Simulation Study of a Multi-Level Shuttle System with In-rack Picking Stations

Simulation Study of a Multi-Level Shuttle System with In-rack Picking Stations ⋆

Andrea Ferrari * **Alessandra Verso** * **Antonio Carlin** *
Carlo Rafele *

* *Politecnico di Torino, Department of Management and Production Engineering, Torino (TO), Italy*
Corresponding author: Andrea Ferrari (email andrea.ferrari@polito.it)

Abstract: This paper addresses the evolving warehouse automation scenario in supply chain management, focusing on the design and simulation of a multi-level shuttle system. Unlike existing studies, the proposed system integrates picking stations within the storage rack, optimising space and improving picking efficiency. A discrete event simulation is proposed to model the system design and operation. The model also integrates different strategies for selecting items and serving picking stations. The paper provides insights into efficient warehouse processes from both a theoretical and practical point of view by presenting a structural model, simulation results and implications.

Keywords: Automated storage and retrieval system, multi-level shuttle, automated warehouse, discrete event simulation, order picking

1. INTRODUCTION

The realm of supply chain management and logistics has been undergoing rapid transformations with the advent of innovative technologies. One such area that has seen significant advancements is warehouse automation (Marolt et al., 2022). It can involve activities related to the storage and retrieval of goods, as well as internal material handling within the facility (Mahdavisharif et al., 2022). A representative implementation of such automation can be found in automated storage and retrieval systems (AS/RS), which can be defined as computer-controlled systems characterised by the storage and retrieval of unit loads (ULs) without the need for human intervention (Azadeh et al., 2019). These systems have gained a lot of interest both in industrial and academic contexts because of the increased efficacy and efficiency they provide to intralogistics processes (Ferrari and Mangano, 2023).

Considering the different warehouse functions, between 50 % and 65 % of the total warehousing operating costs can be attributed to order picking (Chirici and Wang, 2014). As a result, warehouse systems and processes are rapidly evolving towards automation to eliminate labour-intensive and costly order picking. Many automated solutions involve parts-to-picker methods, where products move from storage locations to order pickers using automated solutions (Vijayakumar and Sgarbossa, 2021). Although some researches are available on studying picking activities in the context of AS/RS, only a few papers proposed an AS/RS with picking stations integrated in the storage rack.

Therefore, to address this gap, this paper proposes a discrete event simulation (DES) model the design of a multi-level shuttle (MLS) system, in which an aisle-captive handling machine (HM) operates in an aisle with picking stations integrated in the storage rack. These stations consist of a series of flow racks designed to optimise the interaction between the HM and operators. This compact warehouse configuration is particularly well-suited to industrial environments that are constrained by limited space. In addition, it accentuates human-machine interactions by positioning operators in closer proximity to the HM. Furthermore, different strategies to serve the picking stations with the UL required for the orders are investigated with the objective of providing insights into the selection of the optimal approach based on specific operational contexts.

The remainder of the paper follows this structure. Section 2 reviews current literature on automated warehouse picking. Section 3 describes the system, including a UML class diagram and digital model. Section 4 details the simulation plan and results. Finally, section 5 presents the discussions and conclusions.

2. LITERATURE REVIEW

In the context of recent research on the picking process in automated warehouses, a diverse range of systems, methodologies and objectives have emerged. For instance, in Ma et al. (2023), the authors proposed an order splitting algorithm for crane & shuttle-based storage and retrieval system (CBS/RS) to balance picking tasks, aimed to satisfy specific requested sequences and minimise the order line picking time.

In the work of Liu et al. (2021), the replenishment process was modelled as queuing problem, where the AS/RS aisle-captive machine serves as the server, and picking stations requiring replenishment are the customers. The research of Faria and Reis (2015) had the objective of developing a

⋆ This research was funded by the Italian Ministry of Education via the "Dipartimenti di Eccellenza" financing program, project award "TESUN-83486178370409".

DES model to assess the performance of the order picking, taking in account multiple storage assignment policies and routing methods.

On the other hand, Yang et al. (2022) developed a queuing model to study a multi-deep robotic mobile fulfilment system (RMFS). The approximate analytical solutions for system throughput, robots utilisation, and queue length were verified and evaluated through simulations.

In the study of Dukic et al. (2015) a simulation model for throughput calculation of a vertical lift module (VLM) with a human order-picker was presented. Similarly, in Sgarbossa et al. (2019), analytical models were proposed for different operational configurations and various storage assignment policies to improve the overall performance of the double-bay VLM system. In Calzavara et al. (2019), an economic evaluation was conducted comparing dual-bay VLM with a manual carton shelving warehouse.

In Wang et al. (2016), the matching problem of a miniload AS/RS is studied with the objective of improving picking efficiency. The article discusses how to reduce the travel distance between aisles and picking stations, proposing a multi-stage heuristic algorithm. Boysen et al. (2022) considered the scheduling of a miniload AS/RS that combines a picking request for an Stock Keeping Unit (SKU) container needed at the picking station with a storage request of a container to be restored in the ASRS after picking.

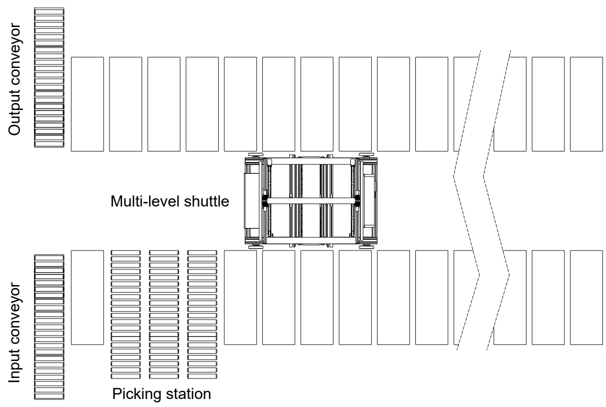
In the article by Nicolas et al. (2017), a linear programming model was developed to minimise the total completion time of a carousel warehouse, in which picking orders are grouped into batches. More recently, Lenoble et al. (2021) studied two batching methods for picking from multiple carousels.

The existing body of research on warehouse processes, particularly focused on the picking process in automated warehouses, reveals a diverse range of studies employing various systems, methodologies, and objectives. However, a noticeable research gap exists in the integration of picking stations into shelving to reduce space utilisation in industrial contexts where space availability is a strict constraint. This research aims to fill this gap by proposing the design of an aisle-captive MLS system with picking stations composed of flow racks integrated within the warehouse rack. Moreover, three distinct strategies for implementing picking operations in such a context are developed. Additionally, the significance of this contribution is contingent upon the utilisation of the Unified Modelling Language (UML) class diagram to conceptualise the system and the reliable DES methodology to implement it.

3. THE MODEL

3.1 System description

This research focuses on a specific application of AS/RS named MLS system (Figure 1) and inspired by Ferrari et al. (2023). In addition to the system presented in by Ferrari et al. (2023), in this study a set of picking station is integrated within the storage rack. This design aims to optimise space utilisation and enhance the efficiency of the picking process. Each picking station is organised in a multi-level set of flow racks, and each level consists of three flow racks with a maximum capacity of 3 ULs. From the aisle, the HM is able to unload a UL directly onto the flow rack, which slides towards the picker by gravity. When the operator has finished picking, the corresponding UL is removed from the flow rack and others behind it become available for picking. At the picking stations, orders are completed one at a time, meaning that there can be a queue of ULs belonging to the same order. The MLS system relies on an Information & Technology (IT) infrastructure supported by a Warehouse Management System (WMS) and a Warehouse Control System (WCS) (Ferrari et al., 2022).



(a) Plant view

(b) Picking stations

Fig. 1. The Multi Level Shuttle

3.2 Notation

The following notation is introduced:

o	Order	p	Product
OL	Set of order lines	ol	Order line
ul	Unit load	UL	Set of unit loads
R	Set of ratios	SL	Set of storage locations
sl	Storage location	ps	Picking station
t	Tier	c	Column
MT	Matrix of travel times	$time$	Travel time
T	Set of travel times	qnt	Quantity of product

3.3 Model structure

In order to develop a simulation model of the system described, a conceptual model was created using the UML class diagram, as a base for the subsequent development of the DES model. The model structure was inspired by Ferrari et al. (2023). The model describes the operation of a MLS system and it divides the model in physical, logical and information classes. Examples of physical classes are the Unit Load and the Aisle, the HM, the Conveyor, and the Storage Location. On the other hand, logical classes represent the IT infrastructure of the system, i.e. the WMS and the WCS. Finally, the information classes set is composed of Task, representing the job to be carried out by the HM, the Mission, that is the single storage/retrieval operation, the Session, which is a group of missions, and the WMS Location, representing logical areas of the warehouse. For further details regarding the single classes composition and their interaction please refer to Ferrari et al. (2023).

However, that model did not consider the picking process, but it was limited to a warehouse system in which only storage and retrieval operations occurred. This study extends the model by introducing additional classes (classes highlighted in Figure 2). The coding of the model works through three different colours: blue for physical classes, green for logical classes and yellow for information classes. Picking Station is the logical class in which orders from the WMS are managed. It is characterised by an identification code, a status indicating its availability and two lists of orders, in process and completed. Flow Rack is the physical class of which the Picking Station is composed, where the ULs are physically managed. It is characterised by an identification code, a status indicating its availability, the maximum capacity and the time to pick an item. Item class represents SKU present in the ULs ordered through orders from outside the warehouse. It has its own identification code. Order class is characterised by an identification code and 1 or more order lines. Finally, the association class Contains links Unit Load and Product by means of a contained quantity. The order also consists of several items with a certain quantity, described in Order lines, and a status, updated by the picking station, which thus takes on both physical and informative connotations.

After analysing the logical system and obtaining the basis for designing the conceptual model, a DES was developed using AnyLogic, software aimed at simulating logistics and supply chain structures of the most varied kinds. This program was chosen because it gives the possibility to take advantage of preset constructs, but it also allows programming the digital model in such a way to detail the simulated case as needed.

For the model development, some parameters were measured on a similar system installed in the laboratory of Politecnico di Torino. Specifically, the times for picking and handling ULs were measured. Following this process, the virtual model was calibrated with the data in the Table 1. The model underwent also the process of validation described in (Ferrari et al., 2023).

Table 1. Parameters for model calibration

Parameter	Value	UoM
Flow rack speed	0.61	m/s
Picking time flow rack (0,0)	1.59	s/item
Picking time flow rack (0,1)/(0,2)	1.76	s/item
Picking time flow rack (1,0)	2.21	s/item
Picking time flow rack (1,1)/(1,2)	2.41	s/item
Handling time	5.92	s

3.4 Picking strategies

Order processing in a parts-to-picker system involves several critical decisions, including UL selection. Once an order is assigned to a picking station, the ULs containing the SKUs requested in the order lines must be selected. This decision is affected by two major factors:

- The SKU requested can be stored in multiple ULs.
- The order quantity may be higher than the quantity contained in a UL.

Therefore, a strategy to select the most appropriate UL to be assigned to the order is needed. In this study, three strategies for UL selection (Random, Min-UL, Zone) are proposed.

The Random strategy (Algorithm 1), chosen as baseline strategy, consists of a random selection of the ULs to complete the picking order. Firstly, for each item requested in the order, a list of ULs containing it and stored in the warehouse is created. Sequentially, random ULs are selected until the total quantity contained in the ULs corresponds to the amount requested in the order line.

Algorithm 1 Picking strategy Random

Require: OL_o
Ensure: $UL_{selected}$
for $ol \in OL_o$ **do**
    $p \leftarrow p_{ol}$
    $UL_p \leftarrow \{ul \in UL_{stored} \mid p_{ul} = p\}$
    while $qnt_{ol} \geq 0$ **do**
        $ul \leftarrow \text{Random}(UL_p)$
        $qnt_{ol} \leftarrow qnt_{ol} - qnt_{ul}$
        $UL_{set} \leftarrow UL_{set} \cup \{ul\}$
        $UL_p \leftarrow UL_p \setminus \{ul\}$
    end while
end for

In the Min-UL strategy (Algorithm 2), the main idea is to minimise the total number of ULs moved, hence minimise the number of movements of the HM. This is done by sorting the list of ULs containing the item in a descending manner based on the ratio between the quantity contained in the UL and the quantity required by the order. The ULs are then selected sequentially from the ordered list.

Algorithm 2 Picking strategy Min-UL

Require: OL_o
Ensure: $UL_{selected}$
for $ol \in OL_o$ **do**
    $p \leftarrow p_{ol}$
    $UL_p \leftarrow \{ul \in UL_{stored} \mid p_{ul} = p_{ol}\}$
    $R \leftarrow \emptyset$
    for $ul \in UL_p$ **do**
        $ratio_{ul} \leftarrow qnt_{ul}/qnt_{ol}$
        $R \leftarrow R \cup \{ratio_{ul}\}$
    end for
    $UL_p \leftarrow \text{SortDesc}(UL_p \mid R)$
    while $qnt_{ol} \geq 0$ **do**
        $ul \leftarrow UL_p[0]$
        $qnt_{ol} \leftarrow qnt_{ol} - qnt_{ul}$
        $UL_{set} \leftarrow UL_{set} \cup \{ul\}$
        $UL_p \leftarrow UL_p \setminus \{ul\}$
    end while
end for

The Zone strategy aims to prioritise the selection of the ULs closest to the picking station assigned to the order (Algorithm 3), with the aim of minimising the space

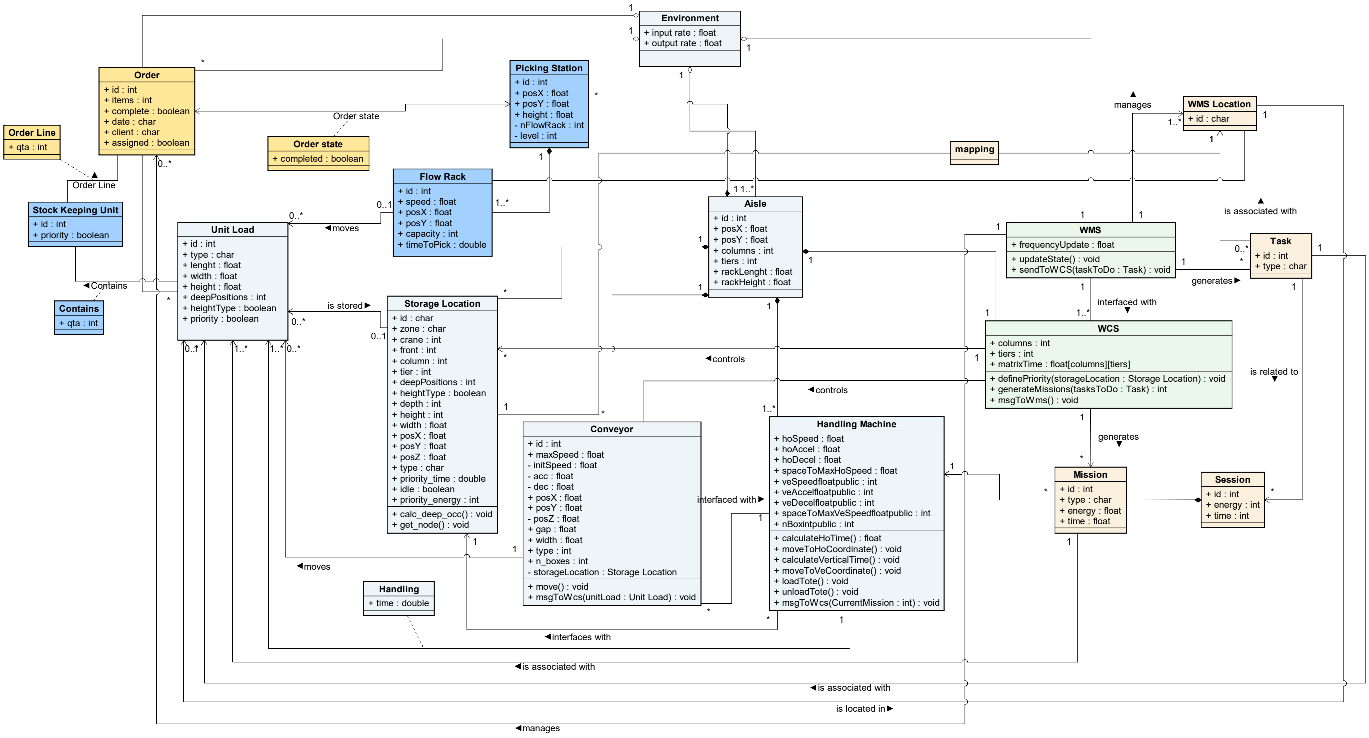


Fig. 2. Conceptual model

travelled by the HM. Therefore, for each order line, the ULs are sorted based on the ascending distance from the storage location in which the UL is stored and the central flow rack of the picking station. Next, the ULs are sequentially selected from the sorted list, following the order previously established.

Algorithm 3 Picking strategy Zone

Require: OL_o
Ensure: $UL_{selected}$
for $ol \in OL_o$ **do**
  $p \leftarrow p_{ol}$
  $UL_p \leftarrow \{ul \in UL_{stored} \mid p_{ul} = p\}$
  for $ul \in UL_p$ **do**
    $sl \leftarrow \{sl \in SL \mid ul \in UL_{sl}\}$
    $time \leftarrow MT[\mid t_{ps} - t_{sl} \mid][\mid c_{ps} - c_{sl} \mid]$
    $T \leftarrow T \cup \{time\}$
  end for
  $UL_p \leftarrow \mathrm{SortAsc}(UL_p \mid T)$
  while $qnt_{ol} \geq 0$ **do**
    $ul \leftarrow UL_p[0]$
    $qnt_{ol} \leftarrow qnt_{ol} - qnt_{ul}$
    $UL_{set} \leftarrow UL_{set} \cup \{ul\}$
    $UL_p \leftarrow UL_p \setminus \{ul\}$
  end while
end for

4. SIMULATION PLAN AND RESULTS

4.1 Model assumptions

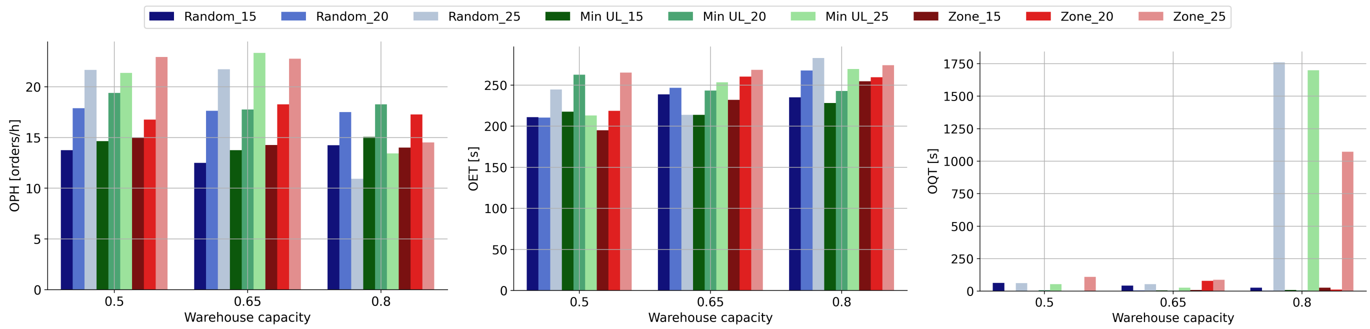
The model represents an automated warehouse with a storage rack consisting of 50 columns, each with 10 tiers. The total number of SKU is 200. They are randomly assigned to ULs at the beginning of the simulation in a random quantity between 10 and 200. Each UL can contain only one SKU at the time. The storage strategy is pure random, while the relocation strategy is nearest neighbour (Marolt et al., 2022). The creation of picking orders follows a Poisson distribution with lambda parameter equal to 1 divided by the order rate. Picking orders are composed of a random number of order lines between 1 and 5. For each order line, an SKU is associated with a quantity ranging from 10 to 20. At the end of the picking process, each UL used is reinserted in the warehouse. If the UL still contains a residual quantity of the SKU, it is reinserted with the remaining contents. Otherwise, it is filled with a quantity between 10 and 200 of the same SKU it contained.

4.2 Scenario configuration

A simulation plan was established with multiple scenarios, in order to compare and determine the best approach for optimising the picking process of MLS systems. Specifically, four parameters were controlled during the simulations, namely the number of picking stations, the starting storage capacity used, the hourly order rate, and the picking strategy. The selection of the four parameters can be justified as they collectively define the configuration, initial conditions, customers demand, and operational approach of the system, essential for assessing its performance. Each parameter can assume three different values (picking stations 2,3,4; starting storage capacity 50%, 65%, 80%; order rate 15,20,25 order/hour; picking strategy 1,2,3). The simulations were performed by varying one parameter at a time, resulting in a total of 81 combinations. Each of them was simulated for a time corresponding to an 8 hour shift, in order to represent a real operating scenario.

4.3 Main results

A number of key performance indicators (KPIs) were tracked. These allowed the overall performance of the



(a) Orders per hour (b) Order execution time (c) Order queue time

Fig. 3. Main results

system to be assessed. Picking station utilisation (PSU) measures the ratio of the time the picking station has an order assigned to its total available time, providing insight into operational efficiency. On the other hand, HM utilisation (HMU) calculates the proportion of time that HM spend in performing storage and retrieval operations, providing valuable insights into HM exploitation. Order execution time (OET) quantifies the time from the initiation of an order to its completion, while order queue time (OQT) evaluates the time that orders spend in the queue before being processed. Orders per hour (OPH) measures the number of orders successfully processed in a one-hour period, while order lines per hour (OLPH) measures the rate at which individual order lines are processed in a one-hour period. Together, these KPIs provide a comprehensive view of the efficiency, productivity and responsiveness of the picking process within the system under study.

Comparing the system performance with different picking stations, it was observed that with 2 picking stations, orders remained in queue for extended periods, due to high PSU. For 3 picking stations, major efficiency loss happened at higher order rates across all capacities; however, PSU appears more balanced, ranging from a minimum of 30% to saturation. With 4 picking stations, performances improved (17.05 orders/hour compared to 15.25 orders/hour with 3 picking stations), but the picking stations reached a maximum utilisation of 64%. Given that, the configuration with 4 picking stations was selected to prioritise the availability of picking stations for order acceptance and completion.

Comparing the Random and Min-UL strategies revealed that, at low capacities, the Min-UL solution reduced OQT while increasing OPH. For intermediate capacities, the Min-UL strategy ensured a higher OPH (18.52 orders/hour vs 16.65 orders/hour) due to lower PSU. At high capacities and high order rates, the random strategy demonstrated marked inefficiency with fewer OLPH, while Min-UL managed to complete orders with lower HMU.

In comparing the Random and Zone strategies, OQT was slightly higher in Random. However, the Zone strategy, by optimising the HM movements, resulted in higher OPH (17.02 orders/hour vs 16.21 orders/hour). For medium and high capacities, the Zone strategy performed better, exhibiting higher OPH due to lower OQT.

Finally, in comparing Min-UL and Zone strategies, at low capacities, the Min-UL strategy achieved slightly better performance for OPH, producing an average of 17.43 orders/hour compared to Zone's 17.3. HMU was very similar between the two strategies. For medium capacities, both strategies performed similarly in terms of OPH, while Min-UL showed better OET. For high capacities, performance was very similar for both OET and OPH.

Comparing order rates, for low values, the Min-UL strategy was better in terms of OQT. For medium order rates, the Zone strategy maintained lower average HMU with very similar OPH: 18.46 orders/hour for Min-UL and 17.42 orders/hour for Zone. For high order rates, the Zone strategy performed better with 20.06 orders/hour, due to Min-UL queue inefficiency for high capacities. However, it is important to note that with a higher number of order lines processed, the Zone strategy managed to maintain similar output to other strategies, losing orders only to a minimal extent.

Figure 3 summarises the most relevant results.

The superior performance of Min-UL can be attributed to the fact that the HM is faster in horizontal movements than vertical and retrieval movements. Consequently, it is more advantageous to pick fewer ULs, albeit farther away, rather than more ULs nearby by moving others to reposition them. In general, under non-stress conditions of the system, the Min-UL strategy offered better performance. However, when the system was pushed to the limit of initial capacity and order rate, the Zone strategy proved to be more effective.

5. DISCUSSION AND CONCLUSIONS

This paper presents a comprehensive examination of a MLS system with integrated picking stations within shelves. The conceptualisation of the system began with the development of a UML class diagram, which provided a structural basis for the approach. The model was then translated into a dynamic and interactive simulation using the DES methodology implemented in AnyLogic. Three different strategies for the selection of the UL to satisfy the customer orders and to be moved to the picking stations were developed. A simulation plan was carried out to compare these strategies under different design and operational scenarios.

In general, based on the obtained results, it can be asserted that both Min-UL and Zone strategies improve overall performance compared to the random strategy. Among the two, Min-UL proves to excel across all capacities, particularly in scenarios with low-medium rack utilisation and low-medium order rate. On the other hand, Zone strategy performs more efficiently in scenarios with a high order rate. It can thus be concluded that, for balanced capacities and order rates, the optimal choice can be Min-UL. However, in the presence of high order rates and a large number of orders, it can be more advantageous to pick more ULs near the picking stations exploiting the Zone strategy.

From a theoretical point of view, this study highlights the importance of the design and operation of MLS system integrated with picking stations, and emphasises the key role that such integration plays in revolutionising traditional warehouse practices. Using UML class diagram and DES methodology, the research also highlights the importance of adopting structured modelling and simulation techniques in the analysis and optimisation of complex intralogistics systems. In addition, the study shows how the integration of a MLS system with picking stations seamlessly aligns with the principles of Industry 5.0, emphasising human-machine collaboration to meet the evolving needs of modern supply chain ecosystems. On the other hand, from a practical perspective, this research suggests that warehouse managers and logistics professionals can benefit from analysing different strategies for serving picking stations in order to select optimal approaches tailored to specific operational contexts. By understanding the trade-offs between these strategies, practitioners can make informed decisions when designing and implementing new MLS systems. In addition, the study can help warehouse managers and logistics professionals to better evaluate potential investments in response to evolving market demands and customer service requirements. Manufacturing companies and logistics consultancies could also benefit from this research, particularly at the tender or pre-study stage. By exploring alternative scenarios, these organisations can provide a range of options tailored to their specific needs and constraints.

However, this study comes with some limitations. For instance, no product classes (such as ABC analysis) were considered, as well as different demand rates for each SKU. Moreover, the effects of changes in the system configuration, such as number of rack columns and tier, or different picking operators skillset were not investigated. Therefore, future research will be addressed in order to overcome these limitations.

REFERENCES

Azadeh, K., De Koster, R., and Roy, D. (2019). Robotized and automated warehouse systems: Review and recent developments. *Transportation Science*, 53(4), 917–945.

Boysen, N., Emde, S., and Stephan, K. (2022). Crane scheduling for end-of-aisle picking: Complexity and efficient solutions based on the vehicle routing problem. *EURO Journal on Transportation and Logistics*, 11, 100085.

Calzavara, M., Sgarbossa, F., and Persona, A. (2019). Vertical lift modules for small items order picking: an economic evaluation. *International Journal of Production Economics*, 210, 199–210.

Chirici, L. and Wang, K.S. (2014). Tackling the storage problem through genetic algorithms. *Advances in Manufacturing*, 2, 203–211.

Dukic, G., Opetuk, T., and Lerher, T. (2015). A throughput model for a dual-tray vertical lift module with a human order-picker. *International journal of production economics*, 170, 874–881.

Faria, F. and Reis, V. (2015). An original simulation model to improve the order picking performance: case study of an automated warehouse. In *Computational Logistics: 6th International Conference, ICCL 2015, Delft, The Netherlands, September 23-25, 2015, Proceedings 6*, 689–703. Springer.

Ferrari, A., Carlin, A., Rafele, C., and Zenezini, G. (2023). A method for developing and validating simulation models for automated storage and retrieval system digital twins. *The International Journal of Advanced Manufacturing Technology*, 1–14.

Ferrari, A. and 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., and Carlin, A. (2022). A roadmap towards an automated warehouse digital twin: current implementations and future developments. *IFAC-PapersOnLine*, 55(10), 1899–1905.

Lenoble, N., Hammami, R., and Frein, Y. (2021). Fixed and rolling batching for order picking from multiple carousels. *Production Planning & Control*, 32(8), 652–669.

Liu, J., Liao, H., and White Jr, J.A. (2021). Stochastic analysis of an automated storage and retrieval system with multiple in-the-aisle pick positions. *Naval Research Logistics (NRL)*, 68(4), 454–470.

Ma, W., Yang, D., Wu, Y., and Wu, Y. (2023). Order dividing optimisation in crane & shuttle-based storage and retrieval system. *Journal of Control and Decision*, 10(2), 215–228.

Mahdavisharif, M., Cagliano, A.C., and Rafele, C. (2022). Investigating the integration of industry 4.0 and lean principles on supply chain: A multi-perspective systematic literature review. *Applied Sciences*, 12(2), 586.

Marolt, J., Kosanić, N., and 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. *The International Journal of Advanced Manufacturing Technology*, 1–18.

Nicolas, L., Yannick, F., and Ramzi, H. (2017). Optimization of order batching in a picking system with carousels. *IFAC-PapersOnLine*, 50(1), 1106–1113.

Sgarbossa, F., Calzavara, M., and Persona, A. (2019). Throughput models for a dual-bay vlm order picking system under different configurations. *Industrial Management & Data Systems*, 119(6), 1268–1288.

Vijayakumar, V. and Sgarbossa, F. (2021). A literature review on the level of automation in picker-to-parts order picking system: research opportunities. *IFAC-PapersOnLine*, 54(1), 438–443.

Wang, W., Wu, Y., and Wu, Y. (2016). A multi-stage heuristic algorithm for matching problem in the modified miniload automated storage and retrieval system of e-commerce. *Chinese Journal of Mechanical Engineering*, 29(3), 641–648.

Yang, P., Jin, G., and Duan, G. (2022). Modelling and analysis for multi-deep compact robotic mobile fulfilment system. *International Journal of Production Research*, 60(15), 4727–4742.