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DOCTORAL DISSERTATION

Designing efficient order picking systems: combining planning problems and integrating real-life features

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Abstract

Complex market conditions and new developments make a warehouse manager's job hard. E-commerce and globalisation intensify competition among warehouses. The high expectations of customers to provide unique products and quick deliveries force warehouses to increase storage capacity, while at the same time reducing pick times. Additionally, expensive industrial land and high labour costs put pressure on the warehouse costs. To cope with these challenges, a wide range of order picking planning problems need to be optimised. Previous academic research focusses mainly on individual planning problems, without accounting for existing real-life features. Optimizing order picking planning problems sequentially may yield a suboptimal overall warehouse performance. Furthermore, excluding real-life features when developing algorithms and decision support tools prevents managers from using the academic findings in practice. Therefore, the objective of this thesis is to design efficient manual order picking systems by combining order picking planning problems and accounting for real-life features (e.g., safety constraints, due time constraints, workload peaks).

The main contributions of this PhD research are as follows. First, a classification of existing literature on tactical and operational order picking planning problems identifies interesting and relevant research directions to narrow the gap between academic research and practice. Second, an interaction analysis explains how and why the four main order picking planning problems (i.e., picker zoning, storage assignment, order batching and routing) are related. It also provides insights into the relevance and importance of incorporating real-life features (i.e., picker blocking, safety constraints and high-level storage) while planning order picking operations. Third, the value of incorporating workload related features is demonstrated by presenting a proof of concept of time series forecasting models in a warehouse context and by introducing a new mathematical programming model that balances the workload of order pickers over a short term planning horizon. Fourth, the benefits of optimising the integrated order batching, routing and job assignment problem are demonstrated, while coping with resource and due time constraints as well as high-level storage locations. Finally, the research provides future research opportunities that will be highly relevant to practice and which are largely unexplored in literature, thereby further reducing the research-practice gap.

Results show that the total order pick time can be substantially reduced by combining order picking planning problems. Combining existing order picking policies may yield performance benefits of 60-75% compared to the current operation in practice. Moreover, this PhD research illustrates the relevance and importance of incorporating real-life features in academic modelling approaches. Results show that safety constraints induce wait times, and cause additional travelling, picker blocking turns out to be minimised 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 for a wide range of practical order picking systems, thereby including the effect of real-life features. Finally, time series forecasting techniques and the operational workload balancing model supports managers to define the daily resource capacity and how to allocate these resources. On average, these decision support tools are able to strongly reduce the daily over- or underestimated resources compared to the individual gut feeling and experience of supervisors. These insights and results can be used to integrate operational order picking planning problems, which may result in additionally reduced pick times of 15-20% in the real-life warehouse. The provided managerial insights and decision support tools increase the control and efficiency of order picking operations and reduces the research-practice gap.

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Part I

Introduction and Review

CHAPTER 1

Introducing an Order Picking Story

Warehouses are challenged with fulfilling the ever increasing customer requirements, differentiating from competitors, and facing the rising costs of resources. This PhD research provides solution methods and insights to deal with these challenges. This chapter introduces the motivation of this PhD research and discusses the main research challenges (Section 1.1). The research objectives are summarised in Section 1.2 and the thesis outline is presented in Section 1.3.

1.1 Motivation and Challenges

As customer markets globalise, supply chains increasingly depend on efficient and effective logistical systems in order to distribute products in a large geographical area. A warehouse is defined as a facility where activities of receiving, storing, order picking, and shipping are performed. Although warehouses may also perform activities like kitting, labelling, and/or customised packaging (De Koster et al., 2007), most warehouse operations do not add value to the product. However, these non-value adding operations are critical to each supply chain (Gong and De Koster, 2011). Therefore warehouse operations need to work in an efficient and effective way in order to create value in the service they provide to customers (e.g., fast delivery).

Among the main warehouse operations, order picking (i.e., retrieval of items in the warehouse to fulfil customer orders) is the most costly warehouse activity (Marchet et al., 2015). Order picking as a warehouse function arises because goods are received in large volumes and customers order small volumes of different products. Each customer order is composed of one or more order lines, with every order line representing a single stock-keeping unit (SKU) (De Koster et al., 2007). Although pick robots are very efficient (Azadeh et al., 2018), manual picker-to-parts order picking systems (i.e., the order picker travels along the aisles to retrieve products) are still widely used in practice; human order pickers can handle unexpected changes in the process, are flexible with respect to capacity, and can retrieve a large variety of stock-keeping-units (SKUs) in terms of size and weight, which is particularly applicable to spare parts (Marchet et al., 2015; Van Gils et al., 2017c). Moreover, the high investment costs (Lamballais et al., 2017) and the risk of interrupting order picking operations during the implementation of pick robots are currently additional barriers for using pick robots (Marchet et al., 2015). These barriers are confirmed in the results of a recent valorisation project performed by our research group (i.e., Smart Logistics Limburg, see Appendix A) on revealing the needs and challenges of logistical companies in Limburg (Belgium). Therefore, this PhD research focusses on manual picker-to-parts order picking systems.

Order picking management, in particular organising efficient and flexible order picking systems, has been identified as an important and complex planning operation (Marchet et al., 2015), especially as a result of new market developments. These market developments include (1) e-commerce and globalisation, (2) increased customer expectations, (3) expensive industrial land and (4) high labour costs. First, e-commerce and globalisation have intensified competition among supply chains and forces warehouses to handle a large number of small orders within tight time windows (Marchet et al., 2015). In order to differentiate from competitors in terms of customer service, warehouses accept late orders from customers while providing delivery in a quick and timely way. By accepting late orders, the remaining time to pick an order is reduced. Furthermore, the order behaviour of customers has changed from ordering few and large orders to many orders consisting of only a limited number of order lines (Van Gils et al., 2018e). Second, customers expect unique products, increasing the assortment of SKUs. Consequently, more storage capacity is required. However, third, industrial land is expensive, especially in Western Europe. The area dedicated for storing SKUs by warehouses is limited. Finally, Western European countries are characterised by high labour costs, making productivity improvements especially beneficial. Since warehouses deliver labour-intensive services to customers, under-performance may result in high (labour) costs and unsatisfied customer demand (Wruck et al., 2017).

In the context of dealing with the complex market conditions, the task of managing order picking operations is perceived as difficult by warehouse managers (Gu et al., 2007). Decisions to manage order picking can be classified into strategic, tactical and operational decisions (see Figure 1.1). Strategic management decisions refer to policies and plans for using the resources in order to fulfil the long term competitive strategy. Examples of strate-

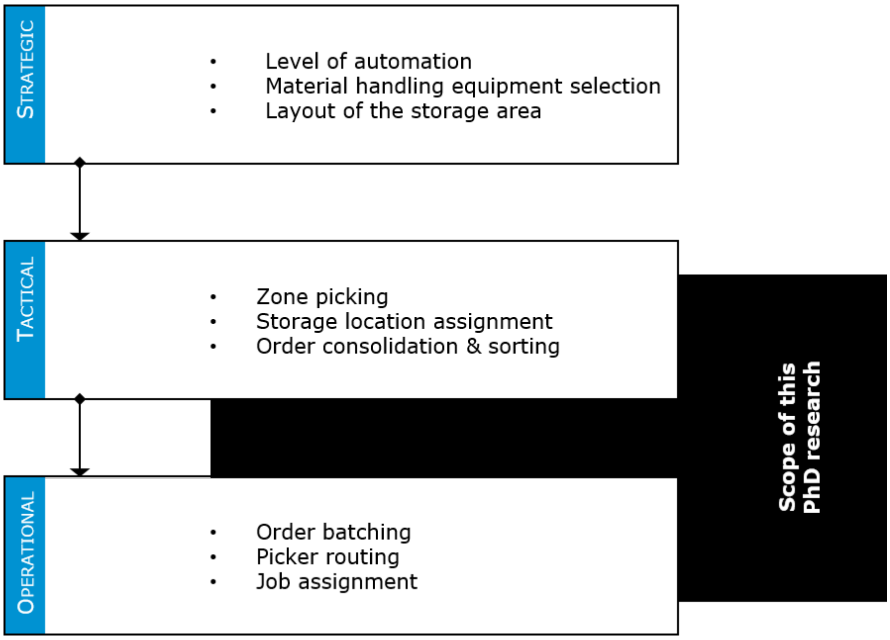


FIGURE 1.1: Examples of strategic, tactical and operational planning problems.

gic decisions are the layout of the storage area (i.e., shape, number of warehouse blocks and depot location), as well as the selection of storage systems, in particular the level of automation and the material handling equipment to retrieve items. Typical strategic decisions are discussed in Rouwenhorst et al. (2000), Davarzani and Norrman (2015) and Marchet et al. (2015). At the tactical level, decisions are taken that impact the medium term. The determination of the resource dimensions, like storage capacity and the size of pick zones, are examples of tactical decisions. Finally, operational decisions typically concern daily operations like batch formation and job assignment. Decisions of operational nature should be considered within the constraints set by the strategic and tactical decisions. This PhD research focusses on planning problems (e.g., order batching and picker routing) for which the time horizon of the resulting decision is short or medium (i.e., operational and tactical planning problems) as optimising these planning problems results in substantial performance benefits with limited capital investments.

1.2 Research Objective

Over the last decades, researchers have developed a wide range of planning models that help to increase the efficiency of order picking systems. Even literature overviews that review and classify existing research on order picking planning problems are comprehensive (Van den Berg, 1999; Rouwenhorst et al., 2000; Gu et al., 2007; De Koster et al., 2007; Gong and De Koster, 2011; Davarzani and Norrman, 2015; Grosse et al., 2015, 2017; Azadeh et al., 2018; Van Gils et al., 2018e; Aerts et al., 2018; Boysen et al., 2018b). Currently, literature mainly focusses on warehouse design (Dallari et al., 2009; Baker and Canessa, 2009; Marchet et al., 2015; Sprock et al., 2017) and individual warehouse planning problems, such as order batching or picker routing (Davarzani and Norrman, 2015; De Koster et al., 2007; Gu et al., 2007; Gong and De Koster, 2011). These review papers conclude that there seems to be a gap between research and practice (Davarzani and Norrman, 2015; De Koster et al., 2007; Van Gils et al., 2018e). 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). Therefore, the general objective of this PhD research is as follows:

Designing efficient manual order picking systems by combining order picking planning problems and accounting for real-life features.

Optimising each planning problem separately may lead to a suboptimal solution for the total warehouse. The new trends in the logistical industry may require even more efficient picking operations, while additionally accounting for crucial real-life features. Real-life features are defined as characteristics (e.g., high-level storage locations, human factors, and varying SKUs in terms of size and weight), constraints (e.g., safety and precedence constraints), and conditions (e.g., picker blocking and workload peaks) that have a substantial impact on the planning and performance of order picking systems in practice. Multiple order picking planning problems need to be considered simultaneously and real-life features need to be integrated in order to solve planning problems that deal with the complex market conditions.

Although fully closing the research-practice gap would be impossible in a single PhD research, the aim is to at least reduce the gap substantially. Past research especially focussed on rigour (i.e., coherent, logically developed theory, and the various dimensions of methodological and analytical validity that are necessary to test theory), while this thesis focusses on relevance of creating knowledge that managers can use to better understand phenomena (Carter, 2008). Following solutions proposed by Carter (2008) are applied to bridge the gap: case study based research, involving practitioners and presenting results to managers, and including a comprehensive discussion on the managerial implications of each chapter. Numerous warehouse visits and multiple interviews with warehouse managers in the context of the Smart Logistics Limburg project reveal the needs and challenges of warehouses and other logistical companies located in Limburg (Belgium) and identify the most relevant real-life features that have been insufficiently taken into account in past research. These results provide the required fundamentals to fulfil the objective of this PhD research. Each of the research parts in this thesis is thoroughly checked and validated using the problem context and data of a real-life warehouse. The problem context and data of three different B2B warehouses are used in this PhD research. All three warehouses deliver B2B customers, distribute spare parts, and operate manually (24 hours per day). However, the order pick design strongly differs among the warehouses, ranging from wide-aisles to narrow-aisles, low-levels to high-levels and single zoned to multi-zone warehouses. The main characteristics of the three warehouses are introduced in Table 1.1, as well as the chapter in which data of the warehouse are used. In addition to the real-life cases, all experiments are generalised by for example varying order structures and varying layouts, in order to provide general insights.

TABLE 1.1: Introduction real-life warehouses.

Warehouse A	Warehouse B	Warehouse C
	B2B automotive spare parts warehouse	
	Fully manually operated	
Low-level storage racks	High-level storage racks	Low- and high-level storage racks
Wide aisles	Narrow aisles	Wide aisles
Single pick zone	Multiple pick zones	Multiple pick zones
Similar (small) SKUs	Varying SKU types across zones, similar SKU types within a pick zone	Varying SKU types across zones, similar SKU types within a pick zone
Applied in Chapter 3	Applied in Chapters 4 & 7	Applied in Chapters 5 & 6

The main contributions of this PhD research are as follows. First, a classification of existing literature on combining tactical and operational order picking planning problems and real-life features identifies interesting and relevant research directions to narrow the gap between academic research and practice. Second, an interaction analysis, including simulation and comprehensive statistical tests, analyses and explains how and why the four main order picking planning problems (i.e., picker zoning, storage, order batching and routing) are related and provides insights into the relevance and importance of incorporating real-life features while planning order picking operations. Third, the value of incorporating workload related factors is demonstrated by presenting a proof of concept of time series forecasting models in a warehouse context and introducing a new mathematical programming model that balances the workload of order pickers over a short term planning horizon. Fourth, the benefits of optimising the integrated order batching, routing and job assignment problem are demonstrated, using the insights provided by the interaction analysis, by developing a new heuristic algorithm that is able to cope with multiple order pickers, high-level storage locations and avoiding tardiness of orders. Finally, the research provides future research opportunities that will be highly relevant to practice and which are largely unexplored in literature, thereby further reducing the research-practice gap.

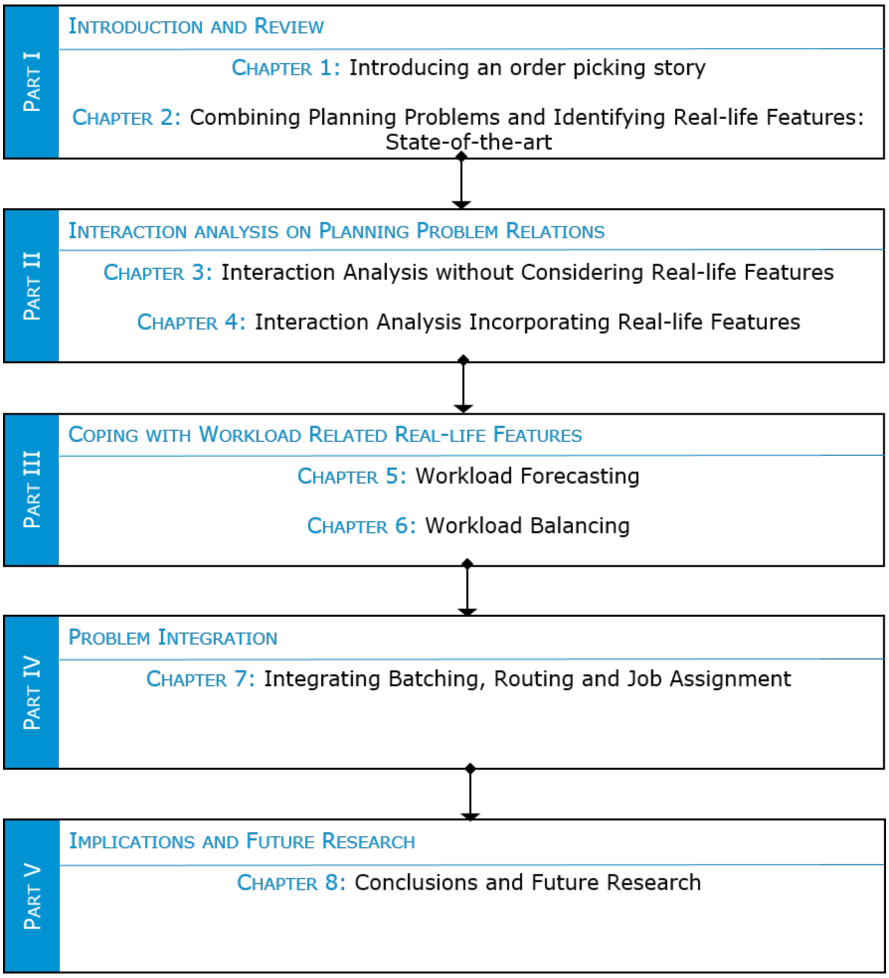


FIGURE 1.2: Thesis structure.

1.3 Thesis Outline

To fulfil the general research objective and realise the contributions discussed in the previous section, this thesis is organised into five parts, including eight chapters in total. The thesis structure is illustrated in Figure 1.2. In addition to an introductory part (i.e., Part I) and concluding part (Part V), Parts II until IV are based on the planning cycle of a warehouse, sorted from a tactical time horizon of the resulting decision to planning problems with an operational (i.e., hourly) time horizon. The content of each part and chapter as well as the corresponding structure are discussed in this section.

Part I consists of the problem introduction and the academic state-of-the-art. *Chapter 2* classifies literature combining order picking planning problems, as well as identifies real-life features that have a substantial impact on the planning and performance of order picking systems in practice. The literature classification of articles combining multiple tactical and operational planning problems in manually operated order picking systems is based on Van Gils et al. (2018e) and extended with the most recent research articles. This part provides insights into which planning problems should be considered simultaneously, as well as which research methodology is suitable to combine planning problems. The findings on interesting and relevant planning problem combinations and research methods to investigate and optimise these combinations are used throughout the remainder of the thesis. Additionally, this chapter identifies real-life features, based on the results of the Smart Logistics Limburg project and existing academic literature. The importance and relevance of the real-features are provided. The insights from the literature and from the warehouse visits are used to combine planning problems and incorporate real-life features throughout the remainder of this PhD thesis.

At a tactical decision level of a warehouse planning cycle (Part II), order picking planning problem with different time horizons of the resulting decision are combined. Interaction analyses, by means of simulation, experimental design and statistical tests, are performed to get insights into the relation among order picking planning problems and create generic explanations with respect to the combined effect of these planning problems on order picking performance. First, in *Chapter 3*, the four main order picking planning problems are combined: picker zoning, storage location assignment, order batching, and picker routing. The interaction analyses of Van Gils et al. (2016a) and Van Gils et al. (2018c) are discussed in wide-aisle order picking systems (without considering real-life features), thereby focussing on why and how order picking planning problems are related. Several policies (i.e., solution methods) for each planning problem are simulated to investigate relationships among these planning problems. Second, in *Chapter 4*, an interaction analysis is performed to explore to what extent these relationships have an effect on the order picking performance of picking systems that are subject to safety constraints, picker blocking, and high-level storage locations, such as narrow-aisle order picking systems. The incorporation of these real-life features changes the nature of the problem, resulting in substantially different results. This interaction analysis is based on Van Gils et al. (2018a) and Van Gils et al. (2019b).

With the knowledge and insights of the real-life features considered in the interaction analyses of Part II, Part III explores the effect of the resource constraint and workload peaks and how to cope with these workload related real-life features while planning daily order picking operations. Based on Van Gils et al. (2017c), *Chapter 5* forecasts order pickers' workload in a zoned order picking system in order to determine the daily required number of order pickers as well as how to divide the order pickers across pick zones (i.e., defining the resource constraint). Based on the forecast workload, this workload can be additionally balanced throughout the daily planning horizon by assigning groups of orders to certain time slots. In this way, workload peaks are avoided, reducing the probability of missing deadlines. A new mathematical programming model balancing the workload throughout the short-term planning horizon (i.e., usually a single day) is presented in the second chapter of this part (*Chapter 6*). The workload balancing problem is based on Vanheusden et al. (2019). This chapter is joined work with my appreciated colleague Sarah Vanheusden.

At an operational level, Part IV incorporates the workload related real-life features while integrating and optimising order picking planning problems. *Chapter 7* provides an effective and efficient algorithm, using the insights of the existing relationships identified in the previous chapters, that integrates and solves three operational order picking planning problems (i.e., order batching, picker routing, and job assignment). As the time horizon of the resulting decisions is similar, order picking operations' efficiency can be improved by integrating these planning problems. Moreover, the algorithm is able to cope with the following real-life features: resource constraints, high-level storage locations and order due time constraints. This chapter is based on Van Gils et al. (2019a).

Finally, Part V concludes the PhD research. *Chapter 8* provides the implications of this research as well as interesting and relevant future research directions to further close the gap between academic research and practice.

CHAPTER 2

Combining Planning Problems and Identifying Real-life Features: State-of-the-art

Recent literature reviews on warehouse planning, such as Rouwenhorst et al. (2000), Gu et al. (2007), De Koster et al. (2007), Gong and De Koster (2011), Davarzani and Norrman (2015), Marchet et al. (2015) and Boysen et al. (2018b) primarily focus on individual planning problems, without considering real-life features such as safety constraints and high-level storage locations. These review papers conclude that order picking planning problems seem to be interdependent and that future research should be more valuable to practice. Optimizing each problem separately may lead to a suboptimal solution for the total warehouse. New trends in the logistical industry require even more efficient picking operations. Multiple order picking planning problems need to be considered simultaneously in order to face these new market developments. Moreover, real-life features need to be considered and integrated while developing new planning models.

This chapter[1] provides a comprehensive classification and review of articles combining multiple tactical and operational planning problems (Section 2.1). Section 2.2 identifies the most crucial real-life features with respect to order picking performance that should be taken into account when planning order picking operations. Finally, Section 2.3 presents conclusions and gaps in current research that will be filled in this PhD thesis.

[1] This chapter is based on Van Gils, T., Ramaekers, K., Caris, A., De Koster, R. B. M., 2018e. Designing Efficient Order Picking Systems by Combining Planning Problems: State-of-the-art Classification and Review. European Journal of Operational Research 267 (1), 1–15 and Van Gils, T., Caris, A., Ramaekers, K., Braekers, K., De Koster, R. B. M., 2019b. Designing efficient order picking systems: the effect of safety constraints, picker blocking, and high-level storage on the relation among planning problems. Transportation Research Part E: Logistics and Transportation Review 125, 47–73.

2.1 Combining Order Picking Planning Problems

This section provides a state-of-the-art review and classifies the scientific literature investigating combinations of tactical and operational order picking planning problems with the aim of answering three research questions. First, based on the classification, we aim to determine how individual order picking planning problems are related and which planning problems should be considered simultaneously in order to optimise the overall order picking performance. Second, by analysing combinations of planning problems, we aim to identify excellent methods for solving combinations of planning problems that may help managers to take better decisions. Third, while order picking systems in previous research are subject to a large number of assumptions to simplify order picking operations (De Koster et al., 2007; Davarzani and Norrman, 2015), our classification is used to identify future research directions narrowing the gap between practice and academic research. This review and classification differs from previous literature reviews by focusing on how warehouse managers can benefit from combining multiple tactical and operational planning problems in manually operated order picking systems.

The remainder of this classification and review section is organised as follows: Section 2.1.1 describes the scope of the review. Section 2.1.2 discusses the classification scheme used to categorise publications investigating combinations of order picking planning problems. The selected publications are classified in Sections 2.1.3, 2.1.4, and 2.1.5 according to the defined classifiers. The managerial implications resulting from the literature overview are discussed in Section 2.1.6.

2.1.1 Scope of the Review

The state-of-the-art classification and review section reviews and classifies recent order picking planning literature, in particular studies that combine multiple tactical and operational planning problems. We do not intend to provide an exhaustive overview of all warehousing literature, but we restrict the reviewed literature by focusing on specific planning problems published in high-quality journals.

Figure 2.1 shows the tactical and operational order picking planning problems that are considered in this review. The overview is based on the planning problems defined by De Koster et al. (2007), complemented with several recent innovative planning problems, such as zone assignment, workforce allocation and job assignment. The reader is referred to Appendix B for an overview and discussion of all order picking planning problems considered in the selection of the literature. Only planning problems that affect an economic goal, such as time or productivity related performance measures, are considered, as these objectives are the most important in any warehouse operation. Consequently, behavioural aspects and ergonomics objectives are beyond the scope of this

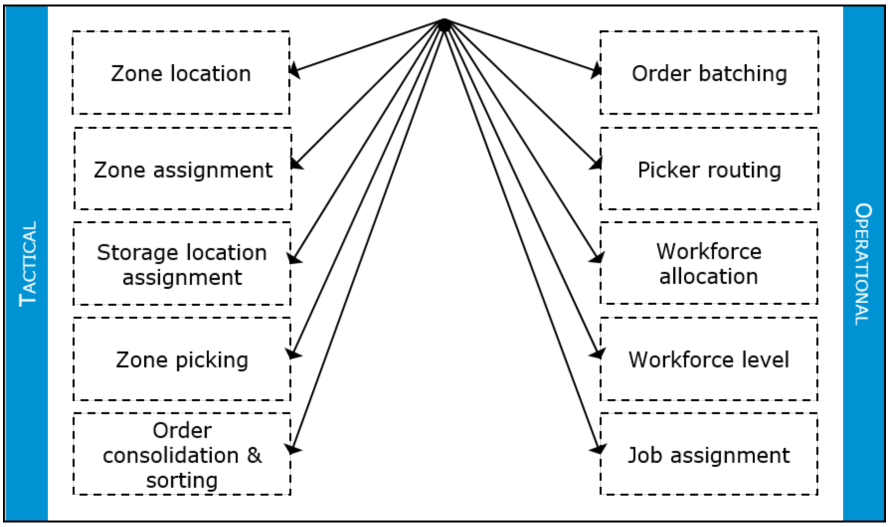


FIGURE 2.1: Overview of tactical and operational order picking planning problems.

review. Moreover, warehouse layout (Pohl et al., 2009), as well as other strategic planning problems, such as storage and material handling technology choice (Marchet et al., 2015), depot location (Petersen, 1997), and number of warehouse blocks (Roodbergen and De Koster, 2001a) are mostly fixed in practice, especially in the short and medium term. Therefore, the scope is limited to tactical and operational order picking planning problems, as these problems are expected to be the most relevant to combine.

In order to meet the objectives of the study, two types of publications are considered: articles *integrating* multiple planning problems and articles examining *interactions* between planning problems in manual order picking systems. Problem integration refers to formulating and solving two or more planning problems jointly, and thus integrating multiple planning problems. Interactions are defined as the joint effect that two or more planning problems have on a performance goal, which can be investigated by considering multiple policies (i.e., solution methods or techniques for organizing a planning problem) for each planning problem and analysing the effect of these policies on warehouse performance. Consequently, the scope of the review is restricted to articles examining multiple policies for at least two planning problems, since these studies are able to show a potential relation between two or more planning problems. For example a study that combines multiple storage location assignment policies (e.g., random storage and turnover based storage) and multiple routing methods (e.g., traversal, largest gap and optimal routing) is included in the overview, whereas articles assuming a single and fixed routing method in combination with different storage location assignment policies (e.g., Yu et al. (2015) and Guo et al. (2016)) are excluded since these studies are not able to provide knowledge on

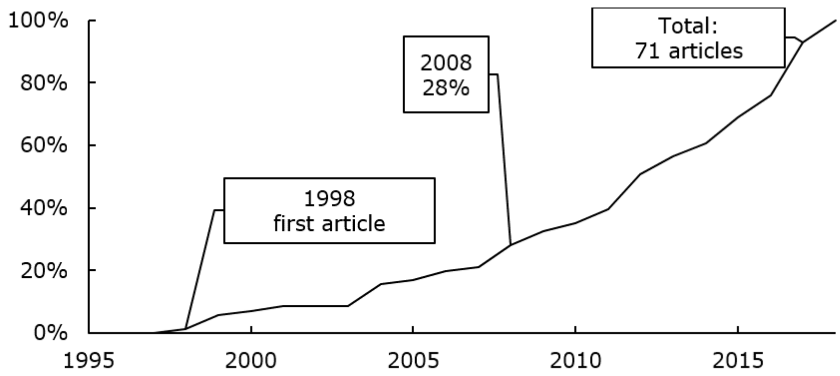


FIGURE 2.2: Time distribution of the reviewed articles.

how to benefit from combining multiple planning problems. Furthermore, studies that sequentially optimise multiple planning problems (e.g., Çelik and Süral (2014)) or optimise a single planning problem (e.g., Scholz et al. (2016)) are excluded from the classification as well.

Only articles published in English-language journals with an Impact Factor of at least 0.500 (based on the Impact Factors of 2015 by Thomson Reuters) are considered. Books and conference proceedings are excluded from the classification, as these publications are often preliminary versions of journal publications.

An initial set of articles is selected by searching for at least two of the defined planning problems in articles' titles. The set of articles is extended by considering the citations of the initial set of articles. Each article is evaluated on the investigated planning problems, as well as on the journal selection criteria mentioned above. This search strategy resulted in a final set of 71 representative publications, which are classified in this literature overview.

Figure 2.2 illustrates graphically the distribution in time of the selected studies. The number of articles considering the combination of different order picking planning problems has grown strongly in the last decade. 73% of all considered articles are published in the last decade. While the number of publications on examining a single order picking planning problem was already substantial before 2007, as outlined in De Koster et al. (2007), Gu et al. (2007), Rouwenhorst et al. (2000), and Van den Berg (1999), analysing multiple order picking planning problems at once has only been a focus since the last decade. The strong increasing line shows the importance of studying multiple order picking planning problems jointly.

2.1.2 Classification Scheme

This section introduces a classification scheme to categorise the selected articles. Table 2.1 lists the classification criteria and features used in this review to categorise the articles. The first classifier divides papers into categories based on the performance measure used to analyse the relation between planning problems with the aim of identifying relevant performance indicators to evaluate the effect of combining planning problems. Next, all 71 considered articles are classified with respect to the research method used to analyse the combination of planning problems. This classification identifies methods for solving combinations of planning problems that may help managers to take better decisions. Finally, articles are classified according to the investigated combination of order picking planning problems in order to identify how planning problems are related and which planning problems should be considered simultaneously to optimise the overall order picking performance. Moreover, the classification identifies how warehouse managers could solve the combination of planning problems.

TABLE 2.1: Classification scheme.

Classifier	Features
Performance measure	Time
	Cost
	Productivity
	Service
Research method	Analytical models
	Simulation
	Mathematical models
Combination	Storage location assignment & routing
	Storage location assignment & order batching
	Order batching & routing
	Combinations of other order picking planning problems

First, all considered articles are classified according to the order picking performance evaluation used to analyse the relations among planning problems. Note that articles are only classified in the performance measures categories that have been used to analyse the combined effect of multiple planning problems. In case of for example analysing the combined effect of batching and routing policies on picker travel time and evaluating the effect of batching policies on the service level, this article is only classified in the time related performance indicator. Articles are classified according to the performance evaluation dimensions distinguished by Staudt et al. (2015), in particular time, cost, productivity, and service (or quality) related performance indicators. These performance evaluation dimensions are commonly used and help warehouse managers to assess the performance of the operations and to make consequential decisions.

Next, the literature is classified according to the research method used to analyse the effect of combining two or more order picking planning problems or to formulate and solve the integrated problem. The reviewed articles either use analytical models, perform a simulation study, or use mathematical programming to evaluate the combined effect of order picking planning problems. Simulation experiments can be used to determine which combination of factors results in the best order picking performance (Chan and Chan, 2011) and how these factors influence each other. Analytical models predict the performance by relating the performance variable to the main order picking parameters, such as batch capacity and layout (Caron et al., 1998). Mathematical programming models refer to the set of equations and related mathematical expressions that describe the problem. An objective function and constraints define the overall structure of the problem (Hillier and Lieberman, 2010).

Finally, the combination classifier categorises articles according to the investigated combination of order picking planning problems. The overview of Figure 2.1 is used to classify the articles.

2.1.3 Classification by Performance Measure

Based on the indicator definitions of Staudt et al. (2015), the reviewed articles are classified according to the performance measure. Table 2.2 gives an overview of the performance metrics applied to evaluate the combined effect of order picking planning problems. Note that the performance metrics are not mutually exclusive: studies can use more than one performance metric.

All publications, except for Bartholdi et al. (2001), Parikh and Meller (2008) and Tsai et al. (2008), evaluate order picking performance using time related performance indicators, either order picking time (i.e., lead time to pick a set of orders (Van Nieuwenhuyse and De Koster, 2009)) or earliness/tardiness (i.e., difference between the order completion time and order due time (Henn, 2015)). The process of order picking starts by composing a pick order for which setup time is required. After setting up, the order picker can start travelling to the storage locations (i.e., travel time) and search and retrieve items (i.e., retrieve time). In case orders are split across zones or batches, these orders should be sorted, consolidated and packed before shipping (i.e., sorting time). Idle time refers to unproductive time, for example time caused by blocking of order pickers within an aisle (Chen et al., 2016), or the time an order spends waiting for a pick batch to be formed (Van Nieuwenhuyse and De Koster, 2009). Other time components include for example the time transferring orders from picking to sorting operations (Yu and De Koster, 2009). Thus, the order picking time metric includes setup time, travel time, search and pick time, waiting time, sorting time and other time consuming activities. Besides order picking time, the time performance indicator can be expressed as the earliness or tardiness of orders. As orders should be picked within tight time windows, earliness and tardiness measures are able to evaluate the extent to which these time windows are fulfilled. Thus, earliness and tardiness are especially useful to analyse combinations of operational planning problems.

TABLE 2.2: Overview of the classification by performance measurement.

Performance indicator	# articles	
Time		
Order picking time	63	Caron et al. (1998); De Koster et al. (1999); Petersen and Schmenner (1999); Ruben and Jacobs (1999); Petersen (2000); Dekker et al. (2004); Hwang et al. (2004); Jewkes et al. (2004); Petersen and Aase (2004); Petersen et al. (2004); Won and Olafson (2005); Ho and Tseng (2006); Hsieh and Tsai (2006); Manzini et al. (2007); Gong and De Koster (2008); Ho et al. (2008); Yu and De Koster (2008); Koo (2009); Van Nieuwenhuyse and De Koster (2009); Yu and De Koster (2009); Chen et al. (2010); Theys et al. (2010); Chan and Chan (2011); Hsieh and Huang (2011); Rubrico et al. (2011); De Koster et al. (2012); Ene and Öztürk (2012); Henn (2012); Henn and Wäscher (2012); Hong et al. (2012a,b); Kulak et al. (2012); Pan and Wu (2012); Chackelson et al. (2013); Heath et al. (2013); Matthews and Visagie (2013); Matusiak et al. (2014); Pan et al. (2014); Shqair et al. (2014); Cheng et al. (2015); Hong et al. (2015); Öncan (2015); Roodbergen et al. (2015); Chen et al. (2016); Hong et al. (2016); Li et al. (2016); Lin et al. (2016); Chen et al. (2017); Dijkstra and Roodbergen (2017); Franzke et al. (2017); Giannikas et al. (2017); Hong and Kim (2017); Matusiak et al. (2017); Scholz et al. (2017); Schrotenboer et al. (2017); Valle et al. (2017); Zhang et al. (2017); Ardjmand et al. (2018); Chabot et al. (2018); Hong (2018); Quader and Castillo-Villar (2018); Žulj et al. (2018a,b)
Earliness/tardiness	5	Henn and Schmid (2013); Chen et al. (2015); Henn (2015); Menéndez et al. (2017); Scholz and Wäscher (2017)
Cost		
Order picking cost	2	Tsai et al. (2008); Parikh and Meller (2008)
Productivity		
Labour	1	Quader and Castillo-Villar (2018)
Picking	6	Ruben and Jacobs (1999); Bartholdi et al. (2001); Koo (2009); Chen et al. (2010); Hong et al. (2016); Quader and Castillo-Villar (2018)
Equipment	3	Ruben and Jacobs (1999); Yu and De Koster (2008); Hsieh and Huang (2011)
Service		
Service level	3	Petersen (2000); Gong and De Koster (2008); Chen et al. (2010)

Earliness and tardiness are mainly used to evaluate models that integrate batching and routing in a dynamic context, allowing orders to arrive during the planning period (Tsai et al., 2008; Henn and Schmid, 2013; Chen et al., 2015; Henn, 2015). Table 2.3 illustrates the number of articles including the components of order picking time. Among all order picking activities, travelling is considered as the most time consuming component (Chen et al., 2015). All articles considering time related performance indicators include at least travel time (or travel distance), assuming other time components to be constant. Especially, the effect of picker blocking on order picking efficiency is underestimated in current literature analysing combinations of planning problems, despite the fact that congestion among workers can be a significant issue in picking areas with high pick densities (Chen et al., 2016). Most articles aim to increase the pick density in order to reduce the travel time by varying combinations of storage location assignment and order batching policies, without taking the picker blocking effect into account (Ruben and Jacobs, 1999; Hsieh and Huang, 2011).

In order to efficiently manage order picking operations, time related performance indicators are used in the large majority of articles to evaluate combinations of order picking planning problems. These time consuming components of order picking time can be expressed in terms of costs: all time depending components are multiplied with a fixed cost,

TABLE 2.3: Overview of articles including each component of time.

Time component	# articles	
Setup	20	Petersen (2000); Gong and De Koster (2008); Yu and De Koster (2008); Van Nieuwenhuyse and De Koster (2009); Yu and De Koster (2009); Chen et al. (2010); De Koster et al. (2012); Hong et al. (2012a); Henn (2012); Pan and Wu (2012); Heath et al. (2013); Henn and Schmid (2013); Henn (2015); Hong et al. (2016); Giannikas et al. (2017); Matusiak et al. (2017); Menéndez et al. (2017); Scholz et al. (2017); Zhang et al. (2017); Quader and Castillo-Villar (2018)
Travel	67	Caron et al. (1998); De Koster et al. (1999); Petersen and Schmenner (1999); Ruben and Jacobs (1999); Petersen (2000); Dekker et al. (2004); Hwang et al. (2004); Jewkes et al. (2004); Petersen and Aase (2004); Petersen et al. (2004); Won and Olafson (2005); Ho and Tseng (2006); Hsieh and Tsai (2006); Manzini et al. (2007); Gong and De Koster (2008); Ho et al. (2008); Yu and De Koster (2008); Koo (2009); Van Nieuwenhuyse and De Koster (2009); Yu and De Koster (2009); Chen et al. (2010); Theys et al. (2010); Chan and Chan (2011); Hsieh and Huang (2011); Rubrico et al. (2011); De Koster et al. (2012); Ene and Öztürk (2012); Henn (2012); Henn and Wäscher (2012); Hong et al. (2012a,b); Kulak et al. (2012); Pan and Wu (2012); Chackelson et al. (2013); Heath et al. (2013); Henn and Schmid (2013); Matthews and Visagie (2013); Matusiak et al. (2014); Pan et al. (2014); Shqair et al. (2014); Chen et al. (2015); Cheng et al. (2015); Henn (2015); Hong et al. (2015); Öncan (2015); Roodbergen et al. (2015); Chen et al. (2016); Hong et al. (2016); Li et al. (2016); Lin et al. (2016); Chen et al. (2017); Dijkstra and Roodbergen (2017); Franzke et al. (2017); Giannikas et al. (2017); Hong and Kim (2017); Matusiak et al. (2017); Menéndez et al. (2017); Scholz and Wäscher (2017); Scholz et al. (2017); Schrotenboer et al. (2017); Valle et al. (2017); Zhang et al. (2017); Ardjmand et al. (2018); Chabot et al. (2018); Quader and Castillo-Villar (2018); Žulj et al. (2018a,b)
Retrieve	29	Petersen (2000); Petersen and Aase (2004); Petersen et al. (2004); Gong and De Koster (2008); Yu and De Koster (2008); Koo (2009); Van Nieuwenhuyse and De Koster (2009); Yu and De Koster (2009); Chen et al. (2010); Chan and Chan (2011); Rubrico et al. (2011); De Koster et al. (2012); Hong et al. (2012a); Henn (2012); Pan and Wu (2012); Chackelson et al. (2013); Heath et al. (2013); Henn and Schmid (2013); Henn (2015); Hong et al. (2015); Chen et al. (2016); Hong et al. (2016); Giannikas et al. (2017); Matusiak et al. (2017); Menéndez et al. (2017); Scholz et al. (2017); Schrotenboer et al. (2017); Zhang et al. (2017); Quader and Castillo-Villar (2018)
Sort	5	Van Nieuwenhuyse and De Koster (2009); Yu and De Koster (2009); Chen et al. (2010); De Koster et al. (2012); Žulj et al. (2018a)
Idle	17	Petersen (2000); Gong and De Koster (2008); Koo (2009); Van Nieuwenhuyse and De Koster (2009); Rubrico et al. (2011); Hong et al. (2012a); Pan and Wu (2012); Heath et al. (2013); Hong et al. (2015); Chen et al. (2016); Hong et al. (2016); Quader and Castillo-Villar (2018); Chen et al. (2017); Schrotenboer et al. (2017); Zhang et al. (2017); Chabot et al. (2018); Hong (2018)
Other	2	Won and Olafson (2005); Yu and De Koster (2009)

such as travel cost per time unit (Tsai et al., 2008). Although order picking time is often used as a proxy for cost, time related measures can additionally inform managers whether due times and operating time windows can be met, while cost performance indicators can include non-time related cost components, such as fixed equipment cost related to a batch or zone order picking system (Parikh and Meller, 2008), to evaluate different order picking systems.

The productivity metric can be either labour productivity, i.e., ratio of the amount of value-added time and the total picking time (Quader and Castillo-Villar, 2018), picking productivity, i.e., the number of items picked per picker per time interval (Ruben and Jacobs, 1999), or productivity of the equipment, e.g., the extent to which the picking vehicle capacity is used (Ruben and Jacobs, 1999; Hsieh and Huang, 2011). Labour and picking productivity mainly evaluate combinations of zone picking and job assignment (Bartholdi et al., 2001; Koo, 2009; Hong et al., 2016; Quader and Castillo-Villar, 2018), while equipment productivity has been used to analyse the relation between storage location assignment and order batching.

Finally, service or quality refers to the service level expressed as the percentage of orders that is picked on time (Gong and De Koster, 2008). The joint effect of combining planning problems on the service level has been analysed in only three articles, despite the fact that quality is the main service delivered to customers. Warehouses aim to increase the order picking efficiency (i.e., using minimal time to handle more orders), while maintaining a high service level to customers (Chen et al., 2010). The increased time pressure as a result of the e-commerce market developments may increase the chance of pick errors. However, most articles do not take the service level or other quality performance indicators (e.g., pick errors) into account.

2.1.4 Classification by Research Method

This section classifies publications with respect to the research method used to analyse or solve the combined problem. The following research methods have been proposed in literature to analyse interactions of order picking policies or to integrate multiple order picking planning problems: analytical models, simulation experiments, and mathematical programming. Analytical models refer to a set of mathematical equations that approximate the performance of a system by relating the performance variable to multiple system parameters. Simulation experiments are defined as methods to imitate the system's operations or characteristics with the purpose of conducting numerical experiments to provide insights into the behaviour of the system. Mathematical programming models refer to the set of mathematical expressions that describe the problem consisting of an objective function and constraints to define the overall structure of the problem. Figure 2.3 illustrates the distribution of these research methods in the scientific literature. Simulation is by far the most popular technique to analyse combinations of order picking planning problems, followed by mathematical programming.

Analytical models have not been considered very often as approach to analyse the impact of combining order picking planning problems. Fourteen articles develop an analytical model to evaluate planning problem combinations. An analytical approach for approximating the systems performance has proven to be accurate in evaluating combinations of order picking planning problems, such as storage location assignment and routing (Caron et al., 1998; Hwang et al., 2004), zone location and workforce allocation (De Koster et al., 2012), and batching and routing (Gong and De Koster, 2008). This last combination is an application of polling models in the context of order picking: a system of multiple queues of orders accessed by a single or multiple order pickers (Gong and De Koster, 2008). The proposed analytical models can be used by warehouse managers

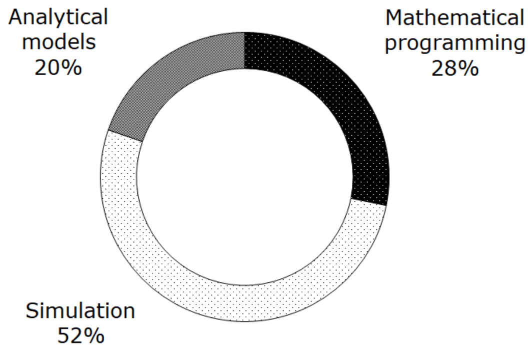


FIGURE 2.3: Research method used to analyse order picking planning problem combinations.

to predict the system performance under different policies, and to compare these alternatives in a stochastic setting. Analytical models outperform simulations with respect to modelling and computing time. While simulation requires model and scenario development time, a thorough validation process and long runs to reduce the stochastic effect of order generation (i.e., to prevent drawing conclusions dedicated to a limited number of orders), analytical models can compare policy combinations by simply defining parameter values and evaluating the performance value resulting from the equation. However, analytical models are complex to develop. Consequently, these models often provide a simplified representation of order picking operations investigating a limited number of policy combinations. Under the assumptions of the analytical model, the provided optimal combination of policies can be used as benchmark policies for real-life operations (Van Nieuwenhuyse and De Koster, 2009).

Simulation studies form the largest category of research methods in this literature classification. Like analytical models, warehouse managers may use simulation results to evaluate the combined effect of multiple order picking planning problems in order to design efficient order picking systems. Simulation models are able to provide a more detailed representation of order picking operations compared to analytical models. A large number of policy combinations can be easily tested once a simulation model has been created. Table 2.4 summarises all publications simulating combinations of order picking planning problems. A large number of articles simulate combinations of order picking planning problems without further analysing the relation between these problems. These studies are mentioned in the footnote of Table 2.4. In most of these studies, a new solution technique is proposed for solving a single order picking planning problem. This new policy is compared with other policies of the same planning problem, and validated for several policies of other order picking planning problems. Their main objective is not to analyse interactions between order picking planning problems. For example, Öncan (2015) intro-

TABLE 2.4: Studies analysing combinations of order picking planning problems using simulation.

	Interaction plots	ANOVA	Multiple comparison tests	Other
Petersen and Schmenner (1999)	•	•		
Ruben and Jacobs (1999)	•	•	•	
Petersen (2000)		•		
Ho and Tseng (2006)		•	•	
Hsieh and Tsai (2006)		•	•	
Manzini et al. (2007)	•			•
Ho et al. (2008)		•	•	
Chen et al. (2010)			•	•
Theys et al. (2010)	•			
Hsieh and Huang (2011)		•	•	
Chackelson et al. (2013)	•	•		
Shqair et al. (2014)	•	•	•	
Roodbergen et al. (2015)				•
Chen et al. (2016)		•		
Quader and Castillo-Villar (2018)		•		
Žulj et al. (2018a)	•			

Following studies simulate combinations of order picking planning problems without further analysing the relation between these problems: De Koster et al. (1999); Dekker et al. (2004); Petersen and Aase (2004); Petersen et al. (2004); Chan and Chan (2011); De Koster et al. (2012); Henn (2012); Henn and Wäscher (2012); Hong et al. (2012a,b); Heath et al. (2013); Henn and Schmid (2013); Pan et al. (2014); Henn (2015); Öncan (2015); Chen et al. (2017); Franzke et al. (2017); Giannikas et al. (2017); Scholz and Wäscher (2017); Schrotenboer et al. (2017); Žulj et al. (2018b).

duces an iterated local search algorithm to solve a mathematical programming formulation of the batching problem. This novel batching policy is compared with two savings algorithms and other metaheuristic batching algorithms, and validated by simulating the batching policies in combination with a traversal, return and midpoint routing policy. As the simulation of multiple batching and routing policies provides insights into the effect of combining planning problems, and the heuristic algorithm is only used to solve a single planning problem (e.g., batching (Henn, 2012; Henn and Wäscher, 2012; Öncan, 2015)), these type of studies are classified as simulation.

More comprehensive studies show interaction plots, and/or perform an analysis of variance (ANOVA) and multiple comparison tests to analyse potential interactions among order picking planning problems. These articles are listed in Table 2.4. Some papers use interaction plots to show the mean performance values of two order picking planning problems in which the mean values of policies of one planning problem are shown at different levels of the other planning problem. These graphs are used to illustrate interaction effects. A wide range of combinations have been graphically illustrated in literature, such as storage location assignment & order batching (Ruben and Jacobs, 1999), storage location assignment & picker routing (Petersen and Schmenner, 1999; Manzini et al., 2007; Theys et al., 2010; Shqair et al., 2014), and order batching & picker routing (Chackelson et al., 2013). ANOVA is the most popular tool to determine the order picking planning problems that have the most significant effect on warehouse performance and confirm whether interactions among order picking planning problems are statistically significant. While lines on the interaction graph can indicate significant interactions, ANOVA is able to prove the statistical significance of interaction terms. All reviewed articles performing an ANOVA analysis test for two-way interactions among planning problems, while Ho and Tseng (2006), Hsieh and Tsai (2006), Ho et al. (2008), and Hsieh and Huang (2011) also test and confirm a statistically significant three-way interaction between storage, batching, and routing. Additionally, a multiple comparison test can give insight into which policies of an order picking planning problem differ and how policies are ranked under different policies of a second order picking planning problem. For example, Ho and Tseng (2006) rank different batching policies under random and turnover based storage location assignment. Performance rankings of the batching policies are different under random and turnover based storage. This result explains why the two-way interaction between storage location assignment and order batching is statistically significant. Other techniques of Table 2.4 refer to multi-level factorial analysis (Manzini et al., 2007), data envelopment analysis (Chen et al., 2010), and ranking and selection procedures (Chen et al., 2010; Roodbergen et al., 2015).

Finally, mathematical programming models use mathematical expressions, i.e., an objective function and constraints, to describe a complex problem concisely. The use of mathematical programming as a research method to integrate different order picking planning problems is limited. Besides exact solution approaches (Jewkes et al., 2004; Hong et al., 2016; Valle et al., 2017), metaheuristic algorithms are mostly used to solve complex mathematical programming problems in warehouses. Metaheuristic algorithms find a good solution for complex planning problems. As optimizing most single order picking planning problems, such as the order batching problem or the picker routing problem, have proven to be NP-hard, combining several planning problems will also result in NP-hard problems (Li et al., 2016). Metaheuristics have proven to solve complex planning problems within reasonable computing times. Despite the popularity of metaheuristics for solving large real-life mathematical programming problems (Sörensen and Glover, 2013), only the integrated problem of batching & routing, job assignment & batching and job assignment & batching & routing have been solved by metaheuristic algorithms (see Table 2.5). Planning job assignment, batching, and routing are operational decisions that have to be made frequently, compared to the other defined planning problems. Each of these decisions is taken multiple times each hour. For this reason, warehouses require fast and effective algorithms to fulfil all customer orders.

Metaheuristic algorithms are especially useful for combining order picking planning problems of operational nature. However, integrating planning problems of tactical and operational nature seems to be less meaningful, due to the different time horizons for deciding on both problems. For example, integrating zone location and batching makes little sense, as batches are created multiple times every hour, while the zone location decision is a constant in short term. Simulation and analytical models are more useful to evaluate

TABLE 2.5: Studies using metaheuristics to solve mathematical programming problems of planning problem combinations ($\mathscr{B}$, $\mathscr{J}$, and $\mathscr{R}$, the batching, job assignment, and routing planning problem, respectively).

	Local search	Constructive	Genetic	Other
Won and Olafson (2005)	$\mathscr{B}$&$\mathscr{R}$			
Tsai et al. (2008)			$\mathscr{B}$&$\mathscr{R}$	
Ene and Öztürk (2012)			$\mathscr{B}$&$\mathscr{R}$	
Rubrico et al. (2011)	$\mathscr{B}$&$\mathscr{J}$			
Kulak et al. (2012)	$\mathscr{B}$&$\mathscr{R}$		$\mathscr{B}$	
Matthews and Visagie (2013)		$\mathscr{R}$&$\mathscr{J}$		
Matusiak et al. (2014)	$\mathscr{B}$	$\mathscr{R}$		
Chen et al. (2015)		$\mathscr{R}$	$\mathscr{B}$&$\mathscr{J}$	
Cheng et al. (2015)		$\mathscr{R}$		$\mathscr{B}$
Li et al. (2016)	$\mathscr{R}$	$\mathscr{R}$		$\mathscr{B}$
Lin et al. (2016)		$\mathscr{R}$		$\mathscr{B}$
Matusiak et al. (2017)		$\mathscr{B}$&$\mathscr{J}$		
Menéndez et al. (2017)	$\mathscr{B}$&$\mathscr{J}$			
Scholz et al. (2017)	$\mathscr{B}$&$\mathscr{R}$&$\mathscr{J}$			
Zhang et al. (2017)		$\mathscr{B}$&$\mathscr{J}$		
Ardjmand et al. (2018)[a]		$\mathscr{B}$	$\mathscr{B}$&$\mathscr{R}$	$\mathscr{B}$&$\mathscr{R}$
Chabot et al. (2018)			$\mathscr{B}$&$\mathscr{R}$	

[a] The authors tested multiple algorithms.

the efficiency of tactical and operational planning problem combinations.

2.1.5 Classification by Investigated Combination of Planning Problems

This section classifies all articles analysing at least two order picking planning problems simultaneously. Appendix C provides a detailed overview of the selected articles according to the investigated planning problems. Figure 2.4 illustrates the distribution of tactical and operational order picking planning problems across the reviewed articles. The zoning (i.e., zone location, zone assignment, and zone picking) and workforce (i.e., workforce level, workforce allocation, and job assignment) related planning problems, as well as the problem of order consolidation and sorting have received little research attention in combination with other planning problems. Note that publications examining a single order picking planning problem have devoted little attention to the last mentioned planning problems either (Gu et al., 2007). Recent publications combining order picking planning problems have strongly focused on storage location assignment, order batching, and picker routing as these three problems should be solved by each warehouse, either small or large, whereas for example picker zoning related planning problems are typically faced in the larger warehouses. Moreover, the relation among these three planning problems could be most easily recognised and explained.

The classification of these studies helps warehouse managers to determine how different individual planning problems are related to each other, at least the combinations that have been investigated, and thus which planning problems should be considered simultaneously (Section 2.1.5.1). Furthermore, the performance of policy combinations is

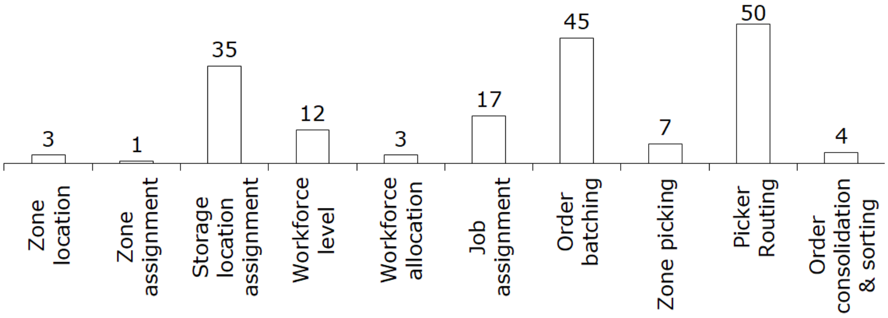


FIGURE 2.4: Distribution of the considered order picking planning problems (in number of articles).

TABLE 2.6: Overview of investigated combination of order picking planning problems.

	Zone location	Zone assignment	Storage location assignment	Workforce level	Workforce allocation	Job assignment	Order batching	Zone picking	Picker routing	Order cons. & sorting
Zone location		-	1	-	1	-	2	-	-	-
Zone assignment			1	-	-	-	-	-	-	-
Storage location assignment				4	2	1	**16**	1	**29**	2
Workforce level					1	4	**6**	1	**7**	2
Workforce allocation						-	2	-	-	1
Job assignment							**11**	**6**	**7**	1
Order batching								2	**30**	4
Zone picking									1	-
Picker routing										-
Order cons. & sorting										

analysed in order to establish several good performing combinations which can be used in practice to optimise order picking performance (Section 2.1.5.2).

2.1.5.1 Relations among Planning Problems

Table 2.6 provides an overview of all investigated combinations of order picking planning problems. The ten defined order picking planning problems give rise to a large number (i.e., 45) of planning problems combinations. However, only 27 combinations have been investigated to improve order picking efficiency, though it makes sense to combine most planning problems. Only combinations that have been analysed in at least six research articles are discussed in this section, in particular storage & batching, storage & routing, batching & routing, workforce level & batching, job assignment & batching, job assignment & routing, workforce level & routing, and job assignment & zoning. Research investigating the effects of combining other order picking planning problems is too limited to draw valid conclusions.

Articles analysing the combination of *storage location assignment and order batching* are rather consistent about the statistical significance of these two planning problems (Petersen and Aase, 2004; Ho and Tseng, 2006; Ho et al., 2008). The storage policy defines rules for assigning items to locations in the order picking area. The batching policy should take these item location rules into account while creating batches in order to efficiently manage the batching planning problem. The use of item location information in batching results in significant performance benefits (Ruben and Jacobs, 1999).

In contrast to the storage and batching interaction, studies are less consistent about the significance of *storage location assignment and picker routing*. In a limited factorial setting, in particular a limited number of analysed policies, storage location assignment and routing are found to be unrelated (Ho and Tseng, 2006; Ho et al., 2008; Chackelson et al., 2013). However, other articles do find a statistically significant interaction between storage and routing, both in single block warehouses (Petersen and Schmenner, 1999; Manzini et al., 2007), and in multiple block warehouses (Theys et al., 2010; Shqair et al., 2014), as these studies take information about the location of fast moving products into account while composing picker routes. Furthermore, storage location assignment policies define the pick density within aisles, which can result in blocking of order pickers if routes do not account for blocking effects. Thus, whether interactions between storage and routing exist or not, depends on which policy combinations are evaluated and which order picking time components are taken into account.

Order batching and picker routing problems have been analysed most often. Several articles analysing combinations of batching and routing policies reveal that these planning problems are unrelated, both in a single block warehouse (Ho and Tseng, 2006; Ho et al., 2008) and a multiple block warehouse (Hsieh and Tsai, 2006), while other studies find significant performance benefits by combining batching and routing in a single block layout (De Koster et al., 1999; Chackelson et al., 2013). These contradicting results may be due to the considered policies, which are more extensive in the studies that find significant effects. The operational planning issues of batching and routing are the most often solved planning problems in warehouses. The construction of batches and the creation of picker routes are the most appropriate problems to be solved jointly as the processing time of a batch is mainly defined by the length of the constructed route. The integrated problem of batching and routing yields significant performance benefits compared to sequentially solving both problems (Won and Olafson, 2005), indicating a strong relation between batching and routing.

Compared to the relations among storage location assignment, batching, and routing, other combinations have not received much research attention. Especially research analysing the effects of a varying workforce level, that mainly affects the waiting times due to picker blocking (Chen et al., 2016), in combination with other planning problems is scarce. Most articles analysing workforce level in combination with other planning problems evaluate the combined effect of *order batching and workforce level*, while disregarding picker blocking. Typically, the mean time for picking an order increases as the number of pickers increase, as more order pickers may increase aisle congestion (Ruben and Jacobs, 1999). However, integrating the picker blocking effects while constructing batches prevents the picking efficiency to decrease when the number of order pickers increases (Hong et al., 2012a).

Similar findings are shown while analysing *workforce level and picker routing*. While considering the effect of picker blocking, certain routing policies (i.e., return routing and optimal routing) yield stronger increased waiting times in comparison with a traversal routing policy in case of increasing the number of pickers (Pan and Wu, 2012). The mean travel time within an aisle, and consequently the time an aisle is occupied by an order picker, is shorter by applying traversal routes in this case. Waiting times can strongly reduce by considering the picker blocking effects while construction routes (Chen et al., 2016).

Few studies are found that integrate *order batching and job assignment*. In a single order picker system, the job assignment problem is limited to sequencing batches of orders (Chen et al., 2015; Menéndez et al., 2017), while the job assignment problem is more challenging for multiple order pickers as batches need to be assigned to order pickers before sequencing the batches (Henn, 2015; Scholz et al., 2017). Compared to a due-date first assignment of jobs, the integrated problem of job assignment and batching of orders yields improved order picking performance with respect to the tardiness of customer orders (Henn and Schmid, 2013; Chen et al., 2015; Henn, 2015).

Furthermore, most studies analysing batching and job assignment additionally consider the picker routing planning problem (Henn and Schmid, 2013; Chen et al., 2015; Henn, 2015). Different routing policies affect the processing time of batches and may cause tardiness if the order due date is missed. Combining job assignment and straightforward routing policies result in similar performances, while integrating *routing and job assignment*, and thus finding a (near) optimal combination of routes and job assignments, results in significant performance benefits (Matthews and Visagie, 2013; Chen et al., 2015).

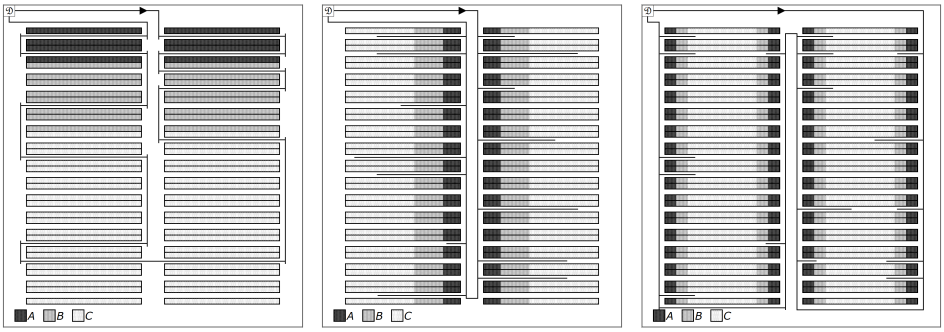
Finally, the combination of *zone picking and job assignment* is mainly studied by integrating both planning problems in the context of bucket brigades. Bucket brigades zoning is defined as a sequential flexible zone picking policy in which order pickers are assigned to flexible zones and sequentially pick an order (or a batch of orders). In contrast to sequential fixed zone picking, the boundaries of each zone vary dynamically as downstream order pickers take over jobs from their predecessors when they are available. If the most downstream order picker completes his order, this picker takes over the order of the immediately upstream order picker. The latter takes over the order of his predecessor, and so on. The first order picker in line can start with a new order or batch. In this way, the job assignment is formulated as the dynamic assignment of orders to order pickers, integrated in the zone picking problem. The efficiency benefits resulting from bucket brigades show the importance of integrating zone picking and job assignment (Bartholdi et al., 2001; Koo, 2009; Hong, 2018).

2.1.5.2 Generally Good Performing Planning Problem Combinations

As recent literature has mainly focused on three order picking planning problems in order to improve the order picking efficiency by combining planning problems, this section establishes several generally good performing policy combinations divided into combinations of these three planning problems: storage location assignment & order batching, storage location assignment & picker routing, and order batching & picker routing. Combinations that have been proven to be efficient in multiple articles are discussed.

Storage Location Assignment and Order Batching Due to the different planning horizons of storage location assignment (tactical) and order batching (operational), literature has focused on analysing the relation between both planning problems. Efficient combinations of storage location assignment and order batching can be achieved by incorporating location information of fast moving items, defined by the applied storage location assignment policy, into the creation of batches. For example seed rules minimizing the number of aisles are preferred in combination with within-aisle turnover based storage location assignment. As fast moving items are assigned to the aisles closest to the depot, batches should be created with the objective of minimizing the number of aisles visited. Selecting the order with the smallest number of picking aisles to visit as seed order and adding orders to the seed that minimises the number of additional aisles that an order picker needs to visit to complete the batch, in combination with within-aisle storage, outperforms other seed batching policies (Ho and Tseng, 2006).

Several more sophisticated batching algorithms have proven to increase the order picking performance in combination with within-aisle turnover based storage location assignment, both in a static (i.e., all orders known in advance) (Hsieh and Huang, 2011; Henn and Wäscher, 2012), and a dynamic (i.e., real time order arrival) context (Henn, 2012). Most studies only consider random and within-aisle storage in combination with these complex batching policies, which may be explained by the fact that straightforward batching algorithms (e.g., FCFS and seed batching) in combination with within-aisle storage outperform other batching and storage policy combinations (Ruben and Jacobs, 1999; Petersen and Aase, 2004; Chen et al., 2010). Disregarding real-life features (e.g., no picker



(A) Within-aisle–traversal. (B) Across-aisle–return. (C) Perimeter–largest gap.

FIGURE 2.5: Examples of good performing combinations of turnover based storage location assignment policies and routing policies.

blocking, single depot), metaheuristic batching algorithms in combination with within-aisle storage is a general good performing storage & batching combination.

Storage Location Assignment and Picker Routing Figure 2.5 illustrates several good performing combinations of storage location assignment policies and straightforward routing policies. In order to reduce order picking travel distance, within-aisle turnover based storage location assignment is preferred while using traversal routing. Since the goal is to reduce the number of aisles visited, fast moving items are assigned to the aisles closest to the depot. Return routing is preferred in combination with across-aisle storage classes, because the aim is to reduce the travel distance within aisles (Caron et al., 1998). Furthermore, the combination of the perimeter storage and the largest gap routing policy on average results in shorter travel times compared to the two previously discussed combinations. Since fast moving stock keeping units (SKUs) are stored along the periphery of the warehouse blocks and largest gap routes tend to follow the periphery of the order picking area, this policy combination increases the order picking performance (Petersen and Schmenner, 1999). Note that the sizing of each storage class does not significantly influence the routing decision and resulting picking performance. Introducing a turnover based storage location assignment policy is more important than selecting the composition of storage classes (Manzini et al., 2007).

Because of simplicity, these straightforward routing heuristics are often used in practice, despite the efficiency benefits of following (near)optimal routes. Optimal routes in combination with within-aisle storage location assignment outperform all other combinations of storage location assignment and routing (Petersen and Schmenner, 1999; Petersen and Aase, 2004; Theys et al., 2010). However, calculating optimal routes for each pick tour may require long computing times depending on the number of storage locations to visit in a pick tour. For single block layouts, the combined routing heuristic is able to approximate the optimal route (Roodbergen and De Koster, 2001a; Petersen and Aase, 2004). The Lin-Kernighan-Helsaun routing heuristic (Helsgaun, 2000) has shown to provide excellent results to approximate the optimal route of order pickers for multiple warehouse blocks as well. Theys et al. (2010) reported an average optimality gap of 0.01% for the combination of within-aisle storage and LKH-routing.

Order batching and Picker Routing Publications examining the relation between order batching and picker routing have mainly focused on solving the integrated problem of routing and batching, rather than considering interactions between batching and routing policies. As batching and routing are both operational decisions, these planning problems are particularly suitable for being solved in an integrated way. Efficient heuristic algorithms have been proposed for the simultaneous construction of batches and picking tours (Kulak et al., 2012; Cheng et al., 2015; Li et al., 2016; Lin et al., 2016), compared to combinations of more straightforward batching and routing policies.

2.1.6 Managerial Implications

The results of this literature study show the importance of combining multiple order picking planning problems in order to efficiently manage order picking operations. This section discusses the practical implications of this research for warehouse managers. We provide guidelines how warehouse managers can solve combinations of tactical and operational planning problems to support decision making processes.

Results of the literature review show that the time horizon of the resulting decisions substantially influences the appropriate approach for solving combined order picking planning problems. On the one hand, problems could be combined by analysing interactions among specific predefined policies for each planning problem. On the other hand, two or more planning problems can be formulated and solved in an integrated manner. Figure 2.6 shows an overview of the approach applied in the majority of the considered articles to solve each combination of order picking planning problems, as well as the number of articles analysing each combination.

Interaction analysis is most often applied to evaluate the joint effect of combining planning problems. Interaction analysis by means of analytical or simulation models has proven to be especially useful to evaluate the joint effect of planning problems with different time horizons of the resulting decision, such as storage location assignment and routing (e.g., Caron et al. (1998); Petersen and Schmenner (1999); Chen et al. (2010); Dijkstra and Roodbergen (2017)). The results of analytical and simulation models can be used by warehouse managers as decision support tool to design efficient order picking systems taking the interactions among order picking planning problems into account.

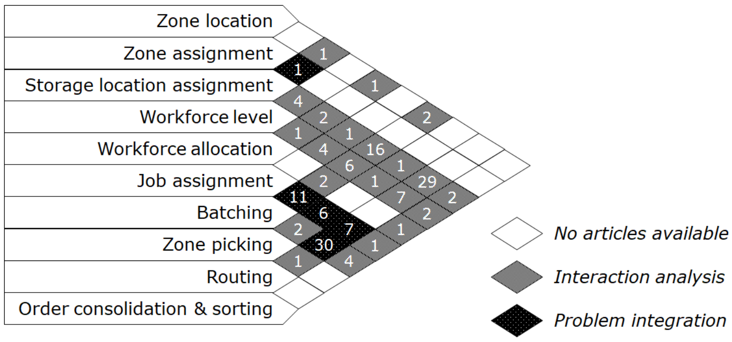


FIGURE 2.6: Best approach to solve each planning problems combination (numbers indicate the number of articles considered in this review).

Problem integration is the appropriate approach to combine order picking planning problems with an operational time horizon, such as batching, routing and job assignment. Mathematical programming models are able to describe integrated planning problems, especially at an operational decision level, while accounting for real-life constraints (e.g., Matusiak et al. (2014, 2017); Zhang et al. (2017)). A wide range of heuristic algorithms have been proposed to provide fast and efficient solutions for the integrated problem of batching, routing and job assignment (e.g., Chen et al. (2015); Scholz et al. (2017)) in accordance with practical needs: in case of short time horizons of decisions, fast and efficient algorithms are required to organise order picking operations.

Finally, we should note that the sample size for most planning problem combinations in Figure 2.6 is rather small . For example, the limited number of articles that combine job assignment and workforce allocation with the workforce level planning problem use interaction analysis, while an integrated model to solve a combination of these three planning problems seems to be more appropriate to support order picking operations. A model that provides the number of required order pickers and allocates this workforce, based on the expected workload, may be highly relevant to practice, as shown in Part III of this thesis. Most combinations of tactical and operational order picking planning problems have not been widely investigated so far. However, articles in this review have proven the importance of combining these planning problems in order to optimise the order picking performance. Warehouse managers should be aware of the strong relation among order picking planning problems to optimise the performance and face the new market developments.

2.2 Identifying Real-life Features

Although many studies optimised order picking planning problems, the developed solution methods often do not sufficiently consider real-life features. The complex nature of order picking operations, caused by the large number of planning problems and resulting relation among these planning problems, require decision supporting tools to manage operations efficiently and effectively. The assumption-restricted models that have been proposed in literature have only limited applicability in practice as real-life features are insufficiently supported by these models. This section provides the main real-life features that are crucial to account for when developing new solution methods in order to support order picking operations in practice. In this PhD thesis, 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 workload peaks) that have a substantial impact on the planning and performance of order picking systems in practice.

Based on current literature and results of our experience in the Smart Logistics Limburg project, in which over 100 warehouses have been visited, a non-exhaustive list of real-life features is identified. These real-life features are expected to be the most influential factors with respect to the order picking performance. The features affect the nature of one or more planning problems and may have a substantial influence on the order picking performance. Articles incorporating one or more real-life features are summarised in Table 2.7. The main real-life characteristics, real-life constraints, and real-life conditions are provided in Sections 2.2.1, 2.2.2, and 2.2.3, respectively. The effect of the real-life features on different planning problems is discussed to show the relevance of integrating them.

TABLE 2.7: Articles incorporating real-life features when combining planning problems.

Real-life feature	# articles	
High-level storage	2	Chan and Chan (2011); Pan et al. (2014)
Scattered storage	-	
Varying SKU properties	1	Dekker et al. (2004)
Human factors	1	Matusiak et al. (2017)
Precedence constraints	2	Matusiak et al. (2014); Žulj et al. (2018a)
Safety constraints	1	Chabot et al. (2018)
Resource constraints	20	Ruben and Jacobs (1999); Yu and De Koster (2008, 2009); Van Nieuwenhuyse and De Koster (2009); Rubrico et al. (2011); De Koster et al. (2012); Hong et al. (2012a); Pan and Wu (2012); Heath et al. (2013); Henn (2015); Chen et al. (2016, 2017); Franzke et al. (2017); Matusiak et al. (2017); Menéndez et al. (2017); Scholz et al. (2017); Zhang et al. (2017); Ardjmand et al. (2018); Hong (2018); Quader and Castillo-Villar (2018)
Due time constraints	-	
Workload peaks	6	Bartholdi et al. (2001); Yu and De Koster (2008); Koo (2009); Hong et al. (2015, 2016); Hong and Kim (2017)
Product returns	1	Schrotenboer et al. (2017)
Picker blocking	5	Hong et al. (2012a); Pan and Wu (2012); Chen et al. (2016, 2017); Franzke et al. (2017)

2.2.1 Identifying Real-life Characteristics

Real-life characteristics are defined as generally existing attributes of order picking systems in practice that are fixed in short term due to strategic decisions such as layout and system selection. Tactical and operational planning problems should integrate these real-life characteristics in order to benefit from the strategic decisions. Following characteristics can be identified, among others: high-level storage locations, scattered storage, varying SKU properties, and human factors. These characteristics are found in existing literature and identified as highly relevant during interviews in practice.

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). Figure 2.7 illustrates a high-level storage system. 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 travelling is defined by the number of levels in a storage system (Thomas and Meller, 2015). In addition to the slow lifting speed that impacts the picker routing problem, the storage location assignment problem is directly influenced. In case of low-level storage systems, SKUs should be only distributed among pick aisles. High-level storage locations require to distribute and assign SKUs among the different levels of the storage racks (Pan et al., 2014; Chan and Chan, 2011), thereby considering that a substantial amount of lifting time is needed to reach the highest storage locations. 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 the replenishment of a pick location, while picking is performed on floor locations requiring only horizontal travel.

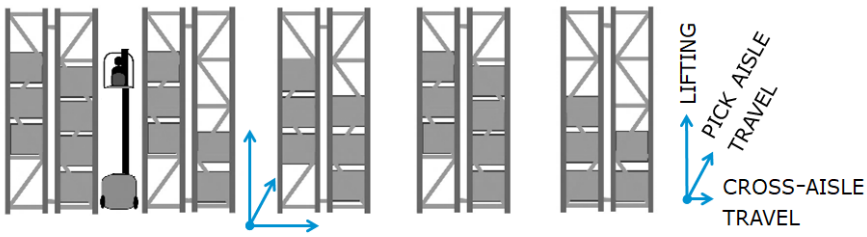


FIGURE 2.7: Illustration of high-level storage racks.

Scattered storage, the assignment of an SKU to multiple storage locations, may be valuable to warehouses to increase order picking performance. Instead of assuming a single storage location for each SKU as in the large majority of planning models in literature, scattered storage can be beneficial, requiring a sufficient storage capacity. Assigning fast moving SKUs to multiple locations most directly influences the nature of the storage location assignment and picker routing problem (Weidinger and Boysen, 2018). In case of small ordered quantities per SKU (e.g., e-commerce orders), items of a single SKU should be distributed all over the warehouse in order to benefit from scattered storage; the probability that a picker is close to one of the locations of the required SKU is large when the SKUs are widely spread. To retrieve higher quantities of an SKU in a pick tour, items of the same SKU should be stored close to each other (Weidinger, 2018). Planning the route between storage locations of a general picker routing problem is extended by selecting the storage positions to be visited; the required SKU can be retrieved from multiple storage locations (Weidinger, 2018). Moreover, in a dynamic context (i.e., real time order arrival), multiple locations of a single SKU may substantially affect the routing problem, as orders can be more easily added to a pick list while the order picker has already started his pick tour.

Varying SKU properties such as weight, size, and/or temperature conditions further complicate the planning of order picking operations. The commonly used assumptions of similar SKUs should be reconsidered. Properties of the SKUs limit the storage location assignment problem as not all SKUs are allowed at all storage locations (Chabot et al., 2017; Dekker et al., 2004). Accorsi et al. (2018) provide a decision support tool to assign temperature-sensitive SKUs to storage locations, thereby optimizing the picking efficiency while considering the safe conservation conditions. Moreover, varying SKU properties result in varying retrieve times at storage locations and different handling methods: retrieving large and heavy SKUs requires substantially more time than small and light SKUs (Jane and Laih, 2005). This results in varying picker productivity levels, especially as most warehouses are divided into pick zones and SKUs are assigned to pick zones based on product properties. The average productivity is low in pick zones storing heavy SKUs, while zones storing smaller items are designed to maximise productivity. Consequently, these productivity differences, as a result of varying SKU properties, strongly influence the zone picking problem, workforce related planning problems (i.e., workforce level and workforce allocation) and the consequent order consolidation and sorting problem. Finally, in the context of the order batching problem, varying SKU properties may result in a varying number of SKUs per batch when the batch capacity is proportional to the SKU property. Consequently, batching orders should take the varying batch capacity into account (instead of a fixed batch capacity).

Human factors impact most of the considered tactical and operational order picking planning problems. Individual employee skills and capabilities significantly impact the order pick time. Incorporating human factors in planning models can improve the model predictability. Planning models should be able to find the best fit between an order picking job and the individual picker in order to benefit from the capabilities of each individual picker (Grosse et al., 2015, 2017). In addition to defining the required number of order pickers, pickers should be assigned to a pick zone (i.e., workforce allocation) and jobs need to be assigned to individual picker (i.e., job assignment) taking physical (e.g., posture), mental (e.g., competency), perceptual (e.g., human information processing) and psychosocial aspects (e.g., motivation or stress) into account.

2.2.2 Identifying Real-life Constraints

Real-life constraints are defined as restrictions the order picking system is subject to in practice. Solution algorithms ignoring these constraints seem to provide efficient solutions, but these solutions lack effectiveness as they are mostly infeasible. Consequently, these models overestimate the real order picking performance. For example, a routing policy that creates routes that are not able to be performed in practice because of safety constraints (e.g., traffic rules) or precedence constraints. Furthermore, resource constraints and order due time constraints may further limit the solution possibilities.

Precedence constraints are introduced because certain SKUs should be retrieved before other SKUs due to weight, fragility, shape and/or size restrictions, or because of customer's preferences. Most studies assume similar SKUs and no customer's preferences and thus ignore precedence constraints. In practice, the picker routing planning problem is most strongly influenced by imposing precedence constraints (Matusiak et al., 2014; Žulj et al., 2018a). To avoid SKUs to be sorted during or at the end of a pick tour, the picker routing problem should incorporate the imposed precedence constraints and for example retrieve heavy SKUs before light SKUs (Žulj et al., 2018a). Precedence constraints may result in longer travelling compared to a picking system without precedence constraints, but avoid additional sorting.

Despite the large number of accidents that happen in warehouses (De Koster et al., 2011; Hofstra et al., 2018), *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; De Vries et al., 2016b). 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).

Resources, such as space, labour, and equipment, need to be allocated among the different warehouse functions, including order picking (Gu et al., 2007). In practice, these resources are limited. Although the resource capacities drive the service quality to customers and resulting order picking performance, labour and equipment resources are mostly assumed to be infinite in literature (De Koster et al., 2007). However, resource capacity is limited and orders or batches need to be assigned to the available resources, such as order pickers. Consequently, these constraints are especially dominant when assigning jobs to resources.

Finally, each customer order is constrained by the due time in order to be shipped on time. As accuracy in delivery times is an essential performance indicator for warehouses (Wruck et al., 2017), respecting *due time constraints* is a critical issue when batching orders and assigning batches to pickers (Henn and Schmid, 2013; Chen et al., 2015). Most studies aim at minimizing total tardiness of all customer orders (i.e., the positive difference between the order due time and the batch completion time to which the order is assigned) (Chen et al., 2015; Scholz et al., 2017) or ignore due times of orders (De Koster et al., 1999; Henn and Wäscher, 2012). These solution algorithms often provide a solution in which one or more customer orders will be picked after the picking due time, resulting in orders that miss the shipping deadline (Henn and Schmid, 2013). In practice, such solutions may not be accepted by most warehouses, as this reduces the customer service level. Rather than accepting tardiness, the resource capacity will be increased (e.g., by shifting workers from other departments) to prevent orders being picked after due time. Consequently, order due time constraints most strongly affect the order batching, job assignment and workforce allocation planning problems.

2.2.3 Identifying Real-life Conditions

Real-life conditions are defined as external situations warehouses should face with in practice on a daily base without having direct control on these conditions. However, these situations substantially impact planning problems. For example, workload peaks, resulting from the moment in time that customers order their products, disturb order picking operations in practice. Although pricing and other stimulating policies may influence the customer order process, this condition is fixed in the short term. Furthermore, the effect of product returns and picker blocking are discussed in this section.

Workload peaks can be defined as time periods for which the required order throughput exceeds the resource capacity. This moment results in a high risk of missed deadlines and therefore may result in a lower customer satisfaction due to delayed order deliveries. In manual order picking systems, order pickers are the most critical resource who undergo a high work pressure during peak periods, resulting in extra stress and fatigue (Vanheusden et al., 2019). Dividing the order picking area into zones can cause workload imbalances among pick zones, which can be solved by varying the size and location of pick zones and varying assignments of SKUs to pick zones (Jane, 2000; Jane and Laih, 2005; Yu and De Koster, 2009). However, the proposed solution methods balance the workload in the long run. Avoiding workload peaks at an operational level (i.e., workload balancing among time slots during the day) can be seen as a new challenging order picking planning problem.

A substantial number of products are ordered by customers and, after receiving, returned to a warehouse without being purchased. First, the returned products are checked in a depot. Next, these products should be returned to the storage location storing the particular SKU . In this way the product is available to be retrieved for another customer order. Consequently, these *product returns* cause a flow of SKUs from a depot to storage locations in addition to the regular order picking flow of SKUs from storage locations to the depot to fulfil customer orders. Restocking of returned SKUs differs from replenishment as replenishing fills a single (or a few) storage location(s), while restocking requires to visit a large number of storage locations in a single pick round (Schrotenboer et al., 2017). Taking product returns into account requires to increase the workforce level, which increases the probability of 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 in most existing planning models, 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 have to 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., 2012a).

2.3 Research Gaps

New market developments such as e-commerce and globalisation, and increased customer expectations force warehouses to handle a growing number of orders in shorter time. Awareness of the influence of an individual order picking planning problem on the overall performance is required to manage operations, resulting in enhanced customer service. This chapter differs from previous warehouse planning overviews by focusing on combinations of order picking planning problems and identifying relevant real-life features. In this research, we provide an overview and classification of the relevant literature with respect to the research method used to combine order picking planning problems, the performance measurement to evaluate the combined problems, as well as with respect to the investigated combination of order picking planning problems. Additionally, the most common real-life characteristics, constraints and conditions are identified based on academic literature and practice. These features need to be incorporated while developing new efficient solution methods.

Articles analysing different tactical and operational order picking planning problems simultaneously are reviewed and classified in this study, with the aim of determining which planning problems are interdependent and how different individual planning problems are related to each other, as well as how warehouse managers can benefit from combining multiple order picking planning problems in order to face new market developments. It does not make sense to integrate all planning problems due to the different time horizons of the resulting decisions. For example, integrating warehouse layout decisions and order batching does not seem relevant as batching is a daily decision, while layout is fixed in short and medium term.

Table 2.8 presents the current academic state-of-the-art of existing literature that combines at least two planning problems (Section 2.1) and additionally integrates one or more of the critical real-life features from Section 2.2. From the 71 articles in Section 2.1, only 32 articles integrate one of the identified real-life features. Note that resource constraints form the main real-life feature, although the problem of defining how to fix the resource capacity has been rarely investigated (Van Gils et al., 2017c; Kim et al., 2018). The table shows a need to include real-life features in studies analysing and optimising order picking operations. Although, there is a trend towards integrating real-life features in recent years, most real-life features have been either not analysed or only to a limited extent.

This PhD thesis goes beyond the current academic state-of-the-art by combining the main order picking planning problems (i.e., zone location, storage location assignment, order batching, picker routing, and job assignment) and additionally considering the large majority of most common real-life features. Different approaches to combine planning problems, provided by the literature review, are applied to a wide range of planning problems. Additionally, most of the identified real-life features are either incorporated when combining planning problems or accounted for when providing new solution methods. First in Part II, by means of an interaction analysis combinations of zone location, storage, batching and routing policies are analysed and explained, thereby showing the relevance and importance of incorporating high-level storage locations, safety constraints and picker blocking. Second in Part III, workload related factors (i.e., resource constraints and workload peaks) are analysed by providing two new solution methods to determine the resource capacity as well as to balance the workload, thereby additionally accounting for order due times. Finally in Part IV, when the resource capacity is determined and

TABLE 2.8: Academic state-of-the-art.

	Zone location	Zone assignment	Storage	Workforce level	Workforce allocation	Job assignment	Batching	Zone picking	Routing	Order cons. & sorting
High-level storage										
Chan and Chan (2011)			•						•	
Pan et al. (2014)			•						•	
Scattered storage										
-										
Varying SKU properties										
Dekker et al. (2004)			•						•	
Human factors										
Matusiak et al. (2017)						•	•			
Precedence constraints										
Matusiak et al. (2014)							•		•	
Žulj et al. (2018a)			•						•	
Safety constraints										
Chabot et al. (2018)							•		•	
Resource constraints										
Ruben and Jacobs (1999)			•	•			•			
Yu and De Koster (2008)			•		•		•			
Yu and De Koster (2009)	•						•			
Van Nieuwenhuyse and De Koster (2009)				•	•		•			•
Rubrico et al. (2011)						•	•			
De Koster et al. (2012)	•		•		•					
Hong et al. (2012a)				•		•	•			•
Pan and Wu (2012)			•	•					•	
Heath et al. (2013)			•	•					•	
Henn (2015)				•		•	•		•	
Chen et al. (2016)				•					•	
Chen et al. (2017)				•			•			
Franzke et al. (2017)			•	•					•	
Matusiak et al. (2017)						•	•			
Menéndez et al. (2017)						•	•			
Scholz et al. (2017)				•		•	•		•	
Zhang et al. (2017)						•	•			
Ardjmand et al. (2018)						•	•		•	
Hong (2018)				•		•		•		
Quader and Castillo-Villar (2018)			•			•		•	•	
Due time constraints										
-										
Workload peaks										
Bartholdi et al. (2001)						•		•		
Yu and De Koster (2008)			•		•		•			
Koo (2009)						•		•		
Hong et al. (2015)						•		•		
Hong et al. (2016)						•		•		
Hong and Kim (2017)			•				•			•
Product returns										
Schrotenboer et al. (2017)				•					•	
Picker blocking										
Hong et al. (2012a)				•		•	•			•
Pan and Wu (2012)			•	•					•	
Chen et al. (2016)				•					•	
Chen et al. (2017)				•			•			
Franzke et al. (2017)			•	•					•	

the workload is balanced, the three order picking planning problems with the shortest time horizon of the resulting decision (i.e., batching, routing and job assignment) are integrated and optimised, thereby taking high-level storage locations, resource constraints and order due time constraints into account. Although the remaining real-life features may be important as well for certain warehouses, the considered real-life features are the most crucial and relevant for the different real-life cases included in this PhD research. The considered real-life features have been proposed by warehouse managers and supervisors as the most complex to account for in practice. In addition, generic explanations with respect to the combined effect of planning problems on the order picking performance and general insights into the consequences of real-life features are missing in current academic literature.

Part II

Interaction Analysis on Planning Problem Relations

CHAPTER 3

Interaction Analysis in a Wide-aisle Order Picking Systems

New market developments force warehouses to increase the order picking efficiency. One way to increase the efficiency is to combine multiple order picking planning problems. While the number of publications dealing with one specific order picking planning problem is extensive, only a limited number of researchers examine different planning problems simultaneously, even though the efficiency of different order picking planning problems seems to be interdependent (Van Gils et al., 2018e; Davarzani and Norrman, 2015). The effect of zone location and zone assignment in combination with other order picking planning problems, such as storage location assignment, order batching and picker routing, has received especially little research attention as shown in the literature classification of previous chapter.

In this chapter[1], zone location (and zone assignment), storage location assignment, order batching, and picker routing are combined without considering real-life features. As the effect of real-life features is expected to be limited in wide-aisle low-level order picking systems, this order picking system is used to illustrate the effect of combining the four order picking planning problems. An interaction analysis has proven to be suitable to analyse relations among planning problems for which the time horizon of the decisions is different. Therefore, several existing policies (i.e., solution methods) for each planning problem are simulated and potential interactions among these planning problems are sta-

[1]This chapter is based on Van Gils, T., Braekers, K., Ramaekers, K., Depaire, B., Caris, A., 2016a. Improving Order Picking Efficiency by Analyzing Combinations of Storage, Batching, Zoning, and Routing Policies. In: Paias, A., Ruthmair, M., Voß, S. (Eds.), Lecture Notes in Computational Logistics. No. 9855 in Lecture Notes in Computer Science. Springer International Publishing, pp. 427–442 and Van Gils, T., Ramaekers, K., Braekers, K., Depaire, B., Caris, A., 2018c. Increasing Order Picking Efficiency by Integrating Storage, Batching, Zone Picking, and Routing Policy Decisions. International Journal of Production Economics 197 (Part C), 243–261

tistically investigated and explained in order to manage order picking operations more efficiently. By combining these four tactical and operational order picking planning problems, we aim to fulfil three research objectives. First, based on a simulation study, we aim to determine which planning problems are statistically significantly related and, consequently, which planning problems should be considered simultaneously. Second, if a relationship is significant, this study analyses why and how the individual planning problems of picker zoning (i.e., zone location and zone assignment), storage, batching, and routing are related. Third, by analysing combinations of picker zoning, storage, batching, and routing, we aim to identify excellent performing policy combinations in several practical situations in order to improve overall order picking performance. Results of the study provide insights in how combining the four main order picking planning problems support new market developments (i.e., e-commerce and globalisation, increased customer expectations, expensive industrial land, and high labour costs).

To the best of our knowledge, this study is the first that explicitly analyses and statistically proves the relationships between zone location (and zone assignment), storage location assignment, order batching, and picker routing. Simulation experiments show the impact of combining order picking planning problems in a real-life warehouse as well as for more generic warehouse designs, both wide-aisle low-level order picking systems. Insights into the interactions among the four main order picking planning problems are provided by performing a full factorial analysis of variance (ANOVA). Furthermore, the study contributes to both practitioners and academia by explaining how the planning problems are related and by formulating guidelines on which planning problem policies to combine in order to improve order picking activities.

The remainder of the chapter is organised as follows. Section 3.1 is devoted to formulating research hypotheses on how order picking planning problems are expected to be related. Section 3.2 introduces the experimental design and the assumptions linked to the case. The first two research objectives are fulfilled in Section 3.3 that provides the empirical results. Section 3.4 discusses the managerial implications of this study and summarises excellent performing policy combinations that help to improve the overall order picking performance in several practical situations. Section 3.5 concludes the chapter.

3.1 Research Hypotheses

This section discusses literature combining picker zoning, storage, batching, and routing planning problems in order to formulate research hypotheses on the relationship among these order picking planning problems. Appendix B defines the four considered order picking planning problems as well as multiple policies for each planning problem to organise operations in a manual order picking system. As zone location (including the number of zones) and zone assignment are closely related, *picker zoning* refers to the combination of both problems in this chapter.

The majority of studies improving order picking operations focus on either picker zoning (e.g., Ho and Lin (2017); Jane and Laih (2005); Petersen (2002)), storage (e.g., Guo et al. (2016); Manzini et al. (2015); Yu et al. (2015)), batching (e.g., Gademann and Van De Velde (2005); Muter and Öncan (2015)), or routing (e.g., Elbert et al. (2017); Scholz et al. (2016); Theys et al. (2010)), assuming all other decisions being given. The reader is referred to De Koster et al. (2007), Gu et al. (2007), and Boysen et al. (2018b) for an extensive overview of publications optimizing a single order picking planning problem.

In accordance with the previous chapter, this section summarises studies analysing interactions among the four tactical and operational order picking planning problems (i.e., picker zoning, storage, batching, and routing), with the aim of constructing hypotheses on which interactions among planning problems are found to be significantly related. Interactions are defined as the joint effect that two or more planning problems have on a performance goal, which can be investigated by considering multiple policies (i.e., solution methods or techniques for organizing a planning problem) for each planning problem and analysing the effect of these policies on the order picking performance (Van Gils et al., 2018e). Table 3.1 gives an overview of studies analysing combinations of order picking planning problems, mainly using simulation. Based on the findings of the literature, we formulate research hypotheses on the expected relationship among the four main order picking planning problems. Note that the hypothesis construction is sorted from planning problems with the longest to the shortest time horizon of the resulting decision.

TABLE 3.1: Previous research combining operational order picking planning problems.

	Significant relationship	No significant relationship
Zoning–storage	Petersen (2002)	De Koster et al. (2012)
Zoning–batching	Petersen (2000); Yu and De Koster (2009)	-
Zoning–routing	-	-
Storage–batching	Ho and Tseng (2006); Ho et al. (2008); Hsieh and Tsai (2006); Petersen and Aase (2004); Ruben and Jacobs (1999)	Chackelson et al. (2013)
Storage–routing	Manzini et al. (2007); Petersen and Schmenner (1999); Petersen and Aase (2004); Shqair et al. (2014); Theys et al. (2010); Žulj et al. (2018a)	Chackelson et al. (2013); Ho and Tseng (2006); Ho et al. (2008); Quader and Castillo-Villar (2018)
Batching–routing	Chen et al. (2015); Cheng et al. (2015); Chackelson et al. (2013); Kulak et al. (2012); Petersen and Aase (2004); Scholz and Wäscher (2017); Won and Olafson (2005)	Ho and Tseng (2006); Ho et al. (2008)

Picker zoning decisions in combination with other order picking planning problems have received little research attention yet (Van Gils et al., 2018e), despite of its importance in order picking system performance (Petersen, 2002). The relationship between zone size and storage location assignment planning problems has been investigated, but studies show contradicting results about the significance of the relation between zone size and storage location assignment (De Koster et al., 2012; Petersen, 2002). As the size of the zone defines the number of aisles within each pick zone, the zone size is expected to significantly influence the efficiency of the storage location assignment. Furthermore, the joint effect of zone assignment and storage location assignment has not been analysed so far. Both zone assignment policies and storage location assignment policies impact the pick densities in the order picking area. Consequently, the zone picking planning problem and the storage location assignment planning problem are expected to be significantly related (Hypothesis 3.1).

HYPOTHESIS 3.1 *The joint effect of picker zoning and storage location assignment on order picking performance is significant.*

Just as the storage location assignment and picker zoning relation, research analysing the relation between order batching and picker zoning is limited. By only comparing whether or not to batch (FCFS batching) and varying the number of zones, the batching and zoning problem are found to be interrelated (Petersen, 2000; Yu and De Koster, 2009). In case more sophisticated batching policies are used, the effect of zoning on the order picking performance is expected to reduce as these batching rules help order pickers to avoid travelling throughout the entire order picking area. Furthermore, storage zone assignment as well as batching impact the density of picking activities and, consequently, we expect the picker zoning and batching planning problem to be strongly interrelated as stated in Hypothesis 3.2.

HYPOTHESIS 3.2 *The joint effect of picker zoning and order batching on order picking performance is significant.*

The joint effect of the picker zoning and routing planning problems is currently unknown (Van Gils et al., 2018e). As zoning decisions have substantial impact on the distribution of pick density across the order picking area, and the efficiency of routing policies is determined by the distribution of pick densities, we hypothesise that both planning problems will be significantly related (Hypothesis 3.3).

HYPOTHESIS 3.3 *The joint effect of picker zoning and picker routing on order picking performance is significant.*

Articles analysing the combination of storage location assignment and order batching are rather consistent about the statistical significance of the storage and batching relation (Ho and Tseng, 2006; Ho et al., 2008; Hsieh and Tsai, 2006; Petersen and Aase, 2004). The storage location assignment policy defines rules for assigning items to locations in the order picking area. The batching policy should take these item location rules into account while creating batches in order to efficiently manage the batching planning problem (Ruben and Jacobs, 1999). Therefore, Hypothesis 3.4 states that storage location assignment and order batching are related as the use of item location information while batching orders is expected to result in significant performance benefits.

HYPOTHESIS 3.4 *The joint effect of storage location assignment and order batching on order picking performance is significant.*

In contrast to the storage–batching interaction, publications investigating the relation between storage location assignment and routing are less consistent about the significance of the storage location assignment and routing relation. In a limited factorial setting, in particular a limited number of analysed policies, storage location assignment and routing are found to be unrelated (Chackelson et al., 2013; Ho and Tseng, 2006; Ho et al., 2008). However, other articles do find a statistically significant interaction between the storage and routing planning problems, both in single block warehouses (Manzini et al., 2007; Petersen and Schmenner, 1999), and in multiple block warehouses (Shqair et al., 2014; Theys et al., 2010). These studies take information about the location of fast moving products into account while composing picker routes. Therefore, the efficiency of routing policies is expected to be strongly depending on the applied storage location assignment policy as indicated by Hypothesis 3.5.

HYPOTHESIS 3.5 *The joint effect of storage location assignment and picker routing on order picking performance is significant.*

A large number of articles analysing the combination of batching and routing policies reveal that these planning problems are unrelated (Ho and Tseng, 2006; Ho et al., 2008), while other studies do find significant performance benefits by combining batching and routing (Chackelson et al., 2013). Moreover, integrating the construction of routes while creating batches results in considerable performance benefits compared to solving the planning problems sequentially (Chen et al., 2015; Cheng et al., 2015; Kulak et al., 2012; Won and Olafson, 2005). This can be explained by the fact that the performance of the created batch is mainly defined by the length of the constructed route. Therefore, Hypothesis 3.6 states that a significant interaction exists between the batching and routing planning problems.

HYPOTHESIS 3.6 *The joint effect of order batching and picker routing on order picking performance is significant.*

In summary, several articles analysed storage-batching, storage-routing and batching-routing. Whether interactions among these three planning problems exist or not, depends on the number of analysed policies for each planning problem, as well as which policies have been evaluated. Most articles of Table 3.1 are limited to analysing two or three policies for each planning problem. Furthermore, research evaluating the effect of picker zoning on other order picking planning problems is scarce. To the best of our knowledge, this study is the first to analyse the interaction among the four main order picking planning problems. In order to evaluate the contradicting findings, a wide range of policies for each planning problem are included in the simulation experiments. Additionally, the effect of the number of zones and the zone assignment in relation with storage location assignment, order batching, and picker routing on the order picking efficiency is analysed for the first time.

3.2 Methodology for Empirical Study

This section outlines the research methodology used to achieve the objectives of this study. The general approach is presented in Section 3.2.1. Sections 3.2.2 and 3.2.3 describe the business case and the operational measures. The experimental design and data generation are outlined in Sections 3.2.4 and 3.2.5. Section 3.2.6 describes the statistical analysis used to provide insights into the relationships among order picking planning problems.

3.2.1 General Approach

An interaction analysis with simulation and comprehensive statistical tests is performed to test our research hypotheses. Interactions are defined as the combined effect that multiple planning problems have on a performance goal. An interaction analysis is considered to be especially useful if the time horizon of the resulting decisions is different (Van Gils et al., 2018e). Although picker zoning, storage location assignment, batching, and picker routing are all tactical or 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.

Using simulation as modelling method allows to include the stochastic elements of order generation and assignment of SKUs to pick zones and storage locations. Although analytical-based modelling 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). Simulation can accurately present the four order picking problems (Chen et al., 2010; Manzini et al., 2007). Monte Carlo simulation is adequate for calculating travel distances in wide-aisle order picking systems (Petersen and Aase, 2004). Results of the simulation are statistically analysed to evaluate the policy decisions covered in the research hypotheses. Simulation experiments allow us to include the necessary stochastic elements needed to generalise 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). Unsystematic variation is included by the stochastic elements of order generation and assignment of SKUs to pick zones and individual storage locations, while varying planning problem policies induce systematic variation in the experiments of this study.

3.2.2 Case Study

Real-life data of a large warehouse located in Belgium are used to show the practical relevance of combining picker zoning, storage, batching, and routing policy decisions. The warehouse stores approximately 90,000 SKUs on a surface of 30,000 square meter. All stored SKUs are rather homogeneous with respect to volume and weight, implicating that the sequence in which SKUs are retrieved from the storage locations is not restricted and all storage locations are equally sized. The warehouse delivers four customer types: each SKU belongs to a single customer type and orders consist of SKUs of a single customer type.

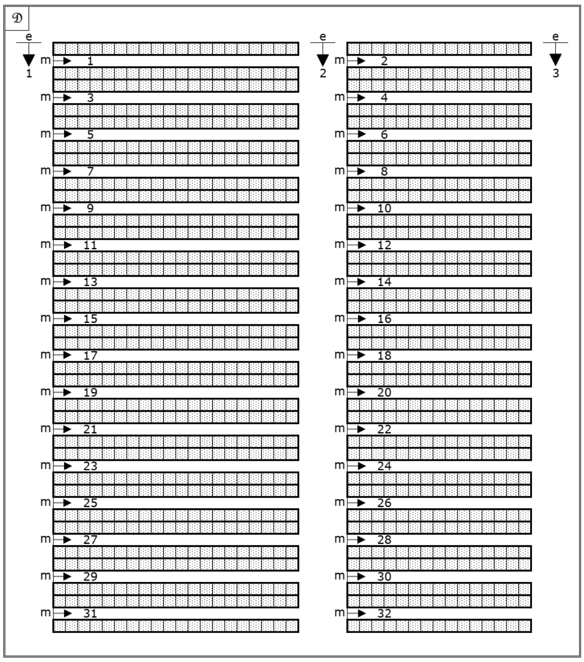


FIGURE 3.1: Warehouse layout.

The warehouse part under consideration is a new building. The layout is shown in Figure 3.1. The traditional multiple-block warehouse layout is frequently used in practice (Roodbergen, 2012), making results of the study easily transferable to other warehouses.

Furthermore, cross-aisles (denoted by e) have proven to result in significant efficiency benefits (Roodbergen and De Koster, 2001a). The order picking area is divided into two warehouse blocks, each consisting of sixteen pick aisles (denoted by m). The pick aisles are two-sided and wide enough for two-way travel. However, crossing the aisle is required in order to pick items from both sides of the same aisle, as the aisle width is 2.7 m. The warehouse block configuration is shown in Figure 3.1. The depot is marked with a $\mathscr{D}$ in the figure. The dimensions of the warehouse are provided in Table 3.2.

TABLE 3.2: Layout parameters of the wide-aisle order picking system.

Warehouse parameter		Parameter value
Depot location	$\mathscr{D}$	single decentralised depot
Number of blocks	$E-1$	2 blocks
Number of cross-aisles	E	3 cross-aisles
Number of pick aisles	M	16 pick aisles per block
Number of storage rack sections		
West warehouse block	L_1	40 storage rack sections per pick aisle
East warehouse block	L_1	30 storage rack sections per pick aisle
Number of levels	J	1 levels per storage rack
Storage rack section length	l_{length}	1.0 m
Storage rack section depth	l_{depth}	1.0 m
Pick aisle width	m_{width}	2.7 m
Cross-aisle width	e_{width}	4.0 m

The warehouse is fully manually operated, consisting of a single pick zone. Products are currently assigned randomly to the storage locations. Customer orders are transformed into pick lists according to the FCFS rule. A sort-while-pick strategy is used, maintaining order integrity, so that no downstream sorting is required. As the picking vehicle can transport 26 boxes, the batch capacity is fixed at 26 customer orders per pick round in order to prevent the need of a downstream sorter. Order pickers follow the aisle-by-aisle routing policy to retrieve all items on the pick list. Each picking tour starts and ends at the decentralised depot. The depot is marked as $\mathscr{D}$ in the top left corner of Figure 3.1. Picking vehicles travel at one side of a pick aisle and the pick aisle width is taken into account when the picker should retrieve SKUs from both sides of the pick aisle. The policy combination of a single zone, random storage, FCFS order batching, and aisle-by-aisle routing is used as benchmark in order to evaluate other storage, batching, zoning, and routing policies. This simple policy combination has been applied by the warehouse to ensure a smooth transition of integrating this new warehouse part in the current operations. After the implementation phase, choosing the optimal combination of different order picking policies is crucial for warehouse managers in order to improve the overall order picking performance and consequently improving the service to customers.

3.2.3 Operational Measures

In order to handle the large number of orders in short time intervals, the efficiency of order picking operations needs to be improved. Manual order picking is characterised by the large number of time consuming activities: setup time, search time, retrieve time, and travelling to, from, and between pick locations. These four time components account for 95% of the total order pick time (Tompkins et al., 2010). The simulated order picking policies are evaluated with respect to the setup activity, the search activity, as well as travelling of order pickers. Travelling is the most substantial time consuming activity (50%). Searching and setup account for 20% and 10% of the total order pick time, respectively. The time spent on retrieving items (15%) at storage locations is assumed to be independent of the applied zoning, storage, batching, and routing policy.

Minimizing total order pick time is a convenient way for evaluating a non-dynamic order picking system in which orders are assumed to be known at the beginning of the planning period (Petersen and Aase, 2004; Quader and Castillo-Villar, 2018). In a dynamic order picking system, order throughput time is more convenient to evaluate performances. As in our case a non-dynamic order picking system is assumed and both performance measures are highly correlated, total order pick time is minimised in this study as this mostly results in the smallest order throughput time as well (Giannikas et al., 2017).

The setup activity refers to the time consumed by administrative and setup tasks at the beginning and end of each pick round. The setup time is assumed to be proportional to the number of pick rounds. Searching is defined as the time to identify the storage locations and identification of SKUs. The search time is approximated by evaluating the number of locations that should be visited to retrieve all orders. Remark that the number of locations may be smaller than the number of order lines in a pick round as order lines of different orders can contain the same SKU and thus the same storage location. Finally, the average travel speed in both cross-aisles and pick aisles is assumed to be equal. Given a constant travel velocity, minimizing the distance travelled by order pickers is equivalent to minimizing the average travel time of order pickers. Order pickers are assumed to be able to traverse aisles in both directions and to be able to change direction within aisles. Pick aisles are assumed to be wide enough to allow order pickers to pass each other within aisles, preventing wait times as a result of aisle congestion.

3.2.4 Experimental Design

First, the experimental design of the simulation experiments in the real-life warehouse is discussed (Section 3.2.4.1). In order to validate and generalise the results of the case study, the Section 3.2.4.2 describes a second experimental factor setting that is used in addition to the experiments of the real-life case (i.e., generalised experimental design).

3.2.4.1 Experimental Design of Real-life Case Study

In the experiments of the wide-aisle real-life order picking system, a wide range of policies is evaluated: five picker zoning policies, five storage location assignment policies, three order batching policies, as well as five routing policies are analysed. The four factors and their associated factor levels of the real-life case are summarised in Table 3.3. The baseline scenario of this experiment, indicated in italic in Table 3.3, corresponds to the current operation of the warehouse. In the simulation experiments, policies that are widely used in practice (e.g., FCFS batching, traversal routing), as well as policies that have often been considered in academic literature (e.g., savings batching algorithms, largest gap and optimal routing) are tested and evaluated. Due to technological or practical constraints, such as the effects of maverick picking (i.e., pickers deviate from the proposed optimal route) (Glock et al., 2017), warehouses are not able to apply the complex policies provided by academics (Chen et al., 2010). Section 3.4 returns to this point by providing policy combinations that are able to improve the overall picking performance under different technological and practical constraints.

TABLE 3.3: Experimental factor setting of the real-life case.

Factor	Factor levels
Picker zoning policy	(1) *1 zone*
	(2) 2 zones & customer type (CT) zone assignment
	(3) 2 zones & pick frequency (PF) zone assignment
	(4) 4 zones (CT)
	(5) 4 zones (PF)
Storage location assignment policy	(1) *Random*
	(2) Within-aisle
	(3) Across-aisle
	(4) Diagonal
	(5) Perimeter
Order batching policy	(1) *FCFS*
	(2) Seed
	(3) Saving
Picker routing policy	(1) *Aisle-by-aisle*
	(2) Traversal
	(3) Return
	(4) Largest gap
	(5) Optimal (approximated by LKH)

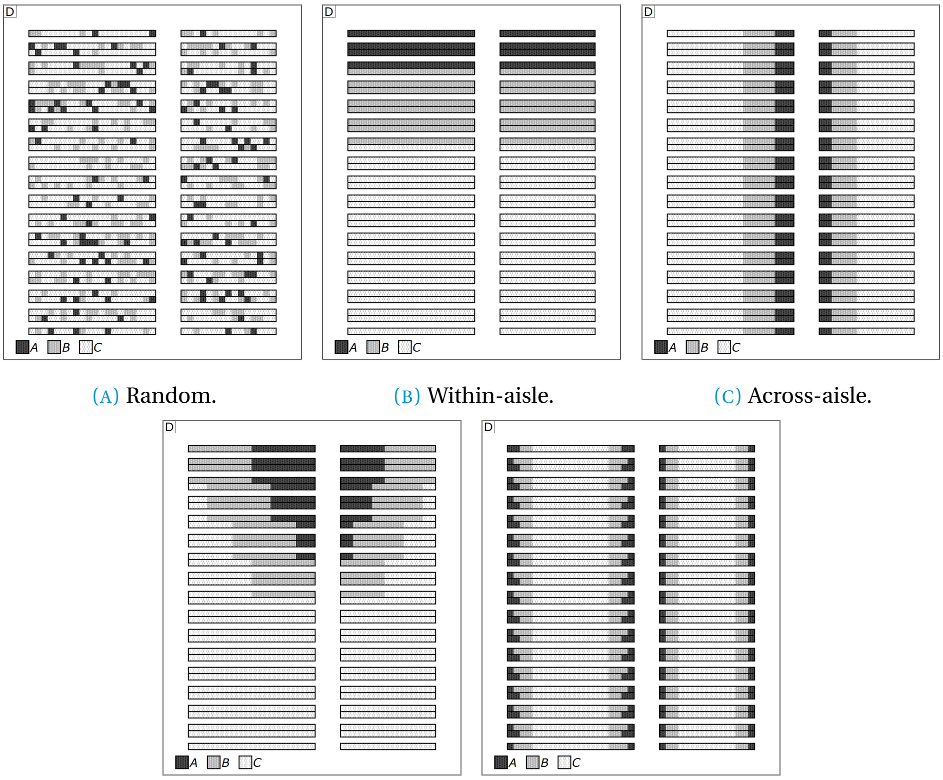
The order picking area consisting of a single zone is compared to four picker zoning policies. Both the number of zones as well as the storage zone assignment policy should be determined in case of zone picking. In the simulation experiments, the warehouse is divided into either two or four pick zones, and SKUs are assigned to pick zones based on customer type (CT) or pick frequency (PF). This setting results in four additional picker zoning policies. The location of the zones is provided in Table 3.4.

Besides randomly assigning SKUs to storage locations, four turnover-based storage location assignment policies are simulated, in particular across-aisle assignment, within-aisle assignment, diagonal assignment and assigning SKUs across the perimeter of the

TABLE 3.4: Location of picker zoning policies.

# zones (picker zoning policy)	Zone 1	Zone 2	Zone 3	Zone 4
1 zone (1)	1-32	-	-	-
2 zones (2)-(3)	1-16	17-32	-	-
4 zones (4)-(5)	1-8	9-16	17-24	25-32

order picking area. The turnover-based policies consists of three product classes: class A stores the fast moving SKUs, class B represents the moderate ordered SKUs and class C stores slow moving SKUs. Within each product class each SKU is randomly assigned to a single storage location. The location of the product classes is shown on Figure 3.2. In case multiple zones are combined with a turnover-based storage location assignment policy, the location of storage classes in each pick zone is similar to the location of storage classes in a single pick zone as shown on Figure 3.2.



(A) Random. (B) Within-aisle. (C) Across-aisle.

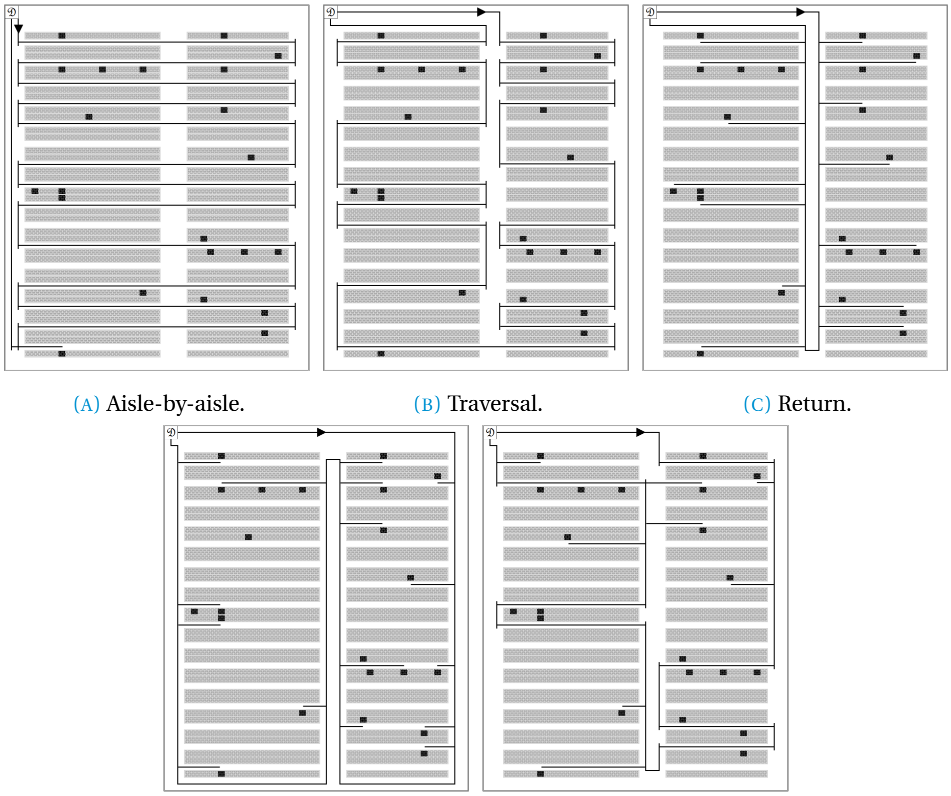
(D) Diagonal. (E) Perimeter.

FIGURE 3.2: Storage location assignment policies.

The currently used FCFS batching policy actually results in a random creation of pick lists in terms of travel distance, as FCFS batching does not take the location of SKUs in the order picking area into account. A seed order batching algorithm is used as an alternative to create batches. The order that requires the smallest number of pick aisles to visit, is selected as seed order. Next, the order that minimises the number of additional pick aisles to visit in the route is added to the pick list. This algorithm is repeated until the batch contains 26 orders. Subsequently, a new seed order is selected. The cumulative variant of the seed selection rule is simulated, where the number of aisles that should be visited in a batch is renewed every time an order has been added to a batch. The combination of this seed order selection rule and this accompanying order selection rule has yielded good results for different storage location assignment and routing policies in previous research (De Koster et al., 1999; Ho and Tseng, 2006; Ho et al., 2008). Both FCFS and the seed algorithm are often used in practice because of their simplicity. Additionally, a more sophisticated savings algorithm is tested to compose batches. Savings algorithms are based on the algorithm of Clarke and Wright (1964) for the vehicle routing problem. Pick orders are composed based on the distance saving that can be obtained by combining two or more customer orders into a single pick round. Due to computing time limitations, the basic variant of Clarke-and-Wright, denoted by C&W(i), is analysed in the simulation experiments: the savings matrix is calculated only once, the savings are sorted in decreasing order, and orders are combined in a batch if the batch capacity constraint is not violated by combining both orders. In case both orders have been assigned to a batch, the C&W(i) algorithm tries to combine both batches. Other Clarke-and-Wright algorithm variants result in strong increasing computing times and only minor improvements (De Koster et al., 1999).

In addition to the aisle-by-aisle routing heuristic, the travel distance for return, traversal, largest gap, and the optimal route is computed. Examples of the four dedicated routing heuristics are shown on Figure 3.3. As the routing problem cannot be solved to optimality for a multiple-block warehouse in reasonable computing times, the Lin-Kernighan-Helsgaun (LKH) heuristic for the travelling salesman problem (TSP) is used to approximate the optimal route (Helsgaun, 2000). The LKH heuristic has shown to provide excellent results, both in a general TSP context, and in the context of routing order pickers in a warehouse. Theys et al. (2010) reported an average optimality gap of 0.1 % for different warehouse settings.

To sum up, the simulation experiment consists of 375 possible combinations of policies (i.e., five picker zoning policies × five storage location assignment policies × three order batching policies × five routing policies). The factorial setting results in a 5×5×3×5 full factorial design.



(A) Aisle-by-aisle. (B) Traversal. (C) Return.

(D) Largest gap. (E) Optimal.

FIGURE 3.3: Picker routing policies.

3.2.4.2 Generalised Experimental Design

In order to validate the conclusions of the case study, the simulation experiment of the real-life warehouse is enlarged to other warehouse settings. As the real-life case study is dedicated to a single warehouse setting, findings should be validated to generalise the conclusions of this study to other warehouse settings. Validation is performed by testing and analysing the research hypotheses for more generic warehouse designs. In this way, findings and explanations on the relationships among order picking planning problems can be used to identify generally well performing policy combinations and formulate general conclusions. Three additional factors that are frequently used in literature to validate new solution methods, will be used to generalise the conclusions of the real-life case: a varying warehouse layout (Petersen, 2002; Theys et al., 2010), a varying order size (De Koster et al., 2012; Petersen, 2002; Theys et al., 2010), and a varying batch capacity (Manzini et al., 2007; Yu and De Koster, 2009). Each of the additional factors consists of three factor levels. Other factors and assumptions formulated in the previous section are similar to the case study.

Compared to the case study (i.e., 32 pick aisles), the warehouse is enlarged to 64 pick aisles and 96 pick aisles. Additionally a more general order picking layout is simulated: the two unequal warehouse blocks are replaced by two equal warehouse blocks in correspondence with the traditional warehouse layouts used in academic literature (Roodbergen and De Koster, 2001a; Roodbergen, 2012; Shqair et al., 2014; Theys et al., 2010). Furthermore, order sizes are exponentially distributed with a mean of one, three, and five order lines. Finally, the batch capacity factor is set to 10 orders, 25 orders, and 40 orders. Table 3.5 summarises the experimental factor setting of the generalised case.

TABLE 3.5: Experimental factor setting of the generalised case.

Factor	Factor levels
Picker zoning policy	(1) 1 zone
	(2) 2 zones (CT)
	(3) 2 zones (PF)
	(4) 4 zones (CT)
	(5) 4 zones (PF)
Storage location assignment policy	(1) Random
	(2) Within-aisle
	(3) Across-aisle
	(4) Diagonal
	(5) Perimeter
Order batching policy	(1) FCFS
	(2) Seed
	(3) Saving
Routing policy	(1) Aisle-by-aisle
	(2) Traversal
	(3) Return
	(4) Largest gap
	(5) Optimal (approximated by LKH)
Warehouse layout	(1) 32 aisles
	(2) 64 aisles
	(3) 96 aisles
Order size	(1) 1 order line
	(2) 3 order lines
	(3) 5 order lines
Batch capacity	(1) 10 orders
	(2) 25 orders
	(3) 40 orders

To sum up, the simulation experiment of the generalised case consists of 10,125 possible combinations of policies (i.e., five picker zoning policies × five storage location assignment policies × three order batching policies × five routing policies × three warehouse layout levels × three order size levels × three batch capacity levels). The factorial setting results in a $5 \times 5 \times 3 \times 5 \times 3 \times 3 \times 3$ full factorial design.

3.2.5 Data generation

All combinations of picker zoning, storage, batching, and routing are tested on the same 1,690 randomly generated orders (i.e., 65 pick lists × 26 orders in each batch). The order size and composition of these 1,690 orders is based on the historical composition of more than 15,000 orders. Order sizes are exponentially distributed with a mean of 2.65 order lines and more frequently ordered SKUs have a higher probability to be generated as order line.

The performance of the combination of the four planning problems is evaluated using the same randomly generated order list. With respect to the real-life case study, the 375 possible combinations of zoning, storage, batching, and routing policies are tested on the same list of 1,690 customer orders. 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. To induce unsystematic variation, thirty lists of customer orders are randomly created for the experimental design of the real-life case to reduce the stochastic effect from order generation.

By varying the warehouse layout, mean order size, and batch capacity, additional unsystematic variation is induced in the experiments by generating new lists of orders for each of these factor levels. In total, $30 \times 3 \times 3 \times 3$ lists of orders are generated for the experimental design of the generalised case (each list consisting of 1,690 orders) and tested with respect to the policies of the four planning problems. These unsystematic variation allows us to easily generalise the conclusions of the experiments to other warehouses.

Note that customer orders are generated based on the real-life case data 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.

3.2.6 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 3.1. To test whether or not a relationship is statistically significant, an analysis of variance (ANOVA) is performed, both on travel distance (i.e., distance for picking 1,690 orders in a single replication), number of pick rounds (per replication), and number of visited locations (per replication). Although multiple independent ANOVAs are performed which 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 full factorial design with a mixture of between-groups (only in the generalised experimental design) and repeated-measures factors. The between-groups factors consist of the three independent factors (i.e., warehouse layout, order size and batch capacity), while the repeated-measures factors correspond to the picker zoning, storage, batching, and routing factors. This mixed factorial design requires a mixed model ANOVA (Petersen, 1997), at least for the generalised experimental design. The experiments of the real-life case require a simple repeated measures design as the experimental design consists of only repeated-measures factors.

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. Due to the large number of tested factor combinations, sphericity and homogeneous variances are rather unlikely. 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 relationhips 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 Dunnett's 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, Dunnett's correction approach (as well as for example Bonferroni) 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.

3.3 Empirical Results

In order to get a first insight into the results of the simulation experiments, the performance measures of the different factor combinations are analysed by a full factorial repeated measures ANOVA on average travel distance, average number of pick rounds and average number of visited locations. The results of the ANOVA are presented in the next sections as follows: first, Section 3.3.1 fulfils the first two research objectives of this study: results of the real-life warehouse simulation are analysed to test the research hypotheses and to explain why and how the individual planning problems of zoning, storage, batching, and routing are related. The conclusions of the real-life case study are validated and generalised to other warehouses by analysing the simulation results of the generalised case in Section 3.3.2.

3.3.1 Results of Real-life Case Study

In the simulation experiments of the real-life warehouse, a balanced 5×3×5×5 full factorial repeated measures ANOVA, with zoning, storage, batching, and routing as the within-subjects factors, is used to prove the value of combining the four order picking planning problems. The results of the repeated measures ANOVA on average travel distance, number of pick rounds, and number of visited locations are shown in Tables 3.6, 3.7, and 3.8, respectively. The first three columns show the sum of squares, the G-G degrees of freedom (df) and the resulting mean square for the main and interactions effects, as well as for the residuals. The last two columns are devoted to the F statistic and the p-value for testing the statistical significance of zoning, storage, batching, and routing, as well as the interactions among the four planning problems.

Tables 3.6, 3.7, and 3.8 indicate that the main effects of picker zoning, storage location assignment, order batching, and routing are statistically significant with respect to the three performance measures. This means that there is a significant difference between the five zoning policies, the five storage location policies, the three order batching policies, as well as the five different routing policies on the average distance travelled by order pickers, the average number of pick rounds, and the number of visited storage locations. The decision on which storage, which batching, which zoning, and which routing policy to use does influence the order picking performance.

Furthermore, Tables 3.6, 3.7, and 3.8 show that all factors in the simulation experiment are significantly interacting with each other with respect to each of the three performance

TABLE 3.6: 5×3×5×5 full factorial repeated measures ANOVA on average travel distance.

	Sum of squares	df	Mean square	F	p-value
Main effects					
Zoning	303,589,976,898	2.40	126,491,824,693	51,642.26	0.000
Storage	28,565,916,920	3.00	9,528,113,270	19,512.62	0.000
Batching	421,484,570,256	1.81	232,630,801,415	502,015.57	0.000
Routing	52,259,090,330	3.14	14,663,524,503	94,142.19	0.000
Two-way interaction					
Zoning × storage	17,292,769,630	7.76	2,228,256,294	3,812.92	0.000
Zoning × batching	50,034,223,170	5.25	9,529,532,547	23,747.10	0.000
Zoning × routing	7,651,407,057	4.14	1,848,894,174	5,230.31	0.000
Storage × batching	2,115,987,384	6.16	343,569,720	2,357.78	0.000
Storage × routing	9,970,923,340	6.92	1,440,588,668	8,359.33	0.000
Batching × routing	6,756,931,911	3.27	2,065,561,184	13,980.56	0.000
Residuals					
Between subjects	1,652,597	29.00	56,986		
Within zoning	146,767,923	72.54	2,023,312		
Within storage	42,455,169	86.94	488,305		
Within batching	24,347,955	52.54	463,394		
Within routing	16,098,134	91.03	176,850		
Within zoning × storage	137,355,065	219.48	625,831		
Within zoning × batching	61,101,886	152.26	401,293		
Within zoning × routing	42,424,016	120.01	353,496		
Within storage × batching	26,026,054	178.61	145,718		
Within storage × routing	34,590,906	200.72	172,333		
Within batching × routing	14,015,963	94.87	147,745		
Total	900,342,164,257	1,338.72			

TABLE 3.7: 5×3×5×5 full factorial repeated measures ANOVA on average number of pick rounds.

	Sum of squares	df	Mean square	F	p-value
Main effects					
Zoning	1,367,788.93	2.56	533,355.21	13,804.38	0.000
Storage	2.51	3.40	0.74	26.95	0.000
Batching	28.87	1.00	28.87	201.96	0.000
Routing	6.7	2.96	2.26	53.87	0.000
Two-way interaction					
Zoning × storage	1.85	8.70	0.21	4.64	0.000
Zoning × batching	14.26	2.14	6.65	21.48	0.000
Zoning × routing	7.05	5.90	1.19	13.72	0.000
Storage × batching	5.02	3.40	1.47	26.95	0.000
Storage × routing	5.77	7.84	0.74	14.26	0.000
Batching × routing	13.40	2.96	4.53	53.87	0.000
Residuals					
Between subjects	2,305	29.00	0.08		
Within zoning	2,873.43	74.37	38.64		
Within storage	2.70	98.70	0.03		
Within batching	4.15	29.00	0.14		
Within routing	3.61	85.83	0.04		
Within zoning × storage	11.60	252.33	0.05		
Within zoning × batching	19.25	62.16	0.31		
Within zoning × routing	14.91	171.19	0.09		
Within storage × batching	5.40	98.70	0.05		
Within storage × routing	11.74	227.34	0.05		
Within batching × routing	7.21	85.83	0.08		
Total	1,373,133.36	1,255.32			

measures. As three out of the four factors in the experiment contain five levels, the 30 replications give rise to a large number of observations. Null hypotheses are much easier

TABLE 3.8: 5×3×5×5 full factorial repeated measures ANOVA on average number of visited locations.

	Sum of squares	df	Mean square	F	p-value
Main effects					
Zoning	538,617,997	2.82	190,785,132	14,516.94	0.000
Storage	19,857,165	3.44	5,774,199	2,801.40	0.000
Batching	1,606,293,435	1.21	1,322,451,977	50,892.63	0.000
Routing	2,556,886	3.22	794,644	4,689.53	0.000
Two-way interaction					
Zoning × storage	3,731,458	9.12	409,260	121.47	0.000
Zoning × batching	68,883,249	4.69	14,672,337	2,622.27	0.000
Zoning × routing	446,489	9.96	44,835	202.84	0.000
Storage × batching	16,008,512	5.31	3,013,365	1,803.96	0.000
Storage × routing	140,542	10.08	13,945	57.63	0.000
Batching × routing	5,113,772	3.22	1,589,288	4,689.53	0.000
Residuals					
Between subjects	80,942	29.00	2,791		
Within storage	205,561	99.73	2,061		
Within batching	915,309	35.22	25.985		
Within zoning	1,075,979	74.10	14,520		
Within routing	15,812	93.31	169		
Within storage × batching	257,349	154.06	1,670		
Within storage × zoning	890,827	264.41	3,369		
Within storage × routing	70,719	292.27	242		
Within batching × zoning	761,788	136.15	5,595		
Within batching × routing	31,624	93.31	339		
Within zoning × routing	63,836	288.79	221		
Total	2,266,019,250	1,613.17			

rejected with a large number of factor levels and a large number of observations because of a greater probability that one of the factor levels is interacting with another factor level (Field, 2013). However, the ANOVA shows strong statistically significant effects, at least with respect to the travel distance, and for some interactions regarding the number of visited locations (e.g., zoning-batching, storage-batching, and batching-routing).

The next six paragraphs are devoted to explaining and discussing why planning problems are related. As ANOVA results show that interaction terms are most strong in terms of travel distance and travelling is the most time consuming activity, each combination of planning problems is discussed with respect to the distance travelled by order pickers. As differences in number of pick rounds are too small to be relevant in practice, this performance measure does not contribute to the discussion on why planning problems are related. For example, the maximum difference in number of pick rounds between the combinations of storage and batching policies is only 0.16 pick rounds. The number of pick rounds only slightly increase in case of a savings batching policy (i.e., batches are created in parallel and not necessarily filled to capacity), or increase significantly in case of increasing the number of zones (i.e., batch capacity is expressed as number of orders). Consequently, the main effects on number of pick rounds are relevant, but interactions among planning problems with respect to the number of pick rounds are not relevant in practice and thus not discussed throughout the next sections. The performance measure 'number of visited locations' is discussed only for combinations that show substantial differences (i.e., zoning-batching, storage-batching, and batching-routing).

Zoning and Storage The order picking system's performance is expected to be significantly influenced by the combined effect of picker zoning and storage location assignment. Table 3.6 shows that the two-way interaction is statistically significant with respect to the travel distance. In the context of the two other performance measures, the joint effect of picker zoning and storage location assignment on order picking performance is statistically significant as well. Thus, Hypothesis 3.1 is supported by the ANOVA results. However, variations are practically irrelevant with respect to the number of pick rounds and the number of visited locations. The next paragraphs focus on explaining why the interaction between picker zoning and storage location assignment is statistically significant with respect to the travel distance.

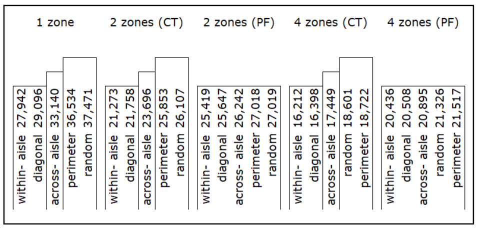
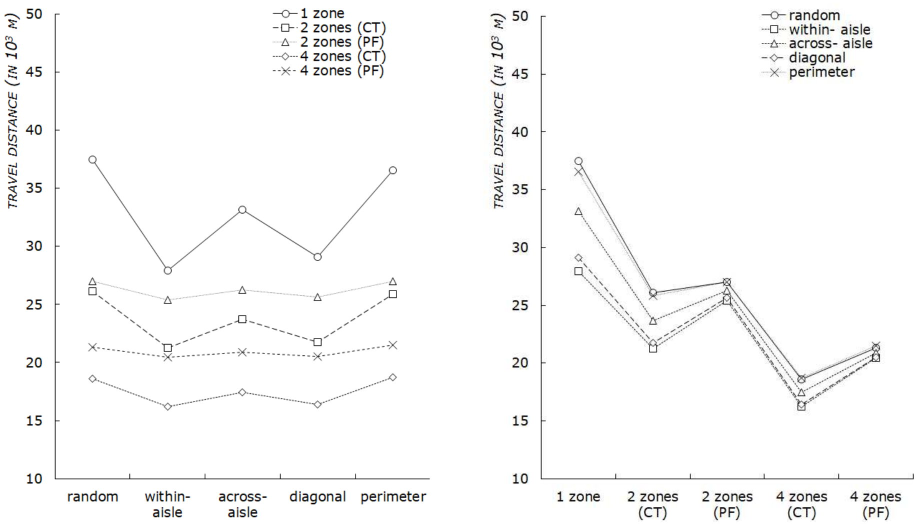


FIGURE 3.4: Multiple Dunnett's t-test (familywise error rate = 0.01) for storage policies by zoning policies (travel distance in m).

Results of the post hoc tests, shown in Figure 3.4, explain why picker zoning and storage location assignment are strongly related. If two order picking policies are listed in the same subset in Figure 3.4, differences fail to be statistically significant. In case of assigning SKUs to pick zones based on the pick frequency, the applied storage location assignment policy seems to be irrelevant. A single subset containing all storage policies is created in case of pick frequency assignment of SKUs to pick zones, indicating that the travel distance is not statistically significantly different for each of the five storage policies. Products assigned to each pick zone are characterised by a similar demand. If demand is distributed uniformly, turnover-based storage location assignment policies are not able to reduce picker travelling compared to randomly assigning products to storage locations. This effect is illustrated on Figure 3.5a by the rather flat line for 2 zones (PF) and 4 zones (PF).

The single zone, as well as the customer type assignment of SKUs to zones (2 zones (CT) and 4 zones (CT)) result in the same composition of subsets. Within-aisle storage and diagonal storage outperform other storage assignment policies with respect to travel distance. The example shown in Figure 3.5 further illustrates why the statistically significant interaction exists: the effect of different storage location assignment policies is not



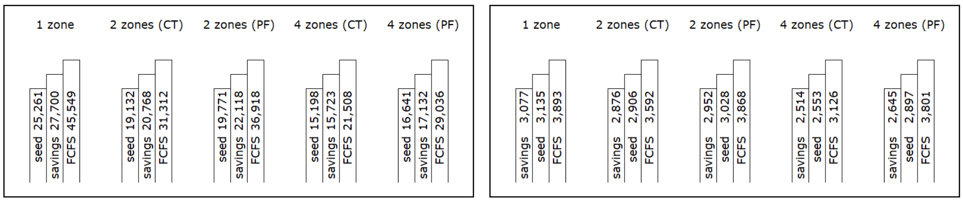
(A) Zoning–storage interaction.

(B) Storage–zoning interaction.

FIGURE 3.5: Average travel distance (in meters) for each combination of zoning and storage policy.

consistent over all levels of zoning. By dividing the warehouse into pick zones, the effect of shifting to a more efficient storage policy on the route length is reduced compared to the single pick zone. The reason for this significant interaction term can be found in the smaller area that is crossed by order pickers to retrieve all items on the pick list in case of two or four pick zones, as well as in case of turnover-based storage location assignment. Zoning policies as well as storage policies aim to increase the density of SKUs retrieved in each aisle. Consequently, the performance impact resulting from changing the storage policy is far greater in combination with a single zone, compared to other picker zoning policies. Thus, decreasing the zone size by increasing the number of zones diminishes the efficiency benefits resulting from turnover-based storage as order pickers are limited to a small pick area. Dividing the order picking area into more than four zones may adversely affect the order picking efficiency in the case study. If the number of zones exceeds the number of customer types, sorting operations increase and more order picking routes are composed. Order pickers are operating at less than full capacity, especially for unpopular zones. Since orders should be picked before due dates, pick lists are released before the capacity has been reached.

Zoning and Batching ANOVA results of Tables 3.6, 3.7 and 3.8 support Hypothesis 3.2 that picker zoning and order batching planning problems are strongly related. The joint effect on the number of pick rounds is not discussed due to the lack of practical significance of the observed differences among the policy combinations. Especially with respect to the distance travelled by order pickers to retrieve all items, Table 3.6 shows a strong two-way interaction between picker zoning and order batching.



(A) Travel distance (in m).

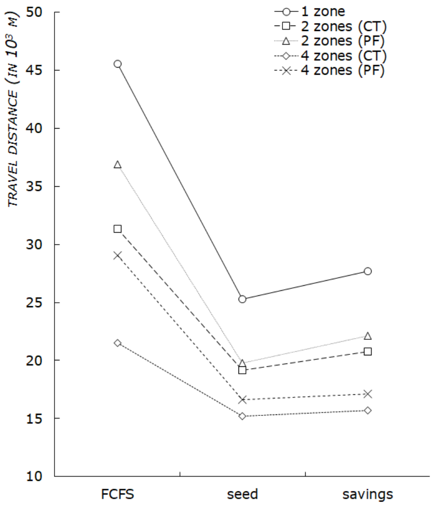
(B) # visited locations.

FIGURE 3.6: Multiple Dunnett's t-test (familywise error rate = 0.01) for batching policies by zoning policies.

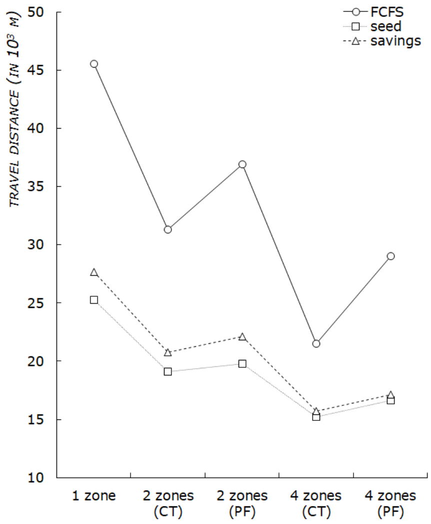
The post hoc test, shown in Figure 3.6, creates three identical subsets for each picker zoning policy. All five picker zoning policies result in the same composition of subsets. The three batching policies result in statistically significantly different performances, in terms of both travel distance and number of visited locations. The seed batching policy yields the shortest routes, while the C&W(i) savings algorithm scores better on 'number of visited locations' by combining more orders that should visit identical storage locations on the created pick lists. Differences between the seed and savings batching policy with respect to the number of visited locations are minor in practice, except for the pick frequency assignment of SKUs to pick zones (i.e., 2 zones (PF) and 4 zones (PF)). The number of visited locations decreases in combination with the savings batching policy. Orders within each zone are smaller, because the pick frequency zone assignment results in splitting orders across zones. So, within each pick zone, the small orders are more likely to be identical in terms of visited locations. These orders are combined more likely by the C&W batching algorithm. Therefore, the number of visited locations strongly decreases while combining the savings batching algorithm with the pick frequency zone assignment.

Figure 3.7 further explains the relationship between picker zoning and order batching. Lines on the graph strongly converge when changing from a straightforward FCFS batching policy to more complex batching policies. The efficiency benefits resulting from zoning decrease in combination with smart batching algorithms compared to FCFS batching. SKUs on the pick list are diffused over the entire order picking area in case of a single zone and FCFS batching. Batching policies resulting in short travel distances reduce the effect of zoning (e.g., varying picker zoning policies show small route length differences in combination with seed batching). Moreover, increasing the number of zones, resulting in a smaller order picking area, reduces the effect of batching algorithms (e.g., the savings algorithm approximates the seed batching travel distance in combination with four zones).

This can be explained by the fact that both batching and zoning aim to reduce the pick area during each pick round by combining equivalent orders and splitting the pick area, respectively.



(A) Zoning–batching interaction.



(B) Batching–zoning interaction.

FIGURE 3.7: Average travel distance (in meters) for each combination of zoning and batching policy.

Zoning and Routing This paragraph analyses the currently unknown effect of combining the picker zoning and routing planning problems. Hypothesis 3.3, that expects the joint effect of zoning and routing to be related, is tested using the full factorial repeated measures ANOVA on mean travel distance, the average number of pick rounds and the average number of visited locations. Based on the results shown in Tables 3.6, 3.7, and 3.8, the hypothesis is statistically supported: the joint effect of picker zoning and picker routing on order picking performance is found to be statistically significant. Practical relevance lacks with respect to differences in number of pick rounds and number of visited locations.

The results of the post hoc test decomposed in picker zoning policies are summarised in Figure 3.8. The different composition of subsets explains the statistical significance of the picker zoning and picker routing planning problem. Again, the optimal routing policy is found to outperform all dedicated routing heuristics in combination with all picker zoning policies. Since routing policies only determine the sequence of SKUs on the pick list, in other words, since SKUs on the pick list are distributed over the order picking area in the same way for all routing policies, the average route length differences among the

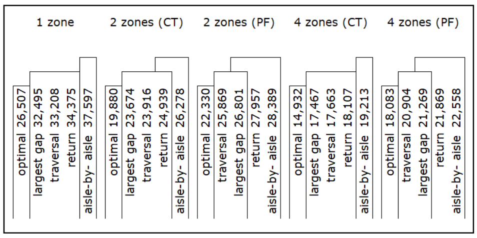
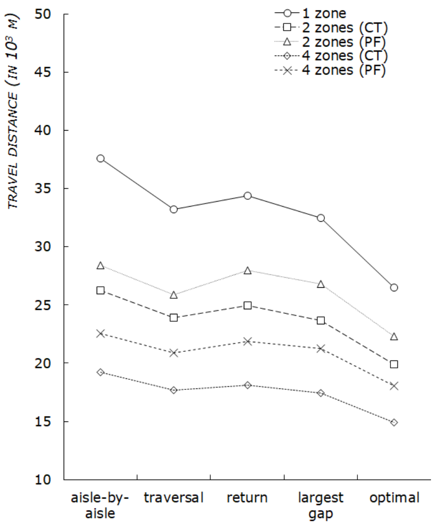
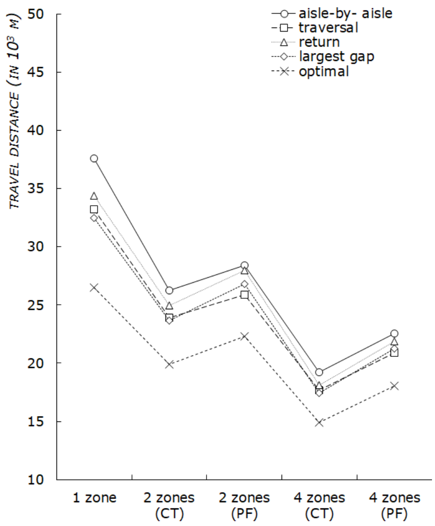


FIGURE 3.8: Multiple Dunnett's t-test (familywise error rate = 0.01) for routing policies by zoning policies (travel distance in m).



(A) Zoning–routing interaction.



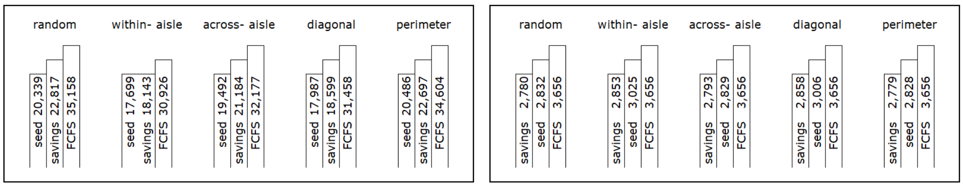
(B) Routing–storage interaction.

FIGURE 3.9: Average travel distance (in meters) for each combination of zoning and routing policy.

routing policies increases as the pick area of a pick tour increases: decreasing the number of zones, slightly increases the effects of the routing policies as shown on Figure 3.9.

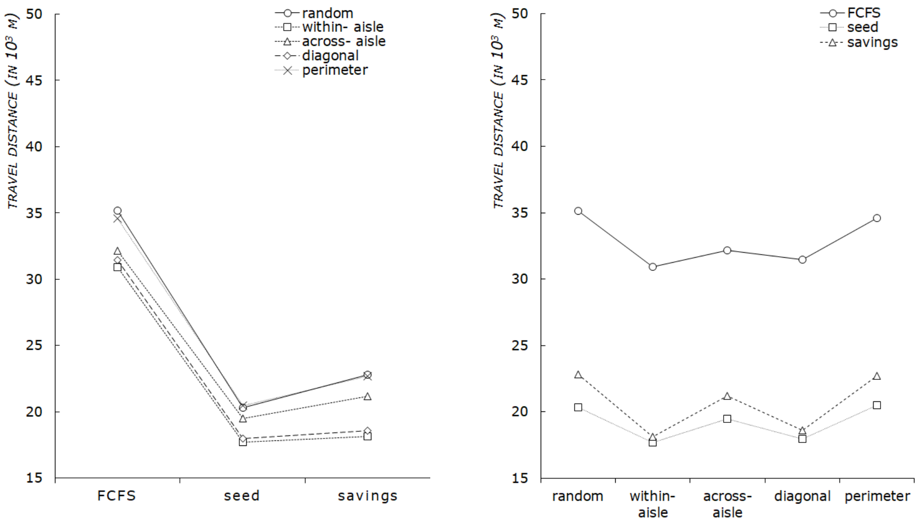
Storage and Batching The fourth hypothesis states that the joint effect of storage location assignment and order batching significantly impacts order picking performance (Hypothesis 3.4). The ANOVA results of Tables 3.6, 3.7 and 3.8 support the hypothesis of the relationship between storage and batching. The two-way interaction of storage and batching is statistically significant with respect to the distance travelled, the number of pick rounds, and the number of visited locations. However, differences in number of pick rounds are too small to be relevant in practice.

In order to analyse why the relationship between storage and batching planning problems is important, the statistical significance of all levels of the batching factor is analysed



(A) Travel distance (in m). (B) # visited locations.

FIGURE 3.10: Multiple Dunnett's t-test (familywise error rate = 0.01) for batching policies by storage policies.



(A) Storage–batching interaction. (B) Batching–storage interaction.

FIGURE 3.11: Average travel distance (in meters) for each combination of storage and batching policy.

for each storage factor level using Dunnett's method. Figure 3.10 summarises the test results of a post hoc test. Minor differences exists in the composition of subsets among different storage location assignment policies. In terms of travel distance, all batching policies are located in a separate subset except for the combination with within-aisle storage classes. Results of the post hoc tests indicate that the route length difference between the seed and savings batching policies is not statistically significant in combination with within-aisle storage classes, while in combination with other storage policies, the seed batching outperforms other batching policies. FCFS batching is situated in the last subset for each storage assignment policy.

No differences in the composition of subsets can be observed with respect to the number of visited locations. However, the seed algorithm shows strong differences among storage location assignment policies. A decreased number of visited locations can be observed in combination with random, across-aisle and perimeter storage classes. This can be explained as follows: fast moving items are located in all pick aisles in case of random, across-aisle and perimeter storage and the considered seed batching policy minimises the number of aisles to visit. Consequently, if a particular aisle should be visited in a pick round, the limited number of A-locations in the aisle are most likely to be visited, while aisles of within-aisle and diagonal storage classes consist of a large number of A-locations with equal probability of being visited.

The interaction plots of Figure 3.11 further illustrate why storage location assignment and order batching are related with respect to travel distance. The savings algorithm shows strong performance improvements in combination with within-aisle and diagonal storage location assignment policies, compared to the other storage policies. The savings algorithm is able to approximate the average travel distance of the cumulative seed batching algorithm in case of within-aisle or diagonal storage classes. These storage policies locate classes over the entire subaisle and storage locations within each subaisle have an equal probability of being visited. As seed batching only aims to minimise the number of visited subaisles in a pick round and the savings algorithm additionally takes the travel distance within a pick aisle into account while creating batches, the efficiency benefits resulting from within-aisle and diagonal storage are much larger in combination with savings batching. In case the number of A-locations is small in each subaisle, seed batching results in shorter route lengths.

Storage and Routing Simulation results support the fifth hypothesis (Hypothesis 3.5): Tables 3.6, 3.7 and 3.8 show that storage location assignment and picker routing are statistically significantly related with respect to the travel distance, the number of pick rounds, and the number of visited locations. Differences in number of pick rounds and number of visited locations are negligibly small.

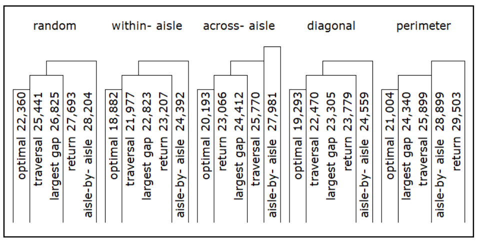
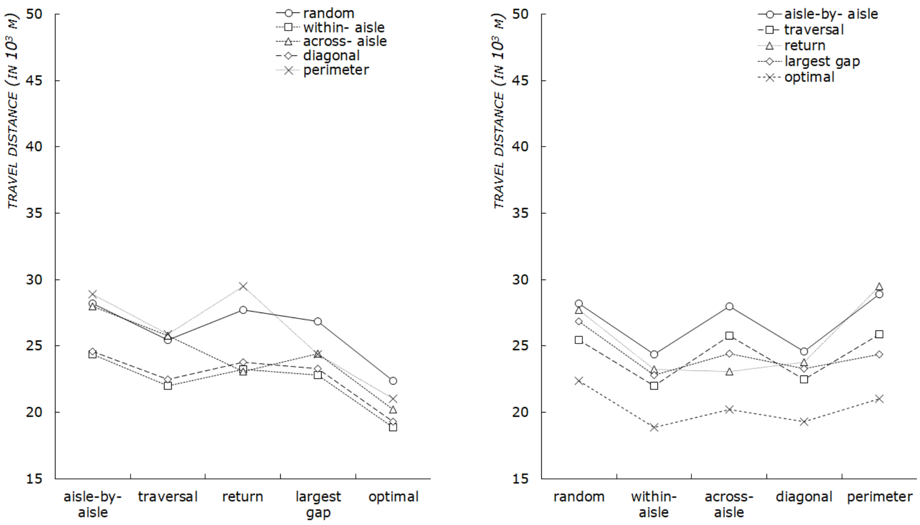


FIGURE 3.12: Multiple Dunnett's t-test (familywise error rate = 0.01) for routing policies by storage policies (travel distance in m).

The statistical significance of all levels of the storage factor, decomposed in routing policies, is analysed using Dunnett's method for pairwise comparisons in order to explain why both planning problems are related. Figure 3.12 presents the results of the post hoc



(A) Storage–routing interaction.

(B) Routing–storage interaction.

FIGURE 3.13: Average travel distance (in meters) for each combination of storage and routing policy.

test. The strong statistically significant interaction between storage and routing planning problems gives rise to the creation of varying subsets for each storage location assignment policy. Over all storage levels, the optimal routing policy outperforms the other routing policies that are often used in practice with respect to the average travel distance. The composition of the other subsets strongly differs across the different storage location assignment policies.

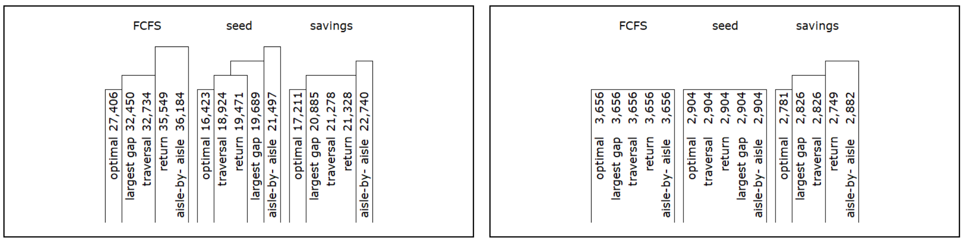
When randomly assigning SKUs to storage locations, only minor differences exist in the performance of the dedicated routing heuristics. All pick aisles and all storage locations have an equal probability of being visited in a pick tour. In other words, as pick densities are equally distributed across aisles as well as within each pick aisle, random storage does not clearly favour any of the dedicated routing heuristics. No clear subsets of routing policies in combination with random storage have been formed by the post hoc test.

Including information about the location of fast moving products while composing picker routes favours certain routing heuristics. From Figure 3.13, the combination of perimeter storage policy and largest gap routing policy is an example of a well performing combination. Since fast moving SKUs are stored along the periphery of the warehouse blocks and the largest gap routes tend to follow the periphery of the warehouse, this policy combination outperforms aisle-by-aisle and return routing in combination with perimeter storage location assignment. Other routing policies show a strong increase in travel distance in combination with the perimeter storage compared to other storage location assignment policies. Furthermore, return routes are preferred in combination with across-aisle storage classes: return routes aim to reduce the travel distance within aisles and across-aisle storage location assignment increases pick densities in the front of each pick aisle. Equivalent to the perimeter-largest gap combination, routing methods show increasing route lengths in combination with across-aisle storage, except for return routing. Finally, the traversal routing is preferred in combination with within-aisle and diagonal storage classes as the aim is to increase the pick density within an aisle (i.e., within-aisle and diagonal) and reduce the number of visiting aisles in a pick tour (i.e., traversal). However, this difference is not found to be statistically significant by the post hoc tests.

In summary, the statistically significant interaction between storage location assignment and order picker routing originates from the fact that some combinations of storage and routing policies yield excellent performances, while other combinations result in large average travel distances. Fast moving items should be assigned to storage locations that could be accessed most easily, which strongly depends on the routing policy.

Batching and Routing Hypothesis 3.6 states that a significant interaction exists between the batching and routing planning problems. The two-way interaction between order batching and picker routing is found to be statistically significant with respect to all three performance measures. ANOVA results do not reject Hypothesis 3.6: the efficiency of order batching is significantly influenced by the applied routing method. With respect to the number of pick rounds, differences between policy combinations of batching and routing are too small to discuss them meaningfully.

In order to analyse why the batching and routing planning problems are related, the simulation results are analysed using Dunnett's post hoc test (see Figure 3.14). Additionally, the results are illustrated on the interaction plots of Figure 3.15.

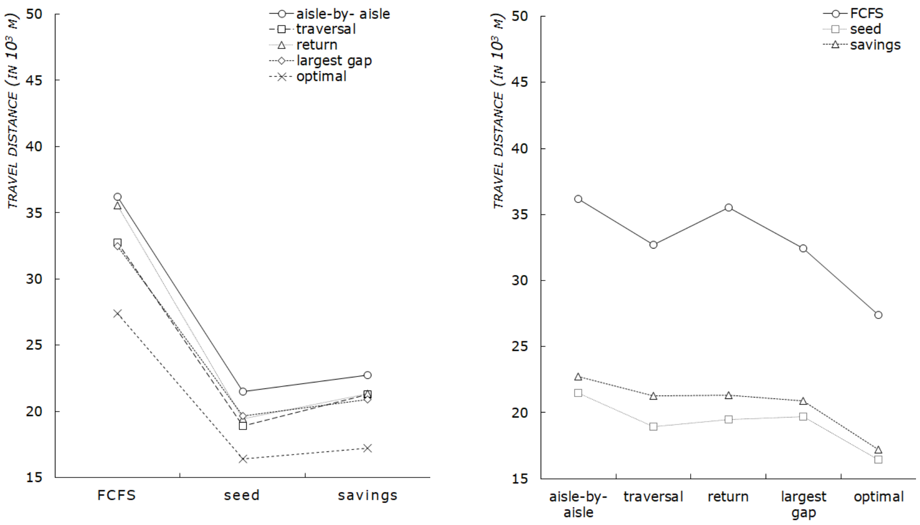


(A) Travel distance (in m).

(B) # visited locations.

FIGURE 3.14: Multiple Dunnett's t-test (familywise error rate = 0.01) for routing policies by batching policies.

Combinations of more straightforward routing policies (i.e., aisle-by-aisle and return) with FCFS batching appear to be inefficient in terms of travel distance (see Figure 3.15).



(A) Batching–routing interaction. (B) Routing–batching interaction.

FIGURE 3.15: Average travel distance (in meters) for each combination of batching and routing policy.

The post hoc test shows that aisle-by-aisle and return routing form the last subset in combination with FCFS batching. FCFS batching, which in fact results in a random creation of batches, generates pick lists with SKUs located in a large number of aisles and SKUs are diffused within each aisle. Aisle-by-aisle routes can work efficiently only if the number of aisles to be visited is minimised, while return routes aim to minimise the travel distance within a pick aisle. This results in a large travel distance when combining FCFS batching with either the aisle-by-aisle or return routing policy. The average route length difference between FCFS batching and seed or savings batching is much larger when combined with aisle-by-aisle and return routing compared to other routing policies. Moreover, the efficiency of the return routing policy strongly increases in combination with the seed batching policy and the savings batching policy. Especially, when integrating the routing policy while creating batches (i.e., savings batching), the importance of the decision which routing policy to use substantially reduces. As the savings algorithm is based on the travel distance reduction of combining orders, the route length of combinations of orders, depending on the applied routing policy, is calculated before batches are composed. As a result traversal, return and largest gap routing policies form a single subset in case of savings batching.

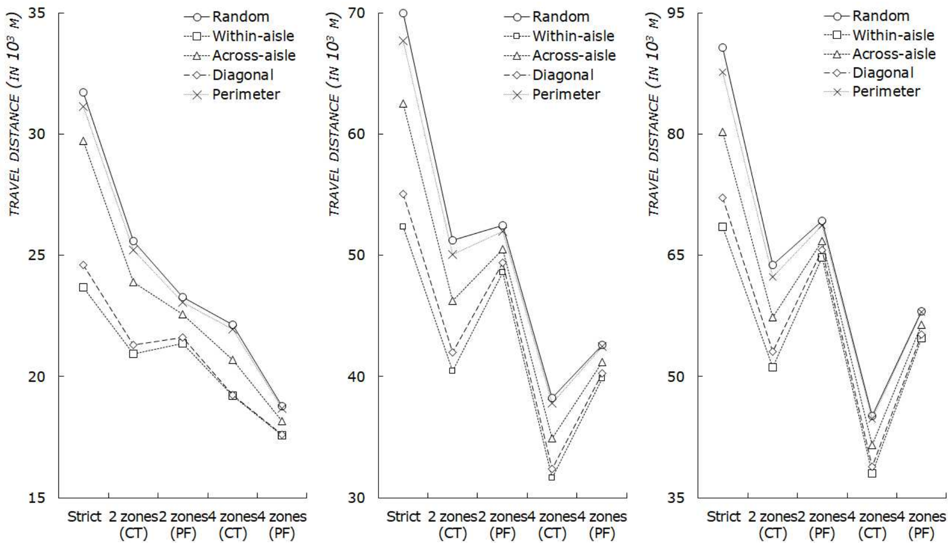
Minor differences exist in the number of visited locations between the combinations of batching and routing (see Figure 3.14). In case of FCFS batching and seed batching, the number of visited locations is insensitive to the routing policy. As the savings algorithm takes the routing policy into account while calculating the savings between combinations of orders, the composition of batches differ between the routing policies. Consequently, the number of visited locations varies for different routing policies in combination with the savings batching policy. However, the statistically significant differences between the routing policies are rather small: the number of visited locations vary only 4.8 % in case of savings batching.

3.3.2 Generalised Results

In order to validate and generalise the results and findings of case study to other warehouses, other warehouse properties have been included in the second simulation experiment. The hypotheses formulated in Section 3.1 are tested and analysed using the generalised experimental design. A 5×5×3×5×3×3×3 full factorial mixed model ANOVA, with zoning, storage, batching, and routing as within-subjects factors is used to test the hypotheses and validate the results of the real-life case study. The ANOVA results are presented in Appendix D.

In accordance with the findings of the real-life case study, the results of the mixed model ANOVA show that the main effects of picker zoning, storage location assignment, order batching and routing are statistically significant. Furthermore, all six formulated hypotheses about the relationships among the four order picking planning problems are statistically proven with respect to the distance travelled in Table D.1 of Appendix D. In addition to the real-life warehouse, the relationships among zoning, storage, batching, and routing are found to be statistically significantly related under varying warehouse layout, varying order size and varying batch capacity: warehouse layout, order size and batch capacity statistically significantly impact the joint effect of the order picking planning problems. Besides travelling, the six hypotheses are supported with respect to the number of pick rounds and the number of visited locations as well, as shown in Appendix D.

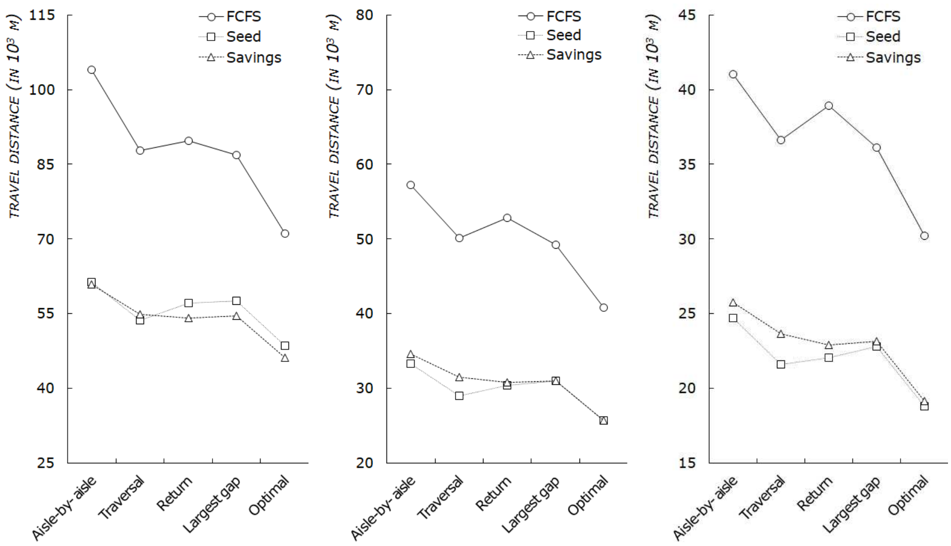
Results of the full factorial mixed model ANOVA on average travel distance indicate that the order picking layout, the order size and the batch capacity statistically significantly influence the relationship among the order picking planning problems. Two examples that demonstrate the most clear interaction are discussed. Figure 3.16 illustrates the impact of order picking layout on the combination of picker zoning and storage location assignment. The average travel distance for each combination of zoning and storage policy is shown for the three layout factor levels. The three interaction plots illustrate different patterns for each level of the order picking layout. The combined effect of zoning and storage strongly increases as the number of aisles in the order picking area increases. In case of 16 aisles, the pick frequency assignment of SKUs to pick zones outperforms other zoning policies in combination with most storage location assignment policies. Increasing the number of aisles results in an increased travel distance of the pick frequency assignment compared to assigning SKUs to zones based on customer type in combination with all storage location assignment policies. This effect may be explained by the larger distance for travelling from the depot to the first storage location and returning to the depot at the end of a pick round. Assigning SKUs to pick zones based on pick frequency results in an increased number of pick rounds due to order splitting. Thus, orders pickers should travel more often to the depot compared to customer type zoning policies, and this travel distance has been increased in the 64 aisles and 96 aisles layout.



(A) Layout: 32 aisles. (B) Layout: 64 aisles. (C) Layout: 96 aisles.

FIGURE 3.16: Average travel distance (in meters) for each combination of zoning and storage policy.

In a second example, Figure 3.17 illustrates the impact of the capacity of the picking vehicle on the joint effect of batching and routing. The average travel distance resulting from the seed and savings algorithm under different routing policies are of particular interest. In case of a small batch capacity the savings algorithm results in a smaller route length in case of return, largest gap and optimal routing, whereas the route length differences are insignificant in combination with aisle-by-aisle and traversal routing. This effect reverses as the batch capacity increases. The seed algorithm outperforms the savings algorithm in combination with the aisle-based routing policies (i.e., aisle-by-aisle and traversal), while the mean route lengths are at the same level in combination with the other three routing policies. The seed selection and accompanying order selection rule under consideration aim to minimise the number of aisles to visit in a pick tour. Consequently, this seed algorithm favours the aisle-based routing policies. As the batch capacity increases, the efficiency of the basic Clarke-and-Wright variant slightly decreases: orders are combined in a pick tour based on large savings with a single order in the batch, but the combination with other orders that have already been assigned to the batch may be small (savings between orders are calculated only at the start of the algorithm). This effect is larger when a batch consists of a large number of orders. Consequently the savings algorithm is outperformed by the seed batching policy, at least in combination with aisle-based routing policies.



(A) Batch capacity: 10 orders. (B) Batch capacity: 25 orders. (C) Batch capacity: 40 orders.

FIGURE 3.17: Average travel distance (in meters) for each combination of batching and routing policy.

3.4 Managerial Implications

The results of the simulation experiments show the importance of combining picker zoning, storage, batching, and routing decisions in order to manage order picking activities efficiently. This section discusses the practical implications of this research for warehouse managers and provides policy combinations that help to improve the overall order picking performance in several practical situations.

Compared to the benchmark of the real-life warehouse (i.e., a single pick zone in combination with random storage assignment, FCFS batching, and aisle-by-aisle routing), all proposed combinations perform better, except for the benchmark including perimeter instead of random storage. Over the 30 replications, the benchmark results in an average travel distance of 57,406 meters. The order picking process can be performed 79.3 % more efficiently by dividing the warehouse into four pick zones in combination with customer type zone assignment, within-aisle storage location assignment, savings batching, and optimal routing. This combination results in a mean route length of 11,886 meters. The benefits are huge in this case as the real-life warehouse can divide their orders across customer types and consequently prevent additional order consolidation operations.

Similar travelling savings (77.9 %) can be observed when evaluating the best performing combination (i.e., 4 zones (CT), within-aisle storage, savings batching, and optimal routing) and the benchmark policy combination in the context of the generalised case. Note that the savings batching policy outperforms the seed batching policy in this specific combination in contrast to the previous discussed results. Four zones (CT), within-aisle storage, savings batching, and optimal routing yields to a mean of 95 pick rounds and 3,269 visited locations, which is only 1.7 % and 4.7 % larger than the best performing policy combination in terms of 'number of pick rounds' and 'number of visited locations', respectively. In the discussion below, the overall best performing combination refers to the policy combination that yields the shortest mean route length: 4 zones (CT), within-aisle storage, savings batching, and optimal routing. As the simulation experiments have focused on tactical and operational order picking planning problems only, the proposed combinations are rather easy to implement and result in large performance benefits.

The applicability of the best performing combination is subject to several practical constraints (e.g., order integrity, policy complexity, picker blocking) that will be discussed below with respect to the simulation results of the generalised experiment. Due to the practical constraints, several policies should be eliminated from the original results, thereby making other policy combinations preferable. The best performing policy combination under the practical constraints are discussed and the implications with respect travel distance, number of visited locations and number of pick rounds is discussed.

First, maintaining order integrity can not be generalised to all warehouses as not all warehouses can divide their orders across customer types. When SKUs are assigned to zones based on pick frequency (i.e., 4 zones (PF), within-aisle storage, savings batching, and optimal routing), the average route length increases by 18.8 % compared to the best performing combination. Additionally, this combination of 4 zones (PF) zoning, within-aisle storage, savings batching, and optimal routing, may result in sorting activities in case of parallel picker zoning, an increased number of visited locations (6.4 %) and a strong increasing number of pick rounds (39.4 %) as orders are split across zones.

Second, the use of complex algorithms to solve the batching and routing planning problems have not been widely used in practice as calculating optimal batches and routes for each pick round may require long computing times and solutions may seem illogical pickers (Glock et al., 2017). In the context of the factor levels in this simulation study, the savings batching algorithm and LKH-routing heuristic (i.e., optimal) have a substantial impact on computing times compared to other batching and routing policies. Especially, the combination of savings batching and optimal routing requires a large amount of computing time. Furthermore, the effects of maverick picking prevent warehouses from using optimal routes to visit storage locations. Ignoring the savings and LKH-heuristic, the best performing policy combination includes 4 zones (CT) zoning within-aisle storage location assignment, seed batching, and traversal routing. This combination yields an increased route length of 15.0 % and an increased number of visited locations of 5.4 % compared to the overall best policy combination. The number of pick rounds remains similar.

Finally, the experiments under consideration assume a wide-aisle warehouse, disregarding picker blocking. Narrow-aisle picking systems are designed to increase storage capacity, but multiple order pickers may require to enter the same aisle which results in blocking of order pickers. The within-aisle and diagonal storage location assignment policy strongly concentrates picking activities in a small number of aisles, increasing the probability of picker blocking in aisles that mainly consist of class A locations. The probability of picker blocking in narrow-aisle warehouses will be substantially smaller in combination with other storage policies as class A locations are diffused across pick aisles. An increased route length of only 9.6 % compared to the overall best policy combination, can reduce efficiency losses due to picker blocking. Moreover, the search time, in terms of number of visited locations, reduces with 2.7 % and the setup time, in terms of number of pick rounds, is similar compared to the overall best policy combination. Thus, in narrow-aisle order picking systems, the combination of across-aisle storage, savings batching, 4 zones (CT) and optimal routing is expected to improve the overall order picking performance as within-aisle and diagonal storage are expected to result in picker blocking. We return to this point in Chapter 4 which directly accounts for picker blocking.

3.5 Conclusions

The simulation results and statistical analysis provide insights and general findings into the relationships among picker zoning, storage, batching, and routing. In contrast to previous studies (see Table 3.1), all main effects as well as all interaction effects have been proven to be statistically significant. Warehouse managers should take these interactions among order picking planning problems into account to design efficient order picking systems. For example, picker zoning increases pick efficiency substantially, but reduces potential efficiency benefits resulting from optimizing other order picking planning problems. Furthermore, policies for each planning problem need to aim at increasing the pick density in the same area of the warehouse to reduce travelling: examples are the combination of the cumulative seed batching algorithm and traversal routing, seed batching in combination with within-aisle storage classes, and return routes combined with across-aisle storage.

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 planning problems. The results of the study clearly indicate that warehouses can achieve significant benefits by considering picker zoning, storage, batching, and routing decisions simultaneously. The simulation results and statistical analysis provide policy combinations that help practitioners to improve the overall order picking performance in several practical situations. The simulated order picking policies can be easily implemented and immediately result in significant performance benefits.

CHAPTER 4

Interaction Analysis Incorporating Real-life Features in Narrow-aisle Order Picking Systems

As industrial land is expensive, especially in Western Europe, the area dedicated for storing 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 characterised by high labour 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 travelling 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 many studies address individual order picking planning problems (De Koster et al., 2007) and some articles combine planning problems (Dijkstra and Roodbergen, 2017; Petersen and Aase, 2004; Van Gils et al., 2016a, 2018c), real-life features, such as safety constraints, picker blocking, and high-level storage locations, are rarely taken into account (Van Gils et al., 2018a). This chapter goes beyond the current state-of-the-art literature by statistically analysing combinations of picker zoning, storage location assignment, order batching, and picker routing policies taking real-life features into account in a picker-to-parts order picking system. The research methodology of this study is similar to the previous chapter, that investigates the same planning problems in wide-aisle order picking systems, without considering real-life features. This chapter analyses to what extent these relationships have an effect on the order picking performance if real-life features are included. This study significantly differs from the previous chapter as including the real-life features changes the nature of the problem, resulting in substantially different results. We refer to wide-aisle systems in general to compare our study with throughout the paper.

Existing wide-aisle order picking policies are adapted to manage the real-life features and simulated to investigate relationships among these planning problems under the constraints of safety rules, picker blocking, and high-level storage locations. We aim to find robust and efficient order picking policy combinations. The problem context of this study is inspired by a real-life B2B spare parts warehouse. Different from the real-life warehouse of the previous chapter, the real-life case in this chapter[1] consists of a narrow-aisle high-level order picking system.

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 analysed 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, which are clearly different from the policies that are the most efficient in wide-aisle order picking systems. These policies can be used by warehouse managers to improve overall order picking performance and to support new market developments.

The remainder of this chapter is organised as follows. Section 4.1 provides the state-of-

[1]This chapter is based on Van Gils, T., Caris, A., Ramaekers, K., 2018a. Reducing picker blocking in a high-level narrow-aisle order picking system: insights from a real-life spare parts warehouse. In: 2018 Winter Simulation Conference (WSC). IEEE, Gothenborg, pp. 2953–2965 and Van Gils, T., Caris, A., Ramaekers, K., Braekers, K., De Koster, R. B. M., 2019b. Designing efficient order picking systems: the effect of safety constraints, picker blocking, and high-level storage on the relation among planning problems. Transportation Research Part E: Logistics and Transportation Review 125, 47–73

the-art and formulates research hypotheses on how order picking planning problems are related with respect to travelling and picker blocking in a manual order picking system. The methodology to analyse the relationship among the order picking planning problems is described in Section 4.2. Section 4.3 provides empirical findings. Finally, Section 4.4 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. Section 4.5 concludes the chapter.

4.1 Research Hypotheses

The previous interaction analysis of Chapter 3 shows strong relationships among the main order picking 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 order picking planning problems and formulates research hypotheses on the relationship among the four main order picking planning problems (i.e., picker zoning, storage location assignment, order batching, and routing) in narrow-aisle order picking systems.

Based on numerous warehouse visits by the authors in the context of a valorisation 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 4.2.2), 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. Table 2.8 shows that there is a need to include real-life features while designing efficient order picking systems; the number of articles including picker blocking, high-level storage and safety constraints is very limited. 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 analysing and explaining relationships among the four main order picking planning problems and by accounting for the three crucial real-life features.

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 performance. Note that the total order pick time, which consists of setup time for

TABLE 4.1: Main effect of order picking planning problems.

	Travelling	Picker blocking
Zoning	↘	↘
Storage	↘	↗
Batching	↘	↘
Routing	↘	↗

preparing batches, retrieve 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 section. 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., 2018c) and the considered real-life features would have a minor impact on setup and retrieve and search time, these components are not included in the research hypotheses.

Table 4.1 provides a summary of the main effects when evolving from an inefficient policy for a particular planning problem to a more efficient policy in terms of travelling. Dividing the order picking area into zones results in smaller covered areas of order pickers during a pick round and consequently leads 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 travelling 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 storage locations (Franzke et al., 2017). Order batching aims to limit travelling 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., 2012a). Routing policies aim to reduce travelling by sequencing the order lines (and resulting storage locations) within each batch (Theys et al., 2010). While sequences may be optimal with respect to travelling, 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).

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., 2018c). As both planning problems have a positive effect on travelling, we expect fewer benefits if picker zoning and storage location assignment are combined (see Hypothesis 4.1a). 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 4.1b.

HYPOTHESIS 4.1a *The marginal travelling benefits from turnover-based storage location assignment policies decrease when the order picking area is divided into pick zones.*

HYPOTHESIS 4.1b *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 travelling decreases significantly with more pick zones in wide-aisle systems (Yu and De Koster, 2009; Van Gils et al., 2018c). 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 travelling effects of traffic rules. Moreover, incorporating the effect of traffic rules (e.g., one-way travelling) while creating batches may limit the negative effects of these safety constraints on travelling. As both planning problems have a positive effect on travelling and both limit the negative effects of traffic rules on travelling, the joint effect of picker zoning and order batching on travelling is expected to be significant under the constraints of the real-life features (Hypothesis 4.2a). 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 4.2b.

HYPOTHESIS 4.2a *The marginal travelling benefits from efficient batching policies decrease when the order picking area is divided into pick zones.*

HYPOTHESIS 4.2b *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., 2018c) 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 travelling. 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 travelling differences among the routing policies is expected to be much higher compared to small pick zones, indicating a strong relationship (see Hypothesis 4.3a). Moreover, picker zoning and routing may jointly affect picker blocking as stated in Hypothesis 4.3b: 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 4.3a *The marginal travelling benefits from efficient routing policies decrease when the order picking area is divided into pick zones.*

HYPOTHESIS 4.3b *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 travelling 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., 2018c). Travelling 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 travelling is typically very slow. Considerable travelling benefits can be gained from efficient batching policies if vertical travelling is limited, which is the case when fast moving SKUs are more evenly divided across the order picking area (see Hypothesis 4.4a). 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 4.4b 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 4.4a *The marginal travelling benefits from efficient batching policies decrease when turnover-based storage location assignment policies assign fast moving SKUs to a small picking area.*

HYPOTHESIS 4.4b *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 travelling 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 travelling (Dijkstra and Roodbergen, 2017; Manzini et al., 2007; Petersen and Schmenner, 1999; Petersen and Aase, 2004; Shqair et al., 2014; Van Gils et al., 2018c). In narrow-aisle order picking systems, routing policies are revised to meet safety constraints (e.g., one-way travelling 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 travelling and wait time. Pan et al. (2014) develop analytical models to evaluate the storage-routing relationship. These relationships are summarised in Hypotheses 4.5a and 4.5b.

HYPOTHESIS 4.5a *The marginal travelling benefits from efficient routing policies decrease when turnover-based storage location assignment policies assign fast moving SKUs to a small picking area.*

HYPOTHESIS 4.5b *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 travelling 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., 2018e). 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., 2018c). 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 travelling) 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 travelling benefits from efficient routing policies (see Hypothesis 4.6a). 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 4.6b).

HYPOTHESIS 4.6a *The marginal travelling benefits from efficient routing policies decrease when the covered area of a pick round is limited by efficient batching policies.*

HYPOTHESIS 4.6b *The marginal picker blocking effect from efficient routing policies decreases when the covered area of a pick round is limited by efficient batching policies.*

4.2 Methodology for Empirical Study

This section outlines the research methodology used to achieve the objectives of this study. The research methodology is similar to Chapter 3. Therefore, this section highlights the main differences compared to the interaction analysis of the wide-aisle order picking system. The general approach is presented in Section 4.2.1. Sections 4.2.2 and 4.2.3 describe the business case and the operational measures. The experimental design and data generation are outlined in Sections 4.2.4 and 4.2.5. Section 4.2.6 describes the statistical analysis used to provide insights into the relationships among order picking planning problems.

4.2.1 General Approach

We conducted an interaction analysis with simulation and comprehensive statistical tests to test our research hypotheses in accordance with the previous section. In addition to the Monte Carlo simulation that creates customer orders and pick lists and calculates the distances for travelling through the warehouse, a discrete-event simulation model is created using `Arena`. As the storage capacity of the considered narrow-aisle high-level order picking systems is much larger compared to the picking system of Chapter 3, the Monte Carlo simulation creates new customer orders. 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 requires more comprehensive simulation models. The created pick lists using the Monte Carlo simulation model form the input of the discrete-event simulation model. Discrete-event simulation facilitates the modelling of a sequence of events in time, thereby allowing to take safety constraints and picker blocking into account. Results of the simulation are statistically analysed to evaluate the policy decisions covered in the research hypotheses and assess the effect of real-life features on order picking performance.

4.2.2 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 analysing 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 4.1. The depot is marked with a $\mathscr{D}$ on the figure. Distance parameters are provided in Table 4.2. Distance and time measures described in this and the next sections are based on the real-life warehouse and are similar to measures used in other academic studies.

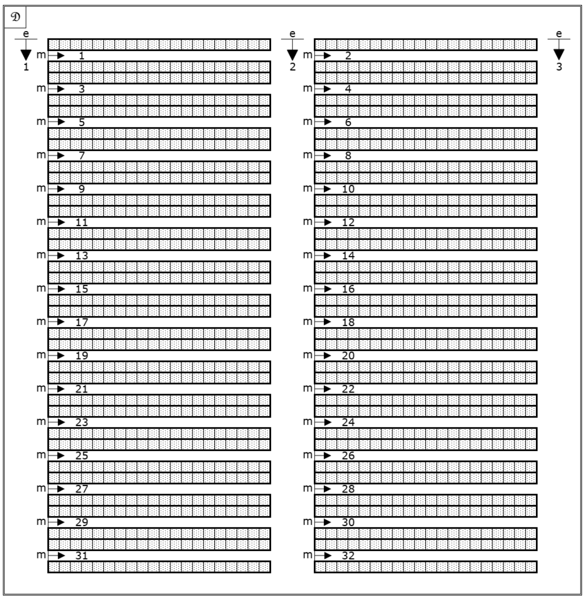


FIGURE 4.1: Warehouse layout.

TABLE 4.2: Layout parameters of the narrow-aisle order picking system.

Warehouse parameter		Parameter value
Depot location	$\mathscr{D}$	single decentralised depot
Number of blocks	$E-1$	2 blocks
Number of cross-aisles	E	3 cross-aisles
Number of pick aisles	M	16 pick aisles per block
Number of storage racks	L	70 storage rack sections per pick aisle
Number of levels	J	8 levels per storage rack
Storage rack section length	l_{length}	1.3 m
Storage rack section depth	l_{depth}	0.9 m
Storage rack section height	l_{width}	1.0 m
Pick aisle width	m_{width}	1.5 m
Cross-aisle width	e_{width}	6.0 m

4.2.3 Operational Measures

The components of total order pick time (i.e., setup time, search and retrieve 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 retrieving 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 retrieve 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 retrieve items are assumed to be only minor. All time components are summarised in Table 4.3.

TABLE 4.3: Time components.

Parameter	Parameter value
Picker travel velocity	
in cross-aisles	1.0 m/s
in pick-aisles	1.5 m/s
Picker lifting velocity	0.2 m/s
Turn time	20 s
Setup time	180 s per pick round
Search and retrieve time	15 s + 1.5 s per item

Travelling is measured by dividing the distance travelled by the travel speed of the high-level pick trucks. Travelling 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 of 20 s 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 travelling (Clark and Meller, 2013).

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 travelling 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 4.2.4.

The analysis and explanation of the relationship among order picking planning problems (i.e., Section 4.3) is based on the mean total travel time for picking all orders of a replication (i.e., travelling) 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 behaviour of the order picking planning problems on each of the performance measures to explain a potential relation. Section 4.4 accumulates travelling, picker blocking, setup and search and retrieve time to evaluate the implications of this study in terms of total order pick time (i.e., the mean total order pick time per replication).

4.2.4 Experimental Design

The relationships among the four order picking planning problems are analysed by simulating a comprehensive experimental design. Table 4.4 outlines the experimental design, comprising four decision factors and two factors to generalise the conclusions of our study. Note that in contrast to the interaction analysis of the wide-aisle order picking system, this section consists of a single experimental design simulating a generalised case. Except for the generalised layout of the order picking area, all time and order related data (see Section 4.2.3) are based on the real-life case. The reader is referred to Van Gils et al. (2018a) for the experiments of the real-life case.

TABLE 4.4: Experimental factor setting of the empirical case.

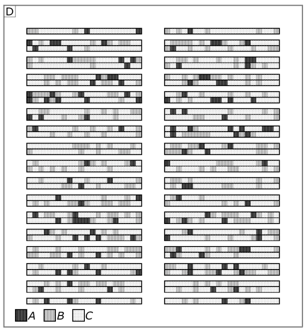
Factor	Factor levels
Picker zoning policy	(1) 1 zone (2) 2 single-block zones (3) 4 single-block zones (4) 2 multi-block zones (5) 4 multi-block zones
Storage location assignment policy	(1) Random (2) Within-aisle (3) Across-aisle (4) Diagonal (5) Perimeter
Order batching policy	(1) FIFO (2) seed (3) saving
Picker 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

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 4.5. The effect of varying pick zone configurations is analysed 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., 2017c). 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.

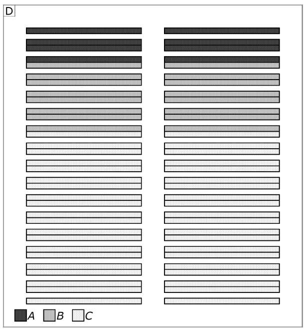
TABLE 4.5: Location of picker zoning policies.

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

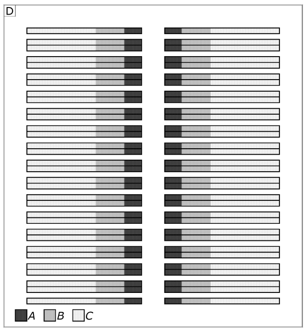
Storage location assignment policies decide on how SKUs are assigned to storage locations within a zone. Besides randomly assigning SKUs to storage locations (see Figure 4.2a), four turnover-based storage location assignment policies are simulated. The turnover-based storage policies consist of three 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 4.2b–4.2e. 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. Although locations at higher levels could be used for bulk storage, all storage locations in the experiments are assumed to be pick locations. Bulk storage locations are assumed to be in a separate system (e.g., automated storage and retrieval system). 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 4.2.



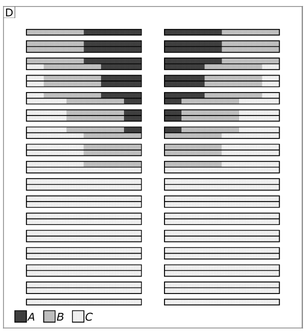
(A) Random.



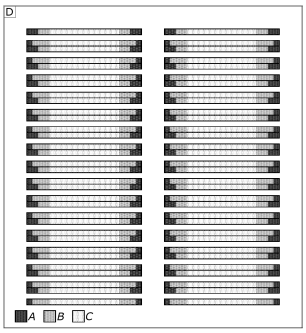
(B) Within-aisle.



(C) Across-aisle.



(D) Diagonal.



(E) Perimeter.

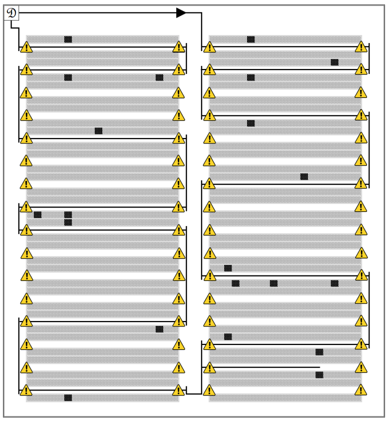
FIGURE 4.2: Storage location assignment policies.

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 travelling. 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 minimise 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 (De Koster et al., 1999; Ho et al., 2008). This seed batching policy is interesting for practical applications as it is simple and produces good results (Ho and Tseng, 2006). The basic Clarke and Wright savings batching policy (i.e., combining customer orders in a batch to maximise travel time savings) can further reduce travelling. Therefore, the C&W(i) savings policy is included in the simulation experiments. We are aware of more sophisticated heuristic batching algorithms that minimise travelling (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., 2012a)), 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.

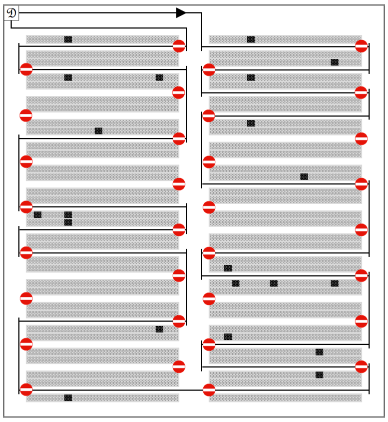
After a pick list has been created by the batching algorithm, the routing policy defines the sequence of the locations on the pick list. Existing routing policies are revised to include the safety constraints considered in the experiments. The width of pick aisles and a risk-averse strategy towards traffic accidents is considered when deciding on the maximum allowable number of pickers in a pick aisle. Figure 4.3 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 4.3a). 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 4.3b, 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 travelling. 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 travelling 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 4.4.

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 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, 2001a) 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.

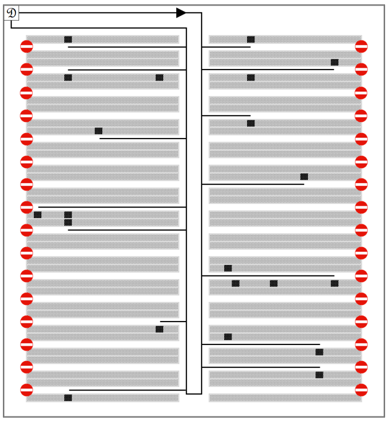
In order to generalise the conclusions of the empirical study, the planning problem combinations are simulated in multiple warehouse settings. Two main variations have been proposed in literature to generalise experiments: a varying number of picks during a pick round (Manzini et al., 2007; Theys et 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.



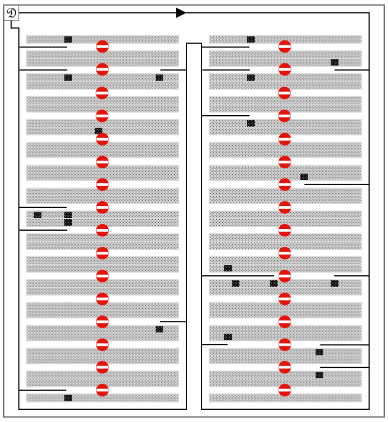
(A) Traversal.



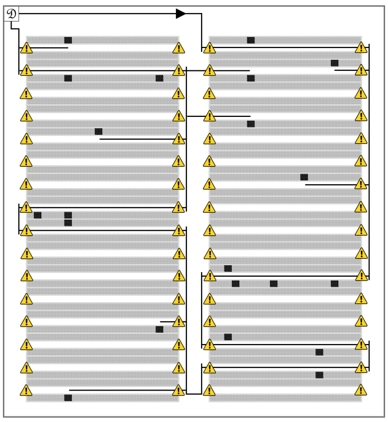
(B) Traversal$^+$.



(C) Return.



(D) Midpoint.



(E) Optimal.

FIGURE 4.3: Picker routing policies.

4.2.5 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., 2018c), 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 picker 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 all other factors 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 the 500 customer orders are assumed to be released in a single wave and due times are assumed to be at the end of the wave.

4.2.6 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 4.1. To test whether or not a relation is statistically significant, an analysis of variance (ANOVA) is performed, both on travelling (i.e., travel time for picking 500 orders in a single replication) and picker blocking (i.e., total wait time per replication). The underlying assumptions of the ANOVA are similar to the generalised experimental design proposed in Section 3.2.4. 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). Afterwards, interaction plots and post hoc tests are performed with respect to the relations that are confirmed by ANOVA.

4.3 Empirical Results

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 4.3.1. Section 4.3.2 analyses the direction of the relation and explains the interactions using interaction plots and post hoc tests. Section 4.3.3 summarises whether or not the research hypotheses are supported.

4.3.1 Factor Analysis

All relations formulated in the research hypotheses of Section 4.1 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. Tables 4.6 and 4.7 provide the results with respect to travelling and picker blocking. The first columns are devoted to the sum of squares, the G-G adjusted degrees of freedom and the mean squares 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 travelling 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 travelling. Note that the number of pickers (picker density) is irrelevant since the total distance travelled is independent of the number of available order pickers. Routes are calculated independent from the picker who is going to perform the pick round. Furthermore, route deviations in case of picker blocking are not allowed, making the travel distance independent from the picker density.

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, five storage policies, the three batching policies and the five routing policies. Moreover, picker blocking is substantially

TABLE 4.6: 5×3×5×5×3×3×3 full factorial mixed model ANOVA on travelling.

	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			

influenced by the combined effect of these policy decisions. In contrast to travelling, the picker density is significantly influencing picker blocking, as well as the batch capacity.

To summarise, 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 minimise order picking time. Travelling measures are insufficient to evaluate the efficiency of the planning problems. Wait times should be taken into account, at least in narrow-aisle order picking systems.

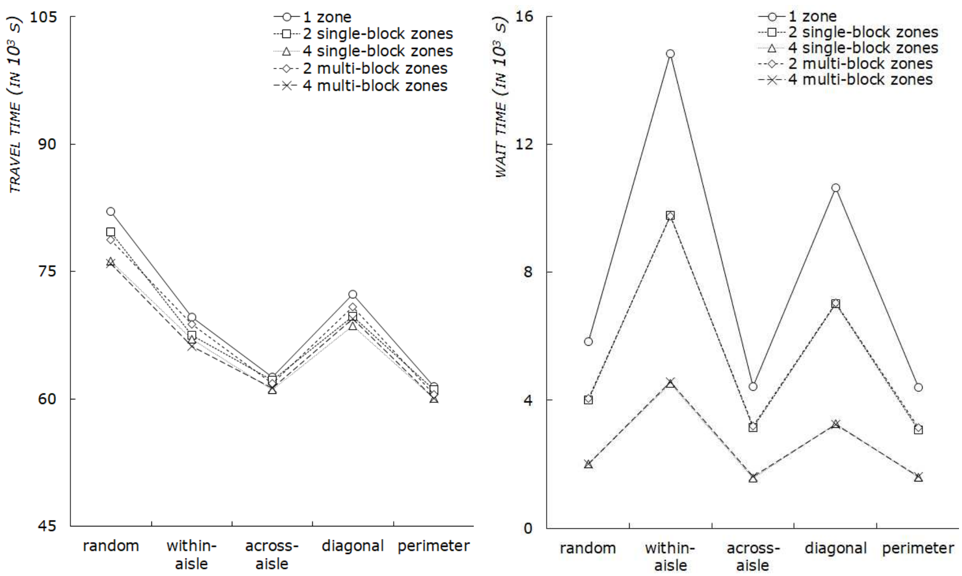
TABLE 4.7: 5×3×5×5×3×3×3 full factorial mixed model ANOVA on picker blocking.

	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			

4.3.2 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 analysed and relations are explained in this section, providing insights into the behaviour of order picking policies for both travelling and picker blocking. For each planning problem combination, this section provides interaction plots with respect to travelling (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 E.

Zoning-storage relationship The relation formulated in Hypotheses 4.1a and 4.1b are supported by the ANOVA results. Figures 4.4, 4.5, and E.1 illustrate that the direction of the picker zoning and storage location assignment relation (i.e., decreasing marginal effects) is supported as well.

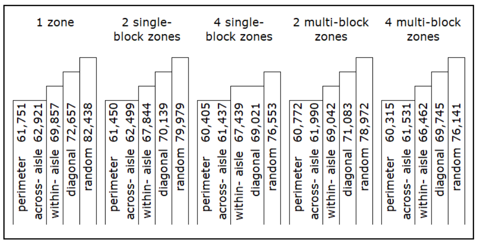


(A) Travelling.

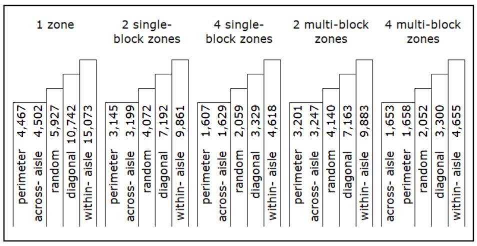
(B) Picker blocking.

FIGURE 4.4: Interaction plot of zoning-storage combinations.

Both picker zoning and storage location assignment aim to reduce the area covered by pickers in a pick round, resulting in a significant travelling relationship. Due to the large travelling benefits of across-aisle or perimeter storage classes (see Figure 4.5a), travel times are minimal irrespective of the applied picker zoning policy. The effect of picker zoning policies on travelling is stronger when combined with the other three storage location assignment policies. This relationship is illustrated in Figure 4.4a 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.



(A) Travelling.



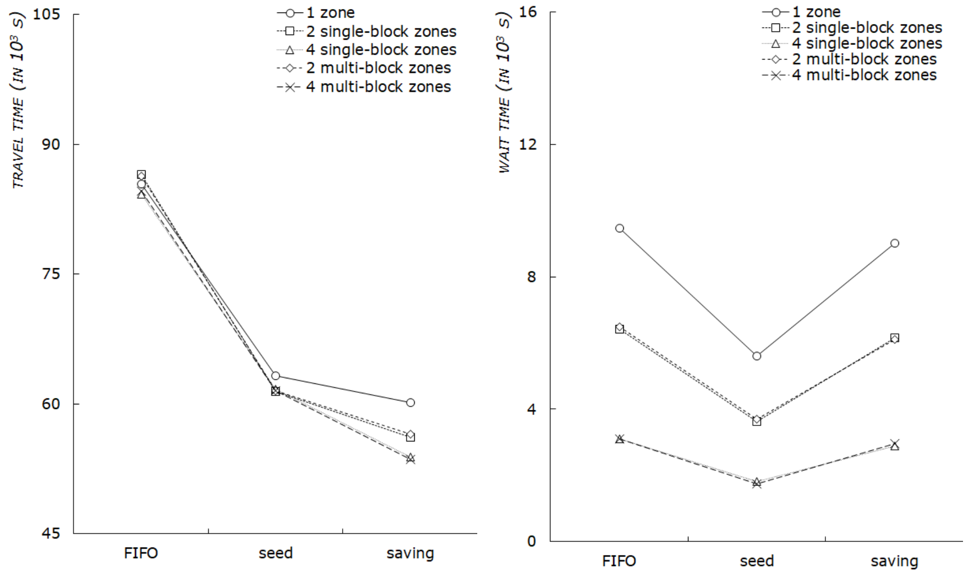
(B) Picker blocking.

FIGURE 4.5: Multiple Bonferroni t-test (familywise error rate = 0.01) for storage policies by zoning policies (in s).

This interaction can be explained by the dominant effect of vertical travelling: 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., single-block and multi-block zones yield similar travel times).

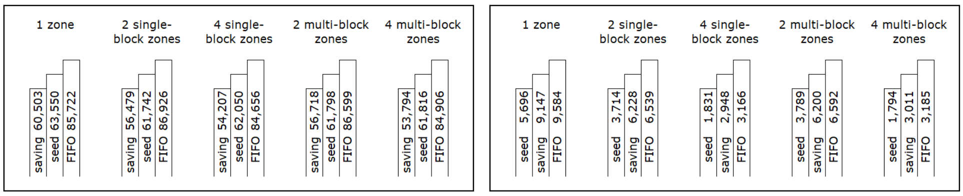
The combined effect on picker blocking is depicted in Figures 4.4b and 4.5b. The interaction plot reveals no effect of zone location, and the post hoc test creates identical subsets. However, the interaction plot shows a strong relationship between the concentration of fast moving items and picker blocking. 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 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 4.4b) in case of more pick zones.

Zoning-batching relationship The relations formulated in Hypotheses 4.2a and 4.2b are supported by the ANOVA results. Although the relation is found to be significant, the expected decreasing marginal travelling and picker blocking effects from efficient batching policies when the order picking area is divided into pick zones are not supported by Figures 4.6, 4.7, and E.2.



(A) Travelling. (B) Picker blocking.

FIGURE 4.6: Interaction plot of zoning-batching combinations.



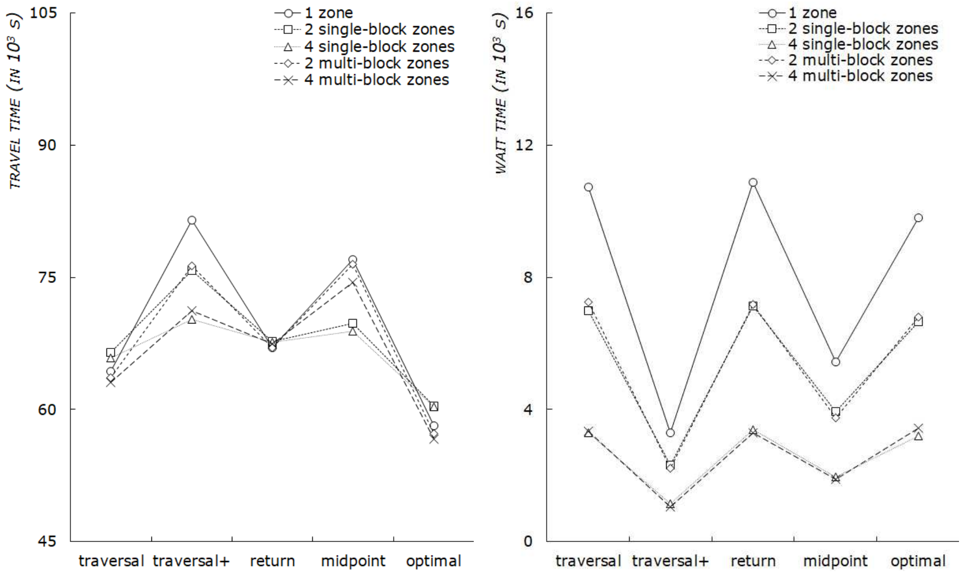
(A) Travelling. (B) Picker blocking.

FIGURE 4.7: Multiple Bonferroni t-test (familywise error rate = 0.01) for batching policies by zoning policies.

The interaction plot illustrating the travelling interaction between zoning and batching (Figure 4.6a) 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 as shown by the post hoc tests of Figure 4.7a.

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 4.6b. 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 4.7b). The seed policy is in accordance with the traffic rules: orders are batched to minimise 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).

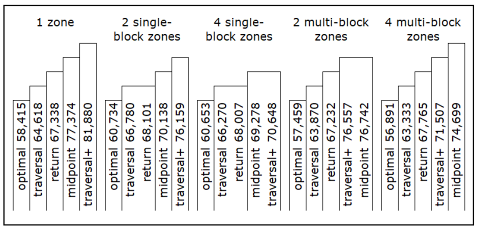
Zoning-routing relationship The relations formulated in Hypotheses 4.3a and 4.3b are supported by the ANOVA results. Furthermore, the marginal travelling and picker blocking effects from efficient routing policies decrease when the order picking area is divided into pick zones, as illustrated in Figures 4.8, 4.9, and E.3.



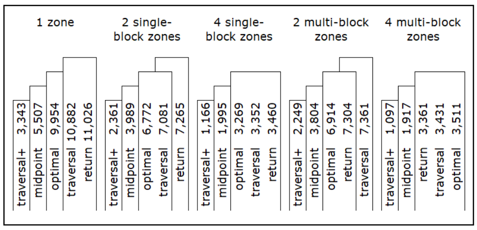
(A) Travelling. (B) Picker blocking.

FIGURE 4.8: Interaction plot of zoning-routing combinations.

The optimal routing policy results in the shortest travel time, irrespective of the picker zoning policy (see Figure 4.9a). Only minor differences exist among the picker zoning



(A) Travelling.



(B) Picker blocking.

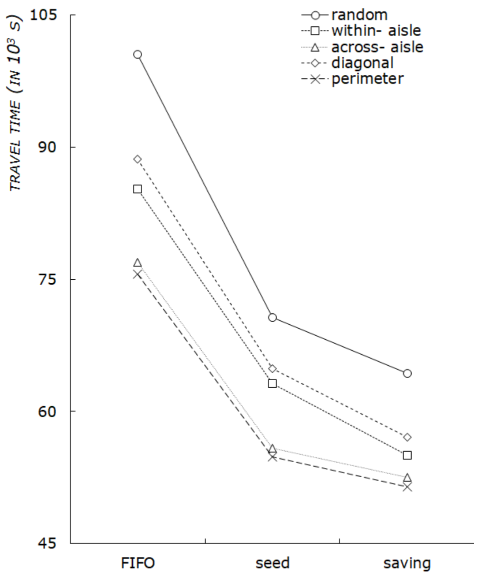
FIGURE 4.9: Multiple Bonferroni t-test (familywise error rate = 0.01) for routing policies by zoning policies.

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 4.8a) reveals that the unidirectional traversal routes (i.e., traversal$^+$) favour 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 4.9a 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 travelling effect decreases in combination with efficient routing policies.

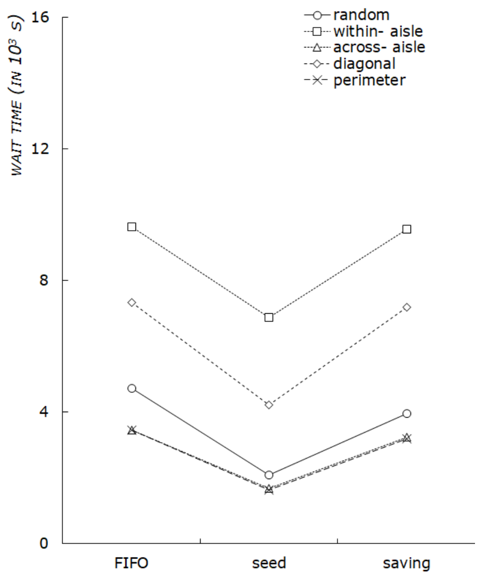
While the optimal route length results in the shortest travel time, optimal routes are in the lowest subsets with respect to picker blocking in combination with most picker zoning policies (see Figure 4.9b). Traversal$^+$ and midpoint routes benefit from safety constraints since two pickers can work 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 4.8b. 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 4.8b) in case of more pick zones.

Storage-batching relationship The ANOVA results demonstrates that the combined effect of storage location assignment and order batching significantly influences travelling as well as picker blocking. Based on Figures 4.10, 4.11, and E.4, the expected direction of the relation (see Hypotheses 4.4a and 4.4b) is not supported.

Although the savings batching policy outperforms seed and FIFO batching, in combination with all storage location assignment policies with respect to travelling (see Fig-

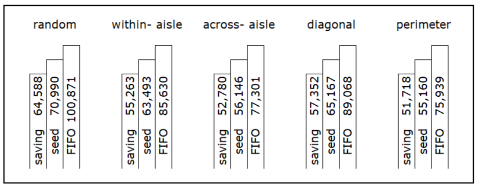


(A) Travelling.

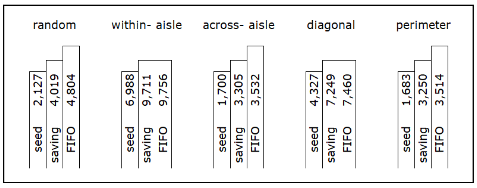


(B) Picker blocking.

FIGURE 4.10: Interaction plot of storage-batching combinations.



(A) Travelling.



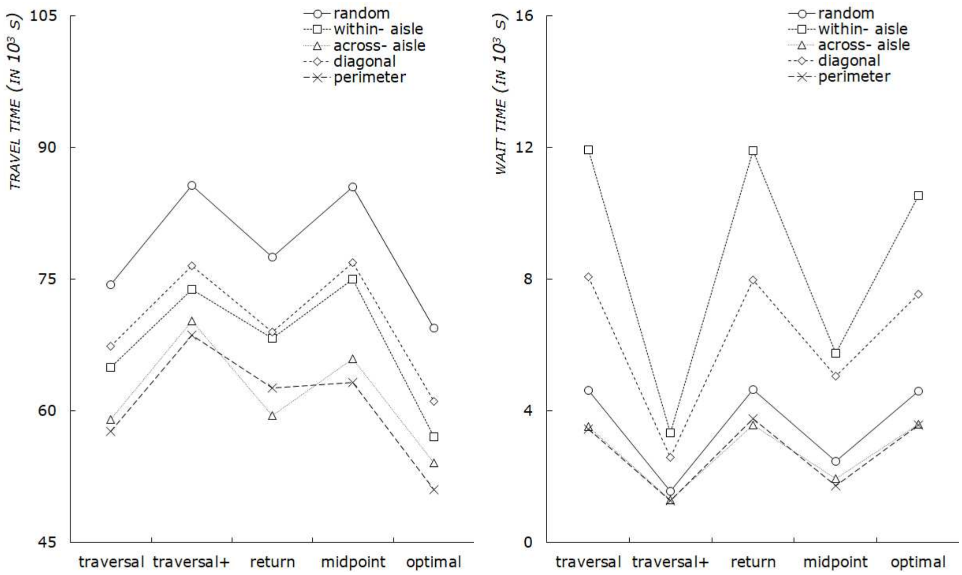
(B) Picker blocking.

FIGURE 4.11: Multiple Bonferroni t-test (familywise error rate = 0.01) for batching policies by storage policies.

ure 4.11a), the interaction plot in Figure 4.10a provides insights into the interaction. The aisle-based seed batching algorithm and the random FIFO batching policy neglect the vertical travelling 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 travelling gap compared to, for example, across-aisle storage classes. Since vertical travelling is taken into account with the savings algorithm when creating batches, the four turnover-based storage location assignment policies show only minor travelling differences. So, the varying marginal effects of the within-aisle and diagonal storage classes over the batching policies explains the relation. The hypothesised decreasing marginal travelling 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 4.10a.

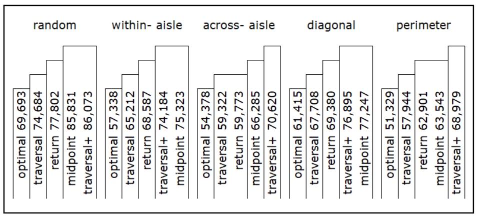
ANOVA results show a significant storage-batching effect on picker blocking as well. The interaction plot in Figure 4.10b does not provide the expected decreasing marginal picker blocking effect from efficient batching policies in combination with turnover-based storage classes as explanation for the 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) minimises wait times due to picker blocking (see Figure 4.11b). Concentrating fast moving SKUs in a small number of aisles or batching orders randomly (i.e., FIFO) or based on a travelling 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 4.10b when comparing picker blocking for within-aisle and diagonal storage with e.g., random storage.

Storage-routing relationship The relations formulated in Hypotheses 4.5a and 4.5b are supported by the ANOVA results. Figures 4.12, 4.13, and E.5 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 travelling effect is not supported.

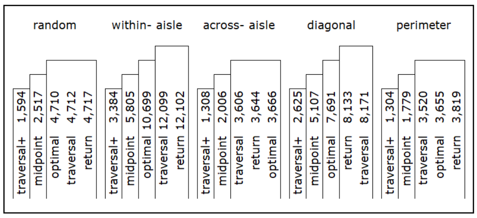


(A) Travelling. (B) Picker blocking.

FIGURE 4.12: Interaction plot of storage-routing combinations.



(A) Travelling.



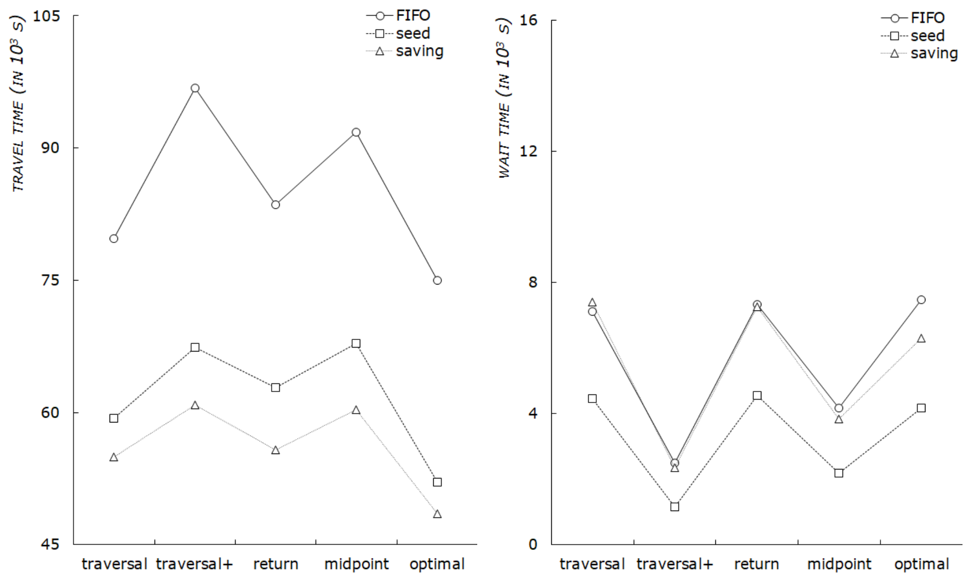
(B) Picker blocking.

FIGURE 4.13: Multiple Bonferroni t-test (familywise error rate = 0.01) for routing policies by storage policies.

The interaction plot of Figure 4.12a 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 increasing or decreasing marginal effect). The optimal route performs best in combination with all storage policies (see Figure 4.13a). However, optimal routes are rarely used in practice (Van Gils et al., 2018c). The composition of the other subsets differs considerably across the storage policies. When excluding optimal routes, return routes are favoured in combination with across-aisle storage classes as fast moving SKUs are stored at the beginning of an aisle, thereby minimizing travelling 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 favours 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.

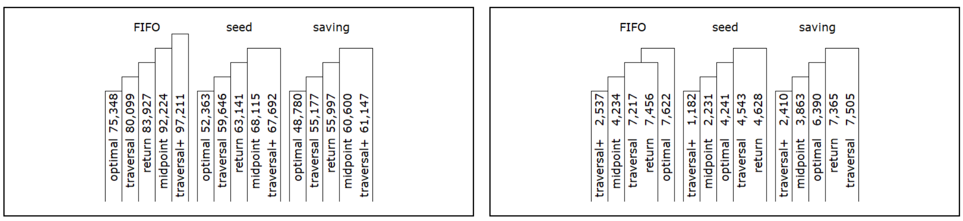
In terms of wait time, the negative effects of safety constraints are minimal in traversal and midpoint routes, as these routing policies allow two order pickers to work concurrently within pick aisles. The interaction effect can be explained by the converging and diverging lines in the graph (Figure 4.12b) and the creation of varying subsets by the post hoc test (Figure 4.13b). 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).

Batching-routing relationship The relations formulated in Hypotheses 4.6a and 4.6b are supported by the ANOVA results. The decreased marginal travelling effect is fully supported by Figures 4.14, 4.15, and E.6, 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) Travelling. (B) Picker blocking.

FIGURE 4.14: Interaction plot of batching-routing combinations.



(A) Travelling. (B) Picker blocking.

FIGURE 4.15: 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 travelling effects of the traversal$^+$ and midpoint routing policies over the batching policies (see Figure 4.15a). The seed and savings batching policy can partly compensate the inefficiency with respect to travelling of the traversal$^+$ and midpoint routing policies caused by the traffic rules. However, applying these routing policies in combination with FIFO batching, substantially increases travelling in comparison to the more efficient routing policies (see Figure 4.14a). As the savings algorithm integrates the routing policy while

TABLE 4.8: Results summary (• hypothesised relation/direction is supported; ◦ hypothesised relation/direction is not supported).

	Travelling		Picker blocking	
	Relation	*Direction*	*Relation*	*Direction*
Zoning-storage	•	•	•	•
Zoning-batching	•	◦	•	◦
Zoning-routing	•	•	•	•
Storage-batching	•	◦	•	◦
Storage-routing	•	◦	•	•
Batching-routing	•	•	•	◦

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 4.15b. Especially wait times of optimal routes vary significantly across the batching policies. Figure 4.14b 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 4.15b.

4.3.3 Results Summary

Table 4.8 summarises 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 relations could not be supported for all research hypotheses.

4.4 Implications

This section outlines the implications of the existing relationships to academics (Section 4.4.1) and practice (Section 4.4.2). 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.

4.4.1 Academic Implications

The graph in Figure 4.16 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 4.16 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 4.2). 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 travelling (see for example Figure 4.15a). Thus, safety constraints not only induce picker blocking but also increase travelling 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 pick time by the model underestimates the real order pick time, 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 minimised, thereby optimizing order picking operations. Although the risk of traffic accidents is minimised in pick aisles, routes can still cross in cross-aisles under the current routing policies, at least in the middle cross-aisle. Although the cross-aisle width is 6 m, which is wide enough for two-directional travelling, a substantial risk on accidents remain when entering or leaving pick aisles. Wider cross-aisles and separate lanes to travel in two directions can further reduce accident risks.

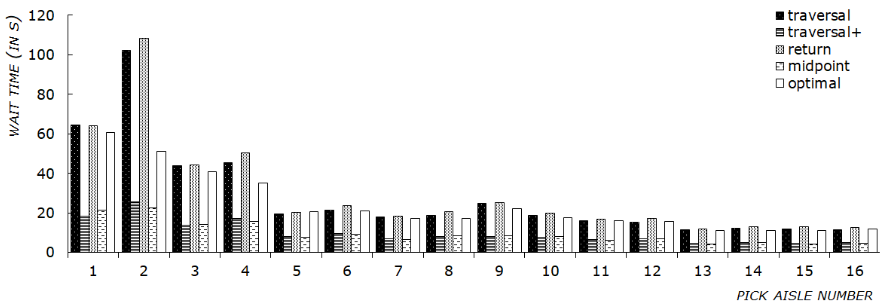


FIGURE 4.16: Mean wait time (in s) for a pick aisle visit (limited to pick aisles 1–16) per routing policy in case of twelve pickers and batch capacity of twelve orders.

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 4.8b). 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 4.17). Thus, picker blocking induces inefficient wait times, which can be minimised 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 optimise order picking operations.

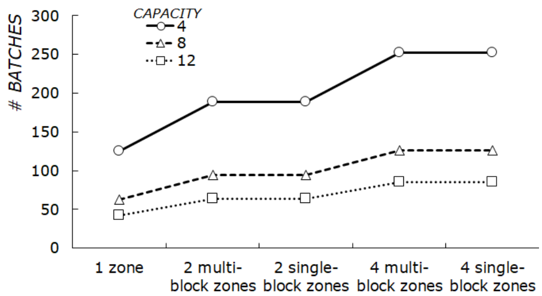


FIGURE 4.17: Mean number of batches per zone picking policy and batch capacity level.

The effect of high-level storage locations is illustrated by the relatively slow lifting speed of pick trucks. The additional vertical travelling 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 4.18, especially when SKUs at higher levels are retrieved in an aisle. The effect of high-level storage locations on both travelling and picker blocking is dominant 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 travelling, aisles are occupied longer, increasing aisle-entrance blocking. Neglecting the effect of vertical travelling would result in significantly underestimated travelling and wait times. Consequently, the effect of vertical travelling should be taken into account while evaluating order picking policies.

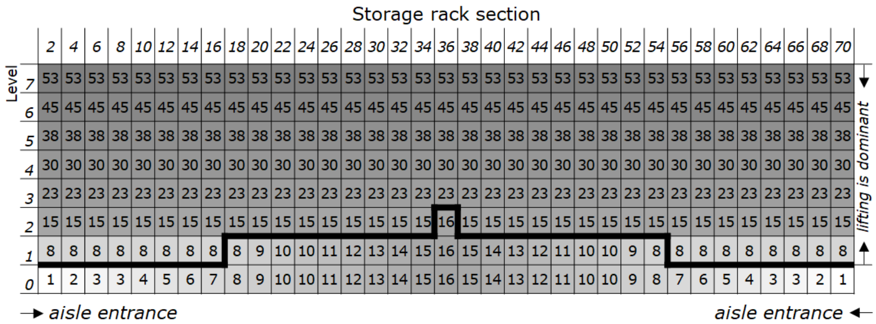


FIGURE 4.18: Shortest travel time (in s) to reach each location within a pick aisle (vertical travel time is dominant for locations above the bold line).

4.4.2 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 optimises the order picking system. Figure 4.19 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 pick time across the different time components. As the proportion of each time component in these experiments is equivalent to the typical distribution of order pickers' time (Tompkins et al., 2010) and given the realistic and widespread boundaries of batch capacity and picker density values, the conclusions of this study are easily generalizable to other narrow-aisle order picking systems. Note that varying batch capacity values capture the effect of varying order sizes as well (i.e., larger orders or larger batch capacities both result in more order lines per pick round) and that the varying number of pickers similarly approximate the effects of the size of the order picking area (i.e., more pickers or a smaller pick area increases the picker density).

Figure 4.19 shows a varying distribution of time components across batch capacities and picker densities. Increasing batch capacity appears to reduce total order pick 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 travelling from and to the depot, making pick zones more favourable. Customer orders are split with multiple zones which leads to more pick rounds to retrieve items. Consequently, travelling from and to the depot with a small batch capacity is more expensive compared to the distance reduction of travelling in a small pick zone. Although the workload among the pick zones is assumed to be equal in the simulation experiment, workload variations as well as other challenges (e.g., assigning SKUs and resources to pick

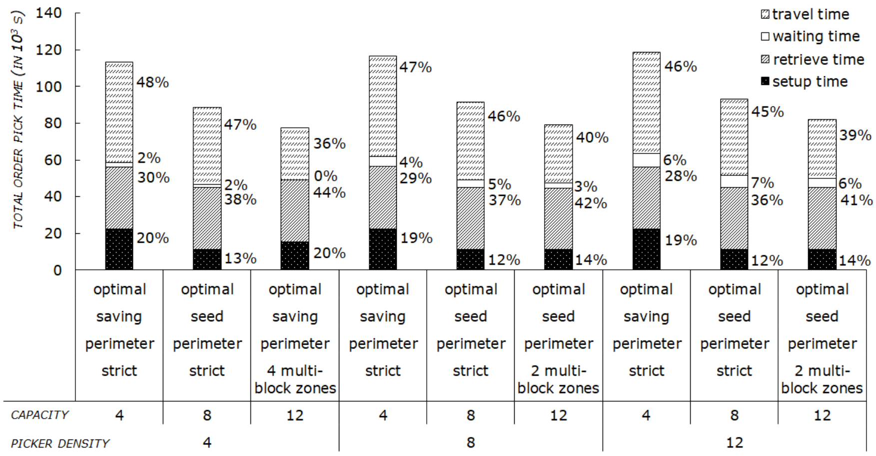


FIGURE 4.19: Total order pick time distribution for the best performing policy combination per batch capacity and picker density factor level.

zones) should be faced with in practice when dividing the order picking area into zones. 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 4.19 reveals a slightly increased total order pick 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 4.8b). Other external factors impacting the density of order pickers (e.g., varying layout) are expected to provide similar results.

Figure 4.19 illustrates that the optimal routing policy is robust to batch capacity and picker density. The travelling 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 4.20 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 narrow-aisle order picking systems (i.e., this section) and applying the best policy combination (i.e., four zones, within-aisle storage, savings batching, and optimal routing) in wide-aisle picking systems (i.e., proposed in Chapter 3); 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 in wide-aisle order picking systems 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.

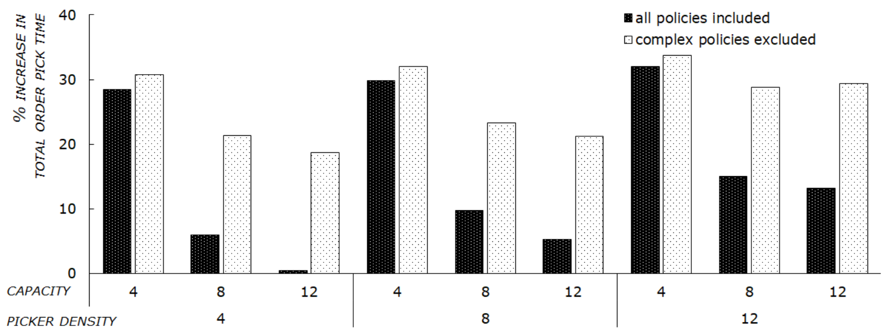


FIGURE 4.20: Percentage increase in total order pick time when ignoring existing real-life features (baseline is best policy combination).

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.

4.5 Conclusions

In addition to the wide-aisle low-level order picking system of previous chapter, results in the narrow-aisle high-level order picking system, subject to multiple real-life features, demonstrate strong relations among the order picking planning problems. Furthermore, 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, at least in narrow-aisle order picking systems. 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. 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 storage 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.

Variations in batch capacity, order size, number of pickers, and size of the order picking area are captured making conclusions about the relations among planning problems and the effects of real-life features easily generalizable to other order picking systems. Based on the extensive range of evaluated policies for the four tactical and operational planning problems, there could be no doubt that planning problems should be considered simultaneously in order to optimise order picking operations. In order to explore the effects of real-life features, picker blocking, safety constraints, and high-level storage (i.e., the main real-life features observed in the real-life case), are incorporated in the order picking policies. Although other real-life features (e.g., varying workloads across pick zones, precedence constraints and scattered storage) can be relevant and important to incorporate as well, results show that the three considered real-life features are crucial to take into account. Furthermore, due times could additionally impact the results, especially the efficiency of the batching policies as batches are expected to be smaller and consequently less efficient in case of tight deadlines (see Chapter 7).

Given the general knowledge on the relations among planning problems and the first insights into the effects of real-life features, the next part (Part III) explores the effect of workload related real-life features, in particular resource constraints and workload peaks, in order to make research more valuable to practice. Furthermore, Part IV incorporates the workload related real-life features while integrating and optimizing three operational order picking planning problems.

Part III

Coping with Workload Related Real-life Features

CHAPTER 5

WORKLOAD FORECASTING

Warehouses are generally confronted with highly seasonal demand patterns. The primary tool in coping with demand fluctuations is the labour force. Temporary workers are often hired in order to capture workload peaks. Forecasting the daily workload is a key issue in controlling the amount of staff (De Koster et al., 2007; Ruben and Jacobs, 1999). This chapter[1] focusses on forecasting order pickers' workload in order to control the number of order pickers (i.e., defining the size of the resource constraint). Workload forecasting can be defined as predicting the future amount of work to be performed in order to meet demand. The workload forecast can be translated into a required number of order pickers depending on order pickers' productivity. On the one hand, an insufficient number of available order pickers reduces the service level. On the other hand, planning too many order pickers causes unnecessarily high labour costs.

A large number of workforce related studies have been conducted in manufacturing environments, but similar studies in warehouses are rather limited (Davarzani and Norrman, 2015). The strongly fluctuating daily demand, which requires maximum flexibility, differentiates warehouses from manufacturing environments. Warehouses deliver labour-intensive services to customers. Personnel capacity drives the service quality to customers and resulting warehouse performance. Forecasting and scheduling workers are the main tools to guarantee order fulfilment operations in a timely way (Sanders and Ritzman, 2004; Defraeye and Van Nieuwenhuyse, 2016). Therefore, this chapter provides decision support tools to define the resource constraint in each zone of the order picking area. Several ex-

[1]This chapter is based on Van Gils, T., Ramaekers, K., Caris, A., Cools, M., 2017c. The use of time series forecasting in zone order picking systems to predict order pickers' workload. International Journal of Production Research 55 (21), 6380–6393.

isting forecasting methods are tested and analysed in an order picking context for the first time aiming to support the workforce level and workforce allocation planning problems, making research more relevant to practice.

New market developments require more efficient order picking operations. One way of moving to a more efficient order picking process is dividing a warehouse into different smaller areas, or pick zones. Each pick zone is dedicated to a few order pickers. As a consequence, each order picker travels in a pre-specified part of the warehouse, and thus travel time is reduced. Furthermore, order pickers become familiar with the item locations in the zone. Besides the efficiency benefits resulting from the division of the warehouse into several pick zones, two disadvantages are linked to zone picking: orders are split and must be consolidated again before shipment, and labour resources should be allocated across all pick zones. Either sequential zoning or parallel zone picking is used to deal with the first disadvantage. In sequential zoning, orders are picked zone by zone. Parallel zoning refers to the policy where all order pickers can work on the same order at the same time, each picker in his own zone. After picking, all orders are consolidated through a sorting system (De Koster et al., 2007; Boysen et al., 2018a).

This chapter focusses on opportunities to deal with the second disadvantage of zone picking. By fulfilling customer orders in a quick and timely way, space, labour, and equipment resources should be allocated across all pick zones (Gu et al., 2007). Moreover, a flexible workforce planning is required to allocate the order pickers across warehouse zones. For example, order pickers can be transferred to different pick zones, which results in the necessity to cross-train workers. Thus, reliable and accurate forecasting is required to support warehouse supervisors in determining the daily required number of order pickers, as well as in allocating the order pickers across zones. This chapter concentrates on the first step of personnel capacity planning, in particular forecasting the workload based on empirical data. Although highly relevant in warehouses, the three other steps introduced by Defraeye and Van Nieuwenhuyse (2016) (i.e., determining staffing requirements, shift scheduling, and shift assignment) are beyond the scope of this chapter. The resource capacity as well as the allocation of the resources across the order picking area, information provided by the decision support tools in this chapter, is required to solve other operational planning problems, such as the job assignment problem (see Part IV).

To the best of our knowledge, our study (Van Gils et al., 2017c) is the first to forecast order pickers' workload in a warehouse. The daily number of order lines is used as surrogate for pickers' workload. Most order picking publications treat demand as known in advance (De Koster et al., 2007, 2012; Hwang and Kim, 2005). As warehouses accept late orders, the assumption of a constant given demand should be reconsidered. Based on real demand data, Jane (2000) and Jane and Laih (2005) balance the workload by analysing different zone sizes in a sequential zone picking warehouse and different assignments of products to pick zones in a parallel zone picking warehouse, respectively. These approaches are expected to balance the workload among zones in the long term. Dynamic zone picking systems, such as bucket brigades, can be used to solve the balancing problems in the short term. Bucket brigades are flexible order picking systems and self-balancing with respect to the workload of order pickers. However, bucket brigades can result in efficiency losses and assume that the picking area is divided into several serial zones (Koo, 2009). Another approach to balance pickers' workload among order pickers in the short term is to forecast the workload. Reliable daily forecasts can be used to schedule order pickers. For daily planning purposes, the total number of order lines, as well as the distribution of these aggregated order lines across the different pick zones, are required to determine the required number of order pickers as well as to allocate the order pickers across zones. The forecasting approach is not restricted to serial zone picking systems, which can result in buffers, as orders should be consolidated.

The gap between academic research and practice (Davarzani and Norrman, 2015; De Koster et al., 2007; Gu et al., 2007), as well as the fact that almost all research in order picking treats demand as given (De Koster et al., 2007) and ignores the determination of the number of personnel (Rouwenhorst et al., 2000), are common conclusions in recent literature reviews on warehouse planning. The main contribution of this study is to show how existing forecasting models and approaches provide accurate and reliable forecasts for the next-day workload of order pickers. A real-life case study demonstrates the value of applying time series forecasting models to predict the daily number of order lines. Moreover, two hierarchical forecasting approaches, including top-down forecasting and bottom-up forecasting, are analysed and evaluated in order to provide accurate aggregated forecasts (i.e., total daily number of order lines) as well as accurate forecasts of the workload at zone level. Forecasts at different levels of aggregation are required to help warehouse supervisors defining the total required number of pickers and scheduling the order pickers across pick zones on a daily basis. Accurate forecasts for each pick zone ensures a sufficient number of pickers in each pick zone to retrieve all customer orders timely.

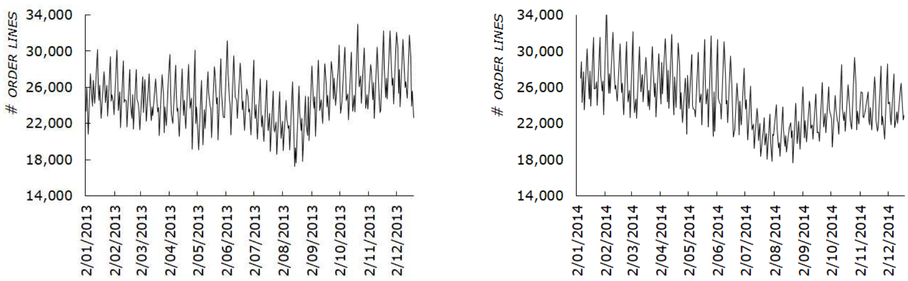
The remainder of this chapter is organised as follows: the next section (Section 5.1) introduces the case study. Section 5.2 outlines the research methodology used in this study, followed by the empirical results of the real-life case in Section 5.3. Section 5.4 is devoted to the managerial and academic implications. Section 5.5 concludes this chapter.

5.1 Description Case Study

The case of this study is based on a large international warehouse located in Belgium. The warehouse, which stores and delivers automotive spare parts to delivery points all over the world, is a fully manually operated warehouse. This conventional handling results in fast, frequent, and reliable deliveries. The warehouse focusses on distributing products in order to provide customers first-class service that contributes to a maximum operating time for their vehicles. For example, customers expect certain order types, especially spare parts for vehicles off road, to have a throughput time of only two hours in order to minimise the downtime. Determining the daily required number of human resources in order to provide the high customer service level is perceived as a complicated task by warehouse supervisors. As customers are allowed to order two hours before the shipping deadline, forecasting is required to determine the daily required number of order pickers.

The daily number of order lines of the warehouse is used as surrogate for the workload of order pickers. The forecasts of order lines, along with order pickers' productivity, are used by the warehouse supervisors to determine the daily required number of order pickers in order to provide a high customer service level. Supervisors are currently only forecasting the total daily number of order lines. At zone level, no forecasts are currently available, although supervisors recognise such disaggregated forecasts to be relevant and necessary to make adequate decisions. These forecasts are based on experience and personal judgement, without using forecasting models. Each day another supervisor may forecast the workload for the next day. The supervisors' forecasts are used as benchmarks for evaluating the proposed time series forecasting models in this paper. The objective of the case study is to find time series that are able to produce more reliable forecasts compared to current non-statistical forecasts, making the workforce planning less dependent on the availability of experienced supervisors.

Order lines for the years 2013 and 2014 are considered. The demand of 2013 is used to estimate model coefficients, and the order lines of 2014 are used as out-of-sample values. This method of ex post forecasting is applied to validate the proposed forecasting models. In Figure 5.1, the real daily number of order lines for the years 2013 and 2014 is plotted, in particular the accumulated daily number of order lines of each pick zone. For both years, order lines strongly fluctuate.



(A) Insample. (B) Holdout sample.

FIGURE 5.1: Real daily number of order lines.

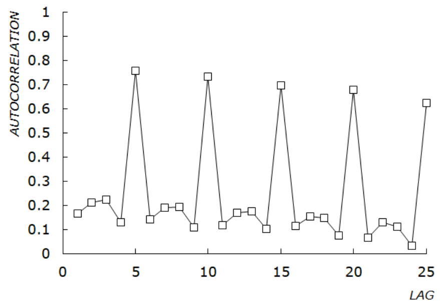


FIGURE 5.2: Autocorrelation of aggregated daily number of order lines.

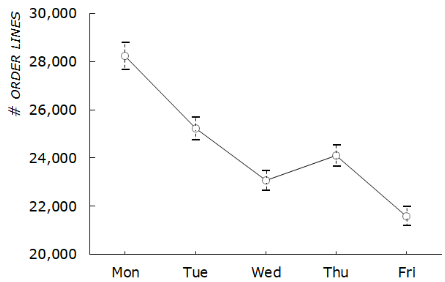
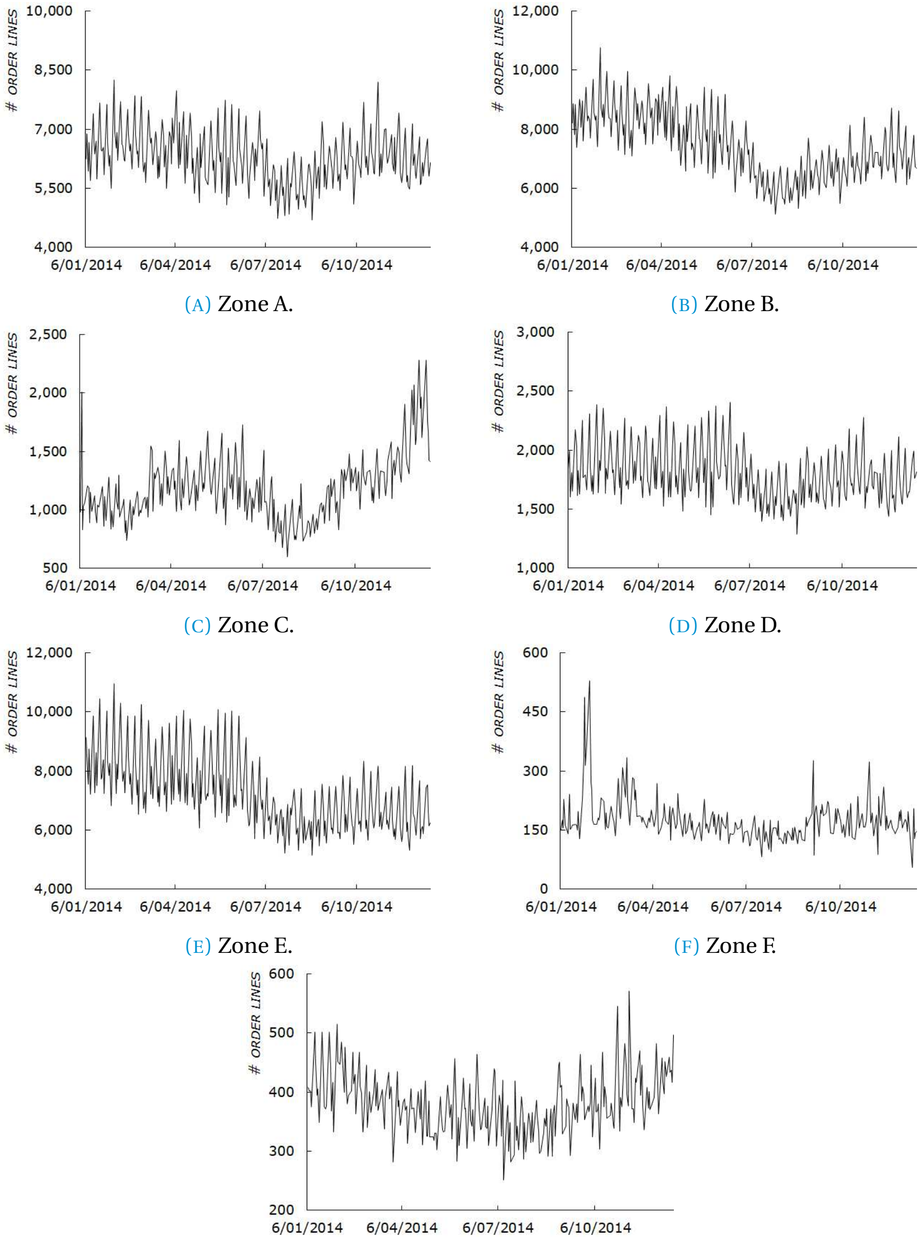


FIGURE 5.3: Mean and 95% confidence intervals illustrating the weekly seasonal cycle.

An autocorrelation plot is provided in order to gain prior insight into the potential seasonal cycles in the daily number of order lines (Cools et al., 2009). By looking at the results of the autocorrelation plot presented in Figure 5.2, a weekly recurring cycle can be identified in the data as indicated by the peaks at lags 5, 10, 15, 20, and 25. This means that the number of order lines is highly correlated with the number of order lines of the previous week (note that weekends are not considered). The weekly recurring cycle is shown in Figure 5.3. On average, the number of order lines is high on Mondays and decreases all other days of the week, except on Thursdays. The curve shows a significant rise on Thursdays, as illustrated by the narrow, non-overlapping 95% confidence intervals in Figure 5.3. Additionally, a Bonferroni's test is performed to compare the mean values. Note that Bonferroni's test controls the Type I error rate and has sufficient statistical power when the number of comparisons is limited (Field, 2013). The test demonstrates a statistically significant difference between the number of order lines for every pair of working days, using 0.01 as the critical significance level.

The studied warehouse is divided into seven different pick zones, named zone A to zone G. Figure 5.4 depicts the real number of order lines in each pick zone for the year 2014. In terms of order line volume, three large pick zones (i.e., zones A, B, and E) can be distinguished. Furthermore, the warehouse consists of two middle-sized zones (i.e., zones



(A) Zone A.
(B) Zone B.
(C) Zone C.
(D) Zone D.
(E) Zone E.
(F) Zone F.
(G) Zone G.

FIGURE 5.4: Real daily number of order lines in each pick zone (2014).

C and D) and two rather small zones (i.e., zones F and G). Order line data for zones A, B, D, and E show a similar weekly seasonal cycle as shown in Figure 5.3. This seasonal pattern is less clear in the other pick zones.

Dividing the warehouse into pick zones implies that all order pickers should be distributed across the different pick zones. A parallel zone picking policy is employed in the warehouse under consideration in order to retrieve a large number of orders in short time windows. Because of the efficiency benefits resulting from parallel zone picking, this zone picking policy is commonly employed in warehouses (Le-Duc and De Koster, 2005) and is especially useful in serving e-commerce markets. Furthermore, the proposed forecasting techniques can be generalised to sequential zoning in order to provide insights into the workload, as balancing the workload over order pickers is an important issue in sequential zoning, as well (Jane, 2000; Jane and Laih, 2005).

Because disaggregated forecasts are currently lacking, allocating order pickers across zones is perceived as a hard activity by supervisors in practice. Therefore, hierarchical forecasting is introduced in the zoned order picking system. Hierarchical forecasting refers to the problem of identifying a level of forecasting aggregation that provides adequate information for decision making. Forecasting can be done on an aggregated as well as a disaggregated level. A top-down forecasting process uses aggregate demand data to forecast total demand, after which individual forecasts can be derived from the aggregated forecast. In a bottom-up approach, demand is forecast for each individual demand segment. Subsequently, these forecasts are accumulated to produce an aggregated forecast (Schwarzkopf et al., 1988; Song and Li, 2008; Zotteri et al., 2005).

In a warehouse context, demand forecasting on aggregate data is relevant for determining the daily total number of order pickers required to fulfil all customer orders, while forecasting the number of order lines at a disaggregate level will additionally help supervisors allocate the order pickers across all pick zones. The different disaggregated demand segments in a warehouse are defined by the daily order lines of each pick zone.

Both aggregated and disaggregated forecasts are required for flexible workforce scheduling. The flexible workforce scheduling problem in a zone picking warehouse includes the distribution of order pickers across different pick zones, when a cross-trained worker should be transferred to another zone and to which new pick zone a worker should be assigned.

5.2 Forecasting Models and Accuracy Measures

This section outlines the mathematical and theoretical framework of different time series forecasting methods. Time series forecasting is considered as an important forecasting area, where a variable is explained with regard to its own historical observations and a random error term. Time series are able to recognise historical trends and patterns and extrapolate these trends into the future (Song and Li, 2008). De Gooijer and Hyndman (2006) give an overview of past research in the area of time series forecasting. Methods like exponential smoothing and different variants of seasonal autoregressive integrated moving average (SARIMA) are extensively discussed by De Gooijer and Hyndman (2006). Gardner Jr. (2006) specifically focusses on exponential smoothing forecasting models and presents state of the art research on exponential smoothing. Time series forecasting has been extensively used in areas other than warehousing, such as urban water consumption (House-Peters and Chang, 2011), energy consumption (Suganthi and Samuel, 2012), and tourism demand (Athanasopoulos et al., 2011; Song and Li, 2008).

This chapter analyses and applies twelve different forecasting models to the order line data in the case study. The major difference among these methods is the way trends and seasonal patterns are treated. Time series forecasting models are classified into different categories, in particular the Naïve method, moving average methods, exponential smoothing models, SARIMA forecasting models, and finally composite forecasting, in which different previously defined models are combined. The mathematical representations of the forecasting methods are summarised in Table 5.1. All forecasting methods are briefly outlined in this section. More elaborated time series forecasting discussions can be found in Chase Jr (2013) and De Gooijer and Hyndman (2006).

The first method, *Naïve I*, is the most straightforward forecasting method. Potentially existing trends and seasonal patterns in the data are neglected. The naïve method can be extended by taking multiple historical periods into account. The simple *moving average model* ($\mathrm{MA}_{T^{MA}}$) averages T^{MA} previously observed values. By averaging multiple periods, more historical information is considered in the forecasting value. By giving equal weight to each historical value, the simple moving average model assumes neither trend nor seasonality (Goh and Law, 2002; Song and Li, 2008). Seasonality can be incorporated into a moving average model by allowing each component to have a different weight, ω_i, in the moving average equation. Large weights are an indication of highly influential observations in the forecasting value. This forecasting method is known as a weighted moving average model ($\mathrm{wMA}_{T^{MA}}$)(Jacobs et al., 2010).

Exponential smoothing models can be defined as special time series models in which historical values are averaged. In contrast to the above described moving average models, the averaging of historical values is done in an exponential way. In other words, the weights in the forecasting model drop exponentially for older values. Various exponential smoothing models can be distinguished based on the way trends and seasonal patterns are considered. Three models are discussed in this chapter, in particular simple exponential smoothing ($\mathrm{ES}_{\text{N-N}}$), Holt's exponential smoothing (additive trend, no seasonality, ES_{n}A-N), and exponential smoothing considering a multiplicative seasonality ($\mathrm{ES}_{\text{N-M}}$)

TABLE 5.1: Summary of time series forecasting models.

Forecasting model	Formula
Naïve I	$\bar{o}_{t+1} = o_t$
$\text{MA}_{T^{MA}}$	$\bar{o}_{t+1} = \frac{1}{T^{MA}} \sum_{i=1}^{T^{MA}} o_{t-i+1}$
$\text{wMA}_{T^{MA}}$	$\bar{o}_{t+1} = \sum_{i=1}^{T^{MA}} \omega_i o_{t-i+1} : \sum_{i=1}^{T^{MA}} \omega_i = 1, 0 \le \omega_i \le 1$
$\text{ES}_{\text{N-N}}$	$\bar{o}_{t+1} = \alpha o_t + (1-\alpha)\bar{o}_t : 0 \le \alpha \le 1$
$\text{ES}_{\text{A-N}}$	$\bar{o}_{t+1} = \bar{o}_t^L + \bar{o}_t^T : \bar{o}_t^L = \alpha o_t + (1-\alpha)(\bar{o}_{t-1}^L + \bar{o}_{t-1}^T), \bar{o}_t^T = \beta(\bar{o}_t^L - \bar{o}_{t-1}^L) + (1-\beta)\bar{o}_{t-1}^T, 0 \le \alpha \le 1, 0 \le \beta \le 1$
$\text{ES}_{\text{N-M}}$	$\bar{o}_{t+1} = \bar{o}_t^L \bar{o}_{t-T^S+1}^S, \bar{o}_t^L = \alpha \frac{o_t}{\bar{o}_{t-T^S}^S} + (1-\alpha)\bar{o}_{t-1}^L, \bar{o}_t^S = \gamma \frac{o_t}{\bar{o}_t^L} + (1-\gamma)\bar{o}_{t-T^S}^S, 0 \le \alpha \le 1, 0 \le \gamma \le 1$
AR_{T^p}	$\bar{o}_{t+1} = o_0 + \sum_{i=1}^{T^p} \phi_i o_{t-i+1}$
$\text{ARMA}_{T^p;T^q}$	$\bar{o}_{t+1} = o_0 + \sum_{i=1}^{T^p} \phi_i o_{t-i+1} + \sum_{i=1}^{T^q} \theta_i o_{t-i+1}^E$
$\text{ARIMA}_{T^p;1;T^q}$	$\bar{o}_{t+1} = o_t + \sum_{i=1}^{T^p} \phi_i (o_{t-i+1} - o_{t-i}) + \sum_{i=1}^{T^q} \theta_i o_{t-i+1}^E$
$\text{SARIMA}_{T^p;0;T^q}^{T^P;1;T^Q}\{T^S\}$	$\bar{o}_{t+1} = o_{t-T^S+1} + \sum_{i=1}^{T^p} \upsilon_i (o_{t-i+1} - o_{t-i-T^S+1}) + \sum_{i=1}^{T^P} \Upsilon_i (o_{t-iT^S+1} - o_{t-(i+1)T^S+1}) + \sum_{i=1}^{T^q} \theta_i o_{t-i+1}^E + \sum_{i=1}^{T^Q} \Theta_i o_{t-iT^S+1}^E$
$\text{ARIMAX}_{T^p;1;T^q}$	$\bar{o}_{t+1} = o_t + \sum_{T^j=1}^{T^J-1} \rho_j Y_j + \sum_{i=1}^{T^p} \upsilon_i (o_{t-i+1} - o_{t-i}) + \sum_{i=1}^{T^q} \theta_i o_{t-i+1}^E$
CF($\text{ES}_{\text{N-M}}$ & SARIMA & ARIMAX)	$\bar{o}_{t+1} = \frac{1}{3}(\bar{o}_{t+1}^{ES_{N-M}} + \bar{o}_{t+1}^{SARIMA} + \bar{o}_{t+1}^{ARIMAX})$

t = time period
t^s = seasonal period
o_0 = regression constant
o_t = real number of order lines in period t
$\bar{o}_t$ = forecast number of order lines in period t
o_t^E = forecasting error in period t
$\bar{o}_t^L$ = smoothed level of the series in period t
$\bar{o}_t^T$ = smoothed additive trend in period t
$\bar{o}_t^S$ = smoothed seasonal index in period t
T^{MA} = number of historical periods averaged
T^S = number of periods in one seasonal cycle
T^j = working day (T^1 = Monday; T^2 = Tuesday; T^3 = Wednesday; T^4 = Thursday)
T^J = number of working day ($T^J = 5$)
T^p = number of nonseasonal autoregressive periods
T^P = number of seasonal autoregressive periods
T^q = number of nonseasonal moving average periods
T^Q = number of seasonal moving average periods
Y_j = binary working day variable
α = smoothing parameter for the level of the time series
β = smoothing parameter for the trend
γ = smoothing parameter for the seasonal indices
θ = nonseasonal moving average parameters
Θ = seasonal moving average parameters
ρ = working day regression parameters
υ = nonseasonal autoregression parameters
Υ = seasonal autoregression parameters
ω = weight

(De Gooijer and Hyndman, 2006; Goh and Law, 2002). The reader is referred to Gardner Jr. (2006) for an overview of other exponential smoothing methods.

Seasonal autoregressive integrated moving average models (SARIMA) exist in many different forms. The full formulation of a $\text{SARIMA}_{T^p;0;T^q}^{T^P;1;T^Q}\{T^S\}$ model is given by:

$$\upsilon(B)\Upsilon(B^{T^S})\nabla^{T^d}\nabla_{T^S}^{T^D} o_{t+1} = o_0 + \theta(B)\Theta(B^{T^S}) o_t^E, \tag{5.1}$$

with:

$\upsilon(B) = 1 - \upsilon_1 B - \ldots - \upsilon_{T^p} B^{T^p}$	nonseasonal autoregressive operator
$\Upsilon(B^{T^S}) = 1 - \Upsilon_1 B^{T^S} - \ldots - \Upsilon_{T^P} B^{T^P T^S}$	seasonal autoregressive operator
$\theta(B) = 1 - \theta_1 B - \ldots - \theta_{T^q} B^{T^q}$	nonseasonal moving average operator
$\Theta(B^{T^S}) = 1 - \Theta_1 B^{T^S} - \ldots - \theta_{T^Q} B^{T^Q T^S}$	seasonal moving average operator
∇^{T^d}	nonseasonal $T^{d\text{th}}$ differencing term
$\nabla_{T^S}^{T^D}$	seasonal $T^{D\text{th}}$ differencing at T^S lags
B^i	backshift operator on o_t with $B^i(o_t) = o_{t-i}$

Those operators will only be present in Equation 5.1 in case the values T^p, T^P, T^d, T^D, T^q, and T^Q are different from zero (Cools et al., 2009). Four different SARIMA variants are outlined below.

Starting with the most straightforward SARIMA model where only T^p differs from zero, the SARIMA model is a pure autoregressive model (AR) of order T^p. The AR_{T^p} forecasting model assumes that the forecasting value is only related to the T^p most recent historical values (Chase Jr, 2013; Cools et al., 2009).

The simple $AR(T^p)$ model can be extended by adding T^q moving average components. In the autoregressive moving average (ARMA) model, both T^p and T^q differ from zero. The forecasting value not only depends on its own past values, but also on T^q previous forecasting errors (Chase Jr, 2013; Cools et al., 2009).

The major disadvantage linked to both AR_{T^p} and $ARMA_{T^p;T^q}$ is the assumption of stationarity. Stationarity requires that there is no trend in the data. The best way of eliminating a trend is by differencing the data, in particular taking the difference of observation t and observation $t-1$. This model is known as an autoregressive integrated moving average (ARIMA) forecasting model. The forecasting value is calculated by the sum of last observation and a forecast shift compared to last period (Athanasopoulos et al., 2011; Chase Jr, 2013; Cools et al., 2009).

While the ARIMA model is able to eliminate trends, the full SARIMA model, as represented by equation 5.1, is able to additionally take seasonal cycles into account. If seasonality exists in the data, seasonal differencing may be required. A seasonal difference is the difference between two corresponding observations from two consecutive seasonal cycles. The seasonal difference can be mathematically represented by $o_{t-i} - o_{t-i-t^s}$. By seasonal differencing, both trend and seasonal patterns can be eliminated at once. Therefore, the resulting time series may become stationary and require no further differencing (Athanasopoulos et al., 2011; Chase Jr, 2013; Cools et al., 2009).

In contrast to the pure time series variants of SARIMA, an ARIMA model with intervention Y-variables is applied to the order line data. Four dummy variables are created to model the weekly seasonality. Those dummy variables represent the first four working days of the week (i.e., Monday, Tuesday, Wednesday, and Thursday). Friday is used as reference day to prevent multicollinearity (Cools et al., 2009).

SARIMA models are complex models to develop, as well as to use as forecasting method. However, SARIMA models generally predict demand accurately in the short, medium, and long term due to the ability to account for both trends and seasonality (Chase Jr, 2013).

Finally, *composite forecasting* (CF) describes methods of combining forecasting values of alternative forecasting models. By combining different forecasts, biases among methods compensate for one another. The strengths of each method are merged, resulting in better forecasting performances compared to individual forecasts. The most simple method of composite forecasting is applied in this study: averaging the three best performing forecasting methods. Other composite forecasting models are described in Chase Jr (2013).

Improving forecast accuracy is of great importance in reducing uncertainty and meeting demand requirements (Sanders and Ritzman, 2004). Many forecast accuracy measures have been used in past research. In order to evaluate the forecasting models, three different accuracy measures are used, namely root mean square error (RMSE), mean absolute percentage error (MAPE), and finally mean absolute scaled error (MASE). These three accuracy measures are mathematically represented in Table 5.2. In Hyndman and Koehler (2006), more previously used measures of accuracy are discussed and compared.

The first proposed accuracy measure, RMSE, is a scale-dependent measure in comparing forecasting methods. The main advantage of using RMSE as forecasting accuracy measure is the straightforward interpretation, as RMSE is on the same scale as the data. Because the forecasting objective is to minimise forecasting error, a low value for RMSE is preferred (Hyndman and Koehler, 2006). The quadratic term in the RMSE formula, which penalises large errors harder, is the main advantage of RMSE compared to other scale-dependent measures (such as the mean absolute deviation). Small values of RMSE pro-

TABLE 5.2: Summary of forecast accuracy measures.

Forecast accuracy measure	Formula
RMSE	$\sqrt{\frac{1}{T}\sum_{t=1}^{T}(o_t - \bar{o}_t)^2}$
MAPE	$\frac{1}{T}\sum_{t=1}^{T}\frac{\lvert o_t - \bar{o}_t\rvert}{o_t}$
MASE	$\frac{1}{T}\sum_{t=1}^{T}\frac{o_t - \bar{o}_t}{\frac{1}{T_i - 1}\sum_{j=2}^{T_i}\lvert o_{t_i} - o_{t_{i-1}}\rvert}$

$\bar{o}_t$ = forecasting value in period t
t = time period
t^I = in-sample time period
T = total number of forecast periods
T_i = number of in-sample periods
o_t = observed value in period t

vide forecasting errors that are more equally distributed across the forecasts, compared to other scale-dependent measures. In terms of workload forecasts, equally distributed (small) errors are preferred as these can be captured by the human pickers by working harder, while large errors would result in missing shipping deadlines or unnecessarily high labour costs.

MAPE is an accuracy measure based on percentage errors. MAPE is scale-independent and thus useful for comparing forecasting performance across different data sets. It has the disadvantage of having an extremely skewed distribution when any value of o_t is close to zero (Hyndman and Koehler, 2006). MAPE has been identified as especially useful when units of measurement are relatively large (Goh and Law, 2002). In the forecasting context a low value for MAPE is preferred, because a low value can be interpreted as a low percentage error. Because the daily number of order lines in a warehouse is different from zero and units of measurement are rather large, MAPE is a reliable forecasting accuracy measure.

A final accuracy measure proposed by Hyndman and Koehler (2006) is a scaled error. MASE is independent of the data scale. If MASE has a value smaller than one, the proposed forecasting method gives, on average, smaller errors compared to the in-sample errors from the naïve method. The naïve method is thus used as benchmark in evaluating the forecasting accuracy by MASE (Hyndman and Koehler, 2006).

5.3 Empirical Results

This section analyses and discusses the results of the study. Hierarchical forecasting is performed by applying both a bottom-up and a top-down approach to the order line data in the case study. Using the top-down forecasting process, first total daily number of order lines is forecast using time series forecasting models. Next, the zone-level forecast is derived from the aggregated forecast using a factor that defines the percentage of total number of order lines that should be picked in the pick zone. For the bottom-up approach,

TABLE 5.3: Top-down approach: forecasting accuracy aggregated forecast.

	RMSE		MAPE		MASE
	In-sample	*Holdout sample*	*In-sample*	*Holdout sample*	*Holdout sample*
Benchmark	1,820.40	1,485.75	5.79%	4.65%	0.33
Naïve I	4,018.37	3,767.99	14.14%	12.81%	0.89
MA_5	2,714.83	2,538.54	8.94%	8.35%	0.58
wMA_5	1,670.93	1,622.22	5.34%	5.32%	0.37
$ES_{N\text{-}N}$ ($\alpha = 0,106$)	2,792.15	2,603.14	9.36%	8.73%	0.61
$ES_{A\text{-}N}$ ($\alpha = 0,106$, $\beta = 0,000$)	2,791.86	2,606.10	9.38%	8.78%	0.61
$ES_{N\text{-}M}$ ($\alpha = 0,174$, $\gamma = 0,114$)	1,405.92	1,371.19	4.46%	4.35%	0.30
AR_4	1,653.81	1,602.76	5.32%	5.22%	0.36
$ARMA_{4;1}$	1,644.78	1,598.48	5.31%	5.23%	0.36
$ARIMA_{4;1;1}$	1,658.52	1,608.89	5.28%	5.29%	0.37
$SARIMA^{0;1;1}_{3;0;1}\{5\}$	1,421.43	1,401.41	4.51%	4.46%	0.31
$ARIMAX_{2;1;1}$	1,377.18	1,415.11	4.35%	4.53%	0.31
CF	1,363.26	1,350.64	4.33%	4.27%	0.29

the time series forecasting formulas are used to predict demand on zone level, after which these zone level forecasts are accumulated to derive aggregated demand.

This section is organised as follows: Sections 5.3.1 and 5.3.2 present the results of the top-down forecasting process and the forecasting errors resulting from the bottom-up approach, respectively. Both forecasting approaches are statistically compared in Section 5.3.3.

5.3.1 Top-down Forecasting Approach

All twelve forecasting methods presented above are applied to the warehouse demand data. Results of the twelve forecasts, as well as the performance of non-statistical forecasts made by supervisors (benchmark) are presented in Table 5.3. Coefficients of wMA_5, all exponential smoothing models and all variants of SARIMA are determined by minimizing the in-sample sum of squared residuals (SSR), using the `Excel Solver`.

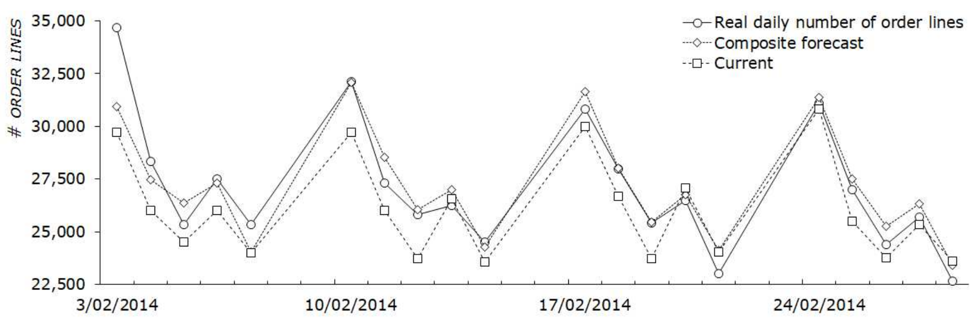


FIGURE 5.5: Benchmark forecasts, composite forecasts, and the real daily number of order lines for February 2014.

TABLE 5.4: Top-down approach: analysis absolute scaled error (ASE) for the out-of-sample aggregated forecast.

	MASE	σ ASE	Minimum ASE	Maximum ASE
Benchmark	0.33	0.27	0.00	1.46
Naïve I	0.89	0.61	0.00	3.19
MA_5	0.58	0.44	0.01	2.20
wMA_5	0.37	0.29	0.00	1.32
$ES_{N\text{-}N}$ ($\alpha = 0,106$)	0.61	0.43	0.00	2.24
$ES_{A\text{-}N}$ ($\alpha = 0,106, \beta = 0,000$)	0.61	0.43	0.00	2.23
$ES_{N\text{-}M}$ ($\alpha = 0,174, \gamma = 0,114$)	0.30	0.25	0.00	1.27
AR_4	0.36	0.29	0.00	1.30
$ARMA_{4;1}$	0.36	0.28	0.00	1.28
$ARIMA_{4;1;1}$	0.37	0.28	0.00	1.33
$SARIMA^{0;1;1}_{3;0;1}\{5\}$	0.31	0.26	0.01	1.21
$ARIMAX_{2;1;1}$	0.31	0.27	0.00	1.41
CF	0.29	0.25	0.00	1.25

Results in Table 5.3 show that all three forecasting accuracy measures are consistent in identifying the best performing forecasting method, both for in-sample forecasts and for out-of-sample forecasts. Although the forecasts of the experienced supervisors are already very accurate, the composite forecast of $ES_{N\text{-}M}$, SARIMA, and ARIMAX improves the benchmark by 25.3%$\left(1 - \frac{4.33\%}{5.79\%}\right)$ and 8.2%$\left(1 - \frac{4.27\%}{4.65\%}\right)$ in terms of the in-sample MAPE and holdout-sample MAPE percentage reduction, respectively (note that the difference is significant on a 0.01 significance level). All three forecasting accuracy measures, both in-sample and out-of-sample, of $ES_{N\text{-}M}$, $SARIMA^{0;1;1}_{3;0;1}\{5\}$, as well as $ARIMAX_{2;1;1}$ provide similar conclusions as the CF method. Neither other SARIMA variant nor the more simple forecasting models are able to accurately describe the seasonal cycles in the data; these models are not able to outperform current predictions done by supervisors (i.e., benchmark). Figure 5.5 illustrates the forecasts, both benchmark and CF, as well as the real daily number of order lines. The figure is limited to the month of February 2014 because of visibility. However, other months show similar patterns.

Besides demonstrating the best performing forecasting model, Table 5.3 shows that almost all forecasting errors produced by the holdout sample are lower compared to the corresponding in-sample forecasting errors. Because supervisors were able to forecast more accurately in the year 2014, compared to 2013, this observation seems to be caused by the nature of the data. Order lines seem to deviate less from the general pattern in 2014 compared to 2013.

A final remark on Table 5.3 can be made concerning the results of $ES_{N\text{-}N}$ and $ES_{A\text{-}N}$. By including the trend component in the exponential smoothing model, only in-sample RMSE is slightly decreasing. All other forecasting errors have risen due to the inclusion of a trend component. This is in accordance with the observations on Figure 5.1 that the trend is not significant.

Table 5.4 presents a more profound overview of the absolute scaled error (ASE). For

TABLE 5.5: Top-down approach: forecasting accuracy aggregated and disaggregated forecast.

	RMSE		MAPE		MASE
	In-sample	*Holdout sample*	*In-sample*	*Holdout sample*	*Holdout sample*
Aggregated					
Total *CF*	1,363.26	1,350.64	4.33%	4.27%	0.29
Disaggregated					
Zone A *(23.4%)*	476.39	529.20	7.06%	6.69%	0.51
Zone B *(31.2%)*	563.43	545.62	5.76%	5.92%	0.42
Zone C *(4.4%)*	264.52	265.93	20.32%	16.04%	1.03
Zone D *(7.3%)*	129.40	130.17	5.71%	6.02%	0.34
Zone E *(31.7%)*	663.94	587.62	6.65%	6.94%	0.33
Zone F *(0.6%)*	38.88	53.71	22.74%	18.73%	1.01
Zone G *(1.4%)*	42.62	52.86	10.08%	10.32%	0.86

each of the twelve forecasting models, the mean absolute scaled error, the standard deviation of the absolute scaled error, as well as the minimum and maximum value of the absolute scaled error are given for the out-of-sample aggregated forecasts in order to analyse the daily variation of the errors. Only minor differences in the minimum ASE between the forecasting models can be observed, in contrast to the maximum ASE. All SARIMA forecasting models, as well as $ES_{\text{N-M}}$ and the composite forecast result in lower maximum scaled errors compared to the maximum ASE of supervisors' forecasts. In general, the composite forecast is the best performing forecasting technique in terms of mean, standard deviation, and maximum ASE. The standard deviation and maximum forecasting error of the composite forecast reduce by 5.0% and 14.6%, respectively, compared to benchmark forecasts.

The best performing forecasting model for aggregated data, CF, is used to create forecasts at zone level. The results are shown in Table 5.5. The percentages in the first column represent the average daily workload (in number of order lines) of each zone as percentage of the total daily workload, based on the in-sample data. Note that forecasts may be further improved by varying the fractions of each zone (e.g., by using a simple moving average forecast to predict the daily workload fraction of each zone). The scaled error MASE, which is independent of the data scale, is used to compare the accuracy of forecasts at zone level.

Forecasts for the three large zones (i.e., zones A, B, and E), as well as zone D, are accurate using the top-down approach. Forecasting errors of those four pick zones are on average a factor of 0.33 to 0.51 smaller than the in-sample forecasting errors from the naïve method. A slightly bigger forecasting error is produced in zone G. In the remaining two zones, C and F, the top-down approach does not forecast the daily number of order lines as successfully as the naïve method's in-sample forecasting values.

5.3.2 Bottom-up Forecasting Approach

In the bottom-up forecasting approach, the daily number of order lines is forecast for each individual zone. All time series models presented in Table 5.1 are applied to each pick zone. Forecasting accuracy measures of the best performing model are summarised in Table 5.6. These disaggregated forecasts are accumulated to produce the aggregated demand. Again, MASE is used to compare forecasts of all pick zones.

TABLE 5.6: Bottom-up approach: forecasting accuracy aggregated and disaggregated forecast.

	RMSE		MAPE		MASE
	In-sample	*Holdout sample*	*In-sample*	*Holdout sample*	*Holdout sample*
Aggregated					
Total	1,368.34	1,347.33	4.36%	4.24%	0.29
Disaggregated					
Zone A *CF*	332.58	383.57	4.58%	4.80%	0.38
Zone B *CF*	489.90	459.42	4.99%	4.92%	0.38
Zone C $ES_{N\text{-}M}$	166.64	166.00	12.11%	10.37%	0.66
Zone D *CF*	109.42	109.45	4.84%	4.85%	0.29
Zone E $ES_{N\text{-}M}$	498.47	447.04	4.99%	4.75%	0.25
Zone F AR_4	33.78	52.10	16.98%	17.51%	1.01
Zone G $ES_{N\text{-}M}$	36.16	41.04	8.07%	7.87%	0.69

Comparison of disaggregated demand using the bottom-up forecasting process results in similar conclusions as in the previous section. Order lines of the main four pick zones, in particular zones A, B, D, and E, can be forecast highly accurately. Forecasting errors are on average a factor of 0.25 to 0.38 smaller than the in-sample forecasting errors from the naïve method. The AR_4 model outperforms all other forecasting models only in zone F. However, the forecasting errors resulting from the autoregressive model are rather large. The $\mathrm{ES}_{\mathrm{N\text{-}M}}$ forecasting model results in the most accurate forecasts in zones C, E, and G. Other pick zones are most accurately forecast using the composite forecasting technique.

5.3.3 Comparing Top-down and Bottom-up Forecasting

A paired-samples t-test is used to compare forecasting errors of the top-down and bottom-up forecasting process. Differences of the scale independent forecasting accuracy measures, including MAPE and MASE, are tested for the out-of-sample forecasting values. In the first t-test, the mean absolute forecasting error of the top-down forecasting process is compared to MAPE of the bottom-up approach. Secondly, MASE of both forecasting approaches are compared. Differences of performances between the top-down and bottom-up approaches, both relative difference and absolute difference, as well as results of the two-sided paired-samples t-tests are summarised in Table 5.7. First, the disaggregated test results are presented, followed by the aggregated performance differences among the top-down and bottom-up forecasting approaches.

TABLE 5.7: 2-tailed significance levels for the paired-samples t tests on mean difference for the top-down and bottom-up forecasting approach.

	MAPE					MASE				
	relative Δ_{MAPE}	*absolute* Δ_{MAPE}	t	df	p	*relative* Δ_{MASE}	*absolute* Δ_{MASE}	t	df	p
Aggregated										
Total	−0.55%	−0.02	0.67	238	0.504	−0.39%	0.00	0.48	238	0.631
Disaggregated										
Zone A	−28.31%	−1.89	5.92	238	0.000	−24.28%	−0.12	5.12	238	0.000
Zone B	−16.84%	−1.00	4.17	238	0.000	−8.90%	−0.04	2.14	238	0.033
Zone C	−35.34%	−5.67	6.74	238	0.000	−36.02%	−0.37	6.21	238	0.000
Zone D	−19.34%	−1.16	4.62	238	0.000	−14.99%	−0.05	3.49	238	0.001
Zone E	−31.53%	−2.19	7.12	238	0.000	−25.84%	−0.09	5.79	238	0.000
Zone F	−6.49%	−1.21	1.49	238	0.139	−0.44%	0.00	0.11	238	0.914
Zone G	−23.76%	−2.45	5.19	238	0.000	−19.95%	−0.17	4.36	238	0.000

Δ_{MAPE} = difference between bottom-up and top-down MAPE
Δ_{MASE} = difference between bottom-up and top-down MASE

Significance levels of both accuracy measures are consistent in determining the best disaggregated forecasting approach. For all pick zones, except for zone F, the bottom-up approach results in statistically significant lower forecasting errors, while for zone F the null hypothesis of equal forecasting errors cannot be rejected. This result can be explained by the fact that an equal daily distribution of total order lines across zones, as assumed in the top-down approach, is rather unlikely to occur. In the bottom-up forecasting process, daily number of order lines is forecast for each single pick zone, resulting in a variable fraction of each zone's demand in total demand. Zone F is one of the smaller pick zones in the warehouse in which the seasonal pattern is less clear compared to other pick zones. The strong fluctuating demand as well as the absence of a weekly recurring cycle results in large forecasting errors in both forecasting approaches.

Forecasting errors of aggregated demand prediction using a top-down approach are compared to the bottom-up approach in an equivalent way. Neither percentage errors nor the scaled errors are statistically significantly different using the CF forecasting model for aggregated demand or accumulating the disaggregated forecasts. As a large amount of the order line variation of each single zone can be explained by the time series forecasting methods in the main pick zones, the derived aggregated forecasting in the bottom-up approach is a reliable forecast of the real total number of order lines. As the time series forecasting models are able to reliably forecast the total number of order lines in the top-down approach, as well, the null hypothesis of equal forecasting errors cannot be rejected.

From the results in Table 5.7, it can be concluded that the bottom-up approach outperforms the top-down approach in forecasting disaggregated demand, except for forecasting order lines in zone F. Average forecasting errors for predicting neither the total number of order lines nor the order lines in zone F are statistically significantly different.

5.4 Managerial Implications

Multiple forecasting methods and approaches are shown to be applicable in an order picking context. Order picker's workload in terms of number of order lines in the case study can be forecast in a highly accurate way. Several presented forecasting models are able to outperform the benchmark, i.e., the non-statistical forecasts done by supervisors. The combined forecasting method results in most accurate predictions for daily total number of order lines, followed by the exponential smoothing model with multiplicative weekly seasonality, the full SARIMA model, and the ARIMAX forecasting model.

As warehouses are often divided into different pick zones to achieve a more efficient order picking process, planning of order pickers is done at zone level. For those planning purposes, forecasting order lines should be disaggregated. More accurate forecasts are produced by using a bottom-up forecasting approach, to the detriment of a top-down forecasting approach. The CF and the $ES_{\text{N-M}}$ forecasting models have proven to be especially useful in predicting the number of order lines at zone level.

As a result of our study, the daily forecasts produced by the forecasting models are currently used by the warehouse supervisors to determine the daily required number of order pickers and to allocate order pickers across zones. Based on the average absolute forecasting deviation in number of order lines and the mean productivity of order pickers in the warehouse (i.e., 146 order lines per FTE), the mean absolute forecasting error in number of full-time equivalents (FTEs) could have been reduced from 10 to 7 in 2013 and from 8 to 7 in 2014 by using the composite forecasting method to predict the total number of order lines. This means that, on average, the daily number of either overestimated or underestimated number of order pickers could have been reduced by 1–3 FTEs in this case. This performance measure provides an estimation of the benefits that could be attained when using the forecasting method instead of the benchmark. Over- and underestimated forecasts are equally likely to occur. In practice, supervisors tend to underestimate the required number of pickers with the aim of motivating pickers to increase their productivity and enabling supervisors to present good results to managers if all orders are picked on time with a small number of pickers. However, underestimation is in contrast to the aim of the warehouse to ensure a high customer service level which would justify overestimation. An overestimated forecast ensures that the number of pickers is large enough to retrieve all customer orders timely.

Although the current practice of supervisors is to underestimate the number of order lines when forecasting, this practice is highly discouraged when using the proposed forecasting methods. As most time series forecasting methods include a forecasting error component when making new forecasts, forecasts will be biased when intervening in the forecasts. In order to stimulate and motivate pickers to increase their performance, supervisors can intervene when translating the forecast into a required number of pickers (e.g., by raising the mean productivity level). However, this intervention should be limited in order to prevent demotivating pickers because of a high workload.

5.5 Conclusions

Workload forecasting is an essential activity in the labour-intensive environment of warehouses. Accurate planning is required in order to provide a high service level, as well as to avoid unnecessary high labour costs. Forecasting the daily workload, disaggregated into pick zones enables warehouse managers and supervisors to determine the required number of order pickers as well as to allocate the order pickers among pick zones. The forecasting methods provide a statistical and objective forecast of the daily workload for which overestimation and underestimation are small and equally likely to occur.

The well-performing time series forecasting models clearly illustrate the added value of defining the resource capacity in practice. Moreover, the planning of order pickers will be less depending on the availability of experienced supervisors, as the forecasting methods are able to accurately predict both aggregated and disaggregated demand without manual intervention. The forecasting methods of our study can be easily implemented, and the implementation immediately helps warehouse managers to schedule order pickers. The provided information of the forecasting approach (i.e., the resource capacity as well as the allocation of the resources across the order picking area), is required to optimise other order picking planning problems, in particular planning problems that should be solved multiple times per working day, such as the job assignment problem (see Part IV).

CHAPTER 6

WORKLOAD BALANCING

While the previous chapter focusses on forecasting the daily workload of order pickers, this chapter[1] further elaborates by balancing the forecast workload over the planning horizon of a working day. Deriving the number of pickers on forecasts results in a constant number of pickers during the planning horizon. Without balancing the workload, the resource capacity is too small during peak periods, while too many order pickers are available other time periods of a working day. Despite the importance of human operators in the order picking process, research on human factors and workload balancing in warehouses is limited with respect to all literature on warehouse planning (Grosse et al., 2015).

The problem studied in this chapter is motivated by a large international B2B warehouse located in Belgium, responsible for the storage and distribution of automotive spare parts. The problem is defined as the operational workload balancing problem (OWBP) and determines which orders to pick during which period of the day. Workload balancing has been intensively studied in a production context (e.g., assembly line (Becker and Scholl, 2006) and job shop (Kingsman, 2000) balancing). However, the labour-intensive operations and the strongly fluctuating daily demand, differentiate warehouses from production facilities (Van Gils et al., 2017c). Therefore, existing workload balancing methods do not cover all challenges of order picking environments. This study goes beyond the current state-of-the-art order picking literature by balancing the workload over a planning day (which is divided into time slots), instead of balancing on a strategic level (Jane,

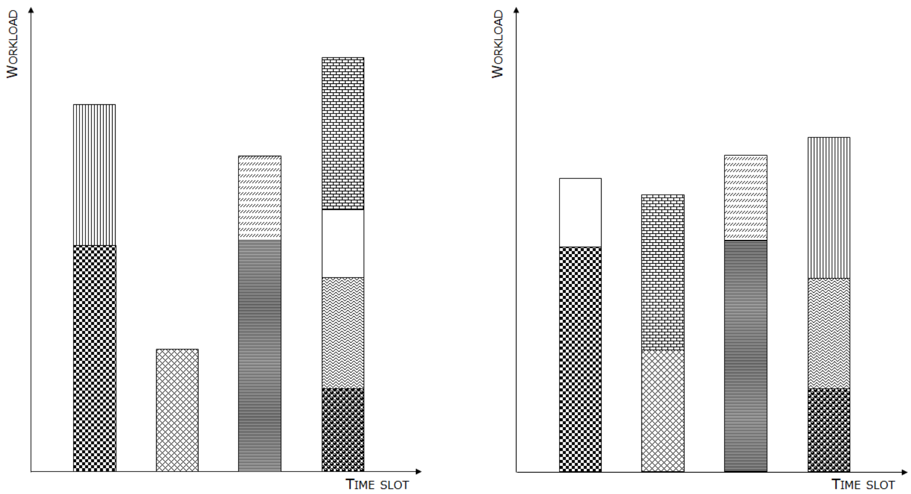
[1]This chapter is based on Vanheusden, S., Van Gils, T., Braekers, K., Caris, A., Ramaekers, K., 2019. Operational workload balancing problem in manual order picking. Computers & Industrial Engineering, under review.

2000; Jane and Laih, 2005).

Figure 6.1 visualises the operational workload balancing problem and a potential solution of the OWBP. Each block on the graph represents the workload of a set of orders, which are scheduled in a certain time slot (horizontal axis). Figure 6.1a represents an undesirable situation in which workload peaks occur, caused by unevenly divided daily shipping deadlines of shipping trucks on top of late customer order acceptance. Work pressure is very high during the first and last time slot (e.g., one hour) of the example, but on the other hand, rather low during others. Workload peaks can be defined as situations for which the required order throughput exceeds the capacity of available resource, defined by the daily forecasts (see Chapter 5), at certain points within the planning horizon. This results in a higher risk of missed departure deadlines of shipping trucks and therefore may result in a lower customer satisfaction due to delayed order deliveries. Work pressure in these situations is very high for both warehouse supervisors and order pickers, resulting in extra stress and fatigue. Warehouse supervisors currently try to cope with these peaks in daily workload by assigning workers of other departments in the warehouse to the order pick zones in need of extra hands. Peaks are generally noticed very late and last minute reassignment of workers, based on individual experiences and judgement of supervisors, often results in inefficiencies in these corresponding activities. These activities often get delayed or even shut down. Thus, in order to create a more stable order picking process without above mentioned inefficiencies, workload needs to be balanced in every order pick zone, for every working hour of the day. The objective of the OWBP is to balance the daily workload by deciding on which sets of orders to pick during which periods of the day. The right-hand side of Figure 6.1b represents the desired outcome of a balanced daily workload.

The operational workload balancing problem is defined as the decision of which particular order lines to pick during which time slot of the day. The aim is to equally divide these order lines over the different time slots of a working day (e.g., a single time slot for every working hour). The challenge of balancing these order lines over time slots is coherent with their corresponding time window (the available time to pick a customer order). Order lines can only be scheduled for picking in time slots between the time customers order their products and the departure of the corresponding shipping truck, which is assumed to be fixed at the operational decision level. Equally dividing order lines during the day accomplishes an equally distributed workload among order pickers for every zone.

This chapter has two main contributions. First, the new highly relevant operational workload balancing problem, unexplored in the domain of order picking, is introduced and mathematically described. Second, the effect of multiple warehouse factors (e.g., number of pick zones and number of shipping trucks) on the balancing possibilities is analysed and evaluated, as well as the effect of the warehouse factors on the complexity



(A) Example of workload imbalance. (B) Outcome of the OWBP.

FIGURE 6.1: Example of the OWBP (each block represents the workload of a set of orders).

of OWBP. The complexity of the problem and the performance of the optimisation model are analysed using an extensive experimental study. The results of this study show that a balanced workload results in a more stable order picking process and overall productivity improvements for the total warehouse operations.

The remainder of this chapter is organised as follows. The new operational workload balancing problem in the context of order picking is described in Section 6.1. Section 6.2 highlights the differentiating elements of the OWBP compared to existing models in literature. The problem formulation is provided in Section 6.3. Section 6.4 is devoted to the experimental design and computational results, which shows the applicability of balancing the workload of order pickers during a working day. Section 6.5 provides managerial implications of this study and shows the benefits of balancing in a real-life case study. Section 6.6 concludes this chapter.

6.1 Operational Workload Balancing

The operational workload balancing problem investigated here is observed in the large international B2B warehouse introduced in the previous chapter (see Section 5.1). The case study warehouse is used to further clarify the OWBP. In Section 6.1.1, the problem context of the OWBP is discussed and some problem specific terminology is introduced. Section 6.1.2 explains the origin of daily workload peaks within order picking and how the workload imbalance can be measured and solved.

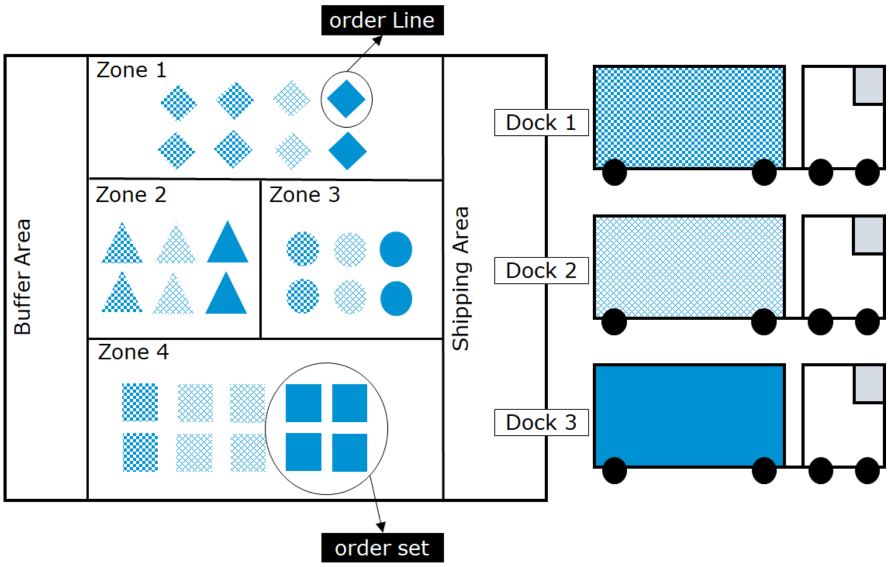


FIGURE 6.2: Simplified warehouse ground plan.

6.1.1 Case Study and Problem Context

The warehouse under consideration is responsible for the storage of automotive spare parts and the distribution of these parts around the globe. The mission of the company is to maximise the operating time of their sold vehicles by aiming at fast throughput times and reliable deliveries of spare parts. The warehouse is fully manually operated and is divided into multiple order pick zones. A simplified ground plan of the warehouse is illustrated in Figure 6.2, including only the four largest pick zones.

Products have been assigned to the different zones based on their product properties such as weight and size. This division is required because different handling methods are used for products with different dimensions. One of the zones is designed to maximise throughput, storing only light weighted SKUs. For example, small buttons and screws are stored in plastic boxes within a single zone. Heavy and large products that do not fit standard Euro pallet measurements are grouped in another pick zone. The specific characteristics of the pick zones result in different average productivity levels among the zones (i.e., the mean number of retrieved SKUs per time unit): the average productivity is low in the pick zone storing heavy SKUs, while the zone storing smaller items is designed to maximise the productivity. To mimic a realistic scenario, it is important to take these productivity differences into account when balancing the workload.

Spare parts warehouses are characterised by customer orders that can be grouped based on their destination. In other words, customer orders for the same geographical location are assigned to the same shipping truck. In Figure 6.2 there are three trucks shipping multiple customer orders for three different geographical locations. Customers can order multiple spare parts in each customer order. This means that each customer order consists of one or more order lines with each order line representing a single SKU. When picking order lines of a customer order, multiple zones have to be visited in the warehouse. A set of order lines that have to be picked in a single zone and have a common geographical destination (i.e., order lines that need to be loaded into the same shipping truck), are referred to as an order set. An example of an order set is visualised in Figure 6.2. By combining order lines into order sets, the workload expressed as number of order lines is grouped by pick area (i.e., pick zone) and shipping truck, keeping order lines with the same pick deadline together. This increases the process control and prevents that these order lines need to be consolidated after retrieval. Therefore, each order set can be assigned to only a single time slot. Splitting order sets is undesirable due to a loss of control. After balancing the workload, all order sets that have been scheduled in a time slot are used to create batches. In this way, wave picking (i.e., each time slot corresponds to a wave) can be efficiently applied (Petersen, 2000).

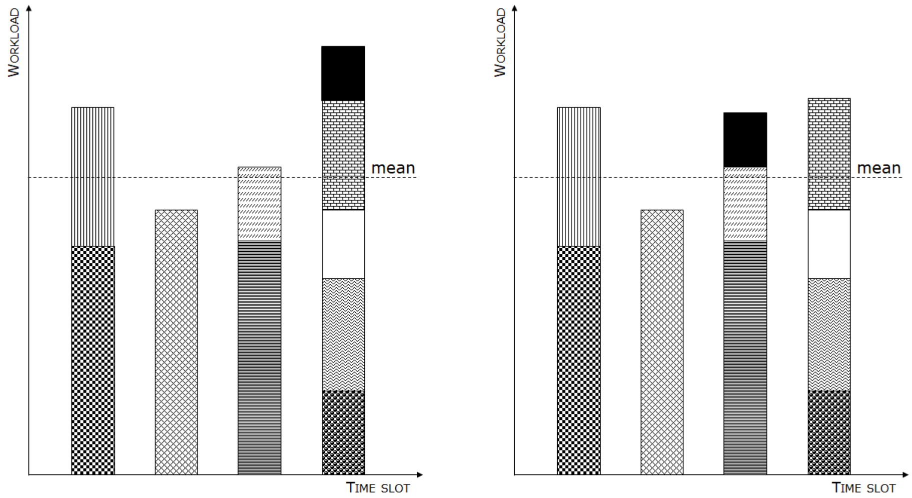
Within the warehouse, a parallel zone picking policy is in place. In parallel zone picking systems, order sets have to wait for each other in the shipping area of the warehouse before they can be loaded into their respective shipping truck. Each shipping truck can consist of multiple order sets (i.e., a single order set for each pick zone). A shipping dock is assigned to a shipping truck whenever the first order set of a shipping truck is picked. This does not mean that the shipping truck actually arrives at that moment. The dock is reserved for a particular shipping truck from the time slot that the first order set of a shipping truck is scheduled (note that only a single truck can be assigned to a dock per time slot). The shipping dock stays occupied until the shipping deadline of that truck (i.e., until all order sets are loaded into the respective truck). Whenever all shipping docks are occupied, no order sets of new shipping trucks can be picked. In order to prevent shipping docks from overcrowding, the shipping dock capacity should be accounted for in the mathematical model.

All order sets of a shipping truck should be retrieved before the shipping deadline. The challenge of balancing these order sets over time slots is in accordance with their corresponding time window (i.e, the available time to pick a customer order). At different points in time, customers send their orders. This is possible until the system release time slot of the truck that is going to ship the orders. This release time slot is fixed in the short term as a result of negotiations with customers. Based on negotiations with shipping companies, the shipping deadline is fixed at an operational level. Order sets can only be scheduled for picking between the system release time slot (i.e., release) and the deadline of their corresponding shipping truck. The assignment of the order sets to a shipping truck as well as the deadline of these shipping trucks are assumed to be fixed at an operational level. The time schedule of shipping trucks is based on the delivery preferences of customers in order to increase the service level.

6.1.2 Measuring Workload Imbalance

The number of order lines, grouped in order sets, that needs to be retrieved on each day gives an indication of the daily workload. The total pick time (i.e., workload) is assumed to be directly proportional to the number of order lines. The assignment of order sets to shipping trucks, as well as the shipping schedule are set by the distribution planning department, based on transportation costs and service agreements with customers. Therefore, these elements are assumed to be fixed at the operational level. The fixed shipping schedule often leads to workload peaks during the day, as order patterns and the available time to pick the orders vary across customers and geographical locations (e.g., order sets contain varying numbers of order lines, shipping trucks have different deadlines). In order to balance the workload, one must be able to measure and correct existing imbalances in the system.

To measure and compare imbalances between solutions, the right equity function has to be determined. Selecting the right equity function does not only depend on the decision makers' interpretation and understanding of the concept of fairness, but is also subject to several underlying theoretical properties that differ among equity measures (Karsu and Morton, 2015). In general, variance, standard deviation, mean absolute deviation (MAD), and range are considered as good metrics to measure balancing objectives (Nguyen and Wright, 2014). In order to solve the OWBP, the range is chosen as suitable objective function for several reasons. First, the range is a linear function in contrast to variance or standard deviation which penalise deviations from the average at a quadratic rate. Quadratic objective functions can be less intuitive measures for decision makers in practice and these also have a higher computational complexity (Matl et al., 2017). Second, range is able to minimise peaks and maximises the minimum value simultaneously in contrast to for example MAD, maximum or minimum, although these functions are linear as well. MAD is not always able to minimise peaks in workload as shown in the examples in Figure 6.3. The MAD is equal in both examples, but the workload peak is substantially higher in Figure 6.3a than Figure 6.3b because transfers of order sets on the same side of the mean will not affect this measure. Minimising the maximum workload or maximising the minimum workload are not considered to be suitable objective functions for balancing the workload. For example, if the maximum is minimised, further balancing of the solution is not performed whenever peaks are at their minimal value. Although any changes between the extremes (i.e., minimum and maximum) have no effect on the range, it already provides more information than the simple min-max. Range is therefore



(A) Imbalanced solution. (B) Balanced solution.

FIGURE 6.3: Example of different solutions with equal MAD.

the best linear metric for solving the OWBP. Furthermore, the range is easy to interpret and implement and is therefore frequently used in various applications (Matl et al., 2017).

6.2 Related Planning Problems

Related planning problems, both in the context of workload balancing in general as well as workload balancing in order picking, are discussed in this section to show the academic contribution of OWBP. This section is organised as follows. Section 6.2.1 highlights the importance of workload balancing and discusses relevant differences from workload balancing problems in other research domains. Section 6.2.2 on the other hand, discusses related warehousing literature with a focus on zoning and workforce scheduling in connection to workload balancing.

6.2.1 Workload Balancing

In general, workload balancing is defined as managing the variability of workloads over a time horizon (Irastorza and Deane, 1974). This concept of balancing workload is studied within various industries and research streams such as logistics, production and manufacturing environments and project scheduling, and is considered in various operational research problems such as knapsack and resource allocation problems (Becker and Scholl, 2006; Bichescu et al., 2009; Eiselt and Marianov, 2008; Hillier and Brandeau, 2001; Huang et al., 2006; Karsu and Morton, 2014; Kingsman, 2000; Kumar and Shanker, 2001; Matl et al., 2017; Rieck et al., 2012). Although these problems are related to the OWBP, the operational order picking context of our problem consists of clearly distinguishable elements, as explained below: flexible capacity, a fixed planning period, and fixed time windows without precedence constraints. As a result, existing solution approaches cannot be directly applied to the OWBP.

Warehouses differ from production and manufacturing environments by delivering labour-intensive services to customers instead of goods assembled or produced by machines. The capacity of these production and manufacturing facilities is usually fixed in the short term (although overtime and subcontracting can be used in case of shortage) (Becker and Scholl, 2006), while warehouses can hire additional order pickers in case of shortage (Van Gils et al., 2017c; Wruck et al., 2017). Consequently, instead of including capacity as constraint before balancing, the workload is balanced without capacity constraints in the OWBP. Afterwards, the required number of pickers is derived from the balanced workload schedule.

In contrast to the project scheduling problem (Rieck et al., 2012) or balancing in the context of vehicle routing (Matl et al., 2017), the duration of the planning period is assumed to be fixed and the workload is balanced over this fixed planning period (i.e., usually a single working day). Instead of reducing the makespan to fulfil the tasks by increasing the number of resources or vehicles (Rieck et al., 2012; Matl et al., 2017), the OWBP assumes a fixed planning period and variable capacity to ensure that all order sets are picked before the deadline.

Existing methods often presume strict precedence constraints among tasks, such as assembly line balancing (Kingsman, 2000) and project scheduling (Rieck et al., 2012) problems, or completely independent tasks (e.g., workload balancing among facilities (Huang et al., 2006)), while scheduling order sets in the OWBP is not subject to precedence constraints, nor is scheduling completely independent. In the OWBP, order sets are picked independently from each other in each pick zone, while scheduling order sets from different pick zones is dependent as the shipping area is limited. Instead of precedence constraints, order sets are subject to fixed time windows, bounded by a release and deadline time slot in which they should be scheduled.

6.2.2 Workload Balancing in Order Picking

Zoning and workforce scheduling are well-known topics in warehousing literature. Both zoning and workforce scheduling can cause substantial workload peaks. Dividing the order picking area into different zones can cause workload imbalances between order pick zones (Jane and Laih, 2005). Poor workforce scheduling induces workload imbalance over time (Kim et al., 2018). Related literature, focussing on each of these planning problems, is shortly discussed below.

A well-known opportunity to increase order picking performance is the division of the warehouse into different order pick zones (De Vries et al., 2016a). Each order picker is assigned to a dedicated zone, and only picks the items of an order that are located in this pick zone (Yu and De Koster, 2009). Zone picking reduces travelling as pickers traverse only a small area of the warehouse. Furthermore, picker congestion is reduced, which results in substantial performance benefits compared to strict order picking (De Koster et al., 2012; Ho and Lin, 2017). Either parallel zoning (i.e., all zone pickers work on the same batch of orders) or sequential zoning (i.e., a batch of orders is sequentially passed from one zone to the other), causes workload imbalances among pick zones, as pick densities vary across these zones (Yu and De Koster, 2009). By varying the size of the pick zone and varying the assignment of SKUs to pick zones, workload of the zones can be equalised in the long run (Jane, 2000; Jane and Laih, 2005; Van der Gaast, 2016). However, the proposed solution methods will be less suitable to balance the workload among pickers in the short term. Short term balancing can be achieved by considering dynamic zone picking systems, such as bucket brigades. Bucket brigades assume sequential zone picking with flexible zone borders, resulting in a self-balancing picking system with respect to the workload of order pickers (Hong et al., 2016).

Another way to assure customer service against peaks in workload is efficient scheduling and staffing of the order picking personnel. Efficient employability of human resources is necessary because of the labour intensive nature of warehousing operations. Warehouses are forced to deal with strong fluctuations in daily demand and should simultaneously be able to meet fixed deadlines in short time intervals. To face these challenges, warehouses need to be highly flexible (Van Gils et al., 2017c). Adaptations in the labour force can be used to cope with fluctuations in demand (Van den Bergh et al., 2013). Temporary workers are often hired in order to capture workload peaks between different days (Grosse et al., 2013). On the one hand, an insufficient number of workers cause a large picker workload and may reduce the service level because of missed deadlines. On the other hand, planning too many workers will cause unnecessarily high labour costs, and a decrease in picking efficiency due to a small workload (Van Gils et al., 2017c). Personnel capacity planning is therefore an important factor in covering the workload (Defraeye and Van Nieuwenhuyse, 2016). Long term and short term demand forecasts allow warehouses to maintain a pool of fixed and temporary order pickers to balance the workload among days (Van Gils et al., 2017c).

While most papers that cover the issue of workload balancing start at a strategic or tactical level (Jane, 2000; Jane and Laih, 2005; Hong et al., 2016), the emphasis of the OWBP is on the operational level, to avoid peaks in the number of orders to be picked in certain time slots during the day. Therefore, the operational workload balancing problem differs from existing literature in zoning and workforce scheduling. Previous literature on zoning aims to balance the workload over the different zones, the OWBP balances daily workload over time within each zone. Additionally, the OWBP goes beyond the current state-of-the-art workforce scheduling literature by balancing the workload for every hour of the day instead of balancing over shifts or days.

6.3 Mixed Integer Linear Programming Model

This section describes the operational workload balancing problem. A mixed integer linear programming (MILP) model is developed to formulate the operational workload balancing problem in an order picking context. The notation outlined below is used throughout the chapter:

Sets:

$\eta = \{1, 2, ..., H\}$	set of pick zones with index h.
$\lambda = \{1, 2, ..., L\}$	set of shipping trucks with index l.
$\lambda_t \subset \lambda$	subset of λ containing all $l : t_l^r \leq t \leq t_l^d$.
$\tau = \{1, 2, ..., T\}$	set of time slots with index t.
$\tau_l \subset \tau$	subset of τ containing all $t : t_l^r \leq t \leq t_l^d$.

Parameters:

o_{hl}	number of order lines for shipping truck l in zone h.
p_h	mean productivity in minutes per order line in zone h.
a_{hl}	workload of shipping truck l in zone h with $a_{hl} = o_{hl} p_h, \forall l \in \lambda, \forall h \in \eta$.
d	number of shipping docks.
t_l^r	release time slot of shipping truck l.
t_l^d	deadline time slot of shipping truck l.

Decision variables:

$$V_{hlt} \begin{cases} 0 & \text{order set } (h;l) \text{ is not scheduled in time slot } t. \\ 1 & \text{order set } (h;l) \text{ is scheduled in time slot } t. \end{cases}$$

$$Y_{lt} \begin{cases} 0 & \text{truck } l \text{ does not reserve a shipping dock in time slot } t. \\ 1 & \text{truck } l \text{ reserves a shipping dock in time slot } t. \end{cases}$$

U_l first time slot that a shipping truck l occupies a dock

A_h^{max} maximum planned workload over all time slots in zone h.

A_h^{min} minimum planned workload over all time slots in zone h.

In the formulation, each combination of h and l represents an order set with workload a_{hl}, expressed as time to pick a number of order lines. To reduce computation time, decision variables V_{htl} are only created if t is between the release and deadline time slot ($t_l^r \leq t \leq t_l^d$). This variable reduction is included by creating subsets λ_t and τ_l which represent the subset of trucks that could be scheduled at time slot t and the subset of time slots at which shipping truck l can be scheduled, respectively, without violating the releases and deadlines.

Objective function

$$\min \sum_{h \in \eta} \left(A_h^{max} - A_h^{min} \right) \tag{6.1}$$

Subject to

$$\sum_{l \in \lambda_t} a_{hl} V_{hlt} \leq A_h^{max} \qquad \forall t \in \tau, \quad \forall h \in \eta \tag{6.2}$$

$$\sum_{l \in \lambda_t} a_{hl} V_{hlt} \geq A_h^{min} \qquad \forall t \in \tau, \quad \forall h \in \eta \tag{6.3}$$

$$\sum_{t \in \tau_l} V_{hlt} = 1 \qquad \forall l \in \lambda, \quad \forall h \in \eta \tag{6.4}$$

$$\sum_{t \in \tau_l} t V_{hlt} \geq U_l \qquad \forall l \in \lambda, \quad \forall h \in \eta \tag{6.5}$$

$$t - U_l + 1 \leq T Y_{lt} \qquad \forall t \in \tau_l, \quad \forall l \in \lambda \tag{6.6}$$

$$\sum_{l \in \lambda} Y_{lt} \leq d \qquad \forall t \in \tau \tag{6.7}$$

$$V_{hlt}, Y_{lt} \in \{0, 1\} \qquad \forall t \in \tau, \quad \forall l \in \lambda, \quad \forall h \in \eta \tag{6.8}$$

The objective function of the OWBP is defined by Equation 6.1. The objective function minimises the range, which is the difference between the maximum and minimum workload over all time slots in each pick zone. Constraints 6.2 and 6.3 define the maximum and minimum workload over all time slots for each order pick zone. The total scheduled workload of a time slot t in a pick zone h is imposed to be smaller (greater) than or equal to the maximum (minimum) workload over all time slots of pick zone h. Constraints 6.4 assign each order set $(h;l)$ to a single time slot. The shipping dock capacity is included by Constraints 6.5 to 6.7, assuming that a shipping dock is reserved, or at least the buffer area in front of the shipping dock, from the first time slot that order sets of a shipping truck are scheduled until the shipping deadline of the truck. Constraints 6.5 define the first time slot that order sets of each shipping truck are planned among the pick zones by imposing that the first scheduled time slot of shipping truck l (represented by U_l) is smaller than or equal to the time slot that shipping truck l is scheduled in a pick zone h. Constraints 6.6 define the time slots that a shipping truck reserves a shipping dock (i.e., from time slot U_l until t_l^d): if the difference between time slot t and the first time slot a truck reserves a dock (U_l) is strictly smaller than zero, shipping truck l does not reserve a dock in time slot t (otherwise the constraints force Y_{lt} to be equal to 1). Constraints 6.7 limit the number of reserved docks to the shipping dock capacity. Finally, Constraints 6.8 define the domain of the decision variables. Note that although the domain of decision variable U_l is unrestricted, the formulation forces the U_l to be an integer value. Omitting this domain restriction reduces computation times.

6.4 Computational Experiments

In this section, experiments are performed to assess the performance of the MILP formulation. The MILP model is implemented in `C++`. To solve the MILP formulation, `ILOG Cplex 12.6` is used with a runtime limit of 4 h. `Cplex` has been running on an Intel Xeon Processor E5-2680 at 2.8 gigahertz, using a single thread, provided by the Flemish Supercomputer Center. Section 6.4.1 provides a detailed description of the problem instances that have been generated as well as the experimental design to show the potential of balancing the workload in an order picking context. Results of the experiments are discussed and analysed using ANOVA, that shows the effect of the experimental factors both on solution quality and complexity of OWBP (Section 6.4.2).

6.4.1 Problem Instances

The operational workload balancing problem aims at balancing the workload during the day in manual order picking systems. The generated input data are based on data of a real-life spare parts warehouse. First, this section describes the warehouse parameter values which are summarised in Table 6.1. Second, the factors and associated factor levels of the experiments (Table 6.2) are outlined.

The OWBP balances the workload for every time slot of the day. Parameter T represents the number of time slots and corresponding wave length for batching orders. A single time slot for every hour of the day is assumed, which results in a total of 24 time slots. This wave length results in a sufficient number of order lines per time slot facilitating the creation of efficient batches. Moreover, limiting the number of time slots to 24 allows to easily plan and control the workload during the day as supervisors can check each hour if all scheduled order sets have been retrieved. Increasing T would increase computation effort and reduce the efficiency of batches as the maximum duration for picking a batch is restricted by the length of a time slot (defined by $24/T$ h). Reducing T would decrease computation time, but also reduces control as supervisors can only check T times per day if all order sets have been retrieved.

Parameter a_l represents the number of order lines to ship in truck l. The number of order lines in a shipping truck is normally distributed with an average of 175 order lines and a standard deviation that varies by the experimental factor σ_a as discussed in Table 6.2. Order lines of a shipping truck are picked in multiple pick zones. As the assignment of SKUs to pick zones is based on product properties, we assume that the number of order lines from a shipping truck (a_{hl}) is more or less proportionally divided over the zones (H). However, a uniform distribution $U(-0.05;0.05)$ induces a slight variation in the number of order lines of each shipping truck among zones. For example, if a shipping truck contains 175 order lines, originating from two zones, the number of order lines in the first zone is $175 \times U(0.45;0.55)$ and the remaining order lines should be picked from the second zone.

Each shipping truck is characterised by a release time slot (t_l^r) and a deadline time slot (t_l^d). The release time slot and deadline time slot of a shipping truck are assigned to all order sets of this shipping truck. The release time slot of shipping truck l is uniformly distributed between 1 and $T-1$. This simulates a real-life situation for international warehouses as customers enter orders in the system from all over the world. The deadline time slot t_l^d is equal to time slot t_l^r raised with the number of available time slots to retrieve order lines from shipping truck l (t_l^p). Whenever this time slot exceeds the last time slot, t_l^d is set to time slot T. Parameter t_l^p, which provides the available number of time slots to pick order lines from shipping truck l, is uniformly distributed within the range $[\max\{0;\mu_{t^p}-2\};\mu_{t^p}+2]$, with experimental factor μ_{t^p} (Table 6.2).

Productivity values are different for each pick zone due to the specific characteristics of the products that are stored in each zone. Parameters p_h ($\forall h \in \eta$) represent the mean productivity level in pick zone h. The productivity varies over the zones without influencing the total workload (i.e., the overall mean productivity is equal to 1 irrespective of H). Values for p_h are denoted in Table 6.1.

In order to increase the practical applicability, we consider breaks that employees are allowed to take during the day. Because order pickers are unavailable during their break,

TABLE 6.1: Warehouse parameter values.

Warehouse parameter		Parameter value
Number of time slots	T	24 time slots
Number of order lines of shipping truck l	a_l	$N(175;\sigma_a)$
Number of order lines of order set $(h;l)$	a_{hl}	$a_l\left(\frac{1}{h}+U(-0.05;0.05)\right)$
Release time slot of orders in shipping truck l	t_l^r	$U(1;T-1)$
Deadline time slot of orders in shipping truck l	t_l^d	$\min\left(T;t_l^r+t_l^p\right)$
Available number of time slots to pick shipping truck l	t_l^p	$\max(U(\mu_{t^p}-2;\mu_{t^p}+2);0)$
Mean productivity in zone h	p_h	$H=1: p_1=1$
		$H=2: p_1=0.5, p_2=1.5$
		$H=3: p_1=0.5, p_2=1, p_3=1.5$

the available time to pick orders is smaller in time slots containing a break compared to regular time slots. Assuming that all pickers take a break in the same time slot, the available time to pick order lines is reduced in the time slots containing a break by including artificial order sets in proportion to the unavailable time for which $t_l^r = t_l^d$. A small break of 10 minutes is included in time slots 7, 11 and 22. A large break of 20 minutes is added to time slots 4, 14 and 20.

The experimental factor setting is outlined in Table 6.2. Factors have been selected based on preliminary tests. These tests showed that the number of shipping trucks L, order pick zones H, and shipping docks d are the most influential warehouse parameters. Additionally, two factors related to order characteristics are investigated: the variation in number of order lines between trucks (σ_a) and the mean number of available time slots to pick an order set (μ_{t^p}): the number of time slots between release and deadline time slots of a shipping truck. Factor levels have been fixed by varying the observations of the real-life case. By simulating a wide range of parameters, we aim to evaluate the behaviour of the problem.

The first factor L contains three factor levels, that varies the number of shipping trucks. The number of shipping trucks approximates the number of order sets in every zone. For example, in case of the departure of 100 shipping trucks, 100 order sets need to be planned in every zone of the warehouse, assuming that each shipping truck contains order lines in every pick zone. Factor H defines the number of pick zones, which varies from one to three zones. The third factor in the experiment is the shipping dock factor d, which is tested at three levels. The size of d is of practical relevance as this factor determines the number of shipping docks as percentage of L (i.e., buffer space before the docks) and thus limits the number of order sets of different shipping trucks that can be picked simultaneously. The fourth factor σ_a defines the variation in number of order lines for every shipping truck. The parameter value can be 50, 75 or 100 order lines, assuming a normal distribution with a mean of 175 order lines for every shipping truck. The fifth factor μ_{t^p} summarises the possibilities for the mean number of time slots between the release and deadline time slots of a shipping truck.

From Table 6.2, it can be observed that the factorial setting results in a $3 \times 3 \times 3 \times 3 \times 3$ full factorial design. To reduce the stochastic effect of data generation, each factor level combination is replicated 10 times, resulting in 2,430 problem instances. This large number of factors and wide range of factor levels allow us to evaluate and analyse the effects of the considered warehouse parameters on the ability to balance the workload and provide insights into the complexity of the operational workload balancing problem that can be easily generalised to other warehouses.

TABLE 6.2: Experimental factor setting.

Factor		Factor levels
Number of shipping trucks	L	(1) 100 trucks (2) 150 trucks (3) 200 trucks
Number of pick zones	H	(1) 1 pick zone (2) 2 pick zones (3) 3 pick zones
Number of shipping docks	d	(1) $0.10L$ docks (2) $0.15L$ docks (3) $0.20L$ docks
Variation in number of order lines for each l	σ_a	(1) 50 order lines (2) 75 order lines (3) 100 order lines
Mean number of time slots between t^r and t^d for each l	μ_{tp}	(1) 1 time slot (2) 2 time slots (3) 3 time slots

6.4.2 Results and Discussion

The operational workload balancing problem is solved using `Cplex` with a time limit of four hours for each problem instance. Due to the complex nature of the operational workload balancing problem, `Cplex` is not able to solve all instances to optimality. In total, 72.6 % of the instances have been solved to optimality within the runtime limit (i.e., 1,765 instances). Figure 6.4 shows the mean range of the instances solved to optimality per factor level, demonstrating to what extent workload balancing is possible under the different warehouse factors. Figure 6.5 illustrates the distribution of the instances not solved to optimality as well as the mean optimality gap (i.e., the percentage difference between the best found integer solution and the lower bound). This graphs illustrates the complexity of OWBP among the factors. Overall, the mean optimality gap of the 665 instances is rather small (i.e., 5.2 %), although some outliers as shown in Figure 6.6. The graph illustrates the relation between de optimality gap of instances and the corresponding objective function value of the best found feasible solution. Although a substantial number of instances could not be solved to optimality, the large majority of these instances has a very small range. This means that these solutions are balanced very well despite the optimality gap. Therefore, we included all instances in the discussion below as the non-optimal instances have only minor impact on the results.

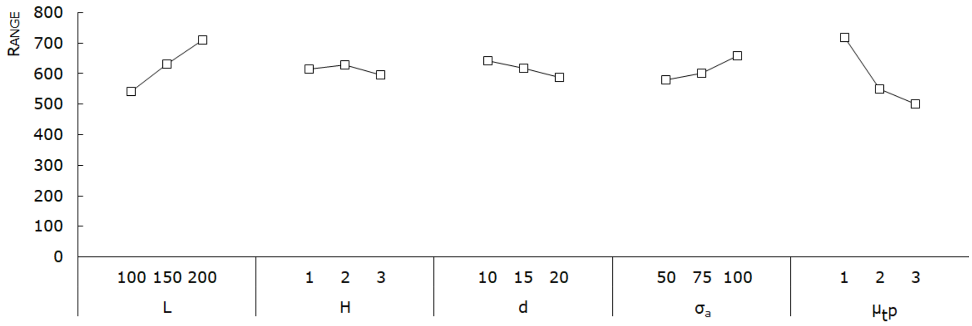


FIGURE 6.4: Mean range for solving the MIP model using `Cplex`.

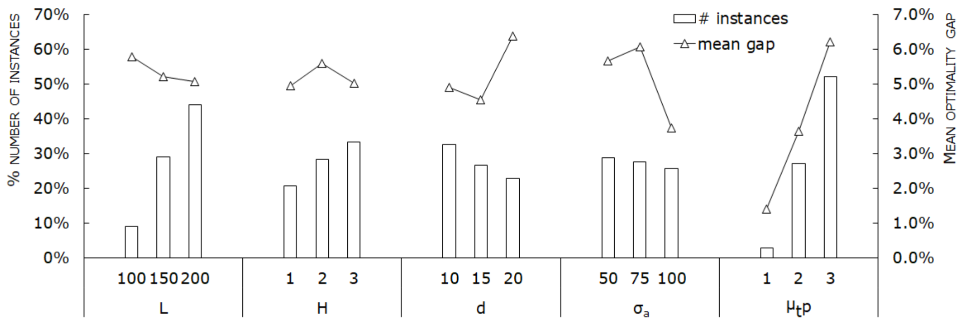


FIGURE 6.5: % number of instances not solved to optimality within the 4 h runtime limit and optimality gap (total of 810 instances per factor level).

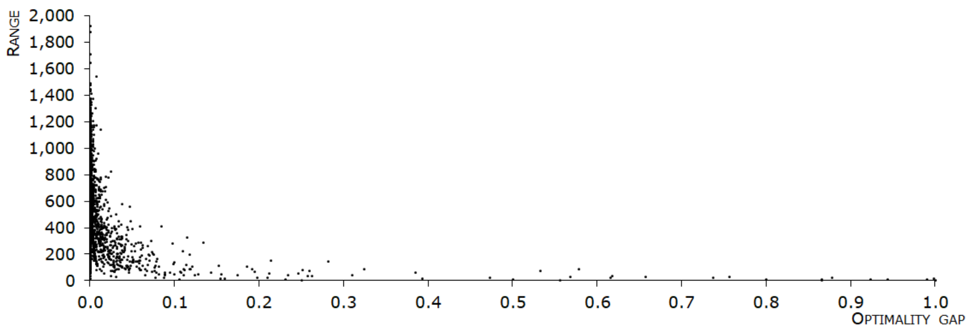


FIGURE 6.6: Relation between optimality gap and objective function value.

To support the illustrations on the figures, a balanced 3×3×3×3×3 full factorial ANOVA is performed on the mean range to get a first insight into the effects of the warehouse factors on the workload balancing problem. ANOVA is frequently used to evaluate the effect of different warehouse parameters on the performance of order picking planning problems (Petersen, 2000; Quader and Castillo-Villar, 2018; Van Gils et al., 2018c). ANOVA re-

TABLE 6.3: 3 × 3 × 3 × 3 × 3 full factorial ANOVA on range.

	Sum of squares	df	Mean square	F	p-value
Main effects					
L	1,823,014.05	2	911,507.03	12.24	0.000
H	322,899.56	2	161,449.78	2.17	0.115
d	625,725.67	2	312,862.83	4.20	0.015
σ_a	2,256,458.46	2	1,178,229.23	15.82	0.000
μ_{tp}	33,408,810.94	2	16,704,405.47	224.34	0.000
Two-way interaction effects					
$L \times H$	503,492.37	4	125,873.09	1.69	0.149
$L \times d$	106,185.63	4	26,546.41	0.36	0.840
$L \times \sigma_a$	347,932.08	4	86,983.02	1.17	0.323
$L \times \mu_{tp}$	1,108,663	4	277,166.00	3.72	0.005
$H \times d$	22,197.12	4	5,549.28	0.07	0.990
$H \times \sigma_a$	22,393.52	4	5,598.38	0.08	0.990
$H \times \mu_{tp}$	528,035.38	4	132,008.84	1.77	0.132
$d \times \sigma_a$	161,618.90	4	40,404.72	0.54	0.704
$d \times \mu_{tp}$	763,822.30	4	190,955.58	2.56	0.037
$\sigma_a \times \mu_{tp}$	267,328.46	4	66,832.12	0.90	0.464
Residuals					
Between subjects	177,137,672.47	2.379	74,458.88		
Total	219,506,250.91	2.429			

sults are shown in Table 6.3. The first three columns show the sum of squares, the degrees of freedom and the resulting mean squares for each factor and each two-way interaction among the factors, as well as for the residuals. The last two columns are devoted to the F statistic and the p-value for testing the statistical significance of the five factors and ten interaction effects. Table 6.3 indicates that the main effects of L, σ_a, and μ_{t^p} statistically significantly impact the range and resulting workload balance. Additionally, the two-way interaction effect between the number of shipping trucks and the mean number of available time slots to schedule order sets is statistically significant at a significance level of 5 %. Table 6.3, Figure 6.4 and Figure 6.5 are used in the upcoming paragraphs to analyse and explain the effects of the five experimental factors.

Number of Shipping Trucks Varying the number of shipping trucks does significantly influence the mean range. Figure 6.4 shows a slightly increasing range in case of scheduling more shipping trucks. More shipping trucks increases the probability of peaks that cannot be balanced due to restricted release and deadline time slots. This explanation additionally contributes to the explanation of the statistically significant interaction effect between the number of shipping trucks and the available number of time slots to schedule order sets: the effect of shipping trucks is larger when the release and deadline time slots are tight.

Furthermore, the complexity of OWBP strongly increases when increasing the number of shipping trucks as shown in Figure 6.5. Although more shipping trucks yields a smaller mean optimality gap, the number of instances not solved to optimality strongly increases when the number of shipping trucks is larger. More shipping trucks results in more order sets to assign to time slots, resulting in a strongly increasing solution space. This effect is shown in Figure 6.5 as well: doubling the number of shipping trucks (i.e., moving from 100 to 200 shipping trucks) increases the number of non-optimal instances by a factor four. Consequently, the number of shipping trucks is one of the main factors defining the complexity of the OWBP.

Number of Pick Zones Varying the number of order pick zones may result in significant performance benefits in terms of order picking efficiency (De Koster et al., 2012). ANOVA results show that the effect of a varying number of zones does not statistically significantly influence the mean range. Either balancing the aggregated workload in case of a single pick zone, or balancing a disaggregated workload in each pick zone does not affect the overall workload balance. Dividing the order picking area into zones does not induce additional workload imbalance, at least under the assumption that the number of order lines of a pick truck is equally divided across the pick zones. Only when some pick trucks create a large workload in a single (or a few) pick zone(s), the possibility to balance the workload may be affected by the number of zones. However, a proper storage zone assignment policy should prevent unevenly divided workloads.

The effect of factor H on the complexity of OWBP is limited. The number of order sets to schedule increases with a factor H which results in a small increased number of non-optimal instances. While zoning slightly increases the complexity of the OWBP, the operational workload imbalance (i.e., mean range) is insensitive to applying zone picking. This means that from the perspective of workload balancing, a single pick zone is favourable as this results in the smallest complexity. However, zone picking can result in significant efficiency benefits in most practical situations (e.g., reduced travel time and increased learning). These efficiency benefits may be dominant when deciding on the picker zoning policy.

Number of shipping docks Dividing the order picking area into multiple order pick zones means that order sets have to be consolidated in the staging area before the shipping truck can be loaded. A shipping dock is assigned to a particular shipping truck whenever the first order set of a shipping truck is scheduled until the shipping deadline. Whenever all shipping docks are occupied, no order sets of new shipping trucks can be scheduled. The effect of the number of shipping docks is not statistically significant. Even in case of a small number of shipping docks, the workload can be balanced effectively.

Figure 6.5 illustrates a slightly increased number of non-optimal instances in case of a smaller number of shipping docks, although the mean optimality gap strongly increases with an increased number of shipping docks. Two contradictory effects can be observed in Figure 6.5. On the one hand, solving the OWBP to optimality seems to be more difficult in case of a small number of shipping docks. Balancing over different zones is harder in this situation, as the shipping dock factor limits the number of feasible time slots to schedule order sets of the same shipping truck in different zones. On the other hand, enlarging the number of shipping docks, substantially increases the solution space, resulting in large optimality gaps of the non-optimal instances.

Variation in Number of Order Lines among Shipping Trucks The ANOVA test results (Table 6.3) show a significant effect of the variation in number of order lines among shipping trucks. Enlarging the variation in the number of order lines among trucks yields larger workload imbalances (see Figure 6.4). A large value for σ_a means that shipping trucks are very dissimilar regarding the workload, which results in a stronger imbalance in comparison to planning more similar shipping trucks. A larger variation in the number of order lines among shipping trucks results in the existence of large order sets, increasing the probability of peaks that can not be balanced. Consequently, the workload imbalance statistically significantly grows in case of strong varying shipping trucks. Therefore, in addition to other objectives (e.g., minimising transportation cost) the distribution planning department should aim to balance the workload among shipping trucks when creating a shipping schedule; a smaller variation in number of order lines among shipping trucks yields a more balanced workload during the day.

While balancing becomes more difficult, the complexity of solving the OWBP to optimality is insensitive to the variation in number of order lines among shipping trucks. Figure 6.5 shows that the number of non-optimal instances is similar for each factor level. However, the mean optimality gap strongly decreases in case of diverse shipping trucks. When the variation in number of order lines is small, symmetric solutions may exist as order sets are equal. Switching between these solutions which are characterised by the same range, seems to negatively impact the mean optimality gap. Reducing the symmetry, reduces the complexity of the problem, although the number of non-solved instances is similar.

Number of Time Slots to Schedule Order Sets The last warehouse factor turns out to be the most influential factor, both in terms of objective function and complexity. The larger the difference between deadline and release, the more planning possibilities exist for scheduling an order set. Figure 6.4 shows a strong decreasing line when increasing the mean number of time slots to schedule order sets. The earlier customers order their products, the easier a warehouse is able to balance the workload during the working day. Moreover, the balanced schedule provided by the OWBP can reveal for which customers the available number of pick time slots is too small. The distribution planning department could reconsider current shipping schedules for certain clients. Negotiations could be started on earlier order entry by the customer or delayed shipping truck departures.

Although balancing is easier with higher values of μ_{t^p}, Figure 6.5 shows that both the number of non-optimal instances and the mean optimality gaps strongly increase when the number of available time slots is large. The number of instances that could not be solved to optimality in case of $\mu_{t^p} = 3$, is seventeen times higher in comparison with the lowest factor level of μ_{t^p}. This result makes the mean number of available time slots to schedule a shipping truck the most influential factor in the experiment, both in terms of workload balance as in terms of complexity.

6.5 Managerial Implications

If peaks in workload are observed during the day, the required order throughput may exceed the capacity of the available order pickers at certain points within their shift. This results in missed departure deadlines and lower customer satisfaction. The operational workload balancing model developed in this chapter creates a more stable order picking process, which ultimately results in more efficient warehouse operations. This section discusses the practical implications of this research for warehouse managers and supervisors by showing the results of solving OWBP for a real-life case.

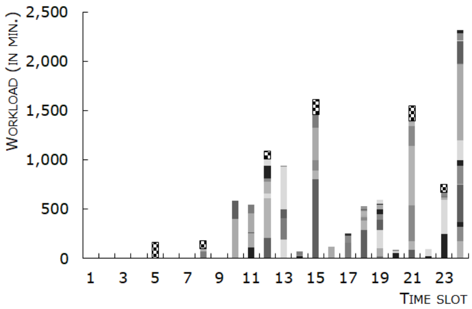
In the real-life warehouse, order pickers gradually pick orders that enter the system, with a priority given to order sets with pressing deadlines (i.e., earliest-due-time). Every day, a rough estimate is made of the total number of order lines that need to be picked the next working day, and at the same time the total number of order lines for each pick zone is guessed. The number of workers and the assignment of these workers to zones is based on individual experience and personal judgement. The earliest-due-time policy to pick orders fails to provide information about the progress of the picking process during the working day. Workload peaks are noticed too late, causing last minute assignments of employees of other warehouse activities to the order picking process. Using other warehouse employees for covering peaks in order picking workload, results in inefficiencies in the corresponding activities. Sometimes these other activities are delayed or even shut down. Workload peaks are often noticed in a late stadium and solved by increasing the number of order pickers. The increased number of pickers increases the probability of picker blocking, reducing order picking efficiency. By balancing the workload, peaks can be predicted by the model and the resulting schedule can be used by warehouse supervisors to control the order picking process. The OWBP provides an hourly schedule of orders that should be picked in a certain time slot. Supervisors can intervene when the workload in a time slot can not be completely performed.

Figure 6.7 shows the initial unbalanced workload schedule (i.e., all order sets are planned on the deadline time slot) on the left-hand side. The right-hand side of the figure illustrates the balanced workload schedule of the OWBP model for the different pick zones. Figures 6.7a, 6.7c, 6.7e, and 6.7g illustrate the most extreme case of imbalance by planning all order sets at the deadline of their respective shipping truck. The initial workload schedule shows that shipping deadlines for order sets are not equally divided over all time slots, resulting in workload peaks. In the current situation of the warehouse, these peaks are more moderate due to the gradual picking of orders with pressing deadlines (i.e., earliest-due-time). However, during certain time slots, shipping truck departures pile up. This means more deadlines need to be met and the order picking system is subject to peaks in workload.

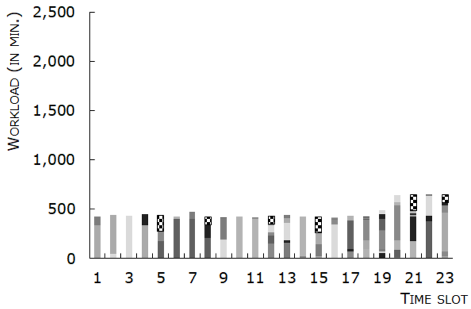
The operational workload balance model developed in this section provides a solution for above mentioned problems. Figures 6.7b, 6.7d, 6.7f and 6.7h show the balanced pick schedules created by the OWBP. Inputs for the OWBP are forecasts of the number of order lines in each order set for the following working day. Time series forecasting have proven to provide accurate forecasts in zoned warehouses. Although the previous section forecast the number of order lines on zone level, we may assume that the workload of order sets can be accurately forecast as well. This resulting balanced pick plan sets goals for picking predefined order sets in certain time slots. All orders within each time slot (or wave) can be used to create efficient batches. This way, warehouse supervisors are better prepared and can check at every moment in time when they are on schedule and if the right order sets have left the system to be loaded into the shipping truck. This solves the problem of the initial situation, were unexpected peaks occurred during the day due to unevenly divided departures of shipping trucks. Warehouse supervisors are now able to intervene timely, without disturbing other warehouse employees and processes.

Figures 6.7b, 6.7d, 6.7f and 6.7h show that further balancing by the OWBP in the latest time slots is not possible due to specific release and deadline time slots of certain shipping trucks and due to the shipping dock constraint. Whenever there are many customers allowed to enter their orders at late time slots, further balancing the workload in the evening hours becomes impossible. Warehouses can hire additional order pickers for these time slots or managers should negotiate on changes in cut-off times for customer order entry and shipping schedules to further reduce these workload imbalances. For example, managers can negotiate with certain clients to put their orders some hours earlier in the system, resulting in more available time to pick orders. If a consensus can be achieved on changing the cut-off time for order entry, the warehouse can offer price reductions to that respective customer in return. These discounts can compensate for loss in customer service (i.e., earlier order entry). By changing the cut-off times, peaks can be further balanced, resulting in a more stable process. This also results in a better utilisation rate of the order pickers, as workload is equally distributed during the day.

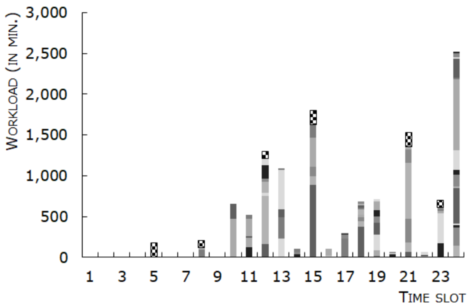
In general, balancing the workload is rather easy when the number of pick trucks is



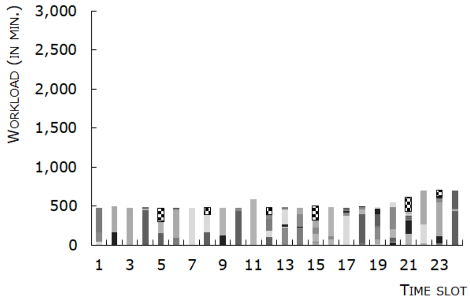
(A) initial workload schedule (zone $h = 1$).



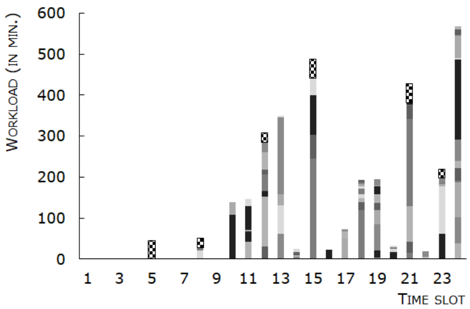
(B) balanced workload schedule (zone $h = 1$).



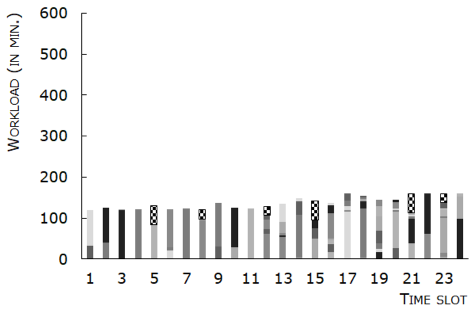
(C) initial workload schedule (zone $h = 2$).



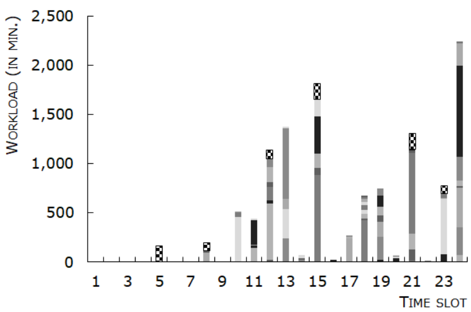
(D) balanced workload schedule (zone $h = 2$).



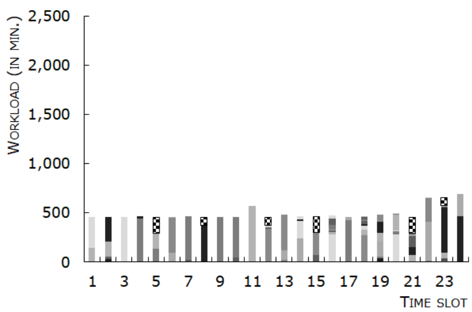
(E) initial workload schedule (zone $h = 3$).



(F) balanced workload schedule (zone $h = 3$).



(G) initial workload schedule (zone $h = 4$).



(H) balanced workload schedule (zone $h = 4$).

FIGURE 6.7: Example of the created workload schedules.

small to medium and in case of a very small mean time between release and deadline, irrespective of the number of zones, the shipping dock capacity and the variation in number of order lines among trucks. In case of an increasing number of trucks or an increasing number available time to schedule trucks, schedules are still very well balanced although the solutions are not always optimal. To further increase the applicability of the OWBP, run times to solve the problem should be further reduced. Although `Cplex` solves most instances to optimality or to a near-optimal solution, CPU times are too high to be used as daily workload scheduling tool. For long run negotiations about release and deadlines of shipping trucks, the substantial run time is less crucial.

6.6 Conclusions

Late customer order acceptance limits time windows to fulfil customer orders, causing peaks in workload during the day, resulting in extra work pressure for both warehouse supervisors and order pickers. Until now, research on how to balance the daily workload is lacking. Practitioners are searching for solutions to determine the resource capacity and allocate the available order pickers as well as to balance the workload over a short term planning horizon to increase the customer service level.

The operational workload balancing model supports and controls the order picking process by defining the workload in each time slot and in this way preventing order picking inefficiencies by last minute assignments of other warehouse employees. In combination with forecasting approaches, these decision support models are effective to solve the workforce level and allocation planning problems, making order picking operations less depending on individual experience of supervisors.

The results of solving both order picking planning problems provide insights into the required (and consequently available) resource capacity as well as the workload on each moment of the day. Moreover, in addition to the substantial effect of safety constraints, picker blocking and high-level storage locations, results of this part show that the considered workload related real-life features are essential features to cope with in practice in order to manage order picking operations. These results can be used to further optimise order picking operations, such as the order batching, picker routing and job assignment problem, as illustrated in the next part (Part IV).

PART IV

PROBLEM INTEGRATION

Chapter 7

Integrating Batching–Routing–Job Assignment

Warehouses can achieve significant efficiency benefits by considering the existing interdependencies among order picking planning problems (as shown in Part II). Moreover, the relevance and importance of considering workload related real-life features are shown in Part III. This chapter[1] provides an effective and efficient algorithm to integrate and solve three crucial operational order picking planning problems (i.e., order batching, routing, and job assignment), while additionally taking essential real-life features into account (i.e., resource constraint, due time constraints, and high-level storage systems). As the time horizon of the resulting decisions is similar, integrating these planning problems is an appropriate approach (Van Gils et al., 2018e). Order picking operations' efficiency is expected to increase by integrating and optimising the planning problems. The order batching problem is concerned with deciding on rules defining which orders to combine in a pick round. The routing decision defines the sequence of items in a pick round. The job assignment problem assigns batches to order pickers to ensure that all orders are picked before due time (Van Gils et al., 2018e). Traditionally, decisions are made sequentially: first orders are batched based on a distance or time related measure (De Koster et al., 1999; Henn and Wäscher, 2012; Pan et al., 2015), followed by routing each batch (Roodbergen and De Koster, 2001b; Theys et al., 2010; Scholz et al., 2016) and finally assigning batches to the first available order picker (Henn, 2015). Although the efficiency of these planning problems has found to be strongly interdependent (Part II), Chapter 2 shows that only a limited number of researchers integrate multi-

[1] This chapter is based on Van Gils, T., Caris, A., Ramaekers, K., Braekers, K., 2019a. Formulating and Solving the Integrated Batching, Routing, and Picker Scheduling Problem in a Real-life Spare Parts Warehouse. European Journal of Operational Research.

ple planning problems, while accounting for real-life features.

The main contributions of this chapter are as follows. First, a mathematical formulation for the new integrated batching, routing and job assignment problem is presented. Second, an efficient heuristic algorithm to solve the integrated problem is provided. Third, a real-life case demonstrates the benefits of optimizing the integrated batching, routing and job assignment problem compared to the current sequential solution of the warehouse. The case is based on an international warehouse located in Belgium that stores automotive spare parts to serve the B2B e-commerce vehicle market.

The remainder of the chapter is organised as follows. Section 7.1 introduces the problem context. Section 7.2 provides the mathematical programming model of the integrated problem. Next, a new, simple but effective iterated local search algorithm to solve the integrated problem is presented (Section 7.3) and thoroughly tested (Section 7.4). Sections 7.5 and 7.6 provide the managerial implications and concluding remarks, respectively.

7.1 Problem Introduction

By simulating existing solution policies for the picker zoning, storage location assignment, order batching and picker routing, the studies in Part II show that decisions on which policy to apply for each planning problem are highly interdependent. In addition to the strong relation, the time horizon of the batching and routing decision is similar, making the integration of both planning problems highly relevant in terms of order picking efficiency. Instead of simulating existing solution methods, a new solution method is created in this study that integrates batching and routing decisions, as well as the job assignment problem. The integrated problem of batching and routing has already been studied several times, as shown in Table 7.1. As both problems are NP-hard (Won and Olafson, 2005), metaheuristic algorithms are typically used to solve either batching, routing, or the integrated problem of batching and routing. These algorithms are able to find good solutions for the integrated batching and routing problem in small computation time, mainly for small warehouses of three to six picking aisles (Chen et al., 2015; Li et al., 2016; Ene and Öztürk, 2012), low-level storage locations (Chen et al., 2015; Scholz et al., 2017) and a single order picker (Li et al., 2016; Matusiak et al., 2014). To increase the practical relevance, solution methods that account for more real-life features are needed (Van Gils et al., 2018e).

As accuracy in delivery times is an essential performance indicator for warehouses (Wruck et al., 2017), respecting due times is a critical issue when batching orders and routing pickers (Henn and Schmid, 2013; Chen et al., 2015). This initiates an additional planning problem: the picking sequence and completion time of all batches should be determined (Chen et al., 2015). Most studies assume that all orders have the same dead-

TABLE 7.1: Studies integrating order picking planning problems (based on Van Gils et al. (2018e)).

	Batching	Routing	Job assignment	
			1 picker	> 1 picker
Won and Olafson (2005)	•	•		
Tsai et al. (2008)	•	•		
Ene and Öztürk (2012)	•	•		
Rubrico et al. (2011)	•			•
Kulak et al. (2012)	•	•		
Henn and Schmid (2013)	•		•	
Matthews and Visagie (2013)		•		•
Matusiak et al. (2014)	•	•		
Chen et al. (2015)	•	•	•	
Cheng et al. (2015)	•	•		
Henn (2015)	•			•
Li et al. (2016)	•	•		
Lin et al. (2016)	•	•		
Matusiak et al. (2017)	•			•
Menéndez et al. (2017)	•			•
Scholz et al. (2017)	•	•		•
Valle et al. (2017)	•	•		
Zhang et al. (2017)	•			•
Ardjmand et al. (2018)	•	•		•
Chabot et al. (2018)	•	•		
This chapter	•	•		•

line making batch sequences irrelevant (Ardjmand et al., 2018) or aim at minimizing total tardiness of all customer orders (i.e., the positive difference between the order due time and the batch completion time to which the order is assigned) (Chen et al., 2015; Scholz et al., 2017). Solution algorithms often provide a solution in which one or more customer orders will be picked after the picking due time, resulting in orders that miss the shipping deadline (i.e., a truck leaves at the shipping deadline) (Henn and Schmid, 2013). In practice, such solutions may not be accepted by some warehouses, as this reduces the customer service level. Rather than accepting tardiness, the number of pickers will be increased (e.g., by shifting workers from other departments) to prevent orders from being picked after due time. For example, in the context of spare parts warehouses, service levels are considered as hard constraints (Kennedy et al., 2002): the objective is to increase order picking efficiency, while maintaining a high service level to customers. Tardiness is assumed to occur only as a result of unforeseen issues (e.g., technical defects and empty storage locations), which are not considered in this study. Furthermore, customer orders have varying deadlines during the planning period (in contrast to Ardjmand et al. (2018)).

Despite the importance of human resources in the labour-intensive environment of warehouses, few articles integrate workforce related planning problems in batching and routing problems. In a single order picker system, the batch sequencing decision simply determines the sequence of picking batches (Henn and Schmid, 2013; Chen et al., 2015). In case of multiple order pickers, the job assignment problem becomes more challenging. Batches need to be additionally assigned to order pickers prior to defining the sequence of picking batches (Henn, 2015; Scholz et al., 2017; Zhang et al., 2017).

Most studies consider travelling in two dimensions (i.e., low-level storage system), while many warehouses store products on high-level storage locations (i.e., each storage rack section consists of multiple levels, requiring the pick truck to lift to reach a location). High-level storage systems strongly increase the storage capacity for a given warehouse surface (Pan et al., 2014), and these systems are especially useful when products are large such as the vehicle spare parts of our real-life case. Solution algorithms are required that account for pick truck lifting. As lifting is typically very slow compared to travelling in horizontal direction, high-level storage locations and consequently lifting strongly influence the picking efficiency (Van Gils et al., 2018e).

This study goes beyond the current academic literature by integrating batching, routing and job assignment in a multiple order picker system. To the best of our knowledge, we are the first to optimise order picking efficiency by integrating order batching, routing, and job assignment while ensuring a high customer service level. Existing assumptions, such as a single order picker (Chen et al., 2015), low-level storage locations (Ardjmand et al., 2018; Chen et al., 2015; Scholz et al., 2017), ignoring due times (Ardjmand et al., 2018) and minimizing tardiness (Chen et al., 2015; Scholz et al., 2017) are revised to increase the applicability of this study in practice. A suitable solution algorithm is provided that is able to cope with multiple pickers (i.e., resource constraint), high-level storage locations and order due times as hard constraints. The benefits of integrating batching, routing and job assignment in practice are shown by a real-life case.

7.2 Integrated Batching, Routing and Job Assignment Problem

The integrated problem of order batching, picker routing and assigning batches to order pickers is introduced in this section. Section 7.2.1 describes the problem. The mathematical model is introduced in Section 7.2.2.

7.2.1 Problem Description

The integrated batching, routing and job assignment problem (IBRJAP) can be summarised as combining a predefined set of orders into batches (i.e., batching), for each batch defining the sequence of storage locations to visit in order to retrieve all orders assigned to the batch (i.e., routing), assigning the batches to the available order pickers and sequencing the batches for each picker (i.e., job assignment). The aim of the integrated problem is to minimise the total order pick time. While most studies aim to minimise the total tardiness of all customer orders (Chen et al., 2015; Scholz et al., 2017), we include order due times as hard constraints in the model in order to guarantee a high customer service level. Each order is assigned to a shipping truck. Order due times are defined by the schedule of shipping trucks. The assignment of orders to shipping trucks as well as the shipping schedule are assumed to be fixed at an operational decision level.

The objective is to increase order picking efficiency, while avoiding tardiness of orders. From a managerial point of view, the main order picking costs are defined by the number of pickers. At the decision level of IBRJAP, the number of pickers is assumed to be constant. Batching, routing and job assignment decisions are usually made multiple times per shift when a sufficient number of orders are available, while the number of pickers has been defined based on forecasts before a shift starts (Van Gils et al., 2017c). Therefore, total order pick time is used as surrogate for order picking efficiency: a smaller total order pick time enables an earlier release of new orders resulting in more retrieved orders in a shift. Under the assumption of little idle capacity, the workload tends to be additionally balanced and the makespan tends to be small when minimizing total picking time and including order due times as hard constraints. As workload forecasts and balancing schedules (see Part III) are used to determine the required number of pickers in practice, the alignment of number of pickers and workload (i.e., little idle capacity) is a reasonable assumption.

The total order picking time consists of following three elements: travel time, search and retrieve time, and batch setup time (Van Gils et al., 2018c). The travel time is assumed to be proportional to the travel distance (either vertically or horizontally), the search and retrieve time is assumed to be directly proportional to the number of order lines in a batch, and the setup time is the fixed amount of time consumed for administrative and setup tasks for a batch. Although travel velocity, search and pick time, and setup time may differ among order pickers, for simplicity we assume the time components to be constant in the model. However, human factors could be easily incorporated by assuming picker-dependent time components (Matusiak et al., 2017).

Batches are created by merging a particular number of orders on a pick list. Each order consists of a number of order lines representing an ordered stock keeping unit (SKU). Each SKU has a unique pick location in the warehouse. In accordance with previous research, the batch capacity is expressed in number of order lines (Valle et al., 2017), assuming that sorting activities should be performed afterwards. An order can only be assigned to a single batch (i.e., order integrity) (Van Gils et al., 2016a). Each batch is assigned to a batch position of an order picker in order to define the sequence in which a picker should pick the batches assigned to him/her. Each batch can only be scheduled at one batch position and each batch position cannot consist of more than one batch of orders.

7.2.2 Mixed Integer Linear Programming Model

A mixed integer linear programming (MILP) model is developed to formulate the problem. The efficient formulation of Valle et al. (2017), describing the integrated batching and routing problem, is used as start point for the new integrated batching, routing and job assignment problem. The formulation is adapted by including the assignment of batches to order pickers, evaluating the total order pick time of each batch and including order due times as hard constraints.

Sets:

$\sigma = \{1, 2, ..., Q\}$	set of order pickers with index q.
$\pi = \{1, 2, ..., P\}$	set of batch positions of a picker with index p.
$\psi = \{0, 1, 2, ..., V\}$	set of vertices with index v (depot is 0).
$\Psi = \{\psi^1, \psi^2, ..., \psi^S\}$	set with all possible subsets of vertices $\psi^s \subset \psi \backslash 0 : \lvert\psi^s\rvert > 1$.
$\alpha = \{1, 2, ..., A\}$	set of arcs with index a connecting vertices $(v'; v'') : v', v'' \in \psi$.
$\alpha_{\psi^s} \subset \alpha$	subset of arcs with $a = (v'; v'') : v', v'' \in \psi^s$.
$\alpha_v^+ \subset \alpha$	subset of arcs ending in a vertex v.
$\alpha_v^- \subset \alpha$	subset of arcs starting in a vertex v.
$\kappa = \{1, 2, ..., K\}$	set of customer orders with index k.
$\psi_k \subset \psi$	subset of vertices that should be visited in customer order k.
$\mu = \{1, 2, ..., M\}$	set of pick aisles with index m.
$\epsilon = \{1, 2, ..., E\}$	set of cross-aisles with index e.
$\iota = \{1, 2, ..., J\}$	set of storage levels with index j.

Parameters:

o_k	number of order lines of order k.
c	batch capacity (in number of order lines).
t_a	travel time when travelling across arc a (in seconds).
t^s	batch setup time (in seconds).
t^r	search and retrieve time for visiting a storage location (in seconds).
t_k	due time of customer order k with respect to the start of the planning horizon ($t = 0$).

Decision variables:

$$X_{qpa} \quad \begin{cases} 0 & \text{arc } a \text{ is not visited by picker } q \text{ at batch position } p. \\ 1 & \text{arc } a \text{ is visited by picker } q \text{ at batch position } p. \end{cases}$$

Z_{qpv} $\begin{cases} 0 & \text{vertex } v \text{ is not visited by picker } q \text{ at batch position } p. \\ 1 & \text{vertex } v \text{ is visited by picker } q \text{ at batch position } p. \end{cases}$

R_{qpk} $\begin{cases} 0 & \text{order } k \text{ is not completed by picker } q \text{ at batch position } p. \\ 1 & \text{order } k \text{ is completed by picker } q \text{ at batch position } p. \end{cases}$

W_{qpv} number of arcs leaving vertex v (i.e., outdegree) by picker q at batch position p.

T_{qp} completion time of the batch completed by picker q at position p.

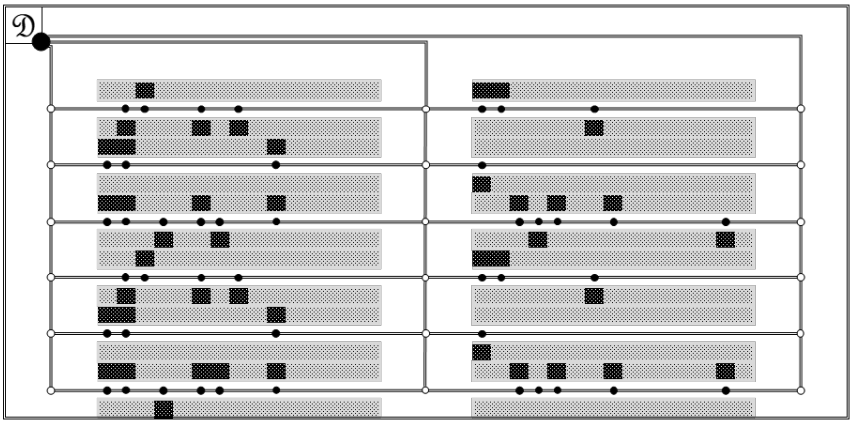


FIGURE 7.1: Directed graph of arcs and vertices representing the Steiner TSP.

The routing problem is formulated as a Steiner Travelling Salesman Problem (TSP) (Cornuéjols et al., 1985; Theys et al., 2010), as illustrated in Figure 7.1. White vertices, located at each intersection of a pick aisle and a cross-aisle, represent artificial vertices to model the warehouse. Black vertices represent the pick locations. White vertices may be visited in a pick round, while black vertices should be visited in at least one pick round (Valle et al., 2017). Arcs are used to connect the vertices: each black vertex is connected to the two neighbouring vertices within a pick aisle (either black or white), and arcs connect the neighbouring artificial vertices within a cross-aisle. Furthermore, for each cross-aisle, the closest artificial vertex with respect to the depot is connected to the depot. Compared to classical TSP formulations, the Steiner TSP has shown substantial computational improvements (Scholz et al., 2016).

To model the batching and job assignment, a set of pickers and batch positions is used. Batches are not explicitly modelled in the mathematical formulation. In this way, the number of sets is limited to four, which simplifies the notation and makes the model easier to read. As each order picker q is able to pick a single batch at each position p, each combination $(q;p)$ represents a batch in the mathematical formulation. The number of created batches (B) in the solution is equal to the number of depot visits:

$$B = \sum_{q\in\sigma}\sum_{p\in\pi} Z_{qp0} \tag{7.1}$$

In the discussion below, a batch refers to a combination of $(q;p)$. The linear MILP model can be stated as follows:

$$\min \sum_{q\in\sigma} T_{qP} \tag{7.2}$$

Subject to

$$\sum_{a\in\alpha_v^+} X_{qpa} = \sum_{a\in\alpha_v^-} X_{qpa} \tag{7.3}$$

$$\forall q\in\sigma,\quad \forall p\in\pi,\quad \forall v\in\psi$$

$$\sum_{a\in\alpha_v^-} X_{qpa} = W_{qpv} \tag{7.4}$$

$$\forall q\in\sigma,\quad \forall p\in\pi,\quad \forall v\in\psi$$

$$\sum_{v'\in\psi^s} W_{qpv'} \geq Z_{qpv} + \sum_{a\in\alpha_{\psi^s}} X_{qpa} \tag{7.5}$$

$$\forall q\in\sigma,\quad \forall p\in\pi,\quad \forall v\in\psi^s,\quad \forall \psi^s\in\Psi$$

$$X_{qpa} \leq Z_{qpv} \tag{7.6}$$

$$\forall q\in\sigma,\quad \forall p\in\pi,\quad \forall v\in\psi,\quad \forall a\in\alpha_v^-$$

$$\sum_{a\in\alpha_0^+} X_{qpa} = \sum_{a\in\alpha_0^-} X_{qpa} = Z_{qp0} \tag{7.7}$$

$$\forall q\in\sigma,\quad \forall p\in\pi,\quad \forall a\in\alpha$$

$$X_{qpa} \leq Z_{qp0} \tag{7.8}$$

$$\forall q\in\sigma,\quad \forall p\in\pi,\quad \forall a\in\alpha$$

$$R_{qpk} \leq Z_{qp0} \tag{7.9}$$

$$\forall q\in\sigma,\quad \forall p\in\pi,\quad \forall k\in\kappa$$

$$\sum_{a\in\alpha_v^-} X_{qpa} \geq R_{qpk} \tag{7.10}$$

$$\forall q\in\sigma,\quad \forall p\in\pi,\quad \forall k\in\kappa,\quad \forall v\in\psi_k$$

$$\sum_{k\in\kappa} R_{qpk} \geq Z_{qp0} \tag{7.11}$$

$$\forall q\in\sigma,\quad \forall p\in\pi$$

$$\sum_{k\in K} o_k R_{qpk} \leq c \tag{7.12}$$

$$\forall q\in\sigma,\quad \forall p\in\pi$$

$$\sum_{q\in\sigma}\sum_{p\in\pi} R_{qpk} = 1 \qquad \forall k \in \kappa \tag{7.13}$$

$$t^s Z_{qp0} + t^r \sum_{k\in\kappa} o_k R_{qpk} + \sum_{a\in\alpha} t_a X_{qpa} = T_{qp} \qquad \forall q \in \sigma, \quad p = 1 \tag{7.14}$$

$$T_{q(p-1)} + t^s Z_{qp0} + t^r \sum_{k\in\kappa} o_k R_{qpk} + \sum_{a\in\alpha} t_a X_{qpa} = T_{qp} \qquad \forall q \in \sigma, \quad \forall p \in \pi \backslash \{1\} \tag{7.15}$$

$$T_{qp} \leq t_k + \mathscr{M}(1 - R_{qpk}) \qquad \forall q \in \sigma, \quad \forall p \in \pi, \quad \forall k \in \kappa \tag{7.16}$$

$$T_{qp} \leq \mathscr{M} \sum_{k\in\kappa} R_{qpk} \qquad \forall q \in \sigma, \quad \forall p \in \pi \tag{7.17}$$

$$X_{qpa}, R_{qpk} \in \{0,1\} \qquad \forall q \in \sigma, \quad \forall p \in \pi, \quad \forall k \in \kappa, \quad \forall a \in \alpha \tag{7.18}$$

$$Z_{qpv} \in [0;1] \qquad \forall q \in \sigma, \quad \forall p \in \pi, \quad \forall v \in \psi \tag{7.19}$$

$$T_{qp} \geq 0 \qquad \forall q \in \sigma, \quad \forall p \in \pi \tag{7.20}$$

The objective function (7.2) minimises the total order pick time to retrieve all customer orders. Constraints (7.3) ensure that the number of arcs visiting a vertex v is equal to the number of arcs leaving the vertex in each batch. Constraints (7.4) define the outdegree of each vertex (i.e., the number of arcs leaving vertex v) in each batch. Constraints (7.5) avoid the creation of sub–tours in a batch: the total outdegree of a subset of vertices should be greater than or equal to the number of vertices and arcs visited in the subset. These sub–tour elimination constraints are derived from the Vehicle Routing Problem (Laporte, 1992) and provide good results in an order picking context (Valle et al., 2017). Constraints (7.6) allow vertices to be visited in a batch only when an arc starts in the vertex. The number of depot visits (i.e., vertex 0) is defined by constraints (7.7): if the depot is visited, a batch should contain an incoming and outgoing arc from the depot. Furthermore, if the depot is included in a batch, at least one arc is used in a batch or at least one order is picked in the batch, as stated by constraints (7.8) and (7.9), respectively. Constraints (7.10) ensure that vertices of orders assigned to a batch are visited by enforcing at least one outgoing arc to be used in the batch. Constraints (7.11) make sure that at least one order is assigned to the batch if the depot is visited. Constraints (7.13) ensure that the number of order lines in each batch does not exceed the batch capacity and constraints (7.12) ensure order integrity (i.e., each order is assigned to a single batch). Constraints (7.14) and (7.15) incorporate the processing time of picking a batch for the first batch position and other batch positions, respectively. Additionally, constraints (7.15) prevent overlapping batches that are assigned to the same order picker. Constraints (7.16) guarantee that all orders are picked before due time, with $\mathcal{M}$ a sufficiently large positive number ($\mathcal{M} = \max\{t_k, \forall k \in K\}$). Constraints (7.17) ensure the calculation of a completion time for all scheduled batches. The domain constraints are provided by constraints (7.18)-(7.20). Note that the formulation forces the Z_{qpv} to be binary as well.

The number of sub–tour elimination constraints (i.e., Constraints 7.5) grows exponentially with the number of vertices in the problem. Therefore, initially these constraints are removed from the formulation and a branch-and-cut procedure is employed to check each integral candidate solution on sub–tours. For each sub–tour in the candidate solution, Constraints (7.5) are included with ψ' containing only vertices of the created sub–tour. To reduce the number of created subtours, and consequent number of cuts, Valle et al. (2017) introduce a series of optimality cuts and symmetry breaking constraints which are shown to substantially reduce the computation time to find the optimal total order pick time. Hence, we adapted these inequalities to our problem setting and include these as well. The applied optimality cuts and symmetry breaking constraints are provided in Appendix F. The reader is referred to Valle et al. (2017) for an comprehensive discussion on the optimality cuts.

7.3 Iterated Local Search Algorithm for IBRJAP

Due to the complex nature of IBRJAP, solving instances of realistic size to optimality in a reasonable amount of computation time does not seem feasible. A metaheuristic algorithm, based on iterated local search, is proposed to approximate the global optimal solution. Iterated local search algorithms have proven to be efficient in optimizing order picking planning problems (Henn and Schmid, 2013; Öncan, 2015; Scholz et al., 2017; Schubert et al., 2018). Although other algorithms may be suitable and efficient to solve the IBRJAP as well (e.g., adaptive large neighbourhood search algorithms (Chabot et al., 2017; Matusiak et al., 2017)), the ILS algorithm is easy to use and understand. The aim is to provide a simple but effective ILS algorithm to solve IBRJAP.

The general principle of ILS is introduced by Lourenço et al. (2003). The main components of ILS include a procedure to generate an initial solution, a local search procedure, and a perturbation procedure. In addition to the general ILS principles, the diversification is increased by maintaining a set of six solutions S (instead of a single solution), as well as considering multiple operators during the local search procedure which is commonly applied in metaheuristic algorithms. While multi-start ILS algorithms start from a randomly constructed new solution each iteration, the solution set allows starting from varying solutions in each iteration and each starting solution is a good solution (i.e., a local optimum). Moreover, multiple local search operators increase the quality of the local search, thereby improving the local optimum, compared to a single local search operator (Sörensen and Glover, 2013).

The ILS algorithm is described in Algorithm 1. First, an initial solution s^0 is created, followed by a local search on s^0 that results in a local optimum. All solutions in S are initialised by this local optimum. Next, four steps are performed iteratively: (1) selecting a solution s^* from $S(s^1; s^2; s^{r1}; s^{r2}; s^{r3}; s^{r4})$ with probability $\Phi(\phi_1; \phi_2; \frac{\phi_3}{4}; \frac{\phi_3}{4}; \frac{\phi_3}{4}; \frac{\phi_3}{4})$, respectively, and Φ a set of algorithm parameters; (2) perturbing s^*; (3) applying local search to reach a new local optimum; (4) updating S. If this procedure results in a solution with either a reduced tardiness or a reduced total order pick time without increasing tardiness, compared to the best (s^1) or second best (s^2) solution, the solution is accepted as new best or second best solution, respectively. Otherwise, the solution is saved as one of the four random solutions (i.e., s^{r1}, s^{r2}, s^{r3}, and s^{r4}). These steps are repeated until there are ξ consecutive iterations with an improvement in total order pick time of the best solution $s^1_{picktime}$ of $\leq 0.005\%$ and a tardiness of zero in the best solution (with a maximum of 5,000 iterations). The number of consecutive iterations without improvement also determines the intensity of the perturbation (see Algorithm 5).

Algorithm 1 Iterated local search algorithm for IBRJAP

create initial solution s^0 (Algorithm 2)
local search batching and job assignment on s^0 (Algorithm 3);
local search routing on s^0 (Algorithm 4);
initialise solution set $S(s^1; s^2; s^{r1}; s^{r2}; s^{r3}; s^{r4}) = (s^0; s^0; s^0; s^0; s^0; s^0)$;
repeat
  select solution s^* from S with probability $\Phi(\phi_1; \phi_2; \frac{\phi_3}{4}; \frac{\phi_3}{4}; \frac{\phi_3}{4}; \frac{\phi_3}{4})$;
  perturbation on s^* (Algorithm 5);
  local search batching and job assignment on s^* (Algorithm 3);
  local search routing on s^* (Algorithm 4);
  if $\left(s^*_{picktime} \leq s^1_{picktime} \textbf{and} s^*_{tardiness} \leq s^1_{tardiness}\right)$ **or** $s^*_{tardiness} < s^1_{tardiness}$ **then**
    new best solution: $s^1 = s^*$;
    count the number of non-improving iterations: $I^* = 0$;
  else if $\left(s^*_{picktime} \leq s^2_{picktime} \textbf{and} s^*_{tardiness} \leq s^2_{tardiness}\right)$ **or** $s^*_{tardiness} < s^2_{tardiness}$ **then**
    new second best solution: $s^2 = s^*$;
    count the number of non-improving iterations: $I^* = \min\{10; I^* + 1\}$;
  else
    new random solution: $s^{r4} = s^{r3}$;
    new random solution: $s^{r3} = s^{r2}$;
    new random solution: $s^{r2} = s^{r1}$;
    new random solution: $s^{r1} = s^*$;
    count the number of non-improving iterations: $I^* = \min\{10; I^* + 1\}$;
  end if
until ξ iterations with improvement $\leq 0.005\%$ **and** $s^1_{tardiness} = 0$;

The generation of an initial solution is described in Algorithm 2. Initially, each order is assigned to a separate batch. Orders are sorted with respect to the due time: the customer order that should be shipped most early (co_1) is assigned to the first batch position ($p =$

Algorithm 2 Create initial solution

```
sort all customer orders with respect to due time;
initialise customer order (k = 1), position (p = 1) and picker (q = 1);
while k ≤ K do
    assign customer order co_k to position p of picker q;
    increase customer order: k = k + 1;
    increase picker: q = q + 1;
    if q > Q then
        return to the first picker: q = 1;
        increase position: p = p + 1;
    end if
end while
local search routing on s^0 (Algorithm 4);
```

1) of the first order picker ($q = 1$). The next order on the sorted list of customer orders is assigned to the first batch position of the second order picker. Once all picker's first positions are occupied, orders are assigned to the second batch positions ($p = 2$). These steps are repeated until all orders are assigned to a batch. Next, locations that should be visited to retrieve all items of a batch are sequenced by the routing algorithm, explained in Algorithm 4, to create initial routes.

The local search phase of the heuristic consists of a batching and order job assignment algorithm (Algorithm 3), and a routing algorithm (Algorithm 4). The batching and job assignment local search phase consists of four move types, adapted from Scholz et al. (2017), applied in a fixed sequence: relocating a single customer order to another batch position and/or picker (i.e., *order shift*), relocating a batch to the same batch position of another picker (i.e., *batch shift*), exchanging two customer orders from different batches (i.e., *order swap*), and exchanging all customer orders from two different batches (i.e., *batch swap*).

Batch swaps and batch shifts are performed for each batch position of each picker. The neighbourhood of the batch moves consists of all positions and all pickers to which a move results in a new solution with reduced or equal total tardiness compared to the current solution. The total order picking time remains equal by shifting and swapping entire batches. In case of tardiness in the current solution, these move types are able to move quickly to a feasible solution (i.e., $s_{tardiness} = 0$). Therefore, a batch swap and batch shift are only performed when the solution is still infeasible with respect to tardiness.

Order shift and order swap moves that result in either a reduced tardiness or a reduced total order pick time (without increasing tardiness) are accepted as new solutions. Once a solution is feasible, a reduced total order pick time is the only binding constraint for accepting new solutions. A first improving move strategy is used to select a new solution. The order shift operator is efficient with respect to computational complexity and particularly effective to reduce the order pick time by reducing the number of batches very fast. The order shift aims to shift all orders (one-by-one) of a single batch before orders of another batch are considered. Initial experiments show that the order shift operator is the most efficient and effective operator. Therefore, this operator is positioned first in the

Algorithm 3 Batching and job assignment

```
repeat
    repeat
        for all batches (q; p) do
            for all customer orders co_k ∈ (q; p) do
                for all batches (q; p)* do
                    if T_{qp*} ≤ t_k + χ or s*_{tardiness} > 0 then
                        create temporary solution: s^t = s*;
                        shift customer order co_k ∈ (q; p) to batch (q; p)* in s^t;
                        insert each order line of co_k on the cheapest position of the route in s^t;
                        if (s^t_{picktime} ≤ s*_{picktime} and s^t_{tardiness} ≤ s*_{tardiness}) or s^t_{tardiness} < s*_{tardiness} then
                            accept solution: s* = s^t;
                            break
                        end if
                    end if
                end for
            end for
        end for
    until no further improvement is possible;
    if s*_{tardiness} > 0 then
        for all batches (q; p) do
            for all batches (q; p)* do
                create temporary solution: s^t = s*;
                shift batch (q; p) to another picker q* and/or another position p* in s^t;
                if s^t_{tardiness} ≤ s*_{tardiness} then
                    accept solution: s* = s^t;
                    break
                end if
            end for
        end for
    end if
    repeat
        for all customer orders co_k ∈ κ do
            for all customer orders co_{k*} ∈ κ do
                if (T_{qp*} ≤ t_k + χ and T_{qp} ≤ t_{k*} + χ) or s*_{tardiness} > 0 then
                    create temporary solution: s^t = s*;
                    swap customer order co_k ∈ (q; p) and an order co_{k*} ∈ (q; p)* in s^t;
                    insert each order line of co_k on the cheapest position of the route of (q; p)*;
                    insert each order line of co_{k*} on the cheapest position of the route of (q; p);
                    if (s^t_{picktime} ≤ s*_{picktime} and s^t_{tardiness} ≤ s*_{tardiness}) or s^t_{tardiness} < s*_{tardiness} then
                        accept solution: s* = s^t;
                        break
                    end if
                end if
            end for
        end for
    until no further improvement is possible;
    if s*_{tardiness} > 0 then
        for all batches (q; p) do
            for all batches (q; p)* do
                create temporary solution: s^t = s*;
                swap batch (q; p) and batch (q; p)* in temporary solution s^t;
                if s^t_{tardiness} ≤ s*_{tardiness} then
                    accept solution: s* = s^t;
                    break
                end if
            end for
        end for
    end if
until no further improvement is possible;
```

local search algorithm. Whereas the effectiveness of the shift operator strongly decreases in case of fully loaded batches, the order swap operator can further decrease order pick times by switching two orders of different batches, at the cost of additional computational complexity. To prevent order shifts or order swaps that will probably be rejected because of tardiness, the completion time of a batch is compared to the order due times of the order(s) considered in the move before the move is performed. Parameter χ is defined as the maximum difference between the current batch completion time and the order due time for a move to be considered (i.e., $T_{qp^*} \leq t_k + \chi$). The order shift and order swap moves are repeated until no further improvement is possible. Note that there is no explicit repair method in the move operators for solutions with tardiness: the move operators create highly efficient batches with respect to travelling and batches are filled to capacity. In this way travel time and setup time are small, reducing the probability of tardiness.

Algorithm 4 Routing

```
for all pickers q ∈ σ do
    for all positions p ∈ π do
        if number of locations to visit in batch (q; p) ≤ 8 then
            calculate exact route length of batch (q; p);
        else
            LKH-routing of batch (q; p);
        end if
    end for
end for
```

The routing algorithm minimises the order picker travel distance by sequencing items in a batch. Only for a small number of locations to be visited, an optimal route can be calculated in reasonable computing times. The Lin–Kernighan–Helsgaun (LKH) heuristic (Helsgaun, 2000) for the TSP is used as alternative to approximate the optimal route length (Theys et al., 2010). Pretests of our algorithm showed that calculating the optimal route length by enumerating all feasible solutions is faster compared to executing the LKH-routing heuristic if the number of storage locations to visit in a batch is smaller than or equal to eight locations, including the depot. For all other batches, the routing problem is solved by the LKH heuristic. The same settings for the LKH heuristic as in Theys et al. (2010) are used.

Applying Algorithms 3 and 4 results in a local optimum. To escape from this local optimum, a large change (i.e., perturbation) is performed to a solution included in solution set Φ. The perturbation of the ILS algorithm consists of splitting I batches: in each of the I perturbation iterations a random number of orders from an existing batch are assigned to a new batch, created at a random position of a random order picker. After the creation of a new batch, the local search routing algorithm is performed to sequence the locations in the initial batch as well as the new batch. A perturbation iteration is repeated (for at most 50 times), starting from the current solution, if the tardiness of the perturbed solution is larger than the tardiness of the current solution. The perturbation intensity (i.e.,

Algorithm 5 Perturbation

for $it = 1$ **to** I **do**
  Initialise count variable: $a = 0$;
  repeat
    $s^t = s^*$;
    choose a random batch $(q; p)$ in s^t;
    choose a random number of orders $k^* \in [1; \sum_{k \in \kappa} R_{qpk}]$ to shift;
    shift k^* orders from $(q; p)$ to a new batch $(q; p)^*$ in s^t;
    local search routing of $(q; p)$ on s^t (Algorithm 4);
    local search routing of $(q; p)^*$ on s^t (Algorithm 4);
    count perturbation attempts: $a = a + 1$
  until $s^t_{tardiness} \leq s^*_{tardiness}$ **or** $a > 50$
  if $a \leq 50$ **then**
    accept solution: $s^* = s^t$;
  end if
  increase iterator: $it = it + 1$;
end for

the number of split batches) depends on the last found best solution and is defined as $I = \lceil \zeta \times B \times I^* \rceil$, with ζ a parameter and I^* calculated in Algorithm 1.

7.4 Computational Experiments

To assess the performance of the proposed ILS algorithm, a series of numerical experiments is performed. All algorithms are implemented in `C++`. To solve the MILP formulation, `ILOG Cplex 12.7` is used with a runtime limit of 4 h. In accordance with Valle et al. (2017), branching priority is given to R_{qpk}. Other parameter settings are left as default as these parameters have minor impact. `Cplex` and ILS are run on an Intel Xeon Processor E5-2680 at 2.8 gigahertz, using a single thread, provided by the Flemish Supercomputer Center.

The properties of the problem instances are introduced in Section 7.4.1 and algorithm parameters are tuned in Section 7.4.2. First, the ILS algorithm is tested on small problem instances. Results are compared with the optimal solutions of the MILP formulation (Section 7.4.3). In a second experimental design (Section 7.4.4), the ILS algorithm is performed on a set of large problem instances to demonstrate its applicability in practice and analyse the effects of different warehouse parameters. Finally, a real-life case is used in Section 7.4.5 to show the real-life benefits of optimizing IBRJAP.

7.4.1 Problem Instances

The problem parameters in this chapter are similar as the generalised experiments in Chapter 3. Table 7.2 summarises the warehouse layout parameters and the time components of the picking operation. Picking aisles are two-sided and wide enough for two-way travel: the effect of picker blocking is assumed to be negligibly small. In addition to the parameters in Chapter 3, time related parameters are included.

TABLE 7.2: Warehouse parameter values.

Warehouse parameter		Parameter value *Small instances*	*Large instances*
Depot location	$\mathscr{D}$	single decentralised depot	single decentralised depot
Number of blocks	$E-1$	2 blocks	2 blocks
Number of cross-aisles	E	3 cross-aisles	3 cross-aisles
Number of pick aisles	M	*	*
Number of storage rack sections	L	*	*
Number of levels	J	1 level per storage rack	1 level per storage rack
Storage rack section length	l_{length}	1.3 m	1.3 m
Storage rack section width	l_{width}	0.9 m	0.9 m
Pick aisle width	m_{width}	3.0 m	3.0 m
Cross-aisle width	e_{width}	6.0 m	6.0 m
Picker travel velocity	v	$\frac{1}{3}$ m/s	1 m/s
Travel time for arc a	t_a	$\frac{d_a}{v}$ s	$\frac{d_a}{v}$ s
Setup time	t^s	540 s	180 s
Search and retrieve time	t^r	30 s	10 s
Planning period	t^{pp}	4 h	4 h

* Experimental design parameter (see Table 7.3).

TABLE 7.3: Experimental factor setting.

Factor		Factor levels *Small instances*	*Large instances*
Layout	(1)	6×60 locations	6×60 locations
	(2)	12×120 locations	12×120 locations
	(3)	18×180 locations	18×180 locations
Storage policy	(1)	random (Ran)	random (Ran)
	(2)	within-aisle (WA)	within-aisle (WA)
	(3)	across-aisle (AA)	across-aisle (AA)
Batch capacity	(1)	4 order lines	15 order lines
	(2)	8 order lines	30 order lines
	(3)	12 order lines	45 order lines
Order structure[a]	(1)	18 orders ($\beta = \frac{4}{3}$)	300 orders ($\beta = \frac{8}{3}$)
	(2)	12 orders ($\beta = 2$)	200 orders ($\beta = 4$)
	(3)	6 orders ($\beta = 4$)	100 orders ($\beta = 8$)
Due time distribution[b]	(1)	uniform (Uni)	uniform (Uni)
	(2)	progressive ($Prog$)	progressive ($Prog$)
	(3)	degressive (Deg)	degressive (Deg)

[a] The number of order lines for each order is generated using following formula: $\min(c; \lfloor Exp(\beta) + 0.5 \rfloor)$, with $Exp(\beta)$ an exponential distribution with mean β.
[b] The uniform due time distribution corresponds to U(1.0; $t_{picking}$), progressive and degressive due time distributions are approximated by triangular distributions as follows: TRIA(1.0; 3.0; $t_{picking}$) and TRIA(1.0; 1.5; $t_{picking}$), respectively.

The heuristic algorithm is tested for a wide range of warehouse parameters. Three layouts, three storage location assignment policies, three batch capacity levels, three different order structures, as well as a varying distribution of due times among orders are included in the experimental design. The five factors and their associated factor levels are summarised in Table 7.3.

The two-block warehouse layout differs in number of aisles, as well as number of storage location per aisle. The layout varies between 360 (6 aisles × 60 locations per aisle × 1 level) and 3,240 (18 aisles × 180 locations per aisle × 1 level) storage locations. An example of the smallest order picking layout is illustrated in Figure 7.1. Other layouts are equivalent. Note that the MILP model and optimality cuts provided in Appendix F are only valid if following assumption is fulfilled: $t_{a_1} = t_{a_2} + t_{a_3}$ with $a_1 = (v_1; v_3), a_2 = (v_1; v_2), a_3 = (v_2; v_3)$. This is only true in case of a linear distance approximation function (e.g., rectilinear distance metric), which is the case for low-level storage systems. In case of high-level storage systems, the Chebychev distance metric includes vertical travel as follows: the travel time between two vertices equals the maximum of the horizontal travel time and lifting time (Clark and Meller, 2013). Consequently, the number of arcs increases tremendously compared to the general Steiner TSP formulation as all vertices within a pick aisle need to be connected by arcs, making the MILP model too hard to solve even for very small instances. Therefore, the performance of the ILS algorithm is compared with the MILP model for a low-level storage system ($J = 1$) in the experimental design. In the real-life case, high-level storage locations are taken into account.

Besides randomly assigning SKUs to storage locations, a within-aisle as well as an across-aisle storage location assignment policy are tested. SKUs are grouped into classes in such a way that class A contains $\frac{1}{6}$ of the SKUs stored in the warehouse. These SKUs account for 60% of the picking activity. Class B and class C contain $\frac{1}{3}$ and $\frac{1}{2}$ of the storage locations and account for 30% and 10% of the order frequency, respectively. From the problem formulation, the complexity of the integrated batching, routing and job assignment problem seems to be independent of the layout and storage policy. Therefore, small and larger instances are tested on the same factor levels with regard to layout and storage policy.

Batch capacity and order structure impact the number of created batches and consequently the complexity of the planning problem, as shown in the formulation. Different factor levels for small and large instances are considered during the analysis, as shown in Table 7.3. Finally, the due time distribution factor describes the distribution of due times of customer orders. The complexity of the planning problem seems to be independent from this factor. Besides a uniform distribution over the planning period t^{pp}, a progressive and a degressive due time distribution are considered. For the progressive distribution most orders are picked at the end of the planning period. In a degressive situation, most orders have a due time in the first time intervals.

This factorial setting results in a $3 \times 3 \times 3 \times 3 \times 3$ full factorial design. Among the 243 possible factor combinations, thirty large instances (i.e., test instances) are randomly selected to derive the relation between the required number of order pickers and the properties of the warehouse. The required number of order pickers may be predicted based on demand forecasts (Van Gils et al., 2017c). Consequently, the number of order pickers is included as a warehouse parameter and assumed to be fixed and known when orders are being batched. As the productivity of order pickers strongly depends on the warehouse parameters, such as layout and batch capacity, the number of order pickers will be derived from the experimental factor levels for the large instances. The following procedure is used to define the required number of pickers for the test instances: each instance is solved using the heuristic with $Q = 10$ order pickers, next the instance is resolved with $Q = 9$ pickers, and so on. The procedure stops when the heuristic provides a solution with tardiness and the required number of pickers for a test instance is defined as $Q' + 1$, with Q' the last value of Q. Using a regression analysis on these results, layout, batch capacity, order structure and due time distribution are proven to be statistically significantly related with the required number of order pickers ($R^2_{adjusted} = 0.987$). The regression coefficients to define the number of order pickers for each factor level combination are as follows $Q^* = \lceil 1.20\left(0.254M + 0.006O - 0.072c + 1.383Deg\right)\rceil$ with O the number of order lines. Note that the number of pickers for each instance is increased with 20% to ensure that the number of pickers is large enough to prevent tardiness in all large instances.

Without loss of generality, the number of pickers is fixed at 2 for the small benchmark instances. Moreover, for running the MILP model, the parameter P, describing the number of batch positions, should be defined. For simplicity, P is set large enough by fixing it at $\left\lceil \frac{K}{Q} \right\rceil$. A more complex upper bound for parameter P could slightly improve the computational efficiency. However, as the MILP model is only used as benchmark, this upper bound provides acceptable solutions to evaluate the solution quality of the ILS heuristic. Note that with respect to the ILS algorithm, only parameter Q is relevant as batch positions can easily be created and removed during computation.

7.4.2 Parameter Tuning

Tuning algorithm parameters may result in significant performance benefits of the tested algorithm (Pellegrini and Birattari, 2011). With respect to the ILS algorithm, parameter tuning is performed on the set of thirty randomly selected test instances. Table 7.4 introduces the experimental design that is used to tune the three algorithm parameters: ξ (i.e., parameter defining the algorithm stop criterion), (ϕ_1;ϕ_2;ϕ_3) (i.e., parameters defining which solution is selected in each iteration), and ζ (i.e., parameter defining the intensity of the perturbation). Pretests of the ILS algorithm were performed to select these factors and fix the factor levels. Note that χ (i.e., parameter limiting the moves in the local search) is not included in the experiments as χ is not related to other algorithm parameters. Based on pretests, the parameter value is fixed at 1 h, meaning that only moves are tested for which the difference between the batch completion time and the order due time is smaller or equal than 1 h. This value is large enough in order not to exclude promising moves and small enough to prevent a large number of non-promising moves, probably resulting in tardiness.

Each factor level combination is tested on all thirty test instances. Five replications per factor level combination are performed. Consequently, the $4 \times 4 \times 7$ factorial design results in 16,800 observations. Figure 7.2 shows the results of the parameter tuning pro-

TABLE 7.4: Experimental factor setting to tune the ILS algorithm.

Factor	Factor levels	
ξ (Algorithm 1)	(1)	100
	(2)	200
	(3)	300
	(4)	400
$(\phi_1;\phi_2;\phi_3)$ (Algorithm 1)	(1)	$(1;0;0)$
	(2)	$(\frac{1}{2};\frac{1}{6};\frac{1}{3})$
	(3)	$(\frac{1}{3};\frac{1}{3};\frac{1}{3})$
	(4)	$(\frac{1}{3};\frac{1}{6};\frac{1}{2})$
ζ (Algorithm 5)	(1)	0.000
	(2)	0.005
	(3)	0.010
	(4)	0.015
	(5)	0.020
	(6)	0.025
	(7)	0.030

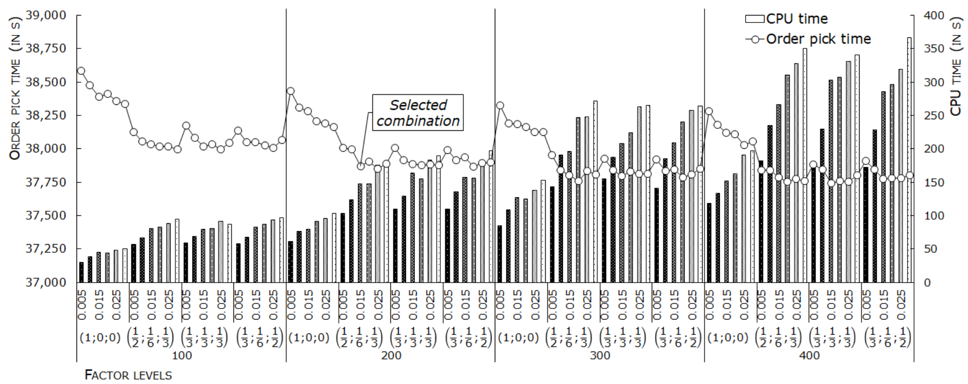


FIGURE 7.2: Comparison of average total order pick time and CPU time per factor level combination.

cedure. Both the average total order picking time and the average CPU time for each factor level combination are illustrated on the graph. Due to the bad performance of $\zeta = 0$ (i.e., no perturbation), this factor level is removed from the graph for visibility reasons.

Computation time increases about linearly with increasing values of ξ. Total order pick time is strongly reduced as ξ is increased from 100 to 200. Further increasing ξ has a much weaker effect on pick time. Therefore, 200 non-improving iterations as stop criterion seems a good compromise between computation time and solution quality. CPU time increases when intensifying the perturbation, while the total order pick time turns out to be minimal with medium values of ζ. Therefore, ζ is set at 0.015. Finally, $(\phi_1;\phi_2;\phi_3)$ seem to have little effect on both solution quality and CPU time, except for the first factor level that shows an increased order pick time, demonstrating the positive effect of maintaining a solution pool. As the number of iterations in the algorithm is large, the impact of the probability values for choosing a solution from the solution pool is negligible. The

TABLE 7.5: Optimality gap after solving the MILP model.

		Instances		Optimality gap (in %)		
		#	%	*Min.*	*Mean*	*Max.*
Layout	6×60	289	35.7	0.2	13.7	38.9
	12×120	325	40.1	0.9	17.5	50.7
	18×180	373	46.0	0.6	17.2	48.7
Storage policy	Ran	352	43.5	0.2	16.4	45.2
	WA	335	41.4	0.6	16.8	50.7
	AA	300	37.0	0.9	15.4	48.7
Batch capacity	4	487	60.1	0.2	19.8	50.7
	8	328	40.5	0.6	14.9	40.2
	12	172	21.2	0.8	9.5	25.8
Order struct.	18	685	84.6	0.9	18.6	50.7
	12	302	37.3	0.2	11.5	38.4
	6	0	0.0	-	-	-
Due time distr.	Uni	328	40.5	0.6	16.5	50.7
	$Prog$	337	41.6	0.9	16.5	48.7
	Deg	322	39.8	0.2	15.4	43.0
Total		987	40.6	0.2	16.2	50.7

values of $(\phi_1;\phi_2;\phi_3)$ are fixed at the second factor level: $\left(\frac{1}{2};\frac{1}{6};\frac{1}{3}\right)$.

7.4.3 Comparison between Exact Algorithm and ILS Algorithm

To assess the performance of the proposed algorithm, its results are compared with the optimal solutions obtained by solving the MILP model with `Cplex`. Due to the complex nature of the integrated problem, `Cplex` is only able to solve small instances, i.e., a small batch capacity and a limited number of customer orders, in reasonable computing times. Ten order lists are generated for each factor level combination of the factorial design (see Table 7.3) in order to reduce the stochastic effect of order generation. This setting results in 2,430 small instances.

Table 7.5 shows the results of solving the MILP model using `Cplex`. For each factor level, the number of observations that have not been solved to optimality by `Cplex` within the run time limit of 4 h is given. In total, 40.6 % instances (987 out of 2,430) have not been solved to optimality. Among these, for 84 instances no feasible integer solution has been formed. The right-hand side of the table presents the minimum, mean and maximum optimality gap of the non-optimal instances for which a feasible integer solution was found (i.e., 903 instances). Layout, storage policy, and due time distribution have a limited effect on the number of non-optimal solutions. Non-optimal solutions are strongly concentrated in the two smallest batch capacity levels and the largest order structure level. These levels result in a large number of batches and increase the number of feasible solutions. Overall, the mean optimality gap of the instances (i.e., 16.2 %) is rather high, even for these small problem sizes. This demonstrates the complexity of the problem.

To assess the ILS performance, the total order pick time of ILS is compared to the optimal solution. The instances for which no feasible integer solution could be obtained

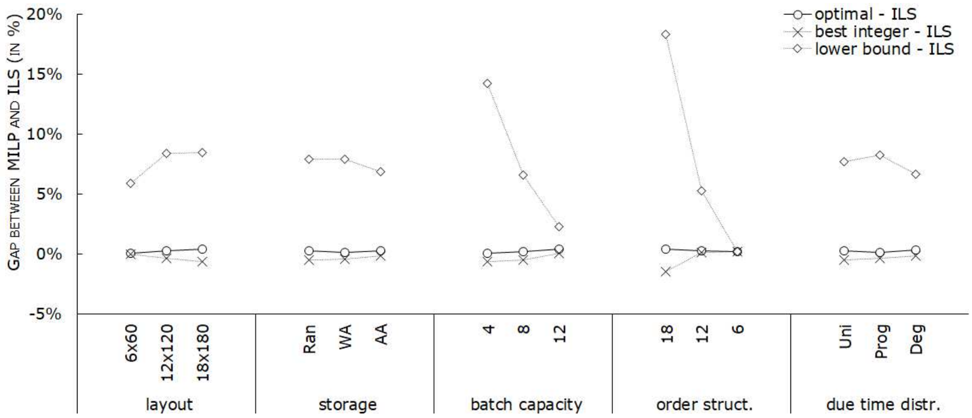


FIGURE 7.3: Percentage gap in order picking time between ILS and MILP for small problems.

by Cplex have been excluded from the analysis. From the 1,443 instances that could be solved to optimality using Cplex, the ILS algorithm is able to provide this optimal solution for 86.9 % of the instances in a single run per instance. The remaining 189 instances yield a mean gap between the ILS solution and the optimal order pick time of only 1.74 %. Figure 7.3 provides an overview of the performance of the ILS algorithm with respect to the total order picking time. The solid line on the graph illustrates the average gap between the optimal solution and the ILS objective function value for 1,443 instances solved to optimality by Cplex, while the other two lines compare the ILS solution to the lower bound and best MILP integer solution for all 2,346 instances for which Cplex finds a feasible solution within the run time limit. The size of the optimality gaps is rather equally distributed across the factor levels. With respect to the lower bound, gaps are substantial, at least for the factor levels with a high number of non-optimal instances (i.e., small batch capacity and a large number of orders). This can be explained by the large gaps between Cplex' best integer solution and corresponding lower bound. In general, the ILS algorithm is providing equal or even smaller order pick times compared to Cplex' best integer solution. To conclude, this analysis indicates that the ILS algorithm is able to effectively solve the integrated batching, routing and job assignment problem, at least for small problem sizes.

In order to evaluate the efficiency of the ILS algorithm, the computation times of the ILS algorithm are compared with the computation times for solving the MILP model with Cplex (Figure 7.4). Computation times decrease substantially when the problem is solved by the ILS algorithm. Furthermore, computation times of both approaches are rather insensitive to the order picking layout, storage policy and due time distribution of orders. With respect to the order structure, computation times strongly increase as the number of

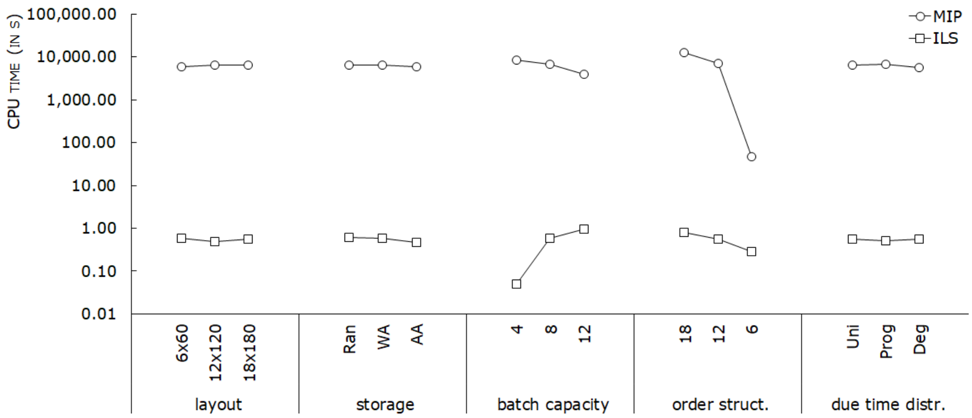


FIGURE 7.4: CPU time (in s) of MILP and ILS for small problems.

orders increases. Contradicting effects can be observed for the MILP model and the ILS algorithm with respect to the batch capacity factor. Computation times of the heuristic algorithm are mainly defined by the complexity of the routing problem. An increasing batch capacity results in more complex TSPs and thus increasing CPU times, whereas computation times of solving the MILP model are mainly defined by the number of created batches. Results show that the ILS algorithm is an efficient tool for solving the integrated batching, routing and job assignment problem, at least for small instances.

7.4.4 Analysis of the ILS Algorithm for Large Problems

This section shows the performance of the ILS algorithm with respect to practically relevant problem sizes. Thirty order lists are generated for each factor level combination (see Table 7.3). A single ILS run is performed on each of the 7,290 resulting instances. Additionally, a full factorial ANOVA is presented to analyse the effect of the experimental factors on the order pick time and CPU time of the ILS algorithm. Tables 7.6 and 7.7 show the statistical significance of the different factors on total order pick time as well as CPU time, respectively. The graph of Figure 7.5 illustrates the average order pick time and mean CPU time for each factor level.

With respect to the order picking layout, the order pick time increases linearly with increasing number of aisles and storage locations as the travel distance of order pickers rises. The computation time for running the ILS rises slightly when enlarging the order picking area. As more storage locations (and more SKUs) are included, while the number of order lines remains equal, the similarity of orders decreases (i.e., the probability of equal locations in multiple orders decreases), resulting in increasing computation times.

Given the position of the depot and the location of the pick aisles, the within-aisle and across-aisle storage policies yield the smallest average order pick time. When designing

TABLE 7.6: 3 ×3 ×3 ×3 ×3 full factorial ANOVA on average order pick time.

	Sum of squares	df	Mean square	F	p-value
Main effects					
Layout	912,819,618,087	2	456,409,809,043	43,780.31	0.000
Storage	58,916,943,244	2	29,458,471,622	2,825.75	0.000
Batch capacity	475,507,803,914	2	237,753,901,957	22,806.13	0.000
Order struct.	6,243,561,363	2	3,117,280,681	299.02	0.000
Due time distr.	332,652,634	2	166,326,317	15,95	0.000
Two-way interaction					
Layout × storage	15,022,966,698	4	3,755,741,674	360.26	0.000
Layout × batch capacity	21,362,500,968	4	5,340,625,242	512.29	0.000
Layout × order struct.	640,314,732	4	160,078,683	15.36	0.000
Layout × due time distr.	215,727,537	4	53,931,884	5.17	0.000
Storage × batch capacity	426,029,184	4	106,507,296	10.22	0.000
Storage × order struct.	253,013,230	4	63,253,308	6.07	0.000
Storage × due time distr.	21,315,277	4	5,328,819	0.51	0.728
Batch capacity × order struct.	25,553,283,352	4	6,388,320,838	612.79	0.000
Batch capacity × due time distr.	41,810,928	4	10,452,732	1.00	0.405
Order struct. × due time distr.	38,378,577	4	9,594,644	0.92	0.451
Residuals					
Between subjects	75,466,590.370	7,239	10,425,002		
Total	1,592,862,510,095	7,289			

TABLE 7.7: 3 ×3 ×3 ×3 ×3 full factorial ANOVA on CPU time.

	Sum of squares	df	Mean square	F	p-value
Main effects					
Layout	103,129	2	51,565	13.01	0.000
Storage	928,521	2	464,261	117.12	0.000
Batch capacity	13,049,663	2	6,524,832	1,646.08	0.000
Order struct.	26,607,029	2	13,303,514	3,356.20	0.000
Due time distr.	1,059,850	2	529,925	133.69	0.000
Two-way interaction					
Layout × storage	224,468	4	56,117	14.16	0.000
Layout × batch capacity	267,300	4	66,825	16.86	0.000
Layout × order struct.	236,227	4	59,057	14.90	0.000
Layout × due time distr.	55,270	4	13,818	3.49	0.008
Storage × batch capacity	275,010	4	68,753	17.34	0.000
Storage × order struct.	444,193	4	111,048	28.02	0.000
Storage × due time distr.	58,342	4	14,585	3.68	0.005
Batch capacity × order struct.	2,147,753	4	536,938	135.46	0.000
Batch capacity × due time distr.	84,043	4	21,011	5.30	0.000
Order struct. × due time distr.	446,724	4	111,681	28.17	0.000
Residuals					
Between subjects	28,694,378	7,239	3,964		
Total	74,701,900	7,289			

order picking systems, the choice of the storage location assignment policy may yield significant performance benefits. Even in case of optimal order batching, routing and job assignment, order picking efficiency can be statistically significantly increased by choosing the right storage policy. On average, a reduction of 14 % (i.e., 1.7 hours in the four hour planning period) can be achieved by within-aisle storage classes, compared to random storage. The effect on CPU time is only minor, except for the slightly increased computation time in case of across-aisle storage location assignment.

A strong and statistically significant negative relation can be observed between batch

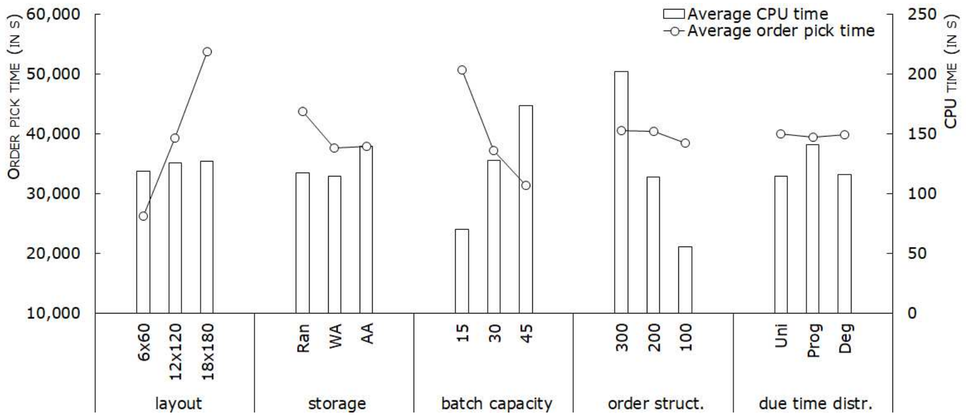


FIGURE 7.5: Order pick time and CPU time (in s) of ILS algorithm for large problems.

capacity and order pick time. Batching more order lines in a single pick round significantly reduces travelling and setup time, resulting in a substantially lower order pick time. On the other hand, increasing batch capacity leads to a larger number of storage locations to be visited in each pick round. This complicates the routing problems, increasing CPU time of the ILS algorithm.

Figure 7.5 indicates a small statistically significant effect of the order structure level on average total order pick time. As more orders should be picked, average pick time increases slightly. However, the order structure does substantially influence the CPU time of the algorithm. A larger number of small orders increases the complexity as the neighbourhood size of the local search increases. Small orders facilitate shifting and swapping of orders, because of a decreasing probability of violating the batch capacity. Within each local search iteration, a larger number of order shifts and order swaps are tested, resulting in a strongly increased CPU time.

Finally, both average order pick time and CPU time are slightly depending on the due time distribution of orders. This small effect can be explained by the large number of orders that is included in the experiments, which facilitates combining similar orders in terms of SKUs. So, even with tight due times (i.e., degressive), the ILS algorithm is able to organise order picking operations efficiently. This means that the ILS algorithm can easily handle the arrival of new orders. As computation times are small enough, even if due times are tight, the initial schedule can be revised in case of the arrival of a significant amount of new orders during the planned period, which allows to use the ILS in a dynamic setting as well.

In summary, the findings show that the proposed heuristic is able to find good solutions in reasonable computation times for problems of realistic size. The mean CPU time is less than four minutes (124 s). The proposed algorithm yields good performances for a

TABLE 7.8: Warehouse parameter values of the real-life case.

Warehouse parameter	Parameter value	
Depot location	$\mathscr{D}$	single decentralised depot
Number of blocks	$E+1$	3 blocks
Number of cross-aisles	E	2 cross-aisles
Number of pick aisles	M	11 pick aisles per block
Number of storage rack sections		
West warehouse block	L_1	16 rack sections per pick aisle
Center warehouse block	L_2	33 rack sections per pick aisle
East warehouse block	L_3	25 rack sections per pick aisle
Number of levels	J	7 levels per storage rack
Storage rack section length	l_{length}	0.9 m
Storage rack section width	l_{width}	0.9 m
Storage rack section height	l_{height}	1.0 m
Pick aisle width	m_{width}	1.5 m
Cross-aisle width	e_{width}	6.0 m
Picker travel velocity	v	1.0 m/s
Picker lifting velocity	v_{lift}	0.2 m/s
Travel time for arc a	t_a	$\max\left\{\frac{d_a}{v}; \frac{jl_{height}}{v_{lift}}\right\}$ s
Setup time	t^s	187 s
Search and retrieve time	t^r	33 s
Planning period	t^{pp}	4 h
Number of pickers	Q	6 to 8 order pickers
Batch capacity	c	13 order lines
Order structure	K	200 orders
	β	4 order lines

wide range of realistic warehouse factors.

7.4.5 Analysis of the ILS Algorithm for a Real-life Case

In order to show the benefits of integrating batching, routing, and job assignment in a real-life situation, the IBRJAP is solved for a real-life case. Real-life data of a warehouse storing automotive spare parts are used to compare the performance of the ILS algorithm to the current operation of the warehouse (i.e., earliest due time (EDT) batching, return routing, batch assignment to the first available picker).

The experiments in this section focus on the order pick zone that stores the automotive spare parts that are ordered on-line. Order picking operations are performed 24 hours a day, divided into three 8 h shifts. As time windows for picking e-commerce orders are tight, orders are released multiple times during the day by supervisors. To simulate this order release mechanism, we assume a planning period of 4 h, meaning that during each release, the set of orders whose due time is within the next four hours are released. We simulate a high demand during each release, consisting of 200 orders. Due times of orders are approximated by an empirical distribution based on historical data of two weeks. Historical data are also used to set the other warehouse parameters, as summarised in Table 7.8.

The layout of the order pick zone is shown in Figure 7.6. Arrows on the figure indicate the direction that order pickers should follow due to safety reasons, which has shown

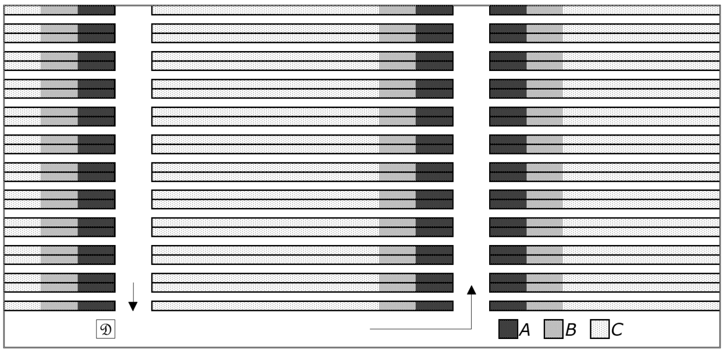


FIGURE 7.6: Layout of the order picking area.

to result in important practical implications (see Chapter 4). The high-level storage system consists of three warehouse blocks and two cross-aisles. Each storage rack consists of seven levels. Consequently, travelling in vertical direction is taken into account when creating picker routes by using the Chebychev distance metric. SKUs are assigned to storage locations based on the across-aisle storage policy.

Thirty order lists, each consisting of 200 orders, are generated and evaluated using the ILS algorithm. The warehouse solves the problem sequentially: batches are created using EDT and assigned to the first available order picker. Order pickers follow a return routing policy. The currently applied policies in the warehouse are used as benchmark to evaluate the performance of the ILS algorithm. To illustrate that efficiency improvements are not possible by only optimizing routes, the LKH heuristic is applied to the batches created by EDT and compared to the integrated solution.

Figure 7.7 illustrates the average order pick time as well as the average CPU time for the real-life case. The EDT batching and return routing results in an average order pick time of 20.5 h (73,669 s), thereby employing 8 order pickers to prevent infeasible solutions due to tardiness. Optimizing order pick routes using the LKH heuristic results in a decline of 4.1 %, while the warehouse under consideration can reduce total order pick time with 16.9 % on average by integrating batching, routing and picker scheduling. The ILS algorithm provides an average order pick time of 17.5 h (62,995 s) with 8 pickers. This means that the effect of optimizing routes is small compared to the efficiency benefits of solving the IBRJAP. Notice that the CPU time of the current policy combination is negligibly small. The ILS algorithm requires 79 s of computation time to find the integrated solution with 8 order pickers. This is acceptable in practice, given the strongly reduced order pick time. At the short term, this reduced order picking time enables an earlier release of a new set of orders. This not only results in more retrieved orders, but also reduces the risk of tardiness due to unforeseen issues as the buffer between order retrieval and deadline is larger.

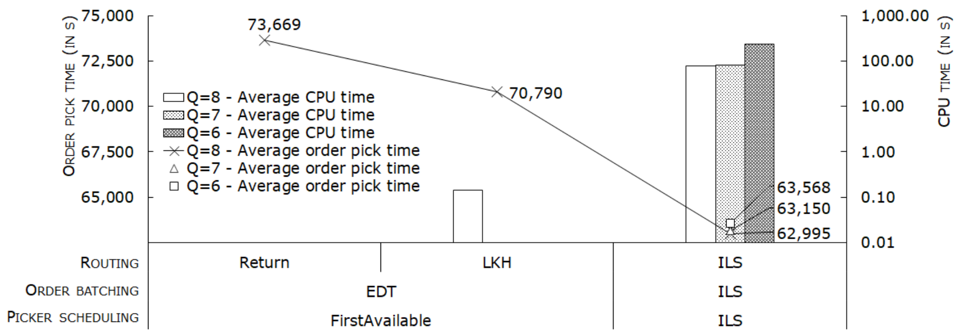


FIGURE 7.7: Order pick time and CPU time (in s) of the real-life case.

The reduction of 10,674 s (73,669 s−62,995 s) in order pick time by solving the IBRJAP using the ILS algorithm, could eventually reduce the number of pickers as the productivity of pickers increases. The workload forecast and mean productivity defines the daily required number of pickers. Therefore, productivity increase reduces the required number of pickers to retrieve the forecast workload. This effect is tested by rerunning the experiments with a reduced number of order pickers. Reducing the available number of pickers from 8 to 7 provides some infeasible instances (i.e., 13.3 %) with respect to the tardiness constraint if the benchmark policies are applied. When only routes are optimised, tardiness occurs in 10% of the instances. This means that 8 pickers are required to prevent tardiness with respect to the benchmark. Due to the infeasible solutions, these results are not shown in Figure 7.7. When applying the integrated problem to solve all instances, even 6 order pickers are enough to pick all orders before the due time. In other words, limiting the number of pickers to 6 does not result in infeasible solutions (i.e., solutions with tardiness) when batching, routing and job assignment decisions are integrated. Figure 7.7 shows that the experiments with 6 pickers result in a slightly higher mean order pick time and a substantial increase in computation time (i.e., from 79 s to 235 s) due to the tight solution space: a large number of moves is tested and rejected during the local search because of tardiness, although moves could reduce the total order picking time. However, results of Figure 7 show that even with a tight solution space, similar picking efficiency benefits are possible compared to the scenario with 8 pickers. Given the strongly increased productivity causing a substantially reduced number of pickers, the mean computation time of 235 s is acceptable in practice.

In summary, the ILS algorithm shows significant performance benefits compared to the current operation of the warehouse. For picking the same orders, the spare parts warehouse can significantly reduce the order pick time, without reducing the service level. Solving the IBRJAP using the ILS algorithm increases the productivity of order pickers, requiring a smaller number of pickers. This reduces the required number of pickers by 25 %

(i.e., from 8 to 6 pickers) in this particular order picking zone of the spare parts warehouse. The ILS algorithm is able to solve the integrated batching, routing and job assignment efficiently even in case of high-level storage locations, in addition to the low-level storage systems that have been tested in previous sections. Consequently, the ILS algorithm can be easily transferred to other pick zones as well, with either low-level or high-level storage locations.

7.5 Managerial Implications

Results of the developed ILS algorithm show that integrating batching, routing and job assignment enables managers to increase the overall productivity of pickers. Consequently, the required number of pickers to fulfil the same number of customer orders reduces substantially, without requiring pickers to work harder. The distribution of time components changes by applying the ILS algorithm. Integrating batching, routing and job assignment mainly reduces picker travelling, while other time components are similar. On a working day, pickers spend more time preparing batches and retrieving products at storage locations at the expense of travelling. Note that retrieving more products could feel as working harder as product retrievals are more physically intense than travelling with a picking vehicle.

As due times are considered as hard constraints in this chapter (i.e., missing deadlines only occur because of unforeseen circumstances), the algorithm could provide an infeasible solution. Picking a set of customer orders could be impossible within the given resource constraint. Although most warehouses move a picker from another warehouse department, supervisors could use the provided schedule with tardiness. The ILS algorithm reduces tardiness in primary order by moving batches (i.e., batch shift/swap) or increasing the efficiency of batches by moving orders (i.e., order shift/swap). This means that in case the ILS algorithm is not able to provide a feasible solution, the best found infeasible solution has minimised tardiness by creating efficient batches. Consequently, the solution with tardiness is an efficient solution with respect to total order pick time and could be used as alternative if no extra picker is available.

7.6 Conclusions

Serving e-commerce markets forces warehouses to handle a larger number of orders in shorter time windows. This chapter considers the integrated batching, routing and job assignment problem, ensuring a high customer service level. As `Cplex` is only able to solve instances of up to 18 customer orders and 8 batches to optimality within reasonable computation effort, a heuristic solution algorithm is developed. The proposed ILS algorithm accounts for order due times, a limited availability of order pickers as well as high-level storage locations to increase the applicability of the algorithm in practice. Results show that the proposed ILS algorithm is able to solve practically relevant problems in reasonable computation times.

Since order batching, picker routing and job assignment are all operational order picking planning problems, the new heuristic algorithm is rather easy to implement. Furthermore, solving the integrated problem results in substantial performance benefits of 16.9 % on average for the real-life spare parts warehouse of our case study. Although other real-life features, such as scattered storage or human different types of pickers (i.e., human factors) are not considered in the current algorithm, scattered storage can be easily implemented in the local search operators and picker dependent time components (e.g., different travel time per picker type) can include human factors simply. The ILS algorithm is expected to provide similar efficiency benefits. Furthermore, including the effect of picker blocking would be highly relevant, especially in narrow-aisle order picking systems. However, including this effect would require more severe algorithm revisions. Finally, the algorithm shows promising results within planning period of 4 h. This planning horizon can be easily adapted and the algorithm provides similar results as long as the number of order lines to retrieve in the planning period is large enough. A smaller number of orders reduces the possibility of creating efficient batches, especially when due times are tight. To conclude, the promising results make the ILS algorithm a simple and effective decision support tool for managers to organise daily order picking operations and face the new market developments.

PART V

IMPLICATIONS AND FUTURE RESEACH

CHAPTER 8

Conclusions and Future Research

Complex market conditions and new developments make warehouse manager's job hard to fulfil. E-commerce and globalisation intensify competition among warehouses. The ever increasing expectation of customers to provide unique products and quick deliveries force warehouses to increase storage capacity, and at the same time reducing pick times. Additionally, expensive industrial land and high labour costs put pressure on the warehouse costs. This PhD thesis presents effective and efficient decision support tools to cope with these market developments (though the conclusions are not limited to these specific market developments), making warehouse manager's life easier. Results provide relevant insights and general findings on how to design efficient order picking systems in practice. The managerial and academic contributions and implications of this research are summarised in Section 8.1. Section 8.2 provides relevant and interesting future research opportunities that may further facilitate the planning of order picking operations.

8.1 Contributions and Implications

In comparison to research on optimising order picking operations, literature on combining order picking planning problems is scarce. Studies that combine planning problems typically only validate a new solution technique for solving a single planning problem by showing the applicability of the new technique under several policies of other order picking planning problems. Although this type of research is relevant, it does not provide insights into how warehouse managers can optimise the overall order picking performance as still only a single planning problem is optimised. Furthermore, managers often do not implement findings from academic research as the provided academic decision support tools rarely account for real-life features. Following this research gap, this PhD research contributes to academic knowledge and practice by providing decision support tools that are able to combine planning problems and account for real-life features. Results of this PhD research show that designing efficient order picking systems is only possible by combining order picking planning problems and in the meanwhile accounting for real-life features.

The literature review of this PhD shows essential gaps in current academic literature. Although there is a trend towards combining two or sometimes three order picking planning problems and/or accounting for a small number of real-life features, generic explanations with respect to the effect of each planning problem on the overall order picking performance and the often negative effects of real-life features are missing. The literature review illustrates that the time horizon of the resulting decisions substantially influences the appropriate approach for solving combinations of order picking planning problems. Interaction analyses by means of simulation and statistical tests are effective in combining planning problems of different time horizons, while problem integration by means of mathematical programming models and heuristic algorithms are able to combine and optimise planning problems with a similar time horizon of the resulting decisions. In addition to combining planning problems, real-life features, such as safety constraints, due time constraints, high-level storage, can be easily taken into account by both of these approaches.

By means of an interaction analysis, the strong relation among the four main tactical and operational order picking planning problems is shown, thereby analysing and explaining the relationship among the planning problems. Warehouse managers can achieve significant performance benefits by considering picker zoning, storage location assignment, order batching, and picker routing decisions simultaneously. Simulating policies for each planning problem and statistically analysing the relation among the planning problems has shown to be an excellent decision support tool for managers to design efficient order picking systems, taking the interactions among the planning problems into account. This approach is especially useful when the time horizon of the resulting decisions is different, such as the assignment of SKUs to storage locations and the creation of batches. Additionally, real-life features can be easily included in the simulation model, making the decision support tool particularly effective in practice.

Most unexplored real-life features negatively impact order picking efficiency or result in infeasible solutions if these practical factors are not incorporated. Warehouse managers may select an inefficient order picking policy combination when only horizontal travel distance or travel time measures are considered, as these measures ignore the effect of safety constraints, picker blocking, and slow vertical lifting. Results show that safety constraints induce wait times, and cause additional travelling, picker blocking turns out to be minimised 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. In order to design efficient order picking systems, these effects should be taken into account when the order picking system is subject to one or more of these real-life features. The interaction analysis shows that the real-life features can be easily accounted for when building a simulation model.

Furthermore, two decision support tools are introduced to manage human resources effectively. The practice of managing human resources in order picking operations is currently unknown. This study contributes by integrating and accounting for resource constraints and workload balancing which is especially relevant when picking operations are performed manually: the resource capacity can be revised on a daily base (in contrast to robotic picking systems) and workload should be balanced throughout the planning day to ensure the well-being of pickers and reduce the risk of missed deadlines. To cope with human resources, forecasting methods are able to accurately predict the required number of pickers as well as to allocate the workforce across the different pick zones. Based on the daily forecasts, the operational workload balancing MILP model is able to additionally balance the workload throughout the planning day. Determining the resource capacity, allocating the available pickers as well as balancing the workload over a short term planning horizon guarantees a stable order picking process. The customer service level increases as the risk of missing shipping deadlines because of workload peaks or an insufficient resource capacity substantially reduces.

Based on the defined resource capacity and hourly workload, order picking operations can be further optimised by integrating planning problems. Problem integration is an appropriate approach to combine planning problems with an operational time horizon. The study contributes by integrating order batching, picker routing, and job assignment, planning problems that should all be solved multiple times per hour. Integrating these operational planning problems significantly reduces pick times compared with sequentially solving the three problems. Additionally, the heuristic algorithm developed in this PhD provides solutions in accordance with practical needs: fast and efficient solutions taking resource and due time constraints into account, as well as the effect of slow vertical travelling due to high-level storage locations. In contrast to existing academic planning models, the heuristic algorithm combines all main operational order picking planning problems, thereby accounting for three critical real-life features.

To conclude, this research provides multiple research approaches and decision support tools to design efficient order picking systems. The study contributes to academics and practice by providing tools that take advantage of existing relations among order picking planning problems and in the meanwhile account for multiple real-life features. Unfortunately, it is impossible to provide a single most efficient combination of order picking policies due to the large amount of real-life features that impact order picking operations as well as strategic decisions that constrain the system. However, the provided approaches and decision support tools are able to cope with existing relations among planning problems. Moreover, the practical applicability of the research is shown by the integration of real-life features and the validation on real-life cases, thereby narrowing the gap between academic research and practice.

8.2 Towards Closing the Research-Practice Gap

By combining planning problems and identifying and accounting for a wide range of real-life features, this PhD research is able to substantially narrow the gap between existing academic research and practice. Though the provided decision support tools show promising results in real-life applications, the research has limitations, such as focussing on efficiency, considering equal human resources, and assuming manual order picking systems. Based on these limitations, this final section provides practically relevant and largely unexplored future research opportunities aimed at closing the research-practice gap.

First, prior studies have strongly focused on reducing the total order pick time. Future research could additionally focus on other performance measures (e.g., quality measures) and other approaches of order pick time (e.g., balancing workload among pickers). Although the provided decision support tools are expected to indirectly increase pick accuracy (i.e., the number of orders picked without errors) and service level (i.e., number of orders picked on time) by for example reducing workload peaks and consequent time pressure, these quality measures are rarely used as explicit performance measure, despite the importance with respect to the customer service quality. Working under an increased time pressure as a result of the tight deadlines may increase the chance of pick errors. Real-life experiments such as in De Vries et al. (2016a) could analyse the effect of implementing the results of this study on pick accuracy and service level.

Next, while this PhD research already incorporated a large number of real-life features as illustrated in Table 8.1[1], there remain some unexplored real-life features that are additionally relevant for practitioners. Despite the importance of human resources in the labour-intensive environment of warehouses, few articles integrate human factors and/or account for differences among the human order pickers. As warehouses deliver labour-intensive services to customers, the availability and performance of the human resources drive the service quality to customers and resulting order picking performance. Individ-

[1] Appendix G provides a full list of publications and research contributions.

ual employee skills and capabilities may significantly impact the order pick time. This research opportunity is highly relevant to practice as considering these human factors can reduce the risk of tardiness due to unforeseen issues: assigning the most critical batches to the best performing pickers reduces the risk of orders that are picked too late, and in this way improves customer service. Consequently, integrating human factors when creating new integrated solution approaches (e.g., incorporating picker-dependent time components in the batching, routing and job assignment heuristic algorithm) is a challenging opportunity for future research.

TABLE 8.1: Overview of studies included in this PhD thesis.

	Van Gils et al. (2016a)	Van Gils et al. (2017c)	Van Gils et al. (2018a)	Van Gils et al. (2018c)	Van Gils et al. (2018e)	Van Gils et al. (2019a)	Van Gils et al. (2019b)	Vanheusden et al. (2019)
Planning problem								
Zone location	•			•	•		•	
Zone assignment	•			•	•		•	
Storage	•		•	•	•		•	
Workforce level		•	•		•		•	•
Workforce allocation		•			•			•
Job assignment					•	•		
Batching	•			•	•	•	•	
Zone picking					•			
Routing	•		•	•	•	•	•	
Order cons. & sorting					•			
Real-life feature								
High-level storage			•			•	•	
Scattered storage								
Varying SKU properties			•					
Human factors								
Precedence constraints								
Safety constraints			•				•	
Resource constraints		•	•			•	•	
Due time constraints						•		•
Workload peaks								•
Product returns								
Picker blocking			•				•	

Furthermore, respecting precedence constraints while creating order picker routes due to weight or fragility restrictions, varying SKU characteristics or considering multiple locations of a single SKU (i.e., scattered storage) are highly relevant real-life features. Existing order picking policies result in infeasible solutions if the order picking system is subject to precedence constraints, varying SKU characteristics or scattered storage. Existing policies need to be revised to account for these real-life features (e.g., in simulation experiments) and new integrated solution approaches should be able to integrate these real-life features to further increase order picking efficiency and practical applicability.

Finally, there is a growing trend towards robotised order picking systems (e.g., robotic mobile fulfilment systems), especially for particular segments such as B2C e-commerce orders. Although the solution approaches and explanations on the relations provided in this study are suitable in robotised picking systems, the question remains to what extent the relations among order picking planning problems have an effect on the order picking performance of these systems, and which of the real-life features should be included when planning operations. For example, workload peaks should be avoided as well as blocking of robots (instead of pickers). However, the effects of high-level storage systems are not directly applicable to all robotised systems. Consequently, insights and conclusions of this study provide a valuable base for future research in robotised order picking systems. Moreover, research combining robotised (or automated) and manual picking systems may be highly relevant as robotised picking systems are currently only useful under particular circumstances (e.g., similar SKUs). Research analysing and optimising the order flow of these combined picking systems would provide highly relevant insights to practice.

Appendix A

Introducing the Smart Logistics Limburg Project

In the context of the SALK Business case *Logistics and Mobility,* the Smart Logistics Limburg project aimed at creating and stimulating innovation in the logistical sector. Four local actors joined forces in the project: UHasselt's Research group Logistics, UHasselt's Research institute IMOB, PXL's Logistics Intelligence Center (LOG-IC) and Logistiek Platform Limburg. The main objectives of the research project is to share and transfer knowledge from the participating knowledge centres to logistical companies in Limburg, a region located in Belgium. Numerous company visits in the context of the Smart Logistics Limburg project reveal the needs and challenges of warehouses and other logistical companies located in Limburg. By stimulating these logistical companies to submit new research and development projects in close cooperation with one or more of the project partners and cooperating in the context of master theses and PhD research, knowledge is created and shared, thereby making logistical companies in the region more competitive.

In total, 437 logistical companies have been visited during the project, of which over 100 warehouses. All problems introduced in this PhD thesis have been initiated by one or more of the companies visited in the context of the Smart Logistics Limburg project. By revealing the needs and challenges of logistical companies in the region, the Smart Logistics Limburg project was a valuable resource for performing this PhD study. Moreover, this PhD research is an example of how to bring the knowledge transfer from knowledge centres to companies into practice.

APPENDIX B

Overview of Order Picking Planning Problems

Table B.1 summarises and defines the considered tactical and operational order picking planning problems of this PhD thesis. Additionally, some predefined and generally used solution methods (i.e., order picking policies) are defined. For an extensive overview of order picking planning problems, the reader is referred to De Koster et al. (2007).

TABLE B.1: Overview of tactical and operational order picking planning problems.

Definitions of order picking planning problems
Zone location A decision should be made how to split the order picking area into zones, in particular the number of zones, the location of zones and the zone shape (Jane and Laih, 2005; Petersen, 2002).
Zone assignment Dividing the warehouse into smaller areas, being order picking zones, requires assigning all SKUs to order picking zones. The allocation of SKUs can be based on product properties like size, weight, safety and/or temperature requirements. Other allocation policies that may be considered are based on product demand properties, such as customer type and order frequency (Petersen, 2002; Jane and Laih, 2005).
Storage location assignment (or simply storage) Storage location assignment policies describe rules to determine the allocation of SKUs to either individual storage locations or storage classes. Storage classes are assigned to a dedicated area within an order picking zone. The determination of storage classes can be turnover based as well as family based in case storage classes are defined by either some measure of demand frequency or respectively product similarities (e.g., complementary products). Note that classes are defined within an order picker zone. As a consequence order pickers are allowed to retrieve items in all storage classes within his zone (Yu et al., 2015; Guo et al., 2016). Following storage location assignment policies are considered: ·) *Random* Storage locations for each product are selected randomly from all eligible empty locations. ·) *Within–aisle* SKUs in a single pick aisle belong to the same storage class. ·) *Across–aisle* Each storage class is located across several pick aisles. ·) *Diagonal* Storage classes are located with respect to the distance to depot. ·) *Perimeter* Storage classes are located around the periphery.
Workforce level Determining the daily number of order pickers to fulfil all customer orders (Van Gils et al., 2017c).

Definitions of order picking planning problems

Workforce allocation Allocating the available workforce across warehouse areas, including allocation across order picking zones and allocation across the picking and sorting area (Van Nieuwenhuyse and De Koster, 2009; Van Gils et al., 2017c).

Job assignment Orders should be retrieved by order pickers within tight time windows. The job assignment planning problem determines the sequence according to which orders or batches of orders should be retrieved, as well as the assignment of these (batches of) orders to a limited number of order pickers (Henn, 2015; Van Gils et al., 2019a).

Order batching (or simply batching) Order batching policies define rules on which customer orders to combine in a single pick round. These policies can be either static (i.e., all orders are known at the beginning of the planning period) or dynamic (i.e., customer orders become available over time) (Van Nieuwenhuyse and De Koster, 2009; Van Gils et al., 2018c). Following order batching policies are considered:

- ·) *Strict order picking* Each pick order is composed of order lines of a single customer order (static).
- ·) *Priority rule based algorithm* In a first step, priorities are assigned to customer orders, followed by the assignment of customer orders to batches in accordance with the previously defined priorities, ensuring that the capacity constraint is not violated such as first-come-first-served (FCFS or FIFO) and earliest-due-date-first (EDD) (static).
- ·) *Seed algorithm* For each pick batch, one customer order is selected as seed, after which additional customer orders are added to the seed in accordance with an order congruency rule. The order congruency rule defines the order for adding customer orders to the seed (static).
- ·) *Savings algorithm* Savings algorithms compose pick orders based on the time saving that can be obtained by combining two or more customer orders into one order picking route. Savings algorithms are based on the algorithm of Clarke and Wright (1964) for the vehicle routing problem (static).
- ·) *Data mining* Data mining is used to determine similarities of customer orders by means of an association rule. Subsequently, orders are clustered into batches based on the similarities using integer programming (static).
- ·) *Metaheuristic* A set of guidelines to develop heuristic optimization algorithms for batching orders (static).
- ·) *Variable time window batching* The order picker starts a picking tour whenever a particular number of customer orders have arrived (dynamic).
- ·) *Fixed time window batching* All customer orders arriving during a particular time interval are assigned to batches (dynamic).

Zone picking Zone picking policies define the flow of customers order through all order picking zones (De Koster et al., 2007; Parikh and Meller, 2008). Following zone picking policies are considered:

- ·) *Sequential zoning* Each order picker starts picking an order. When all parts of an order belonging to his order picking zone are picked, the order is passed to the next zone. Sequential zoning eliminates the requirement of a downstream sorter, however, at the expense of a reduced picking efficiency.
- ·) *Parallel zoning* All order pickers can start picking the same order, each order picker in his own zone. After picking, all orders should be consolidated through a sorting system.

Definitions of order picking planning problems
Picker routing (or simply 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 (Petersen and Schmenner, 1999; Roodbergen and De Koster, 2001a). Following routing policies are considered: ·) *Aisle-by-aisle* Each order picker visits every pick aisle containing at least one pick location through the entire length. ·) *Traversal* Each order picker traverses every subaisle (i.e. the part of a pick aisle that is within one warehouse block) containing at least one pick location through the entire length. ·) *Return* Each order pickers enters and leaves each pick aisle containing at least one pick location from the same end. ·) *Midpoint* Each order picker enters an pick aisle only as far as the midpoint of an aisle and returns to leave the pick aisle from the same end. ·) *Largest gap* Each order picker enters a pick aisle only as far as the start of the largest gap within an aisle and returns to leave the pick aisle from the same end. The largest gap is defined as the maximum distance between any two adjacent pick locations within a single aisle, or the maximum distance between an aisle end and a pick location. ·) *Combined* Each order picker either traverses each pick aisle containing at least one pick location entirely or returns to leave the pick aisle from the same end. ·) *Metaheuristic* A set of guidelines to develop heuristic optimization algorithms for routing order pickers.
Order consolidation & sorting Order consolidation and sorting policies define the organization of the sorting activities in case of either batching or zoning (Van Nieuwenhuyse and De Koster, 2009). Following order consolidation and sorting policies are considered: ·) *Sort-while-pick* Picked items are sorted on the pick cart per order during the picking process. ·) *Pick-and-sort* Sorting activities follow immediately after picking.

APPENDIX

C

CLASSIFICATION BY PLANNING PROBLEM COMBINATION

Table C.1 summarises all articles analysing at least two order picking planning problems simultaneously. The table is adopted from Van Gils et al. (2018e) and extended with the most recent research articles that meet the scope outlined in Section 2.1.1. For an overview of articles discussed in this PhD thesis, Table 8.1 classifies these studies according to the considered planning problem combination and the incorporated real-life features.

TABLE C.1: Classification by Planning Problem Combination.

	Zone location	Zone assignment	Storage	Workforce level	Workforce allocation	Job assignment	Batching	Zone picking	Routing	Order cons. & sorting
Caron et al. (1998)			•						•	
De Koster et al. (1999)			•				•		•	
Petersen and Schmenner (1999)			•						•	
Ruben and Jacobs (1999)			•	•			•			
Petersen (2000)	•						•			
Bartholdi et al. (2001)						•		•		
Dekker et al. (2004)			•						•	
Hwang et al. (2004)			•						•	
Jewkes et al. (2004)		•	•							
Petersen and Aase (2004)			•				•		•	
Petersen et al. (2004)			•						•	
Won and Olafson (2005)							•		•	
Ho and Tseng (2006)			•				•		•	

	Zone location	Zone assignment	Storage	Workforce level	Workforce allocation	Job assignment	Batching	Zone picking	Routing	Order cons. & sorting
Hsieh and Tsai (2006)			•				•		•	
Manzini et al. (2007)			•						•	
Gong and De Koster (2008)							•		•	
Ho et al. (2008)			•				•		•	
Parikh and Meller (2008)							•	•		
Tsai et al. (2008)							•		•	
Yu and De Koster (2008)			•		•		•			
Koo (2009)						•		•		
Van Nieuwenhuyse and De Koster (2009)				•	•		•			•
Yu and De Koster (2009)	•						•			
Chen et al. (2010)			•				•		•	
Theys et al. (2010)			•						•	
Chan and Chan (2011)			•						•	
Hsieh and Huang (2011)			•				•		•	
Rubrico et al. (2011)						•	•			
De Koster et al. (2012)	•		•		•					
Ene and Öztürk (2012)							•		•	
Henn (2012)			•				•		•	
Henn and Wäscher (2012)			•				•		•	
Hong et al. (2012a)				•		•	•			•
Hong et al. (2012b)			•				•			•
Kulak et al. (2012)							•		•	
Pan and Wu (2012)			•	•					•	
Chackelson et al. (2013)			•				•		•	
Heath et al. (2013)			•	•					•	
Henn and Schmid (2013)						•	•		•	
Matthews and Visagie (2013)						•			•	
Matusiak et al. (2014)							•		•	
Pan et al. (2014)			•						•	
Shqair et al. (2014)			•						•	
Chen et al. (2015)						•	•		•	
Cheng et al. (2015)							•		•	
Henn (2015)				•		•	•		•	
Hong et al. (2015)						•		•		
Öncan (2015)							•		•	
Roodbergen et al. (2015)			•						•	
Chen et al. (2016)				•					•	
Hong et al. (2016)						•		•		
Li et al. (2016)							•		•	
Lin et al. (2016)							•		•	
Chen et al. (2017)				•			•			
Dijkstra and Roodbergen (2017)			•						•	
Franzke et al. (2017)			•	•					•	
Giannikas et al. (2017)							•		•	
Hong and Kim (2017)			•				•			•
Matusiak et al. (2017)						•	•			
Menéndez et al. (2017)						•	•			
Scholz and Wäscher (2017)			•				•		•	
Scholz et al. (2017)				•		•	•		•	
Schrotenboer et al. (2017)				•					•	

	Zone location	Zone assignment	Storage	Workforce level	Workforce allocation	Job assignment	Batching	Zone picking	Routing	Order cons. & sorting
Valle et al. (2017)							•		•	
Zhang et al. (2017)						•	•			
Ardjmand et al. (2018)						•	•		•	
Chabot et al. (2018)							•		•	
Hong (2018)				•		•		•		
Quader and Castillo-Villar (2018)			•			•		•	•	
Žulj et al. (2018a)			•						•	
Žulj et al. (2018b)			•				•		•	
Total	3	1	35	12	3	17	45	7	50	4

APPENDIX

D

ANOVA RESULTS OF THE GENERALISED CASE

Table D.1 provides the results of the $5 \times 3 \times 5 \times 5 \times 3 \times 3 \times 3$ full factorial mixed model ANOVA on average travel distance for the generalised experiments of Section 3. ANOVA results of other performance measures are provided in Tables D.2 and D.3.

TABLE D.1: 5×3×5×5×3×3×3 full factorial mixed model ANOVA on average travel distance.

	Sum of squares	df	Mean square	F	p-value
Main effects					
Zoning	19,861,136,109,911	1.14	17,471,263,744,616	17,310.27	0.000
Storage	2,581,068,182,161	1.15	2,252,145,769,126	20,840.87	0.000
Batching	33,580,344,072,124	1.09	30,777,152,758,560	72,464.62	0.000
Routing	5,238,742,190,582	1.16	4,523,368,614,508	7,933.50	0.000
Layout	74,889,003,015,144	2.00	37,444,501,507,572	1,369.28	0.000
Order size	39,478,612,491,554	2.00	19,738,306,245,777	721.83	0.000
Capacity	82,120,906,136,649	2.00	41,060,453,068,325	1,501.50	0.000
Two-way interaction					
Zoning × storage	1,127,150,536,133	2.85	395,129,511,299	21,247.75	0.000
Zoning × batching	2,387,900,915,031	1.66	1,438,432,735,742	18,445.89	0.000
Zoning × routing	601,576,392,051	1.70	354,441,334,759	3,827.88	0.000
Zoning × layout	5,536,682,301,049	2.27	2,435,229,188,715	2,412.79	0.000
Zoning × order size	1,195,409,824,188	2.27	525,783,626,015	520.94	0.000
Zoning × capacity	1,220,803,943,468	2.27	536,952,860,067	532.00	0.000
Storage × batching	90,300,439,821	2.72	33,163,221,224	7,782.71	0.000
Storage × routing	870,166,236,240	1.18	736,466,291,737	5,826.79	0.000
Storage × layout	310,780,615,930	2.29	135,587,903,902	1,254.70	0.000
Storage × order size	229,692,149,974	2.29	100,210,487,918	927.33	0.000
Storage × capacity	442,422,460,243	2.29	193,020,835,112	1,786.17	0.000
Batching × routing	899,200,878,940	1.82	493,131,569,186	7,926.60	0.000
Batching × layout	175,621,334,192	2.18	80,480,483,143	189.49	0.000

	Sum of squares	df	Mean square	*F*	*p*-value
Batching × order size	1,608,240,071,395	2.18	736,994,389,388	1,735.25	0.000
Batching × capacity	4,287,191,394,336	2.18	1,964,654,444,357	4,625.77	0.000
Routing × layout	960,958,655,058	2.32	414,867,735,612	727.63	0.000
Routing × order size	495,592,132,807	2.32	213,958,410,014	375.26	0.000
Routing × capacity	849,590,082,014	2.32	366,787,386,397	643.31	0.000
Three-way interaction					
Zoning × storage × layout	148,682,239,997	5.71	26,060,734,101	1,401.39	0.000
Zoning × storage × order size	72,210,421,440	5.71	12,656,902,347	680.61	0.000
Zoning × storage × capacity	136,145,313,898	5.71	23,863,286,057	1,283.23	0.000
Zoning × batching × layout	319,921,189,170	3.32	96,357,664,689	1,235.65	0.000
Zoning × batching × order size	85,706,172,600	3.32	25,814,003,325	331.03	0.000
Zoning × batching × capacity	150,824,386,979	3.32	45,427,080,792	582.54	0.000
Zoning × routing × layout	175,812,536,365	3.39	51,793,280,853	559.35	0.000
Zoning × routing × order size	72,975,231,492	3.39	21,498,049,787	232.17	0.000
Zoning × routing × capacity	101,062,411,459	3.39	29,772,358,494	321.53	0.000
Storage × batching × layout	30,094,322,817	5.45	5,526,134,131	1,296.87	0.000
Storage × batching × order size	7,327,980,133	5.45	1,345,615,961	315.79	0.000
Storage × batching × capacity	8,078,527,577	5.45	1,483,436,834	348.13	0.000
Storage × routing × layout	217,727,481,050	2.36	92,136,964,122	728.97	0.000
Storage × routing × order size	99,862,577,377	2.36	42,259,409,169	334.35	0.000
Storage × routing × capacity	128,873,750,445	2.36	54,536,230,630	431.48	0.000
Batching × routing × layout	106,622,591,114	3.65	29,236,495,925	469.95	0.000
Batching × routing × order size	97,750,542,763	3.65	26,803,731,886	430.84	0.000
Batching × routing × capacity	283,493,086,062	3.65	77,735,350,163	1,249.52	0.000
Residuals					
Between subjects	21,959,012,878,673	803.00	27,346,217,782		
Within zoning	921,331,257,435	912.84	1,009,300,509		
Within storage	99,448,725,278	920.28	108,063,914		
Within batching	372,112,852,007	876.14	424,719,717		
Within routing	530,246,091,529	929.99	570160182		
Within zoning × storage	42,597,531,064	2,290.65	18,596,295		
Within zoning × batching	103,951,845,341	1,333.04	77,981,200		
Within zoning × routing	126,196,678,465	1,362.89	92,594,663		
Within storage × batching	9,316,966,516	2,186.50	4,261,140		
Within storage × routing	119,919,087,590	948.78	126,393,115		
Within batching × routing	91,093,082,051	1,464.23	62,212,254		
Total	307,657,490,319,680	14,149.62			

TABLE D.2: 5×3×5×5×3×3×3 full factorial mixed model ANOVA on average number of pick rounds.

	Sum of squares	df	Mean square	*F*	*p*-value
Main effects					
Storage	150.3	3.63	41.43	487.16	0.000
Batching	6,210.55	1.00	6,210.55	2,728.06	0.000
Zoning	67,629,631.93	1.01	67,142,707.71	4,228.23	0.000
Routing	746.94	1.33	560.85	520.18	0.000
Layout	17,551,278.69	2.00	8,775,639.34	1,145.66	0.000
Order size	2,369.04	2.00	1,184.52	0.15	0.857
Capacity	1,120,342,143.36	2.00	560,171,071.70	73,130.43	0.000

	Sum of squares	df	Mean square	*F*	*p*-value
Two-way interaction					
Zoning × storage	12.31	14.49	0.85	11.75	0.000
Zoning × batching	188.81	3.43	55.07	73.56	0.000
Zoning × routing	140.40	9.60	14.62	130.69	0.000
Zoning × layout	36,910,024.70	2.01	18,322,138.75	1,153.81	0.000
Zoning × order size	4,090.18	2.01	2,030.37	0.13	0.881
Zoning × capacity	22,406,700.93	2.01	11,122,687.85	700.44	0.000
Storage × batching	300.59	3.63	82.86	487.16	0.000
Storage × routing	433.40	7.06	61.39	426.50	0.000
Storage × layout	92.21	7.26	12.71	149.44	0.000
Storage × order size	3.72	7.26	0.51	6.03	0.000
Storage × capacity	81.94	7.26	11.29	132.79	0.000
Batching × routing	1,493.88	1.33	1,121.71	520.18	0.000
Batching × layout	4,146.89	2.00	2,073.45	910.79	0.000
Batching × order size	0.69	2.00	0.35	0.15	0.859
Batching × capacity	3,965.90	2.00	1,982.95	871.03	0.000
Routing × layout	764.01	2.66	286.83	266.03	0.000
Routing × order size	279.37	2.66	104.89	97.28	0.000
Routing × capacity	534.64	2.66	200.72	186.16	0.000
Three-way interaction					
Zoning × storage × layout	17.26	28.99	0.60	8.23	0.000
Zoning × storage × order size	6.81	28.99	0.23	3.25	0.000
Zoning × storage × capacity	15.83	28.99	0.55	7.55	0.000
Zoning × batching × layout	162.89	6.86	23.75	31.73	0.000
Zoning × batching × order size	11.40	6.86	1.66	2.22	0.031
Zoning × batching × capacity	286.02	6.86	41.71	55.71	0.000
Zoning × routing × layout	60.88	19.21	3.17	28.33	0.000
Zoning × routing × order size	47.77	19.21	2.49	22.23	0.000
Zoning × routing × capacity	130.41	19.21	6.79	60.70	0.000
Storage × batching × layout	184.42	7.26	25.42	149.44	0.000
Storage × batching × order size	7.44	7.26	1.03	6.03	0.000
Storage × batching × capacity	163.87	7.26	22.59	132.79	0.000
Storage × routing × layout	431.97	14.12	30.59	212.55	0.000
Storage × routing × order size	16.37	14.12	1.16	8.05	0.000
Storage × routing × capacity	210.05	14.12	14.88	103.35	0.000
Batching × routing × layout	1,528.02	2.66	573.67	266.03	0.000
Batching × routing × order size	558.75	2.66	209.77	97.28	0.000
Batching × routing × capacity	1,069.27	2.66	401.44	186.16	0.000
Residuals					
Between subjects	6,150,892.20	803.00	7,659.89		
Within zoning	12,843,816.58	808.82	15,879.63		
Within storage	247.74	2,913.18	0.09		
Within batching	1,828.07	803.00	2.28		
Within routing	1,153.05	1,069.43	1.08		
Within zoning × storage	841.39	11,639.17	0.07		
Within zoning × batching	2,061.14	2,753.16	0.75		
Within zoning × routing	862.69	7,711.03	0.11		
Within storage × batching	495.47	2,913.18	0.17		
Within storage × routing	815.99	5,669.34	0.14		
Within batching × routing	2,306.10	1,069.43	2.16		
Total	1,283,876,015.20	38,484,33			

TABLE D.3: 5×3×5×5×3×3×3 full factorial mixed model ANOVA on average number of visited locations.

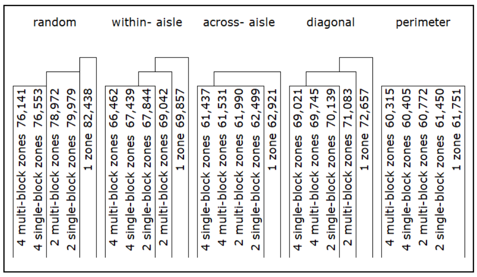
	Sum of squares	df	Mean square	F	p-value
Main effects					
Zoning	13,301,802,850	1.09	12,240,001,150	10,408.60	0.000
Storage	583,256,129	2.17	268,469,533	23,436.92	0.000
Batching	38,366,624,020	1.43	26,776,029,650	122,256.41	0.000
Routing	87,602,723	2.19	40,090,608	14,842.89	0.000
Layout	1,356,917,368,476	2.00	678,458,684,200	1,145.66	0.000
Order size	27,903,628,050	2.00	13,951,814,030	396.90	0.000
Capacity	29,710,345,870	2.00	14,855,172,940	422.60	0.000
Two-way interaction					
Zoning × storage	125,139,890	13.17	9,498,546	2,798.71	0.000
Zoning × batching	847,489,156	2.32	365,496,385	5,450.48	0.000
Zoning × routing	8,395,813	5.37	1,563,276	1,476.54	0.000
Zoning × layout	8,808,436,813	2.17	4,052,656,544	3,446.28	0.000
Zoning × order size	446,264,356	2.17	205,320,899	174.60	0.000
Zoning × capacity	1,278,070,760	2.17	588,025,088	500.04	0.000
Storage × batching	379,340,557	4.52	83,890,741	13,865.63	0.000
Storage × routing	4,211,097	12.66	332,756	1,043.79	0.000
Storage × layout	9,184,924	4.35	2,113,884	184.54	0.000
Storage × order size	874,018	4.35	201,153	17,56	0.000
Storage × capacity	20,661,118	4.35	4,755,098	415.11	0.000
Batching × routing	175,205,446	2.19	80,181,216	14,842.89	0.000
Batching × layout	1,856,955,772	2.87	647,983,815	2,958.62	0.000
Batching × order size	775,399,337	2.87	270,575,222	1,235.42	0.000
Batching × capacity	549,133,249	2.87	191,619,781	874.91	0.000
Routing × layout	25,184,737	4.37	5,762,786	2,133.58	0.000
Routing × order size	1,228,155	4.37	281,027	104.05	0.000
Routing × capacity	4,745,661	4.37	1,085,905	402.04	0.000
Three-way interaction					
Zoning × storage × layout	9,340,857	26.35	354,502	104.45	0.000
Zoning × storage × order size	4,051,851	26.35	153,775	45.31	0.000
Zoning × storage × capacity	3,874,850	26.35	147,057	43.33	0.000
Zoning × batching × layout	498,429,683	4.64	107,478,807	1,602.78	0.000
Zoning × batching × order size	114,260,744	4.64	24,638,598	367.42	0.000
Zoning × batching × capacity	101,586,353	4.64	21,905,557	326.67	0.000
Zoning × routing × layout	6,203,159	10.74	577,505	545.46	0.000
Zoning × routing × order size	1,811,831	10.74	168,679	159.32	0.000
Zoning × routing × capacity	316,780	10.74	29,492	27.86	0.000
Storage × batching × layout	13,497,586	9.04	1,492,488	246.68	0.000
Storage × batching × order size	6,385,266	9.04	706,047	116.70	0.000
Storage × batching × capacity	12,946,125	9.04	1,431,511	236.60	0.000
Storage × routing × layout	50,369,473	4.37	11,525,571	2,133.58	0.000
Storage × routing × order size	2,456,310	4.37	562,054	104.05	0.000
Storage × routing × capacity	9,491,323	4.37	2,171,810	402.04	0.000
Batching × routing × layout	50,369,473	4.37	11,525,571	2,133.58	0.000
Batching × routing × order size	2,456,310	4.37	562,054	104.05	0.000
Batching × routing × capacity	9,491,323	4.37	2,171,810	402.04	0.000
Residuals					
Between subjects	28,226,772,140	803.00	35,151,646		
Within zoning	1,026,203,688	872.66	1,175,950		
Within storage	19,983,628	1,744.54	11,455		
Within batching	251,998,234	1,150.60	219,015		
Within routing	4,739,306	1,754.65	2,701		

	Sum of squares	df	Mean square	F	p-value
Within zoning × storage	35,904,857	10,579.23	3,394		
Within zoning × batching	124,857,632	1,861.94	67,058		
Within zoning × routing	4,565,966	4,312.63	1,059		
Within storage × batching	21,968,749	3,631.04	6,050		
Within storage × routing	3,239,644	10,162.15	319		
Within batching × routing	9,478,611	1,754.65	5,402		
Total	1,512,756,826,184	38,962.81			

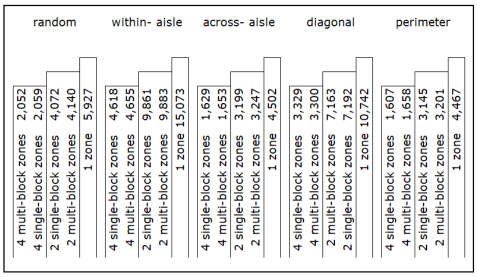
APPENDIX E

MULTIPLE BONFERRONI T-TESTS OF THE NARROW-AISLE SYSTEM

In addition to the post hoc tests presented in Section 4.3.2, Figures E.1 to E.6 provide the post hoc tests in the other direction: for each combination of two planning problems, all policies of the planning problem with the longest time horizon are evaluated for each policy of the planning problem with the shortest time horizon.

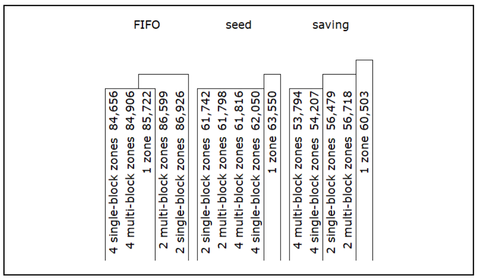


(A) Travelling.

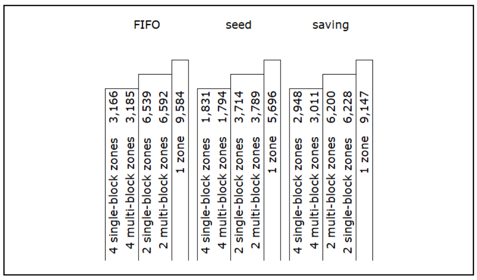


(B) Picker blocking.

FIGURE E.1: Multiple Bonferroni t-test (familywise error rate = 0.01) for zoning policies by storage policies (in s).

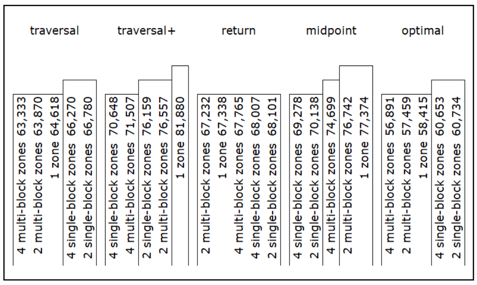


(A) Travelling.

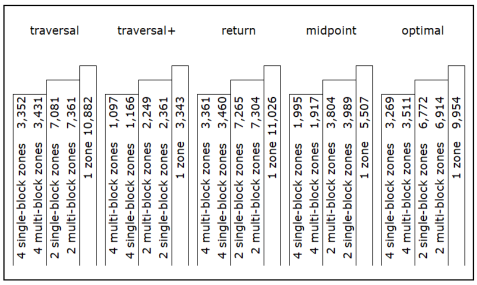


(B) Picker blocking.

FIGURE E.2: Multiple Bonferroni t-test (familywise error rate = 0.01) for zoning policies by batching policies.

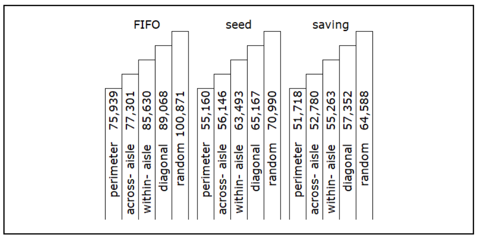


(A) Travelling.

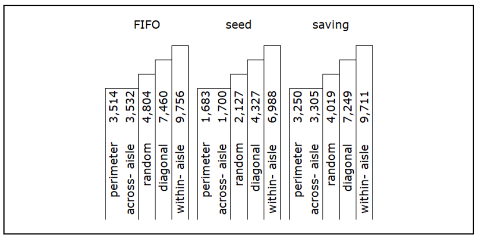


(B) Picker blocking.

FIGURE E.3: Multiple Bonferroni t-test (familywise error rate = 0.01) for zoning policies by routing policies.

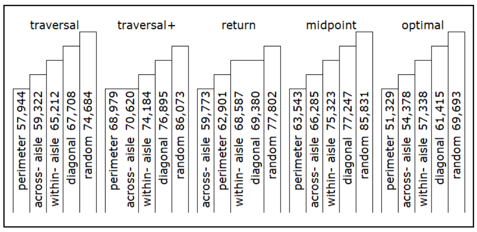


(A) Travelling.

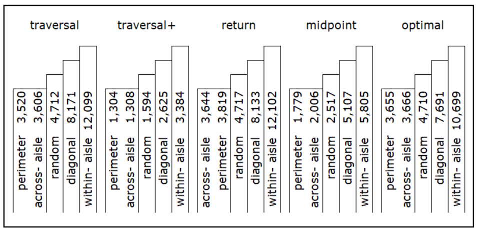


(B) Picker blocking.

FIGURE E.4: Multiple Bonferroni t-test (familywise error rate = 0.01) for storage policies by batching policies.

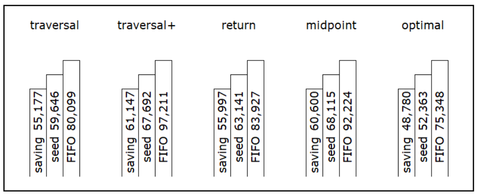


(A) Travelling.

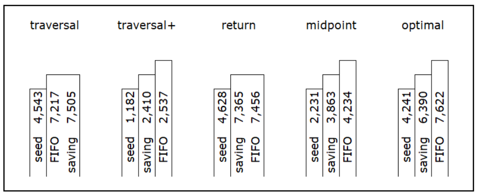


(B) Picker blocking.

FIGURE E.5: Multiple Bonferroni t-test (familywise error rate = 0.01) for storage policies by routing policies.



(A) Travelling.



(B) Picker blocking.

FIGURE E.6: Multiple Bonferroni t-test (familywise error rate = 0.01) for batching policies by routing policies.

APPENDIX F

Optimality Cuts and Symmetry Breaking Constraints of IBRJAP

This appendix outlines the optimality cuts used to strengthen the formulation. For a detailed discussion on the optimality cuts, the reader is referred to Valle et al. (2017). To describe the optimality cuts, each arc a is defined by its starting and ending vertex $(v'; v'')$. Let I_e^m be the number of vertices between the subaisle defined by cross-aisle e and cross-aisle $e+1$ in pick aisle m: a subaisle is defined as the part of a pick aisle between two cross-aisles. Each vertex v can be additionally expressed with respect to the location of intersection between the pick aisle, the cross-aisle neighbouring to the subaisle and most closely located to the depot (i.e., the cross-aisle to the left of the pick location in Figure 7.1) and the other vertices in the subaisle: let $v_e^m\{i\}$ be the ith vertex located in pick aisle m, with e the cross-aisle on the left-hand side of the pick location and i the position of an ordered set of vertices within subaisle between cross-aisle e and $e+1$ in pick aisle m. For artificial vertices, $i = 0$ (i.e., the intersection of a pick aisle and cross-aisle) and i is dropped in the notation. Let $v_0^0\{0\}$ be the vertex located at the depot, or simply v_0.

Order picking performance is assumed to be independent of the individual order picker. Therefore, formulation (7.3)-(7.20) may be subject to symmetry issues (i.e., swapping all orders assigned to two pickers yields an equivalent solution). This symmetry may increase computation times (Valle et al., 2017). Symmetry breaking constraints (F.1) are added to the formulation to overcome this issue by forcing the first order to be assigned to the first order picker, the second order to the first or second picker, and so on.

(F.1)
$$R_{qpk} = 0$$
$$\forall k \in \kappa, \quad \forall q \in \sigma, q > k, \quad \forall p \in \pi$$

As distance is a symmetric function, incoming and outgoing arcs from the depot may be subject to symmetry issues (i.e., travelling is equal when performing a pick round clockwise or counter clockwise). Therefore, constraints (F.2) break symmetry by enforcing that the arc from the depot to a cross-aisle should be closer to the depot compared to the arc from a cross-aisle to the depot.

(F.2)
$$\sum_{\substack{e' \in \epsilon \\ e' \geq e}} X_{qp(v^1_{e'};v_0)} \geq \sum_{\substack{e' \in \epsilon \\ e' \geq e}} X_{qp(v_0;v^1_{e'})}$$
$$\forall q \in \sigma, \quad \forall p \in \pi, \quad \forall e \in \epsilon \backslash \{1\}$$

In addition to symmetry breaking constraints, the feasible region can be reduced by including cuts that should be fulfilled in case of optimality. Let $\kappa_e \subset \kappa$ be a subset of orders for which other subaisles than the first pick aisle between cross-aisle e and $e+1$ should be visited to retrieve all order lines. This implies that the route should visit other pick aisles before returning to the depot as stated by constraints (F.3)-(F.5). For each vertex connected to the depot (i.e., for each cross-aisle), the constraint should be included.

(F.3)
$$X_{qp(v^1_1\{I^1_1\};v^1_2)} + X_{qp(v^1_1;v^2_1)} \geq X_{qp(v_0;v^1_1)} - (1 - R_{qpk})$$
$$\forall q \in \sigma, \quad \forall p \in \pi, \quad \forall k \in \kappa_1$$

(F.4)
$$X_{qp(v^1_e\{I^1_e\};v^1_{e+1})} + X_{qp(v^1_e;v^2_e)} + X_{qp(v^1_{e-1}\{1\};v^1_{e-1});} \geq X_{qp(v_0;v^1_e)} - (1 - R_{qpk})$$
$$\forall q \in \sigma, \quad \forall p \in \pi, \quad \forall e \in \epsilon \backslash \{1;E\}, \quad \forall k \in \kappa_e$$

(F.5)
$$X_{qp(v^1_E;v^2_E)} + X_{qp(v^1_{E-1}\{1\};v^1_{E-1})} \geq X_{qp(v_0;v^1_E)} - (1 - R_{qpk})$$
$$\forall q \in \sigma, \quad \forall p \in \pi, \quad \forall k \in \kappa_E$$

Furthermore, cross-aisle and pick aisle cuts can be included. Each pick aisle (cross-aisle) cut separates the warehouse in two horizontal (vertical) parts, of which one part contains the depot (i.e., depot part). If a pick location of an order is not located in the depot part, at least one arc crossing the separation line from the depot part to the other warehouse part should be used. In addition, at least one arc crossing the separation line in the other direction should be used. Optimality cuts (F.6)-(F.9) provide the cross-aisle cuts, equations (F.10)-(F.11) illustrate pick aisle cuts. Let $\kappa' \subset \kappa$ be the subset of orders containing at least one pick location not located in the depot part.

(F.6) $$\sum_{m\in\mu} X_{qp(v_e^m;v_e^m\{1\})} \geq R_{qpk}$$

$$\forall q\in\sigma,\quad \forall p\in\pi,\quad \forall e\in\epsilon\backslash\{E\},\quad \forall k\in\kappa'$$

(F.7) $$\sum_{m\in\mu} X_{qp(v_e^m;v_e^m\{1\})} = \sum_{m\in\mu} X_{qp(v_e^m\{1\};v_e^m)}$$

$$\forall q\in\sigma,\quad \forall p\in\pi,\quad \forall e\in\epsilon\backslash\{E\},\quad \forall k\in\kappa'$$

(F.8) $$\sum_{m\in\mu} X_{qp(v_{e-1}^m\{I_{e-1}^m\};v_e^m)} \geq R_{qpk}$$

$$\forall q\in\sigma,\quad \forall p\in\pi,\quad \forall e\in\epsilon\backslash\{1\},\quad \forall k\in\kappa'$$

(F.9) $$\sum_{m\in\mu} X_{qp(v_{e-1}^m\{I_{e-1}^m\};v_e^m)} = \sum_{m\in\mu} X_{qp(v_e^m;v_{e-1}^m\{I_{e-1}^m\})}$$

$$\forall q\in\sigma,\quad \forall p\in\pi,\quad \forall e\in\epsilon\backslash\{1\},\quad \forall k\in\kappa'$$

(F.10) $$\sum_{e\in\epsilon} X_{qp(v_e^{m-1};v_e^m)} \geq R_{qpk}$$

$$\forall q\in\sigma,\quad \forall p\in\pi,\quad \forall m\in\mu\backslash\{1\},\quad \forall k\in\kappa'$$

(F.11) $$\sum_{e\in\epsilon} X_{qp(v_e^{m-1};v_e^m)} = \sum_{e\in\epsilon} X_{qp(v_e^m;v_e^{m-1})}$$

$$\forall q\in\sigma,\quad \forall p\in\pi,\quad \forall m\in\mu\backslash\{1\},\quad \forall k\in\kappa'$$

In addition to pick aisle and cross-aisle cuts, computation time is improved by including subaisle cuts (Constraints (F.12)-(F.18)). Let X^1_{qpv} be the minimum X_{qpa} value over all arcs a in the unique path from the left cross-aisle artificial vertex to a vertex v in the subaisle associated with the cross-aisle artificial vertex. X^2_{qpv} is similarly defined from the right cross-aisle artificial vertex to the left. Furthermore, let $\kappa_v \subset \kappa$ be the subset of orders containing at least one pick location at vertex v.

(F.12) $$X^1_{qpv_e^m\{1\}} = X_{qp(v_e^m;v_e^m\{1\})}$$

$$\forall q\in\sigma,\quad \forall p\in\pi,\quad \forall m\in\mu,\quad \forall e\in\epsilon\backslash\{E\}$$

(F.13) $$X^1_{qpv_e^m\{i\}} \leq X_{qp(v_e^m\{i-1\};v_e^m\{i\})}$$

$$\forall q\in\sigma,\quad \forall p\in\pi,\quad \forall m\in\mu,\quad \forall e\in\epsilon\backslash\{E\},\quad \forall i\in[1;I_e^m]\}$$

(F.14) $$X^1_{qpv_e^m\{i\}} \leq X^1_{qpv_e^m\{i-1\}}$$

$$\forall q\in\sigma,\quad \forall p\in\pi,\quad \forall m\in\mu,\quad \forall e\in\epsilon\backslash\{E\},\quad \forall i\in[1;I_e^m]\}$$

(F.15) $$X^2_{qpv_e^m\{I_e^m\}} = X_{qp(v_{e+1}^m;v_e^m\{I_e^m\})}$$

$$\forall q\in\sigma,\quad \forall p\in\pi,\quad \forall m\in\mu,\quad \forall e\in\epsilon\backslash\{E\}$$

(F.16) $$X^2_{qpv_e^m\{i-1\}} \leq X_{qp(v_e^m\{i\};v_e^m\{i-1\})}$$

$$\forall q\in\sigma,\quad \forall p\in\pi,\quad \forall m\in\mu,\quad \forall e\in\epsilon\backslash\{E\},\quad \forall i\in[1;I_e^m]\}$$

(F.17) $$X^2_{qpv_e^m\{i-1\}} \leq X^2_{qpv_e^m\{i\}}$$
$$\forall q \in \sigma, \quad \forall p \in \pi, \quad \forall m \in \mu, \quad \forall e \in \epsilon \backslash \{E\}, \quad \forall i \in [1; I_e^m]\}$$

(F.18) $$X^1_{qpv_e^m\{i\}} + X^2_{qpv_e^m\{i\}} \geq R_{qpk}$$
$$\forall q \in \sigma, \quad \forall p \in \pi, \quad \forall v_e^m\{i\} \in \psi, i > 0, \quad \forall k \in \kappa_{v_e^m\{i\}}$$

Computation time is further reduced by including optimality cuts that prevent routes to return in an artificial vertex. Constraints (F.19) prevent reversals between two artificial vertices, while Constraints (F.20)-(F.23) deal with reversals between a pick location vertex and artificial vertex.

(F.19) $$\sum_{\substack{(v'';v^*) \in \alpha^-_{v''} \\ v^* \neq v'}} X_{qp(v'';v^*)} \geq X_{qp(v';v'')}$$
$$\forall q \in \sigma, \quad \forall p \in \pi, \quad \forall v', v'' \in \bigcup_{m \in \mu} \bigcup_{e \in \epsilon} \{v_e^m\} : (v'; v'') \in \alpha^+_{v''}$$

(F.20) $$\sum_{\substack{(v_e^m;v^-) \in \alpha^-_{v_e^m} \\ v^- \neq v_e^m\{1\}}} X_{qp(v_e^m;v^-)} \geq X_{qp(v_e^m\{1\};v_e^m)}$$
$$\forall q \in \sigma, \quad \forall p \in \pi, \quad \forall m \in \mu, \quad \forall e \in \epsilon \backslash \{E\}$$

(F.21) $$\sum_{\substack{(v^-;v_e^m) \in \alpha^+_{v_e^m} \\ v^- \neq v_e^m\{1\}}} X_{qp(v^-;v_e^m)} \geq X_{qp(v_e^m;v_e^m\{1\})}$$
$$\forall q \in \sigma, \quad \forall p \in \pi, \quad \forall m \in \mu, \quad \forall e \in \epsilon \backslash \{E\}$$

(F.22) $$\sum_{\substack{(v_e^m;v^-) \in \alpha^-_{v_e^m} \\ v^- \neq v^m_{e-1}\{I^m_{e-1}\}}} X_{qp(v_e^m;v^-)} \geq X_{qp(v^m_{e-1}\{I^m_{e-1}\};v_e^m)}$$
$$\forall q \in \sigma, \quad \forall p \in \pi, \quad \forall m \in \mu, \quad \forall e \in \epsilon \backslash \{1\}$$

(F.23) $$\sum_{\substack{(v^-;v_e^m) \in \alpha^+_{v_e^m} \\ v^- \neq v^m_{e-1}\{I^m_{e-1}\}}} X_{qp(v^-;v_e^m)} \geq X_{qp(v_e^m;v^m_{e-1}\{I^m_{e-1}\})}$$
$$\forall q \in \sigma, \quad \forall p \in \pi, \quad \forall m \in \mu, \quad \forall e \in \epsilon \backslash \{1\}$$

Finally, pass through optimality cuts prevent reversals at pick location vertices where no picking occurs. Let $\kappa_{v_e^m\{i\}} \subset \kappa$ be the set of orders that have a pick location at vertex $v_e^m\{i\}$. Then, constraints (F.24)-(F.27) ensure that the route passes through the vertices where no picking occurs, instead of returning.

$$\sum_{k\in\kappa_{v_e^m\{i\}}} -R_{qpk} \leq X_{qp(v_e^m\{i-1\};v_e^m\{i\})} - X_{qp(v_e^m\{i\};v_e^m\{i+1\})} \leq \sum_{k\in\kappa_{v_e^m\{i\}}} R_{qpk} \tag{F.24}$$

$$\forall q\in\sigma,\quad \forall p\in\pi,\quad \forall m\in\mu,\quad \forall e\in\epsilon,\quad \forall i\in[1;I_e^m-1]\}$$

$$\sum_{k\in\kappa_{v_e^m\{I_e^m\}}} -R_{qpk} \leq X_{qp(v_e^m\{I_e^m-1\};v_e^m\{I_e^m\})} - X_{qp(v_e^m\{I_e^m\};v_{e+1}^m)} \leq \sum_{k\in\kappa_{v_e^m\{I_e^m\}}} R_{qpk} \tag{F.25}$$

$$\forall q\in\sigma,\quad \forall p\in\pi,\quad \forall m\in\mu,\quad \forall e\in\epsilon$$

$$\sum_{k\in\kappa_{v_e^m\{i\}}} -R_{qpk} \leq X_{qp(v_e^m\{i+1\};v_e^m\{i\})} - X_{qp(v_e^m\{i\};v_e^m\{i-1\})} \leq \sum_{k\in\kappa_{v_e^m\{i\}}} R_{qpk} \tag{F.26}$$

$$\forall q\in\sigma,\quad \forall p\in\pi,\quad \forall m\in\mu,\quad \forall e\in\epsilon,\quad \forall i\in[1;I_e^m]\}$$

$$\sum_{k\in\kappa_{v_e^m\{I_e^m\}}} -R_{qpk} \leq X_{qp(v_{e+1}^m;v_e^m\{I_e^m\})} - X_{qp(v_e^m\{I_e^m\};v_e^m\{I_e^m-1\})} \leq \sum_{k\in\kappa_{v_e^m\{I_e^m\}}} R_{qpk} \tag{F.27}$$

$$\forall q\in\sigma,\quad \forall p\in\pi,\quad \forall m\in\mu,\quad \forall e\in\epsilon$$

Appendix G

Publications and Conference Contributions

This appendix provides an overview of research publications and conference contributions.

G.1 Journal Publications

Van Gils, T., Ramaekers, K., Caris, A., Cools, M., 2017c. The use of time series forecasting in zone order picking systems to predict order pickers' workload. International Journal of Production Research 55 (21), 6380–6393

Ramaekers, K., Caris, A., Moons, S., Van Gils, T., 2018. Using an integrated order picking-vehicle routing problem to study the impact of delivery time windows in e-commerce. European Transport Research Review 10 (56), 1–11

Van Gils, T., Ramaekers, K., Braekers, K., Depaire, B., Caris, A., 2018c. Increasing Order Picking Efficiency by Integrating Storage, Batching, Zone Picking, and Routing Policy Decisions. International Journal of Production Economics 197 (Part C), 243–261

Van Gils, T., Ramaekers, K., Caris, A., De Koster, R. B. M., 2018e. Designing Efficient Order Picking Systems by Combining Planning Problems: State-of-the-art Classification and Review. European Journal of Operational Research 267 (1), 1–15

Van Gils, T., Caris, A., Ramaekers, K., Braekers, K., 2019a. Formulating and Solving the Integrated Batching, Routing, and Picker Scheduling Problem in a Real-life Spare Parts Warehouse. European Journal of Operational Research

Van Gils, T., Caris, A., Ramaekers, K., Braekers, K., De Koster, R. B. M., 2019b. Designing efficient order picking systems: the effect of safety constraints, picker blocking, and high-

level storage on the relation among planning problems. Transportation Research Part E: Logistics and Transportation Review 125, 47–73

Vanheusden, S., Van Gils, T., Braekers, K., Caris, A., Ramaekers, K., 2019. Operational workload balancing problem in manual order picking. Computers & Industrial Engineering, under review

G.2 Conference Proceedings

Van Gils, T., Braekers, K., Depaire, B., Caris, A., Ramaekers, K., 2015a. Improving Order Picking Efficiency by Analyzing Combinations of Routing and Zone Picking Policies in a 2-block Warehouse. In: Bijdragen Vervoerslogistieke Werkdagen. University Press Zelzate, pp. 45–58

Van Gils, T., Braekers, K., Ramaekers, K., Depaire, B., Caris, A., 2016a. Improving Order Picking Efficiency by Analyzing Combinations of Storage, Batching, Zoning, and Routing Policies. In: Paias, A., Ruthmair, M., Voß, S. (Eds.), Lecture Notes in Computational Logistics. No. 9855 in Lecture Notes in Computer Science. Springer International Publishing, pp. 427–442

Van Gils, T., Caris, A., Ramaekers, K., 2017b. The Effect of Storage and Routing Policies on Picker Blockingi n a Real-life Narrow-aisle Warehouse. In: Bottani, E., Bruzzone, A., Longo, F., Merkuryev, Y., Piera, M. A. (Eds.), Proceedings of the International Conference on Harbour, Maritime & Multimodal Logistics Modelling and Simulation. No. 11. pp. 53–61

Vanheusden, S., Van Gils, T., Ramaekers, K., Caris, A., 2017. Reducing workload imbalance in parallel zone order picking systems. In: Bottani, E., Bruzzone, A., Longo, F., Merkuryev, Y., Piera, M. A. (Eds.), Proceedings of the International Conference on Harbour, Maritime & Multimodal Logistics Modelling and Simulation. No. 13. pp. 68–75

Van Gils, T., Caris, A., Ramaekers, K., 2018a. Reducing picker blocking in a high-level narrow-aisle order picking system: insights from a real-life spare parts warehouse. In: 2018 Winter Simulation Conference (WSC). IEEE, Gothenborg, pp. 2953–2965

Vanheusden, S., Van Gils, T., Braekers, K., Ramaekers, K., Caris, A., 2018a. An Efficient Iterated Local Search Algorithm to Solve the Operational Workload Imbalance Problem. In: 19th free workshop on metaheuristics for industry. pp. 23–26

Caris, A., Molenbruch, Y., Van Gils, T., Verdonck, L. (Eds.), 2019. ORBEL33 - Progam & abstracts. Hasselt

G.3 Other Conference Contributions

Van Gils, T., Ramaekers, K., Braekers, K., Caris, A., 2015b. Improving Operational Workforce Scheduling in a Warehouse Using Time Series Forecasting. In: Abstract from European conference for Operational Research 2015. Abstract from European conference for Operational Research 2015. Glasgow

Van Gils, T., Ramaekers, K., Braekers, K., Caris, A., 2015c. An integrated approach for order picking and flexible workforce planning: a state of the art. In: 29th Annual Conference of the Belgian Operations Research Society. Antwerp

Van Gils, T., Braekers, K., Ramaekers, K., Depaire, B., Caris, A., 2016b. Improving Order Picking Efficiency by Analyzing the Combination of Storage, Batching, Zoning and Routing Policies in a 2-Block Warehouse. In: 30th Annual Conference of the Belgian Operations Research Society. Louvain-la-Neuve

Van Gils, T., Braekers, K., Ramaekers, K., Caris, A., 2017a. Joint Order Batching, Routing, and Picker Scheduling in Manual Order Picking Systems. In: 31st Annual Conference of the Belgian Operations Research Society. Brussels

Van Gils, T., Ramaekers, K., Caris, A., 2018d. Reducing picker blocking in a real-life narrow-aisle spare parts warehouse. In: 32nd Annual Conference of the Belgian Operations Research Society. Liege

Van Gils, T., Vanheusden, S., Braekers, K., Ramaekers, K., Caris, A., 2018f. Daily workload balancing in zoned order picking systems. In: OR2018, International Conference of the German Operations Research Society (GOR). Brussels

Vanheusden, S., Van Gils, T., Ramaekers, K., Caris, A., Braekers, K., 2018b. Iterated local search algorithm for solving operational workload imbalances in order picking. In: 32nd Annual Conference of the Belgian Operations Research Society. Liege

Van Gils, T., Caris, A., Ramaekers, K., Braekers, K., 2018b. Integrating real-life features while planning order picking operations. In: 33rd Annual Conference of the Belgian Operations Research Society. Hasselt

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