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Evaluation of human workload in a hybrid order picking system

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Abstract: Order picking is a labor-intensive and costly process in supply chains, which is performed manually in most cases. Recently, picking robots have been developed which are capable of working together with human pickers in a shared working space. Such hybrid order picking system can ease human pickers' workload and provide ergonomic improvements, because it partially automates the order picking process. We propose a simulation model to measure the energy expenditure of human pickers who work with the support of picking robots. The hybrid order picking system is evaluated based on its operational costs, efficiency, and ergonomic characteristics. Preliminary results presented in this study show that there are assignment rules for items to workers and robots that reduce human energy expenditure and costs per pick, as well as maintain average throughput time at a certain level. The aim of this preliminary study is to closely analyze the hybrid order picking system, evaluate managerial implications, and detect research opportunities for future works.

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Keywords: Order picking, Picking robot, Collaborative order picking, Human factors, Energy expenditure

1. INTRODUCTION

Order picking is defined as retrieving items from inventory to fulfill customer requests. Research shows that the order picking process represents up to 55% of the total warehouse operating costs (Tompkins et al., 2010). As a key function in warehouses, it has received considerable attention in the past decades. With the development of e-commerce, warehouses have faced a variety of challenges, such as tight delivery schedules and varying workloads (Boysen et al., 2019), which increase the demands on the order picking systems.

To improve the order picking process, previous studies mainly focused on its efficiency and economic performance by developing operating strategies such as routing policies and storage assignment rules (de Koster et al., 2007; Masae et al., 2020), while humans, as the key operators, tend to be neglected (Grosse et al., 2017). However, incorporating human factors in the planning of order picking systems can positively impact the performance and quality of the process (Grosse et al., 2015). Apart from that, the incorporation of human factors can improve the human pickers' health and safety. The consideration especially during the design phase of workplaces can reduce the risk of injuries and disorders as well as related expenses, because the demands on the humans are limited and adjusted to their tolerance (Neumann et al., 2021).

Although most warehouses still apply a manual order picking process (Bonkenburg, 2016), i.e. a person-to-goods system, a goods-to-person system provides opportunities to automate the process. Such automated systems are, however, usually very capital-intensive and inflexible (Roodbergen and Vis, 2009) compared to person-to-goods systems. Recently, autonomous pick robots have been introduced to support human pickers in the order picking process. An example is the TORU developed by Magazino GmbH (Magazino, 2020). The so called "pick-by-robot" systems can be integrated into existing manually operated warehouses, as the robots are more flexible compared to common automated systems. Furthermore, it is also reported that the use of such picking robots can reduce the costs per pick by up to 40% compared to manual picking (Magazino, 2019a). Thus, "pick-by-robot" systems promise new possibilities to organize and improve the order picking process, although the pick capacity is still limited in terms of shapes and weights of goods. However, relevant research on these systems is rarely available. In addition, questions arise whether these systems can improve ergonomics.

In light of these developments, this paper proposes a simulation model to study operational cost, efficiency, and ergonomic characteristics in a hybrid order picking system, i.e. a joint manual and "pick-by-robot" system. The remainder of this paper is structured as follows: the next section presents a brief review of relevant literature. Section 3 introduces the simulation model in detail. The results of the simulation experiments are presented in Section 4. Finally, the conclusions are presented in Section 5.

2. LITERATURE REVIEW

Previous studies on the management and control of manual order picking systems mainly focused on maximizing the

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service level or minimizing the total cost. We refer to the reviews of de Koster et al. (2007) or Masae et al. (2020) for an overview. A new tendency in research in manual order picking is to combine tactical and operational planning problems to achieve further improvements (van Gils et al., 2018), which also brings complexity to planning, particularly by developing analytical models. Simulation models can be applied in such cases to overcome the complexity and difficulties in modeling. Among them, the agent-based simulation approach can be applied to achieve more realistic results when managing complex planning problems (Borshchev and Filippov, 2004). An example of application in order picking is to capture the impact of picker blocking in warehouses (Heath et al., 2013; Franzke et al., 2017; Klodawski et al., 2018). Picker blocking describes the situation where one order picker is disturbed by another one in the picking area, such that the process is interrupted (see e.g., Parikh and Meller, 2009). Although these dynamic phenomena can hardly be foreseen and analytically modeled, they impact the performance of order-picking systems (Franzke et al., 2017). Therefore, a tendency to pursue results closer to real-world situations considering more planning aspects can be observed (van Gils et al., 2018).

In addition to these efforts in operational improvements, researchers also considered technological developments in the order picking process. Winkelhaus and Grosse (2020) reviewed the current research on the application of new technologies such as the Internet of Things (IoT) and cyber-physical systems in logistics. They included warehouse operations and order picking processes and concluded that IoT is dominant in this area, whereas research on autonomous robots in the order picking process is difficult to find. With a focus on robotized order picking systems, Azadeh et al. (2019) reviewed the current research on automated warehouse operating systems. They identified the application of picking robots (such as the TORU), which can automate the entire picking process, as a promising direction for future research. In comparison to other automated warehouse solutions like automated guided vehicles (AGVs), see Azadeh et al. (2020), where only parts of the order picking process can be automated, picking robots offer the possibility of full automation and more flexible order picking systems. This raises an interesting question, namely which job should be assigned to human pickers or robots to improve the system performance. This topic is discussed in the paper at hand.

Grosse et al. (2015) provide a framework for incorporating human factors in order picking planning models. They state that human factors were largely neglected in planning manual order picking and can help in developing more realistic models and improving model predictability. This statement also applies to the hybrid order picking system. As noted by Azadeh et al. (2019), human–machine interaction requires more attention. In fact, human performance is one of the key metrics in human–machine interaction (Steinfeld et al., 2006). In cases where humans and robots collaborate, they share the same workplace, system goal, and sub-goals. Picking robots, with the ability to automate the entire order picking process, provide the possibility of collaboration in the warehouse, as they can safely work with human pickers in the picking area (Magazino, 2020), share the system goal (order picking process), and the sub-goals (arbitrarily fulfilling parts of the orders). Collaboration, compared to other forms of human–machine interaction, results in a higher need for system coordination and also leads to higher attention to human factors in the process. As highlighted by Grosse et al. (2015), the possible consideration of human factors can be classified as physical, mental, and psychosocial aspects. Grosse et al. (2017) further emphasized the influence of physical workload on workers' health due to the heterogeneity of the items stored in warehouses. Thus, the tasks to be assigned to human pickers should be carefully considered. With the support of picking robots, this consideration becomes realizable. To evaluate human workload in manual tasks in the order picking process, efforts were made to assess for example the energy expenditure using the method developed by Garg et al. (1978), see e.g. Battini et al. (2016) or Calzavara et al. (2017). However, these works only focused on the manual order picking process and did not study hybrid order picking systems. Following this method, we extend the existing literature to study the energy expenditure in the context of a hybrid, joint manual and autonomous, order picking system.

3. MODEL DEVELOPMENT

Because real-world implementations of hybrid order picking systems are still scarce, we developed a simulation model in the software "Plant Simulation" by Siemens PLM Software. The modeled scenarios are based on the concept of human–machine collaboration. The duties of human pickers and robots are predefined according to the assignment rules of different item classes, such that if one item in a certain class appears on the picking orders, it is assigned to one human picker or one robot according to the predefined assignment rules. As a result, some orders are split and assigned to two pickers (one human and one robot) because the included items lie on the responsibility of both. These orders are then assembled at the depot after both parts are completed. The aim of the model is to determine which assignment rule can help to achieve the optimum condition regarding human energy expenditure, costs per pick, and average throughput time of orders.

In the simulation model, we assume a warehouse that stores items with a cube size of 20×10×30 cm (based on typical shoe boxes). This ensures that human pickers and robots are both capable of retrieving each item from the shelves. The warehouse has a rectangular shape and consists of 10 picking aisles, which has practical applicability and is frequently adopted in the literature (e.g., Elbert et al., 2017; Franzke et al., 2017). Each picking aisle is 3-m wide, which allows a maximum of two pickers moving in parallel (two-way lane). Three cross-aisles (each 3-m wide) exist at the front, back, and middle of the warehouse, separating the storage area into two parts (zones A and B). A single depot, as the start and end points of picking activities, is located in the middle of the front aisle (see also Elbert et al., 2017; Franzke et al., 2017).

One standard shelving unit provides a storage capacity of 126 items on its six layers (21×6). Each sort of item occupies a layer with an inventory level of 21 stock keeping units. The storage assignment follows a modified class-based assignment rule by storing A and B items on the 3rd, 4th, and 5th layers of the shelving units, in zones A and B, respectively. C items are stored on the remaining layers. This leads to a storage space usage of class A: 20%, class B: 30%, and class C: 50%. Figure 1 illustrates the warehouse layout. Other parameters assumed in the simulation model are listed in Table 1.

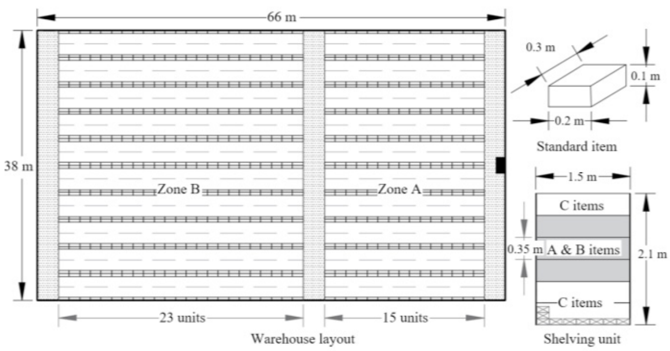

Fig. 1. Warehouse layout, shelving unit, and stored items.

To achieve more realistic results, picker blocking situations are also included in the model, in which the picking process is disturbed by the congestion caused by multiple pickers in the storage area (Franzke et al., 2017). Adopting the classification of picker blockings in Klodawski et al. (2018), the simulated blocking situations are sorted into the following three classes. Based on the "two-way lane" setting, the resolution of picker blocking has its limits and consequences, as pickers have to travel to the neighbor lane to bypass the blocking pickers, which results in adjustments of the original picking routes and leads to extra traveling distance (within-aisle-blocking). If the next picking position is occupied, the pickers wait next to it until the other picker leaves the position (pick-column-blocking). For safety concerns, each picking aisle allows a maximum of two pickers simultaneously, leaving pickers queueing at the entrance in order of arrival until free capacity occurs (total-aisle-blocking). Additionally, it is simulated that human pickers have priority over robot pickers, meaning that robots always adjust their routes for human pickers when blocking occurs.

The measurement of human energy expenditure is based on the model proposed by Garg et al. (1978). Each action in the order picking process is divided into simple tasks and their energy-consuming body posture accordingly. It is assumed that all human pickers are males with a bodyweight of 75 kg, and each item has a load of 1 kg. The picking actions are modeled as lifting/lowering the item from the middle height of each layer to the bench height (0.81 m) on the picking cart. Sorting is simplified as carrying the items from the picking cart (bench height) to the sorting shelf (bench height). Movements in the warehouse are modeled as walking with a picking cart (40 kg) while holding the standing posture. In the case of total-aisle-blocking and pick-column-blocking, the pickers stop their movements, indicating a standing body posture.

To estimate the operating costs, we made the following assumptions based on market information: the monthly costs for one human picker are assumed to amount 3200 EUR and for the robots, the total costs are the sum of the depreciation (55,000 EUR for a service life of 5 years), service (0.06 EUR for each pick action) (Magazino, 2019a), and additional operating costs (estimated 1000 EUR for each robot yearly).

Table 1. Parameters assumed in the model

Order size	Randomly generated with a size of a triangular distribution (1, 2, 6)
Demand distribution	A: 80%, B: 15%, C: 5%
Routing policy	S-Shape policy
Features of human pickers (equipped with a picking cart)	
Batching capacity	8 orders
Velocity	1 m/s
Time for one pick	12 s
Time for sorting	12 s/order
Features of picking robots (based on Magazino, 2019b)	
Batching capacity	max. 16 SKUs
Velocity	0.8 m/s
Time for one pick	20 s/SKU
Time for sorting	20 s/SKU

4. RESULTS

We simulate scenarios in which 1/10 of the stocked items are picked in a hybrid system with a human team (team size: 1-20 human pickers) and a robot team (team size: 1-10 robots). Based on the assumptions made above, the tested scenarios are categorized by different assignment rules in the form of human duties/robot duties. For example, A/BC indicates that human pickers are responsible for picking A items (80% of the demand), whereas robots pick B and C items (20% of the demand). The results are compared with a benchmark scenario in which human pickers are responsible for all picking tasks.

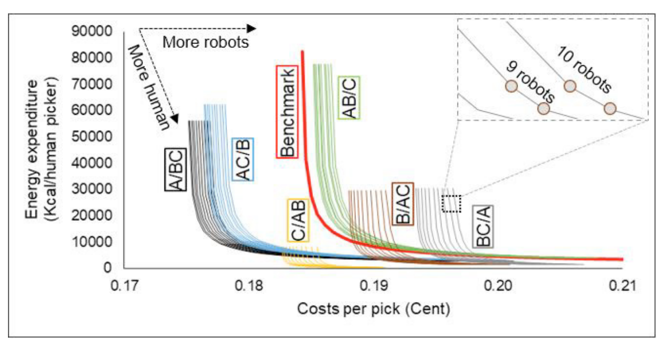

Fig. 2. Energy expenditure over costs per pick.

As shown in Figure 2, each scenario results in a single point, indicating a certain ergonomic and economic measure of the system. To clearly show the tendency, all points with the same robot team size are combined into curves. As can be seen, including more robots in the system leads to a rightward shift of the curves due to higher depreciation costs. In contrast, additional human pickers lead to two observable tendencies. First, as the responsibility of human pickers is already determined by the assignment rules, more human pickers result in a lowered workload of each picker (downward tendency). Furthermore, this also increases the personnel costs (rightward tendency). By comparing the results from different assignment rules, it can be observed that A/BC and AC/B provide the widest range of cost savings, as the curves appear mostly on the left side of the benchmark case. Moreover, if more tasks are assigned to robots, less human energy expenditure can be expected. In scenario C/AB, all curves show fairly low energy expenditure values. On the contrary, scenario AB/C, with the setting of robots taking over only 5% of the picking tasks, do not provide attractive results in this analysis.

In fact, the tendency of increasing depreciation and personnel costs leading to higher costs in Figure 2 result from aggravated crowdedness in the picking area. If picker blocking is not considered, each additional human picker or robot will work at the exact same speed as the original ones. The orders will be finished earlier without unproductive blocked time, leaving depreciation costs and personnel costs allocated in each pick unchanged. Therefore, the costs per pick remain at the original value. The unproductive blocked time is illustrated in Figure 3, showing its cause-effect relationship with the rightward tendencies caused by adding human pickers or robots.

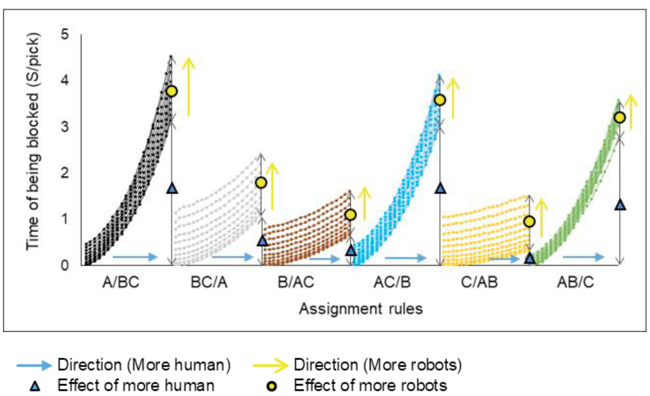

Fig. 3. Blocked time in different assignment rules.

More specifically, the effect of including additional human pickers and robots differs in each assignment rule. Expanding the team with higher responsibility causes larger increasement in blocked time per pick and vice versa. For example, when the human pickers take over most tasks (assignment rules: A/BC, AB/C, AC/B), the effect of adding more humans on the blocked time is larger in Figure 3. Correspondingly, each curve in Figure 2 then covers a larger range of costs per pick, indicating a comparatively more significant rise in costs. On the contrary, in other assignment rules, the effect of adding robots on blocked time is larger, leading to a larger horizontal distance between curves in Figure 2. Thus, picker blocking affects the economic performance of each assignment rule directly. Its ergonomic influence can hardly be observed in the figure, as picker blocking mainly results in longer waiting time that causes very low additional human energy expenditure.

So far, the human energy expenditure was analyzed with the consideration of costs. To provide meaningful managerial implications, another important aspect that should be considered is the efficiency of the system. Thus, we performed a similar analysis with the same system settings, but also with the consideration of average throughput time of each order. Here, the average throughput time serves as an indicator of the system efficiency. Naturally, lower throughput time points to a higher efficiency. The results are shown in Figure 4. Note that to present the details more clearly, only the energy expenditure under 40,000 is shown.

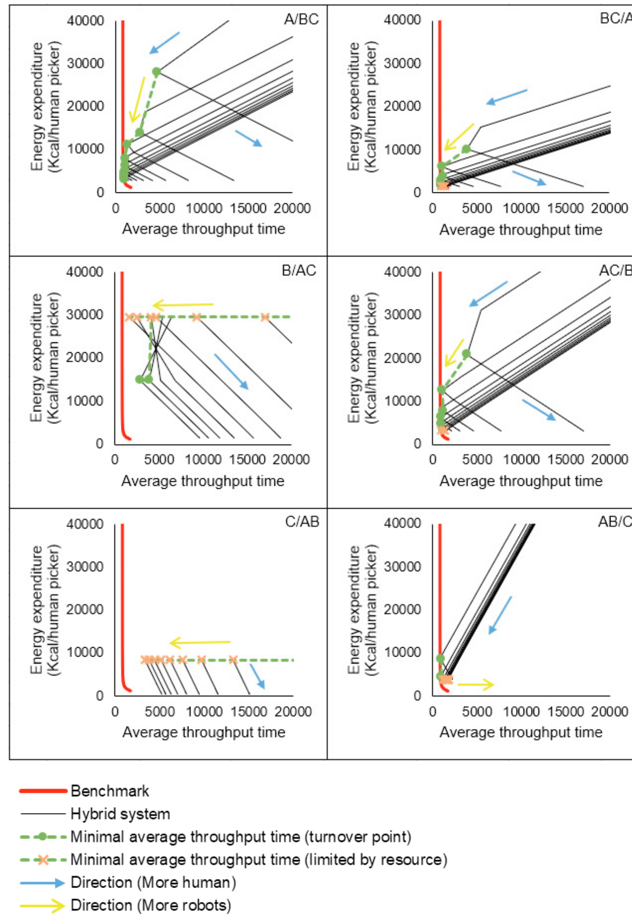

Fig. 4. Energy expenditure over average throughput time.

As can be seen, by successively including additional human pickers, a minimal average throughput time can be observed in some scenarios, causing a turnover point of the curve. In fact, throughput time is strongly in dependance with the quality of the human–robot collaboration, such that if either of the two teams performs the assigned picking tasks faster, a processing backlog can be observed. Hence, one part of the separately assigned order is completed at an earlier time and has to wait at the depot for the other part. This leads to a longer throughput time. Ideally, if human pickers and robots can complete their tasks synchronously, a minimal average throughput time can be achieved. This can be observed in Figure 4 in the form of a turnover point. We thus define these points as signs of good qualified human–robot collaboration. Interestingly, the results show that in some assignment rules, turnover points can hardly be observed. An example is C/AB, in which robots take over most picking tasks, leading to the result that the robot team can never catch up with the human team in range of the simulation experiments (1-10 robots and 1-20 human pickers). A robot team of up to ten robots always causes processing backlog when even only one human picker is employed. Adding more human pickers in the system only causes longer average throughput time (see blue arrow in Figure 3), yet without turnover points. If more robots are employed so that the robot team can catch up with the human team, the existence of turnover points can be expected. Thus, the minimal throughput time in the investigated scenarios is, due to the insufficient number of robots, limited by resource.

Therefore, it can be concluded that more robots are needed to lower the throughput time in C/AB. However, considering the aspect of costs, more robots can cause higher costs per pick while its influence on human energy expenditure is almost negligible (see the arrow direction of more robots in Figure 2), which makes it less attractive. A similar situation can also be observed in B/AC. In contrast, Figure 4 also shows that more human pickers are needed in AB/C, as most curves do not include turnover points due to the small size of the human team and their higher workload (95% of the picking tasks caused by taking over A and B items). Adding more human pickers results also in higher costs per pick (see the arrow direction of more humans in Figure 2). In the scenarios where all curves (A/BC) or most curves (BC/A and AC/B) include a turnover point, the hybrid systems can promise a system efficiency similar to that of a manual system, because average throughputs at turnover points are close to the benchmark scenario. Among these three assignment rules, A/BC and AC/B can especially be recommended, as they can also reduce the costs per pick and human energy expenditure compared to the benchmark scenario according to the cost analysis in Figure 2.

To study the advantage of the hybrid system in more detail, we test the so far best performing assignment rule A/BC with other demand distributions, namely A: 50%, B: 30%, C: 20% (denoted as 50/30/20) and A: 33.34%, B: 33.33%, C: 33.33% (33/33/33), and compare them with the original results with demand distribution A: 80%, B: 15%, C: 5% (80/15/5). Hence, the demand percentages of B and C items increase and the percentage of A items decreases, leading to more picking tasks with longer traveling distance (B items) and with larger energy expenditure in retrieving items (C items). In A/BC, these tasks are all picked by the robots, so that the actual responsibility of human pickers (A items) is reduced. The main results are presented in Figure 5. In addition, on each curve, the point leading to minimal average throughput time is highlighted, so that the system efficiency is also considered. As can be seen, results from all three demand distributions show advantages of the hybrid system in costs per pick and energy expenditure over the manual system, as the green points, representing the optimal situations considering the system efficiency, are all located under the benchmark curves or to the left of them. Nevertheless, note that the system efficiency differs in the three demand distributions. In 80/15/5, the average throughput time in hybrid system is, in the best case, 1.07 times of that in manual system, if the two systems have the same human energy expenditure. Correspondingly, in 50/30/20 and 33/33/33, the hybrid system results in respectively 1.29 times and 1.61 times of average throughput time in the manual system. Moreover, as the demand of A items is reduced in 50/30/20 and 33/33/33, the human team size resulting from the minimal average throughput time is comparatively smaller, leading to higher energy expenditure per human picker. What's more, by comparing the economic performance of the hybrid system with the manual system while maintaining the same energy expenditure value, 80/15/5 promises a larger cost reduction (max. 8.26%).

Summing up, it can be concluded that in assignment rule A/BC, the hybrid system is more suitable for more concentrated demand (e.g. 80/15/5). This way, the system efficiency is nearer to that of manual system and lower human energy expenditure and larger cost reduction can be expected.

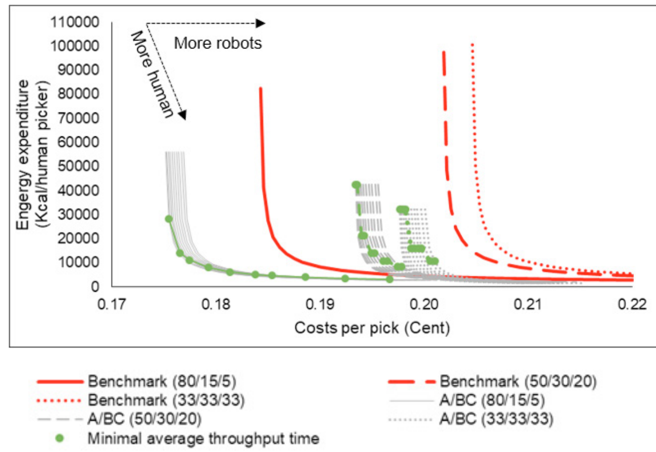

Fig. 5. Energy expenditure over costs per pick in demand distribution 80/15/5, 50/30/20 and 33/33/33.

5. CONCLUSIONS

The developed simulation model evaluated the human energy expenditure of a joint manual and autonomous (hybrid) order picking system with extra consideration of system costs and efficiency. Our preliminary results indicated that by assigning different item classes to human pickers and robots, a reduction in human energy expenditure can be expected. With regard to managerial implications, the hybrid order picking system in the tested scenarios can provide a reduction of both costs and human energy expenditure, while keeping the average throughput time near (1.07 times) to that in a manual system. Further, it is then up to the decision maker whether to pursue more ergonomic or economic improvements. The suggested human and robot team sizes can be adjusted accordingly. For example, when keeping the same human energy expenditure, the hybrid system can promise up to 8.26% of reduction in costs per pick compared to the manual system.

To realize the above stated advantages, certain assignment rules are preferably implemented in the hybrid system. B items, which are stored farther away from the depot, should be firstly considered to be assigned to robots. A items, on the other hand, which are stored near to the depot and have higher demand, should be taken over by human pickers. Furthermore, the results show a slight preference of assigning C items, which are harder for human pickers to retrieve (for example, stored at lower or higher shelf layers), to the robots together with another item class, like B items. As a result, A/BC outperforms other assignment rules in the paper at hand. Furthermore, a more concentrated demand distribution, like 80/15/5 leads to larger advantages of the hybrid system.

As the picker blocking has a huge impact on the costs per pick of the system, future works can focus on including further order picking strategies like other routing policies, storage assignment rules, and order batching, so as to ease the crowdedness in the picking area and enlarge the advantages of the hybrid system. Efforts can be made to further lower the throughput time so that an improvement of system efficiency can be achieved. Another important indicator of system efficiency, the total throughput of the system in a certain time span, can be taken into consideration. These issues will be addressed in an extension of this paper.

REFERENCES

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

Azadeh, K., Roy, D., & de Koster, M. B. M. (2020). Dynamic Human-Robot Collaborative Picking Strategies. Available at SSRN 3585396.

Battini, D., Glock, C. H., Grosse, E. H., Persona, A., & Sgarbossa, F. (2016). Human energy expenditure in order picking storage assignment: A bi-objective method. *Computers & Industrial Engineering*, 94, 147-157.

Bonkenburg, T. (2016). Robotics in logistics: A DPDHL perspective on implications and use cases for the logistics industry. DHL Customer Solutions & Innovation: Bonn, Germany.

Borshchev, A., & Filippov, A. (2004, July). From system dynamics and discrete event to practical agent based modeling: reasons, techniques, tools. Proceedings of the 22nd international conference of the system dynamics society.

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

Calzavara, M., Glock, C. H., Grosse, E. H., Persona, A., & Sgarbossa, F. (2017). Analysis of economic and ergonomic performance measures of different rack layouts in an order picking warehouse. *Computers & Industrial Engineering*, 111, 527-536.

De Koster, R., Le-Duc, T., & Roodbergen, K. J. (2007). Design and control of warehouse order picking: A literature review. *European Journal of Operational Research*, 182(2), 481-501.

Elbert, R. M., Franzke, T., Glock, C. H., & Grosse, E. H. (2017). The effects of human behavior on the efficiency of routing policies in order picking: The case of route deviations. *Computers & Industrial Engineering*, 111, 537-551.

Franzke, T., Grosse, E. H., Glock, C. H., & Elbert, R. (2017). An investigation of the effects of storage assignment and picker routing on the occurrence of picker blocking in manual picker-to-parts warehouses. *The International Journal of Logistics Management*, 28 (3), 841-863.

Garg, A., Chaffin, D. B., & Herrin, G. D. (1978). Prediction of metabolic rates for manual materials handling jobs. *American Industrial Hygiene Association Journal*, 39(8), 661-674.

Grosse, E. H., Glock, C. H., Jaber, M. Y., & Neumann, W. P. (2015). Incorporating human factors in order picking planning models: framework and research opportunities. *International Journal of Production Research*, 53(3), 695-717.

Grosse, E. H., Glock, C. H., & Neumann, W. P. (2017). Human factors in order picking: a content analysis of the literature. *International Journal of Production Research*, 55(5), 1260-1276.

Heath, B. L., Ciarallo, F. W., & Hill, R. R. (2013). An agent-based modeling approach to analyze the impact of warehouse congestion on cost and performance. *The International Journal of Advanced Manufacturing Technology*, 67(1-4), 563-574.

Klodawski, M., Jachimowski, R., Jacyna-Golda, I., & Izdebski, M. (2018). Simulation analysis of order picking efficiency with congestion situations. *International Journal of Simulation Modelling*, 17(3), 431-443.

Magazino (2019a). "6 Cent per pick - Magazino introduces new pricing model “Pay-per-pick” for autonomous picking robot." accessed 24. November 2020. https://www.magazino.eu/pay-per-pick/?lang=en.

Magazino (2019b). "Toru data sheet." accessed 25. November 2020. https://www.magazino.eu/wp-content/uploads/2019/12/191217_TORU_EN_Datasheet.pdf.

Magazino (2020). "Intelligent Logistics." accessed 24. November 2020. https://www.magazino.eu/applications/?lang=en.

Masae, M., Glock, C. H., & Grosse, E. H. (2020). Order picker routing in warehouses: A systematic literature review. *International Journal of Production Economics*, 224, 107564.

Neumann, W.P., Winkelhaus, S., Grosse, E.H., Glock, C.H. (2021). Industry 4.0 and the Human Factor – A Systems Framework and Analysis Methodology for Successful Development. *International Journal of Production Economics*, 233, 107992.

Parikh, P. J., & Meller, R. D. (2009). Estimating picker blocking in wide-aisle order picking systems. *IIE Transactions*, 41(3), 232-246.

Roodbergen, K. J., & Vis, I. F. (2009). A survey of literature on automated storage and retrieval systems. *European Journal of Operational Research*, 194(2), 343-362.

Steinfeld, A., Fong, T., Kaber, D., Lewis, M., Scholtz, J., Schultz, A., & Goodrich, M. (2006). Common metrics for human-robot interaction. Proceedings of the 1st ACM SIGCHI/SIGART conference on Human-robot interaction, 33-40.

Tompkins, J. A., White, J. A., Bozer, Y. A., & Tanchoco, J. M. A. (2010). Facilities planning. John Wiley & Sons.

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

Winkelhaus, S., & Grosse, E. H. (2020). Logistics 4.0: a systematic review towards a new logistics system. *International Journal of Production Research*, 58(1), 18-43.