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# Challenges and Opportunities in Attended Home Delivery

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**Summary.** In this chapter, we focus on home delivery, and, more specifically, on attended home delivery, where the consumer must be present for the delivery. To provide a high service level and to avoid delivery failures as much as possible, it is customary in attended home delivery services for the company to offer the customer a choice of narrow delivery time slots. The objective of this chapter is to highlight and illustrate issues arising in attended home delivery related to these time slots and to present and discuss promising approaches for addressing some of them. We will use Peapod, one of the more successful e-grocers, as an illustrative example.

**Key words:** Consumer direct; home delivery; e-grocery; time slots.

## 1 Introduction

Internet retailing allows customers to purchase goods online and have them delivered directly to their front door. Although a “last-mile” delivery service is convenient for the customer, it creates significant logistical challenges for companies. For example, we have seen the rise and subsequent fall of many e-grocers, including Webvan [11] and Shoplink, who failed to attract the customer volumes needed to make their distribution models viable. Other

e-grocers have been more resilient and have shown that it is possible to design and operate a profitable business, such as Peapod ([www.peapod.com](http://www.peapod.com)) and Albert.nl ([www.albert.nl](http://www.albert.nl)), and many continue to enter the arena, including Fresh Direct [13], with their own ideas on how to succeed.

Home delivery, of course, is not exclusively encountered in the e-grocer space. Many traditional retailers offer an Internet sales channel and home delivery service alongside their conventional sales and distribution structures. The Internet sales channel is part of a multi-channel structure, profiting from synergies such as brand recognition, cross-promotion, purchasing leverage, and an already existing distribution infrastructure. (For a review of the relevant literature on the online channel in a multi-channel environment see [3].) Pure Internet players have entered the market place as well and continue to do so, including Amazon.com, Overstock.com, and Furniture.com. With total annual online sales predicted to be \$213 billion by 2009 [18], home delivery is quickly becoming one of the most important business models.

As mentioned above, the Internet sales channel is often part of a ‘bricks-and-clicks’ multi-channel strategy. In such environments, the delivery component of the Internet sales channel can make use of the existing conventional distribution structure, e.g. using store pick-up points as an alternative method to bridge the last mile. In this chapter, however, we explicitly focus on home delivery, and, equally important, on *attended* home delivery, where the consumer must be present for the delivery. Attended delivery may be necessary for security reasons (e.g. electronics), because goods are perishable (e.g. groceries), because goods are physically large (e.g. furniture), or because a service is performed (e.g. repair or product installation). To provide a high service level and to avoid delivery failures as much as possible, it is customary in attended home delivery services for the company to offer the customer a choice of narrow delivery time slots. Furthermore, we do not consider “same-day delivery,” but focus on environments in which all orders are known at the time delivery operations commence.

In addition to traditional routing issues, several novel challenges and opportunities arise in developing a successful home delivery strategy. Notably, the delivery provider can choose the time slots that are offered to the different customers and the fees associated with deliveries during these time slots, and these choices can facilitate cost-effective routing. Initial time slotting decisions need to be made prior to actual customer order arrival. On a day-to-day basis, as delivery routes begin to fill up, the delivery provider may find that it is impossible to serve a customer in one or more of the offered time slots and that the costs of serving the customer in one of the remaining time slots differ widely. E-commerce allows delivery providers, in real time, the unique opportunity to reduce the number of slots offered to customers and/or change the fees associated with deliveries during each slot. Both aspects, i.e., determining a base time slot schedule and dynamically adjusting the base time slot schedule, intimately tie demand management decisions in attended home delivery to vehicle routing problems with time windows.

The objective of this chapter is to highlight and illustrate issues arising in attended home delivery and to present and discuss promising approaches for addressing some of them. In doing so, we will focus on e-grocers as their environment is one of the most challenging when it comes to attended home delivery due to fierce competition, low profit margins, and perishable bulky products.

The remainder of the chapter is organized as follows. In Section 2, we present the typical issues in attended home delivery by discussing the operations of one of the more successful e-grocers. In Section 3, we discuss service offerings and the construction of time slot schedules. In Section 4, we examine the dynamic, day-to-day aspects of managing time slots. In Section 5, we investigate the use of incentives and penalties to smooth customer demands. Finally, in Section 6, we discuss important areas for future research.

## 2 Home Delivery at Peapod: An Illustrative Case

Peapod is part of Royal Ahold and one of the largest Internet grocers in the U.S.. The company was founded in 1989 by Andrew and Thomas Parkinson. Currently, Peapod serves over 11 million households in cities in the United States, including Chicago, Washington, D.C., and Boston. The company offers attended home delivery service 5 days a week from 6am to 1pm and from 4pm to 10pm and on weekends from 6am to 1pm. Peapod offers more than 10,000 products, including fresh groceries such as farm-fresh produce, deli meats, cheeses and milk. Peapod picks the orders from two state-of-the-art warehouses (Chicago & Washington, D.C.) and from twelve smaller warerooms, adjacent to supermarket partners Stop & Shop and Giant Food. Peapod uses vans to deliver the orders to the customers.

In setting up their delivery operations, Peapod had to decide on the service offering. This involves determining the number of weekly time slots to offer, the length of the time slots, and the actual times at which time slots are offered in the different zipcodes served. At the moment, Peapod offers overlapping 2- and 3.5-hour time slots. Peapod 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. Customer service considerations, as well as delivery cost considerations, play a role in deciding on the service offering. Offering more time slots may increase customer service, but it will likely reduce the drop-density, i.e., the number of visits a delivery truck makes in a specific zip code, which in turn may result in higher delivery costs. Similarly, shorter time slots may provide greater customer convenience, but they decrease routing flexibility and may therefore increase delivery costs. Peapod uses zipcode specific characteristics, such as population density, Internet penetration, and historical demand data to define service requirements for each zipcode. Peapod reevaluates their service offering every six months.

Issues related to service offerings and time slot schedule design are addressed in Section 3.

On Peapod's website, a customer creates an order and then selects a time slot for delivery. In order to have sufficient time for order picking, time slots are closed about 10 hours before actual delivery. Peapod uses morning and evening cut-off times. The cut-off time is 8pm on the day before delivery for morning slots and midnight on the day before delivery for evening slots. While a time slot is open, the number of orders that has to be delivered in a zipcode during that time slot is closely monitored. Based on capacity considerations, certain time slots in certain zipcodes may be closed at some point. Closing a time slot at Peapod means labeling it as "sold out" on their website (see Figure 1). Even before capacity limits are reached, Peapod may open and close time slots for certain customer groups to try to balance the number of orders over the different time slots. For example, it might be beneficial to temporarily close a popular time slot (in a certain zipcode) to force the selection of other time slots. Actively influencing time slots selection enables Peapod to improve the cost-effectiveness of their delivery operations. Determining when to close or open any of the available time slots is a huge challenge. Price incentives, i.e., discounts, can also be used to balance demand over time. Peapod offers discounts to encourage the selection of the longer 3.5-hour time slots when appropriate. Issues related to dynamically opening and closing time slots are discussed in Section 4 and issues related to using incentives to balance demand are addressed in Section 5.

After the order cut-off, delivery routes are determined using a commercial routing package (i.e., a vehicle routing problem with time windows is solved). The routes link orders from different time slots during the same morning or evening shift. Once the delivery routes have been determined, expected delivery times are known and can, in principle, be communicated to the customers. For those customers who select a 3.5 hour time slot, Peapod provides a more precise delivery window to them on the day of delivery. These customers can look on the Peapod website on the day of delivery and find a narrower 2-hour time slot commitment within the original 3.5 hours. During the execution of the delivery routes, the delivery vehicles are tracked using cell phone GPS information. Customer specific stop time information is recorded and uploaded into the routing software for continuous improvements of the planning parameters. Also, estimated arrival times at subsequent stops are computed and customers are notified by phone in case a late arrival is expected. If Peapod 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 assessed an additional fee.

Now that we have presented some of the issues encountered by Peapod, we proceed with a more general discussion of the various components of an effective attended home delivery operation.

## Delivery Times [Return to Shopping](#)

Select an available time for delivery or choose another day from the calendar below.

December 2006						
Su	Mo	Tu	We	Th	Fr	Sa
					1	2
3	4	5	6	7	8	9
10	11	12	13	14	15	16
17	18	19	20	21	22	23
24	25	26	27	28	29	30
31						

- = Delivery Days
- = Selected Date
- = Closed for Holiday

Tuesday, December 12 Delivery		
<b>Morning</b> (Submit Order by 08:00PM Monday Dec 11)		
6:00AM - 8:00AM		<input type="button" value="Select"/>
7:00AM - 9:00AM		<input type="button" value="Select"/>
7:30AM - 11:00AM	ETA	Save \$1.00 <input type="button" value="Select"/>
8:00AM - 10:00AM		Sold Out
9:00AM - 11:00AM		<input type="button" value="Select"/>
9:30AM - 1:00PM	ETA	Save \$1.50 <input type="button" value="Select"/>
10:00AM - 12:00PM		<input type="button" value="Select"/>
11:00AM - 1:00PM		<input type="button" value="Select"/>
7:00AM - 1:00PM	Unattended	<input type="button" value="Select"/>
<b>Evening</b> (Submit Order by 11:59PM Monday, December 11)		
4:00PM - 6:00PM		<input type="button" value="Select"/>
5:00PM - 7:00PM		<input type="button" value="Select"/>
6:00PM - 8:00PM		<input type="button" value="Select"/>
6:30PM - 10:00PM	ETA	Save \$1.00 <input type="button" value="Select"/>
7:00PM - 9:00PM		<input type="button" value="Select"/>
8:00PM - 10:00PM		<input type="button" value="Select"/>
4:00PM - 9:30PM	Unattended	<input type="button" value="Select"/>

[<< Previous Day](#)
[Next Day >>](#)

[Return to Shopping](#)

Fig. 1. Peapod time slots.

### 3 Time Slot Schedule Design

In this section, we present the tactical planning issues related to the design of a time slot schedule.

#### 3.1 Issues

Before we delve more specifically into time slot schedule design, we observe that the use of an Internet sales channel facilitates differentiation of service

offerings. It is possible to develop a customized time slot schedule for each region, for each zip code, for each customer type, or even for each individual customer. In our discussion, however, we differentiate customers based only on their zipcodes which is common practice in many applications.

Time Slot Schedule Design involves two related, but separate sets of decisions, which are usually dealt with in a hierarchical fashion:

- Determine the service requirements and delivery charges for each zipcode;
- Assign specific time slots to each of the zipcodes (respecting the service requirements).

Together, these decisions set the conditions for the delivery routing, which is based on actual customer orders and specific and detailed customer address data.

Each set of time slot schedule decisions has its own specific challenges. Determining the service requirements and delivery charges is primarily driven by marketing considerations, whereas assigning time slots to specific zipcodes is primarily guided by delivery routing considerations. Observe that if the service requirements are such that all time slots are offered in all zip codes, then there obviously is no longer a need to assign time slots to zipcodes. However, in order to increase the demand per time slot per zipcode, it may be beneficial to offer only a limited number of slots in certain zipcodes. Because delivery trucks may visit several zipcodes during a single time slot and a delivery tour spans multiple time slots, assigning specific time slots to a zipcode cannot be done in isolation. Assigning specific time slots to zipcodes has to be done carefully, so as to ensure that cost effective delivery routes can be constructed.

Determining service requirements involves a careful trade-off between marketing and operational considerations. Let us briefly discuss the different design decisions:

- 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 time slots with different lengths, e.g., the 2 and 3.5-hour time slots currently used by Peapod.
- Time slot overlap. The time slot schedule may or may not include time slots that overlap in time. For example, to cover the period from 8am to 12am, it may be possible to 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. A larger number of time slots offered increases customer service, but may also increase delivery

costs as we may have to make far away deliveries more often. 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 zipcodes with low population densities may be offered fewer time slots so as to artificially increase their “density.”

- Delivery charges. Customers, most likely, are willing to pay for the convenience of having their order delivered to their house, but they do not want to pay too much for that convenience. Different delivery charges may be considered depending on the location of the customer, the size of an order, and the time slot of the delivery.

Given a set of service requirements, specific time slots have to be assigned to each of the zipcodes in the coverage area. Several aspects need to be considered. From a customer perspective, a well-balanced offering of time slots over a day (i.e., morning, afternoon, and early evening) and over the week (i.e., weekdays and weekends) is required. From a company perspective, smooth demand over a day and the week is also valuable as it tends to facilitate cost-effective picking and delivery. However, smooth demand patterns are only part of the story, for cost-effective delivery routes it is equally important to have demand be “geographically” smooth. Therefore, routing considerations have to play a significant role in assigning specific time slots to zipcodes.

A time slot design is likely to impact the expected demand in a zipcode. On the other hand, the expected demand in zipcodes drives the time slot design. Therefore, it is clear that understanding demand is crucial. Demand has many dimensions. First and foremost, the size of the demand is important, both in terms of the number of orders and the (physical) volume of orders. Internet sales volume in a zipcode is related to the population density, the average income, the Internet penetration, etc. Order size is often dependent on the customer type (e.g., business or consumer). However, it is not only the size of the demand in a zipcode that is important, it is also necessary to understand the prevalent desired delivery times, e.g., the desired delivery days and the desired times of delivery. Finally, and probably the most difficult characteristic of demand to assess, is what happens with demand when the desired delivery time is not available (not offered). Will demand disappear, i.e., the customer decides not to place an order, or will demand spill over, i.e., the customer decides to place an order in another time slot?

### 3.2 Modeling

Many of the early studies of consumer direct service models primarily examined the impact of different slot lengths. For example, [20] compare transportation costs for attended and unattended delivery and assess the impact of the time slot 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 2-hour time slots. [16] summarize the

delivery policies for many online grocers in the U.S. and use vehicle routing software to evaluate the impact of some of these policies on a few realistic instances of the problem. Both unattended and attended policies are compared, along with different time slot lengths. [21] simulate the delivery costs for two specific models, Streamline.com’s unattended delivery policy and Webvan’s attended 30-minute time slot policy, and find the more restrictive Webvan model to cost five times more. We are aware of only one paper which specifically addresses the delivery pricing problem, i.e., which considers the impact of pricing on delivery efficiency and assesses the revenue versus costs trade-off. [12] 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.

[2] address the problem of assigning specific time slots to zipcodes given a set of service requirements, the Time Slot Schedule Design Problem (TSSDP). The assignment needs to facilitate cost-effective routing of delivery vehicles. Two fundamental assumptions are made: (1) the total demand is known for each zipcode, and (2) the total demand is divided evenly over the set of offered time slots, irrespective of the number of time slots offered. Historical data supports the validity of these assumptions. Two different modeling approaches are presented: continuous approximation and mathematical programming. Continuous approximation relies on simple formulas to approximate routing distances based on problem characteristics, such as vehicle capacity and demand density (see [9] for more details). We use similar concepts to estimate the expected total distance traveled in a day for a given time slot schedule. The approach does not rely on detailed data of individual customer orders, but on concise summaries of “local” data. For example, the expected distance traveled per zipcode for an offered time slot is estimated based on the density of adjacent zipcodes that also offer that time slot. The expected total distance traveled is then approximated by aggregating over all zipcodes and offered time slots. The key assumption of the continuous approximation approach is that the demand density is slowly varying over time and space. The original continuous approximation approach divides the delivery route into two components: (1) the stem distance to the delivery region and (2) the distribution distance between consecutive stops in the delivery region. In our setting, we distinguish between four components of a delivery route:

- distance between stops within the same zipcode within the same time slot;
- distance between stops in different zipcodes within the same time slot;
- distance between stops in two consecutive time slots
- distance between the delivery region and the depot.

Given the evaluation of a time slot schedule, local search is used to improve the schedules.

The quadratic programming approach is based on a combination of two cost approximations. Consider a delivery vehicle. The cost incurred by that delivery vehicle is viewed as consisting of two parts. The first part consists of



the costs incurred during a particular time slot, which is determined by the “cluster” of zipcodes visited during the time slot. The second part consists of the costs incurred by moving from one time slot to the next. The former costs are approximated by identifying a “seed” zipcode for the cluster and considering the distance of each zipcode in the cluster to the seed zipcode. The latter costs are approximated by considering the distance between the seed zipcodes of the clusters visited in subsequent time slots. Because the distance functions are related to the seed zipcodes, the objective function includes quadratic terms.

## 4 Dynamic Time Slotting

In the previous section, we addressed issues related to the time slot design. In this section, we address the real-time management of such a schedule.

### 4.1 Issues

We indicated that Peapod actively monitors demand and adjusts the time slot availability accordingly. When an order is placed, and thus a delivery needs to be scheduled, the home delivery service provider can evaluate the feasibility and costs associated with a delivery in different time slots and can, if deemed beneficial, display a reduced set of options to the customer. The customer can then choose one or can decide to withdraw the order.

The design of a dynamic time slot management scheme depends on the assumptions regarding

- the desired delivery time slot of a customer, and
- the reaction of a customer when presented with a set of time slots that does not contain the desired time slot.

Customer behavior modeling is one of the most challenging aspects of dynamic time slot management.

The fact that customers order online, however, gives the modeler an advantage, because it facilitates monitoring and analyzing individualized customer behavior. This advantage is usually seen only as an opportunity for targeted and personalized marketing, but it is equally important from a delivery planning perspective. By monitoring the time slot selection of a customer, a time slot selection profile may be developed that captures the desired time slot(s) of a customer.

Different strategies can be developed for deciding which time slots to offer to customer. The most basic strategy focuses on feasibility and simply closes a time slot as soon as a certain number of orders for that time slot has been accepted. The limit may be set, for example, based on routing statistics for the zipcode. A more advanced strategy incorporates real-time order information together with information on the already accepted orders and expected future

orders. Of course, only a short amount of time is available to make dynamic time slotting decisions, seconds rather than minutes. Moreover, the order size may not be known at the time the customer selects a slot. For example, Albert.nl lets customers select a time slot before putting the order together.

## 4.2 Modeling

In this section, we review approaches for dealing with (some of) the dynamic slotting issues discussed above. We are aware of only a few papers that consider the home delivery setting explicitly. Both [6] and [7] examine which deliveries to accept or reject. Their proposed approaches exploit stochastic information about future requests to decide on requests under consideration. The objective of [6] is to maximize the number of accepted requests, but the authors do not consider the option of rejecting an “expensive” delivery to preserve resources for more, future deliveries as done in [7]. [5] look at routing of home deliveries, but, motivated by perishable products focus primarily on restricting the time that products can be in the delivery truck. Similar challenges occur in the scheduling of service engineers and repairmen. [17] consider an environment in which requests for service that arrive during one week are scheduled to be served during the following week. The request must be scheduled when it arrives, so the challenge is to commit to a particular delivery time slot that will lead to efficient routing solutions when all remaining requests for the week have arrived. The proposed solution approach involves the selection of seeds for different areas and choosing where to insert requests based on insertion costs into routes containing the nearest seeds. For a similar type of problem, [14] proposes various heuristics based on the average distance between new service requests and already accepted requests.

At this point, we will focus on the model from [7] and two of the proposed heuristics, DIFF and PATH. Providing more detail for this model will serve as a good example of the role customer behavior modeling plays in this context. We will briefly review how [7] addresses the question of dynamic time slotting to account for feasibility, and we will also review how dynamic time slotting is used to maximize profitability. Both models make the following set of assumptions concerning the problem instances and customer behavior. Both models assume a homogeneous set of  $m$  vehicles with capacity  $Q$  to serve the accepted orders, and that requests for a delivery are considered up to a certain cut-off time which precedes the actual execution of the planned delivery routes. Furthermore, for ease of explanation, it is assumed that the time slot schedule offered to all customers has one-hour, non-overlapping time slots covering an entire day, e.g., 8.00 - 9.00, 9.00 - 10.00, ..., 19.00 - 20.00. Note that the time slot schedule can easily be changed and the same ideas will apply. If customer  $i$ 's delivery is accepted, it consumes  $d_i$  of vehicle capacity and results in a revenue of  $r_i$ . For each customer, a time slot selection profile identifies which time slots are acceptable for delivery. Finally, at each point in time  $t$ , customer  $i$  will place an order between  $t$  and the cut-off time with probability  $p_i(t)$ .

Observe that the latter assumption characterizes anticipated future demand. An estimate of future demand, i.e., of demand between the current time and the cut-off time, has a significant impact when maximizing profits, because it may indicate that denying delivery to an expensive customer (in terms of delivery costs) in a particular time slot, may be wise as less expensive customers are anticipated to order in that time slot in the future.

Next, we will summarize the technology, detailed in [7], used to determine dynamically whether a delivery request, characterized by a size and a delivery address, can be feasibly accommodated in any of the time slots based on the set of already accepted customers. Doing this well can increase the number of delivery requests that can be accepted and feasibly delivered. To dynamically determine whether a delivery request can be accommodated in a particular time slot requires evaluating whether there exists a set of routes visiting all previously accepted deliveries as well as the delivery request under consideration, and this must be done quickly. If such a set of delivery routes exists, then the new request can be accepted in the given time slot; if no feasible set of delivery routes exists, then the new request cannot be offered the given time slot.

In [7], the DIFF insertion heuristic is proposed that consists of two phases. In the first phase, all accepted delivery requests are inserted into routes for the  $m$  vehicles, such that the resulting routes are feasible with regard to their committed time slots. In the second phase, the delivery request under consideration is evaluated to see if it can be inserted in one of these partially constructed routes during each of the time slots in its time slot selection profile. This order of insertions is important to ensure that the delivery request under consideration does not prevent any of the previously accepted deliveries from being visited during its committed time slot.

To further improve the chances that the delivery request under consideration can be inserted, randomization is used during construction in the first phase in the form of a Greedy Randomized Adaptive Search Procedure (GRASP) [15]. This enables the creation of several different sets of delivery routes for the already accepted deliveries and the use of each of these to see if there is a feasible insertion for the delivery request under consideration.

If a delivery is feasible within some of the time slots, it is still at the vendor's discretion to decide which time slots, if any, are offered to the customer. This decision can be made based on an evaluation of the expected total profit associated with making the delivery in each feasible time slot versus an expected total profit associated with offering the customer no time slots. Next, we summarize the insertion heuristic proposed by [7] used to address this issue.

The PATH insertion heuristic solves a single instance of a modified vehicle routing problem with time windows (VRPTW) each time a request materializes for each feasible time slot. The created instance of the VRPTW includes all already accepted requests, the request currently under consideration, and all requests that may or may not materialize in the future along with their

probabilities. The objective is to maximize profit given that it may not be possible to satisfy all requests due to limited capacity or time. If the request under consideration is part of the constructed set of delivery routes, it is more valuable to include this request rather than wait for future requests so it is accepted; if the request under consideration is not part of the constructed set of delivery routes, it is rejected. To account for the differences in customer status, i.e., some requests have already been accepted and others have not yet materialized, the revenue and the capacity requirements of the requests that have not materialized yet must be adjusted based on the probability that a delivery request will be received before the cut-off time.

The insertion heuristic consists of two phases. In the first phase, all accepted delivery requests are inserted as described earlier. In the second phase, the remaining customers are inserted until there are no more feasible insertions due to limited capacity. As mentioned above, the size of each delivery request in the second phase is adjusted downward by its probability of being realized, i.e., the size is set to  $p_i(t)d_i$  for request  $i$  at time  $t$ . Note that the request currently under consideration is inserted in the second phase, but it exists with  $p = 1$ . [7] propose several options for evaluating the insertion cost of these proposed deliveries but one method that proved successful was to compute cost of an insertion relative to two already accepted requests, say  $u$  and  $v$ . The expected length of the path between  $u$  and  $v$ , assuming route  $(1, \dots, u, \dots, v, \dots, n + 1)$ , can be computed as follows

$$\sum_{j=u}^{v-1} \sum_{k=u+1}^v d_{jk} p_j(t) p_k(t) \prod_{l=j+1}^{k-1} (1 - p_l(t)).$$

The expected length with and without request  $j$  can be computed as part of the path between  $u$  and  $v$ , with the difference between these two values serving as the cost for inserting  $j$ . The expected revenue  $p_j(t)r_j$  minus this cost yields the value of the insertion.

Extensive computational experiments revealed that

- Dynamically evaluating the feasibility of a delivery in a given time slot (as opposed to limiting the number of deliveries in a time slot to a fixed number) can significantly enhance profitability and reduce the risk of missed delivery windows.
- The value of using profitability rather than feasibility to determine the offered time slots increases as the expected demand to capacity ratio increases.
- The value of using profitability rather than feasibility to determine the offered time slots increases as customer density decreases.

## 5 Dynamic Pricing

In the previous section, we considered dynamically adjusting the time slot offering, i.e. restricting time slot availability. In this section, we consider dynamically changing the corresponding delivery fee.

### 5.1 Issues

Instead of coercively influencing the customer's time slot selection, persuading or dissuading the customer to order in a particular time slot by means of price incentives may form a more customer friendly alternative. The experience of Peapod indicates that even small price incentives (a few dollars) can create significant changes in customers' selection of delivery slots [19].

The decisions that have to be made when determining time slot incentives are:

- What type of incentives to use? Instead of reducing delivery charges, it is also possible to offer free products or coupons. Indicating environmental benefits may suffice to influence customers' choices.
- Use only incentives or also use penalties to dissuade a customer from ordering in a specific time slot?
- In case incentives take the form of delivery charge reductions, will there be a single level, e.g., a \$1 discount, or will there be multiple levels of discounts, e.g., a \$1, \$2, or \$3 discount?
- How much money to make available for incentives for a given day (of execution) or time slot? As customers place orders over a period of time, we have to decide upfront how much money we are willing to spend on providing incentives for a given day of execution, i.e., over the entire period leading up to execution.
- How much money to give to a particular customer? Here we need to consider the trade-off between customer preferences and the cost we expect to incur from delivering to the customer in a certain time slot versus another time slot. This decision is complicated by the fact that we do not yet know all the customers that require a delivery on that day.

### 5.2 Modeling

In recent years, academic research on dynamic pricing has grown significantly (for an overview, see [10]). A related field of research is revenue management, which concentrates on the management of prices and inventory of scarce goods in order to maximize profits. The most successful application area of revenue management is the airline industry. Obvious similarities, but also significant differences, exist between the application of revenue management concepts in the airline industry and home delivery environments (see [1]). The key difference concerns the cost of using inventory, i.e., seats in the context of

airlines and a delivery in a certain time slot in the context of home delivery. The cost of a seat is independent of who gets the seat; however, the cost of a delivery in a certain time slots depends on the location of the customer as well as on the location of other customers requiring a delivery in that time slot.

Not surprisingly, the design of a dynamic pricing scheme depends on the assumptions regarding

- the desired delivery time slots of a customer, and
- the reaction of a customer when presented with a particular set of delivery charges for the time slots.

Only a few papers directly address the subject of pricing in a home delivery context. [4] propose a dynamic pricing model for the delivery windows of a grocery home delivery operation. As in 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 of a Markov decision process and empirically investigate the profit increase relative to a constant pricing policy. We will briefly summarize the approach of [8] to provide an example of how a customer's reaction can be modeled and how such a model can be used to compute incentives. Their model uses the following assumptions. When a request for delivery arrives, the vendor may offer incentives of up to  $B$  dollars per time slot. The probability  $p_i^t$  of a customer  $i$  choosing a particular time slot  $t$  increases by an amount equal to the incentive offered multiplied by rate  $x$ . An increase in the probability of one or more time slots is compensated for by a decrease in the probability of the other time slots. The time slot selection by the customer is based on these modified probabilities. If a delivery in a time slot is infeasible given all the orders that have already been accepted (and assigned a time slot), two options are considered. First, the probability  $p_i^t$  will be redistributed equally among the feasible time slots, and second, the customer can walk away with probability  $p_i^t$ .

A variety of industries, such as package delivery service providers and online grocers, are starting to use historical information about customers to estimate the likelihood of customers requiring a particular service and use this information for planning purposes. As technology and computing resources improve, the number of companies tracking and using such information about their customers and their ordering patterns will only increase. Thus, the ability to estimate and use  $p_i^t$  values seems a realistic assumption.

In the Section 4, we described how to determine quickly whether it is feasible to insert an order in a time slot. Let  $C_t$  denote the insertion cost associated with a time slot  $t$ . If the  $C^t$  values vary widely for different time slots, then an incentive may be offered to choose a time slot with lower costs. Offering incentives raises many challenging questions, such as

- How do we decide which time slot(s) receive an incentive?

- How do we decide on the size of the incentive(s)?

To model this problem, [8] divide the set of time slots with positive probability of being selected into two groups. Let

- $O$  = set of time slots with  $p_i^t > 0$
- $U$  = subset of  $O$  that may receive an incentive
- $V$  = subset of  $O$  not receiving an incentive

The goal is to find

- $I^t$  = the incentive for time slot  $t$
- $z$  = the reduction in probability for all time slots in  $V$

so as to maximize expected profitability.

Given the above and our basic assumption that insertion costs are a good reflection of future costs, the incentive decision for customer  $i$  can be represented by the following incentive optimization problem:

$$\max \sum_{t \in U} (r_i - C^t - I^t)(p_i^t + xI^t) + \sum_{t \in V} (r_i - C^t)(p_i^t - z) \tag{1}$$

subject to:

$$z \leq p_i^t \quad \forall t \in V \tag{2}$$

$$\sum_{t \in U} xI^t = z | V | \tag{3}$$

$$0 \leq I^t \leq B \quad \forall t \in U \tag{4}$$

In the objective, the first portion represents the product of the adjusted profit and adjusted probability associated with awarding an incentive  $I_t$  to time slot  $t$  in  $U$ . This product is the expected profitability from time slots where incentives are offered. Likewise, the second portion represents the expected profits from the slots with no incentives with profits and probabilities adjusted accordingly. The first constraint in Equation 2 limits  $z$  such that the adjusted probability of each slot not receiving an incentive cannot fall below zero. The second constraint, Equation 3, sets  $z$  equal to the increase in probability created by incentives divided by the number of time slots in  $V$ , so the sum of all probabilities will remain equal to 1. Finally, Equation 4 restricts each incentive to be less than the specified limit  $B$ . The quadratic terms can be approximated with a piecewise linear function which transforms the incentive optimization problem into a linear program. As a result, incentives can be computed within a few seconds.

In addition to incentives for choosing among particular 1-hour time slots, it is worthwhile to consider offering incentives to customers to choose a wider time slot. In some situations, customers may be flexible and willing to accept a wider time slot. This may also explain why offering small incentives seems to work for Peapod.

In the model above, an increase in the probability of a time slot due to an incentive is compensated for by a decrease in probability of the time slots in  $V$  (by equal amounts). Now, an increase in the probability of a wider time slot is compensated for by a decrease in the probability of other time slots (again by equal amounts), but now the set  $V$  of other time slots consists of *all* 1-hour time slots with positive probability. In this way, the two incentive models are fairly similar in terms of how money is traded for probability. As before, the quadratic terms can be approximated with a piecewise linear function and transform the incentive optimization problem into a linear program. As a result, incentives for wider time slots can also be computed within a few seconds.

Extensive computational experiments reported in [8] with both models reveal the following insights:

- The use of incentive schemes can substantially reduce delivery costs and thus enhance profits.
- Incentive schemes may substantially reduce the number of walkaways.
- It is sufficient to provide incentives to only a few delivery slots ( $\leq 3$ ).
- It is easier to develop incentive schemes encouraging customers to accept wider delivery slots rather than encouraging customers to select specific time slots.
- The use of incentives can be critical even in the early stages of building a delivery schedule.

## 6 Conclusions

We have presented challenges and opportunities in attended home delivery using e-grocers as a guiding example. It is important to observe and emphasize that even though most of our discussion is relevant in other industries and applications, there may also be substantial differences. When scheduling service engineers or repairmen, for example, the price is typically based on the type of repair. Thus, dynamic pricing is likely not a consideration. Furthermore, the length of the service time may vary quite a bit and may not be known in advance. Thus, short time slots may not be a viable option.

Successfully operating an attended home delivery service requires a careful optimization of both sales and operations processes. The marketing-operations interface, which has been receiving growing attention in the scientific community, takes shape in this application in the interaction between actively managing demand and the resulting transportation efficiency. Understanding this interaction is critical for home delivery providers to be able to maximize their profits.

We have discussed the complexities and potential benefits of such a profit-oriented approach to attended home delivery. While the potential benefits are vast, exploiting them requires sophisticated decision support. The various



interrelated trade-offs between customer preferences, incentives, and routing efficiency are much too complex for simple intuition to suffice. Information technology, in particular in online businesses, provides rich customer data that can serve as a basis for advanced decision making. We have reviewed scientific models that build on this data to optimize decisions in attended home delivery. They make important contributions towards tackling the aforementioned issues.

There remains a vast field of open research questions. One of the interesting issues concerns the appropriate level of detail of routing information in demand management models. Potential approaches may range from coupling demand models with detailed routing models, at the expense of increasing model complexity, to projecting transportation costs in a more aggregate fashion, at the risk of losing accuracy. However, even in the case of more aggregate models, intimate understanding of vehicle routing is a prerequisite for appropriately assessing the profitability of a customer order. In conclusion, we see a huge potential for the vehicle routing community to make significant contributions in the field of attended home delivery.

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## References

1. N. Agatz, A.M. Campbell, M. Fleischmann, and M. Savelsbergh. Demand management in e-fulfillment. Working Paper, RSM Erasmus University, The Netherlands (in preparation), 2007.
2. N. Agatz, A.M. Campbell, M. Fleischmann, and M. Savelsbergh. Time slot schedule design for e-fulfillment. Working Paper, RSM Erasmus University, The Netherlands (in preparation), 2007.
3. N. Agatz, M. Fleischmann, and J. van Nunen. E-fulfillment and multi-channel distribution - a review. to appear in the European Journal of Operational Research, 2007.
4. K. Asdemir, V.S. Jacob, and R. Krishnan. Dynamic pricing of home delivery. Working Paper, University of Alberta, Canada (<http://www.bus.ualberta.ca/kasdemir/research.htm>), 2002.
5. N. Azi, M. Gendreau, and J.-Y. Potvin. Vehicle routing for the home delivery of perishable products. Technical Report C7PQMR PO2004-21-X, CRT, 2004.

6. R. Bent and P. Van Hentenryck. Scenario-based planning for partially dynamic vehicle routing with stochastic customers. *Operations Research*, 52(6):977–987, 2004.
7. A. Campbell and M. Savelsbergh. Decision support for consumer direct grocery initiatives. *Transportation Science*, 39(3):313–327, 2005.
8. A. Campbell and M. Savelsbergh. Incentive schemes for attended home delivery services. *Transportation Science*, 40(3):327–341, 2006.
9. C.F. Daganzo. The distance traveled to visit  $n$  points with a maximum of  $c$  stops per vehicle: an analytic model and an application. *Transportation Science*, 18:331–350, 1984.
10. W. Elmaghraby and P. Keskinocak. Dynamic pricing in the presence of inventory considerations: Research overview, current practices and future directions. *Management Science*, 49(10):1287–1309, 2003.
11. M. Farmer and G. Sandoval. Webvan delivers its last word: Bankruptcy. *News.com*, 2001. Published July 9 on <http://news.com.com>.
12. J. Geunes, Z.-J. Max Shen, and A. Emir. Planning and approximation for delivery route based services with price-sensitive demands. to appear in the *European Journal of Operational Research*, 2006.
13. H. Green. Fresh direct. *Business Week*, page 104, 2003. Published November 24.
14. S. Johns. Heuristics to schedule service engineers with time windows. *The Journal of the Operational Research Society*, 46(3):339–346, 1995.
15. G. Kontoravdis and J. Bard. A grasp for the vehicle routing problem with time windows. *ORSA Journal on Computing*, 7:10–23, 1995.
16. I.I. Lin and H.S. Mahmassani. Can online grocers deliver?: Some logistics considerations. *Transportation Research Record*, 1817:17–24, 2002.
17. O.B.G. Madsen, K. Tosti, and J. Vælds. A heuristic method for dispatching repair men. *Annals of Operations Research*, 61:213–226, 1995.
18. S. Mulpuru, C. A. Johnson, and B. Tesch. 2005 us ecommerce: The year in review. *Forrester Research*, 2006. [www.forrester.com](http://www.forrester.com).
19. T. Parkinson, 2004. executive officer and cofounder Peapod, private communication.
20. M. Punakivi and J. Saranen. Identifying the success factors in e-grocery home delivery. *International Journal of Retail & Distribution Management*, 29(4), 2001.
21. J. Saranen and J. Småros. An analytical model for home delivery in the new economy. Working Paper, The ECOMLOG research program in the Department of Industrial Engineering and Management, Helsinki University of Technology, January 2001.