JOYDEEP PAUL

Online Grocery Operations in Omni-channel Retailing

Opportunities and Challenges

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- Opportunities and Challenges

Online Grocery Operations in Omni-channel Retailing - Opportunities and Challenges

Online supermarktlogistiek in omni-channel detailhandel - Kansen en Uitdagingen

Thesis

to obtain the degree of Doctor from the

Erasmus University Rotterdam

by command of the

rector magnificus

Prof.dr. A.L. Bredenoord

and in accordance with the decision of the Doctorate Board

The public defense shall be held on

10 March 2022 at 13:00 hrs

by

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Erasmus Research Institute of Management – ERIM

The joint research institute of the Rotterdam School of Management (RSM)

and the Erasmus School of Economics (ESE) at the Erasmus University Rotterdam

Internet: http://www.erim.eur.nl

ERIM Electronic Series Portal: http://repub.eur.nl/

ERIM PhD Series in Research in Management, 541

ERIM reference number: EPS-2022-541-LIS

ISBN 978-90-5892-627-2

Cover image: Marijke van Zuilen, marijkevanzuilen@gmail.com

Design: PanArt, www.panart.nl

Print: OBT bv, www.obt.eu

This publication (cover and interior) is printed on FSC® paper Magno Satin MC.

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Acknowledgments

"Pursuit of PhD is an enduring and daring adventure". To be or not to be a doctoral student - is a complex decision which has branches from family, friends, colleagues and most importantly yourself. Now, when I am retrospecting my PhD journey, I am very glad that I choose *to be*. The four years as a doctoral student at the Department of Technology & Operations Management, Erasmus University will stay as one of the most enjoyable times of my life. And, I have quite a long list of people to thank for making it happen.

Let me start it off with my sincere thanks to René de Koster, my PhD promotor. Just couple of doors from his office, I would always see him early in the morning when coming to office and also late in the evening when leaving. His passion for research is stimulating. Despite his busy schedule, he always had time when I reached out to him, not only during my time at T9, but also during the ongoing digital setting. His feedback on the papers and thesis has always been to the point and super pragmatic. So, thank you René for your constant support and guidance. I would like to thank late Prof. Leo G. Kroon, who was also my promotor. During the short period of interaction with him, I was really motivated by his precision to details.

Once someone said you cannot graduate until you start hating your phd supervisor. Thankfully I did not have to reach that stage when I am finishing this last bit of my thesis. On the contrary, I consider myself lucky to have Niels Agatz as my supervisor for my PhD. Discussions with him have always been super engaging and interesting be it for research or otherwise (except for the late night hour long whatsapp discussions on variable names). I never felt inhibited to reach out to him for any research or admin issue, all credits to his candid and friendly demeanor. Beyond the T9, I had fun times with Niels, from beaches in Aruba to bad beat in poker. So, thank you Niels for enabling an enjoyable PhD journey.

I am also thankful to Remy Spliet, Martin Savelsbergh and Jan Fransoo for their valuable contributions to the chapters of the thesis and also being part of my doctoral committee.

Remy, I am a big fan of your rigor for accuracy. I will always remember our lengthy discussion on the inclusion and exclusion of the MILP model in the paper. Thanks to Martin, I got a chance to visit my alma mater Georgia Tech again for a super fruitful one month when we almost wrapped up the third chapter of the thesis. I would also thank Jan for hosting me at Hamburg for our work on the the fourth chapter of the thesis. I am also thankful to Prof.dr. Albert Wagelmans, Prof.dr. Catherine Cleophas and Prof.dr. Moritz Fleischmann for agreeing to be part of my doctoral committee.

I would like to thank ERIM and RSM administration for ease of on-boarding from abroad and the continuous support during the PhD journey. Kim and Miho, thank you for patiently responding to my countless queries during the PhD trajectory. Cheryl, Lianne and Carmen: thank you for all the nice department events, fun chats and always ensuring our queries are answered.

Before joining the PhD program in a new country without a single acquaintance, I was a bit apprehensive of life inside and outside the university. However, the four years at T9 at RSM have been extremely enjoyable, and that is because of the wonderful group of people I got to know, of whom some have become friends for life. Special thanks to my dear WakaWaka group with Alp, Arpan, Frankie and Kaveh. From T9 to T4, Smitse to Sports Center, from Panama to Moldova I could not have asked for a better group of people to learn, sport, travel, drink, party, and most importantly be able to spend hours discussing completely random topics. Alp, thank you for being my travel buddy and driver in different continents during the four years. Arpan, thank you for always enlightening me with your information on almost every topic in the world. Frankie, thank you for your legendary parties and your expertise on unconventional things. Kaveh, thank you for always being helpful with your gadget know-how and helping me get the best deal out of KLM customer service. Jenny, our extended WakaWaka member, thank you for the unforgettable Moldovian experience. Finally, I have an answer to your question “dude, when are you going to submit your thesis”.

Ainara, Alberto, Anirudh, Christina, Johann, Joshua, Jun, Sai, Thomas (Breugem), Vikrant - all of you guys have been such an integral part of my PhD journey. A big thank you! I would also like to thank my dearest friend Abhiyan; dude you are not getting your Harvard application money back. Thank you for always motivating me and being available for any discussion any time.

Though PhD journey has been only last few years, my family has been a constant source of support and motivation all along the way. Babu and Maa, I cannot express my gratitude enough for all the love and blessings. Babu, thank you for always believing in me and being the best advocate of my abilities. Maa, you have been the silent force strengthening us through your selfless love. Barda, you have been always a pillar of strength to me. I could always fly high as I knew I had the solid safety net in you. Boudi, thank you for being so caring. Krissh, apple of our eyes, I love you to the moon and back. Last but definitely not the least, Tushi, thank you for your love and support in the last mile of my PhD journey.

Thank you all for making it happen!

Joydeep Paul

Rotterdam, 2021

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1 Introduction

1.1 Motivation

E-grocery has come a long way since its inception in the early 2000s. In the last decade, we have seen a steady growth of e-grocery across different geographies. In western Europe, the average online food sales grew steadily from less than 1 percent to around 5 percent during the 2012-2020 period (Savills Research 2021). The same growth is also seen in the US online grocery retail (Kearney 2015). One the one hand, this growth is fuelled by improved internet penetration, while on the other hand, the convenience of ordering groceries from your couch any time you want and getting it delivered at your doorstep has become increasingly popular among younger generations that grew up with computers and e-commerce (Pymnts.com (2021), ICR (2021)). Time savings, flexibility in time of ordering, convenient price comparison and last but not the least, mere curiosity have been the main drivers for the growth of e-grocery across different consumer demographics (Treder 2021).

More and more grocery retailers are entering the online ecosystem to attract customers with better offering. In the US, Walmart-owned Sam's Club teamed up with Instacart for same-day grocery delivery (Bosa 2018); Target recently acquired Instacart's rival Shipt for $550 million (Laurenthomas 2017) to boost its online offering. Starting off with selling only wine in the early 90s, Tesco and Sainsbury have around 27% and 15% market share of the UK online grocery market, which has currently more than ten billion pounds in yearly sales (Supermarket News (1995), Mintel (2020), Statista (2021a)). Pure-play online retailers like Ocado in the UK, and Picnic in the Netherlands are gaining popularity with their innovative offerings and business models. Huge investments are being made to support online growth of the grocery retail. In the first half of 2021, venture-backed grocery companies have already raised over $10 billion (Browne 2021). Despite the huge investments, it is still uncertain whether or not these companies will ever make profits. According to Luke Jensen, CEO of

Ocado Solutions, “The amount of money that’s being put against this opportunity is grossly disproportionate to the size of the opportunity” (Browne 2021).

Grocery retailers have seen their profitability going down in order to go online (François 2020). Online grocery is a low margin, high cost business. In 2018, online food retailer Ocado reported a loss of £44.4m (BBC 2019). The low volumes of the e-grocery channel are considered the main reason for its low profitability. Groceries are still predominantly purchased in physical stores. In 2019, e-grocery sales was only 3% of total US grocery sales (Solutions 2020). The United Kingdom has the most developed online-grocery market in Europe, with 6.5 to 6.9 percent overall penetration in 2020, compared with 5.0 percent in France, 1.7 percent in Spain, 1.5 percent in Germany, and 0.7 percent in Italy (Günday et al. 2020). The COVID-19 pandemic in early 2020 was a huge impetus for the growth of online grocery, and online grocery sales skyrocketed by around 50%. In UK for instance, e-grocery grew from zero to 7 per cent in the last two decades, but eight weeks into the pandemic, it went from 7 to 13 per cent (Eley and McMorrow 2020). This led to positive profitability of the e-grocery channel of certain retailers (Eley 2021). However, at the same time the huge surge in online sales also brought high cost to expand resources at equal pace. The high cost of fulfillment of e-grocery orders puts additional pressure on the profitability of the e-grocery channel (Bain 2021). Sainsburys chief executive Simon Roberts summed the situation up, saying Covid-19 was “moving sales out of our most profitable convenience channel and driving a huge step-up in online grocery participation, our least profitable channel” (Eley and McMorrow 2020).

Picking a customer order and delivering it to customer’s home are the most expensive parts of the e-grocery distribution model (De Koster (2002), Lummus and Vokurka (2002)). As it is a competitive market, retailers offer home delivery at low or no delivery fee, which is not necessarily equal to the actual costs. In the UK, estimates in 2015 suggest that an average grocery order costs around £15-16, while larger grocery retailers charge around £1-6 per order (Ram (2015), Twentyman (2015)). There is an ongoing competition among retailers to offer cheaper and faster deliveries, irrespective of the actual costs incurred to attract more market share. E-grocery is fundamentally dilutive for the retailers, however they still don’t want to lose a customer to the competitor (Eley 2019). Bernstein et al. (2008) show that offering an online channel does not necessarily lead to higher profits, but it is a strategic necessity to remain competitive in the market. As the retail market is increasingly seeing a shift towards online, the biggest question all retailers are facing is how to bring down the fulfilment costs of the e-grocery channel, while ensuring the best possible delivery proposition.

1.2 E-grocery business models in omni-channel grocery

In current times, grocery is bought both online and in stores, which is forcing retailers to add new channel for consumers. While traditional retailers are going online, pure online players are also working towards a physical presence. This led to the emergence of a multi-channel approach, whereby products or services are sold across various channels, but without any operational or marketing interaction as such among the channels (Beck and Rygl 2015). While offering products via multiple channels proves attractive to consumers, the siloed structure does not help in leveraging the synergy in sales and operation planning that exist between the two channels. Customers also demand a uniform offering of product and price across all channels. This is why, we are seeing a transition from multi-channel to omni-channel retailing, that aims to offer a seamless unified customer experience across every channel. Strang (2013) defines omni-channel retail as "...a kind of boundary-less retail, where the silos between brick-and-mortar, catalog, and Internet retailers have disappeared - at least as far as the consumer is concerned". However, this transformation to omni-channel retail brings several challenges and opportunities in the operational domain (Jasin et al. 2019).

Different delivery and pick-up models have emerged recently with regard to the fulfilment for the e-grocery channel in an omni-channel setting. With growing popularity of omni-channel strategies in the retail industry, stores are not merely a sales channel, but they also take up a fulfillment function for the online channel (Gao and Su 2019). There is an increasing adoption of Buy-Online-Pick-up-in-Stores (BOPS, also referred to as "Click and Collect") among omni-channel retailers, whereby a customer can make an order online and pick up the order in stores. In a BOPS model, customers get the gratification from the immediate access to the product without having to wait for the delivery. While e-grocery started off with a home delivery model, in an omni-channel setting, the BOPS model is also catching up in grocery retail. From the retailer perspective also, it is highly preferred as it is generally less costly than home delivery. Different grocery retailers like Walmart, Costco, and Target have been using their extensive store networks to blend digital and physical shopping experience (Mkansi and Nsakanda 2019). Target, one of the largest retailers in the US, reports that the pick-up in stores by customers is 90% cheaper for them compared to home delivery (Bain 2021).

Despite the overlap of touch points in the fulfilment process of online and offline channels, it is not often that easy to combine the operations seamlessly. Each of the channels have generally decentralized organization structures since they have organically developed their systems and processes independently (Gallino and Moreno (2014), Rigby (2011), Zhang et al. (2010)). Channel integration can also create disadvantages in one channel, thereby offsetting the advantages of another channel (Herhausen et al. (2015), Falk et al. (2007)). As a result, in practice, we see very few retailers having integrated fulfilment approached across multiple channels. It also requires significant investments to align systems and processes in an integrated omni-channel fulfilment. Hence, in order to effectively exploit the synergies in omni-channel, the focus should be on the opportunities to piggyback on existing flows to ensure easier adoption, rather than disrupting the whole existing set up. In our research, we particularly keep this in mind while developing operational models to consolidate distribution flows of e-grocery with store channels. For an omni-channel retailer to be profitable in a relatively high cost, low margin industry like grocery retail, the benefits from the synergy across operations of different channels can significantly improve the profitability.

Cross-channel conflicts also arise in an integrated approach when one channel cannibalizes the sales from other channels (Steinfield 2004). While that limits the cooperation across channels, it also makes it more challenging for an omni-channel retailers to design their omni-channel strategies. Retailers often subsidize delivery fees for e-grocery or offer same-day delivery to attract more customers to the e-grocery channel. Though adding a new online channel may increase the overall market share of the retailer, it may also cannibalize the sales of the store channels. The rise of online is often associated with the demise of store channel, as we have seen with the impact of US-based online retailer Amazon on book stores (Worstall 2012). However, we see a come back of store in some categories in omni-channel era, but for groceries, stores have never disappeared.

1.3 Research Objectives and Methodology

1.3.1 Research Objectives

Our main objective is to **develop quantitative models to explore the opportunities and challenges of operating an e-grocery channel in an omni-channel environment**. First, we study how an omni-channel retailer can reduce fulfilment costs of the e-grocery channel in a buy-online-pick-up-in-store strategy. We specifically focus on achieving synergies with respect to last-mile planning of two different channels of the retailer in a decentralized setting. We build mathematical models that can effectively capture the operational requirements of the two channels for effective collaboration. Through an extensive numerical study on both artificial and realistic instances, we want to analyse the benefits of the collaboration between online and store channels under different settings. Since the benefits are mainly due to reduction of distribution costs, we therefore aim to improve sustainability of last-mile distribution by reducing vehicle emissions.

Alongside these planning aspects, we also focus on the profitability of the home delivery model of the e-grocery channel in omni-channel grocery setting. We aim to study the interactions between the e-grocery and store channels in the grocery retail by building a stylized model combining customer choice behavior and operational cost of e-grocery for home delivery. Our objective is to perform extensive numerical experiments to understand the impact of operational factors on the profitability of the e-grocery channel.

1.3.2 Research Methodology

In this thesis, we investigate three different types of quantitative models to capture the aspects of last mile logistics in omni-channel distribution. For the models developed in Chapter 2 and 3, we propose mathematical programming formulations. We present some analytical results and exact approaches for several special cases. Theoretically, the underlying optimization problem is a variant of the vehicle routing problem. For small instances, we solve the problem exactly using a standard IP solver, while for larger instances we developed efficient heuristics. We benchmark our heuristics with different set of instances and analyse the potential benefits of the models under different settings. We use both artificial and realistic instances in our experiments.

In Chapter 4, we use an attraction demand model to model customer channel choices, while for estimating the distribution costs, we use a continuous approximation model. We use secondary data to estimate the parameters of the model. We numerically solve the resulting integrated non-linear model to find the optimal delivery fees under different settings.

1.4 Outline of the thesis

This thesis consists of 5 chapters. After the introductory chapter, **Chapter 2** describes a new capacity sharing strategy between the e-grocery and store channels in omni-channel retail distribution. We consider the buy-online-pick-up-in-stores model for the online channel. In this setting, these orders are typically served from a dedicated warehouse. This often means that the stores are visited by different vehicles to replenish the store inventory and to supply the pick-up points. Motivated by a collaboration with an omni-channel grocery retailer in the Netherlands, we study how to best share capacity between the routes associated with these different sales channels. We consider the problem of deciding which customer orders to transfer and which to deliver directly such that the total costs are minimized. We present an exact and a heuristic approach to solve this problem. Computational experiments on both real-world and artificial instances show that substantial savings can be achieved by sharing vehicle capacity across different channels. In this chapter, we will answer the following research questions:

- How can we share capacity across e-grocery and store channels in the *buy online and pick up in store* omni-channel model?
- What are the impacts of transfer cost, spare capacity and service cost on the total cost savings?

Chapter 3 extends the concept of the capacity sharing strategy developed in Chapter 2. We use physical stores as transfer points to move demand from the online channel to the offline channel. We study the benefit of exploiting any spare capacity in the vehicles replenishing store inventories to reduce online order fulfillment cost by transferring online orders to these vehicles at one or more of the stores visited. This involves choosing transfer locations and the set of stores whose online orders are transferred at these locations so as to minimize the online order fulfillment cost. We present a mixed integer linear programming model as well as an effective and efficient heuristic for solving this problem. An extensive computational study shows that significant cost benefits to the retailer can be achieved by sharing capacity across the two channels. In this chapter, we will answer the following research questions:

- How can stores be used transfer points to share capacity across channels in the *buy online and pick up in store* omni-channel model?
- What is the impact of operational factors like demand size, transfer costs and store capacity on the total cost savings?

In **Chapter 4**, we take a broader perspective to understand the profitability of the e-grocery channel in an omni-channel setting. In this setting, the customer has the choice to order her groceries from the e-grocery or store channel of the retailer, or use an outside option. We model the consumer demand by using utility functions for each channel. For the e-grocery channel, the main dis-utility is the delivery fee, while for the store channel it is the travel time to the stores. We model the key fulfillment costs viz. picking and distribution costs of the e-grocery channel. Finally, we validate the parameters of the model using values both from literature and industry. In our numerical analysis, we study the impact of household and store densities on the optimal strategies of the omni-channel retailer. In this chapter, we will answer the following research questions:

- How can we model customer choice behavior and operational costs to gain insights into the profitability of e-grocery channel in an omni-channel setting?
- What are the impacts of store density and household density on the optimal market size and profitability?

Finally, **Chapter 5** presents the conclusions and directions for future research.

Research Statement

This thesis was written during my work at Erasmus University Rotterdam as a PhD candidate. This work is part of the research project "Designing sustainable last-mile delivery services in online retail" with project number 438-13-204, which is funded in the "Sustainable Logistics Program" by the Netherlands Organisation for Scientific Research (NWO) and co-funded by Albert Heijn and Ortec. The chapters in this thesis are self-contained papers written independently under the supervision of the doctoral advisors and the other members of the doctoral committee. The author is responsible for formulating research questions, building models, performing numerical experiments and writing all the chapters of this thesis.

Chapter 2: The content of this chapter is based on the paper, *"Shared capacity routing problem - An Omni-channel retail study"*' (Paul et al. 2019b) [1], which is published in the *European Journal of Operational Research.* For this work, I worked with Dr. Niels Agatz, Dr. Remy Spliet and Prof.dr. René de Koster. Industry data used in this paper was provided by a large Dutch grocery retailer.

Chapter 3: This chapter is based on the paper *"Optimizing omni-channel fulfillment with store transfers"* (Paul et al. 2019a) [2], which is published in the *Transportation Research Part B: Methodological.* For this paper, I collaborated with Dr. Niels Agatz and Prof.dr. Martin Savelsbergh.

Chapter 4: This chapter is based on a working paper, *"Towards Profitable Growth in E-Grocery Retailing – the Role of Store and Household Density"*, which is being prepared for submission to a top journal at the time of writing the thesis. For this work, I worked with Dr. Niels Agatz and Prof.dr. Jan Fransoo.

[1] Paul, J., Agatz, N., Spliet, R., & De Koster, R. (2019). Shared capacity routing problem An omni-channel retail study. European Journal of Operational Research, 273(2), 731-739.

[2] Paul, J., Agatz, N., & Savelsbergh, M. (2019). Optimizing omni-channel fulfillment with store transfers. Transportation Research Part B: Methodological, 129, 381-396.

2 Shared Capacity Routing Problem - An Omni-channel Retail Study

2.1 Introduction

With the advent of omni-channel retailing, many traditional retailers are now operating online sales channels next to their regular stores. At the same time, pure-play internet retailers are expanding their physical presence by opening up regular stores (Speculations 2016). An omni-channel service model that is increasingly popular is one that allows customers to buy goods online and then pick them up in a store (Gao and Su 2016). According to a recent report (Jindal 2017), 64 percent of Europe's top 500 retailers offer such an in-store pick-up service. A similar trend is seen in the U.S.A (Rosenblum and Kilcourse 2013).

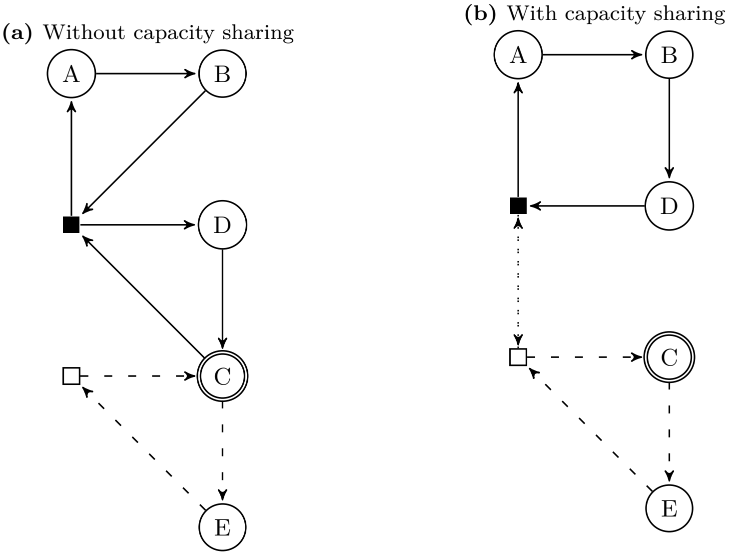
There are different fulfillment strategies for this store pick-up service model. When the number of pick-up orders is small, the goods ordered online can be picked from the store inventory. However, for higher demand volumes, it is often more efficient to pick from a warehouse and then ship to the store (De Koster 2002). The warehouse for online fulfillment is typically different from the warehouse that handles the store replenishment as the different order sizes (item versus pallet) require different layouts and picking processes (De Koster 2002) (Hübner et al. 2016a). Several large retailers, for example, Walmart and Tesco (Bose 2016) (Hübner et al. 2016b) use a dedicated warehouse tailored to handling e-fulfillment orders and a different warehouse for replenishment of stores. In this paper, we focus on this setting in which the pick-up locations at the stores are supplied from one warehouse while the replenishment of the stores is done from a different warehouse.

Our research is motivated by a collaboration with the leading omni-channel grocery retailer in the Netherlands. The retailer has grocery stores that also serve as pick-up point (PUP) for goods ordered online. The PUPs are supplied from a dedicated e-fulfillment warehouse, while the store inventory is replenished from a traditional warehouse. This means that the same stores are currently visited by different vehicles - one for the replenishment of store inventory and one for the supply of the PUP.

In practice, it is often difficult for the retailer to jointly plan the supply of the pick-up points and the replenishment of the stores because of various operational constraints and the cost of synchronizing the different processes. For example, while the replenishment routes need to be planned days in advance to facilitate efficient warehouse operations, the routes to supply the PUPs are planned much later due to their short customer lead-times. Hence, in this paper, we focus on a simple capacity sharing mechanism in which the replenishment routes are fixed in advance and the PUP supply operations can piggyback on those routes.

This works as follows. The retailer fixes the route schedule for the replenishment routes (*fixed* schedule) before planning the routes for the supply of the pick-up points (*flexible* schedule). If there is spare capacity available in the fixed schedule, we can transfer a *shared* customer that is served in both schedules from the flexible schedule to the fixed schedule. The transfer of the relevant customer demands takes place at the transfer point which is for instance the warehouse associated with the fixed schedule. The retailer incurs additional transfer costs to move the load to this transfer point using vehicles with limited capacity. For the capacity sharing to be beneficial, the transfer costs should be less than the savings in the transport costs.

In Figure 2.1, we illustrate this capacity sharing opportunity through an example. When there is no capacity sharing, the flexible schedule needs two vehicles to serve its four customers A, B, C, and D as shown in Figure 2.1a. Customer C is also served in the fixed schedule. The available spare capacity in the fixed schedule makes it possible to *transfer* the shared customer C from the flexible schedule to the fixed schedule. Figure 2.1b shows that as a result, only three customers need to be visited in the flexible schedule, reducing both the travel costs and the number of customer visits. To move the demand of the transferred customers from the depot to the transfer point it requires a transfer trip.



■ : depot, □ : transfer point, ○ : customers, ◎ : shared customer, → : flexible schedule,

--→ : fixed schedule, ←→ : transfer trip

Figure 2.1: Capacity sharing between the fixed and the flexible schedule

In this paper, we introduce the Shared Capacity Routing Problem (SCRP) which aims to design a flexible schedule while potentially making transfer trip(s) to utilize the spare capacity in the fixed schedule, such that total costs are minimized. We specifically focus on investigating the benefits of capacity sharing in different settings.

Our contribution is threefold. First, we describe a new capacity sharing strategy motivated by an application in omni-channel retailing. Secondly, we present an exact and a heuristic approach to solve the associated planning problem. Finally, we present a numerical study to investigate the benefits of the proposed capacity sharing strategy using both real-world and artificial instances.

The remainder of this paper is organized as follows. In the next section, we provide a review of the related literature. In Section 2.3, we formally describe the problem. Section 2.4 provides some theoretical properties that are helpful in designing our solution approaches. In Section 2.5, we present an exact method while in Section 2.6, we describe the heuristic approach to solve the problem. Section 2.7 reports computational results on various instances. Finally, Section 2.8 summarizes our key findings and provides directions for future research.

2.2 Related literature

Conceptually, the SCRP is a selective vehicle routing problem in which only a subset of customers needs to be visited. Most work in this area focuses on settings in which the objective is to maximize the collected profits from the customers given certain constraints on the maximum tour lengths (Archetti et al. 2014). The selective vehicle routing problem is the multi-vehicle version of the selective traveling salesman problem (Laporte and Martello 1990) or the orienteering problem (Golden et al. 1987), where a single vehicle visits a subset of customers to maximize the collection of profits from the customers.

A selective vehicle routing problem that is similar to the SCRP is the vehicle routing problem with private fleet and common carrier (VRPPC). In this problem, there is a penalty cost per customer if it is served by an external carrier, and the objective is to minimize the costs to serve all customers either by the private fleet or by an external carrier (Chu 2005, Bolduc et al. 2008). Most work on the VRPPC is focussed on the design of heuristics with Tabu search (Côté and Potvin 2009, Potvin and Naud 2011) and adaptive variable neighborhood search (Stenger et al. 2013) currently showing the most promising results.

What distinguishes the SCRP from the existing work in the area of selective vehicle routing is that the customers that can be transferred are constrained by the spare capacity in the fixed schedule. Furthermore, the cost and capacity of transfer trips between the depot and the transfer point also play a critical role in deciding which customers will be transferred.

The concept of sharing vehicle capacity is also relevant when we consider independent carriers in a distribution network. Recent work by Fernández et al. (Fernández et al. 2017) considers the centralized planning in a coalition of carriers in which demands of only a limited number of shared customers can be transferred between the carriers. In the SCRP, we also consider a set of shared customers between two distribution channels of a retailer. However, in our setting, the retailer creates the fixed schedule in advance and the spare capacity in the associated fixed routes can be used to serve some shared customers of the flexible schedule. Unlike our paper, Fernández et al. do not specially consider the transfers between the depots of the different carriers.

Research in the collaboration of carriers mostly focusses on the selection of appropriate collaboration partners and mechanisms for exchanging requests among partners (Gansterer and Hartl 2017). Cooperative game theory and combinatorial auctions are used for profit sharing in horizontal collaboration among logistic partners (Krajewska et al. 2008) (Krajewska and Kopfer 2006). These questions are less relevant in our context as our work is motivated by collaboration within a single retailer. We also primarily focus on the question on how to operationally plan the collaboration in order to attain maximum benefits.

2.3 Problem definition

We model the SCRP on a complete directed graph $G = (V, A)$. Here, $V = \{o\} \bigcup N$, where o is the depot and N is the set of customer locations. Each customer $i \in N$ has a demand $q_i \geq 0$, which has to be fulfilled from the depot o. We model two ways in which demand can be fulfilled. Demand of each customer can be fulfilled by direct delivery, and for some customers there is the additional option of fulfilling demand by transferring.

To fulfill demand directly, a sufficient number of vehicles is available, each with capacity Q. We assume $Q \geq q_i, \forall i \in N$. Vehicles are used to drive a *route*, which is a simple cycle in G starting and ending at the depot, and fulfills demand of each customer that is visited along the route. A route is considered feasible if the total demand of the customers that are visited does not exceed the capacity Q. We refer to the each route that we design to fulfill demand directly as a *flexible route* and the set of such routes as the *flexible schedule.* Furthermore, c_{ij} is the cost of traversing an arc $(i, j) \in A$. We assume that c_{ij} satisfies the triangle inequality.

To fulfill demand by transferring, we are given a *fixed schedule.* A fixed schedule represents a separate routing schedule in which deliveries are made, other then the flexible schedule. Let $S \subseteq N$ be a set of customers referred to as *shared customers*, they can be thought of as customers that are also visited in the fixed schedule. Only the orders of these shared customers might be transferred to the fixed schedule. Note that we do not allow splitting of demand while serving a customer, which means that a customer is visited exactly once directly in the flexible schedule or its demand is fully transferred to the fixed schedule.

We represent a fixed schedule as the set routes R, where every route $r \in R$, referred to as *fixed route*, corresponds to a (possibly empty) collection of shared customers $S_r \subseteq S$. We assume all collections S_r to be disjoint. Associated with every fixed route $r \in R$ is a *spare capacity* $E_r \geq 0$, representing the leftover capacity in the vehicle associated with fixed route r. Customers can only be transferred if the spare capacity is not exceeded. That is, a set of customers $T_r \subseteq S_r$ can only be transferred if the total demand of the customers in T_r does not exceed the spare capacity E_r. We refer to such a set T_r as an *r-transfer*. To represent the transfers to all fixed routes, we define a *transfer-set* as a set of customers $T \subseteq S$ which is the union of exactly one r-transfer per route, $T = \bigcup_{r \in R} T_r$.

The demand of the transfer-set customers needs to be transported from the depot to the warehouse associated with the fixed schedule, to transfer the goods to the fixed routes. We refer to this warehouse as the *transfer point*. We use *transfer vehicles* of capacity Q' to make the transfers. A fixed cost F is incurred per transfer trip. Based on the practical case that motivated our research, we make the following assumptions with respect to the transfer trips: (i) There is a sufficient number of transfer vehicles available to move the demands of all transferred customers to the transfer point. (ii) The transfer trips arrive at the transfer point in time to be loaded on to the fixed routes before they depart so we do not have to synchronize the different routes. (iii) Although demand may not be split when serving a customer, it is allowed to split demand of transferred customers on the transfer trips. As a result, for a particular choice of transfer-set T the total transfer costs are given by $F \left\lceil \frac{\sum_{i \in T} q_i}{Q'} \right\rceil$.

As the costs of the fixed schedule are exogenous to the model, the total relevant system costs only include the transfer costs and the routing costs of the customers that are not transferred. The objective of the SCRP is to determine a transfer-set and corresponding routes for non-transferred customers so that the total costs are minimized.

As the SCRP reduces to the vehicle routing problem when there is no spare capacity in fixed routes, the SCRP is NP-hard. The appendix provides a mixed integer linear programming (MILP) formulation for the SCRP based on a two-index formulation for the capacitated VRP (Irnich et al. 2014). In preliminary experiments, we could solve only very small instances with this MILP using the GUROBI solver. In the next section, we discuss theoretical properties of the SCRP which help us to develop our solution strategy for larger instances.

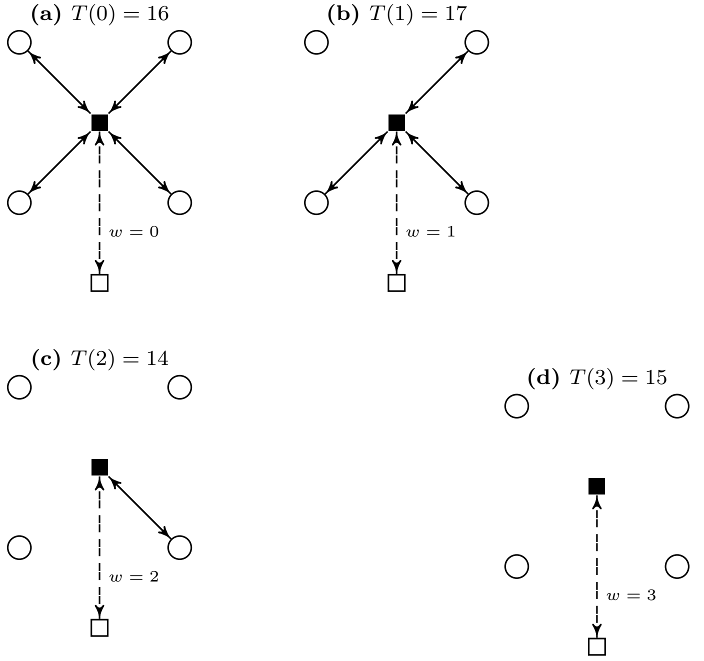
2.4 Theoretical properties

In this section, we present some theoretical properties of the SCRP that help us build our solution strategy. Let w be the number of transfer trips used in a solution and denote by $T(w)$ be the optimal solution value when using exactly w transfers. The associated optimal routing cost for serving all customers that are not transferred is given by $R(w)$, hence $T(w) = R(w) + Fw$.

Proposition 2.4.1. *The optimal cost, $T(w)$, of SCRP is in general neither convex nor concave in w.*

Proof. We prove this proposition by providing an instance for which $T(w)$ is neither convex nor concave in w. Consider an instance with four customers where each of the customers has a demand of $\frac{4}{7}Q$ and the cost of delivering to each of them from the depot is 4. The capacities of the vehicles of the flexible schedule and the transfer vehicles are the same, i.e., $Q = Q'$. The transfer cost per trip F is 5. The spare capacity of the fixed routes is such that all the customers can be transferred. Observe that because demand cannot be split while serving a customer, every non-transferred customer is visited by a separate vehicle.

When $w = 0$, no customers are transferred and every customer is visited by a separate vehicle, hence $T(0) = 16$. For $w = 1$, the optimal decision is to transfer one customer to the fixed schedule, so $T(1) = 17$. In case $w = 2$, three customers can be transferred, now it follows that $T(2) = 14$. Finally, for $w = 3$, it is optimal is to transfer all four customers, hence $T(3) = 15$. We show the optimal solutions when w is fixed to values 0, 1, 2 and 3 in Figure 2.2a, Figure 2.2b, Figure 2.2c and Figure 2.2d respectively. The optimal solution values are plotted in Figure 2.3. Clearly, $T(w)$ is neither convex nor concave for this instance. $\square$



■ : depot, □ : transfer point, ○ : customers, ↔: flexible route, ←→: transfer trip

Figure 2.2: Optimal solutions for our example ($Q' = Q; q_i = \frac{4}{7}Q; F = 5; c_{oi} = 2, \forall i \in N$)

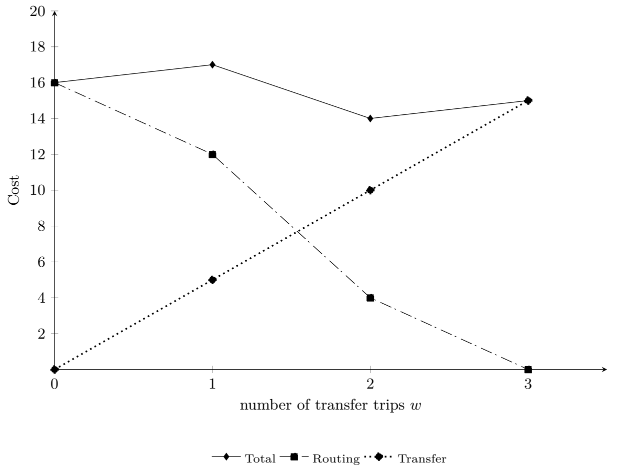


Figure 2.3: Costs of optimal solutions for our example

Since $T(w)$ is in general not convex or concave in w, we pursue an enumerative strategy over w. Next, we show how to bound our search, by defining an upper bound on w.

Proposition 2.4.2. *The following are all upper bounds on w^*, the number of transfer trips in the optimal solution of the SCRP.*

- $UB_1 = \left\lceil \frac{\sum\limits_{r \in R} E_r}{Q'} \right\rceil$,
- $UB_2 = \left\lceil \frac{\sum\limits_{i \in N} q_i}{Q'} \right\rceil$,
- $UB_3 = \left\lfloor \frac{R(0) - R(X)}{F} \right\rfloor$,

where X is an upper bound on w^*, for instance $X = \min\{UB_1, UB_2\}$.

Proof. The total spare capacity in the fixed routes is given by $\sum\limits_{r \in R} E_r$. Since we can split demands in transfer trips, the number of transfer trips required to fully utilize the available spare capacity is $\left\lceil \frac{\sum\limits_{r \in R} E_r}{Q'} \right\rceil$. Hence, $w^* \leq \mathrm{UB}_1$. Similarly, the total transferred demand is limited by $\sum\limits_{i \in N} q_i$, yielding $w^* \leq \mathrm{UB}_2$

Next, we prove that $w^* \leq \mathrm{UB}_3$. As before, denote by $R(w)$ the optimal routing costs when using w transfer trips. Observe that $R(0) \geq R(w^*) + Fw^*$. When the arc costs satisfy the triangle inequality, R is decreasing in w. Therefore, it holds for $X \geq w^*$ that $R(w^*) + Fw^* \geq R(X) + Fw^*$. Combining these observations yields $w^* \leq \left\lfloor \frac{R(0)-R(X)}{F} \right\rfloor$. □

Combining the bounds presented by Proposition 2.4.2, we can bound the optimal number of transfer trips w^* by $\mathrm{UB} = \min(\mathrm{UB}_1, \mathrm{UB}_2, \mathrm{UB}_3)$. Note that UB_1 and UB_2 can be computed efficiently, while computing UB_3 requires solving one VRP ($R(0)$) and one SCRP ($R(X)$) with a given number of transfer trips.

Next, for a fixed number of transfer trips w, we limit the number of transfer-sets that we consider when searching for an optimal solution. We define a transfer-set to be *maximal* if no additional customers can be transferred without violating the available transfer capacity wQ' or the total available spare capacity $\sum_{r \in R} E_r$. We can similarly define maximality of an r-transfer. Note that not all r-transfers that are part of a maximal transfer-set are necessarily maximal themselves.

Proposition 2.4.3. *There exists an optimal solution of the SCRP for which the transfer-set is maximal.*

Proof. Assuming that the triangle inequality holds, we know that the routing cost is decreasing with the number of transferred customers. Hence, if the transfer-set is not maximal, an additional customer demand can be transferred without increasing the costs. □

We can now reformulate our problem in the following way:

$$\min_{0 \le w \le UB} \{Fw + \min_{T \in T_{max}} R(N \backslash T)\}$$

where, T_{max} is the set of all maximal transfer-sets, and $R(S)$ denotes the routing cost for the set of customers S. Next, we present a solution procedure in which we enumerate over all relevant values of w and subsequently solve the subproblem of finding a maximal transfer-set that minimizes the corresponding routing costs.

2.5 Exact solution approach

To solve the problem to optimality, we enumerate the number of transfer trips w from 0 to UB. For each value of w, we enumerate all maximal transfer-sets. Finally, for every maximal transfer-set, we solve the vehicle routing problem (VRP) visiting the non-transferred customers. The best found solution is optimal.

For a given maximal transfer-set, the SCRP reduces to a standard capacitated VRP. We use a standard branch-and-cut procedure to solve the VRP, in which we make use of a 2-index flow formulation including the well known rounded capacity constraints (Irnich et al. 2014). We relax the rounded capacity constraints, identify violated rounded capacity constraints when a feasible integer solution is found and add these to the formulation.

To further speed up our solution procedure, we keep track of the current best solution to the SCRP to terminate the evaluation of certain transfer-sets as follows. If at any stage of the branch-and-cut procedure to solve a VRP, the lower bound plus the transfer costs for the incumbent solution is higher than the current best solution, we discontinue the evaluation of this transfer-set and continue with the next.

2.6 Knapsack-based Heuristic

In the exact approach as described in the previous section, we enumerate all maximal transfer-sets and solve the associated VRP to find the optimal solution. This is not practically feasible for larger instances due to the large number of transfer-sets that need to be evaluated by solving a routing problem. Hence, we develop a heuristic to identify promising transfer-sets and solve the corresponding routing problems. In particular, we present a *knapsack-based* heuristic that aims to find an initial solution by solving a multiple knapsack problem to determine a transfer-set. Subsequently, we implement a local search procedure to improve the initial solution.

2.6.1 Initial solution

Instead of evaluating all maximal transfer-sets, we try to find promising transfer-sets by solving a multiple knapsack problem given the spare capacities in the fixed routes. The main idea is to approximate the savings of transferring customer $i \in N$ and then find the transfer-set that maximizes the approximate total savings. We use the travel cost from the depot to a customer $i \in N$, c_{oi} to approximate the savings of transferring a customer i. The reason for this is that we expect that it would generally be more advantageous to skip customers that are further away from the depot. Preliminary experiments show that this travel cost based approximation measure provides better results than simply maximizing the number of transferred customers or the associated demand volume.

We formulate the corresponding optimization problem as a multiple knapsack problem (Martello and Toth 1981) where the knapsacks correspond to the capacity constraint on the transfer-set, and the capacity constraints on the r-transfers. Let the variable y_i be 1 if customer i is transferred to the fixed schedule, and 0 otherwise. The problem is formulated as follows:

$$
\begin{aligned}
\max \quad & \sum_{i \in N} c_{oi} y_i \\
\text{s.t} \quad & \sum_{i \in S_r} q_i y_i \leq E_r && \forall r \in R && (2.1) \\
& \sum_{i \in N} q_i y_i \leq Q' w && && (2.2) \\
& y_i \in \{0,1\} && && (2.3)
\end{aligned}
$$

The capacity constraints of the fixed routes are captured in constraints (2.1). Constraint (2.2) ensures that the total demand of the transferred customers fits into w transfer vehicles.

As solving a VRP to evaluate the cost of a particular transfer-set is computationally intractable for larger instances, we use our implementation of the adaptive large neighborhood search (ALNS) heuristic by Pisinger and Ropke (Pisinger and Ropke 2007). This approach uses a local search framework based on simulated annealing and several destroy and repair operators.

For each $w = 1, \ldots, UB$, we determine a promising maximal transfer-set by solving the above multiple knapsack problem, and solve the associated VRP to evaluate the transfer-set. The solution with the least total cost, i.e., routing and transfer costs, is chosen.

2.6.2 Improvement phase

To improve the initial solution, we develop a local search heuristic that iterates between an *intensification* phase and a *diversification* phase. In the intensification phase, we improve the solution quality by a neighborhood search procedure. In the diversification phase, we attempt to move away from the local optimum. If the intensification and diversification do not lead to an improvement of the best solution for I iterations, we terminate.

Intensification

At each iteration, we search an r-transfer exchange neighborhood that is specific to our problem. The search continues until no more improving r-transfer exchange is found. For every transfer-set considered during the search, including the initial transfer-set, we use standard 1-point moves and swaps to optimize the corresponding routes. Next, we provide a brief summary of these neighborhoods.

1-point move and swap neighborhood

A 1-point move is a repositioning of a single customer among routes in the solution. Only at initialization of the intensification phase we also consider transferred customers for repositioning. In that case, we do not only consider repositioning customers somewhere in a route but we also consider transferring customers currently included in a route. Similarly, we use swaps to exchange the positions of two customers.

We consider the 1-point move and swap together in a single neighborhood. This means that the best of all possible 1-point moves and swaps across all customers is performed at each iteration.

r-transfer exchange neighborhood

In an *r-transfer exchange*, we exchange an r-transfer T_1 in the current solution with another r-transfer T_2 for fixed route $r \in R$. We perform this exchange as follows. We remove all customers in T_1 and T_2 from the solution. Next, we transfer the customers in T_2. All the remaining customers are inserted to the flexible routes in random order at the cheapest position. Subsequently, we re-optimize the flexible routes with the 1-point move and swaps until no more improvement is found. The difference in the total cost before and after the exchange gives the improvement of the exchange.

The r-transfer exchange corresponding to the best improvement is performed at each iteration.

Diversification

If no more improving moves can be found, we apply a 'destroy and repair' strategy. In particular, we remove m customers from the solution and insert them back to form a feasible solution. The values for m are generated randomly between an instance specific lower and upper limit which depend on the parameters $\delta < 1$, $\gamma < 1$, l and u in the following way:

$$lower = minimum\{\delta|V|, l\} \qquad upper = minimum\{\gamma|V|, u\}$$

This *destroy* operation is similar to the *destroy* operation in the ALNS heuristic by Pisinger and Ropke (Pisinger and Ropke 2007).

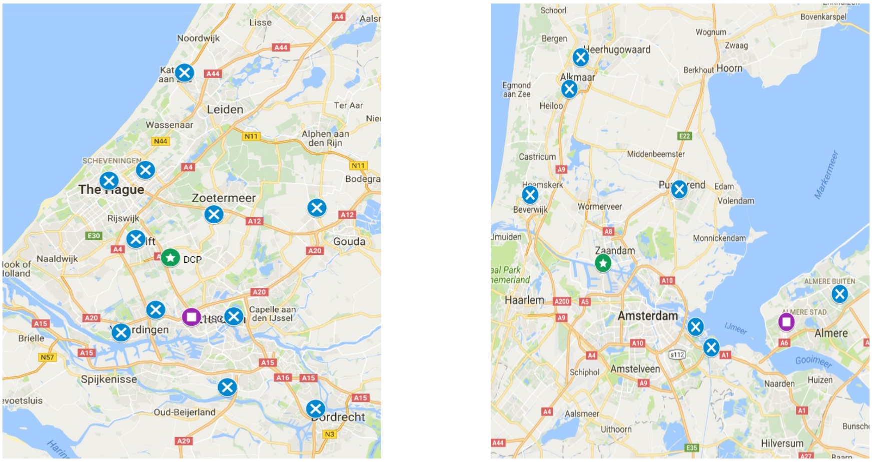
During the repair stage, a customer can either be transferred to the fixed schedule or served in the flexible schedule. If it is feasible to be transferred, we assign it to the fixed schedule with a probability ρ, otherwise we insert the customer at the first position of the first flexible route with sufficient capacity.

2.7 Computational study

In this section, we report the results of our computational experiments. The goal of these experiments is to assess the quality of our heuristics and the benefits of sharing the capacity of the fixed schedule with the flexible schedule under different settings. All algorithms are coded in JAVA and Gurobi 7.0 is used as the MILP solver. The experiments were performed on a laptop computer with an Intel Core i7-4810MQ CPU 2.8 GHz processor.

2.7.1 Real-world case study

To assess the potential savings of our capacity sharing strategy, we apply our model to the distribution network of a large omni-channel grocery retailer in the Netherlands. Some of the retailer's grocery stores also serve as PUP for groceries ordered online. To enable efficient order picking, the PUPs are supplied from one of three e-fulfillment warehouses, while the inventory of the same stores are replenished by one of four regional warehouses.



(a) South-West, 11 stores

(b) North-West, 7 stores

Figure 2.4: Locations of PUPs (cross), Regional (star) and E-fulfillment warehouses (square)

We use route data from ten days in February 2017 for store replenishment and PUP supply for two regions in the Netherlands. Figure 2.4 shows the locations of the regional warehouses, e-fulfillment warehouses and grocery stores in the two regions. Figure 2.4a shows the Southwest region (SW) where there are eleven stores with a PUP that are served in both the channels. Similarly, Figure 2.4b shows the seven PUP stores that are served in both channels in the Northwest region (NW). In this case, the store replenishment takes place before the in-store pick-up points open to the customers, so all transfers are time feasible.

The average store replenishment demand is approximately 40 roll cages. The average demand of a PUP store is around 6 roll cages for the SW case and 10 roll cages for the NW case. All trucks have a capacity of 50 roll cages. The average spare capacity of the replenishment routes is approximately 20%. We set the transfer cost per trip equal to the return distance between the two warehouses. The network structures of the two cases are similar but the transfer costs are significantly different, i.e., 20.8 km for SW and 76 km for NW. To create a benchmark for the case without capacity sharing, we determine the optimal routing costs by solving a VRP in which all *shared* customers, i.e., the stores that have a PUP, are visited in the flexible schedule.

We assume that the transfer trips are done by the same type of vehicles as the PUP deliveries, i.e., $Q' = Q = 50$ roll cages. Since the number of stores is relatively small, we solve the instances using the exact method described in Section 2.5. Table 2.1 shows the results of capacity sharing for the SW and NW cases. We report the savings in routing cost as compared to the costs without capacity sharing while the savings in the number of customer visits is relative to the number of customers (i.e., stores) in the instances.

Table 2.1: Impact of capacity sharing in real-world instances ($F = 20.8$ for SW, $F = 76$ for NW)

Instance	Days with capacity sharing	ΔTransport cost* (%)	ΔCustomer-visit* (%)
SW - 11 stores	10/10	33.4	60.9
NW - 7 stores	4/10	1.6	60.7

*average reduction for instances with capacity sharing

Table 2.1 shows that there are average cost savings of 33.4% for the SW case and only 1.6% for the NW case. Moreover, we see that it is beneficial to consolidate demand by sharing capacity in all ten days in the SW case and only in four out of the ten days in the NW case. One important reason for the different savings is the fact that the transfer distance and the associated transfer costs are much higher for the NW case than for the SW case. This means that the routing costs savings in the NW case are offset by the higher transfer costs. Another reason is that the higher demand per store in the NW case limits the number of possible transfers. In both cases, we do observe around 60% reduction in the number of customer visits for the days with capacity sharing.

Sharing capacity also helps to increase the fill rate of the vehicles that perform the store replenishments. In particular, the fill rate of the vehicles of the fixed schedule increases by 7.4% and 12.1% in the SW and NW instances respectively.

While the current instances are small enough to be solved with our exact approach, the retailer wants to convert many more stores into PUPs which would create larger instances. In the next section, we generate larger instances and test our heuristic.

2.7.2 Generation of artificial instances

We generate artificial instances based on the capacitated VRP instances of (NEO - Networking and Emerging Optimization 2013). In particular, we use these instances to represent the set of shared customers that is served in both the flexible and the fixed schedule. For the flexible schedule, we use the customer demand and vehicle capacities as given in these instances and assume the same capacities for the vehicles for the transfer trips. The best known solutions for these instances represent the benchmark solutions for the situation without capacity sharing.

To create the fixed routes, we specify a maximum number of customers per route (*RouteCap*). We then solve a VRP with the ALNS heuristic as described in Section 2.6.1 to obtain the fixed routes. To generate the spare capacity for each fixed route, we specify the maximum number of customers that can be transferred to each fixed route (*MaxTransfer*). We do this by setting the spare capacity of a route equal to the sum of the demands of the *MaxTransfer* smallest customers from the flexible schedule corresponding to that route. We set the costs per transfer trip to half of the maximum distance between two locations in the graph.

2.7.3 Performance of the Knapsack-based heuristic

To evaluate the performance of our heuristic, we use the VRP instance (Augerat 1995, NEO - Networking and Emerging Optimization 2013) of size 32 (including the depot) for which we are able to find optimal solutions using the exact approach described in Section 2.5. We test our heuristic on different instances generated using different parameter values. In particular, we consider $\mathit{RouteCap} = 2, 3, \ldots, 8$ and relative to this capacity, we use $\mathit{MaxTransfer} = 1, 2, \ldots, \lfloor \frac{\text{RouteCap}}{2} \rfloor$. This means that the maximum number of customers that can be transferred to a fixed route is less than half of the customers in that route. We use three performance measures to evaluate the heuristic: average optimality gap, maximum optimality gap and number of times the optimal solution is found.

Table 2.2 provides the parameter values that are used in the knapsack-based heuristic. The values for the parameters related to the ALNS heuristic are used as reported in (Pisinger and Ropke 2007).

Table 2.2: Parameter settings of the knapsack-based heuristic

Parameters	Description	Values
δ	lower bound parameters on the number	0.1
l	of customers to be removed in the destroy phase	30
γ	upper bound parameters on the number	0.4
u	of customers to be removed in the destroy phase	60
ρ	probability of transferring a customer in the repair stage	0.5
I	number of iterations of the improvement phase	100

Table 2.3: Performance of the knapsack-based heuristic ($|V| = 32$, $Q = Q' = 100$)

RouteCap	*MaxTransfer*	Total possible transfers	Optimality gap (%)	Solution time (s)
2	1	16	1.5	15.1
3	1	11	0.0	19.3
4	1	8	0.0	25.2
	2	16	0.0	28.6
5	1	7	0.0	24.9
	2	13	0.0	18.5
6	1	6	0.0	27.0
	2	11	0.0	19.7
	3	16	0.1	18.9
7	1	5	0.0	34.0
	2	10	0.0	21.1
	3	15	0.0	19.8
8	1	4	0.0	28.7
	2	8	0.0	36.2
	3	12	0.8	31.1
	4	16	0.1	31.1
		Average	**0.2**	**25.0**
		Maximum	**1.5**	**36.2**
		No. of times optimum found	**12/16**	

In Table 2.3, we report the statistics of the solutions obtained by the heuristic for the 16 instances. For each instance, we also report the total maximum number of customers that can be transferred to the fixed schedule.

The table shows that our heuristic provides good quality solutions in reasonable time. The average optimality gap is 0.2%, with a maximum gap of 1.5%. The heuristic finds the optimal solution in 12 out of the 16 instances.

2.7.4 Savings by capacity sharing across different instances

Next, we present the results of the experiments with larger instances using the Knapsack-based heuristic. Similar to Section 2.7.3, we generate the fixed routes for these instances using $RouteCap = 2, 3, 4, 5, 6, 7, 8$ and $MaxTransfer = 1, 2, \dots, \lfloor \frac{\text{RouteCap}}{2} \rfloor$. The total costs of the flexible schedule without capacity sharing and the transfer costs per trip for the instances are given in Table 2.4.

Table 2.4: Description of the instances

Instance	Transport cost (km)	Transfer cost per trip (km)
A-n32-k5	784	64
A-n48-k7	1,073	60
A-n64-k9	1,401	59
A-n80-k10	1,764	69

Table 2.5 shows the relative savings in transport costs and the number of customer-visits due to capacity sharing as compared to the setting without capacity sharing across all instances under different settings. We observe that for a given *RouteCap*, the savings increase with the spare capacity (*MaxTransfer*). Interestingly, the transport costs savings are not proportional to the savings in customer-visits. This is because transferring a single customer that is further away from the depot leads to more transport cost savings than two nearby customers. The instance in which no savings can be achieved indicate that capacity sharing is not always beneficial. That is, even if transfers are feasible, the transfer costs may outweigh the savings in the routing costs.

We see average computation times up to 300 seconds for the largest instance A-n80-k10. Although the number of feasible solutions increases with the spare capacity, we do not see any clear trend with respect to the solution times in this aspect. Note that the improvement phase drives the longer solution times as finding an initial solution is fast in all settings.

2.7.5 Impact of service costs

Thus far, we have primarily focussed on the costs savings related to reducing the total system-wide travel costs. However, there may be other benefits associated with visiting a customer by one vehicle instead of two vehicles. We will refer to these non-distance related costs as service costs. By visiting the customer once instead of twice, it may be possible to save time, e.g., time associated with finding a parking space or waiting at the customer. In this section, we investigate the impact of the potential service cost savings on the solutions of the SCRP.

In our analysis, we focus solely on the service costs that can be avoided by transferring a customer to the fixed schedule. Let τ represent this 'avoidable' service costs per customer. For example, if the total service costs of serving a customer by two vehicles separately is 20 and costs of serving all demands of a customer from both schedules by one vehicle is 15, we can save $\tau = 5$. To normalize the results, we set the value of τ to a percentage of the transfer cost per trip. We use our heuristic to run the experiments on instance A-n48-k7 using *RouteCap*= 6 and *MaxTransfer*= 3.

Table 2.6: Impact of service costs on savings ($Q = Q' = 100, F = 60$)

τ (%)	# of Transfered customers	ΔTransport cost (%)	ΔService cost (%)	ΔTotal cost (%)
0	18	20.9	0.0	20.9
10	21	19.7	44.7	24.9
20	21	19.7	44.7	28.3
30	22	18.2	46.8	30.8
40	23	16.5	48.9	33.1
50	23	17.2	48.9	35.2

Δ denotes reduction here

Table 2.5: Savings (%) by capacity sharing for larger instances

		A-n32-k5			A-n48-k7			A-n64-k9			A-n80-k10		
Route Cap	*Max Transfer*	ΔTransport cost (%)	ΔCustomer -visit (%)	Solution time (s)	ΔTransport cost (%)	ΔCustomer -visit (%)	Solution time (s)	ΔTransport cost (%)	ΔCustomer -visit (%)	Solution time (s)	ΔTransport cost (%)	ΔCustomer -visit (%)	Solution time(s)
2	1	9.9	41.9	15.1	18.8	44.7	31.3	17.7	50.8	82.7	17.8	46.8	255.6
3	1	3.6	35.5	19.3	11.5	27.7	133.4	8.9	33.3	97.3	10.2	25.3	321.4
4	1	1.6	25.8	25.2	5.3	25.5	92.5	6.6	23.8	147.7	6.6	25.3	299.7
	2	11.3	41.9	28.6	20.0	44.7	42.1	16.2	42.9	69.6	17.1	48.1	196.9
5	1	0.0	0.0	24.9	2.6	21.3	93.0	5.1	20.6	203.0	5.5	20.3	285.2
	2	5.9	38.7	18.5	13.8	29.8	88.0	13.0	39.7	111.5	11.3	35.4	187.2
6	1	0.4	19.4	27.0	0.0	0.0	109.8	3.7	17.5	160.0	4.4	17.7	404.4
	2	3.9	35.5	19.7	11.6	29.8	51.5	11.2	27.0	259.8	9.0	29.1	197.7
	3	11.6	32.3	18.9	20.9	38.3	84.7	18.9	41.3	226.1	16.5	44.3	131.9
7	1	0.0	0.0	34.0	0.0	0.0	104.5	1.7	14.3	608.5	3.3	15.2	495.0
	2	2.7	32.3	21.1	9.7	25.5	86.6	7.6	23.8	170.0	8.8	27.8	223.9
	3	11.1	41.9	19.8	15.2	31.9	87.8	15.5	33.3	231.8	12.9	41.8	321.1
8	1	0.0	0.0	28.7	0.0	0.0	84.1	0.4	12.7	170.8	1.4	12.7	357.7
	2	1.5	19.4	36.2	4.8	19.1	76.9	5.8	25.4	208.0	7.2	24.1	268.9
	3	6.7	32.3	31.1	12.2	23.4	106.8	10.5	28.6	250.0	10.2	35.4	340.3
	4	12.4	38.7	31.1	22.4	36.2	75.1	19.6	34.9	206.3	17.2	36.7	496.0
	Average	5.2	27.2	25.0	10.5	24.9	84.2	10.1	29.4	200.2	10.0	30.4	298.9

Δ denotes reduction here

In Table 2.6, we show the solution for different values of τ. To allow a fair comparison with the earlier results, we report the percentage savings in transport cost, service cost and total cost relative to the respective costs when there is no transfer. As expected, we see that the number of transfers increase with the potential service cost savings τ. The results clearly show the trade-off between the transport costs and the service costs. That is, when τ increases, it becomes more beneficial to transfer customers even if this means increasing the routing costs.

Overall, the benefits of capacity sharing increase with the potential service cost savings.

2.8 Conclusion

This paper studies capacity sharing in an omni-channel retail setting. Motivated by a practical problem, we introduce the shared capacity routing problem (SCRP). The presented capacity sharing strategy enables the retailer to make use of the spare capacity in its transport operations to reduce the transport costs and the number of customer visits. We show that our heuristic provides good quality solutions in a reasonable amount of time.

The computational study on the real-life case suggest potential transport cost savings between 2% and 33% by better using the available vehicle capacities in the system. The results show that the transfer costs and the spare capacity are the main drivers of the potential benefits of capacity sharing. The benefits increase with the spare capacity and decrease when the transfer costs increase. Potential service cost savings may further increase the benefits of capacity sharing.

As we are the first to work on this problem, there are still many directions for future research in this area. One potential future research direction is to develop exact solution procedures that can solve larger problem instances. Moreover, an interesting extension of the problem is to consider multiple transfer points instead of a single one. The capacity sharing strategy can also be extended to settings that involve multiple companies, which gives rise to questions related to profit sharing.

Appendix

A mixed integer linear programming formulation

We present a mixed integer linear programming (MILP) formulation for the SCRP. Let the decision variable x_{ij} be 1 if arc (i, j) is used in a flexible route, and 0 otherwise. Furthermore, let the decision variable y_i be 1 if customer $i \in N$ is transferred to the fixed schedule, and 0 if it is served in the flexible schedule. The integer variable w represents the number of required transfer trips. Let u_i indicate the accumulated demand already distributed by the vehicle when arriving at customer $i \in N$. The MILP formulation is given below:

$$\min \quad \sum_{i\in V}\sum_{j\in V} c_{ij}x_{ij} + Fw$$

$$\text{s.t} \quad y_i + \sum_{j\in V} x_{ij} = 1 \qquad \forall i \in N \tag{2.4}$$

$$y_j + \sum_{i\in V} x_{ij} = 1 \qquad \forall j \in N \tag{2.5}$$

$$\sum_{i\in N} q_i y_i \leq Q'w \tag{2.6}$$

$$\sum_{i\in S_r} q_i y_i \leq E_r \qquad \forall r \in R \tag{2.7}$$

$$u_i - u_j + Qx_{ij} \leq Q - q_j \qquad \forall i \in N, j \in N \tag{2.8}$$

$$x_{ij} \in \{0,1\} \qquad \forall i \in V, j \in V \tag{2.9}$$

$$y_i \in \{0,1\} \qquad \forall i \in N \tag{2.10}$$

$$w \in \mathbb{Z}_{\geq 0} \tag{2.11}$$

$$q_i \leq u_i \leq Q \qquad \forall i \in N \tag{2.12}$$

The objective is to minimize the total cost of routing the non-transferred customers and the cost of transferring the demand of the transferred customers to the transfer point. Constraints (2.4) and (2.5) ensure that a customer is either visited by a single vehicle of the flexible schedule or is transferred to the fixed schedule. Constraint (2.6) ensures that the total demand of transferred customers does not exceed the capacity of the vehicles used for the transfer trips. The selection of customers for transferring is constrained by the spare capacity of the fixed routes which is modeled by constraints (2.7). The constraints (2.8) ensure that every subtour includes the depot and does not violate the vehicle capacity constraints, and hence represents a feasible route. Constraints (2.9), (2.10), (2.11) and (2.12) specify the domains of the decision variables.

3 Optimizing Omni-Channel Fulfillment with Store Transfers

3.1 Introduction

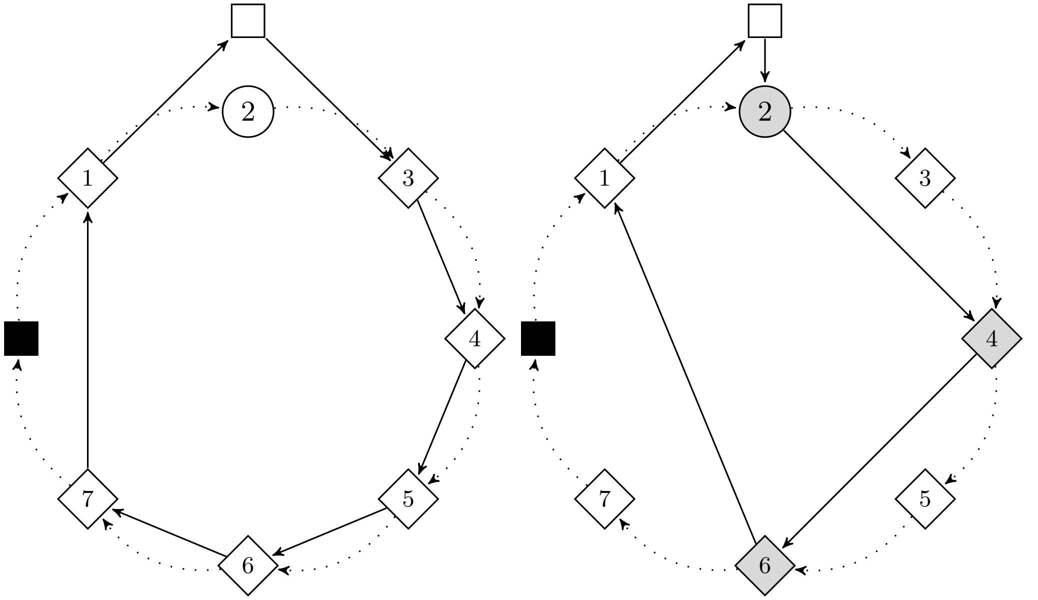
Retail supply chains are changing due to the continuous growth of online sales. Global online retail sales are projected to increase by 20% per year between 2014 and 2021 (Statista 2020). However, despite this growth, online sales still represent only a small fraction of total retail sales (Ali 2018). It is unlikely that the online stores will replace the traditional brick-and-mortar stores (Brown et al. 2013). Instead, retailers are pursuing an omni-channel strategy that combines various sales channels to create an integrated shopping experience across channels. Most traditional retailers now have an online sales channel (Agatz et al. 2008). In the past years, several major online retailers have extended their physical footprint. Amazon, for example, has recently acquired Whole Foods and is rolling out its Amazon Go stores (Levy 2018). The buy online, pick up in store model is increasingly popular in omni-channel retail as it provides flexibility to the customers and helps increase store sales (Gallino and Moreno 2014). According to a study in the U.S. (Bhardwaj et al. 2018), two-thirds of customers shopping online use physical stores somewhere along their buyer's journey (Lemon and Verhoef 2016). Forty percent of Best Buys (Roose 2017) and more than fifty percent of Walmarts online sales (Evans 2018) involve in-store pick-ups. Here, the physical store plays an important role in the omni-channel retail ecosystem as the link between the online and offline channels. However, the fulfillment of in-store pick-ups gives rise to new operational challenges (Hübner et al. 2016b,a, Melacini et al. 2018, Ishfaq et al. 2016).The in-store pick-up points are often supplied from a dedicated warehouse. In the grocery industry, where a typical order consist of 30-60 items, picking orders in the store is inefficient and disruptive for the in-store customers (Delaney-Klinger et al. 2003, Boyer et al. 2003). Moreover, rather than supplying the pick-up points from the warehouse that replenishes the store inventory, a dedicated warehouse is often preferred because preparing pick-up orders for online customers requires different processes than preparing pallets for store replenishment. For a detailed overview of the specific challenges in designing order picking systems in omni-channel retail, we refer to De Koster (2002), Hübner et al. (2016a) and Wollenburg et al. (2018).

Our research is motivated by a collaboration with the leading omni-channel grocery retailer in the Netherlands. The retailer has grocery stores that also serve as pick-up point (PUP) for goods ordered online. Customers can place orders online and pick up their orders the next day, so the PUPs are supplied on a daily basis. The store inventory is also replenished once per day to ensure freshness of perishable items (Van Donselaar et al. 2006, 2010, Brown et al. 2013). This means that the same stores are currently visited by different vehicles - one for the replenishment of store inventory and one for the supply of the PUP. We study the benefits of using available capacity in the vehicles in the offline channel (which replenish store inventories) to reduce the fulfillment costs as well as the number of store visits in the online channel. This is possible, because a retailer typically plans the routes to replenish store inventories, which we refer to as the *fixed* schedule, before planning the routes for the fulfillment of PUPs, which we refer to as the *flexible* schedule. If there is capacity available in the vehicles in the fixed schedule, it may be beneficial to transfer goods destined for a PUP in a store that is served in both schedules from (a vehicle in) the flexible schedule to (a vehicle in) the fixed schedule.

Paul et al. (2019b) consider a setting in which transfers can only take place at the warehouse where the vehicles in the fixed schedule depart by using dedicated transfer trips between the e-fulfillment center and the warehouse. In this paper, we consider the stores as potential transfer locations and integrate store deliveries and transfers in a single route. Using the stores as transfer locations has two main advantages over the more restrictive warehouse-transfer setting. First, there is more capacity available in the vehicle at the stores as the vehicle makes deliveries that free up capacity along the route. Secondly, using stores as transfer locations means we do not have to make (additional) trips to the warehouse which may be far from the delivery region. The main challenge in this setting is the synchronization of the transfers and store visits. That is, the vehicle in the flexible schedule must visit a transfer location before the vehicle in the fixed schedule.

Figure 3.1 provides an illustrative example with one single fixed route and one single flexible route. The diamond-shaped nodes represent the stores that need to be visited by both routes, the circle represents a store that only needs to be visited by the fixed route. The solid black square represents the start of the fixed route and the white square represents the start of the flexible route. Without capacity sharing, Figure 3.1a shows both delivery routes. With capacity sharing, a possible flexible route is shown in Figure 3.1b, where goods for Stores 3, 5, and 7 are transferred at Stores 2, 4 and 6, respectively. This new route is shorter and visits less stores than the original route without capacity sharing. Note that even though store 2 does not need to be served by the flexible route, a transfer can take place there.

(a) Without Capacity Sharing **(b)** With capacity sharing



■ : w/h fixed route, □ : w/h flexible route, ○ : store (fixed route only), ◇ : shared store

● / ◆ : transfer point , ⇢ : fixed route, → : flexible route

Figure 3.1: Capacity sharing with stores as transfer locations

We introduce the Shared Capacity Routing Problem with Transfers (SCRPT), which seeks to determine a flexible schedule that serves all relevant stores (to supply the in-store pick-up points) either directly or through transfers to the fixed schedule and that minimizes the total transport cost. The key decisions include (1) the choice of the transfer locations, (2) for each transfer location, the set of stores for which the goods are transferred at that location, and (3) the vehicle routes (in the flexible schedule) visiting the transfer locations and the stores for which the goods have not been transferred. In this study, we focus on the special case in which both the fixed and the flexible schedule have a single vehicle route.

Our work is related to the general area of vehicle routing with transfers or transshipments (Baldacci et al. 2016). This stream of literature typically involves multiple vehicles that can serve customers directly or through a limited number of transshipment facilities. These problems typically do not consider synchronization or capacity issues at the transfer locations as in our setting. Recently, a number of papers have focused on vehicle routing problems with drones (VRP-D) and travelling salesman problem with drones (TSP-D), which do involve synchronization between vehicles (see the recent survey of Otto et al. (Otto et al. 2018)). In these problems (Agatz et al. 2018)(Poikonen and Golded 2018), a vehicle can transfer parcels to the drone at certain locations. However, due to the size of the drone, it typically has to return to the vehicle after each delivery. Similar to the vehicle routing problem with drones is the truck and trailer routing problem (TTRP), in which the customers are visited by a combination of truck and trailer or just by the truck – the trailer cannot serve a customer by itself (Li et al. 2016). The customers served by a drone in the VRP-D or by a truck in the TTRP can be seen as equivalent to a store whose goods are transferred in the SCRPT. The difference is that in the SCRPT, the ability to transfer goods depends on the available transfer capacity, which, in turn, depends on the position of a store in the fixed schedule.

Our contribution is threefold. First, we describe a new capacity sharing strategy to optimize omni-channel fulfillment using stores as transfer locations. Secondly, we present a mixed-integer linear programming model and an efficient heuristic to solve the associated planning problem. Finally, we present an extensive numerical study to investigate the benefits of sharing capacity via store transfers under different settings.

The remainder of the paper is organized as follows. In the next section, we formally define the problem. In Section 3.3, we present a mixed integer programming formulation for the problem. In Section 3.4, we analyze two special cases of the problem. In Section 3.5, we introduce the heuristics we have developed for solving instances of the problem. In Section 3.6, we report the results of an extensive computational study. Finally, in Section 3.7, we summarize our key findings and provide directions for future research.

3.2 Problem Definition

We consider the special case with a single vehicle for both the fixed and the flexible schedule. This means, there is a single *fixed route* and a single *flexible route*. We assume that the capacity of the vehicles is sufficient to accommodate the total demand of the stores in their schedule. We model the SCRPT on a complete graph $G = (V, A)$. Here, $V = N \cup \{o\} \cup \{d\}$, where o is the warehouse of the fixed route, d is the warehouse of the flexible route, and $N = \{1, \ldots, n\}$ is the set of stores visited in the fixed route (in that order). The cost of traversing an arc $(i, j) \in A$ is denoted by c_{ij}. That is, we assume that the relevant costs are proportional to the travel distance, e.g., fuel costs, and we further assume that these costs satisfy the triangle inequality. The time to traverse an arc (i, j) is assumed to be a scalar transformation of the cost c_{ij}.

Every store $i \in N$ has demand $d_i > 0$, which has to be served in the fixed schedule. Let $S \subseteq N$ be the set of stores that need to be served in the flexible schedule, i.e., S denotes the set of *shared stores*. Every store $i \in S$ has a demand $q_i > 0$, which needs to be fulfilled from warehouse d. Demand of store $i \in S$ can be fulfilled by a delivery from the vehicle operating the flexible route or by a delivery from the vehicle operating the fixed route, if it was transferred to the fixed route at a store visited by that vehicle earlier in its route. We let a_o denote the departure time of the vehicle operating the fixed route, and a_i for $i \in N$ denote the time at which that vehicle visits store i. We let t_d indicate the departure time of the vehicle operating the flexible route. The departure times of the vehicles operating the fixed and flexible routes from their respective warehouses do not have to be the same. The demand of a shared store j can potentially be transferred at any store $i \in \{o, 1, \ldots, j-1\}$. If a transfer takes place at a store i, we refer to i as a *transfer point*. For a transfer at i to be feasible, the time of arrival, t_i, at store i of the vehicle operating the flexible route has to be at or before the arrival of the vehicle operating the fixed route, i.e., a_i. Note that a store $i \in \{o\} \cup N \setminus S$ can be visited in the flexible route just to transfer demand to the fixed route.

At every store $i \in N$, the vehicle operating the fixed route drops off the demand d_i of store i, hence, the capacity available to transfer demand from the flexible route to the fixed route increases. We refer to the capacity available in the vehicle operating the fixed route to accommodate demand from the flexible route as its *spare capacity*. Let e_i^v denote the spare capacity in the fixed route vehicle at location i, i.e., $e_i^v = e_o^v + \sum_{j=1}^{i} d_j$, where e_o^v is the spare capacity at the time of departure from the warehouse. To accommodate a transfer at store i, it is also necessary that store i has enough capacity to temporarily store (and handle) the goods being transferred. Let e_i^s denote the *store transfer capacity* at the store $i \in N$. Therefore, the *transfer capacity* e_i at store i for $i \in \{o\} \cup N$ is $\min(e_i^v, e_i^s)$. If store transfer capacity is not a limiting factor, then the transfer capacity always increases along the fixed route.

The demand of a set of stores $S_i \subseteq \{i+1, \ldots, n\} \cap S$ can only be transferred at store i if the total demand, $\sum_{j \in S_i} q_j$ does not exceed the transfer capacity e_i. We allow partial transfers, i.e., the demand of store $i \in S$ can be transferred at multiple stores (preceding store i in the fixed route). Note that if a store $i \in S$ is visited by in an optimal flexible route, the store's demand, q_i, is delivered during that visit and is not transferred earlier. Moreover, if the store transfer capacity is not limiting, then if the demand of a store $i \in S$ is transferred in an optimal solution, it is transferred in its entirety at a single store j (preceding store i in the fixed route).

The cost of the fixed route is exogenous to the model, so the only relevant cost is the cost of the flexible route, which we seek to minimize. In Section 3.4.3 and Section 3.6.7, we also consider transfer costs, i.e., the costs associated with the transfer of products from the vehicle operating the flexible route to the vehicle operating the fixed route.

As the SCRPT with a single vehicle reduces to a traveling salesman problem (TSP) when the stores have no transfer capacity, SCRPT is NP-hard.

3.3 MILP

We present a mixed integer linear programming (MILP) formulation for the SCRPT. Let the variable x_{ij}, for $i \in V,\ j \in V$, be 1 if arc (i, j) is used in the flexible route, and 0 otherwise. Let variable y_i, for $i \in \{o\} \cup N$, be 1 if location i is used as a transfer point and 0 otherwise. Let variable z_{ij}, for $j \in S$ and for $i \in \{o\} \cup \{o, 1, 2, \ldots, j-1\}$, be the fraction of the demand of store j transferred at store i. Let variable $t_i \in \mathbb{R}_{\geq 0}$, for $i \in \{o\} \cup N$, be the time of arrival at location i. Let variable $w_i \in \mathbb{R}_{\geq 0}$, for $i \in \{o\} \cup N$, be the actual transfer capacity used at i. Furthermore, let M_1 and M_2 be sufficiently large constants. The MILP formulation is given below:

$$\min \quad \sum_{i\in V}\sum_{j\in V} c_{ij}x_{ij}$$

$$\text{s.t} \quad \sum_{j\in N\cup\{o\}} x_{dj} = 1 \tag{3.1}$$

$$\sum_{i\in N\cup\{o\}} x_{id} = 1 \tag{3.2}$$

$$\sum_{j\in V} x_{ij} = \sum_{j\in V} x_{ji} \qquad \forall i \in N\cup\{o\} \tag{3.3}$$

$$\sum_{i\in V} x_{ij} + \sum_{\substack{i\in N\cup\{o\}\\ i<j}} z_{ij} = 1 \qquad \forall j \in S \tag{3.4}$$

$$t_i \le a_i + (1-y_i)M_1 \qquad \forall i \in N\cup\{o\} \tag{3.5}$$

$$y_i \le \sum_{j\in V} x_{ji} \qquad \forall i \in N\cup\{o\} \tag{3.6}$$

$$z_{ij} \le y_i \qquad \forall i \in N\cup\{o\}, j\in S, j>i \tag{3.7}$$

$$\sum_{\substack{j>i\\ j\in S}} z_{ij}q_j \le w_i \qquad \forall i \in N\cup\{o\} \tag{3.8}$$

$$w_i \le e_i^s \qquad \forall i \in N\cup\{o\} \tag{3.9}$$

$$w_i \le e_0^v + \sum_{t=0}^{i} d_t - \sum_{t=0}^{i-1}\sum_{\substack{j>i\\ j\in S}} z_{tj}q_j \qquad \forall i \in N\cup\{o\} \tag{3.10}$$

$$t_j \ge t_i + c_{ij} - (1-x_{ij})M_2 \qquad \forall i \in V, j \in N\cup\{o\} \tag{3.11}$$

$$x_{ij} \in \{0,1\} \qquad \forall i \in V, j \in V \tag{3.12}$$

$$y_i \in \{0,1\} \qquad \forall i \in N \cup \{o\} \tag{3.13}$$

$$0 \leq z_{ij} \leq 1 \qquad \forall j > i, \forall j \in S, i \in N \cup \{o\} \tag{3.14}$$

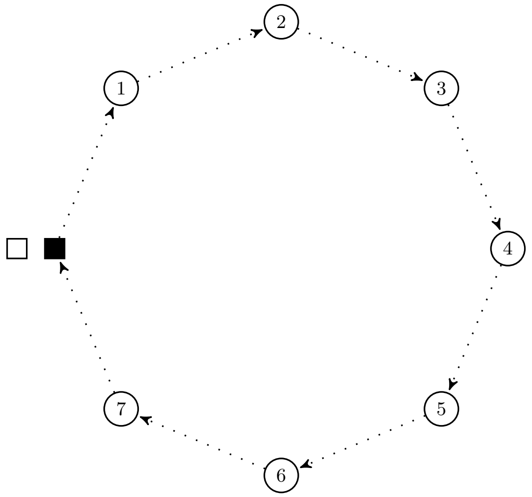
$$t_i \in \mathbb{R}_{\geq 0} \qquad \forall i \in V \tag{3.15}$$

$$w_i \in \mathbb{R}_{\geq 0} \qquad \forall i \in N \cup \{o\}. \tag{3.16}$$

The objective minimizes the cost of the flexible route. Constraints (3.1) and (3.2) ensure that the vehicle of the flexible route leaves the warehouse and returns back to the warehouse. Constraints (3.3) guarantee a vehicle leaves a location if visited. Constraints (3.4) ensure that every store is either visited or transferred to the fixed route. Constraints (3.5) ensure that a transfer can only take place at a store if it is visited in the flexible route before it is in the fixed route. Constraints (3.6) guarantee that a location that is used as a transfer point is visited. At any transfer point, we can only transfer (completely or partially) stores that are visited in the fixed route after the transfer point, which is captured in Constraints (3.7). Constraints (3.8) ensure that the demand of the stores transferred at a transfer point does not exceed the actual transfer capacity at the transfer point. Constraints (3.9) guarantee that the actual transfer capacity used at a store location is less than its store transfer capacity, while constraints (3.10) update the actual transfer capacity used at every location. Constraints (3.11) keep track of the time of the flexible route and also act as sub-tour elimination constraints. Finally, Constraints (3.12 – 3.16) specify the domain of the decision variables.

3.4 Special Cases

In this section, we study two special cases of the SCRPT. The analysis of these special cases helps motivate the heuristic we have developed for solving instances of SCRPT. We consider the case where the warehouses of the fixed and the flexible route are co-located, the warehouses and stores are located on a circle, as shown in the Figure 3.2, and the fixed and flexible route start at the same time. The vehicle operating the flexible route travels at least as fast as the vehicle operating the fixed route. In the optimal fixed route, the stores are visited in the clockwise direction in the fixed route. For convenience, we use 0 to denote the warehouse when it serves as the source (starting point of the route) and $n+1$ when it serves as sink (ending point of the route).



■ : w/h fixed route, □ : w/h flexible route , ○ : store, - - ➝ : fixed route

Figure 3.2: SCRPT on a circle

3.4.1 Store transfer capacity is not restricting ($e_i^s \geq e_i^v$ for all $i \in S$)

If the store transfer capacity is not restricting, then the transfer capacity at store i is $e_i = e_i^v$. Recall that e_i^v always increases along the fixed route. Therefore, if the demand for store j can be transferred at store $i < j$, then it can also be transferred at any store k with $i < k < j$. Next we provide the definitions and notations which will help characterize properties of an optimal solution to the SCRPT in this special case.

Proposition 3.4.1. *If an optimal flexible route visits a set of stores $S' \subseteq S$, then there exists an optimal flexible route that visits the stores in S' in the same order as the optimal fixed route.*

Proof. Since the vehicle operating the flexible route travels at least as fast as the vehicle operating the fixed route and the triangle inequality holds, it is always possible for the flexible route to reach store location before or same time as the fixed route vehicle. Transfers, if capacity feasible, allow us to skip one or more stores after a transfer. This means that a flexible route with transfers is a subset of the stores visited in the fixed route. Now, we have to argue if the optimal flexible route through $S' \subseteq S$ follows the same order of visit as the optimal fixed route. Eilon and Watson-Gandy (Eilon and Watson-Gandy 1971) show that "if H is the convex hull of the nodes in the 2-dimensional space, then the order in which the nodes on the boundary of H appear in the optimal tour will follow the order in which they appear in H". Since the stores in $S' \subseteq S$ are located on a circle, they are all part of their convex hull and are thus visited in the order in which they appear on the circle. This implies they will be visited in the same order as the fixed route. □

Since there exists an optimal flexible route that visits stores in the same order as the fixed route, it suffices to consider only arcs (i, j) with $i < j$ when constructing an optimal flexible route. An arc (i, j) is feasible if stores $i + 1, i + 2, \ldots, j - 1$ can be transferred at i. Let $q_{ij} = \sum_{k=i+1}^{j-1} q_k$ be the *transfer demand* associated with arc (i, j). Furthermore, let $f_{max}(i)$ be the farthest store that can be reached feasibly from i. Note that since the transfer capacity in the fixed route increases along the route (because the store transfer capacity is not restricting), we have that $f_{max}(j) \geq f_{max}(i)$ for $j > i$. The following proposition reduces the number of arcs that need to be considered when constructing an optimal flexible route.

Proposition 3.4.2. *If $i < j < f_{max}(i) = n + 1$, then i and j will not both be visited in an optimal flexible route.*

Proof. This follows Proposition 3.4.1 and the fact that any path that visits stores i, j, and $n + 1$ is dominated by the path that returns to the warehouse $(n + 1)$ immediately after visiting store i, because the triangle inequality holds. □

The above properties are used to build an auxiliary directed graph containing all the arcs that can appear in an optimal flexible route. The problem of finding an optimal flexible route reduces to the problem of finding a shortest path from node 0 to node $n + 1$ in this auxiliary graph. Because of Proposition 3.4.1, the auxiliary graph is acyclic. Finding a shortest path in an acyclic directed graph can be done in linear time ($\mathcal{O}(|A|)$, where $|A|$ is the number of arcs in the graph). The pseudocode for creating the auxiliary graph and for finding a shortest path in this graph is given in the Appendix.

Note that in case it is possible to transfer the demand of store j at multiple store locations preceding j, we aim to use the last store as a transfer point.

3.4.2 Store transfer capacity can be restricting

If the store transfer capacity can be restricting, the transfer capacity $e_i = \min(e_i^s, e_i^v)$ is not necessarily increasing along the fixed route. Consequently, if the demand of store j can feasibly be transferred at store $i < j$, then it *may not* be feasible to transfer the demand of store j at another store k with $i < k < j$.

This situation can be accommodated as follows. As before, when the demand of a store is transferred, we aim to transfer the demand at the last transfer point before that store. Under this assumption, when we consider the transfer capacity at store j, we want to know how much of the demand of stores $j+1, j+2, \ldots, n$ can be transferred. When store transfer capacity is not limiting, this is simply the available capacity in the fixed route vehicle when it visits store j, i.e., e_j^v. However, if the store transfer capacity is limiting, it may be necessary to transfer part of the demand at the previous transfer point. Therefore, we define the *effective transfer capacity*, u_j, at store j, to be the sum of the transfer capacity at j, and the *additional* transfer capacity at i if store i is the store visited immediately before store j.

Consider arc (i, j) and let the effective transfer capacity at store i be u_i. Furthermore, let the demand that needs to be delivered at stores $i+1, i+2, \ldots, j-1$ be $q = \sum_{k=i+1}^{j-1} q_k$. If we use arc (i, j) in the flexible route, then q units of goods have to be transferred at store i to be delivered by the fixed route. Therefore, $u_i - q$ additional transfer capacity is available at store i for demand from stores $j+1, j+2, \ldots, n$, which implies

$$u_j = \min\{e_j^v, e_j^s + (u_i - q)\}. \tag{3.17}$$

If store transfer capacity is not restricting, i.e., $e_j^s \geq e_j^v$, then the effective transfer capacity u_j at store j is the spare capacity e_j^v. If the store transfer capacity can be restricting, then the effective transfer capacity u_j at store j is at least the store transfer capacity e_j^s. Thus, the effective transfer capacity u_j at store j satisfies $e_j^s \leq u_j \leq e_j^v$ and depends on the store i that precedes it in the flexible route.

In the auxiliary directed graph, the nodes represent store states, e.g., (j, u_j), rather than stores, e.g., j. An arc (s, s') from state $s = (i, u_i)$ to state $s' = (j, u_j)$ represents the transition from state s to state s'. Analogous to $f_{max}(i)$, we define $f_{max}(i, u_i)$ to be the state associated with the farthest store that can be be reached from (i, u_i), where we note that effective capacity of that store is uniquely determined by u_i (and the spare and store transfer capacity at that store).

Proposition 3.4.1 holds in this case as well, which means that the auxiliary graph will again be acyclic. The auxiliary graph contains arcs from state (i, u_i) to state (j, u_j) with $i < j$ if the transfer demand, $q_{ij} = \sum_{k=i+1}^{j-1} q_k$, is less than or equal to u_i. The effective transfer capacity u_j of the state (j, u_j) is set using (3.17). The cost of an arc from (i, u_i) to (j, u_j) is c_{ij}. We have $u_0 = 0$, which implies $u_1 = \min\{e_1^v, e_1^s\}$.

The number of nodes in the auxiliary graph grows rapidly as the number of stores increases. The following properties allow us to limit the number of arcs in the auxiliary graph, where we note that each state (i, u) defines a unique path from 0 to i and thus a specific cost to reach that state:

- For any two states (i, u_1) and (i, u_2) associated with store i, (i, u_1) dominates (i, u_2), if $u_1 > u_2$ and $c_{(i,u_1)} \leq c_{(i,u_2)}$, where c_s is the cost incurred to reach the state s.
- If $(i, u) < (k, u') < f_{max}(i, u) = (n + 1, v)$ with $v \geq 0$, then arc $((i, u), (k, u'))$ will not be used in an optimal flexible route.

3.4.3 Store transfer costs

In some settings, we may want to explicitly incorporate the costs associated with performing a transfer. That is, there may be costs associated with the unloading and loading the goods at the transfer location. In this section, we show how to incorporate a transfer costs per store, i.e., a fixed transfer cost c_i^T at store i.

When store capacities are not restricting (as in Section 3.4.1), a transfer of the demand of store j always takes place at the last store i before store j that is visited in the flexible route. This means that in this case, we can account for the transfer cost by simply adding c_i^T to the cost of any outgoing transfer arc from store i.

When the store transfer capacity can be restricting (as in Section 3.4.2), it may not be possible to transfer all demand for store j at the last store i before store j on the flexible route. To facilitate a transfer, part of the demand of store j has to be transferred at one or more stores visited earlier in the flexible route. This means that we have to explicitly account for the possibility of partial transfers.

To accommodate the latter case (stores with restricting transfer space and transfer costs), we define state (i, v_i) for store i where v_i captures the *additional transfer capacity*, i.e., transfer capacity committed at stores in the path up to i, but not including i. For a transition from state (i, v_i) to (j, v_j) by transferring the demand $q_{ij} = \sum_{k=i+1}^{j-1} q_k$, we have the following two options.

1. Do not use the transfer capacity at i, which gives the state $j, v_i - q_{ij}$; the cost of the transition is given by the travel cost c_{ij}.

2. Use transfer capacity at i, which gives state $(j, \min(e_i^v, v_i + e_i^s) - q_{ij})$; the cost of the transition is the sum of the travel cost c_{ij} and the transfer costs c_i^T.

We consider transitions from a given state (i, v_i) to all j such that $v_i \geq q_{ij}$ for option (1), and $\min(e_i^v, v_i + e_i^s) \geq q_{ij}$ for option (2). As before, we build an auxiliary directed graph, where the nodes represent states, e.g., (i, v_i), and the arcs represent feasible transitions. The total cost of a path in this auxiliary graph captures the total travel cost and the total transfer cost.

Note too that it is possible that the arc from i to j is feasible when we use the transfer capacity, but it is not feasible if we do not use the transfer capacity. This is taken into account during the network construction. As before, we use dominance properties to limit the size of the graph.

3.5 Heuristic

The shortest path in the auxiliary graph does not provide an optimal solution when (a) the customer locations are not on the boundary of a convex hull, (b) the start time of the fixed route and flexible route are the same, but the depots are not co-located, and (c) the start time of the flexible route is later than the start time of the fixed route. In the first case, the shortest path in the auxiliary graph provides a feasible, but not necessarily optimal solution. However, in the latter two cases, it is not possible for the flexible route to follow the fixed route from the start as it is not be possible to reach the warehouse where the fixed route starts in time. We develop a heuristic that solves a shortest path on an auxiliary graph, but accounts for the fact that it may not always be possible to reach the warehouse, where the fixed route starts, in time.

The shortest path approach relies on Proposition 3.4.1 and follows the sequence of visits in the fixed route. For the cases (b) and (c), it is not time-feasible to catch-up with the fixed route at its warehouse and then follow it. Let c be the first store in the fixed route where the flexible route can *catch-up*, i.e., $t_c \leq a_c$, where t_c is the arrival time at store c if it is the first store visited in the flexible route. Note that store c might not be in set S, the set of stores that need to be served in the flexible schedule, but it can be used as a transfer point.

We partition S, the set of stores that need to be served in the flexible schedule, into $B = \{i : i \in S \cap \{1, \ldots, c-1\}\}$, the stores that appear before the catch-up point in the fixed route and cannot be transferred and need to be visited in the flexible route, and $A = \{i : i \in S \cap \{c, \ldots, n\}\}$, the stores that appear after the catch-up point and need to be served, but not necessarily visited, in the flexible route. We build the auxiliary graph with the stores in $\{c, \ldots, n\}$ as described in the Section 3.4.2. We determine the shortest path in the auxiliary graph to obtain the initial part of the flexible route, serving the stores in A, but that part of the flexible route should end at a store $j \in B$ rather than back at the warehouse (d), because the stores in B also have to be visited (unless $|B| = 0$). The final part of the flexible route comprises of a minimum cost Hamiltonian path starting at store $j \in B$, ending at warehouse d, and visiting all stores in $B \setminus \{j\}$. Any heuristic for finding a Hamiltonian path can be used to do so. (In our implementation, we use nearest neighbour construction followed by 2-exchange improvement.) The flexible route comprises of the initial shortest path and the final Hamiltonian path. We further improve the flexible route with a 2-exchange improvement.

It is not obvious at which store $i \in B$ the initial part of the flexible route should end. Similarly, it is not obvious that catching up with the fixed route as early as possible, i.e., at store c, is necessarily the best choice. Let store $\bar{c}$ be the store nearest to the warehouse of the flexible route at which the transfer capacity $e_{\bar{c}}$ is sufficient to transfer the demands of all stores in $S \cap \{\bar{c}+1, \bar{c}+2, \ldots, n\}$. Our heuristic explores all possible combinations of a catch-up store $i \in \{c, c+1, \ldots, \bar{c}\}$ and an ending store $j \in B$, and constructs the initial part of the flexible route (from store i to store j) using the shortest path approach, and the final part of the flexible route (from store j to warehouse d) using the Hamiltonian path heuristic. (In the computational study section, we sometimes refer to these parts of the flexible route as SP and HP.)

Note that initial part of the flexible route (obtained using the shortest path approach) gives the sequence of stores to visit, but it does not provide the selection of transfer points and for each of the transfer points a list of stores for which demand is transferred at that transfer point. Typically, there are multiple possible "transfer solutions" for a given initial part of the flexible route. Consider, for example, an initial part $d - 4 - 5 - 6 - 9 - i$ of a flexible route (with $i \in B$), and assume that the demand for stores 7 and 8, both equal to 2, is transferred at store 6. Furthermore, suppose that the store transfer capacities at stores 4, 5 and 6, are 1, 2 and 4, respectively. Because it is allowed to transfer the demand of a store in parts, (4,5,6), (4,6), (5,6), and (6) are all feasible sequences of transfer points for the demand of stores 7 and 8. We have implemented a *greedy* approach that seeks to minimize the number of transfer points used (by considering the store in non-increasing order of transfer capacity). Note that if a store is chosen as a transfer point, the flexible route has to visit that store before the fixed route does. Therefore, the selection of transfer points may affect the cost of the final part of the flexible route.

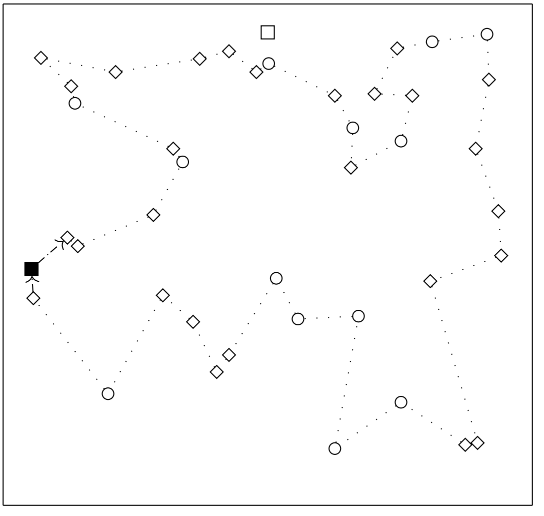
3.6 Computational study

In this section, we report the results of a comprehensive set of computational experiments. First, we assess the performance of our heuristic by comparing the solutions it produces to the optimal solutions (obtained by solving the MILP formulation as presented in Section 3.3). Next, we use solutions produced by the heuristic to study the benefits of sharing the capacity of the fixed route with the flexible route in different settings. All algorithms are coded in JAVA using Gurobi 7.0 (Gurobi Optimization 2018) as the MILP solver. The experiments were performed on a laptop computer with an Intel Core i7-4810MQ CPU 2.8 GHz processor.

3.6.1 Instance generation

We generate n uniformly distributed points inside a square of size l, which represent the locations of the stores visited by the fixed route, i.e., N. The coordinates of the lower left-hand corner of the square are set to (0,0). The depot of the fixed route, o, is located at $(0, \frac{1}{2}l)$. We solve a TSP on $\{o\} \cup N$ to find the fixed route. The stores in N are identified by their position in the fixed route. Figure 3.3 shows an example of a fixed route visiting 40 stores. In our experiments, we consider two locations for the depot of the flexible route:

$(0, \frac{1}{2}l)$, i.e., the warehouses are *co-located*, and $(\frac{1}{2}l, l)$, i.e., the warehouses are *not co-located* (as is the case in the example in Figure 3.3). As the costs in our model are proportional to the travel distance, the costs savings are proportional to the distance savings.



■ : w/h fixed route, □ : w/h flexible route, ○ : store (fixed route only), ◇ : shared store, ····› : fixed route

Figure 3.3: Sample fixed route ($n = 40$)

Without loss of generality, we assume that the fixed route departs from its warehouse at time zero, i.e., $a_o = 0$ and calculate the time of arrival a_i at store i, for $i \in N$, in the fixed route. The demand of each store in the fixed route is $d_i = 20$. The demand of the stores in the flexible route is $q_i = \beta d_i$, for $i \in S$, for some $0 < \beta \leq 1$. That is, β defines the ratio of the demand of a store in the flexible route and the demand of a store in the fixed route. Consequently, if $\beta = 1/10$, then whenever the vehicle operating the fixed route drops off the demand at a store, the increase in spare capacity corresponds to the demand of 10 stores that need to be served in the flexible schedule. We assume that the capacity of the vehicle operating the fixed route is $\sum_{k=1}^{n} d_i$, i.e., the total demand of the stores in the fixed route. This means a fill rate of 100% and no spare capacity when the vehicle departs from the warehouse. As a result, the spare capacity in the vehicle operating the fixed route at store i is $e_i^v = \sum_{k=1}^{i} d_i$. We define α to be the fraction of the number of stores served in the fixed route that also need to be served in the flexible route. That is, $|S| = \alpha|N|$ for some $0 < \alpha \leq 1$. The $|S|$ stores are randomly chosen among the n stores. We consider two types of stores: (1) stores with *restricted* store transfer capacity, equal to 1.5 times the demand of a single store in the flexible schedule, and (2) stores with *unrestricted* store transfer capacity, equal to the total demand of the stores in the flexible route. We let ρ be the probability that a store is of the restricted type.

We use different combinations of n, α, and β to generate instances. Unless mentioned otherwise, the fixed and the flexible routes start at the same time, i.e., $t_d = a_o$, and the fixed transfer cost c_i^T for any store i is zero. We create five instances for each combination of the parameters and any value reported in the result tables in the next sections is the average over the values of the five instances.

3.6.2 Performance of heuristic

To assess the quality of our heuristic, we create instances using $n = 30, 40, 50$, $\alpha = 0.7$, $\beta = 1/10$, $1/2$ and $1/1$, and $\rho = 0.5$. The optimal solutions for these instances are obtained by solving the MILP described in Section 3.3. We define the optimality gap as the difference between the heuristic solution value and the optimal solution value and express it as percentage of the optimal value. To assess the quality of the heuristic, we report, in Table 3.1, the average optimality gap, the maximum optimality gap, and number of times the optimal solution is found across all instances. We also report the solution times (in seconds) for the different approaches.

Table 3.1: Performance of heuristic ($\alpha = 0.7$, $\rho = 0.5$)

Instance information		β	co-located				not co-located			
$\lvert N\rvert$	$\lvert S\rvert$		Avg. opt. gap (%)	Max. opt. gap (%)	Time. opt. (secs)	Time. heu. (secs)	Avg. opt. gap (%)	Max. opt. gap (%)	Time. opt. (secs)	Time. heu. (secs)
30	21	1/10	0.0	0.0	1.0	0.3	0.3	1.3	1.9	2.3
		1/2	0.7	3.2	36.7	0.3	1.1	5.2	10.4	2.6
		1/1	0.1	0.5	303.2	0.3	1.4	7.1	91.9	3.1
40	28	1/10	0.0	0.0	11.8	2.0	1.6	7.8	16.4	2.6
		1/2	0.4	2.0	685.5	2.2	2.1	3.7	152.6	3.4
		1/1	1.6*	4.6	6,378.4*	2.1	9.8	27.6	670.9	3.9
50	35	1/10	0.0	0.0	81.1	2.1	0.0	0.0	4,786.7	2.7
		1/2	0.5*	2.1	853.8*	2.1	0.8*	2.5	2,803.5*	4.3
		1/1	0.7*	2.9	18,524.0*	2.3	1.7*	3.2	29,544.3*	5.8
# of times optimal			**33** / 42				**24** / 43			

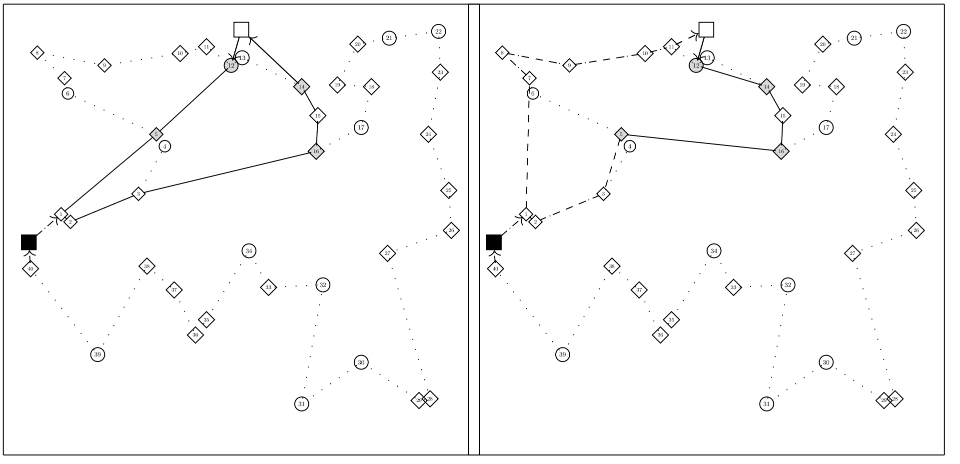
*Average over 4 instances, as the MILP could be solved in 24 hours for one instance

We observe that the heuristic performs well, especially in the setting with co-located warehouses. In this case, the average optimality gap is 0.5% and the maximum optimality gap is 4.6%. The optimal solution is found for 33 of 42 instances. When the warehouses are not co-located, the performance is still good with an average optimality gap of 2.1%. However, the maximum gap is 27.6% and the optimal solution is found for 24 of 43 instances. The heuristic is much faster than the MILP for all but the smallest instances. We did not find a proven optimal solution within 24 hours for 5 instances. This suggest that using the MILP approach for medium- and large-size instances is impractical.

When the warehouses are not co-located, the sequence in which stores are visited in an optimal flexible route can be quite different from the sequence in which the stores are visited in the fixed route, which results in our heuristic being less effective. Consider for example the instance for which the optimality gap is 27.6% (in Table 3.1). The optimal flexible route is *d-12-5-1-2-3-16-15-14-d*, as shown in Figure 3.4a, which does not follow the sequence in which stores are visited in the fixed route. The optimal flexible route first visits store 12, then visits store 5, where the demands of stores 7, 8, 9, 10, and 11 are are transferred. The flexible route produced by the heuristic is *d-12-14-15-16-5-3-2-1-7-8-9-10-11-d*, as shown in Figure 3.4b, which uses store 12 as the catch-up point and then follows the fixed route until store 16, after which it visits stores in S before store 12. As a result, store 5 cannot be used as a transfer point and stores 7, 8, 9, 10, and 11 have to be visited in flexible route (on the Hamiltonian path), thereby leading to a costlier solution.

However, overall our heuristic performs well and hence, we use this heuristic to analyze the benefits of capacity sharing under different conditions.

(a) Optimal Solution (Cost: 80.5) **(b)** Heuristic Solution (Cost: 102.7)



■ : w/h fixed route, □ : w/h flexible route, ○ : store (fixed route only), ◇ : shared store

● / ◆ : transfer point , ⋯> : fixed route, → : flexible route SP, --→ : flexible route HP

Figure 3.4: Case where the heuristic fails
$(|N| = 40, \alpha = 0.7, \beta = 1/1, \rho = 0.5)$

3.6.3 Savings from capacity sharing

In this section, we illustrate the advantages of capacity sharing between the two distribution channels in omni-channel retail. For each instance, we determine the costs without capacity sharing, by solving a TSP on $\{d\} \cup S$, and compare it to the costs with capacity sharing, by using our heuristic to determine a flexible route. We create instances using n = 40, 60, 80, 100, $\alpha = 0.7$, $\beta = 1/2$, and $\rho = 0.5$. In Table 3.2, we report the transport cost savings (Δ transport cost) obtained by sharing capacity across the two channels when the warehouses of both the channels are co-located and when they are not co-located. To better understand how capacity is shared, we also report the number of stores visited in the flexible route, the number of stores whose demand is transferred to the fixed route, and the number of stores used as transfer points in the flexible route. We also report the numbers for stores visited and transferred as a percentage of the number of stores that need to be served in the flexible route, and the number of transfer points as percentage of the number of stores visited in the flexible route.

Table 3.2: Savings by capacity sharing
($\alpha = 0.7, \beta = 1/2,\ \rho = 0.5,\ c_i^T = 0$)

Warehouse location	Instance information		Δ transport cost	Stores visited		Stores transferred		Transfer points	
	$\lvert N\rvert$	$\lvert S\rvert$	(%)	#	%	#	%	#	%
co-located	40	28	72.0	3.8	13.6	25.2	90.0	2.8	80.0
	60	42	77.6	4.4	10.5	38.2	91.0	4.2	95.0
	80	56	78.9	4.2	7.5	53.6	95.7	3.4	81.0
	100	70	81.0	5.2	7.4	66.0	94.3	4.8	95.6
not co-located	40	28	67.5	5.2	18.6	23.2	82.9	2.2	44.3
	60	42	74.3	5.2	12.4	36.8	87.6	2.2	42.7
	80	56	74.4	5.8	10.4	50.8	90.7	2.0	34.7
	100	70	76.7	6.8	9.7	63.8	91.1	2.2	37.4

When the warehouses are co-located, the cost savings range from 72% to 81%, where the cost savings increase with the number of stores in the flexible schedule $|S|$. This can be attributed to a decrease in the fraction of stores visited in the flexible route.

Note that the sum of the (average) number of stores visited and the (average) number of stores transferred is greater than the number of stores $|S|$, that need to be served. This implies that some stores without demand ($i \notin S$) are visited for the sole purpose of transferring demand to the fixed route.

We also observe that the demand of a remarkably large fraction of stores, between 90 to 95%, is being transferred; sharing capacity between the channels is greatly exploited. The reduction in the number of stores visited in the flexible route is not only beneficial because it results in cost savings, but also has environmental benefits as it reduces emissions and reduces congestion in the areas where stores are located.

We see similar trends in cost savings and store visits when the warehouses are not co-located. The cost savings range from 67% to 77%, while the reduction in store visits ranges from 82% to 92%. When the warehouses are not co-located, the benefits of capacity sharing are smaller than when the warehouses are co-located, mainly because the number of stores where transfers can take place is reduced. Since the fixed and flexible routes start at the same time, when the warehouses are not co-located, it is not possible for the flexible route to transfer demand at stores visited early in the fixed route, before the store where the two routes can catch up. Equally important, if these stores also have to be visited in the flexible schedule, then they all need to be visited on the flexible route.

It is interesting to note how few transfer points are used; just over two on average when the warehouses are not co-located.

3.6.4 Joint planning versus SCRPT

In the SCRPT, it is assumed that the route of the vehicle replenishing store inventories is fixed and only the route of the vehicle that supplies the in-store pick-up points is planned. In this section, we compare the savings from this capacity sharing setting to a joint planning setting in which online orders are transferred to the warehouse handling store replenishment, and then deliveries to the stores, of both replenishment goods and pick-up point orders, are planned jointly, i.e., two (flexible) routes are created.

In the joint planning setting, we assume that the vehicle that transfers online orders to the warehouse handling store replenishment, returns to the online order fulfillment center after its last store delivery. The goal in the joint planning setting is to minimize the system-wide costs, i.e., the sum of the costs of the two delivery routes plus the cost of the (one-way) transfer from the online order fulfillment center to the warehouse handling store replenishment.

For this experiment, we consider $|N| = 100, \alpha = 0.7, \beta = 1/2$, and $\rho = 0.5$, and we assume that both vehicles have the same capacity. (In practice, the vehicle delivering online orders to pick-up points tends to be smaller.) Table 3.3 shows the cost savings achieved by the joint planning and the SCRPT for the case where the warehouse and fulfillment center are co-located and for the case when they are not. As both routes in the joint planning setting are flexible, we report the savings as a percentage of the total costs of the fixed and the flexible routes when no sharing takes place. (Note that in previous tables, we reported the savings as a percentage of the cost of flexible route when no sharing takes place.)

Table 3.3: Savings in VRP joint planning vs SCRPT
($|N| = 100, \alpha = 0.7, \beta = 1/2, \rho = 0.5$)

Ins #	Without sharing			Joint planning				SCRPT				Δ
	Fixed route cost	Flexible route cost	Total cost	VRP cost	One way transfer	Total cost	Savings (%)	Fixed route cost	Flexible route cost	Total cost	Savings (%)	savings (% points)
Co-located												
1	396.2	345.8	742.0	415.7		415.7	44.0	396.2	58.7	454.9	38.7	5.3
2	385.9	338.4	724.3	411.2		411.2	43.2	385.9	84.8	470.7	35.0	8.2
3	387.2	331.9	719.1	416.6		416.6	42.1	387.2	70.7	457.9	36.3	5.7
4	396.9	334.5	731.4	423.2		423.2	42.1	396.9	69.7	466.5	36.2	5.9
5	410.5	345.8	756.4	427.9		427.9	43.4	410.5	38.0	448.5	40.7	2.7
Average	395.3	339.3	734.6	418.9		418.9	43.0	395.3	64.4	459.7	37.4	5.6
Not co-located												
1	396.2	341.8	737.9	447.1	35.4	482.4	34.6	396.2	66.8	463.0	37.3	-2.6
2	385.9	340.4	726.3	435.5	35.4	470.8	35.2	385.9	83.8	469.7	35.3	-0.2
3	387.2	325.6	712.8	444.2	35.4	479.5	32.7	387.2	75.5	462.7	35.1	-2.4
4	396.9	330.4	727.3	456.0	35.4	491.4	32.4	396.9	89.9	486.8	33.1	-0.6
5	410.5	340.9	751.5	456.4	35.4	491.7	34.6	410.5	74.1	484.6	35.5	-0.9
Average	395.3	335.8	731.2	447.8	35.4	483.2	33.9	395.3	78.0	473.3	35.3	-1.3

As may have been expected, the table shows that the joint planning setting results in more savings than the SCRPT (43.0 % vs 37.4%) in the co-located case. In this case, the additional flexibility allows for a decrease in the overall travel costs. However, we also observe that the SCRPT results in more savings than the joint planning when the warehouse and fulfillment center are not co-located (35.3 % vs 33.9%). One reason for this is that the SCRPT allows the use of "freed up" capacity in the fixed route, i.e., capacity that becomes available after store demand has been dropped off. Another reason is that the SCRPT does not require transfers to take place at the warehouse, and costs can be saved by choosing the first and last leg of the route carefully.

3.6.5 Effect of store overlap α and relative demand sizes β

In this section, we analyze the effect of the fraction of the number of stores served in the fixed route that also need to be served in the flexible route, i.e., α, and the ratio of the demand of a store in the flexible schedule and the demand of a store in the fixed schedule, i.e., β. We create instances using n = 50, 75, 100, α = 0.1, 0.5, 1.0, β = 1/10, 1/2, 1/1, and ρ = 0.5. Table 3.4 reports the cost savings, the number of stores visited, the number of stores transferred, and the number of transfer points used (in parentheses, we report the numbers for stores visited and transferred as a percentage of the number of stores that need to be served in the flexible route, and the number of transfer points as percentage of the number of stores visited in the flexible route).

A higher value of β means higher demand in the stores that need to be visited in the flexible schedule. For the same transfer capacity at stores in a fixed route, this leads to a reduction in the number of stores transferred and an increase in the number of stores visited. Consequently, for a given α, the savings in transport cost decrease with β as fewer stores get transferred, and more transfer points are required to do so. This trend can be seen across values of n.

Table 3.4: Effect of α and β on capacity sharing [warehouses not co-located] ($\rho = 0.5$)

	$\alpha \rightarrow$	0.1	0.5	1.0	0.1	0.5	1.0	0.1	0.5	1.0
	$\beta \downarrow$	$\|N\| = 50$			$\|N\| = 75$			$\|N\| = 100$		
Δ transport cost (%)	1/10	79.4	75.9	77.2	58.4	78.3	78.8	70.6	77.2	80.1
	1/2	79.4	70.1	72.7	58.4	74.2	74.3	70.6	76.0	76.8
	1/1	79.4	69.6	64.0	58.4	72.0	64.8	70.6	71.6	68.8
# of stores visited	1/10	1.2	2.8	5.4	2.4	2.8	7.0	2.2	3.6	8.4
		(24.0)	(11.2)	(10.8)	(32.0)	(7.5)	(9.3)	(22.0)	(7.2)	(8.4)
	1/2	1.2	4.6	8.4	2.4	4.8	11.0	2.2	5.4	10.8
		(24.0)	(18.4)	(16.8)	(32.0)	(12.8)	(14.7)	(22.0)	(10.8)	(10.8)
	1/1	1.2	4.8	11.0	2.4	6.0	16.4	2.2	8.0	18.4
		(24.0)	(19.2)	(22.0)	(32.0)	(16.0)	(21.9)	(22.0)	(16.0)	(18.4)
# of stores transferred	1/10	4.6	22.8	44.6	5.6	34.4	68.0	8.6	47.0	91.6
		(92.0)	(91.2)	(89.2)	(74.7)	(91.7)	(90.7)	(86.0)	(94.0)	(91.6)
	1/2	4.6	21.0	41.6	5.6	33.2	64.0	8.6	45.8	89.2
		(92.0)	(84.0)	(83.2)	(74.7)	(88.5)	(85.3)	(86.0)	(91.6)	(89.2)
	1/1	4.6	20.8	39.0	5.6	31.8	58.6	8.6	42.8	81.6
		(92.0)	(83.2)	(78.0)	(74.7)	(84.8)	(78.1)	(86.0)	(85.6)	(81.6)
# of transfer points	1/10	1.0	1.0	1.4	1.4	1.0	1.4	1.0	1.0	1.6
		(90.0)	(38.3)	(29.8)	(63.3)	(36.7)	(21.3)	(60.0)	(28.3)	(20.8)
	1/2	1.0	2.0	2.0	1.4	2.0	3.2	1.0	2.6	3.0
		(90.0)	(46.7)	(24.4)	(63.3)	(43.3)	(32.0)	(60.0)	(46.5)	(28.6)
	1/1	1.0	2.2	3.2	1.4	3.0	3.6	1.0	3.2	4.6
		(90.0)	(51.0)	(30.2)	(63.3)	(53.9)	(23.5)	(60.0)	(44.5)	(26.1)

The results in Table 3.4 do not show any clear trend for changes in α. A higher value of α means that a higher number of stores need to be served in the flexible schedule. To better understand the effect of α, we fix the number of stores that need to be served in the flexible schedule. We consider two scenarios: $|N| = 100$ with $\alpha = 0.5$ and $|N| = 50$ with $\alpha = 0.5$, where the *same* set of 50 stores needs to be served in the flexible schedule. The results can be found in Table 3.5. We observe that both the the transport cost savings and the number of stores transferred are higher for the first scenario. When $|N| = 100$, $\alpha = 0.5$, the stores that do not need to be served in the flexible schedule can be and are used as transfer points.

When $|N| = 50$, $\alpha = 1.0$, the option to transfer goods at other desirable locations is no longer available. This is reflected in the results, where for $|N| = 100$, $\alpha = 0.5$, we see that fewer stores are visited and the demands of more stores are transferred, leading to higher transport cost savings.

Table 3.5: Effect of α on capacity sharing [warehouses not co-located] ($|S| = 50$, $\beta = 1/2$, $\rho = 0.5$)

	$\|N\| = 100$, $\alpha = 0.5$	$\|N\| = 50$, $\alpha = 1.0$
Δ transport cost (%)	76.0	68.9
# of stores visited	5.4	8.6
# of stores transferred	45.8	41.4
# of transfer points	2.6	2.6

3.6.6 Effect of store transfer capacity

In the previous experiments, we assumed that about half of the stores had limited space available to temporarily store (and handle) goods being transferred, i.e., $\rho = 0.5$. Here, we consider different values of ρ, the probability that a store has limited transfer capacity, to understand its effect on capacity sharing. The results can be found in Table 3.6, where, as before, we report the transport cost savings, the number of stores visited, the number of stores transferred, and the number of transfer points used.

Table 3.6: Effect of store transfer capacity on capacity sharing [warehouses not co-located] ($|N| = 100, |S| = 70, \alpha = 0.7, \beta = 1/2$)

ρ	Δ transport cost (%)	# of stores visited	# of stores transferred	# of transfer points
0.00	77.3	6.6	63.6	2.2
0.25	77.1	6.8	63.6	2.0
0.50	75.9	9.2	61.6	3.0
0.75	74.3	11.0	59.8	3.6
1.00	50.5	35.0	38.8	26.0

As expected, when store transfer capacity is limited at more stores (i.e., higher values of ρ), more stores are visited and the goods of fewer stores are transferred. This is reflected in the transport cost savings, with the highest saving for $\rho = 0.00$ and the lowest cost savings for $\rho = 1.00$.

Interestingly, the transport cost savings do not differ much for $\rho = 0.00$, 0.25, 0.50, and 0.75. A closer examination of the flexible routes for these instances reveals that stores that have no store transfer capacity limit are chosen as transfer points. Of course, this is not possible when all stores have a store transfer capacity limit ($\rho = 1.00$) and the transport cost savings drop significantly.

3.6.7 Effect of store transfer costs

In this section, we study the impact of a fixed cost for transferring demand at a store, i.e., $c_i^T > 0$ for $i \in N$. In particular, we set the value of the transfer cost at every store to $\tau \geq 0$ times the average distance between any two locations in the network. The total cost is the sum of the transport cost and the transfer cost. In Table 3.7, we report the cost savings, the number of stores visited, the number of stores for which demand is transferred, and the number of transfer points used. Note that the case $\tau = 0.0$ corresponds to the default setting without transfer costs.

Table 3.7: Effect of transfer costs at store on savings of capacity sharing [warehouses not co-located]
($\alpha = 0.7$, $\beta = 1/2$, $\rho = 0.5$)

τ	Instance information		Δ transport cost	Δ transfer cost	Δ total cost	Stores visited		Stores transferred		Transfer points	
	$\|N\|$	$\|S\|$	(%)	(%)	(%)	#	%	#	%	#	%
0.0	40	28	67.5	0.0	67.5	5.2	18.6	23.2	82.9	2.2	44.3
	60	42	74.3	0.0	74.3	5.2	12.4	36.8	87.6	2.2	42.7
	80	56	74.4	0.0	74.4	5.8	10.4	50.8	90.7	2.0	34.7
	100	70	76.7	0.0	76.7	6.8	9.7	63.8	91.1	2.2	37.4
0.2	40	28	67.3	-4.3	63.0	6.0	21.4	22.4	80.0	1.8	31.8
	60	42	74.5	-3.8	70.7	6.2	14.8	35.8	85.2	2.0	33.8
	80	56	74.4	-3.4	71.0	5.8	10.4	50.8	90.7	2.0	34.7
	100	70	76.7	-3.2	73.5	6.6	9.4	64.2	91.7	2.0	31.3
0.5	40	28	65.4	-8.3	57.1	7.0	25.0	21.2	75.7	1.4	22.2
	60	42	74.9	-8.5	66.4	7.4	17.6	34.6	82.4	1.8	27.6
	80	56	73.6	-7.7	65.9	7.4	13.2	49.2	87.9	1.8	28.2
	100	70	76.8	-8.0	68.8	6.6	9.4	64.2	91.7	2.0	31.3
1.0	40	28	62.4	-11.9	50.5	8.2	29.3	19.8	70.7	1.0	12.2
	60	42	71.9	-11.5	60.4	9.8	23.3	32.20	76.7	1.2	14.2
	80	56	69.3	-10.2	59.1	12.8	22.9	43.40	77.5	1.2	12.2
	100	70	72.4	-11.1	61.3	14.0	20.0	56.6	80.9	1.4	14.9

As expected, we see less cost savings in the settings with transfer costs. The reason for this is that some of the transportation cost savings are offset by the additional costs associated with transfers. Intuitively, we see that the number of transfer points used decreases with the transfer costs.

3.6.8 Effect of the capacity of the vehicle operating the fixed route

So far, we have assumed that the vehicle operating the fixed route has no available capacity when it leaves the warehouse. Here, instead, we assume that τ% of the total demand of the stores in the flexible schedule is available as spare capacity in the fixed route at the warehouse. We use $|N| = 100$, $\alpha = 1.0$, and $\beta = 1/2$ in this experiment. Note that by increasing the spare capacity at the warehouse, the transfer capacity, e_i^v, at every store i, for $i \in N$, is increased by the same amount, which can lead to higher transport cost savings. We observe in the results reported in Table 3.8, that this is indeed the case.

Table 3.8: Effect of an increase in capacity of fixed route vehicle on capacity sharing [warehouse not co-located]
($|N| = 100$, $|S| = 70$, $\alpha = 0.7$, $\beta = 1/2$, $\rho = 0.5$)

τ (%)	Δ transport cost (%)	# of stores visited	# of stores transferred	# of transfer points
0	76.7	6.8	63.8	2.2
10	77.6	7.6	62.8	2.6
20	78.0	7.6	63.0	2.8

When the warehouses are not co-located and the fixed and flexible routes start at the same time (as is the case in the default settings), it is, of course, not possible to use the warehouse of the fixed route as a transfer point. However, even when the flexible route can start earlier and the warehouse of the fixed route can be used as a transfer point, in the instances we generated, it never is. It is always better to catch-up at a store that is closer to the warehouse of the flexible route. We note that this is an artifact of our instances. If visiting the warehouse of the fixed route does not require a long detour, it may be beneficial to use it as a transfer point in the flexible route.

3.6.9 Effect of the earliest start time of flexible route

When the warehouse of the flexible route is not co-located with the warehouse of the fixed route, the flexible route needs to catch up with the fixed route before it can transfer goods. A similar situation arises when the warehouses are co-located, but the flexible route starts later than the fixed route. This may occur when the retailer wants to accommodate more online orders and sets a late online order cut-off time. Here, we study how a later start of the flexible route impacts the benefits of capacity sharing.

We use $|N| = 100$, $\alpha = 0.7$, $\beta = 1/2$, $\rho = 0.5$. The duration of the fixed route for this setting is around 400 units of time. We let the flexible route start δ units of time after the fixed route for $\delta = 30$, 45, and 60. The results can be found in Table 3.9.

Table 3.9: Effect of late start of flexible route on capacity sharing [warehouse co-located] ($|N| = 100$, $|S| = 70$, $\alpha = 0.7$, $\beta = 1/2$, $\rho = 0.5$)

δ	Δ transport cost (%)	# of stores visited	# of stores transferred	# of transfer points
0	81.0	5.2	66.0	4.8
30	72.9	12.4	58.4	2.8
45	68.2	16.2	54.6	2.0
60	63.0	18.4	52.2	1.2

As expected, when the transfer options reduce (when δ increases), the transport cost savings decrease (the number of transfer points decreases, the number of stores transferred decreases, and the number of stores visited increases). As δ increases, the flexible route can only catch up with the fixed route at a "later" store. Therefore, fewer stores can be transferred, and more stores have to be visited (at least all those before the catch-up point).

In Figure 3.5, we illustrate the effect of a late start of the flexible route on capacity sharing for a particular instance. When the flexible route starts at the same time as the fixed route ($\delta = 0$), the flexible route is *d-1-3-4-25-10-89-d*, as shown in Figure 3.5a. When the flexible route starts 30 units of time after the fixed route ($\delta = 30$), the flexible route is *d-12-11-25-27-26-10-9-8-6-4-2-1-d*; the first store it can catch up with the fixed route is store 12. Since the stores before the catch-up point cannot be transferred, they have to be visited, which contributes to the increase in transport cost.

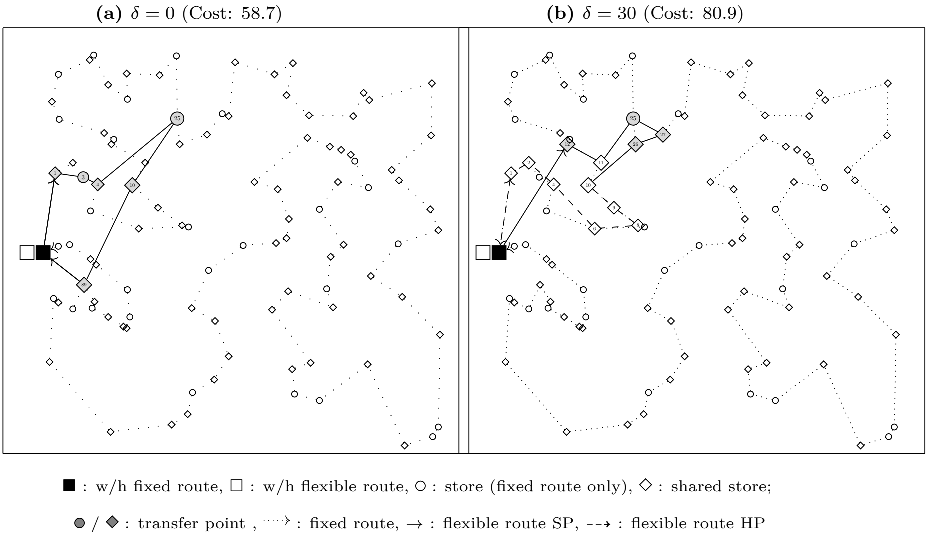


Figure 3.5: Late start of flexible route [warehouse co-located]
($|N| = 100$, $\alpha = 0.7$, $\beta = 1/2$, $\rho = 0.5$)

3.7 Conclusion

We have introduced the Shared Capacity Routing Problem with Transfers to minimize the transport cost of online order fulfillment in an omni-channel retail environment. We have developed an exact as well as a heuristic approach for its solution. We have conducted an extensive computational study to assess the benefits of capacity sharing, in terms of transport cost savings and a reduction in the number of store visits.

The following is a summary of the insights gained from our computational study:

- The benefits of capacity sharing can be significant, especially when the volume of goods to be delivered to the store pick-up points is small compared to the volume of goods for replenishing store inventories.
- To achieve the benefits of capacity sharing, it is sufficient to have just a few stores with ample transfer space.
- The benefits of capacity sharing depend on the locations of the warehouses for store replenishment and online order fulfillment because it impacts the first possible transfer location and time.

- The benefits of capacity sharing will be greater if the vehicle supplying the store pick-up points can depart its warehouse earlier or not much later than the vehicle that replenishes store inventories.
- The benefits of capacity sharing do not depend strongly on the capacity of the vehicle that replenishes store inventories.

A natural extension of the research reported in this paper is to consider multiple fixed routes and multiple flexible routes.

Acknowledgement

This work is part of the research programme Designing sustainable last-mile delivery services in online retail with project number 438-13-204, which is (partly) financed by the Netherlands Organisation for Scientific Research (NWO). Stichting Erasmus Trustfonds also financially supported our research project.

Appendix

Shortest path in topologically sorted directed acyclic graph

Define $dist[i]$ as the shortest path distance of node i from the source s in $G_1 = (V_1, A_1)$

Initialize $dist[i] = \{\infty, \infty, \ldots\}, \forall i = 1, \ldots, |V_1|$ and $dist[s] = 0$, where s is the source vertex

for every vertex u in a topological ordering of G_1 **do**

  for every adjacent vertex v of u **do**

    if $dist[v] > dist[u] + c_{uv}$ **then**

      $dist[v] = dist[u] + c_{uv}$

    end if

  end for

end for=0

During computation of $dist[v]$, we store the u corresponding to the least cost in $P(v)$. We can reconstruct the shortest path bases on $P(v)$.

4 Towards Profitable Growth in E-Grocery Retailing – the Role of Store and Household Density

4.1 Introduction

Online grocery sales have seen spectacular growth rates world wide, especially during the Covid-19 pandemic (ResearchAndMarkets.com 2020). However, online sales still account for only 5%–10% of total grocery sales in most markets. One of the main reasons that e-grocery sales have not developed as rapidly as other categories, such as electronics and books, is the operational challenges involved. Grocery products are bulky and fragile; they also include fresh food with expiration dates and different temperature requirements. A typical grocery order consists of 30–60 different stock-keeping units (Seow et al. 2003) that need to be "picked" individually. Moreover, the customers in home delivery setups must be at home in order to receive the goods – which necessitates the use of time windows to coordinate receipt of the groceries (Agatz et al. 2011).

E-grocery operations are characterized by high costs per transaction. The two primary cost drivers are order picking and last-mile delivery operations. In picking, the cost per customer order depends mostly on the level of automation (Hübner et al. 2016b). In last-mile delivery, costs depend on the drop density (i.e., number of deliveries per fixed area) and the service time spent at the customer. A higher drop density is associated with lower travel times and less distance between customers. Because drop density is related to the number of customers that can be served together in space and time, it is linked also to lead times, time-window options, household density, and total number of customers that shop online. Service time depends on the size of the order and on the retailer's specific service offering. For instance, it generally takes more time to deliver "into the kitchen" than simply to the doorstep.

Since the delivery fee is a barrier to shopping online, grocers typically charge a low fee (or even offer free delivery) to attract more customers. Given the low profit margins of grocery products and the relatively small order sizes, the retailer's per-order fulfillment costs often exceed the associated revenue (Capgemini 2019). Thus e-grocery operations – whether conducted by pure players or multi-channel retailers – generally incur losses. For example, the UK-based e-grocery retailer Ocado reported a £214 million loss in 2019 (Castia 2020).

There is ongoing debate over whether or not online grocery will ever be more than a niche market (Dannenberg et al. 2020). Several industry analysts expect e-grocery market shares to reach double digits in the next 5–10 years (Colliers International 2019, FMI et al. 2020), and hundreds of millions of dollars have been invested in e-grocery operations around the world (Ecommerce News Europe 2019, Begley et al. 2020, Park 2020). At the same time, others are more critical. The retail bank HSBC is "unconvinced of [the] long-term viability of home deliveries for grocery" (Edwards 2016). In a recent study of the German market, Dannenberg et al. (2020) conclude that "even the unprecedented growth in e-grocery during the [Covid-19] crisis does not indicate a fundamental long-term shift from stationary to online food retail."

What is often missing in this debate is a good understanding of the interaction between the store channel and the e-grocery channel. On the one hand, growth in the online market share is typically at the expense of the store channel. On the other hand, studies have shown that e-grocery sales increase disproportionately in areas with less store coverage (Chintagunta et al. 2012). Hence the growth of e-grocery shopping cannot be studied separately from developments in the store channel.

The two sales channels have different value propositions. The e-grocery channel provides customers with the convenience of home delivery, but it may also be perceived as costly and inflexible because it requires customers to plan ahead. In contrast, brick-and-mortar stores provide instant gratification and allow customers to touch and feel fresh items without having to wait or pay delivery fees (NPD 2018). The situation is in constant flux as both channels continuously look for ways to improve the shopping experience for customers.

Our study focuses on how household and store densities affect the market shares of the e-grocery and store channels. For the online channel, higher household density is associated with higher drop densities and thus lower last-mile fulfillment costs – characteristics that allow for more competitive pricing of the online service to win market share. Yet we show that, contrary to conventional wisdom, higher household densities do not always lead to a more competitive e-grocery channel because store densities are then typically higher as well. Thus we observe competing effects, as high *household* densities correspond to lower fulfillment costs whereas high *store* densities limit the appeal of home online grocery. To analyze this intriguing relationship, we develop a stylized model of cross-channel choice behavior that captures the effects of household and store densities while incorporating the different cost structures of each channel. The model considers a grocery retailer that operates both a network of stores and an e-grocery home delivery service. Customers choose to shop for groceries through the e-grocery channel, at the store, or via an outside alternative. We calibrate the model using empirical data from an European context and then derive insights into how market shares could evolve in different environments.

We find that e-grocery channel profits increase with household density but decrease with store density. Picking costs also play a significant role in the profitability of the e-grocery channel. When the retailer's two channels are jointly optimized, e-grocery is a profitable option only when picking costs are low. In addition, we document that increases in customer valuations of the e-grocery channel can significantly boost its profitability. An increase in online sales will come at the expense of sales in the store channel, which jeopardizes that channel's financial viability. One possible outcome is the eventual closing of stores.

Our results suggest three strategic paths to profits in e-grocery: service, niche, or subsidies. The *service* path requires a substantial increase in valuation of the online channel in comparison to the store channel; only such an increase can induce customers to pay higher delivery fees. The *niche* path requires that the online channel focus on areas with high household density and low store density. In these areas, the relative costs of the online channel are most competitive while valuations of the store channel are relatively low – given the costs of traveling to a store. Finally, the *subsidy* path relies on the deep pockets of investors and shareholders to subsidize the online channel until such time that stores face imminent closure. In that event, the store channel's relative valuation declines and so the online channel can charge higher delivery fees.

This study's principal contributions can be summarized as follows. First, we present a stylized model that allows one to study the "cannibalization" of sales between the e-grocery channel and the store channel. Thus we model customer choice behavior across sales channels as well as its effects on operational fulfillment costs. In this model, we bring together different aspects that have previously been studied only in isolation. Second, we provide fundamental new insights into the drivers of the e-grocery channel's profitability and market share. Finally, we calibrate our model based on real-world industry data and thereby illuminate expected developments in the market shares of the different channels in various environments.

The rest of our paper proceeds as follows. Section 4.2 reviews the related literature. In Section 4.3, we formally describe the model. Section 4.4 presents some theoretical results, and Section 4.5 reports the results from our numerical experiments. We conclude in Section 4.6 with a summary of our key findings and suggestions for future research.

4.2 Literature review

This paper contributes to the literature on omni-channel grocery retailing. Our method builds on research addressing customer choice behavior and the literature on e-grocery operations.

So-called attraction demand models are commonly used to model consumer choice in marketing, economics, operations, and revenue management (Harsha et al. 2019). There is a large stream of literature that uses stylized attraction models to study the interaction between different sales channels. Bernstein et al. (2008) focus on the benefits, for a traditional brick-and-mortar retailer, of adding an e-grocery channel. They derive multinominal logit models and study industry equilibria for different market conditions. In a similar vein, these models have been used to study a variety of specific omni-channel retail settings, such as "showrooming" (Balakrishnan et al. 2014) and "buy online with pickup in store" (Gao et al. 2021). Most of the extant work considers channel choice and pricing based on simple linear cost models. In contrast, we focus on effects of the nonlinear fulfillment costs typical of e-grocery retailing. In particular, we model marginal fulfillment costs that – owing to economies of scale – decrease with the number of orders. Moreover, whereas most papers in this stream of work are devoted to developing theoretical frameworks, we collect empirical input data to provide real-world insight on potential market shares and the profitability of grocery operations.

The empirical research on channel choice in grocery retailing is limited. Previous studies on e-grocery shopping compare online and offline purchase behavior in terms of brand loyalty (Danaher et al. 2003), shopping behavior (Andrews and Currim 2004, Breugelmans et al. 2007, Kull et al. 2007), and consumers' perceptions of shopping online for groceries (Ramus and Nielsen 2005). Chintagunta et al. (2012) empirically quantify different types of transaction costs in the online and offline grocery channels. Boyer and Hult (2005) show, in an e-grocery context, the importance of the retailer's website – and of product and service qualities – for encouraging repeat purchase intentions.

A number of papers discuss the advantages and disadvantages of different strategies for e-grocery and omni-channel fulfillment operations (Yrjo et al. 2001, de Koster 2002, Hays et al. 2005, Hübner et al. 2016b). There is a growing body of research on the specific challenges of offering an effective and cost-efficient grocery delivery service, especially as regards last-mile operations. Several early studies focus on how customer density and the length of the delivery time window affect last-mile delivery costs (Lin and Mahmassani 2002, Boyer et al. 2009). Others have addressed optimizing the design of the time-window offering in order to facilitate efficient routing operations and customer service (Agatz et al. 2011, Yang et al. 2016) while discussing the related (dynamic) pricing decisions (Klein et al. 2019, Strauss et al. 2020, Vinsensius et al. 2020). In this paper, we apply continuous approximation (cf. Ansari et al. 2018) to estimate the expected last-mile distances for different drop densities. Such routing approximations are well suited for strategic analysis of the case where customer locations are not precisely known.

Order picking constitutes a large portion of the costs of online order fulfillment (Kämä-räinen et al. 2001). It is well documented that warehouse-based picking is more efficient than store-based picking (Hübner et al. 2016b). Although there is extensive research on warehouse operations and order picking for e-commerce (Boysen et al. 2019), much less attention has been given – in the literature on warehouse layout design and order-picking strategies – to the particular challenges of picking groceries (e.g., temperature zones, sensitive products). One notable exception is the recent work of Vazquez-Noguerol et al. (2021), who study how best to organize picking processes for the e-grocery channel in a regular store. Their empirical work highlights the need to account for different product and order characteristics when designing a process for picking.

4.3 Model

We consider a grocery market of area A in which N^h households and N^s grocery stores are uniformly distributed. Let $\delta^h = N^h/A$ be the household density. Consider an omni-channel grocery retailer that serves the market through its N_s^s stores and also through its e-grocery channel with home delivery service. Households buy fresh groceries at the stores or via the e-grocery channel; they also have the option of obtaining their groceries from an outside option. Since the share of the store channel in the grocery market is large, we represent the outside option by the stores *not* belonging to our retailer. We assume that weekly spending is uniform. The gross margins for the e-grocery and store channels are denoted by m_e and m_s, respectively.

4.3.1 Customer choice model

To model household choice for grocery shopping, we use a general “attraction demand” model (Huang et al. 2013). Customers choose between different channels so as to maximize their utility. Here, each channel has a specific utility that is associated with the attractiveness of the shopping experience in that channel. Let u_e denote the utility of the e-grocery channel, u_s of the store channel, and u_o of the outside option.

A customer incurs also certain *disutilities* when shopping online or in the store. One disutility of shopping online is the delivery fee p. Another disutility of the e-grocery channel is related to the inconvenience of waiting for the groceries to arrive (e.g., lead time, number of time windows, length of the time window). Let w $(0 \leq w \leq 1)$ denote the disutility with respect to waiting time of delivery, where $w = 0$ is the highest level of disutility and $w = 1$ is the lowest. Then the overall utility of the e-grocery channel can be written as

$$u_e = \beta v - \tau^p p - \tau^w (1 - w); \tag{4.1}$$

where v is the valuation of the channel for having groceries at home and β is a multiplier that captures the general customer preference for the e-grocery channel, which is due to such factors as convenience. The values of the parameters τ^p and τ^w (with $\tau^p, \tau^w > 0$) reflect the sensitivity of the customer to (respectively) the delivery fee and the waiting time.

In line with the literature (e.g., Forman et al. 2009, Chintagunta et al. 2012), we suppose that travel time and transportation costs are the main disutilities of visiting the physical store. There is much empirical evidence suggesting that customers are more likely to shop online when they live farther away from a physical store (Cachon 2014). We model the average distance to a store in relation to the store density. With increases in the number N_s^s of retailer's stores, the average distance of a customer to the nearest store decreases – thereby boosting the store channel's utility. Let $\delta_s^s = N_s^s/A$ be the density of stores in the retailer's store channel. We follow Cachon in approximating the average round-trip distance, $\phi_t/\sqrt{\delta_s^s}$, under the assumption that all customers in the store's service area purchase from the retailer's nearest store. The overall utility of the store channel, u_s, can be defined as follows:

$$u_s = \alpha v - \frac{\phi_t}{\sqrt{\delta_s^s}}, \tag{4.2}$$

where ϕ_t depends on the shape of the area. The parameter α (with $\alpha > 0$) determines the customer preference for the store channel that is due to such factors as assortment, freshness, environmental concerns, Internet connectivity and speed, and the hours during which stores are open. Hence β/α captures the relative popularity of the e-grocery channel over the store channel.

The customer has the choice of an outside option whose utility is u_o. Since the outside option is represented by the stores not belonging to our retailer, it follows that the utility of that option is affected only by the customer's cost of traveling to a store. Therefore,

$$u_o = (\beta + \alpha)v - \frac{\phi_t}{\sqrt{\delta_o^s}}. \tag{4.3}$$

In this expression, $\delta_o^s = N_o^s/A$ is the density of grocery stores not belonging to the retailer, with $N_o^s = N^s - N_s^s$. The multiplier $(\beta + \alpha)$ of the valuation of the outside option is chosen such that, in absence of other costs, a customer chooses the retailer and the outside option with equal probability.

We use the attraction demand model (Gallego et al. 2006) to determine the probability of choosing channel $i \in \{e, s, o\}$, where $\gamma_i = u_i/\sum_i u_i$; $u_o = 0$ corresponds to the monopolistic setting in which there is no outside option. The number of customers choosing a channel i to purchase groceries is given by $N_i^h = \gamma_i N^h$. $\gamma_i \leq 0$ implies that the channel i has no customer demand.

4.3.2 Cost model

The store channel is characterized by low variable fulfillment costs and high fixed costs. The costs of serving an additional customer are negligible in the supermarket context. In contrast, the e-grocery channel is characterized by high variable costs that stem from order picking and last-mile delivery operations. For each sales channel, we view the supply of products to the stores and to the e-fulfillment warehouses as fixed costs that are not associated with specific customer orders. So in line with common management accounting practice, we focus on the variable costs and the contribution margin

4.3.2.1 E-grocery channel

The customer orders grocery products that must then be picked and packed into bags or crates for delivery. Picking grocery products is challenging because they require different temperature zones and are both fragile and bulky. Different customer orders are often picked in parallel, and the picking time per order depends on the general picking setup (warehouse or store) and level of automation (Kämä-räinen et al. 2001, Hübner et al. 2016b). In modeling this dynamic, we use c^p to denote the picking cost per order.

Next we consider the costs of the last-mile delivery from an e-grocery fulfillment center to the customer home. The fulfillment center operates a fleet of homogeneous vehicles, each with a capacity of Q orders. We assume there is only one vehicle per shift and consider a single shift per day. Hence the number of vehicles that the e-grocery channel needs for delivering to N_e^h households is given by N_e^h/Q. Each vehicle has a cost c^v that reflects leasing and depreciation expenses. We assume that the vehicle fleet and associated costs can vary with the number of customers, since the size of the (leased) fleet can be adjusted. We use c^l to denote the per-vehicle labor cost of loading orders into the vehicle.

A delivery route consists of three parts: (i) the "stem" distance between the e-fulfillment center and the delivery area; (ii) the travel distance between consecutive customers within the delivery area; and (iii) the service times spent at the customers. We approximate the expected travel distance per route based on the customer density (as in Beardwood et al. 1959, Daganzo 1984). For a fulfillment center that is located in the center of a roughly circular service area of size A, we can estimate the stem distance as $\frac{2}{3}\phi_k\sqrt{A/\pi}$; here ϕ_k depends on the shape of the region (Daganzo 2005). The e-grocery channel has an effective household density of $\gamma_e \delta^h$. Hence the total inter-customer distance traversed in a route is estimated as $\phi_k(Q-1)/\sqrt{\gamma_e \delta^h}$.

Time-window constraints influence the effective spatial density. Multiple narrow time windows require the delivery vehicle to visit the same area multiple times, which means that the density is spread out over time. We use the time windows offered for delivery as a proxy for w, the disutility due to the waiting time for delivery. The higher the number of time windows, the lower the disutility. To incorporate this effect into our cost model, we multiply the household density by w; then the inter-customer distance becomes $\phi_k(Q-1)/\sqrt{\gamma_e \delta^h w}$. When disutility w declines, the inter-customer distance increases because the effective customer density is reduced. The total distance traversed in all routes is therefore

$$d = \left(\frac{4}{3}\phi_k \sqrt{\frac{A}{\pi}} + \phi_k \frac{Q-1}{\sqrt{\gamma_e \delta^h w}} \right) \frac{N_e^h}{Q}. \tag{4.4}$$

The costs related to the travel distance comprise fuel costs and labor costs for the driver. In developed markets, labor accounts for the bulk of all travel costs. Let c^t denote the labor and fuel costs per kilometer (km) of driving. Combining the fixed cost of a vehicle and its loading cost, we can express the total travel cost associated with routes as

$$c^d = \left(c^v + c^l + \frac{4}{3}\phi_k \sqrt{\frac{A}{\pi}} c^t + \phi_k \frac{Q-1}{\sqrt{\gamma_e \delta^h w}} c^t \right) \frac{N_e^h}{Q}. \tag{4.5}$$

A customer order typically consists of several bags or crates of groceries, often sorted by the required product temperature zones. For delivery to the customer, we let c^s represent the service-time cost per order, which reflects the labor costs associated with the service time.

When we combine these cost components, the total cost of distribution (picking cost + transport cost + service cost) for the e-grocery channel is

$$C_e = c^p N_e^h + c^d + c^s N_e^h. \tag{4.6}$$

We can now use (4.6) to write the distribution cost per order as

$$\bar{C_e} = \frac{C_e}{N_e^h} \approx f^v + c^p + c^s + \frac{\phi_k}{\sqrt{\gamma_e \delta^h w}} c^t,$$

where f^v represents the fixed cost per order depending on the vehicle capacity Q and shape of the distribution region.

4.3.2.2 Store channel

For the store channel, most operational costs (e.g., real estate, store labor) are fixed. Stores generally have full-truckload deliveries, so we can assume that each store's distribution costs are fixed. Labor is a high fixed cost for all supermarket operations (Group 2019, Campbell 2021). In the store channel, the average replenishment size of a store is fixed; hence warehouse picking costs are also fixed for stores of a given size. Therefore, our model assumes that there are no variable fulfillment costs associated with the store channel.

4.3.3 Contribution margin and strategies

We focus on maximizing the *contribution margin* – that is, the gross margin minus the variable costs. Recall that m_e and m_s represent the gross margin per order for (respectively) the e-grocery and store channels. The customer choice model gives the total demand for the e-grocery channel as $N_e^h = \gamma_e N^h$. So given the cost model (4.6), we can write the total contribution margin of the e-grocery channel as $\Pi_e = (m_e + p)N_e^h - C_e$. For the store channel, the variable costs per order are negligible and so its contribution margin is $\Pi_s = m_s N_s^h$.

The total contribution margin for the retailer is given by $\Pi = \Pi_e + \Pi_t$. The contributions per order are denoted by $\bar{\Pi}$, $\bar{\Pi}_e$, and $\bar{\Pi}_t$ for (respectively) the retailer, the e-grocery channel only, and the store channel only. (We shall often use "contribution" as shorthand for "contribution margin" when our meaning is clear from the context.)

We consider two different strategies. In the first strategy, the retailer maximizes the contribution margins of the e-grocery and store channels independently – which for our purposes amounts simply to maximizing the e-grocery's contribution only. We refer to this as the *online* strategy. In the second, *omni-channel* strategy, the retailer jointly maximizes the contributions from both channels. The online strategy corresponds to the case where a retailer manages its different sales channels independently, which is a widespread practice. We seek to derive the optimal e-grocery delivery fee that either maximizes the contribution margin from the e-grocery channel alone ("online") or maximizes the total contribution margin ("omni-channel").

4.4 Analytical results

This section presents some analytical results that help us better understand the different trade-offs and interactions. The proofs of Propositions 1, 2, and 3 are given in (respectively) Appendix A, B, and C.

Proposition 4.4.1. *There exists a unique optimal delivery fee p^* that maximizes the contribution margin.*

Maximizing the contribution amounts to balancing the delivery fee's effect on revenues and costs. A lower fee corresponds to less revenue per customer but also creates more demand. And more demand, which yields economies of scale in last-mile delivery, leads to lower marginal costs per customer.

Proposition 4.4.2. *The optimal market share of the e-grocery channel is lower under the omni-channel strategy than under the online strategy.*

Because the e-grocery channel's market share declines with a higher delivery fee, Proposition 2 implies also that the optimal delivery fee p^* is lower for the online strategy than for the omni-channel strategy. The reason is that the omni-channel strategy makes an explicit trade-off between the advantages of gaining more market share from the competition and the disadvantages of cannibalizing the retailer's own store channel by drawing customers from the profitable stores to the less profitable e-grocery channel.

We are unfortunately not able to derive a closed-form expression for the optimal delivery fee – owing to the nonlinear nature of our cost and demand modeling. However, we can analyze the break-even delivery fee to understand how it behaves in relation to our key parameters. Since the margins are low, we expect that the behavior of the break-even delivery fee will be similar to that of the optimal fee. Let the *break-even delivery fee p^b* be the delivery fee at which the marginal revenues of the e-grocery channel are equal to its marginal costs, and let p^0 be the minimum delivery fee at which no customer will choose to shop at the e-grocery channel. The optimal delivery fee p^* is bounded by these two extremes; that is, $p^b \leq p^* \leq p^0$. To determine p^0, we set $u_e = 0$ in (4.1). Then $p^0 = \frac{\beta v + \tau^w (1-w)}{\tau^p}$.

Proposition 4.4.3. *For the e-grocery channel, the break-even delivery fee p^b*

(i) *decreases with the household density, $\delta_e^h = N_e^h / A$;*

(ii) *increases with the picking costs per order,* c^p; *and*

(iii) *increases with the store density of the store channel,* δ_s^s.

It makes sense that the delivery fee required to break even increases with the costs per order of the e-grocery channel, which include both picking costs and distribution costs; the additional revenue from the delivery fee is needed to offset the costs. Less intuitive is that the break-even delivery fee increases with higher store densities. We can better understand this outcome by recognizing that the online market share decreases with the store density as the e-grocery channel becomes relatively less attractive. Fewer online orders reduce drop densities and hence the economies of scale in last-mile delivery, thus leading to higher fulfillment costs per order. Then the revenue loss from lowering delivery fees is greater than the cost reduction from serving more customers. We conclude that the retailer should increase its delivery fee at higher store densities.

4.5 Numerical analysis

To estimate our parameters, we use real-world data from the grocery industry together with social and demographic statistics. In this section we present the results of a series of numerical experiments based on those parameters. Our numerical study offers insights into the relative magnitude of effects of different parameters and into the conditions necessary for profitable growth of the e-grocery market. When deriving the optimal solution, we enumerate the delivery fee's possible values ($p^b \leq p^* \leq p^0$). Because we use realistic values, our study also provides insights into the long-run profitability and expected market shares of the e-grocery channel.

4.5.1 Parameter estimates

Table 4.1 reports our estimates for the parameters of the customer choice and operational cost model described in Section 4.3. The estimates are based on data from the Netherlands. We use public sources but have verified the estimates with several major Dutch online grocery retailers.

Table 4.1: Model parameters

Parameter	Notation	Baseline value	Sources
Preference of customer for store channel	α	2.8	Authors' estimate based on current prices and market shares
Sensitivity to delivery fee	τ^p	2.4	Authors' estimate based on current prices and market shares
Sensitivity of customer to service quality w.r.t time	τ^w	5.0	Authors' estimate based on current prices and market shares
Picking cost per order	c^p	€12.5	Reinhardt (2001), Moons et al. (2019), Ehrler et al. (2019)
Service time cost per order	c^s	€4.2	Drive (2018), Yang et al. (2014)
Annual cost per vehicle	c^v	€19,000	Schonewille (2016)
Loading cost per vehicle	c^l	€8.3	Punakivi and Saranen (2001), Moons et al. (2019)
Vehicle capacity in orders	Q	18	Industry partner data
ϕ_k		1.32	Daganzo (1984)
Cost per km	c^i	€1.8	Statista (2020), Mock (2014), Moons et al. (2019)
Gross margin	m_e, m_s	13%	Marshoek (2018), Galante et al. (2013)

To model demand, we consider a weekly cycle because it corresponds to the typical online grocery shopping cycle (Statista 2019). We model the operating costs per shift while assuming that weekly demand is spread equally across six shifts. Weekly spending on groceries is about €100 per household in the Netherlands (Nibud 2021). For grocery products, we assume a gross margin of 13% (Galante et al. 2013, Marshoek 2018) irrespective of the channel (so $m_e = m_s$). This assumption is reasonable since empirical evidence on the impact of different order patterns online and offline is not conclusive (Kacen 2003, Belavina et al. 2017, Acosta 2020). We consider a disutility cost of €4 per kilometer traveled per store visit; this cost reflects opportunity and fuel costs as well as urban travel speeds (Mock 2014, Schonewille 2016, Belavina et al. 2017, Statista 2020).

Now we evaluate fulfillment costs in the e-grocery channel. Estimates from OW Robots (2021a) indicate that it takes some 30 minutes to pick a grocery order in a "manual" warehouse setting. At an average hourly wage of €25 (Moons et al. 2019), this time corresponds to picking costs of €12.5 per order. For the last-mile distribution operations, we consider the labor cost, fuel costs, and vehicle cost. We use a yearly fixed cost of €19,000 per vehicle for leasing and damage costs (Schonewille 2016). The number of vehicle trips needed depends on the number of orders per vehicle trip. The maximum number of orders per vehicle depends on the their size (i.e., volume and weight) in relation to vehicle capacity. For an average order of €100, we assume a vehicle capacity Q of 18 orders. We assume an average loading time of 20 minutes per vehicle trip (Punakivi and Saranen 2001, Moons et al. 2019), which corresponds to a loading cost of €8.3 per vehicle. The delivery costs per kilometer – based on urban speed, fuel consumption, and labor costs – is €1.8. We further assume an average service time at the customer of 10 minutes, which is consistent with our industry partner's experience and that of other European retailers offering service "up to the kitchen table" (Klein et al. 2019). Using the average hourly wage of a driver, we obtain a service cost of €4.2.

To fit the utilities of shopping online and in the store as well as the price sensitivity with respect to delivery fees, we compare the market shares of two competing grocery retailers in the Dutch market: Albert Heijn Online and Picnic (Statista 2020a, 2021b). Whereas Picnic offers its customers free delivery but with no time-window choice, AH Online charges a delivery fee of about €8 yet offers more delivery time windows. The product prices are similar at the two grocers (Els 2017). We estimate price sensitivity parameters based on these observed combinations of delivery fees and market share.

Next we shall vary the household and store densities to generate insights into how these aspects affect overall online performance.

4.5.2 Impact of household density and store density

In our first set of experiments, we find the delivery fees and corresponding online market shares that maximize the e-grocery channel's contribution margin for different household densities and store densities (i.e., under the "online" strategy). Panel (a) of Figure 4.1 shows the profit per order for the e-grocery channel; panels (b) and (c) plot the corresponding market shares and delivery fee, respectively.

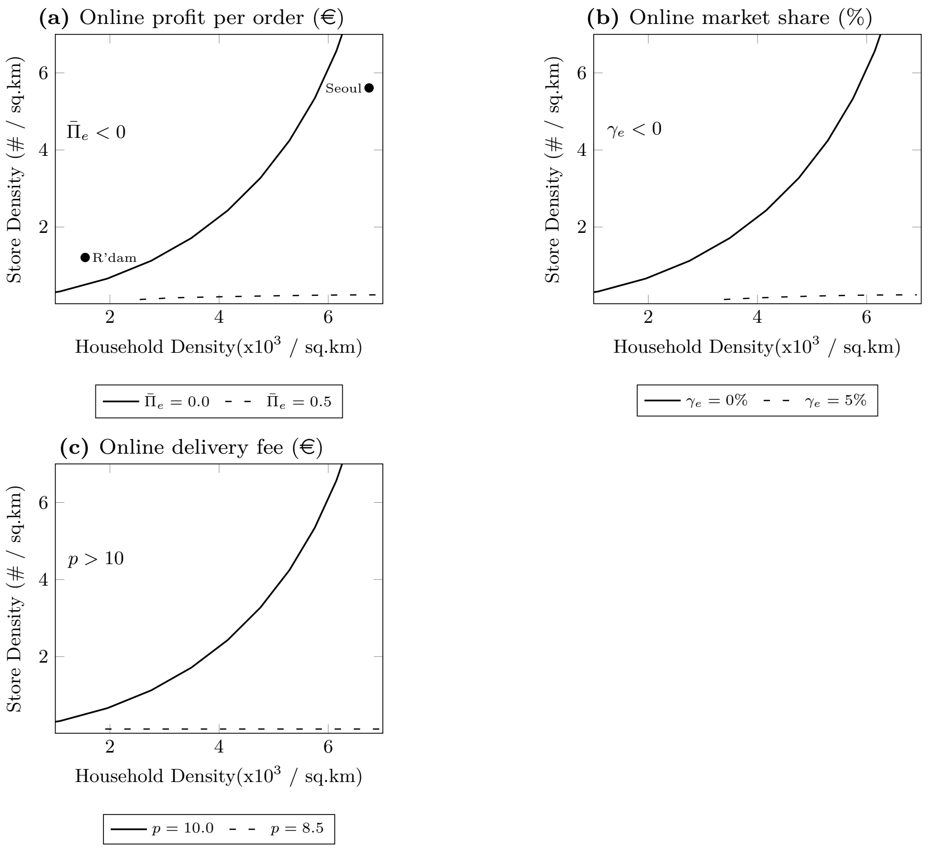


Figure 4.1: Online profitability versus household density and store density for the online strategy

In these experiments, we vary the household density between 1,000 per km^2 and 7,000 per km^2. We consider the household density because it is more commonly used, than is population density, to model grocery shopping. For reference, Rotterdam (the Netherlands) has nearly 1,400 households per km^2, which corresponds to a population density of 2,900 per km^2 (Rotterdam-Partners 2018, Statista 2020b); Seoul (South Korea) has a household density of 6,600 per km^2 for a population density of 16,700 per km^2 (Statistics Korea 2016, City Mayors Statistics 2018). We similarly vary the store density from 1 to 7 per km^2.

Looking at the impact of *household* density, we see that the e-grocery channel's profitability (Figure 4.1a) increases with household density. A greater number of households per square kilometer results in smaller inter-customer distances and thus lower fulfillment costs per order. This cost reduction has a positive effect on the e-grocery channel's profitability. Hence the e-grocery market share increases also with household density (Figure 4.1b) because the lower fulfillment costs enable lower delivery fees (Figure 4.1b). This dynamic is consistent with the analytical results (presented in Section 4.4) for the break-even delivery fee. We can see that, at lower household densities, the unit profits are negative and so the retailer might as well shut down the e-grocery channel (zero market share) by way of charging an exorbitant delivery fee. These results reveal that per-unit profitable e-grocery operations are possible only for higher household densities. In particular, the e-grocery channel generates losses for all combinations of household and store densities to the left of the figure's $\bar{\Pi} = 0.0$ line.

For the city of Rotterdam, which has one of the highest household densities in the Netherlands, our results indicate that per-unit profitability is impossible. Indeed, real-world evidence suggests that none of the Dutch online grocers is currently profitable (NU.nl 2020, RTL Nieuws 2021). One reason for the relatively low online market shares and profitability is that store density in the Netherlands is high (Belderok et al. 2019). According to various surveys of Dutch shoppers, the argument given most often for *not* buying food online is that there is already a supermarket close to their home (Statista 2021b).

As for the impact of *store* density on the e-grocery channel's profitability, we see that the latter decreases with the store density. At high store densities, the average distance between the store and the consumer is small, which makes the store channel more attractive and hence more competitive. For example, the US grocery retailer Trader Joe's recently discontinued its delivery services in New York City, citing the high store density and being "already [in] close proximity to customers" as compelling reasons. Only at very low store densities and high household densities ($>$ 2,500 households per km^2) do we observe higher market shares and profits per order. Despite the theoretical interest of this result, high household densities are in fact often associated with high store densities (McGuirt et al. 2015). Figure 4.1a also shows where Rotterdam (our baseline city) and Seoul (another high-density city) are located on the graph in terms of their household and store density.

Figure 4.1c illustrates that the delivery fee increases with the store density. This outcome is consistent with our analytical results and with a recent study of Capgemini (2019). These findings indeed suggest that the optimal fee behaves similarly to the break-even delivery fee, as the contribution margin per order is generally low for the e-grocery channel and there is little room for reducing the delivery fee in order to protect the retailer's online market share. Our results indicate that an average delivery fee of at least €8 is needed to be profitable. In the United Kingdom, which features a mature and competitive e-grocery market, we see that several grocery retailers charge a lower fee. Yet this observation is still consistent with our results because these e-groceries are, in effect subsidized and do not generate any profits (Eley and McMorrow 2020). The positive relationship between store density and the delivery fee depends on β/α, or the relative consumer preferences for each sales channel. We discuss (in Section 4.5.4) how this result is affected by changed consumer preferences.

In the next set of experiments, we consider the omnichannel strategy in which we explicitly model the interaction between the different channels and maximize the joint contribution of the e-grocery and store channel of a single grocery retailer.

Under the omni-channel strategy, it is not profitable to operate the e-grocery channel in any scenario – even when household density is high and store density is low. Although adding the e-grocery channel may help boost the retailer's overall market share, that benefit does not offset the costs of cannibalizing sales from its own store channel. The reason is that the *effective* contribution margins of the e-grocery channel are lower than those of the store channel, a difference that is due to the additional revenues from the delivery fee failing to offset the high online fulfillment costs. The implication is that, in the short term, online sales reduce the omni-channel retailer's overall profitability. Some grocery retailers (e.g., Albert Heijn) have acknowledged this reality. For that reason, grocery discounters such as Lidl have decided not to open an e-grocery channel: "The costs of going online just don't add up" (Lidl's UK in the CEO, Christian Härtnagel, quoted in Retailweek 2021).

4.5.3 Impact of household density and picking costs

Picking is one of the main cost drivers in the e-grocery channel. A recent study by McKinsey (Kuijpers et al. 2018) suggests that the best retailers can achieve picking costs of €5 per order at a dedicated pick location. Grocery retailer Ocado claims that heavy warehouse automation enables it to pick a 50-item order in 10 minutes (Financial Times 2020, OW Robots 2021b, This Is Money 2021), which would correspond to even lower picking costs per order. Note that picking times in a regular supermarket are typically much longer. A recent empirical analysis by Vazquez-Noguerol et al. (2021) reports average picking times of 43 minutes per order in this context (the equivalent of about €18). Here we study the impact of picking costs by varying that cost between €0 and €12 per order. Moreover, we vary the household densities because they are a key driver of last-mile distribution costs. We fix the store density to the base-case value of 1.2/km^2.

Figure 4.2 plots the contribution margin per order for different household densities and picking costs for the online strategy. As expected, the profitability of the e-grocery channel decreases with picking costs. For the base case, the retailer's e-grocery channel is not profitable and breaks even only at an extremely high household density. At the current picking cost, even when household density increases, the retailer finds it suboptimal to lower its delivery fee and thereby increase market share – as shown in panel (b) of the figure. The primary reason for this outcome is that an order's contribution margin is negative at the current cost structure. The graph confirms that a retailer's online market share increases when picking costs are lower. So if the picking cost is €5 per order, for example, then online sales account for 10% of the retailer's total grocery market.

Warehouse automation can increase contribution margins by 8% by reducing the fulfilment cost (Capgemini 2019). However, this comes at very high investment costs of hundreds of millions of euros (Pooler 2018).

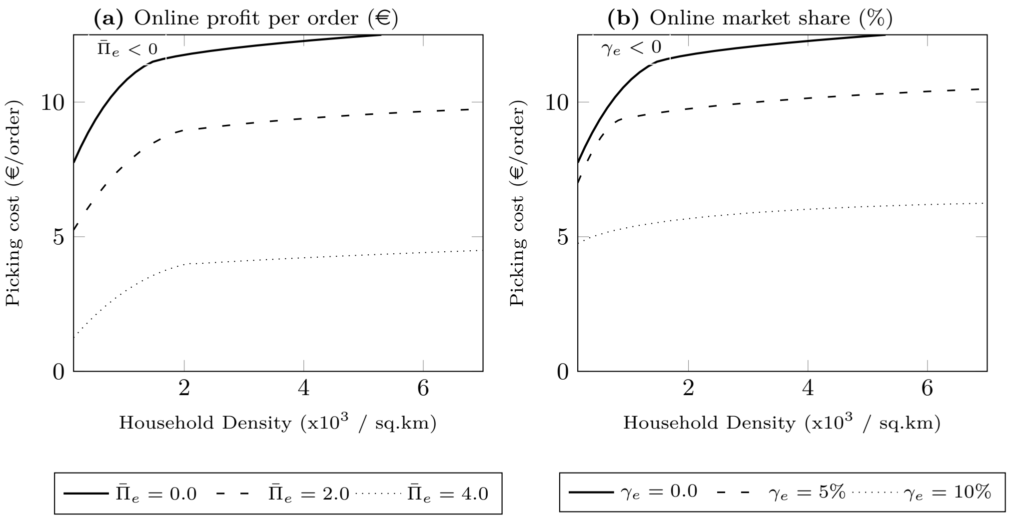


Figure 4.2: Online profitability versus household density and store density for the online strategy

The positive effect of lower picking costs on the online market share is observed also in the omni-channel strategy. With a picking cost of €12.5 per order (as in Section 4.5.2), it is not profitable to operate the e-grocery channel for any store and household density combination. Yet when the picking cost is halved, the retailer benefits from operating an e-grocery channel alongside its store channel – provided that the household density is high enough (see Figure 4.3).

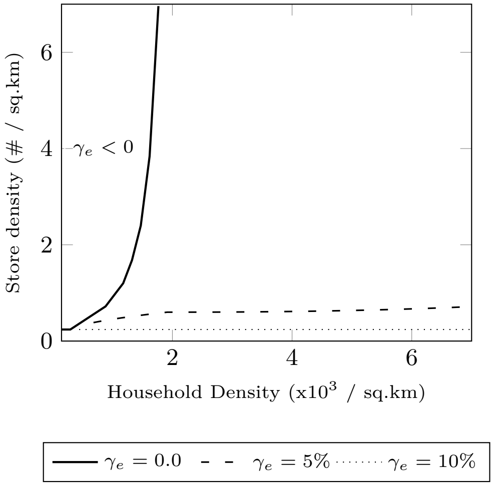


Figure 4.3: Online market share for the omni-channel strategy (picking cost = €6.25/order)

4.5.4 Cannibalization of the store channel

Our experiments based on current estimates for the costs and customer valuation across channels usually result in online market shares well below 10%. We find that it is not profitable to operate an e-grocery channel when household density is low, which suggests that online grocery sales should not much affect the supermarket landscape. However, customer preferences may change over time. One pertinent example is that the long-term effect of the Covid-19 pandemic on grocery shopping preferences remains still unclear. We shall now explore the impact both of higher customer valuation and of lower picking costs on e-grocery market shares; our aim is to identify the point at which cannibalization by the e-grocery channel threatens the store channel's profitability.

Recall from our online utility function (4.1) that β/α captures customers' relative preference for the e-grocery channel over the store channel. A customer's willingness to pay for the e-grocery channel increases with β. To determine the break-even point, we estimate the fixed costs F per store. The store channel's contribution is then $\Pi_s = m_s N_s^h - F N_s^s$. In view of the Dutch supermarket data from Marshoek (2018), we consider a cost F of €25,000 per week for a store whose weekly revenue is between €150,000 and €250,000; this cost includes fixed labor, rent, and replenishment costs. From the same report, we obtain 13% as the gross product margin available to cover these costs.

In Figure 4, panel (a) illustrates the regions in which the e-grocery and the store channel are not profitable under the online strategy – that is, while maximizing the e-grocery channel's contribution. We observe that, when the relative online valuation is low ($\beta/\alpha < 0.35$), the e-grocery channel is not profitable for scenarios with higher picking costs. The graph shows that, as picking costs rise, we need a greater valuation (and thus a higher delivery fee) to offset the costs. At the other end of the spectrum, we see that if online valuations are relatively high then the retailer should close its physical stores and operate only the e-grocery channel. For $\beta/\alpha > 1.8$ (i.e., when online valuation is almost double the offline valuation), the market share of the store channel is too low to cover its fixed costs. Note that the corresponding optimal delivery fee in this case ranges between €26 and €36 for the e-grocery channel when $1.8 < \beta/\alpha < 3.0$. The optimal delivery fee increases with relative online valuation. We remark that these "optimal" delivery fees seem unrealistically high, which suggests that store closures via this mechanism are unlikely in the short term.

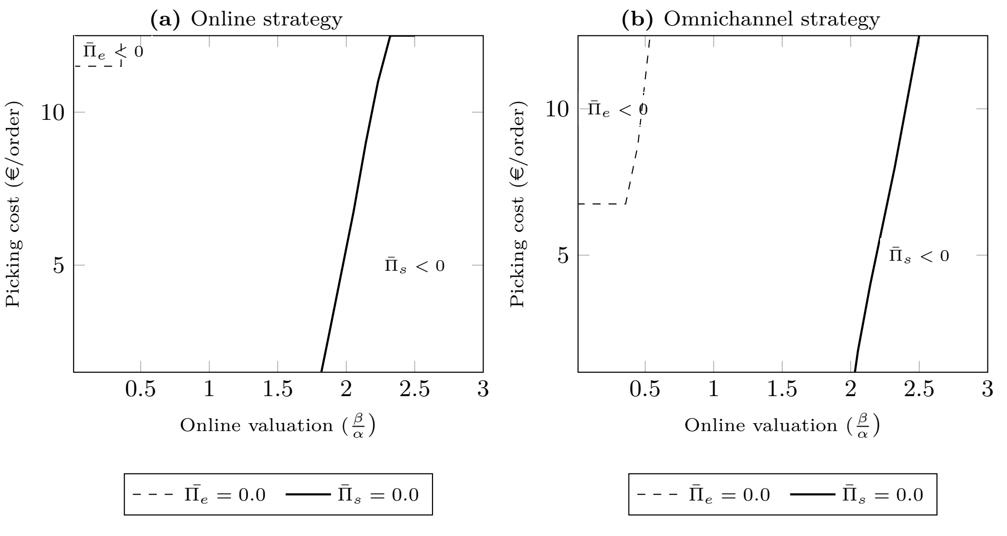


Figure 4.4: E-grocery and store channels' no-profit zones for different relative online valuations and picking costs

Panel (b) of Figure 4 shows similar no-profit zones for the e-grocery and store channels when the total contribution margin is maximized under the omni-channel strategy. Although similar trends are evident, the “tipping points” have shifted. In the omni-channel strategy, if picking costs exceed €10 then the e-grocery channel is not profitable when the relative online valuation is low ($\beta/\alpha < 0.55$). From the store channel perspective, unprofitability begins under higher relative online valuations ($\beta/\alpha > 2.1$). The corresponding optimal delivery fee is from €30 to €41 for the e-grocery channel when $2.1 < \beta/\alpha < 3.0$. In the omni-channel strategy, the interaction between the two channels comes into play. We conclude that, when the omni-channel strategy is pursued, it takes higher relative online valuations for the e-grocery channel to cannibalize sales of grocery stores to the extent that stores start generating losses.

4.6 Conclusion

This study addresses the effect of household and store densities on the e-grocery channel's profitability. We develop a stylized model to capture the principal cost factors affecting customers' utility and hence their choice of channel when purchasing groceries. Whereas the delivery fee and service level (with respect to time) drive online utility, for the store channel a major factor is the cost of visiting the store. By assessing both customer choice behavior and operational costs, we generate insights into what drives the profitability and market shares of the different channels in their optimal settings. We use real-world data to estimate the model's parameters. This approach gives us a solid benchmark based on realistic scenarios – one against which we can compare the effects of relevant parameters on the resulting equilibria.

We find that the e-grocery channel becomes profitable with increasing household density and decreasing store density. The former's effect is due to reducing the distribution costs; the latter's effect stems from increasing the relative consumer disutility of using the e-grocery channel. The cost of picking individual orders in the e-grocery channel plays a crucial role in that channel's profitability. The e-grocery channel is not profitable at the cost structure estimate based on current industry data; this finding accords with current market conditions, where the e-grocery channel yields very low (or even negative) profitability. Considering the retailer's optimal overall strategy, we conclude that – for almost any realistic estimate of store and households density – it is never optimal to launch an e-grocery channel owing to its high operational costs.

It is clear that these basic insights can be strongly affected only by changes in the relative consumer preferences for the online channel. Substantial increases in the online channel's perceived value may induce consumers to pay much higher delivery fees. In that event, the store channel's market share could decline to the extent that the fixed cost of a store network cannot be recovered. Such high customer valuations may develop first in some specific markets.

Our results suggest three strategic paths toward profitability in e-grocery: service, niche, or subsidies. The service path requires a large increase in valuations of the online channel vis-à-vis the store channel without which it will be difficult for customers to accommodate themselves to paying higher delivery fees. In the United States, for example, this effect has been observed during the Covid-19 pandemic: many consumers appreciated the perceived health safety benefits of home delivery compared to visiting a store.

The niche path requires that the online channel focus on areas with high household density and low store density. In such areas, the relative costs of the online channel are most competitive and the valuation of the store channel is relatively low because of the travel costs to reach a store. These niches can be observed in many Chinese cities with very high household densities and very low supermarket density. For instance, Beijing has a population of about 20 million people but fewer than than 200 supermarkets. In comparison, the Netherlands is home to more than 2,000 supermarkets serving 17 million people; hence it is a much less attractive market environment for pursing a niche strategy.

The subsidy path relies on the deep pockets of investors and shareholders to subsidize the online channel until such time that physical stores can respond only by closing. This dynamic reduces the relative valuation of the store channel and thus allows the online channel to charge higher delivery fees. The subsidy path is a challenging one because it requires not only a longer-range perspective but also deep-pocketed investors willing to bet on some of the e-grocery "pure players". We expect to see more differentiation in strategies as the market develops.

Appendix

Appendix A

A function $f(x)$ defined on the domain $x \in \Omega$ has a unique maximal solution if f is strictly concave on Ω. Furthermore, f is strictly concave if and only if $\frac{d^2 f}{dx^2} < 0$. So once we show $\frac{d^2\Pi_e}{dp^2} < 0$, it will be sufficient to prove that there exists a unique optimal delivery fee p^* that maximizes the e-grocery channel's contribution margin under the online strategy. Formally, we have

$$\begin{aligned}\frac{d^2\Pi_e}{dp^2} &= \left(m_e + p - f^v - c^p - c^s - \frac{\phi_k c^t}{2\sqrt{\delta^h w \gamma_e}}\right)\frac{d^2\gamma_e}{dp^2} \\ &\quad + \left(2 - \tau^p \frac{\phi_k c^t}{2\sqrt{\delta^h w}} \frac{u_s + u_o}{(u_e + u_s + u_o)^2}\right)\frac{d\gamma_e}{dp}. \end{aligned} \tag{4.7}$$

Recall that the cost per order for the e-grocery channel is given by $\bar{C}_e = f^v + c^p + c^s - \phi_k c^t / \sqrt{\delta^h w \gamma_e}$. Hence the e-grocery channel has a positive contribution margin only when $m_e + p - f^v - c^p - c^s - \phi_k c^t/\sqrt{\delta^h w \gamma_e} > 0$. Also, $\frac{d^2\gamma_e}{dp^2} = -(\tau^p)^2 \frac{2(u_s+u_o)}{(u_e+u_s+u_o)^3} < 0$ because $u_s + u_o > 0$.

For the second term in (4.7), we have $\frac{d\gamma_e}{dp} = -\tau^p \frac{u_s+u_o}{(u_e+u_s+u_o)^2} < 0$. In our model, δ^h is the household density. An average urban city has household density greater than 1,000/km^2, for which $2 - \tau^p \frac{\phi_k c^t}{2\sqrt{\delta^h w}} \frac{u_s+u_o}{(u_e+u_s+u_o)^2} > 0$. Combining all these expressions, we obtain $\frac{d^2\Pi_e}{dp^2} < 0$.

We can similarly establish the inequality $\frac{d^2\Pi_s}{dp^2} < 0$, which implies that $\frac{d^2\Pi}{dp^2} < 0$. Hence there also exists a unique optimal delivery fee that maximizes the contribution margin in the omni-channel strategy. Note that the optimal delivery fee need not be same for the online strategy as for the omni-channel strategy.

Appendix B

Let Π^1 be the total contributions of the e-grocery channel (Π_e^1) and the store channel (Π_s^1) for the online strategy (i.e., $\Pi^1 = \Pi_e^1 + \Pi_s^1$), and let p^1 denote the corresponding optimal delivery fee. Let Π^2 analogously be the total contribution in the omni-channel strategy and p^2 the corresponding optimal delivery fee. Proposition 1 shows that the optimal fees are unique. Since the omni-channel strategy maximizes Π^2, it follows that $\Pi^1 \leq \Pi^2$. By definition, $\Pi_e^2 \leq \Pi_e^1$ because the online strategy maximizes Π_e. Therefore, $\Pi_s^1 < \Pi_s^2$. The implication is that, for a marginal contribution m per order in both channels, the store channel's market share is higher in the omni-channel strategy: $\gamma_s^2 > \gamma_s^1$.

We know that γ_s is increasing with the delivery fee p – that is, since $\frac{d\gamma_s}{dp} > 0$. If p^1 and p^2 are the optimal delivery fees for (respectively) the online and omni-channel strategies then, for $\gamma_s^2 > \gamma_s^1$, we have $p^1 > p^2$. According to equation (4.1), the market share of the e-grocery channel decreases with a higher delivery fee. So for $p^1 > p^2$, the e-grocery channel has a lower market share in the omni-channel strategy than in the online strategy.

Appendix C

Setting $\Pi_e = 0$ yields

$$p^b = f^v + c^p + c^s - m_e + \frac{c^t \phi_k}{\sqrt{\delta^h w}} \frac{1}{\sqrt{\gamma_e}}. \tag{4.8}$$

Parts (i) and (ii) of the proposition are proved as follows. It is clear from (4.8) that, if $\gamma_e > 0$, then p decreases with household density δ^h and increases with the picking cost c^p.

It is intuitive that high household density and automated picking reduce the total cost of serving a customer. Hence, the break-even delivery fee decreases in both cases.

(iii) The e-grocery channel's utility u_e is independent of store density δ_s^s. However, if δ_s^s increases then so does the store channel's utility. Since $\frac{d\gamma_e}{du_s} < 0$, it follows that the e-grocery channel's market share decreases with the utility of the store channel and thereby also with the store density. By (4.8), the break-even delivery fee decreases with the e-grocery channel's market share and therefore increases with store channel's store density.

5 Conclusions and Future Research

This thesis studies opportunities and challenges of online grocery operations in omni-channel retail. First we focus on strategies to exploit the synergy between last-mile operations of online grocery and the store replenishment. We build mathematical models and effective solution approaches to solve the associated problems. Through extensive numerical experiments, we study the impact of different operational factors on the benefits of capacity sharing across the distribution channels.

We also study the interactions of the online and store channels to understand the profitability and market shares of the online grocery channel. We combine the customer choice model with operational cost modeling to investigate the impact of household and store densities on the profitability of the online channel.

Below, we first summarize the main results of our research and then, discuss several new directions for future research.

Main results

In the second and third chapters we focus on building an operational model to share capacity of vehicles in the online and store replenishment channels, when the online channel uses the *buy online pick up in stores* model. Chapter 2 focuses on a simple and practical capacity sharing strategy whereby a fixed transport schedule (i.e., store replenishment from a store fulfilment center) and a flexible transport schedule (i.e., online order fulfilment from an online fulfilment center) of an omni-channel retailer have a common set of customer visits. We introduce the shared capacity routing problem (SCRP) to present a strategy by which the spare capacity in the vehicles of the fixed schedule can be used to serve the customers of the flexible schedule. Our problem is motivated by a practical problem faced by one of the largest grocery retailers in the Netherlands.

In the SCRP described in Chapter 2, the flexible schedule can reduce its distribution costs by transferring its demand to the fixed schedule. However, there is a transfer cost involved. While the MILP developed by us can be solved in reasonable time for smaller instance, we also develop an efficient matheuristic to solve the SCRP for large set of instances. In our heuristic, we try to find promising sets of customers to transfer by solving a multiple knapsack problem given the spare capacities in the fixed routes. Finally, we build an ALNS-based improvement phase to improve the solution quality. We then assess the benefits of this capacity sharing strategy using both real-world and artificial instances. The following are the key results from our numerical study:

- The computational study on the real-life case suggests potential transport cost savings between 2% and 33% by better using the available vehicle capacities in the system.
- The results show that the transfer costs and the spare capacity are the main drivers of the potential benefits of capacity sharing. The benefits increase with the spare capacity and decrease when the transfer costs increase.
- There is potential savings in service costs at customer location due to reduction in number of visits to customers.

In Chapter 3, we extend the SCRP model to increase the capacity sharing between the two channels. In the SCRP we have two main challenges viz. limited spare capacity at the start of the fixed schedule, and ensuring the transfer of demand before the departure of the fixed routes. We develop the shared capacity routing problem with transfers (SCRPT) to address those challenges. In the SCRPT, stores are also used as potential transfer points, which creates more spare capacity as customers are served in the fixed route. The key decisions include choice of transfer locations and set of stores whose demand need to be transferred. We develop an efficient heuristic to solve the SCRPT for large instances. To assess the benefits of capacity sharing in the SCRPT, we perform an extensive numerical study. The following is a summary of the insights gained from our numerical study:

- The benefits of capacity sharing can be significant, especially when the volume of goods to be delivered to the store pick-up points is small compared to the volume of goods for replenishing store inventories.
- To achieve the benefits of capacity sharing, it is sufficient to have just a few stores with ample transfer space.

- The benefits of capacity sharing depend on the locations of the warehouses for store replenishment and online order fulfillment because it impacts the first possible transfer location and time.
- The benefits of capacity sharing will be greater if the vehicle supplying the store pick-up points can depart from its warehouse earlier or not much later than the vehicle that replenishes store inventories.
- The benefits of capacity sharing do not depend strongly on the capacity of the vehicle that replenishes store inventories.

Finally in Chapter 4, we move our focus to the home delivery model of the online grocery and study the interaction between the store and the e-grocery channel in an omni-channel setting. We combine customer choice behavior and operational costs, which allows us to analyse the interaction of the online and store channels under different settings. In particular, we study the impact of household and store density on the profitability of the retailer. We calibrated our model with real-world data. The following are the key results from our numerical study:

- The profitability of the e-grocery channel increases with household density due to reduction in distribution costs.
- The profitability of the e-grocery channel decreases with store density due to the relative decrease in the online market share with store density.
- Picking costs significantly affect the profitability of the e-grocery channel, making it almost impossible for the e-grocery channel to be profitable using a manual dark-store setting.
- Increase in consumer preference of the online channel will substantially impact the current dynamics. If customers are willing to pay more for delivery fee, it might lead to cannibalization of sales of the store channel to an extent that reducing the number of stores is cost-wise optimal.

Future research

In this thesis, we build mathematical models and carried out extensive numerical experiments to understand the opportunities and challenges of online grocery in omni-channel retail. The results not only provide valuable insights but also point towards interesting directions for future research. In this section, we discuss the potential extensions of the problems described and analysed in this thesis.

In Chapters 2 and 3, we have seen significant reduction in transportation costs can be achieved for the online channel by sharing the capacity of the vehicles in the store replenishment channel. We build on the premise that there is a fixed schedule and common set of customer locations visited in both the fixed schedule and a flexible schedule. The planning of the flexible schedule is dependent on the fixed schedule to be ready so that decisions on the transfer sets and locations can be made. This potentially can make capacity sharing planning challenging as the flexible schedule might need to be prepared ahead of time. In such cases, a tentative fixed schedule using *anticipatory vehicle routing* techniques can be used to develop the capacity sharing strategies for the flexible schedule. In future research, it will be interesting to evaluate the benefits and challenges of capacity sharing when a tentative fixed schedule is used.

In our capacity sharing strategies, we consider two distribution channels of the same omni-channel retailer. However, this capacity sharing between a fixed and flexible schedule can be applied across two or more different organizations. This will raise additional challenges of profit sharing across the participating organizations. In collaborative vehicle routing (refer to Gansterer and Hartl (2018) for a detailed survey), several profit sharing mechanisms are used. An interesting extension of our capacity sharing strategy will be to incorporate the profit sharing between the carriers involved.

Finally in Chapter 4, we take a strategic lens to understand the profitability of online grocery channel of an omni-channel retailer. The insights derived from our analysis throw light on the optimal market share and delivery fee of the online channel under different settings of household and store densities. Our stylized customer choice model is based on customer's preference for delivery fee, quality of service and walking to store. The factors affecting customer's choice are not limited to these only, and more importantly the customer's preferences change over time due to several external influences. Consider the Covid-19 pandemic affect, which drastically changed the customer choice model. An interesting direction for future research will be to perform empirical studies to estimate the impact of these factors into the customer utility and accordingly, determine the market shares and delivery fees in optimal settings.

Bibliography

Acosta, 2020. Online grocery shopping can help retailers increase their reach, boost impulse buys. `https://www.smartbrief.com/original/2020/02/online-grocery-shopping-can-help-retailers-increase-their-reach-boost`.

Agatz, N., Bouman, P., Schmidt, M., 2018. Optimization approaches for the traveling salesman problem with drone. Transportation Science 52, 965–981.

Agatz, N., Campbell, A., Fleischmann, M., Savelsbergh, M., 2011. Time slot management in attended home delivery. Transportation Science 45, 435–449.

Agatz, N.A., Fleischmann, M., Van Nunen, J.A., 2008. E-fulfillment and multi-channel distribution–a review. European journal of operational research 187, 339–356.

Ali, F., 2018. A decade in review: Ecommerce sales vs. retail sales 20072017. `https://www.digitalcommerce360.com/article/e-commerce-sales-retail-sales-ten-year-review/`.

Andrews, R.L., Currim, I.S., 2004. Behavioural differences between consumers attracted to shopping online versus traditional supermarkets: implications for enterprise design and marketing strategy. International Journal of Internet Marketing and Advertising 1, 38–61.

Ansari, S., Başdere, M., Li, X., Ouyang, Y., Smilowitz, K., 2018. Advancements in continuous approximation models for logistics and transportation systems: 1996–2016. Transportation Research Part B: Methodological 107, 229–252.

Archetti, C., Speranza, M.G., Vigo, D., 2014. Vehicle Routing: Problems, Methods, and Applications. SIAM. volume 18. chapter Vehicle routing problems with profits. pp. 273–297.

Augerat, P., 1995. Approche polyèdrale du problème de tournées de véhicules. Ph.D. thesis. Institut National Polytechnique de Grenoble-INPG.

Bain, M., 2021. An analysis of 250 retailers shows what online shopping does to profit margins. URL: `https://qz.com/2027482/what-online-shopping-is-doing-to-retail-profit-margins/amp/`.

Balakrishnan, A., Sundaresan, S., Zhang, B., 2014. Browse-and-switch: Retail-online competition under value uncertainty. Production and Operations Management 23, 1129–1145.

Baldacci, R., Ngueveu, S.U., Calvo, R.W., 2016. The vehicle routing problem with transhipment facilities. Transportation Science 51, 592–606.

BBC, 2019. Ocado losses widen but sales grow. URL: https://www.bbc.com/news/business-47127468.

Beardwood, J., Halton, J.H., Hammersley, J.M., 1959. The shortest path through many points, in: Mathematical Proceedings of the Cambridge Philosophical Society, Cambridge University Press. pp. 299–327.

Beck, N., Rygl, D., 2015. Categorization of multiple channel retailing in multi-, cross-, and omni-channel retailing for retailers and retailing. Journal of retailing and consumer services 27, 170–178.

Begley, S., Marohn, E., Mikha, S., Rettaliata, A., 2020. Digital disruption at the grocery store. https://www.mckinsey.com/industries/retail/our-insights/digital-disruption-at-the-grocery-store.

Belavina, E., Girotra, K., Kabra, A., 2017. Online grocery retail: Revenue models and environmental impact. Management Science 63, 1781–1799.

Belderok, A., Einwachter, M., van Aalst, M., Winkelman, J., Veul, R., 2019. The Dutch grocery sector in 2030 - Roland Berger. https://www.rolandberger.com/publications/publication_pdf/roland_berger_online_grocery_shopping.pdf.

Bernstein, F., Song, J.S., Zheng, X., 2008. bricks-and-mortar vs.clicks-and-mortar: An equilibrium analysis. European Journal of Operational Research 187, 671–690.

Bhardwaj, A., Chugh, G., Sane, N., Mishra, S., 2018. Evolving the role of the retail store in an omnichannel world. https://fractalanalytics.com/wp-content/uploads/2018/03/WP_Evolving-the-role-of-the-retail-store-in-an-omnichannel-world.pdf.

Bolduc, M.C., Renaud, J., Boctor, F., Laporte, G., 2008. A perturbation metaheuristic for the vehicle routing problem with private fleet and common carriers. Journal of the Operational Research Society 59, 776–787.

Bosa, D., 2018. Instacart to team up with walmart's sam's club for same-day delivery, countering amazon-whole foods. URL: https://www.cnbc.com/2018/02/26/walmart-sams-club-signs-grocery-delivery-deal-with-instacart.html.

Bose, N., 2016. Wal-Mart's next move against Amazon: More warehouses, faster shipping. https://www.reuters.com/article/us-walmart-ecommerce/wal-marts-next-move-against-amazon-more-warehouses-faster-shipping-idUSKCN12609P.

Boyer, K.K., Hult, G.T.M., 2005. Extending the supply chain: integrating operations and marketing in the online grocery industry. Journal of Operations Management 23, 642–661.

Boyer, K.K., Prud'homme, A.M., Chung, W., 2009. The last mile challenge: evaluating the effects of customer density and delivery window patterns. Journal of business logistics 30, 185–201.

Boyer, K.K., Tomas Hult, G., Frohlich, M., 2003. An exploratory analysis of extended grocery supply chain operations and home delivery. Integrated Manufacturing Systems 14, 652–663.

Boysen, N., De Koster, R., Weidinger, F., 2019. Warehousing in the e-commerce era: A survey. European Journal of Operational Research 277, 396–411.

Breugelmans, E., Campo, K., Gijsbrechts, E., 2007. Shelf sequence and proximity effects on online grocery choices. Marketing Letters 18, 117–133.

Brown, M., Farmer, D., Ganenthiran, N., 2013. Recasting the retail store in todays omnichannel world. AT Kearney .

Browne, R., 2021. As billions flow into a crowded online grocery market, a wave of consolidation could be on the way. URL: https://www.cnbc.com/2021/07/02/grocery-startups-vc.html.

Cachon, G.P., 2014. Retail store density and the cost of greenhouse gas emissions. Management Science 60, 1907–1925.

Campbell, J., 2021. Is Owning a Grocery Store Profitable? (Not always Heres why). https://thegrocerystoreguy.com/is-owning-a-grocery-store-profitable/.

Capgemini, 2019. The last-mile delivery challenge. https://www.capgemini.com/wp-content/uploads/2019/01/.

Capgemini, 2019. The last mile delivery challenge. https://www.capgemini.com/wp-content/uploads/2019/01/Report-Digital-%E2%80%93-Last-Mile-Delivery-Challenge1.pdf.

Castia, M., 2020. Ocado Group 2019 pretax loss widens despite growing revenue . https://www.marketwatch.com/story/ocado-group-2019-pretax-loss-widens-despite-growing-revenue-2020-02-11.

Chintagunta, P.K., Chu, J., Cebollada, J., 2012. Quantifying transaction costs in online/off-line grocery channel choice. Marketing Science 31, 96–114.

Chu, C.W., 2005. A heuristic algorithm for the truckload and less-than-truckload problem. European Journal of Operational Research 165, 657–667.

City Mayors Statistics, 2018. The largest cities in the world by land area, population and density. http://www.citymayors.com/statistics/largest-cities-density-125.html.

Colliers International, 2019. SUPERMARKET REPORT. https://www2.colliers.com/nl-nl/research/20190726supermarkten.

Côté, J.F., Potvin, J.Y., 2009. A tabu search heuristic for the vehicle routing problem with private fleet and common carrier. European Journal of Operational Research 198, 464–469.

Daganzo, C.F., 1984. The length of tours in zones of different shapes. Transportation Research Part B: Methodological 18, 135–145.

Daganzo, C.F., 2005. Logistics systems analysis. Springer Science & Business Media.

Danaher, P.J., Wilson, I.W., Davis, R.A., 2003. A comparison of online and offline consumer brand loyalty. Marketing Science 22, 461–476.

Dannenberg, P., Fuchs, M., Riedler, T., Wiedemann, C., 2020. Digital transition by covid-19 pandemic? the german food online retail. Tijdschrift voor economische en sociale geografie 111, 543–560.

De Koster, R.B., 2002. The logistics behind the enter click, in: Quantitative approaches to distribution logistics and supply chain management. Springer, pp. 131–148.

Delaney-Klinger, K., K. Boyer, K., Frohlich, M., 2003. The return of online grocery shopping: a comparative analysis of webvan and tescos operational methods. The TQM Magazine 15, 187–196.

Drive, G., 2018. Peeking inside the pod: A deep look inside Peapod's grocery delivery business. https://www.grocerydive.com/news/grocery--peeking-inside-the-pod-a-deep-look-inside-peapods-grocery-delivery-business/533816/.

Ecommerce News Europe, 2019. Picnic raises €250 million for robotized distribution center. https://ecommercenews.eu/picnic-raises-e250-million-for-robotized-distribution-center/.

Edwards, J., 2016. HSBC makes a huge, counterintuitive call: Online grocery delivery is 'the emperor's new clothes'. https://www.businessinsider.in/hsbc-makes-a-huge-counterintuitive-call-online-grocery-delivery-is-the-emperors-new-clothes/articleshow/51313570.cms?mobile=no.

Ehrler, V.C., Schöder, D., Seidel, S., 2019. Challenges and perspectives for the use of electric vehicles for last mile logistics of grocery e-commerce–findings from case studies in germany. Research in Transportation Economics , 100757.

Eilon, S., Watson-Gandy, C.D.T., 1971. Distribution management; mathematical modelling and practical analysis. Technical Report.

Eley, J., 2019. The difficulties of making online delivery pay. URL: https://www.ft.com/content/8aa756ac-3c35-11e9-b72b-2c7f526ca5d0.

Eley, J., 2021. Covid growth turns online grocery profitable. URL: https://www.ft.com/content/00559d14-84da-4184-bc8f-1d6ec090b106.

Eley, J., McMorrow, R., 2020. Why supermarkets are struggling to profit from the online grocery boom. URL: https://www.ft.com/content/00559d14-84da-4184-bc8f-1d6ec090b106.

Els, v.A., 2017. How cheap is online supermarket Picnic really? We took the test. https://www.businessinsider.nl/hoe-goedkoop-online-supermarkt-picnic-nou-echt-deden-de-test/.

Evans, K., 2018. Walmart is making it easier for more shoppers to pick up online orders in stores. https://www.digitalcommerce360.com/2018/04/06/walmart-wants-more-shoppers-to-pick-up-online-orders-in-its-stores/.

Falk, T., Schepers, J., Hammerschmidt, M., Bauer, H.H., 2007. Identifying cross-channel dissynergies for multichannel service providers. Journal of Service Research 10, 143–160.

Fernández, E., Roca-Riu, M., Speranza, M.G., 2017. The shared customer collaboration vehicle routing problem. European Journal of Operational Research .

Financial Times, 2020. Why supermarkets are struggling to profit from the online grocery boom%. https://www.ft.com/content/b985249c-1ca1-41a8-96b5-0adcc889d57d.

FMI, Nielsen, Dialogic Group LLC, 2020. The Omnishopper Imperative for Food Retailers. https://www.fmi.org/forms/store/ProductFormPublic/the-omnishopper-imperative-for-food-retailers.

Forman, C., Ghose, A., Goldfarb, A., 2009. Competition between local and electronic markets: How the benefit of buying online depends on where you live. Management science 55, 47–57.

François, J.M., 2020. The future of a profitable online grocery service is here. URL: https://www.forbes.com/sites/jeanmarcfrancois/2020/05/20/the-future-of-a-profitable-online-grocery-service-is-here/?sh=3d33d95647ce.

Galante, N., López, E.G., Monroe, S., 2013. The future of online grocery in Europe. https://www.mckinsey.com/~/media/McKinsey/Industries/Retail/Our%20Insights/The%20future%20of%20online%20grocery%20in%20Europe/The_future_of_online_grocery.ashx.

Gallego, G., Huh, W.T., Kang, W., Phillips, R., 2006. Price competition with the attraction demand model: Existence of unique equilibrium and its stability. Manufacturing & Service Operations Management 8, 359–375.

Gallino, S., Moreno, A., 2014. Integration of online and offline channels in retail: The impact of sharing reliable inventory availability information. Management Science 60, 1434–1451.

Gansterer, M., Hartl, R.F., 2017. Collaborative vehicle routing: a survey. arXiv preprint arXiv:1706.05254 .

Gansterer, M., Hartl, R.F., 2018. Collaborative vehicle routing: a survey. European Journal of Operational Research 268, 1–12.

Gao, F., Agrawal, V.V., Cui, S., 2021. The effect of multichannel and omnichannel retailing on physical stores. Management Science .

Gao, F., Su, X., 2016. Omnichannel retail operations with buy-online-and-pick-up-in-store. Management Science 63, 2478–2492.

Gao, F., Su, X., 2019. New functions of physical stores in the age of omnichannel retailing, in: Operations in an Omnichannel World. Springer, pp. 35–50.

Golden, B.L., Levy, L., Vohra, R., 1987. The orienteering problem. Naval Research Logistics 34, 307–318.

Group, M.R.W.I., . FIGHTING FOR THE FUTURE OF THE SUPERMARKET INDUSTRY. https://www.oliverwyman.com/br/insights/2019/dec/retail-consumer-journal-vol-7/fighting-for-the-future-of-the-supermarket-industry.html.

Gurobi Optimization, L., 2018. Gurobi optimizer reference manual. URL: http://www.gurobi.com.

Günday, G., Kooij, S., Moulton, J., Karabon, M., Omeñaca, J., 2020. How european shoppers will buy groceries in the next normal. URL: https://www.mckinsey.com/industries/retail/our-insights/how-european-shoppers-will-buy-groceries-in-the-next-normal.

Harsha, P., Subramanian, S., Ettl, M., 2019. A practical price optimization approach for omnichannel retailing. Informs Journal on Optimization 1, 241–264.

Hays, T., Keskinocak, P., De López, V.M., 2005. Strategies and challenges of internet grocery retailing logistics, in: Applications of supply chain management and e-commerce research. Springer, pp. 217–252.

Herhausen, D., Binder, J., Schoegel, M., Herrmann, A., 2015. Integrating bricks with clicks: retailer-level and channel-level outcomes of online–offline channel integration. Journal of retailing 91, 309–325.

Huang, J., Leng, M., Parlar, M., 2013. Demand functions in decision modeling: A comprehensive survey and research directions. Decision Sciences 44, 557–609.

Hübner, A., Holzapfel, A., Kuhn, H., 2016a. Distribution systems in omni-channel retailing. Business Research 9, 255–296.

Hübner, A., Kuhn, H., Wollenburg, J., 2016b. Last mile fulfilment and distribution in omni-channel grocery retailing: a strategic planning framework. International Journal of Retail & Distribution Management 44, 228–247.

ICR, 2021. A shift in behavior: Why grocery shoppers are going digital. URL: https://www.ncr.com/blogs/retail/grocery-shoppers-going-digital.

Irnich, S., Toth, P., Vigo, D., 2014. Vehicle Routing: Problems, Methods, and Applications. SIAM. volume 18. chapter The Family of Vehicle Routing Problems. pp. 1–33.

Ishfaq, R., Defee, C.C., Gibson, B.J., Raja, U., 2016. Realignment of the physical distribution process in omni-channel fulfillment. International Journal of Physical Distribution & Logistics Management 46, 543–561.

Jasin, S., Sinha, A., Uichanco, J., 2019. Omnichannel operations: Challenges, opportunities, and models, in: Operations in an Omnichannel World. Springer, pp. 15–34.

Jindal, I., 2017. A performance ranking of Europes Top500 ecommerce and multichannel retailers. http://viewer.zmags.com/publication/5f09e229#/5f09e229/22.

Kacen, J., 2003. Bricks & clicks & the buying impulse: An investigation of consumer impulse buying behaviour in an online and a traditional retail environment. European Advances in Consumer Research 6, 271–276.

Kämä-räinen, V., Småros, J., Holmström, J., Jaakola, T., 2001. Cost-effectiveness in the e-grocery business. International Journal of Retail & Distribution Management .

Kearney, 2015. Capturing the online grocery opportunity. URL: https://www.kearney.com/consumer-retail/article?/a/capturing-the-online-grocery-opportunity.

Klein, R., Neugebauer, M., Ratkovitch, D., Steinhardt, C., 2019. Differentiated time slot pricing under routing considerations in attended home delivery. Transportation Science 53, 236–255.

de Koster, R.M.B., 2002. Distribution structures for food home shopping. International Journal of Physical Distribution & Logistics Management 32, 362–380.

Krajewska, M.A., Kopfer, H., 2006. Collaborating freight forwarding enterprises. OR spectrum 28, 301–317.

Krajewska, M.A., Kopfer, H., Laporte, G., Ropke, S., Zaccour, G., 2008. Horizontal cooperation among freight carriers: request allocation and profit sharing. Journal of the Operational Research Society 59, 1483–1491.

Kuijpers, D., Simmons, V., Van Wamelen, J., 2018. Grocery Stores Industry Profitability. https://www.mckinsey.com/industries/retail/our-insights/reviving-grocery-retail-six-imperatives.

Kull, T.J., Boyer, K., Calantone, R., 2007. Last-mile supply chain efficiency: an analysis of learning curves in online ordering. International Journal of Operations & Production Management .

Laporte, G., Martello, S., 1990. The selective travelling salesman problem. Discrete Applied Mathematics 26, 193–207.

Laurenthomas, 2017. Target to buy grocery delivery service shipt for $550 million. URL: https://www.cnbc.com/2017/12/13/target-to-buy-grocery-delivery-service-shipt-for-550-million.html.

Lemon, K.N., Verhoef, P.C., 2016. Understanding customer experience throughout the customer journey. Journal of marketing 80, 69–96.

Levy, N., 2018. How amazon's expanding u.s. brick-and-mortar footprint stacks up against other big retailers. https://www.geekwire.com/2018/amazons-expanding-u-s-brick-mortar-footprint-stacks-big-retailers.

Li, H., Lv, T., Lu, Y., 2016. The combination truck routing problem: a survey. Procedia engineering 137, 639–648.

Lin, I.I., Mahmassani, H.S., 2002. Can online grocers deliver?: Some logistics considerations. Transportation Research Record 1817, 17–24.

Lummus, R.R., Vokurka, R.J., 2002. Making the right e-fulfillment decision. Production and Inventory Management Journal 43, 50.

Marshoek, 2018. Benchmark Supermarketen 2018. https://www.marshoek.nl/file/download/default/C371F8D049EA6B023266DB9D1C7FFBD4/Totaal%20Benchmark%20-%20Rapport%20versie%2022%20mei.pdf.

Martello, S., Toth, P., 1981. Heuristic algorithms for the multiple knapsack problem. Computing 27, 93–112.

McGuirt, J.T., Pitts, S.B.J., Ammerman, A., Prelip, M., Hillstrom, K., Garcia, R.E., McCarthy, W.J., 2015. A mixed methods comparison of urban and rural retail corner stores. AIMS Public Health 2, 554.

Melacini, M., Perotti, S., Rasini, M., Tappia, E., 2018. E-fulfilment and distribution in omni-channel retailing: a systematic literature review. International Journal of Physical Distribution & Logistics Management 48, 391–414.

Mintel, 2020. Mintel predicts uk online grocery sales to grow by 33% in 2020. URL: https://www.ift.org/news-and-publications/news/2020/april/29/mintel-predicts-uk-online-grocery-sales-to-grow-by-33-percent-in-2020.

Mkansi, M., Nsakanda, A.L., 2019. Leveraging the physical network of stores in e-grocery order fulfilment for sustainable competitive advantage. Research in Transportation Economics , 100786.

Mock, P., 2014. Eu co2 standards for passenger cars and light-commercial vehicles. International Council on Clean Transportation , 1–9.

Moons, S., Braekers, K., Ramaekers, K., Caris, A., Arda, Y., 2019. The value of integrating order picking and vehicle routing decisions in a b2c e-commerce environment. International Journal of Production Research 57, 6405–6423.

NEO - Networking and Emerging Optimization, 2013. Augerat et al. http://neo.lcc.uma.es/vrp/vrp-instances/capacitated-vrp-instances/.

Nibud, 2021. What do I spend on food? https://www.nibud.nl/consumenten/wat-geeft-u-uit-aan-voeding/.

NPD, 2018. U.S. Consumers Take an Omnichannel Approach When It Comes to Grocery Shopping. https://www.npd.com/wps/portal/npd/us/news/press-releases/2018/us-consumers-take-an-omnichannel-approach-when-it-comes-to-grocery-shopping/.

NU.nl, 2020. Boodschappen bezorgen is voor albert heijn nog steeds geen goudmijn. URL: https://www.nu.nl/economie/6079344/boodschappen-bezorgen-is-voor-albert-heijn-nog-steeds-geen-goudmijn.html.

Otto, A., Agatz, N., Campbell, J., Golden, B., Pesch, E., 2018. Optimization approaches for civil applications of unmanned aerial vehicles (uavs) or aerial drones: A survey. Networks 72, 411–458.

OW Robots, 2021a. Picking rates across the sectors: Where do you stand? https://www.owrobotics.co.uk/2021/02/08/picking-rates-across-the-sectors-where-do-you-stand/.

OW Robots, 2021b. Welcome to the automated warehouse of the future - How British supermarket Ocado is using robots to make online grocery shopping faster. https://www.theverge.com/2018/5/8/17331250/automated-warehouses-jobs-ocado-andover-amazon.

Park, S., 2020. Online grocery store operator Kurly attracts $163 mln investment. http://www.ajudaily.com/view/20200508153352194.

Paul, J., Agatz, N., Savelsbergh, M., 2019a. Optimizing omni-channel fulfillment with store transfers. Transportation Research Part B: Methodological 129, 381–396.

Paul, J., Agatz, N., Spliet, R., de Koster, M., 2019b. Shared Capacity Routing Problem - An Omni-channel Retail Study. European Journal of Operational Research 273, 731–739.

Pisinger, D., Ropke, S., 2007. A general heuristic for vehicle routing problems. Computers & Operations research 34, 2403–2435.

Poikonen, S., Golded, B., 2018. A branch and bound approach to the tsp with drone. INFORMS Journal on Computing . In press.

Pooler, M., 2018. Robots gain ground in ecommerce warehouses. URL: https://www-ft-com.eur.idm.oclc.org/content/a7e8d282-e0e1-11e7-a0d4-0944c5f49e46.

Potvin, J.Y., Naud, M.A., 2011. Tabu search with ejection chains for the vehicle routing problem with private fleet and common carrier. Journal of the Operational Research Society 62, 326–336.

Punakivi, M., Saranen, J., 2001. Identifying the success factors in e-grocery home delivery. International Journal of Retail & Distribution Management .

Pymnts.com, 2021. Millennials lead grocery's digital shift. URL: https://www.pymnts.com/news/retail/2021/millennials-lead-grocerys-digital-shift/.

Ram, A., 2015. Uk retailers face high cost of online deliveries. URL: https://www-ft-com.eur.idm.oclc.org/content/516aa75a-a04c-11e5-beba-5e33e2b79e46.

Ramus, K., Nielsen, N.A., 2005. Online grocery retailing: what do consumers think? Internet research .

Reinhardt, 2001. Tesco Bets Small–and Wins Big. https://www.bloomberg.com/news/articles/2001-09-30/tesco-bets-small-and-wins-big.

ResearchAndMarkets.com, 2020. Global online grocery market: Insights & forecast with potential impact of covid-19 (2020-2024). https://www.researchandmarkets.com/reports/2311034/. [Online; accessed June 30 2021].

Retailweek, 2021. Lidl boss: The costs of going online just dont add up. https://www.retail-week.com/grocery/lidl-boss-the-costs-of-going-online-just-dont-add-up/7036689.article?authent=1.

Rigby, D., 2011. The future of shopping. Harvard business review 89, 65–76.

Roose, K., 2017. Best buys secrets for thriving in the amazon age. https://www.nytimes.com/2017/09/18/business/best-buy-amazon.html.

Rosenblum, P., Kilcourse, B., 2013. Omni-channel 2013: The long road to adoption, RSR 2013 benchmark report, Retail Systems Research.

Rotterdam-Partners, 2018. Facts & Figures Rotterdam General. https://rotterdammakeithappen.nl/en/media-objects/facts-figures-rotterdam-general/.

RTL Nieuws, 2021. Overvol op markt voor online supers; kunnen ze wel winst maken? URL: https://www.rtlnieuws.nl/economie/bedrijven/artikel/5217367/online-supermarkt-webwinkel-crisp-picnic-albertheijn-jumbo-plus.

Savills Research, 2021. European food and groceries. https://pdf.euro.savills.co.uk/european/europe-retail-markets/spotlight---european-food-and-groceries-sector---2021.pdf.

Schonewille, G.A., 2016. Calculation of transport cost for freight carriers on the last mile: Conducting a case study in the municipality of delft to validate and improve usage of the last-mile scan calculation model.

Seow, C., Delaney-Klinger, K., Boyer, K.K., Frohlich, M., 2003. The return of online grocery shopping: a comparative analysis of webvan and tescos operational methods. The TQM Magazine .

Solutions, I.S., 2020. How is omnichannel retail changing the grocery industry? URL: https://intelligentshoppersolutions-global.com/resources/how-is-omnichannel-retail-changing-the-grocery-industry/.

Speculations, G., 2016. Why Would Amazon Open Physical Stores? URL: https://www.forbes.com/sites/greatspeculations/2016/02/11/why-would-amazon-open-physical-stores/#44c11c2f964d.

Statista, 2019. How often do you order foodstuffs online? https://www.statista.com/statistics/1023847/frequency-of-ordering-foodstuffs-online-in-the-netherlands/.

Statista, 2020. Average prices of diesel fuel in the Netherlands from 2000 to 2020. https://www.statista.com/statistics/603745/diesel-fuel-prices-netherlands/.

Statista, 2020. Retail e-commerce sales worldwide from 2014 to 2024. https://www.statista.com/statistics/379046/worldwide-retail-e-commerce-sales/. [Online; accessed 20-November-2018].

Statista, 2020a. Supermarkets with the highest market share for online grocery shopping in the Netherlands from 2015 to 2020. https://www.statista.com/statistics/659373/leading-online-supermarkets-based-on-share-of-shoppers-in-the-netherlands/.

Statista, 2020b. Total number of households in the Netherlands in 2020, by type. https://www.statista.com/statistics/519863/total-number-of-households-in-the-netherlands/.

Statista, 2021a. Great britain: Grocery market share 2017-2021. URL: https://www.statista.com/statistics/280208/grocery-market-share-in-the-united-kingdom-uk/.

Statista, 2021b. Online grocery shopping in the Netherlands - Statistics & Facts. https://www.statista.com/topics/6479/online-grocery-shopping-in-the-netherlands/.

Statistics Korea, 2016. Population Census. http://kostat.go.kr/portal/eng/pressReleases/8/7/index.board?bmode=read&aSeq=356507&pageNo=&rowNum=10&amSeq=&sTarget=&sTxt=.

Steinfield, C., 2004. Does online and offline channel integration work in practice, in: Workshop on e-commerce impacts revisited, DIW-Berlin.

Stenger, A., Vigo, D., Enz, S., Schwind, M., 2013. An adaptive variable neighborhood search algorithm for a vehicle routing problem arising in small package shipping. Transportation Science 47, 64–80.

Strang, R., 2013. Retail without boundaries. Supply Chain Management Review 17.

Strauss, A., Gülpınar, N., Zheng, Y., 2020. Dynamic pricing of flexible time slots for attended home delivery. European Journal of Operational Research .

Supermarket News, 1995. Tesco, sainsbury launch online shopping. URL: https://www.supermarketnews.com/archive/tesco-sainsbury-launch-online-shopping.

This is Money, 2021. Online supermarket shopping has skyrocketed as Britons in lockdown buy their food from home like never before - But will this last and can it be profitable? https://www.thisismoney.co.uk/money/markets/article-9173751/Online-grocery-shopping-took-year-profitable.html.

Treder, T., 2021. 10 reasons why your customers will try online grocery shopping. URL: https://www.the-future-of-commerce.com/2018/03/23/10-reasons-why-your-customers-will-try-online-grocery-shopping/.

Twentyman, J., 2015. Delivery charges cost online retailers dear. URL: https://www-ft-com.eur.idm.oclc.org/content/fd88f556-70bc-11e5-9b9e-690fdae72044.

Van Donselaar, K., van Woensel, T., Broekmeulen, R., Fransoo, J., 2006. Inventory control of perishables in supermarkets. International Journal of Production Economics 104, 462–472.

Van Donselaar, K.H., Gaur, V., Van Woensel, T., Broekmeulen, R.A., Fransoo, J.C., 2010. Ordering behavior in retail stores and implications for automated replenishment. Management Science 56, 766–784.

Vazquez-Noguerol, M., González-Boubeta, I., Portela-Caramés, I., Prado-Prado, J.C., 2021. Rethinking picking processes in e-grocery: A study in the multichannel context. Business Process Management Journal .

Vinsensius, A., Wang, Y., Chew, E.P., Lee, L.H., 2020. Dynamic incentive mechanism for delivery slot management in e-commerce attended home delivery. Transportation Science 54, 567–587.

Wollenburg, J., Hübner, A., Kuhn, H., Trautrims, A., 2018. From bricks-and-mortar to bricks-and-clicks: logistics networks in omni-channel grocery retailing. International Journal of Physical Distribution & Logistics Management 48, 415–438.

Worstall, T., 2012. Amazon is killing the book business. URL: https://www.forbes.com/sites/timworstall/2012/04/07/amazon-is-killing-the-book-business/?sh=267e65462ba1.

Yang, X., Strauss, A.K., Currie, C.S., Eglese, R., 2016. Choice-based demand management and vehicle routing in e-fulfillment. Transportation science 50, 473–488.

Yang, X., Sun, Z., Ban, X.J., Holguín-Veras, J., 2014. Urban freight delivery stop identification with gps data. Transportation Research Record 2411, 55–61.

Yrjo, H., et al., 2001. Physical distribution considerations for electronic grocery shopping. International Journal of Physical Distribution & Logistics Management .

Zhang, J., Farris, P.W., Irvin, J.W., Kushwaha, T., Steenburgh, T.J., Weitz, B.A., 2010. Crafting integrated multichannel retailing strategies. Journal of interactive marketing 24, 168–180.

About the author

Joydeep Paul was born in Tripura, India on April 26, 1988. He holds a Bachelor's degree in Industrial Engineering from the Indian Institute of Technology, Kharagpur - India. He obtained his double Master's degree in Supply Chain Engineering from Georgia Institute of Technology, Atlanta - USA and in Logistics and Supply Chain Management from National University of Singapore, Singapore. Prior to starting his doctoral studies, Joydeep worked at Singapore Post in Singapore for around 3 years in setting up their last-mile delivery network in South-east Asia. In September 2015, he joined the Department of Technology and Operations Management at Rotterdam School of Management, Erasmus University for his doctoral studies under the supervision of Prof. René de Koster and Dr. Niels Agatz.

Joydeep's research interests revolve around optimization in last-mile logistics in omnichannel retail with specific focus on the grocery retail. His work has been published in renowned journals like the European Journal of Operational Research and Transportation Research Part B: Methodological. He has also presented his research at several international conferences such as POMS Annual Meeting, TRISTAN, VeRoLog and Odysseus.

In August 2019, Joydeep joined Coolblue as Manager for their network and route planning operations of truck and bike delivery in the Netherlands, Belgium and Germany. Currently, Joydeep is working as Management Consulting Manager for supply chain operations at Accenture - the Netherlands.

Portfolio

Publications

Publications in Journals:

Paul, J., Agatz, N., Spliet, R., & De Koster, R. (2019). & Shared capacity routing problem An omni-channel retail study. European Journal of Operational Research, 273(2), 731-739.

Paul, J., Agatz, N., & Savelsbergh, M. (2019). Optimizing omni-channel fulfillment with store transfers. Transportation Research Part B: Methodological, 129, 381-396.

Working Papers:

Paul, J., Agatz, N. & Fransoo, J., (2021). Towards Profitable Growth in E-grocery retailing - the Role of Store and Household Density. *Available at SSRN 3924272.*

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Thesis supervision

Master Thesis Supervision 2016 - 2019

Tutorial Lecturer:

Pricing and revenue management 2018-2019

Guest Lecturer:

Pricing and revenue management 2019

Conferences and Workshops

TRISTAN 2016, Aruba

VeRoLog 2017, Amsterdam, The Netherlands

Last Mile Workshop 2017, Mannheim, Germany

TSL Workshop 2018, Chicago, USA

Last Mile Workshop 2018, Magdeburg, Germany

Odysseus 2018, Cagliari, Sardinia-Italy

Last Mile Workshop 2019, Rotterdam, The Netherlands

POMS 2019, Washington, USA

TRISTAN 2019, Hamilton Island, Australia

Summary

Online grocery has grown rapidly in different parts of the world over the last two decades. Many grocery retailers are making substantial investments to develop an online sales channel next to the traditional stores. However, it is still not clear whether online grocery retailing can be profitable in the long run. Grocery retail is a low margin, high cost business. Picking and delivering an online grocery order is labor intensive and costly. The delivery fee typically does not cover all the fulfilment costs.

With the emergence of omni-channel grocery retail, customers are provided with a seamless experience across online and offline channels. There are many synergies that exist between online and offline distribution, which if utilized properly can lead to significant cost savings to the retailer. We develop capacity sharing strategies between the vehicles of store replenishment and online fulfillment in *buy-online-pick-up-in-store* omni-channel model. Through an extensive numerical study on artificial instances and realistic instances (from our industry partner), we show that significant savings in distribution costs can be achieved by sharing capacity of vehicles across two channels. The savings in distribution costs also have a positive impact in reducing vehicle emissions, thereby, improving the sustainability of last-mile distribution in omni-channel retail.

Alongside these planning aspects, we also study the interaction between the online and store channel in an omni-channel setting. We build a stylized model to capture customer choice behavior and operational costs. We analyse the interaction of the online and store channels under different settings. In particular, we study the impact of household and store density on the profitability of the retailer. Our results show that online profitability increases with household density and decreases with store density. Picking costs significantly affect the profitability of the e-grocery channel, making it almost impossible for the e-grocery channel to be profitable using a manual dark-store setting. We also find that that an increase in the popularity of the online channel could substantially impact the current dynamics to the point where it would be profitable to reduce the number of physical stores.

Samenvatting (Summary in Dutch)

In verschillende delen van de wereld is de online verkoop van levensmiddelen in de laatste decennia sterk gegroeid. Veel supermarkteninvesteren in de ontwikkeling van een online verkoopkanaal naast de bestaande winkels. Toch is het niet duidelijk of de het thuisbezorgen van boodschappen op de lange termijn winstgevend kan zijn. De marges op levensmiddelen zijn laag. Het orderpicken en bezorgen van e boodschappen is arbeidsintensief en gaat gepaard met hoge kosten. Het bezorgtarief dekt doorgaans niet alle kosten van een bestelling.

Met de opkomst van de omnichannel supermarkt kunnen klanten hun aankopen doen in verschillende online en offline kanalen. Er bestaan veel synergieën tussen online en offline logistieke distributieprocessen en het goed benutten daarvan kan tot aanzienlijke kostenbesparingen leiden. In dit proefschrift hebben we strategieën ontwikkeld voor de capaciteitsverdeling tussen de voertuigen voor winkelbevoorrading en online afhaalorders in een buy-online-pick-up-in-store (online kopen, in de winkel afhalen) omnichannel model. Door middel van een uitgebreide numerieke studie op basis van verschillende data (o.a. van onze praktijkpartner) laten we zien dat er aanzienlijke besparingen op de distributiekosten mogelijk zijn door de voertuigcapaciteit over twee kanalen te verdelen. De besparing op distributiekkilometers heeft ook een positief effect op het verminderen van voertuigemissies, waardoor de fijndistributie van de omnichannel supermarkt duurzamer wordt.

Naast deze planningsaspecten onderzoeken we ook de interactie tussen het onlinekanaal en de fysieke winkel . We hebben een gestileerd model gemaakt dat het keuzegedrag van klanten en de operationele kosten meeneemt. Hiermee hebben we de interactie tussen het onlinekanaal en de fysieke winkel onder verschillende omstandigheden geanalyseerd. We hebben daarbij voornamelijk gekeken naar het effect van de winkel en bevolkingsdichtheid op de winstgevendheid van de supermarkt. Onze resultaten laten zien dat winstgevendheid van het onlinekanaal toeneemt bij een hogere bevolkingsdichtheid en afneemt bij een hogere winkeldichtheid. De pickkosten hebben een grote invloed op de winstgevendheid van het onlinekanaall, waardoor het bijna onmogelijk is om winstgevend te zijn als de boodschappen handmatig worden verzameld in de winkel of het distributiecentrum. We zien ook dat een grote groei van de vraag binnenin het onlinekanaal een aanzienlijke impact kan hebben op de bestaande dynamiek en dat het op een bepaald moment rendabel wordt om het aantal fysieke supermarkten te verminderen.

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Online grocery has grown rapidly in different parts of the world over the last two decades. However, it is still not clear whether online grocery retailing can be profitable in the long run. Grocery retail is a low margin, high-cost business. Picking and delivering an online grocery order is labor intensive and costly. The delivery fee typically does not cover all the fulfilment costs. Many grocery retailers are making substantial investments to develop an online sales channel next to the traditional stores. With the emergence of omni-channel grocery retail, customers are provided with a seamless experience across online and offline channels. There are many synergies that exist between online and offline distribution, which if utilized properly can lead to significant cost savings to the retailer.

In this thesis we explore capacity sharing strategies between the vehicles of store replenishment and online fulfillment in *buy-online-pick-up-in-store* omni-channel model. Through an extensive numerical study, we show that significant savings in distribution costs can be achieved by sharing capacity of vehicles across two channels. Alongside the planning aspects, we also study the interaction between the online and store channel in an omni-channel setting. Our results show that online profitability increases with household density and decreases with store density. We also find that that an increase in the popularity of the online channel could substantially impact the current dynamics to the point where it would be profitable to reduce the number of physical stores.

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