Chapter 26
Mobile Picking Robots: A First Study of the Effects of Human-Robot Interactions in Conventional Order Picking Systems

Dirk Kauke, Florian Sailer, and Johannes Fottner

26.1 Introduction

Order picking systems (OPS) form the centerpiece of all warehouse operations. The rapid growth of e-commerce, in particular in recent decades, has led companies to focus on their OPS processes. Over 80% of all warehouses are still operated manually, and up to 55% of the total costs for warehousing can be assigned to the order picking process [1]. On the other hand, more and more companies are facing increasing staff shortages [2]. A solution was therefore sought that would meet the flexibility requirements of manual picking and keep the scalability of the system. The most promising approach is the use of mobile robots. Like humans, mobile robots can be used flexibly as required and do not represent a rigid solution as in the case of automated storage and retrieval systems. When using mobile robots, a distinction can be made between fixed and movable shelves. In the case of movable shelves, the mobile robot picks up a shelf and transports it to a defined spot where a human does the actual pick. One of the most famous systems is the Amazon Robotic System. In the scientific world, these systems are often called Mobile Robotic Fulfillment System (MRFS). If the shelves are fixed, the mobile robot either picks the goods on its own or assists the human and provides empty picking cases [2]. This paper focuses on the mobile picking robots (MPR), which can actually pick goods.

D. Kauke (✉) · F. Sailer · J. Fottner
Chair of Materials Handling, Material Flow, Logistics, Technical University of Munich, Munich, Germany
e-mail: dirk.kauke@tum.de; florian.sailer@tum.de; j.fottner@tum.de
www.tum.de

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Regardless whether it is a classic OPS or a hybrid OPS, these types of systems must be validly planned and designed. An essential distinguishing feature of hybrid OPS is the direct co-existing between humans and robots which must be considered during planning and design.

This paper presents a simulation model that can represent a hybrid OPS. The performance relevant effects of the joint interactions shall be highlighted, and first conclusions on the layout design shall be drawn.

For this purpose, the scientific literature is first consulted in Sect. 26.2. In Sect. 26.3, the structure of the model is presented, and in Sect. 26.4 the results are discussed. The paper concludes with a summary and an outlook on future research.

26.2 Related Literature

Manual picking systems have been scientifically investigated for many years. In the course of time, the different issues have been categorized accordingly, so that a distinction can be made between strategic, tactical, and operational decisions [3]. The degree of automation or the layout is determined within the strategic decision-making process. In the course of the tactical considerations, the warehouse occupancy, among other things, is determined. The operational department decides, e.g., on batching or routing [3]. Reference [3] has examined the research method to analyze the OPS. Simulation has been used the most.

Since this paper investigates the usage of mobile robots within OPS, the literature review should rather focus on papers dealing with this specific topic. First and foremost, the work of Azadeh should be mentioned, who conducted a very extensive literature review on the various uses of mobile robots in OPS [2]. In addition, two works [4, 5] will be highlighted. There, a simulation model for Mobile Robot Fulfillment Centers was developed, which not only examines the general performance but also considers failure-handling strategies. A much older reference is [6], which already investigated the design of Kiva-Robots systems, an example for MFRS in 2008. A further literature review on shelf-moving robots was carried out by [7]. Recent work related to mobile robotics in OPS are [8, 9]. Reference [8] developed a queuing network to minimize the order throughput time. A similar approach was chosen by reference [9]. However, they clearly varied the size of the layout.

In summary, it can be concluded that there is already a large number of scientific papers dealing with different questions in the field of strategic, tactical, and operational design of MFRS. However, at this point, no scientific work can be found that has developed a model for investigating mobile pick robots, which work together with humans. The next chapter therefore serves to present this type of model.

26.3 Model Design

26.3.1 General Design

The model has been designed with the Tecnomatix Plant Simulation software. Plant Simulation is a discrete event simulation tool that is commonly used to investigate material flows and production processes. The layout of the OPS can be divided into following aspects:

A: Number of aisles per block
B: Number of blocks
W_a: Aisle width
L_a: Aisle length
W_s: Shelf width
L_p: Path section length
W_p: Path section width
D: Depot location
W_p: Pre-zone width
S: Number of workstations
C: Back cross-aisle available

Figure 26.1 shows the exemplary structure of a layout. The special feature here is that any number of blocks and storage aisles can be considered, although it is possible to display both common positions of the depot.

Each aisle consists of individual path sections. Each path section operates as a node that can be traveled in both X and Y directions. The time required to cross a path section depends on the speed of the respective participant. If an agent changes direction on a path section, the time needed to cross the section is taken into account as well as the amount of time for turning.

$t_{t,h}$: Turning human
$t_{t,r}$: Turning robot

This has the advantage that storage locations on the same side of the shelf are preferred when orders are allocated, since additional turning operations would be necessary.

26.3.2 Interaction

As robots make use of safety sensors to navigate safely throughout the warehouse environment, modeling the safety areas is therefore crucial for depicting the robot behavior, so that time losses and changes in moving speed as a result of interaction can be taken into consideration. In general, robots have two different safety areas, namely, *the protective zone* and *the warning zone*. If an object is located within

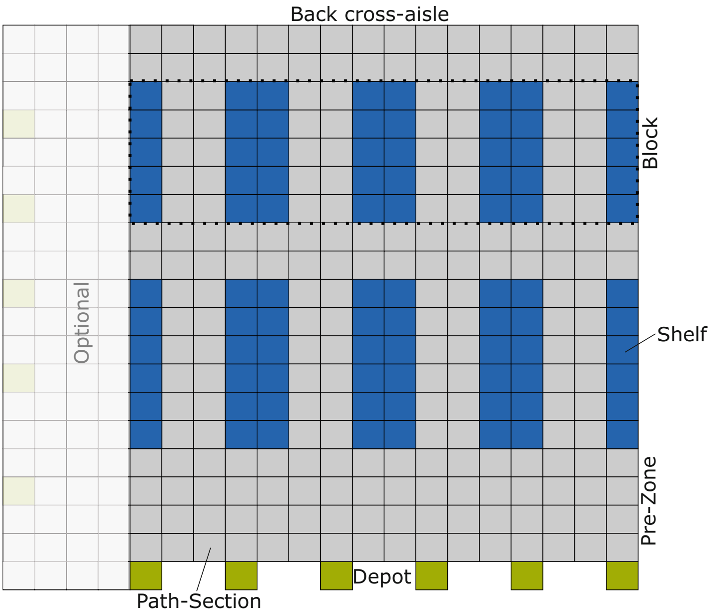

Fig. 26.1 Layout components

the borders of the protective zone, the robot stops its operation immediately. When the object is located within the warning zone, then the robot continues at creep speed until the detected object crosses the borders of the protective zone. Similarly, human order pickers observe their environment and adapt their behavior depending on occurring interactions. Therefore, the same safety concept is also applicable to human order pickers.

The protective zone When a robot or a human worker is located on a specific frame, the adjacent frames represent its protective zone in the simulation model. Therefore, system participants should recognize the objects in the adjacent frames. Depending on the position of the frame in the warehouse model, the number of adjacent elements varies between 2 and 4. The created model monitors the contents of all available successors, and interaction occurs if any of the areas are occupied.

The warning zone Similar to the monitoring of the protective zone, the content of the warning zone needs to be monitored. The warning zone in the created simulation model is defined as the frame, which is located beyond the protective zone in the movement direction of a system participant. The protective zone and the warning zone are illustrated in Fig. 26.2.

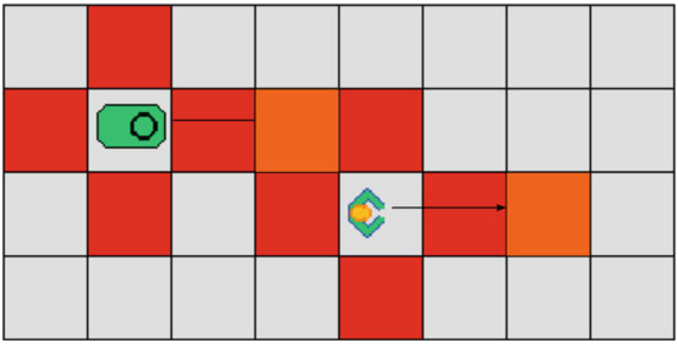

Fig. 26.2 Protective and warning zone

26.3.3 Modeling Humans and Robots

Both the humans (h) and robots (r) are based on the class transporters. Their main differences can be seen in the following variables:

v_h:	Velocity of the human	1.5 m/s
$v_{h,red}$:	Reduced velocity of the human	0.75 m/s
v_r:	Velocity of the robot	1 m/s
$v_{r,red}$:	Reduced velocity of the robot	0.5 m/s
$t_{wait,h,h}$:	Interact.loss betw. h and h	1 s
$t_{wait,h,r}$:	Interact.loss betw. h and r	3 s
$t_{wait,r,r}$:	Interaction loss of robot	5 s
Cap_r:	Capacity of a robot	12 units
Cap_h:	Capacity of a human	12 units

26.3.4 Operation and Order Structure

The sequence of the picking process is based on the classic procedure of an order picking system. A new picking order is generated at the start of every picking tour. For this purpose, a heuristic is applied based on the existing orders in the order pool. The aim is to generate a tour that is as short as possible. Once the picking order is completed, it will be handed over to either a human or robot. Currently, specific peculiarities of humans and robots are not taken into account when releasing orders. In the future, it would be conceivable that orders with higher priority could be picked primarily by humans. In addition, when allocating orders and allocating storage space, it must be taken into account which article types the robot can handle.

After the order has been assigned, it will be processed according to the generated tour. With the completed picking order, the participant returns to the depot to hand over the picked items and receive a new order.

26.4 Simulation and Analysis

26.4.1 Objective and Relevant Parameters

The main goal of the simulation study is to find out what influence the interaction between humans and robots has on the overall performance of the OPS. The previous chapter described the design of the model, including all sub-elements. The number of orders (N) processed within 1 day is used as a key figure. Each day (t_{day}) corresponds to two shifts (t_{shift}), each with 8 h of working time reduced by the break and battery charging times of the humans and robots, respectively.

The maximum number of agents ($P_{h,r}$) in the system is limited to 20. The composition is varied with each simulation run. Besides the number of humans and robots in the system, the layout is also varied. A distinction is made between the width of the aisle as well as whether a cross-aisle at the end is available. If a cross-aisle is available, the routing can change between return and traversal depending on the order. A summary of all relevant parameters can be found in Table 26.1.

Table 26.1 Basic parameters in experiments

Variable	Value
A	4
B	1
W_a	4, 6
L_a	24 m
W_s	2 m
L_p	2 m
W_p	2 m
D	South
W_p	8 m
S	8
C	True, false
t_{day}	2 shifts
t_{shift}	8 h
$P_{h,r}$	$1, \ldots, 20$

26.4.2 Total Throughput in a Homogeneous OPS

During the first step, the performance development of the overall system with a continuous increase in the number of participants in the system should be considered. In this case, the system is homogeneous, i.e., either only humans or only robots is represented in the system. Figure 26.3 illustrates the performance curve among 1 and 20 participants. The highest performance is achieved by a system operated by humans only, with 6-meter-wide aisles. Furthermore, it can be seen that the cross-aisle does not provide any significant added value with regard to system throughput. If you look at the performance curve of the robots within the same system, you can see that it is significantly lower on one hand and, on the other hand, there is no difference at all between return and traversal routing. The lower performance is caused by the fact that the motion sequences of the robot are significantly slower and the time loss due to interactions (waiting, evasion, etc.) is significantly higher.

If one looks at the remaining two pairs of curves, different aspects can be determined. With seven or more participants, both pairs of curves are below the performance of the 6-meter-wide systems. This is mainly because the narrow aisles provide less space for both groups of participants to move without interaction. Consequently, the interactions increase and the performance decreases. It can be seen that the loss of performance of the human compared to the robot is significantly

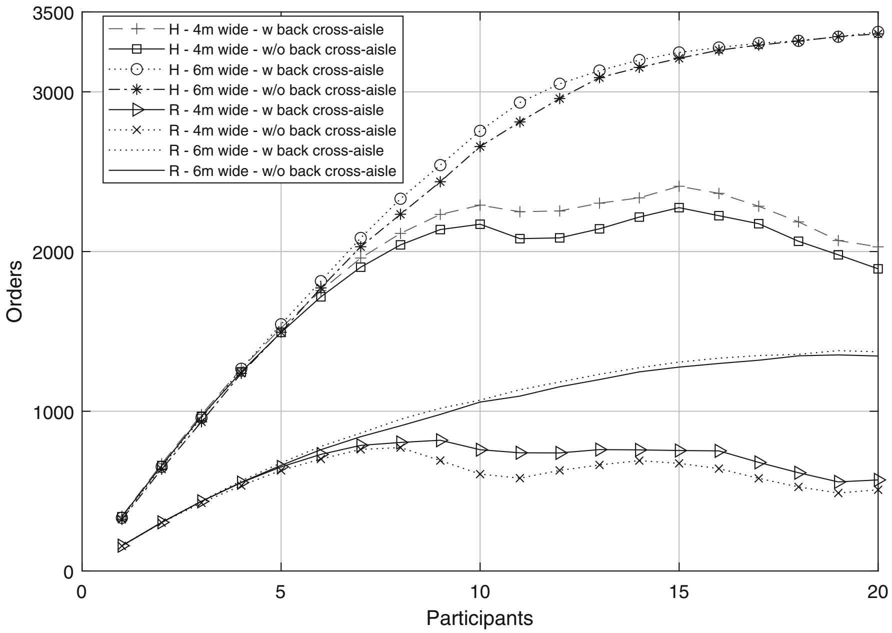

Fig. 26.3 Performance curve for different system configurations

higher. Finally, it becomes apparent that in the 4-meter-wide systems that have between 7 and 20 participants, the performance both increases and decreases. Despite repeated experiments, this can only be explained by the increase in interactions. Since order release is independent of the utilization of individual aisles, a higher number of interactions can therefore occur in individual configurations, although the maximum number of participants has not yet been reached. It can thus be stated that the width of the aisles has a considerable influence on the performance of the overall system.

26.4.3 Average Throughput

In the previous chapter, it became obvious that with an increasing number of participants, the performance can vary. In the following chapter, the question of average performance development will be examined. Figure 26.4 shows the average performance trends of humans and robots in a 6-meter-wide aisle system with a back cross-aisle.

At first, the difference between human and robot performance is noticeable, as shown in Fig. 26.3. Furthermore, it can be seen that the performance curve of the robot is an equable curve, whereas the other graph decreases more rapidly between 10 and 20 humans. However, the average performance is reduced by around 50% in both cases. The average human performance starts at a homogeneous system at about 340 orders and drops to 160 orders within 2 shifts. A single robot, on the other hand, manages almost 150 jobs within 2 shifts. When a total of 20 robots are in operation, the average output per robot in 2 shifts is reduced to about 70 orders.

Figures 26.3 and 26.4 show the course of performance, with an increase in the number of actors of the same type. In other words, how does the human-operated system behave when more people are added. The performance loss shown in the

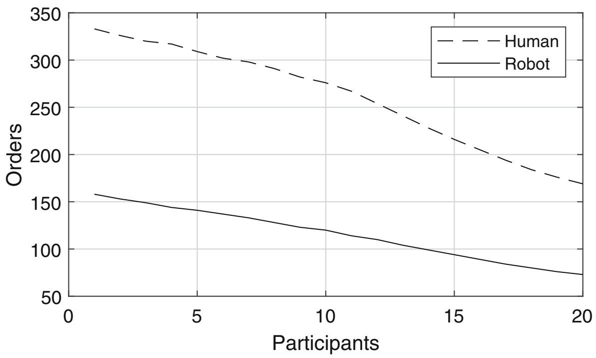

Fig. 26.4 Average performance trends of humans and robots in a 6-meter-wide aisle system within two shifts

figure proves the effectiveness of the warning and protection zone. In the following chapter, the performance development in the hybrid system will be more closely examined.

26.4.4 Performance in Hybrid OPS

There is currently no other simulation model that can determine the performance of a hybrid OPS. Due to the constant increase in different market-ready solutions in this area, a tool for system design is absolutely necessary. One of the primary questions in this type of system designs is the performance and which human-robot combination best achieves this. Figure 26.5 illustrates the performance of the above-defined system.

Figure 26.5 shows the single performance of humans and robots as before. Additionally, all possible combinations of humans and robots and their performances are shown. Assuming a target value of 2000 orders per day, different combinations of humans and robots are possible. In theory, the minimum number of humans and robots would be an optimal solution ($P_{7,1}$). However, a predominant lack of human resources can lead to the fact that a continuous availability of, in this case, seven humans cannot be guaranteed in practice. For this reason, it may be necessary to fall back on other possible combinations. The next variant with a capacity $\geq$ 2000

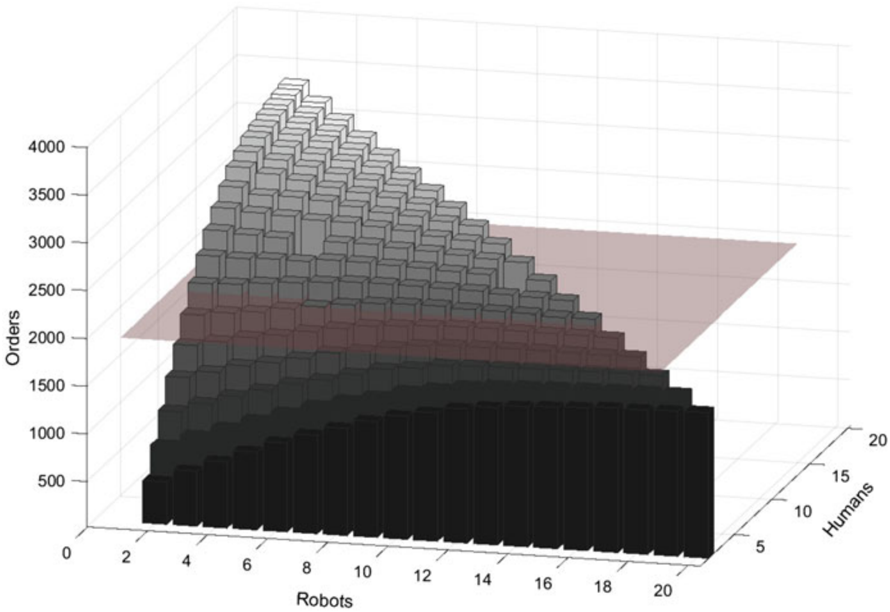

Fig. 26.5 Combination of all possible participants in OPS and their performances

orders would be ($P_{6,5}$). This means that the loss of one human in this system configuration must be compensated by five robots. It becomes clear that the greater the sum of $P_{i,j}$, the greater is the necessary compensation of a human by robots. This shows the high necessity of a perfectly coordinated system, so that possible shortfalls in human resources have to be compensated for by only a few robots. In addition, the system should of course be able to provide a solid base performance through possible strategy adjustments. Zoning is one possible strategy adjustment for increasing the system's basic performance. This is examined in more detail in the following chapter.

26.4.5 Zoning

In this context, zoning means that humans and robots pick in different aisles of the picking system. This means that the orders are assigned to either a human or a robot, depending on the aisle. An interaction can therefore only take place around the depot. Figure 26.6 describes the applied scenario.

In industrial applications, the aim is to ensure that humans and robots can work more freely in their work processes. It should be apparent that people work more efficiently if they work exclusively with humans. The same applies to robots. Due to the significantly faster and less comprehensible movements of humans, it can be assumed that the robot's performance is more often disrupted, which results in a

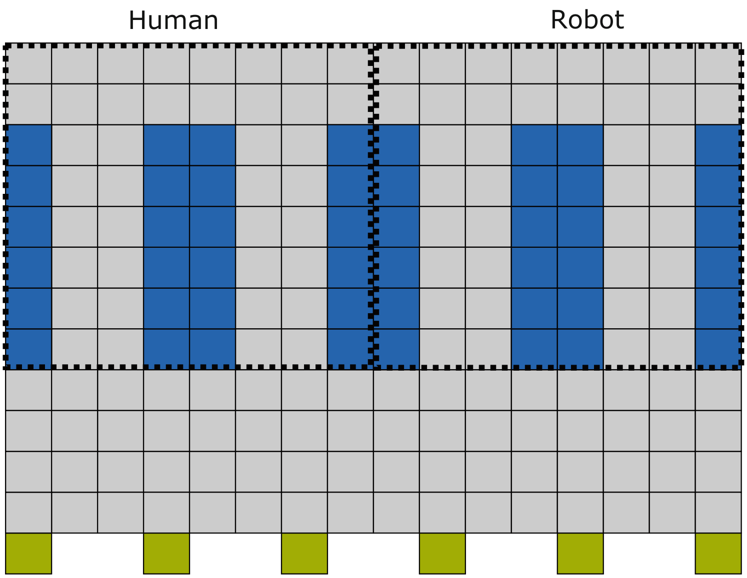

Fig. 26.6 Application of a zoning

decreased overall performance. Therefore, in this chapter, the development of the overall performance is shown. The effects can be found in Table 26.2.

All in all, it can be stated that the performance increases through the use of zoning in the OPS. However, the performance decreases in some constellations. In most cases, however, these are homogeneously aligned systems, which means that the fixed allocation of aisles can have a negative effect because too many agents have to operate in only two aisles, which leads to more interactions. In a balanced system, however, an increase in performance in the middle single-digit range can be detected without exception. This is mainly due to the fact that by working separately, both agents are not confronted by behavior different from their own, which again leads to an increase in efficiency. Since the reference system is a relatively small system with only four aisles, the question arises whether the added value of fixed zoning is more drastic in larger systems. This should be considered more closely in future studies.

In practice, however, such strict zoning poses a number of challenges. In particular, warehouse occupancy and batching can make such an approach difficult. The robot will probably not be able to pick the entire range of articles. This means that the size of the robot zone is directly dependent on the assortment of pickable articles by the robot if a strict separation within the aisles is desired.

On the other hand, turnover frequency and thus batching play a role. There is no question that the robots are less efficient. If the articles in the robot zone are fast-moving items, the robot may not be able to provide the required performance and the warehouse builds up backlogs. Accordingly, fast-moving articles should be kept in the human zone as a precaution, although it is conceivable that the robot is not working at full capacity due to slow-moving articles and, therefore, is not operating economically.

It is difficult to find a generally valid solution for this problem. In individual cases, the reference system with the specific warehouse occupancy and order load must be examined. However, a semi-fixed zoning represents a conceivable alternative. Here, the robot moves exclusively in the assigned aisles. In exceptional cases, however, humans can also pick in the robot zone. The performance development could then be compared with that of fixed zoning (Table 26.2).

26.5 Conclusion and Future Research

The increasing lack of human resources in logistics is leading to an increase in demand for flexibility initiatives in manual OPS. The presented MPRs are one possible approach to meet this demand for flexibility. For the first time ever, this paper has presented an approach in which hybrid OPS can be investigated using a simulation model. Initially, the interaction between humans and robots was the main focus. It became clear that in homogeneous systems, the interactions increase with an expansion of the agents and the performance decreases accordingly. Especially the width of the aisle as well as the presence of a back cross-aisle influences

Table 26.2 Increased performance through zoning

	Human																		
Robot	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	4%	5%	5%	4%	3%	4%	2%	2%	1%	0%	0%	−1%	−1%	−1%	−1%	−3%	−1%	−2%	−10%
2	5%	6%	7%	−8%	2%	6%	4%	5%	4%	3%	3%	1%	0%	−9%	−1%	−1%	−2%	−10%	–
3	5%	6%	7%	7%	7%	8%	6%	5%	5%	3%	1%	0%	0%	0%	−1%	−10%	−15%	–	–
4	4%	6%	7%	8%	9%	8%	7%	6%	18%	−9%	0%	0%	0%	−1%	−1%	−1%	–	–	–
5	2%	6%	6%	9%	8%	8%	6%	4%	4%	1%	0%	−16%	0%	−1%	−2%	–	–	–	–
6	1%	4%	7%	7%	7%	2%	4%	3%	2%	1%	0%	0%	0%	−1%	–	–	–	–	–
7	−1%	3%	5%	7%	6%	5%	4%	3%	2%	1%	0%	0%	0%	–	–	–	–	–	–
8	−1%	3%	3%	5%	5%	3%	3%	2%	1%	1%	0%	0%	–	–	–	–	–	–	–
9	−3%	1%	3%	4%	4%	3%	2%	−3%	−5%	0%	0%	–	–	–	–	–	–	–	–
10	−2%	1%	2%	2%	2%	3%	2%	1%	1%	0%	–	–	–	–	–	–	–	–	–
11	−4%	0%	1%	2%	2%	2%	2%	13%	1%	–	–	–	–	–	–	–	–	–	–
12	−4%	−1%	2%	2%	2%	2%	2%	1%	–	–	–	–	–	–	–	–	–	–	–
13	−4%	−1%	2%	2%	2%	2%	2%	–	–	–	–	–	–	–	–	–	–	–	–
14	−3%	−1%	1%	1%	1%	1%	–	–	–	–	–	–	–	–	–	–	–	–	–
15	−2%	0%	1%	1%	1%	–	–	–	–	–	–	–	–	–	–	–	–	–	–
16	−3%	−1%	0%	0%	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
17	−2%	−1%	0%	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
18	−2%	−1%	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
19	−3%	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–

the performance. It was shown that the average performance of both participants decreases equally with an increase in the number of participants.

In the second part of the paper, the hybrid systems were examined more closely. The previous results were again confirmed. However, it also became clear that different constellations are possible if a specific target performance (e.g., 2,000 orders per day) is taken into account. A minimum total number of actors always lead to a high number of humans and only a few robots. Reducing the number of humans by replacing them with robots cannot be achieved at a one-to-one ratio. In the presented application scenario, the performance of one human could only be replaced by five robots. This illustrates the necessity of an optimally coordinated system, possibly even by adapting individual strategies.

One such strategy is to zone the picking system. Two aisles were assigned to robots and two aisles to humans. This means that they also pick in only their two aisles. It became clear that in balanced systems (e.g., $P_{6,5}$), an increase in performance is to be expected. For an industrial application, however, the batching and storage assignment must be considered more closely.

Future research should first consider the influence of zoning for different system sizes. Since the examined system is a rather small-scale system, the effects could be more significant for larger systems. Furthermore, the influence of multiple cross-aisles on human-robot interactions is still unclear. Furthermore, the influence of multiple cross-aisles on human-robot interactions is still unclear, and the presented semi-fixed zoning should be further explored. In conclusion, it can be stated that the use of MPRs will increase in the future and so will the need for suitable planning tools.

References

1. R. de Koster, T. Le-Duc, K.J. Roodbergen, Design and control of warehouse order picking: a literature review. Eur. J. Oper. Res. **182**(2), 481–501 (2007)
2. K. Azadeh, R. de Koster, D. Roy, Robotized and automated warehouse systems: review and recent developments. Transp. Sci. **53**(4), 917–945 (2019)
3. T. van Gils, K. Ramaekers, A. Caris, R.B.M. de Koster, Designing efficient order picking systems by combining planning problems: state-of-the-art classification and review. Eur. J. Oper. Res. **267**(1), 115 (2018)
4. T. Lienert, L. Stigler, J. Fottner, Failure-Handling Strategies For Mobile Robots In Automated Warehouses, in *33rd International ECMS Conference on Modelling and Simulation*, 2019, pp. 199–205
5. T. Lienert, T. Staab, C. Ludwig, J. Fottner, Simulation-based performance analysis in robotic mobile fulfilment systems – analyzing the throughput of different layout configurations, in *8th International Conference on Simulation and Modeling Methodologies, Technologies and Applications*, 2018, pp. 383–390
6. R. D'Andrea, P. Wurman, Future challenges of coordinating hundreds of autonomous vehicles in distribution facilities, in *2008 IEEE International Conference on Technologies for Practical Robot Applications*, 2008, pp. 80–83
7. N. Boysen, R. de Koster, F. Weidinger, Warehousing in the e-commerce era: a survey. Eur. J. Oper. Res. **277**(2), 396–411 (2019)

8. T. Lamballais Tessensohn, D. Roy, R.B.M. de Koster, Inventory allocation in robotic mobile fulfillment systems. IISE Trans. **52**(1), 117 (2020)
9. W. Wang, Y. Wu, J. Zheng, C. Chi, A comprehensive framework for the design of modular robotic mobile fulfillment systems. IEEE Access **8**, 13259–13269 (2020)