Title: Revenue Management in Last-Mile Delivery: State-of-the-Art and Future Research Directions

Authors, Affiliations:
André Snoeck
Daniel Merchán
Matthias Winkenbach

MIT Center for Transportation and Logistics

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André Snoeck, MIT Center for Transportation and Logistics
Daniel Merchán, MIT Center for Transportation and Logistics
Matthias Winkenback, MIT Center for Transportation and Logistics

Abstract

This paper explores future avenues of research for revenue management in last-mile delivery. First, we review earlier efforts in this field, which have focused primarily on the problem of attended home deliveries (AHD) of groceries. Second, based on a topological classification of last-mile delivery characteristics, we identify relevant extensions inspired in current industry trends. Finally, we outline how existing models should be extended for these new problems and discuss promising streams of future research.

Corresponding Author:
André Snoeck
MIT Center for Transportation and Logistics
1 Amherst Street, Building E90-9, Cambridge, MA 02142, USA
asnoeck@mit.edu

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Keywords: Revenue management, Last-mile delivery, dynamic pricing, urban logistics

1. Introduction

Internet retailing (e-retailing) has become an essential part of customer shopping behavior over the past 15 years. Incumbents such as Amazon in the USA, and Lojas Americanas (through the acquisition of B2W Digital) in Brazil are trying to adapt their business model to compete with new entrants such as Jet.com, CNova and Flipkart (India). Although home delivery is convenient for the customer, the last-mile of delivery service poses significant logistical challenges for companies. Marketing, operational and urban context considerations add layers of complexity to an inherently difficult planning and routing problem.

Email addresses: `asnoeck@mit.edu` (Andre Snoeck), `dmerchan@mit.edu` (Daniel Merchan), `mwinkenb@mit.edu` (Matthias Winkenbach)

Nevertheless, new opportunities arise to design profitable last-mile delivery strategies [2]. In particular, companies can influence customer behavior by choosing the lead-times or time-slots that are offered (capacity controls) and as well as their associated fees (pricing controls). These decisions ultimately seek to balance the capacity utilization and increase the profitability of the delivery operation. Not surprisingly, revenue management (RM) for last-mile delivery (LMD) receives increasing attention in both literature and industry. However, to the best of our knowledge, the available literature on last-mile delivery revenue management (LMD-RM) strategies focuses on only one subsection of deliveries: the attended home delivery (AHD) of groceries.

Recent industry trends unveil potential research extensions and new problems in this field. For instance, e-grocers such as Amazon now offer unattended *grocery* deliveries. Moreover, in contrast with grocery delivery options that are defined on a time-slot basis, delivery options and prices for *dry-goods* are usually defined on a lead-time basis (e.g. same-day, or 2-day). As e-retailers continue to offer shorter lead-times, the associated pricing, capacity and inventory management decisions could benefit from a revenue management framework. Similarly, several e-retailers now offer order pick-ups at designated locations. These options that significantly impact delivery capacity, cost and customer choices. Furthermore, the expansion of crowd-sourced delivery services provides e-retailers an alternative to increase delivery capacity *on-demand*.

In this paper, we aim to explore opportunities to extend the scope of LMD-RM. After a survey of the existing body of literature, our first contribution, building on the work of Winkenbach and Janjevic [16], is to provide a topology of last-mile delivery characteristics that influence capacity and pricing decisions. In particular, we elaborate on extensions to LMD-RM driven by product exchange location, customer service, distribution and order preparation. The suggested extension of scope also requires an extension of methods. The second contribution of this paper is to assess the strengths and limitations of the existing literature in light of the extended scope, outline modeling extensions, and suggest promising avenues of future research.

The rest of the paper is structured as follows. In Section 2, we provide an overview of the currently available literature. Next, we focus our attention on a subset of the most recent contributions. Our discussion of model extensions in section 4 builds on these state-of-the-art papers.

2. Literature Review

In this section, we first discuss the fundamentals of RM and compare how its application differs from traditional RM problems in the airline industry. Next, we present a survey the literature in RM-LMD.

2.1. Revenue Management

RM refers to the set of strategies and tactics that companies can use to scientifically manage demand for their products and services [15]. Its origin can be found in the airline industry following the Airline Deregulation Act of 1978. American Airlines tried to compete with low-cost airlines to retain leisure travelers without losing the higher margins on their less price sensitive business customers. They started offering different categories of tickets, where discounts came with purchase restrictions. Furthermore, they dynamically controlled the capacity of tickets sold for the different categories, to make sure that the low margin customers would not cannibalize on the highly profitable business customers. In other words, American Airlines applied *price controls* and *quantity controls* to manage demand and match it with the available supply. van Ryzin and Talluri [15] provide a comprehensive overview of classical methods and problems in RM.

Agatz et al. [3] compare airline revenue management with e-retailing. The main conditions for revenue management hold for e-retailing. The retailer faces a heterogeneous market with limited short-term flexibility regarding capacity. Furthermore, it is able to change prices and product availability to specific customers easily. However, the authors note two significant differences compared to traditional revenue management. First, e-retailers sell both a physical product and a delivery service. This is important when making decisions regarding order acceptance. High profit product orders should get priority and product with different sizes influence the capacity of the delivery service differently. Second, the location of a customer, as well as the locations of other customers in the same delivery route, influences the cost of delivery [5]. This is different in, for example, an airplane, where the operational cost are fixed before orders start flowing in and independent of exactly which customer buys. Consequentially, demand management in e-retailing refers to profit management rather than revenue management [3].

Third, the data acquired to calibrate customer choice models for last-mile delivery is generally of high quality. If customers purchase certain products online, it is only at the end of their visit that they are directed to the page

where they choose a delivery option. This means that they already committed to buy. If they don't buy, it is highly likely that this is caused by the price or availability of the available delivery options. This is different in, for example, the case of airlines, where customers often check multiple prices at different websites before returning to the flight of their preference. So many customers that look at a flight, but do not buy it, might just be in this exploration step, without actual commitment to buy. This leads to noise in the data that is almost non-existent in last-mile delivery.

2.2. Current literature in LMD-RM

The available literature that studies the AHD problem, which spans nearly 12 years, can be split according to four criteria: control policy, decision time-frame, routing model and customer choice model (Table 1). We note that all case studies relate to grocery deliveries in the European market

Table 1: Overview of LMD Revenue Management Literature

	Control	Time-frame	Routing
Campbell and Savelsbergh [5]	Quantity	Dynamic	VRP Heuristics
Campbell and Savelsbergh [6]	Price	Dynamic	VRP Heuristics
Asdemir et al. [4]	Price	Dynamic	-
Agatz et al. [1]	Quantity	Static	Continuous approximation
Hernandez et al. [11]	Quantity	Static	VRP Heuristics
Ehmke and Campbell [9]	Quantity	Dynamic	VRP Heuristics
Cleophas and Ehmke [7]	Quantity	Dynamic	VRP Heuristics
Klein et al. [13]	Price	Static	Seed-based approximation
Yang et al. [18]	Price	Dynamic	VRP Heuristics
Klein et al. [12]	Price	Dynamic	Seed-based approximation
Yang and Strauss [17]	Price	Dynamic	Continuous approximation
	Customer choice	Case study	
Campbell and Savelsbergh [5]	Exogenous probability	-	
Campbell and Savelsbergh [6]	Exogenous probability	-	
Asdemir et al. [4]	Multinomial logit	-	
Agatz et al. [1]	Take whatever available	Albert.nl, Nijmegen	
Hernandez et al. [11]	Exogenous probability	-	
Ehmke and Campbell [9]	Exogenous probability	Stuttgart	
Cleophas and Ehmke [7]	Exogenous probability	Stuttgart	
Klein et al. [13]	Non-parametric rank-based	-	
Yang et al. [18]	Multinomial logit	UK grocer, London	
Klein et al. [12]	Multinomial logit	-	
Yang and Strauss [17]	Multinomial logit	UK grocer, London	

Control policy and time-frame have been the two primary criteria to frame AHD problems in the literature. First, price controls entail the definitions of price points for a given time-slot, whereas quantity controls determine which time-slots to offer to a given set of customers. Second, static decisions are of a tactical nature and do not depend on online data, whereas dynamic decisions are of an operational nature and based on online data. We outline the state-of-the-art literature in greater detail below.

Agatz et al. [1] explore the tactical problem of defining time-slot schedule to be offered in a given zip-code, considering its demand potential, service requirements (i.e. time-slot options) and delivery efficiency, in the context of grocery delivery operations. They obtain a cost-optimal schedule for each zip-code, using routing cost approximations and efficient improvement heuristics. Their results indicate savings of up to 10% in delivery costs due to this regional differentiation in delivery time slots. Similarly, they note an increase of up to 25 % in delivery costs as a result of narrower time-slots. Klein et al. [13] extend this problem to account for differentiated pricing for each time-slot offering. They model customer preferences using a non-parametric rank model, which is instrumental to anticipate future operational routing costs, as a result of demand responses to different prices.

Yang et al. [18] develop a dynamic slot pricing policy to manage demand over a finite booking horizon prior to the actual delivery, i.e. all demand is booked when delivery starts. Customers select a (one hour) time slot and this can be influenced by pricing. Their policy relies on a a stochastic dynamic program, which currently serves as the de facto standard for dynamic pricing problems and we will introduce this model in greater detail in section 4. Klein et al. [12] build on this model by improving the approximation of the opportunity cost. Simultaneously, Yang and Strauss [17] build on this standard framework by focusing on finding a methodology that is suitable for industry scale optimization. Our work adds to this by suggesting opportunities to adapt this framework to allow for different operational last-mile delivery networks.

Building on the two criteria, previous works classify AHD problems based in four categories: differentiate slotting, differentiated pricing, dynamic slotting and dynamic pricing (See Table 2) [3, 18, 13].

The goal in *differentiated slotting* is to find which time windows to offer in which delivery area. For example, the Dutch grocery store AH.nl only makes certain time slots available to suburban towns, while typically every time-slot is available in city centers. *Differentiated pricing* aims to find the

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Table 2: Classification of revenue management in AHD [3, 18, 13]

	Time slot allocation	Time slot pricing
Static (off-line)	Differentiated slotting [1], [11]	Differentiated pricing [13]
Dynamic (online)	Dynamic slotting [5], [7], [9]	Dynamic Pricing [6], [4], [18], [12], [17]

optimal static price selection for each delivery time slot for each delivery area. Event though differentiated pricing might result in additional revenues, its main goal is to influence customer choices to balance delivery capacity and reduce delivery costs [13].

Dynamic decisions are made while an order is placed and are based on the opportunity cost associated to the order. *Dynamic slotting* entails that with every incoming request, a decision is made either to accept the order or to reject it and save capacity for a more profitable order in the future. This means that, in practice, the offered time slots could be different for two customers ordering different products in the same neighborhood. Lastly, *dynamic pricing* evaluates the price offered for each time-slot for a particular order.

A second major categorization of literature in the field of AHD entails the inclusion of routing cost. This aspect is particularly defining for revenue management in (last-mile) logistics operations. Two major approaches can be distinguished (see Table 1). Most papers include explicit routing decisions into their models, following the seminal paper of Campbell and Savelsbergh [5] [6, 11, 9, 7, 18]. Nonetheless, given the complexity of vehicle routing problems with time-windows (VRPTW), most researchers build on heuristics rather than exact methodologies to build routes. In [1] and [17], authors use routing cost approximations building on the work of Daganzo [8]. Alternatively, Klein et al. [12] and Klein et al. [13], build on seed-based approximations first introduced by Fisher and Jaikumar [10].

We also observe an evolution in the approaches to model customer behavior: while earlier (and some more recent) works use simple probabilistic models [5, 6, 7, 9, 11]; latest works leverage more advanced techniques, namely multinomial logit or non-parametric rank-based models [4, 12, 13, 17, 18].

3. A Topology of Last-Mile Delivery Models

As discussed in section 2, most research on LMD-RM has focused on ADH in the context of online grocery services. Nevertheless, over the past decade, new delivery models have emerged driven by raising customer expectations in service quality, speed and product availability, and by overall new market opportunities for online retailers and last-mile delivery service providers. These delivery models have been tailored to serve different product segment and services needs. For instance, Amazon operates different delivery models for its grocery business (Amazon Fresh) and its dry-goods retail business, with specific pricing strategies for each model.

In this section, we build on a topology of variables that define delivery models, to present extensions to the AHD problem. Our discussion is supported by examples from logistics practice. In section 4 we explore how analytical frameworks in RM should be extended to model these extensions.

3.1. Topological characterization of LMD models

Winkenbach and Janjevic [16] introduce a classification of LMD models in e-retail based upon five key variables: order lead time, place of order preparation, distribution, intermediary transshipment and product exchange point. We build on this classification to explore extensions to the classical AHD problem used in existing literature in LMD-RM (see Table 3).

Table 3: A topological analysis of AHD and extensions (adapted from [16])

Variables	Assumptions in AHD	Relevant Extensions
Product exchange	Home or office	Designated pickup locations
	Attended delivery	Unattended Delivery
Customer service	Time-slot driven choice	Lead-time driven choice
Distribution	Homogeneous fleet	Heterogeneous fleet
	Fixed short-term capacity	Crowd-sourced capacity
Order preparation	Unrestricted product availability	Inventory delays

3.1.1. Product exchange

Regardless of the product type, delivery models have usually operated under a *home-delivery* paradigm. Nevertheless, over the past few years, designated pick-up locations have emerged as an alternative that offers convenience to both e-retailers and consumers. This delivery option entails specified locations where customers can pick up the goods. Examples include

Walmart's and B2W's in-store pickups, and the Amazon lockers. Overall, designated pick-up locations increase the efficiency of the delivery tour by consolidating multiple orders in a single stop. For customers, designated pick-up locations provide more service flexibility but requires them to travel to the designated locations.

A pick-up service has important capacity and pricing implications. Since it frees up delivery capacity and/or increases routing efficiency at the expense of customer travel, proper incentives need to be defined, usually in the form of price discounts. At the tactical (static) level, retailers might need to determine the type and location of pick-up services. At the dynamic, operational (dynamic) level, retailers would need to define price levels based on available capacity and order forecasts. As customer segments might have different preferences for different pick-up services, choice models will also need to be extended.

Paradigms on product exchange *modes*, i.e. attended or unattended, have also changed. e-Grocers have traditionally operated attended deliveries, while dry-goods delivery services have been usually unattended; a division that has influenced past research efforts. Nevertheless, industry practice provides many counter-examples. For instance, Amazon now offers unattended grocery deliveries, while B2W operates an attended service for its dry-goods due to safety concerns. Future LMD-RM research should consider the variety of (interrelated) factors that influence the choice of product exchange mode

3.1.2. Customer service

Grocery deliveries generally operate under daily *time-slots*, which need not to be fixed in duration and may overlap. For instance, Walmart offers two-hour overlapping time-slots respectively, whereas Peapod offers time-slots ranging from two to six hours. The delivery *lead-time* (i.e. the number of days from purchase to delivery) ranges from one day to several weeks. Generally, time-slots drive the pricing decision. On the other hand, dry-goods usually operate under a delivery lead-time logic, with differentiated pricing. For instance, B2W offers three delivery lead-time options at different price levels: same-day, up-to three days and up-to five days.

While the allocation and pricing of time-slots has been well studied in the literature, lead-time driven problems have received scant attention. Certainly, time-slot decisions constitute richer problems for analysis, given their strong implications for route planning and executions. Nevertheless, as delivery lead-times become shorter (e.g. 2-hours, 4-hours or, more generally,

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same-day delivery), the impact of related pricing and capacity decisions will have a greater effect on the overall efficiency of the last-mile operation.

3.1.3. Distribution

Fleet ownership options range from fully-owned to fully outsourced, although hybrid approaches are commonly observed in practice. For instance, Amazon delivers through both, third-party service provide such as UPS and through its own vehicle fleet. More recently, crowd-sourced models have emerged. Two examples include Instacart and Walmart's pilots for LMD using ride-sharing services such as Uber and Lyft. The ownership of the fleet has important capacity and cost implications.

Current models assume that a fixed fleet with fixed capacity is available and that the cost associated to owning this fleet is sunk. However, the opportunity to use ride-sharing services relaxes this assumption. This has important implications for the computation of opportunity cost in dynamic pricing models. Since capacity is not fixed, a grocer might want to use more of its own fixed capacity, even when it is expecting higher value customers later on.

3.1.4. Order preparation - inventory delays

e-Retailers are increasingly competing in terms of speed of service to the customer. Companies design their inventory network to provide this service by having inventory of most fast-moving products close to big customer hubs (e.g. Amazon has a warehouse for these fast-movers in Boston) while the slow-movers are stored in large warehouses in areas with lower cost. However, while an order can consist of a combination of slow- and fast-movers, the lead-time for the total order is equal to the maximum lead-time of any of the products. This is unsatisfactory to some customers, who might decide to drop the order completely and to buy the product at a competitor. To ensure maximal customer service and avoid lost product sales, a company can offer to ship both products separately. Amazon is one of the companies providing this service.

The main decision to make while splitting an order in multiple deliveries is related to the rules of splitting the order. From a marketing and communication perspective, it does not seem to be ideal to offer an individual delivery option and associated fee for, for example, five products and their combinations. However, it is reasonable to assume two categories of products, slow-movers and fast-movers.

4. Model extensions and new problems

In this section, we discuss extensions to existing research contributions and new research avenues in the broader LDM context. We divide this discussion in two major parts. First, we review extensions to the existing body of literature in AHD of groceries. For instance, current contributions generally assume a homogeneous vehicle fleets with fixed capacity (owned fleet) (e.g. [13], [12]). Thus, we explore how models should be extended to account for fleet heterogeneity and flexible capacity. Second, we define new problems and discuss potential modeling approaches. For example, we introduce the problem of differentiated lead-time pricing for UHD .

We concentrate our discussion in dynamic models. Certainly, interesting extensions can also be introduced for static problems. Nonetheless, dynamics models offer a much richer set of modeling extensions from a revenue management standpoint. Furthermore, the static problems discussed in section 2 can be framed as extensions of more general logistics network design problems. Thus, in the remainder of this paper we focus on dynamic decisions and leave static problems for future work.

4.1. Dynamic model and extensions

We believe an understanding of the de-facto framework for dynamic pricing in last-mile delivery operations is paramount for understanding possible extensions, even though we do not aim to extend the model in this paper. The stochastic dynamic framework developed by Yang et al. [18] and extended by Yang and Strauss [17] and Klein et al. [12] is presented in Equation 1.

$$
\begin{aligned}
V_t(\mathbf{x}) = \max_{\mathbf{g}} \{ &\lambda_t \sum_{s \in S(\mathbf{x})} P_{s,S(\mathbf{x})}(\mathbf{g})[r + g_s + V_{t+1}(\mathbf{x} + \mathbf{1}_s)] \\
&+ [1 - \lambda_t \sum_{s \in S(\mathbf{x})} P_{s,S(\mathbf{x})}(\mathbf{g})]V_{t+1}(\mathbf{x})\}
\end{aligned}
\tag{1}
$$

with the boundary conditions

$$
V_{T+1}(\mathbf{x}) = -C(\mathbf{x}), \forall \mathbf{x} \in X
\tag{2}
$$

Where

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$$\mathbf{x} = \text{Vector of accepted orders for time slot s}$$
$$X = \text{all } \mathbf{x} \text{ that denote feasible delivery schedule,}$$
$$C(\mathbf{x}) = \text{Minimum delivery cost at time T given } \mathbf{x},$$
$$P_{s,S(\mathbf{x})}(\mathbf{g}) = \text{Probability that a customer chooses delivery slot } s \in S(a) \text{ if}$$
$$\text{it is offered prices } \mathbf{g},$$
$$S(\mathbf{x}) = \text{Available time slots given } \mathbf{x},$$
$$\mathbf{g} = \text{Price vector offered to a customer for time slot s,}$$
$$\lambda_t = \text{Probability of an order arrival in period } t,$$
$$r = \text{Revenue of an order before distribution.}$$

The model aims to find the profit optimal price vector $\mathbf{g}$ to offer to a particular customer that arrives in period t. We assume that the periods are small enough, so that maximum one customer arrives with probability λ_t. Customer preferences are captured by defining probabilities $P_{s,S(\mathbf{x})}(\mathbf{g})$, based on a multinomial logit model. For a more in depth introduction of this model we refer to Yang et al. [18]. We can see that the revenue we gain if the customer choses a delivery window captures both the price charged for that particular time-slot, g_s, as well as the revenue of the order, r. If the customer decides to buy, we update our state-space $\mathbf{x}$, which captures all the currently excepted orders. Naturally, after the cut-off time T, the remaining value is just the cost of delivering all accepted orders.

The price vector that maximizes $V_t(x)$ in Equation 1 is given by

$$\mathbf{g}^* = \arg\max_{\mathbf{g}} \sum_{s \in S(\mathbf{x})} P_{s,S(\mathbf{x})}(\mathbf{g})[r + g_s - (V_{t+1}(\mathbf{x}) - V_{t+1}(\mathbf{x}+\mathbf{1}_s)O_{xts}], \quad (3)$$

with

$$O_{xts} = V_{t+1}(\mathbf{x}) - V_{t+1}(\mathbf{x}+\mathbf{1}_s) \quad (4)$$

being the opportunity cost of a customer request for time-slot s in period t. Klein et al. [13] argue that O_{xts} cannot be determined exactly given the large state-space. Furthermore, for an exact definition of the opportunity cost, we would need to solve the VRPTW problem, which is known to be NP-complete [14]. Therefore, an approximation of $\tilde{V}_{t+1}(\mathbf{x})$ is required to approximate $\tilde{O}_{xts}$. The approaches of Yang et al. [18], Yang and Strauss [17] and Klein et al. [12] differ, as can be seen in Table 1.

4.2. Distribution - Flexible crowd sourced fleet

Relaxing the assumption of an homogeneous fixed fleet does not influence the formulation the dynamic pricing framework of Equation (1). Decision variables $\mathbf{g}$ still need to be found for every time slot. However, the option to flexibly operate crowd-sourced capacity affects the approximation of O_{xts} in two ways. First, if a prospective order is located in isolated areas it might be cheaper to send an on-demand vehicle towards that order instead of requiring one of our delivery trucks to make a large detour. This situation will lead to a decrease in $\tilde{V}_t(\mathbf{x})$ and we are able to charge a lower delivery fee and increase the probability that the order will be placed, leading to higher profits. Second, we don't run out of capacity since we always have the option to use the on-demand service. Consequently, the opportunity cost associated to accepting a current order and thereby losing a potential big future order decrease. Both components drive an increase in $\tilde{V}_t(\mathbf{x})$ and a decrease in some of the components of $\mathbf{g}$.

4.3. Product exchange - Pick-up

Currently, most Internet retailing websites provide the option to choose between delivery and pick-up before time-window specific prices are shown. This means that when customers make the decision to go for delivery, they are not aware of the pick-up prices and therefore are highly unlikely to revert their decision. From a company perspective, it might be worthwhile to influence customers to go for a pick-up option using discounts, if this significantly reduces the cost of accepting the order.

The main challenge of including pick-ups lies at the tactical planning level, including integrating determining the location of the pick-up locations. The influence on the dynamic pricing framework is less invasive, but it requires a slight adaption of the framework, as well as an extension to the approximation of $\tilde{V}_t(\mathbf{x})$ and the customer choice model.

Currently $\mathbf{g}$ includes a delivery charge for each time slot. This should be extended by providing delivery charges for pick-up options. In the original framework, $\mathbf{g}$ captured a price for each time slot s, but in the situation with pick-ups it should also provide a price for every pick-up time slot p. Note that these time-windows do not have to be the same. In practice, time-windows on pick-ups are wider (in the range of one or more days) than for delivery (in the range of hours). The pick-up option also has to be included in the calculation of the opportunity cost. Similar to flexible crowd-sourced fleets, we always have an option to accept customer orders. This is a bit more

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restrictive, since customers should be willing to go for a pick-up. Similarly, we might be able to convince customers that are located at inconvenient delivery locations to choose for pick-up, customers that otherwise would have been lost. Both factors drive an increase in $\tilde{V}_t(\mathbf{x})$. Naturally, if no customer chooses pick-up, we remain with similar values as in the original problem. Lastly, a major practical contribution is required in updating the customer choice model with the appropriate utilities for pick-up. Currently, this is not captured by existing contributions.

4.4. Order reparation - Inventory delays

Building on the discussion in section 3 about thee implications of fast- and slow-moving inventory for demand management, if an order consists of all slow-movers or fast-movers, no changes are required in the dynamic pricing model. However, for a mixed order, we see changes in the framework, the computation of the opportunity cost and the calibration of the customer choice model. For a mixed order, we should define two different sets of available time windows $S(\mathbf{x})$. The set of available time-windows for the combined order as well as for the slow-movers separately will be smaller than the set for the fast-movers, i.e. the latter includes time-window options that are closer to the order time since the lead-time is lower. At the same time, we also need to extend $\mathbf{g}$. It should provide a delivery charge for ordering all orders together for the available time-windows and it should provide a price for letting fast-movers and slow-movers being delivered separately.

However, the impact on the computation of the opportunity cost is minor. The structure of the model does not have to change, but we need to compute the cost associated to delivering together or separately simultaneously and communicate those two options trough the price vector.

Since we provide new options to the customer, new data is required to calibrate the the customer choice model to approximate the utilities associated to each of the options.

4.5. Customer-service: Lead-time

The available literature focuses on the pricing of time-windows, however in practice most online purchases of dry-goods promise delivery within a certain lead-time. Of the four proposed extensions, the redefinition of this assumption leads to the biggest changes of the dynamic pricing model. We outline the complications of using the current framework for lead-time

customer-service promises, but redefining the current framework is beyond the scope of this paper.

The main benefit of offering lead-times from a last-mile delivery company perspective is also its major challenge to the current pricing framework. With a certain lead-time, companies have the flexibility to deliver orders earlier than the promised lead-time (e.g. if you promise delivery within two days, it is fine if you deliver the same day). Especially in neighborhoods with lower demand density, you want use this flexibility to avoid visiting certain areas of the city a couple of days in a row for a low number of orders. This consolidation provides the option to provide discounts shorter lead-times. For example, if you know you are going to visit a certain area today, it might be worthwhile to provide a discount to same-day delivery in that area. However, these consolidation opportunities provide themselves on a continuous scale and the decision to actually start the route is more flexible compared to time-windows. With time-windows, there is limited flexibility in consolidating orders. One of the advantages of this property is that each time-window (or group of overlapping time-windows) can be considered as a separate problem regarding capacity. There is a hard cut-off time T for choosing a specific time-window, after which no orders are accepted because the route has to start to deliver all customers in that time-window. When we look at lead-times however, we are essentially looking at a rolling horizon, so such a cut-off does not exists in the same way with lead-times, since ordering later also implies delivering later (if the same lead-time option is chosen). However, something similar could be constructed combining orders with different lead-time orders, but with the same 'deadline', e.g. a four day lead-time ordered four days ago and a same-day delivery ordered today both need to be delivered today.

Naturally, the flexibility of delivering an order earlier than required also influences the structure of the opportunity cost approximation. Furthermore, it is important to extend these cost by a penalty for early delivery. If customers know that there product is generally delivered within two days, even if they chose a lead-time option of five days, there is no incentive for them to switch to the more expensive two day lead-time option.

However, the main decisions remain similar to delivery in the case of time-windows. We need to decide what prices to offer for which lead-time options to which customers. It is therefore also important to update the customer choice model accordingly.

5. Conclusion

In this review paper, we discuss relevant extensions to modeling frameworks in RM-LMD. Based upon the state-of-the-art literature and current trends in the field, we present several future research directions with particular interest in dynamic problem settings. We also outline many relevant extensions to revenue management models, beyond the classical attended home delivery problem.

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