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Abstract

This study illustrates the relevance and importance of incorporating safety constraints, picker blocking, and vertical travel due to high level storage locations when developing order picking systems (i.e., deciding on zoning, storage, batching, and routing). Results show that safety constraints induce wait times, and cause additional traveling, picker blocking and consequent wait time can be minimized at the expense of additional setup time, and slow vertical travel results in additional travel and wait times. Consequently, ignoring these real-life features causes substantial performance inefficiencies. Robust policies for organizing operations efficiently are provided, even if the system is subject to real-life features.

Keywords: picker zoning, storage location assignment, order batching, picker routing, warehouse management

1. Introduction

As industrial land is expensive, especially in Western Europe, the area dedicated for storing stock keeping units (SKUs) by warehouses is limited. As customers expect unique products (a wide assortment of SKUs), more storage capacity is required. Moreover, Western European countries are characterized by high labor costs, making productivity improvements especially beneficial. To deal with these market conditions, warehouses typically consist of narrow aisle, high level order picking systems to store SKUs densely, while still allowing individual access to retrieve them rapidly to fill customer orders. Narrow aisles and high level storage locations increase the storage capacity per square meter. These order picking systems allow a large number of SKUs to be stored in a small area and reduce unproductive travel of narrow aisle order pick trucks compared to, for example, wide aisle order picking systems. However, narrow aisles cause wait times due to picker blocking, especially when multiple order pickers retrieve products in the same area. Moreover, multiple order pickers working in a small area increases the risk of accidents in the warehouse (De Koster et al., 2011; Mowrey and Parikh, 2014; Venkitasubramony and Adil, 2017).

Although pick robots are upcoming because of their efficiency (Azadeh et al., 2018), manual picker-to-parts order picking systems are still predominantly used in practice (De Koster et al., 2007; Marchet et al., 2015), especially in for example spare parts warehouses; human order pickers can handle unexpected changes in the process, are flexible with respect to capacity, and can retrieve a large variety of SKUs in terms of size and weight, which is particularly applicable to spare parts (Marchet et al., 2015; Van Gils et al., 2017). Moreover, the high investment costs (Lamballais et al., 2017) and the risk of interrupting order picking operations during the implementation are additional barriers for using pick robots (Marchet et al., 2015). Though these barriers may fade in the next decades enabling (spare parts) warehouses to consider the implementation of robotized order picking systems, this study supports managers to cope with market developments such as increased customer expectations, expensive industrial land and high labor costs immediately.

Managing order picking operations effectively and efficiently is identified as an important but complex planning process. While order picking costs account for the majority of all warehouse operations costs (Dijkstra and Roodbergen, 2017; Parikh and Meller, 2008), the performance of the order picking process drives the customer service level. A wide range of planning problems need to be solved to manage order picking processes efficiently. Dependencies among order picking planning problems further increase the complexity of managing order picking operations (Altarazi and Ammouri, 2018; Van Gils et al., 2018b). At an operational level, picker zoning, storage location assignment, order batching, and picker routing are the main drivers of order picking performance. Combining decisions on these planning problems is essential for designing an effective and efficient order picking process (Van Gils et al., 2018b).

Although many studies address individual order picking planning problems (De Koster et al., 2007) and combinations of multiple planning problems (Dijkstra and Roodbergen, 2017; Petersen and Aase, 2004; Van Gils et al., 2016, 2018b), managers often do not implement findings from academic research and at the same time researchers rarely integrate real-life features while developing new planning models (Carter, 2008). This study flew in the face with conventional assumptions in academic literature: a single picker or pick aisles wide enough to overtake, using travel distance of travel time as single performance metric, and low level storage systems thereby ignoring the effect of a very slow lifting speed compared to horizontal travel (e.g., Altarazi and Ammouri (2018); Petersen and Aase (2004); Van Gils et al. (2018b)). Several picker zoning, storage location assignment, order batching, and picker routing policies (i.e., solution methods) are simulated to investigate relationships among these planning problems under the constraints of safety rules, picker blocking, and high level storage locations, with the aim of finding robust and efficient order picking policy combinations.

The research methodology of this study is similar to Van Gils et al. (2018b), who investigate the same operational planning problems in wide aisle order picking systems, thereby ignoring real-life features. However, this study significantly differs as including the real-life features changes the nature of the problem, resulting in substantially different results. Instead of comparing our study repeatedly throughout the paper with Van Gils et al. (2018b) and other studies simulating order picking policies that ignore real-life features (e.g., Petersen and Aase (2004); Roodbergen et al. (2015)), we refer to wide aisle systems in general to compare our study with throughout the paper. The problem context of this study is inspired by a real-life B2B spare parts warehouse (Van Gils et al., 2018a). The research methodology of empirically-driven simulation is relatively new in a warehousing context (e.g., Altarazi and Ammouri (2018); Chackelson et al. (2013)).

The main contributions of this study, which illustrate the main differences with wide aisle order picking systems, are as follows. First, existing picker zoning, storage location assignment, order batching, and picker routing policies that are suitable for wide aisle picking systems are adapted to manage real-life features in narrow aisle systems (i.e., safety constraints, picker blocking, and high level storage locations). Second, the simulation results and statistical analyses give evidence on how and why picker zoning, storage location assignment, order batching, and picker routing are related with respect to travel time and picker blocking (instead of travel distance that is generally used in wide aisle systems). The relations are analyzed and explained using the constraints and consequences of the real-life features. Third, the empirical study illustrates the relevance and importance of incorporating real-life features while planning order picking operations and provides insights into the negative effects on performance if existing real-life features are ignored. Fourth, robust and efficient policy combinations of the four main order picking planning problems are identified under various practical situations. Results of wide aisle picking systems are strongly biased when picking systems are subject to the considered real-life features. The provided policies can be used by warehouse managers to improve overall order picking performance and to support new market developments.

The remainder of the paper is organized as follows. Section 2 provides the state-of-the-art and formulates research hypotheses on how order picking planning problems are related with respect to travel and picker blocking in a manual order picking system. The methodology to analyze the relationship among the order picking planning problems is described in Section 3. Section 4 provides empirical findings. Section 5 discusses implications of this study for researchers as well as for practitioners; the importance of incorporating real-life features is illustrated, and robust and efficient policy combinations are provided. Finally, Section 6 concludes and suggests future research directions.

2. Literature review and hypotheses

The recent literature review of Van Gils et al. (2018c) shows the importance of combining order picking planning problems while designing manual order picking systems, whereas planning problems of robotized picking systems are mainly optimized without addressing the relation between planning problems (Azadeh et al., 2018; Boysen et al., 2018). In this section, we review and develop the relevant constructs and theories, focusing on real-life features in manual order picking operations (Section 2.1) and formulate research hypotheses on the relationships among the operational order picking planning problems subject to the constraints of the real-life features (Section 2.2).

2.1. Real-life features in order picking operations

Although many studies have optimized a single planning problem or a combination of order picking planning problems, they have not sufficiently considered real-life features when optimizing order picking planning problems (Van Gils et al., 2018c). In this paper, real-life features are defined as characteristics (e.g., high level storage locations and varying SKUs in terms of size and weight), constraints (e.g., safety and precedence constraints), and conditions (e.g., picker blocking and human factors) that have a substantial impact on the planning and performance of order picking systems in practice. Based on numerous warehouse visits by the authors in the context of a valorization project on revealing the needs and challenges of logistical companies in Limburg (Belgium), multiple interviews with warehouse managers and the specific case of a B2B spare parts warehouse (see Section 3.2), the effects of safety constraints, picker blocking, and high level storage locations are expected to be the most essential and relevant factors to include in order picking policies. Safety constraints, picker blocking, and high-level storage locations impact the nature of the problem, which is expected to result in substantially different results when these features are ignored. Literature incorporating each of these three real-life features is discussed below.

Safety constraints. Despite the large number of accidents that happen in warehouses (De Koster et al., 2011), safety constraints are not considered sufficiently when optimizing order picking operations. Safety rules, such as prohibiting truck backing to avoid that retrieved products fall on the picker, ensure the safety of individual order pickers (Chabot et al., 2018). However, time pressure is high and pick trucks work in close proximity, resulting in an enhanced risk of accidents involving multiple order pickers (De Koster et al., 2011). Traffic rules, such as limiting the number of pickers within aisles, imposing one-way traffic directions within aisles, and prohibiting vehicle turns, prevent routes from crossing which reduces the risk of accidents (Çelik and Süral, 2016).

Picker blocking. Multiple order pickers, who operate concurrently in the same order picking area inevitably cause wait times as pickers can block each other when picking in the same region of the order picking system (Pan and Wu, 2012). Picker blocking induces idle time of order pickers, increasing the total order picking time (Parikh and Meller, 2008, 2009). Areas storing fast moving SKUs, which are introduced to reduce travel, are particularly subject to substantial wait times due to picker blocking. Picker blocking occurs when a picker cannot reach a storage rack because another picker is retrieving items at that storage rack (i.e., storage-rack blocking), or when a picker cannot overtake in an aisle (i.e., within-aisle or in-the-aisle blocking). The latter is caused by narrow pick aisles, whereas storage-rack blocking can occur in both wide aisle and narrow aisle order picking systems (Mowrey and Parikh, 2014). Traffic rules to increase safety, such as limiting the number of pickers within aisles, can induce additional blocking in cross aisles (i.e., aisle-entrance blocking): pickers should wait in the cross aisle before entering the pick aisle if the maximum allowable number of pickers has already entered the pick aisle (Hong et al., 2012).

High level storage systems. Storage racks in high level storage systems consist of multiple levels, storing multiple SKUs in a single storage rack section, in contrast to low level storage systems (single level storage rack sections). In addition to horizontal travel, high level storage systems require order pickers to travel vertically to pick products from storage locations at higher levels (i.e., pick truck lifting) (Pan et al., 2014). The footprint of a storage system (i.e., the number of aisles and aisle length) strongly impacts horizontal travel time, whereas the amount of vertical travel is defined by the number of levels in a storage system (Thomas and Meller, 2015). The Chebychev distance metric measures vertical travel in narrow aisles: the high level pick truck can move both horizontally and vertically making within-aisle travel time equal to the maximum of the horizontal travel time and vertical travel time (Clark and Meller, 2013). In case of using higher levels as storage and replenishment locations and lower levels (i.e., floor locations) for picking, the impact of high level storage systems on travel time is negligible: vertical travel is limited to replenish a pick location, while picking is performed on floor locations requiring only horizontal travel. The high level storage system under consideration uses all locations as pick locations. Bulk storage locations are assumed to be in a separate system (e.g., automated storage and retrieval system).

2.2. Combining storage, batching, zoning, and routing planning problems

Table 1 describes the four operational planning problems that should be solved to design efficient order picking systems. Although layout and other strategic decisions may have a substantial impact on the performance (Pohl et al., 2009), these strategic planning problems are fixed in the short term. The total

	description
zoning	Zoning policies decide on how to split the order picking area into zones and determine the location of the order pick zones. Each order picker is assigned to a single zone. In narrow aisle high level picking systems, parallel zoning is more applicable than sequential zoning.
storage	Storage location assignment policies describe rules to determine the allocation of SKUs to storage locations. Storage location assignment defines the distribution of fast moving SKUs across the order picking area.
batching	Order batching policies define rules on combining customer orders in a single pick round.
routing	Routing policies define the sequence of storage locations that should be visited in each pick round to retrieve all items on a pick list.

Table 1: Definition of the four main order picking planning problems (Van Gils et al., 2018c).

order pick time, which consists of setup time for preparing batches, pick and search time at each visited location, travel time and wait time due to picker blocking, is used as surrogate for order picking performance in this paper. As the first two time components have proven to be of minor importance when evaluating combinations of planning problems in wide aisle systems (Van Gils et al., 2018b) and the considered real-life features would have a minor impact on setup and pick and search time, these components are not included in the research hypotheses.

The recent simulation study of Van Gils et al. (2018b) shows strong relationships among operational planning problems with respect to mainly horizontal travel distance in wide aisle order picking systems, thereby ignoring the real-life features. The question remains to what extent these relationships have an effect on the order picking performance of picking systems that are subject to crucial real-life features, such as narrow aisle order picking systems. Compared to wide aisle systems, travel times are expected to increase as a result of the real-life features and additional wait times due to picker blocking should be taken into account. This section reviews relevant theories on interactions among operational order picking planning problems in wide aisle order picking systems and transforms existing knowledge to narrow aisle systems taking the real-life features into account. To structure the section, research hypotheses on the combined effect are formulated, sorted from the planning problem combination with the longest time horizon to the shortest time horizon of the resulting decisions.

Table 2 summarizes state-of-the-art publications on combining operational order picking planning problems and examines to what extent these articles include the real-life features that are studied in this paper. Studies simulating combinations of order picking planning problems and analyzing the relations are included, as these studies are most closely related to our paper. While ignoring safety constraints, picker blocking, and high level storage locations, most papers show significant benefits in terms of travel by combining order picking planning problems. However, there is clearly a need to include real-life features in such studies; the empty cells in Table 2 are dominant in the real-life features columns, especially in the upper part of the table (note that papers are included in chronological order). Recent papers are starting to include additional real-life features, but to a limited extent. This study goes beyond the current state-of-the-art by analyzing and explaining relationships among the four main operational order picking planning problems, thereby accounting for the three crucial real-life features.

	planning problems						real-life features		
	zoning-storage	zoning-batching	zoning-routing	storage-batching	storage-routing	batching-routing	safety constraints	picker blocking	high level storage locations
Petersen and Schmenner (1999)					•				
Petersen (2002)	•								
Petersen and Aase (2004)				•	•	•			
Hsieh and Tsai (2006)				•					
Ho and Tseng (2006)				•	○	○			
Manzini et al. (2007)					•				
Ho et al. (2008)				•	○	○			
Yu and De Koster (2009)		•							
Chen et al. (2010)				•	•	•			
Theys et al. (2010)						•			
Pan and Wu (2012)					•		*	*	
Chackelson et al. (2013)				○	○	•			
Pan et al. (2014)					•				*
Shqair et al. (2014)					•				
Chen et al. (2017)						•		*	
Dijkstra and Roodbergen (2017)					•				
Franzke et al. (2017)					•			*	
Quader and Castillo-Villar (2018)					○				
Van Gils et al. (2018b)	•	•	•	•	•	•			

Table 2: State-of-the-art publications (• significant relationship; ○ no significant relationship; * real-life feature included).

To formulate our research hypotheses on the relationship among order picking planning problems, we first investigate the main effect of each planning problem on order picking efficiency. Table 3 provides a summary of the main effects when evolving from a bad policy for a particular planning problem to a more efficient policy in terms of travel and in terms of picker blocking. Dividing the order picking area into zones results in smaller covered areas of order pickers during a pick round and consequently lead to shorter travel times: a picker can only travel in a limited number of aisles during each pick round (De Koster et al., 2012). Moreover, wait times due to picker blocking decrease as zoning limits the order picking area covered by pickers in a pick round (De Koster et al., 2012). Storage location assignment policies aim to reduce travel by concentrating fast moving SKUs in a small order picking area, resulting in a large pick density in certain areas and thus increasing the risk of picker blocking compared to randomly assigning SKUs to

	travel	picker blocking
zoning	↘	↘
storage	↘	↗
batching	↘	↘
routing	↘	↗

Table 3: Main effect of order picking planning problems.

storage locations (Franzke et al., 2017). Order batching aims to limit travel by combining similar orders in a pick round. Efficient batches consist of closely located storage locations, thereby reducing picker blocking as the covered area in a pick round is limited (Hong et al., 2012). Routing policies aim to reduce travel by sequencing the order lines (and resulting storage locations) within each batch (Theys et al., 2010). While sequences may be optimal with respect to travel, these routing policies are subject to stricter traffic rules to limit the chance of crossing routes of different order pickers. Stricter traffic rules, expressed as a smaller allowable number of pickers within an aisle, result in higher wait times (Van Gils et al., 2018a). Based on the main effects, research hypotheses are formulated, stating whether or not a planning problem combination is expected to be related as well as hypothesizing the expected direction of the relation (i.e., increasing or decreasing marginal effects). Research hypotheses are formulated with respect to travel (thereby excluding setup time and pick time at storage locations) and picker blocking. The travel hypotheses formulate the expected combined effect of planning problems in a new context by transforming existing knowledge in wide aisle picking systems to narrow aisle picking systems, thereby accounting for safety constraints and high level storage locations. Hypotheses stating the combined effect of planning problems on picker blocking have not been investigated before.

Zoning-storage relation. If the real-life features of safety constraints, picker blocking, and high level storage systems are ignored, the relationship between the number of zones and storage location assignment is significant with respect to travel distance (or time): order pickers cover smaller areas if there are more pick zones and if turnover-based storage location assignment policies are adopted (Petersen, 2002; Van Gils et al., 2018b). As both planning problems have a positive effect on travel, we expect fewer benefits if picker zoning and storage location assignment are combined (see Hypothesis 1a). The number of zones is also expected to significantly influence the efficiency of the storage location assignment policies with respect to wait times. Picker zoning policies divide pickers across the order picking area by assigning them to a single pick zone, thereby reducing the possibility of picker blocking, whereas storage location assignment policies increase the pick density in a small area, thereby increasing the probability of picker blocking. As picker zoning reduces the number of pickers in each zone, we propose that the negative picker blocking effects of turnover-based storage location assignment policies are smaller when the order picking area is divided into pick zones as stated in Hypothesis 1b.

Hypothesis 1a *The marginal travel benefits from turnover-based storage location assignment policies decrease when the order picking area is divided into pick zones.*

Hypothesis 1b *The marginal picker blocking effect from turnover-based storage location assignment policies decreases when the order picking area is divided into pick zones.*

Zoning-batching relation. As picker zoning and order batching both aim to increase the pick density in small areas, the marginal effect of batching policies on travel decreases significantly with more pick zones in wide aisle systems (Yu and De Koster, 2009; Van Gils et al., 2018b). Increasing the number of zones and consequently decreasing the zone size, increases the probability of visiting all aisles within a zone during a pick round, thereby reducing the negative travel effects of traffic rules. Moreover, incorporating the effect of traffic rules (e.g., one-way travel) while creating batches may limit the negative effects of these safety constraints on travel. As both planning problems have a positive effect on travel and both limit the negative effects of traffic rules on travel, the joint effect of picker zoning and order batching on travel is expected to be significant under the constraints of the real-life features (Hypothesis 2a). Moreover, as both zoning and batching reduce picker blocking by decreasing the area covered during a pick round, we expect that the combined effect of planning problems on wait time is significant as stated in Hypothesis 2b.

Hypothesis 2a *The marginal travel benefits from efficient batching policies decrease when the order picking area is divided into pick zones.*

Hypothesis 2b *The marginal picker blocking benefits from efficient batching policies decrease when the order picking area is divided into pick zones.*

Zoning-routing relation. Only one study (Van Gils et al., 2018b) has investigated the combined effect of picker zoning and routing: both decisions jointly influence travel distance in wide aisle order picking systems. More pick zones and consequently small zone sizes reduce the effect of routing policies on travel. The effect of routing policies depends on the traffic rules in narrow aisle order picking systems. Especially when pick densities are low (i.e., a small number of pick zones), the travel differences among the routing policies is expected to be much higher compared to small pick zones, indicating a strong relationship (see Hypothesis 3a). Moreover, picker zoning and routing may jointly affect picker blocking as stated in Hypothesis 3b:

routing policies cause picker blocking by the imposed traffic rules, while picker zoning reduces picker blocking by assigning pickers to dedicated order picking areas. The marginal picker blocking effect from efficient routing policies (subject to stricter traffic rules) is expected to decrease as picker zoning reduces the number of pickers in each zone.

Hypothesis 3a *The marginal travel benefits from efficient routing policies decrease when the order picking area is divided into pick zones.*

Hypothesis 3b *The marginal picker blocking effect from efficient routing policies decreases when the order picking area is divided into pick zones.*

Storage-batching relation. The joint effect of storage location assignment and order batching on travel is rather consistent in literature. The efficiency of batching policies increases when the rules for assigning SKUs to storage locations when creating batches are taken into account (Ho and Tseng, 2006; Ho et al., 2008; Hsieh and Tsai, 2006; Petersen and Aase, 2004; Van Gils et al., 2018b). Travel differences among storage location assignment policies are expected to be greater in high level storage systems (i.e., more fast moving SKUs in a small number of aisles causes more fast moving SKUs to be stored at higher locations) as vertical travel is typically very slow. Considerable travel benefits can be gained from efficient batching policies if vertical travel is limited, which is the case when fast moving SKUs are more evenly divided across the order picking area (see Hypothesis 4a). Furthermore, picker blocking may be significantly influenced by the combined storage-batching decision as well. Both planning problems aim to limit the covered area of a pick round. However, storage policies increase picker blocking as this small covering area is equal for all pickers (i.e., the locations that store fast moving SKUs), while batching policies may reduce wait times as the small covering areas can be different across pickers. Therefore, Hypothesis 4b states that the marginal picker blocking effect from efficient batching policies decreases when turnover-based storage location assignment policies assign fast moving SKUs to a small picking area.

Hypothesis 4a *The marginal travel benefits from efficient batching policies decrease when turnover-based storage location assignment policies assign fast moving SKUs to a small picking area.*

Hypothesis 4b *The marginal picker blocking effect from efficient batching policies decreases when turnover-based storage location assignment policies assign fast moving SKUs to a small picking area.*

Storage-routing relation. Storage location assignment and picker routing is by far the most intensively studied combination of planning problems. Besides studies simulating a limited number of storage and/or routing policies (Chackelson et al., 2013; Ho and Tseng, 2006; Ho et al., 2008; Quader and Castillo-Villar, 2018), the storage-routing combination is found to strongly affect travel in wide aisle order picking systems: taking information about the location of fast moving SKUs into account while determining the routing policy can significantly reduce travel (Dijkstra and Roodbergen, 2017; Manzini et al., 2007; Petersen and Schmenner, 1999; Petersen and Aase, 2004; Shqair et al., 2014; Van Gils et al., 2018b). In narrow aisle order picking systems, routing policies are revised to meet safety constraints (e.g., one-way travel in pick aisles and limited number of allowable pickers within aisles). By including aisle-entrance blocking and only allowing one order picker in each narrow aisle, the efficiency of storage and routing policy combinations is found to be strongly related by a single study, both in terms of travel and wait time. Pan et al. (2014) develop analytical models to evaluate the storage-routing relationship. These relationships are summarized in Hypotheses 5a and 5b.

Hypothesis 5a *The marginal travel benefits from efficient routing policies decrease when turnover-based storage location assignment policies assign fast moving SKUs to a small picking area.*

Hypothesis 5b *The marginal picker blocking effect from efficient routing policies increases when turnover-based storage location assignment policies assign fast moving SKUs to a small picking area.*

Batching-routing relation. The substantial effect of batching and routing on travel has been proven by integrating both planning problems instead of solving the batching and routing planning problems sequentially (Won and Olafson, 2005; Van Gils et al., 2018c). In wide aisle order picking systems, the length of the routes mainly define the performance of the created batches (Chackelson et al., 2013; Van Gils et al., 2018b). In narrow aisle order picking systems, this performance depends on the travel time, defined by the routing policy, as well as on the wait time, defined by the traffic rules (Chen et al., 2017). Travel time (both horizontal and vertical travel) and picker blocking are defined by the routing policy and traffic rules. As an efficient batching policy is used, the covered area of a pick round is small, reducing the travel benefits from efficient routing policies (see Hypothesis 6a). Furthermore, the marginal picker blocking effect from efficient routing policies is expected to decrease when the covered area of a pick round is limited by efficient batching policies in narrow aisle order picking systems (see Hypothesis 6b).

Hypothesis 6a *The marginal travel benefits from efficient routing policies decrease when the covered area of a pick round is limited by efficient batching policies.*

Hypothesis 6b *The marginal picker blocking effect from efficient routing policies decreases when the covered area of a pick round is limited by efficient batching policies.*

In summary, twelve research hypotheses are formulated of which six hypotheses transforming existing knowledge in a new context and six complete new research hypotheses. These hypotheses are used as theoretical ground to explain how and why order picking planning problems are related when real-life features play a crucial role.

3. Methodology for empirical study

We conducted an interaction analysis with simulation and comprehensive statistical tests to test our research hypotheses. Interactions are defined as the combined effect that multiple planning problems have on a performance goal (Van Gils et al., 2018b). An interaction analysis is considered to be especially useful if the time horizon of the resulting decisions is different (Van Gils et al., 2018c). Although picker zoning, storage location assignment, batching, and picker routing are all operational planning problems, the time horizons of the resulting decisions differ. Batches and routes are created multiple times per hour, while decisions on picker zoning and storage assignment have a longer time horizon.

This section outlines the research methodology used to achieve the objectives of this study. The simulation modeling approach is presented in Section 3.1. Sections 3.2 and 3.3 describe the business case and the operational measures. The experimental design and data generation are outlined in Sections 3.4 and 3.5. Section 3.6 describes the statistical analysis used to provide insights into the relationships among order picking planning problems.

3.1. Simulation model

Using simulation as modeling method allows to include the stochastic elements of order generation and assignment of SKUs to pick zones and storage locations. Although analytical-based modeling methods are faster and can provide accurate performance estimates (Schleyer and Gue, 2012), they are usually subject to assumptions that simplify the real system (Azadeh et al., 2018). Empirically-driven simulation, i.e., simulation studies based on real-life operations, have been frequently used to model and analyze order picking operations (e.g., Altarazi and Ammouri (2018), Chackelson et al. (2013), Dekker et al. (2004), and Petersen and Aase (2004)).

Simulation can accurately present the four order picking problems and easily incorporate the real-life features (Chen et al., 2010; Manzini et al., 2007). While Monte Carlo simulations are adequate for calculating travel distances in wide aisle order picking systems (Petersen and Aase, 2004), even in case of high level storage locations, including safety constraints and picker blocking require more comprehensive simulation models. Discrete-event simulation facilitates the modeling of a sequence of events in time, thereby allowing to take safety constraints and picker blocking into account. Results of the simulation are statistically analyzed to evaluate the policy decisions covered in the research hypotheses and assess the effect of real-life features on order picking performance. Simulation experiments allow us to include the necessary stochastic elements needed to generalize the results (i.e., unsystematic variation), while in the meantime controlling stochasticity when varying the operational policies of the four planning problems (i.e., systematic variation).

To generate customer orders, including a random number of order lines, Monte Carlo simulation is employed in Visual Studio using `C++` programming language. Monte Carlo simulation is also used to convert the order lists into pick lists, thereby accounting for the zoning, storage, batching, and routing policy. In this way, the computational intensive batching and routing policy are computed using `C++`, thereby benefiting from the high computational efficiency of `C++` compared to the lower computational efficiency of discrete-event simulation software. The created pick lists, representing batches of orders and sequences of locations to be visited in each batch, form the input of the discrete-event simulation model. The discrete-event simulation model, created using `Arena`, simulates the pick events over time. In this way waiting times due to picker blocking and safety constraints could be taken into account as the discrete-event simulation model is able to derive where each order picker is operating at each moment in time.

3.2. Case study

The problem context of this study is motivated by a real-life B2B spare parts warehouse located in Belgium. A preliminary study focused on the combined effect of storage location assignment and picker routing and was dedicated to the unconventional layout of the real-life spare parts warehouse (Van Gils et al., 2018a). The current study goes beyond this previous study by analyzing and explaining the relationship among the four main order picking planning problems in a general rectangular parallel aisle warehouse that is commonly used in research (Gue et al., 2012; Schleyer and Gue, 2012; Thomas and Meller, 2015). Narrow and parallel aisles are commonly used in practice as well, especially for distributing spare parts.

The layout under consideration comprises two warehouse blocks, each consisting of 16 pick aisles. There are 70 storage rack sections in each pick aisle, each with eight levels. The storage capacity equals $17,920$ SKUs. A single SKU can be assigned to each storage location. The layout is shown in Figure 1. The depot is marked with a D on the figure. Distance and time measures described in this and the next sections are based on the real-life case and are similar to measures used in other academic studies.

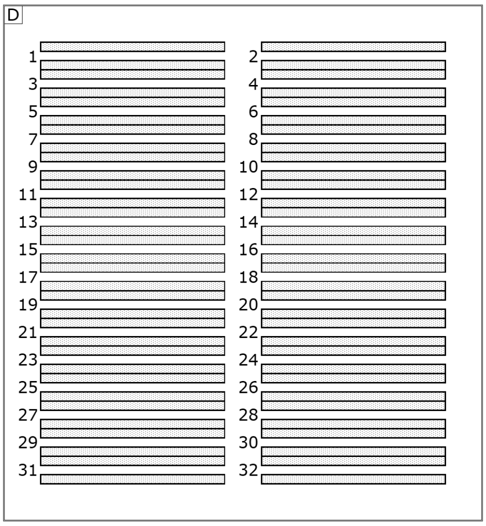


Figure 1: Warehouse layout.

3.3. Operational measures

The components of total order picking time (i.e., setup time, search and pick time, travel time, and wait time) are used to measure order picking efficiency (Chen et al., 2010). The setup time is directly proportional to the number of pick rounds and time for searching and picking is assumed to be proportional to the number of items to be picked at each storage location. Based on the observations of the real-life case, the setup time (i.e., collecting pallets and packaging material and printing a pick list) is fixed at 180 seconds and search and pick time are set to 15 seconds plus 1.5 seconds per item. The number of items per order line is approximated by a geometric distribution with a mean of five items. This is a reasonable number assuming B2B warehouses deal with larger order sizes than B2C warehouses. However, conclusions will be similar in a B2C context as the effect of the policy decisions of the planning problems on the time to setup a pick round as well as to search and pick items are assumed to be only minor.

Travel is measured by dividing the distance traveled by the travel speed of the high level pick trucks. Distance parameters are provided in Table 4. Travel in pick aisles is faster than in cross aisles because high level pick trucks are induction guided in the narrow lanes. However, when returning (i.e., turning around) in a pick aisle, an additional 'turn' time is included due to truck backing in and out the aisle. Order pickers can travel at a speed of 1.0 $\frac{m}{s}$ in the wide cross aisles compared to 1.5 $\frac{m}{s}$ in pick aisles. High level pick trucks have a vertical lifting speed of only 0.2 $\frac{m}{s}$. As high level storage systems are considered, both horizontal and vertical travel distances are included in the travel metric. The distance within aisles is calculated by the Chebychev scenario, where the pick truck can concurrently lift vertically and move horizontally. As a result, travel time within aisles equals the maximum of horizontal and vertical travel (Clark and Meller, 2013).

parameter	parameter value
depot location	single decentralized depot
number of blocks	2 blocks
number of cross aisles	3 cross aisles
number of pick aisles	16 pick aisles per block
number of storage racks	70 storage rack sections per pick aisle
number of levels	8 levels per storage rack
storage rack section length	1.3 m
storage rack section depth	0.9 m
storage rack section height	1.0 m
pick aisle width	1.5 m
cross aisle width	6.0 m

Table 4: Layout parameters of the order picking area.

Wait times are measured by accumulating within-aisle blocking, storage-rack blocking, and aisle-entrance blocking for each narrow pick aisle. Within-aisle blocking and storage-rack blocking only occur when multiple pickers are allowed in an aisle. Aisle-entrance blocking occurs when the maximum allowable number of order pickers is either travel or picking in an aisle and another picker attempts to enter this pick aisle. The main factors influencing the decision on the maximum allowable number of pickers in each pick aisle in practice are the aisle width, attitudes of warehouse managers towards safety, and the routing policy. Practitioners may allow more pickers per aisle in case of wider aisles as pickers can overtake. Therefore, blocking is assumed to be negligible in cross aisles, as these aisles are wide enough to overtake. Limiting the number of allowable pickers induces waiting times, thereby reducing order picking efficiency. On the other hand, reducing the number of pickers in an aisle decreases the risk of accidents. The maximum allowable number of pickers in each pick aisle depends on the routing policy and is discussed in Section 3.4.

The analysis and explanation of the relationship among order picking planning problems (i.e., Section 4) is based on the mean total travel time for picking all orders of a replication (i.e., travel) and the mean total wait time occurred when picking all orders of a replication (i.e., picker blocking) as it is important to understand the behavior of the order picking planning problems on each of the performance measures to explain a potential relation. Section 5 adds travel, picker blocking, and setup and pick time to evaluate the implications of this study in terms of total order picking time (i.e., the mean total order pick time per replication).

3.4. Experimental design

The relationships among the four order picking planning problems are analyzed by simulating a comprehensive experimental design. Table 5 outlines the experimental design, comprising four decision factors and two factors to generalize the conclusions of our study.

factor	factor levels
picker zoning policy	(1) 1 zone (2) 2 single-block zones (3) 4 single-block zones (4) 2 multi-block zones (5) 4 multi-block zones
storage location assignment policy	(1) random (2) within-aisle (3) across-aisle (4) diagonal (5) perimeter
order batching policy	(1) FIFO (2) seed (3) saving
routing policy	(1) traversal (2) traversal$^+$ (3) return (4) midpoint (5) optimal (approximated by LKH)
batch capacity	(1) 12 orders (2) 8 orders (3) 4 orders
picker density	(1) 4 pickers (2) 8 pickers (3) 12 pickers

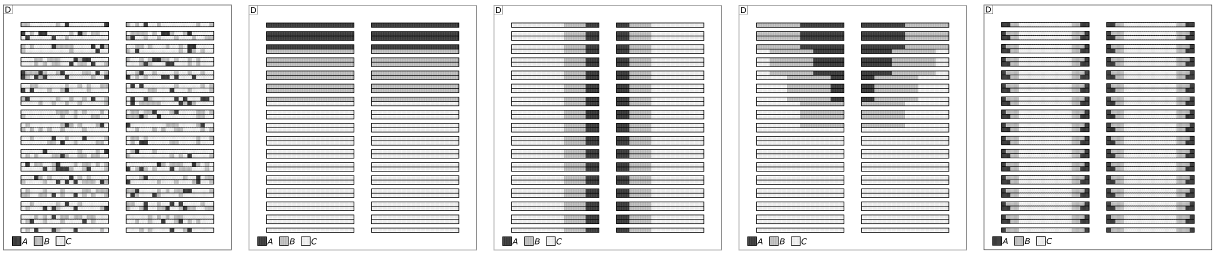
Table 5: Experimental factor setting of the empirical case.

Picker zoning policies decide on how the order picking area is split into zones. Besides a single zone, the order picking area may be split into two or four pick zones, each with two different configurations. The location of each pick zone is outlined in Table 6. The effect of varying pick zone configurations is analyzed for the first time in combination with other planning problems. SKUs are randomly assigned to the pick zones: each zone consists of the same number of fast and slow moving SKUs. Thus, the demand distribution of SKUs is equally distributed across pick zones and the number of order lines that should be picked in each zone is assumed to be similar. As all pick zones consist of an equal number of order lines and the number of pickers in each zone is equal, the workload across zones is balanced. As the workload is balanced, situations in which no jobs are assigned to a particular zone are very rare and thus not taken into account. Orders are picked in parallel in case of multiple pick zones, a common practice in spare part warehouses to reduce order throughput time (Van Gils et al., 2017). As order consolidation is typically performed in the dock lanes, the additional time for consolidating a single order from different zones is assumed to be negligible.

picker zoning policy	zone 1	zone 2	zone 3	zone 4
1 zone	1-32	-	-	-
2 single-block zones	1-32 (odd)	1-32 (even)	-	-
4 single-block zones	1-16 (odd)	1-16 (even)	17-32 (odd)	17-32 (even)
2 multi-block zones	1-16	17-32	-	-
4 multi-block zones	1-8	9-16	17-24	25-32

Table 6: Location of picker zoning policies.

Storage location assignment policies decide on how SKUs are assigned to storage locations within a zone. Besides randomly assigning SKUs to storage locations (see Figure 2(a)), four turnover-based storage location assignment policies are simulated. The turnover-based storage policies consist of three classes with the following demand distributions: 4 (class A), 1.4 (class B), and 0.25 (class C) expressed as the mean number of picks per storage location. The location of the storage classes for each turnover-based storage policy is illustrated in Figures 2(b)–2(e). When multiple storage classes are assigned to a pick aisle, the fast moving items are stored at the most easily accessible storage locations: the storage locations with the shortest travel time starting at aisle entrance. When multiple zones are applied, the size of the storage classes (in number of locations) is equal in each pick zone and the location of the storage classes is similar as in Figure 2.



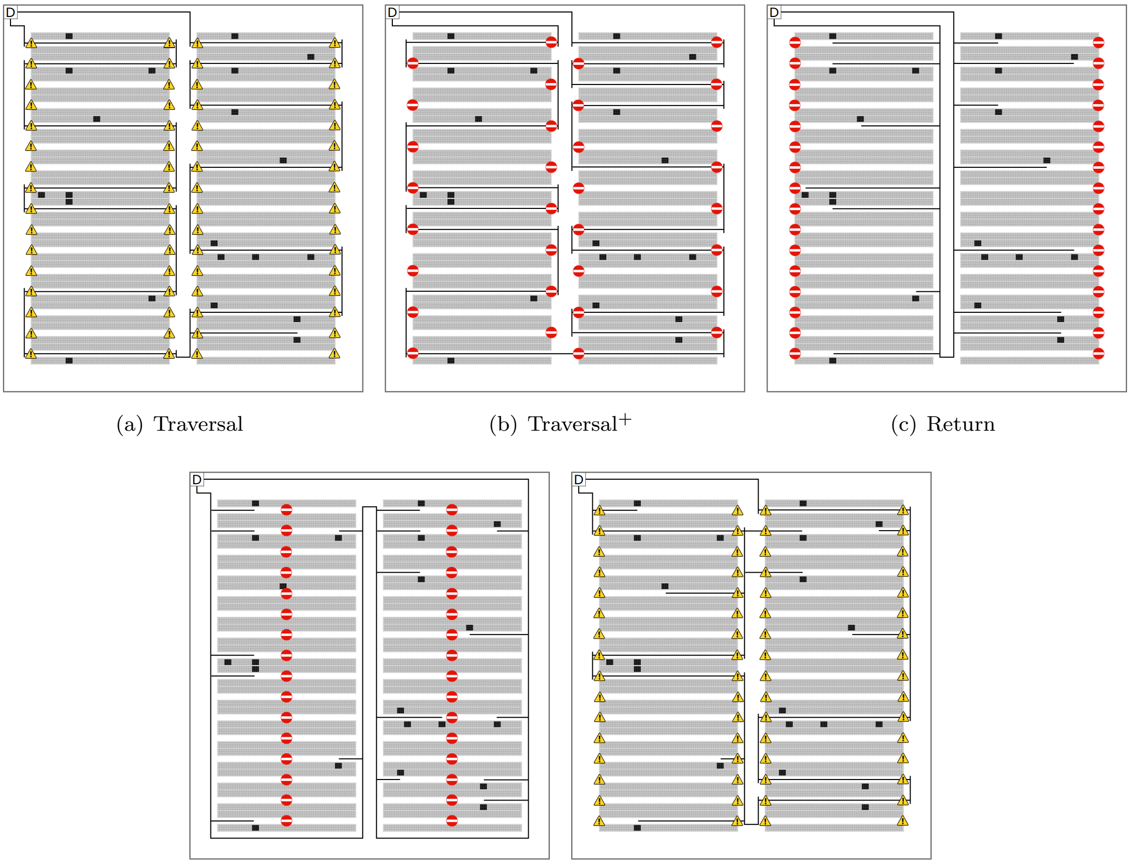
(a) Random (b) Within-aisle (c) Across-aisle (d) Diagonal (e) Perimeter

Figure 2: Storage location assignment policies.

Order batching policies define which customer orders are combined in a single pick round. First-in-first-out (FIFO) batching results in a random composition of batches as the location of SKUs is not considered while creating batches. A seed and a savings batching policy are additionally considered to reduce travel. The seed batching policy creates batches by selecting the order that requires visiting the smallest number of aisles, and adding orders to the pick list that minimize the number of additional aisles to be visited in the pick round until batch capacity is reached. The number of additional aisles to be visited is recalculated when an order is assigned to a batch (i.e., cumulative seed selection rule). Combining this seed order selection rule and this accompanying order selection rule provided efficient pick rounds for various storage and routing policies in previous research. This seed batching policy is interesting for practical applications as it is simple and produces good results (De Koster et al., 1999; Ho and Tseng, 2006; Ho et al., 2008). The basic Clarke and Wright savings batching policy (i.e., combining customer orders in a batch to maximize travel time savings) can further reduce travel. Therefore, the C&W(i) savings policy is included in the simulation experiments. We are aware of more sophisticated heuristic batching algorithms that minimize travel (e.g., C&W(ii) savings policy (De Koster et al., 1999) or local search algorithms (Öncan, 2015)) or even algorithms that include the negative picker blocking effects (e.g., (Hong et al., 2012)), but these policies greatly increase computing times and are thus inapplicable in this comprehensive simulation study. Additionally, due to this complexity and simplifying assumptions, these heuristic policies are rarely used in practice. The batches created using FIFO, seed or savings policy are assigned to the first available order picker. Consequently, the order pick time is rather balanced across order pickers (i.e., the order pick time per picker is similar for each picker). Therefore, the order pick time per picker is not considered as separate performance measure.

After a pick list has been created by the batching algorithm, the routing policy defines the sequence of the locations on the pick list. Existing routing policies are revised to include the safety constraints considered in the experiments. The width of pick aisles and a risk-averse strategy towards traffic accidents is considered when deciding on the maximum allowable number of pickers in a pick aisle. Figure 3 depicts an example of each of the five routing policies. Traversal routes are included in the experiments with the constraint that a single order picker is allowed in each pick aisle (Figure 3(a)). An alternative traffic rule is considered in combination with traversal routes (i.e., traversal$^+$): all pick aisles are strictly unidirectional as indicated by the traffic signs in Figure 3(b), allowing two order pickers in a pick aisle. In this way, travel times are expected to increase, but picker blocking reduces as more pickers can work concurrently within an aisle compared to traversal routing. Return and midpoint routes allow two-directional travel. To prevent routes of multiple pickers from crossing within aisles, the maximum allowable number of pickers is limited to a single picker in return routing and two pickers (i.e., one at each side of the pick aisle) in midpoint routing. Finally, an optimal routing policy is considered. In this simulation, optimal routes are approximated by solving a traveling salesman problem using the Lin Kernighan Helsgaun (LKH) heuristic (Helsgaun, 2000). On average, resulting routes deviate only 0.1 % from optimality in an order picking context (Theys et al., 2010). Aisle entrance is possible from both sides. However, only a single picker is allowed to work in each pick aisle: other pickers should wait until the first picker has left the aisle. Although a largest gap routing policy outperforms midpoint routes with respect to travel distance, largest gap routes only prevent routes from crossing within aisles if the number of pickers per aisle is limited to one. However, in that case largest gap routes will be outperformed by the optimal routing policy, which is why we do not consider largest gap routing in Table 5.

Note that most policies of the experimental design are revised in comparison to general wide aisle order picking systems ignoring real-life features. Only picker zoning policies could be included in a similar way as in wide aisle picking systems. The storage location assignment problem enlarges due to the high level storage



(a) Traversal (b) Traversal$^+$ (c) Return

(d) Midpoint (e) Optimal

Figure 3: Picker routing policies.

locations: storage classes need to be assigned to multiple levels taking the slow lifting speed into account (i.e., the fast moving items are stored at locations with the shortest travel time starting at aisle entrance). Moreover, the Chebychev distance metric should be included while calculating the savings between orders in case of a savings batching policy. Finally, the general principles of the routing policies (Roodbergen and De Koster, 2001) are revised to include traffic rules and reduce the risk of traffic accidents (e.g., strictly unidirectional pick aisles in combination with traversal routes). Consequently, the real-life features are taken into account as follows. Safety constraints are incorporated in the simulation study by imposing traffic rules (i.e., traffic directions and a maximum number of allowable pickers working concurrently in a pick aisle). Picker blocking is included by accounting for the waiting times that result from the maximum number of allowable pickers and the inability to overtake within pick aisles. Finally, the Chebychev distance metric accounts for the slow lifting speed to include the effect of high level storage locations.

In order to generalize the conclusions of the empirical study, the planning problem combinations are simulated in multiple warehouse settings. Two main variations have been proposed in literature to generalize experiments: a varying number of picks during a pick round (Manzini et al., 2007; Theys et al., 2010; Yu and De Koster, 2009) and a varying picker density (Petersen, 2002; Theys et al., 2010), both consisting of three levels. To capture a varying number of picks during a pick round, a varying batch capacity is included in the experimental design. Picker density can be expressed as the number of pickers relative to the number of storage locations. Picker density is varied by changing the number of pickers given the number of storage locations.

3.5. Data generation

Based on historical data of the real-life spare parts case warehouse, 500 orders are randomly generated for each replication, which corresponds to the number of orders that should be picked in an eight-hour shift. The number of order lines per order is geometrically distributed with a mean of three order lines. As variations in this parameter value would result in a varying number of picks during a pick round (Van Gils et al., 2018b), these variations are captured by varying the batch capacity in the experimental design.

The same randomly generated order list is used to test policy combinations of the picker zoning, storage location assignment, order batching, and routing planning problems. In this way, the variation in the results among the four planning problem factors is only systematic variation as a result of a revised operational policy. This systematic variation allows us to control the policy decisions covered in the research hypotheses. A new list of 500 orders is generated for each factor in the experimental design. In this way, unsystematic variation resulting from revising the batch capacity and/or picker density is induced in addition to the systematic variation. To reduce the stochastic effect from order generation, each factor level combination is replicated 30 times. In total, $30 \times 3 \times 3$ lists of orders are generated (each list consisting of 500 orders) and tested with respect to the policies of the four planning problems. As the unsystematic variation is limited to the order generation and the assignment of SKUs to pick zones and storage locations and each factor level combination is replicated 30 times, $15,000$ orders have been simulated for each factor level combination. This seems to be large enough to draw reliable conclusions.

Note that orders are generated based on the real-life case instead of using existing historical order data. The generation of new order lists prevents results that are only applicable to a particular order list. It enables us to broaden experiments to contexts other than the real-life case, making conclusions easily generalizable to a wide range of warehouses.

3.6. Statistical analysis

The results of the simulation experiments provide the required data for performing the statistical tests that evaluate the research hypotheses formulated in Section 2.2. To test whether or not a relation is statistically significant, an analysis of variance (ANOVA) is performed, both on travel (i.e., travel time for picking 500 orders in a single replication) and picker blocking (i.e., total wait time per replication). Although multiple ANOVAs are performed that may justify performing a multivariate analysis of variance (MANOVA), we want to explain the effect of planning problem decisions on each of the performance measures. In this case, multiple ANOVAs pertained to individual performance measures meet the research objectives of this study (Huberty and Morris, 1989). ANOVA tests are subject to independency, variance, and normality assumptions (Altarazi and Ammouri, 2018) as discussed below.

The empirical study consists of a $5 \times 5 \times 3 \times 5 \times 3 \times 3$ full factorial design with a mixture of between-groups and repeated-measures factors. The between-groups factors consist of the two independent factors (i.e., batch capacity and picker density), while the repeated-measures factors correspond to the picker zoning, storage, batching, and routing policy factors. This mixed factorial design requires a mixed model ANOVA (Petersen, 1997).

The assumption of homogeneity of variance with respect to the between-groups factors, and sphericity (i.e., variances of the differences between results from a single order list are equal) of repeated-measures factors are likely to be violated as we expect certain factor level combinations to be more strongly varying. For example, when a picker covers a smaller area (e.g., increasing the number of zones), the effect of routing policies on travel is likely to be much smaller compared to the effect of these policies in a single pick zone. Appendix A.1 shows that all sphericity hypotheses are rejected at a 5 % significance level by Mauchly's test. Furthermore, 31 % of the 375 homogeneity of variance hypotheses with respect to travel are rejected by Levene's test at a 5 % significance level. All Levene's test hypotheses on wait times are rejected. ANOVA F statistics are quite robust to violations in homogeneity of variance when group sizes are equal (as in this study). However, violating the sphericity assumption increases the probability that a genuine effect is shown, while in reality, there is no effect. The degrees of freedom are adjusted by the conservative Greenhouse-Geisser (G-G) correction to compensate for this increased Type I error rate (Geisser et al., 1958).

The last ANOVA assumption is normality. The F statistic controls the Type I error rate well under conditions of non-normality (Glass et al., 1972), especially when the degrees of freedom are sufficiently large (at least 20) and group sizes are equal (Field, 2013). To ensure these conditions, the simulation is replicated

30 times to ensure sufficient degrees of freedom. Moreover, the experimental design is balanced, meaning that group sizes are equal. These elements prevent negative effects of non-normality, making robust checks, such as bootstrapping, redundant in this context.

With respect to the relations among planning problems that can be confirmed by ANOVA, interaction plots and post hoc tests provide insights into the direction of the relation (i.e., increasing or decreasing marginal effect) and allows us to explain why relationships among the four order picking planning problems exist. A post hoc test is performed to compare the performance of policies. The Bonferroni correction of the significance level is used to ensure the overall Type I error rate across all comparisons remains at 0.05. When evaluating multiple hypotheses, the Bonferroni correction approach is robust in terms of power and control of the Type I error rate (Field, 2013). Post hoc tests are performed for each combination of two planning problems; all policies of the first planning problem are evaluated for each policy of the second planning problem. In this way, the test results create subsets of policies for which the performance is not statistically significantly different. If two policies (e.g., return and midpoint routing) are listed in the same subset, differences between the respective policies fail to be statistically significant. In case of a statistically significant interaction between two planning problems, the post hoc tests will likely create varying subsets for each policy of the second planning problem.

4. Empirical findings

This section presents the results of the study. The ANOVA results to test the expected relation formulated in the research hypotheses are discussed in Section 4.1. Section 4.2 analyses the direction of the relation and explains the interactions using interaction plots and post hoc tests. Section 4.3 summarizes whether or not the research hypotheses are supported.

4.1. Factor analysis

All relations formulated in the research hypotheses of Section 2.2 are supported by the mixed-model ANOVA. Note that ANOVA does not provide insights into the direction of the relation, but only support that a significant relation exists. Appendix B.1 and Appendix B.2 provide the results with respect to travel and picker blocking. The first columns are devoted to the sum of squares (SS), the G-G adjusted degrees of freedom (df) and the mean squares (MS) of the main and interaction effects. The F statistic and p-value for testing the statistical significance of the six experimental factors and the interaction effects are shown in the last two columns. Due to limited relevance and intricate interpretation of three-way and four-way interactions among planning problems, these effects are ignored in the analysis.

The mixed-model ANOVA on travel reveals that all main effects of the four planning problems, as well as all interaction effects among zoning, storage, batching, and routing are statistically significant. This means that the joint effect of the planning problems significantly impacts the mean travel time of order pickers in narrow aisle order picking systems. In other words, the decision on which zoning, storage, batching, and routing policy to use in order picking operations influences the travel time of order pickers. Additionally, the joint effect of these policy decisions substantially impacts travel. Note that the number of pickers (picker density) is irrelevant since the total distance traveled is independent of the number of available order pickers.

We find similar results when evaluating the hypotheses with respect to picker blocking. All main effects as well as all interaction effects are statistically significantly influencing wait time as a result of picker blocking. This means that there is a significant difference in mean wait time of order pickers between the five zoning and five storage policies, the three batching policies and the five routing policies. Moreover, picker blocking is substantially influenced by the combined effect of these policy decisions.

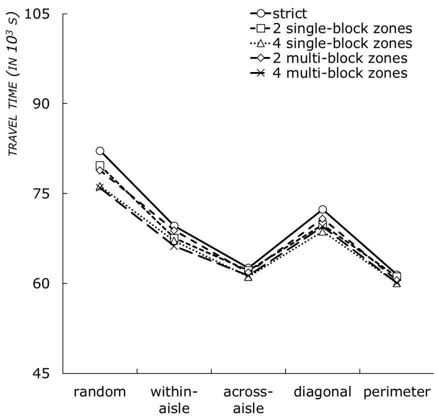
To summarize, all relations formulated in the research hypotheses are supported by the ANOVA tests. This implies that warehouse managers should consider decisions on zoning, storage, batching, and routing simultaneously to minimize order picking time. Travel measures are insufficient to evaluate the efficiency of the planning problems. Only considering travel measures will not necessarily reduce the order completion time or order throughput, which is of main interest for warehouse managers (Giannikas et al., 2017). Wait times should be taken into account, at least in narrow aisle order picking systems.

4.2. Discussion

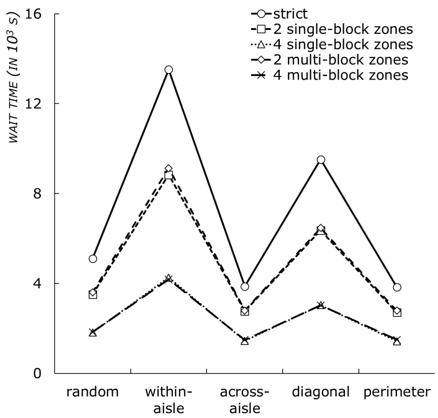
Although the experimental design gives rise to a large number of instances, and null hypotheses are much easier to reject in larger samples (i.e., the probability that at least one of the factor levels interacts with another factor level increases), the ANOVA shows strong statistically significant effects. Therefore, the directions of each planning problem combination are further analyzed and relations are explained in this section, providing insights into the behavior of order picking policies for both travel and picker blocking. For each planning problem combination, this section provides interaction plots with respect to travel (i.e., the mean total travel time per replication) and picker blocking (i.e., the mean total wait time per replication), illustrating the planning problem with the shortest time horizon of the resulting decision on the horizontal axis. Furthermore, post hoc tests are provided in this section for each combination of two planning problems, where all policies of the planning problem with the shortest time horizon are evaluated for each policy of the planning problem with the longest time horizon. Post hoc tests with planning problems in the other direction are provided in Appendix C.

4.2.1. Zoning-storage relationship

The relation formulated in Hypotheses 1a and 1b are supported by the ANOVA results. Figures 4, 5, and C.21 illustrate that the direction of the picker zoning and storage location assignment relation (i.e., decreasing marginal effects) is supported as well.

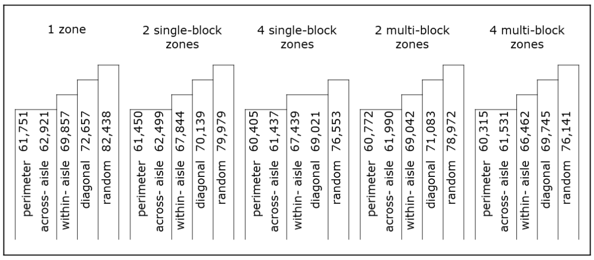


(a) Travel

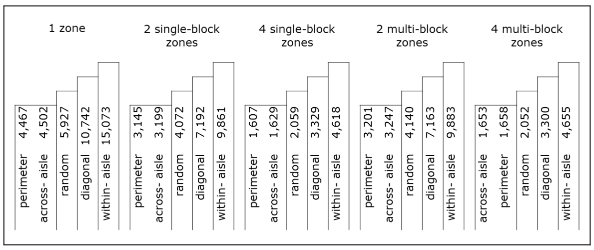


(b) Picker blocking

Figure 4: Interaction plot of zoning-storage combinations.



(a) Travel



(b) Picker blocking

Figure 5: Multiple Bonferroni t-test (familywise error rate = 0.01) for storage policies by zoning policies (in s).

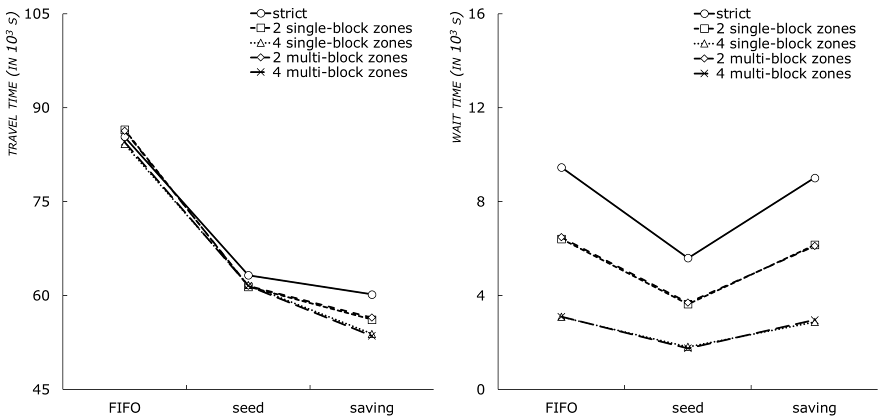
Both picker zoning and storage location assignment aim to reduce the area covered by pickers in a pick round, resulting in a significant travel relationship. Due to the large travel benefits of across-aisle or perimeter storage classes (see Figure 5(a)), travel times are minimal irrespective of the applied picker zoning policy. The effect of picker zoning policies on travel is stronger when combined with the other three storage location assignment policies. This relationship is illustrated in Figure 4(a) by similar travel times of the picker zoning policies in combination with across-aisle and perimeter storage classes, while travel times are more varying in combination with other storage policies. This interaction can be explained by the dominant effect of vertical travel: across-aisle and perimeter storage classes locate fast moving items to the easiest accessible locations with respect to the point of entrance of a pick aisle, making the effect of zoning negligible. The locations with minimal Chebychev travel time with respect to the point of entrance are dedicated to the fast moving SKUs in across-aisle or perimeter storage classes, whereas within-aisle and diagonal storage classes concentrate fast moving SKUs within a few aisles and are consequently assigned to higher locations as well. Moreover, the effect of zone location is negligible (i.e., both single-block and both multi-block zones yield similar travel times).

The combined effect on picker blocking is depicted in Figures 4(b) and 5(b). The interaction plot reveals no effect of zone location, and the post hoc test creates identical subsets. However, the interaction plot shows a strong relationship between the concentration of fast moving items and picker blocking. A single pick zone in combination with within-aisle or diagonal storage classes substantially increases wait times due to picker blocking. In these combinations, class A SKUs are most strongly concentrated resulting in a high pick density in a small area, thereby increasing the probability of picker blocking. Either changing the picker zoning policy or storage location assignment policy (or both) significantly reduces wait times as fast moving SKUs are distributed more equally across the order picking area. So, the marginal picker blocking effect of from turnover-based storage location assignment policies decreases when the order picking area is divided into pick zones, as illustrated by the smaller fluctuating lines of the interaction plot (Figure 4(b)) in case of more pick zones.

4.2.2. Zoning-batching relationship

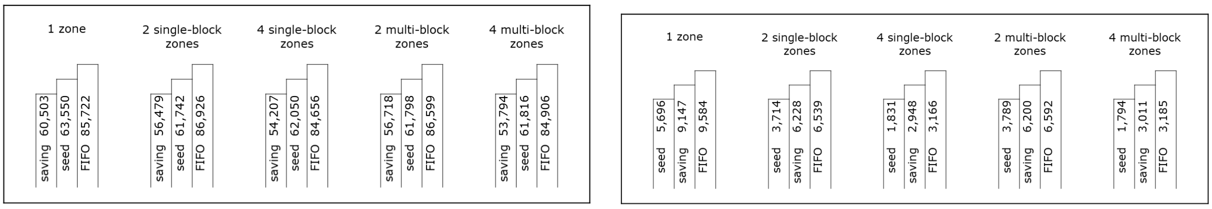
The relations formulated in Hypotheses 2a and 2b are supported by the ANOVA results. Although the relation is found to be significant, the expected decreasing marginal travel and picker blocking effects from efficient batching policies when the order picking area is divided into pick zones are not supported by Figures 6, 7, and C.22.

The interaction plot illustrating the travel interaction between zoning and batching (Figure 6(a)) reveals diverging lines (i.e., increasing marginal effect) when moving from FIFO to a more efficient batching policy. This can be explained by the trade-off between creating a small number of batches (i.e., a small number of zones combined with FIFO or seed batching) or creating a larger number of batches that cover a small area (i.e., multiple zones and savings batching). Multiple zones require more batches as orders are split into different zones and the batch capacity is expressed in number of orders. Moreover, the savings algorithm results in a larger number of batches compared to FIFO or seed batching as batches are unlikely to be filled to capacity under a savings batching policy. Under the assumptions of these experiments, the savings batching policy outperforms the seed and FIFO batching policy in combination with all picker zoning policies



(a) Travel (b) Picker blocking

Figure 6: Interaction plot of zoning-batching combinations.



(a) Travel (b) Picker blocking

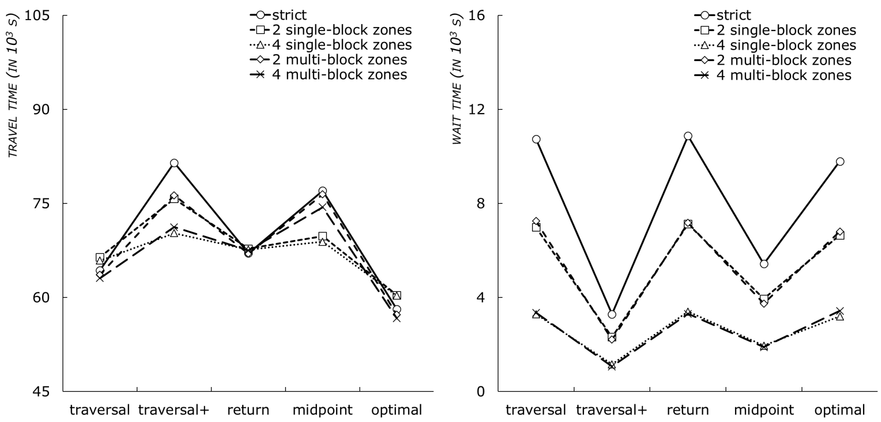
Figure 7: Multiple Bonferroni t-test (familywise error rate = 0.01) for batching policies by zoning policies.

as shown by the post hoc tests of Figure 7(a).

Similar to the zoning-storage relationship, the joint effect of zoning and batching on picker blocking is not caused by the location of order pick zones. Both single-block and both multiple-block zoning policies result in equal mean wait times as can be seen in Figure 6(b). The significant relationship can be explained by the combined effect of the seed batching policy and multiple zones. The seed batching policy outperforms the FIFO and savings batching policies with respect to picker blocking (see Figure 7(b)). The seed policy is in accordance with the traffic rules: orders are batched to minimize the total number of aisle visits, and traffic rules cause picker blocking by allowing a maximum number of pickers to work concurrently within aisles. Under an efficient zoning policy, the marginal wait time benefits of seed batching are smaller compared to, for example, a single pick zone. This decreasing marginal effect is not shown with respect to the most efficient batching policy (i.e., savings batching).

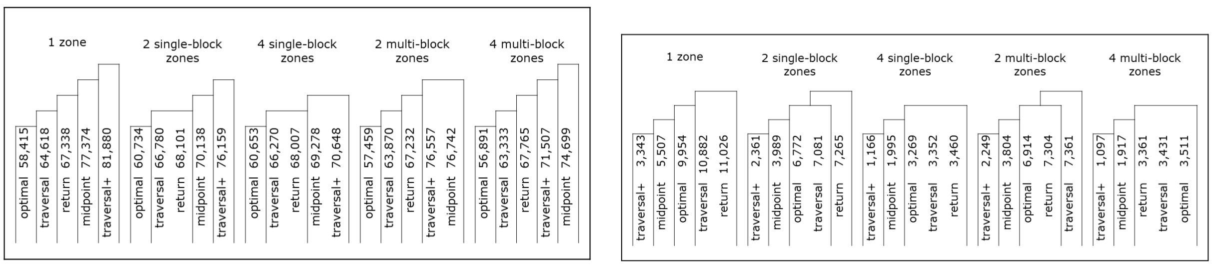
4.2.3. Zoning-routing relationship

The relations formulated in Hypotheses 3a and 3b are supported by the ANOVA results. Furthermore, the marginal travel and picker blocking effects from efficient routing policies decrease when the order picking area is divided into pick zones, as illustrated in Figures 8, 9, and C.23.



(a) Travel (b) Picker blocking

Figure 8: Interaction plot of zoning-routing combinations.



(a) Travel (b) Picker blocking

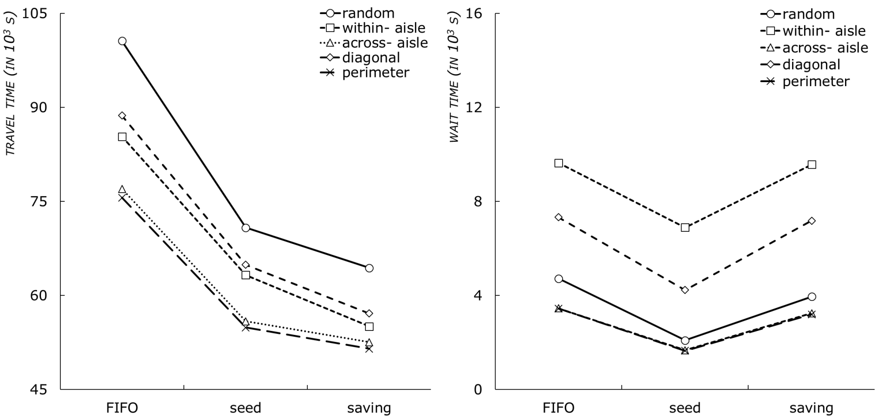
Figure 9: Multiple Bonferroni t-test (familywise error rate = 0.01) for routing policies by zoning policies.

The optimal routing policy results in the shortest travel time, irrespective of the picker zoning policy (see Figure 9(a)). Only minor differences exist among the picker zoning policies in combination with optimal routes in terms of travel time (i.e., small marginal effect). In combination with other routing policies, travel time increases. The interaction plot (Figure 8(a)) reveals that the unidirectional traversal routes (i.e., traversal^{+}) favor more zones, either single-block or multi-block zones. More and thus smaller zones limit the probability of visiting a pick aisle without picks forced by the imposed traffic directions of traversal^{+} routes. There is an even number of aisles in the experiment to ensure that a route ends at the side of the depot. Moreover, midpoint routes are preferred in combination with single-block zones as routes are created along the periphery of each warehouse block. Figure 9(a) illustrates that the effect of zoning policies is substantial in combination with the routing policies yielding the largest travel times (i.e., traversal^{+} and midpoint), while the marginal travel effect decreases in combination with efficient routing policies.

While the optimal route length results in the shortest travel time, optimal routes are in the lowest subsets with respect to picker blocking in combination with most picker zoning policies (see Figure 9(b)). Traversal^{+} and midpoint routes benefit from safety constraints since two pickers can work concurrently in a pick aisle. Only a single picker can enter an aisle in traversal, return, or optimal routes, resulting in increased wait times, particularly with inefficient picker zoning combinations as shown in Figure 8(b). The marginal picker blocking effect of from efficient routing policies decreases when the order picking area is divided into pick zones, as illustrated by the smaller fluctuating lines of the interaction plot (Figure 8(b)) in case of more pick zones.

4.2.4. Storage-batching relationship

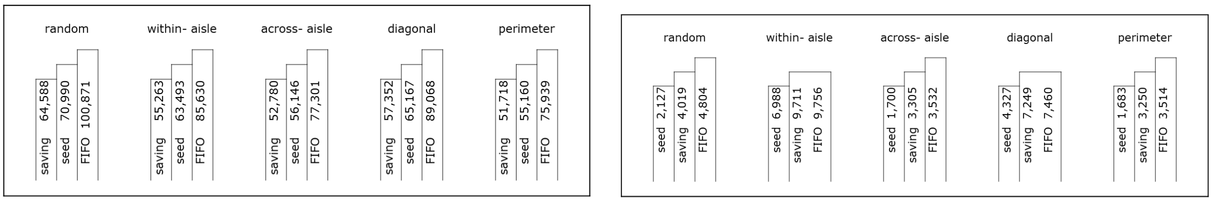
The ANOVA results turn out that the combined effect of storage location assignment and order batching significantly influences travel as well as picker blocking. Based on Figures 10, 11, and C.24, the expected direction of the relation (see Hypotheses 4a and 4b) is not supported.



(a) Travel (b) Picker blocking

Figure 10: Interaction plot of storage-batching combinations.

Although the savings batching policy outperforms seed and FIFO batching, in combination with all storage location assignment policies with respect to travel (see Figure 11(a)), the interaction plot in Figure 10(a) provides insights into the interaction. The aisle-based seed batching algorithm and the random FIFO batching policy neglect the vertical travel when creating batches. As more fast moving SKUs are stored in high level locations in within-aisle or diagonal storage classes, the interaction plot shows a large travel



(a) Travel

(b) Picker blocking

Figure 11: Multiple Bonferroni t-test (familywise error rate = 0.01) for batching policies by storage policies.

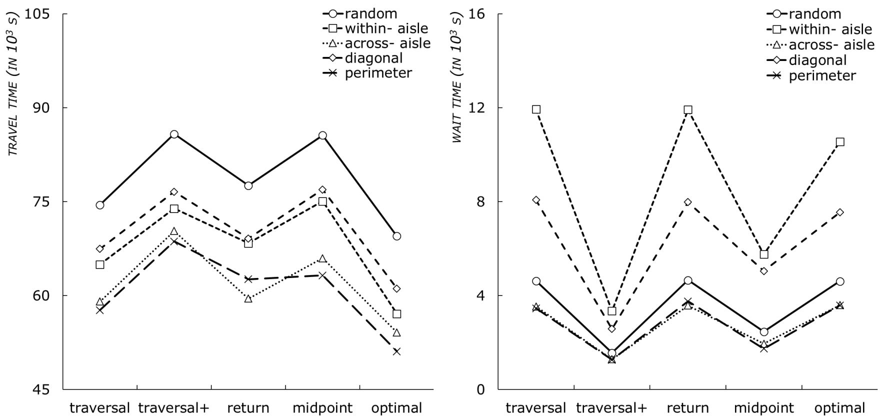
gap compared to, for example, across-aisle storage classes. Since vertical travel is taken into account with the savings algorithm when creating batches, the four turnover-based storage location assignment policies show only minor travel differences. So, the varying marginal effects of the within-aisle and diagonal storage classes over the batching policies explains the relation. The hypothesized decreasing marginal travel benefits from efficient batching policies when turnover-based storage location assignment policies assign fast moving SKUs to a small picking area is not clearly illustrated in Figure 10(a).

ANOVA results show a significant storage-batching effect on picker blocking as well. The interaction plot in Figure 10(b) does not provide the expected decreasing marginal picker blocking effect from efficient batching policies in combination with turnover-based storage classes as explanation for the significant relation. Reducing the number of aisles to be visited in a pick round (i.e., seed batching policy) in combination with storage policies that diffuse fast moving SKUs across pick aisles (i.e., random, across-aisle, and perimeter storage policies) minimizes wait times due to picker blocking (see Figure 11(b)). Concentrating fast moving SKUs in a small number of aisles or batching orders randomly (i.e., FIFO) or based on a travel metric significantly increases wait times, particularly when FIFO batching and random storage are combined. This effect is illustrated for the seed batching policy in Figure 10(b) when comparing picker blocking for within-aisle and diagonal storage with e.g., random storage.

4.2.5. Storage-routing relationship

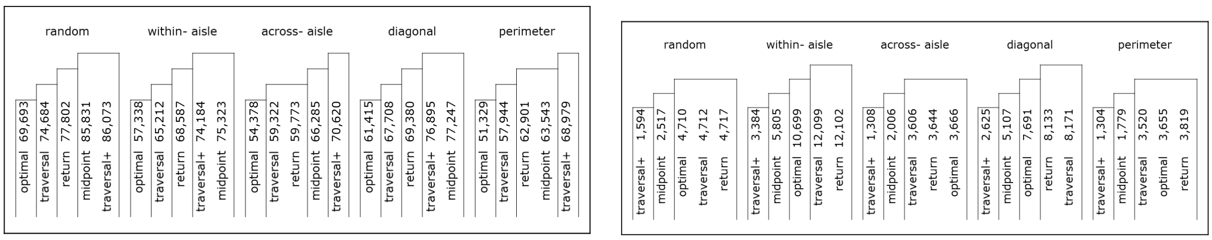
The relation formulated in Hypotheses 5a and 5b is supported by the ANOVA results. Figures 12, 13, and C.25 illustrate that the marginal picker blocking effect from efficient routing policies increases when turnover-based storage location assignment policies assign fast moving SKUs to a small picking area, while the expected direction of the travel effect is not supported.

The interaction plot of Figure 12(a) reveals strong variations in mean travel time among combinations of storage and routing policies as shown by the crossing lines on the graph (i.e., results do not provide an



(a) Travel (b) Picker blocking

Figure 12: Interaction plot of storage-routing combinations.



(a) Travel (b) Picker blocking

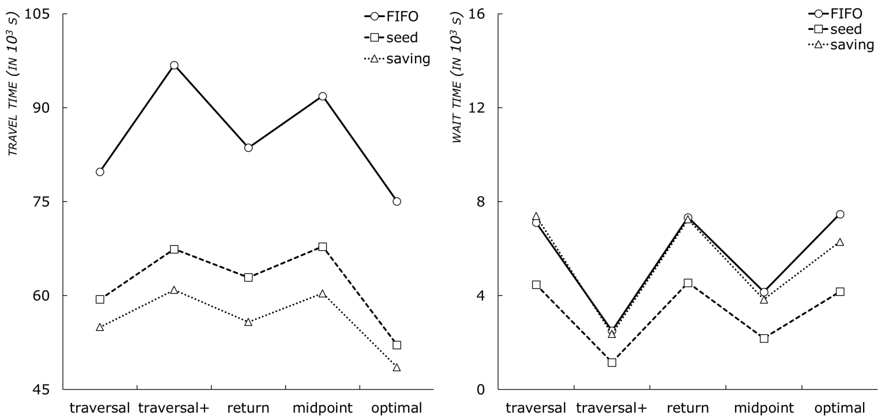
Figure 13: Multiple Bonferroni t-test (familywise error rate = 0.01) for routing policies by storage policies.

increasing or decreasing marginal effect). The optimal route performs best in combination with all storage policies (see Figure 13(a)). However, optimal routes are rarely used in practice (Van Gils et al., 2018b). The composition of the other subsets differs considerably across the storage policies. Excluding optimal routes, return routes are favored in combination with across-aisle storage classes as fast moving SKUs are stored at the beginning of an aisle, thereby minimizing travel within aisles. Midpoint routes result in the shortest travel time in combination with perimeter storage classes. Including information about the location of fast moving SKUs while composing routes favors certain routing heuristics. Because pick trucks have to travel vertically to reach high level storage locations, dominant in within-aisle storage classes, the generally well performing combination of within-aisle storage and traversal routing policies yields long travel times in high level order picking systems. Perimeter and across-aisle storage classes outperform within-aisle storage location assignment in combination with both traversal and the traversal$^+$ routing policies.

In terms of wait time, the negative effects of safety constraints are minimal in traversal and midpoint routes, as these routing policies allow two order pickers to work concurrently within pick aisles. The interaction effect can be explained by the converging and diverging lines in the graph (Figure 12(b)) and the creation of varying subsets by the post hoc test (Figure 13(b)). The storage location assignment policy is of less importance when allowing multiple pickers to work concurrently within a pick aisle, whereas strong variations among the storage policies are found in case of traversal, return, or optimal routing (i.e., the routing policies that turn out to be efficient in terms of travel time).

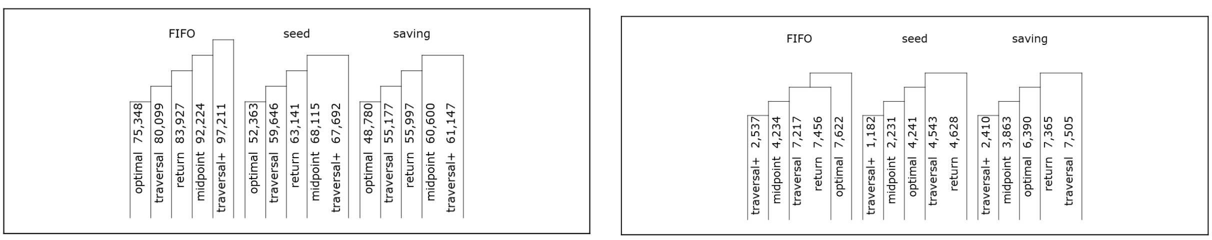
4.2.6. Batching-routing relationship

The relation formulated in Hypotheses 6a and 6b are supported by the ANOVA results. The decreased marginal travel effect is fully supported by Figures 14, 15, and C.26, in contrast to the expected decreased marginal picker blocking effect from efficient routing policies when the covered area of a pick round is limited by efficient batching policies.



(a) Travel (b) Picker blocking

Figure 14: Interaction plot of batching-routing combinations.



(a) Travel (b) Picker blocking

Figure 15: Multiple Bonferroni t-test (familywise error rate = 0.01) for routing policies by batching policies.

The interaction between batching and routing originates from the increased marginal travel effects of the traversal^{+} and midpoint routing policies over the batching policies (see Figure 15(a)). The seed and savings

	travel		picker blocking	
	relation	direction	relation	direction
zoning-storage	•	•	•	•
zoning-batching	•	◦	•	◦
zoning-routing	•	•	•	•
storage-batching	•	◦	•	◦
storage-routing	•	◦	•	•
batching-routing	•	•	•	◦

Table 7: Results summary (• hypothesized relation/direction is supported; ◦ hypothesized relation/direction is not supported).

batching policy can partly compensate the inefficiency with respect to travel of the traversal^{+} and midpoint routing policies caused by the traffic rules. However, applying these routing policies in combination with FIFO batching, substantially increases travel in comparison to the more efficient routing policies (see Figure 14(a)). As the savings algorithm integrates the routing policy while creating batches (i.e., savings between orders are calculated according to the routing policy), this batching algorithm results in the shortest travel time.

The mean time that order pickers are blocked while picking SKUs is significantly influenced by the combined effect of batching and routing as well. Post hoc tests reveal strong varying subset creations as illustrated in Figure 15(b). Especially wait times of optimal routes vary significantly across the batching policies. Figure 14(b) illustrates the diverging lines when combining batching policies with the optimal routing policy. However, as the most efficient batching policy and least efficient batching policy (in terms of travel time) result in similar picker blocking effects, the decreased marginal picker blocking effect is not shown in Figure 15(b).

4.3. Results summary

Table 7 summarizes the results of the research hypotheses. The ANOVA results support all relations formulated in the research hypotheses with respect to both travel time and picker blocking. However, the expected direction of the relation could not be supported for all research hypotheses.

5. Implications

This section outlines the implications of the existing relationships to academics (Section 5.1) and practice (Section 5.2). It also shows the negative effects on performance if existing real-life features are ignored and provides robust and efficient policy combinations that can be used in practice.

5.1. Academic implications

The graph in Figure 16 shows the effects of safety constraints for the example of routing policies, as traffic rules are integrated in the routing policies. It describes the mean wait time for a pick aisle visit under all picker zoning, storage, and batching policies. Figure 16 reveals that the safety constraints result in considerably increased wait times, especially in a high pick density area (e.g., pick aisles 1–4) in combination with traversal, return, or optimal routing. Within-aisle, and to a minor extent diagonal, storage classes cause high pick densities in the first pick aisles (see Figure 2). Depending on the picker zoning policy, these pick densities vary across pick aisles 1–4 (e.g., pick aisles 1–2 mostly contain fast moving SKUs in combination with all zoning policies, whereas pick aisles 3–4 do so only in a single zone or two pick zones). With respect to the routing policies, traversal, return, and optimal routes limit the number of pickers working concurrently in a pick aisle to a single order picker, resulting in high wait times. Midpoint routes allow two order pickers to work concurrently in a pick aisle, with the constraint of one picker at each side of the pick aisle, resulting in significantly reduced wait times. Finally, traversal$^+$ routes further reduce wait times as the capacity of pick aisles is two without constraints. Within-aisle blocking and storage-rack blocking seem to be negligible in this case. However, the single direction traffic significantly increases travel (see for example Figure 15(a)). Thus, safety constraints not only induce picker blocking but also increase travel with certain routing policies due to one-way traffic. Ignoring safety constraints in planning models results in infeasible solutions if traffic rules exist or the predicted order picking time by the model underestimates real performance, resulting in the risk of choosing an inefficient policy combination. By considering the most efficient combination of order picking policies while accounting for safety constraints, the negative effects of the safety rules are minimized, thereby optimizing order picking operations.

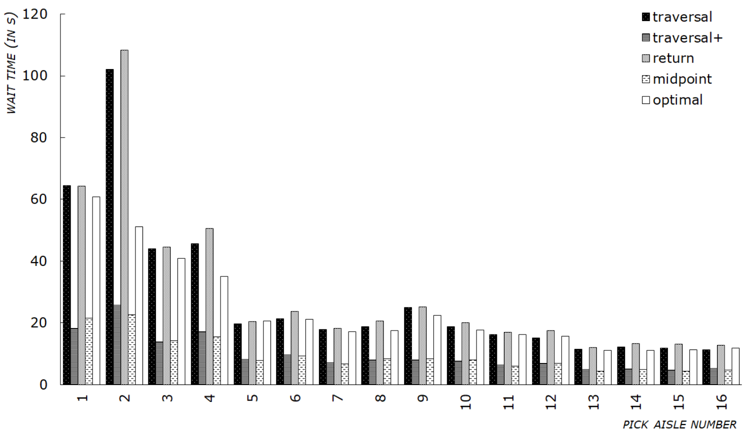


Figure 16: Mean wait time (in s) for a pick aisle visit (limited to pick aisles 1–16) per routing policy in case of twelve pickers and batch capacity of twelve orders.

Safety constraints induce aisle-entrance blocking, but reduce the other two blocking components (i.e., within-aisle blocking and storage-rack blocking). In traversal, return, midpoint, or optimal routes, the within-aisle and storage-rack blocking are reduced to zero as order pickers cannot approach each other within pick aisles, reducing the probability of accidents compared to traversal$^+$ routes. Moreover, dividing the order picking area into zones can additionally reduce aisle-entrance blocking as fewer pickers work in the same area (see for example Figure 8(b)). Limiting the working area of pickers by including pick zones reduces the probability of crossing vehicles and the consequent risk of traffic accidents in the warehouse. However, picker zoning may increase setup time (i.e., more batches are created and orders should be sorted), especially when batch capacity is limited to a small number of orders (see Figure 17). Thus, picker blocking induces inefficient wait times, which can be minimized at the expense of additional setup time. Travel time or travel distance metrics alone are inadequate to evaluate the efficiency of planning problems, especially in narrow aisle order picking systems. Wait times due to picker blocking should be included to optimize order picking operations.

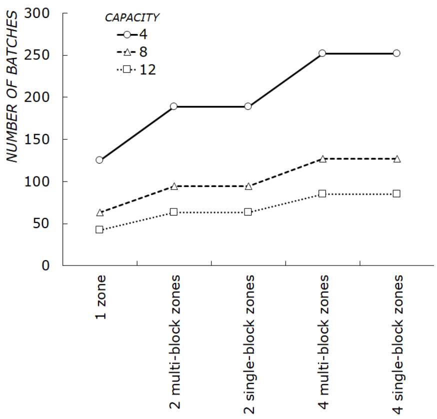


Figure 17: Mean number of batches per zone picking policy and batch capacity level.

The effect of high level storage locations is illustrated by the relatively slow lifting speed of pick trucks. The additional vertical travel increases travel time within pick aisles for the large majority of storage locations as can be seen by the large number of storage locations above the bold line in Figure 18, especially when SKUs at higher levels are retrieved in an aisle. The effect of high level storage locations on both travel and picker blocking is mostly pronounced when within-aisle storage location is applied as many fast moving SKUs are assigned to high level locations. As a result of more within-aisle travel, aisles are occupied longer, increasing aisle-entrance blocking. Neglecting the effect of vertical travel would result in significantly underestimated travel and wait times. Consequently, the effect of vertical travel should be taken into account while evaluating order picking policies.

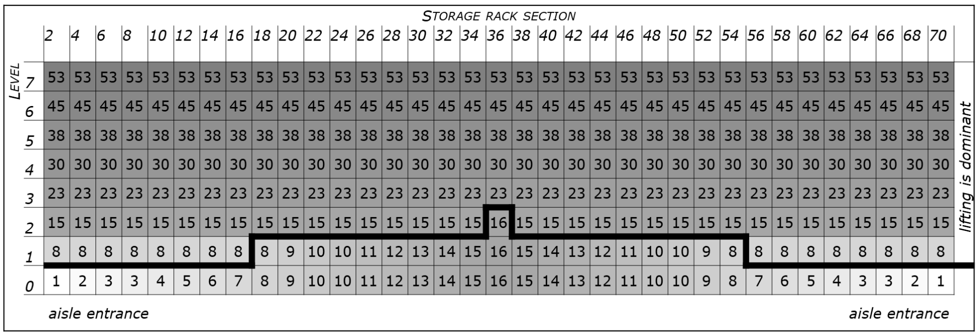


Figure 18: Shortest travel time (in s) to reach each location within a pick aisle (vertical travel time is dominant for locations above the bold line).

5.2. Managerial implications

The relationships among the order picking planning problems as well as the effect of real-life features in narrow aisle order picking systems have been thoroughly discussed. The question remains which policy combination optimizes the order picking system. Figure 19 provides the best performing policy combination for each batch capacity and each picker density factor level. Additionally, the graph shows the distribution of the total order picking time across the different time components. Note that the proportion of each time component in these experiments is equivalent to the typical distribution of order pickers' time (Tompkins et al., 2010), making the conclusions of this study easily generalizable to other narrow aisle order picking systems.

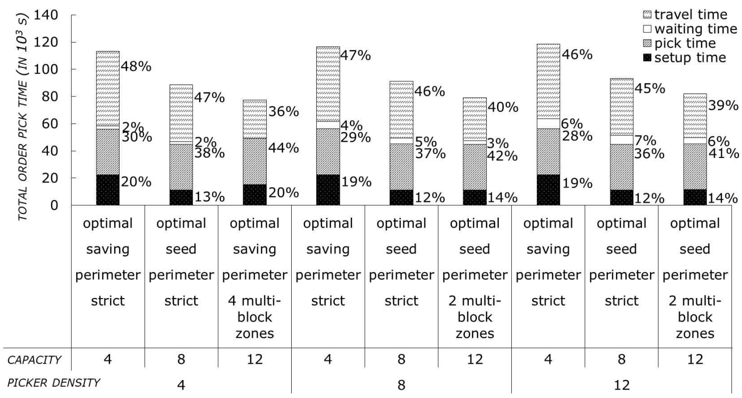


Figure 19: Total order picking time distribution for the best performing policy combination per batch capacity and picker density factor level.

Figure 19 shows a varying distribution of time components across batch capacities and picker densities.

Increasing batch capacity appears to reduce total order picking time. A closer look at the order picking policies reveals that the efficiency of the cumulative seed batching algorithm and the division of order picking area into zones tends to increase as batch capacity grows. Increasing batch capacity results in fewer pick rounds which reduces travel from and to the depot, making pick zones more favorable. Customer orders are split in picker zoning which leads to more pick rounds to retrieve items. Consequently, travel from and to the depot with a small batch capacity is more expensive compared to the distance reduction of travel in a small pick zone. Furthermore, increasing batch capacity causes a cumulative variant of batching policies to be more efficient as information about the location of all orders in a batch is taken into account while adding an additional order to a batch (e.g., the seed batching policy in these experiments). This effect is larger with more picks in a pick round. Other external factors impacting the number of picks per pick round (e.g., variations in order size) are expected to provide similar results.

Figure 19 reveals a slightly increased total order picking time with a larger picker density. This effect is mainly due to increased wait times if there are more pickers in a given layout. Note that wait times in the best policy combinations are relatively short compared to the total order pick time. However, choosing a less efficient order picking policy combination increases wait times significantly (see for example Figure 8(b)). Other external factors impacting the density of order pickers (e.g., varying layout) are expected to provide similar results.

Figure 19 illustrates that the optimal routing policy is robust to batch capacity and picker density. The travel benefits of optimal routes far outweigh the rather long wait times compared to other routing policies. However, complex algorithms to solve the routing problem are not widely used in practice as the optimal routing policy requires relatively long CPU times, and optimal routes are subject to the effects of maverick picking (Glock et al., 2017). By excluding the optimal routing policy from the analysis, the combination of a single pick zone, perimeter storage, seed batching, and traversal routing is the most efficient with respect to total order pick time. Moreover, this combination results in an increased total pick time of only 5.6 % and performs best for all levels of batch capacity and picker density.

Figure 20 shows that results of studies that ignore existing real-life features fail to be useful when order picking systems are subject to safety constraints, picker blocking, and high level storage locations. The graph shows the percentage increase in total order pick time when comparing the best policy combination of this study and applying the best policy combination (i.e., four zones, within-aisle storage, savings batching, and optimal routing) proposed by Van Gils et al. (2018b); warehouse characteristics are similar, but real-life features are ignored. Additionally, the gap is shown if complex policies are excluded (i.e., optimal routing and savings batching) from the analysis as these policies are rarely used in practice. In this case, the best combination when including real-life features is a single pick zone, perimeter storage, seed batching, and traversal routing; the best combination of Van Gils et al. (2018b) corresponds to four zones, within-aisle storage, seed batching, and traversal routing. The results show that ignoring real-life features when designing order picking systems results in substantial increases of up to 30 % in order pick times, especially when picker density is large.

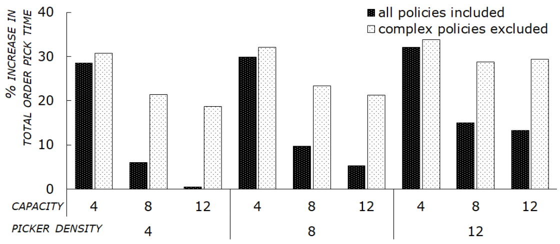


Figure 20: Percentage increase in total order pick time when ignoring existing real-life features (baseline is best policy combination).

In summary, the simulation results provide a robust policy combination (i.e., single pick zone, perimeter storage, seed batching, and optimal/traversal routing) for organizing order picking operations efficiently (i.e., wait times are limited), even if the system is subject to safety constraints, picker blocking, or high level storage locations. When one or more of these real-life features apply, which is the case in most order picking systems, total order pick time increases substantially as inefficient policy combinations are chosen.

6. Conclusions

Decisions on locating pick zones, assigning SKUs to storage locations, creating batches as well as routing order pickers should be considered carefully when planning order picking operations to face new market developments. Simulation results show strong relationships among the four operational planning problems. Recent academic literature has failed to examine the effect of real-life features such as safety constraints, picker blocking, and vertical travel in high level order picking systems on order picking planning problems. This empirical study shows the relevance, benefits, and necessity of considering and incorporating these real-life features when optimizing order picking operations. This study has considered a varying number of picks in a pick round as well as varying picker densities. In this way, variations in batch capacity, order size, number of pickers, and size of the order picking area are captured making conclusions about the effects of real-life features easily generalizable to other order picking systems that are subject to these real-life features.

Most unexplored real-life features negatively impact order picking efficiency or result in infeasible solutions if these practical factors are not incorporated. Empirical results show that travel distance and travel time measures are insufficient to evaluate the efficiency of order picking policies. Warehouse managers may choose an inefficient order picking policy combination when only horizontal travel is considered, as this performance metric ignores the impact of wait times and vertical travel. Moreover, traffic rules as a result of safety constraints limit movements of pickers and lead to additional waiting.

Investigating the effects of other real-life features, such as human factors and precedence constraints, may further reduce the gap between academic research and practice. Future research could focus on optimizing order picking operations while considering human factors, such as learning and forgetting. Human factors may be incorporated by worker dependent pick times and travel speeds. Moreover, ignoring precedence constraints while proposing picker routes 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 if the required routing sequence is violated. The effects of these real-life features will be valuable knowledge for practitioners to further reduce picker blocking and to design efficient order picking systems.

In addition to analyzing and explaining the effects of the real-life features, new solution approaches (e.g., metaheuristic algorithms) that use the knowledge and insights about the effects of real-life features are needed. Multiple order picking planning problems should be solved and optimized simultaneously while integrating the negative effects of these real-life features. This is a necessary condition for the use of complex academic algorithms in practice.

Finally, there is a growing trend towards robotized order picking systems (e.g., robotic mobile fulfillment systems), especially for particular segments such as B2C e-commerce orders. The question remains to what extent the relations among order picking planning problems have an effect on the order picking performance of robotized picking systems, and which real-life features should be included when planning operations. Theoretical constructs and findings of this study can support future research analyzing and explaining planning problems of robotized picking systems.

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Appendix A. Mauchly's test results on sphericity

factor	Mauchly's W	χ^2	*df*	p-value
travel				
zoning	0.871	36.3	9	0.000
storage	0.171	465.1	9	0.000
batching	0.151	498.8	2	0.000
routing	0.003	1,516.9	9	0.000
zoning × storage	0.223	389.4	135	0.000
zoning × batching	0.086	642.3	35	0.000
zoning × routing	0.008	1,241.1	135	0.000
storage × batching	0.246	368.1	35	0.000
storage × routing	0.004	1,459.9	135	0.000
batching × routing	0.041	839.7	20	0.000
picker blocking				
zoning	0.263	352.0	9	0.000
storage	0.016	1,081.5	9	0.000
batching	0.820	52.4	2	0.000
routing	0.142	513.8	9	0.000
zoning × storage	0.001	1,739.0	135	0.000
zoning × batching	0.114	569.6	35	0.000
zoning × routing	0.002	1,606.7	135	0.000
storage × batching	0.011	1,183.9	35	0.000
storage × routing	< 0.001	3,028.3	135	0.000
batching × routing	0.066	710.7	20	0.000

Table Appendix A.1: Mauchly's test results on sphericity.

Appendix B. ANOVA Results

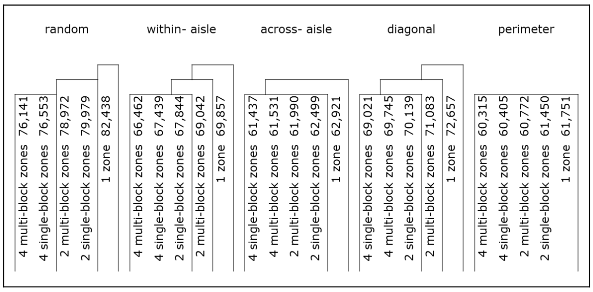
	Sum of squares	df	Mean square	F	p-value
Main effects					
zoning	128,568,345,320	3.72	34,519,689,885	5,393.46	0.000
storage	4,218,438,335,278	1.99	2,116,071,668,468	83,602.59	0.000
batching	16,373,786,713,729	1.08	15,136,030,814,730	618,503.75	0.000
routing	3,628,588,696,977	1.26	2,875,938,701,982	135,016.63	0.000
capacity	23,423,604,753,572	2.00	11,711,802,376,786	6,791.67	0.000
picker density	212,645,930	2.00	106,322,965	0.06	0.940
Two-way interaction					
zoning × storage	53,824,631,240	13.53	3,977,054,213	650.08	0.000
zoning × batching	107,002,822,203	4.47	23,954,000,941	7,172.10	0.000
zoning × routing	519,311,668,853	8.61	60,308,399,816	67,568.56	0.000
zoning × capacity	363,108,750,009	7.45	48,746,063,479	3,446.28	0.000
zoning × picker density	70,541,906	7.45	9,470,001	1.48	0.166
storage × batching	408,853,054,506	5.73	71,397,279,167	35,807.75	0.000
storage × routing	155,210,457,286	7.63	20,346,287,849	18,418.06	0.000
storage × capacity	71,043,841,612	3.99	17,818,662,797	703.99	0.000
storage × picker density	57,574,884	3.99	14,440,484	0.57	0.684
batching × routing	326,381,072,529	4.03	80,953,931,134	114,650.70	0.000
batching × capacity	546,985,914,833	2.16	252,818,599,842	10,330.93	0.000
batching × picker density	44,549,391	2.16	20,590,868	0.84	0.440
routing × capacity	176,652,606,703	2.52	70,005,463,673	3,286.54	0.000
routing × picker density	10,781,543	2.52	4,272,606	0.20	0.865
Three-way interaction					
zoning × storage× capacity	4,788,013,921	27.07	176,891,049	28.91	0.000
zoning × storage × picker density	156,004,301	27,07	5,763,510	0.94	0.550
zoning × batching × capacity	14,718,752,935	8.93	1,647,494,030	493.28	0.000
zoning × batching × picker density	38,978,562	8.93	4,362,934	1.31	0.229
zoning × routing × capacity	51,208,732,317	17.22	2,973,471,316	3,331.43	0.000
zoning × routing × picker density	11,920,905	17.22	692,196	0.78	0.725
storage × batching × capacity	3,113,552,896	11.45	271,857,092	136.34	0.000
storage × batching × picker density	16,486,592	11.45	1,439,512	0.72	0.724
storage × routing × capacity	47,911,704,019	15.26	3,140,333,900	2,842.72	0.000
storage × routing × picker density	7,336,607	15.26	480,872	0.44	0.970
batching × routing × capacity	132,221,006,587	8.06	16,397,719,051	23,223.21	0.000
batching × routing × picker density	4,682,277	8.06	580,684	0.82	0.584
Residuals					
between subjects	456,975,452,002	265.00	1,724,436,668		
within zoning	6,317,028,530	986.99	6,400,292		
within storage	13,371,429,621	528.28	25,311,078		
within batching	7,015,403,693	286.67	24,472,011		
within routing	7,121,908,028	334.35	21,300,626		
within zoning × storage	21,941,161,733	3,586.46	6,117,785		
within zoning × batching	3,953,619,941	1,183.76	3,339,888		
within zoning × routing	2,036,710,314	2,281.90	892,551		
within storage × batching	3,025,770,995	1,517.51	1,993,906		
within storage × routing	2,233,175,613	2,021.54	1,104,692		
within batching × routing	754,386,872	1,068.40	706,092		
total	51,280,700,977,564	14,325.15			

Table Appendix B.1: 5×3×5×5×3×3×3 full factorial mixed model ANOVA on travel.

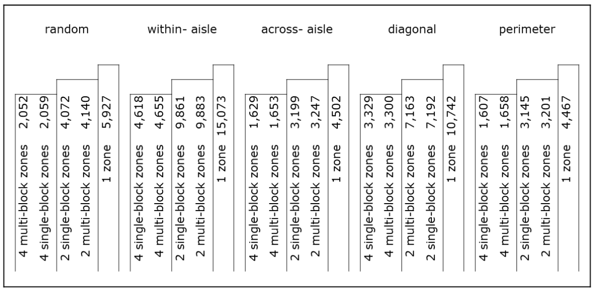
	Sum of squares	df	Mean square	F	p-value
Main effects					
zoning	431,902,771,197	2.47	175,119,725,879	25,983.78	0.000
storage	558,237,310,703	1.48	376,762,412,369	17,850.89	0.000
batching	120,074,595,920	1.58	75,782,689,676	6,477.06	0.000
routing	334,304,704,517	1.92	174,197,324,680	22,587.57	0.000
capacity	19,830,419,280	2.00	9,915,208,640	123.82	0.000
picker density	945,235,580,200	2.00	472,617,790,100	5,901.79	0.000
Two-way interaction					
zoning × storage	126,225,176,131	8.58	14,705,543,203	3,765.99	0.000
zoning × batching	19,290,903,395	5.00	3,855,800,798	879.56	0.000
zoning × routing	68,974,650,529	8.53	8,084,024,102	3,874.76	0.000
zoning × capacity	1,671,754,167	4.93	338,915,551	50.29	0.000
zoning × picker density	57,705,717,923	4.93	11,698,708,805	1,735.82	0.000
storage × batching	7,485,575,064	3.21	2,332,397,398	300.25	0.000
storage × routing	98,358,422,301	4.34	22,658,818,968	3,845.62	0.000
storage × capacity	1,353,604,488	2.96	456,783,596	21.64	0.000
storage × picker density	271,360,204,028	2.96	91,572,457,744	4,338.68	0.000
batching × routing	13,203,802,172	4.04	3,266,545,738	994.89	0.000
batching × capacity	9,417,180,226	3,17	2,971,732,868	253.99	0.000
batching × picker density	34,984,823,881	3.17	11,039,987,398	943.58	0.000
routing × capacity	2,475,856,448	3.84	645,051,601	83.64	0.000
routing × picker density	141,317,523,315	3.84	36,818,408,714	4,774.12	0.000
Three-way interaction					
zoning × storage× capacity	152,318,538	17.17	8,872,742	2.27	0.002
zoning × storage × picker density	30,453,866,781	17.17	1,773,975,158	453.30	0.000
zoning × batching × capacity	1,606,019,272	10.01	160,502,861	36.61	0.000
zoning × batching × picker density	1,160,765,802	10.01	116,004,980	26.46	0.000
zoning × routing × capacity	1,213,079,946	17.06	71,088,200	34.07	0.000
zoning × routing × picker density	12,655,494,549	17.06	741,629,875	335.47	0.000
storage × batching × capacity	5,710,053,625	6.42	889,585,243	114.52	0.000
storage × batching × picker density	1,993,600,356	6.42	310,588,582	30.98	0.000
storage × routing × capacity	2,519,597,317	8.68	290,219,679	49.26	0.000
storage × routing × picker density	57,525,651,664	8.68	6,626,089,035	1,124.57	0.000
batching × routing × capacity	13,203,802,172	8.08	417,234,179	127.08	0.000
batching × routing × picker density	3,859,634,726	8.08	477,425,866	145.41	0.000
Residuals					
between subjects	21,221,316,780	265.00	80,080,441		
within zoning	4,404,833,430	653.58	6,739,578		
within storage	8,287,142,085	392.64	21,106,082		
within batching	4,912,683,983	419.88	11,700,161		
within routing	3,922,101,596	508.57	7,712,088		
within zoning × storage	8,882,047,070	2,274.63	3,904,831		
within zoning × batching	5,812,080,515	1,325.82	4,383,770		
within zoning × routing	4,717,264,232	2,261.04	2,086,327		
within storage × batching	6,606,816,881	850.49	7,768,260		
within storage × routing	6,777,839,016	1,150.32	5,892,113		
within batching × routing	3,516,971,221	1,071.16	3,283,316		
total	3,464,694,792,850	11,382.94			

Table Appendix B.2: 5×3×5×5×3×3×3 full factorial mixed model ANOVA on picker blocking.

Appendix C. Multiple Bonferroni t-tests

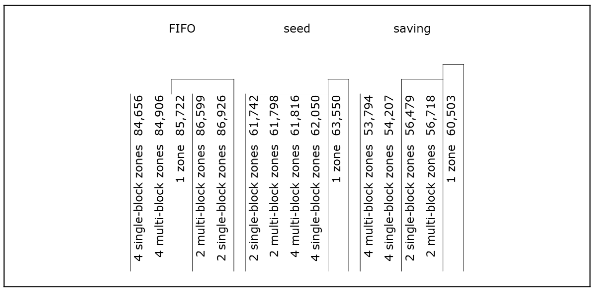


(a) Travel

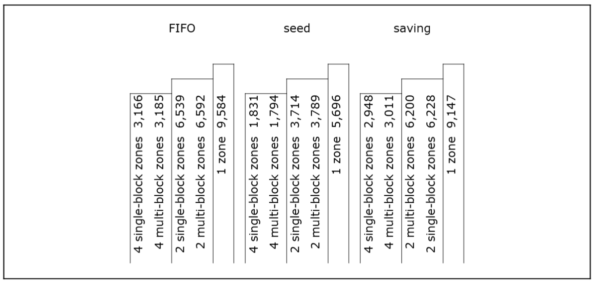


(b) Picker blocking

Figure C.21: Multiple Bonferroni t-test (familywise error rate = 0.01) for zoning policies by storage policies (in s).

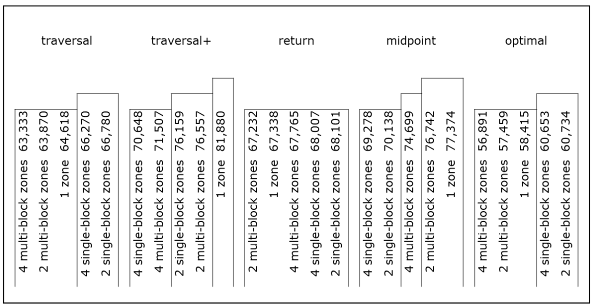


(a) Travel

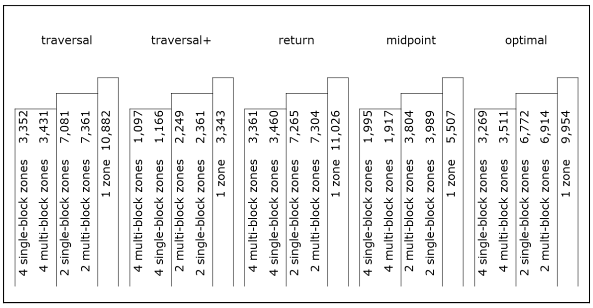


(b) Picker blocking

Figure C.22: Multiple Bonferroni t-test (familywise error rate = 0.01) for zoning policies by batching policies.

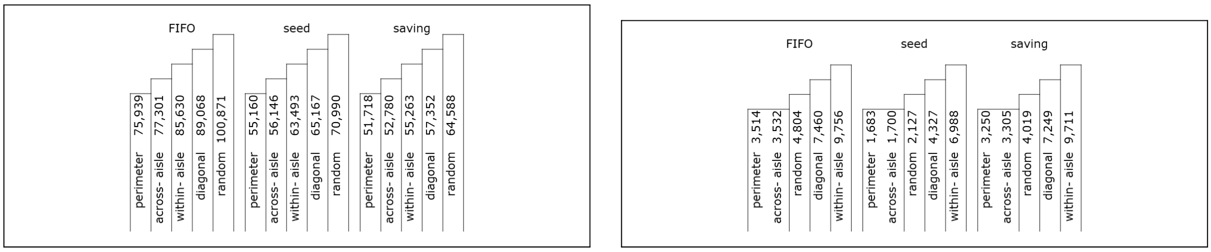


(a) Travel



(b) Picker blocking

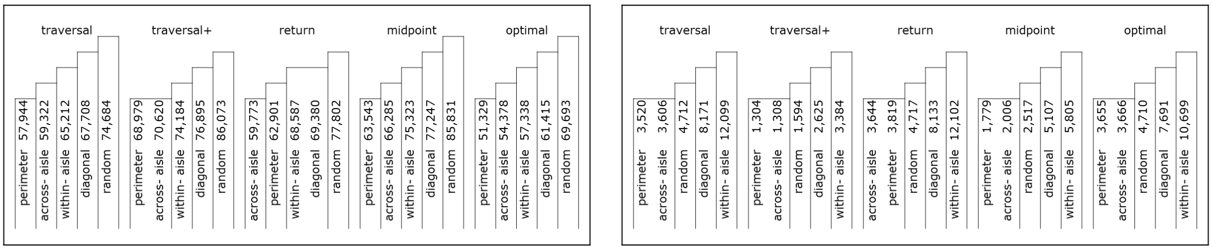
Figure C.23: Multiple Bonferroni t-test (familywise error rate = 0.01) for zoning policies by routing policies.



(a) Travel

(b) Picker blocking

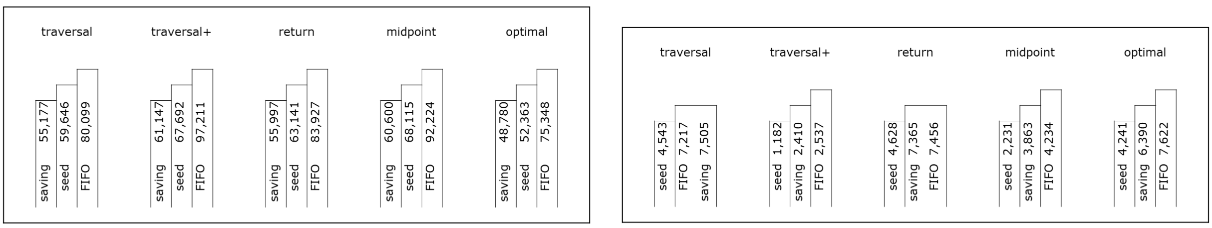
Figure C.24: Multiple Bonferroni t-test (familywise error rate = 0.01) for storage policies by batching policies.



(a) Travel

(b) Picker blocking

Figure C.25: Multiple Bonferroni t-test (familywise error rate = 0.01) for storage policies by routing policies.



(a) Travel

(b) Picker blocking

Figure C.26: Multiple Bonferroni t-test (familywise error rate = 0.01) for batching policies by routing policies.