THE EFFECT OF STORAGE AND ROUTING POLICIES ON PICKER BLOCKING IN A REAL-LIFE NARROW-AISLE WAREHOUSE

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ABSTRACT

Upcoming e-commerce markets force warehouses to handle a large number of orders within short time windows. Narrow-aisle order picking systems allow to store a large number of products in small areas. In manual order picking systems, narrow aisles can result in substantial waiting time compared to wide-aisle systems. The objective of this study is to analyse the joint effect of the two main operational order picking planning problems, storage location assignment and order picker routing, on order picking time, including travel time and waiting time due to picker blocking. Multiple horizontal and vertical storage assignment policies, as well as multiple routing policies are simulated with the aim of reducing order picking time. The results of a full factorial ANOVA are used to formulate managerial guidelines to increase order picking efficiency in narrow-aisle systems in order to face the new e-commerce market developments resulting in enhanced customer service.

Keywords: warehouse planning, order picking, picker blocking, simulation

1. INTRODUCTION

Upcoming e-commerce markets force warehouses to handle a large number of orders within short time windows. In order to differentiate from competitors with respect to customer service, warehouses aim at providing quick deliveries to customers. Consequently the remaining time to handle orders is reduced. Moreover, the order behaviour of e-commerce customers is characterised by many orders consisting of only a limited number of order lines (De Koster et al. 2007).

In order to fulfil customer orders, order pickers should retrieve the ordered products from storage locations (i.e. order picking). In this paper, two of the main operational planning problems are studied in a narrow-aisle order picking system: storage location assignment (i.e. determining the physical location at which incoming products are stored) and order picker routing (i.e. determining the sequence of storage locations to visit to compose customer orders) (De Koster et al. 2007).

Order picking management has been identified as an important and complex planning operation as a consequence of the existing relations among planning problems (Van Gils et al. 2016) and the existing trade-offs among decisions. Narrow-aisle picking systems are designed to increase the storage capacity, but multiple order pickers may require to enter the same aisle which results in blocking of order pickers. Moreover, most storage location assignment policies aim to increase the pick density by assigning fast moving stock keeping units (SKUs) to storage locations closely located to the depot in order to reduce the order picker travel time. High pick densities in certain order picking areas increase the probability of picker blocking (Pan and Shih 2008).

The objective of this study is to analyse the joint effect of the two main operational order picking planning problems, storage location assignment and order picker routing, on order picking time, including travel time and waiting time due to picker blocking. Multiple combinations of storage and routing policies are simulated in a real-life narrow-aisle order picking system with the aim of reducing order picking time. Order picking systems in previous research are subject to a large number of assumptions to simplify operations, such as ignoring picker blocking (De Koster et al. 2007; Petersen and Aase 2004) and low-level storage locations (Pan and Wu 2012; Petersen and Aase 2004; Van Gils et al. 2016). Our study narrows this gap between practice and academic research by simulating a real-life business-to-business (B2B) warehouse storing automobile spare parts in a narrow-aisle high-level order picking system, which is a convenient system to store spare parts.

To the best of our knowledge, we are the first to analyse the joint effect of storage and routing policies on the trade-off between travel time and picker blocking time in high-level order picking systems. The main contributions of this paper are managerial insights into the trade-off between reducing travel time and picker blocking by varying storage location assignment and routing policies in a narrow-aisle picking system. Results of this study can be used by warehouse managers to increase order picking efficiency in order to face the new e-commerce market developments.

The remainder of this paper is organised as follows. Section 2 describes the problem context and related literature, followed by the introduction of the case study and the experimental design used in our simulation in Section 3 and Section 4, respectively. In Section 5 results of the simulation study are presented. Section 6 concludes the paper.

2. PROBLEM CONTEXT

As industrial land is expensive in Western Europe, storage space of most warehouses is limited. However, a rising number of customised products require an increased storage capacity. Narrow-aisle warehouse systems allow to store a large number of SKUs in small areas. In manual order picking systems, narrow aisles can result in substantial waiting time due to picker blocking compared to wide-aisle systems (Parikh and Meller 2009). The effect of picker blocking is mainly influenced by three operational factors: storage location assignment (Pan and Shih 2008), routing (Chen et al. 2016), and batching (Hong et al. 2012). As storage location assignment and routing are expected to have the largest influence on picker blocking, we assume the current first-come-first-served batching policy as given. Related literature analysing storage and routing planning problems to minimise the picker blocking is discussed below.

Storage location assignment policies have been introduced in order to reduce the time travelled by order pickers. By increasing the pick density in pick areas close to the depot, picker blocking typically increases as 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 picking area. In this way, order pickers generally utilise the picking area more uniformly resulting in minimal picker blocking to the detriment of an increased travel time (Pan and Shih 2008). Pan and Shih (2008) deal with the effect of storage location assignment policies on blocking and traveling of order pickers in low-level picking systems. High-level order picking systems require traveling in both horizontal and vertical direction (Chan and Chan 2011). As travel time increases, 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 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.

A wide range of routing methods (e.g. traversal, return, largest gap) have been evaluated in literature in a system with a single order picker, focusing on reducing either travel time or travel distance (De Koster and Van Der Poort 1998; Theys et al. 2010). In practice, multiple order pickers are working in the same order picking area to retrieve items. Efficient methods have been proposed to dynamically change order picking routes during the pick tour for two order pickers and multiple order pickers (Chen et al. 2013; Chen et al. 2016). These complex methods require innovative automation technologies to implement the dynamic order picker routing methods in practice to minimise travel time and picker blocking time simultaneously. Due to this complexity, straightforward routing methods are still widely used in practice (Van Gils et al. 2016).

Previous research considering picker blocking has focused on either storage or routing to minimise the order picking time. Most studies develop analytical models to estimate the travel and picker blocking time, which are subject to a large number of assumptions to simplify order picking operations, such as similar SKUs in terms of size and weight and low-level order picking systems (Pan and Shih 2008; Pan and Wu 2012; Parikh and Meller 2009). This study significantly differs by simulating and evaluating the joint effect of storage location assignment policies and routing policies on the order picking time, considering both traveling and picker blocking in a real-life warehouse, including varying product categories and a high-level order picking system. Incorporating these real-life characteristics makes research more valuable to practitioners.

3. CASE STUDY

Real-life data of a warehouse storing automobile spare parts are used to analyse the joint effect of storage location assignment and routing policies on travel time and picker blocking time. The case is based on an international warehouse located in Belgium that serves the B2B e-commerce market. The simulation focusses on the fully manually operated part of the warehouse with a storage capacity of approximately 20,000 storage locations. The automobile spare parts that are stored in this warehouse area are characterised by a rather large weight. Small and light products are stored in the automated Miniload. The Miniload products are picked separately from all other products. The Miniload is beyond the scope of this study. Besides the Miniload, the order picking area is divided into two other order picking zones: a zone located at the northern part of the warehouse storing the regular weighted product categories and a zone located at the southern part of the warehouse to which the heaviest products are assigned. The layout of the warehouse is shown in Figure 1.

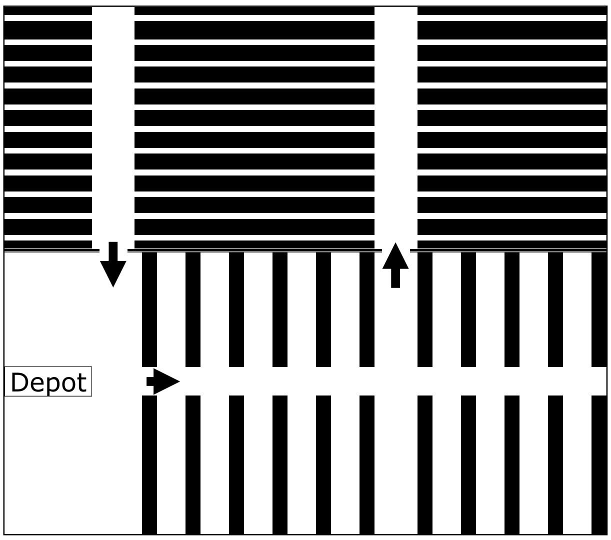

Figure 1: Layout of the Order Picking Area

Both order picking zones consist of three and two warehouse blocks. The number of pick aisles is as follows: eleven and twelve pick aisles in the respective northern and southern zone. A traditional warehouse layout consisting of parallel aisles and cross aisles is frequently used in practice (Roodbergen et al. 2015). Furthermore, cross aisles have proven to result in reduced travel time (Roodbergen and De Koster 2001). However, the number of cross-aisles in the case is limited to a single cross-aisle in the southern zone and two cross-aisles in the northern zone.

Products are divided into eleven product categories, depending on the weight and size, as summarised in Table 1. The heaviest product categories are stored in the southern part of the building in which (vertical) aisles are wide enough to leave the pick truck and pick the items. Leaving the pick truck is not possible in the northern horizontal pick aisles.

Table 1: Order Summary

Product category	Pick zone	# orders (in %)	# storage locations (in %)
A	North	10.53	24.29
B	North	0.26	1.20
C	North	1.15	13.63
D	South	11.57	1.27
E	South	1.32	2.50
F	North	48.92	34.22
G	South	5.53	6.59
H	South	19.71	14.19
I	South	0.08	1.10
J	South	0.16	0.21
K	North	0.76	0.81

The warehouse used for the simulation experiments has the following properties:

- Order picking is performed manually using a picking vehicle with a capacity of four orders. Orders are batched on a first-come-first-served (FCFS) base. Orders from product categories assigned to northern locations cannot be in the same batch as orders from southern product categories.
- Each picking tour starts and ends at the depot in the southern part of the warehouse.
- Due to safety constraints, a maximum of two order pickers is allowed in each subaisle of the southern zone and a single order picker in the smaller subaisles of the northern order picking zone.
- A sort-while-pick strategy is used, maintaining order integrity, so that no downstream sorting is required. Only consolidation of orders from different zones is required after picking.
- Setup times are approximated by an empirical distribution and assumed to be proportional to the number of pick rounds.
- Travel speed is approximated by a Weibull distribution with scale parameter 0.882 and shape parameter 2.29.
- Search and pick times depend on the product category. Times are much larger in case of heavy products compared to the regular products.

4. EXPERIMENTAL DESIGN

The objective of this research is to reduce the order picking time, which results in a more efficient order picking process, by simulating and analysing combinations of storage location assignment and routing policies in a narrow-aisle multi-level warehouse.

Table 2 provides an overview of the three factors and their associated factor levels that will be simulated in this study. The currently applied storage and routing policies are shown in italic and will be used as benchmark to evaluate the proposed policies. In order to generalise the results of the simulation to different order and picker levels, a third 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 using RSMIN, 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.

Table 2: Experimental Factor Setting (Currently Applied Storage and Routing Factor Levels *in Italic*)

Factor	# Levels	Factor levels
Demand	3	8 pickers (300 orders) 10 pickers (375 orders) 12 pickers (450 orders)
Storage	5	random within-aisle 2D perimeter 2D *across-aisle 3D* perimeter 3D
Routing	3	*return* traversal midpoint

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 3D across-aisle storage location assignment policy, three policies that are commonly used in studies considering low-level order picking systems are evaluated: random storage, two dimensional (2D) within-aisle (i.e. all items in a pick aisle belong to the same class), and 2D perimeter storage (i.e. storage classes are located around the periphery of the warehouse block). These 2D policies assume racks consisting of a single storage class. Additionally, a 3D perimeter storage location assignment policy is analysed: storage classes are located around the periphery of the warehouse block. Different from the 2D perimeter policy, multiple storage classes can be assigned to different levels of a single storage rack, particularly, storage classes are diagonally distributed within each aisle, as shown in Figure 2: the storage racks are shown horizontally, while the different levels of each rack are illustrated vertically.

A	B	B	C	C	C	C	C	C	B	B	A
A	B	B	C	C	C	C	C	C	B	B	A
A	B	B	C	C	C	C	C	C	B	B	A
A	B	B	C	C	C	C	C	C	B	B	A
A	B	B	C	C	C	C	C	C	B	B	A
A	B	B	C	C	C	C	C	C	B	B	A

2D Perimeter

C	C	C	C	C	C	C	C	C	C	C	C
B	C	C	C	C	C	C	C	C	C	C	B
B	B	C	C	C	C	C	C	C	C	B	B
A	B	B	B	C	C	C	C	B	B	B	A
A	A	B	B	B	C	C	B	B	B	A	A
A	A	A	B	B	B	B	B	B	A	A	A

3D Perimeter

Figure 2: Perimeter Assignment of Storage Classes within each Pick Aisle

Routes are currently constructed based on the 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. In addition to return routing, the effects of traversal and midpoint routing policies in the middle warehouse block of the northern zone are analysed. As other warehouse blocks are connected to a single cross-aisle, routing is limited to returning to this cross-aisle.

To summarise, the simulation experiment consists of 45 factor level combinations (i.e. three demand levels × five storage levels × three routing levels). The factorial setting results in a 3×5×3 full factorial design. 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 order lines in a pick round. Both setup time and search and pick time are assumed to be independent of the storage and routing policy.

5. RESULTS AND DISCUSSION

This sections analyses and discusses the results of the simulation experiments. The simulation model was built in ARENA. Section 5.1 presents the results of the ANOVA test. The interaction effect of storage location assignment and routing is analysed and explained in Section 5.2 using post hoc tests. Managerial implications are provided in Section 5.3.

5.1. ANOVA Results

In order to get a first insight into the results of the simulation experiments, the policy combinations of storage location assignment and routing are statistically analysed with respect to the travel time, waiting time and total order picking time. In accordance with Petersen and Schmenner (1999) and Van Gils et al. (2016), the results of the simulation experiments are evaluated by a full factorial ANOVA to analyse which factors impact travel and waiting time. Moreover, the ANOVA tests whether the interaction of storage and routing decision policies significantly influences the order picking time. The assumptions under which the ANOVA *F* statistic is reliable, are normally distributed observations, homogeneity of variance, as well as independent observations. When group sizes are equal, the *F* statistic is quite robust to violations of normality (Cohen et al., 2011). As the experimental design is balanced and each factor level combination is tested for thirty replications to reduce the stochastic effect resulting from the random generation of orders, normality can be assumed. The homogeneity assumption is violated in the experiments, resulting in an increased type I error rate. The Greenhouse-Geisser (*G-G*) adjustment is the most conservative correction to compensate for the violation in homogeneity. To compensate for the increased error rate, the degrees of freedom in the *F*-test are reduced in accordance with *G-G* (Geisser et al. 1958). In order to ensure the last ANOVA assumption (i.e. independency), the simulation results are analysed by a mixed-model ANOVA (Cohen et al. 2011). Independency is violated as each combination of storage and routing policy is tested on the same randomly generated list of customer orders to stress the effects of the policy decisions. Consequently, the simulation results are not independent and a mixed-model ANOVA with storage and routing as within-subjects factors is required to analyse the main and interaction effects of the policy decisions.

Table 3: 3×5×3 Mixed-Model ANOVA on Travel Time with Storage (*S*) and Routing (*R*) as Within-Subjects Factors and Demand (*D*) as Between-Subjects Factor

Factors	*SS* ($\times 10^9$)	*df*	*F*	Sign.
D	1,001.16	2.0	147.81	0.000
S	88.30	3.4	1,052.07	0.000
R	679.03	1.4	4,515.15	0.000
D×S	1.80	6.9	10.75	0.000
D×R	15.32	2.8	50.94	0.000
S×R	13.34	6.7	100.58	0.000
D×S×R	0.40	13.5	1.50	0.109
Betw. subj.	294.63	87.0		
Within S	7.30	299.4		
Within R	13.08	122.1		
Total	2,114.36	545.3		

The results of the full factorial ANOVA are presented in Table 3, Table 4, and Table 5 showing the importance of each experimental factor, as well as the interaction effect among the factors with regard to travel time, waiting time and total order picking time, respectively. The first columns show the sum of squares (*SS*) and *G-G* adjusted degrees of freedom (*df*) of the main and interaction effects. The last two columns are devoted to the *F* statistic and *p*-value for testing the statistical significance of the demand factor, storage factor, routing factor, and the interaction effects among the three factors.

Table 4: 3×5×3 Mixed-Model ANOVA on Waiting Time with Storage (*S*) and Routing (*R*) as Within-Subjects Factors and Demand (*D*) as Between-Subjects Factor

Factors	*SS* ($\times10^9$)	*df*	*F*	Sign.
D	36.65	2.0	263.91	0.000
S	56.94	2.0	1,222.32	0.000
R	10.47	1.7	837.38	0.000
D×S	11.79	4.0	126.51	0.000
D×R	1.50	3.3	60.08	0.000
S×R	3.20	5.0	114.83	0.000
D×S×R	0.56	10.1	10.13	0.000
Betw. subj.	6.04	87.0		
Within S	4.05	173.1		
Within R	1.09	144.9		
Total	132.29	433.1		

Table 5: 3×5×3 Mixed-Model ANOVA on Total Order Picking Time with Storage (*S*) and Routing (*R*) as Within-Subjects Factors and Demand (*D*) as Between-Subjects Factor

Factors	*SS* ($\times10^9$)	*df*	*F*	Sign.
D	2,971.98	2.0	213.64	0.000
S	94.30	2.9	600.38	0.000
R	606.65	1.6	3,943.92	0.000
D×S	10.72	5.7	34.13	0.000
D×R	13.90	3.1	45.19	0.000
S×R	11.43	5.5	54.15	0.000
D×S×R	0.59	10.9	1.41	0.167
Betw. subj.	604.92	87.0		
Within S	13.67	249.8		
Within R	13.38	136.4		
Total	4,340.55	504.9		

In accordance with previous academic literature (Petersen and Schmenner 1999; Van Gils et al. 2016), our results indicate that the main effect of storage location assignment and picker routing, as well as the interaction effect of storage location assignment and picker routing are statistically significant regarding travel time (see Table 3). Furthermore, Table 4 shows that both storage location assignment and the picker routing policy decisions statistically significantly influences waiting time of order pickers. This means that there is a significant difference in average waiting time of order pickers between the five storage location assignment policies, as well as between the three routing policies. In other words, the decision on which storage and which routing policy to use in order picking operations does influence the waiting time of order pickers and resulting total order picking time, as shown in Table 5. These results show that either travel distance or travel time measures are insufficient to evaluate the efficiency of storage and routing policies.

In addition to the main effects of storage and routing, the joint effect of storage location assignment and picker routing is statistically significantly impacting travel time, waiting time and total order picking time. This implicates that warehouse managers should consider decisions on storage and routing simultaneously in order to minimise order picking time.

5.2. Post Hoc Test Results

While the ANOVA results show that storage and routing are related, 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 levels of the routing factor for each storage factor are analysed using a Bonferroni t-test. The Bonferroni method seems to be the most robust technique in terms of power and control of the Type I error rate for evaluating multiple hypotheses (Field, 2013).

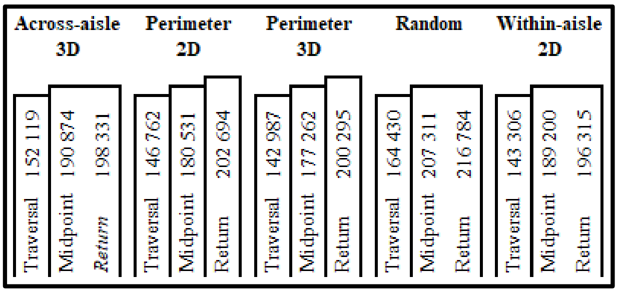

Figure 3: Multiple Bonferroni t-Test (Familywise Error Rate = 0.01) for Routing Policies by Storage Policies on Average Travel Time (in Seconds)

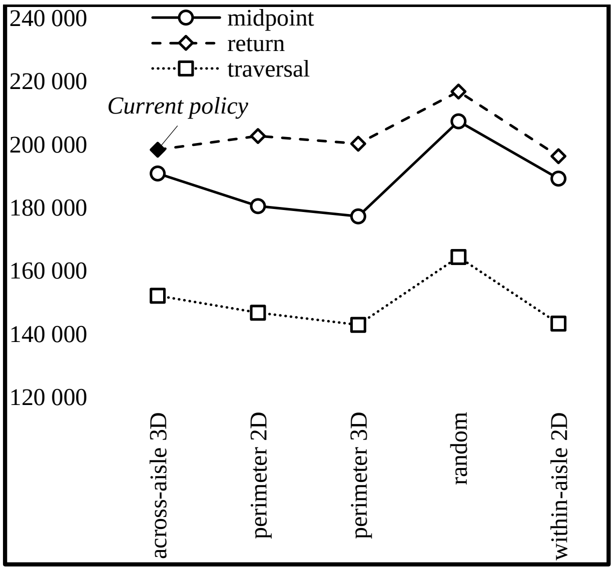

Figure 4: Average Travel Time (in Seconds) for each Combination of Storage, and Routing Policy

Figure 3 shows the results of the post hoc test on average travel time. If two routing policies are listed in the same subset, differences fail to be statistically significant. Minor differences exist in the composition of subsets

between the different storage policies. With respect to the travel time of order pickers, the traversal routing policy outperforms return and midpoint routing policies in combination with all storage location assignment policies. The traversal routing policy is located in a separate subset in combination with all storage location assignment policies, while results of the post hoc test indicate that the travel time difference between return and midpoint routing policies is only statistically significant in combination with the 2D and 3D perimeter storage policies. 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 the return routing method. The interaction plot of Figure 4 illustrates the decreased travel time by combining perimeter storage and midpoint routing. Furthermore, the interaction plot shows that on average the combination of traversal routing with either 3D perimeter or 2D within-aisle storage classes yields the minimum travel time.
Post hoc test results on average waiting time are illustrated in Figure 5. The creation of different subsets for the storage policies explain why the storage and routing planning problems are related with respect to average waiting time. The midpoint routing policy outperforms other routing policies in combination with all other storage location assignment policies. Remember that the routing methods only differ in the middle warehouse block of the northern zone. The midpoint routing policy allows two order pickers entering simultaneously in each aisle of the middle warehouse block: 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.
Figure 6 illustrates that the benefits resulting from two-side entering (i.e. midpoint routing) increase in combination with perimeter storage policies and random storage. 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 single pick aisle, respectively. Consequently, the combination of midpoint routing and either perimeter or random 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 or random storage cause additional blocking within a pick aisle (i.e. traversal routing) or the number of pickers that is 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.

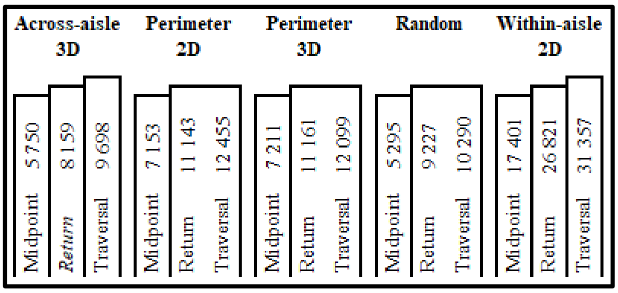

Figure 5: Multiple Bonferroni t-Test (Familywise Error Rate = 0.01) for Routing Policies by Storage Policies on Average Waiting Time (in Seconds)

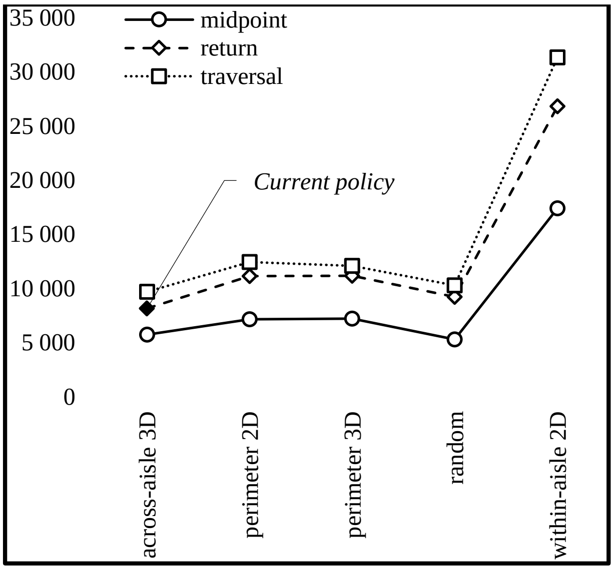

Figure 6: Average Waiting Time (in Seconds) for each Combination of Storage, and Routing Policy

The results of the post hoc test with respect to the average total order picking time, including setup time, search and pick time, travel time, and waiting time are illustrated in Figure 7. Analysing perimeter storage classes, three subsets of routing policies are created, while combining either midpoint or return routing with other storage policies does not result in statistically significant different order picking times, despite the significant lower waiting times resulting from midpoint routing.
While the interaction plot illustrating picker traveling shows that on average the combination of traversal routing with either 3D perimeter or 2D within-aisle storage classes yields the minimum travel time, Figure 8 shows that traversal routing in combination with 2D within-aisle storage classes results in a substantially higher total order picking time compared to the traversal routing combined with 3D perimeter storage. This result supports the ANOVA results that warehouse managers may choose an inefficient storage and routing policy when only travel distance or travel time are considered

as these performance measures ignore the strong increase in waiting time in case of within-aisle storage classes. Finally, the interaction plots show that the difference between 2D and 3D storage locations is rather small with respect to all three performance measures. More structured experiments, in which all storage assignment policies are tested on a 2D as well as a 3D factor level, are required to generalise and explain this finding.

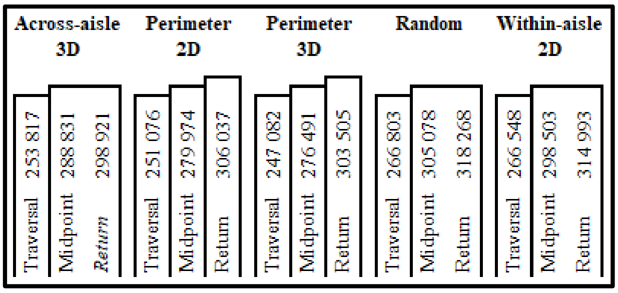

Figure 7: Multiple Bonferroni t-Test (Familywise Error Rate = 0.01) for Routing Policies by Storage Policies on Average Total Order Picking Time (in Seconds)

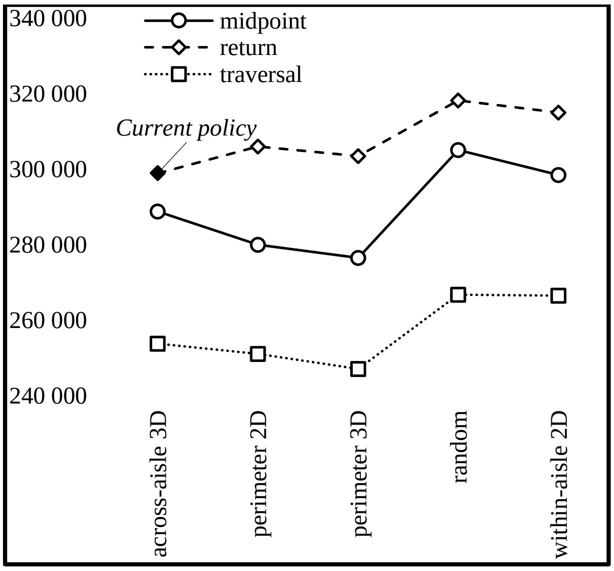

Figure 8: Average Order Picking Time (in Seconds) for each Combination of Storage, and Routing Policy

To summarise, traversal routes results in the shortest average travel times, while order pickers are blocked longer in case of traversal routes. Midpoint routes yield the shortest waiting times, but travel times increase significantly compared to traversal routes. With respect to the average total order picking time, traversal routes outperforms midpoint routes as travel time accounts for a larger part of the total order picking time.

5.3. Managerial Implications

The results of the simulation experiments show the importance of combining storage and routing decisions in order to manage order picking activities efficiently. The benchmark policy combination corresponds to the current applied policy combination to manager order picking operations in the warehouse: 3D across-aisle storage location assignment and return routing, limited to a single order picker per aisle. The results of the benchmark and the best performing policy combination are summarised in Table 6.

Table 6: Total Order Picking Time for Benchmark and Best Policy Combination

	Total order picking time (in s)
Benchmark: across-aisle 3D – return	
High demand	359,241
Regular demand	296,937
Low demand	240,583
Average	298,921
Best policy combination: perimeter 3D – traversal	
High demand	298,292
Regular demand	245,083
Low demand	197,870
Average	247,082
Reduction (in %)	
High demand	17.0
Regular demand	17.5
Low demand	17.8
Average	17.3

The benchmark results in an average total order picking time of 298,921 seconds, including setup time, search and pick time, travel time and waiting time. The simulation experiments show that the 3D perimeter storage policy in combination with traversal routing yields a substantially reduced order picking time, in shifts with high, regular, as well as low demand. On average, the order picking process can be performed 17.3% more efficiently by reconsidering the storage location assignment and routing policy. The average reduced order picking time corresponds to a reduction of 5.4 full time equivalents per day $\left(\frac{17.3\% \times 298{,}921\ \text{s}}{28{,}800\ \text{s}} \times 3\right)$, assuming three 8-hour shifts (28,800 s) per day. As the simulation experiments have focused on operational order picking planning problems only, the proposed combinations are rather easy to implement and result in substantial performance benefits.

6. CONCLUSIONS

Serving e-commerce markets forces warehouses to handle a growing number of orders in shorter time windows. 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 in order to optimise order picking operations.
In this paper, the joint effect of the two main operational order picking planning problems (i.e. storage location assignment and picker routing) on order picking time, including travel time and wait time, is analysed and explained for the first time. The simulation results and statistical analysis provides policy combinations that help practitioners to improve the overall order picking performance under varying order picker levels and order levels. The traversal routing policy and 3D perimeter

storage classes can be easily implemented and immediately result in performance increases of up to 17%.

Moreover, the real-life case study shows the value of combining storage and routing decisions in practice. By considering a wide range of real-life characteristics, such as picker blocking, high-level storage locations, and product weight restrictions, the results are highly relevant to practice and largely unexplored in literature combining order picking planning problems. However, we should note that the simulation experiments are based on a single case study. In order to generalise the conclusions of this study, storage location assignment policies and routing policies should be tested on traditional rectangular picking layouts (i.e. order picking areas consisting of parallel pick aisles and one or more straight cross aisles). Moreover, the effect of 3D storage location assignment policies, compared to 2D storage policies, will be valuable knowledge that can be used to design efficient order picking systems.

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