

EVALUATING THE PERFORMANCE OF AUTONOMOUS MOBILE ROBOTS IN AN AUTOMATED PALLETIZING SYSTEM: A SIMULATION MODEL

Tea Castellucci, Elena Tappia, Emilio Moretti and Marco Melacini
Department of Management, Economics and Industrial Engineering
Politecnico di Milano
Via Raffaele Lambruschini 4b, Milano 20156, Italy
E-mail: tea.castellucci@polimi.it

KEYWORDS

Mobile robots, Agent-based simulation, Warehousing, Logistics automation

ABSTRACT

Challenged by an unprecedented increase in product variety and demand variability, logistics systems are required to fulfill small customer orders at competitive costs and within short lead times, while keeping a high level of flexibility. In this context, companies are increasingly adopting flexible material handling solutions based on autonomous mobile robots (AMRs). This paper deals with AMR-based Automated Pick to Pallet Systems (APPSs), a novel solution for mixed-case palletizing that has never been studied in scientific literature. In these systems, palletizing robots pick boxes from single-item source pallets and place them on mixed pallets under construction. AMRs replenish the palletizing robots with source pallets and transport the mixed pallets to and from the different palletizers until completion. An agent-based simulation model for the estimation of AMR-based APPS performance is presented and validated. The developed model can be modified and adapted to consider different layout configurations and operating policies. Therefore, it provides support to companies evaluating the introduction of such systems and lays the grounds for further research on their suitability in different contexts, also in comparison with existing systems.

INTRODUCTION

In recent years, logistics systems have been characterized by an ever-growing need of flexibility. Changing customer requirements have led companies to shorten delivery lead times and increase product variety, shifting from a mass production to a mass customization strategy (Emde and Schneider 2018). This raises the pressure on logistics systems called to perform frequent small-lot deliveries to the assembly lines (Emde and Gendreau 2017) and to manage a large assortment of items in warehouses (Zhang et al. 2019). Such requirements, coupled with the need of coping with highly volatile demand, shortage of labor force, and tight fulfilment schedules (Boysen et al. 2019), have led to the replacement of traditional automated systems with robotized warehousing solutions able to replicate

manual systems' flexibility and scalability to varying workloads (Žulj et al. 2022).

Among such systems are Autonomous Mobile Robots (AMRs), "industrial robots that use a decentralized decision-making process for collision-free navigation to provide a platform for material handling, collaborative activities, and full services within a bounded area" (Fragapane et al. 2021). Commonly seen as an evolution of Automated Guided Vehicles (AGVs), AMRs navigate autonomously, thus not depending on the surrounding infrastructure. AMRs' adoption has been growing in recent years: in 2021, AMRs' sales have surpassed the more established AGVs' with over 82000 AMRs shipped against 18000 AGVs (Interact Analysis 2022). Logistics applications have been driving AMRs' demand, mainly due to the growing adoption of AMRs for order fulfilment (Interact Analysis 2020).

Also scientific literature has focused on AMR-based order fulfilment solutions (e.g., Žulj et al. 2022), developing either analytical or simulation-based models to estimate such systems' performance, optimize their design, and evaluate the adoption of different operating policies. In their review of recent robotic automated picking systems, Azadeh et al (2019) show a comprehensive set of AMR-based systems, distinguishing more diffused "movable rack" goods-to-person solutions, namely Robotic Mobile Fulfilment Systems, from recently emerged "static rack" solutions such as Pick Support Systems. Besides picking solutions, literature shows how recent AMR-based systems have been introduced also in other warehousing contexts such as parcel sorting hubs (Zou et al. 2021) and cross-docking terminals (He and Prabhu 2022).

However, the extant literature does not cover the entire range of AMR-based systems recently developed by material handling providers. Among the latter are AMR-based Automated Pick to Pallet Systems (APPSs), which have been lately introduced in food and beverage distribution centers to automate mixed-case palletizing operations, namely the creation of customer order pallets. APPSs are systems in which palletizing robots use a vision system to localize the different items' boxes on single-item source pallets, pick the boxes from the source pallets and place them on target pallets (Wurll 2016). In the AMR-based configuration, AMRs replenish the palletizing robots with single-item source pallets and transport the mixed pallets under

construction to and from the different palletizers until completion. Thanks to the introduction of AMRs for the transportation of pallets within the system, the newly born solution reduces the amount of fixed mounted equipment that characterizes the existing robotized palletizing systems while maintaining their benefits of higher performance and improved efficiency with respect to manual systems (Lamon et al. 2020).

As no study has yet been made on AMR-based APPS, the objective of this work is to develop a simulation model for the estimation of their performance, providing useful support to companies evaluating the introduction of such systems and laying the grounds for further research on their suitability in different contexts, also in comparison with existing systems.

The remaining of this paper is organized as follows. First the layout and working principles of the system under consideration are presented, then the simulation model and its validation are described. Lastly, conclusions and further developments are presented.

SYSTEM DESCRIPTION

An AMR-based APPS is a fully automated parts-to-picker configuration in which mixed pallets are created by palletizing robots picking from single-item full pallets. Such configuration includes two main systems. A mixed pallets' fulfilment system manages the creation and internal transportation of customer order pallets. Concurrently, a full pallets' replenishment system ensures that palletizing robots are fed with enough pallets to perform the picking activity. An area of length L and width W is dedicated to the system (Figure 1).

Single-item full pallets that come from reserve storage enter this area through an input point. The empty pallets needed for mixed pallet construction are kept in a dedicated area within the system, while the palletizing activity is articulated in N picking modules. Every module contains $2n_{ps}$ palletizing stations (PSs). Each station (Figure 2) comprises an anthropomorphic robot that runs on a slide to reach all the pallets which are laying on both its sides. On one side of the slide (picking aisle) there are n_{fp} locations for single-item full pallets, facing the slide with their short side. Behind each full pallet location, there is an additional location to store a full pallet waiting to be fed to the station (forward storage area). On the other side of the slide (output aisle) there are n_{mp} locations for mixed pallets, facing the slide with their long side. Finally, mixed pallets leave the system through an output point. Transportation activities inside the system are performed by two distinct fleets of AMRs: fulfilment-system AMRs and replenishment-system AMRs. Each fulfilment-system AMR is equipped with a lifting platform for the handling of mixed pallets and its travel path is bounded to output aisles and areas outside the picking modules. The areas outside the picking modules can also be travelled by replenishment-system AMRs. Beyond such areas, replenishment-system AMRs can move along picking aisles and are equipped with forks for the handling of full pallets. When idle, fulfilment-system AMRs remain at the point of service completion, as they can stay under the pallet without taking up additional space. Instead, replenishment-system AMRs travel to predetermined dwell points.

The allocation of tasks to the two fleets is managed by a

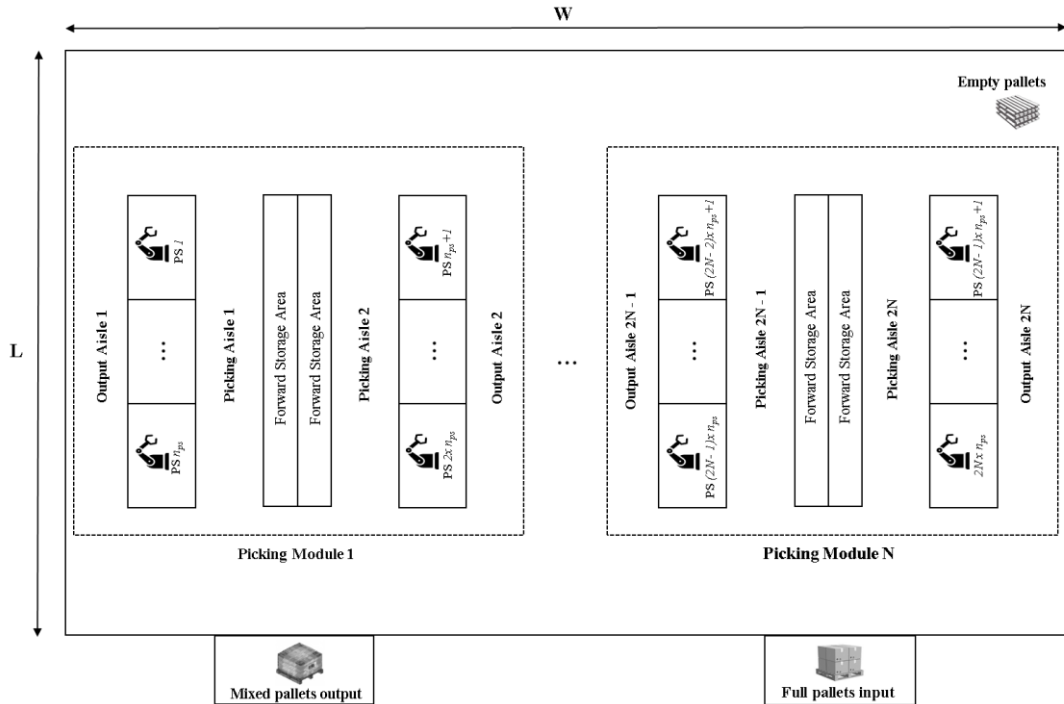


Figure 1: Layout of the System

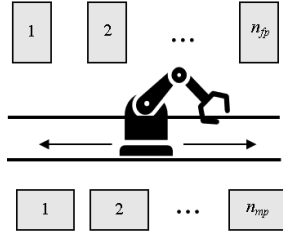


Figure 2: Palletizing station layout

central control unit that has visibility over the state of the system resources (AMRs' fleets, picking stations). This centralized task allocation is the most commonly used according to previous literature in which only few studies report the possibility of decentralizing task allocation to AMRs (Fragapane et al., 2021). Starting from the list of pallets required by customer orders, the central control unit progressively releases palletization requests and sets the sequence of stations that each mixed pallet under construction has to visit. In this way, the control unit also regulates the number of mixed pallets that are being simultaneously built within the system. When a request to build a mixed pallet enters the system, the control unit assigns a task to the first available fulfilment-system AMR. Such task entails the transfer of an empty pallet from the area of empty pallets storage to a free location at the first palletizing station to be visited by the pallet under construction. Upon the mixed pallet arrival at the station, the transfer task is terminated, and the AMR is free to receive a new one. At the palletizing station, when choosing the mixed pallet to work on, the robot follows a "first come, first served" logic based on the pallets' order of arrival at the station. Once the pallet has been chosen, the robot picks from the full pallets the needed boxes and places them onto the mixed pallet. Afterwards, the first available fulfilment-system AMR is tasked with the transportation of the pallet. If the pallet does not need to visit additional stations, it is transported to the system output, otherwise it is transferred to a new station. Concurrently, replenishment-system AMRs carry out the replenishment of the full pallet locations at the palletizing stations. The quantity remaining at a full pallet location is checked every time a robot picks from that location, triggering a replenishment in case such remaining quantity is less than the replenishment threshold. If this is the case, the control unit tasks the first-available replenishment-system AMR with the retrieval of the required full pallet from the forward storage area. From there, the pallet is brought to the location that needs to be replenished, eventually waiting if the current pallet on the location to be replenished has not been fully consumed yet. Instead, the replenishment of the forward storage area is considered out of scope. Hence, it is assumed that such replenishment is carried out outside the system operating hours and that the system is refilled with enough full pallets to never experience stock out.

SIMULATION MODEL DESCRIPTION

As the goal of this work is to estimate the performance of the AMR-based APPS, an agent-based simulation model has been developed. The agent-based methodology was deemed appropriate as the behavior of the system under analysis stems from the complex interactions among the palletizing robots, the two AMRs' fleets, and the central control unit. The adoption of the agent-based technique to model warehousing operations problems has been recently growing, including examples of application for the analysis of AGV-based and AMR-based systems (Ribino et al. 2018; Winkelhaus et al. 2022). In agent-based models, a system is modelled as a collection of autonomous decision-making entities called agents (Bonabeau 2002). Each agent is associated with a set of attributes, either static or dynamic, and methods. The latter represent the agents' behavioral rules which connect their state, namely variables that represent their current situation, with their potential actions. Among an agent's methods, some define how and with whom the agent interacts, comprising also eventual interactions between the agent and the environment it populates (Macal and North 2010).

The agents of the developed model are both AMRs' fleets, palletizing robots, and the central control unit. Instead, the remaining elements of the system, namely customer orders and mixed pallets, have been considered as passive entities that need agents' actions to advance in the simulation model, thus they have been modelled as standard classes of objects. Finally, the system area has been modelled by means of a graph through which AMRs can reach any point of the system area without crossing palletizing stations and storage racks.

The model has been developed in Python language using Mesa, an open-source framework for building agent-based simulation models (Masad and Kazil 2015).

Simulation Model Structure

The developed model is structured in three main blocks. The first block corresponds to a pre-processing phase in which customer orders are generated and divided into a list of mixed pallets to be built. Each mixed pallet in the list is associated with the sequence of palletizing stations needed for its construction and the quantity of boxes required at each station.

The second block corresponds to the simulation of the system's operations. In this block, the agents' behavior and interactions determine the advancement of the system's operations, causing periodic changes in the states of the agents themselves. To represent this dynamic side of the modelled system, UML statechart diagrams have been produced. Statechart diagrams schematize the behavior of an agent by showing its possible states and the events-triggered transitions to and from the different states, with the agent's eventual responses and actions (Booch et al. 1999). As an example, Figure 3 reports the statechart diagram of

fulfilment-system AMR agents in the system. A fulfilment-system AMR agent stays idle until receiving a transfer task. Consequently, it starts moving and transitions to “Moving” state. AMRs move in the graph at constant speed from their origin node to their destination following the shortest path computed by means of the Dijkstra algorithm. Following previous literature (e.g., Bozer and Aldarondo 2018; Lienert et al. 2018), acceleration and deceleration delays are considered negligible, and aisles are assumed to be wide enough to avoid congestion. The transfer tasks assigned to fulfilment-system AMRs correspond to the transfer of a mixed pallet to the next palletizing station or to the output point. Therefore, two separate paths are generated for the two portions of each task. The first path goes from the current position of the AMR to the node where the mixed pallet needs to be loaded. Such loading node coincides with a pallet location in one of the output aisles or, in case the palletization request has just entered the system, with the empty pallet storage area. The second path goes from this location to the unloading node. The latter corresponds to the station where the mixed pallet needs to be processed or, in case the mixed pallet is complete, to the system’s output point. Both in case of the first and the second path, upon the arrival at the last node before destination, the AMR checks the status of the loading/unloading node to ensure it is not occupied by another AMR. If the node is occupied, the AMR transitions to “Waiting” state and waits until the destination becomes available. Then, it resumes the “Moving” state. Else, if the node is empty, the AMR remains “Moving” and the loading/unloading node is declared occupied as the AMR is about to reach it. Once the AMR arrives at the loading node, it stops

and loads the pallet. Then, its movement is resumed and the loading node is declared empty. Instead, upon the arrival at the unloading node, the AMR unloads the pallet and evaluates whether such destination is the system’s output point. If this is the case, the AMR assumes the “Moving_to_dwell_node” state and travels to a nearby area to make the output node available for other AMRs. Once arrived at the dwell node, the AMR returns to the initial “Idle” state. Otherwise, if the unloading node is a pallet location at a palletizing station, the AMR becomes “Idle” and remains at such location until receiving a new task.

The third block of the model is a post-processing phase in which performance measures are computed. When the simulation time is reached, the model checks how many and which of the orders and related mixed pallets released into the system have been completed. At this point, the model also computes utilization and productivity measures. The utilization of AMRs and palletizing stations is computed as the percentage of the system operating time in which such resources are performing their tasks (i.e., not idle). Productivity is measured as the number of boxes palletized per operating hour at each station and in the whole system..

Validation and Verification

The design and development of the simulation model are not the sole activities to be performed in the process of modelling and simulation of a system. Indeed, model validation and verification activities are necessary to ensure simulation model accuracy (Balci 1997) and should be performed throughout the entire lifecycle of the modeling and simulation process (Yin and McKay 2018).

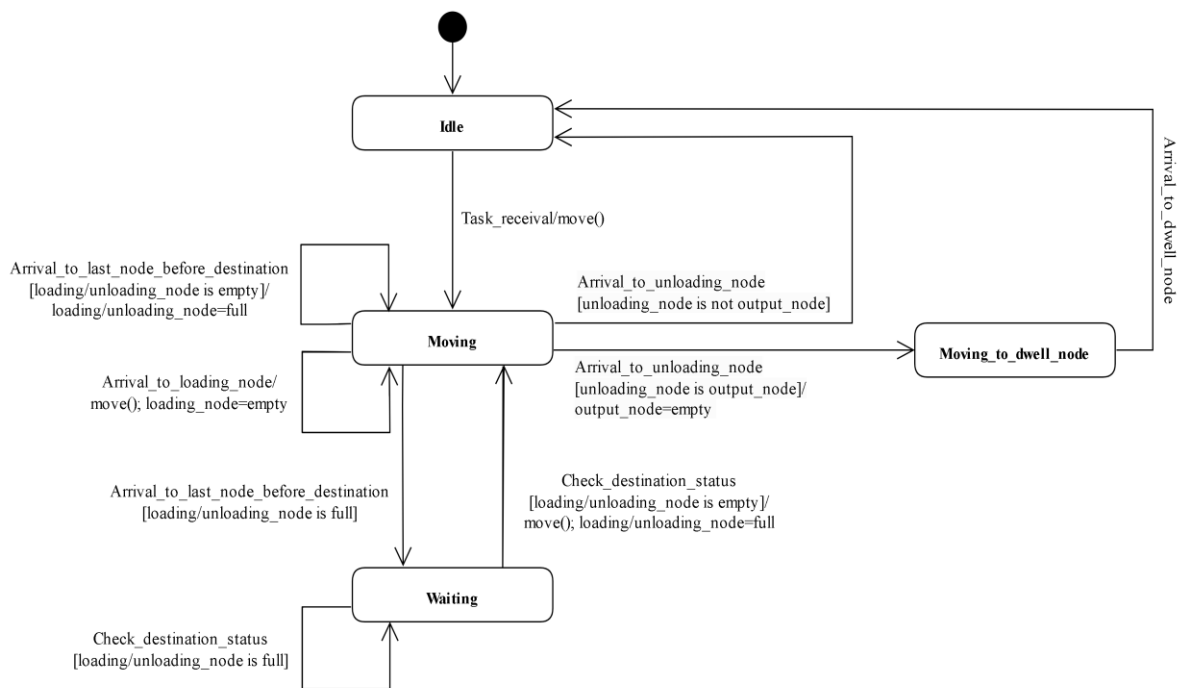


Figure 3: Statechart Diagram of the Fulfilment-System AMR agent

Table 1: Simulation model output

Performance measures (avg)	System	Palletizing robots	Fulfil.-system AMRs	Replen.-system AMRs
Productivity [boxes/h]	2413	201	-	-
Utilization	-	83,4 %	82,5 %	22,2 %

Validation and verification concern the conceptual model, computer model, and simulation results (Franzke et al., 2017).

Conceptual model validation aims at evaluating the accuracy of the model in representing the real-world research problem (Sargent 2010). As in Winkelhaus et al. (2022), considering that AMR-based APPS are a novel technological solution and their application in real-world cases is still scarce, the conceptual model was built and validated based on both relevant research on AMR-based order fulfilment solutions and on practical observations. Indeed, before building the model, the authors visited two grocery distribution centers where the AMR-based APPS solution had recently been introduced for the creation of respectively fresh produce and beverage order pallets. Although the systems were still in a testing phase and not fully operational yet, it was possible to gain some qualitative and quantitative insights on the systems' structure and operating conditions. Furthermore, the model structure and assumptions were discussed with the technological provider that has developed the AMR-based APPS solution under analysis.

For the verification of the computer model, namely the assurance that "the computer programming and implementation of the conceptual model are correct" (Sargent 2010), software engineering offers various techniques. Among these, dynamic techniques are among the most widely used (Heath et al. 2013; Winkelhaus 2022). Accordingly, a debugging activity was performed on the developed simulation model. As finding the source of error is often challenging, additional code lines and printed statements were inserted at specific locations of the model to monitor its behavior. Moreover, the computer model was created using a bottom-up testing approach which entails the development of the code "from the sub-model up" (Whitner and Balci 1989). Once terminated, each portion of the model was extensively tested both by itself and after being integrated with the rest of the code. Finally, the simulation model output validation aims at determining whether the model is sufficiently accurate for its intended purpose (Sargent 2010). To obtain the simulation output, the computer model must be provided with input data. The latter include layout parameters, operational parameters, as well as demand and item-related parameters. These data have been selected from different sources (the visited AMR-based APPS, simulation studies on AMR-based warehousing systems, and material handling providers) according to their availability and appropriateness. Specifically, layout parameters are based on one of the two visited distribution centers. The considered layout includes 12

palletizing stations (2 picking modules composed of 2 rows of 3 palletizing stations each) and two areas for full pallets' storage. On one side of each station there is a picking aisle with 12 full pallet locations. On the other side, there is an output aisle with 8 mixed pallet locations. Picking aisles are replenished by a fleet of 3 replenishment-system AMRs, while output aisles are served by 15 fulfilment-system AMRs.

Operational parameters characterize palletizing robots and AMRs. Palletizing robots pick one box at a time and place it onto a mixed pallet. For the picking and placing of the box a fixed time of 7 seconds has been considered, while the time palletizing robots spend running on the slide is estimated considering a speed of 1 m/s. For fulfilment-system and replenishment-system AMRs a speed of 1,3 m/s and 1 m/s has been respectively considered. The pallet loading/unloading time has been set equal to 25 s for both AMR fleets.

Finally, parameters related to the characteristics of the customers' demand and of the items handled in the system have been set as follows. Based on the data gathered during the distribution centers visits and on relevant scientific literature (Winkelhaus 2022), the number of lines per each order has been generated from a triangular distribution (12,15,18). Similarly, each line has been associated a quantity of boxes chosen from a triangular distribution (2,5,8). Given such characteristics, each order corresponds to one or more mixed pallets composed of up to 60 boxes. Instead, the number of boxes per full pallet goes from 50 to 80 depending on the item features. The system handles 120 items with different demand profile: 24 best-selling items account for 50% of the overall quantity of boxes to be palletized. Because of this difference, alternative allocations of the items to the palletizing stations can be evaluated. For the validation, the same choice made by the supplier for one of the visited distribution centers has been replicated: 4 palletizing stations are dedicated to best-selling items to minimize the expected number of stations needed for mixed pallet creation. Furthermore, these items are assigned 2 full pallet locations instead of a single one to avoid an excessive workload on the 4 dedicated stations.

Given the presented input parameters, simulation results (Table 1) have been obtained by performing 10 replications of a finite simulation horizon of 8 hours. The number of replications has been selected to obtain a ratio between the half-width of the 95% confidence interval and the mean value of system productivity over the sample of runs lower than 0,5%. The simulation horizon has been set to study the system under working conditions (e.g., working hours, overall material consumption and resources' utilization) that are close to

the ones in which the visited distribution centers operate.

The validation technique of directly comparing the model results with the results of a real-world system was not deemed feasible as both the performance and the complete set of parameters were not available yet for either one of the visited sites. Indeed, the systems were in an early implementation phase at the time of the visits, thus still undergoing fine-tuning and testing operations. Anyhow, the resulting performance measures (Table 1) are in line with the expected values discussed with the technology provider for the visited distribution centers. In particular, the relatively low utilization of replenishment-system AMRs was also expected by the technology provider because most replenishments are concentrated in a narrow time frame. Therefore, the small fleet size cannot be further reduced to avoid slowing down the palletizing operations due to delays in full pallets replenishments. Furthermore, to determine whether the model behaved as intended, its input-output behavior was evaluated. For this purpose, as in Franzke et al. (2017), several of the presented parameters were modified. For instance, by increasing the maximum number of boxes per mixed pallet, the number of stations visited by each pallet increases as expected and so does the time needed to create a mixed pallet. Even by changing the demand profile of the items the model behaves as expected. Indeed, as operations become increasingly more concentrated around few items, the average number of stations visited by a mixed pallet decreases, as the picking of best-selling items is performed at few dedicated stations.

CONCLUSIONS AND FUTURE WORK

This work deals with AMR-based Automated Pick To Pallet Systems, a novel solution for mixed-case palletizing operations that has never been studied in scientific literature. Specifically, an agent-based simulation model for the estimation of such systems performance has been developed and validated. Although developed starting from real cases, the model can be adapted to different layout configurations by changing input parameters such as the number of picking modules in the system or the number of full and mixed pallet locations per station. With simple modifications to some of the agents' methods, the model can also be adapted to consider different operating policies. Therefore, it can be employed both to support practitioners in the adoption and management of AMR-based APPSs and as a base for future research on such systems. A natural development of this work could leverage the presented simulation model to evaluate the robustness of AMR-based APPSs to varying parameters related to customers' demand and to items' characteristics. For instance, some preliminary experiments have been carried out, suggesting that the effect of changing demand profile on system performance is a worth-exploring aspect. Further experiments on the system could also study the effect of

different operating policies on its performance, for instance by comparing alternative task dispatching rules to the AMRs or item allocation policies to palletizing stations. Moreover, future studies could perform an economic evaluation of AMR-based APPS in different fields, also in comparison with other systems in which palletizing stations are served by different transportation technologies. Finally, future works could extend the model to overcome some of its limitations, with a particular focus on considering the effects of congestion within the aisles and modelling the charging activity of AMRs.

REFERENCES

- Azadeh, K., R. De Koster, and D. Roy. 2019. "Robotized and Automated Warehouse Systems: Review and Recent Developments". *Transportation Science* 53, No. 4 (Jul), 917–945.
- Balci, O. 1998. "Verification, validation, and accreditation". In *Proceedings of the 1998 winter simulation conference* (Washington, DC). IEEE, 1, 41-48.
- Booch, G., Rumbaugh, J. and Jacobson, I. 1999. "The Unified Modeling Language User Guide Addison-Wesley". Reading.
- Bonabeau, E. 2002. "Agent-Based Modeling: Methods and Techniques for Simulating Human Systems". *Proceedings of the National Academy of Sciences* 99, No. suppl_3 (May), 7280–7287.
- Boysen, N., R. de Koster, and F. Weidinger. 2019. "Warehousing in the E-Commerce Era: A Survey". *European Journal of Operational Research* 277, No. 2 (Sep), 396–411.
- Bozer, Y.A., and F.J. Aldarondo. 2018. "A Simulation-Based Comparison of Two Goods-to-Person Order Picking Systems in an Online Retail Setting". *International Journal of Production Research* 56, No. 11 (Jun), 3838–3858.
- Emde, S., and M. Gendreau. 2017. "Scheduling In-House Transport Vehicles to Feed Parts to Automotive Assembly Lines". *European Journal of Operational Research* 260, No. 1 (Jul), 255–267.
- Emde, S., and M. Schneider. 2018. "Just-In-Time Vehicle Routing for In-House Part Feeding to Assembly Lines". *Transportation Science* 52, No. 3 (Jun), 657–672.
- Fragapane, G., R. de Koster, F. Sgarbossa, and J.O. Strandhagen. 2021. "Planning and Control of Autonomous Mobile Robots for Intralogistics: Literature Review and Research Agenda". *European Journal of Operational Research* 294, No. 2 (Oct), 405–426.
- Franzke, T., E.H. Grosse, C.H. Glock, and R. Elbert. 2017. "An Investigation of the Effects of Storage Assignment and Picker Routing on the Occurrence of Picker Blocking in Manual Picker-to-Parts Warehouses". *The International Journal of Logistics Management* 28, No. 3 (Aug), 841–863.
- He, X., and V.V. Prabhu. 2022. "Design and Analysis of AGV-Based Cross-Docking Operations Using Analytical Models". *Production & Manufacturing Research* 10, No. 1 (Dec), 428–449.
- Heath, B.L., F.W. Ciarallo, and R.R. Hill. 2013. "An Agent-Based Modeling Approach to Analyze the Impact of Warehouse Congestion on Cost and Performance".

The International Journal of Advanced Manufacturing Technology 67, No. 1–4 (Jul), 563–574.

- Interact Analysis. 2020. “Over a million AMRs for order fulfillment to be installed by end of 2024”. <https://www.cobottrends.com/order-fulfillment-install-1m-mobile-robots-2024-interact-analysis/> (Accessed: 1 February 2023).
- Interact Analysis. 2022. “100,000 Mobile Robots Shipped In 2021”. <https://interactanalysis.com/insight/100000-mobile-robots-shipped-in-2021/> (Accessed: 1 February 2023).
- Lamon, E., M. Leonori, W. Kim, and A. Ajoudani. 2020. “Towards an Intelligent Collaborative Robotic System for Mixed Case Palletizing”. In *2020 IEEE International Conference on Robotics and Automation (ICRA)* (Paris, France). IEEE, 9128–9134.
- Lienert, T., T. Staab, C. Ludwig, and J. Fottner. 2018. “Simulation-Based Performance Analysis in Robotic Mobile Fulfillment Systems - Analyzing the Throughput of Different Layout Configurations”. In *Proceedings of 8th International Conference on Simulation and Modeling Methodologies, Technologies and Applications* (Porto, Portugal). SCITEPRESS - Science and Technology Publications, 383–390.
- Macal, C.M., and M.J. North. 2010. “Tutorial on Agent-Based Modelling and Simulation”. *Journal of Simulation* 4, No. 3 (Sep), 151–162.
- Masad, D., and J. Kazil. 2015. “Mesa: An Agent-Based Modeling Framework”. In *14th PYTHON in Science Conference* (Austin, TX). 53–60.
- Ribino, P., Cossentino, M., Lodato, C. and Lopes, S. 2018. “Agent-based simulation study for improving logistic warehouse performance”. *Journal of Simulation* 12, No.1, 23–41.
- Sargent, R.G. 2010. “Verification and Validation of Simulation Models”. In *Proceedings of the 2010 Winter Simulation Conference* (Baltimore, MD). IEEE, 166–183.
- Whitner, R.B. and Balci, O. 1989. “Guidelines for selecting and using simulation model verification techniques”. In *Proceedings of the 21st conference on Winter simulation* (Washington D.C.). 559–568.
- Winkelhaus, S., M. Zhang, E.H. Grosse, and C.H. Glock. 2022. “Hybrid Order Picking: A Simulation Model of a Joint Manual and Autonomous Order Picking System”. *Computers & Industrial Engineering* 167 (May), 107981.
- Wurll, C. 2016. “Mixed Case Palletizing with Industrial Robots”. In *Proceedings of ISR 2016: 47th International Symposium on Robotics* (Jun 21–22). VDE, 1–6.
- Yin, C., and A. McKay. 2018. “Introduction to Modeling and Simulation Techniques”. In *Proceedings of ISCIIA 2018 and ITCA 2018* (Leeds).
- Zhang, J., F. Yang, and X. Weng. 2019. “A Building-Block-Based Genetic Algorithm for Solving the Robots Allocation Problem in a Robotic Mobile Fulfillment

System”. *Mathematical Problems in Engineering* 2019 (Feb), 1–15.

- Zou, B., R. De Koster, Y. Gong, X. Xu, and G. Shen. 2021. “Robotic Sorting Systems: Performance Estimation and Operating Policies Analysis”. *Transportation Science* 55, No. 6 (Nov), 1430–1455.
- Žulj, I., H. Salewski, D. Goeke, and M. Schneider. 2022. “Order Batching and Batch Sequencing in an AMR-Assisted Picker-to-Parts System”. *European Journal of Operational Research* 298, No. 1 (Apr), 182–201.

AUTHOR BIOGRAPHIES

TEA CASTELLUCCI is a Ph.D. student in Management, Economics and Industrial Engineering at Politecnico di Milano, where she currently undertakes research on logistics. Her primary research interests include synchronization of logistics activities and automated warehousing systems design and management.

ELENA TAPPIA is an Associate Professor at Politecnico di Milano, Department of Management, Economics and Industrial Engineering, where she currently lectures and undertakes research on logistics. She is author of a number of publications, including contributions in international scientific journals and international conference proceedings. Her main current research interests include automated warehousing systems, Logistics 4.0, logistics system for omnichannel systems, and factory logistics.

EMILIO MORETTI is an Assistant Professor of logistics at Politecnico di Milano, Department of Management, Economics and Industrial Engineering, where he currently undertakes research on logistics. His primary research interests include parts feeding systems design and management, automated warehousing systems, and global distribution networks design. He has authored scientific publications in international journals and conference proceedings.

MARCO MELACINI is a Full Professor at Politecnico di Milano, Department of Management, Economics and Industrial Engineering. He holds the courses Logistics Management and International Distribution. He was involved in over 40 research/technology transfer projects, and he is the scientific responsible for the Contract Logistics Observatory. His research interests include warehousing and material handling systems, global logistics networks, supply chain risk management, Logistics 4.0, and sustainability. He is an author of over 100 publications, including contributions in international scientific journals, books, and conference proceedings.