DOI: 10.22032/dbt.57900

Simulation in Produktion und Logistik 2023
Bergmann, Feldkamp, Souren und Straßburger (Hrsg.)
Universitätsverlag Ilmenau, Ilmenau 2023
DOI (Tagungsband): 10.22032/dbt.57476

Evaluation of Different Use Case Configurations in a Robotic Mobile Fulfilment System

Beurteilung unterschiedlicher Use Case-Konfigurationen in einem Robotic Mobile Fulfilment System

Julia Wenzel, Giorgi Tadumadze, Ralf Elbert, Felix Weidinger,
Technische Universität Darmstadt, Darmstadt (Germany),
wenzel@log.tu-darmstadt.de, giorgi.tadumadze@tu-darmstadt.de,
elbert@log.tu-darmstadt.de, felix.weidinger@tu-darmstadt.de

Simon Emde
Friedrich-Schiller-Universität Jena, Jena (Germany),
simon.emde@uni-jena.de

Abstract: In recent years, hybrid order picking systems like Robotic Mobile Fulfilment Systems (RMFS) have become established and widely used in e-commerce. Companies from other logistics areas with different use cases often decide against investing in RMFS due to high investment risks or unknown performance benefits. This work contains a performance evaluation of three different use case configurations based on logistics areas in e-commerce and production conducted by a simulation model for multi-level RMFS with an integrated rolling planning approach. The model leads to a demonstrator supporting logistics managers in their decision-making. Those and other users can vary input parameters in the demonstrator, create different use case configurations, and run the simulation model to evaluate performance by key performance indicators (KPIs). The work depends on several discussions and interviews with logistics experts to define realistic use cases the logistics manager can identify.

1 Introduction

Mobile picking robots have been increasingly used in logistics for several years (Azadeh et al., 2019; Boysen et al., 2017a). In contrast to manual person-to-goods picking and automatic goods-to-person picking, individual shelves are moved by mobile robots and transported to a stationary picking base. A particular type of mobile picking robot is the Robotic Mobile Fulfilment System (RMFS), where mobile robots transport shelves (pods) through the shop floor to picking stations with order pickers

(Boysen et al., 2019). Compared to traditional order picking systems (picker-to-parts) in which pickers move to shelves in the warehouse, RMFS as a parts-to-picker system increases productivity (Boysen et al., 2017b).

Limited storage density and the possibility of analysing the performance of RMFS prevent companies from investing in this technology. A few recent publications about their performance by simulation studies exist (Merschformann et al., 2019). Nevertheless, performance evaluations in science are not attractive enough to logistics managers and their investment decision-making process if they do not seem predictable to them. Based on interviews with experts in logistics areas, we implemented a simulation model for multi-level RMFS with an integrated rolling planning horizon for analysing the performance of RMFS. In order to make the results more transparent and to support logistics managers, and other users, in their decision-making, the simulation model based on the software AnyLogic is extended to a demonstrator. It allows users to make decisions based on well-founded arguments resulting from the quantitative study of performance analysis of different use case configurations of RMFS that are similar to their shop floor. The user can define the input of the quantitative study via the demonstrator interface and vary different structures of order sizes, article types, or robot numbers. The performance analysis involves typical KPIs of throughput definitions, which are necessary to decide for or against a new logistics system resulting from discussions with logistics experts.

2 Recent literature

The integrated planning problems for the simulation model are described in this section to give an overview of the current state of the literature. Merschformann et al. (2019) present a simulation tool for RMFS, solving different planning tasks and problems and analysing performance. It becomes visible that the several solutions of the planning problems (see below) significantly influence the RMFS performance and, thus, the decision whether to use RMFS or not. The publications stated below revive the planning tasks introduced by Merschformann et al. (2019).

1. Allocating goods to individual shelves (cf. Weidinger and Boysen, 2018; Weidinger et al., 2018; Guan and Li, 2018, Kim et al., 2020).
2. Assignment of orders to picking stations & assignment of shelves to picking stations (cf. Tadumadze et al., 2022).
3. Order processing at the picking stations (cf. Boysen et al., 2017b).
4. Space allocation of shelves in the warehouse (cf. Merschformann et al., 2019; Li et al., 2021).
5. Control of transport orders of individual robots (cf. Zhu and Li, 2022; Xie et al., 2021).

It should be noted that there has not yet been a simulation study of the complexity of Merschformann et al. (2019). Other simulation studies in the context of RMFS relate to solving one or more (maximum two) planning problems. Simulation studies have not been used as a basis for comparison in this paper, as they do not have generic planning problems.

Further research was included to get a related simulation study with the central aspect of improvement of the system performance of RMFS. The current state of research is used to extend the considered assumptions in the work of Merschformann et al. (2019). An example is the use of ground-level storage RMFS warehouses which causes the disuse of available warehouse height. Approaches, e.g., Xie et al. (2021) and Tadumadze et al. (2022), create multiple levels in RMFS to compensate for that. Furthermore, recent works on the performance analysis of RMFS also exist (cf. Duan et al., 2021; Gong et al., 2021; van Gils et al., 2018; Jaghbeer et al., 2020; Hanson et al., 2018; Duan et al., 2021; Gong et al., 2021; Lamballais et al., 2017).

3 Simulation approach and implementation

This section describes how simulation and optimization solutions are combined, and the discussion with focus interviews with experts from logistics fields is integrated.

This work addresses all mentioned planning problems and performance analysis approaches in the implemented simulation model to design the demonstrator. The simulation model extends the approach of RMFS of Merschformann et al. (2019) by creating a simulation model for multi-level RMFS with a rolling planning approach. Often, exact optimization solutions are verified with simulation studies as mathematical optimization (Juan et al., 2015). With this work, we want to present a realistic simulation model (combined with heuristic solutions) for use in practice and integrate experts' decision outcomes in the implementation phase: The demonstrator aims to make optimization approaches more accessible to users and logistics managers by implementing a parametrized simulation model. The user can handle it by defining input parameters for each optimization instance (performed in optimization heuristics).

For performance evaluation of different use cases in RMFS and better height utilization (dimensions comparable to an automated warehouse), this work pursues a multi-level RMFS warehouse designed for high-bay racking. As illustrated in Figure 1, three steps had to be implemented to create the demonstrator. The planning problems mentioned in section 2 are implemented in the simulation model in the first step, followed by constructing an initialization instance (step 2) and the consolidation into a demonstrator in step 3.

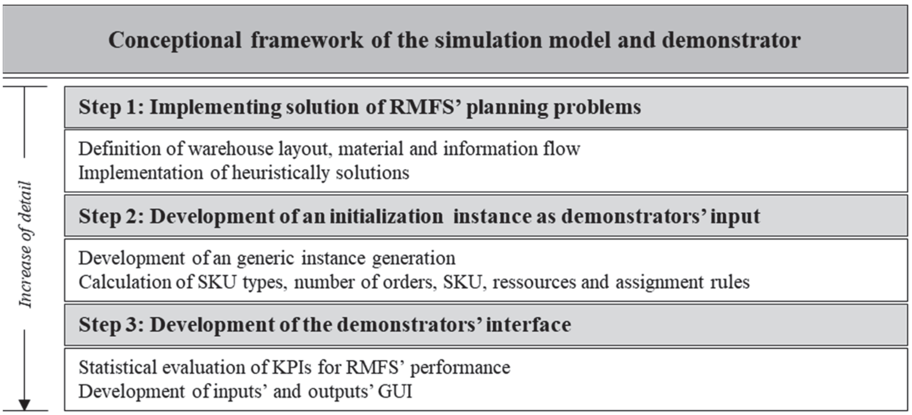

Figure 1: Process of creating the demonstrator for evaluating configurations of RMFS

3.1 Step 1: Implementing planning problems' solutions

The demonstrator includes a simulation model extending the approaches of Xie et al. (2021) (multi-level RMFS) and Merschformann et al. (2019) (demonstrator for RMFS). The development of the demonstrator is based on a simulation concept that reflects the order picking process from the robot's perspective. For that reason, agent-based simulation is used to implement the robot as an interactive agent and analyse its behaviour and interactions with other robots in the fleet (Borshchev, 2013).

The simulation model displays the material and information flow of the mobile robots in RMFS. All planning problems, according to section 2, have been considered and solved heuristically in the simulation model with a focus on the heuristic solution of Tadumadze et al., 2022 which aims to distribute all orders evenly on the order picking stations, minimize the robots' movements and maximize the order picking stations' throughput. Furthermore, the simulation model also includes a rolling planning approach with a planning horizon t. Rolling planning horizons are introduced in production and warehouse planning to control and optimize stock levels or order processing. Rolling planning is profitable in this context to regularly set new orders into the system. In this way, continuous planning and management of arrivals are replicated, which are the main aspects regarding the interviews with logistics experts. A distinction between different planning horizons also allows the definition of different scenarios and is considered an input parameter for the following step. The associated concept is shown as a flow chart in Figure 2.

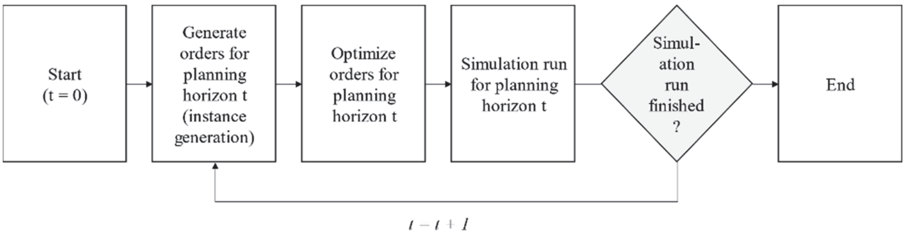

Figure 2: Concept of rolling approach

3.2 Step 2: Development of initialization instance

The aim of instance generation at the second level of detail is to capture an initial state. An essential aim of the validation and verification is the definition of a most realistic instance. Therefore, the discussions with logistics experts resulted in the decision that the orders be processed in the time horizon t under consideration, their composition from the individual Stock Keeping Unit Types (SKU types), and the number of ordered SKUs and SKUs available in the warehouse define the most influencing parameters for RMFS. To create a demonstrator, it is necessary to avoid transient phases and use generic but realistic input variables in the simulation. Therefore, input parameters for an instance in this simulation model are:

- the average order size
- the number of robots used
- the number of SKU types
- number of pods

- number of orders in one planning horizon t
- number of stations
- the time window for planning horizon t

Different numbers of robots, pods, and picking stations are considered resources. Further components of the instance generation are the ABC structure of the shelf storage. The Pareto principle represented an exponential distribution function in the first dimensioning. Thus, it was assumed that the group of A-items represents 80 % of the total orders of a planning period. These contain 20 % of the available articles. This ratio can also be varied via a factor $lambda$.

3.3 Step 3: Development of the demonstrator

The user of the demonstrator can vary the initial state of input parameters, mentioned in section 3.2, via Graphical User Interface (GUI), shown in Figure 3. The input parameters define an instance for optimization and the necessary input for starting the simulation model. Thus, the user can adopt different system configurations, reflecting different use cases. Handling multiple configurations of RMFS resulted from the discussion with logistics experts. The interpretation of the performance analysis is more comprehensible for users if they can identify the use case configuration with their logistics application area. Existing instances from given studies can only be interpreted in a limited way.

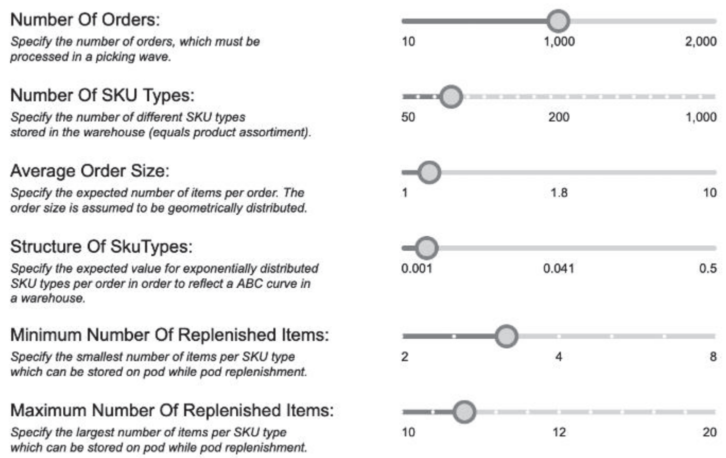

Figure 3: Exemplary screenshot of the demonstrator's input parameters (own illustration)

4 Analysis of different use case configurations

To illustrate how to analyse different configurations of use cases in RMFS, a simulation study is performed in the next section of this paper. Three use cases reflect hypothetical scenarios of different application areas for RMFS. The objective is to show how to use the simulation model and to clarify the interfaces between the simulation and the demonstrator.

A simulation study with three different instances is conducted as part of this work. Each instance represents a different use case configuration which can be selected via the demonstrator's input GUI. The selected use case configurations are listed in Table 1. The analysis of the different use cases is intended to identify an optimal configuration for RMFS for the user of the demonstrator. It will also be investigated which configuration best adapts to the system. Use case configuration 1 reflects a typical e-commerce scenario (e.g., Same-Day-Delivery of different products); use case configurations 2 and 3 correspond to a production warehouse. First one (use case configuration 2) represents a supermarket with low SKU type variety in the production line (e.g., containers with screws next to a pre-assembly line). Use case configuration 3 is an example of a warehouse with many products (e.g., a warehouse after assembling the products). The design of instance implementation is based on interviews with experts who validate those use case scenarios.

Table 1: Assumptions for simulation study according to each use case configuration

	Configuration 1	Configuration 2	Configuration 3
use case area	e-commerce	supermarket	outbound
the average order size	1,4	4,6	10,6
the number of SKU types	200	50	500
number of pods	750	750	750
number of orders in t	1000	1000	200
lambda	0,041	0,160	0,018
number of stations	15	15	15
the time window for t	30 min	30 min	30 min
the number of robots	9	9	9

With the provided simulation data of the input GUI, it is possible to run Monte-Carlo simulations based on internal sources of randomness (Borshchev, 2013). It enables the analysis of the different scenarios in comparison to each other. The stochastic random distributions are implemented in the instance generation and thus form an integrated stochastic model. Many repetitions are carried out with the assumptions made to map Monte Carlo simulations. The determination of the simulation frequency and thus the necessary number of simulation runs n is based on the defined key performance indicator $Hit\ Rate$ according to Merschformann et al. (2019) which is defined as ratio between the "Total Number of Picked SKUs" and the "Total Number of Pod Visits". The ratio is measured at the end of the simulation runs (simulation period $L(t) = 60\ min$). A negative value of this ratio would reveal a faulty simulation run in which too frequent or unresolvable blocking operations of the picking robots occur. The system performance in the respective use case configuration is measured by the typical key performance indicator "Total Number of Fulfilled Orders" and

"Total Number of Picked SKUs" in a logistics system. The first KPI reflects the possible warehouse throughput. The second is a central KPI for picking efficiency. Both KPIs are used in science (in reference to the literature of section 2) and practice to measure the performance and efficiency of a logistics process and form the framework for decisions by logistics managers. The simulation study results are summarized in Table 2 as averaged values. The results are considered at all levels of this multi-level RMFS.

Table 2: Simulation study results

	Configuration 1	Configuration 2	Configuration 3
use case area	e-commerce	supermarket	outbound
Total Number of Fulfilled Orders	1268	205	92
Total Number of Picked SKUs	1978	1732	1739
Hit Rate	9,374	16,654	7,464

Based on the simulation study results, evaluating different use case configurations for RMFS is possible. Visualization with GUI is important for interpreting simulation results (Wenzel et al., 2003). We use this possibility to connect the simulation model with GUI and create the demonstrator. All output parameters are collected in a database and displayed in the GUI (Figure 5). To consolidate the results, the demonstrator's approach is to represent the mentioned KPIs as output parameters.

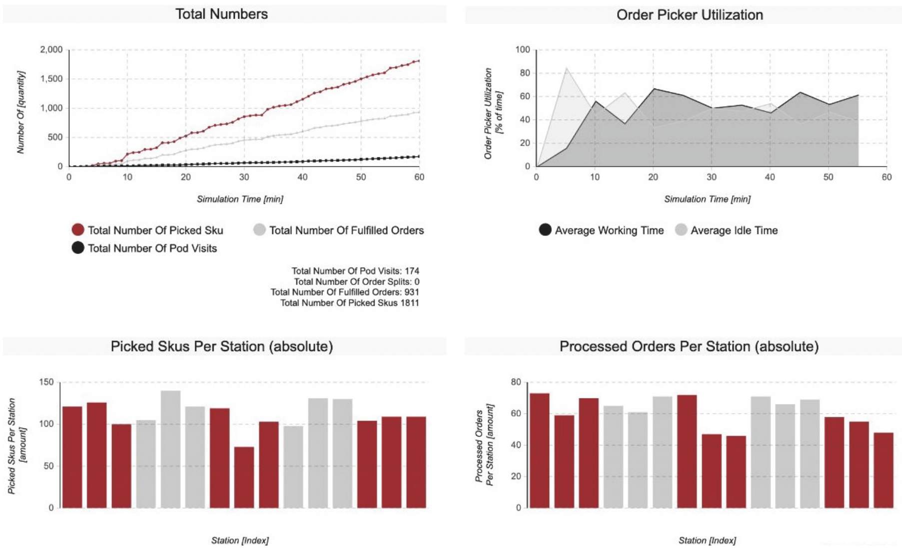

Figure 4: Exemplary screenshot of the demonstrator's output parameters (own illustration)

The decision on the system variables and input parameter variation are based on interviews with practical experts from logistics areas or production fields. On the one hand, they validate the opportunity to take the demonstrator as a tool for consultation hours with simulation experts. On the other hand, the interviews conclude with the construction of use case scenarios close to reality. In this regard, it is obvious that using the demonstrator is more cost-effective than implementing the system directly.

The demonstrator operates as decision-support, and the subsequent analysis of the different configurations aims to make clear the advantages of simulation for supporting decisions in logistics areas. The main advantages are the closeness to reality, the flexibility, the scalability, and the predictability of the simulation model (Borshchev, 2013). Furthermore, the agent-based simulation enables the mapping of different behaviours and, in this context, the behaviour of the logistical system. The model can be flexibly extended in the simulation in order to be able to carry out further investigations if the previously set conditions have changed or the analysis focus of logistics areas is changed.

To give an example of flexibility, the GUI of output parameters (Figure 5) represents additional KPIs related to RMFS. These are the "Total Number of Pod Visits", the "Order Picker Utilization", as well as the distributions of the "Picked SKUs Per Station" and the "Processed Order Per Station". Those KPIs enable the evaluation of the utilization of a picker and the distribution of individual orders to the different stations.

5 Conclusion

Evaluating different use case configurations of RMFS is essential in decision-making to find the best possible configuration for the respective requirements and thus ensure an effective and efficient logistics solution. This work shows how a simulation model of multi-level RMFS with integrated rolling planning approach can be integrated into a demonstrator. A simulation study is performed to present how users of the demonstrator can analyse different use case configurations. Therefore, three use case configurations of logistics areas in e-commerce and production are defined and analysed by the main KPIs.

The variation of input parameters can analyse new use case configurations. Therefore, logistics managers can achieve initial information about the performance of RMFS. Ideally, they can identify with the use case configuration and take these results as support for or against the system. For better validation, the input and output parameter decisions are grounded on interviews with experts from several logistics areas.

However, the discussions with those experts have created a realistic model. Some assumptions of the system (e.g., neglect of energy consumption or cost calculation) are limitations of the work. Those aspects can also be content of future work implemented in the presented simulation model. The focus can therefore be shifted from analysing the whole system's performance to analysing each robot's performance. Further research can include evaluating robot blocking processes on the shop floor and analysing robot behaviour - adding KPIs such as the waiting time of each robot in front of order picking stations or the delay times of each robot due to blocking.

Acknowledgement

This work is funded by the Federal Ministry for Economic Affairs and Climate Action based on a resolution of the German Bundestag, specifically by the German Federation of Industrial Research Associations (AiF), Industrial Collective Research (IGF): Project number IGF-20351 N, further project results are available via IGF. The authors would also like to thank the project partners (logistics providers and experts from the industry) for their insightful comments and suggestions, who declare they have no financial interests.

References

Azadeh, K.; Koster, R. de; Roy, D.: Robotized and Automated Warehouse Systems: Review and Recent Developments. Transportation Science 53 (2019) 4, pp. 917–945.

Borshchev, A.: The big book of simulation modeling: Multimethod modeling with AnyLogic 6. S.l.: AnyLogic North America 2013.

Boysen, N.; Briskorn, D.; Emde, S.: Parts-to-picker based order processing in a rack-moving mobile robots' environment. European Journal of Operational Research 262 (2017a) 2, pp. 550–562.

Boysen, N.; Briskorn, D.; Emde, S.: Sequencing of picking orders in mobile rack warehouses. European Journal of Operational Research 259 (2017b) 1, pp. 293–307.

Boysen, N.; Koster, R. de; Weidinger, F.: Warehousing in the e-commerce era: A survey. European Journal of Operational Research 277 (2019) 2, pp. 396–411.

Duan, G.; Zhang, C.; Gonzalez, P.; Qi, M.: Performance evaluation for Robotic Mobile Fulfillment Systems with time-varying arrivals. Computers & Industrial Engineering 158 (2021), pp. 107365.

Gong, Y.; Jin, M.; Yuan, Z.: Robotic mobile fulfillment systems considering customer classes. International Journal of Production Research 59 (2021) 16, pp. 5032–5049.

Guan, M.; Li, Z.: Genetic Algorithm for Scattered Storage Assignment in Kiva Mobile Fulfillment System. American Journal of Operations Research 08 (2018) 06, pp. 474–485.

Hanson, R.; Medbo, L.; Johansson, M.I.: Performance Characteristics of Robotic Mobile Fulfillment Systems in Order Picking Applications. IFAC-PapersOnLine 51 (2018) 11, pp. 1493–1498.

Jaghbeer, Y.; Hanson, R.; Johansson, M.I.: Automated order picking systems and the links between design and performance: a systematic literature review. International Journal of Production Research 58 (2020) 15, pp. 4489–4505.

Juan, A. A.,; Faulin, J.; Grasman, S. E.; Rabe, M.; Figueira, G.: A review of simheuristics: Extending metaheuristics to deal with stochastic combinatorial optimization problems. Operations Research Perspectives (2015) 2, pp. 62-72.

Kim, H.-J.; Pais, C.; Shen, Z.-J.M.: Item Assignment Problem in a Robotic Mobile Fulfillment System. IEEE Transactions on Automation Science and Engineering 17 (2020) 4, pp. 1854–1867.

Lamballais, T.: Inventory Allocation in Robotic Mobile Fulfillment Systems. SSRN Electronic Journal (2017).

Lamballais, T.; Roy, D.; Koster, M. de: Estimating performance in a Robotic Mobile Fulfillment System. European Journal of Operational Research 256 (2017) 3, pp. 976–990.

Li, X.; Yang, X.; Zhang, C.; Qi, M.: A simulation study on the robotic mobile fulfillment system in high-density storage warehouses. Simulation Modelling Practice and Theory 112 (2021), pp. 102366.

Merschformann, M.; Lamballais, T.; Koster, M. de; Suhl, L.: Decision rules for robotic mobile fulfillment systems. Operations Research Perspectives 6 (2019), pp. 100128.

Tadumadze, G.; Wenzel, J.; Emde, S.; Weidinger, F.; Elbert, R.: Assigning orders and pods to picking stations in a multi-level robotic mobile fulfillment system. Flexible Services and Manufacturing Journal (2023), pp. 1-38.

van Gils, T.; Ramaekers, K.; an Caris; Koster, R.B. de: Designing efficient order picking systems by combining planning problems: State-of-the-art classification and review. European Journal of Operational Research 267 (2018) 1, pp. 1–15.

Weidinger, F.; Boysen, N.: Scattered Storage: How to Distribute Stock Keeping Units All Around a Mixed-Shelves Warehouse. Transportation Science 52 (2018) 6, pp. 1412–1427.

Weidinger, F.; Boysen, N.; Briskorn, D.: Storage Assignment with Rack-Moving Mobile Robots in KIVA Warehouses. Transportation Science 52 (2018) 6, pp. 1479–1495.

Wenzel, S.; Bernhard, J.; Jessen, U.: A taxonomy of visualization techniques for simulation in production and logistics. Proceedings of the 2003 Winter Simulation Conference, (2003), pp. 729-736 Vol.1.

Xie, L.; Thieme, N.; Krenzler, R.; Li, H.: Introducing split orders and optimizing operational policies in robotic mobile fulfillment systems. European Journal of Operational Research 288 (2021) 1, pp. 80–97.

Zhu, L.; Li, H.: Workstation layout strategies in Robotic Mobile Fulfillment Systems considering carbon emissions. Cleaner Logistics and Supply Chain 4 (2022), pp. 100050.