NIELS AGATZ

Demand Management in E-Fulfillment

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Vraagmanagement in E-fulfillment

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To my parents

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Niels Agatz, Rotterdam, February 2009

Contents

Chapter 1

Introduction

The success of many e-commerce businesses hinges upon their ability to offer efficient and effective order fulfillment. After some initial failures in the late 1990s, Internet retailers have been improving their fulfillment efficiency in many different ways. These include the 'bricks-and-click' bundling of online and offline channels to leverage buying power, the incremental expansion of delivery networks instead of a rush to giant automated fulfillment centers, and the smart deployment of inventories across the delivery network to offer a large assortment while limiting the risk of overstocking. However, these supply-side decisions cover only half of the supply-demand equation. Demand management has an equally strong impact on profitability, affecting both costs and revenues, and may hold a much greater potential for many of today's Internet retailers than further supply-side optimization. This is the central theme of this dissertation.

The remainder of this chapter is organized as follows. In the next section, we further motivate our research. In Section 1.2 we provide some additional background on the Internet channel to set the stage. In Section 1.3 we discuss the research goals, questions and address the scope of our research. In Section 1.4 we discuss the research methodology. Finally, in Section 1.5 we present the outline of the thesis.

1.1 Motivation

Effective demand management requires a good understanding of customer demand and the flexibility to tailor the product proposition to them. Internet retailers are in a unique position in both respects. First, online transaction and click-stream data provides a wealth of information on customer behavior. Second, online communication allows close interaction with the customer, and the opportunity to customize and adjust, in real-time, the product and service offering to customers and to change the corresponding prices.

Internet retailers are successfully using available transaction data for targeted marketing, personalized recommendations and active cross-selling (Netessine et al., 2006, Zhang and Krishnamurthi, 2004). Several Internet retailers, especially those operating in the logistically challenging grocery sector, are exploiting the unique demand management opportunities and actively manage demand to enhance their profitability. Consider the following illustrative examples:

- Tesco.com the world's largest e-grocer, applies differentiated delivery fees to smoothen demand over time to balance the operational workload. The delivery fees range from £3.75 for delivery after 9pm up to £6.25 in the morning. The Internet grocer temporarily raised its average delivery fee by £1.5 in the run-up to the busy Christmas period of 2007 (Tozer, 2007).

- Peapod, one of the largest e-grocers in the US, offers a different set of time slots in different delivery regions. For example, rural low demand areas only receive a limited number of time slots in an effort to cluster demand, and increase the drop-density (Boyer et al., 2003, Agatz et al., 2008b). Peapod carefully takes into account customer service considerations, as well as delivery cost considerations to define the service offering for each zip code.

- Ocado is appealing to the customers' environmental concerns by indicating which delivery slot would minimize the fuel consumption for their order. The company uses a "green van" to indicate that a delivery van is already in the customer's neighborhood at a certain time (www.ocado.com).

Research on demand management so far has focussed primarily on the airline, hotel and car rental business, which have been very successful in adopting demand management practices over the last 30 years (Chiang et al., 2007). The term 'revenue management' is typically used in this setting to represent the whole range of methods, decisions and technologies involved in demand management (Talluri and van Ryzin, 2004). Revenue management aims at maximizing revenues for a given supply quantity. Pricing and inventory allocation are the main levers to achieve this goal. The core idea is to segment the market, differentiate the product offering in a flexible way, and to prioritize service to the most profitable segments.

Revenue management is concerned with optimizing revenues when marginal costs are negligible. Marginal costs do, however, play an important role in Internet retailing which make the possible benefits even greater: demand management has the potential to enhance profitability by influencing both costs and revenues. Campbell and Savelsbergh (2005a) show that actively managing demand in Internet direct delivery can produce substantial cost savings.

While the potential benefits are vast, exploiting them requires sophisticated decision support. The various interrelated trade-offs between customer preferences, incentives, and operational considerations are much too complex for simple intuition to suffice. The number of quantitative models currently available in the literature to support demand management in e-fulfillment is rather limited. In addition, the specific issues related to demand management in this setting are also not completely clear yet.

The goal of our work is identifying the real-life issue and specific characteristics of demand management in e-fulfillment. In addition, we aim to develop quantitative models to support decision-making in this setting.

1.2 Background of E-fulfillment

In contrast to what some dot-com pioneers may have thought during the e-hype years, the Internet channel is unlikely to make the physical store obsolete. It does, however, represent a very interesting market segment. In 2007, for example, online retail sales represented 6% of overall US retail sales, resulting in revenues of $175 billion (Mulpuru et al., 2008). In 2008, this share is expected to rise slightly to 7%. In Europe, online retail is predicted to surge to €263 billion in 2011, with travel, clothes, groceries, and consumer electronics as the big online sellers (Favier and Bouquet, 2006).

The continuously growing Internet and broadband penetration fuel further growth of e-commerce. Eurostat reports that in the EU, 54% of households had access to the Internet during the first quarter of 2007, compared to 49% during the first quarter of 2006, and 42% of them had access to a broadband connection, compared to 30% in 2006. In 2007, the Netherlands recorded the highest proportion of household Internet access (83%) and broadband connection (74%) of the EU. Broadband Internet substantially enhances the online shopping experience, enabling easy and rapid navigation, visualization, customization and ordering. In addition, Internet retailers have improved their web site quality and online payment methods to increase trust and make people more comfortable with shopping online (Duh et al., 2007, Salo and Karjaluoto, 2007). In the US, for example, 94% of those with Internet access have used it to shop, 57% of which in the past month (The Nielsen Company, 2007).

Nowadays, the Internet channel is often part of a 'bricks-and-clicks' multichannel portfolio. From a marketing perspective, different channels differ in their ability to provide various service outputs. The advantage of the Internet retail channel is the fact that it is particularly powerful in providing information to the customer, thereby reducing the buyer's search costs. Moreover, electronic shopping offers customers a higher level of convenience since the customer does not have to go out to shop, which can be particularly advantageous for heavy and bulky products like groceries (Verhoef and Langerak, 2001). On the other hand, the advantage of the conventional retail channel is its proximity to customers, making it possible for the customer to feel and touch the product, and to take it home immediately after they have bought it.

Channel preference can vary for different customers and, in different situations even for the same customer (Neslin et al., 2006). For example, one may prefer the supermarket for regular weekly groceries, but favor the e-grocery service for the holiday and birthday party supplies. Offering the consumer multiple complementary channels can potentially enhance customer satisfaction and appeal to a broader range of customer segments by making available a greater mix of service outputs.

However, despite the potential of the Internet as a sales channel, the e-tailer faces many logistical challenges in the successful fulfillment of online demand. Internet order fulfilment, also called e-fulfilment, is generally considered the most challenging and critical operation of companies engaging into selling physical goods online (Ricker and Kalakota, 1999, Lee and Whang, 2001). Handling small individual orders and shipping them to the customer's home in a timely and cost-efficient manner has proven difficult. Many e-commerce pioneers simply did not have the capability to fulfill their delivery promises. Accenture reported that 67% of the orders that were placed in the 2000 holiday season were not received as ordered, leaving customers unhappy and dissatisfied (Saliba, 2001). Partly as a result of this dissatisfaction, we have seen many dot-com failures at the turn of the twenty-first century, such as high profile e-grocer Webvan, burning a staggering $1.2 billion before closing its doors.

The logistical challenges are especially apparent in attended home delivery, which is common for many types of products that cannot easily be delivered in the customer's mailbox, such as grocery, electronic equipment, or white goods and furniture. In attended home delivery, time slots are typically used by the e-tailer to coordinate the receipt of the purchased item(s) with the customer. The design of the time slot offering gives rise to several cost-service trade-offs. For example, a narrow delivery window is convenient to the customer but in general implies higher costs for the retailer by limiting the retailer's flexibility (see e.g. Punakivi and Saranen (2001)). Internet retailers have learned from past failures to make this trade-off carefully. For example, most of today's Internet grocers use one to four hour delivery windows rather than the aggressive 30 minute window offered by Webvan in the late nineties. In a similar vein, almost all current Internet retailers charge customers a delivery fee in addition to the retail price of the purchased items and do not systematically offer free delivery to attract customers.

1.3 Research Goals, Questions and Scope

This dissertation concerns decision making for demand management in e-fulfillment. In particular, it aims at contributing relevant practical and theoretical insights to support decision making in such an environment. There is vast body of literature on quantitative decision support models in operations management as well as in revenue management. Revenue management is a relatively new but quickly growing field of academic study. For the traditional revenue management applications such as the airline, car rental, hotel and hospitality sector, a wide range of broadly recognized standard practices and mathematical models have been developed to facilitate decision making (Talluri and van Ryzin, 2004). Given the short history of Internet retailing and e-fulfillment, standard practices and models on demand management do not exist to date. What is more, the related issues and problems are not yet well defined.

To summarize, the main research objectives are the following:

- To identify relevant demand management issues in e-fulfillment;
- To analyze the specific characteristics of demand management in e-fulfillment;
- To develop new quantitative tools and models;
- To provide theoretical insight and improve managerial decision making;

1.3.1 Research Questions

To achieve these objectives, we organize our research around several research questions. The first step is to better understand the important issues in e-fulfillment. Therefore we analyze current practice and recent literature.

RQ1: *What specific planning issues arise in e-fulfillment?*

RQ2: *What characterizes demand management in e-fulfillment and how does it differ from 'traditional' demand management environments like the airline industry?*

Besides a good understanding of the fulfillment processes of the Internet retailer, effective demand management also requires insights into customer behavior. That is, we need to understand the customer's reaction to demand management online. Therefore, the second part is aimed at answering the following question.

RQ3: *What is the customer's response to demand management in e-fulfillment?*

Once the main issues and corresponding drivers have been identified they will be translated into quantitative models that allow for systematic analysis. The aim of this step is to prescribe the way to deal with the identified trade-offs and provide practical insights. Therefore, we try to quantify the impact of demand management on the efficiency of the e-fulfillment processes.

RQ4: *How do we capture the relevant trade-offs in quantitative models that help decision making in e-fulfillment?*

1.3.2 Scope

Throughout this dissertation, we use the term 'e-fulfillment' to denote the operational activities required to satisfy online B2C demand. These activities encompass the typical supply chain stages purchasing, warehousing, delivery and sales. Throughout this thesis, we characterize the term e-fulfillment by the following three features.

B2C retail First of all, we see e-fulfillment from the perspective of a retailer offering B2C e-commerce. We distinguish this setting from B2B e-commerce where the Internet primarily changes the information processes (see for example Muffatto and Payaro (2004)). B2C e-fulfillment operations differ considerably from traditional B2B operations as they involve handling relatively small individual order sizes, rather than large quantity batch operations. The issues in our setting also differ from those in a manufacturer's Internet channel where channel conflicts due to disintermediation are a prime concern. In this case the manufacturer becomes a direct competitor to its intermediate reseller parties. This is an important field of its own right that has been extensively addressed in the literature (see e.g. Tsay and Agrawal (2004b,a)).

Internet sales Second, e-fulfillment is concerned with sales over the Internet. While there are many commonalities between e-fulfillment and catalogue or mail order fulfillment, the Internet component gives rise to several differences. A clear advantage of the Internet is the flexibility it gives the e-tailer with respect to their product, pricing and service offering. This provides the potential for increased revenues by customization and differentiation. On the downside, the advanced technological possibilities of the internet raise customer expectation and Internet customers tend to be more demanding in terms of the fulfillment service than their traditional counterparts (Mann, 2000, Lummus and Vokurka, 2002).

Tangible goods Third, we explicitly focus on the distribution of physical items and therefore do not consider online channels of purely service-oriented businesses, such as banking, travel and stock brokerage firms. Note that digitized products such as software, music, movies and reports can be delivered electronically. Netflix, for example, lets customers watch rental movies instantly on their PC's (www.netflix.com).

1.4 Research Methodology

Many researchers in the Operations and Supply Chain Management have pointed to the necessity of empirical input in the discipline (Flynn et al., 1990, Meredith et al., 1989, Bertrand and Fransoo, 2002, Fisher, 2007). They point out that Operations Management has drifted far away from its original empirical source. Fisher (2007) states: '*the way to avoid the risk of separating into al multitude of insignificant branches is to have a healthy injection of empirics*'. To provide such a '*healthy injection*', our research focusses on in *identifying* relevant issues and *developing* new tools and models to support decision making on these issues. To adequately address each of these goals we apply multiple research methods, notably a case study, a literature review, empirical modeling and quantitative modeling.

To answer RQ1 and RQ2, we consider a case study at Albert.nl, the leading e-grocery in the Netherlands. Albert.nl is the Internet channel of Albert Heijn, the largest supermarket chain in the Netherlands and subsidiary of grocery retail multinational Royal Ahold. To gain a deeper understanding of the important issues, we spoke to managers, observed the actual operations and participated actively in in-company projects on demand management. We compliment this in-depth study with several case studies from recent literature.

To answer RQ3, we apply a highly structured form of empiricism, econometric analysis, to analyze sales transaction data. Therefore, we use a natural experiment in a field setting. This approach provides greater external validating than laboratory experiments or survey-based methods because we measure the *true behavior* of *actual* customers. We model the main variables of interest and their relationships in a mathematical form and empirically evaluate and analyze this model applying linear regression. Econometric tools are particularly useful in dealing with data that is observational, rather than produced in a controlled experimental environment.

To answer RQ4, we try to capture the relevant aspects of e-fulfillment into quantitative models that enable us to further analyze the important trade-offs. Quantitative models and algorithms have proved to be powerful tools to support decision-making in Operations and Supply Chain Management. Mathematical optimization and simulation are core ingredients of the academic field of Operations Research. We specifically focus on the impact of demand management on the efficiency of the delivery processes. Therefore, we adapt several standard Operations Research models on vehicle routing problems. In particular, we use Continuous Approximation, Integer Programming and Route Construction Heuristics. We test our methods via numerical experiments on real-life instances from Albert.nl.

1.5 Outline of the Thesis

This thesis consists of 8 chapters. After the introductory chapter, **Chapter 2** provides an in-depth study of e-fulfillment with attended home delivery in practice. Material in this chapter is based on co-operation with e-grocer Albert.nl, Zaandam, the Netherlands.

Chapter 3 gives a systematic overview of the relevant planning issues in e-fulfillment and links them to the available operations research models in the literature. The chapter provides a better understanding of e-fulfillment, by documenting the current state of affairs, and identifies gaps between relevant managerial issues and available academic literature. The content of this chapter is based on the paper '*E-fulfilment and Multi-Channel Distribution - A review*' (Agatz et al., 2008e).

In **Chapter 4**, we identify opportunities for Internet retailers to reduce costs and enhance service inspired by proven revenue management concepts. To this end, we compare the e-fulfillment context to the prototypical revenue management setting, the airline industry. We see that the main conditions for revenue management also apply to the Internet retailing, but also see significant differences between Internet retailing and traditional revenue management environments. A framework is presented to structure the different demand management opportunities in e-fulfillment based on the demand management lever and the decision level. This framework serves as a reference point for the remainder of the thesis. This chapter is based on the paper '*Demand Management in E-fulfilment - What Internet Retailers Can Learn From Revenue Management*' (Agatz et al., 2008d). Recently, an article was published in the Wall Street Journal (Agatz et al., 2008a), based on this chapter.

Effective demand management requires a good understanding of customer preferences and the flexibility to tailor the product proposition to them. In **Chapter 5**, we analyze actual transaction data from e-grocer Albert.nl aimed at identifying the customer's response to changes in his time slot options for delivery. In particular, we focus on the customer's reaction to (i) a permanent change in the time slot choices and (ii) the short-term unexpected unavailability of a time slot. We apply a system of regression equations to estimate uncensored demand and control for seasonalities over time.

In **Chapter 6**, we address the problem of selecting time slots for different interrelated zip codes. This selection needs to facilitate efficient vehicle routing while offering acceptable service to the customer. We present two fully-automated models that are capable of producing high-quality solutions within reasonable time. Computational experiments reveal the value of our approaches and the impact of the environment on the underlying trade-offs. The main results of this chapter are presented in the paper '*Time Slot Management in Attended Home Delivery*' (Agatz et al., 2008c).

In **Chapter 7**, we address the dynamic version of the time slot problem. Since actual demand fluctuates around the expected demand, it may be beneficial to decide on the time slot offering in real-time. We present different policies to manage the dynamic time slot offering, where these policies differ with respect to the level of detail of routing cost estimates. We compare the performance of the proposed policies for different characteristics of the environment by means of computational experiments.

Finally, **Chapter 8** presents the conclusions and directions for future research.

Chapter 2

E-fulfillment at Albert.nl: An Illustrative Case

To help make things concrete, this chapter presents an analysis of the different fulfillment strategies of past and present e-grocers. In particular, we provide an in-depth overview of the fulfillment process of a specific Internet retailer, namely Dutch e-grocer Albert.nl. The grocery sector is commonly recognized as one of the most challenging environments for successful e-fulfillment, due to fierce competition, low profit margins and logistically demanding products, such as fresh food. Not surprisingly, the sector has seen some of the most spectacular e-business failures. On the other hand, practices that work in e-grocery have a high chance of success with other Internet retailers. The material discussed in this chapter is based on a collaboration with Albert.nl as part of the Transumo program, a platform of companies, governmental organizations and universities aimed at collectively developing knowledge on sustainable mobility in the Netherlands (see www.transumo.nl).

2.1 Albert.nl

Albert.nl is the Internet home delivery channel of Albert Heijn, a subsidiary of Royal Ahold, the retail multinational that also owns Peapod, one of the major U.S. e-grocers. Albert Heijn is the leading grocery chain in the Netherlands in terms of market share (29.5% in 2007), with 750 stores and about 6 billion euro in sales. Established in 1887, it is by far the oldest grocery retailer in the Netherlands. The company operates in the high-end of the market and aims at offering excellent customer service in terms of quality, choice and inspiration. Besides the internet channel, Albert Heijn has several other sales channels: the everyday supermarket, the larger XL store for the weekly groceries and the convenience stores AH-To-Go. By offering multiple complementary channels, Albert Heijn provides the customer with more choice, enhancing its overall value proposition.

Albert Heijn already started experimenting with grocery home delivery around 1988. The delivery service was originally called "James Telesuper" but soon changed its name to "AH thuisservice". Orders had to be placed either by telephone or fax and were picked in the conventional Albert Heijn stores. The service was initially only available in the densely populated areas of western Holland but gradually expanded to other parts of the country. However, due to the growing order volumes, the store-based picking system became inconvenient and inefficient, as the stores were simply too small to properly facilitate order picking. Therefore, plans were made to change to a warehouse-based fulfillment structure.

On November 5, 2001, Albert.nl was launched as a fully Internet-based home delivery channel. Initially it operated three dedicated warehouses for e-fulfillment, located in Beverwijk, Rotterdam and De Meern. However, demand was lower than expected and the warehouses were not operating at full capacity. As a result, the warehouse in Beverwijk was closed in January 2003 and all warehousing activities were consolidated in the two remaining warehouses.

Since 2001, the company has gradually been expanding its delivery area, the most important expansions being the hub-and-spoke connections of the provinces of Noord-Brabant and Gelderland in 2004. In the hub-and-spoke system, a large truck transports up to 100 picked orders to a hub where they are transferred to regular delivery vans. A hub essentially serves as a parking and transshipment point. On March 9, 2004, a hub was opened in Tilburg, Noord-Brabant and on April 28, 2004, in Nijmegen, Gelderland. Since its start-up, Albert.nl has consistently experienced annual sales growth rates of 25-30%. The delivery service is currently available to about 65% of the 7.2 million Dutch households. Figure 2.1 depicts the delivery areas of the two e-fulfillment warehouses.

In the early days, pure-play e-grocer Max Foodmarket was Albert.nl's main competitor. The company was founded in June 2000 and financially backed up and supplied by Jumbo supermarket, subsidiary of the Van Eerd Group. Max Foodmarket operated three dedicated warehouses and offered free grocery home delivery in 2-hour time slots. The company guaranteed timely delivery and when an order was not delivered on time, the customer would receive a refund of *f*25,-. However, due to

Figure 2.1: Delivery Area at Albert.nl (dark)

slower growth than expected, Max Foodmarket ran out of money and had to close its doors on December 10, 2002. Currently, the only large-scale competitor of Albert.nl is PLUS, a subsidiary of the Dutch Sperwer Holding, who provides Internet-based home delivery in about 40 of its 280 supermarkets (www.plussupermarkten.nl). On a smaller scale, retail chain Coop of the CoopCodis group offers e-grocery home delivery at 7 of its supermarkets (www.cooponline.nl). The online sales of groceries accounted for about 1% of the 24 billion euros spent on food and beverage grocery purchases in the Netherlands in 2006 (BMI, Verdict European Grocery 2007).

2.1.1 Marketing

Albert.nl primarily targets well educated, service-oriented consumers, time-starved double-income families with young children, customers that are (temporarily) not able to go out for grocery shopping (e.g. elderly people) and customers dissatisfied with regular grocery shopping (Albert Heijn, 2004). This group accounts for about 75% of demand. The additional 25% comes from small businesses without professional catering service such as child-care centers, professional services firms, advisory firms and IT firms. These types of customers are harder to acquire, but in general they order more often, purchase more items and are more loyal.

Albert.nl's marketing activities are relatively small scale, primarily relying on word-of-mouth advertisement. A €10 discount is rewarded for recommending the online service to a friend, the so called "Vriendendienst". The e-grocer uses low-profile advertisements in Albert Heijn's "Allerhande" magazine with a circulation of 4,700 copies a month and has its own advertising brochure which is sent out to about 70,000 of its subscribed customers. The national advertisement campaigns and weekly offers follow the conventional Albert Heijn stores, but Albert.nl also provides several regular Internet-only deals.

Albert.nl offers about 10,000 SKUs, including fresh groceries such as meat, milk and fruit, thereby corresponding with a mid-sized Dutch supermarket. The assortment is specifically tailored to target customer requirements, e.g. a relatively large share of large volume and nonperishable products. Additionally, the assortment encompasses items from two other subsidiaries of Royal Ahold, Etos, health and beauty care, and Gall and Gall, wine and liquor. The product prices of all items are identical to those in the conventional stores, plus a time-dependent delivery fee, ranging from €4.95 to €9.95. To allow Albert.nl enough time for order picking and transportation, time slots are closed about 16 hours before delivery. The company uses morning and evening cut-off times, noon for delivery the next morning and midnight for delivery the next afternoon. The minimum order size is €60. Payment for groceries and associated delivery fees is due at the time of delivery.

2.1.2 Operations

Albert.nl operates a 4,500 square meter dedicated distribution center or Home Shopping Center (HSC) in Rotterdam and a 6,000 square meters facility in de Meern. In comparison, the size of a conventional supermarket ranges between 800 and 3,500 square meters, and the size of a conventional Albert Heijn distribution center ranges between 20,000 and 25,000 square meters. The company owns a fleet of 129 dedicated delivery vans and has about 700 employees. The HSCs are supplied by the Albert Heijn warehouse in a similar fashion as the regular stores, i.e. 3 deliveries per day with an order lead-time of one day.

The fulfillment operations are organized around two shifts per day which correspond with the morning and evening cut-off times. Next, we discus the process from the initial order intake to the actual delivery at the customer. To structure our discussion, we distinguish between the four stages depicted in Figure 2.2, order intake, route planning, order picking and order delivery.

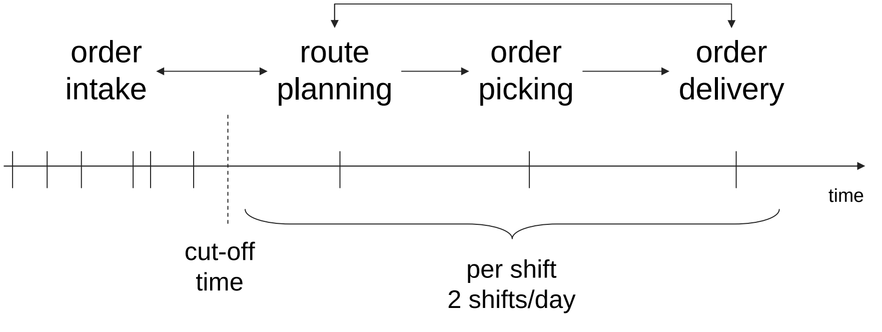


Figure 2.2: Fulfillment process at Albert.nl

1. Order Intake: After registration at the Albert.nl website, the customer gets a personal account. Upon login, before actually putting together an order, the customer reserves a two-hour delivery slot. The customer can choose from

a menu of partly overlapping time slots, up to 3 weeks in the future (see Figure 2.3). After reserving a time slot, the customer develops an order. Customers can use the search engine to find particular items or browse by department, e.g. vegetables, nonperishable and dairy. A picture and additional product information such as food value is provided for each product item. The website offers the possibility to specifically browse the weekly special offers. It is also possible to make a personal shopping lists. Additionally, the customer can find items from previous orders and items previously purchased in the conventional (off-line) Albert Heijn store. The information on the items bought in the regular store is available to the e-grocer through the Albert Heijn loyalty card, the Bonus card. The Albert Heijn Website provides product and menu suggestions to stimulate additional purchases and increase the customer's basket size.

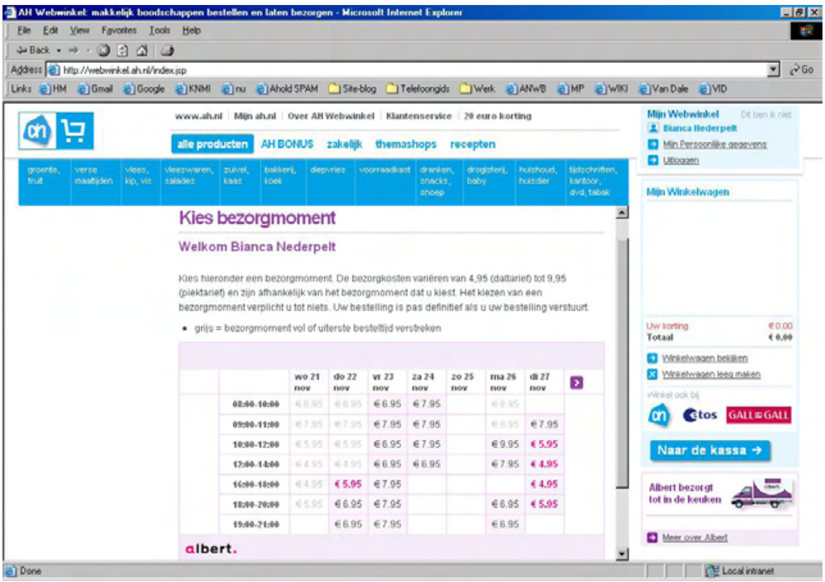


Figure 2.3: Time Slot Schedule at Albert.nl (Amersfoort)

2. Route Planning: After the cut-off point, when all the orders for the given shift are known, the company plans the corresponding delivery routes with a commercial routing package from Ortec, Shortrec (www.ortec.com). The routing package takes time windows, dwell times and vehicle capacities into account. The dwell times at the customer are estimated based on the order size (i.e. number of crates) and the characteristics of the customer's home, in particular

high-rise or low-rise. Shortrec uses different vehicle speeds for different road types and different times of the day (e.g. to account for rush hour traffic). The accuracy of these estimates has a direct impact on the timeliness of the actual deliveries.

3. Order Picking: Based on the planned delivery routes, a commercial software package determines efficient order picking routes through the warehouse. These routes are determined in such a way that the heaviest items come first and the smaller, more delicate items will not be crushed. The warehousing operation is relatively low-tech. The orders are picked manually in batches of about 7 customers. The order picker receives the pick locations of the items and the corresponding amounts on a hand-held portal. With an average of about 67 SKUs per customer order, the picking process is quite labor-intensive. The process is organized in five different product flows, bulk, high-value, perishable, deep-frozen and nonperishable. The five flows are picked in parallel and grouped together by delivery vehicle. The order is packed in plastic folding crates. The frozen items are transported in a cooler with dry ice and are stored in the deep-frozen area until delivery.

4. Order Delivery: A typical delivery route visits between 10 and 20 customers. The courier delivers the ordered goods to the customer's home, right up to the kitchen table. This also applies to upstairs apartments. The courier has a mobile PIN device which allows the customer to pay using his or her debit card. The courier will take back deposit bottles and folding crates if necessary. If Albert.nl cannot deliver the order, or must make an additional delivery because no one is at the delivery address to receive and pay for the order at the specified time, the customer will be charged an additional fee of €3 for delivery or assessed a €10 cancelation fee.

2.2 Demand Management: Planning Tasks

In this section, we describe the demand management planning tasks that arise at Albert.nl. We distinguish between *off-line/forecast-based* planning tasks and *on-line/real-time* planning tasks. Both tasks encompass the matching of supply and demand. Off-line, before actual demand materializes, both demand and supply are relatively flexible. In the short-term, however, supply is essentially fixed, making managing demand the most relevant issue at this point in time. Demand management at Albert.nl involves the management of time slots and delivery fees. The Internet makes it possible to easily customize and adjust the time slot offering and prices.

2.2.1 Offline Planning

Demand

On the demand side, the e-grocer needs to decide on the time slots to offer each customer. Albert.nl provides the customer with a menu of 2-hour delivery slot to choose from. The time slots partly overlap and span the time period between 8am - 2pm in the morning and 4pm - 9pm in the afternoon (see Figure 2.3). Each time slot has a corresponding delivery fee ranging from €4.95 to €9.95, depending on the day and time of delivery. This differentiated delivery fee aims to counterbalance the popularity difference between time slots. The Monday morning slots, for example, have a relatively high delivery fee due to their popularity with business customers that like to have their groceries in at the start of a new week.

Albert.nl uses a differentiated time slot offering linked to the demand characteristics of each zip code. This means that a zip code with low demand potential receives only a few weekly time slots in an attempt to concentrate that demand, where high demand zip codes receive a larger number of slots. The slots offered, regardless of the total number, must also exhibit a balance over the week between morning and afternoon time slots to ensure an acceptable level of service and choice to the customers. Determining the specific time slots for each zip code involves a careful trade-off between marketing and operational considerations. After deciding the number of morning and afternoon slots that will satisfy marketing needs, referred to hereafter as service requirements, the specific time slots are selected for each zip code to satisfy operational needs such as a low-cost delivery schedule. Because delivery vehicles may visit several zip codes during a single time slot and a delivery route spans multiple time slots, routing considerations should play a vital role in the construction of a time slot schedule. Assigning specific time slots to a zip code should not be done in isolation, but should be considered jointly for neighboring slots. This results in a complex planning problem. The time slot schedule employed at Albert.nl is created manually.

Supply

Off-line supply planning tasks range from long-term (e.g. distribution network design) to mid-term (required staffing levels). The long-term decisions form the input to the mid-term tasks. That is, the physical size of the distribution center provides a strict-upper limit on the potential order throughput. Currently, the main physical capacity constraint at Albert.nl is the available room for the storage of orders between order-picking and transportation. The company plans its required staffing levels (order-pickers and delivery couriers) six weeks in advance based on sales forecasts, which are based on past sales developments, seasonalities, and sales promotions. These staffing requirements form a directive for the acquirement of new personnel. Note that Albert.nl has a high turnover, especially for the delivery staff, mostly part-timers and students.

2.2.2 Online Planning

Demand

In the short-term, the e-grocer should decide whether to accept or reject a new request for delivery in a certain time slot. Albert.nl applies order limits per time slot for each HSC, which are based on the available psychical fulfillment capacity (warehouse capacity, staff, vehicles) and time constraints (number of drops per hour). The order limits are set in a way that ensures a balanced distribution of demand over the slots. If the order limits is reached for a particular slot, it is closed for customers in the entire delivery region and turns "grey" on the website.

Supply

Delivery is the most important interface with the customer, and it requires well-trained delivery personnel. This essentially limits the options for using temporary employment and thereby short-term flexibility. At this point, supply and corresponding costs are essentially fixed.

2.3 Alternative E-grocery Models

Some of the above details are, of course, specific to Albert.nl. However, the main steps of the fulfillment process - order in-take, routing, picking, execution - and the corresponding planning tasks are generic and apply to many other Internet retailers with attended home delivery and even to other delivery services. In this section, we look at several other e-grocers and consider the ways in which they differentiate themselves. Besides several current players, we also consider now-defunct Webvan,

Table 2.1: E-grocers in Europe and US

(a) Fulfillment Methods

		picking method		*delivery method*			
	country	warehouse	store/wareroom	unattended	attended	store pickup	same-day
Albert.nl	NL	*			*		
Sainsburys.co.uk	UK	*	*		*		
Ocado.com	UK	*			*		
Tesco.com	UK		*		*		
Peapod.com	US	*	*	*	*		
Albertsons.com	US		*		*	*	
Simondelivers.com	US	*		*	*		*
Freshdirect.com	US	*				*	
Waldbaums.com	US		*		*	*	*
Safeway.com	US		*		*		
Webvan.com[b]	US	*			*		

[b] bankruptcy July 7, 2001

(b) Demand Management Policies

	country	slot lenght(hour)	timing	delivery fee	min. size	dynamic incentives
Albert.nl	NL	2	8am – 2pm/ 4pm – 9pm	€4.95 – €8.95[t]	€60	
Sainsburys.co.uk	UK	1	10am – 10pm	£5	–	
Ocado.com	UK	1	6am – 11pm	£3 – £6[t,s]	£40	*
Tesco.com	UK	2	9am – 11pm	£3.75 – £6.25[t]	–	
Peapod.com	US	2 and 3.5	6am – 1pm/ 4pm – 9.30pm	$6.95 – $9.95[t,s]	$50	*
Albertsons.com	US	1.5	10am – 2.30pm/ 3.30pm – 9.30pm	$9.95	–	
Safeway.com	US	2 and 4	10am – 3pm/4pm – 9pm	$9.95[s]	$50	
Simondelivers.com	US	2	-	$7 – $9.95[l]	–	
Freshdirect.com	US	2	8am – 11.30pm	$4.99 – $6.99[r]	$30	
Waldbaums.com	US	2	9am – 9pm	$5.95 – $9.95[s,l]	–	
Webvan.com	US	0.5	8am – 10pm	$0 – $4.95[s]	–	*

delivery fee index: t dependent on time/s dependent on order size/ l dependent on lead-time / r dependent on region

a high-profile e-grocer from the late 1990s. We structure our discussion around the picking and delivery methods highlighted in Table 2.1(a).

Table 2.1(a) shows that several multi-channel e-grocers currently use the existing stores for order picking (including Tesco, the world's largest e-grocer), while several others pick their orders in a dedicated warehouse. Both approaches have their own pros and cons (see e.g. De Koster (2002a,b), Boyer et al. (2003), Hays et al. (2004)). Although store-based picking has the advantage of requiring relatively limited capital investments, it is considered less efficient than warehouse picking. The reason for this is that the design of a grocery store is typically based on marketing considerations rather than efficiency considerations. In addition to the inefficient store layout, customers asking questions may further slow down in-store order picking. Boyer and Hult (2005) estimate that in-store picking rates range from 80 to 120 items per hour versus 150 to 300 items per hour at a specifically designed e-commerce warehouse.

However, the higher picking efficiency comes at the price of substantial investments and potentially increased average delivery distances. That is, a typical warehouse serves a larger delivery area than a typical grocery store. Especially high-tech facilities require enormous investments, such as the automated warehouses of Webvan, costing $35 million each. Javelin Group Consultancy estimate that at about

5,000 orders a week a warehouse could become competitive against a store picking method. Another alternative is the use of a dedicated non-customer area in the existing store, so-called warerooms, for order picking. Peapod works with twelve of such warerooms adjacent to supermarket partners Stop & Shop and Giant Food, in addition to two freestanding high-tech warehouses.

Due to the perishable nature of the products, most e-grocers offer *attended* delivery, using narrow delivery time slots, ranging from one to four hours. Short time slots are convenient for the customer but very hard to meet in a cost-efficient way by the Internet retailer. Webvan initially offered 30-minute time slots for delivery, which proved very hard to meet as missed delivery times were one of Webvan's most frequent customer complaints (Lunce et al., 2006). Shortly before its bankruptcy in 2001, Webvan announced that it would implement a 60-minute delivery window, allowing more flexibility in planning delivery routes (Mcafee and Ashiya, 2001).

A few e-grocers, including Peapod, offer unattended delivery besides the standard attended delivery in certain designated (rural) areas, using insulated coolers with dry ice to ensure that the grocery items remain at the proper temperature. Simondelivers assigns a fixed weekly time slot for delivery to each customer. That is, not the customer but the company selects the delivery time slot. They apply a delivery route model where delivery trucks follow a fixed neighborhood-based route on a weekly bases to more efficiently deliver groceries. This is facilitated by the fact that most apartments in their delivery region have a door man to receive the deliveries. This basically makes this an unattended delivery service as the actual customer does not need to be present. An alternative to offering delivery altogether is providing customers the possibilities to pick-up their order, either in-store or at a third-party pickup point. FreshDirect enables customers to pick-up their orders at the Long Island warehouse facility and previously also offered pick-up at train stations and office parks (Hays et al., 2004).

Akin to Albert.nl, the majority of e-grocers ask the customer to place his order at least one day before the actual delivery. This gives the company sufficient time to pick, pack and ship the orders to the customers. Only a few e-grocers also provide same-day deliveries, such as Waldbaum's and Simondelivers. Waldbaum's, a subsidiary of A&P operating in the Brooklyn, Queens and Long Island areas (New York City, NY), offers its customers same-day delivery in the afternoon when orders are placed and updated at least four hours in advance of the selected scheduled delivery. Simondelivers provides the possibility for same-day delivery at a higher delivery fee of $9.95 instead of $7.

E-grocers typically offer the customer a weekly schedule of time slots for delivery to choose from. Almost all e-grocers use demand management in some way. Table 2.1(b) summarizes the different approaches for several e-grocers in Europe and the US. Many e-grocers apply a differentiated delivery fee structure, in which the fee depends on either time, order size, lead-time or delivery region. Peapod, for example, charges a delivery fee dependent on the order size: $6.95 for orders over $100, $7.95 for orders between $75 and $100, and $9.95 for orders less than $75.00. Freshdirect differentiates according to the delivery neighborhood, e.g. charging $4.99 for delivery in Manhattan and $6.99 for delivery in Staten Island. Some grocers, such as Peapod, apply dynamic incentives such as discounts to encourage the customer to select a certain time slot, facilitating cost-efficient routing (Agatz et al., 2008b).

2.4 Conclusions

In this chapter, we have discussed the typical demand management issues that arise in the delivery of goods ordered online by focussing on e-grocer Albert.nl. Due to the perishable nature of the products, the e-grocer typically offers attended home delivery, where the customer has to be home to receive the goods. The customer can choose from a menu of time windows for delivery. The set of offered time slots and corresponding delivery fees forms the main interface between the customer and the company. Although narrow time slots are desirable from a marketing perspective, they make cost-efficient delivery very challenging.

Some of the key insights from looking at current e-grocery practice are:

- the home delivery of groceries proves logistically very challenging: the initial e-grocery failures often underestimated the operational implications of their delivery service offering;
- demand management gives rise to a variety of novel demand management task for Internet retailers;
- many current Internet grocers use demand management by differentiating the delivery charge based on the delivery time and/or order size;
- since supply is usually relatively inflexible in the short term, dynamically managing the slots and corresponding fees as demand unfolds provides promising opportunities;

Chapter 3

Literature review: Issues and Models in E-fulfillment

The examples in the previous chapter illustrate some of the planning issues that arise in e-fulfillment. In this chapter[1], we provide a systematic overview of relevant issues in e-fulfillment and link them to available operational research/decision support models. Our objective is to twofold, namely to enhance the understanding of e-fulfillment by documenting the current state of affairs, and to identify gaps between relevant managerial issues and available academic literature. We proceed as follows. Section 3.1 provides a framework that structures our discussion. Section 3.2 and Section 3.3 form the core of this chapter. They discuss supply- and delivery-related e-fulfillment issues, respectively. Each section first discusses managerial planning issues observed in practice and then reviews corresponding operational research models. Section 3.4 summarizes our conclusions.

3.1 Scope and Framework

Several excellent review papers are available that address the impact of the Internet on supply chain management, including (Keskinocak and Tayur, 2001), Johnson and Whang (2002), Swaminathan and Tayur (2003), and Gimenez and Lourenco (2004). In addition, the handbook edited by Simchi-Levi and Wu [2004] provides a detailed overview of related research areas. What distinguishes our contribution is

[1]This chapter is based on the paper: 'E-fulfillment and Multi-Channel distribution - a review' (Agatz, Fleischmann, and van Nunen, 2008e)

(i) the specific focus on fulfillment operations, and (ii) the systematic comparison of managerial issues and quantitative tools, and (iii) the particular attention to multi-channeling.

In the subsequent sections we address various planning issues arising in e-fulfillment. To structure the discussion we map the planning tasks on two dimensions, namely, the supply chain stage and the planning horizon (comp. Fleischmann et al. (2002)).

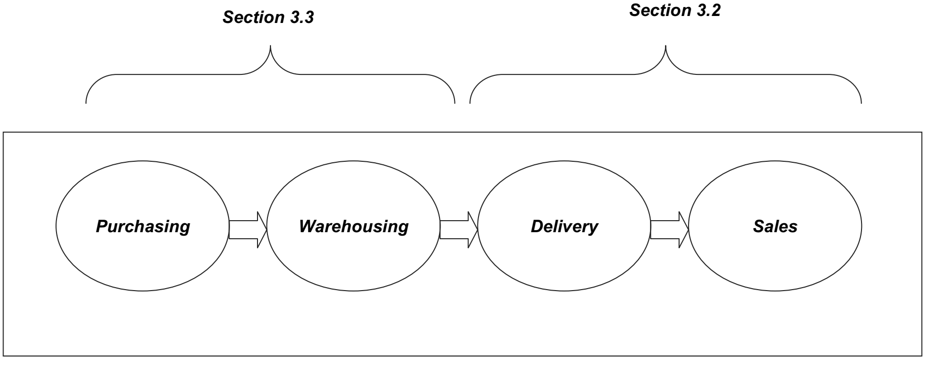


Figure 3.1: Structuring the e-fulfillment distribution process

Along the first dimension we distinguish the four supply chain stages depicted in Figure 3.1:

- *Sales* denotes all processes that directly interface with customer demand, such as pricing, order promising, and forecasting;
- *Delivery* encompasses the activities that physically move the product to the customer. In the case of home delivery, this is known as 'the last mile';
- *Warehousing* is concerned with the storage and handling function. Depending on the supply chain's decoupling point, the warehousing stage may be omitted or shifted to an upstream supply chain party;
- *Purchasing* is our term for all supply processes, notably ordering of final products.

Throughout this chapter, we use the term 'e-fulfillment' to denote the collection of these processes. Note that, in line with the previously explained retail perspective, we do not include a manufacturing stage. On the second dimension, supply chain planning tasks are commonly structured according to their planning horizon, i.e. from long-term strategic to short-term operational. We follow this approach within each of the above supply chain stages.

For each planning task we first discuss what, if anything, distinguishes e-fulfillment from traditional supply chains. Second, we consider the potential interaction with other channels in a multi-channel context. This concerns, in particular, trade-offs between integration and separation of processes across multiple channels.

We emphasize that the above structuring only serves as a means for organizing our discussion. We do not mean to imply that the different planning tasks are independent or that the different supply chain stages should be managed in isolation. On the contrary, we recognize online information exchange as an important enabler of supply chain integration. The marketing-operations interface has been receiving much attention in the recent supply chain management literature (Marketing Science 50, 2004, Journal of Operations Management 20, 2002). This interface is particularly relevant in e-fulfillment since the delivery service is an essential component of the product offering. In other words, the customer buys a bundle of a physical product and a delivery service (and possibly other after-sales services). Consequently, companies need to coordinate their sales promises and their delivery capabilities. Because of this close interaction, we discuss sales and delivery planning tasks jointly in Section 3.2. Similarly, Section 3.3 encompasses warehousing and purchasing issues.

3.2 Sales and Delivery Planning

Traditional sales-related supply chain planning tasks include long-term product program planning, medium-term pricing and forecasting, and short-term order promising (see e.g. Fleischmann and Meyr (2003)). Particular features of these tasks in an e-fulfillment environment notably arise from the fact that the delivery service makes part of the product offering. Embedding in a multi-channel structure gives rise to additional trade-offs. In what follows, we discuss the impact of these factors by planning task. Subsequently, we relate the observed issues to quantitative decision support models presented in the academic literature. Table 3.2 at the end of this chapter lists the models by category.

3.2.1 Delivery Service Design

Issues

As with any company, Internet sellers need to determine their product offering. This involves specifying both the product assortment and the offered delivery service, which is an important determinant of customer satisfaction (Boyer and Hult, 2005). Product assortment decisions are strongly interrelated with investments in inventory. By decoupling customer location and inventory location, the Internet drastically changes the underlying economics of assortment planning. Specifically, online channels may achieve strong pooling effects and thereby can afford a broader assortment than physical stores. For a further discussion of these issues we refer to Section 3.3.1. The quality of the fulfillment service is addressed in a growing body of literature on Physical Distribution Services (Rabinovich and Bailey, 2004).

From a customer service perspective, concepts for bridging the 'last mile' to the customer can be divided into customer pick-up versus (home) delivery (Daduna and Lenz, 2005). The latter can be further subdivided into attended and unattended delivery (Kamarainen and Punakivi, 2002). While unattended delivery increases delivery flexibility, this concept is only applicable for products that can be safely deposited, e.g., in the customer's mailbox. The well-known example of US online grocer Streamline illustrates the difficulty of extending unattended delivery to more sensitive product categories. Streamline went bankrupt after being unable to earn back its investments of providing customers with refrigerated reception boxes.

For attended home delivery, a company and its customer need to agree on a delivery time window (see for example Figure 2.3). The length of this window and its timing during the day are important aspects of the customer's perceived service. The same goes for the delivery lead time, i.e. the time between order placement and delivery. At the same time, all of these factors have an immediate impact on the seller's delivery costs. Striking the right balance between cost and service is challenging, in particular in highly competitive environments, such as the grocery market (see Boyer et al. (2003)).

Another e-fulfillment service element concerns the handling of customer returns. Internet sales face particularly high return rates since customers cannot try and feel the product beforehand. For example, online apparel retailers experience return rates totaling up to 45% of their orders (Tarn et al., 2003, De Koster, 2002a). Costs of return handling, which include bridging the expensive 'last mile' for a second time, can easily eradicate the economic viability of an online channel. On the other hand, customer-friendly return policies will influence customers' perceptions and intention to repurchase (Mollenkopf et al., 2007). Therefore, designing efficient return processes is of prime importance (Min et al., 2006). This again leads to a trade-off between customer service (i.e. the return policy) and operational costs (Yalabik et al., 2005).

One way, in which companies are trying to shift this balance is by offering support services, such as installation support for electronic products, as a method to reduce product returns.

Traditional sales channels offer many potential synergies for the marketing of an Internet channel. In particular, a well-established brand name helps build trust with the customer, which is essential for online sales (Chen and Dhillon, 2003). The presence of a traditional distribution structure also yields additional options for the delivery service design in e-fulfillment. As we have already seen in Section 2.3, physical store pick-up points are a fairly common alternative to customer home delivery. Online orders are picked and packed in a store where the customers can then pick them up (www.bestbuy.com, www.freerecordshop.nl), possibly via a dedicated pick-up lane (www.lowesfoods.com, www.foodfactory.nl). In this approach it is the customer who bridges the crucial 'last mile'. Other advantages of a pick-up structure include low capital investments and possible carry-over effects on in-store sales (Boyer et al., 2005, Johnson and Whang, 2002).

The presence of a physical distribution structure can be particularly beneficial for return handling. Most multi-channel retailers offer online consumers the option to return products via offline stores. This approach not only helps reduce return handling costs but it is also greatly valued by the customers (Forrester, 2005).

Models

Regarding the choice of the e-fulfillment product offering, the modeling focus in the literature has been on the delivery service. Several authors have addressed the issue of choosing an appropriate delivery service level, in terms of time windows and lead times. Some of the proposed models directly optimize the service offering by considering both costs and revenues. Other models take a what-if approach, highlighting the cost impact of a given service offering.

Several papers related to the Ecomlog[2] project of the Helsinki University of Technology present simulation-based analysis of different delivery strategies for e-groceries (Punakivi and Saranen, 2001, Punakivi et al., 2001, Punakivi and Tanskanen, 2002, Yrjölä, 2001). Yrjölä (2001) develops cost estimates for several alternative fulfillment strategies. The results award particular potential to hybrid structures that gradually expand e-fulfillment capabilities of traditional stores. Punakivi and Saranen (2001), Punakivi et al. (2001), Punakivi and Tanskanen (2002) compare transportation costs for attended and unattended delivery and assess the impact of the delivery window

[2]A research programm focussed on supply chain management for e-commerce that took place between 1999 and 2002, see http://www.tuta.hut.fi/logistics/ecomlog

length. The results illustrate the efficiency gains of relaxed time constraints. Fully flexible, unattended delivery reduces costs by up to a third, relative to attended delivery within two-hour windows. Similarly, Lin and Mahmassani (2002) use simulation to evaluate the impact of different delivery policies on the operations of an e-grocer. They illustrate the trade-off between delivery cost and customer service by highlighting the potentially significant cost impact of tight delivery time windows. Geunes et al. (2007) model the delivery pricing problem when both the size of demand and the demand frequency is price sensitive. They focus on the question of which customer regions to serve, at which price, in order to maximize profitability. Robuste et al. (2003) model the effect of time windows on delivery efficiency by continuous approximation. They demonstrate that the impact of time windows increases with increasing delivery vehicle capacity. Hsu and Li (2006) seek optimal delivery shipment cycles that strike a balance between delivery costs and customer service in terms of delivery lead times. They present a non-linear profit maximization model with lead-time dependent demand. Costs include purchasing, transportation, and inventory. Numerical examples illustrate the benefit of adjusting shipment frequencies to temporal and regional demand variations, rather than imposing a static policy.

We are not aware of any optimization models that explicitly consider delivery service choices in a multi-channel setting, e.g. choosing between home delivery and store pick-up. The reason may be that the number of alternatives for these strategic choices is small, and they can therefore be addressed separately, rather than requiring a comprehensive overall model. What may be more remarkable is the scarcity of optimization models for return policies in e-fulfillment. This is in sharp contrast with the extensive literature on end-of-life returns on the one hand (see e.g. Dekker et al. (2003)) and with the many models of buy-back contracts for supply chain coordination on the other hand (see e.g. Tsay et al. (1998)). In the spirit of the latter, Yalabik et al. (2005) propose a game theoretic model that is tailored towards a retail environment. Specifically, they model a retailer's buy-back price decision, which influences demand of two customer segments.

3.2.2 Pricing and Forecasting

Issues

Pricing decisions play a key role in any business. Service components, notably delivery, add an extra dimension to this issue in e-fulfillment. Companies need to set prices both for the physical products and for the delivery service. Common policies often combine both price elements, e.g. in the form of free delivery of sufficiently large orders.

Two factors render pricing a particularly powerful lever in online sales, namely significant pricing flexibility and extensive data availability. Typically, online sellers can change prices much more easily than traditional stores. Consequently, they can use pricing for short-term demand management (Baker et al., 2001). Besides dynamic posted prices, common online pricing policies include various types of auctions (Kambil and Van Heck, 2002). Interestingly, many firms are selling almost identical products online through auctions and fixed prices simultaneously (Etzion et al., 2006). What complicates e-fulfillment pricing decisions is the need to anticipate the ensuing cost consequences in the delivery operation. In addition, overly complex pricing policies may leave customers confused and distrustful (Garbarino and Lee, 2003).

The second major factor that increases pricing power in e-fulfillment is data availability. What is a major challenge for operations, namely dealing with individual customer orders, is a rich opportunity for marketers. Availability of transaction data of individually identified customers not only provides a rich basis for forecasting but, more importantly, allows targeted communication with the customer. This explains the particular relevance of customer relationship management (CRM) in online retailing.

Detailed data provides a basis for segment-specific pricing and promotion. In particular, firms can effectively cross-sell products and services that closely match a particular customer's preferences, as in the example of Amazon.com suggesting additional book titles, based on the customer's browsing behavior (Akcura and Srinivasan, 2005). Effective cross-selling requires a firm to select appropriate product bundles and to design a corresponding pricing strategy. In summary, we see a shift from reactive forecasting to a much more active demand management in e-fulfillment.

The presence of a traditional sales channel adds further dimensions to the pricing decision. In particular, retailers need to choose whether to offer the same prices - and price changes, such as promotions - across all channels or whether to price-differentiate. Some retailers choose identical prices for the physical products and use additional delivery fees as the main steering element of the online channel (see e.g. Albert.nl in previous Chapter). In addition, traditional sales channels benefit from the rich data collected in the online channel. Forrester (2005) argues that advanced multi-channel tactics include CRM across multiple channels.

Models

The marketing literature reflects a long history of customer choice models (Erdem and Winer, 2002). Detailed data on Internet browsing and on e-commerce transactions opens significant opportunities for additional empirical research in this field. Van Den Poel and Buckinx (2005) and Jenamani et al. (2003) are examples of recent papers, which concentrate on explaining and predicting customer behavior on the Web. The aforementioned models are primarily descriptive. In addition, a significant stream of prescriptive models is available for short term price optimization. Making part of the well-publicized field of Revenue Management (Talluri and van Ryzin, 2004), these models assess in particular the benefits of dynamic pricing policies over more stable prices (see for example Gallien (2006)). While not all of these models are focusing on e-fulfillment specifically, many of them appear to be applicable, due to the particular pricing flexibility in online sales. The same goes for the large set of auction and bidding models (Kalagnanam and Parkes, 2004).

The above models essentially maximize revenues. Another line of research explicitly integrates cost and revenue effects of dynamic pricing. In particular, many authors have proposed combined inventory-pricing models. For a more detailed review of this rapidly expanding stream of research we refer to Chan et al. (2004) and to Elmaghraby and Keskinocak (2003).

As discussed in the previous subsection, the impact of dynamic pricing on e-fulfillment delivery costs appears to be particularly relevant. We are aware of two models explicitly addressing this issue. Asdemir et al. (2009) propose a dynamic pricing model for the delivery windows of a grocery home delivery operation. Similar to standard revenue management models, demand is stochastic and includes several customer classes. The model uses dynamic prices per customer class to balance capacity utilization. The authors analyze the structure of the optimal pricing policy as a Markov decision problem and numerically investigate the profit increase relative to a constant pricing policy. Campbell and Savelsbergh (2005b) also consider price incentives to influence a customer's choice of a delivery window in a home-delivery operation. They propose a deterministic optimization model for choosing the discounts that explicitly captures the routing costs of a given order. A simulation analysis indicates that the suggested incentive schemes can significantly enhance profit.

Another stream of pricing-related research is concerned with optimal cross-selling. Kamakura et al. (2003) use a combination of survey data and customer databases to identify opportunities for cross-selling. They propose a statistical model to predict customers' likely buying behavior. This then serves as a basis for selecting the best prospects for cross-selling new products or services. Wong et al. (2005) propose a data-mining algorithm for finding a profit-maximizing set of items for cross-selling. They approximate the initial model by a quadratic program, which they solve heuristically. Netessine et al. (2006) consider the problem of dynamically cross-selling products or services in an e-commerce setting. Following a revenue-management approach, they develop a stochastic dynamic program for a finite horizon, multi-item inventory system. In each period, the company needs to decide which products to bundle and which price to charge for this bundle. The authors suggest several solution heuristics and test them numerically. The results suggest that dynamic cross-selling is most beneficial when inventory approximately equals expected demand. In a slightly different setting, Akcura and Srinivasan (2005) consider an online retailer's opportunities for cross-selling customer information to a third party. The paper proposes a game-theoretic model for the interaction between the retailer and the consumer. The results suggest that firms can achieve customer intimacy by committing to not cross-selling excessively.

Pricing models for a multi-channel setting appear to be scarce as of yet. For a review of general coordination issues between traditional and Internet channels see Cattani et al. (2004). We are aware of only two papers that specifically addresses pricing decisions of a multi-channel retailer. Cattani et al. (2006) analyze optimal pricing policies in this setting for different degrees of autonomy of both channels. They assume that an individual customer's utility of buying a product decreases in the product price and in the channel-specific purchasing effort. Based on computational experiments, the authors conclude that optimizing web-channel prices without changing store prices often provides a reasonable heuristic for maximizing total profits. Huang and Swaminathan (2009) study optimal pricing strategies for a product that is sold via two channels, the Internet and a traditional channel. They assume a stylized deterministic demand model where the demand in a channel depends on prices, degree of substitution across channels, and the overall market potential. The authors demonstrate that the prevalent practice of providing the Internet channel with limited autonomy in terms of pricing is not such a bad idea.

3.2.3 Order Promising and Revenue Management

Issues

Traditionally, short-term sales planning centers around order promising, roughly speaking the seller's response to an incoming customer request (see Quante et al. (2009)) for a recent review on demand fulfillment in supply chain management). Order promising plays an important role in manufacturing. The specific planning issues depend on the production environment. In a make-to-stock environment, planning systems calculate available-to-promise (ATP) quantities, indicating the number of products that can be committed to a given delivery date, based on projected replenishments (Fleischmann and Meyr, 2003). In a make-to-order environment, delivery dates depend mainly on downstream production capacity, and throughput time estimates play an important role. In traditional retailing, order promising is more straightforward since products are typically sold directly from stock. It is again the service component that adds to the complexity of order promising in e-fulfillment. In order to satisfy a customer order not only the requested product has to be available but also sufficient delivery capacity (analogous to assemble-to-order production). Based on these factors, the Internet retailer has to commit to a certain lead-time or estimate-to-ship date. Flexibility in the quoted lead-times can help increase e-fulfillment efficiency (Xu et al., 2006). In addition, the retailer may have some flexibility regarding where to retrieve the product - as opposed to physical stock in a traditional retail store (see Section 3.3 for a detailed discussion of inventory considerations in e-fulfillment).

In general, customer orders differ with respect to their contribution margins and their delivery costs. This gives rise to revenue-management issues in e-fulfillment, similar to those well known in the airline and hospitality industry (McGill and Ryzin, 1999). E-tailers have an incentive to use their inventories and delivery capacity for the most profitable orders. In the case of high utilization it may not be optimal to simply accept all orders first-come-first-serve until inventory or capacity are exhausted. Online order intake provides the retailer with additional flexibility in the allocation of inventories and capacity to customer orders. The benefits of exploiting this flexibility for a more selective order acceptance increase with increasing order heterogeneity and with decreasing inventory and capacity. This allocation decision also plays a role in the online rental business (e.g. www.Netflix.com). What distinguishes revenue management in e-fulfillment from classical revenue management is the potential cost impact. In contrast with the prototypical ‘airline’ setting, marginal costs of an order are non-negligible in e-fulfillment and, what is more, delivery costs for different orders may be interdependent.

E-tailers have different revenue management levers at their disposal, including dynamic pricing and a dynamic adjustment of the offered delivery options (e.g. time slots). This links order promising to the short-term pricing decisions discussed above. In all of these cases, revenue management benefits from the real-time availability of rich customer data. Again, maintaining a certain level of transparency may be important for customer satisfaction.

In a multi-channel setting, order promising may cross the boundaries of individual channels. For example, in-store inventories may be available to online buyers. In this case, customer segmentation based on channel type, and a corresponding prioritization in order promising, may be beneficial since opportunity costs of missed sales tend to differ by channel.

Models

The large body of research on lead-time quotation and due-date management in manufacturing (see e.g. Keskinocak and Tayur (2004)) seems a natural starting point for order promising models in e-fulfillment. However, standard models do not appear to be immediately applicable to delivery services, due to significant differences in the underlying costs structures. Bundling of individual orders into delivery routes creates interdependencies between orders that differ from those in manufacturing. The waiting for a complete delivery tour accounts for a major part of the customer lead time. We are not aware of any models in the literature that specifically address lead-time quotation in e-tailing.

Revenue management has grown into a major field of research over the past decade. Model variants abound (Talluri and van Ryzin, 2004). Broadly speaking, the underlying managerial task is to sell scarce resources to the most profitable customers. Abraham et al. (2006) address the specific allocation decisions that arise in an online rental environment. In a retail setting, the allocation decisions are often intertwined with inventory replenishment decisions. We discuss the corresponding models in Section 3.3 in the context of inventory management.

As explained above, the e-fulfillment delivery process yields additional criteria for differentiating between customers. Depending on the requested delivery time and location, some customers may be more expensive to serve than others. Thus, if capacity is scarce, delivery cost differences should be taken into account when deciding which orders to accept. We are aware of only one paper that explicitly addresses this issue. Campbell and Savelsbergh (2005a) propose a model for deciding whether to accept or reject an incoming home delivery request. Their analysis is based on insertion heuristics for a vehicle routing problem. They suggest several variants for incorporating expected future orders. A numerical study compares these variants and underlines their superiority over a simple first-come-first-serve order acceptance.

We see the development of revenue management approaches for home delivery operations among the most relevant current research issues in e-fulfillment and expect significant additional contributions in the future.

3.2.4 Transportation Planning

Issues

On the delivery side, short-term planning concerns the actual transportation of the goods to the customer. The scope of this operation closely depends on the chosen delivery concept, as indicated earlier. In the case of in-store pick-up, 'transportation' may be limited to moving the goods to a check-out counter. Combining shipments with regular store replenishments may yield economies of scale. Home-delivery implies a more extensive operation. Cost-efficient processing of small transaction sizes is a major challenge. Especially in the case of low-value items, such as groceries, transportation costs are a key determinant of the business viability. Hub-and-spoke networks provide a common way to create economies of scale while expanding geographical coverage. See the previous chapter for more information about the Albert.nl hub-and-spoke network.

Dedicated home delivery, as opposed to delivery by mail, requires the planning of appropriate transportation routes. The degree of routing flexibility and thus transportation efficiency closely depends on the delivery service design, notably on the offered delivery time-windows.

In B2C Internet retailing new routing schedules have to be planned more frequently (usually daily or twice a day) than in a traditional B2B delivery environment. The reason is that many B2C orders are impulse buys whereas B2B purchases are often repetitive (Buck Consultants, 2006). This leads Du et al. (2005) to argue that B2C environments exhibit a greater need for quick-response dynamic vehicle dispatching systems than B2B environments.

Models

Vehicle routing is a classical field of combinatorial optimization. Modeling and algorithmic contributions abound (see e.g. Golden et al. (2008), Toth and Vigo (2001)). Braysy and Gendreau (2005a,b) provide a recent survey of solution algorithms for vehicle routing problems with time windows (VRPTW).

Many of these models appear also to be applicable in e-fulfillment. The particular challenges of this environment, such as significant cost pressure, seem to affect parameter values primarily, rather than the underlying problem structure. VRP variants that seem particularly relevant in an e-fulfillment setting include the

Dynamic Vehicle Routing Problem (DVRP), in which new orders arrive during operation (Fleischmann et al. (2004). Similarly the Period Vehicle Routing problem with Service Choice (PVRP-SC), in which delivery routes must be constructed for multiple periods and delivery frequency is a decision variable, is relevant to home delivery operations (Francis et al., 2006, Francis and Smilowitz, 2006). Weigel and Cao (1999) report on a vehicle routing problem with time windows in e fulfillment at Sears, Roebuck and Company. Sears operates the largest furniture and appliances home-delivery service in the US. The authors construct a series of algorithms tailored to handling the large problem size. Du et al. (2005) emphasize the dynamic nature of e-fulfillment and propose a combination of several existing algorithms for quick-response delivery in an online B2C environment.

Xu et al. (2006) link transportation planning to inventory deployment. Specifically, they consider the re-allocation of accepted customer orders to different warehouses while maintaining the original lead time commitment. Re-allocation may reduce transportation costs by taking into account more recent additional orders. The magnitude of these benefits depends on the degree of lead-time flexibility. This problem highlights the hierarchical planning structure of order promising and execution. The authors formulate the re-evaluation problem as a multi-commodity flow model. They propose near-optimal heuristics and apply them to an illustrative case involving a global Internet retailer.

3.3 Supply Management

In the previous section we addressed issues and models related to the delivery and sales function of e-fulfillment. In this section we consider the processes further upstream in our supply chain framework (see Figure 3.1). Supply and storage are the key functions at these stages. Corresponding planning issues range from long-term design issues to short-term execution. Particularities of e-fulfillment mainly arise from small transaction sizes. Important trade-offs of multi-channeling pertain to the aggregation of inventories. In what follows, we first discuss these issues systematically. Analogous with the previous section, we then review models from the Operational Research literature that correspond with the identified issues. Table 3.2 summarizes these models.

3.3.1 Distribution Network Design

Issues

Network design, including the choice of facility locations and corresponding transportation links, is a key strategic decision in any supply chain. In a retail environment, location choices mainly concern storage and transshipment facilities. The same is true in e-fulfillment. What is unique to e-fulfillment is the fact that inventories are decoupled from customer display. This increases the e-tailer's flexibility in locating inventories and allows for a larger assortment (Randall et al. (2006); see also Section 3.2.1). On the other hand, inventory locations are closely linked to the design of the delivery process discussed in the previous section. In conclusion, it is a trade-off between economies of scale and risk pooling on the one hand and delivery efficiency on the other hand that drives inventory locations and, in particular, the degree of inventory centralization. The impact of the delivery component is particularly important because of the relatively small transaction sizes, which often entail significant transportation costs.

The absence of physical inventory on display allows Internet retailers to avoid inventory ownership altogether by delivering customer orders directly from their suppliers' inventories. In this arrangement, known as drop-shipping, the retailer focuses on the sales function, and leaves the physical fulfillment processes to the supplier (Bailey and Rabinovich, 2005). Drop-shipping is a common practice for non-perishable make-to-stock items, such as books and CD's. It provides a means for risk pooling by integrating the inventories of multiple retailers or retail outlets, which enables them to offer a larger assortment. On the other hand, the retailer concedes some of his margins, control, and customer proximity to his supplier (Randall et al., 2002). For a viable co-operation, retailer and supplier need to strike a balance between service level agreements and delivery costs.

A multi-channel setup yields obvious potential synergies on the supply side. Arguably, the biggest advantage concerns greater purchasing power and the leverage of established supplier relationships. Other synergies may arise in the physical distribution network. In particular, multiple channels may share inventories, thereby reaping pooling benefits. However, economies of scale can be hampered by different transaction sizes in different channels, e.g. pallet-sized orders of a retail store versus individual items in e fulfillment. In this context, it is worth noting that storage facilities of an e-fulfillment channel share characteristics both with traditional warehouses and with traditional stores. The specific e-fulfillment channel indicates which characteristics prevail. This is reflected in three types of e-fulfillment structures commonly distinguished in the literature (De Koster, 2002b,a, Lummus and Vokurka, 2002):

- Integrated fulfillment - building e-fulfillment capability into existing distribution centers that also deliver to conventional stores;
- Dedicated fulfillment - via a purpose-built "green-field" operation;
- Store fulfillment - picking online orders from regular retail shelves for separate, dedicated delivery;

Murphy (2003) discusses some of the key e-grocery initiatives in North America, distinguishing between store-based versus warehouse-based fulfillment. He underlines that space constraints limit the e-fulfillment volume in the store-based model since professional order pickers and regular customers interfere with each other. Yrjölä et al. (2002) propose a hybrid approach in which the fulfillment structure differs by product. It is not only the online channel that benefits from the synergies of a multi-channel approach. Conversely, a traditional retailer may expand his assortment by adding an online channel (Singh et al., 2006). This gives rise to new planning issues, concerning which products to offer through which channel(s). In general, fast movers are suitable for physical stores, whereas slow movers are more suitable for an online channel. Since the Internet channel comes at the expense of longer customer lead times, customer service preferences also play a role in these channel assortment decisions. In addition, the presence of an online channel may affect product display decisions in a physical store, e.g. if customers can order through online terminals in the store.

Models

Discrete location-allocation models form the prevalent modeling approach to distribution network design. Countless modeling variants are available in the literature, ranging from simple single-stage, single-product models to complex non-linear probabilistic models. For a recent and extensive review and classification of facility location models see Klose and Drexl (2005).

In principle, many of the standard models also appear to be applicable to the network design of an online channel. This may explain why one does not find many network design models that focus on e-fulfillment specifically. A notable exception concerns drop-shipping models, with a focus on inventory placement. Typically, these models combine strategic inventory allocation issues and operational inventory control. We discuss those models that focus primarily on the operational component in a separate subsection on inventory management (Section 3.3.3). Among the more strategic models, Netessine and Rudi (2006) examine drop-shipping arrangements from a supply chain coordination perspective. They propose a game-theoretic model of a two-echelon supply chain comprising a wholesaler and multiple retailers. A single-period analysis reflects the trade-offs related to inventory risk and its impact on the optimal channel choice. Netessine and Rudi (2004) consider a multi-period variant of this model. They argue that drop-shipping entails a marketing-operations misalignment that results both in under-stocking and in deficient customer acquisition. Consequently, for both the retailer and the wholesaler drop-shipping is only beneficial in the case of a relatively high wholesale price. The authors show how to coordinate this supply chain by means of contracts.

Several models in the literature consider the impact of product returns on logistics network design (see e.g. Fleischmann and Meyr (2003)). Min et al. (2006) focus on e-fulfillment specifically. They propose a model for locating return centers that consolidate returned products before shipping them to a central repair facility. The model focuses on trade-offs between freight rate discounts and inventory reduction. The authors formulate a non-linear mixed-integer programming model and solve it using a genetic algorithm.

Despite the apparent trade-offs and the heterogeneous solutions observed in practice, we found few quantitative models addressing a multi-channel distribution network design. The available models focus mainly on inventory aggregation effects and rely on multi-echelon inventory theory. Specifically, they consider divergent two-echelon systems with a central warehouse at the top echelon and retail stores at the bottom echelon. Alptekinoglu and Tang (2005) develop a model of the distribution of a single product to multiple sales locations through multiple cross-docking depots. The authors determine ordering and allocation policies for each depot that minimize total expected distribution costs. They compare two fulfillment scenarios, namely fulfillment from the store or from the warehouse. The model highlights the risk pooling benefits of inventory aggregation. Chiang and Monahan (2005) study a two-echelon inventory model comprising two alternative distribution channels, namely traditional retail stores and an Internet-enabled direct channel that is served from a central warehouse. The system receives stochastic demand from two customer segments that differ in their channel preferences. The paper compares three different distribution strategies, namely store-only, Internet-only, and a combined bricks-and-clicks approach. Numerical examples show the dual-channel strategy to outperform both of the single channels. Mahar et al. (2008) address the assignment of online orders to retail stores for fulfillment, taking into account holding, backorder and transportation costs. The paper compares a static assignment strategy with a dynamic assignment that uses the information on the inventory positions in the stores. Their findings suggest that a dynamic policy can reduce system costs by about 8 percent over the optimal static policy.

Some other related models are rooted in the literature on assortment planning. See Kök et al. (2008) and Pentico (2008) for two recent reviews. The majority of the available planning models considers a single assortment, namely either the same assortment in all channels or the assortment of a single channel. We see assortment planning over multiple channels as a valuable area of future research. We are aware of one paper that explicitly considers assortment and stocking decisions in a multi-channel retail setting. Singh et al. (2006) propose an analytical inventory model using a stochastic choice process to generate demand according to a multinomial logit (MNL) random utility model. The results confirm the intuitive conclusion that adding an Internet channel enables a retailer to provide a wider product assortment, using the Internet channel to offer the less poplar products.

3.3.2 Warehouse Design

Issues

Another set of strategic issues is the internal design of storage facilities. Traditional issues in warehouse design include the selection of a proper storing method, the choice of appropriate handling equipment, and the warehouse layout (de Koster et al., 2007). Order picking costs account for the largest part of warehousing operating costs. This is even more true in B2C e-fulfillment operations, which typically involve small pick quantities from a large number of items. This underlines again the assemble-to-order nature of e-fulfillment. Split-case or piece-picking are common picking methods in these environments, methods that are relatively more labor-consuming than case or pallet picking. In a B2C environment, picking quality is highly important since the assembled order is delivered directly to the end-customer. Picking quality can be supported by advanced picking technologies, such as radio frequency terminals, wireless speech technology, and pick/put-to-light systems. However, viability of the corresponding investments requires high order volumes.

In Section 3.2 we discussed the particular relevance of product returns in e-fulfillment. This is also reflected in the warehouse design. A large fraction of the returned products is essentially as good as new and can therefore be resold. However, this requires a systematic process for feeding returns back into inventory, possibly after inspection or cleaning (de Brito and De Koster, 2003). As discussed above, a multi-channel setting offers opportunities for integrating inventories of different channels at a single location, which can be a warehouse or a store. In general, however, this will require design adjustments to make these locations fit for efficient Internet order picking.

Models

For a general review of models concerning the design and control of order-picking operations we refer to de Koster et al. (2007). Small transaction sizes render order picking more labor intensive for an Internet channel, thereby increasing the need for efficiency. A few authors have proposed specific models for warehouse operations in a B2C e-commerce setting.

Two papers consider split-case sorting systems that sort items from opened (or 'split') cases into the corresponding customer orders. Johnson and Meller (2002) study the performance of such an automated split-case sorting system. They develop analytic performance models for different system configurations. Russell and Meller (2003) address the decision of whether or not to automate the split-case sorting process. They develop a descriptive model of the major trade-off between picking and packing efficiency. Batching increases the picking efficiency but decreases the packing efficiency. The model is used to evaluate alternative system designs. Xu (2005) studies a two-region warehouse in an e-tailing setting. One region is used for order picking, the other holds reserve stock. The author models this system as a stochastic multi-item two-stage, serial inventory system with space constraints.

We are not aware of any quantitative models addressing the integration of product returns into warehousing processes in e-fulfillment. For a qualitative discussion we refer to de de Brito and De Koster (2003).

3.3.3 Inventory and Capacity Management

Issues

Medium and short term planning tasks on the supply side of e-fulfillment focus on inventory replenishment. Based on demand forecasts, appropriate stocking levels must be determined for each storage location. In particular, this includes setting safety stocks to buffer against demand uncertainty.

At first sight, inventory management in an Internet channel differs little from any other channel. What adds novel characteristics to this process is the interrelation with demand fulfillment. We have argued in Section 3.2 that online sales offer particularly rich opportunities for dynamic pricing and revenue management. Inventory management must also anticipate this type of short-term demand management for setting appropriate stocking levels. This particularly holds in the case of joint inventories for multiple channels. As discussed earlier, different channels may imply different opportunity costs for lost sales and therefore require different service levels. These different requirements should be aggregated into an overall inventory level and an accompanying fulfillment policy.

The aforementioned product returns may further impact inventory management in an Internet channel. If the return volume is significant it may be advisable to take outstanding returns into account when placing a replenishment order, especially in the case of long supplier lead times. In addition to physical product inventory, e-tailers must manage their fulfillment capacity. This again reflects the service component of the Internet channel's product offering. Capacity management, notably workforce planning, corresponds with the 'replenishment' of this service component. One of the challenges in retailing concerns seasonal demand fluctuation. In a traditional retail store these fluctuations affect decisions on order quantities, shelf space allocation, markdown pricing and sales force levels. In e-fulfillment, demand fluctuations, with respect to the moment of delivery, also affect the utilization of the delivery capacity and therefore tend to have an even stronger impact than in traditional retailing. In addition to annual demand patterns, demand differences during the day (morning - evening) and during the week (mid-week - week-end) are particularly important in e-fulfillment. Staffing levels need to be adjusted to these demand fluctuations. This includes both delivery and order picking capacity. Since delivery requirements tend to be more variable and more interrelated across orders than picking requirements, capacity management of the delivery process is considered to be a greater challenge.

Models

As discussed in the previous subsection, inventory management issues specific to e fulfillment arise from the interaction with short-term demand management. Some of these issues are addressed by inventory rationing models. Inventory rationing is a yield management strategy for a heterogeneous market that reserves some inventory for high margin customers. The corresponding models generally consider two customer segments with different contribution margins and different service time requirements. Kleijn and Dekker (2003) surveyed many of the early papers in this field. More recent contributions to the inventory rationing literature that specifically address online channels include Cattani and Souza (2002) who compare the benefits of inventory rationing over a simple first-come-first-serve policy in different scenarios. In particular, their numerical study considers different customer reactions to delay, namely lost sales and backlogging. Ayanso et al. (2006) consider a similar model. They assume that orders that cannot be satisfied from stock are drop-shipped from the supplier. Their paper illustrates the impact of several problem parameters in a simulation study. In addition, it highlights the importance of determining the correct threshold level in inventory rationing. Ding et al. (2006) consider the use of dynamic price discounts to encourage backlogging of demand from those customer classes that are denied immediate service. The paper develops dynamic programming algorithms to determine both the optimal discount offer and the quantity allocated in each period.

As discussed earlier, a few authors have analyzed inventory control policies for e-fulfillment with drop-shipping. Bailey and Rabinovich (2005) propose a model that is inspired by the situation of an Internet book retailer who can serve demand either from his own inventory or by drop-shipping. Assuming fixed plus linear cycle costs, the authors develop analytic expressions for the optimal order quantities of both fulfillment options and analyze their sensitivity to several input parameters. The results show in particular, that it may make sense to use both fulfillment options simultaneously. Khouja (2001) comes to a similar conclusion based on a news vendor type of analysis. He assumes that only a fraction of the customers is willing to accept drop-shipping in the case of in-house inventory shortage. The model identifies the optimal mix between both fulfillment options. An extensive stream of literature addresses the integration of product return flows into inventory systems (see e.g. Van der Laan et al. (2003)). Most of these models are concerned with the remanufacturing of end-of-life returns. Recent models that consider returns from direct channel sales include Vlachos and Dekker (2003). They develop news vendor formulations for several problem variants and derive analytic expressions for the corresponding optimal order quantities. Mostard et al. (2005) and Mostard and Teunter (2006) extend this model by allowing more general demand-return relationships. They compare the optimal order quantities for different demand distributions and develop a distribution-free heuristic that appears to perform well in most realistic cases.

3.4 Conclusions

In this chapter, we addressed key issues in B2C e-fulfillment from a multi-channel perspective. Moreover, we reviewed corresponding quantitative models in the operations research literature. In this section we summarize our main observations.

Table 3.1 highlights the main planning issues in e-fulfillment and multi-channeling identified in Sections 3.2 and 3.3. Many standard supply chain management issues are also relevant for e-fulfillment. However, a few aspects appear to be specific. This includes the service component inherent to e-fulfillment. An online channel not only provides a physical product but also several related services, most notably delivery. The delivery service may range from making the product available for pick-up to time-specific home delivery. The management of this service component of e-fulfillment gives rise to novel planning issues. Specially demand management is an important issue in e-fulfillment. Typically, online sellers are more flexible than traditional retail channels with respect to pricing and order promising. While this flexibility generates a significant potential for increasing revenues through differentiation, it also implies the need for appropriate strategies to be successful. Notably the aforementioned service elements underline this need. Demand management has an immediate impact on service requirements and thus on costs, thereby requiring both factors to be coordinated in order to maximize profit.

Many standard Operations Research models provide a basis for addressing supply chain planning issues in e-fulfillment and multi-channel distribution. Yet, specific issues warrant modeling extensions and novel approaches. Table 3.2 lists the models that we reviewed in this chapter, which address specific e-fulfillment issues. We observe that the number of dedicated models to date is remarkably small. Moreover, very few contributions have specifically addressed the integration of supply and demand management in e-fulfillment (Asdemir et al., 2009, Campbell and Savelsbergh, 2005a, Xu et al., 2006). This thesis aims to fill this gap by contributing relevant decisions support tools for demand management in e-fulfillment. The next chapter will specifically focus on demand management in e-fulfillment.

Table 3.1: Summary of Issues in E-fulfillment

Sales and Delivery Planning	Delivery service design	last-mile service, delivery time windows, return options, store pick-up, in-store returns
	Forecasting and pricing	delivery fees, dynamic pricing, cross selling, lead-time quoting, price coordination,
	Order promising and revenue management	delivery yield management, cost and revenue based segmentation, cross-channel yield management
	Transportation planning	routing for home delivery, dynamic routing, joint delivery
Supply Management	Distribution network design	inventory location, drop-shipping, inventory aggregation, shared facilities, assortment planning
	Warehouse design	degree of automation, warehouse layout, return handling, different transaction sizes
	Inventory and capacity management	safety stocks, integration with demand management, inventory rationing, integration of returns, staffing levels, aggregate stock levels, service differentiation

Table 3.2: Quantitative models for e-fulfillment

Sales and Delivery Planning	Delivery service design	Yrjölä (2001), Punakivi et al. (2001), Punakivi and Saranen (2001), Punakivi and Tanskanen (2002), Lin and Mahmassani (2002), Robuste et al. (2003), Hsu and Li (2006), Geunes et al. (2007), Yalabik et al. (2005)
	Forecasting and pricing	Kalagnanam and Parkes (2004)[a], Chan et al. (2004)[a], Elmaghraby and Keskinocak (2003)[a], Asdemir et al. (2009), Campbell and Savelsbergh (2005b), Kamakura et al. (2003), Wong et al. (2005), Netessine et al. (2005), Akcura and Srinivasan (2005), Cattani et al. (2004)[a], Cattani et al. (2006), Huang and Swaminathan (2009)
	Order promising and revenue management	Talluri and van Ryzin (2004)[a], Campbell and Savelsbergh (2005a)
	Transportation planning	Golden et al. (2008)[a], Toth and Vigo (2001)[a], Braysy and Gendreau (2005a,b)[a], Fleischmann et al. (2004), Francis et al. (2006), Francis and Smilowitz (2006) Weigel and Cao (1999), Du et al. (2005), Xu et al. (2006)
Supply Management	Distribution network design	Klose and Drexl (2005)[a], Netessine et al. (2006), Netessine and Rudi (2004), Min et al. (2006), Alptekinoglu and Tang (2005), Chiang and Monahan (2005), Singh et al. (2006), Mahar et al. (2008)
	Warehouse design	de Koster et al. (2007), Johnson and Meller (2002), Russell and Meller (2003), Xu (2005), de Brito and De Koster (2003)[a]
	Inventory and capacity management	Kleijn and Dekker (2003)[a], Cattani and Souza (2002), Ayanso et al. (2006), Ding et al. (2006), Bailey and Rabinovich (2005), Khouja (2001), Van der Laan et al. (2003), Vlachos and Dekker (2003), Mostard et al. (2005), Mostard and Teunter (2006)

[a] Review paper/ textbook

Chapter 4

A Framework for Demand Management in E-fulfillment

After reviewing the key issues and corresponding models in e-fulfillment in the previous chapter, it is clear that there is significant room for relevant contributions in the field of demand management for e-fulfillment. Therefore, we now narrow the focus of this chapter to the core theme of this thesis, demand management in e-fulfillment. In this chapter[1], we develop a framework to classify different ways to manage demand in e-fulfillment. The purpose of this framework is to highlight the main characteristics and dimensions of different demand management approaches. The framework will serve as a reference point for the models developed in the remainder of the thesis. We proceed as follows. First, in Section 4.1 we compare the Internet retailing processes to those in airline revenue management. We show that both settings share a number of essential characteristics, which makes revenue management an interesting option also in Internet retailing. However, there are also important differences, which require modifications to classical revenue management in an Internet retailing context. In Section 4.2 we describe the characteristics of the available demand management levers for Internet retailing in detail. Section 4.3 summarizes our findings and presents a framework which classifies the different approaches in 4 categories, based on their demand management levers and their planning horizon.

[1]This chapter is based on the paper: 'Demand management in E-fulfilment'(Agatz, Campbell, Fleischmann, van Nunen, and Savelsbergh, 2008d)

4.1 Learning from Revenue Management

Inspiration for effective demand management for e-fulfillment comes from the example of revenue management. In fact, revenue management *is* demand management. Research on revenue management has grown into one of the most successful applications of operations research. There is a substantial literature of journal articles available on the topic, see e.g. Chiang et al. (2007), Boyd and Bilegan (2003), McGill and Ryzin (1999). While revenue management has been adopted by many industries, airline ticket sales are still the prototypical application. We therefore take a closer look at the ingredients of revenue management in this setting and compare them with Internet retailing. For the sake of simplicity, we restrict ourselves to the simplest case of a single-leg passenger flight, recognizing that today's airline revenue management systems address many additional complexities, notably the optimization of flight networks rather than single flights (Talluri and van Ryzin, 2004).

Comparing the prototypical airline and Internet retail settings reveals many similarities, which suggests that Internet retailers can learn from revenue management. However, we also find significant differences, which require traditional approaches to be modified. We structure our comparison around the key ingredients of revenue management, comprising the supply-side and demand-side factors highlighted in Table 4.1.

Table 4.1: Key Characteristics of Airline and E-Fulfillment

	Airline	*E-Fulfillment*
Supply		
Product	Travel service	Physical product + delivery service
Capacity	Number of seats: Fixed, perishable	Product inventory: Flexible Picking + delivery capacity: Inflexible, perishable
Costs	Sunk at order in-take	Variable, interdependent transportation costs
Booking	Up to months in advance, specific departure time	Days in advance, delivery time window
Demand		
Revenues	Fare	Product margin + delivery fee
Transaction size	Single seat	Varying order size + driving time
Customer heterogeneity	Willingness to pay, flexibility, travel time	Willingness to pay, flexibility, delivery time, order size, delivery location
Response to out-of-stock	Lost, up-sell/down-sell, alternative flight	Lost, alternative delivery time, off-line store

4.1.1 The supply side

Product

The airline industry is a pure service business. The core product of a passenger airline is the transportation of a traveler from A to B on a specific date. In contrast, the core product offered by an Internet retailer consists of physical product(s) plus a delivery service. Therefore, essentially all of the supply and demand elements in Table 1 have a (physical-) product and a service-dimension for the Internet retailer, as compared to the mere service dimension of the airline.

Capacity

The capacity of a given flight is determined by the number of seats (per cabin class) of the assigned aircraft. This assignment is typically made several months in advance, due to the complexity of the schedule planning (see e.g. Lohatepanont and Barnhart (2004)). In the short term, the flight capacity is therefore essentially fixed. Moreover, the capacity is perishable; an empty seat on a given flight cannot be used to satisfy demand in a later period.

For the e-tailer, we have to distinguish the product- and the service-component. The product-based 'capacity' concerns the available product inventory. For most products, this inventory can be stored at least for a short while, and it can typically be replenished with a short lead time. The e-tailer's service-related capacity resembles the airline setting more closely. This concerns order-picking and delivery capacity, which both involve physical constraints (warehouse size, fleet size) as well as corresponding staffing levels. Similar to the airline case, the physical capacity is perishable and relatively inflexible in the short term. While the degree of flexibility of the labor capacity depends on contract types, full short-term flexibility is rare.

Costs

The main costs of the airline operation, such as personnel and fuel expenses, are determined during the schedule planning. At the time of order in-take, most costs are sunk. The incremental costs of an additional passenger are negligible. Therefore, the objective of short-term demand management boils down to maximizing revenues.

This is not true for Internet retailing. Delivery routes and schedules typically do not have to be made until after the order intake. See, for example, the fulfillment operations at Albert.nl as discussed in Chapter 2. This flexibility makes the delivery routes and thereby transportation costs order-dependent. What is more, transportation costs may differ significantly between orders, depending on the delivery location. In addition, transportation costs of different orders are interdependent if delivery routes encompass multiple stops. Figure 4.1 highlights this important difference between the airline and the e-fulfillment context and links it to the differences in the underlying planning processes.

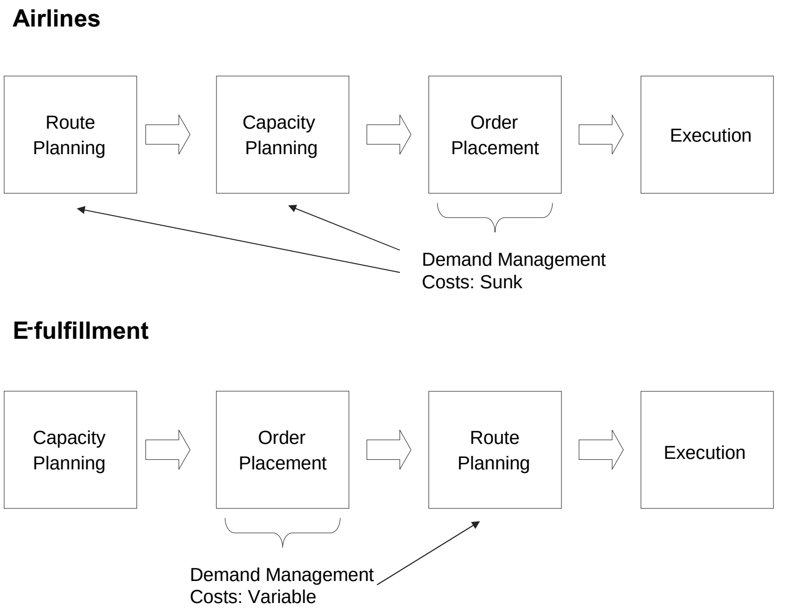


Figure 4.1: Airline and e-fulfillment process

Booking

In both environments the customer books his or her order in advance. The length of the booking period differs, from multiple months for airlines to a few days or weeks in Internet retailing. Moreover, the airline customer books a specific flight whereas the Internet retailer only commits to a delivery within a certain time window, the length of which may range from an hour to an entire day.

4.1.2 The demand side

Revenues

The ticket fares paid by the customers are the airline's main source of revenues. Managing these fares is a key lever of airline revenue management. The Internet retailer's revenues encompass two components, namely the margins earned on the physical products plus any delivery charges. Most e-tailers price these two components separately.

Transaction size

In the basic airline scenario each customer consumes the same amount of capacity, namely a single seat. In contrast, retail orders differ in their capacity requirements. Different order sizes imply different picking effort and different space requirements in the delivery vehicle. Furthermore, different delivery locations imply different travel times, thereby affecting the number of orders that can be delivered, within a given time interval.

Customer heterogeneity

One of the key elements of revenue management is market heterogeneity, i.e. substantial differences between the customers that make use of the same service. In the airline case, the classical segmentation is between business and leisure travelers. Business travelers tend to have a higher willingness-to-pay and value flexibility regarding late booking and cancelations. Leisure travelers have a lower willingness-to-pay but are more flexible, in general. In addition, both groups prefer different travel times, such as weekend stays. Airlines target these different customer segments through different fare classes.

Also Internet shopping is attracting a wide variety of different customers. As in the airline setting, customers differ with respect to their willingness to pay, their flexibility, and their preferences regarding the delivery time. However, Internet retailing customers also differ in the size and margin of their order and in the requested delivery location. This provides e-tailers with additional opportunities for market segmentation.

Response to out-of-stock

The last element of our review is the customer's reaction if his or her preferred product is not available. The most basic airline revenue management approaches assume that a customer is only interested in a single fare class for a specific flight and leaves if it is not available. More advanced approaches also consider up-selling or down-selling to a different fare class for the same flight. Of course, a customer may also switch to a different flight. However, due to the enormous complexity of an entire flight network, few revenue management systems explicitly assess this effect.

In Internet retailing we need to distinguish between an out-of-stock of the physical product and the delivery service. The customer response to a physical stockout involves the same alternatives as in a traditional store - buying an alternative product, omitting the item, or even canceling the entire order (Breugelmans et al., 2006). In the case of a delivery time 'out-of-stock', the customer may be willing to switch to a substitute delivery time. Another alternative is for the customer to switch to a traditional off-line store, be it the retailer's own store, in the case of 'bricks & clicks', or a competitor.

4.1.3 Revenue management

The essence of traditional revenue management is to exploit market heterogeneities in order to maximize the revenues generated with a given amount of capacity. The key insight is that due to these heterogeneities one can do better than simply selling the capacity first-come-first-served at a constant price. Instead, companies such as the airlines can segment the market by exploiting the correlation between the customers' willingness to pay and their other preferences, such as flexibility and the time of booking.

Approaches for achieving this segmentation are commonly divided into price-based and quantity-based revenue management (Talluri and van Ryzin, 2004). In the first case, companies directly manage the product price, e.g. in the form of dynamic pricing or through auctions. This requires the flexibility to quickly and easily change prices. In the second case, companies design multiple product variants, e.g. regular fares and discount fares plus associated purchase restrictions, and dynamically manage the amount of capacity that they allocate to each of them.

Our comparison above illustrates that the main conditions for revenue management also apply to Internet retailing. The Internet retailer serves a heterogeneous market with a delivery capacity that is relatively inflexible in the short run, and he can change prices and customer access relatively easily. This implies that also Internet retailers can potentially do better than offering delivery on a first-come-first-served basis for a constant price.

However, our comparison also highlights significant differences between Internet retailing and traditional revenue management environments. First, Internet retailing concerns the combination of physical products plus a delivery service. Effective demand management needs to take the product dimension into account, notably through its effects on margins and capacity requirements. Second, demand management has a significant cost impact in Internet retailing. Sales and operations are more closely intertwined than in the airline setting which fixes operations prior to order in-take. Consequently, demand management in Internet retailing means profit management rather than revenue management. Third, demand for different delivery times is interdependent since many customers consider multiple delivery alternatives. This provides additional flexibility to the retailer; however it also increases the complexity of demand management.

In what follows, we consider the possible options for revenue management in Internet retailing.

4.2 Demand Management in E-fulfillment

As discussed, Internet retailing concerns a combination of physical products and a delivery service. Demand management can address either component separately. Physical product inventory is often more flexible than the delivery capacity, at least in the grocery sector. Most retailers replenish their inventories frequently, up to multiple times a day, and with short lead times. This creates opportunities for matching supply to demand. Product-oriented demand management can therefore focus on sales effects primarily. Similar to traditional off-line retailing, pricing incentives such as quantity-discounts and promotions can help stimulate demand. Internet retailing offers particular opportunities for cross-selling and for customized offers targeted to individual customers (Netessine et al., 2006).

Since the delivery capacity is more rigid, at least in the short term, matching demand to supply is the most relevant option for this component. This is where sales and operations require close coordination and revenue management concepts offer opportunities. Furthermore, while inventory rationing and inventory pricing have received plenty of attention (see Sections 3.2.2 and 3.3.3 for a detailed overview), the unique features of the service component in Internet retailing have only scarcely been addressed in literature. Therefore, we focus on demand management tools that address the delivery service in particular.

Akin to traditional revenue management, we consider both quantity-based and price-based options. The first concerns decisions on which delivery options, namely which time slots, to make available to which customers. The second focuses on the delivery fee as the main lever to manage customer demand. A retailer can apply both options, slotting and pricing, at different moments in the sales process, either off-line prior to the actual order in-take, or real-time as demand unfolds. These distinctions leave us with four different types of demand management in e-fulfillment, as summarized in our framework in Table 4.2. We next discuss each of these options and explain its key issues.

Table 4.2: Demand Management Framework

	Capacity allocation	**Pricing**
Static *Off-line,* *Forecast-based*	***Differentiated slotting*** Regional demand clustering Balance service offering and delivery efficiency	***Differentiated pricing*** Demand smoothing Increase capacity utilization
Dynamic *Real-time,* *Order-based*	***Dynamic slotting*** Differentiate service Maximize contribution of congested capacity Avoid inefficient routes	***Dynamic pricing*** Counterbalance underutilized capacity Stimulate efficient routes Segment on customer flexibility

4.2.1 Differentiated Slotting

The first lever for managing demand in Internet retailing concerns the allocation of fulfillment capacity to the customer. In particular, this relates to the set of delivery time slots offered to the customer. Many retailers communicate these in terms of a weekly schedule. The design of such a weekly schedule involves a variety of decision-making problems. To structure the design-process and reduce its complexity, one could first establish a base schedule of possible delivery time slots, and then determine which slots from the base schedule to make available to each individual customer (or region). Relevant questions for the base schedule involve the time slot length and overlap, while one needs to consider the number of slots and their specific timing for the assignment of the slots to the regions. In the following, we consider these issues in more detail.

Time slot length

The length of a time slot impacts the level of customer service as well as the delivery costs. A shorter time slot implies higher customer service, but reduces the delivery flexibility and therefore may lead to higher delivery costs. It is possible and may be beneficial to design time slot schedules involving slots of different lengths, e.g., the 2 and 3.5-hour time slots currently used by Peapod (see Chapter 2).

Time slot overlap

The time slot schedule may or may not include time slots that overlap. For example, to cover the period from 8am to 12am, one may offer two 2-hour time slots from 8am to 10am and from 10am to noon, or, alternatively, three overlapping 2-hour time slots from 8am to 10am, from 9am to 11am, and from 10am to noon. Overlapping might provide marketing advantages as it offers customers more choices.

Number of time slots offered

The number of time slots offered impacts the level of customer service as well as the delivery costs. The more choices, both in terms of time and length, the more attractive the service offering is for the customer, which translates into higher expected sales. At the same time, however, the offered delivery slots directly affect the efficiency of the delivery operations and thus transportation costs. Note that the number of time slots offered does not have to be the same for every customer. Customers far away from the distribution center or living in zip codes with low population densities may be offered fewer time slots so as to consolidate customer orders, thereby reducing the distance traveled per order. Recall from Chapter 2 that both Albert.nl and Peapod limit the number of delivery slots in rural areas.

Timing

The timing of the time slots in nearby customer areas (see Figure 4.2) may potentially impact the routing efficiency. Because delivery vans usually visit several zip codes during a single time slot and a delivery tour spans multiple time slots, assigning specific time slots to a zip code cannot be done in isolation. Assigning specific time slots to zip codes has to be done carefully, so as to ensure that cost effective delivery routes can be constructed. On the one hand, this involves clustering nearby areas together in a single time slot to reduce the distance traveled between successive stops. On the other hand, it means smoothing demand over time to balance the work load over time and maximize the vehicle utility. Again, customer considerations play a role as some delivery times may be more popular than others.

4.2.2 Differentiated pricing

We now turn to pricing instead of capacity as the primary lever to manage demand. Pricing is probably the most well-known demand management lever. Since we focus on delivery capacity, pricing concerns the delivery fee charged for an order. The

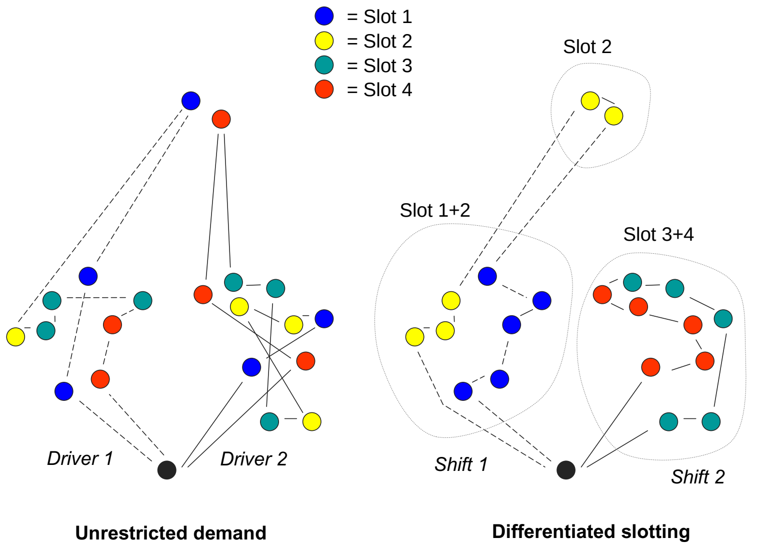


Figure 4.2: Differentiated Slotting

delivery charge is not only an important source of revenue for the company, it also also provides means for differentiating between different delivery options offered to the customer. In that sense, pricing and slotting are complementary tools. Specifically, pricing can provide incentives for attracting customers to a particular slot.

Differentiated pricing is fairly intuitive and is commonly practiced by many businesses including hotels (weekends vs. weekdays) and package delivery services (Monday-Friday vs. Saturday delivery). In Table 2.1(b), we summarize several criteria for price differentiation used by e-grocers in practice. In this section, we systematically discuss the bases upon which price differentiation may be affected in more detail.

Region-based pricing

The costs of delivery typically differ per region, dependent on e.g. the distance from the warehouse, the population density or the frequency of service. The e-tailer can decide to pass on these cost differences to the customer through its fees. E-grocer Freshdirect, for example, differentiates its delivery fees based on the distance to the warehouse of a particular neighborhood (see Chapter 2). What is more, Internet retailers can also apply different prices between regions to address local competitive conditions, or differences in willingness-to-pay. However, they need to be careful with this because the Internet enables customers to find out what people in other regions are paying, and thereby spark feelings of resentment (Balkan, 2008).

Time-based pricing
Since attended delivery requires the customer to be present, some delivery times, for example in the evening or in the weekend, are more popular than others. From a marketing view, this alone suggests charging different prices for different delivery times. There is also an operations argument for this conclusion. Uniform pricing typically results in imbalanced demand. Since the delivery capacity is relatively inflexible, in general, this means either costly over-capacity, or losing peak-load demand. Differentiated pricing, such as peak-load premiums and off-peak discounts, help counter the above effects by smoothing demand (see Figure 4.3).

Size-based pricing
Furthermore, delivery prices may also impact the basket composition and corresponding revenues of Internet retailing. In order to stimulate sales, several retailers offer delivery fee discounts for large orders. In a recent paper, Lewis et al. (2006) find that the use of incentives for larger orders can successfully persuade customers to switch to a larger order size. Other effects may be less obvious. Albert.nl, for example, experienced that a lower delivery fee at off-peak moments attracted customers with a smaller basket size.

Service-based pricing
Pricing allows a differentiation not only between different delivery times but also between different lengths of the delivery windows. Peapod, for example, offers the customer a $1 discount for choosing a delivery window of 3.5 hours instead of 2 hours. In this way, the Internet retailer can exploit differences in the customers' flexibility by offering windows of different lengths simultaneously, granting a discount for wider windows. In this case, the discount should not only reflect the willingness-to-pay of the different customer segments but also the e-tailer's efficiency gain due to greater planning flexibility. This closely links length-based pricing to the slotting analysis discussed previously.

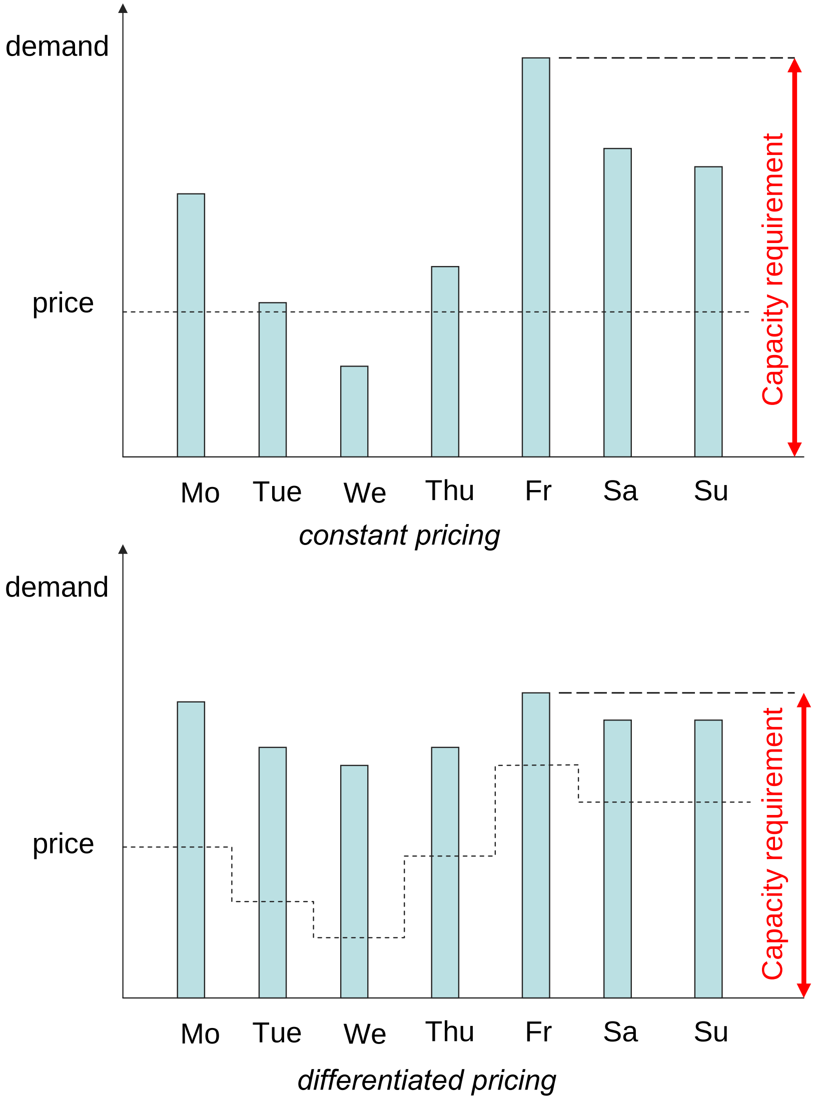


Figure 4.3: Differentiated Pricing

4.2.3 Dynamic Slotting

The previously discussed demand management approaches are purely forecast-based in the sense that they set conditions prior to receiving the actual orders. However, even richer opportunities arise for Internet retailers through their interaction with the customers during the actual sales process.

The actual real-time demand information can be extremely valuable, especially in the case where future demand is rather uncertain. The additional flexibility of using real-time levers allows the Internet retailer to postpone (some of) the demand management decisions to a later point in time. For example, instead of fixing a particular time slot offering upfront, the retailer may initially offer a broad range of choices to the customer and, if deemed beneficial, reduce the number of options along the way. This improves customer service without hurting delivery efficiency.

Analogous to revenue management, dynamic slotting considers booking policy decisions. In particular, it considers the allocation of the delivery capacity to the different requests for delivery. Dependent on the order intake process, the question then is whether or not to make a particular delivery slot available to the customer or whether to accept or reject a request for a particular delivery option. An important aspect of this allocation decision is the customer's assumed behavior when not presented with his preferred time slot. The dynamic time slot decision properly has to take the possibility of switching into account. This is one of the most challenging aspects of dynamic time slot management.

The most basic example of a dynamic slotting decision regards closing a time slot once the corresponding capacity is depleted. While some kind of capacity check is in fact a necessity for any Internet retailer, an accurate assessment of remaining available capacity is less obvious than it may look at first sight. Effective capacity involves the picking capacity in the warehouse, physical fleet size, and available driving time (Campbell and Savelsbergh, 2005a). The latter depends on the clustering of orders into routes and thereby directly links slotting to transportation planning. Systematically assessing this interaction helps Internet retailers increase their capacity utilization.

However, the potential of dynamic slotting goes much further. As we have discussed in Section 4.1.3, the fundamental lesson from revenue management is that there is a smarter way than simply selling the capacity first-come-first-serve until its depletion. Heterogeneous markets call for more differentiation between orders. In the prototypical airline case, this leads to a trade-off between selling a seat at a discount fare now versus reserving it for a potential full-fare customer later. Thus,

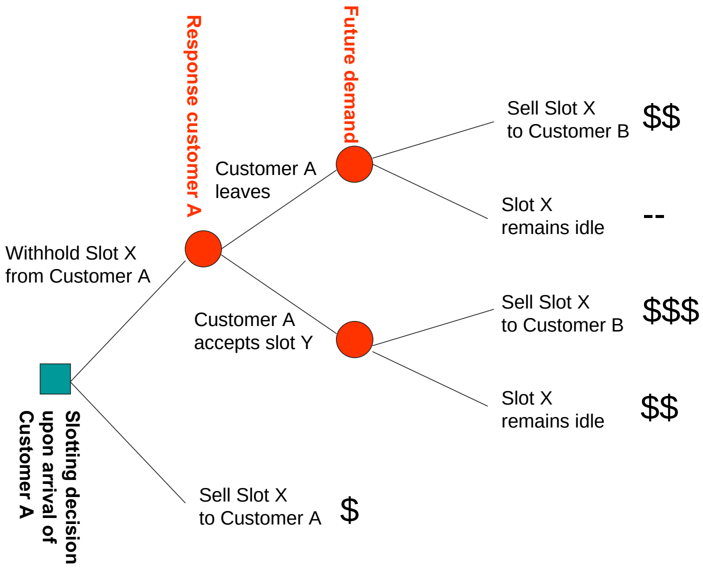


Figure 4.4: Dynamic Slotting

in e-fulfillment it may be beneficial to reserve scarce capacity, i.e. busy time slots, for the most profitable customers. Transportation costs add another dimension to the trade-off, namely whether to serve a customer in the given time slot or whether to try and convert him to another slot that allows for a more efficient delivery (see Figure 4.4). In essence, revenue management shifts the focus from capability (*Can we deliver this order at that moment?*) to profitability (*Is it profitable to deliver this order at that moment?*).

Similar to the airline case, the e-tailer can segment the market based on customer value. Yet, in e-fulfillment, customer value is not only related to the customer's willingness to pay in terms of delivery fee, but also to the margins on the physical products (see Table 4.1). Many e-grocers segment by order size. One way in which they do this is by imposing a minimum order size (see Table 2.1(b)). For example, Ocado has a minimum order size of £40 which is increased to £90 in the Christmas period (Tozer, 2007). The second segmentation is by delivery location. Given the already accepted and the still expected future orders, a delivery to A in a given slot may result in a less costly route than a delivery to B. Similarly, a delivery to A may be cheaper in slot X than in slot Y. Third, the degree of customer flexibility is of importance. A busy slot is best used for the customer that is least willing to accept an alternative slot.

Literature on real-time management of time slots in attended home delivery which draws on revenue management concepts is still scarce. Both Bent and Hentenryck (2004) and Campbell and Savelsbergh (2005a) examine which deliveries to accept or reject. Their approaches exploit stochastic information about future requests to decide on requests under consideration. Bent and Hentenryck (2004) aim to maximize the number of accepted requests by controlling the time slots offered, but they do not consider rejecting an 'expensive' delivery to preserve resources for more profitable future deliveries, in contrast with Campbell and Savelsbergh (2005a).

4.2.4 Dynamic pricing

Dynamic pricing provides an even richer tool for real-time demand management. Pricing allows a much finer gradation of incentives than the binary (yes-no) type of decisions in slotting. In addition, pricing can provide incentives for pulling customers to a particular delivery option whereas dynamic slotting pushes them away from certain options.

Delivery-related price incentives can aim at many different goals. Traditional airline revenue management uses dynamic pricing as a means for segmenting based on customers' willingness to book in advance. Typically, prices increase as the departure draws nearer. In a similar vein, delivery services often segment their customers based on their lead-time preferences, e.g. standard (5-7), two-day or next-day. Simondelivers in Chapter 2 is an example of an e-grocery that charges a substantial higher price for same-day delivery. As in the airline case, customers with different lead-time preferences and different willingness-to-pay then compete for the same delivery slots.

Another option is to use price incentives, namely discounts, to steer an order to a time when it can be delivered efficiently. The underlying economics are similar to those of dynamic slotting, involving the same trade-offs of delivery efficiency and customer flexibility. For example, discounts can be used for matching a delivery with a visit to a nearby customer, and for moving demand to temporarily underutilized delivery periods, thereby enhancing capacity utilization. The experience of Peapod indicates that even a small discount (e.g. \$1) can change the customer's slot selection (Campbell and Savelsbergh, 2005b).

One of the particular challenges of dynamic pricing is its appropriate communication to the customer. More than in the case of dynamic slotting, customers may perceive unexpected price changes as unfair (Kimes and Wirtz, 2003, Xia et al., 2004).

The fierce criticism of Amazon's differentiated pricing experiments starkly illustrates these challenges (Bicknell, 2000). However, the fact that it seems normal that our seat neighbors on a flight pay a different ticket price than ourselves illustrates that acceptance of dynamic pricing may be a matter of habituation (Wirtz and Kimes, 2007). To assure visibility of temporary price discounts, Internet retailers may approach target customers proactively, e.g. by means of SMS or e-mail notifications. Another challenge concerns opportunistic customer behavior. If discounts follow a regular pattern customers will learn to anticipate them and thereby limit the directive effect of the pricing tool (Talluri and van Ryzin, 2004). This is another argument for a careful use of dynamic price incentives.

As with any price discounts, dynamic pricing in Internet retailing involves the danger of conceding margins without achieving measurable benefits. In principle, the right amount of discount is the minimum price reduction that achieves the intended customer reaction, as long as this amount is smaller than the resulting efficiency gain. Affecting customer behavior alone does not make a price incentive successful. The key question is whether the incentive is profitable. The example of Ocado illustrates that even non-monetary incentives may suffice to influence the customer's delivery choice (www.ocado.com). The company is appealing to the customers' environmental concerns by indicating which delivery window would minimize the fuel consumption for their order.

4.3 Conclusions

In contrast to classical revenue management, the cost side plays an important role in e-fulfillment. Delivery costs differ between customers and, for the same customer, between different delivery windows. These cost effects add a second dimension to demand management in e-fulfillment. Internet retailers have strong levers at their disposal for actively steering demand. From a fulfillment perspective, the offered delivery time windows and their associated prices are of particular relevance. Internet retailers can use both of these levers off-line to manage systematic demand patterns, such as weekly demand peaks and regional demand clustering. Even more importantly however, they can adjust time slot offering and delivery fees real-time, based on actual orders, thereby tailoring their service proposition to individual customers.

However, applying these demand management levers involves complex trade-offs between marketing and operations, revenues and costs. What is more, they are all strongly interrelated. Evaluating these trade-offs is an extremely challenging task which is virtually impossible without prober decision support tools. Yet, while the number of models available in the revenue management literature is vast, only few consider demand management in e-fulfillment. Table 4.3 lists the available papers in our demand management framework. It is clear that there is room for contribution in all categories.

Table 4.3: Demand Management Framework

	Capacity allocation	**Pricing**
Static *Off-line,* *Forecast-based*	***Differentiated slotting*** Lin and Mahmassani (2002) Punakivi and Tanskanen (2002) *Chapter 6*	***Differentiated pricing*** Lewis et al. (2006)
Dynamic *Real-time,* *Order-based*	***Dynamic slotting*** Campbell and Savelsbergh (2005a) Bent and Hentenryck (2004) *Chapter 7*	***Dynamic pricing*** Campbell and Savelsbergh (2005b)

In the remainder of this thesis, we add to this stream of literature by developing quantitative decision support for demand management in e-fulfillment. We focus primarily on the capacity allocation/ time slot decisions, because they have a strong operations management component, as they set the conditions for the underlying vehicle routing problem. In Chapter 6, we address the static forecast-based problem of the design of a time-slot offering which provides an acceptable service to the customer and facilitates efficient routing. In Chapter 7, we focus on the dynamic slotting problem in which we decide on the time slot offering in a real-time fashion. These time slot decisions, both static and dynamic, require a proper understanding of customer behavior with respect to the offered time slots. To provide this insight, the next chapter presents an empirical analysis of transaction data from e-grocery Albert.nl.

Chapter 5

Customer Behavior in E-fulfillment: An Empirical Analysis

In the previous chapter, we systematically explored possible approaches for demand management in e-fulfillment. To exploit the potential of any demand management system, it is crucial to understand customer behavior. In this chapter, we focus on customer behavior with respect to the delivery time slot offering. The goal is to provide insights in customer response to a change in his time slot choices. Therefore, we analyze actual sales data from e-grocer Albert.nl and conduct two empirical studies. In line with the framework presented in the previous chapter, we distinguish between the response to static and dynamic time slot management. First, we consider the long-term impact of a structural change in the time slot offering on overall demand. Second, we consider the customer's behavior when faced with the unexpected non-permanent reduction in the number of slots, a stockout. The chapter is organized as follows. In Section 5.1 we present related literature. In Sections 5.2 and 5.3 we investigate the impact on demand of the structural time slot offering and time slot out-of-stocks, respectively. In Section 5.4 we discuss the results and address some of the limitations of the study. Finally, in Section 5.5, we summarize our main insights and discuss directions for future research.

5.1 Related literature

Our research on customer behavior with respect to delivery time slots addresses the interface of three existing streams of research: (i) customer behavior in revenue management (ii) consumer response to assortment reductions and (iii) consumer response to category stockouts. We briefly review each of these streams.

Using demand forecasts to establish the future availability of products to maximize revenues is at the core of revenue management (Boyd and Bilegan, 2003). As a result, demand modeling and forecasting is arguably the most important component of any revenue management application. One of the reoccurring issues in the revenue management literature is the interdependence between demand for different fare classes. Customer choice models have been proposed to take into account substitution behavior between fare classes, e.g. buy-up and buy-down factors. Talluri and van Ryzin (2004), for instance, explicitly model the customer's buying behavior. They present a very general choice model which simply specifies the probability of purchase for each fare product as a function of the set of fare products offered. However, most of the work in this area lacks empirical foundation (see e.g. Algers and Beser (2001), Andersson (1998) for notable exceptions).

The literature on assortment planning is huge, and spans the areas of operations and marketing (see e.g. Kök and Fisher (2007)). Motivated by the cost disadvantages of ever increasing assortments, recent research in both the academic and practitioner literature has focussed on the impact of large-scale assortment reductions on sales. On the one hand, assortment reductions may lead to negative sales effects because a percentage of customers will no longer be able to find their preferred product. On the other hand, a reduced assortment can simplify shopping by reducing search complexity (Gourville and Soman, 2005). Research thus far shows mixed evidence of the impact of assortment reductions on sales. Several studies in the grocery sector suggest that retailers can reduce their product assortment with little or no loss in (long-term) sales (Sloot et al., 2006a, Boatwright and Nunes, 2001). Conversely, Borle et al. (2005) show that a significant reduction in assortment by eliminating slow-selling items can reduce overall store sales.

A closely related issue is the customer response to retail out-of-stocks, which is addressed in a significant stream of empirical research in marketing (Campo et al., 2000, Fitzsimons, 2000, Corsten and Gruen, 2004, Sloot et al., 2005, 2006b). Although an assortment reduction may lead to substantially larger losses for the retailer than a stockout, consumer response to a stockout may provide valuable information to the reactions to permanent assortment reductions (Campo et al., 2004). Evidence from this body of research suggests that substitution is the predominant response to a category stock-out. Yet, the individual reactions can vary significantly between customers, product categories and situations (Campo et al., 2000).

Most of the empirical research on the response to stockouts is survey-based. However, it is well known that the use of surveys has several serious shortcomings in terms of validity. The fact that surveys somewhat artificially draw attention to an out-of-stock may entail a risk of overestimating the strength of the response (Campo et al., 2003) or even induce responses that otherwise wouldn't occur to the customer (Dholakia and Morwitz, 2002). Moreover, it has long been known that the correlation between self-reported behavioral intentions and actual customer behavior can vary quite a bit (Chandon et al., 2005, Morwitz et al., 2007, Van Woensel et al., 2007).

To overcome some of these validity threats, a few papers use scanner panel or actual sales data to analyze substitution behavior in case of stockouts. Sales data is often less detailed than scanner panel data because it does not link the purchase information to a particular customer. Campo et al. (2003) use scanner panel data to estimate the impact of stock-outs on purchase incidence, quantity and choice in a certain grocery category. For two product categories, cereals and margarine, the authors show that stock-outs can affect incidence, quantity and choice behavior. Moreover, they demonstrate that a stock-out may not only have an immediate impact on the purchasing decisions but can also influence sales in the period after the stock-out occurred.

Others have used sales data rather than scanner panel data to estimate substitution behavior. Anupindi et al. (1998) presents a method to estimate consumer demand with stock-out based substitution and lost-sales. They derive maximum likelihood estimates of the demand parameters under the assumption of Poisson demand arrivals. The model is applied to retail vending based on sales and stocking data. The analysis shows that an out-of-stock of a particular item can significantly impact the demand rates for the other (in-stock) items. In a similar fashion, Kalyanam et al. (2007) analyze sales and out-of-stock data in apparel retailing. They assume demand to be compound Poisson distributed. The results suggest that the presence of an item in an assortment can impact sales of that assortment over and above its own sales.

In this chapter, we study the customer's response to a change in his delivery time slot choices. In line with the aforementioned stream of marketing research and the framework that was presented in the previous chapter, we distinguish between the customer response to a permanent assortment change and to an unexpected temporary stock-out. First, we study the impact on sales of a permanent change in the set of delivery time slots offered, the time slot assortment. Second, we address the customer response to a time slot stock-out in case a delivery slot is unexpectedly made unavailable.

Our studies extend current assortment and stock-out studies by considering the service offering of an e-tailer in terms of time slots rather than physical items. Furthermore, we add to this literature stream by explicitly dealing with the non-stationarity of the demand distribution. To reduce the aforementioned validity threats of surveys, we exploit the huge amount of available transaction data in the Albert.nl case.

5.2 Response to Static Time Slot Management

In the previous chapter, we already argued that while a wider variety of time slots can make the service more attractive for the customer, it can also increase delivery costs. The goal of the first study is to investigate the long-term impact on sales of a permanent increase or decrease of the pool of offered time slot. Therefore, we study actual observed sales before and after a change in the set of time slot choices. The data comes from a permanent time slot change at Albert.nl which can be viewed as a natural experiment.

5.2.1 Data

In August 2005, a team of Albert.nl and academics from Rotterdam School of Management Erasmus University, carried out a project to enhance the efficiency of the fulfillment operation. The company decided to make the following two changes with respect to its delivery offering.

First, the company made a transition from a flat to a differentiated delivery fee: instead of a €6.80 delivery charge for all time slots, prices were made dependent on the time and day of the slot, ranging from €4.95 to €7.95. The differentiated delivery fees served to counterbalance the popularity differences between the slots and to smooth demand over time, thereby reducing operational costs. In addition, the relatively low delivery fee (€4.95) may help to attract new customer segments.

Second, the company, who already applied a differentiated slot offering, reconsidered the number of time slot offered in several zip codes. The service was expanded in some zip codes and reduced in others. These changes were based on routing considerations and were aimed at either increasing, or reducing the drop density per time slot per zip code to facilitate more efficient routing of home deliveries. Another reason to expand the number of time slots in certain zip code regions was to facilitate further growth by offering more time slot capacity.

From a total of 293 zip codes, 58% received additional delivery time slots, 34% lost time slots and 8% kept the same number of slots. The adjustments ranged from one to 19 slots, a relative change in slots offered ranging from minus 89% to plus 67%. From the customers who placed at least one order in the last 5 weeks before the change, 85% received one or more additional slots, 13% lost one or more time slots and 2% kept the same number of slots.

Weekly sales data per zip code is available over a two-year period (2005 and 2006).

5.2.2 Model Description

Determining the long-term effect of the changes in the time slot assortment is challenging because the e-grocery environment is highly dynamic and the market is constantly growing. To establish reliable estimates, we need to separate the assortment effect from the numerous other factors that potentially have an impact on demand for e-grocery, particularly the entrance of new buyers. Since we focus on the long-term effect on sales, we do not consider the fluctuations of demand on a daily basis in a detailed fashion.

To model the impact of the time slot changes, we specify a simple multivariate linear regression model. As we are interested in the impact on the growth, the dependent variable represents a measure of the annual sales growth Ag_i per zip code i. This value is the absolute difference between sales in the first 10 weeks of 2006 as compared to the same period in 2005. Note that the time slot changes took place in week 32 of 2005, which means that we compare demand in the same period before and after the changes. We use this particular 10-week period because it does not have any substantial promotions or holidays that affect sales. We must also realize that sales growth may differ per zip code independent of the time slot changes, e.g. because zip codes have different sizes and demographics. To control for this observation, we include a weekly base growth variable Bg_i per zip code i, which expresses the weekly growth over the first 10 weeks of 2005.

Moreover, we specify four variables to express the potential effects of the time slot changes on sales (see Figure 5.1). The sales impact may either be directly determined by the absolute difference in offered time slots or reliant on the (growth) characteristics of the zip code. We include both effects by specifying two different coefficients for the increase in slots (β_3 and β_5) and the decrease in time slots (β_2

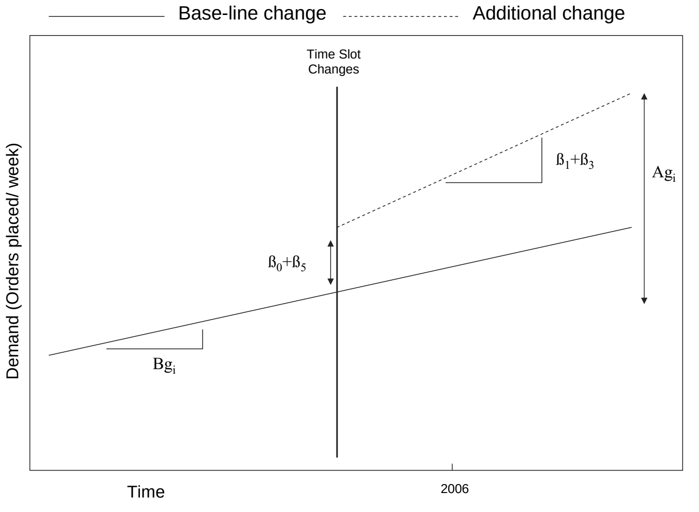


Figure 5.1: Impact of Time Slot Choice on Demand

and β_4). This leads to the following model specification:

$$Ag_i = (\beta_1 + \beta_2 LESS_i + \beta_3 MORE_i)Bg_i + \beta_4 LESS_i + \beta_5 MORE_i + \beta_0 + \epsilon_i \quad (5.1)$$

for $i = 1....I$ (zip codes), where

Input Parameters
Ag_i = Annual Growth: the total number of orders in zip code i in weeks 1 to 10 of 2006 minus the total number of orders in zip codes i in weeks 1 to 10 of 2005;
Bg_i = Weekly Base Growth: the average weekly absolute growth over the first 10 weeks of 2005;
$MORE_i$ = the expansion of the number of time slots permanently offered in zip code i in August 2005;
$LESS_i$ = the reduction of the number time slots permanently offered in zip code i in August 2005;

Estimation coefficients
β_0 = the baseline change in demand;

β_1 = the baseline change in demand rate;
β_2 = the change in demand growth rate per time slot reduction;
β_3 = the change in demand growth rate per time slot increase;
β_4 = the change in base demand per time slot reduction;
β_5 = the change in base demand per time slot increase;
ϵ_i = disturbance term for zip code i.

5.2.3 Results

Using the REG procedure in SAS 9.1, we perform a linear regression, the results of which are given in Table 5.1. The adjusted R^2 value indicates a reasonable fit.

The statistical significance of β_1 implies that the individual base growth rates contribute significantly in the 'prediction' of the annual growth. We observe from Table 5.1 that the value of β_1 is larger than 52 which suggest that the annual growth is higher than expected based on the weekly base growth. This implies that the growth rate changed over time. One reason for this might be the positive impact of the differentiated delivery fees, both in terms of marketing as in capacity utilization. Alternatively, the growth rate of e-grocery sales is likely to relate to the number of previous buyers according to the Bass diffusion model for the timing of initial purchases of new products (Bass, 1969). This model implies exponential growth of initial purchases to a peak and then exponential decay.

The coefficients for the expansion of the time slot assortment (β_3 and β_5) are both statistically significant, and suggest that offering a wider assortment has a positive impact on both the growth rate as well as the base level demand. The positive effect on sales is substantial, and indicate about 4% ($\frac{\beta_3}{\beta_1}$) additional growth a year per time slot. This finding may suggest that offering more time slot choices make the service more attractive to the customer, and thereby increase sales. A more plausible explanation, however, is that this additional sales growth is facilitated by the increase in time slot capacity. That is, the time slot choices are closely linked to the available capacity because each time slot represents a part of the delivery capacity. As a result, the expansion of the number of time slots can reduce loss sales by relaxing some of the capacity constraints in the busy regions.

The LESS slot coefficients do not approach significance. This means that the values are not significantly different from zero. The Growth LESS value does have the expected sign and is larger than the value for MORE. This suggests that the negative impact on the growth rate may be greater than the positive impact. However, the difference is not even close to being statistically significant.

Table 5.1: Impact Time Slot Change

	estimate	*standard error*
β_0: Base Demand Change	9.78	10.49
β_1: Base Demand Growth Change	69.97*	17.33
β_2: Additional Change Demand Growth LESS	-8.74	6.63
β_3: Additional Change Demand Growth MORE	2.71*	1.27
β_4: Additional Change Demand Level LESS	0.66	3.07
β_5: Additional Change Demand Level MORE	7.06*	1.64
adj. R^2	0.53	
sample size	290	

$*$ *Significantly different from zero,* $p < 0.05$.

5.3 Response to Dynamic Time Slot Management

The previous section considers the impact of the permanent time slot assortment on long-term sales. However, we must realize that the full time slot assortment is not always available to the customer. On a day-to-day basis, when delivery capacity becomes tight, certain time slots in certain zip codes may be closed. The time slot is then no longer available for the customer to choose and it turns "grey" on the web site. In this section, we examine the immediate short-term response of a customer to such a time slot stockout. When faced with a stockout, the customer can either respond by canceling his intended purchase or by selecting a substitute delivery moment.

To study the actual customer reaction, we first need to know the number of customers who were unable to select their first choice time slot, that is, the unsatisfied demand. In addition, we need to find out whether demand for still available alternative delivery time slots inflates shortly after a particular slot is closed. Together, the ratio between the incremental demand in the "open" time slots and the demand that could not select their first choice time slot provides us with a measure of the substitution rate.

5.3.1 Data

To analyze the short-term response to a time slot stock-out requires detailed transaction data. Transaction data from Albert.nl reveals the exact time that an order was placed by a specific customer for a certain time slot. The data also specifies the size of the order in euros, excluding the delivery fee. Although data for a much longer period is available, we use a data set which covers a 1-year period because this is a period without substantial changes in the time slot offering and corresponding delivery fees.

Based on demand forecasts and available capacity, Albert.nl establishes specific order limits per time slot on a weekly bases. Each warehouse has its own specific capacity limits and serves a specific fixed delivery region. If capacity limits are reached, the time slot is closed for the entire delivery region, and does not reopen afterwards. Since capacity is managed per warehouse, we consider the data from one of two warehouses of Albert.nl for our analysis.

Identification of time slot stockouts

The retailer does not systematically record the time at which a slot was closed nor the specific order limits. Therefore, we have to identify this from the data. The identification of time slot stock-outs is complicated because zero-sales in a given period does not necessarily imply a time slot stock-out (Campo et al., 2003). However, if the period without sales between the last order and the cut-off is long in comparison with the expected inter-order arrival time, a slot was most likely closed. In that case, the last observed order automatically triggered the out-of-stock, which makes the time of out-of-stock equal to the arrival time of the last order. The period between the last order and the cut-off time represents the zero-sales period.

The detailed transaction data enables us to heuristically track the time a specific time slot was closed. Based on the arrival time of the last order in each delivery time slot, we know the zero-sales period remaining for that specific slot until its cut-off point. We estimate the average inter-order arrival time I_a for a time slot a based on previous order arrivals for this time slot. In particular, we estimate the inter-order arrival time based on the last 10 orders for a certain slot. (The last 8 and 12 orders provide similar results.)

Given I_a, we then can calculate the probability that we observe no additional order arrival within the observed zero-sales period Z_a for time slot a. If this probability is below a certain threshold value α we assume that the time slot must have been closed. For the analysis, we assume Poisson distributed order arrivals which seems reasonable since the population of potential customers is large enough to assume the time interval between successive orders to be independent. This means we consider a slot a was closed if $\alpha > e^{Z_a/I_a}$. In particular, we assume a time slot was closed if the probability of not receiving an order in the time remaining to the cut-off point is less than 5%. Feedback from managers at Albert.nl confirmed that the results have face validity.

5.3.2 Model Description

In this section, we introduce our demand model. In our analysis, we focus on the time of order placement on the website, as the customers make their purchase decisions at that time. The actual delivery then takes place at a later point in time that depends on the specific time slot that is chosen by the customer. Note that the orders for specific time slots always have to be placed before a given cut-off point, at least 16 hours before delivery. This lead-time is necessary to allow the e-tailer enough time to plan the delivery routes and pick the orders from the warehouse. The sequence in which customers place their orders does not necessarily correspond with the sequence in which the delivery takes place.

Furthermore, it should be noted that the recorded sales data does not truly represent core customer demand, that is, the demand with all time slots available. First, demand for the closed slots is right-censored because new requests are no longer accepted in these slots for delivery. Second, demand for the slots that were not closed may be inflated due to substitution. What further complicates the analysis is the fact that we cannot distinguish between a customer's first choice and a substitute choice. In addition, we do not observe customers that visit the Internet store but do not make a purchase.

For ease of exposition, we introduce the different elements of our model before presenting the complete model. We first present our uncensored demand model, which models core demand in case no stock-outs occur. Subsequently, the censoring effect of a time slot stock-out is introduced.

Uncensored Demand Model

Demand for e-grocery is characterized by strong fluctuations and exhibits hourly, daily, and weekly seasonalities. Figure 5.2 depicts the average number of orders placed per hour of the week at Albert.nl (where the averages are taken over a one year period). We observe that the majority of orders is placed between 8am and 12pm and there is virtually no traffic at night. We also see that the activity drops shortly before the evening-peak around dinner time. Moreover, the number of orders placed in the weekend, and especially Sunday, appear to relatively low. Apparently, the consumer may want to receive his groceries in (or slightly before) the weekend but does not like to shop online in the weekends.

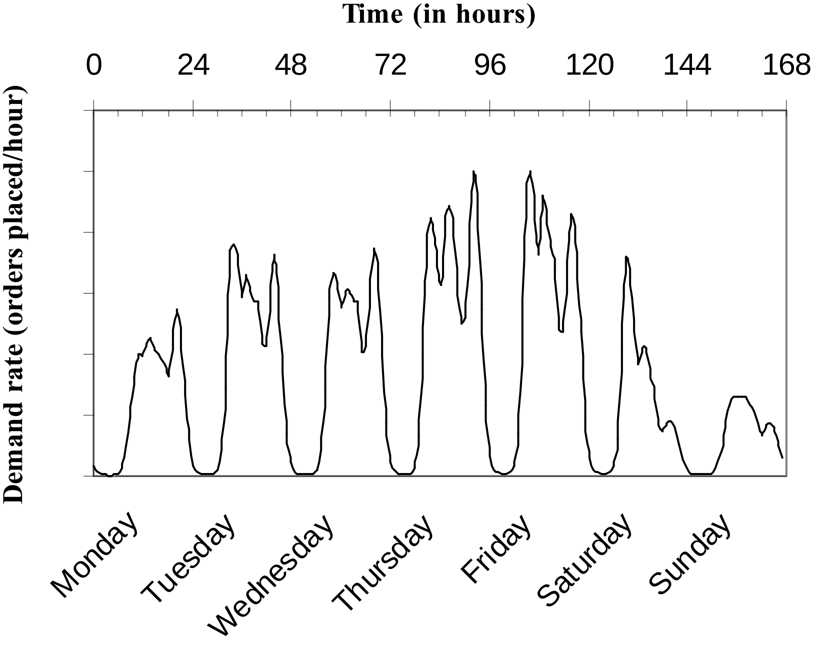


Figure 5.2: Online Traffic Over Time

If no stock-outs occur, the observed sales reflect the core demand. That is, we do not consider assortment-based substitution because the time slot assortment is fixed over the period of study. To estimate this core demand for each slot j, we specify a simple linear regression model. To control for the hourly demand fluctuations, we focus on the order placement in a specific daily period. The first part of this period serves to forecast the demand placed in the second part of the period. For each day i, we then use the demand in the first part of the period ($D_{1,i}$) as an exogenous variable to predict the demand in the second part of the period ($D_{2,i}$). The regression can be expressed as follows:

$$D^j_{2,i} = \alpha^j D^j_{1,i} + \epsilon^j_i \tag{5.2}$$

To control for the other variables that could potentially impact demand, we include two control variables (covariates) in our model that are commonly used in demand forecasting for groceries (Kök and Fisher, 2007). The first one controls for the different demand patterns over the days of the week by including a dummy for each day of the week $W_{d,i}$. That is, different days of the week may attract distinct customer segments which may exhibit different order placement behaviors (see also Figure 5.2). The second one controls for the weather by include a $1-0$ dummy Y_i for the 5 warmest months of 2006: May, June, July, August and September (www.knmi.nl). This variable captures the difference (if any) in the order placement patterns over the year, and specifically the impact of warmer weather on these patterns.

$$D^j_{2,i} = (\alpha^j + \sum_{d\in D} \alpha^d W_{d,i} + \alpha^y Y_i) D^j_{1,i} + \epsilon^j_i \tag{5.3}$$

$$\tag{5.4}$$

Censoring of Demand

In case of a stockout, we no longer observe the core demand for a particular time slot. To analyze this impact, we simply assume that the expected unsatisfied demand depends linearly on the fraction of time $T^j_{2,i}$ (between 0 and 1) that time slot j was not available in Period 2. To control for the fact that the assumption on linearity may be too restrictive, we include a auxiliary scale parameter θ. If $\widetilde{\alpha} = \alpha + \sum_{d\in D} \alpha^d W_{d,i} + \alpha^y Y_i$, the expected unsatisfied demand is then $(\theta T^j_{2,i})\widetilde{\alpha} D^j_{1,i}$ and the actual observed sales is:

$$D_{2,i}^{j} = (1 - \theta T_{2,i}^{j})\widetilde{\alpha} D_{1,i}^{j} + \epsilon_i^j \tag{5.5}$$

On the other hand, demand for the still available alternative slots may inflate due to spill-overs from the closed time slot. A portion $\widetilde{\beta}$ of the total expected unsatisfied demand may switch to an alternative slot. In case slot j is closed in Period 2, the expected substitute demand can be expressed as $(\widetilde{\beta}\theta T_{2,i}^{j})\widetilde{\alpha} D_{1,i}^{j}$. If $\beta = \widetilde{\beta}\theta$, the actual observed sales for the in-stock slot(s) can then be expressed as follows:

$$D_{2,i}^{\text{in-stock}} = \widetilde{\alpha} D_{1,i}^{\text{in-stock}} + \beta T_{2,i}^{j}\widetilde{\alpha} D_{1,i}^{j} + \epsilon_i^j \tag{5.6}$$

Full Demand Model

Now we have all components, we can try to estimate (i) the unsatisfied demand in a closed slot, (ii) the substitution to the open time slots and (iii) lost sales. The most straightforward model specification would consider the expected demand for each individual time slot separately. However, since the customer can chose any delivery time slot up to three weeks in the future, we believe this would yield too many separate variables. Therefore, we particularly focus on a subset of slots, for which we model demand separately, and consider an aggregate demand model for all slots beyond this subset (naming this “rest”). Since most time-slot closures occur in the evening, we focus on order placement in that period. Specifically, we use the order placement between 7pm and 9pm to predict the order placement between 9pm and 10pm. In particular, we separately model demand for each of the following three slots in the next available delivery shift: (a) 4pm – 6pm, (b) 6pm – 8pm and (c) 7pm – 9pm, and aggregate demand for all future slots.

This leaves us with 4 streams of demand, 3 for the individual time slots, and one stream of demand for all other future time slots. We use separate coefficient $(\alpha^a, \alpha^b, \alpha^c)$ for the 3 individual slots of interest and one coefficient (α^{rest}) for the rest. To analyze the direction of the substitution, we estimate separate coefficients for substitution across shifts (β) and within the shift (γ). Figure 5.3 depicts the situation in which slot a is made unavailable in Period 2, and where demand moves to either slot b, slot c or one of the future time slots.

In case of a time slot out-of-stock in Period 1 (7pm – 9pm), the corresponding

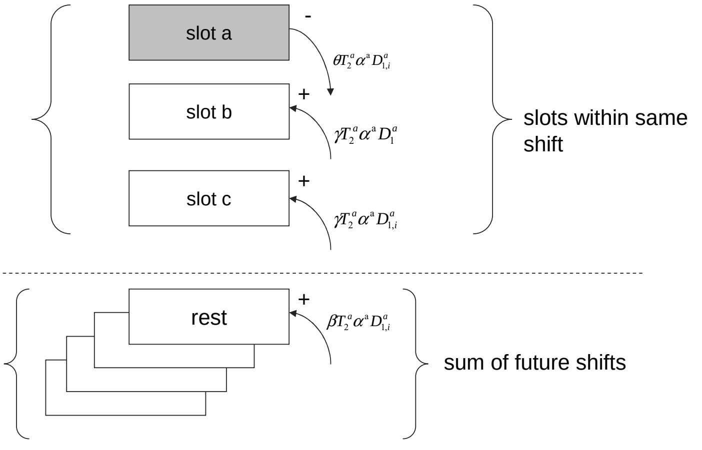


Figure 5.3: Demand Substitution Model

data is dropped from the data set because it does not provide us the information that we need. That is, we cannot forecast demand in Period 2 without the core demand information from Period 1. Instances with more than one time slot stock-out in Period 2 are also dropped from the data set. This is done to prevent a possible confound in our analysis of the impact of a time slot stock-out. This leaves us with 142 data points (dates), i.e. i=1 to 142 of which 56 with a time slot stock-out.

$$
\begin{aligned}
D^a_{2,i} &= (1 - T^a_{2,i} \cdot \theta)(\alpha^a + \sum_{d \in D} \alpha^d W_{d,i} + \alpha^y Y_i) D^a_{1,i} \\
&+ \gamma \cdot T2b_i \cdot (1 - \widetilde{T}^a_{2,i}) \cdot (\alpha^b + \sum_{d \in D} \alpha_d W_{d,i} + \alpha^y Y_i) D^b_{1,i} \\
&+ \gamma \cdot T^c_{2,i} \cdot (1 - \widetilde{T}^a_{2,i}) \cdot (\alpha^c + \sum_{d \in D} \alpha^d W_{d,i} + \alpha^y Y_i) D^c_{1,i} + \epsilon^a_i
\end{aligned} \tag{5.7}
$$

$$
\begin{aligned}
D^b_{1,i} &= (1 - T^b_{2,i} \cdot \theta)(\alpha^b + \sum_{d \in D} \alpha^d W_{d,i} + \alpha^y Y_i) D^b_{1,i} \\
&+ \gamma \cdot T^a_{2,i} \cdot (1 - \widetilde{T}^b_{2,i}) \cdot (\alpha^a + \sum_{d \in D} \alpha^d W_{d,i} + \alpha^y Y_i) D^a_{1,i} \\
&+ \gamma \cdot T2c_i \cdot (1 - \widetilde{T}^b_{2,i}) \cdot (\alpha^c + \sum_{d \in D} \alpha^d W_{d,i} + \alpha^y Y_i) D^c_{1,i} + \epsilon^b_i
\end{aligned} \tag{5.8}
$$

$$
\begin{aligned}
D^c_{1,i} &= (1 - T^c_{2,i} \cdot \theta)(\alpha^c + \sum_{d \in D} \alpha^d W_{d,i} + \alpha^y Y_i) D^c_{1,i} \\
&+ \gamma \cdot T^a_{2,i} \cdot (1 - \widetilde{T}^c_{2,i}) \cdot (\alpha^a + \sum_{d \in D} \alpha^d W_{d,i} + \alpha^y Y_i) D^a_{1,i} \\
&+ \gamma \cdot T^b_{2,i} \cdot (1 - \widetilde{T}^c_{2,i}) \cdot (\alpha^b + \sum_{d \in D} \alpha^d W_{d,i} + \alpha^y Y_i) D^b_{1,i} + \epsilon^c_i
\end{aligned} \tag{5.9}
$$

$$
\begin{aligned}
D^{\text{rest}}_i &= (\alpha^{\text{rest}} + \sum_{d \in D} \alpha^d W_{d,i} + \alpha^y Y_i) D^{\text{rest}}_{1,i} \\
&+ \beta \cdot T^a_{2,i} \cdot (\alpha^a + \sum_{d \in D} \alpha^d W_{d,i} + \alpha^y Y_i) D^a_{1,i} \\
&+ \beta \cdot T^b_{2,i} \cdot (\alpha^b + \sum_{d \in D} \alpha^d W_{d,i} + \alpha^y Y_i) D^b_{1,i} \\
&+ \beta \cdot T^c_{2,i} \cdot (\alpha^c + \sum_{d \in D} \alpha^d W_{d,i} + \alpha^y Y_i) D^c_{1,i} + \epsilon^{\text{rest}}_i
\end{aligned} \tag{5.10}
$$

for i =1,...,I (dates), where

Input parameters

$T^a_{2,i}$ = fraction (between 0 and 1) of Period 2 that time slot a is closed, analogously for slot b and c,

$\widetilde{T}^a_{2,i}$ = a dummy variable that is 1 if slot a is closed in Period 2 and zero otherwise; analogously for slot b and c,

$D^a_{1,i}$ = the number of orders placed on date i in Period 1 for delivery in time slot a the next day; analogously for slot b and c and Period 2

$D^{\text{rest}}_{1,i}$ = the number of orders placed on date i in Period 1 for all time slots beyond the next available evening shift; analogously for Period 2,

$W_{d,i}$ = dummy that equals 1 if date i is on weekday d (day of order placement), and zero otherwise,

Y_i = dummy that equals 1 if date i is in May, June, July, August or September, and zero otherwise,

Estimation coefficients

α^a = the average ratio between uncensored demand for slot a in Period 2 and Period 1 with order placement on Thursday; analogously for slots b, c and 'rest',

α^d = the day-specific increase in the average ratio between uncensored demand in Period 2 and Period 1 compared to Thursday,

α^y = the increase in the average ratio between uncensored demand in Period 2 and Period 1,

θ = scale parameter to estimate the expected unsatisfied demand due to a stock-out,

β = the average fraction of expected demand that switched to a delivery time slot in a different shift,

γ = the average fraction of expected demand that switched to a delivery time slot in the same shift,

ϵ^a = disturbance term for slot a, analogously for slot b, slot c and 'rest'.

The intra shift substitution rate is the total substitution within the shift divided by the total unsatisfied demand. If $\widetilde{D}_2$ denotes the expected core demand in Period 2 for a particular slot that was not available during the fraction of time T_2, then $\gamma T_2 \widetilde{D}_2$ is the expected demand that substitutes to any of the available slots in the same shift. The total intra shift substitution is twice this value since there are two available substitute slots in this shift. The substitution rate is thus, $\frac{2\gamma T_2 \widetilde{D}_2}{\theta T_2 \widetilde{D}_2}$, which gives:

Sub Intra (*intra shift substitution rate*) $= \frac{2\gamma}{\theta}$,

Similarly, we can express the cross shift substitution as:

Sub Cross (*cross shift substitution rate*) $= \frac{\beta}{\theta}$,

5.3.3 Results

To simultaneously estimate the parameters in our model we use the Full Information Maximum Likelihood method in SAS 9.1. This is a well-known econometric technique for estimation simultaneous equation models. We run two variants of the model. One in which demand is represented by the number of order placements, and one in which we express demand as the sum of the revenues from these placed orders. The revenues are the prices payed for the physical products and exclude the delivery fees. Table 5.2 reports the parameter estimates for both models.

All demand coefficients ($\alpha^a, \alpha^b, \alpha^c, \alpha^{\text{rest}}$) are statistically significant. Note that a demand ratio of 0.5 would imply an equal hourly demand volume in both periods because the first period is twice as long as the second period. The α for time slot c, the 7pm - 9pm time slot, is significantly bigger than the earlier two time slots. This denotes relatively more demand for this slot in Period 2 than Period 1, which suggests that customers who prefer delivery at a later point in time also place their order at a later point in time. Moreover, we observe differences between the days of the week. In particular, all days but Wednesday are significantly different from Thursday, the day of reference, in terms of the demand ratio between Period 2 and 1. The results specifically show a lower demand ratio for the days earlier in the week.

We also observe a substantial increase in the ratio between Period 2 and 1 in the warmer months. This suggest that customers order placement in this time of the year. The longer period of daylight available together with the warmer weather may change people's daily rhythm, and thereby influence the timing of their online shopping.

Table 5.2: Parameter Estimates

	orders		*revenues*	
	estimate	*standard error*	*estimate*	*standard error*
α^a	0.41**	0.02	0.41**	0.02
α^b	0.38**	0.01	0.38**	0.01
α^c	0.50**	0.02	0.51**	0.02
α^{rest}	0.55**	0.02	0.57**	0.02
Sun	-0.08**	0.03	-0.10**	0.03
Mon	-0.12**	0.02	-0.14**	0.02
Tue	-009**	0.02	-0.10**	0.02
Wed	-0.03	0.02	-0.02	0.02
Summer	0.10**	0.01	0.10**	0.01
θ	1.07*	0.25	1.06*	0.34
β	0.70*	0.36	0.56*	0.29
2γ	0.25*	0.13	0.39*	0.13
Sub Intra	23%		37%	
Sub Cross	65%		53%	
Lost	12%		10%	

$*$ *Significantly different from zero, $p < 0.05$ (one-tailed).*
$**$ *Significantly different from zero, $p < 0.01$.*

With respect to the substitution behavior, we observe that all coefficients (θ, β, γ) are statistically significant. Note that the estimate for θ suggest that the linearity assumption appears reasonable. The results show that customers switch to a substitute time slot when their first-choice slot is not available in the majority of cases. That is, only 12% of demand is lost. Substitution across shifts seems dominant, which suggests that customers rather move to a different day than to a different slot on the same day. This implies that customers may have a stronger preference for a certain time (e.g. 7pm – 9pm) than for a certain day.

For the revenue model, we observe that all demand coefficients $(\alpha^a, \alpha^b, \alpha^c, \alpha^{\text{rest}})$ are similar to the base model. Moreover, we observe that 23% of the substitutions within the same shift correspond with 37% of the revenues. That is, the relatively large orders predominantly switch to a substitute slot within the same shift, possibly because they are more time critical. This would be in line with the paper by Milkman and Bazermn (2008), which shows that e-grocery customers spend more as the lead-time between order placement and delivery is smaller.

Another interesting observation is the fact that relatively more demand is lost in terms of orders than in terms of revenues. While 12% of the orders is lost, this corresponds with only 10% of the revenues. To investigate the statistical significance of this finding would require further analysis, but it seems intuitive that primarily "small" orders are lost. The customers who are more likely to order a larger portion of their weekly groceries online are probably also the ones that are more likely to switch to an alternative time slot when faced with a stock-out.

5.4 Discussion

In this chapter, we have reported the findings from two studies conducted at e-grocer Albert.nl to get more insight into the customer's flexibility with respect to his delivery time slot choice. Our findings suggest that many customers are relatively flexible with respect to their delivery time slot choice.

The first study suggest that a moderate permanent reduction in time slots does not have a significant long-term effect on overall sales. In the second study, the estimates indicate that demand for other slots inflates when a certain time slot is closed. This can either mean that customers may be willing to switch to a different time slot when their preferred time slot is not available or that customers do not have any real preferences and are fairly indifferent about a set of slots.

These results are specific to Albert.nl and the specific magnitudes of substitution will almost certainly vary across companies and markets. The flexibility with respect to the time slot choice depends on the attractiveness of the available alternatives. When faced with a time slot out-of-stock, a customer can either switch to a substitute slot, switch to a competitor online, switch to an offline store or postpone his purchase. The perceived convenience of getting goods delivered at home determines the customer's willingness to go out to shop and switch to an offline store. This perceived convenience is likely to differ per customer and per product type. That is, not having to go out to shop for heavy and bulky groceries may be very advantageous, especially for people with physical disabilities (Verhoef and Langerak, 2001).

With respect to switching to an online competitor, we believe that it is not unusual for customers to be fairly loyal to a certain online store for the following reasons:

(i) Moving to another Internet retailer can require quite some effort from customers since they will have to familiarize themselves with a new online store environment. Kull et al. (2007) demonstrate a substantial learning effect of e-grocery customers after the first few orders in a particular web store, reducing the time to complete an order by up to 50%;

(ii) Buying at an online store that is already well-known to the customer rather then switching to a less-known store has less perceived risk (Danaher et al., 2003).

This chapter makes a methodological contribution by presenting a method to measure the impact of out-of-stocks time slot when only sales data is available. In practice, this is usually the case as it is very difficult to track the customer's actual demand. That is, it is often impossible to distinguish between the customer's first choice and a substitute choice. On the Internet, a potential way of recording true demand preferences is by not making stock-outs visible until after a click on the desired product or service. However, this may be undesirable from a marketing perspective. Breugelmans et al. (2006) show that the use of such a non-visible policy for e-grocery products, reduces category purchases for the majority of customers. More research is needed on the use of click-stream data from the retailer's website to provide more insights in the customer's shopping behavior online.

A potential limitation of the study is the lack of data on the exact times a slot was closed. The inferred out-of-stock variables are likely to contain errors, which may impact the estimated impact of the stock-outs. However, the results appear to be robust for the choice of the threshold value that is used to determine whether a slot was closed or not. Experiments with threshold values of 10% and 1% give the same results. This makes sense if you consider the fact that we specifically focus our analysis on time slot stockouts in the period between 9pm and 10pm, with several hours remaining before the cut-off point at 12pm. If we do not observe any sales for a particular time slot in this relatively long period, this almost certainly implies that this time slot was closed.

As this is the first study of customer behavior with respect to home delivery time slots for e-fulfillment, we see many opportunities for further research. We specifically see room for relevant future research on the customer's response to dynamic slot pricing. Pricing provides even richer opportunities for demand management in this setting because prices impact both costs and revenues. However, it also gives rise to many challenges. What is, for example, the effectiveness of different dynamic incentive strategies, e.g. discounts vs. non-monetary incentives. What is the impact of the pool of displayed time slot prices on the customer's price perception? Can we predict the customer's price elasticity and slotting preferences based on customer characteristics? Does the customer learn to anticipate price changes and try to game the system?

5.5 Conclusions

The results in this chapter imply that there is a great potential for more advanced demand management initiatives which exploit the customer's flexibility to gain operational benefits. The fact that the customer seems to be fairly indifferent about the set of offered time slots, provides the retailer with the opportunity to select the time slot offering in a way that facilitates cost-efficient fulfillment. Campbell and Savelsbergh (2005a) show that one can substantially decrease routing costs by serving the customer in the time slot that allows for more efficient delivery given the already accepted orders. In the previous chapter we discussed several potential approaches for demand management in e-fulfillment, inspired by revenue management in the airlines. To fully exploit the potential of these demand management approaches, sophisticated decisions support is needed. The following chapters aim to contribute such decision support tools and investigate the potential of such demand management approaches in detail. We specifically consider the use of the time slot offering to steer customer demand, both forecast-based and real-time.

Chapter 6

Time Slot Management for E-Fulfillment

In Chapter 4 we saw that the time slot offering is an important demand management lever in E-fulfillment. In this chapter[1], we formally model the impact of this lever and quantify this impact. More specifically, we consider the tactical problem of selecting the time slots to offer in each zip code of the delivery region. This selection needs to offer an acceptable level of service in each zip code and needs to be able to yield cost-effective daily delivery routes. Once such a time slot schedule is put in place, there is the operational problem of managing the availability of the offered time slots. The operational dynamic slotting problem will be addressed in the next chapter.

The remainder of the chapter is organized as follows. In Section 6.1 we formalize the problem. In Section 6.2, we introduce notation and outline our modeling framework. In Sections 6.3 and 6.4, we present two different modeling and optimization approaches to solve the problem. In Section 6.5, we describe the design of our computational experiments and present the results. Finally, in Section 6.6, we summarize our main insights and discuss directions for future research.

6.1 Introduction

Our research effort is motivated by operations at Albert.nl as described in Chapter 2. The time slot schedule currently employed at Albert.nl is created manually. Due to

[1]This chapter is based on the paper: 'Time Slot Management in Attended Home Delivery' (Agatz, Campbell, Fleischmann, and Savelsbergh, 2008c)

its complexity, this task takes several weeks to complete. Clearly, this is undesirable in an environment that continually changes as a result of a 30% annual growth rate. In particular, this manual process greatly limits their ability to assess and compare potential future scenarios. Therefore, Albert.nl is considering options for automating the time slot schedule generation. In this chapter, we present two approaches for making the time slot decision. They apply not only to Albert.nl, but also for many other companies offering attended delivery services (see Chapter 2).

More specifically, we address the following time slot management problem (TSMP). Given service requirements and average weekly demands for each zip code in the delivery region, determine the set of time slots to offer in each zip code so as to minimize expected delivery costs while meeting the service requirements.

Anticipating the impact of the offered time slots on delivery routes is crucial when solving the TSMP. This links the TSMP to the vast body of literature on vehicle routing with time windows. See Braysy and Gendreau (2005a,b) for an extensive review.

Given the computational complexity of the vehicle routing problem alone, it is unrealistic to incorporate a full routing model in the tactical TSMP. Instead, routing costs resulting from time slot selections have to be approximated. One way is to model routing costs using the continuous approximation method (Daganzo, 1987b,a). This approach represents demand by continuous functions and assesses system-wide costs by aggregating over "local" cost estimates. For an overview of continuous approximation models in logistics, see Daganzo (2005) and Langevin et al. (1996). Another option is to explicitly model routing decisions through Integer programming but on a more aggregate level than a full Vehicle Routing Problem. We will explore both of these alternatives.

The continuous approximation focuses on a realistic evaluation of a given time slot schedule and then uses relatively simple optimization techniques to improve the schedule. The integer programming approach uses simpler routing cost approximations but more sophisticated optimization machinery.

6.2 Assumptions and Notation

The objective of the TSMP is to minimize the expected delivery costs for the customer orders ensuing from the offered delivery time slots. This requires assumptions on the demand response to a certain time slot offering. Throughout our analysis in this chapter, we make the following two key assumptions, where demand is measured in number of customer orders:

1. The expected weekly demand for each zip code is known and independent of the set of offered time slots.

2. The expected weekly demand for each zip code is divided evenly over the set of offered time slots.

The first assumption supposes that customers exhibit a certain degree of flexibility, such that changing the time slots offered does not result in lost sales. In Chapter 5 we saw that historical data from Albert.nl support the validity of this assumption for moderate changes in the time slot offering. The second assumption implies that all time slots are equally popular. Differentiated delivery fees are introduced specifically for this reason. They counterbalance differences in time-slot popularity and smooth demand. Historical data from Albert.nl show the effectiveness of differentiated delivery fees and indicate that the equal time slot popularity assumption is reasonable.

We further assume that all orders are the same size in terms of the number of totes. The size of an order impacts the number of orders that fit in a delivery vehicle. We conducted a few computational experiments in which we varied order sizes and found that it had little or no impact on the results.

The marketing-imposed service requirements limit the set of feasible time slot offerings. Our models treat these service requirements as exogenous. The service requirements employed at Albert.nl specify for each zip code the required number of available delivery slots in each shift, e.g. one on Monday morning and two on Tuesday afternoon. As a result of these specific service requirements and the above demand assumptions, the problem decomposes by shift. Thus, separate problems need to be solved for each shift.

Our objective function considers fixed costs as well as variable costs, incorporating both distance-related and time-related costs. Initially, we do not take into account delivery fees and solely focus on minimizing expected delivery costs. Later, in Section 6.5, we consider the delivery fee revenues as part of the objective function.

In Table 6.1, we introduce notation that is common to both of our modeling approaches. The cost per mile for vehicle and driver usage include (1) the cost per distance mile representing gas, vehicle wear and tear, etc. and (2) the cost per time unit representing labor costs. We assume vehicle speed to increase with the travel distance. Therefore, we specify different cost factors (c^n, c^z, c^t, c^0) for the different types of trips. For example, the speed for driving between stops within a zip code is lower than for the (longer) stem distance to and from the depot. Note that e_i is the weekly demand for zip code i divided by the number of time slots that need to be offered in zip code i.

$\mathcal{Z}$:	set of zip codes (indexed by i)
$\mathcal{T}$:	set of time slots (indexed by s)
$\mathcal{V}$:	set of vehicles
e_i:	expected demand for zip code i for each time slot
Q:	vehicle capacity (in terms of the number of orders that can be accommodated)
f:	vehicle fixed cost
c^n:	cost per mile for vehicle and driver usage when driving within a zip code and within a time slot
c^z:	cost per mile for vehicle and driver usage when driving between different zip codes within a time slot
c^t:	cost per mile for vehicle and driver usage when driving between zip codes in consecutive time slots
c^0:	cost per mile for vehicle and driver usage when driving to or from the depot
d_{ij}:	distance between centers of zip codes i and j
τ:	dwell time per order

Table 6.1: Notation

6.3 Continuous Approximation Approach

At the heart of the continuous approximation approach is a model for estimating the delivery cost of a *given* time slot schedule for a set of zip codes. Based on this delivery cost estimate, a local search is performed to iteratively improve the time slot schedule. The original continuous approximation approach proposed by Daganzo (1987b) does not consider time slots and distinguishes two components of a vehicle tour, namely the stem distance between the depot and the delivery area and the distance between consecutive stops within the delivery area. To account for time slots, we expand these ideas and distinguish four components of a vehicle tour (see Figure 6.1):

- d^0: the stem distance to or from the depot to a stop in a time slot;
- d^n: the distance between stops within a zip code within a time slot;

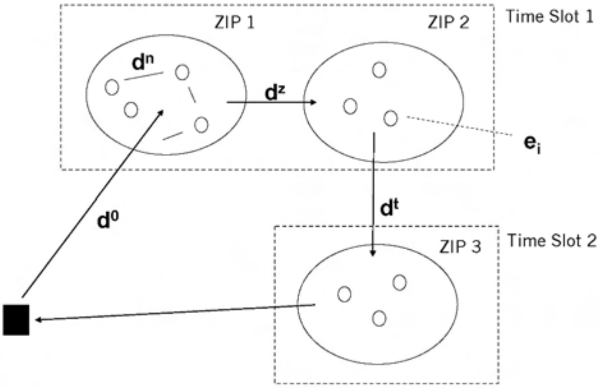


Figure 6.1: Routing components

- d^z: the distance between stops in different zip codes within a time slot; and
- d^t: the distance between stops in consecutive time slots.

The corresponding travel times are denoted by h^0, h^n, h^z, and h^t.

In line with the continuous approximation methodology, we estimate the distance values for these components of a vehicle tour based on *local* data. We estimate the distance values from the perspective of each zip-code time-slot combination (i, s) in the time slot schedule. These local estimates are then used to compute a local estimate of the distance per order (excluding the stem distance to and from the depot) as follows:

$$DPO(i,s) = \frac{1}{n_{is}} \left[n_{is}^t \left(\frac{n_{is}^t - 1}{n_{is}^t} d_{is}^t + n_{is}^z (\frac{n_{is}^z - 1}{n_{is}^z} d_{is}^z + (n_{is}^n - 1) d_{is}^n) \right) \right],$$

where

- n_{is} denotes the estimated number of orders per route,
- n_{is}^t denotes the estimated number of time slots covered by a route,
- n_{is}^z denotes the estimated number of zip codes visited in time slot on a route, and
- n_{is}^n denotes the estimated number of orders delivered in a zip code in a time slot on a route.

These n-values are again estimated based on local data from the perspective of a given zip-code time-slot (i, s).

By multiplying the distance per order with the cost per kilometer, we obtain a local estimate for the distance-related costs (excluding stem distances). This, in turn, yields a local estimate of the cost per order (excluding stem costs and fixed vehicle costs):

$$CPO(i,s) = \frac{1}{n_{is}} \left[n_{is}^t \left(\frac{n_{is}^t - 1}{n_{is}^t} d_{is}^t c^t + n_{is}^z \left(\frac{n_{is}^z - 1}{n_{is}^z} d_{is}^z c^z + (n_{is}^n - 1) d_{is}^n c^n \right) \right) \right].$$

We obtain an estimate of the expected delivery cost associated with a given time slot schedule by multiplying the expected number of orders e_i for a zip-code time-slot combination (i,s) with the cost per order $CPO(i,s)$, aggregating over all zip codes and time slots, and adding stem costs and fixed vehicle costs:

$$\text{expected delivery cost} \approx \sum_{i \in \mathcal{Z}} \sum_{s \in \mathcal{T}} e_i \, CPO(i,s) + d^0 c^0 + fv,$$

where d^0 is the estimated total stem distance and v is the estimated number of vehicles required. Note that we sum over all zip codes and all *offered* time slots for that zip code. Also note that we omit labor costs for the dwell times since these costs are constant and independent of the offered schedule.

6.3.1 Estimating Vehicle Tour Components – Part I

In this subsection, we discuss how the vehicle tour components are estimated from the perspective of a given zip-code time-slot combination (i,s). We start with the vehicle tour components used in the calculation of the cost per order.

Distance between stops within a zip code within a time slot (d_{is}^n)

Statistical analysis of recent routing data at Albert.nl shows that the driving distance between two customers within the same zip code is similar across zip codes; we use d^n to represent this distance. The same is true for the travel time between two customers within the same zip code, so we use h^n to represent this travel time.

Distance between stops in different zip codes within a time slot (d_{is}^z)

Daganzo (2005) approximates the distance between two consecutive stops of a route through a region with a slowly varying demand density δ by $k/\sqrt{\delta}$, where k is a dimensionless constant that is independent of the region shape. We apply this approach on a zip code level and consider the density of *open* zip codes in time slot s in the neighborhood of i. Let $\mathcal{Z}_i$ be a collection of zip codes in the neighborhood of zip code i (including zip code i itself). In our calculations, we take $\mathcal{Z}_i$ to be the set of zip codes within a given maximum distance from the center of zip code i. Let δ_{is} be the density of open zip codes in $\mathcal{Z}_i$ during time slot s. If a_j denotes the surface area of zip code j and $\mathcal{I}_{js}$ denotes whether zip code j is open during time slot s ($\mathcal{I}_{js} = 1$) or whether it is closed during time slot s ($\mathcal{I}_{js} = 0$), then

$$\delta_{is} = \frac{\sum_{j \in \mathcal{Z}_i} \mathcal{I}_{js}}{\sum_{j \in \mathcal{Z}_i} a_j}.$$

The estimate of d^z_{is} is then $k/\sqrt{\delta_{is}}$. We impose an upper bound $\bar{d}^z$ on this estimate to handle very low densities δ_{is}. In our calculations, we set $\bar{d}^z$ equal to twice the average diameter of a zip code. Thus, $d^z_{is} = \min(k/\sqrt{\delta_{is}}, \bar{d}^z)$.

The above calculation of δ_{is} does not take into account that there may be open zip codes with an expected demand per slot e_i smaller than 1. To account for this situation, we modify δ_{is} to be a weighted density:

$$\delta_{is} = \frac{\sum_{j \in \mathcal{Z}_i} \min(1, e_j)\mathcal{I}_{js}}{\sum_{j \in \mathcal{Z}_i} a_j}.$$

This can be interpreted as treating values of e_i smaller than 1 as probabilities of a demand occurrence.

Distance between stops in consecutive time slots (d^t_{is})

We take a similar approach when computing d^t_{is}, but using zip code densities in preceding and succeeding time slots. We set $d^{pre} = d^n$ if time slot $s-1$ is open for zip code i, i.e., for consecutive open time slots we simply use the average distance between stops within a zip code. Otherwise, we set $d^{pre} = \min\{\bar{d}^z, k/\sqrt{\delta_{i,s-1}}\}$, where $\delta_{i,s-1}$ is the density of open zip codes in $\mathcal{Z}_i$ in time slot $s-1$. Analogously, $d^{suc} = d^n$ if time slot $s+1$ is open for zip code i and $d^{suc} = \min\{\bar{d}^z, k/\sqrt{\delta_{is+1}}\}$ otherwise, where $\delta_{i,s+1}$ is the density of open zip codes in $\mathcal{Z}_i$ in time slot $s+1$. Finally, we set $d^t_{is} = d^{pre}$ (d^{suc}) if s is the first (last) time slot of the shift and $d^t_{is} = (d^{pre} + d^{suc})/2$ otherwise.

Number of stops in a zip code in a time slot on a route (n^n_{is})

The number of stops in a zip code in a time slot is limited by the demand e_i and by the length of the time slot l. Let ν^n be the maximum number of stops that can be made during a time slot of length l and recall that τ denotes the dwell time. Then $l - h^t_{is} = \nu^n \tau + (\nu^n - 1)h^n_{is}$ and thus $\nu^n = \frac{l - h^t_{is} + h^n}{\tau + h^n}$, where we subtract h^t_{is} from l

to account for travel time between consecutive time slots. The number of stops in a zip code during a time slot n^n_{is} is therefore $\min\{e_i, \nu^n\}$.

Number of zip codes visited in a time slot on a route (n^z_{is})

Analogously, the number of zip codes visited in a time slot is limited by the number of neighboring open zip codes n^{open} and by the length of the time slot l. Let ν^z denote the maximum number of zip codes that can be visited during a time slot of length l. Then $l - h^t_{is} = \nu^z[n^n_{is}\tau + (n^n_{is} - 1)h^n_{is}] + (\nu^z - 1)h^z_{is}$, and thus $\nu^z = \frac{l - h^t_{is} + h^z_{is}}{n^n_{is}\tau + (n^n_{is} - 1)h^n + h^z_{is}}$. We then set $n^z_{is} = \min\{n^{open}, \nu^z\}$.

Number of time slots covered on a route (n^t_{is})

The number of time slots covered on a delivery tour is limited by the number of time slots in the shift $|\mathcal{T}|$ and by the number of orders that can be accommodated by the delivery vehicle Q. Therefore, we set $n^t_{is} = \min\{|\mathcal{T}|, \frac{Q}{n^n_{is} n^z_{is}}\}$.

Number of stops on a route (n_{is})

Using the previously estimated parameters, the number of stops on a delivery tour is $n^t_{is} n^z_{is} n^n_{is}$.

6.3.2 Estimating Vehicle Tour Components – Part II

In the previous subsection, we have shown how we compute local estimates for the vehicle tour components used in the computation of the local estimate of the cost per order. What remains to be shown is how to estimate the number of vehicles required (v) and the stem distance (d^0).

Number of vehicles (v)

We start with the estimate of the number of vehicles required. The number of vehicles required for serving the total demand of a shift depends on the vehicle capacity and on the number of orders that can be delivered in a time slot, i.e. on physical capacity and on available time. We address each of these constraints separately.

We have local estimates for the number of orders per route (n_{is}). We take a demand-weighted average over these local estimates to obtain a global estimate of the number of orders per route. Dividing the expected demand for a shift by this global estimate of the number of order per route gives an estimate of the number of routes r. More precisely, let $\mathcal{Z}^s$ denote the set of open zip codes in time slot s. Then we have

$$r = \frac{\sum_{i \in \mathcal{Z}^s, s \in \mathcal{T}} e_i}{\sum_{i \in \mathcal{Z}^s, s \in \mathcal{T}} (\frac{e_i}{\sum_{i \in \mathcal{Z}^s, s \in \mathcal{T}} e_i}) n_{is}} = \frac{(\sum_{i \in \mathcal{Z}^s, s \in \mathcal{T}} e_i)^2}{\sum_{i \in \mathcal{Z}^s, s \in \mathcal{T}} e_i n_{is}}.$$

Similarly, we estimate the number of vehicles required to serve all orders in a given time slot v^s, based on the expected demand per time slot and the estimated number of stops per time slot, with

$$v_s = \frac{(\sum_{i \in \mathcal{Z}^s} e_i)^2}{\sum_{i \in \mathcal{Z}^s} e_i \; n^z_{is} \; n^n_{is}}.$$

The number of vehicles required is the maximum of the number of routes r and the number of vehicles required to serve all orders in a time slot v^s. This is represented by $v = \max\{r, \max_{s \in \mathcal{T}} v_s\}$.

Stem distance (d^0)

Next, we consider the stem distance d^0. We estimate d^0_s, the stem distance traveled by a vehicle making its first delivery in time slot s, by taking the average distance between the depot and the open zip codes in time slots s as follows:

$$d^0_s = \frac{\sum_{j \in \mathcal{Z}_i} \mathcal{I}_{js} \times d_{0j}}{\sum_{j \in \mathcal{Z}_i} \mathcal{I}_{js}}.$$

The same estimate applies to the distance traveled by a vehicle returning to the depot after its last delivery in time slot s. We use the estimates of the number of vehicles required in each time slot (v_s) for estimating the number of vehicles that start their trip in time slot s and for estimating the number of vehicles that end their trip in time slot s. Let $v_0 = 0$ and $v_{|\mathcal{T}|+1} = 0$, then we estimate the stem distance as

$$d^0 = \sum_{s=0}^{|\mathcal{T}|} \left(\max\{0, v_{s+1} - v_s\} d^0_{s+1} \; + \; \max\{0, v_s - v_{s+1}\} d^0_s \right).$$

Handling Overlapping Time Slots

A further complication arises if time slots are overlapping, as is the case at Albert.nl. In our calculations, we handle this situation by creating adjusted non-overlapping slots. To this end, we apportion the length of the overlapping part of two windows to both of the individual windows, based on their expected demand volumes. For example, consider two two-hour windows that overlap for one hour. Further, assume that the total expected demand from all open zip codes in the first time slot is twice as large as the total expected demand in the second time slot. Then, we create a first time slot of size 1.66 hours and a second slot of size 1.33 hours.

6.3.3 Solution Method

The discussion above shows how to estimate the expected costs of a given time slot allocation. The next step is to optimize the time slot allocation based on this evaluation. Note that this optimization problem is non-linear and non-convex. Starting from any feasible solution for the time slot schedule, we use a simple greedy iterative improvement heuristic for the optimization. In our experiments, we begin with the schedule currently in place at Albert.nl, Next, we determine for each zip code the time slot allocation for that zip code that results in the minimum expected delivery cost (keeping the time slot allocation for all other zip codes fixed) by complete enumeration. We then adjust the current time slot schedule by implementing the time slot allocation for the zip code that achieves the minimum expected delivery cost. We repeat this process as long as there is a reduction in expected delivery costs greater than some threshold or until a maximum number of iterations is reached.

6.4 Integer Programming Approach

The continuous approximation model presented in the previous section does not model the operational-level routing decisions explicitly. Instead, it aims to reflect them implicitly in the employed cost approximations. In this section, we complement this approach with a model that deals with the embedded routing component of the TSMP in a more explicit way. We formulate TSMP as an integer program. As with the continuous approximation model, the objective is to construct a time slot schedule that satisfies the service requirements and minimizes delivery costs.

6.4.1 IP Formulation

The most straightforward specification of the TSMP would be to incorporate a full specification of the lower level Vehicle Routing Problem with Time Windows (VRPTW). The VRPTW involves finding a set of routes to cover a set of customers with a fleet of vehicles, where the service at any customer must start within a particular time slot. In the traditional VRPTW, the time slots are assumed to be exogenous information, e.g., specified by the customer or set by the sales and marketing department. The model contains decision variables that represent for each vehicle, the sequence of stops at various customers within each time slot, with a constraints to observe the customer time windows and the psychical capacity of the vehicles (see e.g. Toth and Vigo (2001), Kallehauge et al. (2005)).

- $x_{ij}^{v} = 1$ if vehicle v visits zip code j right after zip code i and 0 otherwise;
- $y_i^{vs} = 1$ if zip code i is visited by vehicle v in time slot s and 0 otherwise;

The decision variable w_i^v is defined for each customer i and each vehicle v and denotes the time vehicle v starts to serve customer i. ϕ_i^s is the service requirement which specifies the number of time slots per zip code i. Given the parameters defined in Table 6.1, the problem can be stated as follows:

$$\min \sum_{v \in V} f + \sum_{i \in z, j \in Z, v \in V} c_{ij} x_{ij}^{v} \qquad \text{s.t.,} \tag{6.1}$$

$$\sum_{i \in Z, s \in S} e_i x_i^{vs} \leq Q \qquad v \in V, \tag{6.2}$$

$$x_{ij}^{v}(w_i^v + \tau e_i - w_j^v) \leq 0 \qquad i \in Z, j \in Z, v \in V, \tag{6.3}$$

$$a^s(y_i^{vs} + (1 - y_i^{vs})M) \leq w_i^v \leq b^s(y_i^{vs} + (1 - y_i^{vs})M) \qquad v \in V, \tag{6.4}$$

$$\sum_{j \in Z} x_{ij}^{v} = y_i^{vs} \qquad i \in Z, s \in S, v \in V, \tag{6.5}$$

$$\sum_{v \in V} y_i^{vs} = \phi_i^s \qquad i \in Z, s \in S \tag{6.6}$$

The objective minimizes the travel costs plus the fixed vehicle costs. Constraint 6.2 captures the physical vehicle capacity. Constraints 6.3 establishes the relationship between the vehicle departure time from a customer and its immediate successor. Constraint 6.5, 6.6 and 6.4 are specific for the TSMP and link the time slot decisions to the routing decisions. Constraint 6.4 affirms that the time slots are observed and relates w_i^v to the earliest and latest possible start time in time slot s. In contrast with the traditional VRPTW, the time bounds a^s and b^s depend on the time slot decisions. Furthermore, 6.6 links the service requirements ϕ to the time slot decisions, while constraint 6.5 links the y with the x variables. Note that without the service requirements, this problem resembles a Vehicle Routing Problem (VRP) *without* Time Windows. That is, one could simply solve the VRP and assign the time windows afterwards. However, with the service requirements, the VRPTW is a subproblem of the TSMP, which makes the integer program very hard to solve. Even finding feasible solutions in a reasonable amount of time is quite difficult with modern, sophisticated, and powerful integer programming solvers (Golden et al., 2008, Braysy and Gendreau, 2005a, Toth and Vigo, 2001, Bodin et al., 1983).

6.4.2 Hybrid IP Formulation

Therefore, we approximate the routing costs by using seeds. Even though the number of stops a vehicle makes during a shift may be large, the number of time slots in a shift is small; no more than four in the case of Albert.nl. Solving routing problems with at most four "stops" is much easier. This cost approximation is expressed graphically in Figure 6.2. The dashed circles surround the customers served in a single time slot with the center dot representing the seed. With the use of seeds, we can approximate the routing costs for a vehicle by the sum of two costs: (1) the cost of a route through the seeds associated with each time slot plus (2) a simple estimate of the costs incurred when visiting the customers within each single time slot based on the distance to the seed.

Our integer program has the following variables to represent the different decisions and associated costs:

- y_i^{vs} is 1 if zip code i is the seed for vehicle v for time slot s and 0 otherwise;
- x_i^{vs} is 1 if vehicle v visits zip code i in time slot s and makes a delivery and 0 otherwise;
- X_{ij}^{vs} is the distance from zip code i to zip code j if vehicle v serves customer i in time slot s and zip code j is the seed for time slot s and 0 otherwise;
- Y_{ij}^{vs} is the distance between the seed of time slot $s-1$ and the seed of time slot s for vehicle v if zip code i is the seed of time slot $s-1$ and zip code j is the seed of time slot s and 0 otherwise.

One zip code will serve as the seed (or representative) for the customers served in a particular time slot/vehicle combination, and this decision is represented by the y variable. The set of zip codes served in a particular time slot/vehicle combination is captured by the x variables. The estimate of the cost to serve a set of zip codes in a time slot is based on the sum of the distances between the zip codes and the seed, which are represented by the X variables. The cost of visiting the seeds associated with a vehicle, i.e., the route through the seeds, is captured by the Y variables. Note that the desired time slot schedule is implied by the x variables. Slot s is offered in zip code i if and only if $x_i^{vs} = 1$ for some v.

Given the parameters defined in Table 6.1 and these variables, the objective function can be expressed as:

$$\min \sum_{v \in V} f \cdot z^v + \sum_{i \in Z, j \in Z, v \in V, s \in S : s > 1} c^t Y_{ij}^{vs} +$$

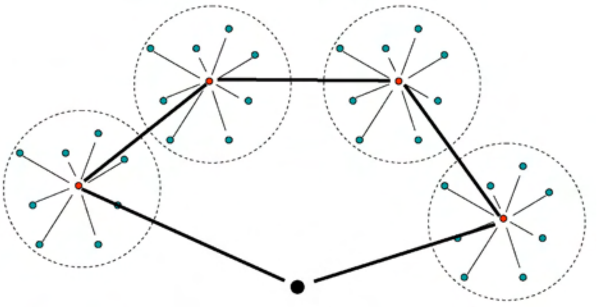


Figure 6.2: Routing with Seeds

$$\sum_{i\in Z, j\in Z, v\in V, s\in S} c^n X_{ij}^{vs} + \sum_{j\in Z, v\in V, s\in S} c^0 X_{0j}^{vs}. \tag{6.7}$$

The first term represents the cost for using vehicles/drivers. We introduce the variable z^v equal to 1 if vehicle v is used and 0 otherwise. This allows for solving the model when the exact number of vehicles required is not known. The second term represents the cost to travel between seeds. The last two sums represent the cost to serve zip codes from seeds and the depot from seeds, respectively. Note that, as in the continuous approximation model, we omit labor costs for the dwell times since they are constant.

The continuous approximation model presented in Section 6.3 evaluates the cost of a *given* time slot schedule. Here, though, the model needs not only to capture the costs, but also needs to define what makes a schedule feasible. To do so, we must include some new parameters:

- r_i: the number of slots that must be open for customer i in a shift, i.e., the service requirement for i,
- t^n: the travel time between customers in the same zip code,
- t^t: a multiplier to convert the distance between zip codes into a travel time between zip codes.

Next, we describe the constraints that define feasible solutions. First, we examine the linkage between the X and Y variables and the x and y variables. For the X variables, the linkage is defined as follows:

$$X_{ij}^{vs} = d_{ij} x_i^{vs} y_j^{vs} \qquad i \in Z, j \in Z, v \in V, s \in S. \tag{6.8}$$

Equation 6.8 sets X_{ij}^{vs} equal to the distance from zip code i to zip code j if zip code i is served in time slot s by vehicle v and zip code j is the associated seed. This quadratic expression can be linearized as:

$$X_{ij}^{vs} \geq d_{ij}(x_i^{vs} + y_j^{vs} - 1) \qquad i \in Z, j \in Z, v \in V, s \in S. \tag{6.9}$$

Equation 6.9 is valid because it forces X_{ij}^{vs} to have nonzero value d_{ij} only if both x_i^{vs} and y_j^{vs} equal 1; otherwise, the right hand side has a value less than or equal to zero. In the same way, we can define the linkage for the Y variables with:

$$Y_{ij}^{vs} \geq d_{ij}(y_i^{vs-1} + y_j^{vs} - 1) \qquad i \in Z, j \in Z, v \in V, s \in S : s > 1 \tag{6.10}$$

Note that Equation 6.10 is only used for $s > 1$ since the cost to travel to the first seed from the depot will be handled by the X variables.

The next set of constraints enforces that every time slot has a seed:

$$\sum_{i \in Z} y_i^{vs} = z^v \qquad v \in V, s \in S, \tag{6.11}$$

Note that enforcing that every time slot has a seed does not create unnecessary travel costs in case a vehicle serves no customers in a time slot, because the seed can be chosen to be the same as the seed of the previous (or subsequent) time slot.

We allow multiple vehicles to visit the same zip code in the same time slot. However, we should circumvent that multiple visits to a particular zip code in the same time slot will be counted towards the zip code's service requirements, which would result in over-counting. Therefore, we introduce binary variable u_i^s representing whether or not a particular time slot s is offered for a particular zip code i and consider the following set of constraints.

$$\sum_{s \in S} u_i^s = r_i \qquad i \in Z$$

and

$$\sum_{v \in V} x_i^{vs} \geq u_i^s \qquad i \in Z, s \in S.$$

Recall that we have assumed that the demand in a zip code is the same in every time slot offered. If multiple vehicles serve a zip code during a particular time slot, then the zip code's demand e_i must be distributed over the different vehicles. Thus, we also introduce variables q_i^{vs} that represents the portion of the demand of zip code i in time slot s that is served by vehicle v. These variables are defined by the sets of constraints

$$\sum_{v \in V} q_i^{vs} \geq e_i u_i^s \qquad i \in Z, s \in S \tag{6.12}$$

and

$$q_i^{vs} \leq \min(e_i, Q) x_i^{vs} \qquad v \in V, i \in Z, s \in S. \tag{6.13}$$

The next set of constraints enforces that the demand served by a single vehicle does not exceed the vehicle capacity Q (equivalent to Constraint 6.2):

$$Q z_v \geq \sum_{i \in Z, s \in S} q_i^{vs} x_i^{vs} \qquad v \in V, \tag{6.14}$$

To properly estimate the routing costs, especially the travel time to and from the depot, we force the depot to be served in the first and last time slot, i.e., time slot 1 and time slot $\bar{s}$:

$$x_0^{v1} = z^v \qquad v \in V, \tag{6.15}$$

$$x_0^{v\hat{s}} = z^v \qquad v \in V. \tag{6.16}$$

Recall from the continuous approximation model that the maximum number of deliveries that a vehicle can make is constrained not only by the vehicle capacity but also by the length of each time slot. Enforcing this time constraint is one of the most complex parts of the integer programming model. The situation is further complicated by the fact that the number and the length of the time slots can vary by day and by shift. Finally, there is a need to distinguish the first time slot, "in between" time slots, and the final time slot.

Let l_1 represent the width of the first time slot, let l_2 represent the width of an "in between" time slot, and let l_3 represent the width of the final slot. Recall that travel from the depot and back to the depot can occur outside of the time windows, so it is does not need to be incorporated within these time window length constraints. Then the constraints to limit the time spent on deliveries during a time slot are:

$$\sum_{i \in Z, j \in Z} t^t X_{ij}^{v1} + \sum_{i \in Z} (\tau e_i + t^n (e_i - 1)) x_i^{v1} + 0.5 \sum_{i \in Z, j \in Z} t^t Y_{ij}^{v2} \leq l_1 \;\; v \in V \tag{6.17}$$

$$0.5 \sum_{i \in Z, j \in Z} t^t Y_{ij}^{vs} + \sum_{i \in Z, j \in Z} t^t X_{ij}^{vs} \tag{6.18}$$

$$+ \sum_{i \in Z} (\tau e_i + t^n (e_i - 1)) x_i^{vs} + 0.5 \sum_{i \in Z, j \in Z} t^t Y_{ij}^{vs+1} \leq l_2 \;\; v \in V \tag{6.19}$$

$$0.5 \sum_{i \in Z, j \in Z} t^t Y_{ij}^{v\hat{s}} + \sum_{i \in Z, j \in Z} t^t X_{ij}^{v\hat{s}} + \sum_{i \in Z} (\tau e_i + t^n (e_i - 1)) x_i^{v\hat{s}} \leq l_3 \;\; v \in V \tag{6.20}$$

Constraint (6.17) concerns the first time slot. The first term captures the travel time to the seed and the travel time between the zip codes visited during the time slot.

The second term in constraint (6.17) captures the stop time at a customer served in a zip code as well as the travel time between customers served in a zip code. The final term in constraint (6.17) captures the travel time from the seed of this time slot to the seed of the next time slot. The 0.5 in the final term reflects the fact that half of this travel time is allocated to this time slot and the other half is allocated to the next time slot. Constraints (6.19) and (6.20) concern the subsequent time slots and are structured similarly.

The situation becomes even more complicated when we consider overlapping time windows. Overlapping windows is a means to provide additional flexibility to both the customer and the firm (see Section 6.5.2). To handle overlapping time windows, we add, in addition to the constraints for each individual time slot, another constraint that assures that the total length of the combined slots is not exceeded. As an example, consider the time slots 8am – 10am and 9am – 11am (referred to below by 1 and 2, respectively) and assume that the 8am – 10am time slot is the first time slot of the shift and that the 9am – 11am time slot is not the last time slot of the shift. Let the total time period covered by the time slots be denoted by l, which is 3 hours in this example. We add the following constraint:

$$\sum_{i \in Z, j \in Z} t^t (X_{ij}^{v1} + X_{ij}^{v2}) + \sum_{i \in Z, j \in Z} t^t (Y_{ij}^{v1} + 0.5\, Y_{ij}^{v2}) +$$

$$\sum_{i \in Z} (\tau e_i + t^t (e_i - 1)) x_i^{v1} + \sum_{i \in Z} (\tau e_i + t^t (e_i - 1)) x_i^{v2} \leq l.$$

Lastly, we add symmetry breaking constraints. These constraints are not necessary for the correctness of the model, but help the integer programming solver find better solutions faster. The symmetry breaking constraints force the lower indexed vehicles to be the ones with the largest number of stops:

$$\sum_{i \in Z, s \in S} x_i^{vs} \leq \sum_{i \in Z, s \in S} x_i^{v-1s} \quad v \in V : v > 1. \tag{6.21}$$

Finally, we again add constraints to reduce the symmetry in the model, which should help reduce solution times. When only a subset of the vehicles is used, there are many equivalent solutions. By imposing

$$z^v \leq z^{v-1} \qquad v \in V : v > 1,$$

the number of equivalent solutions is significantly reduced.

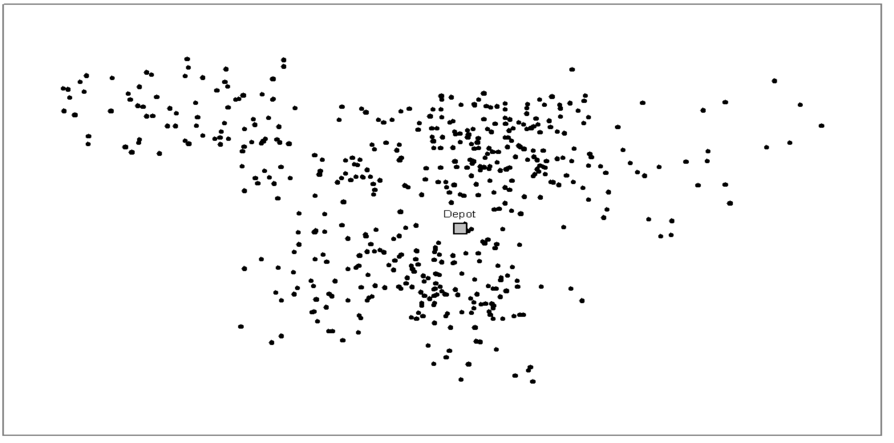


Figure 6.3: Geographical Distribution in Nijmegen Region

6.5 Computational Experiments

In this section, we report on the results of a computational study to evaluate the performance of the proposed models and to analyze the impact of various characteristics of the environment on their performance. Recall that the TSMP is a tactical planning problem with an embedded routing problem on the operational level. We evaluate alternative time slot schedules through simulation. To this end, we generate multiple demand realizations for each schedule and determine the corresponding detailed routing costs using a commercial routing package. To evaluate the impact of characteristics of the environment on the time slot schedules, we vary individual characteristics and analyze the results.

For our study, we use real-life data from Albert.nl. Specifically, we focus on the Nijmegen region, a subset of the service area of Albert.nl consisting of 30 3-digit zip codes with varying demand densities and covering a total area of approximately 1000 km^2. Figure 6.3 shows the geographic distribution of demand in the region. The area is served through a delivery hub in the city of Nijmegen. We consider a typical morning shift and a typical afternoon shift, because they differ in terms of total length, number of time slots, and time slot overlap (see Figure 6.4).

Furthermore, we use the current service requirements at Albert.nl for the Monday morning and the Tuesday afternoon. (We also performed simulations for other weekdays and obtained similar results.) The employed service requirements imply that in the morning schedule 24 zip codes have to receive 1 time slot, 3 zip codes

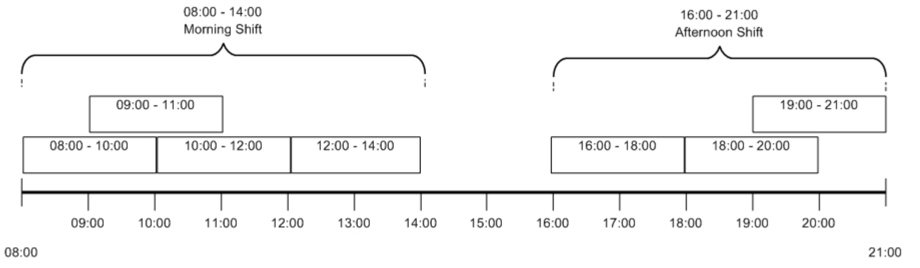


Figure 6.4: Albert.nl Time Slots

have to receive 3 time slots, and 3 zip codes do not receive any time slot. In the afternoon schedule, 25 zip codes have to receive 1 time slot and 5 zip codes have to receive 2 time slots.

In our experiments we evaluate the following time slot schedules:

- CA: The schedule produced by the continuous approximation approach;
- IP: The schedule produced by the integer programming approach;
- ALBERT: The schedule that is currently in place at Albert.nl;
- ALL: The schedule in which all time slots are made available in all zip-codes where Albert.nl currently offers at least one time slot;
- NO-SLOT: The schedule in which a single time slot spanning the entire shift is made available in all zip-codes where Albert.nl currently offers at least one time slot.

The schedules ALL and NO-SLOT are included to provide bounds on the performance and to provide insights into the cost-service trade-off. Note that these two schedules do not use the service requirements of Albert.nl. Instead, the schedule ALL offers the highest level of customer service, and the schedule NO-SLOT offers the lowest level of customer service. The service levels will be reflected in the delivery costs, so the NO-SLOT schedule serves as a lower bound, albeit a weak lower bound, and the ALL schedule serves as an upper bound.

We supplement the comparison outlined above with values derived from the simulation results of a few randomly generated feasible time slot schedules. More precisely, we randomly generate 5 feasible time slot schedules, perform a simulation for each of them, and average the statistics obtained from the simulation runs. In our results tables, the resulting values will be labeled with RAND-ASGN.

For each problem instance, we generate 20 random demand instances for our simulations as follows. We start with a list of 448 customer addresses in the Nijmegen area. For each demand instance, we randomly select a number of addresses from this list for each zip code, based on the expected number of orders per time slot in that zip code. Specifically, we decide randomly and independently for each address whether or not to select it. We set the probability of selection of an address equal to the ratio between the expected number of orders in the zip code to which that address belongs and the total number of addresses in that zip code. Therefore, the total number of orders varies across demand realizations, with an average equal to the number of orders that was used as input to the optimization models.

For 20 different streams of random numbers, this results in 20 different random sets of addresses. We use the same sets for each schedule, in order to reduce variability across schedules to obtain more comparable results. Using this approach, demand realizations for different time slot schedules differ only in terms of the time slots associated with each order. For example, if time slot schedule CA has slots 2 and 4 open and time slot schedule IP has slots 3 and 4 open, then the same customer addresses have to be visited in slots 2 (CA) and 3 (IP) and in slots 4 (CA) and 4 (IP). For the ALL schedules, we determine the time slot associated with an order by means of a uniform random draw. For the NO-SLOT schedule, all orders are associated with a single time slot spanning the entire shift.

The continuous approximation model is implemented in Excel with the heuristic implemented in VBA. The time slot schedules were produced on an Intel Pentium M 1.6GHz machine. The heuristic takes about 2 minutes to converge. The integer programming model is implemented in AMPL with CPLEX 9.0 as the solver. The time slot schedules were produced on an Intel Pentium D CPU 3.20GHz (x2) machine. A limit of 8 hours of CPU time was imposed. The limit was always reached without proving optimality. We used Shortec version 7.3.2.1, the routing tool from ORTEC (www.ortec.com), to construct the delivery routes and determine associated costs for each demand realization. Simulation experiments were run on an Intel Xeon 3.0 GHz machine and take approximately 25 minutes of computing time for 20 demand realizations of a time slot schedule.

6.5.1 Model Comparison

The first set of experiments is aimed at assessing differences in performance, if any, of the different time slot schedules. We compute the following statistics to compare the different time slots schedules: the average cost, the average number of vehicles used, the average distance, and the average total time (where the averages are taken over the 20 demand realizations). For convenience, we also display the percentage cost savings relative to ALL. For confidentiality, the cost figures are normalized by setting the cost for ALL for the morning shift to 100.

The results of the simulation experiments can be found in Tables 6.2 and 6.3. We observe that the gap between the upper bound (ALL) and the lower bound

Table 6.2: Schedule Comparison - Morning

	# veh.	time	distance	cost	% savings
ALL	5.3	1399	443	100	-
RAND-ASG	4.8	1348	408	94	-5.6%
ALBERT	4.5	1361	384	92	-7.5%
CA	4.3	1328	377	90	-9.9%
IP	4.6	1310	393	91	-8.9%
NO-SLOTS	3.9	1210	329	82	-18.4%

Table 6.3: Schedule Comparison - Afternoon

	# veh.	time	distance	cost	% savings
ALL	5.4	1352	444	98	-
RAND-ASG	5.1	1310	417	94	-4.3%
ALBERT	4.6	1266	400	89	-8.9%
CA	4.5	1277	385	89	-9.5%
IP	4.6	1260	386	89	-9.6%
NO-SLOTS	3.9	1171	329	80	-19.0%

(NO-SLOTS) in terms of average cost is substantial. The absence of time slots in NO-SLOTS allows for more cost-effective delivery routes, but of course is inconvenient for the customers as they have to be home during the entire morning or afternoon. This illustrates the core trade-off between service and delivery cost, and is in line with the results of Punakivi and Saranen (2001) and Lin and Mahmassani (2002). Time slot schedules provide a means for managing this trade-off by concentrating demand while still providing acceptable service levels.

Next, we observe that the morning and afternoon schedules currently in place at Albert.nl (ALBERT) are improved by both CA and IP, but that the savings are moderate. Albert's current schedule seems to perform quite well. We also see that randomly constructed time slot schedules (RAND-ASGN) already yield a noticeable improvement over simply offering all time slots (ALL), but do not achieve the quality of Albert.nl's current time slot schedule and that of the time slot schedules produced by our optimization models. We also observe, not surprisingly, that the average number of vehicles required in NO-SLOT is less than the average number of vehicles required by the optimized schedules, which in turn is less than the average number of vehicles required by ALL (and RAND-ASGN). This again reflects the trade-off between efficiency and service.

In addition to comparing performance differences, it is interesting to compare the actual time slot schedules. Figures 6.5(a) and 6.5(b) show the afternoon time slot schedules produced by the continuous approximation model and the integer programming model, respectively. For each zip code, the figure shows the assigned time slot(s). We use the size of the circle to reflect the number of expected orders for the zip code.

We observe that the distinct modeling paradigms of the CA and the IP approach are reflected in different characteristics of the resulting schedules. In Figure 6.5(a), we see that the continuous approximation model assigns the same time slot to zip codes that are geographically clustered together. This is especially the case for the zip codes that receive the late afternoon 7pm – 9pm time slot. In contrast, we see in Figure 6.5(b) that the integer programming model does not necessarily clusters geographically close zip codes, but forms "vehicle routes." A possible explanation for the observed behavior is the fact that the continuous approximation approach aims to increase the demand density within a time slot for each zip code. Therefore, it tends to construct large zip code clusters for each time slot. Because the integer programming model explicitly considers the individual vehicle routes, it is more concerned with the zip code groups that can be visited by individual vehicles over the entire time period. From an application perspective, there does not appear to be a reason for either of these schedules to be preferable.

We conclude from the above experiments that our models achieve our main objective, namely supporting the design of effective time slot schedules in real-life scenarios. By automating the generation of time slot schedules the models significantly reduce the planning effort compared to the current practice of manual planning. Thereby, they allow what-if analysis of different scenarios. In what follows, we address some of these scenarios and discuss the insights that they yield.

6.5.2 Changes in the Environment

As the e-grocery channel is still a relatively new distribution channel, understanding the impact of characteristics of the environment on its performance is of enormous value to companies experimenting with it. Therefore, the second part of our computational study focuses on these issues. All of the percentage differences reported are relative to the costs found in Tables 6.2 and 6.3 for the same schedule type.

Demand

The e-grocery market is experiencing huge annual growth rates. Therefore, it is interesting to study the impact of an increase in demand on the resulting time slot schedules and their performance. We consider a scenario in which the service requirements remain unchanged, but every zip code is experiencing a 30% increase in demand. The results can be found in Tables 6.4 and 6.5. (We omit time slot schedule ALBERT from these and further experiments as it was not designed for these environments.)

Table 6.4: Demand Increase - Morning

	# veh.	time	distance	cost	Δcost
ALL	6.6	1734	522	123	23.00 %
RAND-ASG	5.9	1677	485	116	23.40 %
CA	5.5	1618	451	110	22.22 %
IP	5.8	1664	465	114	25.27 %
NO-SLOTS	5.0	1511	386	101	23.17 %

Table 6.5: Demand Increase - Afternoon

	# veh.	time	distance	cost	Δcost
ALL	6.7	1665	519	120	22.45%
RAND-ASG	6.2	1607	485	114	21.28%
CA	5.9	1570	467	110	23.60%
IP	6.0	1574	462	111	24.72%
NO-SLOTS	4.8	1459	386	98	22.50%

We observe a cost increase of a little over 20% for a demand increase of 30%, which demonstrates, as expected, that there are economies of scale. This supports the importance of growth in order for a company to become more profitable.

Vehicle Capacity

An important consideration when setting up any delivery operation is the vehicle fleet and mix. As Albert.nl wants to operate a homogeneous fleet of vehicles, we focus on the impact of vehicle capacity. We consider two scenarios. One in which larger vehicles are used, i.e., the vehicle capacity is increased by 25%, and one in which smaller vehicles are used, i.e., the vehicle capacity is decreased by 25%. The results can be found in Tables 6.6 and 6.7.

Table 6.6: Vehicle Capacity Change - Morning

		# veh.	time	distance	cost	Δcost
-25%	ALL	5.7	1433.4	456	103	3.00%
	RAND-ASG	5.4	1402.1	433	100	6.38%
	CA	5.3	1414.8	414	99	10.00%
	IP	5.3	1435.3	428	101	10.99%
	NO-SLOTS	5.2	1282.4	370	91	10.98%
+25%	ALL	5.3	1394.9	440	100	0.00%
	RAND-ASG	4.7	1342.1	407	94	0.00%
	CA	4.1	1287.6	371	87	-3.33%
	IP	4.5	1328.5	394	91	0.00%
	NO-SLOTS	3.5	1183.7	311	78	-4.88%

Table 6.7: Vehicle Capacity Change - Afternoon

		# veh.	time	distance	cost	Δcost
-25%	ALL	5.5	1355	444	99	1.02%
	RAND-ASG	5.3	1329	428	96	2.13%
	CA	4.9	1319	418	94	5.62%
	IP	5.1	1324	416	95	6.74%
	NO-SLOTS	4.7	1220	361	86	7.50%
+25%	ALL	5.4	1344	437	97	-1.02%
	RAND-ASG	5.0	1303	412	93	-1.06%
	CA	4.5	1271	401	89	0.00%
	IP	4.7	1256	383	89	0.00%
	NO-SLOTS	3.8	1165	327	79	-1.25%

Not surprisingly, a capacity reduction results in a cost increase whereas a capacity expansion results in a cost decrease. What is interesting, however, is that the cost penalty of a capacity reduction is much stronger than the cost benefit of additional capacity. This suggests a decreasing marginal value of capacity. To understand this, note that the physical vehicle capacity is only one of the factors that limits the number of orders that a vehicle can deliver. In particular, recall from our models that time constraints, based on the length of a time slot and of a shift, form another constraining factor. The above results suggest that these time constraints become more relevant with increasing vehicle capacity.

The extent to which vehicle capacity is binding depends on the shift and on the service level. The optimization-based time slot schedules and the NO-SLOT time slot schedule appear to be more sensitive to capacity changes because they can better exploit capacity, thus achieving a higher utilization. Moreover, the morning shift seems to be more sensitive to a reduction in vehicle capacity (10% versus 7%), most likely because it covers a period of 6 hours, as compared to 5 hours in the afternoon, whereby time constraints are less tight.

Service Level

A key challenge for e-grocers is to find a proper trade-off between service level and delivery costs. A higher service level typically comes at the expense of higher delivery costs. We clearly see this when comparing the simulations results for the NO-SLOTS schedules with those for the schedules that use the service requirements of Albert.nl and with those of the ALL slots schedules. We now investigate this issue further by varying the imposed service requirements.

We consider two scenarios. In the first, we increase the required service level by offering more time slots, more specifically by offering one additional time slot in each zip code except in those zip codes where all time slots are already offered. In the second, we reduce the service level by offering fewer time slots, more specifically by offering one fewer time slot in each zip code except in those zip codes where only a single time slot is currently offered. Note that in the latter scenario, the changes are minor as most zip codes require only a single time slot to be offered in the base case.

Note also that these changes do not affect the ALL and NO-SLOT schedules since they do not use the service requirements. We only recall their performance as a point of reference. The results can be found in Tables 6.8 and 6.9.

As expected, the impact on cost of increasing the service level is much higher than the impact of reducing the service level, as far fewer changes were made to the service level requirements. What may be more surprising is that for the morning shift a reduction of the service level actually leads to a cost increase! This seems counterintuitive, because one would expect to gain operational efficiency from a decrease in customer service. However, we have to realize that we only reduced the number of time slots offered in zip codes in which we used to offer more than one time slot. These zip codes tend to be urban areas with a relatively high demand density. A reduction in the number of time slots offered forces demand to be concentrated in fewer time slots, which results in a less balanced workload and thereby in a lower

Table 6.8: Service Level Adjustments - Morning

		# veh.	time	distance	cost	Δcost
reduce service	ALL	5.3	1399	443	100	0.00%
	RAND-ASG	4.9	1376	412	96	2.13%
	CA	4.4	1325	387	91	1.11%
	IP	4.5	1341	402	92	1.10%
	NO-SLOTS	3.9	1210	329	82	0.00%
increase service	ALL	5.3	1399	443	100	0.00%
	RAND-ASG	5.0	1418	425	99	5.32%
	CA	5.1	1384	416	97	7.78%
	IP	4.9	1434	432	99	8.79%
	NO-SLOTS	3.9	1210	329	82	0.00%

Table 6.9: Service Level Adjustments - Afternoon

		# veh.	time	distance	cost	Δcost
reduce service	ALL	5.4	1352	444	98	0.00%
	RAND-ASG	5.1	1318	412	94	0.00%
	CA	4.5	1265	397	89	0.00%
	IP	4.5	1274	387	89	0.00%
	NO-SLOTS	3.9	1171	329	80	0.00%
increase service	ALL	5.4	1352	444	98	0.00%
	RAND-ASG	5.1	1385	439	98	4.26%
	CA	5.0	1385	443	98	10.11%
	IP	5.1	1342	412	95	6.74%
	NO-SLOTS	3.9	1171	329	80	0.00%

capacity utilization.

This example highlights two opposing effects. Capacity utilization benefits from a well-balanced workload and therefore from spreading demand over multiple time slots. On the other hand, however, the distance between customers decreases when clustering demand in fewer slots. The interplay between both of these effects results in complex trade-offs, which are very hard to make without any analytical support tools.

In both the morning and afternoon shifts, we do see increases in cost associated with improving the service level. This is not surprising, but shows a valuable aspect of developing such models. They reveal the cost associated with such changes, so companies can make better decisions with regard to deciding the level of service to offer to their customers.

Time Slot Template

The set of time slots that may be offered, known as the time slot template, has overlapping time slots in both shifts (see Figure 6.4). A time slot template with overlapping time slots may be attractive for both the delivery company and the customer. Overlapping slots provide more routing flexibility to the company than shorter non-overlapping slots. At the same time, they provide a higher service to the customer than a single overall slot. Note that from a modeling perspective the overlap is challenging.

We investigate the impact of overlapping time slots by analyzing alternative time slot templates. We consider two such time slot templates. The first uses time slots with smaller widths that do not overlap, i.e., 8am – 9:20pm, 9:20am – 10:40am, 10:40am – 12noon, 12noon – 2pm for the morning and 4pm – 6pm, 6pm – 7:30pm, 7:30pm – 9pm for the afternoon. The second uses different overlapping 2-hour time slots, i.e. 8am – 10am, 9:30am – 11:30am, 11am – 1pm, 12noon – 2pm for the morning and 4pm – 6pm, 5:30pm – 7:30pm, 7pm – 9pm for the afternoon. The results for these different time slot templates can be found in Tables 6.10 and 6.11. Note that the different templates do not affect the NO-SLOTS scenario, which is just reported as a benchmark.

Table 6.10: Time Slot Template Changes - Morning

		# veh.	time	distance	cost	
no overlap	ALL	5.7	1469	480	106	6.00%
	RAND-ASG	5.2	1434	446	101	7.45%
	CA	4.5	1430	401	96	6.67%
	IP	4.6	1394	416	96	5.49%
	NO-SLOTS	4.0	1218	330	82	0.00%
alternative overlap	ALL	5.1	1391	435	98	-2.00 %
	RAND-ASG	4.7	1353	409	94	0.00%
	CA	4.4	1325	391	91	1.11%
	IP	4.7	1350	408	94	3.30%
	NO-SLOTS	4.0	1218	330	82	0.00%

As expected, we see that the use of non-overlapping time slots with smaller widths translates in increased costs, especially in the morning shift. The results for the alternative overlap template are less conclusive. In general, the cost effects appear to be smaller than for removing the overlap. Note that the total amount of overlap, the number of hours which fall into more than one slot, is the same as in the original templates, however distributed differently.

Table 6.11: Time Slot Template Changes - Afternoon

		# veh.	time	distance	cost	
no overlap	ALL	6.0	1391	467	103	5.10%
	RAND-ASG	5.3	1339	434	97	3.19%
	CA	4.7	1302	406	92	3.37%
	IP	4.8	1291	403	92	3.37%
	NO-SLOTS	3.9	1171	329	80	0.00%
alternative overlap	ALL	5.4	1351	440	98	0.00%
	RAND-ASG	4.8	1293	407	92	-2.13%
	CA	4.8	1270	403	90	1.12%
	IP	4.6	1279	399	90	1.12%
	NO-SLOTS	3.9	1171	329	80	0.00%

The overlap was a difficult issue in terms of modeling for both CA and IP. The continuous approximation model heuristically adjusts the individual time slot lengths based on the order volumes and virtually removes the overlap. Conceptually, the IP model deals with the issue in a more accurate way by taking into account the exact timing of a zip code delivery. However, this comes at the cost of an increased problem size and it introduces symmetry in the model. But, we see that the overlap does translate to lower cost solutions, so it is important to consider it.

Profit maximization

All of the experiments so far have focused entirely on cost. However, Albert.nl charges for deliveries and the delivery fees vary for the different time slots. The delivery fees charged by Albert.nl for the time slots in the Monday morning shift are €7.95, €7.95, €6.95, and €5.95, and for the time slots in the Tuesday afternoon shift are €4.95, €6.95, and €6.95. Delivery fees are an important demand management mechanism for home delivery services. Differentiated delivery fees can counterbalance popularity differences between time slots and smoothen demand over the time slots. This is vital to effectively utilize the delivery vehicles during a shift and the warehouse capacity during the week. At the same time, the delivery fees directly contribute to the company's bottom line.

It is not difficult to incorporate delivery fees into our optimization models. The reason why we have not done so in our computational experiments up to now is that the available service constraints were not designed to account for differences in delivery fees. Incorporating delivery fees into the optimization models may lead to fewer zip codes receiving the lower priced time slots, which may be undesirable from a marketing perspective. This would call for defining different service requirements. While the interaction between pricing and slotting is certainly a relevant issue for future research, it surpasses the scope of this study.

In order to gain some initial insight into the potential of such a broader demand management approach, we simulated a profit maximization version of our model. To this end, we included the delivery fees plus the average product margin per order into the objective function.

The results can be found in Tables 6.12 and 6.13. We normalized the profit figures by setting the profit of ALL in the morning case to 100. For all schedules we report the relative profit increase compared to ALL. For the optimization based schedules we also report the relative profit increase compared to the cost-minimization version. As the routing software used in our simulation experiments does not allow for profit maximization, we do not present a NO-SLOTS lower bound here.

Table 6.12: Profit Maximization - Morning

	# veh.	time	distance	profit	Δprofit ALL	Δprofit cost min.
ALL	5.3	1399	443	100		
RAND-ASG	4.8	1348	408	115	15%	
ALBERT	4.5	1370	390	112	12%	
CA	4.3	1298	376	131	31%	5%
IP	4.6	1340	400	120	20%	6%

Table 6.13: Profit Maximization - Afternoon

	# veh.	time	distance	profit	Δprofit ALL	Δprofit cost min.
ALL	5.4	1352	444	55		
RAND-ASG	5.1	1310	417	64	17%	
ALBERT	4.6	1266	400	72	31%	
CA	4.5	1251	393	76	37%	4%
IP	4.7	1254	392	79	43%	6%

We observe that the relative profit differences between the solutions are larger than the cost differences in the original scenarios. This is partly due to the fact that the absolute profit figures are smaller than the absolute cost figures. In addition, however, the relatively large differences of up to €2 between the delivery fees create additional room for optimization, which is exploited by the CA and IP methods.

When we compare profit maximization and cost minimization we observe profit increases of around 5%. In the corresponding solutions, we observe a shift of demand (i.e. open zip codes) to time slots with the higher delivery fees. Figures 6.5 and 6.6 illustrate this affect by displaying the expected demand per time during the shift for the different schedules. (Overlapping slots are grouped together.) The differentiated delivery fees introduce another factor in the trade-off between demand smoothing and clustering. Clustering demand now potentially yields the additional benefit of higher revenues from delivery fees. This comes at the expense of a lower capacity utilization and thus potentially more required vehicles. In the morning shift we observe profit improvements without an increase in the number of required vehicles. This may relate to the longer shift length which make time less of a constraining factor. For the afternoon, we observe that the slightly increased number of vehicles in the IP solution is offset by the higher delivery fee revenues.

However, the above comments regarding the validity of our model for the profit maximizing case should be taken into account when interpreting these results. We therefore recommend a broader analysis of appropriate service requirements as an area for future research.

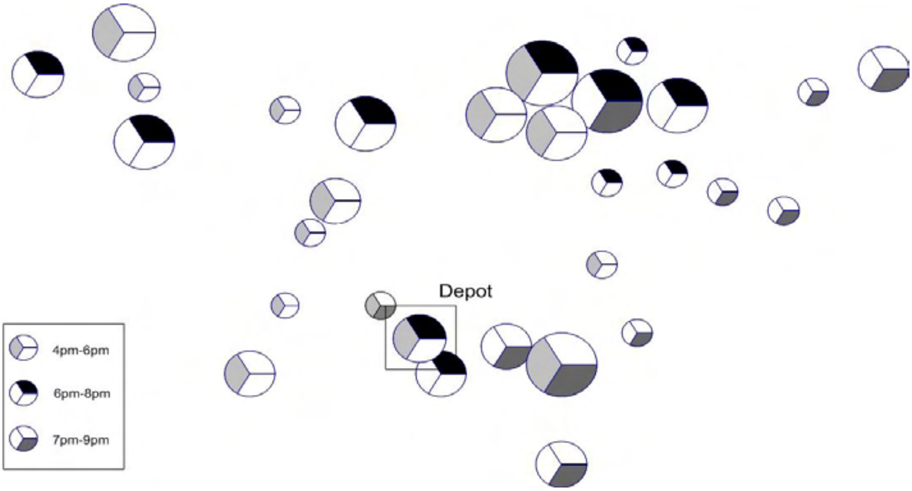
6.6 Conclusions

In this chapter, we introduce the time slot management problem (TSMP), a novel tactical planning problem which is relevant to many businesses that offer attended home delivery, especially e-grocery. The problem entails the decision of which time slots to offer in each zip code so as to minimize expected delivery costs. The use of time slots gives rise to complex interactions between marketing and operational considerations and requires sophisticated decision support tools.

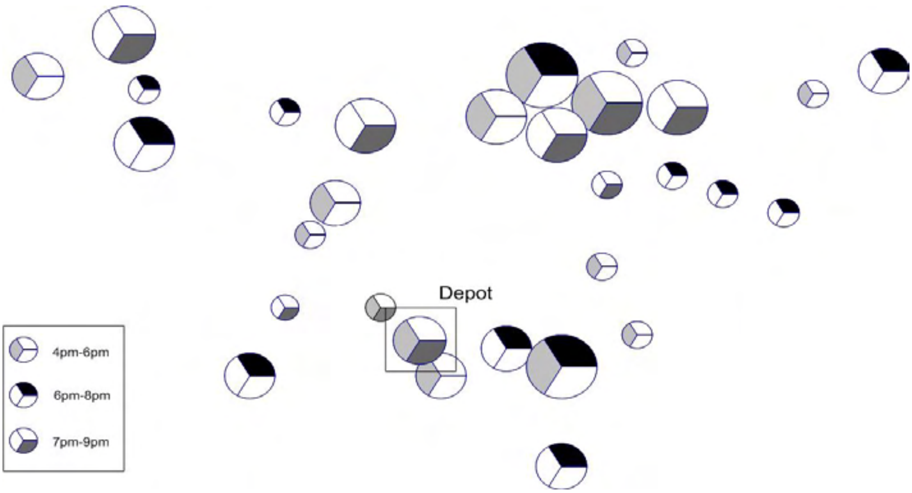
This chapter presents two fully-automated approaches that are capable of producing high-quality solutions within a reasonable amount of time. The two approaches model the vehicle routing component of the TSMP in different ways. The IP approach explicitly models the vehicle routing decisions, while the continuous approximation approach estimates route costs per zip code based on "local" information. Our numerical results indicate that using service requirements together with our optimization methods yield substantial savings over simply offering all time slots.

Several complex interactions govern the time slot schedule design, such as the trade-off between demand clustering and demand smoothing. The advantage of demand clustering is that it minimizes the distances between successive stops, and thus travel costs. The disadvantage is the potential underutilization of the vehicle capacity, and a corresponding increase in vehicle costs. Our numerical experiments suggest that the time slot limits and the vehicle restrictions are critical components in this trade-off.

There remain several interesting directions for future research. We see the joint optimization of the service requirements and the time slot schedule as one of the most challenging. This will not only require a more complete understanding of customer behavior, but also more sophisticated solution approaches.



(a) Afternoon Solution CA



(b) Afternoon Solution IP

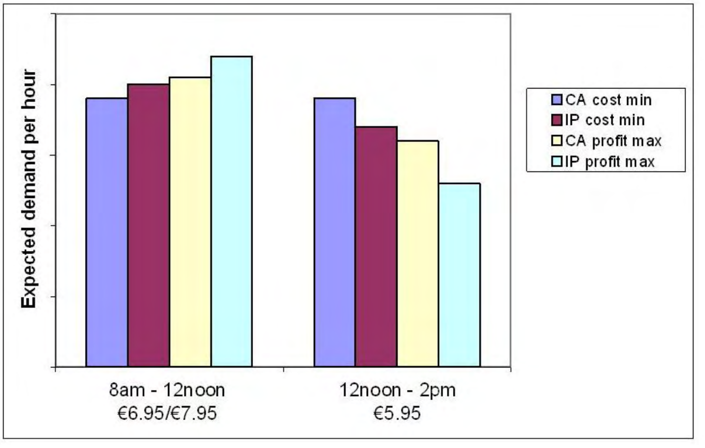


Figure 6.5: Demand Profile Morning

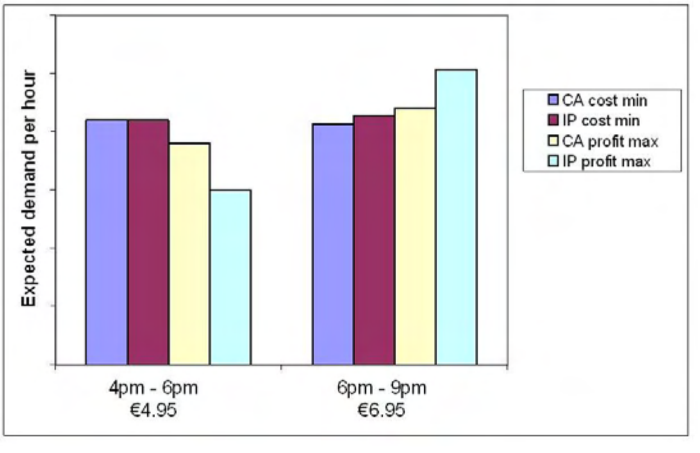


Figure 6.6: Demand Profile Afternoon

Chapter 7

Dynamic Time Slot Management for E-fulfillment

In the framework in Chapter 4 we presented two distinct points in time to make the slotting decisions, one static, prior to the actual order-intake, one dynamically in real-time. In the previous chapter we focussed on the static case and determined the set of time slots to offer in each zip code, based on demand forecasts. In this chapter, we address dynamic time slot management, which uses the real-time information on already accepted demand together with the demand-forecasts. This is especially beneficial in case it is difficult to come up with accurate demand-forecasts. We present different policies to manage the time slot dynamically and compare their performance for different characteristics of the environment.

The remainder of the chapter is organized as follows. In Section 7.1 we introduce the problem. In Section 7.2, we outline our conceptual modeling framework. In Sections 7.3 we present our different slotting heuristics. In Section 7.4, we describe the design of our computational experiments and present the results. Finally, in Section 7.5, we summarize our main insights and discuss directions for future research.

7.1 Introduction

The key lesson from revenue management is that a company should try to use its scarce capacity for its most valuable customers. Instead of accepting demand first-come, first-serve until capacity is depleted, it may be wise to reserve capacity for a more valuable future customer. In traditional revenue management, marginal costs are negligible and the value of a customer is typically represented in terms of willingness-to-pay. The Internet retailers also serves a heterogenous market in which the value of different customers can vary in several ways. First of all, the willingness-to-pay for home-delivery may vary for different customer segments. For example, time-starved double income families may be willing to pay more for the convenience of not having to go out to shop than elderly people. Second, the sales revenues of the physical products may differ per order, either because of varying product margins or differences in order size. Third, the cost of delivery may differ considerably per customer, e.g. because of the distance to the warehouse, or because of the distance to already accepted orders. Marketing literature suggests that companies should not only consider the value of the current purchase but also take note of the potential future benefit of a customer to the firm (Borle et al., 2008). The Internet retailer may, for example, reserve its scarce delivery capacity around the busy Christmas period for its most loyal customers. What is more, the value of customers may also differ in terms of non-financial criteria. The Internet retailer could, for instance, prioritize service to physically disabled people.

In this chapter, we primarily focus on exploiting customers heterogeneity in terms of delivery costs. Therefore, we segment customers by 3-digit zip code. In particular, we address the following dynamic time slot management problem (DTSMP). Given the already accepted demand, expected future demand and the set of possible time slots for each zip code, determine the subset of time slots to offer a customer at login, so as to maximize the expected profit. The set of possible time slots for each zip code consists of the weekly slots which are determined in the static schedule. That way, demand for the relatively far away regions with relatively low expected demand is already clustered together in a few slots. To follow such an hierarchical approach to the slotting decisions may be preferable over exclusively dynamically scheduling slots for two reasons. First, completely dynamic schedules create more variety in the offering over time. This may be undesirable from a marketing perspective because the customer never knows what to expect. Second, the e-tailer makes the time slot decisions when the customer logs in on the website, which means the amount of available time is small, seconds rather than minutes. To manage many time slots solely in real-time may be computationally infeasible given this time constraint.

7.2 Conceptual Model

For the reader's convenience, we recall the typical process of order placement in e-grocery (see Chapter 2):

1. The customer logs in on the retailer's web-site. At this point, the customer's address and transaction history is known but his current time slot preference is often not available to the e-tailer;

2. The e-tailer has to decide on the set of time slots to offer to this customer;

3. The customer then either selects a time slot for delivery or elects to leave without a purchase;

4. After the cut-off point, the delivery routes are constructed for the set of accepted orders.

We particularly address the dynamic time slot management problem of the Internet retailer. Campbell and Savelsbergh (2005a) study this problem in a setting where a profile of acceptable slots is available for each customer at login. We extend this work by considering a situation where the retailer does not have this kind of information. This is often the case in practice since in e-grocery many customers are new to the firm. Moreover, marketing literature suggests that customer preferences can vary in different situations even for the same customer. However, the e-tailer has to anticipate customer behavior in its dynamic slotting decisions. This gives rise to two different models for customer behavior, one to simulate the actual customer behavior and one used by the e-tailer to evaluate the impact of different slotting decisions (see Figure 7.1). Note that if the e-tailer knows the actual customer response upfront, these two models of customer behavior coincide.

7.2.1 Dynamic Time Slot Management

We decompose the problem by slot. The fundamental demand management question is whether or not to make a certain slot available to a particular customer at login. The question relates to the expected benefit of opening versus closing the slot. The slot should only be offered if the expected benefit of offering it is equal to or exceeds the benefit of not offering it. Note that the e-tailer does not *explicitly* accept or reject a new request for delivery, but only *implicitly* does so by its time slot offering. The customer is accepted in any of the offered time slots he selects. However, because we do not know a customer's desired time slot at login, we model the time slot decision

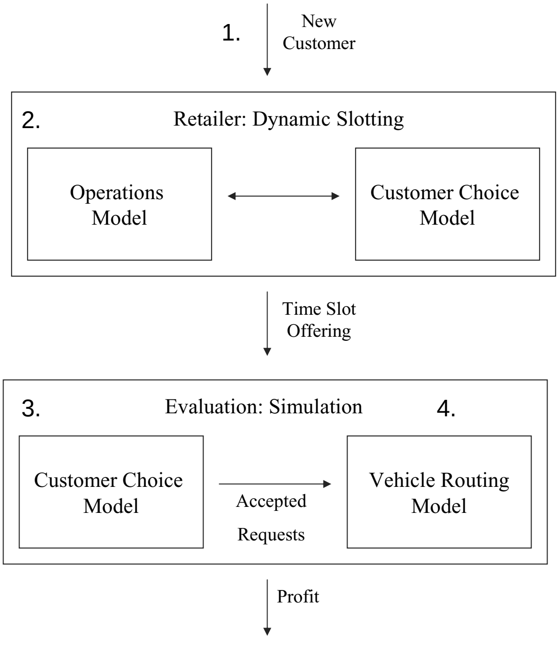


Figure 7.1: Conceptual Model

like an accept-reject decision for each individual slot. Suppose we have x units of capacity remaining and receive a customer from zip code i. If we offer time slot s, we collect a profit of W_i^s (revenues r_i and costs c_i^s). If we do not offer time slot s, we may sell capacity x to a different customer from zip code j with contribution W_j^s, but only if the demand D_s for slot s is x or higher. Thus, we should only offer time slot s in zip code i if:

$$W_i^s \geq p[D_s \geq x] W_j^s \tag{7.1}$$

Besides differences in profitability between customers, the costs of serving a particular customer may differ per time slot, given the already accepted demand. Chapter 5 suggests that customers are often willing to switch to a substitute slot in case their preferred slot is not offered. In contrast with traditional demand assumptions in revenue management, the customer is not necessarily lost if his most preferred choice is not available. This implies that we need to incorporate this switching behavior in our demand management rule. Suppose we know the potential substitution slot q which has $\bar{x}$ units of capacity remaining. If we do not offer time slot s, the customer from zip code i will switch to a substitute slot q with probability δ, and then collect a net profit of $W_i^q - p[D_q \geq \bar{x}]W_j^q$ (the expected profit - opportunity costs). This means it is optimal to offer time slot s in zip code i if:

$$W_i^s - p[D_s \geq x]W_j^s \geq \delta(W_i^q - p[D_q \geq \bar{x}]W_j^q) \tag{7.2}$$

In case the expected demand is equal to the expected delivery capacity in each slot, the opportunity costs are approximately the same in each time slot, which means we can write 7.2 as:

$$W_i^s \geq \delta W_i^q + (1-\delta)p[D_s \geq x]W_j^s \tag{7.3}$$

Note that the assessment of the remaining available delivery capacity x is not trivial as the effective available capacity involves the picking capacity in the warehouse, physical fleet size, and available driving time. The latter depends on the assignment of customers to delivery routes, which thereby links this capacity check to the underlying vehicle routing decisions. To evaluate whether it is possible to accommodate an additional delivery request requires finding a feasible set of routes for the already accepted orders and the new request for delivery, which is NP-complete (Savelsbergh, 1986).

7.2.2 Evaluation model

Once the Internet retailer has set the time slots, the customer makes his purchase decision. At login, each individual customer has preference set, defined as a sequence of time slots that he is willing to select, arranged in decreasing order of preference. This preference set is independent of the slotting decisions of the e-tailer. This is a standard way to model customer choice in assortment planning (see e.g. Honhon et al. (2008), Kök and Fisher (2007). The preference set for a particular customer consist of a subset of the possible weekly time slots in the static time slot schedule. This implies we do not consider assortment-based substitution. The number of acceptable time slot choices differs per customer but each customer has at least one acceptable slot. For example, a customer with preference set (1,2), prefers slot 1 but is willing to switch to slot 2 in case slot 1 is not available. If both slots are not available, the customer elects to leave without a purchase.

To simulate the preference set, we first generate the most preferred time slot for each customer. Each subsequent slot is a substitute slot with probability δ, where δ is the same for each following slot. The probability that the subsequent slot is not a substitute slot is probability 1-δ. Therefore, the expected number of acceptable time slots is then a geometric distribution with mean $\frac{\delta}{1-\delta} + 1$.

Although Chapter 5 provides insights into the expected substitution rate δ, unfortunately we do not have any detailed information on the specific substitution preferences of the individual customers. Therefore, we use the well known location choice approach to model the substitution preferences of the customer (Gaur and Horthon, 2006). This model represents products as bundles of attributes and assumes customers substitute to products closest to their first choice in terms of its attribute characteristics. In particular, we assume that the customer wants to stay as close as possible to his first preference in terms of *timing* and only considers time slots further in the future. That is, the substitution slot is always the next possible time slot in the static time slot schedule. For example, the preference set of a customer with slot 4 as his first choice may be (4,5,6).

After the cut-off point, when all accepted orders for a given dynamic time slot policy are known, we use an insertion heuristic to solve the Vehicle Routing Problem with Time Windows. See Campbell and Savelsbergh (2004) for more information on insertion heuristics for solving the vehicle routing problem. To further improve the reliability of the simulation, we implement a greedy randomized adaptive search procedure (GRASP) (Kontoravdis and Bard, 1995). This means that we randomly pick the order to be inserted next from the top l orders in terms of insertion criterion. Using $l = 2$, we construct 4 different routing schedules and store the one with the lowest costs. In case we cannot find a feasible solution in any of the 4 instances, we increase the number of delivery vehicles for this shift, incur a penalty cost that is equal to 10 times the expected revenues per order, and repeat the procedure.

7.3 Dynamic Slotting Heuristics

In the previous section, we presented the main building blocks of the dynamic time slot management model. Yet, before we can actually use the model, we first need to estimate the following factors in equation 7.2,

1. the profit (W_i^s) of serving zip code i in slot s;
2. the profit (W_i^q) of serving zip code i in substitution slot q;
3. the opportunity costs $p[D_s \geq x]W_j^s$.

Whereas assessing the sales revenues for a particular customer may be relatively straightforward, estimating the delivery costs is more challenging. The incremental costs of serving a certain customer zip code in a particular time slot depends on the delivery routes. These are typically constructed after the cut-off time when all delivery orders are known (see also Figure 4.1). Consequently, there is uncertainty about the routes and the corresponding delivery costs at the time of the slotting decisions. This means the e-tailer needs to anticipate future orders when estimating the costs factors.

In this section, we present two very fast heuristics which use simple "local" cost estimates based on continuous approximation. These methods do not explicitly take the vehicle routing decisions into account. We complement this approach with a model inspired on Campbell and Savelsbergh (2005a) that deals with the routing component of the DTSMP in a more explicit way. The latter serves as a benchmark on the solution-quality of the simple methods.

7.3.1 Continuous Approximation Approach

To approximate the routing costs of a customer in zip code i without solving the corresponding vehicle routing problem, we apply continuous approximation. This method applies simplified aggregated data models to estimate the expected logistic costs. Daganzo (2005) approximates the distance between two consecutive stops of a route through a region with slowly varying demand density σ by $k/\sqrt{\sigma}$, where k is a dimensionless constant that depends on the distance metric used.

To estimate the cost of serving a customer at time t in zip code i in time slot s, we calculate the demand density σ_{tis} based on the number of already accepted orders n_{tis} and the expected future orders e_{tis}. If a_i denotes the surface area of zip code i, then

$$\sigma_{tis} = \frac{n_{tis} + e_{tis} + 1}{a_i}$$

For the substitute time slot q, we simply use the expected demand $(e_{iq} + 1)/a_i$ to calculate σ_{iq}. That is, we assume to have no information on the number of already accepted orders or the remaining time to cut-off for this slot. To calculate the opportunity costs, we use a very rough approximation of the costs of an "average" delivery. Therefore, we use the expected demand for a shift e and the surface area of the complete delivery area a. The probability that the demand for slot s is greater than the remaining capacity $p[D_s \geq x]$ is calculated by assuming Poisson distributed demand with e^i_{ts} as the the expected future orders for all "open" zip codes except zip code i as follows

$$p[D_s \geq x] = (1 - \sum_{n=0}^{x} \frac{e^{-e_{ts}} e_{ts}^n}{n!})$$

Now we have all elements we can write decision rule 7.3 as follows (c^m denotes the costs per mile):

$$(r_i - \frac{kc^m}{\sqrt{\sigma_{tis}}}) \geq \delta(r_i - \frac{kc^m}{\sqrt{\sigma_{iq}}}) + (1-\delta)p[D_s \geq x](r_j - \frac{kc^m}{\sqrt{\sigma}})$$

Note that the expected profit of serving the customer in time slot q is a constant while the expected profit of serving the customer in time slot s is decreasing over time for a given x. That is, the expected costs to serve a customer in zip code i increases over time and decreases with the number of orders accepted n_{tis}. Figure 7.2 illustrates this effect by considering the expected profit of the current order given the remaining time before the cut-off point and given x. The figure shows two zip codes, one with high expected demand and one with low expected demand. The Figure plots the expected profits over time when no demand is accepted in the zip codes. For each of these zip codes, we set the expected profit with 100% of the time remaining, $r - \frac{kc^m}{\sigma}$, to 100.

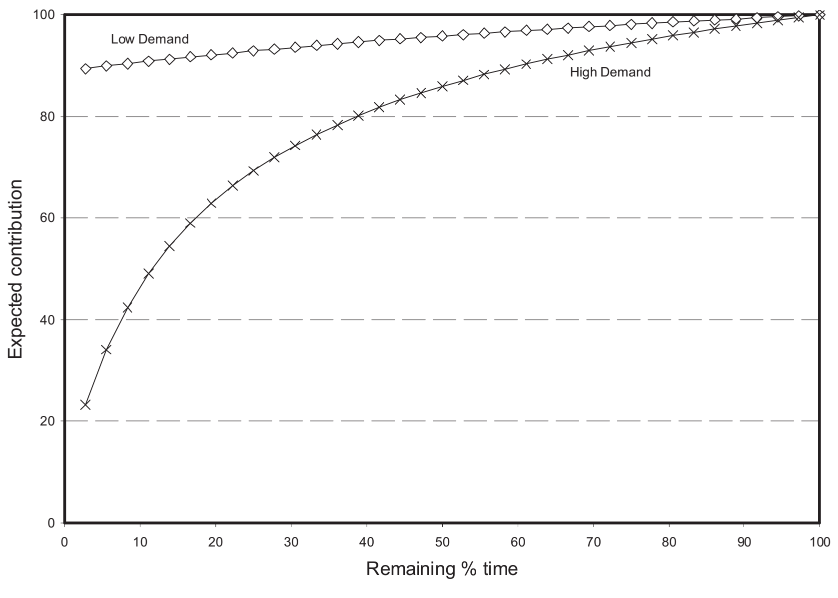


Figure 7.2: Expected profit with 0 Orders Accepted

In the Figure, we observe that while the expected profit is decreasing relatively fast in the large zip code, it remains relatively stable in the small zip code. The reason for this is that smaller zip codes have lower absolute variation in the number of orders. This implies that the substitution trade-off is less relevant for smaller zip codes.

7.3.2 At Least 2 Approach

Instead of using routing costs approximations to decide whether or not to offer a specific time slot, we can also use a simple rule-of-thumb. This decision rule can be seen as a simplification of the CA approach. The two key ideas behind this approach are the following. First, the average delivery costs per stop decrease with the number of stops in a certain region (see Daganzo (2005)). As a result, it is relatively costly to visit a particular zip code to serve only a single customer. Second, the probability of getting an additional order in a certain region decreases with the remaining time until the cut-off point. Hence, the e-tailer can decide to close a time slot in certain regions if they did not receive any orders before a particular threshold time γ. In particular, in this policy we close the time slots in all 3-digit zip codes that do not already have at least one order accepted when 50% of the time is remaining before the cut-off.

7.3.3 Insertion Heuristic Approach

The continuous approximation models presented in the previous section do not model the routing decisions explicitly. In this section, we complement these simple approaches with a model that deals with the embedded routing component of the DTSMP in a more explicit way. Therefore, we draw on the work of Campbell and Savelsbergh (2005a) and adopt their proposed insertion heuristic to solve the vehicle routing problem with time windows. This method determines dynamically whether a certain request can still be accommodated in a particular slot, while taking the opportunity costs into account. In order to decide on the particular set of time slots to offer a specific customer, information is required on his preference set. As this method mainly serves as a benchmark, we not only assume to know the probability δ with which the customer moves to a substitute slot, but also that the possible substitute slot is always the next available slot in the static schedule.

To estimate the expected profit to serve a customer in zip code i in time slot s we calculate its insertion profit in the expected set of delivery routes. The insertion profit of customer j between already inserted customers i and $i-1$ is defined as:

$$r_j - (c_{i-1} + c_{j,i} - c_{i-1,i}), \tag{7.4}$$

We use the insertion heuristic to construct the expected vehicle routes in two phases each time a new customer logs in. In Phase 1, all accepted demand is inserted in the set of routes, where the demand with the greatest profit is always the next to be inserted. In Phase 2, we try to insert the current order under consideration together with the expected future orders. The set of expected future orders consist of orders for each zip code. The size (revenues and capacity consumption) is chosen as the expected values given the time t remaining until the cut-off point. Again, we repeatedly and greedily insert the as of yet unrouted customers based on the insertion profit until feasible insertions are no longer possible because of limited capacity. Note that Phase 2 explicitly takes the opportunity costs into account via the insertion trade-off between the current order under consideration and the potential future orders. In case the current order under consideration cannot be inserted in Phase 2, the slot will not be offered to this customer. Otherwise, we calculate the insertion profit, that is, the profit of inserting this customer in its current route at the end of Phase 2.

Next, we focus on the expected profit if slot s is closed, that is, the profit in the substitute slot W_i^q times the substitute rate δ in decision rule 7.2. In case the order cannot feasibly be inserted in slot q, the customer is always offered slot s. If the order is inserted, we calculate the expected profit in the same way as for slot s.

7.4 Computational Experiments

To evaluate the different slotting policies we use simulation. Therefore, we generate multiple demand realizations for each policy and determine the cost of each set of accepted orders using a insertion heuristic to solve the vehicle routing problem with time windows. To evaluate the characteristics of the environment on the performance of the policies we vary individual characteristics and analyze the results.

In our experiments we evaluate the performance of the presented heuristics and the following two benchmarks:

- ALBERT: The policy that is currently in place at Albert.nl. This policy accepts demand first-come, first-serve given fixed order limits per delivery time slot;
- ALL: This policy simply accepts all requests for delivery, which represents the case without any demand management.

Similar to the previous chapter, we use real-life data from Albert.nl and specifically focus on the Nijmegen area (see Figure 6.3). We consider demand from 101 customer locations (which correspond to the centers of the 4-digit zip codes) in 30 3-digit zip code areas. We simulate a complete delivery week in this area which consists of 4 morning shifts and 3 afternoon shifts, and use one week as a start-up period. Furthermore, we use the optimized static schedule from the CA method in Chapter 6 as a starting point.

For each problem instance, we generate 20 random demand instances as follows. For each zip-code time-slot combination, we randomly generate a number of requests for delivery based on Poisson distributed demand with the expected demand as the Poisson rate. These request then have this specific time slot as their most preferred time slot. In case this slot is not offered when the customer logs in, with probability δ he switches to the next available slot in the static schedule, and with probability $1 - \delta$ he leaves without a purchase. This process repeats itself until the customer finds a substitute slot or elects not to purchase.

For each customer request, we then generate the time of the order arrival, 0 to 2 days prior to the cut-off point for order placement. We assume uniform distributed demand over time. The empirical analysis in Chapter 5 showed that demand is clearly not uniformly distributed over time, but for the numerical experiments the order of arrival is most important. The specific demand distribution is less relevant as long as the operations model anticipates expected future demand in a way that is consistent with the distribution used in the demand simulation.

In the base case, we use identical order sizes in terms of number of totes and identical revenues per request. The revenues represent the sales margins plus the delivery fees minus a fixed term that covers order picking costs (which are assumed fixed due to the identically order sizes). For each individual shift, the number of delivery vehicles based on the expected demand in that shift. This decision on vehicles and drivers takes place offline, before actual demand materializes, and is based on the vehicle estimates from the static time slot management model in the previous chapter. The number of vehicles per shift ranges between 5 and 9, while the expected demand per shift ranges between 60 and 120. The ratio between the expected demand and the available vehicle capacity is about 100% for each individual shift. The substitution probability is set to 0.88, based on our empirical findings in Chapter 5.

The simulation is implemented in C++ and run on a AMD Athlon 2500Mhz Machine. All simple heuristics (ALL, ALBERT, AL2, CA) take less than a second to make the time slot decision for an individual customer while the Insertion Heuristic takes about 5 seconds on average (maximum of 20 seconds). Note that in our simulation, we know the first choice slot (and potential substitute slots) of the customer and only need to decide for this slot whether or not to offer it. In reality the Internet retailer needs to make this decision for each of the time slots in the static time slot menu. The total simulation time per scenario ranges from a few minutes for the simple heuristics to about 30 hours for the Insertion Heuristic.

7.4.1 Policy Comparison

We calculate the following statistics to compare the different slotting policies: the average number of accepted orders, the average costs and the average profits. The averages are taken over 20 weekly demand realizations. We also display the percentage gains in profit relative to ALL. For confidentiality, all figures are normalized by setting the statistics for ALL in the base case to 100. Note that because we consider the revenues per order fixed, the average normalized revenues are equal to the normalized number of accepted orders. The results of the simulation experiments can be found in Table 7.1.

Table 7.1: Policy Comparison

	# orders	cost	profit	% gains
ALL	100	100	100	-
ALBERT	98.9	97.7	108.9	+8.9%
AL2	96.5	93.8	120.4	+20.4%
CA	94.7	90.4	131.6	+31.6%
IH	98.6	96.4	117.2	+17.2%

Not surprisingly, we observe that all policies outperform the policy that simply accepts all demand without taking capacity into account (ALL). The first-come, first-serve approach (ALBERT) already yields substantial gains over ALL. What is more, we observe that additional gains are possible from the use of more sophisticated slotting policies. Each of the presented approaches does considerably better than the current policy in place at Albert.nl (ALBERT). This suggests that even if expected demand is equal to capacity, demand management can help exploit the customer's flexible with respect to his time slot choices. While the expected profits for the solutions of AL2 and IH are similar, CA performs even better. However, these gains come at the expense of the number of accepted orders, and CA makes substantially less deliveries than the other methods.

To better understand the differences in performance, it is interesting to compare the actual solutions. Figure 7.3 shows the weekly demand statistics for ALBERT, AL2, CA and IH. For each zip code, the figure plots the percentage of requests that was not offered its first choice time slot, against the expected order density of this zip code. Note that customers may potentially switch to a substitute slot so these values do not necessarily reflect lost sales. The figure shows that the percentage of customers that is not offered their most preferred time slot is relatively high for AL2 and CA compared to ALBERT and IH. Furthermore, there seems to be a clear relationship between the density of the zip code and the slots offered for CA. The higher the density, the higher the acceptance rate in the most preferred slot. This is intuitive because CA approximates the delivery costs in a particular zip code through the expected demand density and lower densities correspond to higher costs delivery costs. Several very low density zip codes are never offered their first choice by the CA policy (100% closed). This may be justified given the opportunity costs, but it may be undesirable from a marketing perspective.

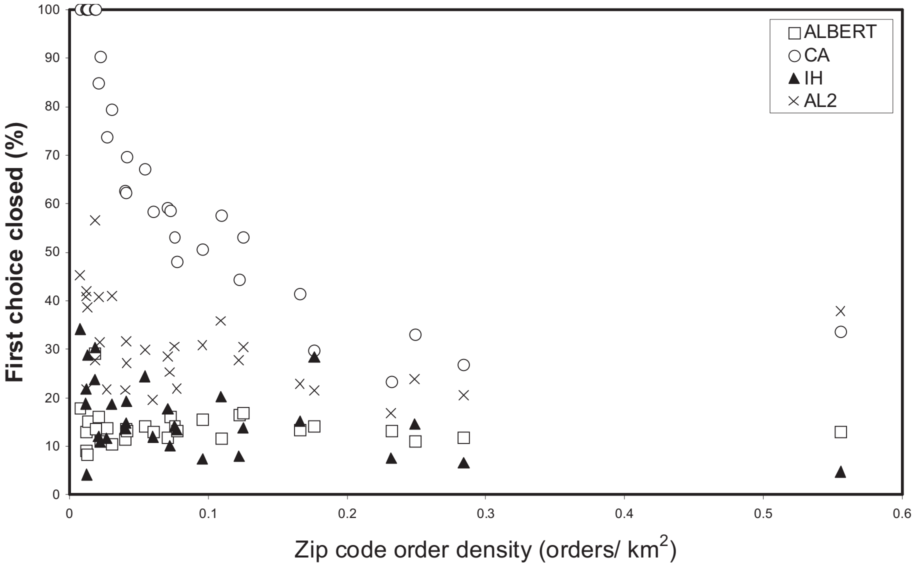


Figure 7.3: Comparison of Solutions

AL2 and CA are very fast heuristics that allow us to experiment with multiple settings of their input parameters. To provide some insights into the impact of the measure of the expected opportunity cost in CA, we multiply the value with respectively 0,2 and 3. Note that an opportunity costs term of 0 means that we open a time slot s only if $W_i^s \geq \delta W_i^q$. Figure 7.4 plots the solutions of the different policies in terms of costs and profits. We observe that the number of accepted orders decreases when the opportunity costs value is increased. The reason for this is that raising the opportunity cost value increases the likelihood that a time slot is closed to reserve capacity for more valuable future customers. However, if these future customers do not arrive, the reserved capacity remains unsold. As long as the cost savings outweigh the losses in revenues, a more selective policy is beneficial. Moreover, the figure show the solutions for AL2 for different values of γ. That is, a 3-digit zip code region is closed if no demand has materialized with respectively 75%, 50% (base case) and 25% of the time remaining before the cut-off point. We see that the profits for AL2 increases with an increasing value of γ. This implies that closing the zip codes without any demand at an earlier point in time appears to be beneficial. Realize though, that the fairly high customer flexibly allows this policy to cluster demand together in particular time slots with only a slight risk of losing demand.

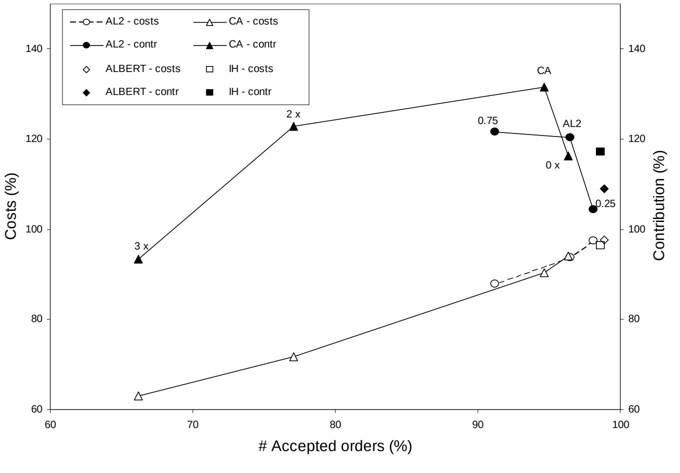


Figure 7.4: Sensitivity Analysis

7.4.2 Changes in the Environment

We focus the second part of our study on understanding the impact of the characteristics of the environment on the performance of the dynamic time slot policies. All the percentage differences reported are relative to the profit in the base case for the same policy.

Demand

The ratio between expected demand and available capacity is an important element in any demand management system. In an environment with relatively scarce capacity, demand management typically has the greatest potential. We consider two scenarios. One in which we increase demand by 30%, and one in which we decrease demand by 30%. The results can be found in Tables 7.2 and 7.3.

Table 7.2: Increase of Demand

	# orders.	cost	profit	Δ profit
ALL	132.1	147.1	4.3	-95.7%
ALBERT	104.5	101.3	120.9	+12.0%
AL2	103.4	101.1	122.8	+18.4%
CA	100.8	93.1	167.8	+36.2%
IH	117.8	108.7	196.0	+62.9%

Table 7.3: Decrease of Demand

	# orders.	cost	profit	Δ profit
ALL	71.7	76.4	30.9	-69.1%
ALBERT	71.7	76.4	30.9	-78.0%
AL2	70.9	74.3	41.1	-79.2%
CA	69.4	71.7	49.6	-67.7%
IH	71.1	75.5	33.1	-84.1%

In Table 7.2, we observe that simply accepting all demand (ALL) leads to a very poor performance in case capacity is relatively scarce. This results in a decrease in profit of 95.7%. Obviously, this is caused by the high costs of incremental vehicle capacity required in the short-term. All other policies perform significantly better in this scenario than in the base case. This is due to economies of scale; the increase in the number of accepted orders outweighs the raise in costs. Moreover, we see that the gap between the methods take the opportunity costs into account (CA and IH) and those that do not (ALBERT and AL2) widens in this scenario. The sophisticated methods seem more effective in selecting the subset of requests which allow for cost-efficient delivery. We also observe that the IH method outperforms the CA method by accepting far more demand. The IH approach does not use a fixed capacity limit but evaluates in real-time whether it can still accommodate an additional request for delivery. Therefore, it can potentially accept more demand than the policies that do use such a fixed capacity limit. Together with the more selective order acceptance which decreases the time per order, this allows for a substantial increase in the number of accepted orders, and corresponding revenues.

In Table 7.3, we observe that the statistics for ALBERT are equal to ALL. This suggests that in this scenario the capacity limits are not restrictive and ALBERT also accepts all demand. Furthermore, we see that the decrease in the number of accepted orders is followed by a lower decrease in costs which again denotes economies of scales. Interestingly, AL2 and CA perform remarkably well in this scenario. To understand this, note that both of these policies specifically try to cluster orders for the same zip code together. At the same time, the customer is flexible enough in this scenario to allow such clustering without substantial losses in demand.

Customer Flexibility

Next we examine the impact of the customer's flexibility by varying the substitution rate δ. Based on our empirical results we assumed a δ of 88% in the base case. Now, we consider two scenarios in which the customer is less flexible and use a δ of respectively 50% and 0%. This corresponds to an expected number of acceptable slots of respectively 2 and 1. The substitution rate values are used as input for both the demand simulation and the slotting decisions in CA and IH. Note that this does not change the ALL scenario which is reported as a benchmark. The results can be found in 7.4.

Table 7.4: Different Customer Flexibility

		# orders.	cost	profit	Δ profit
	ALL	100	100	100	-
0%	ALBERT	93.8	94.5	88.0	-20.9%
	AL2	90.7	90.7	90.7	-13.7%
	CA	93.2	93.8	88.0	-43.6%
	IH	95.2	93.7	108.1	-24.9%
50%	ALBERT	95.7	95.6	97	-11.9%
	AL2	93.9	92.8	102.7	-1.7%
	CA	86.4	84.0	106.8	-22.2%
	IH	97.0	94.4	120.0	-13.1%

We observe that profits go down with decreasing customer flexibility. We also see a substantial decline in the number of accepted orders, and corresponding revenues, especially if the customer is not flexible at all ($\delta = 0$). As a result, the profit in this scenario is even lower than ALL for all policies but IH. This suggests that the loss in revenues outweighs the additional short-term capacity costs incurred in ALL. Only IH does significantly better than first-come, first-serve(ALBERT). Again, this is because the IH approach does not use fixed order limits and is therefore more flexible in the short-term on the supply side. As expected, the potential of demand management is limited in case the expected demand is equal to capacity (low opportunity costs) and it is not possible to move the customer to a time slot that allows for more efficient delivery.

Revenues and Order size

Until now, we have assumed fixed revenues per customer. Next, we investigate what happens when revenues per customer vary. Revenues may vary due to differences in product margins and order-size in terms of the number of items. To address both issues, we consider two scenarios. One in which only the revenues from the total product margins of an order vary around the mean by 25%, and one in which the order size and the corresponding revenues differ around the mean with that same percentage. In the latter scenario we assume that the revenues are proportional to the order size. We assume the dwell time at the customer to be proportional to the order size, and increases with the number of items. We assume to know the revenues from the order at the time of the time slot decision - either because the customer has already developed his order list or based on reliable forecasts from historical transaction data. We include the statistics on the normalized revenues. The results can be found in Tables 7.5 and 7.6.

Table 7.5: Variability in Margins

	# orders.	revenues	cost	profit	Δ profit
ALL	100	100	100	100	-
ALBERT	98.9	98.8	97.7	107.9	-1.1 %
AL2	96.5	96.4	93.8	119.3	-1.1%
CA	87.2	87.7	83.5	123.8	-1.1 %
IH	98.7	98.6	97.7	106.3	-9.9 %

Variability in the margins does not seem to have a significant impact on the overall performance of the system (the differences in revenues seem to average out). However, we observe in Table 7.5 that the IH approach does not perform well in this scenario.

Table 7.6: Variability in Ordersize

	# orders.	revenues	cost	profit	Δ profit
ALL	100.2	99.9	102.5	78	-21.8%
ALBERT	98.9	98.8	99.9	89.0	-19.9 %
AL2	96.5	96.4	95.6	103.4	-17.0%
CA	87.1	87.7	83.9	119.9	-6.3%
IH	98.4	98.2	98.2	98.7	-32.9%

The variability in the revenues seems to complicate the demand management task as it decreases the differences between the customers in different zip codes and increases the differences within a particular zip code. That is, we can no longer simply segment customers by delivery location. The fact that AL2 does better suggests that one should not pay too much attention to the revenue differences and solely consider the delivery costs. In similar fashion, CA tends to overestimate the cost differences, thereby makes the impact of the revenue differences less relevant.

In the scenario with varying order sizes, we observe a substantially lower profit than in the base-case. The variability in the capacity consumption, both in terms of physical capacity as in time, affects the overall delivery efficiency. However, the relative performance of the different policies is in line with the base case. This makes sense because the fact that the increase in revenues is proportional to the order size means there is no fundamental change as compared with the base case.

7.5 Conclusions

In this chapter, we address the dynamic time slot management problem. This problem entails the decisions on the subset of time slots to offer based on real-time information on already accepted demand.

We presents a conceptual model of the time slot problem inspired by traditional models for quantity-based revenue management. The standard revenue management rule is adjusted to take the cost impact and time slot substitution into account. To anticipate the impact on delivery costs, we presents two simple Continuous Approximation heuristics and for comparison a more detailed vehicle routing heuristic based on Campbell and Savelsbergh (2005a). The latter approach takes the actual vehicle routing decisions into account in far more detailed level than the two less sophisticated methods. However, while the simple heuristics take less than a second to run, the vehicle routing heuristic takes up to 20 seconds.

Our numerical experiments show that all presented methods lead to substantially improvements over a simple first-come, first-serve approach. Furthermore, we observe that the potential of real-time demand management policies increases with the relative scarceness of capacity and customer's flexibility with respect to his time slot choice. On the one hand, in case of relatively scarce capacity, simple first-come, first-serve approaches do not exploit the differences in value between customers. On the other hand, when the customer is fairly indifferent about his time slot choice, the e-tailer may offer the time slots in a way that allows for cost-efficient delivery.

Chapter 8

Conclusions and Further Research

In this thesis, we have studied the potential of demand management for e-fulfillment. We have seen that Internet retailers have a variety of powerful demand management levers at their disposal. To effectively use these levers to enhance profits, they need to have a good understanding of the interplay between supply and demand. This thesis has brought forward new quantitative models and decision support tools for demand management, which take both costs and revenue considerations into account.

In this concluding chapter, we summarize the main results of our research. Furthermore, we look ahead and discuss several interesting areas for future research.

8.1 Results

In this section, we discuss the key results by returning to the research questions we posed in chapter 1. The first two questions addressed the identification of the relevant issues in e-fulfillment.

RQ1. What specific planning issues arise in e-fulfillment?
To better understand the important planning issues in B2C e-fulfillment, we analyzed current practice and recent literature. In **Chapter 3** we addressed the various planning tasks arising in e-fulfillment. While many standard supply chain issues, such as distribution network design and inventory management, are also relevant to e-fulfillment, a few issues appear to be specific. With respect to the upstream

supply chain processes, notably storage and warehousing, the main particularities of e-fulfillment originate from the small transaction sizes. The assembly of orders typically involves small pick quantities from a large number of items, which is very labor-consuming. Novel downstream supply chain issues mainly arise from bridging the 'last mile' to the customer.

We have seen that concepts for traversing this 'last mile' include customer pick-up points and (home) delivery. The latter is particulary challenging in the case of attended home delivery, which is common for many types of products that cannot easily be delivered in the customer's mailbox, such as groceries (due to perishability), electronic equipment (value), or white goods and furniture (size). In attended home delivery, the e-tailer typically uses time slots to coordinate the receipt of the purchased item with the customer. The e-tailer is often more flexible than traditional retailers with respect to pricing and order promising. In **Chapter 2**, for example, we saw that many of today's e-grocers use this flexibility to differentiate their delivery fees and delivery options. However, few companies seem to fully exploit the potential for reducing costs and improving service in Internet retailing through systematic demand management.

RQ2. What characterizes demand management in e-fulfillment and how does it differ from 'traditional' demand management environments like the airline industry?
In **Chapter 4** we presented a systematic comparison between demand management in e-fulfillment and at the airlines. We showed that the most important characteristics of traditional revenue management environments also apply for e-fulfillment. The e-tailer serves a *heterogenous* market with delivery capacity that is relatively *inflexible* in the short-term, and can change *prices* and *availability* relatively easily.

However, we also identified important differences. First and foremost, while the marginal costs of an additional customer are negligible in traditional revenue management, the order-intake has a significant cost impact in e-fulfillment. This means that demand management in this environment has to take both costs and revenues into account. Second, Internet retailing entails a combination of physical products plus a delivery service. Effective demand management has to take both dimensions into account.

Akin to traditional revenue management, the e-tailer can consider both quantity-based and price-based demand management options. The first concerns decisions on which delivery options, namely which delivery slots, to make available to which customers. The second focusses on the delivery fee as the main lever to manage customer demand. A retailer can apply both of these options, slotting and pricing, at different moments in the sales process, either *off-line* prior to the actual order intake or *real-time* as demand unfolds. These distinctions leave us with four different types of demand management in e-fulfillment, as summarized in our framework in Table 8.1 (see also Table 4.2 in Chapter 4).

Table 8.1: Demand Management Framework

	Capacity allocation	**Pricing**
Static *Off-line, Forecast-based*	***Differentiated slotting***	***Differentiated pricing***
Dynamic *Real-time, Order-based*	***Dynamic slotting***	***Dynamic pricing***

Next, we translate these issues into quantitative models that allow for systematic analysis. In particular, we focus on the behavior of the customer and the behavior of the operational processes.

RQ3: What is the customer's response to demand management in e-fulfillment?
The time slot offering has an immediate impact on the attractiveness of the service for the customer, and potentially on sales. Customer behavior modeling is one of the most challenging aspects of demand management. The fact that customers order online, however, gives the modeler an advantage, because it facilitates monitoring and analyzing individualized customer behavior.

In **Chapter 5** we applied econometric analyzes on sales data from Albert.nl to infer substitution rates and lost-sales caused by time slot unavailability. We have seen that the major challenge in this kind of analysis is the inherent censored nature of the available sales data. The sales data do not reflect the core demand, that is, the demand with all time slots available. There is generally no record of customers who did not make a purchase because they could not find their time slot of choice. Moreover, the Internet retailer often cannot distinguish between a substitute purchase and a first choice purchase. We have explained how to deal with this censoring issue on an aggregate level by specifying a system of linear regression equations for the demand of each of the time slots. What is more, we explicitly dealt with the non-stationarity of the demand distribution and controlled for hourly and daily seasonalities.

Based on our empirical analysis of real-life sales transaction data from Albert.nl, we found that customers are fairly flexible with respect to their delivery time slot preferences. In particular we have found that:

- Moderate permanent reductions in the weekly number of offered time slots do not have a significant impact on long-term sales.
- If a time slot is closed unexpectedly, the customer switches to a substitute time slot in the majority of cases. In particular, we have found that 88% of the unsatisfied demand moves to a substitute slot, mostly to a slot on a different day.

These results indicate that there is a great potential for demand management methods which aim to exploit the flexibility in customer preferences. That is, the e-tailer may select the time slots offered to the customer in a way that facilitates cost-efficiency fulfillment.

Finally, we address the practical implications for demand management in e-fulfilment.

RQ4: How do we capture the relevant trade-offs in quantitative models that help decision making in e-fulfillment?

Besides the impact on perceived service, the time slots have a direct impact on the expected efficiency of the delivery routes. To support the time slot decisions, it is crucial to anticipate this impact. However, given the full complexity of the vehicle routing problem alone, it is unrealistic to incorporate a full routing model in the time slot management problems.

In **Chapter 6** we have identified and explained the static time slot management problem (upper left corner of in Table 8.1). This tactical decision problem entails the selection of the subset of time slots to offer in each zip code of the delivery area to minimize the expected delivery costs while meeting the service requirements. We have presented two potential ways to model the vehicle routing component. The first one estimates route costs per zip code based on "local" information by using continuous approximation. The second one explicitly models the vehicle routing decisions by adapting the classical specification of the vehicle routing problem with time windows. We have shown that both methods are capable of producing high-quality time slot schedules much faster than the current manual process. However, we have also demonstrated that the added value of very detailed models or sophisticated solution methods is limited due to the high degree of stochastic variation and the tactical nature of the problem.

Our numerical experiments on real-life data from Albert.nl show that:

- While narrow time slots for delivery are more convenient for the customer, they also lead to substantial reductions in delivery efficiency. The results from our simulations indicate a cost increase of up to 25% from using 2-hour time slots instead of time slots that span an entire morning or afternoon. This illustrates the core trade-off between service and delivery costs.

- The use of service requirements to differentiate the number of time slots in different delivery regions results in significant cost savings as compared to simply offering all 2-hour time slots in all zip code regions. The results from our numerical experiments suggest up to 10% savings.

- The optimization of the assignment of the delivery time slots to zip codes yields only moderate additional savings over the manually constructed schedule that is currently in place at Albert.nl. Both optimization approaches, however, are capable of producing high-quality time slot schedules much faster than the current manual process.

- There are clear economies of scale in the delivery operation. The results show potential cost benefits from increasing the number of stops within the current delivery area. This illustrates the importance of growth in order for an e-tailer to become more profitable.

- The time slot constraints and the constraints on physical vehicle capacity interact. Time slot management decisions become more relevant when the vehicle capacity allows a vehicle tour to span several time slots.

- The main trade-off in the time slot schedule design is between demand clustering and demand smoothing. The advantage of clustering demand is that it minimizes the distance between successive stops, and thus travel costs. The disadvantage is the potential underutilization of the vehicle capacity, and a corresponding increase in vehicle costs.

In **Chapter 7** we presented the dynamic version of the time slot management problem, which considers the time slot decisions while taking into account real-time demand information (lower left corner of in Table 8.1). We have explained how to expand the traditional revenue management models to take costs and revenues into account rather than revenues alone. In addition, we adapted traditional revenue management models to allow for substitution between different time slot products. To anticipate the cost impact of the dynamic time slot decisions, we have presented several heuristical methods. We have shown that even very simple heuristics for dynamic slotting have the potential to improve the financial performance of the home delivery service. Although the more sophisticated method outperforms these simple heuristics in certain scenarios (particularly if capacity is tight), the amount of time required to make the slotting decisions at the order in-take may be unacceptable from a customer perspective.

Our numerical experiments on real-life data from Albert.nl show that:

- Taking some measure of the remaining effective available capacity (e.g. an order limit per time slot) into account when determining the time slot offering in real-time results in substantial improvements in profit. The results from our numerical experiments indicate gains of about 9%.

- Taking into account the differences between customers in terms of delivery costs yields substantial improvement in profit over simply accepting demand first-come, first-serve. Our numerical results indicate potential improvements in profit of up to 75%.

- The potential of real-time demand management policies increases with the relative scarcity of capacity and customer's flexibility with respect to his time slot choice. On the one hand, in case of relatively scarce capacity, simple first-come, first-serve approaches do not exploit the differences in value between customers. On the other hand, when the customer is fairly indifferent about his time slot choice, the e-tailer may offer the time slots in a way that allows for cost-efficient delivery.

- Demand management requires a segmentation of the customers with respect to their value to the firm. If no such segmentation is possible because there is no variation in either costs or revenues, there is less potential for demand management.

8.2 Further Research

This thesis provides a systematic study of the potential of demand management in e-fulfillment. Although the results yield valuable insights, they also give rise to several questions that require further research.

- In **Chapter 4**, we distinguished two different demand management levers for e-fulfillment, namely capacity allocation (slotting) and pricing. In this thesis, we focussed primarily on the time slot management decisions. However, besides slotting, pricing also provides a wide spectrum of possibilities to steer demand. Although the general insights from our operational models may also apply to price-based demand management, effective pricing gives rise to several specific challenges.

  First, there is a risk that customers may perceive unexpected price changes as unfair. In a recent paper, Anderson and Simester (2008) show that the price fairness effect on customer demand can even outweigh the direct effects of varying prices. Xia et al. (2004) argue that customers evaluate price fairness against a benchmark. In e-fulfillment, the prices of other available delivery time slots represent an explicit benchmark from which fairness judgements can be made. This suggests that the pricing of a specific delivery time slot can not be done in isolation. To date, very few contributions have addressed these issues in demand management, which leaves ample room for relevant research in this area.

  A second challenge related to pricing is that customers may anticipate future price changes and delay their order placements in the hope for a discount. That is, customers change their behavior as a response to the companies' dynamic pricing practices. Recent papers in revenue and supply chain management have begun to examine the implications of strategic customer behavior in dynamic pricing models (see Su (2007), Liu and van Ryzin (2008), Zhang and Cooper (2008), Aviv and Pazgal (2008)). However, empirical input is required to further develop the work in this area.

  Thirdly, there is often uncertainty about the customer's valuation of the delivery of goods purchased online. Instead of using posted prices, Internet retailers can engage in far richer forms of interaction with their customers by using auctions. Although there is a huge body of research on online auctions (see e.g. Pinker et al. (2003)), we are not aware of any papers that specifically address a setting in which the customer buys a combination of a physical product and a delivery service. This environment gives rise to several interesting questions and challenges. For which type of goods and corresponding delivery services is an auction more appropriate than posted price mechanisms? What is a good mechanism to design these auctions? How can we support these auctions with agent-based technologies?

- In **Chapter 3**, we saw that e-fulfillment is often part of a multi-channel strategy. Technological developments and ever more demanding customers have triggered the proliferation of multiple distribution and sales channels. One recurrent pattern is the combination of 'bricks-and-clicks', the Internet store alongside the traditional store. Although multiple channels are attractive from a marketing perspective, the operational integration of these different channels poses several novel challenges. In particular, the multi-channel retailer needs to decide which processes of the different channels to combine and which ones to separate. The management of these trade-offs would greatly benefit from a systematic quantitative analysis. To date, few contributions have explicitly addressed the multi-channel context of many of today's Internet retailers.

- It is clear that the potential of demand management goes beyond the classical applications like the airline, hotel and car-rental businesses. **Chapter 6** and **Chapter 7** demonstrate the potential of demand management in e-fulfillment with attended home delivery. In this setting costs are not sunk, and both revenue and cost effects have to be taken into account. Here, demand management is closely linked to supply chain management. Other areas that share some characteristics with traditional revenue management environments but have endogenous costs include service logistics, urban distribution (Quak et al., 2008) and even manufacturing (Quante et al., 2009, Spengler et al., 2007). The development of decision support tools that adequately capture the key demand management trade-offs in these areas provide plenty of room for promising future research.

- In **Chapter 5**, we have made the first steps in analyzing customer behavior with respect to delivery options in Internet retailing. However, while we primarily focused on customer behavior on an aggregated level, e-commerce provides unprecedented opportunities to analyze and track customers on an individual level. Transaction and click-stream data provide a wealth of information about individual preferences. While this information is used for personalized promotions and recommendations, demand management often uses fairly simple models of customer behavior (Shen and Su, 2007, Dana, 2008). Future research should focus on the development of more sophisticated models of customer behavior for demand management.

- Global environmental concern has increased the interest in more sustainable ways to do business. While this thesis puts the focus on enhancing the profitability of Internet retailing, we recognize that the consideration of profitability criteria alone may not be sufficient. E-fulfillment, and logistics in general, also has a direct impact on environmental and social performance criteria, such as CO_2 emissions, pollution and traffic congestion. Demand management can provide a powerful tool to increase a firm's triple bottom performance, people-planet-profit. This means that besides the interests of the seller and the customer, the concerns of many more stakeholders, such as governments and future generations, have to be taken into account. Future research can explore the impact of the use of different demand management objectives on the different performance criteria.

Considering the above issues it is clear that demand management provides Internet retailers with powerful levers to enhance profitability. The effective use of these levers gives rise to many challenging optimization problems. Hopefully, the research presented in this thesis motivates many further developments in this area.

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Samenvatting (Summary in Dutch)

In dit proefschrift bestuderen we de mogelijkheden die webwinkels hebben om de vraag van de consument te beïnvloeden. Webwinkels hebben unieke mogelijkheden om het product- en serviceaanbod en de bijbehorende prijzen dynamisch aan te passen en af te stemmen op de consument. Daarnaast hebben zij de beschikking over veel klanteninformatie in de vorm van historische transactiedata. Dit maakt het mogelijk om de klantenvraag actief te sturen en daarmee zowel de kosten als de opbrengsten van de onderneming te beïnvloeden. Hoewel zogenaamd vraagmanagement in deze context veel potentie lijkt te hebben, vraagt het ook om systemen die de vaak complexe onderliggende beslissingen kunnen ondersteunen. Dit proefschrift heeft als doel om bij te dragen aan nieuwe relevante theoretische en praktische inzichten voor beslissingsondersteuning op het gebied van vraagmanagement in e-fulfillment.

De focus van het proefschrift ligt vooral op webwinkels die producten leveren waarbij de klant aanwezig moet zijn op het aflevermoment. Dit betreft producten die niet simpelweg in de brievenbus kunnen worden afgeleverd zoals witgoed en meubels (grootte), boodschappen (bederfelijkheid) en elektronische apparatuur (waarde). Om de ontvangst van de bestelling te coördineren kan de webwinkel verschillende levermomenten aanbieden waaruit de klant kan kiezen. Het beleveren op specifieke levermomenten op een kostenefficiënte manier is een logistieke uitdaging. Het ontwerp van het aanbod van levermomenten brengt verschillende afwegingen tussen kosten en service met zich mee. Korte, specifieke levermomenten zijn bijvoorbeeld handig voor de klant maar zorgen vaak voor hogere kosten omdat de leverancier minder flexibel is in het plannen van de bezorgritten.

In Hoofdstuk 4 identificeren en classificeren we de potentiële methodieken voor vraagmanagement in e-fulfillment. Daartoe vergelijken we de processen van de webwinkel met de processen in de luchtvaartsector, de sector waar op grote schaal revenue management toegepast wordt gebruikt om de vraag optimaal te managen. We laten zien dat de belangrijkste randvoorwaarden voor revenue management ook gelden voor e-fulfillment. De webwinkel bedient een heterogene markt met een operationele capaciteit die relatief inflexibel is op de korte termijn. Dit betekent dat ook webwinkels er goed aan doen om de vraag voor de beschikbare bezorgcapaciteit niet simpelweg te accepteren op basis van het first-come, first-serve (FCFS) principe tegen een constante prijs. Naast overeenkomsten zijn er ook belangrijke verschillen tussen de sectoren. Vraagmanagement heeft een grote invloed op de kosten van de webwinkel omdat de geografische locatie van de klant direct de bezorgkosten beïnvloed. Dit is niet het geval in de luchtvaartindustrie waar de marginale kosten van een passagier verwaarloosbaar zijn omdat op het moment van de ticketverkoop de routes niet meer gewijzigd kunnen worden. De webwinkel kan met behulp van vraagmanagement dus naast zijn opbrengsten ook de kostenefficiëntie van zijn fysieke processen verbeteren. De belangrijkste stuurknoppen in deze situatie zijn de aangeboden levermomenten en de prijzen daarvan. De webwinkel kan beide opties, levermoment en prijzen, zowel statisch, op basis van vraagvoorspellingen, als dynamisch, op basis van de werkelijk gerealiseerde orders, toepassen. In dit proefschrift worden verschillende methoden ontwikkeld om de besturing van de levermomenten te ondersteunen. De centrale vraag hierbij is welke levermomenten worden aangeboden in welke postcodegebieden. De aangeboden levermomenten beïnvloeden enerzijds de door de klant ervaren service en anderzijds de distributieroutes van de leverancier.

In Hoofdstuk 5 onderzoeken we hoe de consument reageert op een verandering in de aangeboden levermomenten door gebruik te maken van daadwerkelijke transactiedata van een grote landelijke internetsupermarkt (Albert.nl). Daarbij bestuderen we de invloed op de klantenvraag van zowel een permanente als een tijdelijke verandering in het aantal aangeboden levermomenten in een bepaalde regio. De uitdaging bij het gebruik van verkoopdata heeft te maken met het feit dat de beschikbare data gecensureerd is. Er is namelijk geen informatie beschikbaar over de klanten die geen aankoop doen of een vervangend moment kiezen omdat hun levermoment van voorkeur niet beschikbaar is. Om de vervangingsaankopen en "lost sales" te achterhalen maken we gebruik van regressieanalyse. We formuleren een stelsel van lineaire vergelijkingen om de werkelijke vraag voor de verschillende levermomenten in een bepaalde periode te voorspellen op basis van de geplaatste bestellingen in de voorafgaande periode. Vervolgens kijken we naar de impact van het wegnemen van een bepaald levermoment op die voorspelde vraag. We houden hierbij ook rekening met de verschillen in het orderpatroon op de verschillende dagen van de week. De analyses laten zien dat de consument redelijk flexibel is met betrekking tot de keuze van zijn levermoment.

In Hoofdstuk 6 richten wij ons op het ontwerp van het statische aanbod van levermomenten aan de klant. Uitgaande van vraagvoorspellingen, richten we ons op het volgende time-slot probleem: Bepaal welke levermomenten moeten worden aangeboden in de postcodegebieden zodat de verwachte bezorgkosten worden geminimaliseerd en de "service requirement" worden gerespecteerd. We presenteren twee verschillende kwantitatieve modellen en optimalisatie methodieken om dit probleem op te lossen. De eerste aanpak schat de routeringskosten per postcode op basis van 'lokale' informatie door middel van de zogenaamde "continuous approximation" methode. De tweede aanpak modelleert de routeringsbeslissingen expliciet door een geheeltallig programmeringsprobleem te formuleren. De bruikbaarheid en de voordelen van beide methoden worden geëvalueerd met computersimulaties aan de hand van daadwerkelijke ordergegevens. In het bijzonder is het model in een pilot-studie toegepast op een deel van het levergebied van Albert.nl. Beide modellen stellen de leverancier in staat snel een passend time-slot schema voor een gegeven levergebied te bepalen en de bijbehorende kosten, opbrengsten en transportstromen in te schatten. Deze methode vergroot de planningsflexibiliteit aanzienlijk, vergeleken met de huidige praktijk waarbij het time-slot schema handmatig wordt opgesteld, hetgeen voor een planner erg arbeidsintensief is. Het model stelt de leverancier nu in staat eenvoudig verschillende scenario's met elkaar te vergelijken.

In Hoofdstuk 7 presenteren we de dynamische variant van het time-slot probleem, waarbij gebruik wordt gemaakt van de informatie over de reeds geaccepteerde orders bij het maken van de time-slot beslissingen. Voor dit time-slot management probleem is in dit hoofdstuk allereerst een conceptueel model ontwikkeld. Met dit conceptuele model modelleren we de afweging tussen het wel aanbieden en niet aanbieden van een bepaald levermoment aan de klant. We houden hierbij zowel rekening met de nog te verwachte toekomstige vraag als de mogelijke flexibiliteit van de klant om een ander levermoment te kiezen. Vervolgens is een simulatiemodel voor het testen van verschillende dynamische strategieën ontwikkeld. De resultaten laten zien dat de dynamische strategieën het in veel gevallen beter doen dan de huidige first-come, first-serve (FCFS) strategie.

About the author

Niels Agatz was born in 's-Hertogenbosch, the Netherlands, on December 26, 1978. He obtained his pre-university education (Atheneum) at the Jeroen Bosch College in 's-Hertogenbosch. From 1998, Niels studied Industrial Engineering and Management Science at the Eindhoven University of Technology, the Netherlands. In 2001, he went on a five month exchange to the Universitat Politècnica de Catalunya, in Barcelona, Spain. The research for his master thesis was carried out at the 'Dienst Vervoer en Ondersteuning', the Dutch Ministry of Justice, where he studied the cost-efficiency of prisoner transport in the Netherlands.

In October 2004, Niels became a PhD candidate at the Department of Decision and Information Sciences of the Rotterdam School of Management Erasmus University. His PhD research was conducted in close collaboration with the home shopping channel of grocery retailer Albert Heijn. The project was part of the Transumo program, a platform of companies, governmental organizations and universities aimed at collectively developing knowledge on sustainable mobility in the Netherlands.

His work has been published in the *European Journal of Operational Research*, *Sloan Management Review* and *Wall Street Journal*. Furthermore, a book chapter has appeared in *The Vehicle Routing Problem: Latest Advances and New Challenges*. He has presented his research at major international conferences, such as the annual conference of the Production and Operations Management Society (POMS), the European Conference on Operational Research (EURO), the INFORMS Revenue Management & Pricing Conference and the International Workshop of Distribution Logistics (IWDL).

In December 2008, Niels was rewarded a Rubicon fellowship from the Dutch Organization for Scientific Research (NWO) which enables him to spend 12 months as a postdoctoral researcher at the School of Industrial Engineering of the Georgia Institute of Technology in Atlanta, USA. His research interests are in demand management, vehicle routing and the interface between marketing and operations.

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DEMAND MANAGEMENT IN E-FULFILLMENT

Internet retailers are in a unique position to adjust, in real-time, the product and service offering to the customer and to change the corresponding prices. Although this flexibility provides a vast potential for demand management to enhance profitability, standard practices and models to support the decision makers are lacking as of to date. This thesis aims to contribute to closing this gap by systematically investigating demand management approaches in e-fulfilment. We identify relevant novel planning issues through an in-depth case study at a Dutch e-grocer. We focus particularly on attended home delivery, where the Internet retailer applies delivery time slots to coordinate the reception of the purchased goods with the customer. The main levers to manage customer demand in such an environment are the offered time slots and the corresponding delivery fees. The Internet retailer may apply both of these options, slotting and pricing, at different moments in the sales process, either off-line prior to the actual order in-take or real-time as demand unfolds. The thesis presents several decision-support models for time slot management, both forecast-based and in real-time. The computational studies on real-life data demonstrate the viability and the merits of these methods. The results show that a more dynamic and differentiated demand management approach can lead to considerable cost savings and revenue gains.

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