corresponds to a feasible sequence of system statuses that facilitates the execution of all assigned tasks. Generally speaking, the initial node can be considered as the system status with all the tasks to be completed, the HM empty and positioned in the last storage location visited. On the other hand, the final node represents a system status in which all the tasks are completed and the HM is again empty. The optimal sequence of nodes can be seen as the shortest path between the initial node and the final node.

The transition cost between two nodes in the graph (for instance node λ_1 and node λ_2) represents the time or energy required to move from one node to the next (i.e. the time or energy required to move from the HM location of node λ_1 and the HM location of node λ_2). Therefore, given a weighted and directed statuses transition graph $G(V, E, c)$, the overall problem can be seen as a shortest-path problem between node λ_1 and node λ_2 . However, it has been demonstrated that minimising travel time does not immediately lead to minimum energy consumption and vice versa (Borovinšek et al., 2016; Ekren, 2020; Yang et al., 2023). Therefore, the transition cost between two nodes was calculated as a weighted linear combination of the normalised time and energy required to move from one node to the next. Each edge was normalised by dividing its weight by the weight of the corresponding shortest path, both in terms of time and energy consumption, and two weighted (normalised) and directed graphs $G_t(V, E, c_t)$

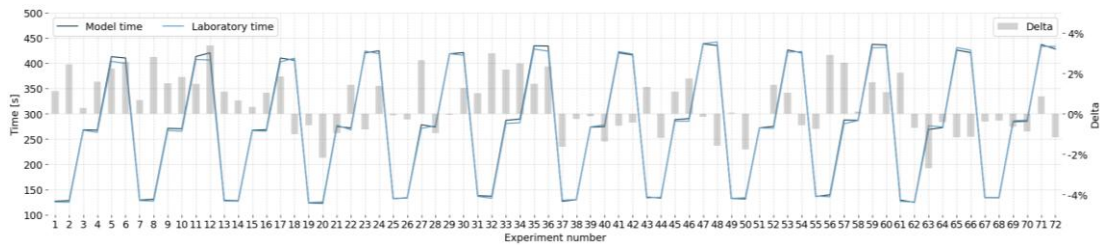
and $G_e(V, E, c_e)$ was obtained. G_t and G_e have the same nodes and edges, but differ from the transition costs between nodes. Hence, given G_t and G_e in form of two adjacency matrices, the resulting graph $G(V, E, c)$ can be generated as:

$$G = \alpha \cdot G_t + (1 - \alpha) \cdot G_e$$

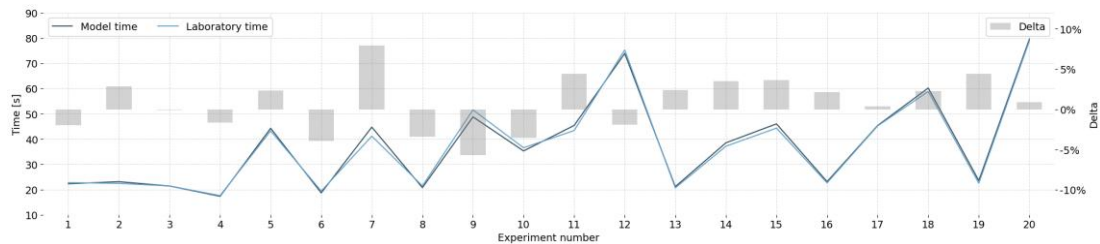
The shortest path between the initial and final nodes was identified using the Dijkstra algorithm. Employing this exact algorithm guarantees an optimal solution to the problem.

5.4. Digital model calibration and validation

The validation process was conducted in the Logistics Laboratory of Politecnico di Torino, which is equipped with a small MLS system with a single-aisle double front storage rack composed of seven tiers and eight columns, and it was divided into two main steps. The first focused only on the storage process, while the second considered the retrieval one. To accurately structure the validation campaign of the storage process, the design of experiments principles were adopted, selecting the total storage time as the dependent variable, and UL type, total number of ULs, and starting warehouse capacity used as independent variables. Considering all the possible combinations of parameters and the number of replications, a total of 72 experiments were conducted. Focusing on the validation of the retrieval process, which employed a less structured yet still reliable approach in comparison to the storage process, it was carried out through 20 experiments. Once all the experiments were conducted in the laboratory, they were exactly replicated in the DM. At the end of a simulated experiment, the results obtained were compared with the data from the physical experiments. Figure 3 shows the result of the comparison between the performance of the DM and the one of a small MLS in laboratory.



(a) Storage process



(b) Retrieval process

Figure 8 : Validation results

6. Integration of artificial intelligence

6.1. Order sequencing problem

A variety of methodologies have been employed to investigate and optimise AS/RS. In order to overcome the limitations of each individual methodology, researchers have developed approaches that combine two or more techniques in an integrated framework. Within this line, simulation-optimisation (SO) represents a promising way to solve complex, uncertain and dynamic problems. SO, also called simulation-based optimisation or optimisation-via-simulation, can be defined as a group of methods used to optimise stochastic simulations, that are simulations that include uncertainty and variability due to random variables as inputs, which logically lead to random outputs (Abid & Mhada, 2021). As opposed to algebraic model-based mathematical programming, SO does not assume that an algebraic description of the simulation is available (Amaran et al., 2016).

Among the operational problems that characterise AS/RS, the order sequencing problem (OSP) poses a significant challenge since it has been demonstrated that efficient order sequencing is crucial for minimising operational costs, enhancing productivity, and improving customer service (Ko & Han, 2022). The objective of the OSP is to find the optimal sequence S of the given N picking orders O that minimises the makespan. The OSP can be mathematically written as follows:

$$\begin{aligned} & \min_S F(S, X) \\ & \text{Subject to} \quad S = \{s_1, s_2, \dots, s_N\} \\ & \quad \quad \quad s_i \in \{O_1, O_2, \dots, O_N\} \quad \forall i \in \{0, N\} \\ & \quad \quad \quad s_i \neq s_j \quad \forall i \neq j \in \{0, N\} \end{aligned}$$

The objective of the problem is to find the optimal order sequence S which minimised the objective function F , i.e. the makespan, which in turn depends on a given order sequence S and a set of system variables X . The constraints ensure that the orders belonging to S do not get replicated. Simulation becomes essential in solving the OSP in real system, because the performance measures of complex systems are hard to be mathematically formulated (Suemitsu et al., 2022). Furthermore, the uncertainty and variability inherent in any industrial system, and thus in automated warehouse processes, adds another layer of difficulty to optimisation problems, making the associated models particularly difficult to solve (Juan et al., 2023). However, the traditional simulation in a SO framework tends to be computationally expensive, which limits the use of the approach in practice. To speed up the solution process, metamodel-based SO arises as an alternative approach, which is also the approach used in this paper. The main idea is to approximate the objective function with a metamodel that is computationally less expensive than a traditional simulation model. Metamodels or surrogate models are often built on simulation output to provide quick predictions without the need to run time-consuming simulations (Xu et al., 2015).

6.2. Metamodelling

The metamodels tested were all based on an NN architecture designed for a regression task and implemented using the PyTorch framework. The choice of an NN as a metamodel was motivated by the fact that certain architectures, for example, recurrent neural networks (RNNs),

excel in handling sequential data, such as the sequence of picking orders. RNNs are designed to capture and model dependencies in sequential data by maintaining a hidden state that evolves as the network processes each element in the sequence. Therefore, RNNs represent a promising approach when addressing problems involving the sequence of picking orders (Suemitsu et al., 2022). However, traditional RNNs may face challenges such as vanishing gradients, limiting their effectiveness in handling long-term dependencies. Long Short-Term Memory (LSTM) networks, a specific type of RNN, address these issues by incorporating memory cells and gating mechanisms. Another promising architecture also able to handle sequential data is Gated Recurrent Unit (GRU), which can capture long-term dependencies in data with a simpler structure and fewer parameters compared to LSTMs. Therefore, these three types of RNNs were compared. Figure 9 illustrates the general architecture of the metamodells, which remained consistent across all the tested metamodells, with the only variation being the type of recurrent cells used.

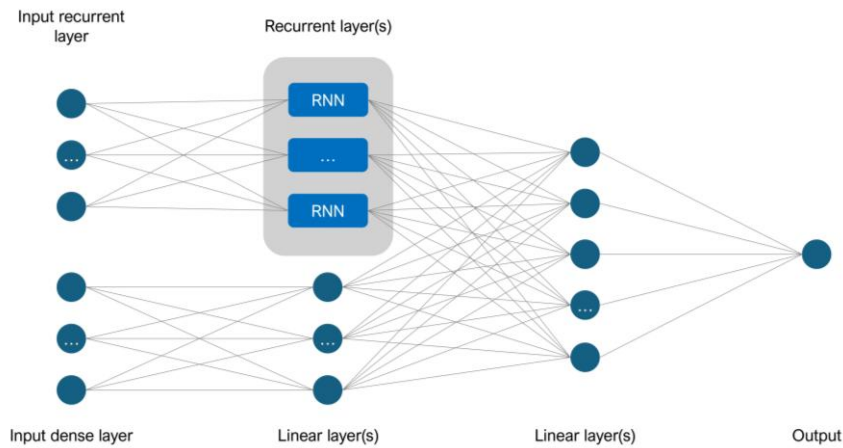


Figure 9 : The structure of the metamodells

To obtain the data to train the metamodel, the DM of the MLS developed was used to simulate random order sets and monitor the makespan. The simulation process began by initialising a random scenario, where the initial warehouse capacity used ranged from 50% to 80%. Each UL was assigned a stock keeping unit (SKU) in a predetermined quantity based on available capacity and the demand value of each SKU. Additionally, the initial positions of the HMs, indicated by their last visited storage location, were randomly selected from all available storage locations within the HM aisle. Subsequently, an order set comprising a random number of orders (between 10 and 50) was generated. Each order included between 1 and 10 order lines, with the quantity of each SKU requested in each order line being randomly sampled from a normal distribution. Each simulation was run until the last order line of the last order was completely picked. A total of 3,500 independent order sets were simulated. The whole dataset was then split in training-validation-testing sub-datasets following the 80-20 rule: 80% of the sample was used for training and validation, while the remaining 20% was used to test the trained metamodels on unseen data and to evaluate their performance.

Figure 10 presents the training and validation curves of the three metamodels. At the end of the training epochs, no overfitting was detected and all the metamodels exhibited small mean absolute error (MAE) and mean absolute percentage error (MAPE) values, indicating their

proficiency in predicting the total makespan for completing a sequence of picking orders. All the metamodels performed quite well, but among all and considering both the metrics, GRU performed slightly better.

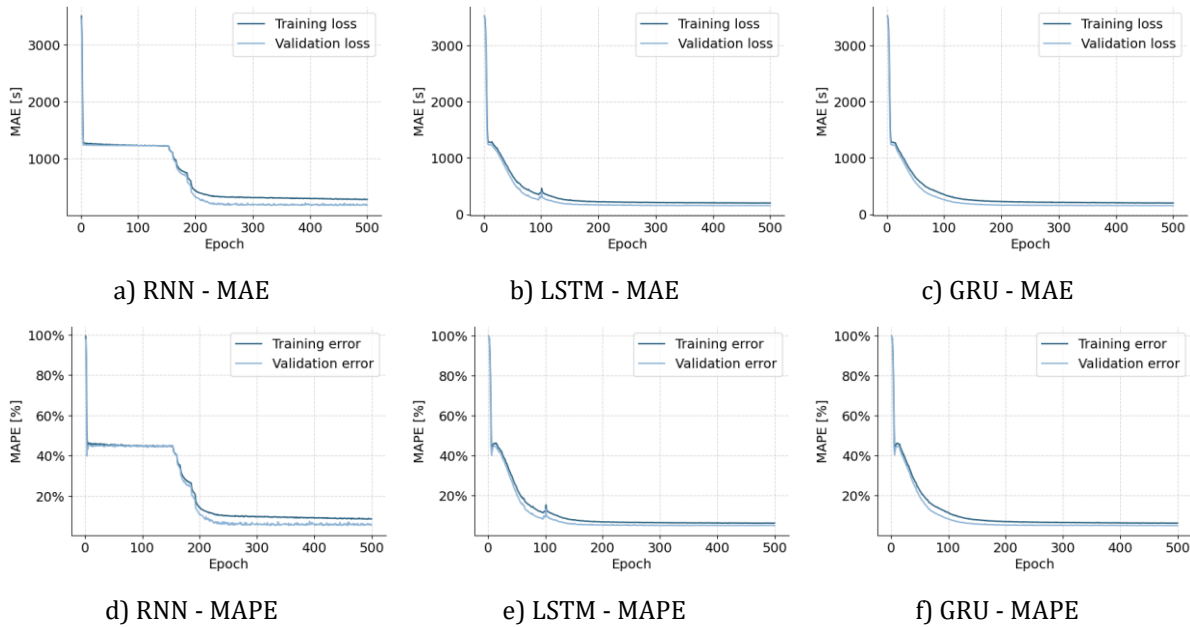


Figure 10 : Training and validation curves

In order to evaluate the effectiveness of replacing the computationally intensive and resource-demanding DES model with the metamodels, the time required to complete the simulation of an order set using the DES model was compared to the time needed to predict the makespan using the already trained and tested NNs. Various scenarios were considered, including order sets of varying sizes (10, 20, 30, 40, 50) and different warehouse capacities (50%, 65%, 80%). Table 2 shows the comparison between the DES model and the metamodels in terms of computation time, conducted on a computer with an Intel Core i9-13900K 3.00 GHz 32-core CPU and a 64 GB RAM. The superior performance of the metamodels in rapidly predicting the picking orders makespan was demonstrated across all configurations tested.

To select the best metamodel, the results of the tests were analysed. Notably, the RNN achieved its peak performance with a much more complex architecture (more layers and neurons) compared to LSTM and GRU. Despite this, the RNN consistently under-performed relative to the other two metamodels. Both LSTM and GRU yielded similar results in terms of training loss, testing loss and prediction speed, with GRU slightly outperforming LSTM in all analyses. Therefore, considering also its simpler internal-cell architecture compared to LSTM, GRU was chosen as the best metamodel.

Table 2: Discrete event simulation model and metamodels comparison

Orders [#]	Capacity [%]	DES [s]	RNN [s]	LSTM [s]	GRU [s]
10	50	1.21958	0.00189	0.00157	0.00155
10	65	1.15768	0.00173	0.00177	0.00156
10	80	1.04001	0.00185	0.00161	0.0016
20	50	2.40945	0.00173	0.00165	0.00154
20	65	2.2885	0.00172	0.00161	0.00153
20	80	1.90644	0.00189	0.00168	0.00157
30	50	3.47374	0.00172	0.00158	0.00154
30	65	3.35356	0.00173	0.00178	0.00151
30	80	2.62179	0.00186	0.00159	0.00157
40	50	4.89953	0.00172	0.00167	0.00152
40	65	4.40991	0.00171	0.00179	0.00152
40	80	3.52436	0.00186	0.0015	0.00158
50	50	6.15346	0.00179	0.00144	0.00151
50	65	5.66116	0.00177	0.0017	0.00153
50	80	4.42533	0.0018	0.00174	0.00158
Average		3.2363	0.00179	0.00165	0.00155

6.3. Swap sequence-based particle swarm optimisation

The GRU-based metamodel was then used to solve the OSP by using it to evaluate the objective function, i.e. the makespan, in an optimisation algorithm. Since it has been demonstrated that OSP is a combinatorial NP-hard problem, it is relevant to find an optimisation methodology able to treat this kind of problems. Metaheuristics are powerful algorithmic frameworks designed to solve NP-hard combinatorial problems in a reasonable time frame. PSO is a well-known swarm intelligence algorithm inspired by the flocking behaviour of birds. In PSO, a population of particles searches for optimal solutions by updating their positions and velocities based on their own experiences and those of their neighbours, following the principles of the optimisation algorithm (Xia et al., 2020).

An example of PSO applied to discrete problems is the swap sequence-based PSO (SSBPSO). The key difference with the continuous PSO is that in SSBPSO a particle position represents a complete sequence of elements, e.g. the sequence of orders in the order set, and a particle velocity is a sequence of swap operators (Emambocus et al., 2021). Each swap operator is a pair of indices indicating which two elements of the particle, e.g. two orders of an order sequence, should be swapped. At each iteration it , the velocity V of each particle is then updated using the following equation:

$$V_{it} = wi \cdot V_{it-1} \oplus cp \cdot r_1 \cdot (P_b \ominus S_{it-1}) \oplus cl \cdot r_2 \cdot (|1 - f_a| \cdot L_b \ominus S_{it-1}) \oplus cg \cdot r_3 \cdot (|1 - f_a| \cdot G_b \ominus S_{it-1})$$

where wi is the inertia weight determining how much of the velocity of the particle at the previous iteration is preserved. cp, cl and cg are three acceleration coefficients denoting the learning weights for the personal best, local best and global best exemplars respectively. r_1, r_2 and r_3 are random numbers between 0 and 1, sampled in the initial phase of the algorithm and maintained constant for all the iterations. P_b, L_b and G_g are the particle personal best, local best, and the global best solutions respectively. f_a is the forgetting ability of the particle. S_{it-1} and V_{it-1} are

respectively the position of the particle, which is an order sequence, and the velocity of the particle, which is a sequence of swap operators, in the previous iteration. Finally, the operator \oplus means that the two swap sequences are merged to form a new swap sequence, while the operator \ominus indicates the subtraction of two particle positions which generates a swap sequence.

The position of the particles is then updated using the following equation:

$$S_{it} = S_{it-1} \oplus V_{it}$$

where the operator \oplus indicates that each swap operator in the swap sequence V_{it} is sequentially applied to S_{it-1} to generate the new solution S_{it} .

7. Services

7.1. Descriptive and predictive services

The DT encompasses different functionalities that can be classified as services. Descriptive services are the cornerstone of DTs, capturing and reflecting the current state of the physical system with high accuracy and enabling effective monitoring. On the other hand, predictive services expand the role of DTs by using data-driven models and simulations to anticipate future conditions and system behaviours. The descriptive and predictive capabilities of the DT were tested simulating different configurations of an MLS system using the DM previously developed and validated. Specifically, configuration 1 (C1) was a 45 column, 8 level warehouse, configuration 2 (C2) was a 60 column, 9 level warehouse and configuration 3 (C3) was a 75 column, 10 level warehouse. Moreover, different values of the average storage capacity used (55%, 70%, 85%) and the α factor (0, 0.5, 1) were also taken into account. Then, optimisation session with different dimensions (4 ULs, 8 ULs) were also compared. Finally, the model was also used to compare the performance of system with different HM capacity (1 UL, 2 ULs), that is the maximum number of ULs that can be moved at the same time. The simulations were performed by varying one parameter at a time, resulting in a total of 108 combinations. Each of them was simulated for a time corresponding to an 8-hour shift, in order to represent a real operating scenario. The input and output rates were set to be Poisson distributed with mean equals to 100 ULs per hour. During each simulation, a set of key performance indicators (KPIs) was measured. During each simulation, a set of KPIs was measured. This included system throughput (TH), which represents the number of tasks performed in a time unit of one hour. In addition, the mean cycle time (CT) was evaluated. Considering a session as a set of missions generated by the DP optimisation algorithm, CT is calculated as the ratio between the session time and the number of tasks completed in that session. Finally, the average energy consumption for a single task (ET) was also tracked, which is the relationship between the electrical energy required to run a session and the number of tasks completed in that session. The effects of the simulation factors on each KPI were analysed through a series of effect plots, which are shown in Figure 11. Each effect was evaluated on the three warehouse configurations studied. In general, across all the metrics analysed, configuration C3 (75 columns and 10 tiers) consistently resulted in poorer performance, potentially due to the increased dimension of the warehouse rack. An increase in storage capacity generally resulted in a deterioration in performance. The α factor did not exhibit a significant impact on the KPIs. Conversely, the maximum number of ULs of the optimisation sessions and the

HM capacity exhibited a discernible impact, with an improvement in system performance observed as parameter values increased.

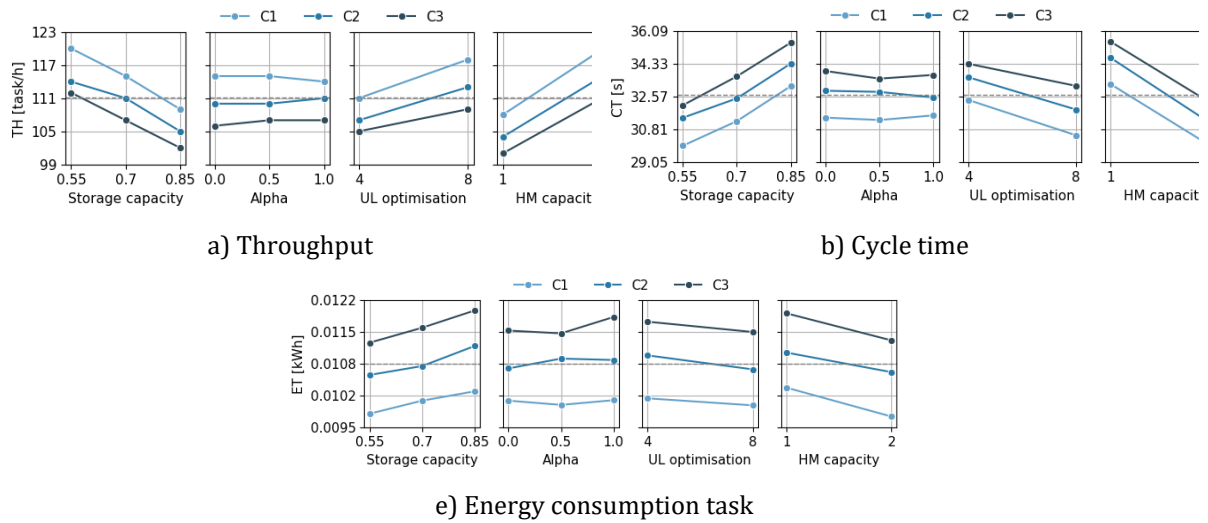


Figure 11 : Main effects plot

7.2. Prescriptive services

Prescriptive services in DTs go beyond monitoring and prediction by providing actionable recommendations and interventions to optimise system performance. In this study, a prescriptive service offered by the DT involves generating optimised sequences of POs by solving the OSP using the AI module. Some numerical experiments were carried out to test the capabilities of the combination of the GRU-based metamodel and the SSBPSO algorithm. Several experimental factors were controlled to cover a good range of potential scenarios. More specifically, to study the performance of the SO approach in different contexts, problem instances with different order set dimension (10, 30, 50 orders) and storage capacity (50, 65, 80%) were considered. As observed in the graphs showed in Figure 12, the algorithm showed continuous improvement of the best solution, with effective exploration during the initial phases, indicated by a high average fitness function value across the population, and strong exploitation in the later stages, evidenced by the convergence of all particles towards the final best solution, further refining it.

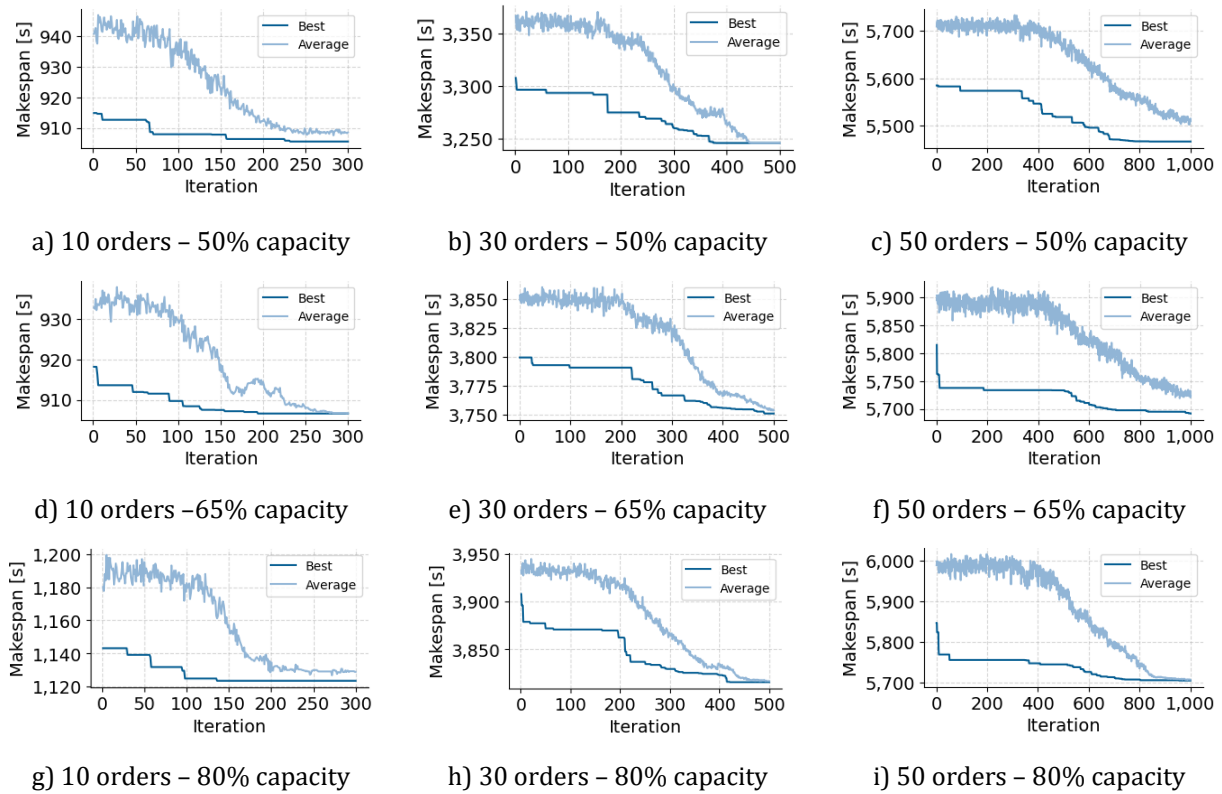


Figure 12 : Test of the SO framework

8. Conclusions

The objective of this study is to investigate the significance and potential applications of the DT technology in AS/RSs. The contribution of this work are multiple. Firstly, it proposes a comprehensive architecture for the implementation of a DT, with a specific focus on the identification of the primary elements that constitute a DT for AS/RS. Secondly, it delineates the principal stages involved in the development and implementation of a DT in AS/RS, ranging from the development of the foundational DM, its validation and its testing. Finally, this research proposes a way to implement an AI module based on a NN and a SSBPSO algorithm to support the DT and the resolution of warehouse related problems such as OSP. In conclusion, this study presents a comprehensive and practical roadmap for the implementation of DTs in AS/RS that can be adapted and extended to a variety of industrial applications, addressing both the theoretical foundations and the practical challenges involved.

This research contributes to the deeper theoretical understanding of DT for AS/RS by providing a detailed and structured approach to their development and integration. Moreover, the developed DM integrates simulation and optimisation, which has been demonstrated to be an effective approach to study and manage automated warehousing systems. By establishing a structured approach for validating such DM, this work also advances the identification of key parameters that should be considered when developing DT-oriented simulation models designed to accurately replicate the operation and performance of an AS/RS system. Finally, by demonstrating the effectiveness of NN-based metamodeling in combination with advanced

optimisation algorithms such as SSBPSO, this study introduces new, powerful methodologies to extend DT capabilities and address the challenges of automated warehouse operations.

From a practical standpoint, implementing the DT has the potential to significantly enhance operational efficiency in automated warehouses, serving as a powerful decision-support tool by providing real-time insights and predictive analytics. This empowers warehouse managers to make informed decisions, anticipate operational issues, and implement optimal strategies. Additionally, the implementation steps outlined in this work offer logistics companies valuable guidance in identifying potential challenges when implementing a DT in an industrial setting. Warehouse practitioners could leverage the findings of this study to better tailor and adjust warehousing operations in response to real-time company and customer needs. Overall, this study provides an effective tool for predicting system behaviour and supporting day-to-day operations in automated warehouse environments. It showcases the feasibility of addressing internal logistics processes and improving decision-making in these settings.

Despite the current stage of development, this work suffers from certain limitations. For instance, the evaluation of the DM performance has yielded valuable insights, but it is essential to acknowledge that the validation was focused exclusively on time metrics, as the absence of specific instrumentation precluded a comprehensive measurement of energy consumption within the physical system. Additionally, the current implementation of the DP algorithm is limited to smaller instances of the HM task sequencing problem, highlighting the need to explore more scalable approaches such as metaheuristics or ML techniques. Then, the DM did not take into account disruptive mechanical issues, such as component repairs within the warehouse system, that could heavily impact maintenance activities. Regarding the development of the AI module, it is fundamental to clarify that the DM operates under the assumptions that inbound and outbound processes are not considered, and stock-outs of SKUs do not occur. Future studies could benefit from relaxing these assumptions to evaluate the approach reliability in more-realistic scenarios, where such events can occur and impact warehouse operations. In addition, order priority was not taken into account, which could have a significant impact on the optimisation process. Focusing on the DT interfaces, the challenge of establishing an effective bidirectional data flow between the physical and digital systems has not yet fully been addressed. The next phase of this research will focus on the comprehensive integration of all DT components into a unified framework. The plan also involves deploying a prototype of DT in a live warehouse setting like the one in the laboratory of Politecnico di Torino, in order to evaluate its performance and accuracy in predicting, optimising, monitoring, and controlling warehouse operations. Successful integration and validation are expected to make the DT scalable and adaptable to various warehouse configurations and operational settings, making it a versatile tool for automated warehousing systems.

9. References

- Abid, S., & Mhada, F. Z. (2021). Simulation optimisation methods applied in reverse logistics: A systematic review. *International Journal of Sustainable Engineering*, 14(6), 1463–1483.
- Amaran, S., Sahinidis, N. V., Sharda, B., & Bury, S. J. (2016). Simulation optimization: A review of algorithms and applications. *Annals of Operations Research*, 240(1), 351–380.
- Assad Neto, A., Ribeiro Da Silva, E., Deschamps, F., & Pinheiro De Lima, E. (2021). Digital twins in

- manufacturing: An assessment of key features. *Procedia CIRP*, 97, 178–183.
- Azadeh, K., De Koster, R., & Roy, D. (2019). Robotized and Automated Warehouse Systems: Review and Recent Developments. *Transportation Science*, 53(4), 917–945.
- Borovinšek, M., Ekren, B. Y., Burinskienė, A., & Lerher, T. (2016). Multi-Objective Optimisation Model of Shuttle-Based Storage and Retrieval System. *Transport*, 32(2), 120–137.
- Boysen, N., & Stephan, K. (2016). A survey on single crane scheduling in automated storage/retrieval systems. *European Journal of Operational Research*, 254(3), 691–704.
- Braglia, M., Gabbrielli, R., Frosolini, M., Marrazzini, L., & Padellini, L. (2019). Using RFID technology and Discrete-Events, Agent-Based simulation tools to build Digital-Twins of large warehouses. *2019 IEEE International Conference on RFID Technology and Applications (RFID-TA)*, 464–469.
- Coelho, F., Relvas, S., & Barbosa-Póvoa, A. P. (2021). Simulation-based decision support tool for in-house logistics: The basis for a digital twin. *Computers & Industrial Engineering*, 153, 107094.
- Drissi Elbouzidi, A., Ait El Cadi, A., Pellerin, R., Lamouri, S., Tobon Valencia, E., & Bélanger, M.-J. (2023). The Role of AI in Warehouse Digital Twins: Literature Review. *Applied Sciences*, 13(11), 6746.
- Ekren, B. Y. (2020). A simulation-based experimental design for SBS/RS warehouse design by considering energy related performance metrics. *Simulation Modelling Practice and Theory*, 98, 101991.
- Emambocus, B. A. S., Jasser, M. B., Hamzah, M., Mustapha, A., & Amphawan, A. (2021). An Enhanced Swap Sequence-Based Particle Swarm Optimization Algorithm to Solve TSP. *IEEE Access*, 9, 164820–164836.
- Epp, M., Wiedemann, S., & Furmans, K. (2017). A discrete-time queueing network approach to performance evaluation of autonomous vehicle storage and retrieval systems. *International Journal of Production Research*, 55(4), 960–978.
- Ferrari, A., Carlin, A., Rafele, C., & Zenezini, G. (2024). A method for developing and validating simulation models for automated storage and retrieval system digital twins. *The International Journal of Advanced Manufacturing Technology*, 131(11), 5369–5382.
- Ferrari, A., & Mangano, G. (2023). Review of Relevant Literature on Modelling and Simulation Approaches for AS/RSs. *IFAC-PapersOnLine*, 56(2), 3680–3685.
- Ferrari, A., Zenezini, G., Rafele, C., & Carlin, A. (2022). A Roadmap towards an Automated Warehouse Digital Twin: Current implementations and future developments. *IFAC-PapersOnLine*, 55(10), 1899–1905.
- Gagliardi, J.-P., Renaud, J., & Ruiz, A. (2012). Models for automated storage and retrieval systems: A literature review. *International Journal of Production Research*, 50(24), 7110–7125.
- Gaku, R., & Takakuwa, S. (2017). Simulation modeling of shuttle vehicle-type mini-load AS/RS systems for E-commerce industry of Japan. *2017 Winter Simulation Conference (WSC)*, 3174–3183.
- Ivanov, D. (2023). Intelligent digital twin (iDT) for supply chain stress-testing, resilience, and viability. *International Journal of Production Economics*, 263, 108938.
- Ivanov, D., & Dolgui, A. (2020). 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.
- Juan, A. A., Keenan, P., Martí, R., McGarraghy, S., Panadero, J., Carroll, P., & Oliva, D. (2023). A review of the role of heuristics in stochastic optimisation: From metaheuristics to learnheuristics. *Annals of Operations Research*, 320(2), 831–861.

- Kembro, J. H., & Norrman, A. (2019). Warehouse configuration in omni-channel retailing: A multiple case study. *International Journal of Physical Distribution & Logistics Management*, 50(5), 509–533.
- Ko, D., & Han, J. (2022). A rollout heuristic algorithm for order sequencing in robotic compact storage and retrieval systems. *Expert Systems with Applications*, 203, 117396.
- Kritzinger, W., Karner, M., Traar, G., Henjes, J., & Sihn, W. (2018). Digital Twin in manufacturing: A categorical literature review and classification. *IFAC-PapersOnLine*, 51(11), 1016–1022.
- Law, A. M. (2015). *Simulation modeling and analysis* (Fifth edition). McGraw-Hill Education.
- Lehmann, T., & Hußmann, J. (2021). Travel time model for multi-deep automated storage and retrieval system with a homogeneous allocation structure. *Logistics Research*, 14(5).
- Leng, J., Yan, D., Liu, Q., Zhang, H., Zhao, G., Wei, L., Zhang, D., Yu, A., & Chen, X. (2021). Digital twin-driven joint optimisation of packing and storage assignment in large-scale automated high-rise warehouse product-service system. *International Journal of Computer Integrated Manufacturing*, 34(7–8), 783–800.
- Lerher, T., Edl, M., & Rosi, B. (2014). Energy efficiency model for the mini-load automated storage and retrieval systems. *The International Journal of Advanced Manufacturing Technology*, 70(1–4), 97–115.
- Marolt, J., Kosanić, N., & Lerher, T. (2022). Relocation and storage assignment strategy evaluation in a multiple-deep tier captive automated vehicle storage and retrieval system with undetermined retrieval sequence. *International Journal of Advanced Manufacturing Technology*, 118(9–10), 3403–3420.
- Suemitsu, I., Bhangara, H. K., Utsugi, K., Hashizume, J., & Ito, K. (2022). Fast Simulation-Based Order Sequence Optimization Assisted by Pre-Trained Bayesian Recurrent Neural Network. *IEEE Robotics and Automation Letters*, 7(3), 7818–7825.
- Tao, F., Cheng, J., Qi, Q., Zhang, M., Zhang, H., & Sui, F. (2018). Digital twin-driven product design, manufacturing and service with big data. *The International Journal of Advanced Manufacturing Technology*, 94(9–12), 3563–3576.
- Wang, B., Yang, X., & Qi, M. (2023). Order and rack sequencing in a robotic mobile fulfillment system with multiple picking stations. *Flexible Services and Manufacturing Journal*, 35(2), 509–547. <https://doi.org/10.1007/s10696-021-09433-8>
- Xia, X., Gui, L., He, G., Wei, B., Zhang, Y., Yu, F., Wu, H., & Zhan, Z.-H. (2020). An expanded particle swarm optimization based on multi-exemplar and forgetting ability. *Information Sciences*, 508, 105–120.
- Xu, J., Huang, E., Chen, C.-H., & Lee, L. H. (2015). Simulation Optimization: A Review and Exploration in the New Era of Cloud Computing and Big Data. *Asia-Pacific Journal of Operational Research*, 32(03), 1550019.
- Yang, P., Tao, P., Xu, P., & Gong, Y. (2023). Bi-objective operation optimization in multi-shuttle automated storage and retrieval systems to reduce travel time and energy consumption. *Engineering Optimization*, 55(9), 1498–1515.
- Zhang, G., MacCarthy, B. L., & Ivanov, D. (2022). The cloud, platforms, and digital twins—Enablers of the digital supply chain. In *The Digital Supply Chain* (pp. 77–91). Elsevier.
- Zhou, C., Ma, N., Cao, X., Lee, L. H., & Chew, E. P. (2021). Classification and literature review on the integration of simulation and optimization in maritime logistics studies. *IIEE Transactions*, 1–39.