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Hybrid order picking: A simulation model of a joint manual and autonomous order picking system

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ABSTRACT

Order picking is a key process in supply chains and a determinant of business success in many industries. Order picking is still performed manually by human operators in most companies; however, there are also increasingly more technologies available to automate order picking processes or to support human order pickers.

One concept that has not attracted much research attention so far is hybrid order picking where autonomous robots and human order pickers work together in warehouses within a shared workspace for a joint target. This study presents a simulation model that considers various system characteristics and parameters of hybrid order picking systems, such as picker blocking, to evaluate the performance of such systems. Our results show that hybrid order picking is generally capable of improving pure manual or automated order picking operations in terms of throughput and total costs. Based on the simulation results, promising future research potentials are discussed.

1. Introduction

During recent decades, warehouses have undergone significant changes with respect to the operating policies and technologies used. Warehousing systems are challenged by rising demands in terms of the variety and volume of products to be stored, for example, because of a continuing trend toward e-commerce and customer requests for short delivery times and high service quality (Boysen et al., 2019; Winkelhaus & Grosse, 2020). These developments have pushed managers to ensure high process efficiency and space utilization in warehouses.

Order picking is a warehousing process in which products are retrieved from storage facilities to satisfy customer orders (van Gils et al., 2018), and it has frequently been the subject of research as it is considered a key determinant of warehouse performance. Traditionally, order picking has been performed manually with operators traveling along the aisles of the warehouse, which is still the most prevalent method in practice (these systems are usually referred to as person-to-goods systems; see de Koster et al. (2007); Grosse et al. (2017)). Order picking is therefore characterized by considerable manual labor, making it a very cost-intensive process step in warehousing (Grosse et al., 2017).

To ensure efficient order picking operations, different decision problems have to be solved, with zoning, batching, routing, and storage assignment among the most important ones (Masae et al., 2020a). Solution methods for these decision problems usually aim on reducing unproductive times, such as the time spent on traveling that often accounts for up to 50% of the total order picking time (Tompkins et al., 2010). Unproductive traveling and searching tasks of humans can also be reduced by IT and automation technologies that increase the pick performance of order pickers. Some of these technical solutions transform person-to-goods systems into goods-to-person systems. In goods-to-person systems, a certain quantity of the requested products is brought to the order picker's location using a technical system (Boysen et al., 2019). The order picker then only physically retrieves the correct quantity and confirms the pick.

Different types of goods-to-person systems have recently gained attention, such as shuttle-based and grid-based automated storage and retrieval systems (AS/RSs) (Azadeh et al., 2019). By reducing the scope of work for human operators to a necessary minimum, goods-to-person systems try to reduce unproductive times and increase the pick frequency of order pickers, and in many cases, they establish separated workspaces with fixed pick stations. Additionally, these systems also impact space requirements or warehouse investment costs, among

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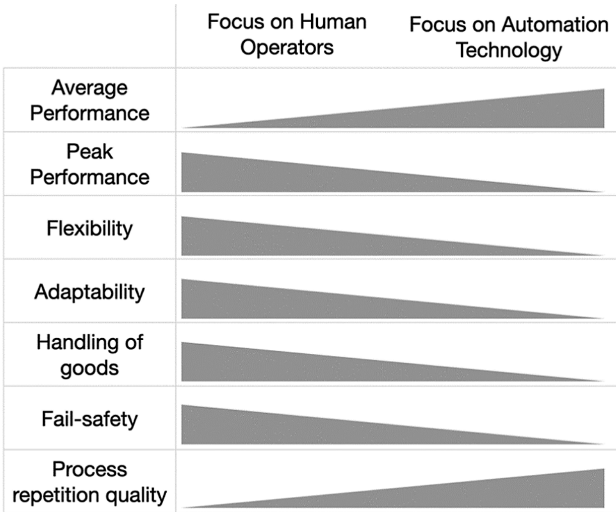

Fig. 1. Simplified capabilities of human operators and ordinary automation technology (Boysen et al., 2019; Huang et al., 2015) to meet the operationalized requirements of the e-commerce warehouse, as formulated by Boysen et al. (2019).

others (Huang et al., 2015). The technology requirements of the warehouse typically depend on the industry. For example, e-commerce warehouses that are often characterized by a varying workload, small orders, large product assortments and tight delivery schedules require special technological support to ensure that orders can be picked efficiently (Azadeh et al., 2019; Boysen et al., 2019; Huang et al., 2015). Fig. 1 conceptually shows how various performance parameters of a warehouse can qualitatively be assessed depending on whether it is operated manually or with ordinary automation technology. For example, automation technologies can efficiently be used to design warehouses with a constant output; however, if there are relevant peak loads to be handled, automated systems could lead to unprofitable high investment costs and a large overcapacity for most of the time. Although human operators have a lower average performance than (partly) automated systems, peak loads can be handled by engaging temporary workers or using overtime. In addition, warehouses with, e.g., stacker cranes draw a large share of their output from just a few units, so the failure of one stacker crane causes a significant loss of output and parts of the assortment may no longer be accessible at all. Since manual warehouses offer often more flexibility and fail-safety, they show advantages over automated systems.

Although most studies expect that logistics managers will continue to rely on human operators in the foreseeable future owing to their flexibility to pick different goods (Correll et al., 2018), current developments in order picking technologies aim to overcome some of the limitations of goods-to-person systems (Winkelhaus et al., 2021). Given the different strengths and weaknesses of human operators and automated systems (Fig. 1), a collaborative order picking system that leverages the individual strengths of both could increase the performance of the warehouse. This paper follows the terminology established by Winkelhaus et al. (2021) and refers to hybrid order picking systems (HOPSs) where autonomous systems and human order pickers work together on one shop floor (Kauke et al., 2020) for a joint target, see Fig. 2 for an example (Winkelhaus et al., 2021). Alternative definitions can be found in Ibrahim et al. (2020). Autonomous systems are highly capable automated systems (Endsley, 2017) that are an important component of HOPSs, as these differ from traditional goods-to-person systems with respect to 1) the extent of temporal interactions, 2) the extent of spatial interactions, 3) the extent of adaption and interaction, and 4) the congruency of task goals and sub-goals (Onnasch et al., 2016) with human order pickers. According to the five levels of automation described by Winkelhaus et al. (2021), technologies applied in a HOPS need to be at least partly context-aware. These systems, for example autonomous mobile robots (see Fig. 2 for an example of such a HOPS) or automated guided vehicles, have at least, semi-autonomous capabilities, i.e. being intrinsically safe for example. Systems that only automate repetitive tasks are not considered as HOPS in this paper.

With this approach, the boundaries of current AS/RSs are dissolved, enabling an order picking system that can handle a large range of diverse products and that can easily be adapted to changing warehousing requirements. Autonomous mobile robots (AMRs) or advanced AGVs could be applied for transporting goods and people, and fully autonomous picking robots could support human operators by taking over certain tasks (Fragapane et al., 2021). Technical systems that work in a hybrid order picking application and that are also able to perform the actual picking of goods have already been introduced in practice (see, e. g., Fig. 2), but in-depth investigations of such warehouse technologies, particularly in a hybrid approach, are scarce.

As HOPSs have not yet been investigated in detail (this is discussed further in Section 2), we address this research gap by studying a HOPS in which human operators and autonomous picking robots share the tasks. The research objective of this study is *to investigate the potential of hybrid order picking systems to improve order picking performance for different warehouse operating policies and market characteristics.*

To reach this goal, we develop an agent-based simulation model. Our analysis shows that HOPSs are generally capable of improving manual and automated order picking operations in terms of system throughput and total costs per pick. The major determinants of HOPS performance are the total workload handled and the assigned item classes (and their demand frequency) as well as the occurrence of blocking.

The remainder of this article is organized as follows: Section 2 reviews related literature to highlight the research gap addressed in this paper. Section 3 describes the simulation methodology and outlines the

Fig. 2. Example of a HOPS at Zalando employing TORU robots by Magazino GmbH.

simulated HOPS in detail. The simulation results are presented in Section 4 and comprehensively discussed in Section 5. In addition, future research possibilities are derived. Finally, Section 6 concludes the paper.

2. Literature review

Order picking, in general, can be performed manually, automatic, or hybrid, with a large variety of possible HOPS setups. We focus on a processual and organizational perspective, acknowledging that the resulting system relies on technologies in the work environment that are not investigated in depth in this article. These enabling technologies are, for example, identification and wireless sensor systems, the internet of things, or advanced data processing tools based on artificial intelligence. For an overview of these technologies, we refer to recent literature reviews (see, e.g., Glock et al. (2021); Winkelhaus and Grosse (2020); Winkelhaus et al. (2021)).

The literature that is relevant to the HOPS considered in this article deals with human–machine interaction in the main physical order picking process steps, i.e. traveling through the aisles to the pick location, retrieving the required quantity of the item and transporting the selected items to the next location or the depot. Technologies employed in HOPSs are at least partly autonomous as described above (Endsley, 2017; Winkelhaus et al., 2021) in contrast to, for example, industrial or forklift trucks. These technologies are operated by employees instead of automatically adopting to the work environment.

Two review articles discussed the context of HOPSs: Winkelhaus et al. (2021) reviewed the literature related to Order Picking 4.0 and considered three relevant order picking systems, among these also HOPSs. The authors found that HOPSs are underresearched and only a few articles were identified dealing with these systems. Focusing on AMRs, Fragapane et al. (2021) surveyed the opportunities of AMRs as decentralized robotic applications for material handling, collaboration, and full-service provision in intralogistics. Focusing on decision problems such as zoning and scheduling as well as the number and type of vehicles, the authors identified several warehousing applications in which AMRs can support and improve work systems. However, the authors concluded that further studies are needed to explore the benefits of AMRs and that agent-based simulation is promising for gaining knowledge in this area.

In the following sub-sections, we take a closer look at two tasks that play an important role in order picking: traveling and the transportation of goods as well as the retrieval of goods. Both tasks can be supported by automated technologies.

2.1. Support of traveling and transportation

The first research stream investigates order picking systems in which operators interact and collaborate with an AGV. AGVs have recently been investigated in an order picking context as robotic mobile fulfillment systems (RMFSs). RMFSs, such as the so-called KIVA system (Li et al., 2020), use AGVs to realize a new form of goods-to-person system, in which racks are lifted and brought to the operator by AGVs (Boysen et al., 2019). RMFSs do not share the workspace with operators and perform tasks without human interaction, and they are thus not seen as HOPSs in a narrow sense. However, AGVs can also be applied on higher levels of automation, which can be considered relevant, owing to a deeper interaction between technology and human operators, be it spatially, timely, or interactively.

An alternative, more adaptive type of co-working is based on a concept in which the operator follows an AGV to the pick location, picks the item, and places it on the AGV. Once the capacity of the AGV has been reached, it autonomously travels to the depot and a new AGV replaces it (Boysen et al., 2019; Löffler et al., 2021). There is an adaptive form of direct human-robot interaction within an OP process step. Even though picks are still performed manually, the unproductive time of a human operator is reduced because of a higher pick density and fewer returns to the depot. To ensure that AGV-supported order picking works as efficiently as possible, some authors, such as Masae et al. (2020b) and Wang et al. (2019), developed routing algorithms that minimize the order picker's travel distance by sequencing picks and defining locations where order pickers and new AGVs meet. In addition, Ono and Ishigami (2019) developed a routing algorithm for collaborative picking in warehouses between operators and AGVs considering different parameters, such as the travel speeds of operators and AGVs. The robots carry items picked by operators and deliver them to a dispatch area. Related to this approach, Yokota (2019) developed a scheduling algorithm in which items are picked and placed on an AGV that collects the items assigned to a certain batch.

In addition to these works, Rey et al. (2019) studied AGV-supported order picking in an experiment where the AGV also weighs the selected items for verification. Finally, Zou et al. (2019) developed a heuristic for AGV-supported order picking by considering a zone-picking approach that aims at minimizing the total time for picking the items of the assigned orders. The investigated system utilizes AGVs to transport items between different zones in which operators perform picking tasks to complete a customer order.

As can be seen, most of the cited studies are first attempts to investigate some types of HOPSs and leave many interactions and scenarios unaddressed, leading to the need for further research.

2.2. Support of retrieving and handling items

The second research stream includes technologies that support the actual retrieval of items; among these systems, cobots are frequently discussed. We found few works that addressed the autonomous picking of items in related applications, and briefly discuss these works in the following.

Kaipa et al. (2014) developed a framework for bin-picking tasks prior to assembly where humans and robots collaborate. In the investigated system, items are retrieved by robots, and humans assist them in solving problems that are detected during this task, such as grasping failures, or humans perform tasks that are too difficult for the robots. Fager et al. (2019) and Fager et al. (2020) investigated cobot-supported picking and kitting tasks. In such systems, the human retrieves the items, and the cobot sorts them. Laboratory experiments indicated that this system setup may lead to a lower cycle time variability. The authors also found that mounting the cobot on an AGV to sort items while the human retrieves items leads to a significant cost reduction when extensive sorting is performed. Boudella et al. (2018) also considered kit preparation and investigated a hybrid human-robot system. The authors studied a kitting system combining both robotic and human picking sections that work in series but that are decoupled from each other. The objective of the authors was to reduce the cycle time by assigning items to the robot and operator. Coelho et al. (2018) provided a simulation tool for a hybrid kit preparation in a manufacturing supermarket. An arriving order is assigned to either a human or a cobot in a shared workspace. The results suggest that humans perform faster but cobots are more flexible, leading to lower variations in the number of kits prepared per minute under uncertainty.

In their simulation study, Kauke et al. (2020) investigated a HOPS in a small warehouse with only four aisles and concluded that spatial interactions between humans and robots while performing their tasks increase with larger numbers of humans and robots, which has a negative impact on the number of orders picked per agent. Relying more on robot picking, Verbeet et al. (2019) investigated a HOPS in which robots perform all order picking tasks but can call for humans in case of picking failures. Based on the resulting human intervention, information in a database used by the robots to learn how to grasp different items and to improve process stability was expanded.

2.3. Summary

Our review shows that studies explicitly addressing the intersection of supported manual tasks and adaptive automation technology in a shared workspace are scarce. Robotic order picking systems such as TORU of Magazino (Magazino GmbH, 2020) were mentioned, for example, in the review by Azadeh et al. (2019); however, no research explicitly dealing with such systems has been identified despite the growing market penetration of these systems (see, e.g., Boston Dynamics (2021)). Most HOPS variants that may lead to benefits for certain warehouse applications have not yet been discussed, which was also highlighted in the review of Winkelhaus et al. (2021). From this, four research gaps emerge. First, the identified systems only provide limited insights into the various applications that may be considered as HOPSs. The operation of autonomous order picking robots together with human operators was less frequently studied than the use of semi-autonomous AGVs and many interaction scenarios have not been studied at all. Second, most of the research on this topic adopts a techno-centric perspective and does not study the operator in depth. Hence, the possible impacts of human factors, such as picking outside the optimal range of the operator, remain unaddressed. Third, the organizational and procedural aspects of the proposed systems are rarely considered, leading to a research gap concerning the circumstances and actual use cases in which the hybrid system has advantages over completely manual or completely automated systems. For example, the application of such systems in night shifts or for picking preparation to make order peaks easier to handle is not discussed, leading to an underestimation of possible system benefits. Fourth, the studies we identified discuss only a selection of the performance indicators that are relevant in a warehousing context, such as the reduction of human errors (Fager et al., 2020), reduction of cycle time (Boudella et al., 2018), and system throughput (Fager et al., 2020; Wang et al., 2019); other important parameters, especially cost efficiency, were not addressed in most cases.

In the following, we address these research gaps and develop a simulation model to investigate a collaborative HOPS for which we assume that human operators and autonomous robots work together in a business-to-consumer (B2C) e-commerce warehouse.

3. Simulation model

3.1. Description of the investigated scenario

The investigated warehouse has to handle a large product assortment with small orders and tight delivery schedules (Boysen et al., 2019). The investigated HOPS combines a traditional manual order picking system with one in which autonomous robots pick the requested items. The functionality of the robots is comparable to that of TORU of Magazino (see Fig. 2), which is a market-ready autonomous robot for order fulfillment in a manual warehouse. Our literature review indicated a research gap with respect to such systems. In the considered HOPS, robots and operators travel through the aisles of the warehouse and pick items from the shelves. The two teams (humans and robots) have the following characteristics:

Human team: The work of human operators in the HOPS is comparable to the traditional manual processes described above. The performance of the operators is not restricted by the externally given performance of the automated system, as would be the case if an AS/RS was used. Therefore, the HOPS can benefit from human flexibility and adaptability and can also manage peak loads through the flexible deployment of operators (which is common in e-commerce warehouses, for example), while humans can benefit from actions the robots perform that lower their workload.

Autonomous robot team: Autonomous picking robots work as co-pickers and can be assigned to tasks that are not performed by humans. The robots are intrinsically safe and thus can perform their tasks together with operators without security fences or similar equipment. The robots receive pick locations, travel to the right location, identify it, pick the items, confirm the pick, transport the items, and deliver the completed batches to the depot, where the items are merged by operators. Although the variety of goods that can be picked by market-ready robots is still limited, a certain level of standardization of goods can be assumed because of pre-packaged or similarly shaped goods such as books or shoe boxes (Magazino GmbH, 2019b). Today, autonomous picking robots are slower in retrieving goods from shelves than humans; however, they are able to work continuously without the need for rest breaks, except for charging. Nevertheless, they require an initial investment and operating costs (Magazino GmbH, 2019a).

Owing to the combination of human operators and decentral-autonomous picking robots, a fail-safe operation of the HOPS is guaranteed. In addition, the HOPS under study also considers a human-centered work design, which matches the definition of Order Picking 4.0 as a sociotechnical system (Winkelhaus et al., 2021).

3.2. Agent-based simulation

We aim to analyze the performance of the HOPS under different operating policies and market characteristics. As real implementations of HOPSs are still scarce and analytical methods usually lose accuracy and efficiency when dealing with highly dynamic and complex systems (Borshchev & Filippov, 2004), simulation is considered to be a more suitable approach for this study. Therefore, an agent-based simulation (ABS) model was developed using Tecnomatix Plant Simulation 15. An ABS usually consists of three components (Borshchev & Filippov, 2004): 1) agents with individual behavior rules, 2) direct or indirect interactions, and 3) environmental models. These unique features makes ABS well-suited for this study. The three components are briefly addressed as follows:

1) Agents and individual behavior rules: The HOPS consists of two teams, human operators and autonomous picking robots, which have different characteristics. This leads to insufficient knowledge about the behavior of the system. By modeling operators and robots as agents, a natural representation of both can be provided, which generates the system behavior from a “bottom-up” perspective.

2) Interactions: With several agents working in the same area, interactions between them are inevitable. For example, one agent may block another in a picking aisle. The occurrence of such interactions is difficult to predict. Hence, for each agent, behavior rules should be defined, based on which they can make individual decisions when different interactions occur. ABS, as a decentralized approach, is a suitable tool for measuring the impact of such interactions on the system’s performance.

3) Environmental models: To create a working environment for the agents, certain process flows need to be represented as a discrete-event simulation (DES) model. In our case, for example, creating orders is actually an external process and thus simulated in a top-down manner that cannot be affected by the behavior rules of each agent. ABS can easily incorporate DES mechanisms and provide a realistic simulation model.

ABS, a fairly novel approach, has recently been introduced in studies of warehouse operations. In an order picking context, ABS has mainly been used to study goods-to-person systems, such as AGV-based (Ribino et al., 2018), multi-shuttle (Güller & Hegmanns, 2014), and cellular transport systems (Güller et al., 2018). Analogously, ABS has also been applied to investigate more traditional person-to-goods systems (e.g. Shqair et al., 2014). Furthermore, efforts have been made to also consider human factors in order picking. Incorporating human route deviations (Elbert et al., 2017), picker blocking (Franzke et al., 2017; Heath et al., 2013), and carrying capacities of pickers (Elbert & Müller, 2017) led to more realistic simulation models. Nevertheless, the difference between ABS and DES is vague (Siebers et al., 2010). ABS, as recommended by Fragapane et al. (2021), is suitable for studying systems with autonomous mobile robots, due to its nature of decentralized

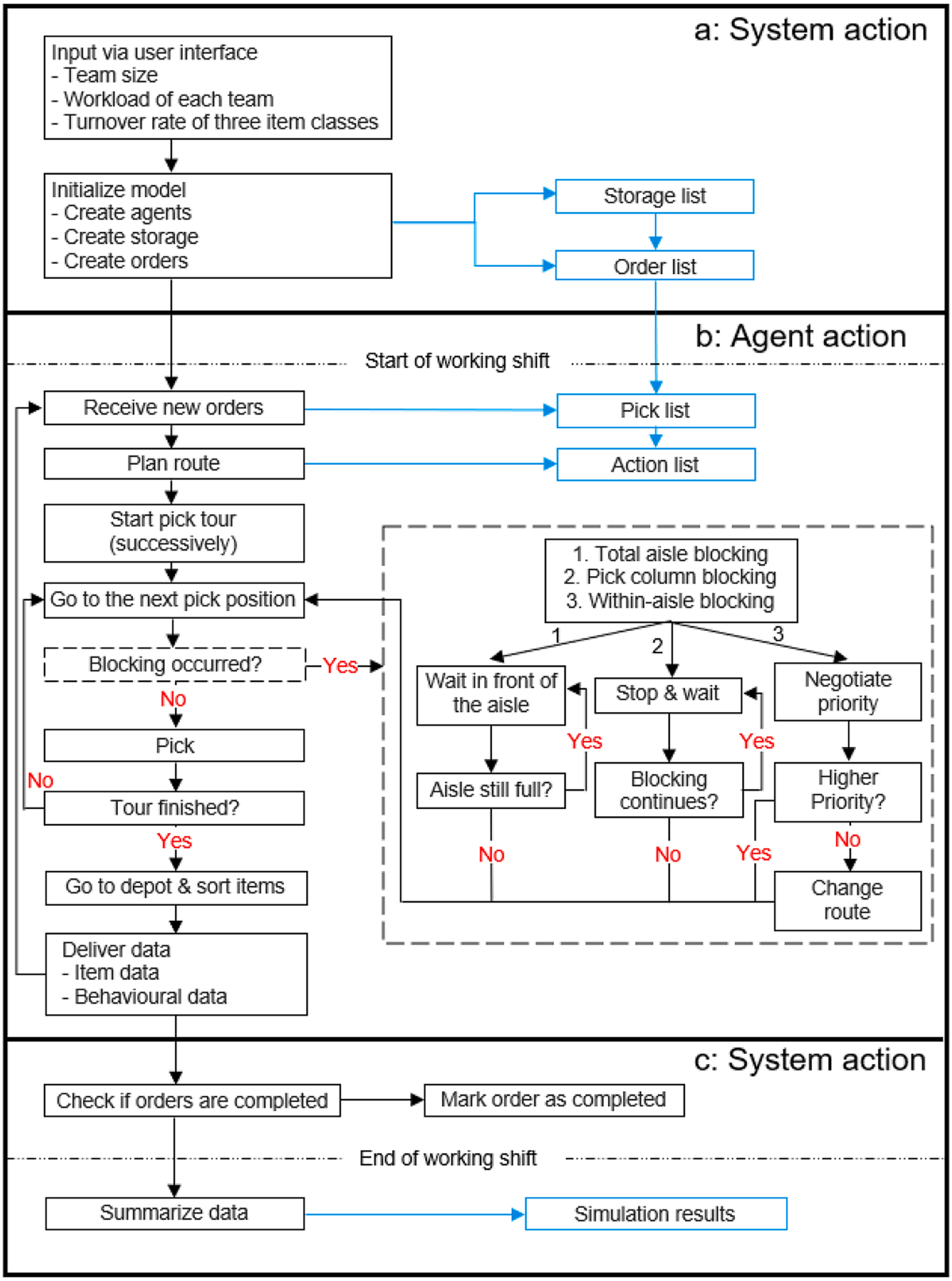

Fig. 3. Conceptualization of the simulation model.

decision making which enables the model to mimic the behaviors of self-regulating and self-governing resource units and their interactions.

3.3. Conceptual model

The simulation model is organized in three functional blocks (a, b, and c), as summarized in Fig. 3. *Block a)* prepares the order picking process on the system's side, which mainly includes setting the parameters for the simulation experiment and creating the warehouse environment. The assumed warehouse applies class-based storage with three item classes (A, B, and C) defined by their sales volume. Each item has the same stock quantity. The simulation model stores the items on a storage list and customer orders on an order list. Two basic rules are applied during the creation of orders. First, orders with out-of-stock items will be ignored in the current working shift because the warehouse is unable to meet all their requirements, which corresponds with

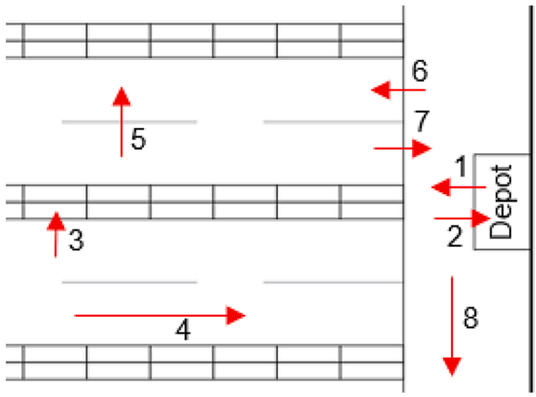

Fig. 4. Eight basic actions in the order picking process.

the real-world situation in which such orders can only be fulfilled after a replenishment process. Second, a turnover rate is assumed so that different sales volumes of the three item classes are guaranteed. The order creation process terminates when the first item class runs out of stock completely. This enables us to create a large number of consistent orders from the stock that is assumed not to be refilled within the simulated period of time (working shift of 8 h) and to fully measure the performance of the HOPS in one working shift without any idle time. For a detailed description of the relevant parameters and assumptions, we refer to Section 3.4.

Based on the two rules stated above, the order generation process is defined as follows:

1) Generate the order size randomly according to the triangular distribution (1,2,6). Order line(s) are generated accordingly;
2) For each order line, define the item class (A, B, or C) randomly according to the predefined turnover rate for the three classes;
3) Define the needed item within the remaining stock of the item class randomly according to a uniform distribution;
4) Mark the item defined in Step 3 as "assigned to orders" and update its stock quantity. When the stock quantity of one item turns to 0, it will be marked as out-of-stock, so that it does not appear on new orders afterwards;
5) Repeat Steps 1 to 4 until any item class runs completely out-of-stock.

Block b) starts with a working shift and is driven by the agents' actions. The system first assigns pick lists to the agents. Accordingly, the agents plan their pick tours by translating their pick lists into a combination of the eight basic actions 1) "Start", 2) "End", 3) "Pick", 4) "Move on aisle", 5) "Switch lane", 6) "Enter aisle", 7) "Exit aisle", and 8) "Move on cross aisle" (see Fig. 4).

The result is an individual action list that serves as a guide for the agent to finish the current pick tour. Each tour starts with the agent leaving the depot. Possible congestion could occur when multiple agents try to start their tours at the same time (Chen et al., 2016). In our case, we avoid such congestion by releasing agents successively from the depot. The time interval between each agent leaving the depot is 3 s, which corresponds to the time a human operator would need to move to the first picking aisle (Franzke et al., 2017). The agents move through the aisles and collect all requested items. Then, they return to the depot, sort the items, and deliver the necessary data to the system. Subsequently, the agents receive new orders and repeat this procedure until the end of the working shift has been reached. In addition to this standard cycle, blocking is a relevant parameter for the system efficiency. In many practical cases, operators have to manage picker-blocking situations in which the process is disturbed by the congestion caused by multiple operators in a storage area (e.g. Chen et al., 2016). Earlier research has focused on two main types of picker blocking: 1) blocking within wide aisles, in which operators are always able to pass each other in the picking aisles (e.g. Parikh & Meller, 2009), and 2) blocking within narrow aisles, in which passing is not possible (e.g. Gue et al., 2006). In our study, passing in picking aisles has certain limitations and consequences, meaning that passing causes lane switching and extra travel distance (see e.g. Heath et al., 2013). Adopting the classification of picker-blocking situations from Klodawski et al. (2018), three types of blocking events are differentiated in our model. Fig. 5 illustrates the different blocking configurations. The events "Pick Column Blocking" and "Total Aisle Blocking" are independent of the actual agent type (human or robot), while the event "Within-Aisle Blocking" depends on the involved agent types (humans and robots) that are described in detail in Table 1.

In addition to blocking, overtaking was also considered. Humans are able to overtake robots within the picking aisles because of their higher travel speed; however, this also requires extra "switch lane" action(s).

The model only considers blocking within the picking aisles, which means that blocking in cross aisles and the associated negotiation process is not considered (see, e.g., Franzke et al., 2017). The blocking situations are detected by humans when another agent stands directly in front of them. The process of determining the priority is immediately

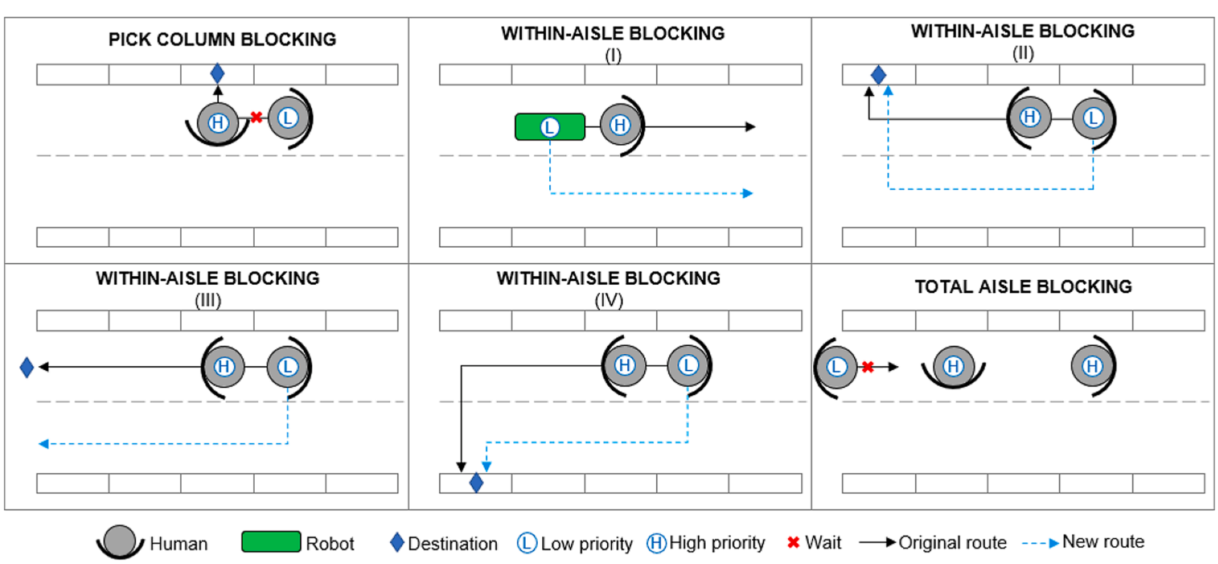

Fig. 5. Classification of picker-blocking events.

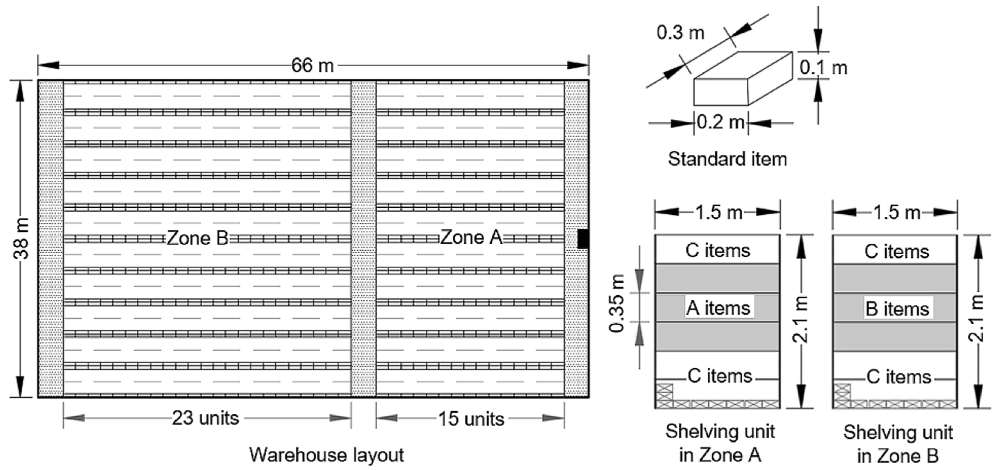

Fig. 6. Warehouse layout, shelving unit, and stored item.

Table 1
Classification of picker blocking and negotiation rules.

Blocking event	Negotiation
Pick Column Blocking	*Definition: Agent's next pick position is occupied.* 1. The performing agent has higher priority; the blocked agent stops and waits until the pick position is free.
Within-aisle blocking	*Definition: Agent is blocked while moving to the next pick position.* 1. The agent executing "Pick" & "Switch lane" has the highest priority and cannot be interrupted. 2. When a human and a robot move against each other in the same lane, humans have priority over robots, and robots switch lanes for humans (I). 3. When two robots move against each other in the same lane, one randomly selected robot changes lanes. 4. When two humans move against each other in the same lane, their priority is defined according to the next action on their original action list: 4.1. The ones with the next action "Pick" (II), "Exit aisle" (III), and "Switch lane" (IV) have high, medium, and low priority, respectively, in accordance with the number of resulting extra "Switch lane" if the agent changes the picking route: II would cause two extra lane switches, III one extra lane switch, and IV no extra lane switch). 4.2. If two humans have the same next action to perform, the one closer to the destination has higher priority. 5. The agent with lower priority adjusts the route on the action list and executes the new picking route.
Total aisle blocking	*Definition: Agent is blocked at the entrance of the aisle.* 1. Each aisle only allows up to two agents in it at the same time. 2. When an aisle is full, the agents coming next queue at the aisle's entrance. 3. The agent next in the queue can enter the aisle as soon as the aisle has free capacity again.

Table 2
Features of the warehouse.

Characteristic	Configuration	Reference
Warehouse shape	*Rectangular, ten equidistant picking aisles, and three cross aisles, as shown in* Fig. 6	Elbert et al., 2017; Franzke et al., 2017
Aisle shape and capacity	*3 m width; two lanes allowing no more than two agents at the same time in each picking aisle, no restriction on cross aisles*	*Assumption for the simulation based on observations in practice*
Storage zones	*Two zones, one with class A items near the depot, the other with class B items in the back of the warehouse*	*Assumption for the simulation based on observations in practice*
Storage assignment	*A&B items: in the respective zones inside the golden zone of picking (on 3rd–5th shelf layers)* *C items: on each shelving unit in both zones outside the golden zone of picking (on 1st, 2nd, & 6th shelf layers)*	*Based on the golden zone concept* (Petersen et al., 2005)
Depot	*One central depot in the middle of the front cross aisle*	Elbert et al., 2017; Franzke et al., 2017
Shelf size	*Width: 1.5 m, depth: 0.4 m, height: 2.1 m*	*Based on observations in practice*
Shelf capacity	*126 items on 6 layers (21 × 6)*	*Result of the assumptions on shelf size and item shapes*
Items per shelf level	*21 identical items*	*Assumption for the simulation*
Item shape	*Cubes 200 × 100 × 300 mm (based on typical shoe boxes)*	*Based on observations in practice*
Storage space per item class	*Class A: 20%, class B: 30%, and class C: 50%*	*See prior assumptions*

activated to solve the blocking problem. The equivalent process for robots starts when they detect another agent via their sensor within 1.5 m. To simulate the braking process, the robots then move at half-speed in this warning zone and stop when coming too close before the resolution of the blocking starts. Otherwise, if the other agent switches lanes during the half-speed period, the robots will directly switch back to the full-speed mode.

Block c) works as an interface between agent actions and simulation results. It is activated at the end of each tour and checks if the orders have been completed. When the working shift ends, the system terminates all activities immediately and summarizes the data for the simulation results. As the main performance measure, the number of items picked in completed orders per shift (throughput) is counted. Furthermore, behavioral data are measured, in particular, the average times for traveling and retrieving and the time to solve blocking situations for each pick tour.

3.4. Simulation parameters and assumptions

The warehouse under study is characterized by several assumptions that rely on relevant literature in this field (see, e.g., Elbert et al., 2017; Franzke et al., 2017) and observations from real-world cases to guarantee the comparability and transferability of results and the relevance for practice. These characteristics are summarized in Table 2.

Customer orders are randomly generated with a size drawn from a triangular distribution (1,2,6), which gives the representative order sizes for B2C e-commerce warehouses (Moons et al., 2019). The turnover rate of the three item classes, representing the probability of one item from classes A/B/C being needed, is either 80%/15%/5% or 50%/30%/20% (see, e.g., Dijkstra & Roodbergen, 2017). The storage capacity for these item classes is predetermined according to the storage areas A,

Table 3
Characteristics of the agents.

	Characteristic	Configuration	Source
Human	Base area (L × W)	*1500 mm × 500 mm*	*Based on one person equipped with a picking cart*
	Batching capacity	*8 orders (max. 60 items)*	Gong and de Koster (2008)
	Velocity	*1 m/s*	Giannikas et al. (2017)
	Time for retrieving one item	*12 s (for A & B items)*	Le-Duc and de Koster (2007)
		16 s or 20 s (for C items)	*Based on the golden zone concept* (Petersen et al., 2005; Battini et al., 2016)
	Time for sorting	*12 s/order*	*Estimated based on* Marchet et al. (2011)
Robot	Base area (L × W)	*1500 mm × 685 mm*	*Based on TORU data sheet* (Magazino GmbH, 2019b)
	Batching capacity	max. *16 items*	
	Speed	*0.8 m/s*	*Based on observations in practice*
	Time for retrieving one item	*20 s/item*	
	Time for sorting	*20 s/item*	
	Range of sensor	*1.5 m*	

B, and C. All orders have the same priority and will be processed in accordance with the "first come, first served" principle.

The warehouse operates one eight-hour working shift every day. All customer orders are assumed to be known at the beginning of each working shift, such that no idle time is required to update orders. The investigated main scenario is based on the concept of a HOPS. Specifically, a human and a robot team are formed. The order assignment follows each team's pre-assigned workload according to the item classes and respective turnover rates. Thus, each item in stock is pre-assigned to a team based on its item class (A, B, or C). If the item appears on an order, a member of the team responsible for that item picks it. As a result, some orders are split into two parts, with one part being processed by a human and the other part by a robot that collaborates for order fulfillment.

The agents have the characteristics outlined in Table 3. We assume that the retrieval time of humans is variable. According to the golden zone concept, items stored between the height of the human waist and shoulders are easier for them to retrieve (in our model, we assign A and B items to this zone). For C items that are stored outside the golden zone, the retrieval time increases accordingly (+4 s to 16 s or +8 s to 20 s per retrieval).

We made the following assumptions based on market information to assess the investment and operating costs of the system. The monthly costs for one human operator are 3200 EUR. For the robots, the total costs are the sum of the depreciation costs (based on the investment costs of 55,000 EUR for each robot with a service life of six years), service costs (0.06 EUR for each selected item) (Magazino GmbH, 2019a), and additional operating costs including maintenance and energy costs (estimated 1000 EUR for each robot yearly).

Table 4 shows that our simulation studies 50 different parameter combinations (see column 2), the results of which are presented in Sections 4 and 5. The simulation study consists of the following experiments: First, as a benchmark, *basic scenarios* in which only human operators or only robots work in the warehouse are considered and throughput and costs are investigated for these systems (experiment 1 in Table 4). The impact of different routing policies (experiment 2 in Table 4), turnover rates (experiment 3 in Table 4) and of the golden zone concept (experiment 4 in Table 4) on warehouse performance are investigated for this basic constellation as well. Routing policies influence the operators' traveling time and are therefore regarded as one of the most important decision problems in order picking (Masae et al., 2020a). Second, different collaboration scenarios are investigated based on the HOPS concept, in which the robots and humans share customer orders based on a pre-assignment of item classes to the two teams (experiments 5 and 6 in Table 4). Again, the impact of different routing policies is investigated (experiment 7 in Table 4). Finally, in Section 5, we study the impact of some limiting assumptions we made in the previous experiments to further discuss the potential economic benefits of the investigated HOPS (experiments 8 and 9 in Table 4).

Note that all the experiments are described in a short form with the following logic: turnover rate of the three item classes (80%/15%/5% or 50%/30%/20%) – assignment rules (independent for human agents and robot agents) – routing policy for humans (H) and robots (R) (S: S-shape, LG: Largest gap, Re: Return) – golden zone retrieval (GZ 16 s or 20 s, only if relevant). The resulting description is then, for example, 80/15/5-A/BC-H(LG)R(Re)-(GZ16), which means that in this case we study an 80/15/5 turnover rate, operators are responsible for A items, and robots are responsible for B and C items. The routing policies implemented here are

Table 4
Parameter configurations of the simulation experiments.

Experiment	No. of experiments	Assignment rules (Human/Robot)	Turnover rate for three item classes	Collaboration	Golden zone	Routing (H(X)R (X))	Zoning	Batching	Storage assignment
1 – Basic runs	2	ABC/- ; -/ABC	80/15/5	None	Constant	H(S)/R(S)	Constant	Constant	Constant
2 – Routing impact	4	ABC/- ; -/ABC	80/15/5	None	Constant	H(Re)/H(LG) /R(Re)/R(LG)	Constant	Constant	Constant
3 – Turnover rate impact	6	ABC/- ; -/ABC	50/30/20	None	Constant	H(S)/H(Re)/H (LG) /R(S)/R (Re)/R(LG)	Constant	Constant	Constant
4 – Golden zone impact	12	ABC/-	80/15/5; 50/30/20	None	16 s/20 s for C items	H(S)/H(Re)/H (LG)	Constant	Constant	Constant
5 – Type of collaboration	4	AB/C ; A/BC	80/15/5; 50/30/20	Collaborative	Constant	H(S)R(S)	Constant	Constant	Constant
6 – Type of collaboration (Appendix A1)	4	BC/A ; C/AB ; AC/B ; B/AC ;	80/15/5	Collaborative	Constant	H(S)R(S)	Constant	Constant	Constant
7 – Routing impact in collaboration	2	A/BC	50/30/20	Collaborative	Constant	H(LG)R(LG) H (S)R(LG)	Constant	Constant	Constant
8 – Impact of cost assumptions (Discussion, Appendix A2 & A3)	8	A/BC	80/15/5; 50/30/20	Collaborative	Constant	H(S)R(S)	Constant	Constant	Constant
9 – Impact of storage assumptions (Discussion & Appendix A4)	8	AI/BC ; I/ABC	80/15/5	Collaborative	Constant	H(S)R(S)	Constant	Constant	Mixed storage

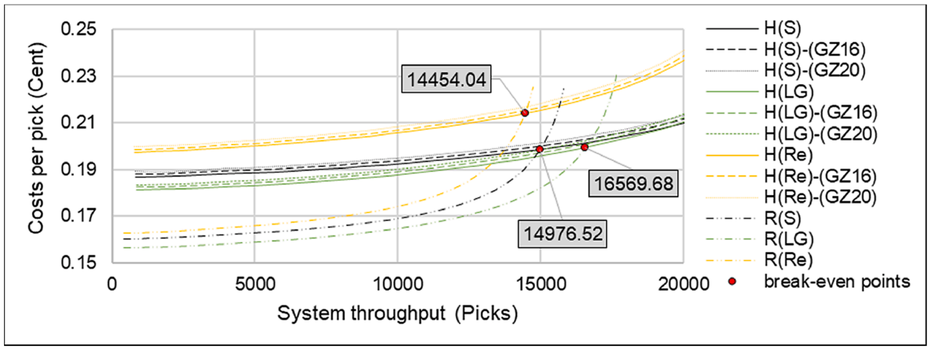

Fig. 7. Cost curves of human and robot OPS for different routing policies (turnover rate: 80/15/5).

the largest gap policy for humans and the return policy for robots. GZ indicates golden zone retrieval, and 16 represents the time in seconds for humans to search the pick location, retrieve an item, and confirm the pick for items outside the golden zone.

3.5. Validation

Simulation models should be validated throughout the entire life-cycle of a simulation study, hence, from the conceptual model to the computer model and the output data. However, there is no single framework or predefined order of activities that is proven to be suitable for every simulation study (Franzke et al., 2017). For this study, because HOPSs are still rarely used in practice, the conceptual model of the simulation was built based on related research and observations in practice and implemented gradually in the simulation software. First, a warehouse with only one picking aisle was built to test if the agents move, stop, and pick as planned. Then, all the other components of the warehouse were successively added to ensure that actions like “Enter/Exit aisle” and “Move on cross aisle” were correctly simulated. By using the debugging and breakpoint functions provided by the software, programming errors could be avoided in the codes. Several check functions were added to ensure that the picking process ran as planned. For example, the accuracy of task execution was checked by the system each time the agents removed an item from the shelves or returned to the depot to ensure that the selected items corresponded to customer orders. The implementation of routing policies and picker blocking situations could be validated by observing the graphical animation of the warehouse and agents during the simulation runs. Moreover, the target values of the agents’ predictable behavior (e.g., the travel time of each tour) were calculated and compared with the measured values to ensure that the results of the simulation are credible. Finally, we validated the output data using the confidence interval. For each system setting, a number of observations (100 in most cases) were made, such that the 95% confidence intervals for the output data were smaller than 1% of their mean values.

4. Results

This section presents the results of the simulation experiments. The cost analysis was based on the costs per pick (on the y-axis) over the system throughput (on the x-axis, indicating the total number of items picked in completed orders per working shift). The experiments for the different scenarios started from the minimum required number of agents in the system, that is, one human or one robot for the benchmark cases (human or robot OPS) and one human and one robot for the HOPS. Each experiment generated one point (cost-throughput combination) in the coordinate system. By involving one additional agent (human or robot) in the system, additional points were recorded as simulation results. This was repeated until either team finishes all the orders within a daily shift (idle time occurred) or the HOPS no longer achieved cost advantages. In the first case, the cost advantages of the HOPS were only partially analyzed as the stock quantity counted as a restriction and the simulation stopped within the eight-hour working shift when the stock was empty. Creating more orders was not possible because replenishment was necessary. Thus, these scenarios were not included in the results. Furthermore, as employing decimal units for the number of agents was not realistic, we transformed the cost-throughput combinations resulting from successively increasing the numbers of agents within each scenario into cost curves to estimate the costs per pick within two points. This estimation can be realized in practice, for example, as a temporary working staff in warehouses.

4.1. Benchmark scenarios: Human and robot OPS

In the first step, the case in which only one type of agent (human or robot) works in the warehouse is analyzed (Figs. 7 and 8). These scenarios serve as benchmarks for evaluating the HOPS’ performance. The figures show increasing costs per pick for all tested scenarios, as higher daily throughput requires more agents in the system, causing more blocking situations (particularly total aisle blocking), which lowers the overall picking speed and effectiveness of assigning additional agents.

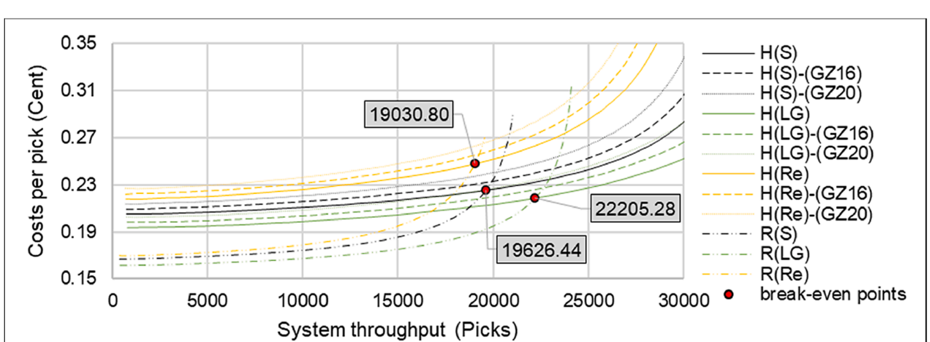

Fig. 8. Cost curves of human and robot OPS for different routing policies (turnover rate: 50/30/20).

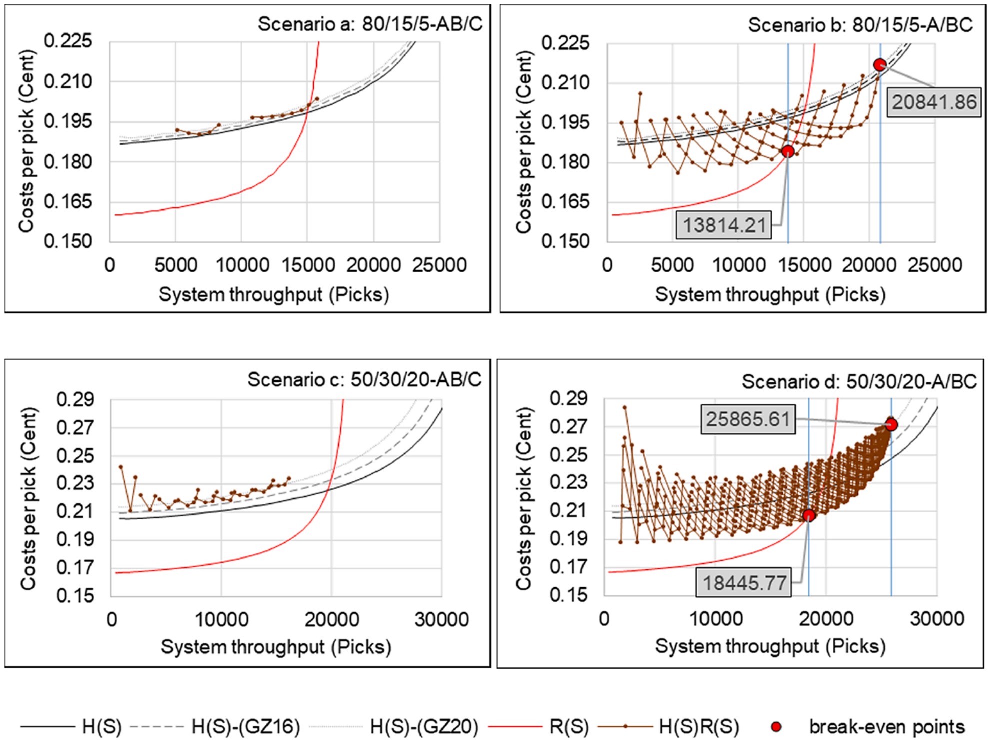

Fig. 9. Cost analysis of HOPS.

As can be seen, robots have cost advantages at lower throughputs per working shift; however, they are outperformed by humans when higher throughputs are required. Because robots work slower than humans, they suffer more from blocking for two reasons: 1) Robots remain longer in the picking aisles and in front of pick locations, which may result in longer blocking times. 2) More robots than humans are needed for the same throughput because robots pick slower, leading to a higher blocking frequency. Thus, break-even points can be observed in Figs. 7 and 8 that indicate the number of picks at which the system favorability changes.

As expected, we found that the applied routing policy has a strong impact on the system performance. For both human OPS and robot OPS, the cost curves show the order LG < S < Re, meaning that the return policy causes the highest costs per pick. Note that within each item class, random storage is applied, and the middle cross aisle separates zone A and B. This indicates that in each zone, most of the pick locations (for A and B items) are randomly distributed. Previous studies have shown that LG is favored for such warehouse settings when the number of picks per aisle is approximately less than 3.8 (Hall, 1993) and Re generally leads to longer travel distance (Dijkstra and Roodbergen, 2017), which was also proven by further results of our validation tests.

In contrast to the turnover rate of 80/15/5, the pick positions are distributed more homogenously when analyzing a 50/30/20 turnover rate. This leads to a longer average travel time per pick and higher costs for the same total number of picks. In contrast, the change in the turnover rate reduces congestion in the warehouse, which flattens the cost curves and enlarges the range of the robots' cost advantages. We can observe this, for example, in the case of total aisle blocking. The agents are spread out more homogenously in the two zones and in different aisles, reducing the probability of being blocked in front of a fully occupied aisle. In the case of 30 human operators with an S-shape policy for example, the average travel time increases from 18.35 s/pick (80/15/5) to 21.67 s/pick (50/30/20), while the total aisle blocking decreases from 4.80 s/pick (80/15/5) to 3.66 s/pick (50/30/20). For 30 robots with an S-shape policy, the travel time is then 29.73 s/pick (80/15/5) and 34.22 s/pick (50/30/20), and the total aisle blocking 6.65 s/pick (80/15/5) and 4.90 s/pick (50/30/20).

Considering different retrieval times for items stored outside the golden zone in the human OPS (see assumptions in Table 3), the average time needed for picking increases accordingly. Because there are more C-items (stored outside the golden zone) to be picked in case of a 50/30/20 turnover rate compared to a 80/15/5 turnover rate, the effect of the golden zone assumptions can be observed more clearly. In particular, the golden zone assumptions counteracted the reduced blocking times for different turnover rates in this scenario.

4.2. *Collaborative HOPS with S-shape routing policy*

We now investigate the case in which humans and robots collaborate in a HOPS. In the first step, it is assumed that all agents use only S-shape routing, which is the most frequently applied policy in practice (Masae et al., 2020a). If we successively add agents to one team (either humans or robots) for a predefined order assignment rule, we obtain a U-shaped system cost curve, meaning that the costs per pick decline first and then increase from a certain turning point. In this section, we explain this U-shaped pattern, based on which a cost analysis is performed.

4.2.1. *U-shaped cost curves*

The shape of the cost curves depends on the extent to which the workload is balanced between collaborating teams. Balancing the workload between teams according to team size has a strong impact on the costs per pick for the overall system. For example, when one team processes tasks faster than the other team, which results from a larger team size, a processing backlog occurs on the order list because some orders are not completed. This will cause higher picking costs in the following manner: initially, the faster team continues to process its share of orders, and the slower team is not able to keep up with this speed. In practice, partially completed orders can often not be delivered to customers and need to wait for completion. Additionally, because agents are not allowed to stay idle until the other team has caught up, the faster team always continues to process new orders, which further decreases the speed of the slower team due to additional blocking. In sum, an

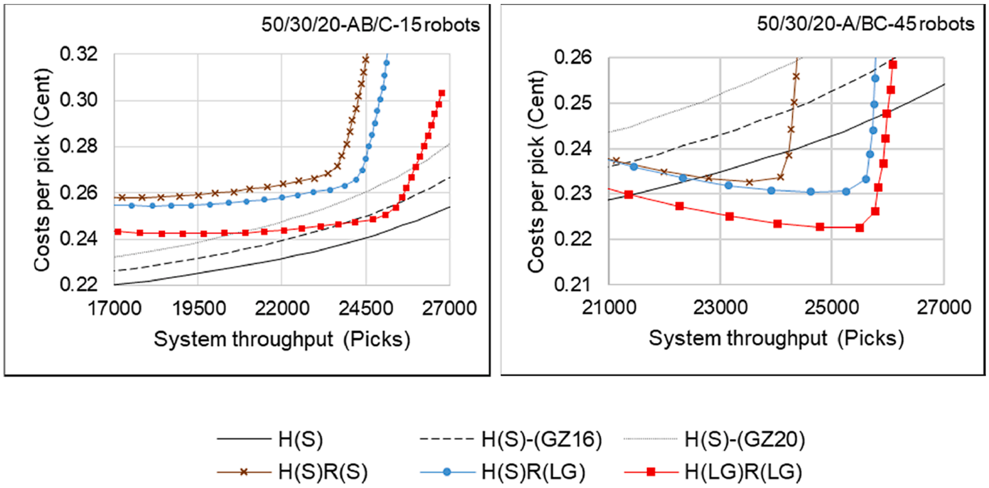

Fig. 10. Exemplary cost curves of HOPS for different routing policy combinations for a varying number of humans and a given number of robots.

efficient constellation of robots and humans allocates agents in a balanced manner according to the tasks assigned to the respective team, so no resources are wasted and orders are processed in an equal pace. We call this new parameter of system design the *team configuration*. To illustrate the impact of team configuration on the system performance, we define the effective throughput as the number of items picked in completed orders per shift. Thus, the items that are picked but not delivered in one working shift due to the unbalanced workload between the teams are not included in the HOPS's throughput and would directly cause higher costs per pick.

4.2.2. Cost analysis

Based on the previous descriptions, we investigate the collaborative HOPS scenarios "AB/C" and "A/BC," in which items outside the golden zone (C items) and, respectively, the items distant from the depot (B items) are assigned to the robot team, as these two item classes cause higher human physical workload. To clearly show the balance of workload between two teams in HOPS (see 4.2.1), points with the same robot team size are combined into curves. The aim is to analyze the cost advantages of the HOPS in these scenarios for two different turnover rates (see Fig. 9). The parts of the cost curves that lead to higher costs per pick than in the human OPS are not shown. As can be seen in Fig. 9, by assigning only C items to robots (scenarios a and c: "AB/C"), the HOPS cost curves lie partially below the human OPS's cost curves with golden zone picking consideration. However, cost advantages are not observed: HOPS is outperformed either by humans or by robot OPS. In contrast, if class B items are also assigned to the robot team (scenarios b and d: "A/BC"), cost reductions comparing to the benchmark scenarios can be observed in HOPS (see red break-even points).

To validate this result, we tested the HOPS with other work assignment options, as shown in the Appendix (Fig. A1), including scenarios in which other duties are assigned to robots (such as picking A items). As can be seen, cost advantages mainly result from assigning B items to robots (scenarios AC/B or A/BC). In other cases, the HOPSs are outperformed either by human OPS (ABC/-) or by robot OPS (-/ABC). For a discussion of these results and the possible benefits of the HOPS, we refer to Section 5.

4.3. Collaborative HOPS with different routing policies

As stated in Section 4.1, the applied routing policies affect the system throughput and costs per pick. In this section, in the light of the results from benchmark scenarios in Section 4.1, we investigate the effect of two new routing policy combinations on the HOPS performance: H(S)R(LG) and H(LG)R(LG). The S-shape policy (H(S)R(S)) serves as a benchmark. Fig. 10 presents two example cases, in which 15 robots (assignment rule: AB/C), 45 robots (assignment rule: A/BC), and a varying number of humans collaborate. As can be seen, LG again,

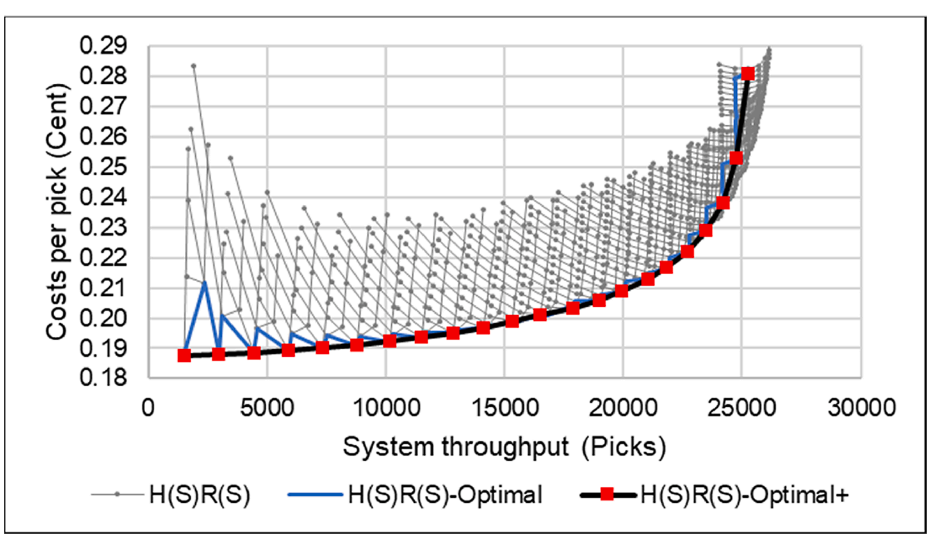

Fig. 11. Logic of creating a representative cost curve for each routing policy combination.

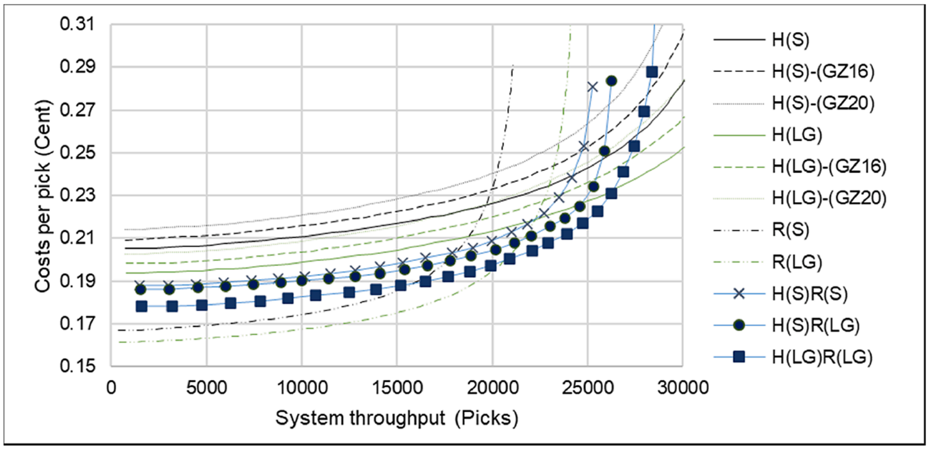

Fig. 12. Comparison of representative cost curves for different routing policy combinations (scenario: 50/30/20-A/BC).

appears to be a better policy for both teams. It generally leads to lower costs per pick than S, similar to the results in benchmark cases. This finding also holds in other cases (other robot team sizes) investigated in this simulation experiment.

To quantify the cost advantages of the HOPS for different team configurations, we plotted curves representing each routing policy combination assuming that it is not realistic to employ decimal units for the number of agents (see Fig. 11). The results (cost-throughput combinations) were obtained by varying the size of either collaborating team by one agent each time, as one agent is the smallest unit when measuring different system performances. Among the two types of agents in the HOPS (humans and robots), robots have a lower speed of processing orders. Adding one robot to the system results in a comparatively smaller increase in system throughput. This entails that when we investigate the simulation results for a fixed robot team size, more system throughputs and the corresponding costs per pick can be sampled to analyze the system performance of the current routing policy combination. Therefore, we start by defining the cost-optimized number of humans for each robot team size. The resulting team configurations point to the number of humans that minimize the system's costs per pick for the current robot team size. These are denoted as "optimal points" in Fig. 11. Connecting all optimal points leads to a saw-toothed curve (blue curve). As mentioned above, robots work slower than humans. Hence, for different sizes of the robot team, the same number of humans could be cost optimal. However, the effectiveness of adding a further human depends on the current robot team's capacity to support the additional picks performed by the additional human to complete orders, which leads to a better or worse workload balance. We then fix the human team size among the optimal points and define the cost-optimized robot team. Those achieving the lowest costs per pick for each human team size are selected again ("optimal + points"). Combining these points, we see a relatively smooth curve representing the costs of a particular routing policy combination.

To quantify the cost advantages of a HOPS, the "50/30/20-A/BC" scenario is chosen for the subsequent analysis (see Fig. 12), as it is the only scenario that is not restricted by the inventory quantity we defined for the analysis. The cost curves derived using the above-mentioned method correspond to the previous findings: with the order of H(LG)R(LG) < H(S)R(LG) < H(S)R(S), LG is preferred in the current HOPS for both teams. We conclude that the HOPS can provide further cost advantages. With varied routing policy combinations, it can be observed that the HOPS always outperforms the two benchmark OPSs for a certain range of system throughput.

5. Discussion

Our results showed that the investigated collaborative HOPSs are generally capable of reducing the costs per pick compared to pure manual or pure robot order picking systems. However, we also found that HOPSs outperformed the benchmark systems only for a relatively small number of parameter configurations. In this section, we discuss some main assumptions made throughout the analyses to gain deeper insights into the possible benefits of HOPSs in real-world applications and to identify future research opportunities for HOPSs.

5.1. Cost advantages

We investigated an ideal situation in which the robots are able to pick all items without additional costs and without making mistakes. In a realistic situation, this would for example imply that goods have to be packaged (e.g. in standardized boxes) prior to storage to allow robot picking. In e-commerce, in which small batch sizes are usually retrieved (Yang et al., 2020), this might be a plausible solution. Nevertheless, this additional cost, together with the increased capital tied up in inventory, needs to be considered. Additionally, in real warehouse applications, errors may occur in which robots need the support of a human operator. The number of interventions would likely increase with the system throughput the robot team is responsible for, leading to additional costs for the robot team that are not yet included in the model.

To simulate these additional costs, we assumed higher costs per pick for the robot team as shown in Figs. A2 and A3 in the Appendix. Because operators can pick all the items (not only standardized ones), no additional costs for the human team were considered. For the case of a turnover rate 80/15/5 A/BC, the number of items and picks the robot team was responsible for was smaller than those in the 50/30/20 case, leading to fewer additional costs for pre-packaging and interventions.

From Figs. A2 and A3, we can conclude the following: The cost curves of the robot system shift upward, while the costs for the manual system remain unchanged. This increases the range of system throughputs for which the collaborative HOPS outperforms the human and robot OPS. This is because the HOPS is less sensitive to increased robot costs than is the pure robot system. Increasing the number of items picked by the robots also increases the additional costs considered in this scenario. This leads to the case in which the collaborative HOPS is beneficial for nearly all system throughputs. As can be seen in Fig. A3, the effect is different in the case of a throughput of 50/30/20. Owing to break-even points that differ in this scenario, the range in which the HOPS is preferable is smaller.

5.2. Mixed storage warehouses

As mentioned above, robots may not be able to grasp all the items stored in the warehouse. Instead of pre-packaging these items (e.g., putting them into cardboard boxes the robots can pick), they could alternatively be assigned to operators. We simulated this situation in which a set of items can only be picked by humans. These robot-incompatible items (denoted as I) occur randomly in the three item classes and are stored together with other standard packed items. We varied the share of these incompatible items ranges between 10% and 70% of the storage quantity and – besides the benchmark scenarios – assigned 1) only incompatible items (I/ABC) and 2) incompatible and A items (AI/BC) to the operators while robots are responsible for all other items (see Fig. A4 in the Appendix). The robot-benchmark scenario is presented in the appendix, but it is not applicable in this scenario as robots are not able to finish all orders owing to incompatible items.

The following conclusions can be drawn from Fig. A4: In AI/BC, humans take over parts of the robots' responsibilities in A/BC, as some items in classes B and C are incompatible with robots. With an increased percentage of incompatible items, the cost curve of the HOPS converges to the human OPS (ABC/-) cost curve. In contrast, I/ABC is comparable to -/ABC, if the share of incompatible items is low. As can be observed in scenario a), the lower bound of the cost curves is similar to the cost curves of the robot system (-/ABC), meaning that cost advantages of the HOPS over the manual system (ABC/-) can only be observed at lower system throughputs. By increasing the number of incompatible items, the workload of humans increases, causing an increase in deviations of the cost curve compared to that of the basic scenario -/ABC.

In fact, in the scenario I/ABC, warehouse zones are not pre-assigned to one team, leading to more frequent blocking between humans and robots. Hence, the resulting system cannot benefit from the robots' lower costs per pick at a lower throughput, and it also leads to longer blocking times in the human team caused by robots. For this reason, I/ABC is, in the tested scenarios, always outperformed by either the manual system or the HOPS with the assignment rule AI/BC. This suggests that, in mixed storage warehouses, our previous statements still hold. A HOPS with assignment rule AI/BC, modified from A/BC, still leads to cost advantages, especially compared with I/ABC, in which humans only perform picks of which robots are incapable.

5.3. Further assumptions

Warehouse assumptions: Further assumptions made throughout the analysis relate to the warehouse itself. One assumption limits the vertical pick range to 2.1 m and six shelf levels. However, robots are generally capable of picking items from shelf levels that operators cannot reach. In warehouses without a second floor, it is common that there is free space between the top of a shelf and the ceiling that is not utilized, because humans can only grasp up to a certain height. HOPSs can utilize this space without the need to reconstruct warehouse buildings. Assuming that a robot can pick from shelf levels up to 2.8 m, two additional levels could be utilized, leading to an additional 33% of storage space compared to a six-level shelf. This can provide an advantage for a HOPS compared to a manual system.

Working-hours assumptions: We assumed in our analyses that robots only work during shifts in which humans work as well. In practice, however, night shifts and extended working hours are common, and in our case, such extra shifts could be assigned to the robot team with minimal support from operators. With this configuration, for example, urgent orders can be handled and directly prepared for shipping during the night shift. Additionally, a continuous output around the clock could be handled by the robot system without employing humans for the entire time (and extra pay for night work). If this is complemented by high peak loads, fully automated systems would be oversized for most of the time and would be inefficient. In such scenarios, a HOPS can employ humans for peak hours and robots for a basic continuous output.

Ergonomics assumptions: HOPSs can also contribute to human well-being and improve ergonomics. Several studies have investigated how economic profitability and improvements in operator well-being can be jointly obtained in an order picking context (see, for an overview, Sgarbossa et al., 2020). In HOPSs, interactions with robots have the potential to improve ergonomics, motivation, and job satisfaction, because HOPSs enlarge and enrich the work tasks of humans instead of trivializing them (Neumann et al., 2021; Winkelhaus et al., 2021). In addition, humans can become supervisors and trouble shooters for the robot team. Concerning physical ergonomics, humans could benefit from shorter travel distances, because long distances are outsourced to robots, and from better grasping conditions because of the consistent use of the golden zone concept for operators. Moreover, robots can also be used for tasks in user-unfriendly environments or periods, for example, for preparing orders during night shifts or in particular climate or spatial conditions. These impacts have the potential to improve physical, mental, and psychosocial ergonomics at work and thus also impact overall system performance, absenteeism and work quality positively, which has not yet been considered.

Overall, HOPSs can lead to further benefits for companies beyond a reduction in costs and could be particularly useful for successfully managing the transition to fully autonomous order picking systems. For example, if enterprises are not willing or capable of investing in a fully autonomous system, it is possible to increase the number of picking robots over a longer period of time and apply a HOPS for the transition period.

5.4. Limitations and future research

This study has limitations that could be addressed in future research. First, the warehouse environment was assumed to be constant over all the experiments except for the sensitivity analysis. However, the order size, warehouse layout, and other aspects can impact the simulation and lead to different results. Second, limiting assumptions regarding the demand distribution within one item class approximates the reality and several assumptions for zoning, batching, storage assignment, and routing were necessary in our study. Some of these parameters have not been investigated and could be extended in future studies. Third, the interaction rules were chosen to be plausible, generalizable, and applicable in the simulation. However, some rules might be questioned in future studies, such as the applied rule for full aisle blocking. Finally, the robot's capabilities are assumed to be fixed. Varying the robot's characteristics, such as the batch size the robot is able to transport before returning to the depot, might lead to different results and varied HOPS benefits.

Despite these limitations, our results highlight the potential of HOPSs. Owing to the real-world restrictions that autonomous robots still face, future research is necessary to investigate these systems in detail. We identified three clusters of future research needs on HOPSs according to the dimensions of the technology-organization-environment (TOE) framework.

Technology: We studied the use of a specific technology, that is, an autonomous picking robot, whose characteristics were derived from relevant literature and market information. However, there are various HOPSs that can be applied to diverse technologies. For example, AGVs are frequently investigated in terms of RMFS, but HOPSs are not yet in the focus of research. Future research could thus focus on different robot characteristics, for example, in terms of speed, pick quality, or in light of the assumptions discussed in Sections 5.1 to 5.3. In addition, real-world systems should be investigated empirically to validate these results.

Organization: We studied different routing policies and assignment strategies for both teams. However, these investigations only built the first set of impact factors. Relevant questions for future work could be, for example, how the system behavior changes if different zones, batching, or storage assignment strategies are used. In addition, we only discussed, but did not explicitly study, possible ergonomic benefits; whether HOPSs have the potential to improve ergonomics and increase job satisfaction in intralogistics 4.0 is an interesting starting point for future research, see for example (Winkelhaus et al., 2022). However, also negative side effects of human-robot interaction need to be analyzed in addition to that in future research (Neumann et al., 2021).

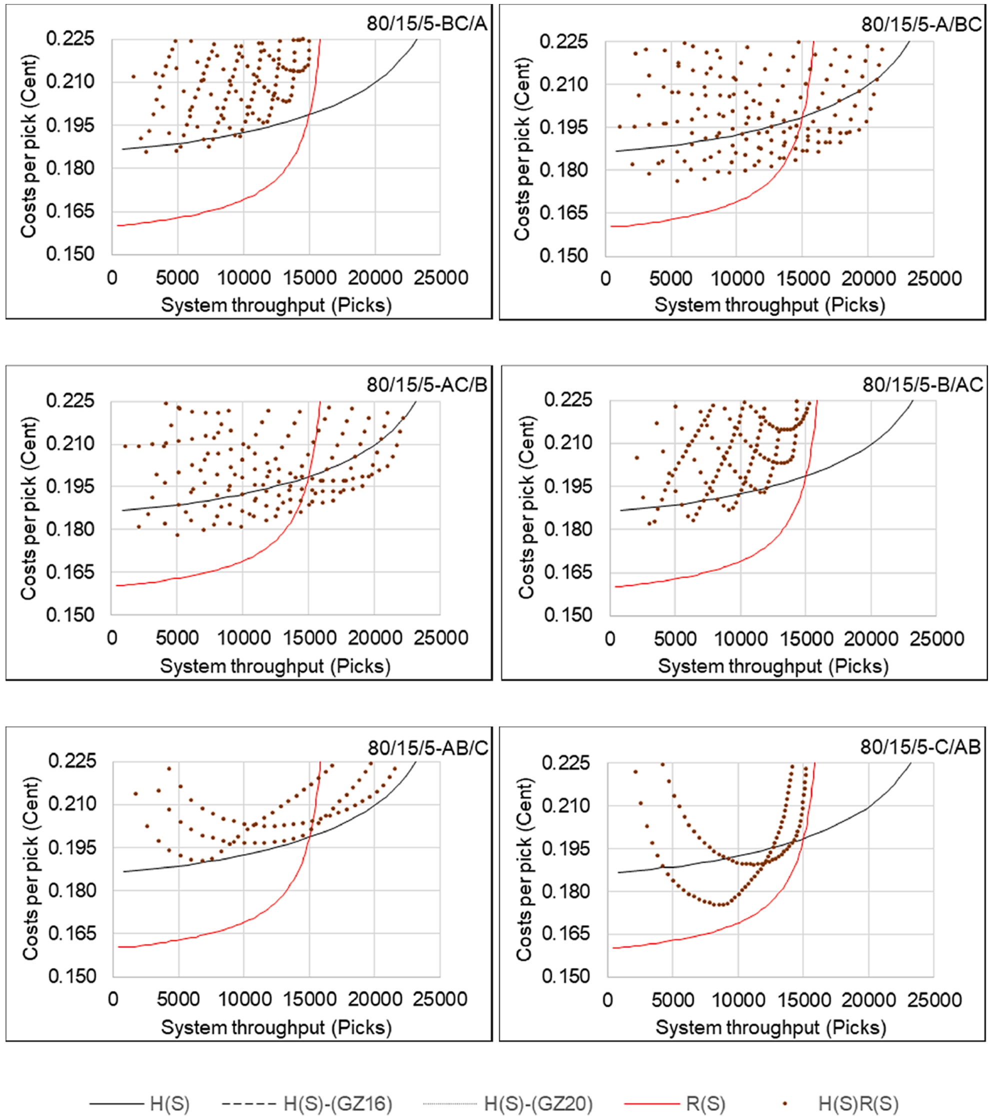

Fig. A1. Cost analysis of HOPS with other work assignment options.

Additionally, refilling the warehouse has not yet been considered, which opens interesting possibilities for collaborative performance. Finally, HOPSs also have the potential to impact strategic decisions, for example, for change management within a continuous development towards fully autonomous warehouses. Regarding the organizational methodology, HOPS, especially its robot team, can be formed as a multi-agent system, so that numerous further approaches can be applied, e.g. different agent architectures, negotiation and bargaining among agents, and distributed optimization (Weiss, 2013). ABS, as a decentralized approach, could further on support these studies.

Environment: The assumptions made for the warehouse were constant for all experiments in terms of size and shape within this study. However, the size and shape of a warehouse depend on the tasks to be fulfilled and, thus, differ for large e-commerce retailers, small city hubs, or production facility warehouses. The results achieved so far could be extended for generalization purposes. Future research could for example investigate how the size and shape of the warehouse impacts the performance of a HOPS. Future research could also investigate how the customer structure impacts HOPS performance. For example, we assumed that all orders are known at the beginning of the shift and work by following the first-come-first-served policy. Hence, it would be interesting to investigate how varying workloads, including peak loads and idle phases, as well as order sizes impact the achieved results.

6. Conclusion

In this work, a simulation model of a hybrid order picking system (HOPS) was developed. We assumed that autonomous picking robots work together with human operators in a shared warehouse workspace. To investigate whether a HOPS can lower the cost of order picking, the simulation model considered different HOPS scenarios with different demand frequencies, routing policies, and collaboration strategies. Although only a representative entity of a HOPS could be investigated, the results showed that HOPSs offer benefits in order picking in diverse ways depending on the exact system characteristics. In our study, HOPSs performed well in cases in which B and C items were assigned to the robot team. The main aspects responsible for this result are the effects of zoning and blocking. Additionally, the team configuration has a major impact on the quality of collaboration, meaning that both teams, humans and robots, must be able to process their part of the collaborative order picking task to not generate a backlog for the other team and minimize the overall costs.

Our sensitivity analyses showed that two model assumptions are especially critical for the relative performance of HOPSs. For example, we have shown that a small increase in costs for the robot team results in the HOPS outperforming the pure robotic and manual system in terms of cost for almost all system throughputs. Hence, this study makes an

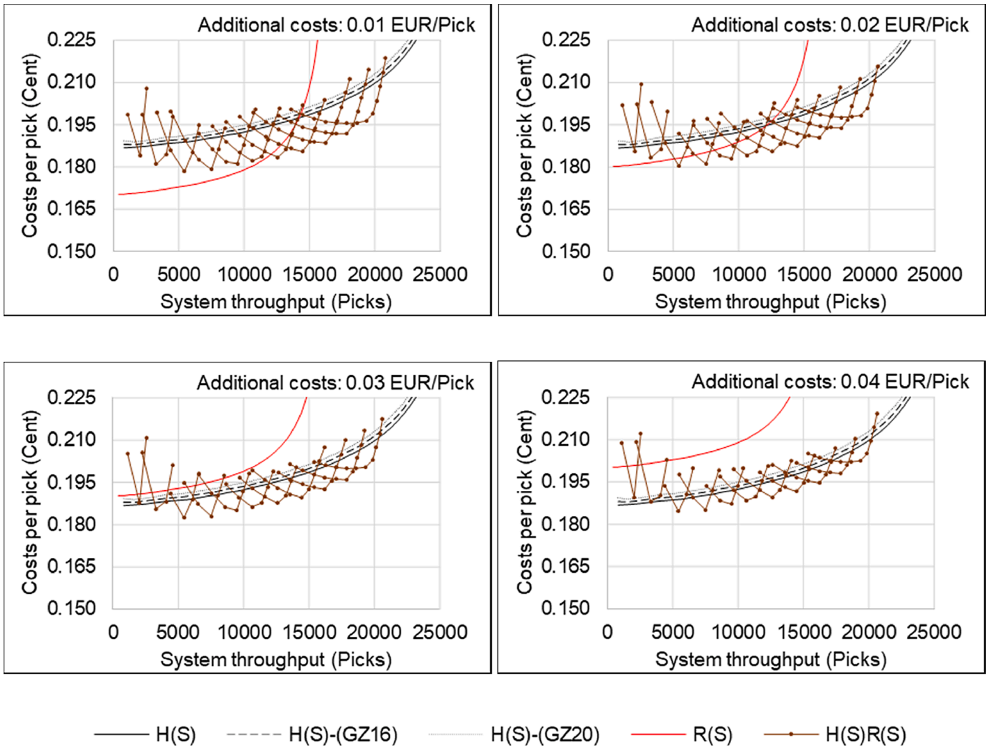

Fig. A2. Cost analysis of HOPS with additional costs per pick for the robot team (scenario: 80/15/5-A/BC).

important managerial contribution: for practitioners, this study shows, using 50 parameter configurations, how a HOPS generally performs in contrast to completely manual and automated systems by applying autonomous picking robots, and which interactions seem to be important. With the sensitivity analysis, additional information about real-world applications is obtained and can be used for the initial evaluation of a HOPS within a company. While considering a HOPS for future applications, simulations can be performed for the specific case of a company and based on the results achieved in this study.

With the results obtained, the first study that allows the evaluation of a possible benefit of HOPSs to certain warehouse types is available to practitioners and researchers. With the diversity of parameter

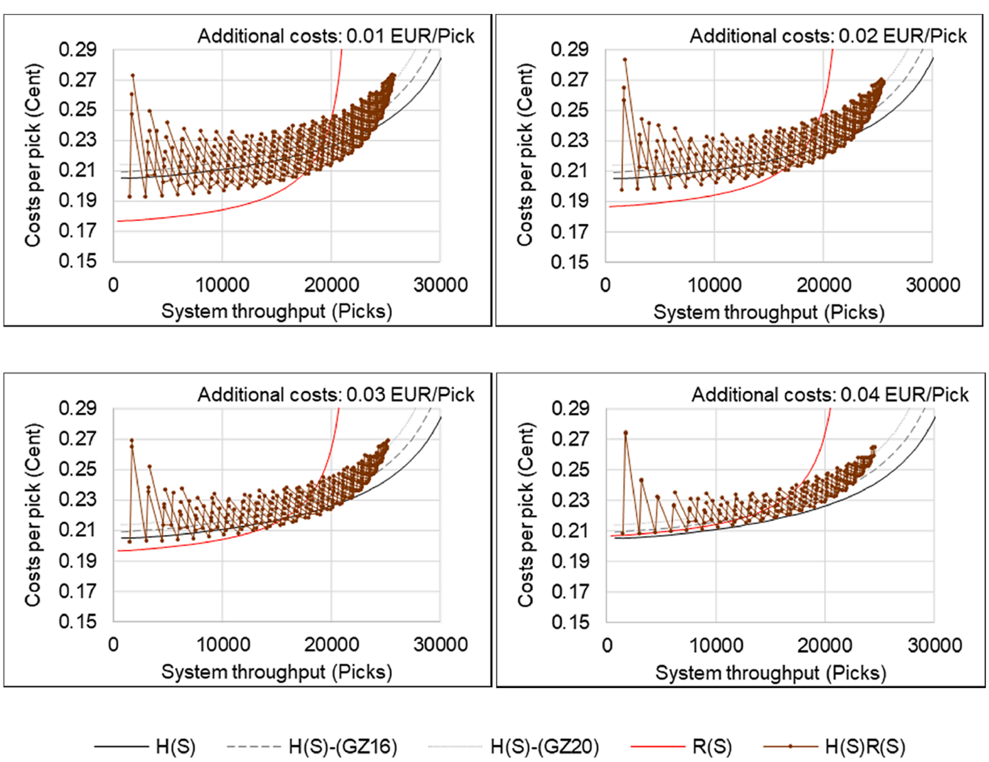

Fig. A3. Cost analysis of HOPS with additional costs per pick for the robot team (scenario: 50/30/20-A/BC).

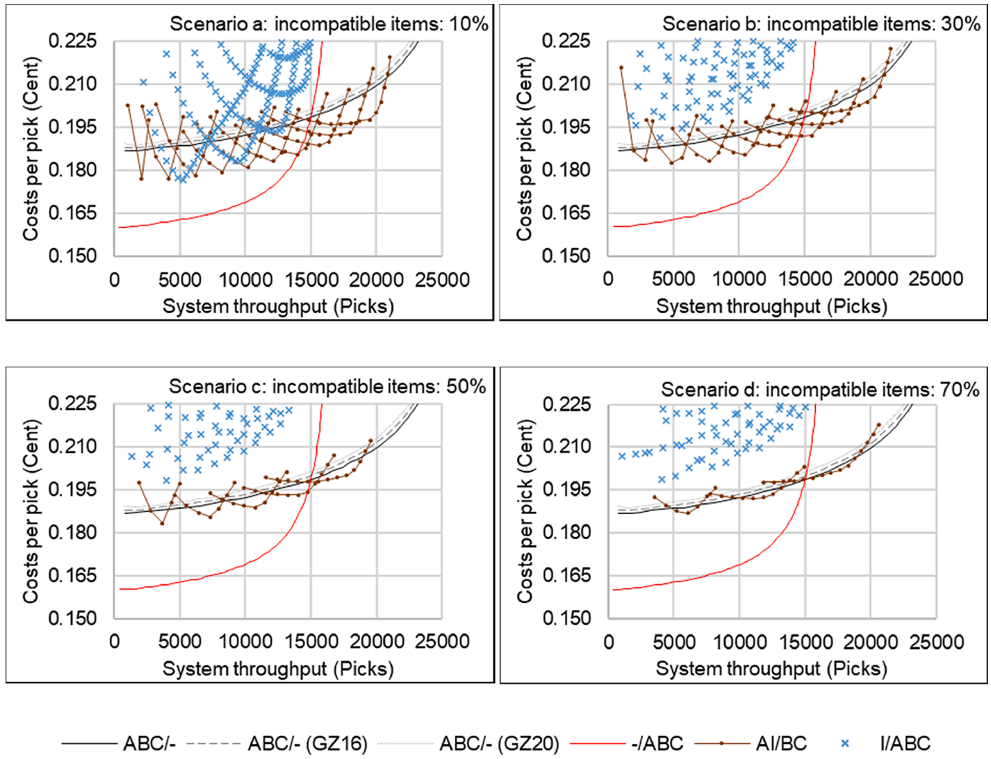

Fig. A4. Cost analysis of HOPS in a mixed storage warehouse with turnover rate 80/15/5 and S-shape routing policy (costs per pick over system throughput).

configurations considered, a broad investigation was provided, which is among the first to investigate HOPSs from an economic and processual perspective.

CRediT authorship contribution statement

Sven Winkelhaus: Conceptualization, Methodology, Investigation, Formal analysis, Writing – original draft, Visualization. **Minqi Zhang:** Methodology, Software, Validation, Formal analysis, Investigation. **Eric H. Grosse:** Conceptualization, Investigation, Validation, Writing – review & editing, Supervision, Project administration. **Christoph H. Glock:** Validation, Resources, Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

See Figs. A1–A4.

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