Reducing picker blocking in a high-level narrow-aisle order picking system: insights from a real-life spare parts warehouse

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REDUCING PICKER BLOCKING IN A HIGH-LEVEL NARROW-AISLE ORDER PICKING SYSTEM

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ABSTRACT

New market developments force warehouses to handle a large number of orders within short time windows. Although research optimizing storage assignment and picker routing is extensive, there remains a gap between academic research and practice. Real-life issues, such as picker blocking, high-level storage locations, precedence constraints, and safety constraints, have been considered insufficiently while optimizing order picking planning problems. This paper goes beyond the current academic state-of-the-art by showing the effects of these real-life issues on order picking efficiency and explaining the importance of incorporating these real-life issues while planning order picking operations. Multiple horizontal and vertical storage assignment policies, as well as multiple routing policies are simulated with the aim of reducing travel and waiting times. The results of a full factorial ANOVA are used to formulate managerial guidelines to increase order picking efficiency in narrow-aisle systems to address the new market developments resulting in enhanced customer service.

1 INTRODUCTION

Recent market developments have forced warehouses to handle a large number of orders within tight time windows. These market developments include e-commerce, globalization and increased customer expectations, and increase the complexity of managing order picking operations. To compete with other warehouses, fast and timely deliveries are promised, resulting in a short remaining time to retrieve the products from the storage locations (Van Gils et al. 018b).

In order to fulfil customer orders, order pickers should retrieve the ordered products from storage locations (i.e., order picking). Order picking management has been identified as an important and complex planning operation (Elbert et al. 2015). The performance of order picking drives the customer service level. Moreover, the main part of the overall operations costs is attributable to the order picking activity (De Koster et al. 2007). The wide range of planning problems that should be solved and existing relations among order picking planning problems make planning order picking operations very challenging (Van Gils et al. 018a).

Although a large number of articles address order picking planning problems (De Koster et al. 2007), there remains a need to account for more real-life issues (Van Gils et al. 018a). A recent literature review of Van Gils et al. (018b) shows that few articles combine multiple planning problems, despite the strong relation among order picking planning problems. Additionally, previous research on order picking systems is subject to a large number of assumptions to simplify operations, such as ignoring picker blocking, considering low-level storage locations, and disregarding precedence constraints and safety constraints (Mellema and Smith 1988; Petersen and Aase 2004; Shqair et al. 2014; Van Gils et al. 2016).

Our study narrows the gap between practice and academic research by analysing the joint effects of storage location assignment (i.e., determining the physical location at which incoming products are stored) and routing (i.e., determining the sequence of storage locations to visit to compose customer orders) in a real-life business-to-business (B2B) warehouse storing automotive parts in a narrow-aisle high-level order picking system, which is a convenient system to store spare parts. As industrial land is expensive in Western Europe, storage space of most warehouses is limited (Venkitasubramony and Adil 2017). However, a rising number of customized products require an increased storage capacity. Narrow-aisle high-level picking systems are designed to increase storage capacity, storing a large number of SKUs in small areas, but multiple order pickers may need to enter the same aisle which results in the blocking of order pickers.

This paper provides both academic and practical contributions. The study goes beyond the current academic state-of-the-art by showing the effects of real-life issues on order picking efficiency and explaining the importance of incorporating these real-life issues while planning operations. Based on observations in a real-life warehouse, the real-life issues of picker blocking, high-level storage locations, precedence constraints, and safety constraints are expected to be most influential in a narrow-aisle order picking system. Furthermore, this paper provides managerial insights into the trade-offs between reducing travel time and picker blocking by varying storage location assignment and routing policies in a narrow-aisle high-level order picking system. Results of this study can be used by warehouse managers to increase order picking efficiency in order to face new market developments. The remainder of this paper is organized as follows. Section 2 describes the related literature. The case study and experimental design are introduced in Section 3, followed by the results in Section 4. Section 5 concludes the paper.

2 RELATED LITERATURE

Recent studies have proven the efficiency benefits of combining storage and routing decisions. Taking information about the location of fast moving SKUs into account while creating pick routes results in significantly reduced traveling (Shqair et al. 2014; Van Gils et al. 018a). However, narrow-aisle order picking systems are subject to multiple real-life issues, such as picker blocking, high-level storage locations, precedence constraints, and safety constraints, which have not been considered in these studies, despite the practical relevance of these factors.

In manual order picking systems, narrow aisles can result in substantial waiting times due to picker blocking compared to wide-aisle systems (Parikh and Meller 2009). Given the layout of the order pick area, the effects of picker blocking are mainly influenced by storage location assignment, and picker routing (Elbert et al. 2015). Previous research considering picker blocking has focused on either storage or routing to minimise order picking time. Turnover-based storage location assignment policies have been introduced to reduce picker traveling. By increasing the pick density in areas close to the depot, picker blocking typically increases as multiple pickers work in the same area (Gue et al. 2006). In contrast to turnover-based storage location assignment, randomly assigning SKUs to storage locations allocates items uniformly over the entire pick area. In this way, order pickers generally utilize the pick area more uniformly resulting in minimal picker blocking to the detriment of an increased travel time (Pan and Shih 2008).

High-level order picking systems, in which multiple SKUs are assigned to a single storage rack consisting of multiple levels, require traveling in both horizontal and vertical directions (Chan and Chan 2011). Compared to low-level storage systems, travel time increases (Chabot et al. 2018) and picking aisles will be occupied longer. Consequently, picker blocking is expected to increase in a high-level order picking system. In low-level picking systems, storage classes need to be assigned in a horizontal direction, while high-level order picking systems additionally require vertical storage assignment. Fast moving items are preferred at lower levels of storage racks to reduce the traveling and blocking of order pickers (Pan et al. 2014).

Studies considering precedence constraints (i.e., requiring certain SKUs to be picked prior to other SKUs in a pick round) while optimizing order picking are limited (Dekker et al. 2004; Matusiak et al. 2014), despite the effects of precedence constraints on order picking efficiency. Storage location assignment and routing should be aligned in order to minimize traveling. Heavy and large products should be assigned to storage locations that are located at the start of a pick round. Instead of assigning all fast moving SKUs to easy accessible locations, priority should be given to heavy and large products in order to prevent additional sorting operations or damaged products. After that, SKU turnover-based storage assignment policies can be considered to reduce traveling. Furthermore, varying size and weights of SKUs cause strong fluctuations in retrieval and sorting times at storage locations. Instead of assuming a constant pick time (Van Gils et al. 018a), varying pick times per product category should be assumed as pick times define the time length an aisle is occupied and consequently these variations may impact waiting times due to blocking.

Despite the large number of accidents that happen in warehouses (De Koster et al. 2011), safety constraints have been insufficiently considered while optimizing order picking operations. Security rules, such as limiting truck movements to a single direction to avoid products falling on the picker, ensure safety of individual order pickers (Chabot et al. 2018). However, time pressure is high and forklifts are working in close proximity, resulting in an enhanced risk of accidents involving multiple order pickers (De Koster et al. 2011).

3 METHODOLOGY

This section introduces the simulation approach and describes a case in which various unexplored real-life issues are incorporated in the simulation experiments. A discrete-event simulation model of a real-life case is created using `Arena`. A list of orders, including a random number of order lines and each order line consisting of a random number of items to be retrieved at storage locations, is generated using Monte Carlo simulation and forms the input of the discrete-event simulation model. The order lists are randomly generated in accordance with the distribution of different product categories of the case. In addition to the order lists, stochasticity is included in the discrete-event simulation model by modelling distributions for travel speed, setup time and pick time. All random distributions have been fitted based on real-life data of the case gathered for a three-month period. All other parameters are assumed to be deterministic. Both the generated order lists and the results of the simulation model have been validated using the real-life data. For example, the operational validity is tested by running the model with two real-life order lists and comparing the simulation results with the real-life performances (i.e., pick time, setup time and travel and waiting times). Furthermore, results have been carefully discussed with the case company, suggesting that the simulation model is valid for the acceptable range of accuracy under the experimental conditions of the case.

The case is based on an international warehouse located in Belgium that stores automotive spare parts. The simulation study focuses on the fully manually operated part of the order pick area, in particular, the two order pick zones storing the respective regular (i.e., northern part) and heavy (i.e., southern part) SKUs. The layout of the order pick area and assignment of product categories to locations are illustrated in Figure 1.

As storage location assignment and routing are expected to have the largest impacts on picker blocking, an interaction analysis, by means of a simulation model, is applied to evaluate the joint effects of combining storage location assignment and picker routing, taking multiple real-life issues and constraints into account. As the time horizons of the resulting storage and routing decision are different (i.e., storage is a daily decision, while routes are constructed multiple times per hour), simulation is an appropriate research method to analyze the interaction between storage and routing (Van Gils et al. 018b). The four experimental factors and their associated factor levels are provided in Table 1. The benchmark corresponds to the currently applied policy combination and is shown in italics. The benchmark policy combination has been fixed by warehouse supervisors and managers based on experience and personal judgment, taking precedence and safety constraints into account.

SKUs of the real-life case are characterized by a varying weight and size, which divides them into eleven product categories. The heaviest product categories are stored in the southern part of the building in which (vertical) aisles are wide enough to get off the pick truck and pick the items. Leaving the pick truck

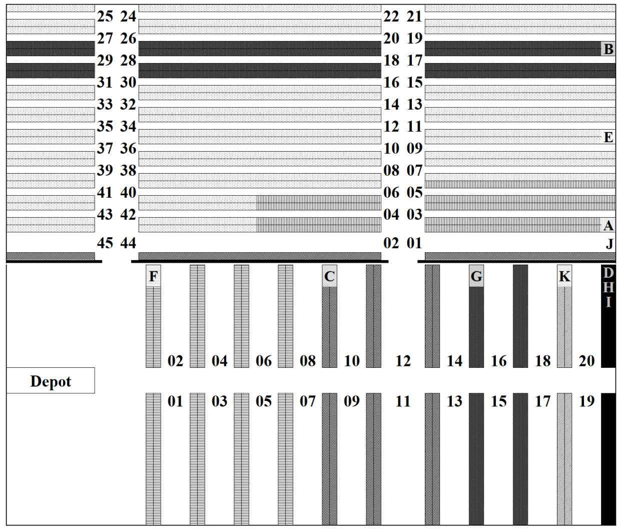


Figure 1: Layout of the order pick area with aisle numbers and product categories.

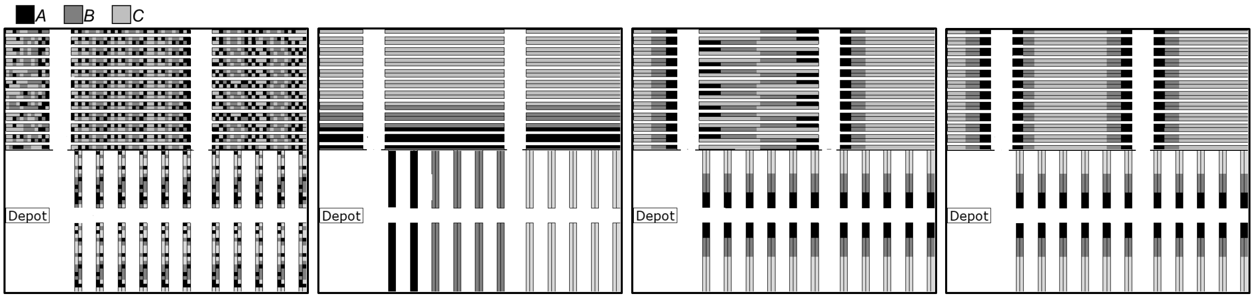
Table 1: Experimental factor setting (currently applied storage and routing factor levels in *italics*).

Factor	# levels	Factor levels
horizontal storage	4	random; within-aisle; *across-aisle*; perimeter
vertical storage	2	two dimensional (2D); *three dimensional (3D)*
routing	3	*return*; traversal; midpoint
demand	3	8 pickers (300 orders); 10 pickers (375 orders); 12 pickers (450 orders)

is not possible in the very narrow northern pick aisles. A sort-while-pick policy is used requiring multiple product categories in the warehouse: heavy products need to picked and loaded into boxes prior to light and fragile products to provide stability and prevent damage during shipment. The current storage location assignment policy corresponds to a three dimensional (3D) across-aisle policy. The fast-moving items of each product category are stored at the beginning of each aisle, and at the lowest levels of the storage rack, while less frequently ordered items are assigned to storage locations at high levels or storage locations at the end of pick aisles. Besides the across-aisle storage location assignment policy, three horizontal storage policies that are commonly used in studies considering low-level order picking systems are evaluated (see Figure 2): random storage, within-aisle (i.e., all items in a pick aisle belong to the same class), and perimeter storage (i.e., storage classes are located around the periphery of the warehouse block).

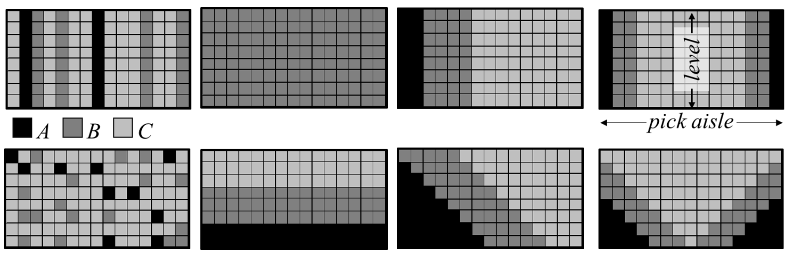
In addition to the horizontal location of storage classes, high-level order picking systems require a decision on the vertical location of storage classes. The 2D policy assumes racks consisting of a single storage class. Different from the 2D policy, multiple storage classes can be assigned to different levels of a single storage rack in a 3D policy. Storage classes are diagonally distributed within each aisle in combination with the horizontal across-aisle and perimeter storage policies. 3D within-aisle storage assigns fast moving SKUs to the lowest levels and slow movers to high level locations. In case of random storage, storage classes are randomly assigned to storage locations. Figure 3 illustrates the vertical storage assignment policies: storage racks are shown horizontally, while the levels of each rack are illustrated vertically.

Routes are currently constructed based on return routing (i.e., order pickers enter and leave an aisle from the same end), except for the last aisle to visit in the middle warehouse block of the northern zone, which is traversed completely from right to left (see Figure 4(a)). Safety constraints are included by introducing traffic rules in the warehouse, to prevent routes from crossing, as indicated by the traffic signs



(a) Random. (b) Within-aisle. (c) Across-aisle. (d) Perimeter.

Figure 2: Horizontal storage location assignment policies.



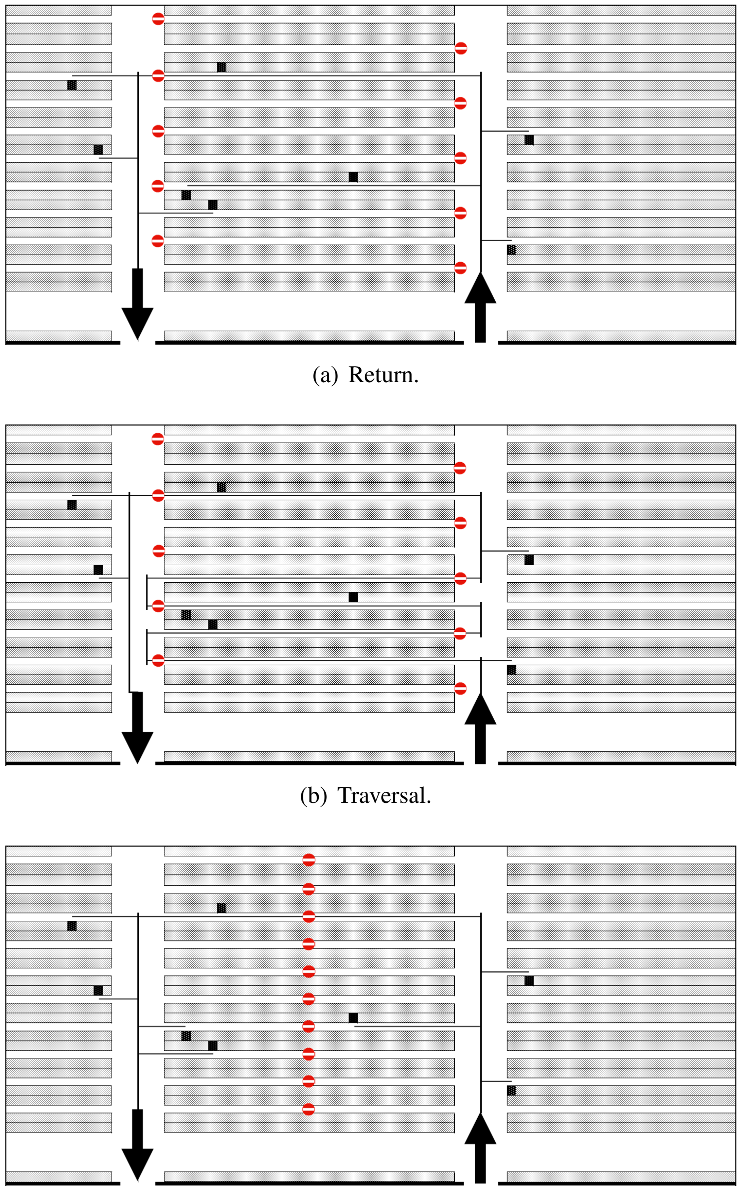
(a) Random. (b) Within-aisle. (c) Across-aisle. (d) Perimeter.

Figure 3: Vertical storage location assignment policies (2D above - 3D below).

on the figure, reducing the risk of accidents. Although complex routing methods, such as largest gap and heuristic algorithms, have proven to significantly reduce travel distance, these routing policies would substantially increase the risk of accidents as it proposes picker routes that cross. Therefore, in addition to return routing, the effects of traversal and midpoint routing policies are analyzed in the middle warehouse block of the northern zone (see Figures 4(b) and 4(c)). As other warehouse blocks are connected to a single cross-aisle, routing is limited to returning to this cross-aisle. To prevent routes from crossing, aisles in the middle warehouse block of the northern zone are one-directional in case of a traversal routing policy. Midpoint routes assume order pickers entering aisles until the midpoint and returning to the cross-aisle, except for the last aisle to visit in the middle warehouse block of the northern zone, which is traversed completely from right to left. Additional safety constraints for traveling within aisles should be respected: a maximum of two pickers is allowed in each sub-aisle of the southern zone and a single order picker in the smaller sub-aisles of the northern pick zone. This constraint causes picker blocking and unproductive waiting times.

To generalize the results of the simulation to different order and picker levels, a final factor includes a varying number of order pickers and corresponding number of customer orders: 300 customer orders and 8 order pickers during a pick shift of eight hours corresponds to a low demand, while 375 orders and 10 pickers, and 450 orders and 12 pickers are defined as regular and high demand shifts, respectively. These factor levels have been determined after performing the Resource Schedule Identification Method (RSIM) of Martin et al. (2016), which retrieves resource availability insights from real event logs. The real availability of order pickers during each shift has been retrieved from the picking log of the company using RSIM, as well as the number of orders corresponding to the levels of order pickers. This method results in a more accurate determination of the demand factor levels.

To summarize, the simulation experiment consists of 72 factor level combinations (i.e., four horizontal storage levels $\times$ two vertical storage levels $\times$ three routing levels $\times$ three demand levels). The factorial setting results in a $4 \times 2 \times 3 \times 3$ full factorial design. To reduce the stochastic effect from order generation,



(a) Return.

(b) Traversal.

(c) Midpoint.

Figure 4: Routing policies.

each factor level combination is replicated 30 times. The performance of the policy decisions is evaluated with regard to the travel time of order pickers, the waiting time as a result of picker blocking, and the total order picking time consisting of setup time, search and pick time, travel time and waiting time. The setup time is assumed to be directly proportional to the number of pick rounds, while searching and picking is proportional to the number of items to pick at each storage location. Pick times are much larger in case of large or heavy items, compared to regular SKUs. Both setup time and search and pick time are assumed to be independent of the storage and routing policy.

4 SIMULATION RESULTS

This section analyses and discusses the results of the simulation experiments. In accordance with previous simulation studies analyzing order picking planning problems (Shqair et al. 2014; Van Gils et al. 018a), results are analyzed and explained using ANOVA, interaction plots and post hoc tests. ANOVA test results are presented in Section 4.1. The relation between storage and routing is analyzed and extensively explained in Section 4.2 using interaction plots and post hoc tests. Managerial implications discussing the effects of considering real-life issues are provided in Section 4.3.

4.1 Factor Analysis

In order to get a first insight into the results of the simulation experiments, the four experimental factors are statistically analyzed by performing ANOVA tests. The results of the full factorial mixed-model ANOVA with horizontal storage (S^h), vertical storage (S^v) and routing (R) as within-subjects factors and demand (D) as between-subjects factor, are presented in Table 2 showing the statistical significance of the horizontal storage factor, vertical storage factor, routing factor, demand factor and the interaction effects among the four factors with regard to travel time, waiting time and total order picking time.

Table 2: p-values of $4 \times 2 \times 3 \times 3$ mixed-model ANOVA with horizontal storage (S^h), vertical storage (S^v) and routing (R) as within-subjects factors and demand (D) as between-subjects factor.

	S^h	S^v	R	D	$S^h \times S^v$	$S^h \times R$	$S^h \times D$	$S^v \times R$	$S^v \times D$	$R \times D$	$S^h \times S^v \times D$	$S^h \times R \times D$	$S^v \times R \times D$
travel	.000	.000	.000	.000	.000	.000	.000	.316	.704	.000	.070	.204	.744
waiting	.000	.000	.000	.000	.000	.000	.000	.000	.000	.011	.000	.000	.011
total	.000	.575	.000	.000	.000	.000	.000	.413	.324	.363	.001	.266	.363

Results of Table 2 show that most main effects are statistically significant, meaning that the storage and routing policy influence order picking time. Additionally, Table 2 reveals that all main effects as well as all interaction effects are statistically significantly influencing the waiting time of order pickers. This means that there is a significant difference in mean waiting time of order pickers between the eight storage location assignment policies, as well as between the three routing policies. The ANOVA results show that either travel distance or travel time measures are insufficient to evaluate the efficiency of horizontal storage and routing policies, as waiting times should be taken into account.

4.2 Explaining the Storage and Routing Interaction

Although the experimental design gives rise to a large number of instances and thereby easily providing statistically significant conclusions (Schmeiser 2001). However, the ANOVA shows strong statistically significant effects, at least with respect to horizontal storage and routing. Therefore, interaction plots and post hoc tests are able to support explaining why the storage and routing planning problems are related. The statistical significance of all horizontal storage levels for each routing and vertical storage factor level combination are analyzed using a Bonferroni t-test.

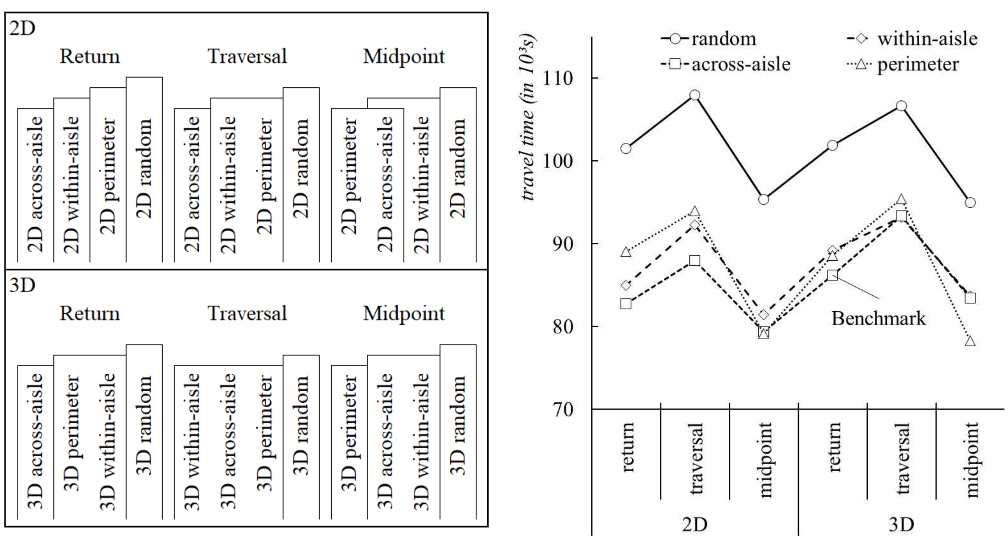
4.2.1 Interaction Effect on Travel Time

Figure 5(a) demonstrates the results of the Bonferroni t-test on mean travel time. If two horizontal storage policies are listed in the same subset, differences fail to be statistically significant. Strong varying subsets are created among the different combinations of vertical storage and routing policies, explaining why storage and routing are related. Randomly assigning SKUs to storage locations, either 2D or 3D, always results in the largest travel time: the 2D and 3D random storage assignment policy forms the last subset in combination with all routing policies.

With respect to the travel time of order pickers, across-aisle storage outperforms all other storage policies in combination with return routing. Both 2D and 3D across-aisle storage policy are located in the first subset in combination with return routing. Fast moving SKUs are located in the beginning of pick aisles and return routes aim to minimize traveling within aisles as the within-aisle distance is traveled twice: moving from the cross-aisle to the storage location and returning to the cross-aisle.

Furthermore, traversal routes do not clearly favor any storage location assignment policy. With respect to 2D storage assignments, the across-aisle storage policy is located in the first subset. However, considering 3D storage policies, all turnover-based storage policies are located in a single subset. Traversal routes aim to minimize the number of visited aisles, as an aisle should be entirely traversed for each location that should be visited in a pick aisle. Therefore, within-aisle storage classes are expected to be best combined with traversal routes. However, since the number of SKUs on a pick list is rather small in spare parts warehouses, this policy combination is not preferred in the warehouse under consideration.

Finally, midpoint routing policies clearly favor the perimeter storage location assignment, especially when using a 3D storage location assignment. This can be explained as follows: perimeter storage classes assign fast moving SKUs along the periphery of the warehouse, and the midpoint routing heuristic follows the periphery of the warehouse blocks, resulting in a significant reduction in travel time compared to other storage policies. The interaction plot of Figure 5(b) illustrates the strongly decreased travel time by combining 3D perimeter storage and midpoint routing.



(a) Bonferroni t-test (family wise error rate = 0.01). (b) Interaction plot.

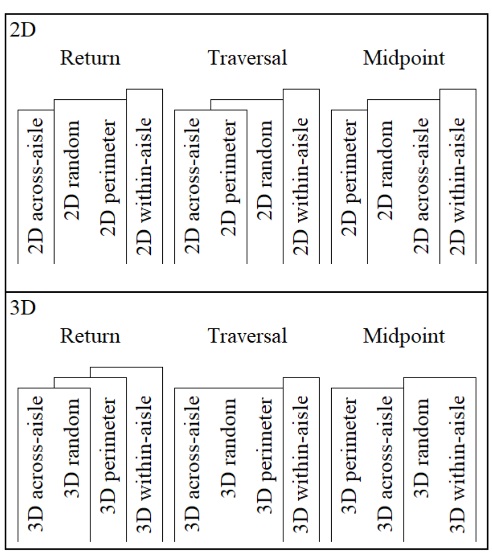
Figure 5: Travel time for each combination of storage and routing policy.

4.2.2 Interaction Effect on Waiting Time

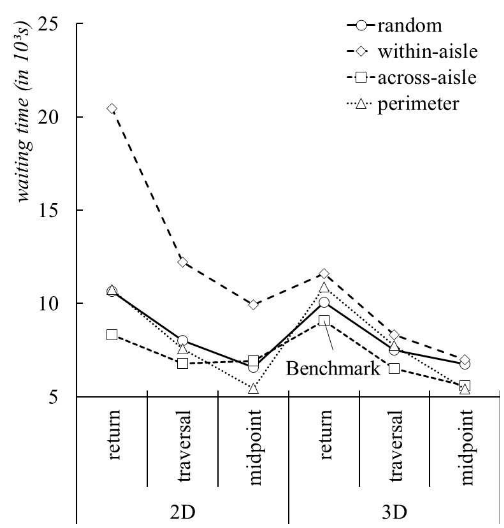
Bonferroni t-test results on mean waiting time are illustrated in Figure 6(a). The creation of different subsets for the routing policies explains why the storage and routing planning problems are related with respect to picker blocking. Within-aisle storage classes are located in the last subset in combination with all routing policies. As within-aisle storage classes concentrate pick densities in a limited number of aisles, the probability that multiple pickers should visit aisles storing fast moving SKUs simultaneously strongly increases. Consequently, waiting times due to picker blocking are statistically significantly higher in case of within-aisle storage classes compared to the other horizontal storage policies.

The favorable combinations with respect to traveling come back in the waiting times (i.e., across-aisle & return and perimeter & midpoint). This can be explained by the fact that these combinations reduce traveling within aisles. Consequently, pick aisles are occupied shorter, which reduces waiting times. No clearly favorable storage policy is shown in combination with traversal routing.

Figure 6(b) further illustrates the relation between storage and routing. The midpoint routing policy outperforms other routing policies. Remember that the routing methods only differ in the middle warehouse block of the northern zone due to the limited number of cross-aisles. Safety constraints allow two order pickers entering simultaneously each aisle of the middle warehouse block in case of midpoint routing policy: one order picker at each side of the warehouse block. Only a single order picker is allowed in each pick aisle in case of return routing and two order pickers may enter each aisle in case of traversal routes, but additional blocking occurs within aisles as the narrow aisles are not wide enough for order pickers to pass each other. The benefits resulting from two-side entering (i.e., midpoint routing) increase in combination with perimeter storage policies. This can be explained by the fact that fast moving SKUs are diffused across the warehouse block, while across-aisle and within-aisle storage policies concentrate fast moving SKUs across one side of the warehouse block and within a few pick aisles, respectively. Consequently, the combination of midpoint routing and perimeter storage enables retrieving A-items by more order pickers simultaneously: two pickers per aisle can visit A-locations simultaneously. Other routing policies in combination with perimeter storage cause additional blocking within a pick aisle (i.e., traversal routing) or the number of pickers that are able to simultaneously visit A-locations is limited to a single picker (i.e., return routing). Combining across-aisle storage with midpoint routing causes A-locations to be visited by a single order picker per aisle as A-items are located at one side of the warehouse block. Within-aisle storage classes allow only two order pickers to visit A-locations simultaneously as all A-items are located in a single aisle resulting in substantially increased waiting times.



(a) Bonferroni t-test (family wise error rate = 0.01).



(b) Interaction plot.

Figure 6: Waiting time for each combination of storage and routing policy.

4.3 Managerial Implications

This section discusses the practical implications of this study, in particular the effects of the considered real-life issues: picker blocking, high-level storage locations, safety constraints and precedence constraints. The currently applied 3D across-aisle storage location assignment and return routing (i.e., benchmark), limited to a single order picker per aisle, results in a mean total order picking time of 170,918 seconds for picking all customer orders of a shift. The simulation experiments show that the 3D perimeter storage policy in combination with midpoint routing yields a substantially reduced order picking time (160,263 s). On average, the order picking process can be performed 6.2 % more efficiently by reconsidering the storage location assignment and routing policy. Especially the effects on waiting time are substantial. In the currently applied policy combination, order pickers are on average blocked 5.30 % of the total time, while the waiting time is reduced by 36.22 % in case of 3D perimeter storage and midpoint routing. The proportion of the other time components are equivalent to the typical distribution of order picker's time (De Koster et al. 2007), making the conclusions of this study easily generalizable to other narrow-aisle order picking systems.

Figure 7 shows the effects of safety and precedence constraints in the northern pick zone in case of 450 orders per shift. The graph illustrates the mean waiting time in seconds before a picker can enter an aisle. Waiting times with respect to the benchmark as well as the best performing policy combination are shown. Figure 7 demonstrates a strongly reduced waiting time in case of 3D perimeter storage assignment and midpoint routing. The even pick aisle numbers can all be entered in case of midpoint routing, while traffic rules do not allow pickers to enter certain pick aisles in case of return routing (e.g., pick aisle 06, 10, 14), resulting in strongly increased waiting times in other aisles. Thus, in addition to increased travel time by the on-way traffic directions in cross-aisles, safety constraints induce picker blocking, which should be minimized by considering the most efficient combination of storage and routing policy.

Additionally, Figure 7 provides insights into the negative effects of including precedence constraints. For example, product category A, consisting of heavy SKUs, is assigned to storage locations at the beginning of the pick round. These heavy SKUs should be picked prior to other product categories. However, the relatively long handling time to retrieve these SKUs and large pick density result in long waiting times for entering these pick aisles. This effect is shown by the peaks in pick aisles 03, 04 and 05. Assigning these SKUs to more pick aisles and including small turnover SKUs from another product category would have further reduced the waiting times, but violates the precedence constraints. Consequently, precedence constraints induce additional waiting times that have been ignored in current academic studies.

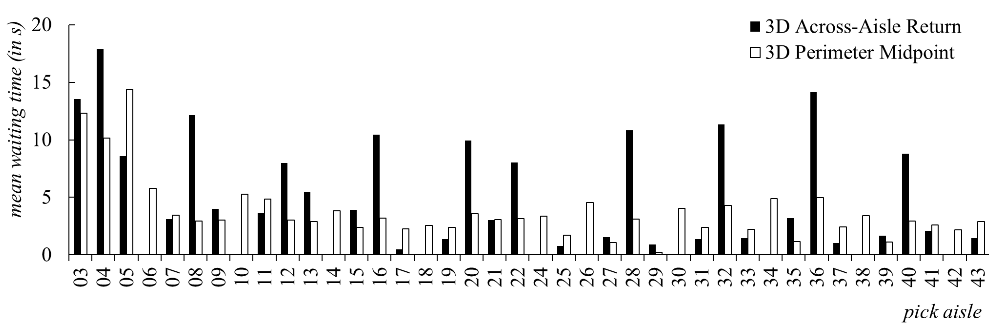


Figure 7: Mean waiting time before entering a pick aisle for the benchmark and best policy combination.

5 CONCLUSIONS

Decisions on the assignment of SKUs to storage locations, as well as the routing of order pickers in a narrow-aisle warehouse, should be considered while planning order picking operations in order to face new market developments. Real-life issues are insufficiently explored in recent academic literature. The real-life spare parts warehouse shows the practical relevance of incorporating these real-life issues while optimizing operations. Under the assumptions of a high pick density in narrow-aisle order picking systems, the conclusions about the effects of real-life issues can be easily generalized to other warehouses.

Most real-life issues that have been largely unexplored in recent academic literature negatively impact order picking efficiency or result in infeasible solutions when these practical factors are not incorporated. Simulation results show that traveling measures are insufficient to evaluate the efficiency of storage and routing policies. Warehouse managers may choose an inefficient storage and routing policy when only traveling is considered as this performance metric ignores the impact of waiting times. Moreover, traffic rules as a result of safety constraints limit movements of pickers, inducing additional waiting. Finally, ignoring precedence constraints results in infeasible solutions, especially in case of varying SKUs in terms of shape and weight, because small products can be damaged or additional sorting activities are required in case of violating the required routing sequence.

Investigating the effects of other real-life issues, such as human factors, may further reduce the gap between practice and academic research. Future research could focus on optimizing order picking operations while considering human factors, such as learning and forgetting. Human factors may be incorporated by varying pick times and travel speeds between individual human pickers. Moreover, the effects of assigning fast-moving SKUs to multiple storage locations in different pick aisles will be valuable knowledge for practitioners to further reduce picker blocking and design efficient order picking systems.

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