2018 | Faculty of Business Economics

UHASSELT

KNOWLEDGE IN ACTION

Doctoral dissertation submitted to obtain the degree of
Doctor of Business Economics, to be defended by

Stef Moons

DOCTORAL DISSERTATION

Integrating order picking and vehicle routing decisions

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D/2018/2451/60

Dedicated to my grandmother, Ma Deurne († 2014)

Acknowledgements

"Every accomplishment starts with the decision to try." (John F. Kennedy)

Writing this dissertation was only possible with the guidance and support of many people. Each of them contributed in their own specific way. Without all these people, obtaining a PhD degree would have been much harder, and maybe, even impossible. Now, after four years, the time has come to thank each of them and express my gratitude.

First of all, I would like to thank my supervisor, Prof. Dr Katrien Ramaekers, for the opportunity she gave me to conduct academic research as her first PhD student. In short, Katrien always supports her PhD students and stands up for them whenever needed. Katrien, the past four years, you were always there to motivate me with your everlasting optimism and enthusiasm. When experiments did not turn out as expected, you always found a new and often creative direction to continue my doctoral research. Katrien, many thanks for the trust you gave me!

A good supervisor is nothing without a good co-supervisor, Prof. Dr An Caris. An, I want to thank you for your critical view and remarks over the past years. With your useful feedback, you learned me to never be satisfied with a first version and to never accept results without analysing them. You provided me with new insights in the topic of my dissertation and academic research in general. All of this with a smile. Your many tips and comments have definitely taken my PhD to a higher level. Thanks for everything!

Prof. Dr Kris Braekers, although you were no member of my doctoral committee, you had an enormous contribution to my doctoral research. Kris, without sharing your knowledge and experience, developing a heuristic algorithm would have been an even harder struggle than it already was. Thank you for all of this!

Prof. Dr Gerrit K. Janssens, the past years you could have been enjoying your retirement in Portugal. Nevertheless, you wanted to be a part of my doctoral committee. Thanks for your time and interest in the topic of my PhD. Prof. Dr Yasemin

Arda, thanks for you critical mindset during the doctoral committee meetings. Your feedback and remarks were valuable for the final version of my dissertation and journal articles. Prof. Dr Ir Birger Raa and Prof. Dr Manfred Gronalt, I would like to thank you both for your time and effort reading my doctoral dissertation and for your valuable comments.

Successfully writing a doctoral dissertation is only possible in an enjoyable working environment. Therefore, I would like to thank my colleagues from the research groups Logistics and Business Informatics for the nice atmosphere in which I have been able to work for the past four years. There are four colleagues I especially want to thank. Niels, Marijke, Jeroen, and Gert, you made the past four years extremely special, and not only during working hours. The many drinks, restaurant dinners, city trips, and many other activities, such as kayaking, in our spare time, will always be great memories for me! Thank you for being not just great colleagues but also fantastic friends!

Besides conducting research, a PhD student has to teach courses, which was a nice distraction for me. One person was always available for giving me advice. Marleen, I want to thank you for the nice collaboration. We had many meetings in the past years, which more than once lasted longer than expected. Marleen, I will always remember you as a warm and caring person.

Finally, many thanks go to my family. I really need to thank my parents for the opportunity they gave me to perform university studies, and later for their support during my PhD. Nothing was too much for them. Many thanks for everything! Hanne, my sister, and her husband Tim, thanks for choosing me as godfather of your daughter Julie. More than once, she provided distraction in the last year and a half. At last, I need to thank, I think even in name of my colleagues, my grandmother Ma Paal for the yearly treat she made for my anniversary.

All of you, many thanks!

Stef Moons
27 September 2018

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List of Abbreviations

3PL	third-party logistics (service provider)
ACO	ant colony optimisation
(A)LNS	(adaptive) large neighbourhood search
B-AGA	backward adaptive genetic algorithm
B2B	business-to-business
B2C	business-to-consumer
DA	deterministic annealing
DC	distribution centre
ELS	evolutionary local search
EU	European Union
F-AGA	forward adaptive genetic algorithm
GA	genetic algorithm
GRASP	greedy randomised adaptive search procedure
ICA	imperialist competitive algorithm
I-PS-VRP	integrated production scheduling-vehicle routing problem
I-OP-VRP	integrated order picking-vehicle routing problem
ILP	integer linear programming (problem)
ILS	iterated local search
INLP	integer non-linear programming (problem)
MA	memetic algorithm
MIP	mixed integer programming (problem)
MILP	mixed integer linear programming (problem)

OPP	order picking problem
RRT	record-to-record travel
SA	simulated annealing
TS	tabu search
VRP	vehicle routing problem
VRP-rd	vehicle routing problem with release dates
VRPTW	vehicle routing problem with time windows
VRPTW-rd	vehicle routing problem with time windows and release dates

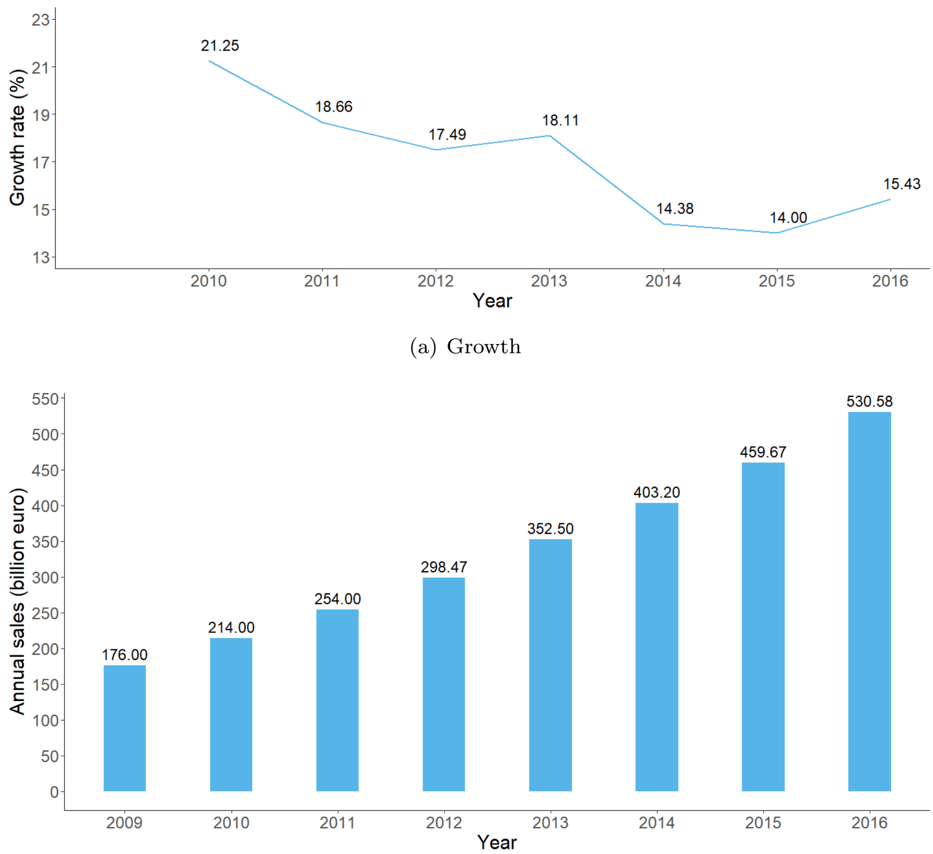
Chapter 1

Introduction and problem statement

1.1 Introduction

In the last decades, the economic landscape in (Western) Europe has drastically changed. Many companies moved their manufacturing plants from Europe to low-cost countries to remain competitive (EESC, 2003, 2014). This offshoring led to a loss of approximately 3.5 million jobs in the manufacturing industry in the European Union (EU) since 2008 (EESC, 2014). At the same time, many multinational companies built a distribution centre (DC) in Europe. These DCs are generally responsible for the deliveries of goods produced outside Europe to European customers, often within the context of e-commerce transactions (Hultkrantz and Lumsden, 2001).

Since 2010, European business-to-consumer (B2C) e-commerce sales have been growing annually with approximately 17% on average. More specifically, in 2016, the B2C e-commerce sales grew with 15.43% in Europe, resulting in a sales figure of 530 billion euro in 2016 (Figure 1.1) (Ecommerce Foundation, 2017). The share of internet users in the EU which made online purchases, increased with 16 percentage points since 2007 up to approximately 65%. Large differences can be noticed across the EU countries. The largest increases in percentage points are recorded in Lithuania, the Czech Republic, Ireland, Hungary, Spain, Italy, and Slovakia. Romania has the lowest proportion of e-shoppers (18%), while the United Kingdom has the largest proportion of internet users that shop online (87%) (Eurostat, 2016). This expansion of the B2C e-commerce sector has led to the creation of approximately 2.5 million jobs



(a) Growth

(b) Sales

Figure 1.1: Annual B2C e-commerce (a) growth rate and (b) sales in Europe from 2009 to 2016 (Ecommerce Foundation, 2017)

in Europe (Ecommerce Europe, 2016). In a business-to-business (B2B) e-commerce environment, the European market grew with 1.8% from 2013 to 2015 (Mehta and Berthelmann, 2017).

In a B2C e-commerce context, customers order more frequently in smaller quantities. As a consequence, the number of consignments increases (Hultkrantz and Lumsden, 2001). Annual revenues of the B2C parcel market in Europe have increased with 114% from 7.14 billion euro in 2010 to 15.4 billion euro in 2015 (Hermes Europe GmbH, 2016) (Figure 1.2). In Europe, approximately 4.2 billion B2C parcels are sent to customers annually (Ecommerce Europe, 2016). This large number of smaller quantities makes it more challenging to consolidate orders in an efficient way.

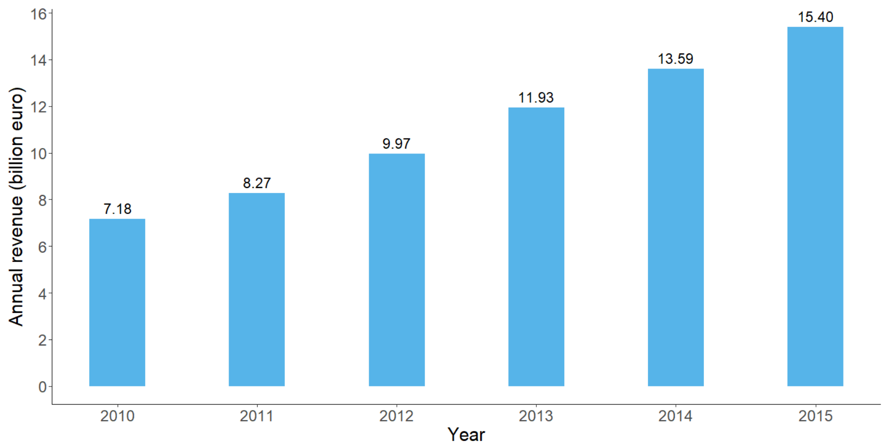


Figure 1.2: Annual revenues of the B2C parcel market in Europe from 2010 to 2015, adapted from Hermes Europe GmbH (2016)

Customers want to be able to choose the moment and location of the delivery of their parcel. The large majority of people expect their parcel to be delivered at home (UPS, 2015; MetaPack, 2016). Compared to traditional shopping behaviour where goods only need to be delivered to a limited number of stores, B2C e-commerce with home-delivery leads to a large increase in the number of possible delivery locations (Hultkrantz and Lumsden, 2001). Thus, due to the rise of e-commerce, new distribution channels and structures arise, which leads to more complex distribution networks. For instance, goods are often transported from a DC directly to the end customer or to a postal office depot from where the goods are delivered to customers by a mailman (Hultkrantz and Lumsden, 2001). As such, compared to traditional distribution networks, wholesalers and retailers are often bypassed.

Furthermore, online shoppers expect a fast and accurate delivery within tight time windows (Fernie and Sparks, 2004) at low cost or even free (de Koster, 2003; UPS, 2015). Often same day or next day delivery is promised to customers. The promise of faster deliveries implies a double logistics challenge: (1) dealing with an increasing pressure on the warehouse operations due to later cut-off times; and, (2) creating an efficient distribution network for parcel delivery (VIL, 2016). Accordingly, handling a large number of orders and parcels in an efficient way puts the logistics activities of the supply chain under pressure. E-commerce companies have to thoroughly rethink and redesign their way of operating. Excellent logistics performance is indispensable in order to fulfil the customer expectations at low cost and to be successful in an e-commerce environment (Hultkrantz and Lumsden, 2001).

In order to achieve such a high performing overall system, extensive coordination among the different stages of the supply chain is necessary (Reimann et al., 2014). To survive in the highly competitive market, companies do not have to (re)optimise separate supply chain processes, but need to reconsider all activities at the same time. Larger savings can be achieved by integrating rather than by improving individual supply chain functions (Chen, 2004). In an e-commerce context, especially the warehousing and delivery operations need to be optimised.

In the first place, internal warehouse processes, such as storage location, batching, zoning, and picking routing decisions, need to be considered carefully. Moreover, after (e-commerce) orders are picked in a warehouse, the goods need to be delivered to customers. Accordingly, order picking and distribution are interrelated. Instead of solving an order picking problem (OPP) and a vehicle routing problem (VRP) separately and sequentially, these two problems can be integrated into a single optimisation problem. In an integrated problem, both subproblems are solved simultaneously to obtain an overall optimal solution.

Although supply chain functions, such as order picking and distribution, are interrelated, historically, these are mostly solved separately and sequentially using the output of one problem as input for the other problem (Archetti and Speranza, 2014b). Unfortunately, optimising a single problem independently disregards the requirements and constraints of the other. Therefore, such an uncoordinated approach will not always lead to an overall optimal solution (Chen and Vairaktarakis, 2005; Pundoor and Chen, 2005; Meinecke and Scholz-Reiter, 2014a; Moons et al., 2017b). Often the subproblems are solved in the same order as these are executed in practice. Ideally, they need to be integrated to resolve the suboptimality problem (Côté et al., 2017). In order to integrate order picking and delivery problems, the classical VRP needs to be integrated with order picking issues. In the classical VRP, goods need to be distributed by a set of vehicles located at one or more depots to a set of geographically scattered customers by constructing routes along a network in such a way that all requirements are fulfilled (Toth and Vigo, 2014).

Speranza (2018) identifies a more systemic, or integrated, approach as one of the major research directions based on the current trends in transportation and logistics. Recently, an increasing number of studies have been conducted on the integration of a VRP with other supply chain functions. Schmid et al. (2013) provide an overview of interesting extensions to the classical VRP. Examples from literature are location-routing problems, inventory-routing problems, production-routing problems, and routing problems with loading constraints. Archetti and Speranza (2014b) demonstrate the value of integration for an inventory-routing problem with average cost savings of approximately 35%. Absi et al. (2018) compare two sequential approaches with an integrated production routing problem. Savings in total cost up to approximately 60% can be achieved depending on the problem characteristics. The integration of a dock-door assignment problem and a VRP can lead to cost savings of approximately 12% (Enderer et al., 2017). In addition to scientific research, managers need to implement more integrated management policies in their companies (Archetti and Speranza, 2014b; Speranza, 2018)

One of the extensions to the VRP highlighted by Schmid et al. (2013) is the integration of order picking and delivery processes. This problem variant is a relatively new research direction. The most related research field studies the integration of production scheduling and vehicle routing decisions. The first studies on the integrated production scheduling-vehicle routing problem (I-PS-VRP) at the operational level were published in the 1990s. Especially since 2010 there is an increasing interest in this research domain (Moons et al., 2017a). The integration of production scheduling and vehicle routing operations can result in savings between 5% and 20% on average. A detailed survey of these studies can be found in Chapter 2.

Recently, a small number of studies have been conducted on the integration of order picking and distribution operations. Zhang et al. (2016, 2018) integrate an order picking system with a distribution system, but only consider direct shipments to customers or outsource the delivery operations. No vehicle routing decisions have to be made. The study of Schubert et al. (2018) is one of the first studies on the integration of order picking and vehicle routing decisions. In Chapter 3, a detailed review of these studies is provided.

To benefit from the integration of both subproblems, it is not necessary that the delivery operations are conducted by the same company as the one responsible for the order picking activities. The only requirement is that there is a good coordination and information exchange between the companies executing the order picking and delivery operations. The implementation of an efficient information system used for the collaboration between the different companies involved is crucial for a successful integration. The integration of order picking, or production scheduling, with vehicle routing decisions has been investigated for various applications, e.g., picking and delivery of perishable goods to supermarkets using owned vehicles (Schubert et al., 2018), production and delivery of ready-mixed concrete using owned vehicles and hired vehicles (Naso et al., 2007), or a make-to-order production environment in which a third-party logistics (3PL) service provider conducts the delivery operations (Zou et al., 2018).

1.2 Research objectives

In literature, there is a call for more integrated approaches of logistic problems (Speranza, 2018). The integration of order picking and vehicle routing is only studied in a few scientific articles. Consequently, the knowledge about this recently formulated problem is limited. Little is known about the value of integration and how to solve this problem efficiently. Therefore, the central research question of this dissertation is the following:

> *What are the benefits of integrating order picking and vehicle routing decisions in a business-to-consumer e-commerce environment?*

The integration of order picking and vehicle routing decisions is especially important when customers expect a fast delivery, preferably within the same day. Therefore, to be able to satisfy this expectation, the distance between the DC and the customer locations has to be relatively small. Thus, the largest benefits of integration can probably be obtained when customers are located in the proximity of the DC.

Although the focus in this dissertation is on B2C e-commerce, the mathematical formulations described and solution method proposed in this dissertation can be applied to B2B e-commerce as well. The main differences between B2C and B2B e-commerce are the average order size and the total number of orders requested. In a B2B e-commerce context, the size of an order is on average larger (Samtani et al., 2002), and a lower number of orders are requested in the same time period compared to B2C e-commerce.

Since the integrated order picking-vehicle routing problem (I-OP-VRP) is a relatively new research area, the *first* contribution of this dissertation is to introduce the I-OP-VRP. The integrated problem and its characteristics are described in detail. In order to be able to analyse the problem, a mathematical formulation for both an uncoordinated and an integrated problem is provided. Since the most related research is situated in the production scheduling field, these studies are used as starting point. Similarities and differences between production scheduling problems and order picking problems are indicated to be able to translate existing integrated studies in a production context to a warehouse context.

The *second* contribution is to measure and indicate the value of integration. A comparison is made between solving an OPP and a VRP in an uncoordinated sequential way and solving an I-OP-VRP. The formulated mathematical models are used to conduct experiments with both approaches. The results of these experiments are analysed to quantify the benefits of an integrated method over an uncoordinated method.

Different problem characteristics are tested to indicate in which circumstances integration is more promising. For example, the impact of the number of customer orders, cost parameters, and customer distance to the DC is evaluated.

The integrated problem studied in this dissertation is hard to solve using an exact method. Therefore, the *third* contribution is to propose a heuristic algorithm which is capable to solve the integrated problem in a reasonable amount of computation time. A heuristic in which local search operators are implemented in a record-to-record travel framework is presented. Record-to-record travel is a heuristic framework in which a new solution is accepted, in case of a minimisation problem, if its objective value is less than the best objective value found so far plus a deviation value (Dueck, 1993).

1.3 Thesis outline

The structure of this thesis is shown in Figure 1.3. Chapter 2 reviews the state-of-the-art literature on integrated operational level production scheduling-vehicle routing problems. A classification matrix based on production, inventory, and distribution characteristics is proposed. The I-PS-VRP studies are classified according to these characteristics. Thereafter, the solution methods used in these studies are discussed.

As production and warehousing operations have relatively similar characteristics, in Chapter 3, first a comparison between production and warehousing concepts is made. Next, the state-of-the-art literature on both order picking and vehicle routing problems with release dates is surveyed. Then, a mathematical model for an order picking problem, a vehicle routing problem with time windows and release dates, and an integrated order picking-vehicle routing problem is formulated. The difference between an uncoordinated approach and an integrated approach is indicated in order to measure the value of integration.

A record-to-record travel algorithm is proposed to solve the I-OP-VRP for large-size instances. In Chapter 4, the design of the heuristic is described. Computational experiments are executed on small-size instances using both a commercial optimisation software and the heuristic to evaluate the performance of the record-to-record travel algorithm. Furthermore, experiments using large-size instances are conducted. Parameters are tuned using a software to automatically configure the parameters. A sensitivity analysis on the impact of the algorithm parameters is executed. The value of integration for large-size instances is quantified.

Since in a warehouse, multiple orders are generally picked in a single batch, an integrated order picking-vehicle routing problem with a batch picking policy is intro-

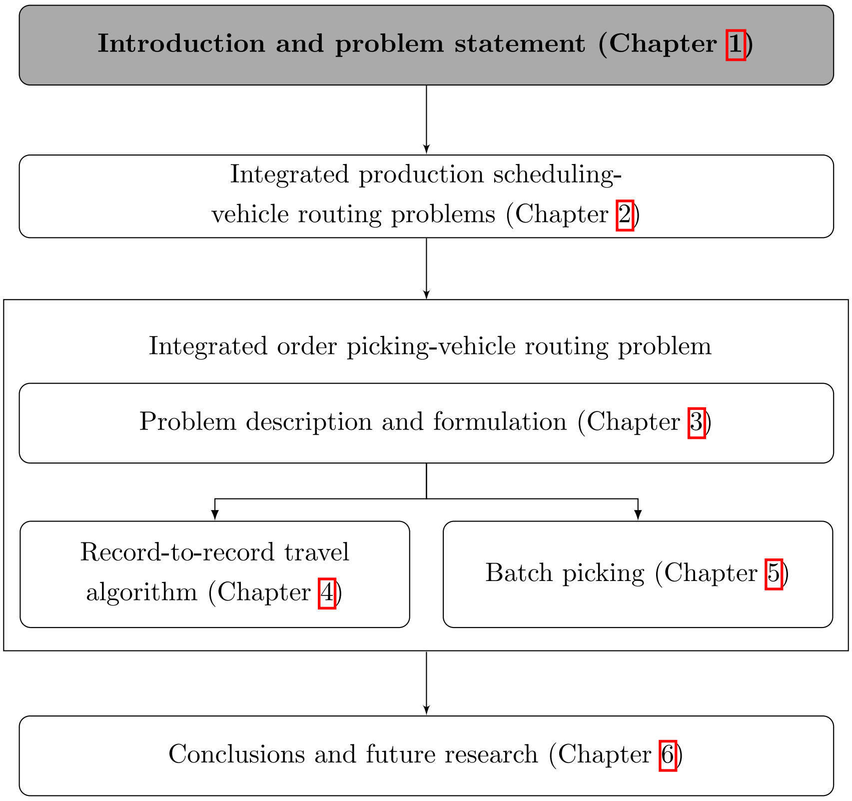


Figure 1.3: Thesis outline

duced in Chapter 5. A mathematical formulation the I-OP-VRP with batch picking is provided. A first exploratory research on the impact of batch picking on the integration of order picking and vehicle routing decisions is conducted.

Finally, in Chapter 6, general conclusions based on the preceding chapters are presented. Managerial implications resulting from the analyses in this dissertation are highlighted. Since the integration of order picking and vehicle routing problems is a relatively new research domain, future research opportunities are identified based on the limitations of this dissertation.

Chapter 2

Integrated production scheduling-vehicle routing problems: Review and discussion

2.1 Introduction

The integration of order picking and vehicle routing decisions is a new research field. Only a few studies are conducted on this topic. The most related research area investigates the integrated operational level production scheduling and vehicle routing problem. In this chapter[1], an overview of the state-of-the-art literature of integrated production scheduling-vehicle routing problems is presented (Figure 2.1). From this review, insights in integrated problems with vehicle routing decisions can be gained. The knowledge gathered, gaps indicated, and future research directions highlighted in this chapter will be used for formulating and analysing an integrated problem of order picking and vehicle routing operations in the following chapters. Based on the current chapter, the integrated order picking-vehicle routing problem (I-OP-VRP) will be introduced and a survey of the limited literature available on the integration of order picking and distribution operations will presented in Chapter 3.

[1]This chapter is an updated version of Moons, Ramaekers, Caris and Arda (2017a), extended with relevant papers published recently.

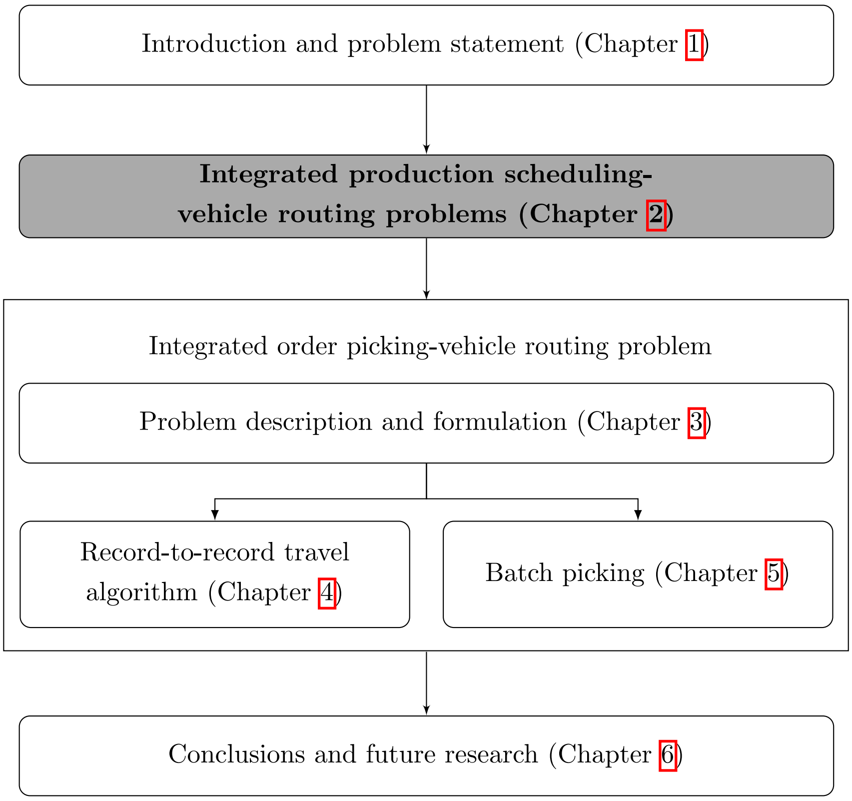


Figure 2.1: Thesis outline - Chapter 2

Similar as for order picking and vehicle routing problems, production scheduling and vehicle routing are related since the latter can only start after the production process is completed. Nevertheless, production and distribution have traditionally been studied separately. Several authors, such as Thomas and Griffin (1996) and Scholz-Reiter et al. (2011), point out some reasons why companies prefer an uncoordinated approach over an integrated one. First, in practice, different departments in a company or even different companies, such as 3PL service providers, are responsible for the production and distribution decisions. Second, the individual problems, e.g., a VRP for distribution planning, are hard to solve by themselves. Third, inventory buffers between the production and distribution functions are often used to separate them and reduce the necessity to integrate those supply chain functions.

However, an increasing trend can be observed to reduce these intermediate buffer stocks to utilise resources more efficiently (Chang and Lee, 2004; Reimann et al., 2014) and to survive in the globalised economy. Therefore, companies increasingly implement a just-in-time policy. In such a setting, tardy deliveries can cause enormous problems at the customer's site, but trying to prevent such situations with high transportation costs is pointless. Hence, integrating production and distribution into a single problem is almost indispensable. Especially for perishable or time-sensitive goods, an integrated approach can be valuable (Ullrich, 2013). Examples in which an integrated approach is applied for perishable goods are newspapers (Hurter and Van Buer, 1996; Van Buer et al., 1999; Russell et al., 2008; Chiang et al., 2009), food (Chen et al., 2009; Farahani et al., 2012), ready-mixed concrete (Garcia et al., 2004; Naso et al., 2007), nuclear medicine (Lee et al., 2014), and industrial adhesive materials (Geismar et al., 2008; Viergutz and Knust, 2014).

Integrating production and routing decisions into a single decision support model can be useful to avoid inefficiencies in the determined schedules (Geismar et al., 2008), which can result in higher operational costs, lower customer service level, or poor utilisation of the resources (Gao et al., 2015). As such, integrating different supply chain functions can lead to significant cost savings and efficiency improvements (Sarmiento and Nagi, 1999). At the operational decision level, integration can result in an average improvement between 5% and 20% compared to an uncoordinated approach as indicated by Chen and Vairaktarakis (2005), Park and Hong (2009), Ullrich (2013), and Meinecke and Scholz-Reiter (2014a).

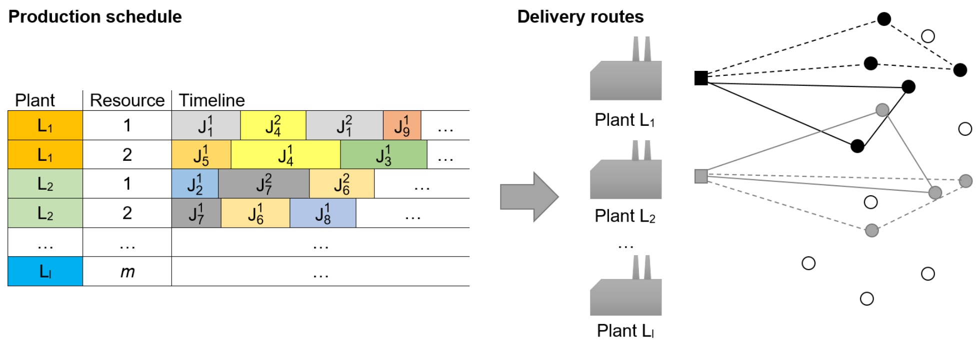
Most existing studies on integrated production-distribution problems consider the strategic or tactical decision level (Chen, 2004, 2010). At the strategic level, decisions about facility location and plant capacity are taken. The tactical level deals with production lot sizes, inventory levels, and delivery quantities. A review of integrated problems at the strategic and tactical level can be found in Vidal and Goetschalckx (1997) and Díaz-Madroñero et al. (2015), respectively. Even though approximately 20 years ago Thomas and Griffin (1996) remarked the scarcity of literature concerning coordinated operational level problems, machine scheduling and distribution decisions are still too often considered independently of each other (Chen, 2010; Reimann et al., 2014; Wang et al., 2015).

The combination of production scheduling and vehicle routing problems is a rather unexplored research direction, whereas both problems on their own are well-studied in the literature. In scientific literature, a large part of the integrated studies considering operational level decisions focuses on relatively simple delivery operations, e.g., direct shipments to customers. A review on this research area can be found in Chen (2004, 2010) and Wang et al. (2015). Some other studies make use of prespecified routes, such as Gupta et al. (2012), or routes with a fixed customer sequence as in Armstrong et al. (2008). Arda et al. (2014) take an intermediate position between a purely sequential approach and a fully coordinated approach. The authors present a stochastic programming formulation for the multi-period vehicle loading problem with stochastic release dates. The problem is used to investigate whether transportation decisions can be improved when forecasts about future releases of items from production are taken into account.

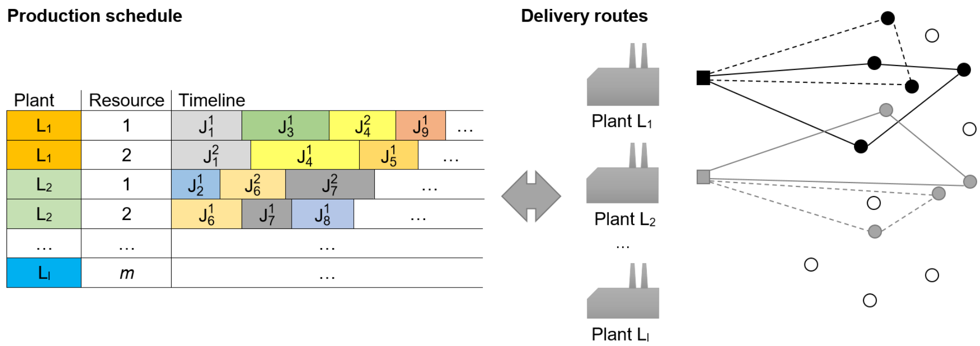
This chapter focuses on integrated operational level problems, which explicitly include vehicle routing decisions. In the literature, different terminology is used for these integrated problems: *integrated production and outbound distribution scheduling* (*IPODS*) *problem* (Chen, 2010; Meinecke and Scholz-Reiter, 2014a; Fu et al., 2017), *production and transportation scheduling problem* (*PTSP*) (Geismar et al., 2008; Scholz-Reiter et al., 2011; Karaoğlan and Kesen, 2017; Lacomme et al., 2018), *integrated production and distribution scheduling problem* (*IPDSP*) (Li and Ferrell, 2011; Zu et al., 2014), and *operational integrated production and distribution problem* (*OIPDP*) (Amorim et al., 2013; Belo-Filho et al., 2015). Two terms refer explicitly to perishable products: *production and distribution planning for single period inventory products* (*PDPSI*) (Park and Hong, 2009) and *production scheduling and vehicle routing problem with time windows for perishable goods* (*PS-VRPTW-P*) (Chen et al., 2009). Furthermore, terms as *medium-sized newspaper production/distribution problem* (*m-NDP*) (Hurter and Van Buer, 1996; Van Buer et al., 1999), and *nuclear medicine production and delivery problem* (*NMPDP*) (Lee et al., 2014) are used for specific problems.

In this review, *integrated production scheduling-vehicle routing problem* (*I-PS-VRP*) is used to refer to the integrated problem, in which the data, requirements, and constraints of the production scheduling and vehicle routing problems are considered simultaneously to obtain an overall optimal solution. The integrated approach provides: (1) the assignment of customer orders to production resources; (2) the production start time and completion time of each customer order; (3) the assignment of completed customer orders to delivery vehicles; (4) the delivery routes; and, (5) the exact delivery time of each customer order. The outcome is a detailed production and distribution schedule with the exact timing at which each individual customer order is executed to satisfy customer demands on time.

In a completely uncoordinated approach, however, the production schedule is determined first. Delivery routes can be established based on the production completion times of each customer. These completion times can be seen as release dates in a VRP. Release dates are the moment goods become available at the depot for delivery to the customer (Cattaruzza et al., 2016; Archetti et al., 2015a). The output of the production scheduling problem is used as input for the VRP. It is also possible



(a) Uncoordinated approach



(b) Integrated approach

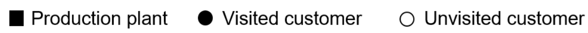


Figure 2.2: Comparison of an uncoordinated and an integrated approach

to first determine a distribution schedule and thereafter a production schedule. Figure 2.2 illustrates production and distribution operations at the operational decision level in an uncoordinated approach (Figure 2.2(a)) and in an integrated approach (Figure 2.2(b)). For each customer order (or job), a number of tasks have to be conducted in the production process. In the figure, J_i^j represents task j of customer order i. Plant location l is expressed by L_l.

The aim of this chapter is not to give a review of production scheduling or vehicle routing problems but of the integration of both problems. The reader is referred to Eksioglu et al. (2009) and Braekers et al. (2016b) for an extensive review of the VRP and to Potts and Strusevich (2009) for a review of scheduling problems. The goal is to explore the existing literature on I-PS-VRPs by analysing both problem characteristics and solution approaches applied to identify gaps in the literature and highlight interesting future research opportunities. The main contributions of this study are to: (1) provide an extensive review of recent research in the field of I-PS-VRPs; (2) propose a classification matrix based on production, inventory, and distribution system characteristics; and, (3) classify and discuss existing literature to indicate promising further research directions.

The review in this chapter differs from other existing literature surveys. Chen (2004) reviews integrated production-distribution problems both at the tactical and operational decision level. However, since operational I-PS-VRPs are a new research domain, at that time only two papers were published, and thus the main focus of the review paper is on direct deliveries. Chen (2010) and Meinecke and Scholz-Reiter (2014b) present a classification scheme for integrated production-distribution studies at the operational level. In both classification schemes different delivery methods are considered, i.e., immediate delivery of each customer order, direct delivery of batched orders of the same customer, delivery with fixed delivery dates, and vehicle routing. In Chen (2010), a classification is made based on a limited number of characteristics: the machine configuration, number and type of vehicles, and equal or general order sizes. Meinecke and Scholz-Reiter (2014b) do not classify all papers in the scheme but only test the robustness of the proposed scheme with a sample of papers. In this sample, only a minority of the studies make use of vehicle routing. Reimann et al. (2014) only review integrated studies in which vehicle routing decisions are included, both at the tactical and operational level. The authors describe the papers based on the machine environment, the number and type of vehicles, and the solution approach used, but no classification is presented. Wang et al. (2015) classify integrated production-distribution papers based on their objective function. No classification based on production and distribution characteristics is proposed. All types of delivery possibilities are included. However, only four of the studies mentioned use a VRP to solve the distribution subproblem.

In contrast to previous literature reviews on integrated production-distribution problems which mainly include studies considering direct shipments, this chapter focuses on operational studies which explicitly consider vehicle routing decisions. Furthermore, a classification matrix is proposed in which the relevant production and distribution characteristics of each paper are indicated. The matrix can be used to identify which combinations of production and distribution characteristics are not well studied yet. The goal is to find gaps in existing research and to identify future research opportunities. This chapter can act as a starting point to gain insight into the integration of production scheduling and vehicle routing operations and what can be learned for the integration of order picking and vehicle routing problems in the following chapters.

The remainder of this chapter is organised as follows. The applied review methodology is described in Section 2.2. A classification scheme including both production and distribution characteristics is given in Section 2.3. The characteristics of each article reviewed in this chapter are indicated in the classification matrix. Section 2.4 reviews existing literature on I-PS-VRPs based on the problem characteristics. An overview of the solution approaches used in existing studies is provided in Section 2.5. Sections 2.4 and 2.5 are structured according to the characteristics which have a major influence on the production method and its complexity: machine configuration, batch processing, and setup operations. Finally, conclusions and further research opportunities are given in Section 2.6.

2.2 Review methodology

The review in this chapter includes studies which fulfil the following selection criteria: (1) production and distribution problems are tackled using an integrated approach; (2) distribution operations are based on vehicle routing decisions; and, (3) integrated problems focus on the operational decision level, i.e., production scheduling decisions are considered; nevertheless, studies sometimes take into account decisions on the strategic or tactical decision level, e.g., lot sizing decisions. More precisely, the studies should tackle the problem to assign customer orders to production resources and vehicles, and to determine a detailed production schedule and vehicle routes.

In order to narrow the scope of this literature review, only articles written in English and published (online) between 1996 and March 2018 are considered. Doctoral dissertations are not included in the review based on the assumption that these are (partly) published in journal articles. Conference papers are only included when no article is published in a scientific journal by the same author(s) on the same problem. The following search strategy is applied. First, articles published in journals with an Impact Factor of at least 1.0 in the domain of Operations Research & Management Science (based on the Impact Factors of 2016 by Thomson Reuters) with the following words in the title are selected: *production* or *machine scheduling* in combination with *delivery*, *distribution*, *routing* or *transportation*. Second, additional articles are collected using scientific-technical bibliographic databases with access to e-journals, such as Google Scholar, Web of Science, and ProQuest. The same search terms are applied. The search results are filtered by additionally searching with the words *integrated*, *synchronised*, *coordinated* or *combined* in the papers. Third, relevant papers cited in review papers on integrated production-distribution problems, such as Chen (2004), Meinecke and Scholz-Reiter (2014b), and Reimann et al. (2014), are included.

The relevance of each paper found is analysed with respect to their content. A first selection is based on the abstract. Thereafter, the full-text of the remaining papers is screened. Papers which do not fulfil the criteria mentioned above are ruled out. More specifically, studies with one of the following elements are excluded: (1) a single customer needs to be delivered; (2) each customer is delivered by a dedicated vehicle, i.e., direct shipments from the manufacturing plant to each customer; and, (3) other transportation modes than vehicles are used, e.g., rail or maritime transport. These studies are filtered out because no vehicle routing decisions can be taken. Furthermore, studies only dealing with the strategic or tactical decision level are ignored for further discussion in this chapter. Finally, bibliographic references of the relevant articles studied serve as a continuous search reference, i.e., ancestry approach.

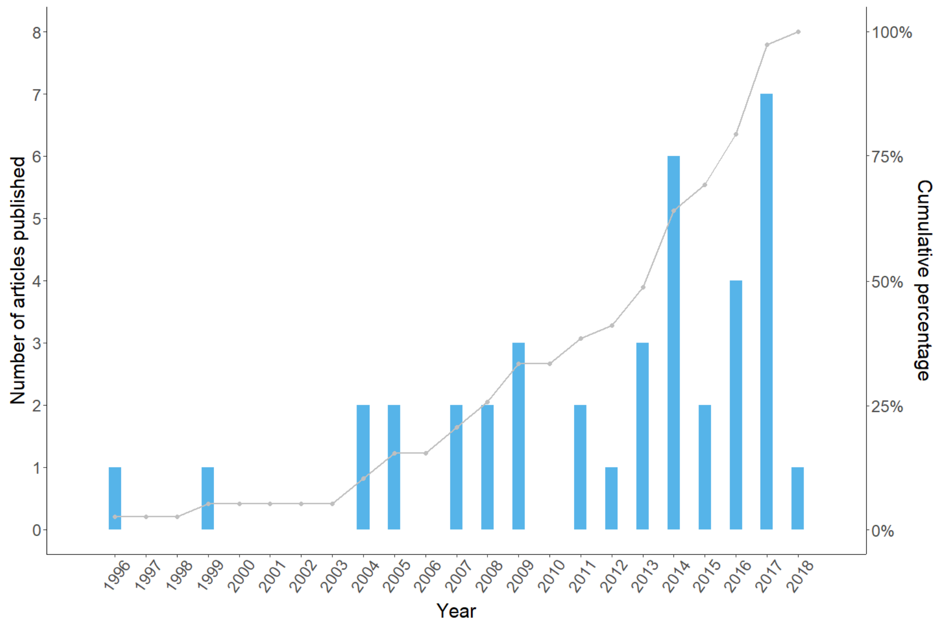


Figure 2.3: Number of articles published per year, including cumulative percentage

This search method leads eventually to the selection of 39 papers which fulfil the selection criteria. This small number of papers is due to the fact that the integration of production scheduling and vehicle routing problem is a recent research area. The first study, to the best of the author's knowledge, on an I-PS-VRP appeared in 1996. Thus, the studies span a period of 22 years. However, in multiple years no article is published, as can be seen in Figure 2.3. More studies on I-PS-VRPs are being published since 2003, and approximately 65% of the papers is published after 2010.

The vast majority, 34 out of 39 studies, is published in scientific journals. In the following sections, the problem characteristics and solution method(s) of each paper are discussed.

2.3 I-PS-VRP: Classification scheme

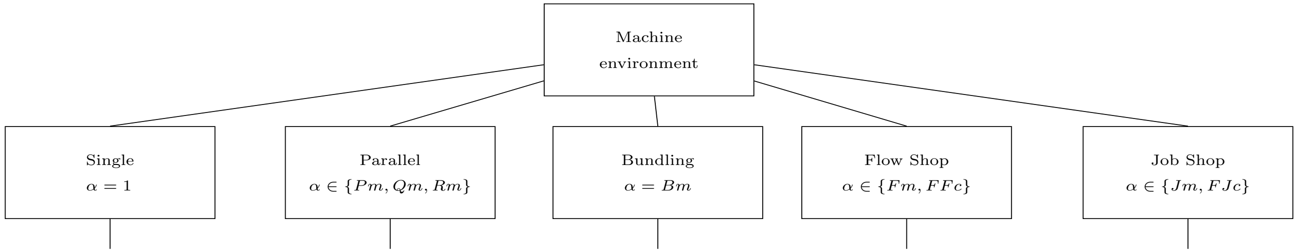
Production scheduling problems are generally classified based on the three-field problem classification $\alpha|\beta|\gamma$ for scheduling problems introduced by Graham et al. (1979) and further investigated by Lawler et al. (1993) and Pinedo (2008), among others. The α-field specifies the machine environment, the β-field describes the job characteristics, and the γ-field refers to the objective criterion. Eksioglu et al. (2009) propose a classification scheme for VRPs, which has recently been updated by Braekers et al. (2016b). The following main categories are used in the scheme: type of study, scenario characteristics, problem physical characteristics, information characteristics, and data characteristics.

Both Chen (2010) and Meinecke and Scholz-Reiter (2014b) extend the three-field notation of Graham et al. (1979) to a five-field representation scheme covering all relevant, according to these authors, parameters for integrated production and distribution scheduling problems. In Chen (2010), delivery characteristics, such as the number of vehicles, vehicle capacity, delivery mode, and the number of customers are added. Meinecke and Scholz-Reiter (2014b) make use of a modification of the VRP classification scheme of Eksioglu et al. (2009) to incorporate distribution parameters into the scheme of Graham et al. (1979). Additionally, inventory characteristics, such as inventory capacity and holding costs, are included.

For I-PS-VRPs, the delivery mode characteristic should not be included as all studies use vehicle routing to deliver goods to customers. Although the schemes are quite extensive, still not all relevant problem characteristics are covered. For instance, in the α-field, machine environments such as a flow shop and bundling machines are not considered in Meinecke and Scholz-Reiter (2014b), whereas in Chen (2010) no job shop and different parallel machine configurations are defined. Furthermore, in many categories of production and distribution characteristics no studies are conducted yet. For example, no study allows split deliveries, and in all studies transportation times are deterministic. Therefore, the classification schemes of Chen (2010) and Meinecke and Scholz-Reiter (2014b) will not be used in this chapter to classify the studies on I-PS-VRPs.

In this review, a general classification scheme based on the machine configuration (α) is illustrated in Figure 2.4. Machine environments with a single machine, parallel

Figure 2.4: State-of-the-art literature classified according to machine environment



Single

Hurter and Van Buer (1996)
Van Buer et al. (1999)
Chang and Lee (2004)
Garcia et al. (2004)
Li et al. (2005)
Chen and Vairaktarakis (2005)
Naso et al. (2007)
Geismar et al. (2008)
Chen et al. (2009)
Park and Hong (2009)
Li and Ferrell (2011)
Low et al. (2013)
Low et al. (2014)
Viergutz and Knust (2014)
Zu et al. (2014)
Li and Zu (2015)
Li et al. (2016)
Jamili et al. (2016)
Cheref et al. (2016)
Devapriya et al. (2017)
Karaoğlan and Kesen (2017)
Low et al. (2017)
Zou et al. (2018)
Lacomme et al. (2018)

Parallel

Pm
Chen and Vairaktarakis (2005)
Russell et al. (2008)
Chiang et al. (2009)
Farahani et al. (2012)
Ullrich (2013)
Qm
Amorim et al. (2013)
Lee et al. (2014)
Belo-Filho et al. (2015)
Kergosien et al. (2017)
Rm
Chang et al. (2014)
Fu et al. (2017)

Bundling

Li and Vairaktarakis (2007)

Flow Shop

Scholz-Reiter et al. (2011)
Ehm and Freitag (2016)
Ramezanian et al. (2017)

Job Shop

Meinecke and Scholz-Reiter (2014a)

machines, bundling machines, flow shops, and job shops are used in the literature on I-PS-VRPs. The single and parallel machine environments are used for jobs which consist of a single operation. In the simplest machine environment, a single machine ($\alpha = 1$) is available to process all jobs. In a parallel machine environment, a job is processed on one of the m machines. The processing time can be machine-independent (identical parallel machines, $\alpha = Pm$), machine-dependent (uniform parallel machines, $\alpha = Qm$), or machine and job-dependent (unrelated parallel machines, $\alpha = Rm$).

When jobs consist of multiple operations, more complex machine environments are used. In a flow shop ($\alpha = Fm$), all jobs have to follow the same sequence along m machines, whereas in a job shop ($\alpha = Jm$), each job has its own predetermined sequence for visiting machines (Graham et al., 1979; Pinedo, 2008). Extensions to a flow shop and a job shop are a flexible flow shop ($\alpha = FFc$) and a flexible job shop ($\alpha = FJc$) which are composed of c stages (or work shops) with a number of identical machines. Each job needs to be processed on only one machine at each stage or work shop (Pinedo, 2008). Furthermore, in a bundling configuration ($\alpha = Bm$), each job consists of m independent operations which need to be processed on m dedicated machines. These operations can be possibly executed simultaneously. Before delivery, all m operations are bundled together (Chen, 2010).

As can be seen from the classification scheme in Figure 2.4, most studies make use of a single machine environment (24 studies) or a parallel machine environment (11 studies). A bundling machine configuration, a flow shop, and a job shop are studied in a single, three, and a single article, respectively. After the classification based on the machine environment, a matrix based on production, inventory, and distribution characteristics is proposed instead of adapting and extending the classification schemes of Chen (2010) and Meinecke and Scholz-Reiter (2014b). Classification matrices for the single production level environments, i.e., e single and parallel machine environment, are presented in Table 2.1. Classification matrices for the flow shop and job shop environments are shown in Table 2.2. Table 2.3 shows the classification matrix for the bundling machine environment.

Only the relevant production, inventory, and distribution characteristics which are applied in at least one I-PS-VRP study are taken into account in the matrix. The advantages of the proposed matrix are that: (1) it gives a clear overview of which combinations of characteristics are already examined in the existing literature on I-PS-VRPs; and, (2) it can easily be extended with additional characteristics whenever applied in future studies. In the classification matrices, the number of studies considering a specific problem characteristic is indicated. For each characteristic, a brief explanation is given.

The following characteristics are used:

1. Production characteristics

   (a) The *number of plants* specifies whether customer orders are processed in a single manufacturing plant or in multiple plants.

   (b) *Batch processing* is defined as producing several customer orders in parallel (p-batching or parallel batching) or sequentially (s-batching or serial batching) by a resource (Pinedo, 2008).

   (c) *Setup times* and *setup costs* can be incurred between orders or batches to prepare resources to be ready for the next order or batch. Setup operations are sequence-dependent if they depend on which order was processed immediately before a next one (Allahverdi and Soroush, 2008).

   (d) *Production times* can be defined either as a unit processing time or as a fixed production rate.

   (e) A *production cost* can be incurred for each item produced or for each time unit producing items.

   (f) A *production due date* specifies the moment in time before which the production of orders has to be completed.

   (g) *Precedence relationships* exist between orders when an order cannot be produced before another specific order is completed (Graham et al., 1979; Pinedo, 2008).

   (h) A *production release date* specifies the earliest moment in time at which processing of an order can start (Graham et al., 1979; Pinedo, 2008).

2. Inventory characteristics

   At the operational level, goods in storage between different steps of the production process and between the end of the production process and the departure of the delivery vehicle are considered to be inventory. Goods are not carried from one planning horizon to the next.

   (a) A limited, an unlimited or no *inventory capacity* can be available.

   (b) An *inventory holding cost* can be incurred when inventory is hold in storage.

3. Distribution characteristics

   (a) The *fleet of vehicles* refers to the number of vehicles available for delivery (single, limited, unlimited) and the heterogeneity of this fleet (identical vehicle properties or not).

   (b) Vehicle drivers can be allowed to conduct *multiple trips* during the planning horizon.

   (c) *Travel times* between two customer locations can be explicitly considered.

   (d) *Transportation costs* can be either a fixed cost for using a vehicle or a cost per kilometre travelled.

   (e) *Service times* specify the time needed to load a vehicle at the DC and to unload the products at a customer location.

   (f) *Pickup and delivery operations* indicate that goods can be both delivered to customers and picked up at suppliers within the same route.

   (g) Customers can have specified a *delivery due date* before or *time window* within which they want the goods to be delivered.

   (h) A *penalty cost* can be incurred if delivery time restrictions are violated.

In short, in the classification matrix in Table 2.1 can be seen that a single machine environment in general is combined with a single vehicle or a homogeneous fleet of delivery vehicles. In two-thirds, i.e., in 12 out of 18 studies which use more than one vehicle, a limited number of vehicles are considered. In approximately 65% of the studies, transportation costs are incurred: variable costs and fixed costs are taken into account in 15 and 13, respectively. By contrast, production costs are in general excluded from the problem. Production and travel times are taken into account in all studies with a single machine. Batch processing is applied in the vast majority of the integrated studies in contrast to setup operations which are only included in a slight minority. Delivery time restrictions, i.e., delivery due date and time windows, are both imposed in 6 studies with a single machine environment.

Rather similar conclusions can be made for studies with a parallel machine environment indicated in the lower part of Table 2.1. Both a homogeneous and a heterogeneous fleet of vehicles are used in half of the studies. A single vehicle in combination with parallel machines is used in a single study. Time windows are included in 8 out of 11 studies. No pickup and delivery operations and inventory decisions are considered in integrated studies with a single or parallel machine environment. It is

Table 2.1: Matrix of production, inventory, and distribution characteristics for a single and parallel machine environment

Distribution	Production										Inventory		
	Single plant	Multiple plant	Batch processing	Production times	Production cost	Setup times	Setup cost	Production due date	Precedence relationships	Production release date	Limited inventory capacity	Inventory holding cost	Number of studies
Single machine													
Single vehicle	6		5	6						1			6
Homogeneous fleet	13	2	14	15	2	3	1			1			15
Heterogeneous fleet	3		3	3									3
Unlimited number	5	1	5	6						1			6
Limited number	11	1	12	12	2	3	1						12
Multiple trips	11	2	12	13		1				1			13
Travel times	22	2	22	24	2	3	1			2			24
Variable transportation cost	13	2	14	15	1	3	1			1			15
Fixed transportation cost	12	1	12	13	1	3	1			1			13
Loading times	3	1	3	4	1	3	1						4
Unloading times	6	2	7	8	2	2	1						8
Pickup and delivery	2		2	2									2
Delivery due date	4	2	5	6	1	3	1			1			6
Time windows	5	1	4	6	1								6
Penalty cost	4	1	4	5	2	1	1						5
Number of studies	22	2	22	24	2	3	1			2			24
Parallel machines													
Single vehicle	1			1						1			1
Homogeneous fleet	5		3	5	2	3	3	1					5
Heterogeneous fleet	5		3	4	1	1	1	2	1	2			5
Unlimited number	4		1	4	2	3	3						4
Limited number	6		5	5	1	1	1	3	1	2			6
Multiple trips	3		1	2	1					1			3
Travel times	11		6	10	3	4	4	3	1	3			11
Variable transportation cost	9		6	8	3	4	4	3	1	2			9
Fixed transportation cost	7		5	6	3	2	2	2	1	2			7
Loading times	4		3	3	1			2	1	2			4
Unloading times	7		3	6	3	3	3	2	1	2			7
Pickup and delivery													
Delivery due date	4		3	4		1	1	3	1	3			4
Time windows	8		4	7	3	4	4	3	1	2			8
Penalty cost													
Number of studies	11		6	10	3	4	4	3	1	3			11

Table 2.2: Matrix of production, inventory, and distribution characteristics for a flow shop and job shop machine environment

Distribution	Production										Inventory		
	Single plant	Multiple plant	Batch processing	Production times	Production cost	Setup times	Setup cost	Production due date	Precedence relationships	Production release date	Limited inventory capacity	Inventory holding cost	Number of studies
Flow shop													
Single vehicle													
Homogeneous fleet													
Heterogeneous fleet	3			3	3					1		3	3
Unlimited number													
Limited number	3			3	3					1		3	3
Multiple trips	2			2	2					1		2	2
Travel times	3			3	3							3	3
Variable transportation cost	3			3	3					1		3	3
Fixed transportation cost	3			3	3					1		3	3
Loading times													
Unloading times	1			1	1							1	1
Pickup and delivery													
Delivery due date	2			2	2					1		2	2
Time windows													
Penalty cost	2			2	2					1		2	2
Number of studies	3			3	3					1		3	3
Job shop													
Single vehicle													
Homogeneous fleet	1			1	1		1	1			1	1	1
Heterogeneous fleet													
Unlimited number													
Limited number	1			1	1		1	1			1	1	1
Multiple trips													
Travel times													
Variable transportation cost	1			1	1		1	1			1	1	1
Fixed transportation cost	1			1	1		1	1			1	1	1
Loading times													
Unloading times													
Pickup and delivery													
Delivery due date	1			1	1		1	1			1	1	1
Time windows													
Penalty cost	1			1	1		1	1			1	1	1
Number of studies	1			1	1		1	1			1	1	1

Table 2.3: Matrix of production, inventory, and distribution characteristics for a bundling machine environment

Distribution	Production										Inventory		
	Single plant	Multiple plant	Batch processing	Production times	Production cost	Setup times	Setup cost	Production due date	Precedence relationships	Production release date	Limited inventory capacity	Inventory holding cost	Number of studies
Flow shop													
Single vehicle													
Homogeneous fleet	1		1	1									1
Heterogeneous fleet													
Unlimited number	1		1	1									1
Limited number													
Multiple trips													
Travel times	1		1	1									1
Variable transportation cost	1		1	1									1
Fixed transportation cost	1		1	1									1
Loading times													
Unloading times													
Pickup and delivery													
Delivery due date													
Time windows													
Penalty cost													
Number of studies	1		1	1									1

observed in Table 2.2 that a flow shop environment is combined with a heterogeneous fleet, while a job shop is integrated with homogeneous vehicles. Both production and transportation costs are considered in these machine environments. No study includes time windows, while 3 out of 4 studies specify a delivery due date. A bundling machine environment is combined with an unlimited number of homogeneous vehicles, as can be seen in Table 2.3. In Section 2.4, each paper is discussed in more detail according to the problem characteristics used in the classification matrix and the objective function.

2.4 I-PS-VRP: Problem characteristics

This section reviews existing literature on I-PS-VRPs. In order to discuss the papers, this section is structured in the following way. The studies are first classified based on the machine environment used in each study. In this way, it can be discovered whether different production, inventory, and/or distribution characteristics are implied in relatively simple environments, e.g., single machine, compared to more complex ones, e.g., job shop or flow shop. Within each subsection, studies are combined according to the following production characteristics: batch processing and setup operations.

These two criteria are selected because they have the largest impact on the way of producing in comparison to the other production characteristics used in Tables 2.1-2.3, such as including production costs and production times. Problems with batch processing are often more complex since a higher number of production schedules are possible. For each moment in time, every possible batch composition needs to be determined. The different production schedules need to be evaluated in order to find the best one related to the objective. Setup operations are related to batch processing as such operations are often necessary between the production of two subsequent batches. However, as can be seen from Tables 2.1-2.3, whereas batch processing is mostly applied in I-PS-VRPs, setup operations are generally neglected.

Sections 2.4.1 - 2.4.3 discuss the papers in the different machine environments. A table in which the problem characteristics of each study are indicated (• if included) is constructed for each machine environment. In Section 2.4.4, a discussion on the problem characteristics is provided, and gaps and future research opportunities are indicated.

2.4.1 Single machine environment

In the majority of the studies a single machine configuration for the execution of customer orders is applied, and orders are combined into batches in most of these articles. Table 2.4 provides an overview of the discussed articles with their main problem characteristics and objective function. As can be seen in the upper part of Table 2.1, only two studies do not process orders in batches, i.e., Naso et al. (2007) and Viergutz and Knust (2014). Setup operations are often not considered in research on I-PS-VRPs with a single machine environment. In studies without batching, setup operations are not incorporated.

Table 2.4: Single machine environment ($\alpha = 1$): Problem characteristics

	Production										**Inventory**		**Distribution**															**Objective**						
													Fleet of vehicles																					
	Single plant	Multiple plant	Batch processing	Production times	Production cost	Setup times	Setup cost	Production due date	Precedence relationships	Production release dates	Limited inventory capacity	Inventory holding cost	Single vehicle	Homogeneous fleet	Heterogeneous fleet	Unlimited number	Limited number	Multiple trips	Travel times	Variable transportation cost	Fixed transportation cost	Loading times	Unloading times	Pickup and delivery	Delivery due date	Time windows	Penalty cost	Cost	Profit	Service	Demand satisfied	Vehicles used	Distance travelled	Quality
Naso et al. (2007)		•		•										•		•		•	•	•	•	•	•		•	•	•	•						
Viergutz and Knust (2014)	•			•									•						•							•					•			
Garcia et al. (2004)		•	•	•										•			•	•	•	•			•		•				•					
Chang and Lee (2004)	•		•	•									•					•	•											•				
Chen and Vairaktarakis (2005)	•		•	•										•		•			•	•	•							•		•				
Li et al. (2005)	•		•	•									•					•	•											•				
Geismar et al. (2008)	•		•	•									•					•	•											•				
Karaoğlan and Kesen (2017)	•		•	•									•					•	•											•				
Devapriya et al. (2017)	•		•	•										•		•		•	•	•	•							•						
Lacomme et al. (2018)	•		•	•										•			•	•	•											•				

Table 2.4: (continued)

	Production										Inventory		Distribution															Objective						
													Fleet of vehicles																					
	Single plant	Multiple plant	Batch processing	Production times	Production cost	Setup times	Setup cost	Production due date	Precedence relationships	Production release dates	Limited inventory capacity	Inventory holding cost	Single vehicle	Homogeneous fleet	Heterogeneous fleet	Unlimited number	Limited number	Multiple trips	Travel times	Variable transportation cost	Fixed transportation cost	Loading times	Unloading times	Pickup and delivery	Delivery due date	Time windows	Penalty cost	Cost	Profit	Service	Demand satisfied	Vehicles used	Distance travelled	Quality
Chen et al. (2009)	•		•	•	•									•			•		•	•			•			•	•		•					
Li and Ferrell (2011)	•		•	•											•		•	•	•	•	•							•						
Zu et al. (2014)	•		•	•										•			•	•	•	•	•			•				•						
Li and Zu (2015)	•		•	•										•			•	•	•	•	•			•				•						
Low et al. (2013)	•		•	•										•			•		•				•			•				•				
Low et al. (2014)	•		•	•											•	•			•	•	•		•			•	•	•						
Low et al. (2017)	•		•	•											•	•			•	•	•		•			•	•	•						
Li et al. (2016)	•		•	•										•			•		•	•	•							•		•				
Jamili et al. (2016)	•		•	•						•				•		•			•	•	•							•		•				
Cheref et al. (2016)	•		•	•						•			•					•	•						•					•				
Zou et al. (2018)	•		•	•										•			•		•											•				

Table 2.4: (continued)

	Production										**Inventory**		**Distribution**															**Objective**						
													Fleet of vehicles																					
	Single plant	Multiple plant	Batch processing	Production times	Production cost	Setup times	Setup cost	Production due date	Precedence relationships	Production release dates	Limited inventory capacity	Inventory holding cost	Single vehicle	Homogeneous fleet	Heterogeneous fleet	Unlimited number	Limited number	Multiple trips	Travel times	Variable transportation cost	Fixed transportation cost	Loading times	Unloading times	Pickup and delivery	Delivery due date	Time windows	Penalty cost	Cost	Profit	Service	Demand satisfied	Vehicles used	Distance travelled	Quality
Hurter and Van Buer (1996)	•		•	•		•								•			•		•	•	•	•	•		•			•						
Van Buer et al. (1999)	•		•	•		•								•			•	•	•	•	•	•			•			•						
Park and Hong (2009)	•		•	•	•	•	•							•			•		•	•	•	•	•		•		•	•						

2.4.1.1 No batch processing

No setup operations Naso et al. (2007) and Viergutz and Knust (2014) investigate an I-PS-VRP which involves a product with a limited lifespan: ready-mixed concrete in Naso et al. (2007) and industrial chemicals in Viergutz and Knust (2014). Therefore, delivery has to take place within a specified period of time after production to prevent the product from expiring. Additionally, customers have indicated a time window in which they want the goods to be delivered. When the vehicle arrives early it has to wait. Late deliveries are not allowed.

In Naso et al. (2007), at each plant a single loading dock is available to process the product and load it directly onto a truck. While some plants own a fleet of homogeneous trucks, other have to rely on the fleet of other plants. More vehicles can be hired from external companies. Thus, a multi-depot vehicle routing problem with time windows is integrated with a production scheduling problem. A penalty cost is incurred when a truck has to wait for loading and unloading. The objective of the non-linear problem is to minimise costs related to transportation, loading and unloading waiting times, outsourced production, additionally hired trucks, and overtime work for drivers.

In Viergutz and Knust (2014), due to the limited lifespan of the product and the use of a single delivery tour, it is possible that not all demand can be satisfied within the time windows at the customer locations. As such, the objective of the mixed integer linear programming (MILP) problem is to maximise total demand satisfied.

2.4.1.2 Batch processing

No setup operations Similar to Naso et al. (2007), Garcia et al. (2004) examine an I-PS-VRP for ready-mixed concrete. In contrast to Naso et al. (2007), at each plant there is sufficient capacity to produce simultaneously multiple orders, i.e., p-batching. Furthermore, no time windows are given, but each order has a due date at which it should be delivered exactly at the customer location. The objective of the integer linear programming (ILP) model is to select orders to maximise profit taking into account distribution costs.

Chang and Lee (2004) investigate a scenario with two customer areas and a single machine environment. Besides a two customer problem variant, Li et al. (2005) study a general situation with more than two customers. Chen and Vairaktarakis (2005) examine two variants with multiple customers for a single-machine context. The problems differ in the performance measure, i.e., mean or maximum delivery time. In the three studies, orders which are delivered by the same vehicle trip are produced immediately after each other, i.e., s-batching. In Chang and Lee (2004) and Li et al. (2005), an order should be delivered in a single tour, but different orders of the same customer can be delivered in different tours. The objective in Chang and Lee (2004) is to minimise the total time for the vehicle to deliver all orders and to return to the plant. In Li et al. (2005), the sum of order arrival times at customers is minimised. Chen and Vairaktarakis (2005) search for a method to optimise the trade-off between distribution costs and customer service level measured by the delivery times.

Geismar et al. (2008) examine an I-PS-VRP for a product with a limited lifespan. In the integrated problem formulated by Geismar et al. (2008), machine scheduling within the plant is not explicitly considered. The focus is on assigning customer orders to production runs, determining the run size, and start time of each run. Furthermore, it is decided which customers are served on which trip and in which order in the specific trip. Additionally, the sequence of the different trips needs to be decided. The objective is to minimise the makespan, i.e., the time required to manufacture and deliver all goods. Karaoğlan and Kesen (2017) propose a mixed integer programming (MIP) model for the same problem as Geismar et al. (2008). Devapriya et al. (2017) extend the problem of Geismar et al. (2008) by considering the fleet size as a decision variable instead of using a single vehicle as in Geismar et al. (2008). Each vehicle of the fleet can conduct multiple trips. A second difference is that a finite planning horizon is considered. The objective of the MILP is to minimise the sum of the fixed vehicle costs and the variable travelling costs. Lacomme et al. (2018) study an extension of Geismar et al. (2008) with multiple homogeneous vehicles. Each vehicle can conduct at most a single tour. The objective is to minimise the makespan, which is the latest arrival at the depot.

Chen et al. (2009) formulate an integer non-linear programming (INLP) model for an I-PS-VRP for perishable goods having all a specific rate of decay at which the quality of goods decreases. In Chen et al. (2009), each customer has a soft time window. If a vehicle arrives early it has to wait, while a late delivery will result in a penalty cost. Since customer demand is stochastic, the determined plan should indicate the production quantities, the start of production, and the delivery routes to maximise the expected profit of the supplier taking into account the price of the goods and the costs related to production, transportation, and goodwill loss.

Similarly, Li and Ferrell (2011) study an I-PS-VRP for a perishable product. The fleet of vehicles differs in capacity and cost. Zu et al. (2014) and Li and Zu (2015) adapt and extend the previous model of Li and Ferrell (2011) with a pickup and delivery problem. An I-PS-VRP for a three-level supply chain, including suppliers, a single plant, and customers, is investigated. Pickup and delivery operations are allowed in the same trip. This can be considered to be a VRP with mixed linehauls and backhauls (Parragh et al., 2008) in which raw materials need to be picked up at suppliers and finished goods need to be delivered at the customers. The objective of the MIP problem is to minimise total transportation cost.

Low et al. (2013, 2014, 2017) investigate an integrated scheduling problem at a multi-product distribution centre. If a customer orders different goods, these are immediately packed in a single batch. Low et al. (2013) use an INLP model to minimise the time to deliver all orders to the customers. In subsequent studies of Low et al. (2014, 2017), the objective is cost minimisation taking into account fixed vehicle costs, transportation costs, and penalty costs incurred for the violation of a time window.

Li et al. (2016) study an integer non-linear bi-objective I-PS-VRP in which both delivery cost and total customer waiting time have to be minimised. The delivery cost consists of a fixed cost incurred for each vehicle used and a variable cost depending on the travel time needed. The total customer waiting time is equal to the sum of the delivery times.

Jamili et al. (2016) also investigate a bi-objective integrated problem formulated as an ILP model. A schedule needs to be determined which minimises both the distribution cost and the average of the delivery times. The two objectives are combined into a single objective by using weights which represent the preference of the decision maker. The production of an order cannot start before the release date of the order imposed by the supplier.

Cheref et al. (2016) are the first authors to study an integrated problem in an uncertain environment. Similar to the study of Jamili et al. (2016), each order has a release date which indicate the earliest moment in time production of that order can start. The release dates, processing times, travel times, and delivery due dates are uncertain. The objective function of the MILP is to minimise a robustness criterion, which is the maximum lateness of delivery in comparison to the delivery due dates.

Zou et al. (2018) integrate a production scheduling problem with an open VRP. A 3PL service provider is responsible for the delivery of the goods. After conducting a route, vehicles return to the vehicle docking station of the 3PL service provider and not to the production plant. The goods delivered in the same route are produced successively on the machine. The objective of the non-linear problem is to minimise the maximum order delivery time.

Setup operations The previously mentioned studies with a single machine environment do not consider setup operations. Hurter and Van Buer (1996), Van Buer et al. (1999), and Park and Hong (2009) take sequence-dependent setup operations into account. In one of the first studies which integrates production scheduling with vehicle routing issues, Hurter and Van Buer (1996) investigate a newspaper production/distribution problem with a single printing facility. Van Buer et al. (1999) investigate a similar non-linear problem in spite of the fact that trucks are allowed to conduct multiple trips. In Hurter and Van Buer (1996), the number of vehicles used is minimised as this is the major distribution cost, whereas in Van Buer et al. (1999) both costs of owning and using vehicles have to be minimised.

An I-PS-VRP for single-period inventory products is examined by Park and Hong (2009). A single production line needs to process different versions of a product. Each version is produced once and thus customer orders for the same product are sequentially processed in a batch. A setup time is required between the production of the different products. Customers have a soft and hard delivery deadline. A violation of the soft deadline is penalised with a delay cost, whereas a violation of the hard deadline is not allowed. Split deliveries of a same product are not allowed, but when customers order multiple products it is possible to deliver each product by a different vehicle. The objective of the MILP is to minimise costs of production, transportation, and delay.

2.4.2 Parallel machine environment

Approximately a quarter of the studies on I-PS-VRPs consider a parallel machine environment. Most of these studies make use of identical parallel machines. Amorim et al. (2013), Lee et al. (2014), Belo-Filho et al. (2015), and Kergosien et al. (2017) study integrated problems with uniform parallel machines. Unrelated parallel machines are considered in the studies of Chang et al. (2014) and Fu et al. (2017). Similar to studies with a single machine environment, the majority of these studies process orders in batches and mostly setup operations are ignored, as can be seen in the lower part of Table 2.1. The problem characteristics of each paper are indicated in Table 2.5.

2.4.2.1 No batch processing

No setup operations In the study of Ullrich (2013), each customer order needs to be processed on one of the identical parallel machines. Time windows are taken into account at the customer locations with a hard lower bound, as orders cannot be delivered early. Late deliveries are allowed, but the objective of the MILP is to minimise total tardiness of the orders.

Table 2.5: Parallel machine environment ($\alpha \in \{Pm, Qm, Rm\}$): Problem characteristics

	Production										**Inventory**		**Distribution**															**Objective**						
													Fleet of vehicles																					
	Single plant	Multiple plant	Batch processing	Production times	Production cost	Setup times	Setup cost	Production due date	Precedence relationships	Production release dates	Limited inventory capacity	Inventory holding cost	Single vehicle	Homogeneous fleet	Heterogeneous fleet	Unlimited number	Limited number	Multiple trips	Travel times	Variable transportation cost	Fixed transportation cost	Loading times	Unloading times	Pickup and delivery	Delivery due date	Time windows	Penalty cost	Cost	Profit	Service	Demand satisfied	Vehicles used	Distance travelled	Quality
Ullrich (2013)	•			•											•		•	•	•			•	•			•				•				
Kergosien et al. (2017)	•			•						•			•					•	•						•					•				
Amorim et al. (2013)	•			•	•	•	•							•		•			•	•	•		•			•		•						
Belo-Filho et al. (2015)	•			•	•	•	•							•		•			•	•	•		•			•		•						
Fu et al. (2017)	•			•		•	•								•	•			•	•			•			•		•						
Chen and Vairaktarakis (2005)	•		•	•										•		•			•	•	•							•		•				
Russell et al. (2008)	•		•	•				•		•					•		•		•	•	•	•	•		•	•						•	•	
Chiang et al. (2009)	•		•	•				•	•	•					•		•		•	•	•	•	•		•	•						•	•	
Lee et al. (2014)	•		•		•										•		•	•	•	•	•	•	•			•		•						
Chang et al. (2014)	•		•	•										•			•		•	•	•							•		•				
Farahani et al. (2012)	•		•	•		•	•	•						•			•		•	•					•	•		•						•

Kergosien et al. (2017) study an I-PS-VRP with uniform parallel machines in a case of chemotherapy production and delivery. Production of an order cannot start before its release date, which is the moment of treatment validation by a doctor. Furthermore, all orders have a delivery due date, which indicates the moment of treatment. Additionally, some orders have a stability time after the completion of the production process. When this time period is violated, the drug can become dangerous. A single delivery man is responsible for the deliveries with an uncapacitated vehicle, and can make multiple tours. The objective is to minimise the maximum tardiness of delivery.

Setup operations Amorim et al. (2013) examine an I-PS-VRP with uniform parallel machines in which some of the products are perishable. The main contribution of this study is to evaluate whether lot sizing decisions, i.e., split a customer order into sublots processed on different machines, may result in better results compared to batching, i.e., process a customer order continuously in one time. The definition of batching in Amorim et al. (2013) differs from the definition used in this dissertation. Setup times and costs are explicitly taken into account as these can strongly affect the results. Hard time window bounds need to be respected. The objective of the formulated mixed integer (linear) models is to minimise total cost of production, setup, and distribution. Belo-Filho et al. (2015) conduct further research on the MILP model using the lot sizing approach.

Fu et al. (2017) study an I-PS-VRP with unrelated parallel machines in the context of a metal packaging company. It is allowed to split a job into subjobs which can be processed independently on one of the machines in parallel, but preemption is not allowed. In the delivery phase, a job needs to be delivered in a single shipment within a time window which cannot be violated. The machines have release times. The objective is to minimise the sum of the sequence-dependent setup costs and the transportation cost. The novelty of this study lies in the transportation cost which depends on transportation type selected, i.e., direct shipment and routing. When direct delivery is chosen, the transportation cost is equal to the direct delivery cost from plant to customer. When routing delivery is chosen, the transportation cost is equal to the most expensive direct delivery cost of a job in the route plus a drop cost for each delivery location in the route.

2.4.2.2 Batch processing

No setup operations Besides a single machine configuration, Chen and Vairaktarakis (2005) investigate a parallel machine context. The same two variants as those for the single machine configuration which differ in the performance measure are studied for an identical parallel machine configuration. Similar as in the single machine environment, the trade-off between distribution costs and customer service level is used as objective criterion.

Similar to Hurter and Van Buer (1996) and Van Buer et al. (1999) with a single machine configuration, Russell et al. (2008) study an I-PS-VRP for newspapers with two parallel production lines. The printing of two types of newspapers cannot start before midnight, which can considered to be a production release date. In a subsequent study, Chiang et al. (2009) examine a similar problem but with an additional newspaper edition. The production of the additional edition must be completed before the production of one of the other two editions can start. In both studies an open VRP with hard time windows and zoning constraints, formulated as a MILP, is considered. There is a limitation on the number of zones which can be delivered by a single vehicle. The objective for the state editions is to minimise total distance travelled, whereas for the city editions the number of vehicles used needs to be minimised.

Lee et al. (2014) study an I-PS-VRP for a nuclear medicine. Each order needs to be assigned to a production run on one of the multiple cyclotrons. Multiple orders can be produced simultaneously in a single production run as long as the machine capacity is not violated, i.e., p-batching. Customers specify hard delivery time windows. The upper bound of the time window is the exact medicine's usage time. The objective of the formulated MILP is production cost and distribution cost minimisation.

Orders of multiple customers are processed on unrelated parallel machines in the study of Chang et al. (2014). All customer orders delivered by the same vehicle are produced sequentially in a batch. The objective function of the non-linear mathematical model formulated is similar to the one of Chen and Vairaktarakis (2005), i.e., minimisation of weighted combination of delivery times and total distribution cost.

Setup operations Farahani et al. (2012) investigate an I-PS-VRP for perishable food products. A caterer produces multiple variants of products which have to be processed on different temperature levels in one of the identical ovens. Several customer orders can be processed simultaneously, i.e., p-batching. Similar to Fu et al. (2017), sequence-dependent setup costs and times are taken into account in the MILP. Tight time windows in which the goods need to be delivered are considered. The objective is a trade-off between setup and transportation costs and the quality of the perishable food products.

Table 2.6: Other machine environments: Problem characteristics

	Production										**Inventory**		**Distribution**															**Objective**						
													Fleet of vehicles																					
	Single plant	Multiple plant	Batch processing	Production times	Production cost	Setup times	Setup cost	Production due date	Precedence relationships	Production release dates	Limited inventory capacity	Inventory holding cost	Single vehicle	Homogeneous fleet	Heterogeneous fleet	Unlimited number	Limited number	Multiple trips	Travel times	Variable transportation cost	Fixed transportation cost	Loading times	Unloading times	Pickup and delivery	Delivery due date	Time windows	Penalty cost	Cost	Profit	Service	Demand satisfied	Vehicles used	Distance travelled	Quality
Bundling machine environment ($\alpha = Bm$)																																		
Li and Vairaktarakis (2007)	•		•	•										•		•			•	•	•							•		•				
Flow shop machine environment ($\alpha \in \{Fm, FFc\}$)																																		
Scholz-Reiter et al. (2011)	•			•	•							•			•		•	•	•	•	•				•		•	•						
Ehm and Freitag (2016)	•			•	•					•		•			•		•	•	•	•	•				•		•	•						
Ramezanian et al. (2017)	•			•	•							•			•		•		•	•	•		•					•						
Job shop machine environment($\alpha \in \{Jm, FJc\}$)																																		
Meinecke and Scholz-Reiter (2014a)	•			•	•		•	•			•	•		•			•			•	•				•		•	•						

2.4.3 Other machine environments

Besides a single machine environment and a parallel machine environment, five studies consider a more advanced environment: bundling machines, flow shop, and job shop. Table 2.6 indicates the problem characteristics and objective function of the studies. Li and Vairaktarakis (2007) investigate an integrated problem in which each of the two tasks of a customer order needs to be processed on a dedicated machine. The two tasks are independent of each other and can be executed in parallel at the same time if necessary. Delivery can start when both tasks are completed. This kind of production operations is called bundling operations. Customer orders delivered in the same vehicle trip are produced immediately after each other. The objective is to minimise the sum of transportation cost and customer waiting cost based on the delivery time at the customer locations.

Whereas the previous studies discussed consider a single production level, Scholz-Reiter et al. (2011), Ehm and Freitag (2016), and Ramezanian et al. (2017) investigate the integration of a VRP with a flow shop and Meinecke and Scholz-Reiter (2014a) with a job shop. These environments have multiple production levels. To the best of the author's knowledge, Scholz-Reiter et al. (2011) is the first paper which explicitly mentions that inventory can be stored before the first production level, between consecutive production levels, and before the departure of a vehicle trip, and takes holding costs into account. In Meinecke and Scholz-Reiter (2014a), intermediate storage is used as a linking element between the production and distribution function. Similarly, in Ehm and Freitag (2016) and Ramezanian et al. (2017), a storage cost is incurred when finished goods need to wait before the delivery starts.

In Scholz-Reiter et al. (2011), Meinecke and Scholz-Reiter (2014a), and Ehm and Freitag (2016), each customer order needs to be processed on one of the machines available at each production level, and thus it can be defined as a flexible flow shop and a flexible job shop as discussed in Section 2.3. In Ramezanian et al. (2017), each order has to be processed on at most one of the machines, but it is not obliged that each order is processed at each work shop of the flow shop. In Scholz-Reiter et al. (2011), a customer can only be visited once in a specific vehicle trip, but can be visited by several vehicles to deliver different orders. A rolling time horizon is considered, and stochastic events can influence the planning. Each order has a desired delivery date before which it cannot be delivered, whereas a late delivery is penalised. The objective of the MIP in Scholz-Reiter et al. (2011) is to minimise total cost, including processing costs, holding costs, penalty costs for delayed deliveries, and transportation costs. The objective of the ILP problem in Meinecke and Scholz-Reiter (2014a) is to minimise costs related to production, setup, distribution, storage, and violations of production and/or delivery due dates. Ehm and Freitag (2016) have the same objective function for their MIP problem. In Ramezanian et al. (2017), the total cost of production and delivery need to be minimised. Two types of distribution are considered: direct deliveries to the customer and routing deliveries.

2.4.4 Problem characteristics: Discussion

2.4.4.1 Production characteristics

A closer look at the characteristics of the considered production systems reveals that previous studies in general consider a relatively simple environment in which each order consists of a single operation. As illustrated in Figure 2.4, most studies use a single machine environment or parallel machine environment. In this latter environment, mostly identical parallel machines are considered. As production environments with multiple production levels, such as job shops and flow shops, are nowadays commonly used for mass production, integrating these with a VRP can be an interesting future research direction. Nevertheless, these machine environments make the integrated problem more complex and harder to solve.

As can be seen in the classification matrices in Tables 2.1 to 2.3, only two studies examine a **multiple-plant** case; both consider a single machine environment. Mostly, the assignment of customer orders to plants is a more tactical decision. However, in the specific cases of Garcia et al. (2004) and Naso et al. (2007) with the production of ready-mixed concrete and not all plants owning vehicles, also operational decisions have to be taken to construct routes between plants and customers. Several authors, such as Chen (2010) and Reimann et al. (2014), highlight the need for more studies which incorporate multiple production sites. Production costs and productivity can vary among plants due to, for example, variations in labour cost and skills. On the one hand, the problem becomes more extensive and complex as orders need to be allocated to machines in plants with different parameter values. On the other hand, coordination between various plants can result in a better solution, i.e., lower costs and/or better schedules (Gupta et al., 2012).

In order to determine reliable production schedules, processing times cannot be ignored. All studies reviewed take **production times** explicitly into account, except Lee et al. (2014) who consider production runs with fixed start and end times. **Production costs** are less generally included. The majority of the articles discussed do not consider processing costs based on the assumption that all goods need to be produced. Consequently, the total quantity produced is equal for all possible production schedules, and as such, production costs are not influenced by the schedule chosen. However, when production costs are machine-dependent or demand is stochastic and the production quantities need to be determined, then these costs should be incorporated into the problem. As such, in all studies with a shop environment, production costs are included.

As already mentioned and as can be seen in the classification matrices, most studies produce orders in batches. Related to batch processing are **setup operations** between consecutive batches. Explicitly taking into account setup times and setup costs can lead to an increase in productivity, a reduction of non-value added activities, and an improvement of resources utilisation (Allahverdi, 2015). Nevertheless, setup operations are often assumed to be negligible. When setup operations are sequence-dependent, these should be incorporated, since these can have an important impact on the decision which schedule is chosen. Thus, its inclusion into models is an important future research direction.

Four studies imply a **production due date**, either unified or order-dependent. Orders need to be processed before this specific moment in time. Production due dates are only incorporated in studies with a parallel machine environment and a job shop. In an I-PS-VRP, the only relevant time restriction is that orders need to be delivered within the specified time windows, and as such, a production due date is less important.

Release dates are considered in six studies. The release date of an order can either be known in advance or be uncertain until the orders are effectively released. Including release dates into the problem makes it more realistic, since not all orders are available at the start of the planning horizon. On the other hand, the problem becomes more complex. Only a single study incorporates **precedence relationships** in the production process.

In short, relatively simple machine environments are generally combined with simple production characteristics. For instance, although in most papers batch processing is applied, setup operations are ignored. More advanced characteristics such as production release dates and precedence relationships are often neglected in I-PS-VRP studies. In addition to the problem characteristics mentioned above, there are constraints which are not incorporated in I-PS-VRPs yet. For example, Fan et al. (2015) include a machine **non-availability** constraint in an integrated scheduling problem of production and distribution. The single machine can be unavailable due to regular preventive maintenance or unexpected breakdowns. However, in the study only a single customer was considered. It can be interesting to incorporate such availability constraints into I-PS-VRPs. The periods in which machines cannot produce any orders may have a significant impact on the production and distribution schedule. Ignoring these constraints when determining the schedules may result in unexpected late deliveries.

2.4.4.2 Inventory characteristics

A remarkable observation is that all research published on the combination of production scheduling and vehicle routing with a single or parallel machine environment do not explicitly consider **inventories** and inventory holding costs, as can be seen in Table 2.1. In contrast, studies considering a production environment with multiple stages do explicitly incorporate inventories. Inventories between different production levels and/or between production and distribution operations are allowed. Associated holding (or waiting) costs are taken into account. Ehm and Freitag (2016) and Ramezanian et al. (2017) consider a waiting cost when completed goods have to wait before delivery starts.

Ullrich (2013) indicates that including inventory holding costs can be valuable to find the optimal trade-off against transportation, earliness, and tardiness costs. Furthermore, Wang et al. (2015) remark that holding intermediate inventory between production and distribution operations can help to balance production rate and delivery speed. As such, including inventory in integrated machine scheduling and vehicle routing problems is a promising research direction. In single-period problems, the inventory which needs to be considered is the work-in-progress inventory between the end of the production of an order and the start of the delivery, or between different production stages. By minimising work-in-progress holding costs, the time between production and delivery is minimised.

2.4.4.3 Distribution characteristics

On the delivery side of the integrated problem, an unlimited availability of vehicles is assumed in 11 studies. In these cases, it is generally supposed that additional vehicles can be hired from external partners or that distribution operations are executed by a 3PL service provider. However, in reality, a company has a **fixed fleet size**. Even when the deliveries are carried out by a third-party carrier, the unlimited availability assumption is not always realistic as their number of vehicles can be limited at a certain moment in time. For instance, Li et al. (2008) investigate a context in which a manufacturer makes use of a 3PL provider for its distribution operations. The 3PL provides services to multiple manufacturers, and as such, each manufacturer has to book the required capacity in a specific vehicle whose departure time is determined by the 3PL. Thus, there is a limited capacity available at each moment in time which should be taken into account when solving the integrated problem.

Furthermore, most studies assume a homogeneous fleet of vehicles. Nevertheless, in real-world applications, vehicle fleets are mostly heterogeneous as these are more flexible and cost-effective (Hoff et al., 2010). Only recently researchers have been considering a **heterogeneous fleet of vehicles** with different capacity restrictions and/or costs. In future research, besides differences in capacity restrictions, heterogeneity in other parameters, e.g., delivery speed, can be valuable to be considered. For example, Toptal et al. (2014) examine heterogeneity in cost structures and time availability. However, in their study vehicle routing is not considered, since consolidation of different orders is not possible.

Travel times are included in all but one study. Similar to the inclusion of processing times, including transportation times are important to obtain a reliable distribution schedule. Furthermore, the majority of papers take into account **transportation costs**, consisting of variable transportation costs based on, for example, the distance or time travelled, and fixed transportation costs for using or hiring a vehicle. The studies which do not consider transportation costs all have a service objective. Furthermore, in 18 studies, each vehicle can conduct **multiple trips**. If fixed transportation costs are incurred based on the number of vehicles a company owns, allowing vehicles to execute multiple trips can lead to cost savings, because a company has to own fewer vehicles, as indicated by Van Buer et al. (1999). Thus, relaxing the single trip constraint can be beneficial. Moreover, it is more realistic to allow drivers to conduct multiple routes per day (Hoff et al., 2010).

Another important issue are **service times**, i.e., loading and unloading times. Some researchers explicitly take service times into account, while other incorporate these in the travel times to the customer. Including service times into travel times can only work in a VRP with time windows (VRPTW) if the service time of the departure location is included. Otherwise, if the service time of the arrival location is included, it can occur that the vehicle arrives at the location at the start of the time window, but in fact then the service is already conducted. Alternatively, to avoid the aforementioned problem, the time window bounds can be recalculated taking into account the service time at each delivery location. Ignoring service times can have an important impact on the delivery times. In order to obtain reliable schedules, loading and unloading times should be included in further studies on I-PS-VRPs. Besides including loading times, loading constraints, such as multi-dimensional packing constraints, unloading sequence constraints, stability constraints, and axle weight limits, can be incorporated in a VRP (Pollaris et al., 2015), and as such, in an I-PS-VRP.

Furthermore, **time windows** are a common characteristic in distribution operations. It can be observed that these are included in the majority of the studies published since 2007. Delivery time windows indicate in which period of time goods should be delivered at the customer locations. In contrast to time windows, a delivery due date indicates the moment in time before or at which goods need to be delivered to a customer. In a single machine environment, time windows are included in all studies without batch processing, whereas when orders are batched only four studies include time windows. Similarly, in a parallel machine context and no batching, all studies except one take time windows into account, and the majority of studies with batching in a parallel machine context considers time windows. In the studies with a bundling machine environment, a job shop, and a flow shop no time windows are included. Thus, time windows are not included in integrated studies with a more complex machine environment.

Related to time windows are **waiting times** during a route. When hard time window bounds are considered, unloading at the delivery location cannot start before the beginning of the time window. Thus, a vehicle has to wait if it arrives early with respect to the lower bound of a time window. All studies in the review considering time windows, except two, do not allow early deliveries, and as a consequence vehicles have to wait in such cases. The two studies allowing early deliveries penalise this earliness with a cost. A second type of waiting times are these before the start of a vehicle route. This variant of waiting times is related to the integration of production scheduling and vehicle routing operations. A vehicle cannot leave the production plant until the production process of all goods delivered by that vehicle is completed. This type of waiting times especially occurs when vehicles are allowed to conduct multiple trips during the planning horizon. When a vehicle returns to the plant before the production process of the goods delivered in the next trip is finished, the vehicle has to wait. Waiting times, both within a route and before the start of a route, have to be avoided as much as possible since these are time-consuming without adding any value.

Penalty costs can be incurred when delivery due dates or time windows are violated. Some studies incorporate a time-dependent penalty cost. The later the goods are delivered compared to the specified delivery deadline or time window upper bound, the higher the penalty cost incurred. Other apply a uniform penalty cost, which is incurred for every violation of delivery due date or time window. In Low et al. (2014, 2017), additionally a time-dependent penalty cost for early deliveries is incurred.

Currently, the major part of the studies is assuming deterministic models. In the literature reviewed, uncertainties are often neglected. For instance, disruptions in production lines or traffic jams are not taken into account in existing studies on I-PS-VRPs. Nevertheless, these unexpected events can lead to violation of production and distribution due dates or time windows. Thus, more research which incorporates **stochastic aspects** can be valuable to be conducted, e.g., uncertainty in travel times and service times (Hoff et al., 2010). A review of stochastic VRP can be found in Toth and Vigo (2014, pp. 213-240) and of stochastic production scheduling in Aytug et al. (2005).

To conclude, the first integrated studies often included a basic VRP with a homogeneous fleet without time windows. Recently, researchers have considered heterogeneity in vehicle characteristics and time windows. However, service times are still only incorporated in a minority of studies. Furthermore, extensions to the classical VRP can be incorporated in I-PS-VRPs. For example, **split deliveries** are not included yet. In all studies discussed before, an order must be delivered to a customer in one time. Some studies allow an intermediate level of load splitting. Customers can be visited in multiple trips to deliver different orders, but a single order still cannot be split. However, when split deliveries are allowed more efficient schedules can be possibly established, which can result in lower inventory holding costs and higher service levels (Koc et al., 2013). Furthermore, **reverse logistics** can be included in the vehicle routing part of the I-PS-VRP problems. Pickup and delivery operations of damaged goods, wrongly delivered goods, or waste collection can be done simultaneously with delivery of new goods. The VRP in the integrated problem can be extended with backhauls. An extended review on vehicle routing problems with backhauls can be found in Parragh et al. (2008).

2.4.4.4 Objective function

The overview of the problem characteristics reveals that most studies only optimise a single objective, mainly cost minimisation or service level maximisation. However, real-world companies have to take into account several goals at the same time. On the one hand, costs have to be minimised in order to be competitive in the globalised economy. On the other hand, customers have high service level expectations when purchasing goods. Additionally, companies have to take care about, e.g., sustainability and pollution. Thus, scheduling problems often have multiple conflicting objectives which need to be considered simultaneously since optimising a single objective can result in a poor performance on another objective. A solution has to be obtained which meets all these objectives. Therefore, **multi-objective integrated**

problems have to be studied in order to find the best possible compromise between conflicting objectives. In most cases several equivalent solutions, i.e., Pareto-optimal solutions, are possible. Based on the decision maker's preferences a solution is selected.

In the review conducted in this chapter, three studies consider two objectives but translate these into a single-objective function by using the weighted sum or scalarization method. In this method, multiple objectives are combined into a single function by giving weights to the different objectives. The method is a relatively easy approach. The disadvantage of this method, however, is that weights have to be chosen by the decision maker, who often does not know what the impact of different weight values is on the solution obtained (Caramia and Dell'Olmo, 2008). Moreover, the different objectives are often non-commensurable and consequently difficult to aggregate (Branke et al., 2008). Only two articles study two objectives which have to be optimised simultaneously, i.e., bi-objective optimisation.

Thus, future research on I-PS-VRPs should consider multi-objective problems. Existing methods for solving multi-objective problems can be used or adapted for a multi-objective variant of an I-PS-VRP. One example of a multi-objective approach is the ϵ-constraints method. In this method, one objective needs to be minimised, while the other objectives are formulated as constraints and need to be less than or equal to a given upper bound (Chankong and Haimes, 1983). For a more elaborate overview of multi-objective methods, the reader is referred to, e.g., Branke et al. (2008) and Caramia and Dell'Olmo (2008).

2.5 I-PS-VRP: Solution approaches

This section describes the solution approaches which have been applied in the studies mentioned in Section 2.4. Following the same structure as in the previous section makes it possible to identify whether there is a link between the problem characteristics, machine environment, and the solution method used. Table 2.7 offers an overview of the solution methods applied in existing literature.

2.5.1 Single machine environment

2.5.1.1 No batch processing

No setup operations The I-PS-VRP for ready-mixed concrete considered by Naso et al. (2007) is decomposed into two subproblems. In the first subproblem, orders are assigned to a production plant. A production and loading schedule at the plants

Table 2.7: Solution methods

Authors	Opt. S.	EX	H	SA	TS	ILS	GA	MA	ACO	LNS	ALNS	GRASP	ELS	ICA	Sim.
Single machine environment															
No batching - No setup operations															
Naso et al. (2007)							•								
Viergutz and Knust (2014)	•				•	•									
Batching - No setup operations															
Garcia et al. (2004)		•	•												
Chang and Lee (2004)			•												
Chen and Vairaktarakis (2005)		•													
Li et al. (2005)		•													
Geismar et al. (2008)							•	•							
Karaoğlan and Kesen (2017)		•													
Devapriya et al. (2017)	•						•	•							
Lacomme et al. (2018)												•	•		
Chen et al. (2009)	•		•												
Li and Ferrell (2011)	•														
Zu et al. (2014)	•														
Li and Zu (2015)						•									
Low et al. (2013)	•						•								
Low et al. (2014)	•						•								
Low et al. (2017)	•						•								
Li et al. (2016)							•								
Jamili et al. (2016)	•		•		•										
Cheref et al. (2016)					•										
Zou et al. (2018)							•								
Batching - Setup operations															
Hurter and Van Buer (1996)			•												
Van Buer et al. (1999)				•	•										
Park and Hong (2009)	•						•								
Parallel machine environment															
No batching - No setup operations															
Ullrich (2013)	•						•								
Kergosien et al. (2017)					•										
No batching - Setup operations															
Amorim et al. (2013)	•														
Belo-Filho et al. (2015)	•		•								•				
Fu et al. (2017)			•												
Batching - No setup operations															
Chen and Vairaktarakis (2005)			•												
Russell et al. (2008)					•										
Chiang et al. (2009)					•										•
Lee et al. (2014)										•					
Chang et al. (2014)									•						

Table 2.7: (continued)

Authors	Opt. S.	EX	H	SA	TS	ILS	GA	MA	ACO	LNS	ALNS	GRASP	ELS	ICA	Sim.
Batching - Setup operations															
Farahani et al. (2012)										•					
Bundling machine environment															
Batching - No setup operations															
Li and Vairaktarakis (2007)			•												
Flow shop environment															
No batching - No setup operations															
Scholz-Reiter et al. (2011)	•														
Ehm and Freitag (2016)	•														
Ramezanian et al. (2017)														•	
Job shop environment															
No batching - Setup operations															
Meinecke and Scholz-Reiter (2014a)			•												

Opt. S. = optimisation software	EX = exact method
H = heuristic	SA = simulated annealing
TS = tabu search	ILS = iterated local search
GA = genetic algorithm	MA = memetic algorithm
ACO = ant colony optimisation	(A)LNS = (adaptive) large neighbourhood search
GRASP = greedy randomised adaptive search procedure	ELS = evolutionary local search
ICA = imperialist competitive algorithm	Sim. = simulation

is determined by using a hybrid genetic algorithm (GA). The second subproblem determines delivery routes using constructive heuristics. The developed solution algorithm is compared with four other constructive heuristics on a case study with five production plants in the Netherlands. The total cost obtained by the GA-based method is approximately 15% to 50% lower than the lowest cost provided by the other solution approaches considered. Furthermore, in general, by applying the GA-based method less requests need to be outsourced and a lower number of vehicles need to be hired.

Recently, Viergutz and Knust (2014) have proposed two heuristics based on a tabu search (TS) algorithm for an I-PS-VRP for industrial chemicals with a limited lifespan. These solution approaches are applied on cases in which the production and distribution sequence are the same. One TS based metaheuristic decomposes the problem into two subproblems, while the other one solves the problem in an integrated way. One subproblem in the decomposition approach determines the sequence, whereas the other chooses the customer orders to process and deliver. For problems in which the production and delivery sequences do not need to be the same, Viergutz and Knust (2014) provide an iterated local search (ILS) algorithm. Instances with up to 4 time window widths and 50 customers for TS and 30 customers for ILS are used. The integrated TS approach leads on average to better results compared with the decomposition based TS method, especially for instances with a larger number of customers. The instances are additionally solved using the optimisation software CPLEX with a one-hour time limit.

2.5.1.2 Batch processing

No setup operations Garcia et al. (2004) solve an I-PS-VRP with multiple plants for ready-mixed concrete using a heuristic based on a minimum cost flow problem. The performance of the heuristic approach is compared with a graph-based exact solution method. In the experiments, 11 combinations with up to 70 orders, 4 vehicles, and 3 plants are used. The performance of the solution algorithm decreases when the number of vehicles increases.

Chang and Lee (2004) investigate a scenario with two customer areas and a single machine. The proposed solution method combines the First Fit Decreasing bin-packing rule and Johnson's (1954) rule. Worst-case analyses are provided for the heuristic. Dynamic programming algorithms can optimally solve the two variants with a single machine environment in Chen and Vairaktarakis (2005) and the problem in Li et al. (2005). Li et al. (2005) show that the complexity decreases if only direct shipments are allowed and if the capacity of the single vehicle is unlimited. The proposed algorithms in Chang and Lee (2004), Chen and Vairaktarakis (2005), and Li et al. (2005) are not applied to data instances or a practical case.

Geismar et al. (2008) make use of a two-phase solution approach to solve an I-PS-VRP for an industrial chemical adhesive with a limited lifespan. In the first phase, an order sequence for production and distribution is generated by applying either a GA or a memetic algorithm (MA). In the second phase, the sequence is divided into trips, the order in which the customers are visited within a trip is optimised, and the trips are reordered using a shortest path algorithm. Six data sets are used of which three have 40 customers each, and three have 50 customers each. Using the GA approach leads to significantly better solutions than the MA approach. However, the efficiency of the algorithm decreases in instances in which the routing component has more influence.

Karaoğlan and Kesen (2017) develop a branch and cut algorithm to solve the same problem as Geismar et al. (2008). In the lower bound procedure, integrality constraints are relaxed and valid inequalities are included. The upper bound procedure make use of the Clarke and Wright (1964) algorithm. In order to sequence the orders optimally, Johnson's (1954) algorithm is applied. The same data as in Geismar et al. (2008) are used to evaluate the algorithm. The experiments show that the branch and cut algorithm outperforms the algorithm of Geismar et al. (2008).

Devapriya et al. (2017) propose a GA and two MAs to solve the presented I-PS-VRP. A "route first, cluster second" method is applied to generate subtours. Next, an algorithm to reduce the makespan is used. The results obtained by the heuristics are compared with lower bounds. Instances with up to only 4 customers can be solved within 20 hours with CPLEX. Experiments with 20, 30, and 40 customers are executed using the three heuristics. For each number of customers, 30 instances are generated. Which heuristic generates the best results, depends on the number of customers included.

In Lacomme et al. (2018), a MILP model is formulated for the integrated problem considering a single perishable product. The authors develop a greedy randomised adaptive search procedure (GRASP) combined with an evolutionary local search (ELS) the problem. Experiments are conducted with a single vehicle in order to compare their results with these of Geismar et al. (2008) and Karaoğlan and Kesen (2017). In these experiments, 72 instances are used based on the instances generated by Geismar et al. (2008). The results show that the proposed GRASP x ELS obtains better solutions in approximately half of the instances. In only six instances, a worse solution is generated. For the problem with multiple vehicles, 150 instances are created. The developed solution algorithm is capable of finding solutions within an average gap of 0.09% compared to the lower bound.

Chen et al. (2009) decompose the I-PS-VRP for perishable goods into two subproblems. The constrained Nelder-Mead (1965) method, which is a direct search method, is used to solve the production scheduling problem. A heuristic making use of insertion and improvement methods is used to solve the VRPTW. Data of 100 retailers are generated based on Solomon's (1987) problem set. Small-size instances are solved with the commercial optimisation software LINGO in order to examine the performance of the proposed solution method. Furthermore, a sensitivity analysis shows that the objective value decreases with an increasing rate of decay and increases with the fleet size independent of the time window requirements. Moreover, using more vehicles leads to lower average loading ratio and less deterioration.

Li and Ferrell (2011) make use of AMPL and Gurobi software to solve an I-PS-VRP for a perishable product. Ten data sets with up to twenty customers are used. However, only small instances up to 7 customers can be solved exactly. The extension of Zu et al. (2014) results in a MILP which is solved for problems with up to 4 suppliers and 4 customers using the same software as used by Li and Ferrell (2011). Instances in which the sum of the number of customers and suppliers is less than or equal to five can be solved to optimality in a reasonable computation time. For larger problems, both studies show that heuristics need to be developed. Li and Zu (2015) develop an ILS approach to solve the problem described in Zu et al. (2014). In the experiments, 16 scenarios are tested with at most 12 customers and 12 suppliers. The optimisation software is able to find a solution within one hour for instances with at most 6 customers and 6 suppliers, while the heuristic can find solutions for instances twice as large.

Low et al. (2013, 2014) apply two versions of a GA in each study in a "route first, cluster second" method to solve a non-linear I-PS-VRP in a DC. The second GA is an adaptive GA (AGA) in which the initial parameter values are dynamically modified. The heuristics are tested on problems with up to 100 customers in Low et al. (2013) and up to 80 customers in Low et al. (2014). The number of customers determines which of the two solution approaches leads to better results. Furthermore, using different vehicle types results in a lower total cost.

In Low et al. (2017), a backward adaptive genetic algorithm (B-AGA) and a forward adaptive genetic algorithm (F-AGA) are developed. The F-AGA first solves the production scheduling problem and later the vehicle dispatching and routing problem, whereas the B-AGA first deals with the routing problem, and thereafter with the vehicle dispatching and production scheduling problem. The two AGAs are compared to each other on instances with up to 80 customers. The B-AGA performs better in most cases, but the F-AGA needs smaller CPU time for cases with more than 50 customers. Moreover, similar to the study of Low et al. (2014), total cost decreases when different types of vehicles are used.

In order to solve the multi-objective I-PS-VRP, Li et al. (2016) develop a non-dominated sorting GA with an elite strategy. The proposed algorithm is compared with a Strength Pareto Evolution Algorithm (see Zitzler and Thiele, 1999). Experiments with 20, 30, and 40 orders are conducted. The developed GA outperforms the method of Zitzler and Thiele (1999). The quality of the solutions increases with the number of iterations. Furthermore, the higher the vehicle capacity, the lower the distribution costs and waiting time.

Jamili et al. (2016) develop a TS metaheuristic to solve the single-objective problem. In the experiments, small, medium, and large instances have up to 7, 40, and 200 orders, respectively. Additionally, two heuristics are proposed for the bi-objective problem in which the weighted sum of the average delivery time and total distribution cost are considered to be two separate objectives. The single-objective variant is solved with CPLEX using a time limit as stopping criterion. The heuristic is capable of obtaining similar solution in a short computation time. A sensitivity analysis is executed to investigate the impact of several parameters on the solutions. Better solutions are obtained when the number of customers increases and the number of suppliers decreases. The vehicle capacity has a positive influence on the distribution cost, but a negative one on the average delivery time. Finally, the integrated approach is compared to an uncoordinated approach. It is illustrated that the integrated approach leads to better solutions, especially for large-size problems.

Cheref et al. (2016) propose two TS methods to solve the integrated problem with uncertainties. The first one is a standard robust optimisation method, while the other is an online recoverable robust optimisation method. Random instances with a number of jobs between 10 and 100 are generated to test the proposed solution approaches. The results show that the online recoverable robust method in general leads to better and more robust solutions.

In Zou et al. (2018), a GA is applied to solve an I-PS-VRP in a make-to-order context. Two variants are proposed in the production scheduling part of the algorithm: backward batching method and forward batching method. The initial solution is improved using a local search method called modified Unstring-String method. Furthermore, a two-phase uncoordinated approach is proposed to which the results of the integrated approach are compared. Instances with up to 100 customers and 15 vehicles are generated based on VRP benchmark data sets. The proposed GA is also compared with the GA of Ullrich (2013) (described in Section 2.5.2). The developed algorithms both outperform the solution method of Ullrich (2013) and the two-phase uncoordinated approach.

Setup operations Hurter and Van Buer (1996) make use of a two-stage “route first, cluster second” procedure to solve an integrated problem for newspapers. The routes are constructed using a forward looking greedy algorithm. The distribution schedule consisting of delivery routes implies a production schedule as the time between the start of production and the latest possible delivery date is limited. Finally, the time feasibility of this implied production schedule is checked. Applying their proposed solution approach to an American newspaper company results in lower distribution costs and distribution time compared with the current practice of the company. For a similar non-linear problem, Van Buer et al. (1999) propose a simulated annealing (SA) and a TS approach. Experiments show that allowing trucks to conduct multiple trips decreases costs significantly. Similar to Hurter and Van Buer (1996), Van Buer et al. (1999) make use of data from an American newspaper company.

Park and Hong (2009) propose a hybrid GA in combination with local optimisation algorithms. Using instances with 100 customers and 9 products, the integrated approach is compared with an uncoordinated solution method in which production sequencing and vehicle routing are treated separately. The obtained total cost is on average 20% lower. Furthermore, the results are compared with the optimal solutions obtained by CPLEX. Additionally, a sensitivity analysis shows a positive relationship between the number of customers and the total cost savings. The influence of the vehicle capacity is less straightforward. Small and large capacities lead to higher cost reductions, whereas intermediate capacities leads to smaller cost savings.

2.5.2 Parallel machine environment

2.5.2.1 No batch processing

No setup operations Besides a GA, for small instances, Ullrich (2013) uses a commercial optimisation software and two decomposition methods to solve an I-PS-VRP. The decomposition approaches solve the production and distribution subproblem sequentially and combine the obtained solutions into an overall solution. Experiments show that the GA leads to better solutions than the decomposition methods on 90 small-size instances with 7 orders, 2 machines, and 2 vehicles. As such, integrating both problems can result in significant performance improvements. Furthermore, the more vehicles or machines are used, the lower the performance of the proposed algorithm becomes. For large instances, the optimisation software and the decomposition methods cannot be applied. In total 4,800 instances with up to 50 orders, 5 machines, and 10 vehicles are generated. The number of orders, vehicles, and machines has a negative impact on the performance. Additionally, the more order destinations are included in the problem, the lower the performance of the genetic algorithm becomes.

Kergosien et al. (2017) propose a Benders decomposition-based heuristic incorporating TS. The problem is subdivided in a master problem, i.e., delivery problem, and a slave problem, i.e., production problem. Random instances are generated based on data of an oncology clinic in France. The instances consist of up to 40 orders and 2 or 3 machines. The developed method is compared with two models which are solved with a commercial solver. The Benders decomposition-based method finds better lower and upper bounds.

Setup operations In order to test the difference between lot sizing and batching in a study with perishable and non-perishable products, Amorim et al. (2013) make use of the optimisation software CPLEX to solve instances with up to 5 customers and 3 products. Computational results show that lot sizing leads to costs which are on average 6.5% lower and results in a lower number of setups, a different sequence, lower setup costs, a lower number of vehicles used, and/or total travelled distance.

Belo-Filho et al. (2015) propose solution methods to tackle large-size instances for the problem setting presented in Amorim et al. (2013). Four solution methods are used by the authors: two standard MILP solvers with and without initial solution, a fix-and-optimise heuristic, and an adaptive large neighbourhood search (ALNS). In order to evaluate the algorithms, 20 combinations were generated with up to 4 production lines, 15 customers, and 10 products. The proposed ALNS performs on average 12.7% better compared with the best solutions provided by the fix-and-optimise method and the MILP solvers after 3,600 seconds.

In Fu et al. (2017), a two-phase iterative heuristic is developed. In the first phase, a MILP for a production scheduling problem is proposed in which an approximation of the transportation cost is integrated. In the second phase, an ILP is used for the distribution problem using the production completion times from the first phase. After each iteration, production completion times and approximated transportation costs are updated. The heuristic is tested on random instances inspired by a metal packaging company with at most 20 jobs. Furthermore, the benefits of an integrated approach are examined by comparing the results with these of an uncoordinated approach. Average cost savings of 7.63% can be obtained by implementing an integrated method. The value of integration increases in cases with short or high setup times and with medium time window widths.

2.5.2.2 Batch processing

No setup operations In contrast to the two discussed scenarios with a single machine solved using exact algorithms, the two problem variants with parallel machines considered in Chen and Vairaktarakis (2005) are solved using a heuristic algorithm. The randomly generated data to evaluate the heuristics consist of up to 160 orders, 8 machines, and 5 customers. The value of integration is determined by comparing a sequential approach and an integrated approach. The improvement is significant in most cases when the objective function is based on the mean delivery time and in some cases when it is based on the maximum delivery time. The effect of integration depends on the number of customers, the vehicle capacity, and the weighting parameter of both functions in the objective function. Hence, integration is more interesting when there are more possibilities to consolidate orders. In most cases, improvements of 5% and more are achieved, and in some cases improvements up to even 40% can be achieved by integration.

Russell et al. (2008) make use of a two-phase approach to solve an I-PS-VRP for newspapers. The production and vehicle loading sequencing problem is solved in phase one. In phase two, an open VRP with time windows and zoning constraints is solved. A TS method is used during the route construction to improve the created routes. Data for 68 state edition delivery locations and 70 city edition delivery locations are provided. In a subsequent study, stochastic aspects in both production and distribution parameters are included by Chiang et al. (2009). A two-phase method using TS is used. The robustness of this deterministic solution in terms of service level is evaluated by a simulation model. Similar to Russell et al. (2008), experiments using real-world data show that a lower number of vehicles are needed and less distance needs to be travelled, while additionally in Chiang et al. (2009) service levels increase.

Lee et al. (2014) develop a large neighbourhood search (LNS) with various improvement algorithms to solve an I-PS-VRP for a nuclear medicine. In the overall algorithm, four algorithms are integrated to solve the problem. By extending Solomon's (1987) problem instances with production run data, 29 instances with 100 orders are developed. Based on the experiments, applying the solution approach leads to a lower number of vehicles used for deliveries which results in lower costs compared to a real-world case with 277 customer stops.

Chang et al. (2014) develop an ant colony optimisation (ACO) based heuristic with a dynamic programming algorithm to solve an I-PS-VRP with unrelated parallel machines. The ACO consists of path construction and pheromone update. The construction is a three-step process. First, a production schedule is determined by assigning orders to machines and determining the customer order sequence. Second, orders are combined into distribution batches based on their completion times and estimated transportation cost. Finally, vehicle routes are constructed. In order to evaluate the proposed solution approach, 162 instances are generated which leads to combinations with up to 8 machines, 20 customers, 100 orders, 3 vehicle capacities, and 3 possible values for the objective relative preference on the customer service and total distribution cost. Integration results in solutions which are on average 18.04% better than these obtained by using a sequential solution approach. The value is positively influenced by the weighting factor in the objective function and the vehicle capacity, and negatively by the number of customers.

Setup operations In order to evaluate the integrated problem formulated for perishable food products, Farahani et al. (2012) develop an iterative solution approach. The problem is decomposed in two subproblems: production and distribution. A block planning concept is used to solve a MILP model for the production schedule. The distribution subproblem is solved using a LNS. Data based on a real-world food caterer in Denmark are used and consist of up to 200 orders, 5 ovens, 25 vehicles, and

5 temperature levels. The integrated approach leads to lower quality decay of approximately 40% with only a small increase in costs compared with a sequential approach currently used by the food caterer. Furthermore, the objective value improves as the products become more perishable. Additionally, a small increase in the weight for decay costs in the objective function leads to a decrease in the quality decay without affecting the setup and transportation costs substantially.

2.5.3 Other machine environments

Li and Vairaktarakis (2007) develop polynomial time heuristics and approximation schemes for an integrated problem with a bundling machine environment. The heuristics make use of dynamic programming and the Shortest Processing Time algorithm to sequence orders. Furthermore, lower bounds are computed. The performance is evaluated using randomly generated problems with up to 80 orders, 5 customer locations, and 3 vehicle capacities.

Scholz-Reiter et al. (2011) test the integrated problem of a flow shop and a VRP on a case study of an original equipment manufacturer in Germany. The problem is solved to optimality by CPLEX. Data with up to 5 vehicles and 25 orders are used in the experiments. For very small instances with up to 7 orders and 2 vehicles, the optimal solution can be generated within short computation time.

Ehm and Freitag (2016) examine the value of integration in a flow shop environment. In the integrated approach, each order has a distribution due date. In order to be able to solve the uncoordinated approach, an intermediate production due date has to be chosen. This production due date is selected as percentage of the time-span between the production release date of the order and the delivery due date. The experiments are conducted by using Gurobi software for instances with six jobs, three production levels with three, two, and three machines, respectively. The results show that when 80% of the time is available for producing the orders, the best solutions are generated. Overall, independent of the selected intermediate due date, the costs of the integrated approach are on average 10% lower in comparison with these of the uncoordinated approach.

Ramezanian et al. (2017) make use of an improved imperialist competitive algorithm (ICA), which is a population-based metaheuristic, to solve an I-PS-VRP in a flow shop environment. After an initial solution is randomly generated, three assimilation policies and three revolution strategies are used to improve the solution. In these operators, variants of swap, reversion, and 2-Opt are included. For the production data, three flow shop benchmark data sets are used, while for the distribution data random values are generated. The largest instances consider 50 jobs and 20 machines. Experiments indicate the value of integration which is between 9% and 17% on average depending on the instance size. Furthermore, the cost reduction obtained by implementing a routing delivery policy instead of direct deliveries ranges between 9% and 21% on average.

Meinecke and Scholz-Reiter (2014a) use a multistep decomposition and integration heuristic to solve an integrated problem of a job shop and a VRP. In the experiments, 17 customers and 3 products are used. The proposed heuristic is compared with three uncoordinated strategies in which first a production schedule is determined and based on this a distribution schedule, or the other way around. The results show that applying the heuristic algorithm results in lower overall costs, with savings ranging from 6.9% up to 17.7%.

2.5.4 Solution methods: Discussion

Although all studies discussed in this review consider an I-PS-VRP, some authors propose an algorithm which solves the problem in a more separated way by dividing the integrated problem into subproblems. Each subproblem is solved using its own neighbourhoods. Afterwards the solutions are integrated and the feasibility of the solutions according to the constraints of both subproblems is checked. Hurter and Van Buer (1996), Naso et al. (2007), Russell et al. (2008), Chiang et al. (2009), Chen et al. (2009), Farahani et al. (2012), Meinecke and Scholz-Reiter (2014a), Chang et al. (2014), Kergosien et al. (2017), Fu et al. (2017), and Zou et al. (2018) make use of such a separated solution method. Van Buer et al. (1999), Chang and Lee (2004), Garcia et al. (2004), Geismar et al. (2008), Park and Hong (2009), Ullrich (2013), Low et al. (2013, 2014, 2017), Lee et al. (2014), Belo-Filho et al. (2015), Li and Zu (2015), Li et al. (2016), Jamili et al. (2016), Cheref et al. (2016), Devapriya et al. (2017), Ramezanian et al. (2017), and Lacomme et al. (2018) apply an integrated solution approach which works on the integrated solution and their neighbourhoods. Viergutz and Knust (2014) present both a separated and an integrated solution algorithm, and compare a decomposition based TS method and an integrated TS method. The integrated method outperforms on average the decomposition approach, especially in cases with a larger number of customers.

When production and distribution functions are solved simultaneously, the complexity of the problem structure increases. The formulation of an integrated planning problem often contains many variables and constraints. Due to this complexity of I-PS-VRPs, exact methods are only applied for studies with a relatively simple single machine environment. Furthermore, in a single machine context without batch production, metaheuristics, such as GA, TS, and ILS, are used as solution approaches. In a single machine environment with batch processing, both heuristics and metaheuristics are proposed as solution methods.

All studies with a parallel machine environment are solved using a heuristic or metaheuristics, such as TS, (A)LNS, GA an ACO. The only exception is the study of Amorim et al. (2013) which only uses a commercial optimisation software as solution method. Belo-Filho et al. (2015) propose a fix-and-optimise heuristic and an ALNS to solve the problem formulated by Amorim et al. (2013). In studies with other machine environments either optimisation software or a (meta)heuristic is used as solution method.

In general, instances with at most 100 customer orders are used to evaluate the performance of the developed (meta)heuristics. A few studies include instances with up to 200 orders. Additionally, often the problem is solved with commercial optimisation software, such as CPLEX and LINGO, to compare the results of both solution approaches. Commercial optimisation software is capable to find optimal solutions for instances with up to 7 customers, except Park and Hong (2009) who are solving instances with up to 21 customers. Furthermore, in a simple single machine environment with batching, Karaoğlan and Kesen (2017) solve instances with up to 50 customers using a branch and cut algorithm.

In short, Table 2.7 reveals that solution methods based on metaheuristics, such as TS and GA, are often applied to find high-quality solutions in reasonable computation time. However, further research to develop fast and robust solution algorithms is necessary to solve real-world problems. A relatively new and promising class of solution approaches are matheuristics, which combine metaheuristics and exact methods. These methods have proven to exhibit excellent performance and to find optimal or close-to-optimal solutions of large instances in very limited computation times (Doerner and Schmid, 2010; Archetti and Speranza, 2014a).

2.6 Conclusions and future research opportunities

Production and distribution are traditionally solved separately. However, this approach leads to suboptimal solutions. Integration can lead to average improvements between 5% and 20% compared to an uncoordinated approach, and even improvements up to 40% can be achieved. Therefore, in the last decade, integrating production scheduling and vehicle routing problems at the operational decision level received more interest in scientific literature.

This chapter focuses on integrated studies in which distribution operations are executed using vehicle routes, i.e., integrated production scheduling-vehicle routing problems (I-PS-VRPs). An extensive review of recent research in the field of operational I-PS-VRPs is provided. Additionally, a classification of existing research based on production, inventory, and distribution characteristics is made. A classification matrix is proposed to identify which combinations of production and distribution characteristics are already investigated. Both problem characteristics and solution methods used in existing studies are reviewed.

In the production scheduling subproblem often a simple machine environment with a single production level in a single plant is considered, i.e., a single or parallel machine(s). In the vast majority of studies, orders are processed in batches. Although setup operations can have an impact on the reliability of the production schedule, these are often neglected in the production process. Additionally, other production characteristics such as order release dates and precedence relationships are generally not considered in I-PS-VRP studies. In the distribution part of the integrated problem, most studies use a basic VRP with homogeneous vehicles. Transportation costs are incurred in the majority of the published I-PS-VRPs. Delivery time restrictions such as time windows and delivery due dates are imposed in approximately half of the studies. Cost minimisation and service level maximisation are most commonly used as objective criterion.

I-PS-VRPs are complex, and as a consequence solving these problems with exact methods is hard for large instances. Only for production environments with a single machine exact methods are developed. Most studies make use of metaheuristics to solve the problem. Especially tabu search and genetic algorithms are frequently applied as solution algorithms.

Based on the classification and discussion of the reviewed papers, the following future research opportunities can be highlighted to extend the current research on I-PS-VRPs:

Real-life characteristics I-PS-VRP models can only become valuable for decision managers when real-life properties of the production, inventory, and distribution system are taken into account.

1. Production characteristics: nowadays, companies use mass production to be able to handle all customer orders as fast as possible. An efficient machine environment for mass production is a flow shop. As such, investigating environments with multiple production levels can be highlighted as an important opportunity for further research on I-PS-VRPs in order to, e.g., minimise the

total time needed for production and distribution. Additionally, in reality, resources need to be prepared before starting the processing of a new order. This setup operation takes time and thus needs to be considered when production schedules are determined.

2. Inventory characteristics: inventory aspects are a common feature of production planning problems. Although inventory decisions are mostly taken at the tactical decision level, when solving an I-PS-VRP inventory capacity restrictions and holding costs should be taken into account as these can influence, e.g., total cost incurred. Thus, further research should deal with holding costs and limited inventory capacity.

3. Distribution characteristics: in future research, the distribution part should extend the classical VRP. Companies often collaborate with a 3PL service provider for their distribution operations. These service providers have a large fleet of vehicles, often differing in loading capacity, cost structures, and travel speed restrictions. Including heterogeneity of vehicles in integrated studies is a valuable research opportunity. Moreover, in order to obtain a reliable production and delivery schedule, service times at the plant and at the customer locations should be taken into account as these can have an influence on the delivery time promised to customers. Additionally, including backhauls into I-PS-VRPs can be interesting in order to model the pickup of wrongly delivered or damaged products at customer locations.

4. Objective criterion: in the current competitive business environment companies have to offer high quality service at the lowest possible cost in order to remain competitive. Therefore, future research should examine multi-objective problems instead of minimising cost or maximising service level separately.

Uncertainty In real life not all orders and parameter values are known in advance. The exact moment of time when orders are placed by customers can often not be known. Additionally, the travel times are influenced by traffic jams. Consequently, instead of using deterministic models for I-PS-VRPs, in future studies stochastic aspects should be incorporated.

Solution algorithms Companies have to deal with a large number of orders. Even for this large amount of data, it is necessary to have a good solution for the integrated problem in short computation time. Furthermore, for stochastic integrated studies, solution algorithms which can cope with uncertainty need to be developed. Therefore, further research needs to focus on fast and robust solution approaches. Matheuristics are highlighted as a promising research direction and have already proven to be capable to obtain high-quality solutions in a short computation time.

Value of integration and sensitivity analysis Little research has been done so far on the value of integration. Future research should be conducted to identify in which situations integration can be most useful. The discussion of the reviewed studies reveals that the influence of some problem characteristics, such as the number of customers and vehicle capacity, on the value of I-PS-VRPs is not straightforward. Thus, there is a need for further research on the impact of problem characteristics on the value of integrating the two subproblems.

The knowledge learned from the review conducted in this chapter can act as basis for the formulation and analysis of integrated order picking-vehicle routing problems in the following chapters. The discussion of the studies and the future research directions highlighted indicate the important problem characteristics which should be considered when modelling the integration of order picking and vehicle routing decisions. It is important that real-life characteristics, such as service times and time windows, are included. Furthermore, solution algorithms developed for the I-OP-VRP need to be efficient and robust. Since little is known about the integration of order picking and vehicle routing operations, the value of integrating these problems has to be investigated in the following chapters of this dissertation.

Chapter 3

Integrated order picking-vehicle routing problem: Problem formulation

3.1 Introduction

Every year, the popularity of e-commerce is increasing, and a higher number of customers buy goods online. When a customer purchases goods online, the products first need to be picked in a DC in which these are stored. After completing the picking process, the goods have to be delivered to the preferred delivery location of the customer. Thus, since orders can only be delivered after they are picked in the DC, picking and delivery decisions are interrelated. The increasing number of orders puts the picking and delivery operations under pressure. E-commerce companies need to reconsider and re-optimise their logistics activities to handle efficiently and effectively the large number of customer requests. Therefore, ideally, the order picking and delivery operations should be integrated into a single optimisation problem similar to the I-PS-VRP discussed in Chapter 2. The integration of the two problems results in an integrated order picking-vehicle routing problem (I-OP-VRP). In this chapter[1], the I-OP-VRP is introduced and the value of integration is examined (Figure 3.1).

[1] This chapter is based on Moons, Ramaekers, Caris and Arda (2017b).

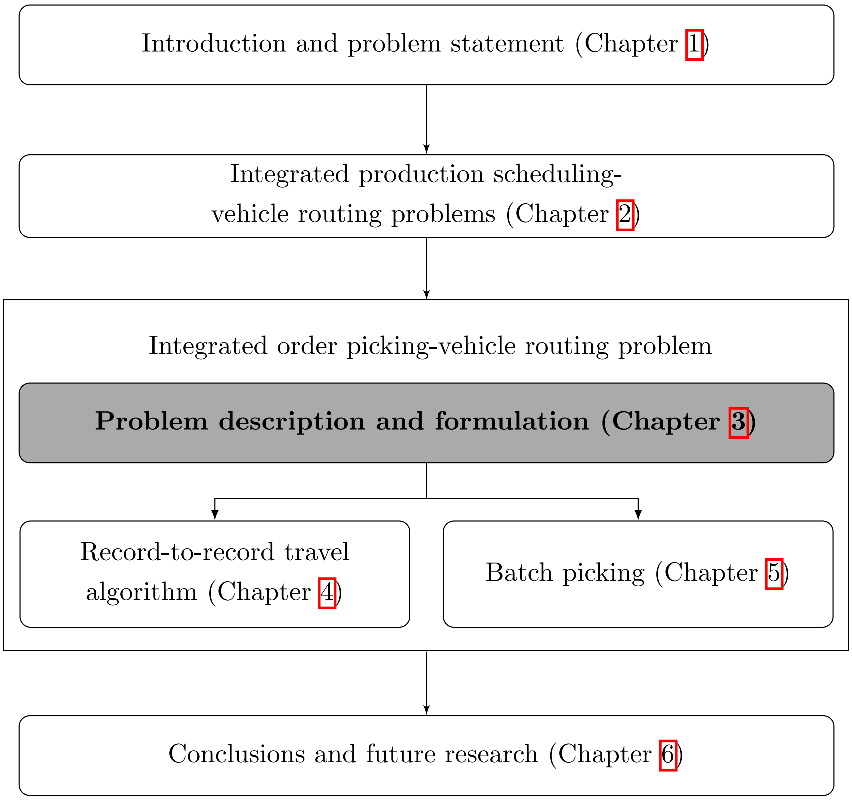
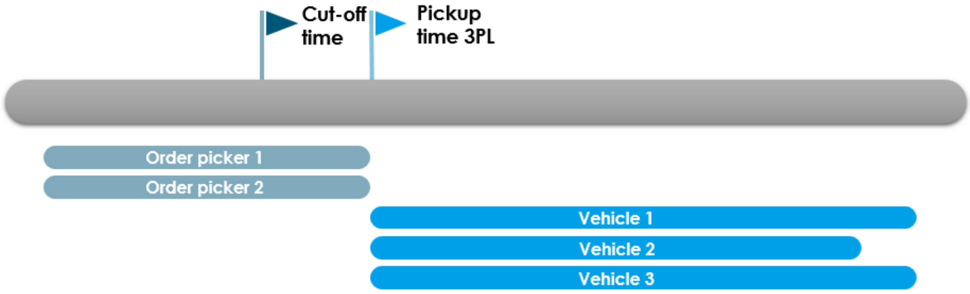


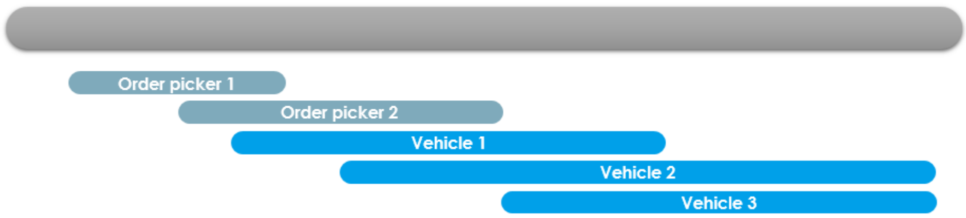
Figure 3.1: Thesis outline - Chapter 3

In the I-OP-VRP, picking lists and vehicle routes are determined simultaneously. Requirements and constraints of both the order picking problem (OPP) and the VRP are considered at the same time. For example, delivery time windows are taken into account when picking lists are established. In the I-OP-VRP, decisions have to be made about the assignment of orders to pickers, the picking schedule of each picker, the assignment of orders to routes, and the vehicle routes.

However, traditionally order picking and delivery decisions are decided in an uncoordinated way. B2C e-commerce companies often outsource their delivery operations to a 3PL service operator. Every day, the 3PL operator picks up the goods at the DC at a fixed time, mostly in the evening. The e-commerce company determines a cut-off time. All goods ordered before this cut-off time are picked before the 3PL service provider arrives at the DC. Goods ordered after the cut-off time are handled in the DC before the next pickup time. As can be seen in Figure 3.2(a), the order picking process and the delivery process are strictly separated by the pickup time implied by the 3PL service provider.



(a) Uncoordinated approach (with 3PL)



(b) Integrated approach

Figure 3.2: Timeline for an uncoordinated and an integrated approach

In an integrated approach, the e-commerce company executes the delivery operations itself, or there is coordination between the e-commerce company and the 3PL service provider. No fixed pickup times are implied any more. By coordinating the order picking and distribution process and exchanging information, a vehicle can leave the DC whenever a sufficient number of orders to conduct a delivery route have been picked. As such, the start of the distribution process is more flexible. The picking and delivery operations overlap in time, as illustrated in Figure 3.2(b). A vehicle has already left the DC to deliver picked orders, while orders which will be delivered by another vehicle are still being picked in the DC. Consequently, goods which are ordered late can possibly still be delivered within short time, whereas in the uncoordinated approach the delivery would be after the next pickup time.

The relevance of the integrated problem in a warehouse environment is demonstrated by the example of Amazon, an international e-commerce company. In Germany, Amazon started with its own package delivery service to deliver customer orders handled in their warehouses instead of outsourcing these activities to a 3PL service provider. By delivering orders itself, Amazon has more flexibility in their delivery services (VerkehrsRundschau, 2015).

This chapter is organised as follows. A comparison of production and warehousing operations is made in Section 3.2. In Section 3.3, the problem characteristics of the proposed I-OP-VRP are explained. A review of the state-of-the-art literature on order picking, vehicle routing with release dates, and I-OP-VRP is given in Section 3.4. Mathematical models are formulated for an order picking problem, a vehicle routing problem with time windows and release dates, and an I-OP-VRP in Section 3.5. The data generation is described in Section 3.6. Section 3.7 sets out the computational experiments executed and assesses the value of integration. Finally, in Section 3.8, conclusions and future research directions are presented.

3.2 Comparing production and warehousing

In this dissertation, the integration of a VRP with an OPP in the context of B2C e-commerce sales is studied. The most related problem is the integration of supply chain functions in a production environment. As production and warehousing have relatively similar characteristics, models comparable to the I-PS-VRPs described in Chapter 2 can be formulated for the integration of order picking and vehicle routing operations. In both problems, jobs need to be assigned to resources in such a way that an objective is met, e.g., cost minimisation or service level maximisation. However, in research on production and warehousing, different terminologies are generally used to describe similar processes. Therefore, the production processes and properties need to be translated to a warehouse context. To the best of the author's knowledge, no other studies compared these combinatorial optimisation problems before. The focus is on the basic concepts of both supply chain functions. It is not the aim to compare all existing production and warehousing concepts. Table 3.1 gives an overview of the related terminology used in production and warehousing environments.

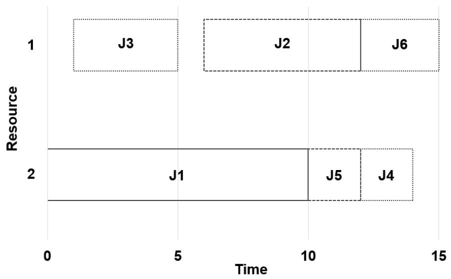
In a manufacturing plant the main activity is production, while in a warehouse it is order picking. *Production* refers to the processes which transform inputs, such as raw materials, into outputs demanded by customers using resources (Jacobs and Chase, 2011). *Production scheduling* is the process of allocating scarce resources, e.g., machines and employees, to jobs over time to optimise a single or multiple objective(s) (Graves, 1981; Lawler et al., 1993). For each resource in a production environment a schedule is determined. The schedules of the multiple resources can be represented in a Gantt chart. An example can be found in Figure 3.3(a) in which Ji represents job i.

Order picking is the warehousing process of retrieving products from specific storage locations in a warehouse to satisfy customer requests (Petersen and Schmenner,

Table 3.1: Terminology used in production and warehouse context

Production context	**Warehouse context**
production	order picking
production scheduling	order sequencing
job	order
task or operation	order line
machine	order picker
production time	retrieval time/order picking time
single or parallel machine scheduling	discrete order picking
single or parallel machine scheduling with p-batching	batch picking
make to order	pick by line/pick to zero
bundling machine environment	synchronised zoning
job shop or flow shop	progressive zoning

1999; Henn, 2015). *Order sequencing* is determining the sequence in which the different customer orders should be picked (Elsayed et al., 1993) to meet the due date of each order. The result is a *pick list* for each order picker which indicates the order lines he/she should pick and in which sequence (Henn et al., 2012), as shown in Figure 3.3(b).



(a) Gantt chart

Order picker number: EMPX3

Order number	SKU Item	Item Description	Pick location	Order quantity
15826	X104	Product X	01.35	3
15826	Y95	Product Y	03.15	1
15837	Y95	Product Y	03.15	6
15815	Z08	Product Z	02.42	4
...	...	...	...	...

(b) Pick list

Figure 3.3: Example of a Gantt chart and a pick list

In order to refer to a customer request, the term *job* is used in a production environment and the term *order* is used in a warehouse environment. A job consists of multiple *tasks* (or *operations*) which should all be completed before the entire job is finished, while an order consists of *order lines*, each of which indicating a different product with the corresponding requested quantity and storage location (de Koster et al., 1999a).

Both in production and order picking, customer requests need to be assigned to a limited number of resources. Resources in a production context, i.e., machines, can be compared with these in a warehouse, i.e., order pickers. In fact, a *resource* can be generally defined as a time scale with certain time intervals available (Conway et al., 1967) to which jobs or orders can be assigned to be processed and completed for delivery. Furthermore, in both problems, decisions have to be made about the sequence in which the different customer requests should be processed.

In order picking, two main types of manual picking systems occur, i.e., picker-to-product systems and product-to-picker systems. In a picker-to-product system, an order picker travels through the warehouse to the storage locations of all items requested. In a product-to-picker system, the items requested are delivered to the order picker by, e.g., automated stacker cranes in an AS/RS (Automated Storage/Retrieval System). Thus, either products are delivered to a resource, an order picker, or the other way around. In contrast, in a production environment, machines are mainly located at a fixed location in the production plant. The orders are transferred to the machines. This corresponds with a product-to-picker system, in which the resource in this situation is a machine instead of an order picker.

The *production processing time* is the time needed using the resources to produce the quantity demanded of a product. A setup time to prepare a resource to process a job (Allahverdi and Soroush, 2008) is often included in the processing time (Allahverdi et al., 1999). The *order picking processing time* (or *retrieval time*) is the time needed by an order picker to complete a route in a warehouse to pick the items requested in a specific order. The picking time consists of several components: travel times between storage locations which need to be visited; search times to find the required items; pick times to grab the required quantity of items; and, setup times. The setup time in an order picking process is the administrative time at the start and end of a picking tour. It includes the time needed for an order picker to obtain a new pick list and an empty picking device at the start point of a tour and to return to this point after completing a tour (Van Nieuwenhuyse and de Koster, 2009). Travel times are the dominant component in the picking time, responsible for approximately half of the total order picking time, while setup times are rather negligible (Tompkins et al., 2003; de Koster et al., 2007; Henn et al., 2012).

In a production environment, the processing time can be machine- and job-dependent in case uniform or unrelated parallel machines are used. However, the production processing time of a job is fixed once it is known to which machine the job is assigned. In a warehouse environment, the picking time is often independent of the order picker to which an order is assigned, since mainly it is assumed that order pickers travel at the same speed. Nevertheless, the order picking processing time depends on the routing policy applied in the warehouse. Several routing policies exist, e.g., S-shape, return, or largest-gap strategy (Wäscher, 2004). Each policy constructs picking routes based on its own decision rule resulting in other travel distances to pick all items. Consequently, picking times differ among the routing policies. Additionally, the storage location policy implemented influences the picking time. When goods are stored in another way, the routes to pick the items requested change and accordingly the picking times differ.

A *discrete order picking policy* (or *pick-by-order*) in which a single order is picked at a time in a warehouse can be compared with, depending on the number of order pickers, single or parallel machine scheduling in the case that each job consists of a single task. In a warehouse context, however, *order batching* (or *pick-by-batch* or *batch picking*), in which several orders are picked in a single picking tour by an order picker (de Koster et al., 1999a, 2007; Henn, 2015), is often applied. The order batching problem investigates how orders can be grouped into batches, given storage locations of items, routing strategies, and picking device capacity, in order to minimise the total length of tours necessary to pick all orders (Wäscher, 2004). Each order has to be assigned to a single batch which results in a set partitioning problem. Order batching in a warehouse can be seen as single or parallel machine scheduling with p-batching in a production environment. In *p-batching* (or *parallel batching*) jobs are processed simultaneously on a machine. The largest processing time of a job in a batch defines the processing time of the batch (Brucker, 2007). However, the picking time of a batch is generally not equal to the largest order picking time in the batch. The batch picking time is greater than the picking time of each individual order in the batch, but in general less than the sum of all individual order picking times. In order to determine the picking time a travelling salesman problem for each order or batch needs to be solved. At the end of a picking route with batch picking, the picked items need to be sorted by each customer order.

A specific picking method is *pick by line* (*pick to zero*). This picking method is mainly applied in a DC which executes cross-docking operations. In a cross-docking DC, goods are not stored for a long period of time. When goods arrive at the DC, they are immediately sorted and loaded into roll cages for each individual store (or customer) in the required quantities. In contrast to a traditional DC, goods are not assigned to a storage location from which the required number of items is picked (Rushton et al., 2001; Fernie and Sparks, 2004). Pick by line can be compared to a *make to order* process in a production environment. In this situation, a manufacturer starts producing after a good has been requested by a customer. Then, the exact number of items is produced. Thus, the customer is not being delivered from stock (Jacobs and Chase, 2011).

Furthermore, a warehouse can be divided into different zones. Order pickers pick only items in the zone to which they are assigned. An order can consist of order lines with picking locations in different zones. Consequently, multiple order pickers should work on the order. Two variants of zoning occur. In the first variant, called *parallel picking* (or *synchronised zoning*), order pickers of each zone work simultaneously (in parallel) on the same order. In each zone, the order lines of which the storage locations are located in that specific zone are picked. At the end, the order lines picked in each zone are merged together. Synchronised zoning can be compared with a *bundling machine environment* in a production context in which m independent tasks of a job need to be processed on m dedicated machines. These m operations need to be bundled together before the job can be delivered (Chen, 2010). The tasks of a job which need to be processed on a specific machine can be compared with order lines of an order which need to be picked in specific warehouse zones. The second variant is called *progressive zoning* (or *pick-and-pass* or *sequential zoning*). In contrast to synchronised zoning, an order is picked sequentially in the different zones. One order picker starts with the order. Once all order lines in one zone are picked, the order is passed on to an order picker in another zone (de Koster et al., 2007). Progressive zoning can be related to a *flow shop* or a *job shop* in a production environment. In a job shop or flow shop, a job is processed on different machines in a specified sequence. Similar to passing on a job to the next machine in a job shop or flow shop, in progressive zoning an order is passed on to an order picker in the next zone.

To summarise, although different terminologies are used, production and warehousing have many concepts in common. Nevertheless, differences arise between these two problems. In a production context, the main decision to be taken is the choice and design of the machine environment including the number of machines. A warehouse context, however, is a more complex environment in which multiple decisions have to be taken. Besides the number of order pickers to hire, a routing policy, storage location policy, batching policy, and zoning policy have to be determined. The choice of these policies has an impact on the picking time.

The comparison of production and warehouse processes in this section has two objectives: (1) to act as a starting point for describing and formulating an I-OP-VRP in a warehouse context; and, (2) to show the relationship between warehousing and production in order to connect the two research communities. It could stimulate the application of concepts and solution approaches in each other's domain.

3.3 Problem description

An I-OP-VRP is investigated to determine an overall solution for both the order picking process and the vehicle routing problem. In a DC, customer orders, each consisting of one or more articles (order lines), need to be picked by order pickers. After the orders are picked, they need to be delivered to customers. Both order picking schedules and vehicle delivery routes need to be determined. Currently, in most warehouses a fixed due date is being implied before which all orders need to be picked. The due date separates the order picking process and the vehicle routing operations and represents the pickup time by a 3PL service provider, or the internal distribution department when there is no coordination. A cut-off time is determined, which indicates the time before which orders should be requested if they need to be picked up by a vehicle at the pickup time. In the integrated problem, the influence of eliminating this picking due date is examined.

The following assumptions related to the DC are made. All customer orders need to be handled in a single DC. A number of order pickers work in parallel in a single zone to pick items requested by customers. The order pickers may have picking devices with different capacities and are available at the beginning of the planning horizon. Additional temporary order pickers can be hired from a fixed pool of workers in case of a high customer demand. However, to avoid congestion in the aisles of the warehouse, the number of order pickers that can work during a specified time period is limited. The labour cost, which is incurred for each minute working, is different for both types of order pickers. The labour cost of a temporary order picker is slightly higher than that of a regular order picker due to the uncertainty they have about their work and to value their flexibility. Each order picker is allowed to work a maximum amount of time during a single shift. In a real-world setting, order pickers will probably be hired for at least half a day or an entire day. In the problem considered in this dissertation, it is assumed that the order pickers are only paid for the time they actually work. In this way, the operational cost of the time needed to actually pick all goods requested is considered. No labour cost is incurred for breaks in the picking schedule during which order pickers have to wait for new orders. During these time periods, the order pickers are conducting other tasks such as storing the incoming goods in the warehouse.

In the DC, a discrete order picking policy in which each order is picked in an individual route through the warehouse, is applied using a picker-to-product system, i.e., manual order pickers travel along the picking locations (van den Berg, 1999). Splitting an order into suborders or combining orders in batches is not allowed. Each order, consisting of one or more order lines, is picked individually without interruption in a single tour. The storage locations of each good in the DC are known in advance. Therefore, the picking routes can be determined in advance using well-known routing policies such as the S-shape heuristic or the midpoint method (de Koster et al., 2007) or by solving a travelling salesman problem (e.g., Theys et al., 2010), and are used as input for the I-OP-VRP. The picking time of an order is independent of whether it is picked by a regular or temporary order picker as these travel at the same speed.

When the picking of a customer order is completed, the corresponding goods are released to be delivered. The routing problem is defined on a complete undirected graph. Travel times of the delivery network are symmetric. The distribution operations are executed by an unlimited number of vehicles (vans) which can have different capacities and costs. Both a cost per time unit of the tour length, which includes the labour cost of the driver and the fuel cost, and a fixed cost for using a vehicle is incurred. The working time during a driver's shift is limited. Service times, which are the loading times at the DC and unloading times at the customer locations, are explicitly taken into account. The fleet is originally located at the DC to which each vehicle should return at the end of a route. Each vehicle is allowed to conduct at most a single route. This assumption is made to fairly compare the uncoordinated approach and the integrated approach in the experiments conducted later in this dissertation. In the uncoordinated approach, all vehicles arrive at the DC at the same moment in time every day once, i.e., the pickup time. Therefore, although in the integrated approach there is more flexibility about the start of the delivery operations, each vehicle is also allowed to conduct only a single trip to compare the results. Allowing multiple trips in the integrated approach may lead to a lower number of vehicles needed and can avoid long waiting times within a route before the start of a time window.

During the online purchase process, customers can select from a limited list, a time window, in which they want the goods to be delivered. In an e-commerce context, the time window corresponds with the time period customers are available at the delivery location to accept the parcel. As such, an early or tardy delivery is not possible. When a vehicle arrives early, it has to wait at the customer location until the start of the time window. A customer order cannot be split, i.e., an order is delivered by a single vehicle. An order can be delivered immediately to the corresponding customer after completion of the picking process or different orders can be consolidated into a route. It is assumed that as long as the total physical space of the orders loaded onto a vehicle does not exceed the capacity of that vehicle, a loading plan can be found in which all orders fit into the vehicle.

In the I-OP-VRP, the following decisions need to be made: (1) the assignment and scheduling of orders to order pickers, (2) the assignment of orders to vehicles,

(3) the construction of vehicle routes, and (4) the scheduling of vehicle routes. The outcome is a detailed picking and distribution schedule indicating for each customer order the exact start and completion time of the picking process, the exact delivery time at the customer location, and the departure time of each vehicle at the DC. Picking schedules and vehicle routes have to be determined for a single shift of order pickers and drivers.

The described problem is a first attempt to integrate order picking processes and vehicle routing in an e-commerce environment. Hence, relatively basic formulations are applied, especially for the order picking subproblem. The author is aware that in a real-world DC the order picking process is more complex. First, several orders are generally batched to be picked in the same route through the warehouse. However, to be able to compute the effective impact of integration, and not the impact of assigning orders to different batches, a discrete order picking policy is applied in the current chapter and Chapter 4. In Chapter 5, an I-OP-VRP with a batch picking policy is introduced to investigate the impact of batch picking on the integrated problem. Second, customers can order goods on the Internet 24/7. Thus, demand cannot be known in advance and the arrival time of the orders is uncertain. As the described problem is static, the scattering of the order placement over time will be simulated in the computational experiments by using different values for the order times, which indicate the moment in time that the orders are requested by customers. Moreover, recent developments in order picking research are not included. For instance, more advanced picking policies, e.g., pick by line (Rushton et al., 2001) are not incorporated.

3.4 I-OP-VRP: Literature review

The described problem is an integration of an order picking problem and a vehicle routing problem with release dates. The state-of-the-art literature on both problems as well as the integrated problem is reviewed in this section.

3.4.1 Order picking problem

In a warehouse, order picking is the major cost component as it is a labour-intensive activity (Tompkins et al., 2003). In a B2C e-commerce environment, a large number of small orders need to be picked, which makes it even more labour-intensive (Agatz et al., 2008). Additionally, late orders are accepted to provide excellent customer service (de Koster et al., 2007). Therefore, the order picking process needs to be planned carefully such that the requested items are picked as fast as possible in a cost-efficient way. In a warehousing context, decisions need to be taken on three major aspects: the picking policy, the routing policy, and the storage policy. For a thorough review on warehousing and order picking, the reader is referred to de Koster et al. (2007), Chen et al. (2010), and van Gils et al. (2018b).

In the majority of papers on order picking, the total route length is minimised (Davarzani and Norrman, 2015). When order pickers travel at a constant speed and there is no congestion, the total order picking time is minimised as well (Chen et al., 2010). The shorter the picking time, the sooner the orders are available to be delivered to customers (de Koster et al., 2007). Additionally, by minimising the route lengths and thus the picking times, a single order picker can pick more orders during his working hours, or a lower number of order pickers are needed to pick the same number of orders. Consequently, lower labour costs are incurred (Ruben and Jacobs, 1999).

In the problem considered in this chapter and Chapter 4, a discrete order picking policy is used as a first step to integrate an OPP and a VRP. Discrete order picking is easy to operate and orders need not to be sorted afterwards which reduces the possibility of errors. Since both the customer orders and the storage locations of each item are considered to be known in advance in the problem studied in this dissertation, the tour length of each order can be determined based on the routing strategy applied. Consequently, based on the tour lengths and the travel speed of the order pickers, the order picking times can be predetermined in a separate optimisation problem. The total order picking time is the sum of the picking time of all orders.

Hence, in contrast with most studies on order picking, in the integrated problem considered in this dissertation, the total route length and picking times are known in advance. Two types of order pickers are considered: regular order pickers and temporarily hired order pickers. The only decision which needs to be made in the OPP is the assignment of orders to regular or temporary order pickers. As the labour cost of a temporary order picker is higher than that of a regular order picker, orders need only to be assigned to temporary order pickers when a picking schedule with only regular order pickers is not feasible. In the latter scenario, temporary order pickers need to pick the orders with the smallest picking times. Consequently, in order to estimate the impact of the I-OP-VRP, total picking costs per minute working for regular and temporary order pickers are minimised instead of minimising total distance travelled which is generally the objective function in order picking problems.

3.4.2 VRP with release dates

In the classical VRP, goods need to be distributed from one or more depot(s) to a set of geographically scattered customers by constructing routes along a network in such a way that all requirements are fulfilled and an objective is met. A fleet of vehicles is located at the depot(s). Both the vehicles and the goods are available at the beginning of the time horizon (Toth and Vigo, 2014). A detailed classification and review of classical VRPs can be found in Braekers et al. (2016b).

Recently, some studies have considered VRPs in which not all goods are available at the beginning of the time horizon. The moment the goods become available at the depot for delivery to customers is called the *release date*. It is the earliest time the orders are ready to be loaded on a vehicle. A vehicle delivering an order cannot leave the depot before the release date of the order. Release dates link different levels in a supply chain: production and delivery, or order picking and delivery. This class of problems is called *vehicle routing problems with release dates* (*VRP-rd*). Including release dates into a VRP results in a trade-off between delaying a vehicle departure to load more customer orders in that vehicle and departing earlier to have a longer time period available for delivering and meeting the deadlines (Reyes et al., 2018).

To the best of the author's knowledge, Cattaruzza et al. (2013, 2014, 2016) are the first ones to investigate a VRP-rd. Time windows are included in the problem resulting in a *VRP with time windows and release dates* (*VRPTW-rd*). The delivery of goods should start within the time window specified. Each of the identical capacitated vehicles can conduct multiple trips. All vehicles have to return to the depot before the end of the time horizon. The objective is to minimise the total time travelled in Cattaruzza et al. (2013), and to minimise the total distance travelled in Cattaruzza et al. (2014, 2016). A genetic algorithm is proposed to solve the VRPTW-rd.

Archetti et al. (2015a) examine the complexity of a VRP-rd when the graph describing the locations of the depot and the customers has a special structure, either a star or a line. For both graph structures, two cases are considered. In the first case, a single vehicle is available which can conduct multiple trips during the time horizon, while in the second case an unlimited number of vehicles are available which all can conduct a single tour. The vehicles have no capacity limitations. For both cases, two different objectives are evaluated: (1) minimise the total travelling distance when there is a delivery deadline, and (2) minimise the maximum value of the sum of travel times and waiting time when there is no delivery deadline. The best way to meet the first objective, i.e., minimise total distance travelled, is to wait until all goods are released at the DC. In the second objective, in order to increase the service level offered to the customers, it can be beneficial to leave the DC earlier to deliver the goods that are already released at the moment the vehicle departs. Thus, although there is no delivery deadline when the second objective function is used, the aim is to have all orders delivered as fast as possible. Choosing between the two objective functions is a trade-off between operational costs and service level. Due to the special structure of the graph, the problem can be solved in polynomial time.

Archetti et al. (2015b) investigate a multi-period VRP with release and due dates between which goods need to be delivered by a fleet of homogeneous vehicles. The objective is to minimise the sum of transportation costs, inventory holding costs, and penalty costs. Three mathematical formulations are proposed: a flow based formulation, a flow based formulation with assignment variables, and a load based formulation. The effect of the flexibility of the due date and the number of vehicles is investigated.

In Reyes et al. (2018), alternative dynamic programming algorithms are proposed for the first case problems of Archetti et al. (2015a) on the half-line structure. A service guarantee is added such that each order is delivered within a fixed amount of time after its release date. The completion time of the last route and the distance travelled taking into account that the last route has to be finished by the deadline are minimised. The service guarantee is also implemented in the second problem case of Archetti et al. (2015a) in which the distance travelled needs to be minimised. Solving these problems can be done in polynomial time.

Shelbourne et al. (2017) study a VRP with release and due dates. The release dates are considered to be the completion times of a machine scheduling problem. Homogeneous vehicles are used for the delivery operations, and each vehicle conduct at most a single route. The objective is to minimise the combination of the total distance cost and the total weighted tardiness. The authors develop a path-relinking algorithm to solve the VRP-rd.

Liu et al. (2017) formulates a VRP with order available times (or release dates) in an e-commerce industry. Similar to the problem in this dissertation, the order available times are the completion times of the order picking and packing process. A fleet of homogeneous capacitated vehicles is used to deliver the parcels. The objective is to minimise the sum of the vehicle completion times, which includes the travel times plus the vehicle departure time at the depot. A TS method is proposed. Additionally, a Lagrangian relaxation algorithm is used to obtain lower bounds.

The vehicle routing part of the I-OP-VRP in this dissertation differs from the above mentioned studies in the following ways. First, a fleet of heterogeneous vehicles is used instead of a single or an unlimited number of uncapacitated vehicles in Archetti et al. (2015a), or a homogeneous capacitated fleet in Cattaruzza et al. (2013, 2014, 2016), Archetti et al. (2015b), Liu et al. (2017), and Shelbourne et al. (2017). In reality, a company often owns vehicles with different capacity restrictions and cost structures. As such, a heterogeneous fleet is a more realistic assumption. Second, hard time windows are considered in the problem in this dissertation. Archetti et al. (2015a,b) and Liu et al. (2017) do not consider time windows. A delivery deadline is imposed in Archetti et al. (2015b), the first case of Archetti et al. (2015a), and Shelbourne et al. (2017). An increasing number of B2C e-commerce companies offer their customers the opportunity to select a time window within which they want the goods to be delivered. Third, a single-period problem is considered instead of a multi-period problem as in Archetti et al. (2015b). Finally, each vehicle can conduct a single trip as in Shelbourne et al. (2017) instead of multiple trips.

Although VRP-rd did not receive a lot of attention in the literature where production (or order picking) and distribution are linked, release dates are indispensable in such integrated studies. Release dates are equal to the completion times of the production process or order picking. Although the term *release date* is not used in the I-PS-VRP, it is required that the distribution can only start after the goods are produced in these integrated studies. In mathematical models, often a constraint is added which requires that the departure time of the vehicle or the arrival time at the customer is greater than the completion time of the production process, e.g., in Park and Hong (2009) and Ullrich (2013). Arda et al. (2014) formulate a multi-period vehicle loading problem with stochastic release dates. This problem intermediates between a purely uncoordinated approach and a fully integrated approach. The problem investigates whether transportation decisions can be improved when forecasts about future releases of items from production are taken into account.

3.4.3 Integrated problem

As discussed in Chapter 2, distribution operations are mostly integrated with production tasks. These integrated studies often focus on relatively simple delivery operations, e.g., direct shipments to customers. In the last decade, integrated studies in which distribution operations are formulated as a VRP have received more attention in the literature. A detailed analysis of I-PS-VRPs is given in Chapter 2. In this section, the most related literature within the research field of integrated studies considering order picking and delivery operations is discussed. Table 3.2 provides an overview of the related literature indicating the main problem characteristics of each study. The table has a similar structure as the overview tables in Chapter 2. The production characteristics are replaced by order picking characteristics. Additionally, delivery mode characteristics are included because not all studies on the integration of order picking and distribution operations consider vehicle routing. In Table 3.2, the problem considered in this dissertation is indicated as well.

Low et al. (2013, 2014, 2017) and Zhang et al. (2016, 2018) make a first step towards the integration of order picking and delivery operations. In Low et al. (2013, 2014, 2017), customer orders need to be handled in a DC by a single work centre, i.e., an order picker. The authors investigate the integration of a practical scheduling problem in a DC with a VRP. Nevertheless, in their problem formulation, production concepts are used. For instance, to calculate the processing time of an order in the DC a unit processing time of a retailer is multiplied by the demand of that retailer. For example, if the unit processing time is equal to 5 and a customer orders 7 units, the total picking time becomes 35. However, order picking processing times are not proportional to the demand requested. Travel times between different picking locations are the major component in order picking times (Tompkins et al., 2003; de Koster et al., 2007), which are independent of the quantity ordered. The travel times depend on the storage locations of the goods in the warehouse.

The problem described in this dissertation differs from the problem formulated by Low et al. (2013, 2014, 2017) in the following ways. First, instead of using a single workstation (or order picker) for picking and packing, multiple order pickers are available in the I-OP-VRP in this dissertation as is the case in most real-life e-commerce DCs. Second, the objective in Low et al. (2013) is to minimise the time required to process and deliver all customer orders. However, a processing time in order picking proportional to customer demand is incorporated, which is not realistic in order picking. As such, in this dissertation, the appropriate order picking terminology is used instead of production concepts. Third, in Low et al. (2014, 2017), costs need to be minimised, but only transportation costs and penalty costs incurred for violation of time windows are incorporated; order processing costs in the DC are neglected. Besides delivery costs, order picking costs are also included in this dissertation, but penalty costs are not relevant since hard time windows which may not be violated are considered. While the aim of Low et al. (2013, 2014, 2017) is to develop an efficient algorithm to solve the integrated problem, in this dissertation indicating the value of integration is the main focus.

Zhang et al. (2016, 2018) consider the integration of an order picking system, in which customer orders arrive dynamically over time, with a distribution system. The authors mainly focus on the processes in the DC considering a dynamic order batching problem, and simplify the delivery operations. To the best of the author's

Table 3.2: Integrated order picking-distribution problems: Problem characteristics

	Order picking					Distribution																	Objective			
						Fleet of vehicles											Delivery mode									
	Batch picking	Processing times	Picking travel speed	Picking cost	Dynamic order arrival	Single vehicle	Homogeneous fleet	Heterogeneous fleet	Unlimited number	Limited number	Multiple trips	Travel times	Variable transportation cost	Fixed transportation cost	Loading times	Unloading times	Outsourced to 3PL	Direct shipments	Vehicle routing	Delivery due date	Time windows	Penalty cost	Cost	Service	Demand satisfied	Vehicles used
Low et al. (2013)	•	•					•			•		•				•			•		•			•		
Low et al. (2014)	•	•						•	•			•	•	•		•			•		•	•	•			
Low et al. (2017)	•	•						•	•			•	•	•		•			•		•	•	•			
Zhang et al. (2016)	•	•	•		•												•							•	•	
Zhang et al. (2018)	•	•	•		•		•		•			•		•				•						•		•
Schubert et al. (2018)		•					•			•	•	•							•	•				•		
Current study		•		•				•	•			•	•	•	•	•			•		•		•			

knowledge, Zhang et al. (2016) are the first authors to study the integration of an OPP with distribution operations in an e-commerce environment. However, in Zhang et al. (2016), the delivery process is outsourced to a 3PL service provider, who picks up the orders at the DC at a fixed moment in time. As such, the OPP is integrated with simple distribution operations, and not with a VRP. In Zhang et al. (2018), the delivery operations are taken into account when solving the problem. Nevertheless, the customer locations are assigned to different zones, and each zone is delivered by a direct shipping method. Thus, in both papers of Zhang et al. (2016, 2018), no vehicle routing decisions need to be taken. The authors highlight the integration of order picking processes and VRP as a future research direction. In a real-world e-commerce context, multiple customers are delivered in a single route, and as such, vehicle routing decisions should be considered. This research is an answer to this call for more research on integrated order picking-vehicle routing problems.

Whereas Zhang et al. (2016, 2018) basically focus on the order picking process and include more realistic characteristics, such as dynamic arrival of orders and batch picking, in this chapter, the focus is on the integration order picking and vehicle routing and its benefits. In Chapter 5, a batch picking policy is implemented in the I-OP-VRP. Furthermore, Zhang et al. (2016) maximise the number of delivered orders and minimise the service time. In Zhang et al. (2018), the objective is to minimise total cost, which is the sum of the makespan and the delivery cost. In the problem formulated in this dissertation, total cost of picking and distribution is minimised in order to indicate the value of integration compared with an uncoordinated approach.

The study of Schubert et al. (2018) is one of the first studies on the integration of order picking and vehicle routing decisions. Similar to problem formulation in this chapter and Chapter 4, a discrete order picking policy is applied in the warehouse. The picking routes to retrieve the requested goods from their storage location in a warehouse are solved in advance in a separate problem. Homogeneous vehicles are used for the delivery operations, and each vehicle is allowed to conduct multiple tours. Schubert et al. (2018) develop an ILS algorithm for an I-OP-VRP with delivery due dates for the supply of perishable goods from a central DC to supermarkets. A variable neighbourhood descent method, with four neighbourhoods impacting the VRP and two adapting the OPP, is proposed. The objective is to minimise total tardiness with respect to the delivery due dates. Experiments with instances with 100 and 200 customers are executed. Tardiness is reduced with on average 37.8% compared to an uncoordinated sequential approach. The problem considered in this chapter differs from Schubert et al. (2018) by using a heterogeneous fleet instead of a homogeneous fleet. Furthermore, total cost is minimised in contrast to total tardiness.

3.5 Mathematical formulation

First, mathematical formulations for an uncoordinated approach are presented. MILP models for each subproblem, i.e., OPP and VRP, are provided in Section 3.5.2 and 3.5.3, respectively. Then, the formulations of the two subproblems are combined into a MILP model for the I-OP-VRP, which is presented in Section 3.5.4. In several constraints, a Big M-parameter is introduced, which has a large value. The value of the Big M-parameter is restricted by the values of the other parameter coefficients in the specific constraints. Thus, each constraint has its own specific value for the Big M-parameter, and, therefore, an index is added to the parameter. By taking the other parameter coefficients into account, the Big M-parameter can be set to a value as small as possible.

3.5.1 Notation

The sets, indices, parameters, and decision variables needed in the mathematical models are defined as follows:

Sets and indices

$I = \{0, ..., n\}$	set of customer orders, indices i and j, where $i = j = 0$ indicates the DC
$P = \{1, ..., \bar{p}, ..., \hat{p}\}$	set of order pickers, index p, where $\{1, ..., \bar{p}\}$ indicates regular order pickers and $\{\bar{p} + 1, ..., \hat{p}\}$ temporary order pickers
$V = \{1, ..., \bar{v}\}$	set of vehicles, index v

The indices are related in the following way: an order i is picked by an order picker p in the warehouse and thereafter delivered to the location of customer order i by a vehicle v.

Parameters

C_p	capacity of order picker p, in number of items
C_v	capacity of vehicle v, in number of items
w_i	capacity utilisation (or size) of customer order i, in number of items
pt_i	time needed to pick customer order i, in minutes
ot_i	order time of customer order i, in minutes
pd	picking due date, in minutes

rd_i	release date for delivery of customer order i ($i \geq 1$), in minutes
s_i	service time at delivery destination of customer order i, in minutes; index $i = 0$ indicates the loading time at the DC
t_{ij}	travel time between delivery destination of customer order i and delivery destination of customer order j, in minutes. When two orders belong to the same customer, then $t_{ij} = 0$.
$[a_i, b_i]$	lower bound a_i and upper bound b_i of delivery time window of customer order i ($i \geq 1$); index $i = 0$ indicates the time window in which vehicles can leave and return to the DC, in minutes
$creg/ctemp$	labour cost minute of a regular/temporary order picker
$wt_{reg}^{max}/wt_{temp}^{max}$	maximum working time of a regular/temporary order picker, in minutes
f_v	fixed cost of using vehicle v
ctl_v	cost per minute of the tour length of vehicle v, also called variable travel cost
TL_{max}	maximum tour length, in minutes

Decision variables

STO_i	start time of picking customer order i ($i \geq 1$), in minutes
CTO_i	completion time of picking customer order i ($i \geq 1$), in minutes
STT_v	start time of loading vehicle v, in minutes
TL_v	tour length of vehicle v, in minutes
DT_i	delivery time of customer order i ($i \geq 1$), i.e., start of unloading, in minutes
X_{ip}	binary variable which is equal to 1 ($X_{ip} = 1$) if customer order i is picked by order picker p
U_{ijp}	binary variable which is equal to 1 ($U_{ijp} = 1$) if customer order j is picked immediately after customer order i ($i \neq j$) by order picker p

Y_{iv}	binary variable which is equal to 1 ($Y_{iv} = 1$) if customer order i is delivered by vehicle v
Z_{ijv}	binary variable which is equal to 1 ($Z_{ijv} = 1$) if customer order j is delivered immediately after customer order i ($i \neq j$) by vehicle v

3.5.2 Order picking subproblem

In the order picking subproblem, a picking due date before which all orders should be picked needs to be respected in such a way that the vehicles delivering the orders can leave the DC on time. This due date is considered to be the time the vehicles arrive at the DC to pick up all orders. The new proposed MILP for the OPP is formulated as a VRP. In both a VRP and an OPP, a sequence needs to be determined. For each order picker, a picking sequence is determined which starts and ends with a dummy order 0. The order picking time pt_0, capacity utilisation w_0, and order time ot_0 of this dummy order are equal to zero.

$$\min creg \cdot \sum_{i=1}^{n} pt_i \cdot \sum_{p=1}^{\bar{p}} X_{ip} + ctemp \cdot \sum_{i=1}^{n} pt_i \cdot \sum_{p=\bar{p}+1}^{\hat{p}} X_{ip} \tag{3.1}$$

subject to

$$\sum_{p=1}^{\hat{p}} X_{ip} = 1, \qquad \forall i \in I \setminus \{0\} \tag{3.2}$$

$$X_{ip} = \sum_{j=0}^{n} U_{ijp} = \sum_{j=0}^{n} U_{jip}, \qquad \forall i \in I, p \in P, i \neq j \tag{3.3}$$

$$\sum_{j=1}^{n} U_{0jp} \leq 1, \qquad \forall p \in P \tag{3.4}$$

$$w_i \cdot X_{ip} \leq C_p, \qquad \forall i \in I, p \in P \tag{3.5}$$

$$STO_i \geq ot_i, \qquad \forall i \in I \tag{3.6}$$

$$STO_j \geq CTO_i - M^1 \cdot \left(1 - \sum_{p=1}^{\hat{p}} U_{ijp}\right), \qquad \forall i, j \in I, i \neq j, M^1 = pd \tag{3.7}$$

$$CTO_i = STO_i + pt_i, \qquad \forall i \in I \tag{3.8}$$

$$CTO_i \leq pd, \qquad \forall i \in I \tag{3.9}$$

$$\sum_{i=1}^{n} pt_i \cdot X_{ip} \leq wt_{reg}^{max}, \qquad \forall p = 1, ..., \bar{p} \qquad (3.10)$$

$$\sum_{i=1}^{n} pt_i \cdot X_{ip} \leq wt_{temp}^{max}, \qquad \forall p = \bar{p}+1, ..., \hat{p} \qquad (3.11)$$

$$CTO_i, STO_i \geq 0, \qquad \forall i \in I \qquad (3.12)$$

$$X_{ip}, U_{ijp} \in \{0,1\}, \qquad \forall i, j \in I, i \neq j, p \in P \qquad (3.13)$$

The objective function (3.1) of the order picking subproblem minimises the sum of the labour costs for both regular and temporary order pickers. Constraints (3.2) guarantee that each customer order is assigned to exactly one order picker. Constraints (3.3) specify that the number of predecessors and successors of a customer order in the picking schedule needs to be equal. Inequalities (3.4) express that each order picker can have at most one order to be picked as first in a sequence. Constraints (3.5) ensure that the capacity of the order picker is not violated. Inequalities (3.6) indicate the earliest possible start time for picking a customer order. Constraints (3.7) and (3.8) compute the start time and completion time of the picking process of a customer order, respectively. Inequalities (3.9) impede that the picking due date is violated. Constraints (3.10) and (3.11) limit the working time of regular and temporary order pickers, respectively. Constraints (3.12) and (3.13) define the domains of the decision variables.

3.5.3 Vehicle routing subproblem

In contrast to a classical VRP, in the I-OP-VRP not all customer orders are available for delivery at the same moment in time. In this dissertation, an order is released for delivery when the order picking process of that order in the DC is completed. This completion time CTO_i can be considered to be the release date rd_i in the VRP-rd. The release dates are considered to be known in the VRP and are used as input from the order picking subproblem. The formulation is based on Ullrich (2013) with the following modifications: (1) All vehicles are available at the beginning of the time horizon and can conduct a single trip. (2) Hard time windows are considered instead of time windows with a soft upper bound. When a vehicle arrives late, it is possible that the customer is no longer at home to accept the parcel which would result in a failed delivery. (3) As tardy deliveries are not allowed, instead of minimising total tardiness, total cost related to the tour lengths and vehicle usage needs to be minimised. (4) The route length of each vehicle trip is limited. Restricting the route lengths and minimising these is similar to the studies of Moon et al. (2012) and Belhaiza et al. (2014). In Moon et al. (2012), the sum of the travel cost, regular drivers' labour cost, and overtime drivers' labour cost is minimised, and in Belhaiza et al. (2014) the sum of the travel times and the waiting times is minimised. These two objective functions are equivalent to minimising the route lengths. A MILP model for a VRPTW-rd is formulated below.

$$\min \sum_{v=1}^{\bar{v}} f_v \cdot Y_{0v} + \sum_{v=1}^{\bar{v}} ctl_v \cdot TL_v \tag{3.14}$$

subject to

$$Z_{ijv} = 0, \qquad \forall i,j \in I \setminus \{0\}, i \neq j, \quad \forall v \in V, a_i + s_i + t_{ij} \geq b_j \tag{3.15}$$

$$\sum_{v=1}^{\bar{v}} Y_{iv} = 1, \qquad \forall i \in I \setminus \{0\} \tag{3.16}$$

$$Y_{0v} \geq Y_{iv}, \qquad \forall i \in I \setminus \{0\}, v \in V \tag{3.17}$$

$$Y_{jv} = \sum_{i=0}^{n} Z_{ijv} = \sum_{i=0}^{n} Z_{jiv}, \qquad \forall j \in I, v \in V, i \neq j \tag{3.18}$$

$$\sum_{i=1}^{n} w_i Y_{iv} \leq C_v, \qquad \forall v \in V \tag{3.19}$$

$$rd_i \leq STT_v + M_i^2 \cdot (1 - Y_{iv}), \qquad \forall i \in I \setminus \{0\}, v \in V, \quad M_i^2 = rd_i \tag{3.20}$$

$$a_0 \leq STT_v, \qquad \forall v \in V \tag{3.21}$$

$$STT_v + s_0 + t_{0j} \leq DT_j + M_j^3 \cdot (1 - Z_{0jv}), \qquad \forall j \in I \setminus \{0\}, v \in V, \quad M_j^3 = b_0 + s_0 + t_{0j} - a_j \tag{3.22}$$

$$DT_i + s_i + t_{ij} \leq DT_j + M_{ij}^4 \cdot \left(1 - \sum_{v=1}^{\bar{v}} Z_{ijv}\right), \qquad \forall i,j \in I \setminus \{0\}, i \neq j, \quad M_{ij}^4 = b_i + s_i + t_{ij} - a_j \tag{3.23}$$

$$a_i \leq DT_i \leq b_i, \qquad \forall i \in I \setminus \{0\} \tag{3.24}$$

$$DT_i + s_i + t_{i0} \leq b_0 + M_i^5 \cdot \left(1 - \sum_{v=1}^{\bar{v}} Z_{i0v}\right), \qquad \forall i \in I \setminus \{0\}, \quad M_i^5 = b_i + s_i + t_{i0} - b_0 \tag{3.25}$$

$$DT_i + s_i + t_{i0} - STT_v \leq TL_v + M_i^6 \cdot (1 - Z_{i0v}), \qquad \forall i \in I \setminus \{0\}, v \in V, \quad M_i^6 = b_i + s_i + t_{i0} \tag{3.26}$$

$$TL_v \leq TL_{max}, \qquad \forall v \in V \tag{3.27}$$

$$DT_i \geq 0, \qquad \forall i \in I \setminus \{0\} \tag{3.28}$$

$$STT_v, TL_v \geq 0, \qquad \forall v \in V \tag{3.29}$$

$$Y_{iv}, Z_{ijv} \in \{0, 1\}, \qquad \forall i, j \in I, i \neq j, v \in V \tag{3.30}$$

In the objective function (3.14) of the VRPTW-rd, the sum of the fixed vehicle usage costs and the variable costs based on the total tour lengths is minimised. Constraints (3.15) ensure that a customer cannot be visited before another customer if the time window of the former one starts after the end of this of the latter one. Constraints (3.16) ensure that each customer order is delivered by exactly one vehicle. Inequalities (3.17) force that the DC is visited in each tour. Constraints (3.18) indicate that each customer order location is entered and left once. Constraints (3.19) guarantee that the capacity of a vehicle is not exceeded. Constraints (3.20) and (3.21) indicate the earliest possible start time of a vehicle tour. Inequalities (3.22) and (3.23) compute the delivery time of each order. Constraints (3.21)-(3.23) are adapted from Braekers et al. (2016a). Inequalities (3.24) ensure that the delivery time is within the time window of a customer order. Each vehicle needs to be back at the DC on time as indicated by constraints (3.25). The maximum tour length is restricted by constraints (3.26) and (3.27). Constraints (3.28)-(3.30) indicate the domain of the decision variables.

3.5.4 Integrated order picking-vehicle routing problem

In the integrated problem, both mathematical formulations are combined into a single optimisation problem. In the order picking process, a due date is no longer considered. The only relevant time restriction is that orders need to be delivered within the specified time windows. By solving the subproblems simultaneously, more flexibility is possible. Vehicles can leave the plant at any time and thus have no fixed departure time which was equal to the picking due date in the uncoordinated approach. Therefore, constraints (3.9) used in the order picking subproblem, is not incorporated in the I-OP-VRP formulation. Furthermore, the computation of the Big M changes in constraints (3.7) as follows:

$$STO_j \geq CTO_i - M_i^7 \cdot \left(1 - \sum_{p=1}^{\hat{p}} U_{ijp}\right), \qquad \forall i, j \in I \setminus \{0\}, i \neq j,$$

$$M_i^7 = b_i - t_{0i} - s_0 \tag{3.31}$$

As already mentioned, the completion times of the order picking in the OP-subproblem in Section 3.5.2 are used as release dates in the VRPTW-rd in Section 3.5.3. In the integrated approach, the release date rd_i, which is a parameter, in constraints (3.20) is replaced by variable CTO_i. As such, constraints (3.20) become:

$$CTO_i \leq STT_v + M_i^7 \cdot (1 - Y_{iv}), \quad \forall i \in I \setminus \{0\}, v \in V, M_i^7 = b_i - t_{0i} - s_0 \tag{3.32}$$

In short, the formulation of the I-OP-VRP is the following:

$$\min \sum_{i=1}^{n} pt_i \cdot \sum_{j=0}^{n} \sum_{p=1}^{\bar{p}} creg \cdot U_{ijp} + \sum_{i=1}^{n} pt_i \cdot \sum_{j=0}^{n} \sum_{p=\bar{p}+1}^{\hat{p}} ctemp \cdot U_{ijp} + \sum_{v=1}^{\bar{v}} f_v \cdot Y_{0v} + \sum_{v=1}^{\bar{v}} ctl_v \cdot TL_v \tag{3.33}$$

subject to (3.2)-(3.6), (3.8), (3.5)-(3.13), (3.15)-(3.19), and (3.21)-(3.32).

3.6 Data generation

3.6.1 Benchmark instances

In the I-OP-VRP, data are required for both the order picking part and the vehicle routing part of the problem. Since this dissertation is one of the first studies in which an integrated problem is solved, no benchmark instances exist for this specific problem. The only study on an I-OP-VRP of which the author is aware, i.e., Schubert et al. (2018), is conducted at the same time of the research described in this dissertation. Consequently, both the data generation procedure and the instances were not available at the time the experiments in this dissertation were executed. Furthermore, these instances are not publicly available. Therefore, these instances are not used in the experiments.

The instances used by Viergutz and Knust (2014) and Belo-Filho et al. (2015) for an I-PS-VRP are publicly available. Nevertheless, these instances could not be used or adapted for the problem considered in this dissertation. Both papers consider the production and delivery of perishable goods. Viergutz and Knust (2014) do not take into account any costs, while in Belo-Filho et al. (2015), the production cost per unit of a product is set equal to zero. Thus, in their experiments only delivery costs, consisting of a travel cost which is incurred for each distance travelled and a fixed vehicle usage cost, are considered. In Viergutz and Knust (2014), a single vehicle executes the delivery operations, whereas in Belo-Filho et al. (2015) the number of vehicles is equal to the number of customers. In both studies, no service times are taken into account. Time windows are considered in both papers. In Belo-Filho et al. (2015), all time windows have a width of 40 time units, while in Viergutz and Knust (2014), the time windows can have any width. In a B2C e-commerce context, customers can choose a delivery time window from a limited number of options. The time window width is mostly a multiple of 60 minutes. Moreover, the time windows start at a fixed moment in time, e.g., every hour. Furthermore, the demand values in these instances are relatively high to be used in an e-commerce context, in which customers order small quantities. In Viergutz and Knust (2014), a mean demand of 50 units is considered, and in Belo-Filho et al. (2015), the demand is generated from U(40,60). In Belo-Filho et al. (2015), the unit production time of a product is set equal to one, and in Viergutz and Knust (2014) a fixed production rate is applied. This cannot be used in an order picking context, where the picking time depends on the travel time through the warehouse to pick all goods at their storage location. Transforming the benchmark instances so that these could be used for the I-OP-VRP without affecting the optimal solutions is not possible.

For the vehicle routing problem, several benchmark instances are available. Solomon (1987) and Gehring and Homberger (1999) generated instances for the capacitated VRPTW for small-size problems and large-size problems, respectively. The same problems occur as with the instances of Viergutz and Knust (2014) and Belo-Filho et al. (2015). The time window can start at any moment in time and have any width. Moreover, the service times, 10 or 90, are too large for usage in an e-commerce context. Additionally, the demand ranges between 1 and 43 units. Solomon (1987) and Gehring and Homberger (1999) use the same coordinates for each instance within each class. New benchmark instances for the capacitated VRP were generated by Uchoa et al. (2017). No time windows and service times are considered. Thus, these VRP benchmark instances cannot be used for the I-OP-VRP.

3.6.2 Instance generation

In order to conduct the experiments, artificial data instances are generated. Three classes of instances with different problem sizes are generated: 10, 15, and 20 customer orders. Each class consists of 20 instances. The generated instances are available online at http://alpha.uhasselt.be/kris.braekers.

The capacity utilisation of an order w_i is randomly generated from $TRIA(1, 2, 6)$, where $TRIA(a, c, b)$ defines a triangular distribution with a the minimum value, c the mode, and b the maximum value. Random numbers generated from a triangular distribution are rounded to the closest integer. The average order size is 3 items, which is the same as in the studies of Ruben and Jacobs (1999), Petersen (2000), and Zhang et al. (2016) considering a mail order or B2C e-commerce problem setting. The capacity of the picking devices is measured in number of items as in, for example, Ruben and Jacobs (1999), de Koster et al. (1999a), and Henn (2012). All order pickers have the same picking device with a capacity C_p of 20 items, similar as in Zhang et al. (2018). Thus, with the instances used, each order picker is capable to pick every order as the maximum order size is less than the picking device capacity. The order processing time pt_i is equal to the sum of a setup time, i.e., two minutes, and the route time. The route time is randomly generated from $U(8, 25)$, where $U(x_1, x_2)$ defines a uniform distribution between x_1 and x_2. The average order processing time is equal to 18.5 minutes which is equivalent to the data used in Gong and de Koster (2008), who consider online retailers. The picking due date pd is equal to 240. Thus, the order pickers have at most four hours to complete the picking process for all customer requests. Two regular order pickers are available to pick the orders. Four order pickers can work at a time, and as such, at most two temporary order pickers can be hired. The variable picking cost per minute working is equal to 1 and 1.5 for regular and temporary order pickers, respectively. Both regular and temporary order pickers work in a half-day shift, and thus are allowed to work 240 minutes. All orders are available for order picking at the same moment in time and have the same order time.

In order to solve the problem with CPLEX, a limited number of vehicles is considered in the distribution part of the problem. The number is sufficiently high to solve small-size instances. Three vehicles are available with a capacity C_v of 100, 50, and 25 items, and a fixed vehicle cost f_v of 250, 200, and 150, respectively. The route length cost ctl_v is equal to 1 for all vehicles. Customer locations are spread in a geographic area having the shape of a square. The x-coordinates and y-coordinates of the destinations of the customer orders are randomly sampled from $U(0, 30)$. The DC is located at the middle of the square, i.e., (15,15). The travel times t_{ij} are equal to the rounded Euclidean distance between the locations of the customer orders and satisfy the triangle inequality, i.e., $t_{ij} + t_{jk} \geq t_{ik}$. The loading time at the plant s_0 is fixed at 20 minutes. The same value is used in the I-OP-VRP of Schubert et al. (2018). Unloading times s_i $(i \geq 1)$ are uniformly distributed from $U(2, 10)$. These bounds are used in the e-grocery problems of Punakivi and Saranen (2001) and Lin and Mahmassani (2002).

In an e-commerce context, companies often propose several time windows from which customers can choose one within which they want the goods to be delivered. In order to obtain a feasible solution, the lower bound of the time window a_i should be at least equal to the picking due date plus the loading time at the DC plus the largest possible travel time between the DC and the farthest possible customer location. This customer location is located at the corner of the square. Then, the largest travel time is computed as follows: $t_{0j}^{max} = \sqrt{(x_{max}/2)^2 + (y_{max}/2)^2}$. For a square of 30 by 30, the maximum rounded travel time between the DC and a customer is equal to 22. The picking due date is at 240 and the loading time at the DC is 20 minutes. Consequently, the lowest value of a_i is equal to 282, i.e., $pd + s_0 + t_{0j}^{max}$. The upper bound of the time window is equal to the lower bound plus 60 minutes. As such, each customer order should be delivered within a one-hour time window. After servicing the last customer in a route, a vehicle has to return to the DC. A driver works in 8-hour shift (480 minutes), starting after the picking due date in the uncoordinated approach. Punakivi and Saranen (2001) have the same restriction on the working time of the drivers. Consequently, the time window of the DC is [240,720]. Since time windows of one hour are offered, seven lower bounds for the time window are possible so that a vehicle can return to the DC on time: {282, 342, 402, 462, 522, 582, 642}.

3.7 Computational experiments

In this section, experiments are executed using the mathematical models formulated in Section 3.5. The value of integration is computed by comparing the results of an integrated approach with these of an uncoordinated approach in which the two subproblems are solved sequentially. For each class with 20 instances, the results obtained by the uncoordinated and the integrated approach are compared. Thus, the value of integration is evaluated for in total 60 instances. The problem class with 10 customer orders which need to be delivered in a square of 30 by 30 is referred to as the basis problem setting. The instances are tested on an Intel Core i5 with 2.6 GHz and 8GB RAM. CPLEX 12.6.2 from IBM is used as MILP-solver.

3.7.1 Solution methodology

3.7.1.1 Uncoordinated approach

In the uncoordinated approach, first the order picking subproblem, formulated in Section 3.5.2, is solved, followed by the VRPTW-rd, formulated in Section 3.5.3. The vehicles arrive at the DC at the picking due date. The lower bound of the TW of the DC is equal to the picking due date. As such, the orders cannot be loaded onto the vehicle earlier and, therefore, the release date in the VRP of all orders is set equal to the picking due date. Thus, $a_0 = pd = rd_i = 240$. Consequently, constraints (3.20) and (3.21) are the same, and to avoid duplicate constraints the latter one is removed from the mathematical formulation in the experiments. Additionally, it is assumed that all picking devices have the same capacity restriction and thus constraints (3.5) are removed from the formulation. The working time of the drivers starts at the moment they arrive at the DC. Therefore, the computation of the tour lengths starts at the lower bound of the time window of the DC. In constraints (3.26), the start time of the tour STT_v is replaced by the TW lower bound a_0:

$$DT_i + s_i + t_{i0} - a_0 \leq TL_v + M_i^{10} \cdot (1 - Z_{i0v}), \quad \forall i \in I \setminus \{0\}, v \in V, \quad M_i^{10} = b_i + s_i + t_{i0} - a_0 \tag{3.34}$$

3.7.1.2 Integrated approach

In the integrated approach, the model formulated in Section 3.5.4 is used. The same data instances as in the uncoordinated approach are used. Similarly as in the uncoordinated approach, constraints (3.5) on the picking device capacity are removed from the formulation since homogeneous devices are considered. As mentioned before, the picking due date is not necessary any more. Due to the increased flexibility, vehicles can arrive at the DC at any moment in time, which results in the following time window of the DC: [0,720]. Again, constraints (3.21) is removed from the formulation as this is equivalent to the non-negativity constraints (3.29). The working time of the drivers starts at the moment the vehicle is loaded.

3.7.2 Value of integration

The results of the two approaches are compared in order to compute the value of integration. The savings in total cost, which represents the value of integration, are computed as follows: $100 \cdot [(TC_{int} - TC_{unc})/TC_{unc}]$, with TC_{unc} the total cost of the uncoordinated approach and TC_{int} this of the integrated approach. A negative percentage indicates that the integrated approach has lower costs in comparison with the uncoordinated approach.

The value of integration is calculated for the basis problem setting using the problem characteristics as described in Section 3.6.2. Additional experiments are conducted with different values for several problem characteristics. First, the value of integration is examined for a larger number of customer orders. Second, the impact of the order time is investigated. A dynamic environment is simulated to get an idea of the value of integrating both problems in a real-world e-commerce context. Third, experiments with different travel cost values are conducted. Finally, the impact of the size of the geographical area in which the customers are located is studied. Detailed results of all experiments can be found in Appendix A. Tables A.1-A.10 present detailed results per instance and per scenario tested.

Table 3.3 shows the average number of regular order pickers, temporary order pickers, and vehicles used in each scenario described in the following sections. Columns 1 and 2 specify the problem characteristics. Columns 3 and 4 show the average number of regular order pickers used in an uncoordinated approach and an integrated approach, respectively. The average number of temporarily hired order pickers is presented in columns 5 and 6 for an uncoordinated and integrated approach, respectively. Columns 7 and 8 indicate the average number of vehicles needed to deliver the orders to customers in either an uncoordinated or integrated approach, respectively.

Table 3.3: Average number of pickers and vehicles used

		Number of regular pickers		Number of temporary pickers		Number of vehicles	
		Unc.	Int.	Unc.	Int.	Unc.	Int.
Basis scenario	$n = 10$ $ot_i = 0$ $ctl_v = 1$ square = 30x30	1.00	1.00	0.00	0.00	1.20	1.20
Changing parameter	Parameter value						
n	15	1.95	1.95	0.00	0.00	1.35	1.35
	20	2.00	2.00	0.00	0.00	1.70	1.70
ot_i	180	2.00	1.85	1.70	0.00	1.20	1.20
	210	-	1.95	-	0.20	1.20	1.20
	{0, 60, 120, 180, 210}	1.85	1.00	0.15	0.00	1.20	1.20
ctl_v	1.5	1.00	1.00	0.00	0.00	1.20	1.30
	2	1.00	1.00	0.00	0.00	1.20	1.50
Square size	20x20	1.00	1.00	0.00	0.00	1.05	1.10
	40x40	1.00	1.00	0.00	0.00	1.60	1.60

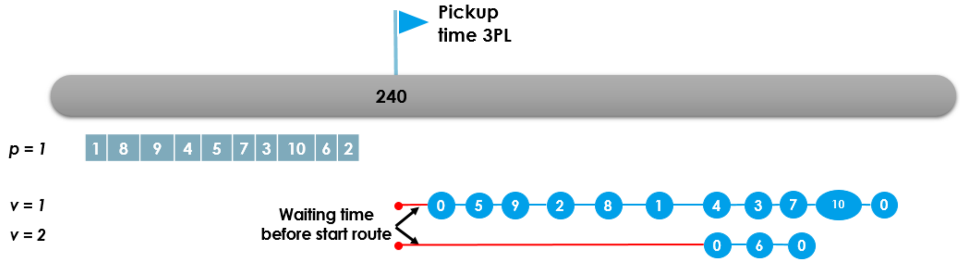
3.7.2.1 Impact of number of customer orders

In Table 3.4, the average cost changes over the 20 instances per class of problem size are shown per cost component. Furthermore, the lowest (min.) and highest (max.) savings in total cost of the 20 instances are presented. The savings in total cost are split per cost component for the instance with the lowest and highest savings. Based on the experiments executed, no relationship can be indicated between the problem size and the value of integration. Nevertheless, the integrated approach always leads to a better solution, as indicated by the lowest savings which are different from zero. The average savings are approximately 12%, which demonstrates the importance of integration. Savings of up to approximately 30% can be achieved by integrating both problems. In more detail, in the uncoordinated and integrated approach, the same number of regular order pickers ($\Delta\ TC_{creg}$) and number of vehicles ($\Delta\ TC_{f_v}$) is used within the same instance (Table 3.3), and as such, no savings are obtained on these cost components. No temporary pickers ($\Delta\ TC_{ctemp}$) are hired in both approaches. The only difference between the uncoordinated and the integrated approach are the variable travel costs ($\Delta\ TC_{ctl_v}$). Tables A.1-A.3 show the results for each individual instance in Appendix A.

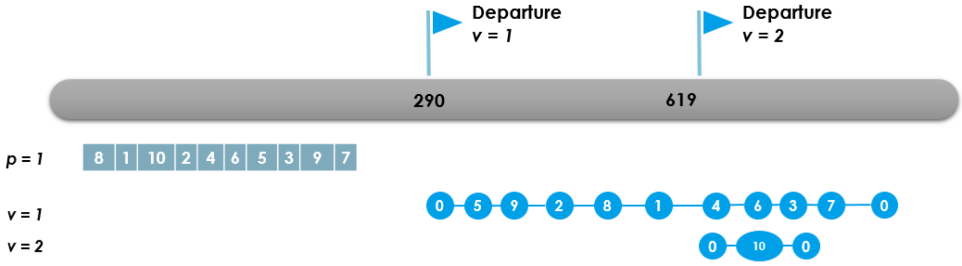
Table 3.4: Impact of number of customer orders

n		$\Delta\ TC$ (%)	$\Delta\ TC_{creg}$(%)	$\Delta\ TC_{ctemp}$(%)	$\Delta\ TC_{ctl_v}$(%)	$\Delta\ TC_{f_v}$(%)
10	avg.	-12.65	0.00	0.00	-22.99	0.00
	min.	-3.86	0.00	0.00	-7.30	0.00
	max.	-29.82	0.00	0.00	-48.16	0.00
15	avg.	-11.83	0.00	0.00	-22.61	0.00
	min.	-2.66	0.00	0.00	-5.72	0.00
	max.	-28.87	0.00	0.00	-49.38	0.00
20	avg.	-11.87	0.00	0.00	-24.50	0.00
	min.	-0.82	0.00	0.00	-1.89	0.00
	max.	-22.64	0.00	0.00	-44.47	0.00

The difference in variable travel costs is caused by the presence of a picking due date in the uncoordinated approach. In this approach, the delivery operations are outsourced to a 3PL service provider, who picks up the goods daily at the same fixed time. The pickup time does not depend on the number of orders requested or the associated delivery time windows. Consequently, even if the customers select the latest possible delivery time window, the pickup time remains the same. In the uncoordinated approach, the driver arrives at the DC at the pickup time, and consequently the labour cost of the driver is incurred starting from this picking due date. However, the actual start of the vehicle tours is often later in time to satisfy the customer delivery time windows. As such, drivers have to wait at the DC before travelling to the first customer in the route. Nevertheless, the drivers are being paid during the waiting period. In the integrated approach, as there is no fixed pickup time any more, the start time of the distribution process is more flexible. The vehicles arrive at the DC just before the actual start of the routes, and as such, the vehicles do not have to wait before leaving the DC. The drivers are paid for the time they actually work. Thus, no waiting costs before the start of a route are incurred any longer. The total variable travel cost decreases. This is illustrated in Figure 3.4 for instance 1 with 10 customer orders.



(a) Uncoordinated approach



(b) Integrated approach

Figure 3.4: Timeline of instance 1 with 10 customer orders

From a service level point of view, looking at the actual vehicle departure time, an e-commerce company can allow customers to request their goods later in time. The waiting time in the uncoordinated approach can be used in the integrated approach for picking operations of goods ordered close to the departure time. For goods ordered at the same time as before, earlier time window options to choose from can be offered to the customers. Thus, the time period between purchasing goods online and their delivery can be shortened by using an integrated approach.

Although in Table 3.4 no improvements on fixed vehicle costs are indicated, in larger examples with more customer orders and a longer time horizon, cost savings on this component may possibly be obtained. In an uncoordinated approach, all goods ordered after the cut-off time are not picked up by the 3PL at the pickup time. In an integrated approach, the cut-off time and fixed pickup time are no longer valid.

Since vehicles depart at different times throughout the day, these goods can be picked and loaded on a vehicle the same day. Thus, in the integrated approach more orders will probably already be picked when a vehicle leaves the DC to deliver goods to the final customers. For example, in Figure 3.4, orders requested between 240 and 290 cannot be delivered the same day in the uncoordinated approach, but can be delivered using an integrated approach. Hence, in examples spanning a longer time horizon, more consolidation options are possible. This can have an impact on the number of vehicles used. Nevertheless, in order to quantify the impact of a longer time horizon and more customer orders, additional experiments need to be conducted in future research. In Chapter 4, experiments with 100 customer orders are executed using a record-to-record travel algorithm.

3.7.2.2 Impact of order times

In order to examine the impact of the moment in time an order is requested, two additional values for the order time are tested on the instances with 10 customer orders: 180 and 210. Each of the 20 instances is tested for each order time value. The other input data of each instance remain the same as in the previous experiments. Thus, the only difference between the experiments in this section and these in Section 3.7.2.1 for the instances with 10 customers is the value of the order time. Average cost savings are indicated in Table 3.5.

Table 3.5: Impact of order time on instances with 10 customer orders

ot_i		$\Delta\ TC$ (%)	$\Delta\ TC_{creg}$(%)	$\Delta\ TC_{ctemp}$(%)	$\Delta\ TC_{ctl_v}$(%)	$\Delta\ TC_{f_v}$(%)
0	avg.	-12.65	0.00	0.00	-22.99	0.00
	min.	-3.86	0.00	0.00	-7.30	0.00
	max.	-29.82	0.00	0.00	-48.16	0.00
180	avg.	-15.75	52.47	-100.00	-22.99	0.00
	min.	-6.63	38.33	-100.00	-7.30	0.00
	max.	-31.50	59.48	-100.00	-48.16	0.00
210	avg.	-	-	-	-	-
	min.	-	-	-	-	-
	max.	-	-	-	-	-
{0, 60, 120, 180, 210}	avg.	-12.76	1.35	-15.00	-22.99	0.00
	min.	-3.86	0.00	0.00	-7.30	0.00
	max.	-30.19	8.82	-100.00	-48.16	0.00

In the uncoordinated approach, all orders still need to be picked before the due date of 240. In the experiments in which all orders have an order time of 180, only 60 minutes per order picker are left to pick orders. In the uncoordinated approach, temporary order pickers need to be hired, whereas in the integrated approach all orders can be picked on time by regular order pickers, as can be seen in Table 3.3. The uncoordinated approach results in higher labour costs of the order pickers for an e-commerce company.

Furthermore, with a common order time of 210, the instances cannot be solved in the uncoordinated approach. With this order time, each order picker has 30 minutes to pick orders before the due date. In total, with four order pickers 120 minutes are available. However, the total time needed to pick all orders is greater than 120 minutes in all instances generated. Thus, in the uncoordinated approach, no feasible solution in which each order is assigned to an order picker within the time period available can be found for these instances even if the maximum number of order pickers is hired. Only partial order picking lists with a part of the customer orders can possibly be created. In the integrated approach, no picking due date has to be respected. All order pickers can work 240 minutes. In four instances, an additional order picker needs to be temporarily hired. Due to the infeasibility of the uncoordinated approach, the value of integration in costs cannot be quantified. The value of integration in this scenario is that the service level increases because requesting goods later in time is possible when an integrated approach is implemented.

The infeasibility of the problem can be solved by increasing the number of order pickers that is allowed to work at the same time. In Chapter 4, experiments on the value of integration are executed with large-size instances. In these experiments, the number of order pickers is increased in the uncoordinated approach in order to avoid infeasibility. Furthermore, there is no guarantee that the integrated problem is always capable of obtaining a feasible solution. However, since there is more flexibility about the start and end of order pickers' working shift, there is a higher probability that a feasible solution can be found without increasing the number of order pickers compared to the uncoordinated approach.

In Table 3.5 can be seen that the value of integration ($\Delta\ TC$) increases with a later order time. The average cost savings with an order time of 180 is 15.75% compared to average savings of 12.65% with an order time of 0. This is mainly caused by the higher picking costs in the uncoordinated approach due to the need of temporary order pickers which have a higher labour cost per minute worked. In the integrated approach, the total regular picking cost ($\Delta\ TC_{creg}$) increases compared to the uncoordinated approach, but this is compensated by a decrease in total temporary picking cost ($\Delta\ TC_{ctemp}$).

In the previously executed experiments, all orders have the same order time. The experiments with order time values equal to 180 and 210 are worst-case scenarios in which all orders are requested close to the picking due date in the uncoordinated approach. Therefore, additional experiments are conducted in which the orders do not have a common order time. The order times are more spread over the time horizon. The same instances with 10 customer orders are used, but the orders have a different order time within an instance. The possible order times are {0, 60, 120, 180, 210}. Thus, the system is updated every hour, and a last time 30 minutes before the due date of 240. Similar findings as in the experiments with $ot_i = 180$ are observed, as indicated in Table 3.5. The value of integration ($\Delta\ TC$) is slightly higher compared with the instances having $ot_i = 0$. The increase in the total picking cost of regular pickers ($\Delta\ TC_{creg}$) in the integrated approach is compensated by savings in the total picking cost of temporary pickers ($\Delta\ TC_{ctemp}$). In the uncoordinated approach, in three instances an additional temporary order picker needs to be hired, while in the integrated approach only regular order pickers are needed in all instances (Table 3.3). Hence, even in a scenario where orders arrive at different points in time as in a real-world e-commerce DC, integration is valuable.

Changing the order time value has no impact on the vehicle routing costs since no delivery characteristics are influenced. The release date of the orders is equal to the picking due date in the uncoordinated approach in each scenario tested. The picking due date is fixed at 240 as it is independent of the order time value. The time windows remain the same and thus the vehicle routes are unaffected. The VRP is only influenced in the scenario with an order time value of 210. Since no feasible picking schedules can be determined in which all orders are picked on time, the orders can not be released to be delivered. Thus, no VRP can be solved. For the other scenarios, the cost changes between the uncoordinated and the integrated approach are the same in Table 3.5. In these scenarios, an average cost decrease ($\Delta\ TC_{ctl_v}$) of 22.99% is obtained.

The order time can also be interpreted as the latest time the company allows customers to place an order with the promise to be delivered in the time windows proposed, i.e., cut-off time. In this case, the order time determines the time period between the order placement and the earliest time window possible. By integration, the company can allow customers to request their orders later in time and still offer the same delivery time window options to their customers, which results in a faster delivery. In other words, at each moment of time a customer requests an order, more and earlier time window options from which the customer can choose during the purchasing process, are available. Hence, integration can lead to a higher service level offered. The total time needed to pick and deliver all orders can be shortened in the integrated approach compared to the uncoordinated approach.

3.7.2.3 Impact of cost parameters

In the experiments in Section 3.7.2.1, the picking cost of the regular order pickers and the variable travel cost have the same value, i.e., $creg = ctl_v = 1$. In order to investigate the impact of an increase in, for example, fuel price, experiments with higher values for the variable travel cost ctl_v are conducted. The same instances as in the basis problem setting with 10 customer orders are used with the only difference being the value of ctl_v which is equal to 1.5 or 2. A summary of the results is set out in Table 3.6.

Table 3.6: Impact of cost parameters on instances with 10 customer orders

ctl_v		$\Delta\ TC$ (%)	$\Delta\ TC_{creg}$(%)	$\Delta\ TC_{ctemp}$(%)	$\Delta\ TC_{ctl_v}$(%)	$\Delta\ TC_{f_v}$(%)
1	avg.	-12.65	0.00	0.00	-22.99	0.00
	min.	-3.86	0.00	0.00	-7.30	0.00
	max.	-29.82	0.00	0.00	-48.16	0.00
1.5	avg.	-14.90	0.00	0.00	-25.45	7.50
	min.	-5.04	0.00	0.00	-32.36	75.00
	max.	-34.28	0.00	0.00	-50.62	0.00
2	avg.	-17.03	0.00	0.00	-29.29	22.32
	min.	-7.15	0.00	0.00	-10.40	0.00
	max.	-37.29	0.00	0.00	-50.62	0.00

The results show that the value of integration ($\Delta\ TC$) increases with the variable travel cost. The higher the variable travel cost, the more valuable integration is. Thus, in the case the variable distribution cost outweighs the picking cost, integration becomes more beneficial. Total picking costs do not change in the integrated approach. Whereas in the experiments with a variable travel cost of 1 no difference in the total fixed vehicle cost ($\Delta\ TC_{f_v}$) is observed, in the experiments with a higher variable travel cost an increase in the total fixed vehicle cost is noticed. When the variable travel cost is higher, it can be more beneficial to conduct more routes if there is a considerable amount of waiting time with a lower number of vehicles, and a higher number of vehicles is needed compared to the basis scenario in the integrated approach (Table 3.3). Thus, the higher total vehicle fixed cost is compensated by a reduction in waiting time per vehicle route. This leads to a decrease in the total variable travel cost ($\Delta\ TC_{ctl_v}$) incurred. As can be seen in Table 3.6, a higher variable travel cost value results on average in a larger decrease of the total variable travel cost. Table 3.3 indicates the increase in the average number of vehicles needed when the variable travel cost increases in the integrated approach.

3.7.2.4 Impact of customer distance to the warehouse

In the basis problem setting, customers are located in a geographic area that has the shape of a square. The square has a width and length of 30 units. In this section, experiments are conducted on the instances with 10 customer orders in which customers are located in a smaller (20x20) or larger (40x40) square. Adapting the square size influences the available time windows since the earliest lower bound of a time window is computed as follows: $pd + s_0 + t_{0j}^{max}$. The largest travel time t_{0j}^{max} changes when the square size is modified. The largest travel time in a 20x20-square and a 40x40-square is 15 and 29, respectively. The corresponding earliest lower bounds are 275 and 289. Compared to the basis problem setting with a 30x30-square, the earliest lower bound is 7 minutes earlier or 7 minutes later. Thus, in the instances, the time windows for each order are updated according to the new time window bounds.

Table 3.7: Impact of customer distance to the warehouse on instances with 10 customer orders

Square size		Δ TC (%)	Δ TC_{creg}(%)	Δ TC_{ctemp}(%)	Δ TC_{ctl_v}(%)	Δ TC_{f_v}(%)
20x20	avg.	-10.05	0.00	0.00	-20.90	3.75
	min.	-4.12	0.00	0.00	-7.80	0.00
	max.	-30.56	0.00	0.00	-53.20	0.00
30x30	avg.	-12.65	0.00	0.00	-22.99	0.00
	min.	-3.86	0.00	0.00	-7.30	0.00
	max.	-29.82	0.00	0.00	-48.16	0.00
40x40	avg.	-18.81	0.00	0.00	-33.18	0.00
	min.	-5.16	0.00	0.00	-9.56	0.00
	max.	-34.09	0.00	0.00	-56.64	0.00

Table 3.7 shows average savings over the 20 instances tested. The experiments indicate that the larger the square in which customers are located, the higher the value of integration due to higher savings in total variable travel cost (Δ TC_{ctl_v}). When customers are located in a larger square, the average distance between two customers is larger. Hence, more vehicles are needed to deliver all orders within their time windows, as indicated in Table 3.3. Consequently, in problems with a larger square, more vehicles arrive at the DC at the picking due date in the uncoordinated approach compared to problems with a smaller square. However, the vehicles have to wait before they depart. During the waiting time a variable travel cost is incurred. The higher the number of vehicles needed, the higher the total waiting time. In the integrated approach, the vehicles arrive at the exact departure time at the DC. Accordingly, there is no waiting time at the depot, and thus the total variable travel

costs decrease. Therefore, with a larger square, the waiting time for a higher number of vehicles is reduced which leads to higher total savings in comparison with a smaller square size.

Additionally, when an integrated approach is applied it can be beneficial to use more vehicles compared to an uncoordinated approach. By using more vehicles, waiting times within a route can be avoided which lead to cost savings. In an uncoordinated approach, however, conducting an additional route probably leads to waiting times before the actual start of this route. No difference is made between waiting times before the start of a route or waiting times within a route. An additional route is only conducted whenever needed to satisfy the delivery time windows selected by customers.

The experiments in this section on the impact of the customer distance to the DC and the experiments in the previous section on the impact of the distribution cost parameters can be related. In the previous section, by increasing the cost value of ctl_v, the travel times and distances are unaffected. Nevertheless, travelling to a customer becomes more expensive although the same distance needs to be travelled. In this section, however, by changing the square size, travel times and distances to customers decrease (increase) when the square becomes smaller (larger). In a smaller square, a vehicle arrives faster at the next customer. Consequently, there is a higher probability that a vehicle arrives early with respect to a delivery time window. In both cases, i.e., a higher distribution cost and a smaller area, it can be more beneficial in the integrated approach to split a route over multiple vehicles when there is a large amount of waiting time within the route. In this section, to avoid waiting times due to earliness, routes can be split, while in the previous section, routes will be split when waiting times become more expensive due to an increase of the variable travel cost compared to the fixed cost of hiring an additional vehicle. No costs are incurred any longer for the waiting times before the departure of the vehicle in the integrated approach.

3.7.2.5 Tour length restriction

The maximum tour length allowed, based on the driving time restriction, is 480 minutes (8 hours). Table 3.8 provides detailed information about the tour lengths conducted by the vehicles in the optimal solutions. Columns 1 and 2 specify the problem scenario considered. Column 3 presents the average tour length, while column 4 shows the maximum tour length observed over the 20 instances. In column 5, the number of instances in which multiple vehicles are used, i.e., 2 or 3 vehicles routes, is presented.

Table 3.8: Tour lengths: Detailed information

		Average TL	Maximum TL	# inst. using multiple veh.
Basis scenario	$n = 10$ $ot_i = 0$ $ctl_v = 1$ square = 30x30	286.32	417.00	4
Changing parameter	Parameter value	Average TL	Maximum TL	# inst. using multiple veh.
n	15	279.61	410.00	7
	20	259.29	466.00	14
ot_i	180	286.32	417.00	4
	210	286.36	381.00	4
	{0, 60, 120, 180, 210}	286.32	417.00	4
ctl_v	1.5	257.56	417.00	5
	2	218.77	417.00	8
Square size	20x20	300.95	414.00	2
	40x40	230.00	402.00	12

The average tour length in all scenarios is not close to the tour length limit of 480 minutes. The maximum tour length is approximately 60 minutes less than the maximum allowed tour length. Thus, based on these results, it can be preliminary concluded that the tour length restriction is not binding in most instances. However, in several instances, multiple vehicles are used to deliver the orders. It cannot be derived from the results whether multiple vehicles are needed because assigning all orders to a single route would violate the tour length restriction or because of a high number of customers with overlapping time windows so that these customers cannot be delivered in the same route without violating the time window bounds.

3.7.2.6 Computation times

Table 3.9 provides the minimum, average, and maximum computation time for each problem scenario tested. In the integrated approach, the instances with 10 and 15 customer orders can be solved in less than one minute on average. The more customer orders are included, the more time is needed to find the optimal solution by CPLEX, with up to approximately 26,000 seconds (7 hours) to solve an instance with 20 orders. Thus, to solve real-world instances with a larger number of orders a heuristic solution method is needed. In Chapter 4, a heuristic algorithm for the I-OP-VRP is proposed.

Table 3.9: Computation times of I-OP-VRP

		Minimum time (s)	Average time (s)	Maximum time (s)
Basis scenario	$n = 10$ $ot_i = 0$ $ctl_v = 1$ square = 30x30	0.28	1.91	9.30
Changing parameter	Parameter value	Minimum time (s)	Average time (s)	Maximum time (s)
n	15	4.23	22.86	141.78
	20	33.49	4,965.16	25,774.23
ot_i	180	0.22	1.68	8.47
	210	0.28	982.56	12,612.72
	{0, 60, 120, 180, 210}	0.20	1.63	6.55
ctl_v	1.5	0.25	2.46	13.55
	2	0.31	2.81	11.97
Square size	20x20	0.20	1.17	6.56
	40x40	0.25	1.94	6.27

Additionally, later order times make the problem less likely to be feasible since the same number of orders have to be scheduled in a shorter planning horizon. The average computation time increases in the experiments with order times equal to 180 and 210. Moreover, the higher the value of the variable travel cost, the higher the average computation time to solve to optimality with CPLEX. Similarly, the size of the delivery area and the computation time are positively related.

3.7.2.7 Symmetry breaking constraints

As indicated in the previous section, computation times increase significantly with the number of customer orders. This can be caused by a higher number of feasible solutions. However, in the I-OP-VRP, symmetry occurs in the possible solutions. For example, whether a picking list is assigned to regular order picker 1 or to regular order picker 2, total cost does not differ. By taking into account and dealing with this symmetry in the mathematical formulation, the computation time can possibly be decreased (Walsh, 2006). Symmetry breaking constraints can be introduced in the mathematical model. In this section, several variants of such symmetry breaking constraints are added to the mathematical formulation presented in Section 3.5, and their impact on the computation time is evaluated.

The first type of symmetry breaking constraints that is tested tries to deal with symmetry between order pickers. The following constraint is added to the mathematical formulation:

$$X_{1,1} + X_{1,\bar{p}+1} = 1 \tag{3.35}$$

This constraint guarantees that the first customer order is assigned to either the first regular order picker or to the first temporary order picker. Since all order pickers of the same type, either regular or temporary, have the same labour cost, it does not have to be checked whether lower total picking costs can be obtained by assigning the order to an order picker of the same type with a higher index number. In the experiments, only two order pickers of each type are available, and thus no additional symmetry breaking constraints of this type can be added without being in overlap with constraints (3.2). Similar symmetry breaking constraints can be formulated for the vehicle routing subproblem when homogeneous vehicles are considered. In this chapter, however, three vehicles with different cost values and capacities are available. Consequently, no symmetry breaking constraints can be used, since it needs to be examined whether assigning a route to another vehicle results in lower total cost.

A second variant of symmetry breaking constraints focuses on the sequence of orders within picking lists. To deal with this type of symmetry, the following constraints can be added to the mathematical formulation:

$$\sum_{p=1}^{\hat{p}} U_{jip} \leq 2 - Y_{iv} - Y_{jv} \qquad \forall i,j \in I \setminus \{0\}, i \leq j, v \in V, \quad a_i + s_i + t_{ij} \leq b_j \tag{3.36}$$

The sequence of orders in itself is not important. The only requirement is that the picking process is finished before the departure time of the vehicle delivering the goods. Constraints (3.36) state that when two orders are delivered by the same vehicle and picked by the same picker, the customer order with the lowest index number needs to be picked first.

Experiments[2] are conducted to examine the impact of these symmetry breaking constraints on the computation time. The effect of each type of symmetry breaking constraints is evaluated by introducing each type individually and by introducing both types simultaneously. The instances with 10, 15, and 20 customer orders are

[2] The experiments are conducted on a 12-core Xeon E5-2680v3 CPUs with 128 GB RAM. The computational resources and services used in this work were provided by the VSC (Flemish Supercomputer Center), funded by the Research Foundation - Flanders (FWO) and the Flemish Government - department EWI.

used for the experiments. In Table 3.10, the average computation times using the different mathematical formulations are provided.

Table 3.10: Computation times using symmetry breaking constraints

Instance size		Basis*	(3.35)	(3.36)	(3.35) & (3.36)
10 orders	min. time (s)	0.18	0.25	0.22	0.25
	avg. time (s)	2.56	2.89	3.11	3.99
	max. time (s)	16.59	19.65	26.34	28.74
15 orders	min. time (s)	2.39	5.26	2.82	10.39
	avg. time (s)	98.86	74.17	140.81	321.97
	max. time (s)	742.18	448.09	894.79	3,338.88
20 orders	min. time (s)	154.38	137.14	206.94	157.60
	avg. time (s)	6,516.55	6,792.62	7,263.81	7,824.47
	max. time (s)	48,880.60	41,604.30	61,474.30	55,324.20

* The computation times differ from these presented in Table 3.9 since different computational resources are used.

As can be seen in Table 3.10, the average computation times in general increase when symmetry breaking constraints are added to the mathematical formulation. When symmetry breaking constraints (3.35) are added to deal with the symmetry of assigning orders to order pickers of the same type, then the average computation times only slightly differ compared to the basis mathematical formulation. For the instances with 10 and 20 customer orders, the average computation times increase, while for the instances with 15 customer orders the average computation time slightly decreases. The second type of symmetry breaking constraints (3.36), dealing with the symmetry in the picking sequence, has a negative impact on the average computation times for all instance sizes. Additionally, when adding both types of symmetry breaking constraints to the mathematical formulation, the negative impact is even larger than when adding a single type of symmetry breaking constraints. Furthermore, both the minimum computation time and the maximum computation time over the 20 instances increase in most cases. Thus, based on these experiments, no important improvement on the computation times is found.

3.7.2.8 Results: An overview

Based on the experiments, integration in an e-commerce context has the following advantages compared to an uncoordinated approach. First, cost savings can be obtained mainly due to a lower number of temporary order pickers needed and by avoiding waiting times before the departure of a vehicle at the DC since the start of the delivery operations is more flexible. Thus, savings on the total labour cost of both the order pickers and the drivers can be achieved. Second, a higher service level can be offered as companies allow customers to order later in time and are still able to deliver within the same time windows. The time period between placing an order and its delivery is shorter. However, allowing these late orders implies that more orders need to be picked closer to the departure times of the vehicles. Consequently, more order pickers need to be hired compared to the case of earlier order times, which results in higher personnel costs. As such, there is a trade-off between customer service offered and personnel costs incurred, which is illustrated in Figure 3.5 for the instances with 10 customer orders. The average picking costs over the 20 instances tested are represented by the line graph and are indicated on the left axis. Both the average number of regular and temporary pickers needed over the 20 instances tested is shown in the column chart and are indicated on the right axis. The order time is indicated on the x-axis. A later order time represents a higher service level.

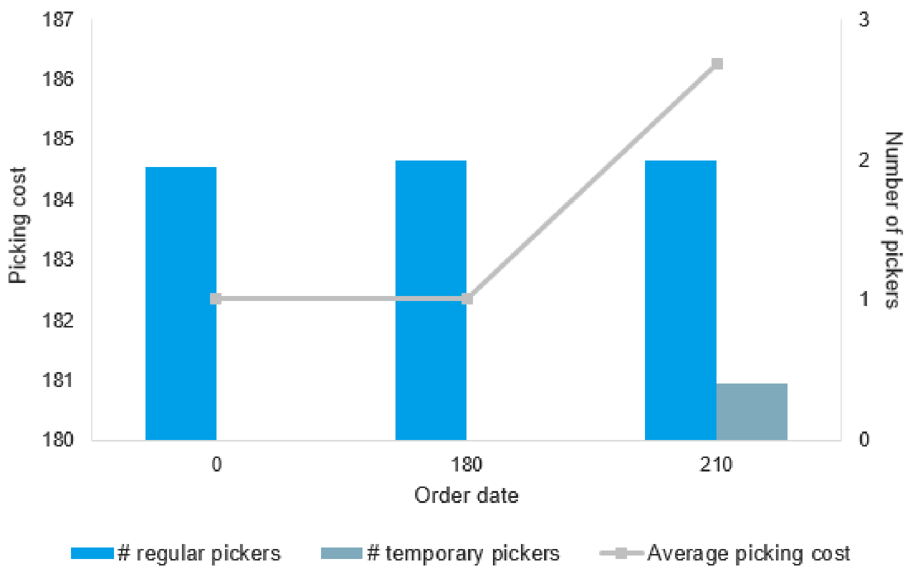


Figure 3.5: Trade-off personnel costs and service level in the integrated approach

Higher service levels result in higher picking costs and a higher number of order pickers needed. In the uncoordinated approach, due to the maximum number of orders pickers allowed and the fixed arrival times of vehicles at the DC, no feasible solution can be obtained when too many orders are requested close to the due date. In similar situations, the integrated approach has a higher probability to find feasible solutions due to the higher flexibility. In the experiments conducted in this dissertation, a higher service level is interpreted as allowing the customers to request their orders later in time.

To conclude, for several scenarios with different parameter values and problem characteristics, an uncoordinated approach and integrated approach are compared. The integrated approach leads in all scenarios and for all instances to better solutions compared to the uncoordinated approach. Hence, independent of the specific parameter values and problem characteristics, companies can benefit from the integration of both subproblems. The exact value of integration is influenced by the actual parameter values and problem characteristics. Although the experiments are conducted using data based on companies in an e-commerce context, companies operating in other sectors can also benefit from integration, especially when short throughput times are crucial.

3.8 Conclusions and future research opportunities

B2C e-commerce sales are increasing every year. Customers expect a fast and accurate delivery. In order to fulfil these high customer expectations supply chain functions have to be optimised simultaneously. In this chapter, an order picking process and a vehicle routing problem in an e-commerce context are integrated into a single optimisation problem, i.e., an integrated order picking-vehicle routing problem (I-OP-VRP). As in the literature, most integrated problems consider a production environment, first production scheduling and order picking processes are compared before an I-OP-VRP is formulated. In general, different terminologies are used to define relatively similar concepts. The related concepts are linked with each other. In both a production context and a warehouse, processed goods need to be delivered to customers. Consequently, there are interdependencies between production and distribution as well as between warehousing and distribution.

This dissertation is one of the first studies in which order picking and vehicle routing decisions are integrated. Mathematical formulations for a discrete order picking problem, a vehicle routing problem with time windows and release dates, and an integrated problem are presented. The performance of the proposed I-OP-VRP is compared to an uncoordinated approach in which first an OPP is solved and afterwards a VRP. The total cost obtained by using an uncoordinated approach is compared to the total cost obtained by using the integrated approach.

Experiments indicate that integrating both problems can lead to cost savings of 14% on average, with even up to approximately 37%. Fewer temporary order pickers need to be hired in an integrated approach. Vehicles can arrive at the DC at any moment of the day, and thus arrive just before a route needs to start. Consequently, vehicles do not have to wait before the start of a delivery route, which leads to lower total driver labour costs. Additionally, e-commerce companies can offer a higher service level when order picking and vehicle routing decisions are integrated into a single optimisation problem. Customers can request their goods later in time and still have the possibility to choose the same delivery time window as an order requested earlier. Companies cannot offer this service in an uncoordinated approach due to the fixed picking due date before which all orders need to be picked. Insufficient time is left to pick orders which are requested close to the due date. Furthermore, a sensitivity analysis indicates that both the variable travel cost and the size of the square in which the customers are located is positively related with the value of integration.

In all scenarios tested, integration is beneficial for companies. Independent of the exact problem characteristics, integrating order picking and vehicle routing decisions leads to better solutions. The results can be generalised to companies operating in other environments than e-commerce. Integration can be valuable for any company, especially when small throughput times are important, e.g., perishable products.

In this chapter, experiments with small-size instances with at most 20 customer orders are conducted. The optimal solution of the I-OP-VRP for instances with 10 and 15 customers is found by CPLEX within one minute. However, solving larger instances with 20 customer orders can take up to approximately seven hours. A real-world distribution centre handles a large number of orders a day. They need to be able to determine order picking schedules and vehicle routes in a small amount of time. Therefore, a heuristic solution method for the I-OP-VRP is proposed in Chapter 4.

Chapter 4

A record-to-record travel algorithm for the I-OP-VRP

4.1 Introduction

In Chapter 3, the integrated order picking-vehicle routing problem has been introduced. A mathematical formulation for both an uncoordinated and an integrated approach is presented. Computational experiments with small-size instances are conducted using CPLEX to solve the MILP model proposed. The experiments show that solving the integrated problem to optimality takes a large amount of computation time, especially for larger instances. Therefore, a heuristic solution algorithm, which could be used by real-world e-commerce companies, needs to be developed to solve the I-OP-VRP. This chapter[1] focuses on the design of a record-to-record travel algorithm to obtain high-quality solutions within a small amount of time (Figure 4.1).

The remainder of this chapter is structured as follows. An adapted objective function is introduced in Section 4.2. In Section 4.4, a record-to-record travel algorithm to solve the I-OP-VRP is proposed. In Section 4.5, random instances are generated. Section 4.6 describes the tuning of the parameters of the heuristic algorithm. The performance of the solution method is evaluated by conducting experiments in Section 4.7. In Section 4.8, the value of integration for large-size instances is examined using the heuristic algorithm. Finally, in Section 4.10, conclusions are highlighted.

[1]This chapter is based on Moons, Braekers, Ramaekers, Caris and Arda (2018).

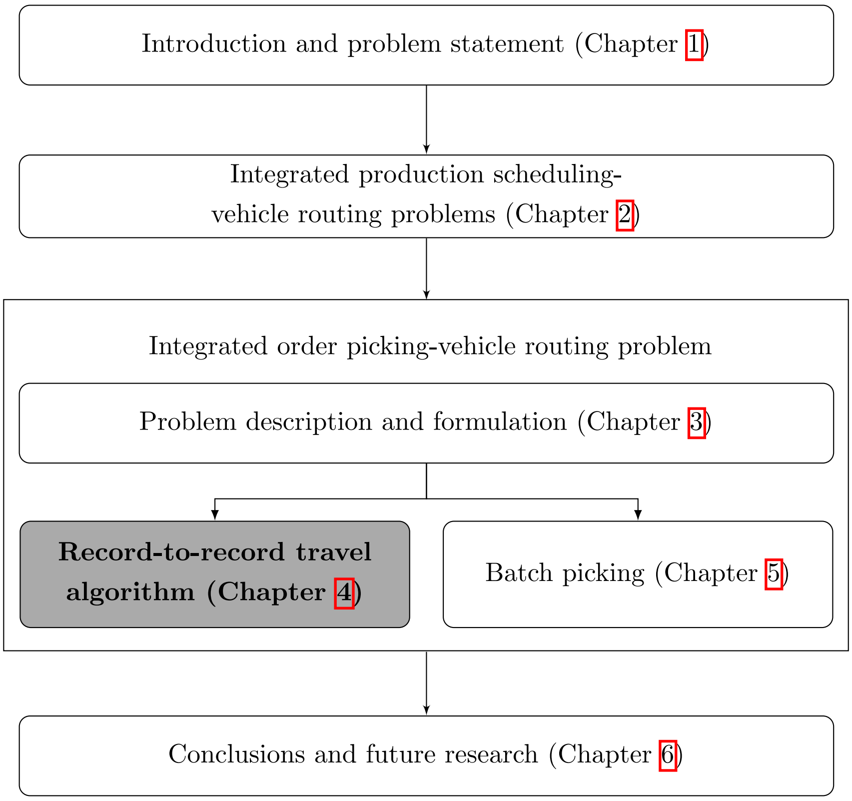


Figure 4.1: Thesis outline - Chapter 4

4.2 Objective function: An update

In Chapter 3, the value of integrating order picking and vehicle routing decisions is indicated using a more conceptual approach in the objective function. The exact benefit obtained by integrating order picking and distribution problems depends on the actual cost figures of a company. In this chapter, the values for the different cost components used in the experiments are based on real-world cost figures. A solution algorithm is proposed which should be useful for real-word e-commerce companies.

Moreover, in the previous chapter, an unlimited number of vehicles is assumed. For each vehicle used, a fixed cost is incurred. However, determining the number of vehicles to acquire is a more strategic and tactical decision. This dissertation focuses on the operational decision level. Therefore, in this chapter, a limited fleet of vehicles for the delivery operations is considered. No fixed costs are incurred any longer. Operational costs, such as fuel, maintenance, and drivers' labour costs, are allocated to each vehicle tour executed based on the tour length and kilometres travelled. Therefore, the objective function is changed in this chapter in comparison with Chapter 3.

The cost structure of the order picking part of the problem is not changed. In the vehicle routing part, however, a cost structure which is commonly used in transport economics replaces the delivery cost components used in Chapter 3. In transport economics, the distribution cost consists of two parts: an hourly cost coefficient and a kilometre cost coefficient. The main part of the hourly cost coefficient is the labour cost of the driver. Additionally, it covers the cost of insurance, depreciation, and road tax. The kilometre cost coefficient includes the cost of fuel, tires, maintenance, and fines (Blauwens et al., 2016). Thus, the fixed vehicle usage cost f_v in the objective function (3.33) in Chapter 3 is removed. A new cost component, ctt_v, is introduced and is incurred for each minute actually travelling. It corresponds with the kilometre cost coefficient.

Summarised, the objective in this chapter is to minimise total cost of the order picking and delivery operations. The order picking costs consist of the labour cost of both the regular and temporarily hired order pickers. The cost structure of the vehicle routing part is composed of two parts: an hourly cost coefficient and a kilometre cost. Consequently, the objective function (3.33) in Chapter 3 is adapted to the following:

$$\begin{aligned}\min creg \cdot \sum_{i=1}^{n} pt_i \cdot \sum_{p=1}^{\bar{p}} X_{ip} + ctemp \cdot \sum_{i=1}^{n} pt_i \cdot \sum_{p=\bar{p}+1}^{\hat{p}} X_{ip} \\ + \sum_{i=0}^{n} \sum_{j=0}^{n} \sum_{v=1}^{\bar{v}} ctt_v \cdot t_{ij} \cdot Z_{ijv} + \sum_{v=1}^{\bar{v}} ctl_v \cdot TL_v \end{aligned} \tag{4.1}$$

where ctt_v and ctl_v represent the kilometre cost coefficient and the hourly cost coefficient of vehicle v, respectively.

4.3 Metaheuristics: An overview

Historically, metaheuristics are often used to solve combinatorial optimisation problems such as the one studied in this dissertation. In this section, a high-level overview on metaheuristics is provided. A definition of metaheuristics is provided by Sörensen and Glover (2013):

> "*A metaheuristic is a high-level problem-independent algorithmic framework that provides a set of guidelines or strategies to develop heuristic*

optimisation algorithms. The term is also used to refer to a problem-specific implementation of a heuristic optimisation algorithm according to the guidelines expressed in such a framework."

The goal of a metaheuristic algorithm is to find the best solution out of all possible solutions within a reasonable amount of computation time. However, since it is not an exact method, it cannot be guaranteed that the optimal solution is found. The solution space is examined by performing operations on solutions in order to find a better one. In general, three ways to manipulate solutions exist. First, make iteratively small changes to a current solution, i.e., local search metaheuristics. Second, construct solutions from their constituting parts, i.e., constructive metaheuristics. Third, combine iteratively existing solutions into new ones, i.e., population-based metaheuristics (Sörensen and Glover, 2013).

A local search metaheuristic starts from a current solution and tries to improve this solution by making moves. A move is a small change in a solution in order to get a new solution. The set of all possible solutions that can be generated by executing a single move on the current solution is called the neighbourhood. Classical neighbourhoods are, e.g., 2-Opt (Croes, 1958), exchange, relocate (Savelsbergh, 1992), and cross-exchange (Taillard et al., 1997). Moves are iteratively conducted until a stopping criterion is reached (Sörensen and Glover, 2013; Toth and Vigo, 2014). Examples of local search metaheuristics are iterated local search, simulated annealing, and tabu search.

Whereas a local search metaheuristic in each iteration works on a complete solution, a constructive metaheuristic starts from an empty solution and adds a single element of the solution in each iteration. Thus, only in the last iteration, a complete solution is obtained (Sörensen and Glover, 2013). Constructive metaheuristics can be used to generate an initial solution to use in other metaheuristic algorithms (Toth and Vigo, 2014). Examples are greedy randomised adaptive search procedure and the pilot method.

In a population-based metaheuristic, a new solution is created by combining two or more (high-quality) existing solutions. It is often inspired by natural concepts such as the evolution of species (Sörensen and Glover, 2013; Toth and Vigo, 2014). Examples of population-based metaheuristics are evolutionary algorithms, e.g., genetic algorithms, or scatter search and path relinking.

Sörensen et al. (2018) describe the history of metaheuristics in five periods. A more elaborate description of various well-known metaheuristics is given in *The Handbook of Metaheuristics* by Glover and Kochenberger (2003) (first edition) and by Gendreau and Potvin (2010) (second edition). More specifically, for an overview of metaheuristics for the classical capacitated VRP, the reader is referred to chapter 4 of Toth and Vigo (2014). An overview of (meta)heuristics for the VRP with time windows can be found in Bräysy and Gendreau (2005) and in chapter 5 of Toth and Vigo (2014).

4.4 Solution procedure

The solution approach proposed is based on a record-to-record travel (RRT) algorithm. A RRT algorithm is an algorithm similar to simulated annealing (SA) with a deterministic acceptance criterion. It is first introduced by Dueck (1993) as a variant on threshold accepting (TA, or deterministic annealing). RRT and SA differ in the following ways. First, in SA, a new better solution is always accepted, while a new worse solution is accepted with a gradually lowered probability. In RRT, each new solution not worse than the best solution found so far (*record*) plus a deviation is accepted. The deviation is a percentage of the record value. Moscato and Fontanari (1990) state that the probabilistic acceptance criterion in SA does not play a major role in the search. Slower computation times are observed compared to a deterministic criterion due to a higher computational effort needed to calculate the accepting probabilities. Second, in RRT, a new solution is always compared with the record, while in SA and TA a new solution is compared with the last accepted solution. Third, in SA a larger number of parameters of the annealing schedule need to be tuned in comparison with a RRT algorithm. Algorithms with only a few parameters are more easy to understand for other users (Cordeau et al., 2002).

The use of RRT leads to better solutions than SA (Dueck, 1993). Recently, a RRT algorithm has been efficiently used to solve several variants of the VRP, e.g., open VRP (Li et al., 2007), consistent VRP (Groër et al., 2009), split VRP (Gulczynski et al., 2010, 2011), and VRP with simultaneous deliveries and pickups (Chen and Wu, 2006). The RRT algorithms in these studies are based on the general idea of Dueck (1993). Benchmark instances are used to evaluate the performance of the heuristics developed in these studies. The results are compared with these obtained by other best heuristics in literature, e.g., tabu search and ALNS. The solution methods developed are competitive with these existing heuristic algorithms. Thus, the RRT algorithms are implemented rather effective and are still easy to be reproduced (Toth and Vigo, 2014).

In the RRT algorithm, local search operators are used. Local search operators, such as *exchange* and *relocate*, are often successfully used to solve a VRPTW. The first step of the proposed algorithm is to generate an initial solution as described in Section 4.4.1. Next, to improve the quality of this solution, five local search operators are used in an iterative way in a record-to-record travel framework for a maximum number of iterations (Section 4.4.2). A general overview of the solution method is outlined in Algorithm 1.

Algorithm 1 Outline of solution procedure

1: Parameters: $numb\_it$, I_{max}
  $numb\_it$: iteration number
  I_{max}: maximum number of iterations
2: Generate initial solution S_0
3: $numb\_it := 0$
4: **repeat**
5:   Local search within a record-to-record travel framework
6:   $numb\_it := numb\_it + 1$
7: **until** $numb\_it > I_{max}$

The proposed solution method can be used by a B2C e-commerce company to determine both a picking schedule and delivery plan. In an e-commerce context, demand is not known completely in advance. Thus, it is hard to establish picking lists and vehicle routes for the entire day at the beginning of the working day. The system is updated on a regular basis throughout the working day, e.g., every hour. The picking schedules and vehicle routes are adapted by eliminating the orders which are already picked or delivered and by assigning the newly arrived orders to a picker and vehicle. There is a strong coordination, communication, and information exchange required between the e-commerce company and the 3PL service provider when deliveries are outsourced. To determine reliable schedules, the e-commerce company needs to have access to all information. The data about the orders are directly obtained from the customers at the moment of the purchase. The 3PL service provider has to send information to the e-commerce company about the availability of the vehicles.

4.4.1 Initial solution: Constructive heuristic

An initial solution is created by using a constructive heuristic consisting of two parts, one for each subproblem. For the assignment of customer orders to pickers the same procedure is used as in Belo-Filho et al. (2015) for the assignment of orders to production lines in an I-PS-VRP. The initial vehicle routes are created by applying the cheapest insertion principle. This procedure is also applied by Du et al. (2005) for a dynamic VRP and by Liu et al. (2017) for a VRP-rd, both in a B2C e-commerce context.

Before assigning orders to pickers, the minimum number of order pickers needed $NPick_{min}$ is calculated as follows: $\lceil$total order picking time needed/maximum working time of a picker$\rceil$. The orders are assigned in a non-decreasing order of the upper bound of their delivery time window, such that orders with an earlier time window are picked first. The assignment procedure depends on $NPick_{min}$. If $NPick_{min}$ is less than or equal to the number of regular pickers available, then an order is assigned to the first position of the picking schedule of each picker in the set of $NPick_{min}$ pickers. Afterwards, orders are assigned to the second schedule position, and so on until all orders are assigned. Before an order is assigned to a picker, feasibility is checked concerning the maximum allowed picker working time, delivery deadline, and picking capacity. If $NPick_{min}$ is greater than the number of regular pickers, then temporary order pickers need to be hired. In this case, orders are first assigned as much as possible to regular order pickers, and thereafter the remaining unassigned orders are assigned to temporary order pickers using the same procedure. If, after this procedure, still some orders are not assigned to a picker, then an additional picker is added to the set of $NPick_{min}$ pickers until all orders are assigned to a picker.

In Figure 4.2, an example of the assignment procedure for the picking schedule is shown. Ten orders, which have a total picking time of 185 minutes, need to be picked. Two regular order pickers are available with each a maximum working time during a single shift of 90 minutes. Thus, $NPick_{min} = \lceil 185/90 \rceil$ is equal to three. Consequently, a third temporary order picker needs to be hired. First, orders are as much as possible assigned to the two regular pickers in an alternating way. Next, the remaining order is assigned to the third temporarily hired order picker.

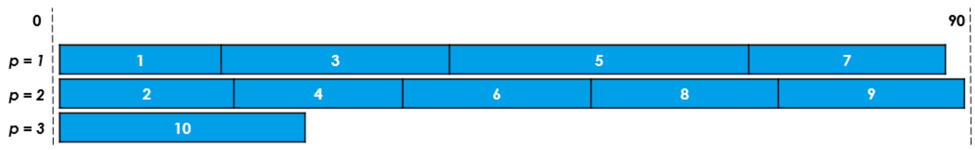


Figure 4.2: Example of the assignment procedure for picking schedules

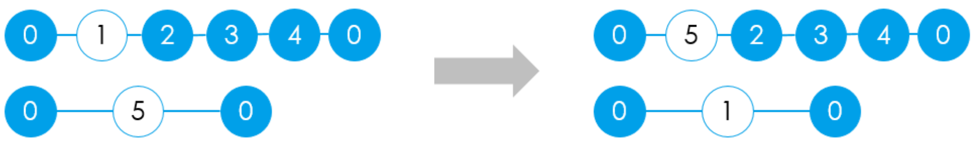
In order to create initial vehicle routes, orders are assigned to vehicles based on the cheapest insertion principle (Rosenkrantz et al., 1977). The first order is assigned to an empty route. Then, the next orders can be inserted before or after each already inserted order, or in a new empty route. The cheapest feasible insertion option is selected. Feasibility needs to be checked concerning the vehicle capacity, maximum allowed route length, and delivery time windows. The time window feasibility check is executed in constant time using the earliest departure time and latest arrival time as described in Vidal et al. (2015). A vehicle leaves the DC at the latest possible moment so that still all orders are being delivered within their time window. In case the vehicle capacity is violated, insertion possibilities are considered in other vehicles. When the maximum route length or a time window is violated, other insertion possibilities in the same vehicle or in another vehicle are examined such that a feasible solution can be found. Additionally, the picking process of the order has to be finished before the start of the vehicle route. If this relationship is violated, it is not possible to delay the start of the route since the vehicle already departs at the latest possible moment. Therefore, to solve the violation, the picking schedule is adapted such that the order can be inserted at the cheapest position without violating the picking-delivery relationship of any other order. The adaptation procedure is described later in Section 4.4.3. If this is not possible, then the order is assigned to the next best feasible insertion position in a route.

For example, if the best insertion position is in a vehicle with a departure time of 180 and the picking operations of that order are completed at 190, the order needs to be rescheduled such that the picking process is completed earlier. However, when this would lead to new violations of the picking-delivery relationship for other orders, the order cannot be rescheduled. The order needs to be assigned to another vehicle with a later departure time, e.g., 200.

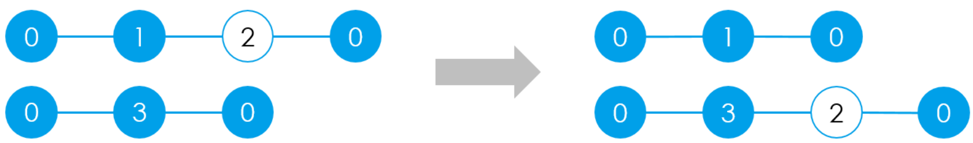
4.4.2 Local search with record-to-record travel

In order to improve the initial solution, three well-known local search operators (neighbourhoods) for the vehicle routing part of the problem and two for the order picking part of the problem are used. For an overview of local search algorithms applied for the VRPTW, the reader is referred to Bräysy and Gendreau (2005) and Toth and Vigo (2014). To adapt the routes constructed, the following three operators are applied: *2-Opt*$_{VRP}$, *exchange*$_{VRP}$, and *relocate*$_{VRP}$. In Section 4.7.3, it is investigated whether each operator contributes to the improvement of the solution quality. The *2-Opt*$_{VRP}$ operator is an edge-exchange operator in which two edges are removed and replaced by two new edges within the same route (intra-route operator). The result is the reversal of the direction of a subpath of a route (Croes, 1958). The edges immediately before and immediately after a subpath of a route are removed. The order immediately before the subpath is connected with the last order of the subpath, and the order immediately after the last order of the subpath is connected with the first order of the subpath (Figure 4.3(a)). The *exchange*$_{VRP}$ (or *swap*$_{VRP}$) operator swaps two customer orders within the same route or between two routes (intra- and inter-route operator). An example of an inter-route exchange is shown in Figure 4.3(b). The operator can only swap an order within the same route if there are at least three edges between the orders in order to avoid overlap with the *2-Opt*$_{VRP}$ operator. For example, in Figure 4.3(b), orders 1 and 3 cannot be swapped, since this is the same as reversing the subsequence 1-2-3 to 3-2-1, as shown in Figure 4.3(a). The first order with which order 1 can be swapped within the same route is order 4. The *relocate*$_{VRP}$ operator removes a customer order from a route and reinserts it at another position in the same route or in another route (intra- and inter-route operator) (Savelsbergh, 1992). An order cannot be relocated to the position before or after its current position to avoid overlap with the *2-Opt*$_{VRP}$ operator. Figure 4.3(c) shows a relocation of an order to another route.

(a) Example of *2-Opt*$_{VRP}$ operator



(b) Example of *exchange*$_{VRP}$ operator



(c) Example of *relocate*$_{VRP}$ operator

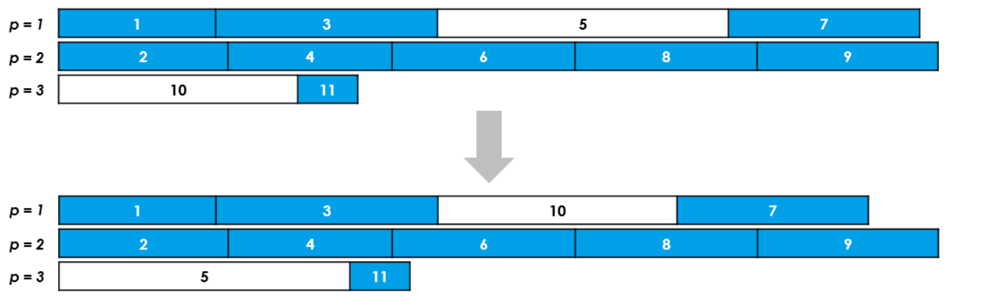
Figure 4.3: Example of VRP operators

The moves are evaluated for feasibility concerning vehicle capacity, time windows, route length, and the relationship between OPP and VRP. When the capacity of a specific vehicle would be violated after a relocation or swap, possibilities for swapping with or relocating to positions in other vehicles are examined. Time window feasibility is checked in constant time with the use of earliest departure time and latest arrival time of each order in a route (Vidal et al., 2015). If an operator move would lead to a TW or route length violation, the operator ignores the current position to which an order would be relocated or swapped with and goes on with the next possible position. In the *2-Opt*$_{VRP}$ operator, the next possible end position of the sequence to reverse is considered in this case. When the OPP-VRP relationship is violated, a move is not discarded directly but it is checked whether feasibility can be maintained by adapting picking schedules using the procedure explained in Section 4.4.3.

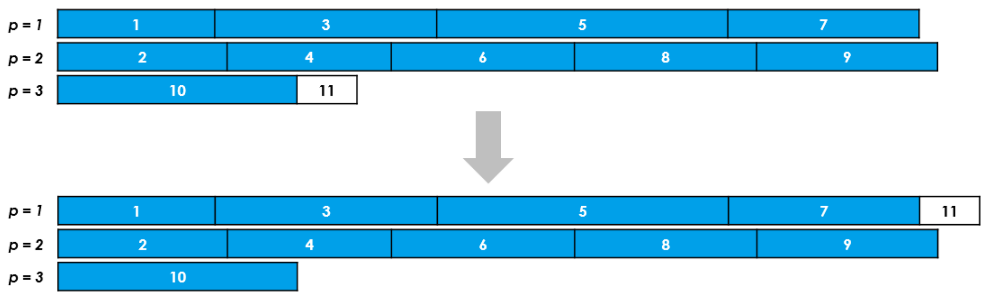
The order picking schedules are changed using the following operators: *exchange*$_{OPP}$ and *relocate*$_{OPP}$. The operators work similarly as in the routing part of the integrated problem. The OPP-operators are only applied to moves between temporary and regular order pickers since only that type of moves could possibly result in a lower total picking cost. Swapping orders between regular order pickers or relocating an order from a regular order picker to another one will never lead to lower picking costs because regular order pickers all have the same labour cost. Multiple picking sequences lead to the same total order picking costs. Consequently, any move which changes the sequence within the picking list of a regular order picker is accepted. To save on computational effort, moves in the picking lists of regular order pickers are only executed when required by the OPP-VRP relationship. When a change in the picking schedules of regular order pickers is needed to obtain feasible vehicle routes with lower costs, this change will be found by a VRP operator as will be explained later in Section 4.4.3.

The *exchange*$_{OPP}$ operator swaps a customer order currently being picked by a temporary order picker with a customer order being picked by a regular order picker (inter-picker operator). In Figure 4.4(a), an order picked by a temporary picker ($p = 3$) is swapped with an order picked by a regular picker ($p = 1$). The *relocate*$_{OPP}$ operator removes a customer order from the picking schedule of a temporary order picker and reinserts it in the schedule of a regular order picker (inter-picker operator). Figure 4.4(b) shows a relocation of an order from a temporary picker to a regular picker. Feasibility checks are executed with respect to maximum working time and the relationship between OPP and VRP. When the maximum working time would be violated by a swap move, the next possible order to swap with is checked. In case of a violation created by the *relocate*$_{OPP}$ operator, relocation possibilities for the order to another regular picker are examined. When the OPP-VRP relationship is violated by an OPP-operator, the procedure explained in Section 4.4.3 is used check whether feasibility can be maintained by adapting vehicle routes.

The operators used in the RRT algorithm are also applied in related studies. Du et al. (2005) and Liu et al. (2017) use the *relocate*$_{VRP}$ and *exchange*$_{VRP}$ operator to improve the initial solution for a VRP in an e-commerce environment. These operators are used as an inter-route operator in both studies. The *relocate*$_{VRP}$ operator is additionally used as an intra-route operator in Du et al. (2005). In Schubert et al. (2018),



(a) Example of *exchange*$_{OPP}$ operator



(b) Example of *relocate*$_{OPP}$ operator

Figure 4.4: Example of OPP operators with two regular order pickers and one temporary order picker

who consider an I-OP-VRP, the same OPP-operators are applied. An *exchange*$_{OPP}$ operator is used for swaps between pickers, and a *relocate*$_{OPP}$ operator as an intra-picker operator. The heuristic algorithm proposed in this dissertation makes use of well-known local search operators which have proven their effectiveness on the VRP with time windows in the past (Toth and Vigo, 2014). In contrast, Schubert et al. (2018) use less common operators to adapt the routes in their ILS algorithm, which are mainly focusing on the changing the composition of the multiple trips conducted by the vehicles.

4.4.3 Algorithmic framework

A detailed outline of the solution procedure is given in Algorithm 2. In each iteration of the local search, the five operators are executed in a random order (line 8). Each operator is executed for a single randomly selected vehicle or order picker and starts from the last accepted solution S_A (line 10). Within a vehicle route or picking schedule

Algorithm 2 Detailed outline of solution procedure with record-to-record travel

Parameters: α, $numb\_it$, I_{max}, I^{non_impr}, $I_{max}^{non-impr}$, M^{non_impr}, $M_{max}^{non-impr}$

α: deviation rate

$numb\_it$: iteration number

I_{max}: maximum number of iterations

I^{non_impr}: number of consecutive iterations without improving the record

$I_{max}^{non-impr}$: maximum number of consecutive iterations without improving the record

M^{non_impr}: number of consecutive moves without improving the record

$M_{max}^{non-impr}$: maximum number of consecutive moves without improving the record

Solutions: S_B = best solution, S_A = last accepted solution

S_0 = initial solution, S = current solution

Operators = $\{$*2-Opt*$_{VRP}$, *exchange*$_{VRP}$, *relocate*$_{VRP}$, *exchange*$_{OPP}$, *relocate*$_{OPP}\}$

Determine S_0

$S_B := S_0$; $S_A := S_B$; $record := Z[S_B]$; $deviation := \alpha \cdot record$

$numb\_it := 0$, $I^{non\_impr} := 0$, $M^{non\_impr} := 0$

repeat

Shuffle operators randomly leading to an operator sequence numbered from 1 to 5

for $operator\_sequence\_number = 1$ to 5 **do**

Select random vehicle or order picker from S_A

$M^{non\_impr} := 0$

repeat

Select random order in vehicle route or order picker schedule

Conduct best move on S_A resulting in solution S

if $Z[S] < record + deviation$ **then**

$S_A := S$

if $Z[S] < record$ **then**

$S_B := S$

update *record* and *deviation*

$M^{non\_impr} := 0$

else

$M^{non\_impr} := M^{non\_impr} + 1$

end if

end if

until $M^{non\_impr} = M_{max}^{non-impr}$

end for

Algorithm 2 (continued)

27: **if** *record* is updated **then**
28: $I^{non\_impr} := 0$
29: **else**
30: $I^{non\_impr} := I^{non\_impr} + 1$
31: **end if**
32: **if** $I^{non\_impr} = I^{non-impr}_{max}$ **then**
33: $S_A := S_B$
34: $I^{non\_impr} := 0$
35: **end if**
36: $numb\_it := numb\_it + 1$
37: **until** $numb\_it = I_{max}$

a random customer order is selected for which the operator is executed (line 13). Within the loop (line 9-26), for each operator the best feasible move for the selected order is conducted. A new solution S is accepted if its objective value $Z[S]$ is less than the best objective value found so far $Z[S_B]$ (*record*) plus a deviation (line 15-16). The deviation value is a fraction α of the record value. Additionally, if the new objective value is less than the record, it becomes the new best solution. In this case, the record and deviation value are updated (line 17-20). Otherwise, the number of non-improving moves $M^{non-impr}$ is increased (line 22). The selected operator is executed for the same vehicle or order picker as long as the number of consecutive moves without improving the record $M^{non-impr}$ is less than a predefined maximum number of consecutive non-improving moves $M^{non-impr}_{max}$ (line 25). Each time the operator is executed, a random order is selected within the same vehicle route or order picking schedule. The next operator continues with the last accepted solution. If after executing the five operators the record is not updated, the number of non-improving iterations $I^{non-impr}$ is increased (line 30). When a maximum number of consecutive iterations without improvement of the record $I^{non-impr}_{max}$ is reached, then the last accepted solution is replaced by the best solution S_B (line 32-35). The RRT heuristic is executed for a maximum number of iterations I_{max} (line 36).

In the VRP-operators, the best move is selected based on the impact of the operator on the total distribution costs, i.e., drivers' labour cost and kilometre cost. In the OPP-operators, the impact of the best move is calculated based on the total labour cost of both types of order pickers. Before actually executing a move, it needs to be evaluated whether the relationship between OPP and VRP is not violated by the move. This is where the integration of the OPP and the VRP is mainly implemented in the RRT heuristic. It is checked whether after a move the order picking process of each order is still finished before the departure time of the vehicle that delivers the order. If a violation occurs, the RRT heuristic tries to solve the violation such that the best move can be conducted. The procedure to solve a violation depends on the type of operator that causes the violation.

When the OPP-VRP relationship is violated by a VRP-operator, the violated orders are removed from their original position in the picking schedules and reinserted at other positions without creating a violation for other orders. A reinsertion position is searched in the picking schedule of each order picker, starting with the first order picker. A removed order is inserted at the first position found which solves the violation. It is possible to insert the removed order at an earlier position in the picking schedule of the order picker to which it was originally be assigned if this solves the violation. If it is not possible to reinsert all the violated orders, the VRP-move is considered not feasible.

If an OPP-operator leads to violations, the violated orders are removed from the vehicle routes and reinserted in routes with a later departure time. Each possible vehicle route is considered, starting with the first vehicle. The removed order is inserted in the first possible route which solves the violation. Again, when it is not possible to reinsert the orders, then the OPP-move is considered not feasible. Additionally, a move by a VRP- or OPP-operator is considered non-acceptable if, after repairing violations, it leads to a total cost increase which is larger than the deviation value.

An operator is labelled as a VRP operator or an OPP operator to refer to the initial moves which are conducted by the operator. Nevertheless, when the OPP-VRP relationship is violated, also changes can be made in the other subproblem to solve the violation. Consequently, the effect of executing an operator is not always purely obtained by changing one of the subproblems. It can be a combined effect of the operator in one subproblem and relocate moves repairing violations in the other subproblem.

In the algorithm proposed in this dissertation, only infeasibilities are allowed which are due to the relationship between the two subproblems, i.e., the picking process of one or more orders is not completed before the departure time of the vehicle delivering these orders. Nevertheless, this type of infeasibility is only allowed when the violation can be immediately fixed by reassigning the violated orders either in the vehicle routes or in the picking schedules. If the violated orders cannot be reassigned to solve the infeasibility, the original operator move creating the infeasibility will not be conducted. Moreover, infeasibilities occurring within a single subproblem are not allowed. More specifically, in the vehicle routing subproblem, violations of the vehicle capacity, maximum route length or time windows are not tolerated. In the order picking problem, assignments of orders to pickers must respect the picking device capacity and working time limit.

4.5 Data generation

Since it is the first time an integrated order picking-vehicle routing problem is solved for large problems, no benchmark instances exist. Thus, to conduct experiments, artificial instances are generated based on real-life data or related studies in the field of B2C e-commerce. Instance classes with three different problem sizes are generated, i.e., 10, 15, and 100 customer orders. For each class, 100 instances are generated resulting in 300 instances in total. The first 50 instances of each class are used for the parameter tuning and sensitivity analysis, the remaining 50 are used for the actual experiments. The randomly generated instances are available online at http://alpha.uhasselt.be/kris.braekers.

For the instances with 10 and 15 customer orders, two regular order pickers, one temporary order picker, and three vehicles are available. For the larger instances with 100 orders, nine regular order pickers, three temporary order pickers, and seven vehicles are used. The number of order pickers that can be temporarily hired is often negotiated with the labour unions. The set of order pickers consists of approximately 75% regular order pickers and 25% temporary order pickers. The total number of order pickers available is calculated as follows: ⌈(maximum picking time of an order · number of orders)/maximum working time of a picker⌉. In real life, the number of orders is not known in advance. To determine the number of order pickers needed, e-commerce companies can use either historical data on the number of orders requested during a specific time period or forecasts about future customer orders.

As described in Section 4.2, in this chapter, more realistic data values are used. Therefore, the data generation differs for some problem characteristics in comparison with Chapter 3. The main differences compared to Chapter 3 are described in this section. Problem characteristics not described in this section are generated in the same way as in Chapter 3. In the order picking part of the problem, only the labour costs are adapted. After consulting a large international logistics service provider, the labour cost of a regular *creg* and a temporary order picker *ctemp* are set equal to 25 and 30 euro per hour, respectively.

In the vehicle routing part of the problem more changes are made. First, homogeneous vehicles are considered instead of a heterogeneous fleet. Considering a homogeneous fleet reduces the complexity of the heuristic algorithm because no decisions have to be made about the type of vehicles to which orders are assigned. Each van has a capacity C_v of 100 items. A similar vehicle fleet is used in Cárdenas et al. (2017) who based this value on data of a Belgian logistics carrier operating in a B2C e-commerce context. Second, as described earlier, the cost structure has been changed. For a small van, a cost of 0.22 euro per kilometre travelled ctt_v is incurred (Blauwens et al., 2016). The labour cost of the driver ctl_v is equal to 25 euro per hour (VIL, 2016). Third, the average unloading time s_i of a parcel is equal to four minutes (VIL, 2016). The unloading time of an order is generated from a triangular distribution $TRIA(2, 4, 6)$. Four, the delivery locations are located in a 50x50-square with the DC located in the centre, as in Liu et al. (2017).

Finally, customers of e-commerce companies can often select a time window from a limited number of options. A survey in the United Kingdom has indicated that in case customers are allowed to choose the length of the delivery time slot approximately 52% would prefer a two-hour time window (Interactive Media in Retail Group, 2014). Additionally, real-world B2C e-commerce companies offering this service mostly propose time slots with a two-hour width (e.g., Albert Heijn, n.d.; Coolblue, n.d.). In the experiments, customers can choose out of nine different time windows. Seven of the nine possible time windows have a width of 120 minutes, and the remaining two options have a four-hour width.

Table 4.1: Time window options

Time window	Width
[176, 296]	2h
[236, 356]	2h
[296, 416]	2h
[356, 476]	2h
[416, 536]	2h
[176, 416]	4h
[416, 656]	4h
[476, 596]	2h
[536, 656]	2h

Since the problem starts in an empty state, the assumption is made that if a customer purchases goods online, then at least a two-hour time period is provided for order picking. In total, each order picker is allowed to work four hours during a single shift. Vehicles can leave the DC when needed to deliver goods on time, while still other orders are being picked by order pickers. The time window bounds are calculated in a similar way as in Chapter 3. In Table 4.1, the time window options used in the computational experiments are shown. When the last customer in a route is visited, the vehicle has to return to the DC before the end of its time window, i.e., $[0, 656]$. The upper bound b_i of the TW of the DC is equal to the upper bound of the earliest TW, i.e., 176, plus the maximum driver work time, i.e., 480 minutes, resulting in a value of 656.

4.6 Parameter tuning

In a record-to-record travel algorithm, the main parameter is the deviation rate α. Furthermore, the number of iterations I_{max}, the maximum number of consecutive non-improving iterations $I_{max}^{non-impr}$, and the maximum number of consecutive non-improving moves by an operator $M_{max}^{non-impr}$ need to be determined. The maximum number of iterations is the stopping criterion of the heuristic algorithm, and, therefore, this value is determined upfront by manual parameter testing using various values for the other parameters. Once the number of iterations is fixed, the remaining parameters are tuned using the irace package of López-Ibáñez et al. (2016).

4.6.1 Stopping criterion

The stopping criterion for the RRT algorithm is the number of iterations. Intuitively, the more iterations executed, the better the solution quality. However, executing unnecessary iterations is time consuming. Especially for small-size instances, it is pointless to keep running the RRT heuristic once the optimal solution is found. Since the irace package does not evaluate parameter combinations on their computation time, manual parameter testing is used to determine the number of iterations. Then, this number of iterations is used in the irace package to tune the other parameters. The parameter values used for the manual experiments are shown in Table 4.2 and are chosen based on preliminary small experiments.

Manual experiments with different parameter combinations are executed for each problem size. The results of the parameter combinations are compared with the optimal solutions obtained by CPLEX or the best solution found by RRT heuristic when the optimal solution is not known. The minimum, average, and maximum gap are calculated for each combination. Two parameters have a direct impact on the computation time: the number of iterations I_{max} and the maximum number of consecutive non-improving moves $M_{max}^{non-impr}$. The number of iterations is the stopping criterion of the algorithm. The maximum number of consecutive non-improving moves $M_{max}^{non-impr}$ has an impact on the computation time as it influences the number of

Table 4.2: Manual parameter testing values

Instance size	Parameter	Tested values
10 orders	α	0.01; 0.05; 0.10; 0.15; 0.20; 0.25; 0.30; 0.50
	$I_{max}^{non-impr}$	5; 10; 15; 20; 25; 30; 50; 100; 200
	$M_{max}^{non-impr}$	0; 1; 2; 3; 4; 5; 6; 7; 8; 9; 10; 15
	I_{max}	100; 200; 300; 400; 500; 600; 700; 800; 900; 1,000; 2,000; 3,000; 4,000; 5,000; 6,000; 7,000; 8,000; 9,000; 10,000; 11,000; 12,000; 13,000; 14,000; 15,000; 20,000; 25,000; 30,000; 35,000; 50,000; 100,000; 125,000; 150,000; 200,000
15 orders	α	0.01; 0.05; 0.10; 0.15; 0.20; 0.25; 0.30; 0.50
	$I_{max}^{non-impr}$	5; 10; 15; 20; 25; 30; 35; 40; 50; 100; 125; 150; 175; 200; 225; 250; 300; 400; 1,000; 1,500; 2,000; 5,000
	$M_{max}^{non-impr}$	1; 2; 3; 4; 5; 10; 20
	I_{max}	500; 1,000; 2,000; 3,000; 4,000; 5,000; 6,000; 7,000; 8,000; 9,000; 10,000; 11,000; 12,000; 13,000; 14,000; 15,000; 16,000; 17,000; 18,000; 19,000; 20,000; 21,000; 22,000; 23,000; 24,000; 25,000; 30,000; 35,000; 40,000; 50,000
100 orders	α	0.01; 0.02; 0.03; 0.04; 0.05; 0.10; 0.15
	$I_{max}^{non-impr}$	5; 10; 15; 20; 25; 30
	$M_{max}^{non-impr}$	0; 1; 2; 3; 4; 5; 10; 15; 20; 25
	I_{max}	1,000; 2,000; 3,000; 4,000; 5,000; 6,000; 7,000; 8,000; 9,000; 10,000; 11,000; 12,000; 13,000; 14,000; 15,000; 16,000; 17,000; 18,000; 19,000; 20,000; 21,000; 22,000; 23,000; 24,000; 25,000; 30,000; 40,000; 50,000; 60,000; 70,000; 80,000; 90,000; 100,000; 125,000; 150,000; 175,000; 200,000; 250,000; 300,000

moves within a single iteration. The number of consecutive non-improving iterations $I_{max}^{non-impr}$ only influences after how many iterations without improvement the RRT heuristic restarts from the best solution. This parameter has no direct impact on the computation time. The results of the manual experiments are combined over the number of iterations I_{max}, the number of non-improving moves $M_{max}^{non-impr}$, and the deviation rate α. For each combination of these three parameters, the minimum, average, and maximum gap over all experiments with a different number of consecutive non-improving iterations $I_{max}^{non-impr}$ is shown. The results are sorted in an ascending order with respect to the average gap, the number of iterations, and the maximum number of consecutive non-improving moves. In Table 4.3, the 10 combinations with the lowest average gap and lowest number of iterations needed are presented for each problem size. Thus, based on these tables, the minimum number of iterations needed to obtain the best results can be determined.

For the instances with 10 customer orders, 25 instances are used with 20 runs per instance. As can be seen in the upper part of Table 4.3, the majority of the combinations, i.e., 7 out of 10, obtain the optimal solutions of the instances tested

Table 4.3: Top 10 parameter combinations with lowest number of iterations - small-size instances

Instance size	I_{max}	α	$M_{max}^{non-impr}$	avg. gap (%)	min. gap (%)	max. gap (%)
10 orders	600	0.15	15	0.00	0.00	0.00
	600	0.20	15	0.00	0.00	0.00
	600	0.30	15	0.00	0.00	0.00
	700	0.15	8	0.00	0.00	0.00
	700	0.15	10	0.00	0.00	0.00
	700	0.20	10	0.00	0.00	0.00
	700	0.25	10	0.00	0.00	0.00
	700	0.15	15	0.00	0.00	0.00
	700	0.20	15	0.00	0.00	0.00
	700	0.25	15	0.00	0.00	0.00
15 orders	6,000	0.15	20	0.00	0.00	0.00
	7,000	0.15	20	0.00	0.00	0.00
	8,000	0.15	20	0.00	0.00	0.00
	9,000	0.15	20	0.00	0.00	0.00
	10,000	0.15	20	0.00	0.00	0.00
	11,000	0.15	20	0.00	0.00	0.00
	12,000	0.15	20	0.00	0.00	0.00
	13,000	0.15	20	0.00	0.00	0.00
	14,000	0.15	20	0.00	0.00	0.00
	14,000	0.30	20	0.00	0.00	0.00

within 700 iterations, but using different values for the other parameters. Therefore, the number of iterations is set equal to 700 to tune the other parameters. Similar experiments are conducted with 17 instances with 15 customer orders. The lower part of Table 4.3 shows that 9 out of 10 combinations make use of the same deviation rate value and number of non-improving moves. Thus, with these specific values for those parameters conducting more iterations is pointless, since it leads to the same results. The first combination to obtain the optimal solutions requires 6,000 iterations. Therefore, to tune the remaining parameters, the number of iterations is set equal to 6,000.

For the large-size instances with 100 customer orders, the optimal solutions are not known. Based on the results of the manual parameter testing, the best solution for each of the 25 instances can be indicated. The parameter combination leading to the best solution found for each instance is shown in Table 4.4. As can be seen, the combination differs for each instance. The highest number of iterations needed to obtain the best solution is 250,000. Therefore, in order to obtain the value for the

Table 4.4: Best solution found for each instance using manual parameter tuning - 100 customer orders instances

Inst.	α	I_{max}	$I_{max}^{non-impr}$	$M_{max}^{non-impr}$	Z
1	0.01	100,000	20	20	1,494.21
2	0.01	7,000	15	15	1,392.39
3	0.02	16,000	25	15	1,457.99
4	0.01	175,000	20	25	1,435.03
5	0.01	200,000	15	5	1,471.11
6	0.01	9,000	25	10	1,410.47
7	0.01	50,000	15	15	1,393.13
8	0.01	200,000	25	10	1,389.90
9	0.01	175,000	10	25	1,444.70
10	0.01	21,000	20	25	1,449.43
11	0.02	250,000	25	25	1,449.24
12	0.03	200,000	15	25	1,451.47
13	0.03	100,000	20	15	1,462.52
14	0.03	125,000	10	25	1,454.05
15	0.02	150,000	25	15	1,450.76
16	0.02	200,000	15	25	1,467.92
17	0.03	125,000	25	15	1,481.69
18	0.01	250,000	10	20	1,509.70
19	0.01	250,000	20	25	1,406.05
20	0.01	200,000	25	20	1,444.36
21	0.01	9,000	30	25	1,461.20
22	0.01	11,000	15	10	1,377.66
23	0.01	11,000	25	15	1,414.46
24	0.03	125,000	15	20	1,449.32
25	0.04	250,000	15	20	1,379.37
	avg.	133,417	19	19	
	mode	200,000	25	25	
	max.	250,000	30	25	

deviation rate, the maximum number of consecutive non-improving iterations, and the maximum number of consecutive non-improving moves, the number of iterations is fixed at 250,000.

4.6.2 Parameter tuning with irace

In order to evaluate which parameter combination leads to the best results, the irace package, developed by López-Ibáñez et al. (2016), is used. The irace package is a software package implementing iterated racing procedures which are used for automatically configuring parameters of algorithms.

The iterated racing procedure consists of three steps. First, new parameter configurations are sampled according to a particular distribution. Second, the best configurations of the newly sampled ones are selected based on a racing procedure including a statistical test. Third, the sampling distribution is updated to bias the sampling towards the best configurations found so far. These steps are repeated.

The following input is needed for the irace procedure: instance set, parameter space, cost (or objective) function, and a tuning budget. The *instance set* refers to the instances which are available for tuning the parameters and on which different parameter combinations are tested. The *parameter space* indicates which parameters of an algorithm needs to be tuned. For each parameter different ranges can be specified. The range indicates the possible values of the parameter. The *cost function* refers to which variable needs to be optimised, e.g., total cost minimisation. The *tuning budget* specifies the number of evaluations the irace procedure will execute during the procedure. The number of iterations, or races, conducted depends on the number of parameters which needs to be tuned.

During each iteration, parameter configurations are tested on the instances available. After a number of steps within an iteration, parameter configurations with a statistically worse performance than at least another one are discarded based on the rank-based Friedman test. The race is continued with the configurations which survived the statistical analysis. From the second race on, the best, or *elite*, configurations of the previous race are combined with newly sampled configurations. The procedure ends when either a minimum number of surviving configurations, a maximum number of instances used, or a pre-defined budget is reached. For a detailed description of irace, the reader is referred to López-Ibáñez et al. (2016).

The following parameters of the RRT algorithm are tuned using the irace package: the deviation rate α, the maximum number of consecutive non-improving iterations $I_{max}^{non-impr}$, and the maximum number of consecutive non-improving moves of an operator $M_{max}^{non-impr}$. The deviation rate is a real number with two digits between zero and one. The other parameters are integer values. The number of iterations, which is the stopping criterion, is determined with manual experiments in Section 4.6.1, since irace do not differentiate parameter combinations on their computation time needed.

The irace package is executed for each problem size separately because the problem size can have an impact on the tuned values. When the irace package is used for all instances simultaneously, the result will be a parameter combination which would lead to good solutions on average. However, on each instance individually the results could be worse. The ranges used for the irace package to find the best parameter values are indicated in Table 4.5. The ranges are based on the results obtained by

Table 4.5: Parameter tuning ranges

Parameter	Type	Range		
		10 orders	15 orders	100 orders
α	real	(0, 0.20)	(0, 0.20)	(0.00, 0.05)
$I_{max}^{non-impr}$	integer	(0, 10)	(0, 25)	(5, 30)
$M_{max}^{non-impr}$	integer	(0, 20)	(5, 25)	(5, 35)

the manual parameter testing executed to obtain the number of iterations needed. The bounds of the ranges are included. The iterated racing configuration process is stopped after 5,000 runs and 2,000 runs for the small-size (10 and 15) and large-size (100) instances, respectively. The first 50 instances of each class are used. For each instance size, the irace package uses 25 instances for training and 25 instances for testing the obtained parameter configurations.

The second column of Table 4.6 indicates for each problem size the time needed for the irace package to identify the elite configurations. These combinations are the best parameter combinations irace could find during the racing procedure and are presented in columns 3 to 5. For each problem size, the three best parameter settings are shown. Irace is capable to identify elite configurations within 3 minutes for the instances with 10 customer orders and within approximately 15 minutes for the instances with 15 customer orders. For the large-size instances, approximately 50 hours are needed to identify the elite configurations as shown in Table 4.6. More detailed results on the irace procedure can be found in Appendix B. For each instance size, the best elite configuration is used as parameter combination in the computational experiments in the following sections. It can be observed that when the instance size increases, the best value for the deviation rate decreases, while the value for the other parameters increases.

Table 4.6: Elite configurations obtained with irace

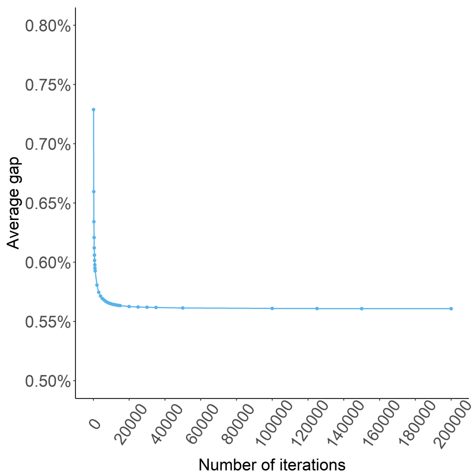
Instance size	Time needed (s)	Elite configurations		
		α	$I_{max}^{non-impr}$	$M_{max}^{non-impr}$
10 orders	157	0.15	5	8
		0.15	6	10
		0.18	7	7
15 orders	922	0.15	10	21
		0.10	17	16
		0.10	5	20
100 orders	177,936	0.01	26	32
		0.01	28	30
		0.01	29	31

4.6.3 Sensitivity analysis of parameters

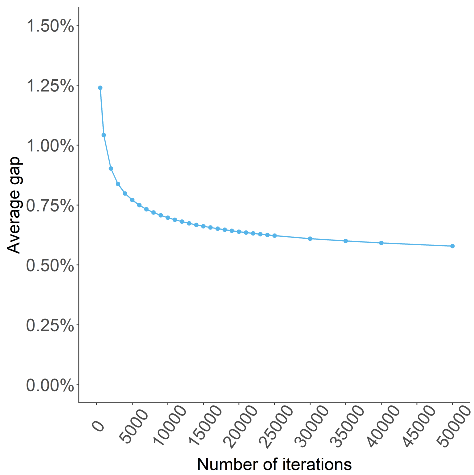
In order to investigate the impact of the different design choices in the RRT heuristic, a sensitivity analysis is conducted. The results of this analysis are based on the manual parameter testing used for obtaining the value of the stopping criterion, i.e., the number of iterations, in Section 4.6.1. The impact of the following parameters are evaluated: number of iterations I_{max}, deviation rate α, the number of consecutive non-improving iterations $I_{max}^{non-impr}$, and the number of consecutive non-improving moves $M_{max}^{non-impr}$. All combinations of the parameter values listed in Table 4.2 for each problem size are used in the experiments. The effect of each parameter is shown in Figures 4.5 to 4.8.

In each figure, the impact of a single parameter is represented for the 10, 15, and 100 customer orders instances. The average gap for a specific parameter value over all instances tested and all values tested for the other parameters is indicated on the y-axis in the graphs. The scale of the y-axis is different for each graph since several parameter combinations can lead to bad results. Especially for the large-size instances bad solutions can be generated since there is a higher probability that the wrong order to conduct a move on is randomly selected. For the 10 customer orders instances, 25 instances are used, while 17 instances are used for the 15 customer orders instances. For these small-size instances, the gap between the optimal solution and the solution found by the RRT algorithm is calculated. For the large-size instances with 100 customer orders, 25 instances are used. The gap between the solution found by the RRT algorithm with a specific parameter combination and the best solution found over all parameter combinations is calculated. The average of these gaps is calculated over all parameter combinations for each value of the parameter of which the effect is studied. Thus, in the graphs, the average gap for each parameter value over all instances and other parameters is shown. Twenty runs are conducted for each instance.

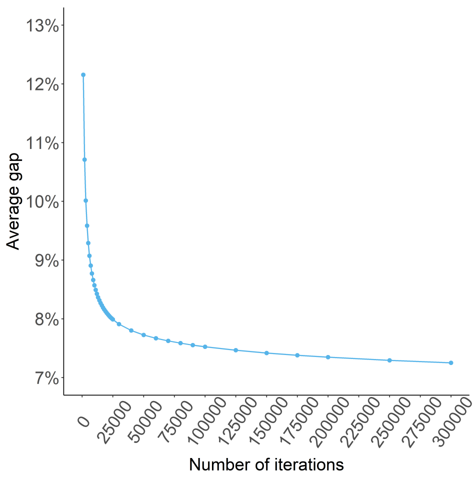
Figure 4.5 shows the impact of the number of iterations conducted on the solutions obtained. In Section 4.6.1, it was supposed that more iterations would lead to better solutions. This assumption is proven by Figure 4.5. The higher the number of iterations conducted, the lower the average optimality gap. The effect levels out once the optimal solution is found for the small-size instances. For the large-size instances, the same pattern is observed. The marginal effect on the solution quality of conducting more iterations decreases. It has to be noted that these graphs show average gaps over all parameter combinations tested. Consequently, the number of iterations at which the graph levels out is greater than the best number of iterations



(a) 10 customer orders

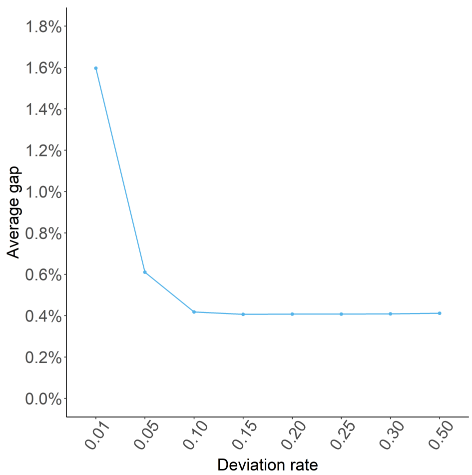


(b) 15 customer orders

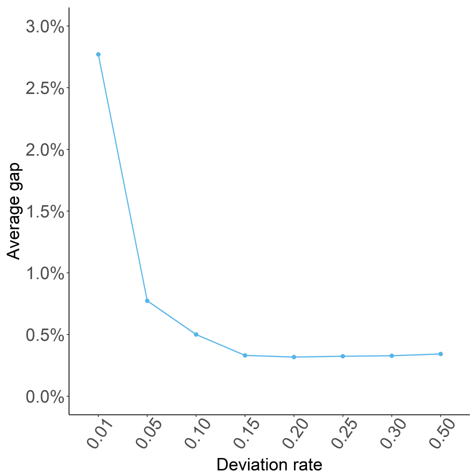


(c) 100 customer orders

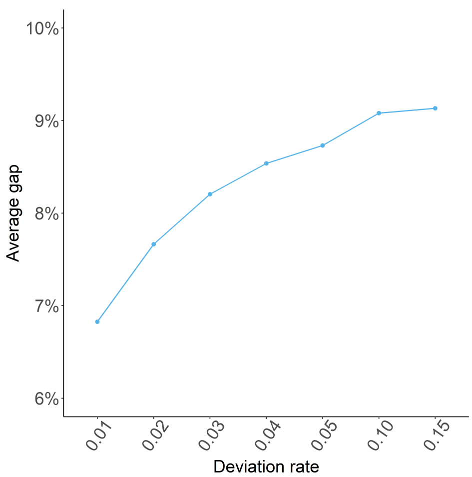
Figure 4.5: Impact of number of iterations on solution quality



(a) 10 customer orders

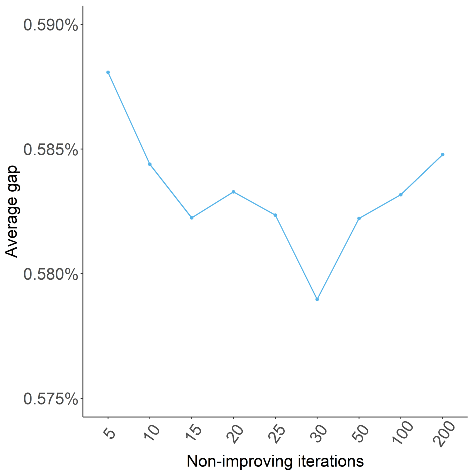


(b) 15 customer orders

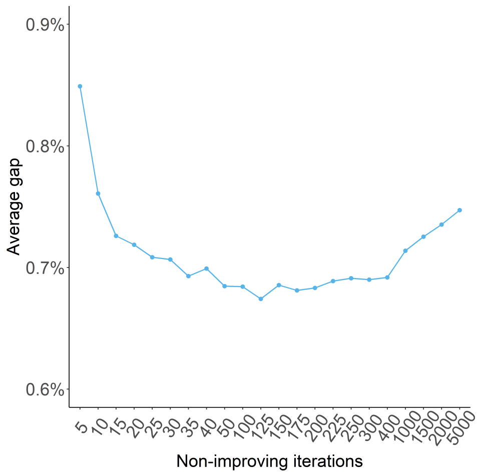


(c) 100 customer orders

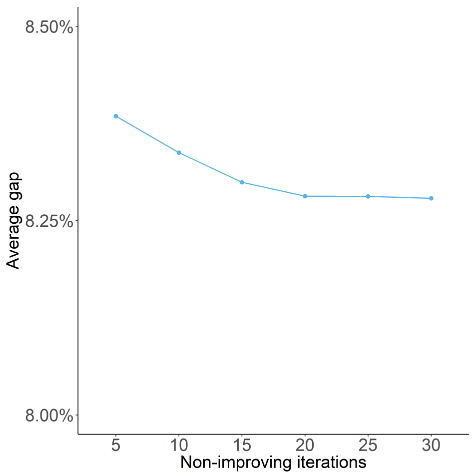
Figure 4.6: Impact of deviation rate on solution quality



(a) 10 customer orders

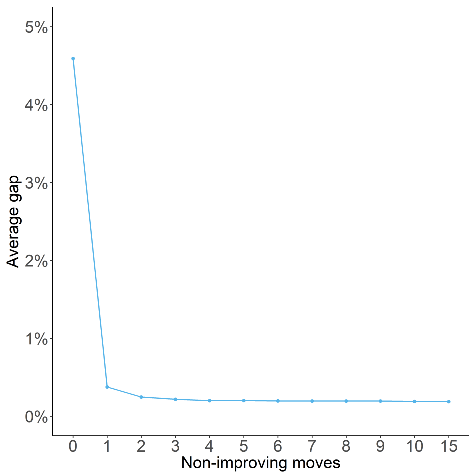


(b) 15 customer orders

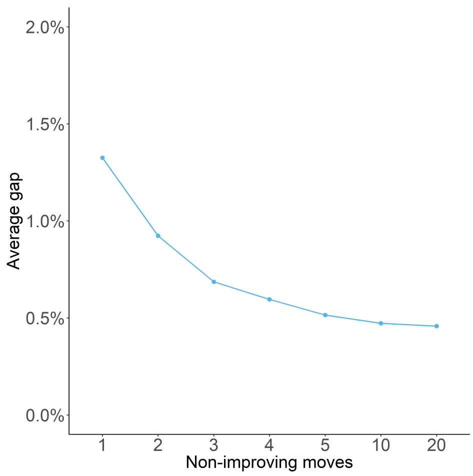


(c) 100 customer orders

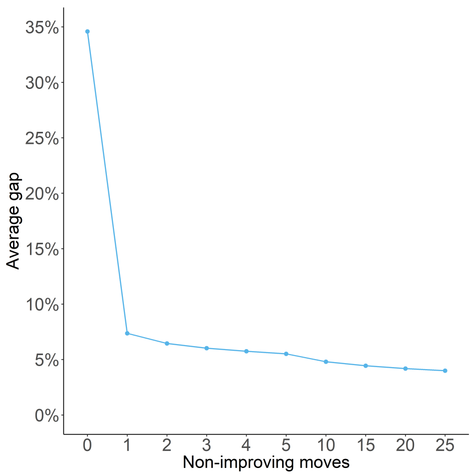
Figure 4.7: Impact of number of consecutive non-improving iterations on solution quality



(a) 10 customer orders



(b) 15 customer orders



(c) 100 customer orders

Figure 4.8: Impact of number of consecutive non-improving moves on solution quality

indicated as stopping criterion in Section 4.6.1. Nevertheless, by using these best number of iterations in combination with the best values of the other parameters, the RRT heuristic is capable of obtaining good solutions.

The effect of different deviation rate values on the solution is indicated in Figure 4.6. A different pattern is observed between the small-size instances and the large-size instances. Small deviation rates lead to higher average gap values for the small-size instances. For both the instances with 10 and 15 customer orders, the deviation rate values greater than 15% leads to similar results. For the instances with 100 customer orders an opposite pattern occurs. A small deviation rate results in a lower gap on average. An explanation may be that for small-size instances only a few number of options for conducting a (good) move are possible. Sometimes a move resulting in a large worsening needs to be allowed before being able to obtain better solutions generated by the subsequent moves. In the experiments with large-size instances, more options are possible to execute a (good) move, and thus allowing worse moves can be more restricted.

A more fluctuating pattern can be observed for the small-size instances in Figure 4.7, which presents the impact of the number of consecutive non-improving iterations on the solution quality. Both a small and large value for this parameter leads to worse solutions in comparison with more intermediate values. For the large-size instances, allowing a higher number of consecutive non-improving iterations results in a lower average gap between the best solution found and the solution found for a specific parameter combination.

Finally, the impact of the selected number of consecutive non-improving moves is shown in Figure 4.8. The parameter value is inversely proportional to the solution quality. A higher number of non-improving moves result in a lower gap on average. The effect diminishes with increasing parameter values for both small-size instances and large-size instances.

In short, a higher number of iterations lead to better solutions. A higher deviation rate value is required for small-size problems in comparison with large-size problems. The number of consecutive non-improving iterations needs to be a more intermediate value, while a large number of consecutive non-improving moves lead to better solutions. The sensitivity analysis confirms the results obtained by the irace package as can be seen by the sampling frequency plots in Appendix B.

4.7 Validation of heuristic algorithm

In this section, computational experiments are described to evaluate the performance of the proposed record-to-record travel algorithm. For the experiments conducted in this section, 50 different instances for each problem size are generated compared to these used for the parameter tuning. The experiments[2] are executed on a 12-core Xeon E5-2680v3 CPUs with 128 GB RAM. The RRT algorithm is implemented in C++. Optimal solutions are found by the optimisation software ILOG CPLEX 12.7.1. Detailed results of the experiments can be found in Appendix C.

4.7.1 Small-size instances: Results

To evaluate the performance of the developed RRT heuristic, experiments on small-size instances are conducted. The solutions obtained by the heuristic algorithm are compared with the optimal solutions obtained by CPLEX. Two different instance sizes are considered: instances with 10 customer orders and with 15 customer orders. For each instance size, the last 50 instances of the 100 instances generated are used for the experiments. The optimal solutions are found for all instances with 10 customer orders and for 43 instances with 15 customer order. For seven instances with 15 orders, the optimal solution could not be found within 500 hours. In the experiments, two regular order pickers are available and one additional temporary order picker can be hired. At most three vans can be used for the delivery operations.

Table 4.7: Summary of the results of experiments with small-size instances

Instance size	avg. gap (%)	avg. time CPLEX (s)	avg. time RRT 1 run (s)	avg. time RRT 20 runs (s)	avg. # pick.	avg. # veh.
10 orders	0.0000	180.36	0.0072	0.1530	1.18	1.58
15 orders	0.0000	227,089.45	0.2283	4.5758	1.98	1.36

Table 4.7 presents a summary of the results of the experiments conducted with the small-size instances. Twenty replications are conducted for each instance. For both instance sizes, the RRT algorithm is capable of obtaining the optimal solution for each of these instances as indicated by the average gap of 0.00 %. For the seven instances with 15 orders for which the optimal solution is not known, the RRT heuristic finds in each run the same objective value. To obtain the optimal solution with CPLEX, an average computation time of approximately 3 minutes is required for the instances

[2] The computational resources and services used in this work were provided by the VSC (Flemish Supercomputer Center), funded by the Research Foundation - Flanders (FWO) and the Flemish Government - department EWI.

with 10 customer orders. For the instances with 15 customer orders, the optimal solution is obtained by CPLEX with an average computation time of approximately 63 hours. Increasing the problem size with five customers already has a large impact on the computation time. For both instance sizes, the RRT solution method finds the same solution in less than a second. This indicates that the algorithm is an effective and efficient tool for solving the I-OP-VRP, at least for small-size instances.

4.7.2 Large-size instances: Results

In order to test whether the RRT heuristic is capable of solving larger size instances, the last 50 instances with 100 customer orders of the 100 instances generated are used in this section. These instances cannot be solved to optimality with CPLEX in a reasonable amount of time. The results presented in Table 4.8 are found by using the best parameter configuration obtained by the irace package in Section 4.6.2. To indicate the impact of the RRT heuristic on the solution, the percentage difference between the initial solution and the best heuristic solution found after 20 runs is provided. The best objective value found is on average 26.83% better than the initial solution. Thus, the heuristic algorithm developed in this study is clearly capable of drastically improving the initial solution. The gap between the best solution found within 20 runs and the solution obtained in any other run is on average 1.37%. Executing the algorithm for a single run takes less than two minutes on average. On average, approximately nine pickers are needed and four vehicles are used for the picking and delivery operations.

Table 4.8: Summary of the results of experiments with large-size instances

Instance size	avg. gap (%)	avg. time RRT 1 run (s)	avg. time RRT 20 runs (s)	avg. # pick.	avg. # veh.	$\Delta Z[S_0](\%)$
100 orders	1.37	101.20	2,024.02	9.13	4.11	-26.83

To be able to evaluate the robustness of the RRT algorithm, 20 runs for each instance are conducted. In literature, 5 runs are executed in general. In the RRT heuristic, however, a high amount of randomness is included since both a vehicle or order picker have to be randomly selected and an order needs to be randomly selected within a vehicle route or picking list. To compensate for this randomness, more runs for each instance are executed. A comparison is made between the results obtained in 5 runs and in 20 runs. In Table 4.9, the average and maximum gap are indicated for each number of runs executed. The gap between the best solution found within the number of runs and the solution obtained in a specific run is calculated.

Table 4.9: Comparison of executing 5 runs and 20 runs

	avg. gap (%)	max. gap (%)
5 runs	0.85	3.15
20 runs	1.37	4.30

In the experiments with the instances with 10 and 15 customer orders in the previous section, the RRT heuristic always obtains the optimal solution when this is known. Hence, executing 5 or 20 runs has no impact on the overall quality of the solutions for the small-size instances. For the experiments with 100 customer orders, the results of the first five runs of each instance are compared with the results of all 20 runs. When only five runs are executed, the average gap is 0.85% and the maximum gap is 3.15%. When executing 20 runs, the average gap is 1.37% with a maximum gap of 4.30%. Based on these figures, executing only 5 runs seems to lead to better results. However, for 40 of the 50 instances, a lower objective function value is found in the last 15 of the 20 runs. Thus, executing 20 runs instead of 5 runs can lead to finding better solutions, although the average and maximum gap are higher.

4.7.3 Contribution of local search operators

In the RRT algorithm, five local search operators are implemented to improve the quality of the initial solution. In the VRP-part of the problem, the following operators are used: $exchange_{VRP}$, $relocate_{VRP}$, and $2\text{-}Opt_{VRP}$. Two operators are applied in the OPP-part of the problem: $exchange_{OPP}$ and $relocate_{OPP}$. In Section 4.4.2, the moves allowed to be conducted by the operators are described. This section analyses the contribution of each operator to obtaining the solutions. The same instances as in the previous sections are used in the experiments in this section, i.e., the last 50 instances generated for each problem size. The best parameter combination for each problem size obtained by the irace package in Section 4.6.2 is applied. In the experiments described in the previous sections, all operators are included in the solution algorithm. Seven variants of the RRT algorithm are analysed to determine the contribution of the operators. In five variants, a single operator is excluded from the algorithm. In variant 6, the two picking operators are excluded, while in variant 7 all VRP operators are left out. Thus, the following variants are studied:

0. All operators included
1. $exchange_{VRP}$ excluded
2. $relocate_{VRP}$ excluded
3. $2\text{-}Opt_{VRP}$ excluded

4. *exchange*$_{OPP}$ excluded
5. *relocate*$_{OPP}$ excluded
6. All OPP operators excluded
7. All VRP operators excluded

In Table 4.10, the results for each variant are presented. The average, minimum, and maximum gap are shown for each variant. For the small-size instances, the gap between the heuristic solution and the optimal solution is presented. For the instances with 100 customer orders and the seven instances with 15 customer orders for which the optimal solution is not known, the gap between the best solution found by the original algorithm and the solution of a run found by the variant is calculated. Since in the experiments with large-size instances the best solution is not found in each run, an average gap for the original variant is computed as well. Row '# best solution found' shows the number of times the best solution is found over all experiments. The total number of experiments is equal to 1,000, i.e., 20 runs for 50 instances. Row '# inst. best found (once)' indicates the number of instances for which in at least one run the best solution is obtained, while row '# inst. best found (all)' indicates the number of instances for which the best solution is found in all 20 runs. For the small-size instances, the best solution is equal to the optimal solution, except for the seven instances with 15 customer orders for which the optimal solution could not be obtained within 500 hours. For the large-size instances, the best solution found indicates the lowest objective function value found by the RRT heuristic. When better solutions are obtained than in the basis scenario, these are counted in '# best solution found'.

The upper part of Table 4.10 presents the contribution of each operator for the experiments with the 10 customer orders instances. Excluding the *relocate*$_{VRP}$ from the RRT heuristic leads to the highest average and maximum gap when a single operator is removed. The *exchange*$_{VRP}$ and *2-Opt*$_{VRP}$ operator have no or a relatively small impact on the performance of the RRT heuristic. Removing a single OPP operator or both the *relocate*$_{OPP}$ operator and the *exchange*$_{OPP}$ operator has no impact on the solution quality. The exclusion of all VRP operators simultaneously has a major impact on the performance of the RRT heuristic.

In the second part of Table 4.10, the contribution of the operators is indicated for the instances with 15 customer orders. The *relocate*$_{VRP}$ operator has overall the largest impact on the quality of the solutions obtained when a single operator is excluded. Only for 15 of the 50 instances the optimal solution is found at least once. In contrast to the experiments with 10 customer orders instances, excluding the *relocate*$_{OPP}$ has a small impact on the solution quality. Removing the other operators

Table 4.10: Contribution of local search operators

Instance size	Variant 0	1	2	3	4	5	6	7
10 orders								
Gap (%)								
- average	0.0000	0.0000	2.3191	0.0089	0.0000	0.0000	0.0000	6.1081
- minimum	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
- maximum	0.0000	0.0000	10.0105	2.3349	0.0000	0.0000	0.0000	18.9151
# best solution found	1,000	1,000	360	990	1,000	1,000	1,000	120
# inst. best found (once)	50	50	18	50	50	50	50	6
# inst. best found (all)	50	50	18	46	50	50	50	6
15 orders								
Gap (%)								
- average	0.0000	0.0000	2.4394	0.0000	0.0000	0.0536	0.0755	9.2229
- minimum	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
- maximum	0.0000	0.0000	10.8139	0.0000	0.0000	1.5291	1.6551	25.4453
# best solution found	1,000	1,000	297	1,000	1,000	880	885	20
# inst. best found (once)	50	50	15	50	50	50	50	1
# inst. best found (all)	50	50	13	50	50	35	34	1
100 orders								
Gap (%)								
- average	1.3650	1.4475	8.1335	1.3910	1.4121	2.6762	3.0470	36.6606
- minimum	0.0000	-0.9959	3.6111	-0.7877	-1.2328	-0.3888	0.1789	25.7560
- maximum	4.3026	5.5862	13.6749	4.7517	4.2977	6.6220	7.0052	49.6177
# best solution found	50	35	0	38	34	3	0	0
# inst. best found (once)	50	19	0	22	22	2	0	0
# inst. best found (all)	0	0	0	0	0	0	0	0

individually has no impact on the solution quality for these instances. Executing the RRT algorithm without any VRP operator leads to a worse performance. The optimal solution is obtained for a single instance.

The lower part of Table 4.10 shows the contribution of the operators for the large-size instances. Similar to the experiments with the small-size instances, the *relocate* operators of both the OPP and the VRP have the largest individual impact. In contrast to the small-size instances, the *exchange* operators do have an impact on the solution quality. The *2-Opt*$_{VRP}$ operator has the smallest individual impact. When all VRP operators are removed, the solution quality decreases with approximately 36%. The solutions obtained by this variant differ only slightly from the initial solutions, with only an average improvement of 0.17%.

A statistical analysis is conducted using a Wilcoxon matched-pairs signed-rank test to examine whether the differences shown in Table 4.10 are statistically significant.

This a non-parametric statistical test for analysing the difference between related pairs equivalent to the paired-samples t-test. The advantage of using a non-parametric test is that less assumptions have to be tested, e.g., no normal distribution is needed. The null hypothesis of the test is that the median of the difference between the matched pairs equals zero (Field, 2013; de Vocht, 2017). In this analysis, it is investigated whether the difference between the average gap over the 20 runs for each instance between the best solution found in the basis variant of the RRT heuristic and the solution found by the variant considered is statistically different. When using the Wilcoxon matched-pairs signed-rank test, the following assumptions need to be met:

1. The data are measured at a continuous level, i.e., interval or ratio data.
2. Each pair is randomly selected.
3. The underlying distribution of the differences is symmetric about the median (Sheskin, 2000).

The first assumption is met since the difference of the average gap, measured in percentage, for each instance between two variants is evaluated. The instances are randomly generated and consequently the second assumption is satisfied. For the third assumption, the skewness of the distribution needs to be investigated. The null hypothesis for this test is that the skewness is zero, resulting in a symmetric distribution. The absolute value of the skewness divided by the standard error of the skewness needs to be less than 1.96 to consider the distribution as symmetric at a 5% significance level (de Vocht, 2017). When the assumption of a symmetric distribution is violated, a sign test can be executed instead of a Wilcoxon matched-pairs signed-rank test. The sign test is a non-parametric method in which the assumption of a symmetric distribution does not need to be met (Russo, 2003; Weiers, 2011).

In Table 4.11, the skewness values are presented for each difference between basis variant 0 and any other variant for each problem size. For the variants in which the solutions found by the RRT algorithm do no differ, no skewness value is indicated (-). The skewness is zero. In fact, for these variants, no statistical analysis has to be conducted to test whether the solutions are statistically different, since there are no differences observed.

As can be seen in Table 4.11, the differences between variant 0 and all other variants for instances with 10 customer orders do not have a symmetric distribution. For each comparison between variants, the null hypothesis of a skewness equal to zero is rejected at a 5% significance level, since the absolute value of skewness divided by its standard error is greater than 1.96. Thus, for the problem size with 10 customer orders, the Wilcoxon matched-pairs signed-rank test cannot be used to evaluate the

Table 4.11: Skewness values

Instance size	Variants compared						
	0-1	0-2	0-3	0-4	0-5	0-6	0-7
10 orders							
$\lvert Skewness/std.error \rvert$	-	2.4331*	16.7257*	-	-	-	2.2391*
15 orders							
$\lvert Skewness/std.error \rvert$	-	1.5837	-	-	8.7367*	9.0698*	1.1164
100 orders							
$\lvert Skewness/std.error \rvert$	0.8880	0.7378	0.2613	0.6282	0.3492	1.4696	0.4892

*statistically different at a 5% significance level

statistical significance of the differences between variants. A sign test is executed for these variants.

For the instances with 15 customer orders, only the differences between variant 0 and variant 2 and between variant 0 and variant 7 have a symmetric distribution. For these differences, the null hypothesis cannot be rejected at a 5% significance level. For the other comparisons between variants, the skewness is statistically different from zero. Consequently, only the difference between variant 0 and variant 2 and between variant 0 and variant 7 can be statistically tested using the Wilcoxon matched-pairs signed-rank test. The other variants for which differences in the results of the RRT heuristic are observed, are tested using a sign test.

For the large-size instances with 100 customer orders, the Wilcoxon matched-pairs signed-rank test can be used to evaluate the difference between variants. The null hypothesis stating that the skewness is equal to zero cannot be rejected at a 5% significance level since all test values are less than 1.96.

The null hypothesis of the Wilcoxon matched-pairs signed-rank test and the sign test states that the median of the difference between the two variants compared is equal to zero. The null hypothesis can be rejected when the significance value is less than 0.05. Table 4.12 presents the results of the Wilcoxon matched-pairs signed-rank test for the comparisons of variants for which the distribution is indicated as symmetric and the results of the sign test for the other comparisons. Column 1 indicates the problem size. In column 2, the variants which are compared are shown. Column 3 indicates whether either the Wilcoxon matched-pairs signed-test (W) or the sign test (S) is used. In column 4, the significance value of the test is shown. In column 5, it is stated whether the null hypothesis can be rejected or not. The variants in which no differences are observed are excluded from Table 4.12.

The results for the instances with 10 customer orders are shown in the upper part of Table 4.12. The null hypothesis of the sign test can be rejected for variant 2 and

Table 4.12: Statistical analysis: results for contribution of operators

Instance size	Variants compared	Test	Significance	Decision
10 orders	0-2	W	0.000	Reject null hypothesis
	0-3	W	0.125	Retain null hypothesis
	0-7	W	0.000	Reject null hypothesis
15 orders	0-2	W	0.000	Reject null hypothesis
	0-5	S	1.000	Retain null hypothesis
	0-6	S	0.000	Reject null hypothesis
	0-7	W	0.000	Reject null hypothesis
100 orders	0-1	W	0.018	Reject null hypothesis
	0-2	W	0.000	Reject null hypothesis
	0-3	W	0.534	Retain null hypothesis
	0-4	W	0.104	Retain null hypothesis
	0-5	W	0.000	Reject null hypothesis
	0-6	W	0.000	Reject null hypothesis
	0-7	W	0.000	Reject null hypothesis

W = Wilcoxon mathed-pairs signed-test S = Sign test

variant 7 at a 5% significance level. Excluding the $relocate_{VRP}$ operator individually or all VRP operators lead to significant different results. All other operators have no significant impact on the solution quality. For the comparisons for instances with 15 customer orders, the null hypothesis of the Wilcoxon matched-pairs signed-rank test or the sign test can be rejected for variants 2, 6, and 7. Thus, excluding the $relocate_{VRP}$ operator individually, all OPP operators or all VRP operators lead to significantly different solutions compared to the variant in which all operators included.

For the instances with 100 customer orders, for five comparisons the null hypothesis can be rejected at a 5% significance level. For two comparisons, the null hypothesis cannot be rejected, i.e., difference between variant 0 and 3 and between variant 0 and 4. When the $exchange_{VRP}$, $relocate_{VRP}$, or the $relocate_{OPP}$ operator is individually excluded from the RRT heuristic, the results significantly differ. Additionally, excluding either all OPP operators or all VRP operators leads to significantly different solutions.

To conclude, excluding the $relocate_{VRP}$ operator has a statistically significant impact on the solution quality independent of the instance size. For large-size instances, additionally, the $exchange_{VRP}$and the $relocate_{OPP}$ influence the solutions obtained by the RRT heuristic. Excluding all VRP operators leads to significantly different solutions in all problem sizes, while excluding all OPP operators only has a significant impact on the results of instances with 15 and 100 customer orders.

Some critical notes on the results have to be made. First, although operators are labelled as VRP operators or OPP operators, in case of OPP-VRP violations also relocate moves are executed in the other subproblem than to which the label of the operator refers. Thus, the large impact of the VRP operators can be a combined effect of the VRP operators and changes made in the order picking subproblem to obtain an overall feasible solution. Second, while the VRP operators are always executed, the OPP operators are only used when temporary order pickers hired, which is only the case in the minority of the instances.

Third, it has to be remarked that when the *2-Opt*$_{VRP}$ operator is excluded not all possible exchange and relocate moves within a route are tested. The *exchange*$_{VRP}$ operator is not allowed to swap adjacent orders, and the *relocate*$_{VRP}$ operator cannot relocate an order to the position immediately before or after its current position. This effect can be an explanation why the impact *exchange*$_{VRP}$ on the solution quality is negligible with the small-size instances. Although the *2-Opt*$_{VRP}$ operator can execute more moves within a route, the impact of excluding this operator for the large-size instances is smaller than excluding the *exchange*$_{VRP}$ operator and *relocate*$_{VRP}$ operator.

Fourth, the experiments are conducted using the best parameter configuration indicated by the irace package in Section 4.6.2. However, this configuration is the best one when all operators are included. In fact, when one or more local search operators are excluded from the algorithm, the irace package should be executed to find the best configuration for the algorithm with the remaining operators.

Finally, only the effect of removing a single operator at once is examined. However, it is possible that there are interaction effects between operators. These effects are ignored in the analysis in this section. To thoroughly investigate the correlation between (combinations of) operators and the performance of the heuristic algorithm, a statistical evaluation method, such as a multi-level regression, is needed. By conducting such an analysis, the impact of operators and problem characteristics on the performance of the heuristic solution method can be investigated (Corstjens et al., 2018; Corstjens, 2018).

4.7.4 Sequence of local search operators

The five local search operators implemented in the RRT algorithm are executed in a random order in each iteration, see line 8 in Algorithm 2. Additional experiments are conducted to investigate whether the sequence of the operators influences the performance of the solution algorithm. The experiments are executed using the best parameter combination obtained by the irace package in Section 4.6.2. The last

50 instances generated for each problem size are used. With five operators, the total number of possible operator sequences is 120. A sample of six different fixed sequences are tested. In sequence 1a - 1c, the VRP operators are executed first, followed by the two OPP operators. In sequence 1a and 1b, first the two VRP operators which can conduct inter- and intra-route moves, i.e., $exchange_{VRP}$ and $relocate_{VRP}$, are conducted. Then, the $2\text{-}Opt_{VRP}$ operator which can only execute intra-route moves. In sequence 1c, first the intra-route operator is conducted and then the inter-route operators. In sequence 2a and 2b, first, the OPP operators are used and thereafter the VRP operators. In sequence 3, the VRP and OPP operators are executed in an alternating way. The following sequences are tested:

- 0 Random sequence of operators
- 1a $exchange_{VRP}$ - $relocate_{VRP}$ - $2\text{-}Opt_{VRP}$ - $exchange_{OPP}$ - $relocate_{OPP}$
- 1b $relocate_{VRP}$ - $exchange_{VRP}$ - $2\text{-}Opt_{VRP}$ - $exchange_{OPP}$ - $relocate_{OPP}$
- 1c $2\text{-}Opt_{VRP}$ - $exchange_{VRP}$ - $relocate_{VRP}$ - $exchange_{OPP}$ - $relocate_{OPP}$
- 2a $exchange_{OPP}$ - $relocate_{OPP}$ - $exchange_{VRP}$ - $relocate_{VRP}$ - $2\text{-}Opt_{VRP}$
- 2b $relocate_{OPP}$ - $exchange_{OPP}$ - $exchange_{VRP}$ - $relocate_{VRP}$ - $2\text{-}Opt_{VRP}$
- 3 $exchange_{VRP}$ - $exchange_{OPP}$ - $relocate_{VRP}$ - $relocate_{OPP}$ - $2\text{-}Opt_{VRP}$

Table 4.13 presents the results of the experiments for each sequence tested. The rows have the same meaning as these in Table 4.10. The additional rows with the 'best iteration found' present the average, median, minimum, and maximum iteration number in which the best solution is found, respectively. The upper part of Table 4.13 presents the results for the 10 customer orders instances. Both the random sequence and all fixed sequences are capable of obtaining the optimal solution in each run for every instance within 700 iterations. Furthermore, based on the iteration number in which the best solution is found, the random and fixed operator sequences have a relative similar performance. Thus, no evidence is found that a specific sequence outperforms other sequences.

The same conclusion can be made for the instances with 15 customer orders. A single fixed sequence, i.e., sequence 2b, does not obtain the optimal solution in a single run for an instance. Moreover, the average, median, and maximum best iteration number do not indicate a specific sequence as dominant. Thus, from this point of view, both a random and fixed operator sequence leads to a good performance of the RRT heuristic.

For the instances with 100 customer orders, the gaps indicated in the lower part of Table 4.13 represent the gap between the best solution found in the basis scenario and the solutions obtained in the other scenarios. All variants with a fixed sequence

Table 4.13: Impact of sequence of local search operators

Instance size	Sequence 0	1a	1b	1c	2a	2b	3
10 orders							
Gap (%)							
- average	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0007
- minimum	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
- maximum	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
# best solution found	1,000	1,000	1,000	1,0000	1,000	1,0000	1,000
# inst. best found (once)	50	50	50	50	50	50	50
# inst. best found (all)	50	50	50	50	50	50	50
Best iteration found							
- average	27	26	27	27	26	26	26
- median	13	12	13	12	12	12	12
- minimum	0	0	0	0	0	0	0
- maximum	411	438	494	499	438	438	438
15 orders							
Gap (%)							
- average	0.0000	0.0000	0.0000	0.0000	0.0000	0.0003	0.0000
- minimum	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
- maximum	0.0000	0.0000	0.0000	0.0000	0.0000	0.3426	0.0000
# best solution found	1,000	1,000	1,000	1,000	1,000	999	1,000
# inst. best found (once)	50	50	50	50	50	50	50
# inst. best found (all)	50	50	50	50	50	49	50
Best iteration found							
- average	150	168	171	150	170	168	175
- median	64	63	76	52	68	68	66
- minimum	1	1	1	1	1	1	1
- maximum	4,839	5,418	3,116	3,538	5,418	5,418	5,418
100 orders							
Gap (%)							
- average	1.3650	1.3071	1.2833	1.4713	1.2913	1.2901	1.2843
- minimum	0.0000	-1.0451	-0.9518	-0.7333	-1.0417	-1.2328	-1.0515
- maximum	4.3026	4.2841	4.9021	4.5838	4.4647	4.9095	4.4917
# best solution found	50	55	53	33	69	69	63
# inst. found (once)	50	25	27	20	32	29	30
# inst. best found (all)	0	0	0	0	0	0	0
Best iteration found							
- average	78,880	105,358	103,138	99,695	109,610	103,980	106,988
- median	54,089	89,156	86,670	80,559	96,946	93,407	91,508
- minimum	2,903	5,530	4,898	1,710	6,360	4,796	7,223
- maximum	249,986	249,981	249,722	249,955	249,683	249,586	249,479

find a better solution compared with the best solution in the original algorithm as indicated by the negative minimum gap. All variants, except 1c, have a slightly lower average gap. At the same time, all variants, except 1a, have a higher maximum gap. Although the RRT heuristic is executed for the same number of iterations for each sequence, the variants with a fixed sequence need on average more iterations to obtain the best solution, as can be seen in the bottom rows of Table 4.13.

A statistical analysis similar to this conducted for examining the contribution of the operators is executed for the large-size instances with 100 customers. For the small-size instances, no analysis is conducted since no differences in the results of the RRT heuristic are observed in Table 4.13. A Wilcoxon matched-pairs signed-rank test is used for the analysis for the large-size instances. The first and second assumption mentioned before are met for the same reasons as in Section 4.7.3, i.e., continuous data and randomly selected independent pairs. The third assumption stating that a symmetric distribution is required is tested based on the skewness values. For each variant, the difference between the average gap obtained with the basis variant and the average gap obtained with the variant considered is calculated for each of the 50 instances. It is tested whether the distribution of these differences is symmetric. Table 4.14 presents the absolute value of the skewness divided by the standard error of the skewness for each comparison of variants. All values are less than 1.96, and, thus the null hypothesis stating that the distribution is symmetric cannot be rejected on a 5% significance level.

Table 4.14: Skewness values

Instance size	Variants compared					
	0-1a	0-1b	0-1c	0-2a	0-2b	0-3
100 orders						
$\lvert Skewness/std.error \rvert$	0.904	1.3201	0.5120	1.3358	0.7332	1.7955

*statistically different at a 5% significance level

The three assumptions of the Wilcoxon matched-pairs signed-rank test are met. The null hypothesis of this non-parametric test states that the median of the difference between the two variants is equal to zero. In Table 4.15, the results of the Wilcoxon matched-pairs signed-rang test are indicated. The null hypothesis cannot be rejected at a 5% significance level for three variants, i.e., 1a, 2a, and 2b. For the other three variants, the null hypothesis is rejected. Based on these results, a fixed sequence in which first the VRP operators are executed or in which VRP and OPP operators are executed in alternating way leads to better solutions.

Table 4.15: Wilcoxon matched-pairs signed-rank test: results for sequence of operators

Instance size	Variants compared	Significance	Decision
100 orders	0-1a	0.066	Retain null hypothesis
	0-1b	0.021	Reject null hypothesis
	0-1c	0.004	Reject null hypothesis
	0-2a	0.092	Retain null hypothesis
	0-2b	0.098	Retain null hypothesis
	0-3	0.013	Reject null hypothesis

To conclude, both for the small-size and large-size instances, random and fixed operator sequences are tested. Based on the results of the experiments, it is hard to conclude whether a fixed sequence leads to better solutions in all cases compared to a random sequence. No sequence variant outperforms the random operator sequence for each instance size. In the experiments with instances with 10 and 15 customer orders, no difference can be observed when executing the operators in either a random sequence or in a fixed sequence. For the large-size instances with 100 customer orders, a fixed operator sequence leads to a better performance of the heuristic algorithm based on the average gap. Only for three of the variants, the difference is statistically significant. Additionally, it has to be noted that only 6 of the 120 possible sequences are tested in this analysis, and, therefore, to take an informed decision all possible sequences should to be tested.

4.7.5 Importance of allowing worsening moves

In this section, it is tested whether allowing moves that lead to worse solutions compared to the best solution found so far results in better solutions at the end of the algorithm. Thus, it is evaluated whether the deviation value is needed. Therefore, experiments are conducted with a deviation rate equal to zero. Consequently, only improving moves are allowed. For each problem size, the last 50 instances generated are used for the experiments. The best parameter combination for each problem size found by the irace package is used with the exception that the deviation rate value is set to zero. Twenty runs are executed for each instance. Each solution found by the algorithm with a zero deviation rate is compared with the best solution found by the algorithm with the deviation rate value indicated by the irace package. In Table 4.16, the results are indicated for each problem size in columns 2 to 4.

For the instances with 10 customer orders, the solutions obtained with a deviation rate equal to zero differ with on average 2.27% from the optimal solutions. For 19 of the 50 instances, the optimal solution is found in each of the 20 runs. In 6 of the 19

Table 4.16: Results of RRT heuristic with $\alpha = 0$

	Instance size		
	10 orders	15 orders	100 orders
Gap (%)			
- average	2.2736	3.9396	8.7725
- minimum	0.0000	0.0000	2.1619
- maximum	12.5856	15.4445	14.9439
# best solution found	444	124	0
# inst. best found (once)	28	9	0
# inst. best found (all)	19	3	0

instances, however, the optimal solution is equal to the initial solutions generated by the constructive heuristic. Thus, in these cases, the value of the deviation rate has no influence on the performance of the RRT heuristic.

Executing experiments for the instances with 15 customer orders and with a deviation rate which equals zero, the solutions are on average approximately 4% worse than the optimal solutions or the best solution found by the RRT heuristic when the optimal solution is not known. For only 3 of the 50 instances, the best solution is obtained in every run conducted. Moreover, for one instance, the initial solution is the optimal one, and thus the deviation rate value is not important.

Using the RRT heuristic with a deviation rate equal to zero and instances with 100 customer orders never leads to the best solution found by the RRT heuristic with the best deviation rate value obtained by irace. The objective values are on average 8.77% worse than the best solutions found using the best parameter setting for the deviation rate.

To conclude, allowing temporarily worse solutions in the RRT heuristic leads to better solutions at the end. The larger the instance size, the higher the need for allowing worse solutions. Thus, the record-to-record travel acceptance criterion implemented in the heuristic proposed in this dissertation is needed to obtain better solutions. However, it has to be noted that when the deviation rate is fixed to zero, actually the irace package should have been executed again to tune the other parameters.

4.8 Value of integration

In Chapter 3, the value of integration is examined for small-size instances using CPLEX. In this chapter, the RRT heuristic is used to quantify the value of integrating order picking and vehicle routing decisions for larger size instances with 100 customer orders. Therefore, an uncoordinated approach is compared with an integrated approach. An uncoordinated version of the RRT heuristic is proposed. A picking due date is introduced in the order picking subproblem to separate both subproblems. The picking process of all orders has to be completed before the due date. No order can leave the DC before the due date. The release date of each order in the VRP is equal to the picking due date. Furthermore, a cut-off time is determined. All orders placed before the cut-off time are picked before the due date. Thus, the cut-off time is the latest possible moment at which customers can order goods so that these can be delivered in the proposed delivery time windows. The due date is the moment in time before which all goods need to be picked in order to be able to deliver all goods on time.

Algorithm 3 Outline of uncoordinated solution approach

1: Parameters: $numb\_it$, I_{max}
    $numb\_it$: iteration number
    I_{max}: maximum number of iterations
  Solving the OPP problem
2: Generate initial OPP solution S_0
3: $numb\_it := 0$
4: **repeat**
5:     Local search within a record-to-record travel framework using two OPP operators
6:     $numb\_it := numb\_it + 1$
7: **until** $numb\_it > I_{max}$
  Solving the VRP problem
8: Generate initial VRP solution S_0
9: $numb\_it := 0$
10: **repeat**
11:     Local search within a record-to-record travel framework using three VRP operators
12:     $numb\_it := numb\_it + 1$
13: **until** $numb\_it > I_{max}$

An overview of the uncoordinated version of the RRT heuristic is given in Algorithm 3. The uncoordinated solution method is mainly the same as the integrated version except that the method is divided in two parts. In the first part of the uncoordinated version of the RRT heuristic (line 2-7), an initial solution for the OPP is constructed. Here, the orders are sorted based on their picking time in descending order. Then, the two OPP operators are used to improve the initial solution. The second part of the uncoordinated heuristic algorithm focuses on the vehicle routing subproblem (line 8-13). The picking due date is used as release date for the orders in the VRP. An initial VRP solution is constructed which is afterwards improved using the three VRP operators.

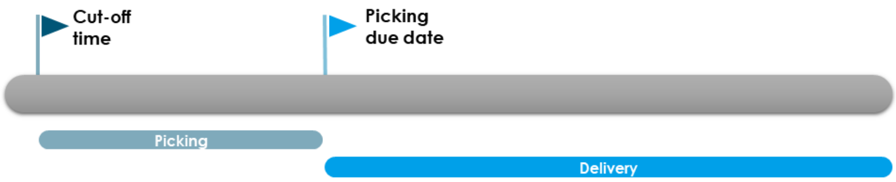
In the experiments with the integrated approach in Section 4.7, a minimum picking time of two hours (120 minutes) is provided for the order picking operations. Vehicles cannot leave the DC in this time period. Based on this, the delivery time window bounds are determined. The earliest time window bound is calculated using the minimal two-hour picking time, taking into account the loading time and the travel time from the DC to the farthest customer. To compare an uncoordinated approach and an integrated approach, two scenarios are possible for the uncoordinated approach:

1. Cut-off time two hours before picking due date: In this scenario, the pickers have two hours to complete all picking operations. Although order pickers are allowed to work four hours within a single shift, there is only a time period of two hours between the cut-off time and the picking due date. Thus, the order pickers cannot work four hours as in the integrated approach. The same number of orders needs to be picked in a shorter amount of time. However, using the same number of order pickers would result in infeasible solutions. With 12 pickers working each two hours, a total picking time of 24 hours is available. Nevertheless, all instances generated with 100 customer orders have a total picking time which is greater than 24 hours. Therefore, in this scenario, the number of pickers available is increased to obtain feasible solutions: 17 regular pickers instead of 9 and 6 temporary pickers instead of 3. Customers can still be delivered within the same time windows as before.
2. Cut-off time four hours before picking due date: Customers have to request two hours earlier in comparison with the integrated approach in order to be able to be delivered within the same time windows. The order pickers can work four hours as in the integrated approach. Alternatively, the delivery time windows can be postponed with two hours compared to the previous experiments. Thus, either the cut-off is two hours earlier or the time windows are postponed with two hours. In both approaches, the service level offered is lower in the uncoordinated approach. The time period between the request of a product and the delivery of the good is extended.

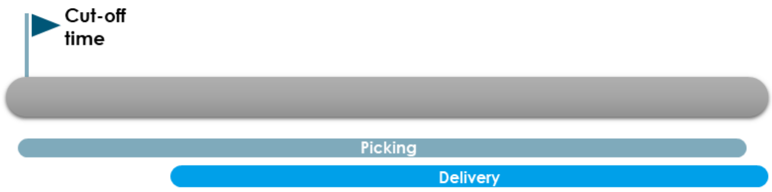
Thus, in scenario 1 additional order pickers are needed to avoid infeasibility, and in scenario 2 the service level offered to customers decreases.

Figure 4.9 shows the time line for each approach. The delivery time windows are spread over eight hours in all scenarios. Figure 4.9(a) indicates the time line for scenario 1 with a two-hour picking time available before the picking due date. In

(a) Uncoordinated approach - scenario 1



(b) Uncoordinated approach - scenario 2



(c) Integrated approach

Figure 4.9: Timeline for an uncoordinated and an integrated approach

Figure 4.9(b), scenario 2 is presented with a four-hour picking time period available. Finally, the integrated approach is shown in Figure 4.9(c). The picking operations start at the same moment as in scenario 1, but do not have a due date. The picking of each order has to be finished such that it can be delivered within its time window.

Similarly as in the previous experiments, 20 replications are conducted for each instance. Each solution obtained by the uncoordinated approach is compared with the best solution found for each instance by the integrated approach. Column 2 of Table 4.17 shows the difference in total cost, which indicates the value of integration. Columns 3 to 6 present the difference per cost component. A negative percentage indicates that the integrated approach outperforms the uncoordinated approach.

Integrating both problems lead to savings in total cost ($\Delta\ TC$) of approximately 1.80% on average in both scenarios, with savings up to 5.30%. In the integrated approach, the regular order picking cost ($\Delta\ TC_{creg}$) is slightly lower, while the labour cost of the temporary order pickers ($\Delta\ TC_{ctemp}$) is on average higher compared to an uncoordinated approach. Hiring temporary order pickers, which have higher labour

Table 4.17: Comparison of an uncoordinated and an integrated approach

Scenario	avg. Δ TC (%)	max. Δ TC (%)	avg. Δ TC_{creg} (%)	avg. Δ TC_{ctemp} (%)	avg. Δ TC_{ctl_v} (%)	avg. Δ TC_{ctt_v} (%)
1	-1.84	-5.36	-0.11	12.10	-3.75	-4.29
2	-1.83	-5.36	-0.15	14.00	-3.75	-4.29

costs, can be beneficial if this lead to lower distribution costs. The cost increase in the order picking problem is compensated by cost savings in the vehicle routing problem (Δ TC_{ctl_v} and Δ TC_{ctt_v}). Thus, by integrating both problems, an overall optimum can be found instead of optimising both problems individually. The impact on the vehicle routing costs is the same in both uncoordinated scenarios since the time windows and customer locations are the same. The average number of vehicles needed, approximately five, does not change when integrating both subproblems, as shown in Table 4.18.

Table 4.18: Average number of pickers and vehicles used

Scenario	avg. # pickers	avg. # vehicles
Integrated	9.10	4.11
1	16.38	4.65
2	8.30	4.65

Scenario 1 is comparable to the experiments in Chapter 3 to quantify the value of integration. The same time windows are used in both approaches. In Chapter 3, however, the time period between the cut-off time and the picking due date is four hours, whereas in this chapter the time period is only two hours. Thus, in the uncoordinated approach, order pickers cannot work four hours in a single shift, although they are allowed to. In Chapter 3, the number of pickers is not increased to avoid infeasibility, while in the current chapter a larger number of order pickers are available.

The average value of integration in this chapter is lower compared to the value obtained in Chapter 3. A different objective function is used in this chapter, as described in Section 4.2. Whereas in Chapter 3 the waiting time before the actual start of a route in the uncoordinated approach is taken into account as a labour cost for the driver, in this chapter only the actual route length is considered. As described earlier, during the waiting time before the actual start of a route in the uncoordinated approach, customers can still request orders in the integrated approach. Thus, while, the savings in total cost are lower in this chapter, the service level improvement is the same as in Chapter 3.

Apart from these savings in operational costs, the integrated approach offers either a large reduction in fixed costs or a drastic increase in the service level. In scenario 1, the main difference between the uncoordinated and integrated approach is the number of pickers needed. In the uncoordinated approach with a picking due date at 120, the order pickers have two hours each to pick all goods. Thus, the same number of orders have to be picked in a shorter time period. Consequently, a higher number of pickers are needed to pick the same number of orders, i.e., 16 instead of 9, as indicated in Table 4.18. As mentioned before, a higher number of regular pickers is available. Thus, although the changes in the total labour cost of regular pickers are small, hiring new pickers does have an additional cost in real life.

In scenario 2, total cost does not change significantly, but there is an impact on the service level. Customers have to order their goods two hours earlier to have these delivered in the same time window as in the integrated approach. Consequently, the service level offered decreases. Thus, by integration, companies can offer their customers the opportunity to purchase goods closer in time to their preferred delivery time using the same number of pickers and vehicles.

To conclude, the integration of order picking and vehicle routing operations results on average in a lower total cost. Furthermore, e-commerce companies can allow their customers to purchase goods online later and still have their goods delivered within the same time window without the need of a higher number of pickers or vehicles. The service level offered increases.

4.9 RRT heuristic: A reflection and opportunities

The integrated order picking-vehicle routing problem is a relatively new research problem. It combines two problems which are already hard to solve individually. In this dissertation, the problem is introduced and described in detail. It is the first time, except from Schubert et al. (2018), a solution method is proposed for the I-OP-VRP. Therefore, the decision was made to select a heuristic framework with a relatively simple structure and relatively few parameters. Algorithms with only a few parameters are easy to understand (Cordeau et al., 2002). In this way, the focus is on the integration of both problems instead of, e.g., finding the optimal parameter configuration. In this section, a critical reflection is made about several aspects of the heuristic proposed: objective function, local search operators, and algorithmic framework. Based on this reflection, future research opportunities can be identified in order to design a more advanced solution algorithm for the I-OP-VRP.

4.9.1 Objective function

Since the integrated order picking-vehicle routing problem is a new problem variant, few is known about the problem. Many objective functions can be interesting to investigate, either focusing on the service level offered or the total cost incurred. Examples are maximising the number of orders picked and delivered within the planning horizon, minimising the maximum delivery time, and minimising the number of order pickers and vehicles needed. In this dissertation, total operational costs related to order picking and vehicle routing activities are minimised.

The current objective function can be replaced by one in which, for the order picking subproblem, the number of order pickers is minimised. Similarly, it can be assumed that order pickers are paid for an entire shift instead of only incurring a labour cost for the actual picking time. When order pickers are paid for working an entire shift, the number of order pickers hired will automatically be minimised, while with the current objective function it does not matter with respect to total cost whether orders are picked by a single order picker or by multiple order pickers. In both situations, the labour cost will be the same.

Although the I-OP-VRP described is a single-objective problem focusing on total operational costs, the impact on the service level offered to the customers is highlighted as well when the results are discussed. When e-commerce companies integrate order picking and vehicle routing operations, customers can be allowed to place their order later in time while the goods can still be delivered within the same time windows. Thus, although the service level offered is not explicitly incorporated into the objective function, the effect on the service level is identified as well.

Nevertheless, real-world (e-commerce) companies have a number of objectives, which are often conflicting. Companies want to both offer the highest possible service level to their customers and have the lowest possible total cost at the same time. Therefore, instead of optimising a single-objective function, multi-objective problems for the I-OP-VRP have to be considered and solution methods which are capable handling a multi-objective problem have to be developed in future research.

4.9.2 Local search operators

In the RRT heuristic, five local search operators are implemented. Three are focusing on the vehicle routing part of the problem, two on the order picking part. The current objective function focuses on operational cost minimisation. In this chapter, no fixed cost is incurred for using an additional order picker or vehicle. Consequently, no local search operator is implemented to reduce the number of resources. Implicitly, by executing an operator iteratively on the same vehicle or order picker, especially the *relocate* operators, it is possible that all orders within a route or picking schedule are relocated to other vehicles or order pickers. In that case, the number of order pickers or vehicles is reduced. An interesting future research direction can be the implementation of a local search operator that explicitly focuses on the reduction of the number of resources used. For example, by selecting the order picker to which the lowest number of customer orders are assigned and trying to reinsert the orders of the selected order picker into the picking list of other order pickers.

In the heuristic algorithm proposed in this chapter, operators are mainly focusing on one of the two subproblems, either the OPP or the VRP. The solution of the other subproblem is only adapted when the relationship between the OPP and the VRP is violated. In that case, moves in the other subproblem than the one in which the local search operator is conducted are executed in order to fix the violated relationship. Thus, although no *integrated* operator is implemented which explicitly conduct moves in both subproblems at the same time, executing an operator for one subproblem can lead to relocation moves in the other subproblem in case of infeasibilities.

With the current objective function, many picking sequences lead to the same total order picking costs. The picking sequence is only important when the picking process of an order is not finished before the departure time of the delivery vehicle. Therefore, only in this case, changes are made in the picking schedules of regular order pickers. When an operator is constructed which simultaneously, e.g., relocates orders both in the picking sequences and in the vehicle routes, then often computation time is used to change the picking sequence which finally leads to the same total order picking costs. With the operators used in this dissertation, computational effort is saved since only moves are conducted in both subproblems when effectively needed.

In future research, however, efficient local search operators can be developed which explicitly execute moves in both subproblems at the same time. For instance, removing orders both from the picking lists and the vehicle routes and reassign them to other positions in the solutions. Analyses can be conducted to investigate whether better solutions are obtained using *integrated* operators instead of using operators working on a single subproblem.

4.9.3 Algorithmic framework

The local search operators used in this dissertation are implemented in a record-to-record travel framework. The basic RRT framework as introduced by Dueck (1993) is used. In further research, the framework can be extended with more advanced features. At the moment, a random resource, i.e., a vehicle or an order picker, and a random order within that random resource is selected to execute a local search operator. However, it is possible to select the same resource or customer order multiple times and even immediately in the subsequent move. A memory structure, such as a tabu list, can be added in which the previous selected orders are saved and are forbidden to be selected in the next operator move. Furthermore, in the current design of the RRT algorithm, after a maximum number of non-improving iterations, the algorithm restarts from the best solution found so far. No perturbation is implemented in which the current solution is largely changed in order to diversify the search procedure. An interesting future research direction is to include a perturbation phase in the RRT algorithm.

In the current RRT heuristic, only temporary infeasible solutions are allowed when these are due to a violation of the relationship between the OPP and the VRP. In other words, solutions in which the order picking operations are not finished before the departure time of the delivery vehicle are not instantly discarded. However, this infeasibility type needs to be solved immediately by reassigning orders in one of the two subproblems. If it is not possible to generate a feasible solution by rearranging orders, the original operator move creating the infeasible solution is not executed. However, Cordeau et al. (2002) state that using a mix of feasible and infeasible solutions reduces the probability of becoming trapped in a local optimum. Additionally, when intermediate infeasible solutions are allowed the search process becomes more flexible and simpler moves and neighbourhood structures can be used (Felipe et al., 2011). Hence, in future research, a more advanced solution algorithm can be developed in which intermediate infeasible solutions are allowed.

In literature, many other metaheuristic frameworks are frequently used, such as tabu search, iterated local search, or multi-start local search. In a tabu search algorithm, operator moves are conducted and in each iteration the best non-tabu move is executed. A memory-structure is implemented in which the last executed moves are saved. These moves are forbidden for a number of iterations and are called *tabu* in order to avoid conducting the same move repeatedly (Glover, 1989, 1990). Iterated local search and multi-start local search are used to escape from local optima. In iterated local search, in each iteration the procedure restarts from the current solution which is largely changed, which is called a perturbation (Lourenço et al., 2003). In multi-start local search, the search restarts from a new, mostly random, initial solution (Martí, 2003). The local search procedure is executed on the newly obtained solution in both approaches. In most of the algorithms highlighted, either a memory-based structure, a perturbation phase or diversification phase is implemented. The future research directions indicated above are thus included in these metaheuristics. Consequently, these metaheuristic frameworks can be used to develop a more advanced algorithm for the I-OP-VRP. The aforementioned metaheuristics are successfully used in related research, e.g., tabu search in Liu et al. (2017) for a VRP-rd in an e-commerce context, iterated local search in Schubert et al. (2018) for an I-OP-VRP, and multi-start local search in Bräysy et al. (2004) for a VRPTW.

4.10 Conclusions

Solving an I-OP-VRP for large-size instances to optimality is hard within reasonable time. Therefore, in this chapter, a heuristic algorithm based on record-to-record travel algorithm is proposed. Five local search operators are implemented within the heuristic solution method. Three operators work on the vehicle routing part of the problem: *relocate*, *exchange*, and *2-Opt*. Two operators adapt the order picking part of the problem: *relocate* and *exchange*. The parameters of the heuristic algorithm are tuned using an automatic configuration software, i.e., the irace software package. Experiments on small-size and large-size instances are conducted. The algorithm proposed is capable of obtaining the optimal solutions for the small-size instances within one second. Solutions for large-size instances can be found within approximately two minutes.

The design of the algorithm is evaluated by investigating the contribution of the operators and the impact of the operator sequence. The *relocate* operator for both the vehicle routing and order picking subproblem have the largest individual impact. The VRP operators have overall a larger impact than the OPP operators. No operator sequence, either a random or a fixed, outperforms the other for all instances tested.

Furthermore, the value of integration is examined by comparing an uncoordinated and integrated approach. Two different uncoordinated scenarios are compared with the integrated approach. In the uncoordinated approach, a picking due date strictly separates the order picking and delivery operations. Integration has two benefits for e-commerce companies. First, cost savings of on average 1.80% and even up to 5.30% can be obtained by integrating both problems. Total labour cost decreases because a lower number of order pickers are required. Second, e-commerce companies which integrate their operations can offer a higher service level. Customers can request their goods later in time and these can still be delivered within the same time windows. The time period between the request of an order and the delivery of goods is shortened by integration. Thus, integration can lead to a faster and more cost-efficient picking and delivery which is a competitive advantage in e-commerce business.

Since the I-OP-VRP is a relatively new problem, the heuristic algorithm proposed in this dissertation has a relatively simple structure. This way the algorithm is understandable for the reader and the focus is on the integration of both problems. A more advanced algorithm can be designed in further research in which, e.g., a perturbation phase is implemented or temporary infeasible solutions are allowed.

Chapter 5

Batch picking in the I-OP-VRP

5.1 Introduction

Order picking is the most labour-intensive activity in a warehouse because most operations are executed manually, especially when a picker-to-part method is applied. Manual picker-to-part order picking systems account for over 80% of all order picking systems in Western Europe (de Koster et al., 2007). As described in Chapter 3, the order picking time is composed of different components: travel times between picking locations, search times to find the requested items, pick times to grab the items from their storage locations, and setup times. The travel times between the different locations which need to be visited account for approximately half of the total picking time (Tompkins et al., 2003). To save labour costs, the total time required for the order picking activities should be minimised.

Furthermore, nowadays, customers expect a short delivery time when they purchase goods online. Consequently, companies have to offer a cut-off time as close as possible to the preferred delivery time. As a result, a large number of orders need to be picked in a short period of time. In order to be able to offer this service level to customers, picking operations have to be performed efficiently such that throughput times of orders are reduced (de Koster et al., 1999b).

Either from a cost minimisation perspective or from a service level maximisation perspective, total picking time needs to be reduced in order to pick orders as efficient as possible. The only component of the total picking time on which savings can be gained are the travel times, which have no value adding function. One way to

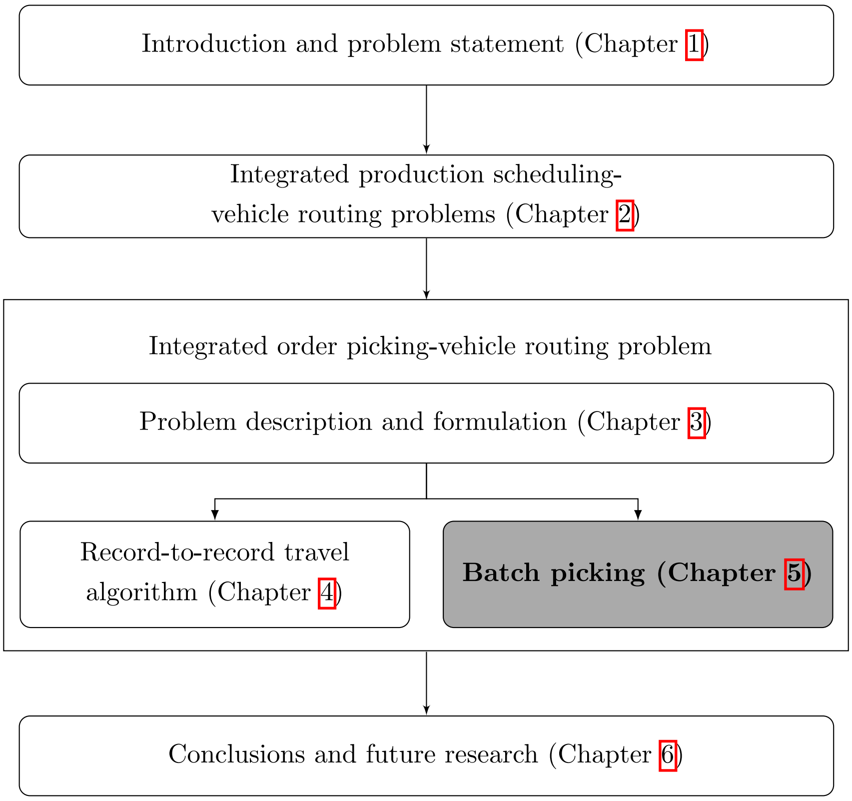
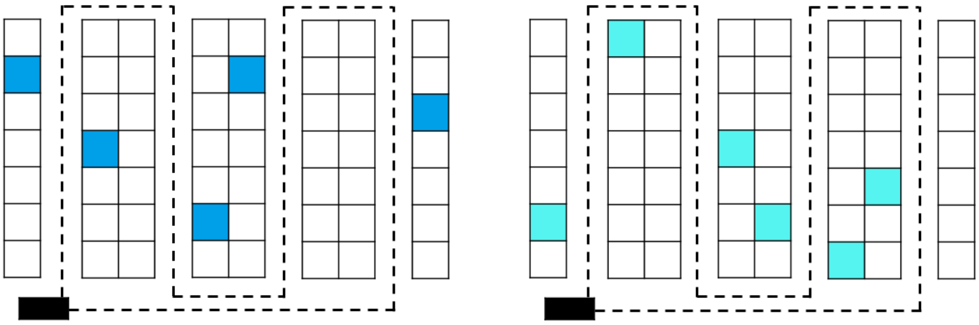


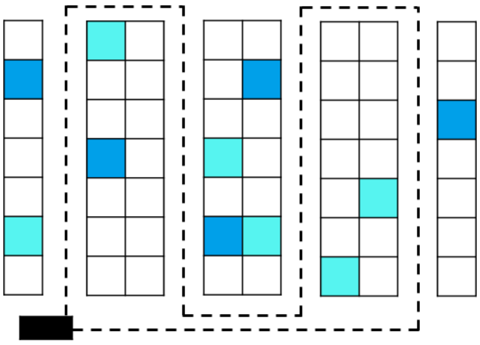
Figure 5.1: Thesis outline - Chapter 5

reduce travel times, and thus total picking time, is to implement a batch picking policy in which multiple customer orders are combined into a single route. In the previous chapters, a discrete order picking policy in which products ordered by a single customer are picked in an individual route is implemented. Since batch picking avoids that order pickers have to travel several times to the same picking locations to pick items that are requested by multiple customers, the reduction in travel time can be significant, especially for fast moving goods which are ordered by a large number of customers. Therefore, in this chapter, batch picking is introduced in the I-OP-VRP considered so far (Figure 5.1).

The difference between a discrete order picking policy and a batch picking policy is illustrated in Figure 5.2. The coloured boxes indicate the storage locations of the items requested by customers. The dashed lines represent the picking routes through the warehouse. In Figure 5.2(a), the picking routes are individually performed for two customer orders using a discrete order picking policy, resulting in an order



(a) Discrete order picking policy for two orders



(b) Batch picking policy for two orders

Figure 5.2: Comparison of picking routes with discrete order picking and with batch picking

picker travelling the same route twice. In Figure 5.2(b), the two customer orders are combined into a single batch. The order picker has to travel the route through the warehouse only once. Thus, in this example, the picking time with batch picking is approximately half of the picking time with a discrete order picking policy. A disadvantage of batch picking is that items of different customer orders need to be sorted when these are picked in the same route. Two types of sorting can be applied. Orders can be sorted either during the picking route, i.e., sort-while-pick, or at the end of the picking route, i.e., pick-and-sort (van den Berg, 1999).

The difficulty of the batching problem is to decide which orders are grouped into a single batch. Different strategies such as priority rule-based algorithms, seed algorithms, and savings algorithms, are developed in literature to solve the problem of assigning orders to batches. For detailed information on these strategies, the reader is referred to de Koster et al. (1999a, 2007) and Wäscher (2004). The assignment procedure is not the focus of this chapter. It is assumed that all demand is known at the beginning of the planning horizon. Thus, all feasible batches can be created in advance and are used as input for the I-OP-VRP. The decisions which have to be made in the order picking part of the I-OP-VRP are to: (1) select the batches that are picked such that each order is included in a batch, and (2) determine the sequence in which batches are picked for each order picker.

Several studies examine the impact of implementing a batch picking policy instead of a discrete order picking policy. de Koster et al. (1999b) find that combining a number of small orders in the same picking route can lead to a reduction in total order picking time of on average 19%. Consequently, a lower number of order pickers is required for the picking activities. The data in the study are based on a large retail organisation in the Netherlands. Petersen (2000) compares five picking policies in a mail order company. When a batch picking policy is used instead of a discrete order picking policy, the travel times decrease with 60%. Petersen and Aase (2004) investigate the picking activities of an online/catalog retailer using a discrete order picking policy. The authors examine the impact of using a different batching, routing, and storage policy. Experiments reveal that batching leads to the largest reduction in total fulfilment time, with savings up to 29%.

The goal of this chapter is to conduct an exploratory study on the impact of a batch picking policy on the value of integration. An integrated problem applying a batch picking strategy is compared with one using a discrete picking policy. Experiments on small-size instances are executed to quantify the difference between the two approaches. Moreover, conceptual scenarios are introduced in which batch picking can enlarge the value of integration compared to discrete order picking. This chapter is a first step towards research on integrated order picking-vehicle routing problems with a batch picking policy.

The remainder of this chapter is organised as follows. In Section 5.2, a mathematical formulation for the I-OP-VRP with batch picking is proposed. Data instances are created in Section 5.3. Experiments on the impact of batch picking in comparison with discrete order picking are conducted in Section 5.4. The value of integration in case of batch picking is quantified in Section 5.5. Additionally, in Section 5.6, problem contexts are described in which I-OP-VRPs with batch picking are compared with I-OP-VRPs with discrete order picking. The goal is to identify what the effect is of a batch picking policy in specific circumstances on the value of integration. Conclusions are formulated in Section 5.7. The aim of this chapter is to create a first insight into the impact of a batch picking policy on the integration of order picking and vehicle routing problems.

5.2 Mathematical formulation

In this section, the mathematical formulation for the I-OP-VRP presented in Section 3.5 is adapted such that batch picking is allowed.

5.2.1 Notation

To update the formulation, additional notation needs to be introduced, and existing notation needs to be adapted. In the adapted parameters and decision variables, the indices i and j indicating a customer order are replaced by indices b and c referring to a batch of orders. The adapted or added sets, indices, parameters, and decision variables needed in the mathematical model with a batch picking policy are defined as follows:

Sets and indices

$B = \{0, ..., \bar{b}\}$	set of feasible batches, indices b and c, where $b = c = 0$ indicates a dummy empty batch

Adapted parameters

pt_b	time needed to pick batch b, in minutes
ot_b	order time of batch b, in minutes

Additional parameters

wb_b	capacity utilisation of batch b, in number of items
g_{ib}	binary coefficient indicating whether order i is picked in batch b

Adapted decision variables

STO_b	start time of picking batch b, in minutes
X_{bp}	binary variable which is equal to 1 ($X_{bp} = 1$) if batch b is picked by order picker p
U_{bcp}	binary variable which is equal to 1 ($U_{bcp} = 1$) if batch c is picked immediately after batch b ($b \neq c$) by order picker p

Additional decision variables

$CTOB_b$	completion time of picking batch b, in minutes

The order picking time pt_0, capacity utilisation w_0, and order time ot_0 of the dummy batches are equal to zero.

5.2.2 I-OP-VRP with batch picking

The mathematical model is based on the formulations in Section 3.5 in combination with the objective function introduced in Chapter 4. Only the formulation of the OPP is influenced by the introduction of a batch picking policy. The OPP formulation is changed to a set partitioning problem such that each customer order is assigned to exactly one batch. The constraints related to the VRP are unaffected.

$$\min creg \cdot \sum_{b=1}^{\bar{b}} pt_b \cdot \sum_{p=1}^{\bar{p}} X_{bp} + ctemp \cdot \sum_{b=1}^{\bar{b}} pt_b \cdot \sum_{p=\bar{p}+1}^{\hat{p}} X_{bp} + \sum_{i=0}^{n}\sum_{j=0}^{n}\sum_{v=1}^{\bar{v}} ctt_v \cdot t_{ij} \cdot Z_{ijv} + \sum_{v=1}^{\bar{v}} ctl_v \cdot TL_v \quad (5.1)$$

subject to

$$\sum_{b=1}^{\bar{b}}\sum_{p=1}^{\hat{p}} g_{ib} \cdot X_{bp} = 1, \qquad \forall i \in I \setminus \{0\} \quad (5.2)$$

$$X_{bp} = \sum_{c=0}^{\bar{b}} U_{bcp} = \sum_{c=0}^{\bar{b}} U_{cbp}, \qquad \forall b \in B, p \in P, b \neq c \quad (5.3)$$

$$\sum_{c=1}^{\bar{b}} U_{0cp} \leq 1, \qquad \forall p \in P \quad (5.4)$$

$$wb_b \cdot X_{bp} \leq C_p, \qquad \forall b \in B, p \in P \quad (5.5)$$

$$STO_b \geq od_b, \qquad \forall b \in B \quad (5.6)$$

$$STO_c \geq CTOB_b - M_b^1 \cdot \left(1 - \sum_{p=1}^{\hat{p}} U_{bcp}\right), \qquad \forall b, c \in B, b \neq c, \quad M_b^1 = \min_{i \in b}\{b_i - t_{0i}\} - s_0 \quad (5.7)$$

$$CTOB_b = STO_b + pt_b, \qquad \forall b \in B \quad (5.8)$$

$$CTOB_b \leq CTO_i + M_{ib}^2 \cdot \left(1 - g_{ib} \cdot \sum_{p=1}^{\hat{p}} X_{bp}\right), \qquad \forall b \in B, \forall i \in I, \quad M_{ib}^2 = \min_{i \in b}\{b_i - t_{0i}\} - s_0 - pt_i \quad (5.9)$$

$$CTO_i \leq CTOB_b + M^1_{ib} \cdot \left(1 - g_{ib} \cdot \sum_{p=1}^{\hat{p}} X_{bp}\right), \qquad \forall b \in B, \forall i \in I$$
$$M^1_{ib} = b_i - t_{0i} - s_0 - pt_b \quad (5.10)$$

$$\sum_{b=1}^{\bar{b}} pt_b \cdot X_{bp} \leq wt^{max}_{reg}, \qquad \forall p = 1, ..., \bar{p} \quad (5.11)$$

$$\sum_{b=1}^{\bar{b}} pt_b \cdot X_{bp} \leq wt^{max}_{temp}, \qquad \forall p = \bar{p}+1, ..., \hat{p} \quad (5.12)$$

$$Z_{ijv} = 0, \qquad \forall i, j \in I \setminus \{0\}, i \neq j,$$
$$\forall \in V, a_i \geq b_j \quad (5.13)$$

$$\sum_{v=1}^{\bar{v}} Y_{iv} = 1, \qquad \forall i \in I \setminus \{0\} \quad (5.14)$$

$$Y_{0v} \geq Y_{iv}, \qquad \forall i \in I \setminus \{0\}, v \in V \quad (5.15)$$

$$Y_{jv} = \sum_{i=0}^{n} Z_{ijv} = \sum_{i=0}^{n} Z_{jiv}, \qquad \forall j \in I, v \in V, i \neq j \quad (5.16)$$

$$\sum_{i=1}^{n} w_i Y_{iv} \leq C_v, \qquad \forall v \in V \quad (5.17)$$

$$CTO_i \leq STT_v + M^7_i \cdot (1 - Y_{iv}), \qquad \forall i \in I \setminus \{0\}, v \in V,$$
$$M^7_i = b_i - t_{0i} - s_0 \quad (5.18)$$

$$a_0 \leq STT_v, \qquad \forall v \in V \quad (5.19)$$

$$STT_v + s_0 + t_{0j} \leq DT_j + M^3_j \cdot (1 - Z_{0jv}), \qquad \forall j \in I \setminus \{0\}, v \in V,$$
$$M^3_j = b_0 + s_0 + t_{0j} - a_j \quad (5.20)$$

$$DT_i + s_i + t_{ij} \leq DT_j + M^4_{ij} \cdot \left(1 - \sum_{v=1}^{\bar{v}} Z_{ijv}\right), \qquad \forall i, j \in I \setminus \{0\}, i \neq j,$$
$$M^4_{ij} = b_i + s_i + t_{ij} - a_j \quad (5.21)$$

$$a_i \leq DT_i \leq b_i, \qquad \forall i \in I \setminus \{0\} \quad (5.22)$$

$$DT_i + s_i + t_{i0} \leq b_0 + M^5_i \cdot \left(1 - \sum_{v=1}^{\bar{v}} Z_{i0v}\right), \qquad \forall i \in I \setminus \{0\},$$
$$M^5_i = b_i + s_i + t_{i0} - b_0 \quad (5.23)$$

$$DT_i + s_i + t_{i0} - STT_v \leq TL_v + M^6_i \cdot (1 - Z_{i0v}), \qquad \forall i \in I \setminus \{0\}, v \in V,$$
$$M^6_i = b_i + s_i + t_{i0} \quad (5.24)$$

$$TL_v \leq TL_{max}, \qquad \forall v \in V \tag{5.25}$$
$$CTOB_b, STO_b \geq 0, \qquad \forall b \in B \tag{5.26}$$
$$X_{bp}, U_{bcp} \in \{0,1\}, \qquad \forall b, c \in B, b \neq c, p \in P \tag{5.27}$$
$$CTO_i, DT_i \geq 0, \qquad \forall i \in I \tag{5.28}$$
$$STT_v, TL_v \geq 0, \qquad \forall v \in V \tag{5.29}$$
$$Y_{iv}, Z_{ijv} \in \{0,1\}, \qquad \forall i, j \in I, i \neq j, v \in V \tag{5.30}$$

Objective function (5.1) minimises the costs incurred for picking batches and the vehicle routing costs. Constraints (5.2) assign each order to exactly one batch and to exactly one picker. The picking sequence of batches is determined by constraints (5.3). At most a single batch can be picked first by a picker as indicated by constraints (5.4). Constraints (5.5) impede that the picking device capacity is violated. Constraints (5.6) specify that the picking process of a batch can only start after the order time of the batch, which is the maximum order time of all orders in the batch. The start and completion times of picking a batch are indicated by constraints (5.7) and (5.8), respectively. The completion time of an order is set equal to the completion time of the batch in which it is picked by constraints (5.10) and (5.9). The completion time of the order is the release date for the VRP. The working time of the regular and temporary order pickers is limited by constraints (5.11) and (5.12), respectively. The interpretation of the VRP constraints (5.13)-(5.25) is not changed compared to Section 3.5. Constraints (5.26)-(5.30) specify the domain of the variables.

5.3 Data generation

The data which are analysed in the computational experiments is based on the instances used in Chapter 4. Implementing a batch picking policy leads to a higher complexity of the I-OP-VRP. Consequently, the computation times to solve the problem to optimality by CPLEX increases. To get a first insight in the impact of batch picking, only the 50 instances with 10 customer orders generated in Section 4.5 are transformed into instances with batch picking. The data with respect to the delivery operations, e.g., time windows and customer locations, remain the same. The data related to the picking operations are adapted from individual order data to batch data. The number of possible batches is calculated as follows: $\sum_{r=1}^{n} \frac{n!}{r! \cdot (n-r)!}$, with n the total number of orders and r the number of orders in a batch. The total number of possible combinations with $n = 10$ is equal to 1,023.

The batch capacity utilisation wb_b is the sum of the number of items w_i in each customer order included in the batch. The order time of a batch ot_b is the maximum order time ot_i of the orders assigned to the batch. Since the focus of this chapter is not to select the best batching and routing policy, the picking time of a batch pt_b is randomly generated based on the picking times of the orders included. In more detail, the picking time of a batch with a single order ($r = 1$) is equal to the picking time of that order. The picking time of a batch with multiple orders ($r > 1$) is randomly generated between the maximum picking time over all subbatches with $r - 1$ orders selected out of the orders in the batch and the sum of the picking times of the orders included. For example, the picking time of the batch with order 1, 2, and 3 is randomly generated within the range of the maximum picking time of the subbatches, i.e., (1, 2), (1, 3), and (2, 3), and the sum of the individual picking times, i.e., $U(max(pt_{(1,2)}, pt_{(1,3)}, pt_{(2,3)}), pt_1 + pt_2 + pt_3)$. Thus, picking a batch takes at least as long as picking a smaller batch with some of the orders inside the larger batch, but no longer than the sum of picking each order individually. The time needed to sort the different customer orders in a batch is assumed to be negligible.

The batches with an infeasible weight utilisation with respect to the picking device capacity of 20 items and a picking time greater than the picking time available for a single order picker are excluded from the input data in the computational experiments. Since by using a batch picking policy the total picking time needed decreases, the time period available for the picking operations is shortened in comparison with the previous chapters. Therefore, in the uncoordinated approach in this chapter, the picking due date is after 60 minutes, while in Chapter 4 the picking due date is after 120 minutes. Thus, the picking time available for each picker in the uncoordinated approach is only 60 minutes. The time window bounds are 60 minutes earlier than in Chapter 4. The instances are available online at http://alpha.uhasselt.be/kris.braekers.

5.4 Impact of batch picking

In this section, the impact of implementing a batch picking policy on total cost is examined. The results of an I-OP-VRP with batch picking and of an I-OP-VRP with discrete order picking are compared. The experiments[1] are executed on a 12-core Xeon E5-2680v3 CPUs with 128 GB RAM. The optimisation software ILOG CPLEX

[1]The computational resources and services used in this work were provided by the VSC (Flemish Supercomputer Center), funded by the Research Foundation - Flanders (FWO) and the Flemish Government - department EWI.

12.7.1 is used to solve the mathematical formulation. The mathematical formulation for the I-OP-VRP with batch picking described in Section 5.2.2 is used to obtain the optimal solution for the instances with batches. For the I-OP-VRP with discrete order picking, the mathematical formulation presented in Section 3.5 is used with an order time equal to 60. In Table 5.1, the changes per cost component and in total cost are presented. Detailed results are provided in Appendix D.

Table 5.1: Comparison of discrete order picking and batch picking

$\Delta\, TC$ (%)	$\Delta\, TC_{creg}$ (%)	$\Delta\, TC_{ctemp}$ (%)	$\Delta\, TC_{ctl_v}$ (%)	$\Delta\, TC_{ctt_v}$ (%)
-12.07	-37.60	0.00	0.00	0.00

Implementing a batch picking policy instead of a discrete order picking policy leads to savings in total cost (TC) of approximately 12%. Costs related to the delivery operations (TC_{ctl_v} and TC_{ctt_v}) are not influenced by changing the picking policy for these instances. The labour costs of the regular order pickers (TC_{creg}) decrease with 37.60% on average. While in an I-OP-VRP with discrete order picking on average 1.16 regular order pickers are needed, in an I-OP-VRP with batch picking a single order picker can pick all orders on time. In both integrated approaches, no temporary order pickers are used.

Investigating an I-OP-VRP with batch picking leads to a higher number of possible picking schedules compared to an I-OP-VRP with discrete order picking. Consequently, the computation time required to obtain the optimal solution by CPLEX increases. Solving instances with discrete order picking has an average computation time of approximately two minutes, while the average computation time for instances with batch picking is two hours.

5.5 Value of integration

In previous chapters, the value of integration has already been indicated for an I-OP-VRP in which a discrete order picking policy is applied. In this chapter, the value of integration is quantified for an I-OP-VRP with a batch picking policy. An uncoordinated approach is compared with an integrated approach. The mathematical formulation presented in Section 5.2 needs to be divided into two parts. A strict picking due date is introduced in the order picking subproblem. Release dates at which the goods become available for delivery are added to the vehicle routing subproblem.

In more detail, a constraint concerning the picking due date pd needs to be introduced. This constraint is similar to constraints (3.9), but is adapted to batch picking as follows:

$$CTOB_b \leq pd, \qquad \forall b \in B \setminus \{0\} \tag{5.31}$$

Furthermore, in constraints (5.7) the calculation of the Big M value needs to be changed: $M_b^1 = pd$. Finally, in constraints (5.18), the completion time of the picking process of an order needs to be replaced by a release date rd_i, resulting in the following constraint:

$$rd_i \leq STT_v + M_i^2 \cdot (1 - Y_{iv}), \qquad \forall i \in I \setminus \{0\}, v \in V, \quad M_i^2 = rd_i \tag{5.32}$$

Due to the large computation times to solve such an I-OP-VRP, experiments are conducted using instances with only 10 customer orders. In the uncoordinated approach, a picking due date after 60 minutes needs to be respected. Such a small time period for the picking operations is considered because by implementing a batch picking policy the total picking time needed is less than in case of a discrete order picking policy. The impact of a small picking period is examined in more detail in Section 5.6. The problem is similar to the scenario in Section 3.7.2.2 in which all orders have an order time equal to 180 and thus only 60 minutes are left to pick these goods. The ten orders are ordered at the beginning of the time horizon, i.e., the cut-off time, and need to be picked before the due date. Although order pickers are allowed to work 240 minutes during a single shift, only 60 minutes are left to pick these orders on time.

Table 5.2: Cost difference between an uncoordinated and an integrated approach

$\Delta\, TC(\%)$	$\Delta\, TC_{creg}(\%)$	$\Delta\, TC_{ctemp}(\%)$	$\Delta\, TC_{ctl_v}$ (%)	$\Delta\, TC_{ctt_v}$ (%)
-0.32	7.70	-46.00	0.00	0.00

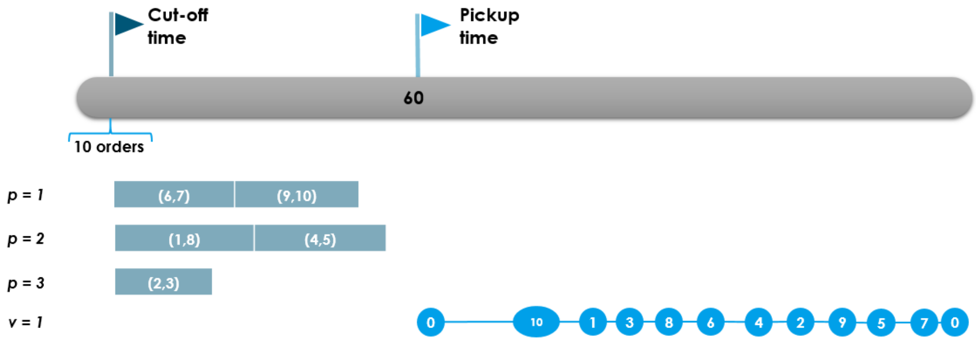
The value of integration, indicated by the changes in total cost ($\Delta\, TC$) in Table 5.2, is on average 0.32%. By integrating the subproblems, savings on the labour costs of the order pickers are achieved. In the integrated approach, a single regular order picker can pick all goods on time. In the uncoordinated approach, however, in all instances two regular order pickers are needed and, in 23 instances an additional temporary order picker needs to be hired to avoid violating the picking due date. The labour costs of the regular order pickers (TC_{creg}) in the integrated approach are on average 7.70% higher than in the uncoordinated approach since all orders are picked by regular pickers in the integrated approach. The labour costs of the temporary order pickers (TC_{ctemp}) decrease with 46.00%. Thus, the increase in the labour costs of the regular order pickers is compensated by the decrease in the labour costs of the temporary order pickers. Detailed results are provided in Appendix D.

In Chapter 3, similar results are obtained for an I-OP-VRP with a discrete order picking policy. As can be seen in Table 3.3, in the uncoordinated approach a higher number of both types of order pickers is required compared to the integrated approach. In the integrated approach, no temporary order pickers need to be hired.

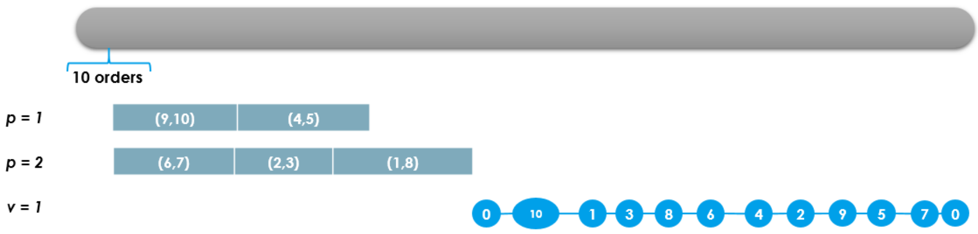
The general results described in this section are illustrated by examining the specific results of one instance in more detail. In the uncoordinated approach, two regular pickers both pick two batches of two orders (Figure 5.3(a)). Order picker 1 and 2 work 47 minutes and 55 minutes, respectively. The pick time of the remaining batch of two orders is 20 minutes. Consequently, this batch needs to be assigned to a temporary order picker to avoid violating the picking due date. In the integrated approach (Figure 5.3(b)), the order pickers can work 240 minutes without fixed end time of a shift since it is not longer restricted by the picking due date. The batch which is picked by a temporary order picker in the uncoordinated approach can be picked by a regular order picker in the integrated approach. No additional order pickers need to be temporarily hired which lead to lower labour costs. Order picker 1 works 50 minutes and picks two batches of two orders. Order picker 2 has a working time of 72 minutes and picks the remaining three batches. Thus, the same batches are picked, but fewer order pickers are need for the picking operations. The same delivery route is conducted in both approaches.

A critical remark has to be added on the relatively low value of integration indicated in the experiments when a batch picking policy is applied. A reason for the low value can be the way in which the batches and the associated picking times are created. All feasible combinations of customer orders with respect to the picking device capacity are created. The picking time of the batches are randomly generated. As described in Section 5.3, the picking time of a batch with r number of orders is randomly generated between the maximum picking time of all subbatches with $r-1$ orders and the sum of the picking times of the individual orders in the batch. The storage locations and picking routes are not taken into account since these data are not available in the artificial generated instances.

In literature, batches and their picking times are generally created using batching policies. Examples of batching policies are proximity batching and seed algorithms. In proximity batching, customer orders are combined in a batch based on the proximity of their storage locations in the warehouse. In a seed algorithm, first an order is selected as seed order. Then, orders are added to the current batch based on a distance measure (de Koster et al., 2007). Thus, when using such batching rules,



(a) Uncoordinated approach with a temporary picker ($p = 3$)



(b) Integrated approach

Figure 5.3: Comparison of an uncoordinated approach with a single temporary picker and an integrated approach

orders which are located close to each other are combined. Consequently, more travel distance is saved in comparison to a discrete order picking policy and a random batch policy. A first step in further research has to be conducted to investigate the value of integration when such batch picking rules are applied. Furthermore, higher efficiency improvements can be obtained when order batching, picking routes, and pickers scheduling are optimised in a coordinated way instead of each problem individually (van Gils et al., 2017, 2018a). Therefore, a second step in future research is to examine the value of integrating order picking and vehicle routing decisions when the internal warehouse operations are conducted in a coordinated way.

5.6 When is integration more valuable: examples

Although the value of integration is rather small in the previous section, problem contexts exist in which integration leads to higher gains when batch picking is applied instead of discrete order picking. In this section, several problem contexts are described. For each problem context, a numerical example is provided which demonstrates the value of integration in case of batch picking in the order picking part of the problem.

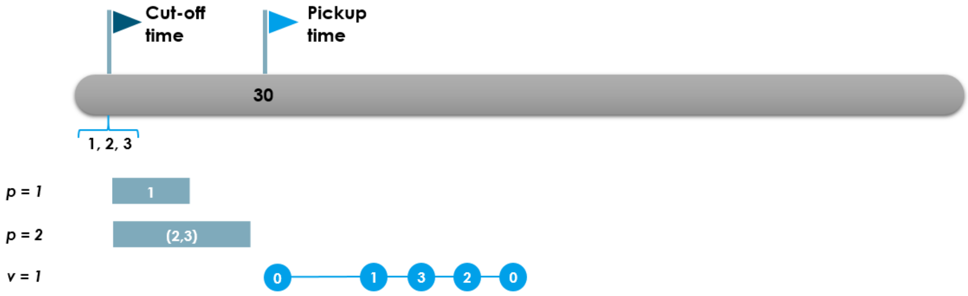
5.6.1 Problem context 1: Small picking time period

In an e-commerce environment, customers expect a fast delivery. Thus, the time period between the purchase of goods and their delivery has to be small. To offer this service level, the cut-off time has to be close in time to the picking due date in an uncoordinated approach. Consequently, the time available for picking goods that are ordered close to the cut-off time is limited. To pick all orders on time, multiple order pickers need to work at a time. Additionally, batches which require a larger picking time than the time available cannot be selected. Therefore, when determining picking schedules a lower number of possible batches are available to select from. Probably a higher number of batches consisting of a small number of orders need to be picked.

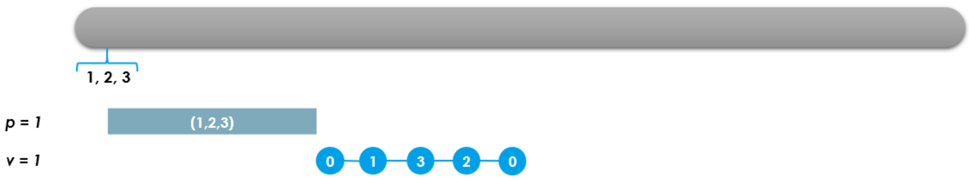
In the uncoordinated approach, the delivery operations are outsourced to a 3PL service provider. A picking due date is negotiated with the 3PL service provider. At the due date, the 3PL service provider arrives at the DC and pick ups the goods. This picking due date is fixed and the same for every day. The e-commerce company and the 3PL service provider do not contact each other daily to discuss the due date for that specific day based on the customer orders requested.

In an integrated approach, the only time restriction is the maximum working time of an order picker during a single shift. No picking due date has to be respected. The entire time period between the request of an order and the departure time of the vehicle delivering the order can be used for picking the order. The batches with a large picking time which cannot be considered in the uncoordinated approach are no longer excluded in the integrated approach. These batches, which probably combine a higher number of orders and lead to a lower total time for picking all orders, can be selected.

A numerical example with three customer orders is presented. The three orders are requested by customers at the cut-off time. After the cut-off time, 30 minutes are available before the picking due date in the uncoordinated approach (Figure 5.4(a)). The smallest possible total picking time is 42 minutes. Order picker 1 picks customer order 1 (15 minutes). A batch consisting of orders 2 and 3 is picked by order picker 2 (27 minutes). In the integrated approach, however, a single order picker picks all three customer orders in a single batch (Figure 5.4(b)). The picking time is 41 minutes. The batch with the three orders cannot be picked in the uncoordinated approach



(a) Uncoordinated approach with a small picking time period available



(b) Integrated approach

Figure 5.4: Comparison of an uncoordinated approach with a small picking time period available and an integrated approach

since the picking time is larger than the time available between the cut-off time and the pickup time. In the uncoordinated approach, the picking due date is fixed at the same time every day. It is not possible to change the due date in order to be able to reduce the total picking time for a specific day, especially because the goods are ordered close in time to the picking due date. Thus, by integrating order picking and vehicle routing decisions, the total picking time can be decreased in case batch picking is applied, and the number of order pickers required decreases.

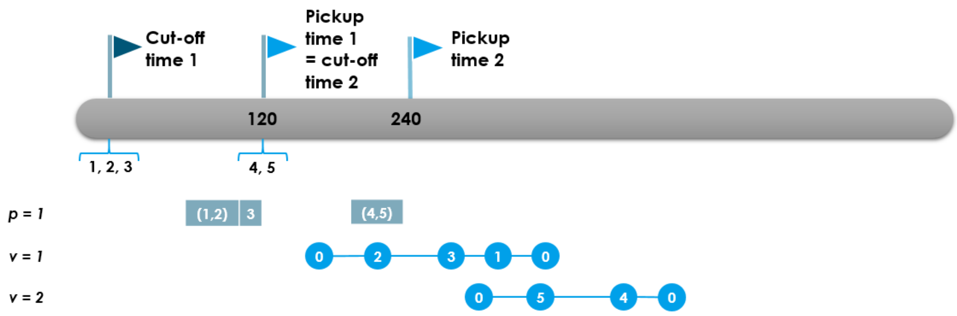
In case a discrete order picking strategy is implemented, the problem of a small time period available for picking only leads to hiring more order pickers in an uncoordinated approach, as described in Section 3.7.2.2. The smaller the time period between the cut-off time and the picking due date, the higher the number of temporary order pickers needed in the uncoordinated approach. When the time period is too small and the number of order pickers available is insufficient to pick all goods on time, the uncoordinated problem becomes infeasible. Orders are picked by a lower number of order pickers when the order picking and vehicle routing problems are integrated, and in most cases no additional order pickers need to be hired. In contrast to a discrete order picking policy in which the sum of the individual picking times remains the same after integration, the total picking time decreases by integrating the two subproblems in case of batch picking. Thus, not only the number of order pickers needed decreases, also the total picking time is reduced in an integrated problem with batch picking.

5.6.2 Problem context 2: Outsourcing to multiple 3PLs

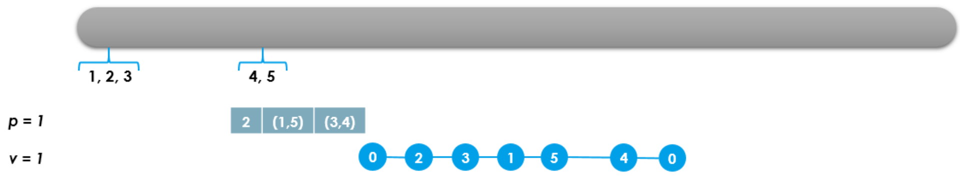
An e-commerce company can outsource its delivery operations to more than one 3PL service provider in an uncoordinated approach. The e-commerce company negotiates with each 3PL service provider a pickup time at which the goods are picked up that are delivered by that specific 3PL. For each pickup time, an associated cut-off time before which goods need to be ordered, is determined.

Suppose, a contract is negotiated with two 3PL service providers leading to two pickup times and two cut-off times. The second cut-off time is equal to the first picking due date. All goods ordered before the first cut-off time need to be picked before the first pickup time in such a way that the 3PL can deliver these goods to the customers. The goods ordered after the first cut-off time have to be picked before the second pickup time. Thus, only orders which are picked in the same period can be combined in a batch. In this situation, two picking schedules are determined: one for the time period between the first cut-off time and the first pickup time and another for the time period between the first pickup time (second cut-off time) and the second pickup time.

In the integrated approach, however, no fixed pickup times occur. The delivery operations are conducted by the e-commerce company itself or the 3PL service providers collaborate with the e-commerce company. A picking schedule is determined for the entire period. All possible combinations of orders can be assigned to a batch as long as the capacity of the picking device is not violated. The picking process of orders which need to be delivered in a late time window, i.e., after pickup time 2, can be postponed. The system is updated regularly and new orders become available. In this way, new batching combinations with orders from both time periods are possible. Combinations with newly arrived orders can result in a lower picking time than combining orders which are requested earlier. Furthermore, whereas in the uncoordinated approach each 3PL service provider determines its delivery route, in the integrated approach, vehicle routes for the entire delivery period are determined. Thus, all orders can be considered at the same time when establishing vehicle routes resulting in more consolidation possibilities. The number of routes needed to deliver all goods can decrease.



(a) Uncoordinated approach with multiple 3PLs



(b) Integrated approach

Figure 5.5: Comparison of an uncoordinated approach with multiple 3PLs and an integrated approach

In Figure 5.5, an uncoordinated and integrated approach are shown. In the uncoordinated approach (Figure 5.5(a)), order 1, 2, and 3 need to be picked before pick due date 1 at 120, while the picking process of order 4 and 5 has to be completed before pick due date 2 at 240. In the first time period, order 1 and 2 are combined in a batch (28 minutes), and order 3 is picked in an individual tour (17 minutes). In the second time period, order 4 and 5 are combined in a single batch with a picking time of 31 minutes. The total picking time of the uncoordinated approach is equal to 76 minutes. Two vehicle routes are conducted. The first route leaves the DC at picking due date 1 and delivers all goods ordered before cut-off time 1. The second route leaves the DC at the second picking due date and delivers the remaining orders.

In the integrated approach, different orders are combined into batches (Figure 5.5(b)). Order 1 and 5 are assigned to a batch with a picking time of 20 minutes. A second batch is composed of order 3 and 4 and has a picking time of 21 minutes. Order 2 is picked individually (24 minutes). The total picking time is equal to 65 minutes. As can be seen, orders requested in different time periods in the uncoordinated approach are combined in batches in the integrated approach. Thus, by postponing the picking process of order 1 and 3 until additional orders have arrived in the system, the total picking time is reduced by 14.5%. Consequently, lower labour costs are incurred. Additionally, all orders are delivered by a single vehicle. In the uncoordinated approach, each 3PL service provider conducts a delivery route. In the integrated approach, however, by collaborating all orders can be delivered in a single route.

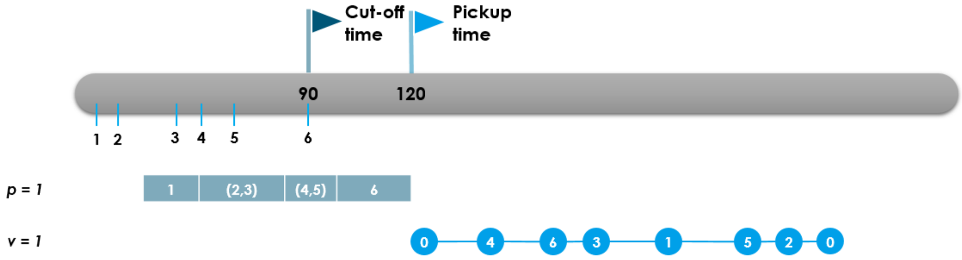
These savings cannot be achieved when a discrete order picking policy is applied in the DC. In such a situation, no orders are combined in a batch, and the total picking time is the sum of all individual picking times. The total order picking time is not influenced when orders are postponed to be picked. Thus, integration can be more beneficial when batch picking is applied in a situation with multiple 3PL service providers with multiple cut-off times in an uncoordinated approach.

5.6.3 Problem context 3: Dynamic environment

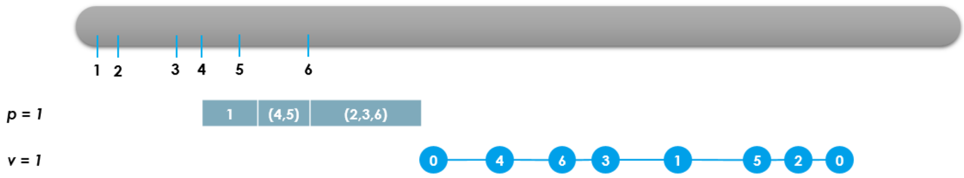
A typical characteristic for e-commerce sales is that goods can be ordered on the Internet 24/7. Orders arrive in the system of the e-commerce company at any moment in time. Every time a new order is placed, the existing picking schedules and vehicle routes need to be updated. The picking process of the newly arrived order has to be added to the picking list of one of the pickers, and the order needs to be inserted in one of the vehicle routes. In contrast to the previous problem context in the uncoordinated approach, the system is not longer updated only at the cut-off times.

In the integrated approach, the picking process of orders can be postponed. By postponing, orders can be batched with orders that are requested later. More batching possibilities are created. Some of these can lead to a lower total picking time needed. In the uncoordinated approach, all orders have to be picked before the due date. Postponing the picking process of all orders can be risky as the possibility exists that the picking due date will be violated. In the integrated approach, a decision rule has to be determined that indicates which orders can be postponed and to what extent. For example, the picking process of an order can be postponed until no later than two hours before the upper bound of the delivery time window of the order.

An example of a dynamic situation in both an uncoordinated and integrated approach is presented in Figure 5.6. Only orders placed in the time period before the cut-off time in the uncoordinated approach are considered. Six orders are placed in this time period. Order 6 is requested on the last possible moment in the uncoordinated approach, i.e., at the cut-off time. After the cut-off time 30 minutes are left for conducting picking operations. The time needed to pick order 6 in an individual tour is 27 minutes.



(a) Uncoordinated approach



(b) Integrated approach

Figure 5.6: Comparison of an uncoordinated approach and an integrated approach in a dynamic environment

As can be seen in Figure 5.6, orders are combined in different batches in the uncoordinated and integrated approach. In the uncoordinated approach (Figure 5.6(a)), order 2 is combined with order 3, while in the integrated approach (Figure 5.6(b)) orders 2, 3, and 6 are combined in a single batch. The picking process of batch (2,3) is postponed in the integrated approach. The postponement creates the opportunity to combine batch (2,3) with order 6 in a single batch which has a picking time of 49 minutes. When batch (2,3) is postponed in the uncoordinated approach, the batch (2,3,6) would violate the picking due date since order 6 is requested at time 90 and the picking due date is at 120.

In case of discrete order picking in a dynamic environment, postponing the picking process of orders has no impact on the total time required to pick all orders. Each customer order is picked in an individual tour through the DC. Postponement does not change the picking time of an individual tour. Consequently, integrating order picking processes and vehicle routing operations in a dynamic environment has a higher value in case a batch picking policy is applied instead of a discrete order picking policy.

5.7 Conclusions and future research opportunities

In this chapter, a batch picking policy is introduced in the I-OP-VRP used in the previous chapters. Instead of picking each customer order in an individual picking tour through the warehouse, multiple orders are combined in a batch to be picked in the same tour. Batch picking reduces the total picking time needed. Consequently, total labour cost decreases with approximately 37% on average for the instances with 10 customer orders. Total cost is reduced with approximately 12% on average.

The mathematical formulation for the I-OP-VRP introduced in Chapter 3 is adapted. The order picking constraints are changed to a batch picking policy. The constraints related to the delivery operations are unaffected by the implementation of a batch picking policy. The mathematical model formulated in this chapter is a set partitioning problem in which each customer order needs to be assigned to exactly one batch.

The value of integration is quantified in case batch picking is applied in the order picking part of the problem. Experiments with instances with 10 customer orders are executed. Similar results as in case of a discrete order picking policy are obtained. In an integrated approach, a lower number of order pickers are required to pick all goods since there is more flexibility for conducting the picking operations. Consequently, total labour cost of the order pickers decreases.

This chapter describes three problem contexts in which the integration of order picking and vehicle routing problems has a larger value when batch picking is used instead of discrete order picking. If the time period between the cut-off time and the picking due date is small in the uncoordinated approach, then integration can have a larger value if batch picking is applied instead of discrete order picking. If the subproblems are integrated, then different orders can be batched than in the uncoordinated approach leading to a lower total picking time. In discrete order picking, the total order picking remains the same as it is the sum of the individual picking times. If in an uncoordinated approach an e-commerce company outsources its delivery operations to multiple 3PL service providers, then the value of integration is larger when batch picking is used compared to when discrete order picking policy is applied. Similar findings are obtained for the I-OP-VRP with batch picking in a dynamic environment. In the integrated approach, the picking process of orders which have a late time window compared to their order time can be postponed. Both the number of order pickers required and the number of vehicles needed decreases in the integrated approach. By postponing, more batch combinations with the orders arriving later in the system are created. Postponing orders is not always possible in the uncoordinated approach as it can result in a violation of the picking due date. When a discrete order picking policy is applied, the postponement of orders has no impact since no orders are batched and the individual picking times are not influenced.

In this chapter, an exploratory study has been conducted on the impact of implementing a batch picking policy in an I-OP-VRP. The aim is to gain a first insight into the effect of batch picking on the value of integration. Experiments with small-size instances with 10 customer orders are executed. In further research, the value of integration for larger problem sizes has to be examined. The problem contexts provided indicate a first impression of which benefits can be obtained when integrating an order picking problem using batch picking with a vehicle routing problem. The savings obtained by integrating order picking and vehicle routing decisions depends on the batching policy, routing policy, and storage policy used in the DC. In this dissertation, the picking times of both individual orders and batches are randomly generated. Future research should investigate the impact of different batching, routing, and storage policies on the I-OP-VRP.

Chapter 6

Final conclusions and future research

This dissertation focuses on the integration of order picking and vehicle routing decisions in a single optimisation problem. The aim is to investigate the value of integrating both subproblems, especially in an e-commerce context. In Chapter 2, a detailed review of integrated production scheduling-vehicle routing problems is conducted in order to get a first insight in integrated problems of supply chain functions. In Chapter 3 to 5, the integrated order picking-vehicle routing problem is analysed. In Chapter 3, the I-OP-VRP is introduced and described in detail. A heuristic algorithm to solve the problem is proposed in Chapter 4. The integrated problem with a batch picking policy is investigated in Chapter 5. Finally, in this chapter, the main conclusions are summarised, managerial implications are identified, and future research directions are indicated (Figure 6.1).

6.1 Final conclusions

Integrating multiple supply chain functions in a single problem is currently identified as a major research direction. In recent years, an increasing number of studies have been conducted on integrated vehicle routing problems, in which the classical VRP is extended with real-life characteristics or integrated with other supply chain functions. In this dissertation, a new variant of integrated problems is introduced, i.e., the integrated order picking-vehicle routing problem. The problem is analysed in an e-commerce context. In the last decade, B2C e-commerce sales have been increasing

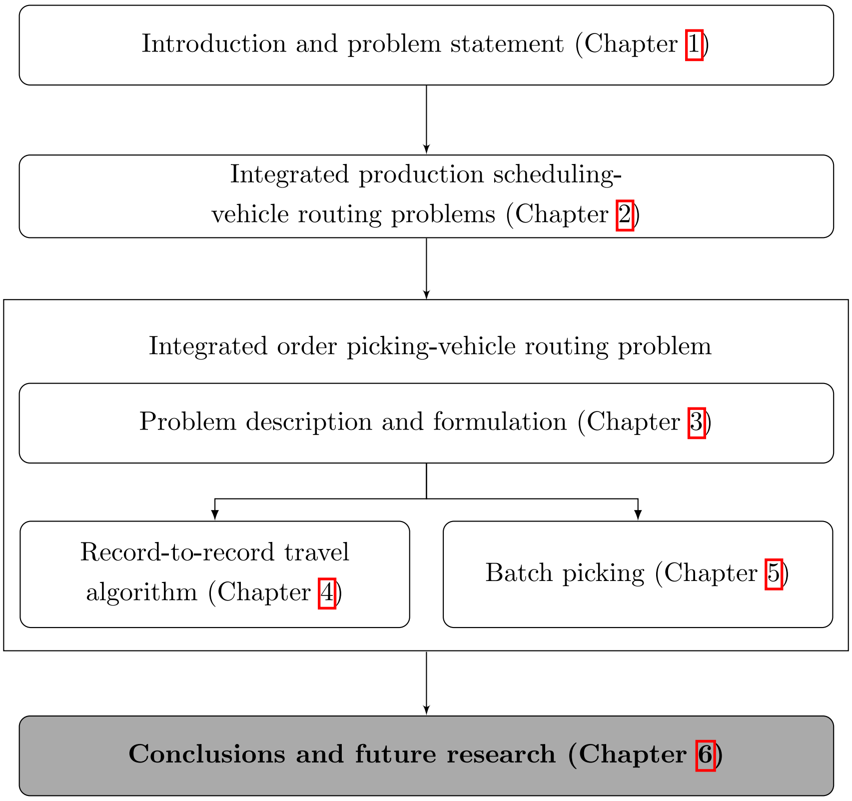


Figure 6.1: Thesis outline - Chapter 6

yearly. The higher number of customer orders and associated customer expectations put the logistics activities of e-commerce companies under pressure. To be successful in the highly competitive e-commerce market, companies have to thoroughly rethink their way of working, especially concerning the picking and delivery operations. Higher savings and efficiency improvements can be gained by integrating rather than by improving individual supply chain functions. Therefore, this dissertation focuses on integrating order picking and vehicle routing problems.

The integration of order picking and vehicle routing problems is a relatively new research domain. The most related literature is on the integration of production scheduling and vehicle routing problems at the operational decision level. Therefore, in the first part of this thesis, a detailed review of and discussion on integrated production scheduling-vehicle routing problems is conducted. Since production scheduling and order picking have similar characteristics, insights can be gained from the review.

Based on the classification matrices proposed for the I-PS-VRP, it is remarked that a relatively simple machine environment is integrated with a basic VRP. Real-life characteristics, such as production setup times and delivery service times, are often ignored in I-PS-VRPs, but should be included in further research. Most solution methods proposed are metaheuristic algorithms using tabu search or genetic algorithms. Furthermore, average improvements of 5% to 20% can be obtained by the integration of the two subproblems. However, more research should be conducted to investigate in which circumstances integration is most beneficial. Sensitivity analyses to identify the impact of problem characteristics on the value of integration need to be done. These future research directions for the I-PS-VRP act as starting point for the formulation of an I-OP-VRP in the following chapters.

The second part of the dissertation analyses the integrated order picking-vehicle routing problem in an e-commerce context. Little research has been conducted on I-OP-VRPs. A few studies are published which make a first step towards the integration of order picking and distribution. The distribution operations are mostly simplified to direct shipments to each individual customer or are outsourced to a 3PL service provider. In this dissertation, order picking and vehicle routing operations are integrated into a single optimisation problem. Mathematical formulations for an uncoordinated approach in which the two subproblems are solved separately, and for an integrated approach are proposed.

Sensitivity analyses on small-size instances are conducted to investigate the impact of various problem characteristics on the value of integration. A higher variable travel cost leads to a higher value of integration. Similarly, when customers are located in a larger square around the DC, the value of integration increases. The effect of the number of customer orders is not straightforward.

Extending a VRP, which is already NP-hard, with order picking operations results in a complex combinatorial problem. Solving the integrated problem to optimality by CPLEX in a small amount of computation time is difficult. In an e-commerce environment, however, good picking schedules and vehicle routes need to be determined using a fast and efficient solution tool. Therefore, a heuristic algorithm based on a record-to-record travel framework is proposed in this dissertation to solve the problem in a small amount of time, even for larger size instances.

Experiments on artificial instances with up to 100 customers are conducted to quantify the value of integration. A first observation is that the service level offered to customers can be increased. An efficient and fast delivery is a competitive advantage. Using an integrated approach, e-commerce companies can allow customers to purchase goods later in time and still deliver these goods in the same time window as goods requested earlier. The time between placing an order and receiving the goods can be shortened.

Second, a lower number of order pickers is needed to pick all orders on time when an integrated approach is applied. Temporary order pickers need to be less often hired in comparison with an uncoordinated approach. In an uncoordinated approach, it is even possible that the problem becomes infeasible due to a lack of order pickers available. In the integrated approach, a feasible solution can be obtained due to a higher flexibility of the start and end times of the order pickers' shift.

Third, costs incurred for drivers waiting at the DC before the actual start of its route are saved in the integrated approach. Drivers arrive at the DC at the actual start time of the delivery route. Thus, by integrating both problems, order picking and delivery operations can be executed in a faster and more cost-efficient way.

In most real-word e-commerce DCs, orders are combined in batches to be picked together in a picking route. The impact of batch picking on the value of integration is studied in the last part of this dissertation. In comparison with a discrete order picking policy, batch picking leads to a lower total time needed to pick all orders. Furthermore, batch picking can result in larger gains obtained by integration compared to discrete order picking, for example, in a dynamic environment or when delivery operations are outsourced to multiple 3PL service providers. In these contexts, the picking process of orders can be postponed in order to be able to combine these postponed orders with orders which are requested later. The system is updated regularly to include newly arrived customer orders in the picking lists and vehicle routes. New batching combinations are created of which some can result in a lower total picking time.

6.2 Managerial implications

The B2C e-commerce market is highly competitive with a large number of online stores. Customers are searching for the cheapest selling price of goods, which are delivered fast and at low cost. To survive in this market, B2C e-commerce companies have to execute their picking and delivery in a cost-efficient way. Throughput times need to be as small as possible. The findings obtained in this dissertation can provide insights for managers, especially but not limited to those working for B2C e-commerce companies.

The analyses executed in this dissertation indicate that integration can lead to higher service levels offered to customers. There is higher flexibility about the start of the picking and delivery operations since no fixed picking due date needs to be respected any longer. Consequently, B2C e-commerce companies can allow customers to purchase their goods later in time and still be delivered within the same time windows as goods ordered earlier. The time between the request of goods and their delivery is shortened. Thus, by integrating order picking and distribution operations, customers can be delivered faster which is an important competitive advantage, especially in the e-commerce market.

Additionally, order picking is the most labour-intensive warehouse activity and thus has a large impact on the costs incurred by an e-commerce company. When order picking and vehicle routing problems are integrated, the number of order pickers needed to pick all goods decreases. Temporary order pickers need to be rarely hired, which leads to savings in costs because these have a higher hourly labour cost. Moreover, since in the integrated approach, no fixed picking due date has to be respected, order picking operations can be more spread over time. The schedules of the order pickers are more balanced over time instead of having a high workload before the picking due date.

In the integrated approach, there is higher flexibility in the departure time of vehicles leaving the DC. The drivers of a 3PL service provider do not arrive at the same fixed time every day. Good communication and coordination between the e-commerce company and the 3PL service operator is indispensable in order to fully benefit from integration. Each driver needs to be informed when to pick up goods at the DC. An information system to collaborate with the 3PL service provider should be implemented in order to efficiently share information.

In short, integrating the order picking and vehicle routing decisions into a single problem can be a useful way to save costs and increase service levels. In the dynamic environment of e-commerce sales, the higher flexibility obtained by integration can be of significant value for e-commerce companies.

6.3 Future research opportunities and critical reflections

The integration of order picking and vehicle routing problems is a relatively new research area. In this dissertation, first insights in the value of the integration are gained. However, many research directions are still open for further research. In this dissertation, a rather basic order picking problem is analysed in the I-OP-VRP. No storage policy or routing policy are included. It is assumed that the storage locations of the goods are considered to be known in advance. The picking times are randomly generated instead of calculating these using a routing policy. The I-OP-VRP studied in this dissertation can be extended with internal warehousing decisions, such as storage assignment, picking routes, zoning, and batching.

In this dissertation, a first exploratory study is conducted to investigate the effect of batch picking on the value of integration. Numerical examples for various problem contexts are provided. Nevertheless, the savings obtained by batch picking are dependent of the batching policy applied in the DC. Therefore, future research should compare the effect of different policies.

In real life, customers can purchase goods at the Internet 24/7. Orders arrive in the system at any moment in time. Demand is not completely known in advance. On a regular basis, the existing picking schedules and vehicle routes are updated to include newly arrived customer orders. Thus, a dynamic order picking problem should be solved simultaneously with a dynamic VRP. Therefore, to convince real-world e-commerce companies of the benefits of integration, more research should be conducted on dynamic integrated order picking-vehicle routing problems. Furthermore, the heuristic algorithm proposed in this dissertation needs to be adapted to be applicable in a dynamic environment handling a large number of orders. The algorithm should be able to deal efficiently with the arrival of new customer orders. In a dynamic and uncertain environment, the solution method should be robust. However, the record-to-record travel algorithm proposed is efficient and fast, and thus can be useful in such a context.

Moreover, B2C e-commerce companies often deliver parcels to a large number of customers in a single vehicle route. To maximise the number of customers that can be delivered within a single route without violating the driver's working hour restriction, the service time needed at each customer location needs to be as small as possible. Therefore, the visiting sequence in a route needs to be taken into account when loading the parcels into the vehicle at the DC. It must be avoided that parcels which are delivered later in the route block the parcels that need to be delivered at a delivery location earlier in the route. Thus, considering loading sequence constraints in integrated order picking-vehicle routing problems can be an interesting future research direction.

The focus of this dissertation is on a B2C e-commerce environment. Nevertheless, the integrated modelling approach can also be applied in a B2B e-commerce environment. The main difference is the average size of an order which is generally larger in a B2B context. Thus, in the I-OP-VRP, the capacity of the picking devices and the vehicles should be enlarged.

Furthermore, the integrated problem investigated and the solution method proposed can be used in other environments as well. Since integration can lead to a shorter time period between the request and the delivery of goods, it can be especially useful in contexts where the throughput time needs to be as small as possible, e.g., in the context of perishable products, such as food.

Appendix A

Detailed results value of integration: Small-size instances

This appendix presents detailed results of the experiments conducted in Chapter 3, in which an uncoordinated and integrated approach are compared for small-size instances. Based on the results of these experiments the value of integration is indicated.

Furthermore, for each different scenario tested, a table with the detailed results per instance is given. Column 1 indicates the instance number. Columns 2 to 6 provide information about the uncoordinated approach. Columns 2 and 3 give the total labour cost of the regular and temporary pickers, respectively. In columns 4 and 5, the total variable travel cost and total fixed vehicle cost is presented, respectively. Column 6 indicates the total cost for the uncoordinated approach. In columns 7 to 11, the results for the integrated approach are presented, and the same information as in columns 2-6 is provided. In the remaining columns, i.e., columns 12-16, the comparison between the two approaches is made for the total cost and each cost component individually. Column 12 represents the savings in total cost which indicate the value of integration. The difference in total picking cost for both types of pickers is presented in columns 13 and 14. The cost changes with respect to the distribution operations are indicated in columns 15 and 16.

Tables A.1-A.3 show the results for the experiments with 10, 15, and 20 customer orders. The impact of other problem characteristics is studied using the instances with 10 customer orders having an order time of 0 and located in a square of 30x30.

The results for the impact of the order time are presented in Tables A.4-A.6. The impact of the cost parameters is indicated in Table A.7 and Table A.8. Finally, the effect of the square size in which the customers are located is shown in Table A.9 and Table A.10.

Table A.1: Detailed results value of integration - 10 customer orders

	Uncoordinated					Integrated									
	OPP		VRP			OPP		VRP							
Inst.	$\sum creg$	$\sum ctemp$	$\sum ctl_v$	$\sum f_v$	TC_{unc}	$\sum creg$	$\sum ctemp$	$\sum ctl_v$	$\sum f_v$	TC_{int}	(a)	(b)	(c)	(d)	(e)
1	185	0	870	350	1,405	185	0	451	350	986	-29.82	0.00	0.00	-48.16	0.00
2	181	0	418	200	799	181	0	344	200	725	-9.26	0.00	0.00	-17.70	0.00
3	194	0	796	350	1,340	194	0	430	350	974	-27.31	0.00	0.00	-45.98	0.00
4	171	0	729	350	1,250	171	0	360	350	881	-29.52	0.00	0.00	-50.62	0.00
5	180	0	399	200	779	180	0	354	200	734	-5.78	0.00	0.00	-11.28	0.00
6	164	0	662	350	1,176	164	0	410	350	924	-21.43	0.00	0.00	-38.07	0.00
7	157	0	435	200	792	157	0	362	200	719	-9.22	0.00	0.00	-16.78	0.00
8	182	0	419	200	801	182	0	348	200	730	-8.86	0.00	0.00	-16.95	0.00
9	168	0	435	200	803	168	0	360	200	728	-9.34	0.00	0.00	-17.24	0.00
10	206	0	437	200	843	206	0	353	200	759	-9.96	0.00	0.00	-19.22	0.00
11	198	0	360	200	758	198	0	313	200	711	-6.20	0.00	0.00	-13.06	0.00
12	182	0	415	150	747	182	0	341	150	673	-9.91	0.00	0.00	-17.83	0.00
13	184	0	423	200	807	184	0	379	200	763	-5.45	0.00	0.00	-10.40	0.00
14	173	0	417	200	790	173	0	284	200	657	-16.84	0.00	0.00	-31.89	0.00
15	193	0	425	200	818	193	0	358	200	751	-8.19	0.00	0.00	-15.76	0.00
16	192	0	429	200	821	192	0	335	200	727	-11.45	0.00	0.00	-21.91	0.00
17	166	0	411	200	777	166	0	381	200	747	-3.86	0.00	0.00	-7.30	0.00
18	190	0	452	200	842	190	0	376	200	766	-9.03	0.00	0.00	-16.81	0.00
19	202	0	419	200	821	202	0	319	200	721	-12.18	0.00	0.00	-23.87	0.00
20	179	0	370	200	749	179	0	300	200	679	-9.35	0.00	0.00	-18.92	0.00
										average	-12.65	0.00	0.00	-22.99	0.00

(a) $\Delta\ TC$ (%) (b) $\Delta\ TC_{cpreg}$(%) (c) $\Delta\ TC_{cptemp}$(%) (d) $\Delta\ TC_{ctl_v}$(%) (e) $\Delta\ TC_{f_v}$(%)

Table A.2: Detailed results value of integration - 15 customer orders

	Uncoordinated					Integrated									
	OPP		VRP			OPP		VRP							
Inst.	$\sum creg$	$\sum ctemp$	$\sum ctl_v$	$\sum f_v$	TC_{unc}	$\sum creg$	$\sum ctemp$	$\sum ctl_v$	$\sum f_v$	TC_{int}	(a)	(b)	(c)	(d)	(e)
1	277	0	435	200	912	277	0	403	200	880	-3.51	0.00	0.00	-7.36	0.00
2	292	0	779	350	1,421	292	0	396	350	1,038	-26.95	0.00	0.00	-49.17	0.00
3	277	0	883	350	1,510	277	0	447	350	1,074	-28.87	0.00	0.00	-49.38	0.00
4	261	0	449	200	910	261	0	390	200	851	-6.48	0.00	0.00	-13.14	0.00
5	292	0	472	200	964	292	0	410	200	902	-6.43	0.00	0.00	-13.14	0.00
6	285	0	416	200	901	285	0	355	200	840	-6.77	0.00	0.00	-14.66	0.00
7	287	0	881	350	1,518	287	0	448	350	1,085	-28.52	0.00	0.00	-49.15	0.00
8	275	0	729	350	1,354	275	0	398	350	1,023	-24.45	0.00	0.00	-45.40	0.00
9	275	0	430	200	905	275	0	395	200	870	-3.87	0.00	0.00	-8.14	0.00
10	296	0	475	200	971	296	0	389	200	885	-8.86	0.00	0.00	-18.11	0.00
11	302	0	441	250	993	302	0	404	250	956	-3.73	0.00	0.00	-8.39	0.00
12	277	0	653	350	1,280	277	0	372	350	999	-21.95	0.00	0.00	-43.03	0.00
13	261	0	459	200	920	261	0	357	200	818	-11.09	0.00	0.00	-22.22	0.00
14	300	0	422	200	922	300	0	392	200	892	-3.25	0.00	0.00	-7.11	0.00
15	273	0	457	200	930	273	0	391	200	864	-7.10	0.00	0.00	-14.44	0.00
16	254	0	692	350	1,296	254	0	395	350	999	-22.92	0.00	0.00	-42.92	0.00
17	262	0	402	200	864	262	0	379	200	841	-2.66	0.00	0.00	-5.72	0.00
18	255	0	408	350	1,013	255	0	380	350	985	-2.76	0.00	0.00	-6.86	0.00
19	279	0	412	200	891	279	0	334	200	813	-8.75	0.00	0.00	-18.93	0.00
20	229	0	463	200	892	229	0	394	200	823	-7.74	0.00	0.00	-14.90	0.00
										average	-11.83	0.00	0.00	-22.61	0.00

(a) $\Delta\ TC$ (%) (b) $\Delta\ TC_{cpreg}$(%) (c) $\Delta\ TC_{cptemp}$(%) (d) $\Delta\ TC_{ctl_v}$(%) (e) $\Delta\ TC_{f_v}$(%)

Table A.3: Detailed results value of integration - 20 customer orders

	Uncoordinated					Integrated									
	OPP		VRP			OPP		VRP							
Inst.	$\sum creg$	$\sum ctemp$	$\sum ctl_v$	$\sum f_v$	TC_{unc}	$\sum creg$	$\sum ctemp$	$\sum ctl_v$	$\sum f_v$	TC_{int}	(a)	(b)	(c)	(d)	(e)
1	390	0	670	350	1,410	390	0	407	350	1,147	-18.65	0.00	0.00	-39.25	0.00
2	373	0	808	350	1,531	373	0	563	350	1,286	-16.00	0.00	0.00	-30.32	0.00
3	399	0	415	250	1,064	399	0	375	250	1,024	-3.76	0.00	0.00	-9.64	0.00
4	396	0	462	250	1,108	396	0	436	250	1,082	-2.35	0.00	0.00	-5.63	0.00
5	321	0	758	350	1,429	321	0	482	350	1,153	-19.31	0.00	0.00	-36.41	0.00
6	367	0	475	250	1,092	367	0	466	250	1,083	-0.82	0.00	0.00	-1.89	0.00
7	337	0	453	250	1,040	337	0	375	250	962	-7.50	0.00	0.00	-17.22	0.00
8	363	0	671	350	1,384	363	0	450	350	1,163	-15.97	0.00	0.00	-32.94	0.00
9	396	0	617	350	1,363	396	0	449	350	1,195	-12.33	0.00	0.00	-27.23	0.00
10	353	0	723	350	1,426	353	0	463	350	1,166	-18.23	0.00	0.00	-35.96	0.00
11	350	0	724	350	1,424	350	0	620	350	1,320	-7.30	0.00	0.00	-14.36	0.00
12	377	0	445	250	1,072	377	0	394	250	1,021	-4.76	0.00	0.00	-11.46	0.00
13	336	0	674	350	1,360	336	0	460	350	1,146	-15.74	0.00	0.00	-31.75	0.00
14	373	0	718	350	1,441	373	0	510	350	1,233	-14.43	0.00	0.00	-28.97	0.00
15	395	0	469	250	1,114	395	0	417	250	1,062	-4.67	0.00	0.00	-11.09	0.00
16	381	0	552	350	1,283	381	0	494	350	1,225	-4.52	0.00	0.00	-10.51	0.00
17	357	0	733	350	1,440	357	0	407	350	1,114	-22.64	0.00	0.00	-44.47	0.00
18	367	0	612	400	1,379	367	0	447	400	1,214	-11.97	0.00	0.00	-26.96	0.00
19	354	0	627	350	1,331	354	0	421	350	1,125	-15.48	0.00	0.00	-32.85	0.00
20	367	0	744	350	1,461	367	0	439	350	1,156	-20.88	0.00	0.00	-40.99	0.00
										average	-11.87	0.00	0.00	-24.50	0.00

(a) $\Delta\ TC$ (%) (b) $\Delta\ TC_{cpreg}$(%) (c) $\Delta\ TC_{cptemp}$(%) (d) $\Delta\ TC_{ctl_v}$(%) (e) $\Delta\ TC_{f_v}$(%)

Table A.4: Detailed results value of integration - order time = 180

	Uncoordinated					Integrated									
	OPP		VRP			OPP		VRP							
Inst.	$\sum creg$	$\sum ctemp$	$\sum ctl_v$	$\sum f_v$	TC_{unc}	$\sum creg$	$\sum ctemp$	$\sum ctl_v$	$\sum f_v$	TC_{int}	(a)	(b)	(c)	(d)	(e)
1	116	103.5	870	350	1,440	185	0	451	350	986	-31.50	59.48	-100.00	-48.16	0.00
2	120	91.5	418	200	830	181	0	344	200	725	-12.60	50.83	-100.00	-17.70	0.00
3	120	111	796	350	1,377	194	0	430	350	974	-29.27	61.67	-100.00	-45.98	0.00
4	120	76.5	729	350	1,276	171	0	360	350	881	-30.93	42.50	-100.00	-50.62	0.00
5	119	91.5	399	200	810	180	0	354	200	734	-9.33	51.26	-100.00	-11.28	0.00
6	120	66	662	350	1,198	164	0	410	350	924	-22.87	36.67	-100.00	-38.07	0.00
7	120	55.5	435	200	811	157	0	362	200	719	-11.29	30.83	-100.00	-16.78	0.00
8	120	93	419	200	832	182	0	348	200	730	-12.26	51.67	-100.00	-16.95	0.00
9	119	73.5	435	200	828	168	0	360	200	728	-12.02	41.18	-100.00	-17.24	0.00
10	120	129	437	200	886	206	0	353	200	759	-14.33	71.67	-100.00	-19.22	0.00
11	120	117	360	200	797	198	0	313	200	711	-10.79	65.00	-100.00	-13.06	0.00
12	120	93	415	150	778	182	0	341	150	673	-13.50	51.67	-100.00	-17.83	0.00
13	120	96	423	200	839	184	0	379	200	763	-9.06	53.33	-100.00	-10.40	0.00
14	120	79.5	417	200	817	173	0	284	200	657	-19.53	44.17	-100.00	-31.89	0.00
15	120	109.5	425	200	855	193	0	358	200	751	-12.11	60.83	-100.00	-15.76	0.00
16	120	108	429	200	857	192	0	335	200	727	-15.17	60.00	-100.00	-21.91	0.00
17	120	69	411	200	800	166	0	381	200	747	-6.63	38.33	-100.00	-7.30	0.00
18	120	105	452	200	877	190	0	376	200	766	-12.66	58.33	-100.00	-16.81	0.00
19	120	123	419	200	862	202	0	319	200	721	-16.36	-68.33	-100.00	-23.87	0.00
20	118	91.5	370	200	780	179	0	300	200	679	-12.89	51.69	-100.00	-18.92	0.00
										average	-15.75	52.47	-100.00	-22.99	0.00

(a) $\Delta\ TC$ (%) (b) $\Delta\ TC_{cpreg}$(%) (c) $\Delta\ TC_{cptemp}$(%) (d) $\Delta\ TC_{ctl_v}$(%) (e) $\Delta\ TC_{f_v}$(%)

Table A.5: Detailed results value of integration - order time = 210

	Uncoordinated					Integrated									
	OPP		VRP			OPP		VRP							
Inst.	$\sum creg$	$\sum ctemp$	$\sum ctl_v$	$\sum f_v$	TC_{unc}	$\sum creg$	$\sum ctemp$	$\sum ctl_v$	$\sum f_v$	TC_{int}	(a)	(b)	(c)	(d)	(e)
1			infeasible			185	0	452	350	987	-	-	-	-	-
2			infeasible			181	0	344	200	725	-	-	-	-	-
3			infeasible			194	0	430	350	974	-	-	-	-	-
4			infeasible			171	0	360	350	881	-	-	-	-	-
5			infeasible			150	45	354	200	749	-	-	-	-	-
6			infeasible			164	0	410	350	924	-	-	-	-	-
7			infeasible			157	0	362	200	719	-	-	-	-	-
8			infeasible			182	0	348	200	730	-	-	-	-	-
9			infeasible			168	0	360	200	728	-	-	-	-	-
10			infeasible			206	0	353	200	759	-	-	-	-	-
11			infeasible			154	66	313	200	733	-	-	-	-	-
12			infeasible			182	0	341	150	673	-	-	-	-	-
13			infeasible			148	54	379	200	781	-	-	-	-	-
14			infeasible			173	0	284	200	657	-	-	-	-	-
15			infeasible			193	0	358	200	751	-	-	-	-	-
16			infeasible			192	0	335	200	727	-	-	-	-	-
17			infeasible			120	69	381	200	770	-	-	-	-	-
18			infeasible			190	0	376	200	766	-	-	-	-	-
19			infeasible			202	0	319	200	721	-	-	-	-	-
20			infeasible			179	0	300	200	679	-	-	-	-	-
										average	-	-	-	-	-

(a) $\Delta\ TC$ (%) (b) $\Delta\ TC_{cpreg}(\%)$ (c) $\Delta\ TC_{cptemp}(\%)$ (d) $\Delta\ TC_{ctl_v}(\%)$ (e) $\Delta\ TC_{f_v}(\%)$

Table A.6: Detailed results value of integration - order time $\in \{0, 60, 120, 180, 210\}$

	Uncoordinated					Integrated									
	OPP		VRP			OPP		VRP							
Inst.	$\sum creg$	$\sum ctemp$	$\sum ctl_v$	$\sum f_v$	TC_{unc}	$\sum creg$	$\sum ctemp$	$\sum ctl_v$	$\sum f_v$	TC_{int}	(a)	(b)	(c)	(d)	(e)
1	170	22.5	870	350	1,413	185	0	451	350	986	-30.19	8.82	-100.00	-48.16	0.00
2	181	0.0	418	200	799	181	0	344	200	725	-9.26	0.00	0.00	-17.70	0.00
3	194	0.0	796	350	1,340	194	0	430	350	974	-27.31	0.00	0.00	-45.98	0.00
4	171	0.0	729	350	1,250	171	0	360	350	881	-29.52	0.00	0.00	-50.62	0.00
5	180	0.0	399	200	779	180	0	354	200	734	-5.78	0.00	0.00	-11.28	0.00
6	164	0.0	662	350	1,176	164	0	410	350	924	-21.43	0.00	0.00	-38.07	0.00
7	157	0.0	435	200	792	157	0	362	200	719	-9.22	0.00	0.00	-16.78	0.00
8	182	0.0	419	200	801	182	0	348	200	730	-8.86	0.00	0.00	-16.95	0.00
9	168	0.0	435	200	803	168	0	360	200	728	-9.34	0.00	0.00	-17.24	0.00
10	206	0.0	437	200	843	206	0	353	200	759	-9.96	0.00	0.00	-19.22	0.00
11	198	0.0	360	200	758	198	0	313	200	711	-6.20	0.00	0.00	-13.06	0.00
12	168	21.0	415	150	754	182	0	341	150	673	-10.74	8.33	-100.00	-17.83	0.00
13	184	0.0	423	200	807	184	0	379	200	763	-5.45	0.00	0.00	-10.40	0.00
14	173	0.0	417	200	790	173	0	284	200	657	-16.84	0.00	0.00	-31.89	0.00
15	193	0.0	425	200	818	193	0	358	200	751	-8.19	0.00	0.00	-15.76	0.00
16	192	0.0	429	200	821	192	0	335	200	727	-11.45	0.00	0.00	-21.91	0.00
17	166	0.0	411	200	777	166	0	381	200	747	-3.86	0.00	0.00	-7.30	0.00
18	190	0.0	452	200	842	190	0	376	200	766	-9.03	0.00	0.00	-16.81	0.00
19	202	0.0	419	200	821	202	0	319	200	721	-12.18	0.00	0.00	-23.87	0.00
20	163	24.0	370	200	757	179	0	300	200	679	-10.30	9.82	-100.00	-18.92	0.00
										average	-12.76	1.35	-15.00	-22.99	0.00

(a) $\Delta\ TC$ (%) (b) $\Delta\ TC_{cpreg}$(%) (c) $\Delta\ TC_{cptemp}$(%) (d) $\Delta\ TC_{ctl_v}$(%) (e) $\Delta\ TC_{f_v}$(%)

Table A.7: Detailed results value of integration - $ctl_v = 1.5$

	Uncoordinated					Integrated									
	OPP		VRP			OPP		VRP							
Inst.	$\sum creg$	$\sum ctemp$	$\sum ctl_v$	$\sum f_v$	TC_{unc}	$\sum creg$	$\sum ctemp$	$\sum ctl_v$	$\sum f_v$	TC_{int}	(a)	(b)	(c)	(d)	(e)
1	185	0	1305	350	1,840	185	0	676.5	350	1,212	-34.16	0.00	0.00	-48.16	0.00
2	181	0	627	200	1,008	181	0	516	200	897	-11.01	0.00	0.00	-17.70	0.00
3	194	0	1194	350	1,738	194	0	645	350	1,189	-31.59	0.00	0.00	-45.98	0.00
4	171	0	1093.5	350	1,615	171	0	540	350	1,061	-34.28	0.00	0.00	-50.62	0.00
5	180	0	598.5	200	979	180	0	531	200	911	-6.90	0.00	0.00	-11.28	0.00
6	164	0	993	350	1,507	164	0	615	350	1,129	-25.08	0.00	0.00	-38.07	0.00
7	157	0	652.5	200	1,010	157	0	543	200	900	-10.85	0.00	0.00	-16.78	0.00
8	182	0	628.5	200	1,011	182	0	370.5	350	903	-10.69	0.00	0.00	-41.05	75.00
9	168	0	652.5	200	1,021	168	0	540	200	908	-11.02	0.00	0.00	-17.24	0.00
10	206	0	655.5	200	1,062	206	0	529.5	200	936	-11.87	0.00	0.00	-19.22	0.00
11	198	0	540	200	938	198	0	469.5	200	868	-7.52	0.00	0.00	-13.06	0.00
12	182	0	622.5	150	955	182	0	511.5	150	844	-11.63	0.00	0.00	-17.83	0.00
13	184	0	634.5	200	1,019	184	0	568.5	200	953	-6.48	0.00	0.00	-10.40	0.00
14	173	0	625.5	200	999	173	0	426	200	799	-19.98	0.00	0.00	-31.89	0.00
15	193	0	637.5	200	1,031	193	0	537	200	930	-9.75	0.00	0.00	-15.76	0.00
16	192	0	643.5	200	1,036	192	0	502.5	200	895	-13.62	0.00	0.00	-21.91	0.00
17	166	0	616.5	200	983	166	0	417	350	933	-5.04	0.00	0.00	-32.36	75.00
18	190	0	678	200	1,068	190	0	564	200	954	-10.67	0.00	0.00	-16.81	0.00
19	202	0	628.5	200	1,031	202	0	478.5	200	881	-14.56	0.00	0.00	-23.87	0.00
20	179	0	555	200	934	179	0	450	200	829	-11.24	0.00	0.00	-18.92	0.00
										average	-14.90	0.00	0.00	-25.45	7.50

(a) $\Delta\ TC$ (%) (b) $\Delta\ TC_{cpreg}$(%) (c) $\Delta\ TC_{cptemp}$(%) (d) $\Delta\ TC_{ctl_v}$(%) (e) $\Delta\ TC_{f_v}$(%)

Table A.8: Detailed results value of integration - $ctl_v = 2$

	Uncoordinated					Integrated									
	OPP		VRP			OPP		VRP							
Inst.	$\sum creg$	$\sum ctemp$	$\sum ctl_v$	$\sum f_v$	TC_{unc}	$\sum creg$	$\sum ctemp$	$\sum ctl_v$	$\sum f_v$	TC_{int}	(a)	(b)	(c)	(d)	(e)
1	185	0	1740	350	2,275	185	0	902	350	1,437	-36.84	0.00	0.00	-48.16	0.00
2	181	0	836	200	1,217	181	0	688	200	1,069	-12.16	0.00	0.00	-17.70	0.00
3	194	0	1592	350	2,136	194	0	578	600	1,372	-35.77	0.00	0.00	-63.69	71.43
4	171	0	1458	350	1,979	171	0	720	350	1,241	-37.29	0.00	0.00	-50.62	0.00
5	180	0	798	200	1,178	180	0	530	350	1,060	-10.02	0.00	0.00	-33.58	75.00
6	164	0	1324	350	1,838	164	0	820	350	1,334	-27.42	0.00	0.00	-38.07	0.00
7	157	0	870	200	1,227	157	0	724	200	1,081	-11.90	0.00	0.00	-16.78	0.00
8	182	0	838	200	1,220	182	0	494	350	1,026	-15.90	0.00	0.00	-41.05	75.00
9	168	0	870	200	1,238	168	0	720	200	1,088	-12.12	0.00	0.00	-17.24	0.00
10	206	0	874	200	1,280	206	0	706	200	1,112	-13.13	0.00	0.00	-19.22	0.00
11	198	0	720	200	1,118	198	0	626	200	1,024	-8.41	0.00	0.00	-13.06	0.00
12	182	0	830	150	1,162	182	0	682	150	1,014	-12.74	0.00	0.00	-17.83	0.00
13	184	0	846	200	1,230	184	0	758	200	1,142	-7.15	0.00	0.00	-10.40	0.00
14	173	0	834	200	1,207	173	0	568	200	941	-22.04	0.00	0.00	-31.89	0.00
15	193	0	850	200	1,243	193	0	552	350	1,095	-11.91	0.00	0.00	-35.06	75.00
16	192	0	858	200	1,250	192	0	670	200	1,062	-15.04	0.00	0.00	-21.91	0.00
17	166	0	822	200	1,188	166	0	556	350	1,072	-9.76	0.00	0.00	-32.36	75.00
18	190	0	904	200	1,294	190	0	594	350	1,134	-12.36	0.00	0.00	-34.29	75.00
19	202	0	838	200	1,240	202	0	638	200	1,040	-16.13	0.00	0.00	-23.87	0.00
20	179	0	740	200	1,119	179	0	600	200	979	-12.51	0.00	0.00	-18.92	0.00
										average	-17.03	0.00	0.00	-29.29	22.32

(a) $\Delta\ TC$ (%) (b) $\Delta\ TC_{cpreg}$(%) (c) $\Delta\ TC_{cptemp}$(%) (d) $\Delta\ TC_{ctl_v}$(%) (e) $\Delta\ TC_{f_v}$(%)

Table A.9: Detailed results value of integration - square = 20x20

	Uncoordinated					Integrated									
	OPP		VRP			OPP		VRP							
Inst.	$\sum creg$	$\sum ctemp$	$\sum ctl_v$	$\sum f_v$	TC_{unc}	$\sum creg$	$\sum ctemp$	$\sum ctl_v$	$\sum f_v$	TC_{int}	(a)	(b)	(c)	(d)	(e)
1	185	0	469	200	854	185	0	414	200	799	-6.44	0.00	0.00	-11.73	0.00
2	181	0	403	200	784	181	0	333	200	714	-8.93	0.00	0.00	-17.37	0.00
3	194	0	436	200	830	194	0	223	350	767	-7.59	0.00	0.00	-48.85	75.00
4	171	0	703	350	1,224	171	0	329	350	850	-30.56	0.00	0.00	-53.20	0.00
5	180	0	397	200	777	180	0	333	200	713	-8.24	0.00	0.00	-16.12	0.00
6	164	0	412	200	776	164	0	356	200	720	-7.22	0.00	0.00	-13.59	0.00
7	157	0	417	200	774	157	0	350	200	707	-8.66	0.00	0.00	-16.07	0.00
8	182	0	406	200	788	182	0	340	200	722	-8.38	0.00	0.00	-16.26	0.00
9	168	0	416	200	784	168	0	345	200	713	-9.06	0.00	0.00	-17.07	0.00
10	206	0	415	200	821	206	0	309	200	715	-12.91	0.00	0.00	-25.54	0.00
11	198	0	347	200	745	198	0	280	200	678	-8.99	0.00	0.00	-19.31	0.00
12	182	0	408	150	740	182	0	339	150	671	-9.32	0.00	0.00	-16.91	0.00
13	184	0	405	200	789	184	0	352	200	736	-6.72	0.00	0.00	-13.09	0.00
14	173	0	386	200	759	173	0	256	200	629	-17.13	0.00	0.00	-33.68	0.00
15	193	0	415	200	808	193	0	348	200	741	-8.29	0.00	0.00	-16.14	0.00
16	192	0	421	200	813	192	0	321	200	713	-12.30	0.00	0.00	-23.75	0.00
17	166	0	410	200	776	166	0	378	200	744	-4.12	0.00	0.00	-7.80	0.00
18	190	0	438	200	828	190	0	371	200	761	-8.09	0.00	0.00	-15.30	0.00
19	202	0	414	200	816	202	0	339	200	741	-9.19	0.00	0.00	-18.12	0.00
20	179	0	372	200	751	179	0	305	200	684	-8.92	0.00	0.00	-18.01	0.00
										average	-10.05	0.00	0.00	-20.90	3.75

(a) $\Delta\ TC$ (%) (b) $\Delta\ TC_{cpreg}$(%) (c) $\Delta\ TC_{cptemp}$(%) (d) $\Delta\ TC_{ctl_v}$(%) (e) $\Delta\ TC_{f_v}$(%)

Table A.10: Detailed results value of integration - square = 40x40

	Uncoordinated					Integrated									
	OPP		VRP			OPP		VRP							
Inst.	$\sum creg$	$\sum ctemp$	$\sum ctl_v$	$\sum f_v$	TC_{unc}	$\sum creg$	$\sum ctemp$	$\sum ctl_v$	$\sum f_v$	TC_{int}	(a)	(b)	(c)	(d)	(e)
1	185	0	896	350	1,431	185	0	492	350	1,027	-28.23	0.00	0.00	-45.09	0.00
2	181	0	423	200	804	181	0	347	200	728	-9.45	0.00	0.00	-17.97	0.00
3	194	0	827	350	1,371	194	0	466	350	1,010	-26.33	0.00	0.00	-43.65	0.00
4	171	0	780	350	1,301	171	0	385	350	906	-30.36	0.00	0.00	-50.64	0.00
5	180	0	730	350	1,260	180	0	391	350	921	-26.90	0.00	0.00	-46.44	0.00
6	164	0	669	350	1,183	164	0	383	350	897	-24.18	0.00	0.00	-42.75	0.00
7	157	0	751	350	1,258	157	0	392	350	899	-28.54	0.00	0.00	-47.80	0.00
8	182	0	432	200	814	182	0	357	200	739	-9.21	0.00	0.00	-17.36	0.00
9	168	0	459	200	827	168	0	391	200	759	-8.22	0.00	0.00	-14.81	0.00
10	206	0	757	350	1,313	206	0	353	350	909	-30.77	0.00	0.00	-53.37	0.00
11	198	0	379	200	777	198	0	320	200	718	-7.59	0.00	0.00	-15.57	0.00
12	182	0	666	350	1,198	182	0	371	350	903	-24.62	0.00	0.00	-44.29	0.00
13	184	0	437	200	821	184	0	367	200	751	-8.53	0.00	0.00	-16.02	0.00
14	173	0	791	350	1,314	173	0	343	350	866	-34.09	0.00	0.00	-56.64	0.00
15	193	0	436	200	829	193	0	348	200	741	-10.62	0.00	0.00	-20.18	0.00
16	192	0	548	350	1,090	192	0	375	350	917	-15.87	0.00	0.00	-31.57	0.00
17	166	0	429	200	795	166	0	388	200	754	-5.16	0.00	0.00	-9.56	0.00
18	190	0	452	200	842	190	0	384	200	774	-8.08	0.00	0.00	-15.04	0.00
19	202	0	556	350	1,108	202	0	399	350	951	-14.17	0.00	0.00	-28.24	0.00
20	179	0	632	350	1,161	179	0	338	350	867	-25.32	0.00	0.00	-46.52	0.00
										average	-18.81	0.00	0.00	-33.18	0.00

(a) $\Delta\ TC$ (%) (b) $\Delta\ TC_{cpreg}(\%)$ (c) $\Delta\ TC_{cptemp}(\%)$ (d) $\Delta\ TC_{ctl_v}(\%)$ (e) $\Delta\ TC_{f_v}(\%)$

Appendix B

Detailed irace results

The irace package[1], developed by López-Ibáñez et al. (2016), is used to tune the parameters of the record-to-record travel algorithm in Chapter 4. For each instance size, a table with more detailed results of the parameter tuning is shown in the following sections. The second column of the table shows the number of parameter configurations sampled at the beginning of each race. From the second race on, the best configurations found (*elite*) in the previous race are used in the next race. The last column of the table indicates the number of configurations which could not be discarded after statistical testing using the Friedman test, which means that the performance of these combinations is not significantly worse than the performance of the elite configurations.

Additionally, for each instance size, a parameter sampling frequency plot is shown. During the iterative tuning process, irace focuses on the best regions for each parameter when sampling new combinations. The frequency plot provides insight in the promising search space for each parameter within the given range. Thus, based on the plots, for each parameter an interval can be determined within which the value of the parameter should be to obtain good results using the RRT algorithm.

[1] More information can be found at http://iridia.ulb.ac.be/irace/, at which a user guide, a tutorial, and examples are provided.

B.1 Detailed irace results for 10 customer order instances

Table B.1: Detailed irace results - 10 customer orders

Race	Number configurations sampled	Number alive at end of race
1	277	175
2	245 + 3 elite	245
3	212 + 3 elite	215

Table B.1 presents detailed information of the iterated racing procedure executed on the instances with 10 customer orders. As can be seen, a high number of configurations are alive at the end of each race. In the last race, no configuration has been discarded. This means that multiple variants of the parameter configuration lead to good results. Figure B.1 indicates the frequency of the parameters sampled, and gives a better idea in which interval the value of each parameter should be. The deviation rate is mainly sampled from the interval (0.13, 0.17). The maximum number of consecutive non-improving iterations should be approximately between 3 and 7. The value of the maximum number of consecutive non-improving moves by an operator is mostly sampled from the interval (8, 12).

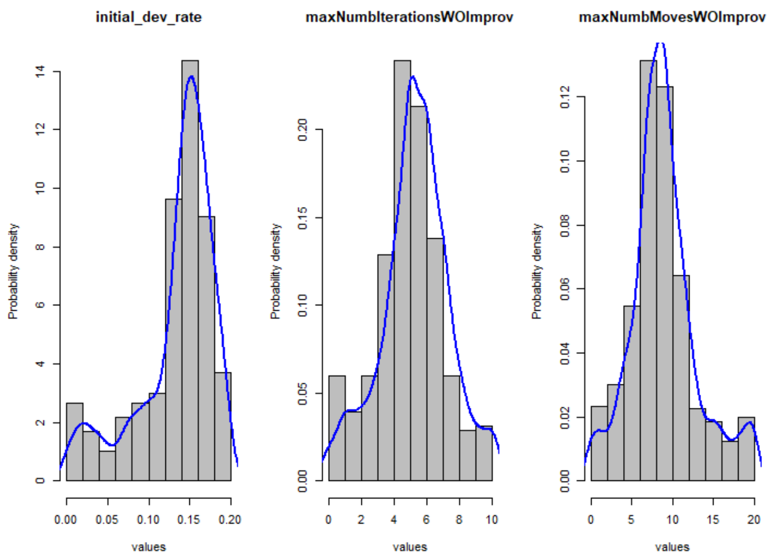


Figure B.1: Parameter sampling frequency - 10 customer orders

B.2 Detailed irace results for 15 customer order instances

Table B.2: Detailed irace results - 15 customer orders

Race	Number configurations sampled	Number alive at end of race
1	277	208
2	242 + 3 elite	237
3	213 + 3 elite	175
4	14 + 3 elite	16

Table B.2 shows similar results as for the instances with 10 customer orders. Figure B.2 presents the sampling frequency for each parameter for the instances with 15 customer orders. To obtain a good solutions, the parameters should have the following values: a deviation rate of approximately 15%, a maximum number of consecutive non-improving iterations of approximately 10, and a maximum number of consecutive non-improving operator moves between 15 and 20.

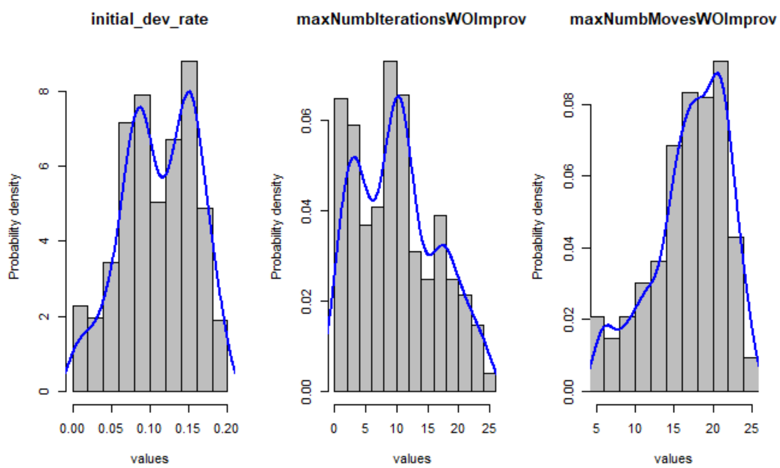


Figure B.2: Parameter sampling frequency - 15 customer orders

B.3 Detailed irace results for 100 customer order instances

Table B.3: Detailed irace results - 100 customer orders

Race	Number configurations sampled	Number alive at end of race
1	111	37
2	85 + 3 elite	48
3	75 + 3 elite	31
4	17 + 3 elite	9
5	4 + 3 elite	6

In Table B.3, it can be seen that in the first four races between 30% and 50% of the configurations survive the statistical test. The parameter frequency plot is shown in Figure B.3. The best parameter value of the deviation rate is approximately 1%. The maximum number of consecutive non-improving iterations has to be close either to the lower bound or to the upper bound of the parameter range. However, the three best elite combinations all have a maximum number of consecutive non-improving iterations of between 25 and 30. The maximum number of consecutive non-improving operator moves should be greater than 25.

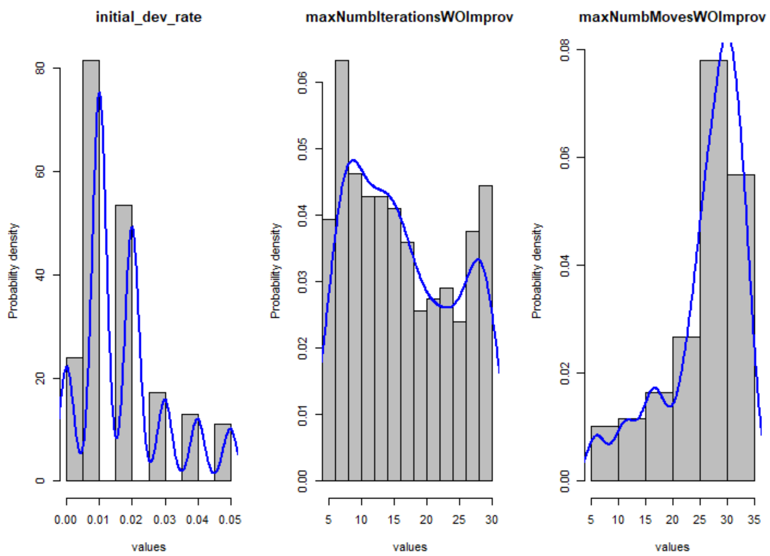


Figure B.3: Parameter sampling frequency - 100 customer orders

Appendix C

Detailed results: Record-to-record travel algorithm

In this appendix, detailed results of the experiments executed in Chapter 4 with both the small-size and large-size instances are presented. For each instance size, a table with the results is given. Only for the small-size instances the optimal solutions are known. Therefore, the tables for the small-size and large-size instances show slightly different information. Column 1 indicates the instance number. For the small-size instances, the optimal solution Z^* found by CPLEX is shown in column 2. The best Z_B^{RRT} and average solution Z_{avg}^{RRT} found by the RRT algorithm are indicated in columns 3 and 4, respectively. Columns 5 and 6 show the average and maximum optimality gap, respectively. In column 7, the solution time for obtaining the optimal solution with CPLEX is presented. Columns 8 and 9 indicate the computation time required by the RRT algorithm for a single run and for 20 runs, respectively.

For the large-size instances, column 2 shows the best solution obtained by the RRT algorithm. The average solution over the 20 runs is indicated in column 3. The average and maximum gap between the heuristic solution and the best heuristic solution is presented in columns 4 and 5, respectively. The average run time and the total computation time is indicated in columns 6 and 7, respectively. The initial objective value $Z[S_0]$ is given in column 8, and the difference between the initial solution value and the best heuristic solution value ($\Delta Z[S_0]$) is indicated in column 9.

C.1 Detailed results for 10 customer orders instances

Table C.1 presents the results of the experiments conducted on the 50 instances with 10 customer orders. As can be seen in the table, the RRT algorithm finds the optimal solution for every instance in each of the 20 replications, as can be seen by the maximum gap of 0.00%. The average computation time to solve the problem to optimality by CPLEX is approximately 3 minutes, while a single replication of the RRT algorithm finds a high-quality solution in 0.0072 seconds on average as shown in columns 8 and 9, respectively.

Table C.1: Detailed results of instances with 10 customer orders with a 15% deviation rate, 700 iterations, and 20 replications

Inst.	Z^*	Z_B^{RRT}	Z_{avg}^{RRT}	avg. gap (%)	max. gap (%)	time (s) CPLEX	avg. time (s) RRT	total time (s) RRT
51	246.71	246.71	246.71	0.00	0.00	37.68	0.0070	0.14
52	285.33	285.33	285.33	0.00	0.00	55.24	0.0075	0.15
53	228.42	228.42	228.42	0.00	0.00	153.52	0.0050	0.13
54	229.10	229.10	229.10	0.00	0.00	38.59	0.0065	0.14
55	268.00	268.00	268.00	0.00	0.00	376.13	0.0070	0.15
56	252.67	252.67	252.67	0.00	0.00	186.48	0.0060	0.13
57	217.87	217.87	217.87	0.00	0.00	53.75	0.0075	0.15
58	245.47	245.47	245.47	0.00	0.00	69.49	0.0065	0.14
59	248.42	248.42	248.42	0.00	0.00	106.83	0.0075	0.15
60	256.77	256.77	256.77	0.00	0.00	129.33	0.0080	0.17
61	266.20	266.20	266.20	0.00	0.00	65.96	0.0070	0.14
62	220.97	220.97	220.97	0.00	0.00	359.50	0.0080	0.16
63	258.08	258.08	258.08	0.00	0.00	1,120.79	0.0080	0.17
64	289.11	289.11	289.11	0.00	0.00	109.54	0.0080	0.16
65	249.19	249.19	249.19	0.00	0.00	67.32	0.0070	0.14
66	227.88	227.88	227.88	0.00	0.00	281.27	0.0085	0.17
67	277.93	277.93	277.93	0.00	0.00	152.33	0.0080	0.17
68	251.54	251.54	251.54	0.00	0.00	100.73	0.0070	0.15
69	254.22	254.22	254.22	0.00	0.00	79.91	0.0070	0.14
70	217.26	217.26	217.26	0.00	0.00	61.34	0.0070	0.14
71	208.99	208.99	208.99	0.00	0.00	667.07	0.0080	0.16
72	259.87	259.87	259.87	0.00	0.00	73.82	0.0070	0.15
73	255.19	255.19	255.19	0.00	0.00	132.44	0.0070	0.14
74	238.78	238.78	238.78	0.00	0.00	94.00	0.0080	0.17
75	240.71	240.71	240.71	0.00	0.00	235.25	0.0070	0.16

Table C.1: (continued)

Inst.	Z^*	Z_B^{RRT}	Z_{avg}^{RRT}	avg. gap (%)	max. gap (%)	time (s) CPLEX	avg. time (s) RRT	total time (s) RRT
76	227.90	227.90	227.90	0.00	0.00	382.86	0.0070	0.17
77	205.39	205.39	205.39	0.00	0.00	232.66	0.0085	0.18
78	261.35	261.35	261.35	0.00	0.00	143.05	0.0070	0.16
79	225.96	225.96	225.96	0.00	0.00	39.43	0.0055	0.13
80	260.25	260.25	260.25	0.00	0.00	32.77	0.0065	0.14
81	245.14	245.14	245.14	0.00	0.00	57.86	0.0050	0.13
82	237.59	237.59	237.59	0.00	0.00	91.91	0.0065	0.14
83	247.83	247.83	247.83	0.00	0.00	53.32	0.0080	0.16
84	225.35	225.35	225.35	0.00	0.00	113.60	0.0070	0.15
85	250.78	250.78	250.78	0.00	0.00	71.23	0.0075	0.16
86	235.42	235.42	235.42	0.00	0.00	76.82	0.0075	0.15
87	253.16	253.16	253.16	0.00	0.00	69.88	0.0075	0.16
88	255.10	255.10	255.10	0.00	0.00	365.93	0.0080	0.16
89	206.96	206.96	206.96	0.00	0.00	1,654.88	0.0090	0.20
90	256.91	256.91	256.91	0.00	0.00	123.35	0.0080	0.16
91	242.99	242.99	242.99	0.00	0.00	53.97	0.0080	0.16
92	259.23	259.23	259.23	0.00	0.00	23.37	0.0065	0.15
93	253.41	253.41	253.41	0.00	0.00	60.23	0.0070	0.16
94	292.19	292.19	292.19	0.00	0.00	24.80	0.0065	0.14
95	269.22	269.22	269.22	0.00	0.00	85.70	0.0080	0.16
96	268.49	268.49	268.49	0.00	0.00	232.60	0.0080	0.17
97	257.36	257.36	257.36	0.00	0.00	51.18	0.0070	0.15
98	253.24	253.24	253.24	0.00	0.00	36.66	0.0065	0.14
99	250.47	250.47	250.47	0.00	0.00	63.44	0.0070	0.15
100	213.56	213.56	213.56	0.00	0.00	68.18	0.0075	0.15
			avg. gap	0.00	avg. time	180.36	0.0072	0.1530

C.2 Detailed results for 15 customer orders instances

In Table C.2, the results of the experiments executed on the 50 instances with 15 customer orders are indicated. For seven instances, the optimal solution could not be obtained with CPLEX within 500 hours. For these instances, the gap between the best solution found by the RRT heuristic and the solution of each run is calculated. In each of the 20 runs, the RRT algorithm obtains the optimal (or best known) solution for every instance, as indicated by the maximum gap of 0.00%. Approximately 63 hours are needed to obtain the optimal solution by CPLEX. The RRT algorithm finds the same solution within a second.

Table C.2: Detailed results of instances with 15 customer orders with a 15% deviation rate, 6,000 iterations, and 20 replications

Inst.	Z^*	Z_B^{RRT}	Z_{avg}^{RRT}	avg. gap (%)	max. gap (%)	time (s) CPLEX	avg. time (s) RRT	total time (s) RRT
51	-	313.69	313.69	0.00	0.00	-	0.2665	5.34
52	287.37	287.37	287.37	0.00	0.00	108,650.00	0.2210	4.42
53	294.64	294.64	294.64	0.00	0.00	396,035.00	0.2370	4.75
54	321.98	321.98	321.98	0.00	0.00	9,275.08	0.2100	4.20
55	316.95	316.95	316.95	0.00	0.00	95,038.70	0.2385	4.77
56	-	312.12	312.12	0.00	0.00	-	0.2635	5.28
57	321.10	321.10	321.10	0.00	0.00	812,810.00	0.2540	5.08
58	326.98	326.98	326.98	0.00	0.00	161,221.00	0.2565	5.13
59	312.27	312.27	312.27	0.00	0.00	137,414.00	0.2445	4.90
60	369.74	369.74	369.74	0.00	0.00	251,960.00	0.2225	4.47
61	306.22	306.22	306.22	0.00	0.00	733,052.00	0.2685	5.38
62	353.06	353.06	353.06	0.00	0.00	88,437.70	0.2050	4.11
63	342.30	342.30	342.30	0.00	0.00	445,411.00	0.2195	4.40
64	-	302.16	302.16	0.00	0.00	-	0.2875	5.76
65	312.63	312.63	312.63	0.00	0.00	40,266.80	0.2335	4.68
66	-	315.76	315.76	0.00	0.00	-	0.2445	4.89
67	273.94	273.94	273.94	0.00	0.00	79,786.00	0.2180	4.36
68	317.44	317.44	317.44	0.00	0.00	79,229.50	0.2310	4.64
69	366.92	366.92	366.92	0.00	0.00	62,590.90	0.2135	4.27
70	313.30	313.30	313.30	0.00	0.00	8,677.67	0.2020	4.04
71	327.10	327.10	327.10	0.00	0.00	65,436.50	0.2040	4.11
72	328.36	328.36	328.36	0.00	0.00	18,406.10	0.2105	4.22
73	339.59	339.59	339.59	0.00	0.00	229,562.00	0.2195	4.40
74	363.12	363.12	363.12	0.00	0.00	249,025.00	0.2585	5.19
75	283.75	283.75	283.75	0.00	0.00	63,330.60	0.2055	4.11

Table C.2: (continued)

Inst.	Z^*	Z_B^{RRT}	Z_{avg}^{RRT}	avg. gap (%)	max. gap (%)	time (s) CPLEX	avg. time (s) RRT	total time (s) RRT
76	353.13	353.13	353.13	0.00	0.00	174,255.00	0.1980	3.97
77	-	336.10	336.10	0.00	0.00	-	0.2120	4.24
78	311.56	311.56	311.56	0.00	0.00	64,534.20	0.2180	4.37
79	332.71	332.71	332.71	0.00	0.00	562,515.00	0.2205	4.42
80	268.33	268.33	268.33	0.00	0.00	1,068,850.00	0.2660	5.33
81	294.96	294.96	294.96	0.00	0.00	92,332.30	0.1880	3.78
82	335.76	335.76	335.76	0.00	0.00	315,838.00	0.2530	5.07
83	332.55	332.55	332.55	0.00	0.00	142,786.00	0.2370	4.76
84	324.25	324.25	324.25	0.00	0.00	95,669.90	0.2275	4.55
85	304.05	304.05	304.05	0.00	0.00	979,171.00	0.2750	5.50
86	325.89	325.89	325.89	0.00	0.00	93,256.20	0.2260	4.54
87	335.29	335.29	335.29	0.00	0.00	63,069.90	0.2075	4.17
88	328.72	328.72	328.72	0.00	0.00	610,314.00	0.2430	4.87
89	345.74	345.74	345.74	0.00	0.00	274,608.00	0.1795	3.59
90	-	313.66	313.66	0.00	0.00	-	0.2565	5.14
91	335.40	335.40	335.40	0.00	0.00	71,796.30	0.2125	4.26
92	306.26	306.26	306.26	0.00	0.00	40,675.30	0.2030	4.08
93	-	310.66	310.66	0.00	0.00	-	0.2335	4.69
94	336.51	336.51	336.51	0.00	0.00	36,700.80	0.2105	4.21
95	318.91	318.91	318.91	0.00	0.00	38,866.10	0.2140	4.28
96	327.13	327.13	327.13	0.00	0.00	21,283.30	0.2020	4.06
97	356.53	356.53	356.53	0.00	0.00	20,238.90	0.2200	4.41
98	340.98	340.98	340.98	0.00	0.00	538,161.00	0.2340	4.70
99	334.61	334.61	334.61	0.00	0.00	250,336.00	0.2215	4.44
100	307.24	307.24	307.24	0.00	0.00	73,973.50	0.2225	4.46
			avg. gap	0.00	avg. time	227,089.45	0.2283	4.5758

C.3 Detailed results for 100 customer orders instances

The detailed results for the large-size instances with 100 customer orders are provided in Table C.3. No optimal solutions are known for these instances. To indicate the impact of the RRT heuristic on the solution, the percentage difference between the initial solution and the best heuristic solution found is provided. The best heuristic solution value found is on average 26.83% better than the initial solution value. The gap between the best objective value found for each instance over the 20 runs and the objective value of the specific run is calculated. The developed RRT heuristic is capable of finding a solution in less than two minutes.

Table C.3: Detailed results of instances with 100 customer orders with a 1% deviation rate, 250,000 iterations, and 20 replications

Inst.	Z_B^{RRT}	Z_{avg}^{RRT}	avg. gap (%)	max. gap (%)	avg. time (s) RRT	total time (s) RRT	$Z[S_0]$	$\Delta Z[S_0](\%)$
51	1,458.82	1,478.55	1.35	3.56	156.60	3,132.06	2,053.63	-28.96
52	1,407.00	1,422.78	1.12	2.36	83.19	1,663.79	1,857.80	-24.27
53	1,453.03	1,473.68	1.42	3.14	119.50	2,389.95	2,176.07	-33.23
54	1,369.58	1,389.41	1.45	2.59	81.21	1,624.27	1,901.33	-27.97
55	1,470.26	1,486.47	1.10	2.49	95.62	1,912.37	2,028.65	-27.53
56	1,424.38	1,439.70	1.08	2.49	115.40	2,307.99	2,017.86	-29.41
57	1,434.37	1,451.31	1.18	3.00	106.44	2,128.85	1,901.34	-24.56
58	1,416.95	1,441.18	1.71	3.17	94.56	1,891.27	1,861.80	-23.89
59	1,434.21	1,454.56	1.42	2.43	101.46	2,029.11	1,911.77	-24.98
60	1,443.20	1,463.40	1.40	2.87	116.41	2,328.27	2,014.80	-28.37
61	1,436.77	1,459.32	1.57	2.44	95.91	1,918.17	2,037.17	-29.47
62	1,486.39	1,506.41	1.35	2.71	87.83	1,756.60	2,009.84	-26.04
63	1,490.26	1,507.73	1.17	2.77	96.51	1,930.24	1,959.02	-23.93
64	1,488.57	1,502.62	0.94	1.74	93.13	1,862.63	1,880.11	-20.83
65	1,406.13	1,431.47	1.80	3.67	99.19	1,983.81	1,940.18	-27.53
66	1,420.86	1,442.93	1.55	3.36	83.98	1,679.58	1,915.89	-25.84
67	1,419.43	1,434.03	1.03	2.31	114.84	2,296.71	1,871.85	-24.17
68	1,421.84	1,443.30	1.51	3.03	91.64	1,832.75	2,082.59	-31.73
69	1,458.22	1,477.97	1.35	2.85	89.86	1,797.25	1,947.93	-25.14
70	1,420.59	1,435.36	1.04	2.44	123.56	2,471.14	2,019.60	-29.66
71	1,380.15	1,397.15	1.23	2.09	88.64	1,772.78	1,895.46	-27.19
72	1,441.83	1,462.05	1.40	2.62	87.86	1,757.21	1,857.22	-22.37
73	1,470.68	1,486.55	1.08	3.15	109.98	2,199.54	1,990.02	-26.10
74	1,488.53	1,523.49	2.35	3.70	123.29	2,465.80	2,019.08	-26.28
75	1,357.69	1,380.34	1.67	3.45	86.65	1,732.92	1,873.76	-27.54

Table C.3: (continued)

Inst.	Z_B^{RRT}	Z_{avg}^{RRT}	avg. gap (%)	max. gap (%)	avg. time (s) RRT	total time (s) RRT	$Z[S_0]$	$\Delta Z[S_0](\%)$
76	1,402.91	1,433.75	2.20	4.13	85.22	1,704.32	1,901.15	-26.21
77	1,440.56	1,456.74	1.12	2.95	129.40	2,588.02	2,076.17	-30.61
78	1,428.18	1,441.08	0.90	2.06	127.77	2,555.48	1,823.25	-21.67
79	1,454.26	1,479.71	1.75	3.51	80.39	1,607.69	2,140.56	-32.06
80	1,472.62	1,491.55	1.29	2.78	95.01	1,900.27	2,019.05	-27.06
81	1,424.00	1,444.62	1.45	3.40	91.44	1,828.77	2,040.38	-30.21
82	1,471.71	1,491.98	1.38	3.15	101.91	2,038.22	2,111.98	-30.32
83	1,447.24	1,471.04	1.64	4.06	98.86	1,977.29	1,993.56	-27.40
84	1,440.92	1,467.12	1.82	3.15	123.18	2,463.56	1,980.48	-27.24
85	1,456.23	1,483.02	1.84	3.74	88.73	1,774.61	1,957.68	-25.61
86	1,418.20	1,441.25	1.63	4.30	88.48	1,769.64	1,885.15	-24.77
87	1,475.02	1,495.62	1.40	2.28	120.74	2,414.80	1,928.36	-23.51
88	1,445.90	1,465.40	1.35	3.50	119.73	2,394.56	2,033.98	-28.91
89	1,474.48	1,491.53	1.16	2.57	80.90	1,618.00	1,907.29	-22.69
90	1,441.21	1,459.20	1.25	2.67	115.33	2,306.69	2,058.66	-29.99
91	1,446.85	1,463.56	1.16	3.18	88.22	1,764.40	2,062.84	-29.86
92	1,401.45	1,424.99	1.68	3.99	83.21	1,664.24	1,926.19	-27.24
93	1,493.03	1,508.89	1.06	2.45	140.29	2,805.75	2,025.27	-26.28
94	1,476.80	1,488.76	0.81	1.84	99.41	1,988.27	1,965.88	-24.88
95	1,422.23	1,435.67	0.95	2.43	80.59	1,611.87	1,959.59	-27.42
96	1,429.75	1,443.46	0.96	1.97	85.49	1,709.78	1,974.58	-27.59
97	1,452.75	1,471.34	1.28	2.39	99.55	1,991.03	1,831.66	-20.69
98	1,469.48	1,486.98	1.19	2.73	93.23	1,864.51	1,907.64	-22.97
99	1,434.58	1,449.64	1.05	2.95	86.91	1,738.15	2,009.33	-28.60
100	1,464.22	1,488.74	1.67	3.12	112.81	2,256.22	2,119.20	-30.91
		avg. gap	1.37	avg. time	101.21	2,024.02	avg. Δ	-26.83

Appendix D

Detailed results batch picking

The impact of implementing a batch picking policy instead of a discrete order picking policy is investigated in Chapter 5. Table D.1 provides detailed results for each instance tested in the experiments. Column 1 indicates the instance number. Columns 2-7 show the results for the I-OP-VRP with a discrete order picking policy, while columns 8-13 provide the results for the I-OP-VRP with a batch picking policy. In columns 2 and 8, the total time to pick all orders is presented. The number of pickers required is indicated in columns 3 and 9. The total labour cost of the order picking subproblem is shown in columns 4 and 10. Columns 5 and 11 present the total cost of the vehicle routing subproblem. The total cost of the integrated probem is shown in columns 6 and 12. The computation times to obtain the optimal solution by CPLEX is indicated in columns 7 and 13. The savings in total picking time needed by implementing a batch picking policy are presented in column 14. Column 15 shows the savings in total cost.

In a discrete order picking policy, on average 1.16 order pickers are required to pick all orders in an individual tour, while with batch picking a single order picker can pick all orders. The picking times decrease with approximately 37% on average, with even savings up to 65%. Savings in total cost of approximately 12% are obtained. Solving an instance with a discrete order picking policy to optimality takes approximately two minutes on average, while the average computation time for an instance with batch picking is two hours.

Detailed results of the experiments executed with the I-OP-VRP in which a batch picking policy is implemented for an uncoordinated and an integrated approach, are provided in Table D.2. For each instance, the costs per component for both the uncoordinated and integrated approach are presented. The difference per cost component are indicated for each instance. On average, integrating order picking and vehicle routing decisions into a single optimisation problem has value of 0.32%. The maximum value of integration obtained in the experiments is 0.93%. Fewer order pickers are required to pick all goods on time. No temporary orders pickers are needed in the integrated approach. The labour costs of the regular order pickers increase, but are compensated by a decrease in the labour costs of the temporary order pickers, which have a higher labour cost per hour.

Table D.1: Detailed results of impact of batch picking

	Discrete order picking						Batch picking							
Inst.	$\sum pt_i$	$\#pickers$	TC_{OPP}	TC_{VRP}	TC_{discr}	Time (s)	$\sum pt_b$	$\#pickers$	TC_{OPP}	TC_{VRP}	TC_{batch}	Time (s)	$\Delta \sum pt(\%)$	$\Delta\ TC(\%)$
1	155	1	64.58	143.08	207.67	8.99	98	1	40.83	143.08	183.92	5,691.10	-36.77	-11.44
2	186	1	77.50	170.44	247.94	44.09	109	1	45.42	170.44	215.85	3,543.16	-41.40	-12.94
3	197	2	82.08	143.67	225.76	358.90	122	1	50.83	143.67	194.51	7,663.89	-38.07	-13.84
4	153	1	63.75	190.75	254.50	95.74	107	1	44.58	190.75	235.34	35,352.20	-30.07	-7.53
5	192	2	80.00	165.85	245.85	197.65	120	1	50.00	165.85	215.85	1,242.23	-37.50	-12.20
6	201	1	83.75	199.78	283.53	22.50	124	1	51.67	199.78	251.45	3,543.50	-38.31	-11.32
7	193	2	80.42	173.12	253.54	41.66	118	1	49.17	173.12	222.29	4,909.63	-38.86	-12.33
8	164	1	68.33	147.76	216.09	311.71	104	1	43.33	147.76	191.09	2,947.42	-36.59	-11.57
9	174	2	72.50	145.97	218.47	171.93	111	1	46.25	145.97	192.22	2,218.70	-36.21	-12.02
10	179	1	74.58	135.14	209.73	408.53	106	1	44.17	135.14	179.31	21,387.10	-40.78	-14.50
11	222	1	92.50	173.62	266.12	94.88	138	1	57.50	173.62	231.12	7,295.57	-37.84	-13.15
12	203	1	84.58	159.12	243.70	198.72	131	1	54.58	159.12	213.70	13,008.40	-35.47	-12.31
13	194	1	80.83	147.69	228.52	68.91	120	1	50.00	147.69	197.69	4,086.31	-38.14	-13.49
14	188	2	78.33	173.32	251.65	1,159.61	117	1	48.75	173.32	222.07	1,395.28	-37.77	-11.76
15	191	1	79.58	169.58	249.16	64.68	120	1	50.00	169.58	219.58	7,695.85	-37.17	-11.87
16	183	1	76.25	174.01	250.26	81.11	64	1	26.67	174.01	200.68	8,424.44	-65.03	-19.81
17	205	1	85.42	174.21	259.63	71.33	112	1	46.67	174.21	220.88	258.72	-45.37	-14.93
18	180	1	75.00	159.97	234.97	100.28	108	1	45.00	159.97	204.97	7,126.33	-40.00	-12.77
19	215	2	89.58	151.67	241.26	152.96	125	1	52.08	151.68	203.76	254.50	-41.86	-15.54
20	174	1	72.50	138.23	210.73	38.52	107	1	44.58	138.23	182.82	8,908.61	-38.51	-13.25
21	185	1	77.50	155.94	233.44	83.35	113	1	47.08	155.94	203.03	9,437.52	-38.92	-13.03
22	184	1	76.67	201.85	278.52	57.17	118	1	49.17	201.85	251.02	5,019.10	-35.87	-9.87
23	168	1	70.00	179.20	249.20	34.72	105	1	43.75	179.20	222.95	6,577.22	-37.50	-10.53
24	166	2	69.17	182.39	251.56	26.42	110	1	45.83	182.39	228.23	7,581.51	-33.73	-9.28
25	191	1	79.58	177.56	257.14	38.98	121	1	50.42	177.56	227.97	2,406.48	-36.65	-11.34

Table D.1: (continued)

	Discrete order picking						Batch picking							
Inst.	$\sum pt_i$	$\#pickers$	TC_{OPP}	TC_{VRP}	TC_{discr}	Time (s)	$\sum pt_b$	$\#pickers$	TC_{OPP}	TC_{VRP}	TC_{batch}	Time (s)	$\Delta \sum pt(\%)$	$\Delta\ TC(\%)$
26	175	1	72.92	154.42	227.33	109.91	110	1	45.83	154.42	200.25	16,492.80	-37.14	-11.91
27	192	1	80.00	168.55	248.55	341.55	123	1	51.25	168.55	219.80	3,890.00	-35.94	-11.57
28	201	1	83.75	133.71	217.46	82.11	131	1	54.58	133.71	188.29	4,993.11	-34.83	-13.41
29	198	1	82.50	197.35	279.85	19.31	131	1	54.58	197.35	251.93	2,521.04	-33.84	-9.98
30	199	1	82.92	194.84	277.75	32.62	124	1	51.67	194.84	246.50	2,393.29	-37.69	-11.25
31	164	1	68.33	154.24	222.58	63.85	111	1	46.25	154.24	200.49	4,895.97	-32.32	-9.92
32	211	1	87.92	143.04	230.95	28.94	124	1	51.67	143.04	194.70	1,552.39	-41.23	-15.70
33	185	1	77.08	141.76	218.85	122.64	126	1	52.50	141.76	194.26	4,268.48	-31.89	-11.23
34	206	2	85.83	178.35	264.19	30.68	137	1	57.08	178.35	235.44	2,177.80	-33.50	-10.88
35	160	1	66.67	157.62	224.29	38.20	102	1	42.50	157.62	200.12	11,686.40	-36.25	-10.77
36	153	1	63.75	166.62	230.37	75.93	99	1	41.25	166.62	207.87	11,102.80	-35.29	-9.77
37	170	1	70.83	183.59	254.42	53.35	119	1	49.58	183.59	233.17	9,854.79	-30.00	-8.35
38	198	1	82.50	211.95	294.45	85.47	114	1	47.50	211.95	259.45	7,018.02	-42.42	-11.89
39	170	1	70.83	139.66	210.49	92.62	107	1	44.58	139.66	184.24	8,783.28	-37.06	-12.47
40	194	1	80.83	184.66	265.50	45.31	126	1	52.50	184.66	237.16	4,378.73	-35.05	-10.67
41	196	1	81.67	152.14	233.80	149.59	122	1	50.83	152.14	202.97	8,579.67	-37.76	-13.19
42	168	1	70.00	138.78	208.78	56.79	108	1	45.00	138.78	183.78	17,942.50	-35.71	-11.97
43	191	1	79.58	160.67	240.25	42.97	120	1	50.00	160.67	210.67	5,859.31	-37.17	-12.31
44	188	1	78.33	134.29	212.62	155.06	119	1	49.58	134.29	183.87	688.34	-36.70	-13.52
45	194	1	80.83	152.36	233.19	139.11	126	1	52.50	152.36	204.86	7,901.81	-35.05	-12.15
46	172	1	71.67	174.99	246.65	93.43	102	1	42.50	174.99	217.49	1,089.12	-40.70	-11.82
47	203	1	84.58	173.76	258.34	64.68	128	1	53.33	173.76	227.09	5,964.13	-36.95	-12.10
48	217	1	90.42	158.34	248.76	84.43	138	1	57.50	158.34	215.84	4,096.82	-36.41	-13.23
49	155	1	64.58	157.09	221.67	43.62	94	1	39.17	157.09	196.26	9,773.96	-39.35	-11.47
50	167	1	69.58	187.99	257.57	105.48	108	1	45.00	187.99	232.99	24,125.60	-35.33	-9.54
	average	1.16			average	121.82	average	1.00			average	7,200.10	-37.60	-12.07

Table D.2: Detailed results value of integration with batch picking

	Uncoordinated					Integrated									
	OPP		VRP			OPP		VRP							
Inst.	$\sum creg$	$\sum ctemp$	$\sum ctl_v$	$\sum ctt_v$	TC_{unc}	$\sum creg$	$\sum ctemp$	$\sum ctl_v$	$\sum ctt_v$	TC_{int}	(a)	(b)	(c)	(d)	(e)
1	40.83	0.00	104.58	38.50	183.92	40.83	0.00	104.58	38.50	183.92	0.00	0.00	0.00	0.00	0.00
2	45.42	0.00	122.92	47.52	215.85	45.42	0.00	122.92	47.52	215.85	0.00	0.00	0.00	0.00	0.00
3	42.50	10.00	105.83	37.84	196.17	50.83	0.00	105.83	37.84	194.51	-0.85	19.61	-100.00	0.00	0.00
4	44.58	0.00	133.33	57.42	235.34	44.58	0.00	133.33	57.42	235.34	0.00	0.00	0.00	0.00	0.00
5	50.00	0.00	118.33	47.52	215.85	50.00	0.00	118.33	47.52	215.85	0.00	0.00	0.00	0.00	0.00
6	42.92	10.50	145.00	54.78	253.20	51.67	0.00	145.00	54.78	251.45	-0.69	20.39	-100.00	0.00	0.00
7	49.58	0.00	122.08	51.04	222.71	49.17	0.00	122.08	51.04	222.29	-0.19	-0.84	0.00	0.00	0.00
8	46.25	0.00	104.17	41.80	192.22	46.25	0.00	104.17	41.80	192.22	0.00	0.00	100.00	0.00	0.00
9	46.25	0.00	104.17	41.80	192.22	46.25	0.00	104.17	41.80	192.22	0.00	0.00	100.00	0.00	0.00
10	44.17	0.00	97.08	38.06	179.31	44.17	0.00	97.08	38.06	179.31	0.00	0.00	0.00	0.00	0.00
11	49.58	9.50	125.00	48.62	232.70	57.50	0.00	125.00	48.62	231.12	-0.68	15.97	-100.00	0.00	0.00
12	47.50	8.50	112.92	46.20	215.12	54.58	0.00	112.92	46.20	213.70	-0.66	14.91	-100.00	0.00	0.00
13	41.67	10.00	108.75	38.94	199.36	50.00	0.00	108.75	38.94	197.69	-0.84	20.00	-100.00	0.00	0.00
14	48.75	0.00	122.50	50.82	222.07	48.75	0.00	122.50	50.82	222.07	0.00	0.00	0.00	0.00	0.00
15	43.75	7.50	122.50	47.08	220.83	50.00	0.00	122.50	47.08	219.58	-0.57	14.29	-100.00	0.00	0.00
16	26.67	0.00	125.83	48.18	200.68	26.67	0.00	125.83	48.18	200.68	0.00	0.00	0.00	0.00	0.00
17	46.67	0.00	126.25	47.96	220.88	46.67	0.00	126.25	47.96	220.88	0.00	0.00	100.00	0.00	0.00
18	45.00	0.00	121.25	38.72	204.97	45.00	0.00	121.25	38.72	204.97	0.00	0.00	0.00	0.00	0.00
19	45.00	8.50	108.33	43.34	205.17	52.08	0.00	108.33	43.34	203.76	-0.69	15.73	-100.00	0.00	0.00
20	44.58	0.00	100.83	37.40	182.82	44.58	0.00	100.83	37.40	182.82	0.00	0.00	0.00	0.00	0.00
21	47.08	0.00	114.58	41.36	203.03	47.08	0.00	114.58	41.36	203.03	0.00	0.00	0.00	0.00	0.00
22	41.67	9.00	143.33	58.52	252.52	49.17	0.00	143.33	58.52	251.02	-0.59	18.00	-100.00	0.00	0.00
23	43.75	0.00	127.50	51.70	222.95	43.75	0.00	127.50	51.70	222.95	0.00	0.00	0.00	0.00	0.00
24	45.83	0.00	133.33	49.06	228.23	45.83	0.00	133.33	49.06	228.23	0.00	0.00	0.00	0.00	0.00
25	42.50	9.50	125.42	52.14	229.56	50.42	0.00	125.42	52.14	227.97	-0.69	18.63	-100.00	0.00	0.00

(a) $\Delta\ TC$ (%) (b) $\Delta\ TC_{cpreg}$(%) (c) $\Delta\ TC_{cptemp}$(%) (d) $\Delta\ TC_{ctl_v}$(%) (e) $\Delta\ TC_{ctt_v}$(%)

Table D.2: (continued)

	Uncoordinated					Integrated									
	OPP		VRP			OPP		VRP							
Inst.	$\sum creg$	$\sum ctemp$	$\sum ctl_v$	$\sum ctt_v$	TC_{unc}	$\sum creg$	$\sum ctemp$	$\sum ctl_v$	$\sum ctt_v$	TC_{int}	(a)	(b)	(c)	(d)	(e)
26	45.83	0.00	110.42	44.00	200.25	45.83	0.00	110.42	44.00	200.25	0.00	0.00	0.00	0.00	0.00
27	43.75	9.00	121.25	47.30	221.30	51.25	0.00	121.25	47.30	219.80	-0.68	17.14	-100.00	0.00	0.00
28	46.67	9.50	99.17	34.54	189.87	54.58	0.00	99.17	34.54	188.29	-0.83	16.96	-100.00	0.00	0.00
29	46.67	9.50	141.25	56.10	253.52	54.58	0.00	141.25	56.10	251.93	-0.62	16.96	-100.00	0.00	0.00
30	46.25	6.50	142.92	51.92	247.59	51.67	0.00	142.92	51.92	246.50	-0.44	11.71	-100.00	0.00	0.00
31	46.25	0.00	109.58	44.66	200.49	46.25	0.00	109.58	44.66	200.49	0.00	0.00	0.00	0.00	0.00
32	42.50	11.00	105.42	37.62	196.54	51.67	0.00	105.42	37.62	194.70	-0.93	21.57	-100.00	0.00	0.00
33	44.58	9.50	104.58	37.18	195.85	52.50	0.00	104.58	37.18	194.26	-0.81	17.76	-100.00	0.00	0.00
34	47.92	11.00	130.83	47.52	237.27	57.08	0.00	130.83	47.52	235.44	-0.77	19.13	-100.00	0.00	0.00
35	42.50	0.00	112.08	45.54	200.12	42.50	0.00	112.08	45.54	200.12	0.00	0.00	0.00	0.00	0.00
36	41.25	0.00	120.42	46.20	207.87	41.25	0.00	120.42	46.20	207.87	0.00	0.00	0.00	0.00	0.00
37	49.58	0.00	131.67	51.92	233.17	49.58	0.00	131.67	51.92	233.17	0.00	0.00	0.00	0.00	0.00
38	40.83	8.00	151.67	60.28	260.78	47.50	0.00	151.67	60.28	259.45	-0.51	16.33	-100.00	0.00	0.00
39	44.58	0.00	102.92	36.74	184.24	44.58	0.00	102.92	36.74	184.24	0.00	0.00	0.00	0.00	0.00
40	45.00	9.00	132.08	52.58	238.66	52.50	0.00	132.08	52.58	237.16	-0.63	16.67	-100.00	0.00	0.00
41	44.58	7.50	107.92	44.22	204.22	50.83	0.00	107.92	44.22	202.97	-0.61	14.02	-100.00	0.00	0.00
42	45.00	0.00	102.92	35.86	183.78	45.00	0.00	102.92	35.86	183.78	0.00	0.00	0.00	0.00	0.00
43	44.17	7.00	116.67	44.00	211.83	50.00	0.00	116.67	44.00	210.67	-0.55	13.21	-100.00	0.00	0.00
44	49.58	0.00	96.67	37.62	183.87	49.58	0.00	96.67	37.62	183.87	0.00	0.00	0.00	0.00	0.00
45	47.92	5.50	107.92	44.44	205.77	52.50	0.00	107.92	44.44	204.86	-0.45	9.56	-100.00	0.00	0.00
46	42.50	0.00	124.17	50.82	217.49	42.50	0.00	124.17	50.82	217.49	0.00	0.00	0.00	0.00	0.00
47	45.83	9.00	122.50	51.26	228.59	53.33	0.00	122.50	51.26	227.09	-0.66	16.36	-100.00	0.00	0.00
48	47.50	12.00	115.00	43.34	217.84	57.50	0.00	115.00	43.34	215.84	-0.92	21.05	-100.00	0.00	0.00
49	39.17	0.00	113.75	43.34	196.26	39.17	0.00	113.75	43.34	196.26	0.00	0.00	0.00	0.00	0.00
50	45.00	0.00	131.67	56.32	232.99	45.00	0.00	131.67	56.32	232.99	0.00	0.00	0.00	0.00	0.00
										average	-0.32	7.70	-46.00	0.00	0.00

(a) $\Delta\ TC$ (%) (b) $\Delta\ TC_{cpreg}$(%) (c) $\Delta\ TC_{cptemp}$(%) (d) $\Delta\ TC_{ctl_v}$(%) (e) $\Delta\ TC_{ctt_v}$(%)

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Samenvatting

In het laatste decennium zijn de Europese e-commerce verkopen jaarlijks gestegen met ongeveer 17%. Steeds meer internetgebruikers kopen producten online. Klanten van webshops kopen frequenter, maar in kleinere hoeveelheden. Bijgevolg stijgt het aantal te verzenden pakjes. Jaarlijks worden in Europa gemiddeld ongeveer 4,2 miljard pakketjes verzonden naar consumenten. Dit toenemende aantal maakt een efficiënte afhandeling van deze pakjes steeds moeilijker.

Bijkomend willen klanten zelf de plaats en het tijdstip van de levering kunnen bepalen. Levering aan huis geniet de voorkeur bij de meerderheid van de klanten. Ten opzichte van het traditionele winkelgedrag waarbij distributiecentra enkel winkels moeten bevoorraden, leidt het aan huis leveren van pakjes tot een grote toename van het aantal leveringsplaatsen. Deze nieuwe distributiekanalen zorgen voor een complexer distributienetwerk.

E-commerce klanten verwachten een snelle en accurate levering binnen een klein tijdsvenster tegen een lage kost of liefst zelfs gratis. Bedrijven beloven hun klanten vaak een levering op dezelfde of de volgende dag. Deze belofte betekent een dubbele logistieke uitdaging voor de bedrijven. Ten eerste, het kunnen omgaan met de stijgende druk op de distributiecentra door een latere *cut-off* tijd, d.i. het tijdstip tot wanneer bestellingen worden aanvaard om nog in deze periode geleverd te kunnen worden. Ten tweede, het creëren van een efficiënt transportnetwerk om de pakjes af te leveren bij de eindconsument.

De hoge verwachtingen van klanten en het toenemend aantal af te handelen pakjes zetten de logistieke activiteiten in de toeleveringsketen onder druk. E-commerce bedrijven moeten hun werkwijze grondig analyseren en herontwerpen. Excellente logistieke prestaties zijn noodzakelijk om op een kostenefficiënte manier aan de eisen van klanten te voldoen. Hiervoor is een goede samenwerking en coördinatie tussen de verschillende stappen in de toeleveringsketen noodzakelijk.

Om te overleven in de e-commerce markt kunnen bedrijven niet langer elke logistieke activiteit afzonderlijk optimaliseren, maar moeten alle activiteiten gezamenlijk geoptimaliseerd worden. Een geïntegreerde kijk op de kritische logistieke beslissingen leidt tot grotere kostenbesparingen en verbeteringen van het dienstverleningsniveau dan het individueel verbeteren van elke logistieke functie. In een e-commerce bedrijf moeten voornamelijk de activiteiten gerelateerd aan de afhandeling van de bestellingen in het distributiecentrum en de levering van de goederen zo optimaal mogelijk op elkaar afgestemd worden. Hiervoor is nood aan geïntegreerde beslissingsondersteunende modellen.

Traditioneel worden in de wetenschappelijke literatuur de verschillende functies van een toeleveringsketen afzonderlijk onderzocht. De verschillende logistieke problemen worden sequentieel opgelost. De resultaten van het ene probleem worden gebruikt als invoergegevens voor het andere probleem. Deze sequentiële, ongecoördineerde aanpak leidt echter tot suboptimale oplossingen, aangezien de vereisten en beperkingen van het andere probleem genegeerd worden.

Het gecoördineerd oplossen van verschillende functies van een toeleveringsketen wordt gezien als één van de belangrijkste trends in de logistieke wereld. In deze doctoraatsthesis worden beslissingen omtrent order picking en rittenplanning gecombineerd in een geïntegreerd optimalisatieprobleem. Onder order picking wordt het verzamelen van de bestelde producten in het distributiecentrum verstaan. Een rittenplanning beschrijft de routes die afgelegd moeten worden om alle goederen tijdig tot bij de eindconsument te brengen.

Het doel van deze doctoraatsthesis is om te onderzoeken wat de voordelen zijn van het integreren van order picking en rittenplanningsbeslissingen in een e-commerce omgeving. Deze thesis levert drie bijdragen aan de wetenschappelijke literatuur. Ten eerste, het introduceren en gedetailleerd beschrijven van het geïntegreerd order picking en rittenplanningsprobleem. Ten tweede, het onderzoeken en meten van de waarde en de voordelen van de integratie van de twee problemen. Ten derde, het voorstellen van een heuristische methode om het probleem in een aanvaardbare tijdspanne op te lossen.

De integratie van deze twee problemen is een relatief nieuw onderzoeksgebied. De meest gerelateerde literatuur onderzoekt de integratie van productie- en rittenplanningsbeslissingen. In het eerste deel van deze doctoraatsthesis wordt een gedetailleerd literatuuroverzicht gegeven van het geïntegreerd productie- en rittenplanningsprobleem. Classificatiematrixen op basis van de belangrijkste productie- en distributie-eigenschappen worden opgesteld. In deze matrixen worden voor elk gerelateerd wetenschappelijk artikel de eigenschappen aangeduid die hierin in beschouwing zijn genomen.

De basisconcepten van productieplanning en order picking tonen veel overeenkomsten. Bijgevolg kunnen de eerder vermelde literatuurstudie en de opgestelde classificatiematrixen als startbasis dienen voor het onderzoek naar geïntegreerde order picking en rittenplanningsproblemen. Interessante onderzoekspistes voor toekomstig onderzoek worden geïdentificeerd dewelke gebruikt kunnen worden voor het introduceren van een geïntegreerd order picking en rittenplanningsprobleem.

In het tweede deel van deze doctoraatsthesis wordt de integratie van order picking en rittenplanningsbeslissingen in een e-commerce markt onderzocht en geanalyseerd. De meeste studies gepubliceerd over het integreren van order picking beslissingen met distributiebeslissingen veronderstellen eenvoudige leveringsmethoden zoals het individueel leveren van elke afzonderlijke klant vanuit het distributiecentrum. Op deze manier moeten geen routes bepaald worden, aangezien het om een heen-en-terug transport tussen de klant en het distributiecentrum gaat. In dit doctoraatsonderzoek wordt de distributie uitgebreid naar een rittenplanningsprobleem.

Eerst wordt een gedetailleerde beschrijving van het geïntegreerde probleem gegeven. Vervolgens worden wiskundige formuleringen opgesteld voor zowel het individuele order picking probleem en rittenplanningsprobleem alsook voor het geïntegreerde probleem. Voor kleine problemen tot 20 klanten wordt de optimale oplossing gevonden met behulp van een optimalisatiesoftware. Een sensitiviteitsanalyse wordt uitgevoerd op deze kleine problemen om de impact van verschillende probleemeigenschappen op de waarde van integratie te onderzoeken. De variabele verplaatsingskost en de grootte van het distributiegebied zijn positief gerelateerd aan de waarde van integratie. Het effect van het aantal klanten is niet eenduidig.

Het optimaal oplossen met een optimalisatiesoftware is enkel mogelijk in een aanvaardbare tijd voor kleine problemen. Voor problemen met een hoger aantal klanten is een exacte methode niet meer toepasbaar binnen een redelijke tijd. Hiervoor moet een heuristisch algoritme ontwikkeld worden. In deze doctoraatsthesis wordt een *record-to-record travel* algoritme voorgesteld om het geïntegreerd probleem op te lossen.

Met behulp van de voorgestelde heuristiek wordt de waarde van integratie ook voor grotere artificiële problemen onderzocht. Een eerste vaststelling is dat het dienstverleningsniveau dat e-commerce bedrijven kunnen bieden aan hun klanten verhoogd kan worden door integratie. De tijdspanne tussen het moment van aankoop door de klant en de levering van de bestelde goederen kan verkort worden. E-commerce bedrijven kunnen hierdoor hun klanten de mogelijkheid bieden om hun bestelling later te plaatsen en de producten toch nog te leveren binnen dezelfde tijdsvensters als producten die eerder besteld werden. Het efficiënt en snel leveren van producten is een belangrijk competitief voordeel voor e-commerce bedrijven.

Een tweede vaststelling is dat een lager aantal order pickers nodig is in het geïntegreerd probleem om alle bestellingen op tijd af te handelen in het distributiecentrum. Minder tijdelijke order pickers moeten ingehuurd worden in vergelijking met een niet-geïntegreerde aanpak. De kans om een toegelaten oplossing te vinden is groter wanneer een geïntegreerde methode wordt gebruikt. Wanneer beide problemen geïntegreerd worden, is er meer flexibiliteit over de start en het einde van de werktijd van de order pickers.

Een laatste vaststelling is dat kosten verbonden aan wachttijden voor de start van een route vermeden kunnen worden door integratie. Chauffeurs komen aan bij het distributiecentrum net op het moment dat de voertuigen geladen moeten worden. Op deze manier worden chauffeurs enkel betaald voor de effectieve tijd die ze werken. In een niet-geïntegreerde aanpak komen chauffeurs elke dag aan op een vast tijdstip bij het distributiecentrum. Hierdoor moeten ze vaak wachten vooraleer effectief te vertrekken om zo de tijdsvensters van de klanten te respecteren.

Algemeen kan dus besloten worden dat door integratie van order picking en rittenplanningsproblemen zowel het dienstverleningsniveau verbeterd kan worden alsook de totale kosten kunnen dalen. De integratie zorgt ervoor dat deze logistieke activiteiten op een snellere en kostenefficiëntere manier uitgevoerd kunnen worden.

Publications and conference participations

Journal publications

Moons, S., Ramaekers, K., Caris, A., Arda, Y., 2017. Integrating production scheduling and vehicle routing decisions at the operational decision level: A review and discussion. Computers & Industrial Engineering, 104, 224-245. doi:10.1016/j.cie.2016.12.010

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Conference participations

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Ramaekers, K., Caris, A., Moons, S., 2018. Using an integrated order picking-vehicle routing problem to study the impact of delivery time windows in e-commerce. In: Nectar Cluster 3 “Logistics and Freight” meeting on “The future of Freight Transport”, Venice, Italy, 8-9 March, 2018.