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Flexible dynamic time window pricing for attended home deliveries

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Abstract In the challenging environment of attended home deliveries, pricing of different delivery options can play a crucial role to ensure profitability and service quality of retailers. To differentiate between standard and premium delivery options, many retailers include time windows of various lengths and fees within their offer sets. Customers want short delivery time windows, but expect low delivery fees. However, longer time windows can help to maintain flexibility and profitability for the retailer. We present flexible dynamic time window pricing policies that measure the impact of short time windows on the underlying route plan during the booking process and set delivery fees accordingly. Our goal is to nudge customers to choose time windows that do not overly restrict the flexibility of route plans. To this end, we introduce three dynamic pricing policies that consider temporal and/or spatial routing and customer characteristics. We consider customer behavior through a nested logit model, which is able to mimic customer choice for time windows of multiple lengths. We perform a computational study considering realistic travel and demand data to investigate the effectiveness of flexible dynamic time window pricing. Our pricing policies are able to outperform static pricing policies that reflect current business practice.

Keywords Dynamic Pricing, Time Windows, Customer Acceptance, Attended Home Deliveries, Vehicle Routing with Time Windows, Route Flexibility

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1 Introduction

The worldwide growth of e-commerce has led to a rapid increase in demand for home delivery services. New online businesses continue to enter the market, and also brick-and-mortar retailers are expanding through online channels providing pick-up or home delivery services. At the same time, customers have high service expectations. For deliveries of groceries or white goods, for example, a customer has to be present during the delivery, and this requires the use of delivery time windows. Studies have shown that customers prefer time windows of two hours or less for such deliveries (Mintel 2014). These attended deliveries are very expensive from a logistics' point of view, and customers do not want to pay much for them.

Creating a profitable business model within this environment, especially arranging tight delivery time windows and maintaining logistics efficiency, is challenging. Hence, retailers need to decide which delivery options to offer to a customer and at which price. For instance, a brick-and-mortar retailer may want to differentiate between offering a standard option – the free store pick-up – and a premium delivery option to the customer's doorstep within a time window chosen by the customer. Since the latter channel uses scarce delivery resources, the retailer needs to decide carefully at which price to offer this premium option. Within this paper, we will use long and short time windows as an illustrative example for standard and premium delivery options. However, this framework could be easily extended to any multichannel situation where a retailer has to decide how much to charge for the premium option when it costs the retailer more in terms of using scarce resources than the standard option.

One of the most challenging applications of e-commerce are online supermarkets, which we will use in this paper to demonstrate our approach. Profit margins for groceries are known to be low, and therefore it is important to create cost-efficient last-mile deliveries. A typical booking process includes the selection of groceries and the choice of a time window for order delivery. For these attended home deliveries, the customer chooses from a set of possible time windows, and the order is confirmed immediately. We refer to this step as "order acceptance". Retailers have to define which time windows to display to each customer without knowing the overall demand. Offering short delivery time windows decreases the degrees of freedom that are needed to create efficient delivery routes (Lin & Mahmassani 2002). Less efficient delivery routes lead to an increase in delivery costs, a loss in the number of customers that can be serviced, and reduce the retailer's profit.

To differentiate between standard and premium delivery options or simply to nudge customers to unpopular time windows, many online supermarkets offer time windows of different lengths and delivery fees. To define fees for delivery time windows, they have to decide on the number of price points and whether they want to adapt fees dynamically during the booking process. First, retailers can choose between a one-price policy (all time windows have the same delivery fee) and a multi-price policy (delivery fees differ among the time window options). Second, they need to decide whether prices remain static during the booking process (delivery fees do not change in the course of time) or if prices are dynamic (delivery fees are adapted dynamically to, e.g., customer or capacity characteristics). In the case of a simple *static one-price* policy, customers will base their time window choice solely on time window characteristics like time of the day. This policy is common among online supermarkets that do not have to balance demand among the different time window options, and if only time windows of one particular length are offered. Examples for online supermarkets employing this policy are AllyouneedFresh (Germany), which utilizes an almost unlimited delivery capacity from DHL, and Picnic (Netherlands), which follows fixed routing patterns to service customers. Online supermarkets that follow a static multi-price policy include Tesco (UK), Peapod (US), AlbertHeijn (Netherlands) and Bringmeister (Germany). Usually, these supermarkets offer less popular time windows at lower delivery fees to help balance demand. For all these policies, short time windows are available if the customer is willing to pay more. At Tesco, for example, customers have to pay double and at Bringmeister even five times as much for choosing a 1-hour time window (premium option) compared to a 4-hour long time window (standard option).

In our previous paper, we developed time window management mechanisms that consider the flexibility in the evolving route plans to decide when to offer short and long time windows (Köhler et al. 2019). Considering temporal and/or spatial characteristics, we showed that systematically offering short or long time windows can result in more customers accepted while maintaining a high service quality. In the literature, this is known as *slotting*. However, withholding short time windows may not be satisfying for customers. Therefore, within this work, we offer all short time windows, but offer them at different delivery fees, which is known as *pricing*. The fees reflect the time window's impact on routing flexibility. Time window pricing aims at balancing customers' willingness to pay (and earning some extra revenue via the attached delivery fees) with demand offerings at different time window options.

In this work, we present flexible dynamic time window pricing policies that adapt delivery fees according to spatial and temporal characteristics of the evolving route plan. In particular, our policies consider the impact of short time windows on the routing flexibility in the course of the booking process. We extend approaches from Köhler et al. (2019) and translate them into multi-price policies that determine dynamically how much a retailer should charge a customer for choosing a particular short time window. For this purpose, we introduce a nested logit customer choice model considering choice probabilities for different time window lengths. We investigate the effectiveness of our pricing policies in terms of the number of customers that can be accepted and the resulting sum of fee/overall revenue that can be achieved. We also examine in which situations our approaches are able to create a higher level of customer service by accepting more customers within a short time window at no extra costs for the retailer and/or decrease the customers' delivery fees relative to a simpler static price policy that reflects common business practice.

The paper is organized as follows. In the next section, we present related literature on time window pricing and slotting. Then, we formalize our problem and introduce the customer choice model for multiple time window lengths. We demonstrate and evaluate our approaches with a computational study based on data from Berlin, Germany. Finally, we conclude the paper with a summary and an outlook on future work.

2 Related literature

In this section, we give an overview of approaches that support retailers in the management of delivery time windows. In particular, retailers can assign delivery fees to time windows to control or influence customer choice (*pricing*). They can also limit the availability of time windows systematically (*slotting*). Pricing and slotting can be implemented either before the booking process begins (*differentiated*) or in real-time while the booking process runs (*dynamic*). Hence, in total, there are the following four types of time window management concepts, which we will consider in the following: *differentiated pricing*, *dynamic pricing*, *differentiated slotting*, and *dynamic slotting* (Agatz 2009). First, we will present literature that considers the pricing of time windows, which is also the area we are contributing to with this paper. We will especially review how routing flexibility and time windows of different lengths can be included in pricing decisions. Then, since we derive flexibility information from recent slotting approaches, we will also provide an overview of slotting approaches.

2.1 Pricing of delivery time windows

Charging customers for delivery aims at covering expenses arising from the "last mile" to the customer's home and/or influencing customer's time window choice to enable better utilization of available delivery resources. Generally, customers do not want to pay much for time-window based deliveries and tend to cancel the booking process rather than book expensive time windows (Paas et al. 2018). Offering time windows for a small delivery fee usually results in higher customer satisfaction and more customers willing to book. In this context, Paas et al. (2018) show that lower delivery fees can even increase the basket value of a customer's order. Klein et al. (2017) are the first to follow the idea of *differentiated pricing* for attended home deliveries. Routing costs are anticipated to create offline pricing decisions for a retailer. They show that to influence customer choices, not only the amount of the delivery fee, but also the fee differences between time window options matter, and even small differences can make a big difference. Although their approach clearly outperforms static one-price policies, no customer-individual characteristics can be considered in the pricing decision as is possible with dynamic pricing.

Known from airline industry applications, *dynamic pricing* is particularly effective to control perishable resources and demand that is stochastic and price sensitive (Bitran & Caldentey 2003). Agatz et al. (2013) show that attended home deliveries represent a relevant application for dynamic pricing due to the fixed delivery capacity that has to be assigned dynamically during the booking process. With dynamic pricing of attended home deliveries, different delivery fees are attached to time windows during the booking process. Campbell & Savelsbergh (2006) consider the interaction of incentives and routing costs on the overall profit during order acceptance. Asdemir et al. (2009) analyze delivery fees in relation to available capacities and increase the delivery fees as capacities become scarce during the booking process. However, they test their approach only in a rather simple setting with only two time window options. Yang et al. (2014) analyse the customer's willingness to pay as well as the likelihood of choosing a specific time window. Similar to our approach, they also use an insertion heuristic to decide which time windows can be offered. They build possible route plans to estimate the costs of a request whereas we measure the current flexibility in our route plans to enable accepting more customers. Ulmer (2017) employs dynamic pricing for deliveries with deadlines, proposing a pricing policy that considers the arrival time or the location of a request during the order horizon. This is similar to our ideas of dynamic flexibility pricing. However, Ulmer (2017) uses fixed points in time and static vicinity measures of customer location's in relation to the depot. We consider the actual utilization of delivery capacities and the proximity of requesting customers relative to our tentative route plans. This allows us to measure the potential flexibility loss in the underlying route plans more precisely.

The effectiveness of dynamic pricing strongly correlates with the suitability of offered time windows with customers' temporal and monetary expectations. Thus, in order to create time window offer sets and assign delivery fees, the expected customer choice behavior needs to be modelled carefully. Vulcano et al. (2010) name two fundamental challenges when estimating customer choice models: all relevant attributes that have an impact on customer choice must be considered, and sufficient data has to be available to estimate customer choice models.

A simple possibility to incorporate customer choice is assuming probabilities for different time window options. In Campbell & Savelsbergh (2006), incentives are used to influence the customers' booking behavior, and these incentives increase the probability of a customer choosing a specific time window by a given factor. The probabilities of customers for choosing a specific time window as well as customers' price sensitivities are assumed to be known. The model ignores interdependencies of time window choices and does not include a "no-purchase option". In Klein et al. (2017), a rank-based choice model is presented, in which customer choice is modelled using preference lists instead of probabilities for each customer. Given historical order data, creating preference lists seems to be easily doable for a retailer. However, compared to general choice probabilities, preference lists cannot be adapted easily if the retailer decides to change the design of time window offerings, for example.

To mimic customer choices in attended home deliveries more thoroughly, the multinomial logit (MNL) model is commonly used. The MNL is based on the assumption that a customer-individual utility is attached to each potential alternative and that customers behave as utility maximizers. The customer's utility for an alternative a is $U_a = V_a + R_a$. The variable V_a depicts the part of a customer's choice that is predictable and is hence deterministic (e.g., through setting price incentives). The second part, R_a, adds randomness to the utility function to consider that estimating customer choice behavior is not fully foreseeable (Vulcano et al. 2010). Corresponding model variants for attended home deliveries can be found in Asdemir et al. (2009), Yang et al. (2014), Yang & Strauss (2016), Klein et al. (2016), and Ulmer (2017). While customer choice can be estimated in a very realistic way with MNL models, incorporating a MNL model into an online retailer's booking process can become quite complex and requires historical data that does not only reflect the actual booking decisions of past customers, but also all time window alternatives offered to them. In Mackert (2019), a general attraction model (GAM) is proposed, which is a generalization of the MNL that can represent dissatisfaction of customers better than the MNL in some cases. For time window pricing, the GAM is limited, and it is rather beneficial for slotting of time windows.

Our focus is on how customers behave when time windows of different lengths are offered. Customers want short time windows, but short time windows increase the retailer's delivery costs. Lin & Mahmassani (2002) analyse the correlation between decreasing time window size and increasing delivery costs. Gevaers et al. (2014) quantify logistics costs of customer acceptance and find that the average delivery cost for a retailer is around 3€ for deliveries in 4-hour time windows and almost 6€ for deliveries in 1-hour time windows. Manerba et al. (2018) show that shorter time windows decrease the environmental sustainability of deliveries. In this paper, we assume that each customer's offer set contains multiple short and multiple long time windows. Among these, interdependencies exist, which are not reflected by the standard formulations of the MNL models (Koppelman & Wen 1998). Therefore, we will introduce a nested logit (NL) model for attended home deliveries that reflects customer choice under different time window lengths. The relation of MNL and NL is discussed in general in Li & Huh (2011). Recently, the NL has been used to model travelers choosing between different travel modes (Thrane (2018), Zimmermann et al. (2018)), for example. We will present more details of our customer choice model in Section 3.4.

2.2 Slotting of delivery time windows

Differentiated slotting can help companies decide on which time windows to offer to serve the expected demand and best utilize the available delivery resources. Based on historical customer data, for tactical slotting, demand is forecasted in an aggregated way to determine which time windows to offer in the subsequent booking process. Agatz et al. (2011) and Hernandez et al. (2017) determine the required number of offered time windows to fulfill expected demand in each delivery area. The latter also update a-priori decisions once customers arrive. Bruck et al. (2017) consider the practicability of differentiated slotting approaches and show the complexity of creating automated cost-efficient time window designs for retailers. Motivated by the business model of the online supermarket Picnic (The Netherlands), Visser & Savelsbergh (2019) examine the value of the tactical decision to offer only one time slot in each delivery region. However, for all these approaches, the resulting offer sets are based on fixed patterns. We claim that especially for the competitive field of online retailing, more flexible solutions are needed.

Creating individual time window offerings during the booking process is the core idea of *dynamic slotting*. Corresponding approaches consider which customers to accept in which time window. Campbell & Savelsbergh (2005) were the first to introduce insertion-based dynamic customer acceptance mechanisms to determine which time windows would be feasible to offer an incoming request. Insertion heuristics often serve as fast feasibility check and provide information on the cost of inserting a current request as well as its impact on the route plan (Lu & Dessouky 2006). Ehmke & Campbell (2014) also use insertion heuristics and show in a real-world setting that dynamic slotting can handle spatio-temporal information of customer locations and utilize delivery capacities better than a-priori acceptance mechanisms. For this paper, we assume full knowledge of the customer's location. Cleophas & Ehmke (2014) control which customers to accept or reject based on delivery cost and revenue information attached to delivery areas.

Some slotting approaches consider the time of commitment to a time window during the booking process and its impact on the route plan's flexibility. Ulmer (2017) and Vareias et al. (2017) approximate the (optimal) arrival time at a customer and derive "self-imposed" time windows to maintain flexibility. The latter also minimize the time window length to increase customer service. However, the planned arrival times of customers can still change significantly as long as more customers are being accepted and the final route plan is evolving. Köhler et al. (2019) use an insertion heuristic to determine feasible time windows and combine this with flexibility measures to manage long and short time window offerings dynamically. They especially measure the impact of short time windows at different stages of the booking process. Results show that considering temporal and spatial routing characteristics can help to limit the resulting costs when offering short time windows and hence enable accepting more customers and also increase the service level. Hungerländer et al. (2017) aim to create the largest possible selection of time windows for each requesting customer to achieve a higher probability of meeting the customer's preferred time window. Shao et al. (2019) propose to only communicate the length of time windows to customers and adjust beginning and end time of time windows whenever more customer requests are known to limit the impact of short time window offerings. Given current business practices of online retailers, we assume that even one single time window offering can be satisfactory as long as the time window meets the customer' requirements, and that customers expect short time window offerings at a fixed delivery time specified by the customer and not by the retailer.

3 Methodology

In this chapter, we formalize our problem and present different ideas on how to create offer sets containing long and short delivery time windows. Our offer set creation includes dynamic pricing of time windows according to expected demand and spatio-temporal characteristics of the route plan. We present dynamic flexible pricing policies and a customer choice model that is able to define delivery fees for offer sets with different time window lengths.

3.1 Problem description

Our problem is motivated by an online supermarket which operates its own delivery fleet with a fixed number of vehicles. The retailer offers attended home deliveries and wants to create a high service level to customers as well as maximize profit. During the booking process customers arrive in real-time and requests are considered until a specific cut-off time that is early enough to assemble accepted orders sufficiently and deliver them to the customers subsequently. We do not consider dynamic routing.

More formally, for each request j arriving during the booking process, the retailer presents a time window offer set O_j from which the customer can choose exactly one time window; the request is confirmed immediately with the customer choosing one time window out of the offer set. To ensure flexibility and a high customer service level, offer sets include time windows of different lengths. In particular, each offer set can contain a set of short and long time windows represented by S and L, respectively. The set of short time windows, S, contains m non-overlapping short time windows of length w_s and a no-purchase option. The set of long time windows, L, includes n non-overlapping long time windows of length w_l and also the no-purchase option. We describe beginning and ending times of each time window by $a_m^S \in S, a_n^L \in L$ and $b_m^S \in S, b_n^L \in L$.

The decision on which time windows to offer to a customer at which fee depends on the already accepted requests, has to be made in real-time, and is based on a flexible pricing policy. We will present the flexible pricing policies in Section 3.3. If available, all long time windows from set L will be offered for free. For the short time windows from set S, a particular delivery fee d_m is attached to each option. Based on the pricing policy, the delivery fee d_m can either be the same for all offered short time windows or vary between the short time window options (one-price or multi-price). For all flexible pricing policies, delivery fees change along the course of the booking process *dynamically.* For the pricing decision, we consider the impact of a request on the route plan's flexibility of a customer choosing a specific short time window. We use $|Q|$ flexibility stages to categorize the impact on the route plan's flexibility from low to high. The current flexibility stage for each request will be computed as described in Section 3.3. The price function P reflects the price point that is attached to each flexibility stage.

We maintain tentative route plans during the booking process to ensure that we do not exceed the overall delivery capacity limited by the number of delivery vehicles $|V|$ and the available total time for servicing customers T (e.g., maximum shift time of a driver). We cannot withdraw a time window promise after a time window was chosen by the customer. Hence, before presenting time window options within the offer set, we have to make sure that each time window offering does not violate time window promises of already accepted customers. Within the offer set O_j, all feasible time windows for the present request j are displayed, and no time windows are being withheld. If we can find at least one feasible insertion position for request j, then our offer set will contain at least one corresponding long and short time window attached to that insertion position.

We assume that we do not have any information about future customers and can only consider the incrementally available information of already accepted customers during the booking process as well as the information of the current request. For each request (and all accepted customers), we assume to know the delivery location, which is a realistic assumption for online supermarkets, since customers usually have to reveal at least their zipcode before getting to choose a time window. We assume that there is enough historical data to estimate the varying demand for different time window options as well as their price sensitivity with regard to time window length. When choosing a time window, we assume that customers take the particular time of the day, the time window length as well as the attached delivery fees into consideration. If we cannot present a suitable time window option, we assume that the customer will cancel the booking process.

Our objective is to maximize profit as well as to provide good service quality. To achieve this, we maximize the number of accepted customers and try to accept as many as possible within a short time window. We will analyze the impact of different flexible time window pricing policies on the retailer's revenue in terms of the collected delivery fees and also the amount customers have to pay when booking a short time window.

3.2 Offer set creation

The creation of a request-specific offer set works as follows. For each request j arriving on the retailer's website, our algorithm creates the request-specific offer set O_j containing time window options of different lengths and different fees. The pricing of the offered time windows is based on a flexible pricing policy, which considers the request's spatial and/or temporal characteristics and the resulting impact on the flexibility in the underlying route plan. To do so, we maintain tentative route plans R^v for each available delivery vehicle $v \in V$ while the booking process is evolving.

The general process of offer set creation is shown in Algorithm 1. For each request j, the algorithm considers inserting it within any possible insertion position (with the depot being first and last position on each route). Based on the set of already accepted customers, it is considered within which long and short time windows out of the time window sets L and S a request could be inserted feasibly and could hence be offered to a customer. In general, time windows are considered feasible if there is sufficient delivery capacity to accommodate them and if no already made time window promises are violated. We follow the ideas of feasibility evaluation presented by Köhler et al. (2019) and summarize their approach below.

To check feasibility within our tentative route plans, we use an insertion-based heuristic which determines all feasible time windows for request j. We compute the feasible time span $s^v_{i,i+1}$ between already accepted customers i and $i+1$ on vehicle v in which the request j can be serviced. To this end, at each insertion position, we compute the earliest time $e^v_{i,i+1}$ we can arrive at a request (which depends on the previous customer and his/her earliest arrival time e^v_i as well as the service time u_i and the time needed to travel from customer i to request j, the travel time $t_{i,j}$). We also compute the latest time $f^v_{i,i+1}$ the vehicle has to depart at request j (considering the latest arrival time f^v_{i+1} and service time u_j at the next customer and the time needed to travel there $t_{j,i+1}$). The time span $s^v_{i,i+1}$ reflects the difference between these values and must be non-negative for the insertion of j to be feasible for any considered time window.

Based on the feasible insertion positions, the corresponding feasible time windows can be derived. To this end, starting and ending times of all long and short time windows are matched with the time span of the feasible insertion positions and will be added the sets $L'^v_{i,i+1}$ and $S'^v_{i,i+1}$, respectively. For the latter, we also determine which delivery fee d_m to assign based on a flexible pricing policy (AssignDeliveryFee) presented in detail in Section 3.3. Note that in case the same time window is derived from different insertion positions and is evaluated with different fees, we always charge the minimum fee.

After we have finalized determining all feasible time windows and the according delivery fees, we can assemble the resulting time window options in the last step of the algorithm and create a single offer set O_j for request j (*CreateOfferSet*). Then, the customer can choose a particular time window option (long or short, *SelectTimeWindow*) or cancel the booking process (no-purchase option). Customer behavior is modeled through a customer choice model presented in Section 3.4. If a requesting customer accepts one of the offered time windows, the request is inserted in the tentative route plan within the selected time window at the cost-minimal insertion point. If needed, the beginning of service for the following customers on that route is updated (*UpdateRoute*).

```
for each request j ∈ J do
    O_j ← ∅ // initialize offer set
    for each vehicle v ∈ V do
        for each insertion position between i and i+1, i ∈ R^v do
            S'^v_{i,i+1} ← ∅, L'^v_{i,i+1} ← ∅ // initialize time window sets
            e^v_{i,i+1} ← e^v_i + u_i + t_{i,j}
            f^v_{i,i+1} ← f^v_{i+1} − u_j − t_{j,i+1}
            s^v_{i,i+1} ← f^v_{i,i+1} − e^v_{i,i+1}
            if s^v_{i,i+1} ≥ 0 // insertion position is feasible
            then
                for each long time window n ∈ L do
                    if a^L_m ≤ e^v_{i,i+1} ≤ b^L_m || a^L_m ≤ f^v_{i,i+1} ≤ b^L_m || (e^v_{i,i+1} ≥ a^L_m & b^L_m ≤ f^v_{i,i+1}) then
                        L'^v_{i,i+1} ← L'^v_{i,i+1} ∪ {n}// add long time window
                    end
                end
            end
            for each short time window m ∈ S do
                if a^S_m ≤ e^v_{i,i+1} ≤ b^S_m || a^S_m ≤ f^v_{i,i+1} ≤ b^S_m || (e^v_{i,i+1} ≥ a^S_m & b^S_m ≤ f^v_{i,i+1}) then
                    AssignDeliveryFee(j, v, i)
                    S'^v_{i,i+1} ← S'^v_{i,i+1} ∪ {m} // add short time window
                end
            end
            return {S'^v_{i,i+1}, L'^v_{i,i+1}}
            O_j ← CreateOfferSet({S'^v_{i,i+1}, L'^v_{i,i+1}})
        end
    end
    SelectTimeWindow(O_j), UpdateRoute
end
```

Algorithm 1: Offer set creation for a request j

3.3 Flexible dynamic pricing policies

In this section, we present three flexible dynamic pricing policies that assign delivery fees to short time windows before presenting them to the requesting customers: *Time of Booking* (ToB), *Location of Request* (LoR), and *Impact on Route* (IoR). The first policy, ToB, is based on a route plan's utilization and considers temporal aspects, i.e., how early or late a request is posed during the booking process. LoR considers spatial characteristics of the tentative route plan. IoR investigates which part of a tentative route plan would be affected by a request and sets delivery fees accordingly. To evaluate the benefits of flexible dynamic pricing policies, we also introduce a benchmark policy that is motivated from current business practices of online supermarkets.

We need to define a delivery fee d_m for each short time window $m \in S'$. For each policy, we present the underlying idea and classify it according to a pricing scheme category (*one-price* vs. *multi-price* and *static* vs. *dynamic*). The flexible dynamic pricing policies consider different metrics describing the impact of a request on the current route plan's flexibility. The value of the particular metric is assigned to a particular price point according to $|Q|$ different flexibility stages defined by $[x_q, x_{q+1}]$, which represent the minimum and maximum of the flexibility metric for a particular flexibility stage of the policy. We call the price points assigned to the $|Q|$ flexibility stages of a policy the "configuration" of the policy.

1. **Time of Booking (ToB), dynamic one-price policy:** Since requests only become known incrementally during the booking process, each accepted request adds more information about how the final route plan will look like. In Köhler et al. (2019), it has been shown that it can be advantageous to offer long time windows at the beginning of the booking process and short time windows only later when there is more information about the structure of the route plan. This idea is quite similar to markdown pricing: High prices are announced when the product is new on the market, and they are adapted later once the actual demand is known (Kwon et al. 2012). With ToB, delivery fees are set according to the point in time a request is posed, evaluating the request in the light of already consumed delivery resources.

   To quantify the ongoing utilization of delivery resources, we measure how much of the available service time T for the set of available delivery vehicles V has already been consumed by all accepted customers. The utilized time for delivery consists of the service time at each customer and the travel times between the customers or depot (0 and z). With each additional portion of the route plan defined, we assume that the impact of a further request on the route plan decreases. Delivery fees are set according to flexibility stages, which are defined by x_q^{ToB}. The algorithm for setting delivery fees according to the time of booking is shown in Algorithm 2.

   AssignDeliveryFee(j, v, i)
   for *each stage boundary* $q \in Q$ **do**
       if $x_q^{ToB} \leq (t_{0,1}^v + \sum_{i=1}^{q-1}(t_{i,i+1}^v + u_i) + t_{z,0}^v)/(|V| * T) < x_{q+1}^{ToB}$ **then**
           $d_m = P(\left[x_q^{ToB}, x_{q+1}^{ToB}\right])$
       end
   end

   Algorithm 2: ToB price policy

   With ToB, delivery fees change dynamically during the booking process, reflecting the current route plan's utilization. However, no individual customer characteristics are taken into account, and all requests that arrive at the same time during the booking process will be presented all available short time windows at the same delivery fee. Note that like with all one-price policies, customers may develop a strategic shopping behavior and may learn about when delivery fees change. With ToB, we only focus on the time of booking instead of popularity of a time window. Therefore, in contrast to the benchmark, we can also offer popular time windows at low delivery fees, which can increase customer satisfaction.

2. **Location of Request (LoR), dynamic multi-price policy:** With LoR, we want to make delivery fees dependent on whether we are already serving customers in the vicinity of a request. Previous results showed that offering short time windows in the vicinity of already accepted customers has less impact on the tentative route plans and is hence advantageous for profitability and service quality (Köhler et al. 2019). To this end, we check if a new request is in the vicinity of already accepted customers. The vicinity is defined by the relative travel time from the location of any accepted customer to the location of the new request relative to the total time capacity. We measure beginning and ending of the flexibility stages through x_q^{LoR} to determine which delivery

fee is to be set with the following formulation (Algorithm 3):

AssignDeliveryFee(j, v, i)
for *each stage boundary* $q \in Q$ **do**
  if $x_q^{LoR} \leq t_{i,j}^v / (|V| * T) < x_{q+1}^{LoR}$ *or* $x_q^{LoR} \leq t_{j,i+1}^v / (|V| * T) < x_{q+1}^{LoR}$ **then**
    $d_m = P(\left[x_q^{LoR}, x_{q+1}^{LoR}\right])$
  end
end

Algorithm 3: LoR price policy

With LoR, we consider for each insertion position how much travel time we need to connect the current request to already accepted customers and dynamically adapt the delivery fee. Since the travel time is different for each insertion position, delivery fees can vary, and the time window offer set can contain multiple prices. Some online retailers already communicate time windows that cause smaller detours as "eco-friendly" to foster their selection. We consider communicating different delivery fees based on a request's location as quite comprehensible for the customer.

3. **Impact on Route (IoR), dynamic multi-price policy:** Whereas some parts of the route plan might already be fixed through customers with short time windows, other parts can provide greater flexibility and therefore greater potential to accommodate future requests. With IoR, we want to quantify how much potential the affected part of the route plan has to include further requests. The longer this time span is, the more likely are major changes in the near future, and we hence may not want to offer a short time window to maintain flexibility. In particular, we consider the relative length of the time span that is affected by the insertion of request j at a specific insertion position. Algorithm 4 summarizes this approach more formally. In particular, the current flexibility stage is determined according to the size of the insertion span x_q^{IoR} in relation to the total available time T for all vehicles V.

AssignDeliveryFee(j, v, i)
for *each stage boundary* $q \in Q$ **do**
  if $x_q^{IoR} \leq s_{i,i+1}^v / (|V| * T) < x_{q+1}^{IoR}$ **then**
    $d_m = P(\left[x_q^{IoR}, x_{q+1}^{IoR}\right])$
  end
end

Algorithm 4: IoR price policy

Similar to LoR, IoR sets delivery fees for short time windows dynamically. Since we consider the request's impact on flexibility on different parts of the route plan, it is possible that multiple delivery fees are contained in the offer set, and some short time windows will be offered at lower prices than others. In contrast to ToB and LoR, however, the pricing of time windows is not as easy to understand for customers, preventing strategic shopping behavior, but also making it difficult to communicate how delivery fees are set.

4. **Benchmark (B), static multi-price policy:** To understand the value of dynamically adapting delivery fees through flexible pricing policies, we propose to compare their results with a static multi-price policy benchmark reflecting common business practice. Many online supermarkets offer a mix of long and short time windows and price different time window options differently. Assigned delivery fees differ among time window lengths and times of the day, and delivery fees remain static throughout the booking process. Following this idea, with the benchmark, we assign a fixed set of delivery fees to the offered short time windows, and we do not change them along the course of the booking process. Short time windows that have shown to be more popular in the past will be

assigned higher delivery fees. Note that customers can anticipate these delivery fees easily.

3.4 Customer choice modeling with multiple time window lengths

The success of any pricing policy strongly depends on the customers' acceptance of alternatives in the current offer set. Therefore, retailers need to consider the expected customer behavior when developing pricing policies. However, estimating choice behavior for attended home deliveries is not trivial: Customers can choose from a plurality of delivery days and delivery options (at different lengths and prices) and may decide not to book at all. Furthermore, customer decisions can be influenced by the current availability and fee of time windows.

For our problem formulation, time window options are not only characterized via suitability, availability and the attached delivery fee, but also by their length: Each customer's choice set of offered time windows can contain multiple short and multiple long time windows. This creates interdependencies in the choice probabilities that violate the often applied MNL model's assumption of independence of irrelevant alternatives (IIA). With IIA, it is assumed that the relative probability of each pair of choice alternatives does not depend on the availability of a third alternative (Koppelman & Wen 1998). Since we are offering time window options that overlap temporally (e.g., a long morning time window and several short morning time windows in parallel), some demand from the long time window options could be cannibalised by the short time window options. Hence, IIA is violated and we cannot follow standard MNL formulations any more.

For our flexible pricing policies, we consider a nested logit (NL) model, in which groups of alternatives are considered as "nests" (Hensher & Greene 2002; Koppelman & Wen 1998). The NL model assumes a hierarchical structure of choice, where the first level depicts the choice for a group of alternatives (branches) and the second level the choice for one alternative within each nest (twig) (Hensher & Greene 2002). The customer's utility can then be described as:

$$U(Twig) = U(Branch) * U(Twig \parallel Branch). \tag{1}$$

As offering a long time window that overlaps with offered short time windows clearly affects the odds of time window choice, we consider long time windows as constituting one nest and short time windows as constituting another nest of alternatives. The resulting NL model formulation contains four dimensions: The *suitability* of a time window (where some time windows are more suitable to customers' schedules than others and some time windows are not suitable at all), the *availability* of a time window (where customers can only choose alternatives available in the offer set), the *price* level for a particular alternative, and the *length* of a time window (where a long time window can span multiple more or less suitable short time windows).

Figure 1 presents the structure of the NL model that defines choice probabilities for each customer depending on the current offer set O_j. Within the first level, each branch describes the customer's probability for choosing a nest containing short (P_S) or long (P_L) time windows. The second level represents the customer's probabilities of choosing a specific alternative from the nests, i.e., the probabilities for each of the short time window options $\{P_1^S...P_m^S\}$, the probabilities for choosing one of the long time window options $\{P_1^L...P_n^L\}$, and the no-purchase probabilities P_0^S and P_0^L. Even though we only differentiate between long and short time windows, this nested logit model could also handle further differentiations of time window lengths.

We outline the customer choice for a specific alternative out of an offer set in Section 3.4.1. In Section 3.4.2, we explain how we extend the choice model to consider different time window lengths. In Section 3.4.3, we demonstrate the implications of the choice model using an example.

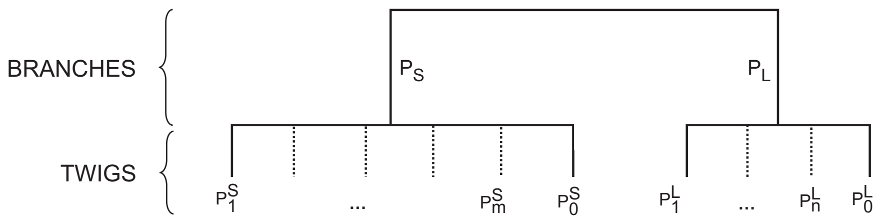


Figure 1: Nested Logit Model for customer choice of long and short time windows

3.4.1 Twig selection

Each nest contains a group of time windows of equal length, i.e., either long or short time windows. Hence, within each nest, customer choice is only affected by suitability, availability and price of the options in an offer set. Once the relevant branch has been determined, choice probabilities no longer depend on time window length. We use a MNL formulation for describing the choice of one specific alternative, a twig. The formulation follows Yang et al. (2014) and relies on four parameters. First, the base utility β_0 indicates the customers' general likelihood of purchasing any alternative. This base utility is independent from the current offer set. Next, a time window specific utility β_t reflects that some of the alternatives are more suitable than others. The value of β_d describes the customer's price sensitivity. The lower this value is, the more customer choice is influenced by a tagged price. Lastly, the attached delivery fee d_t of an alternative is considered.

The probability of a customer choosing time window $t \in S'$ given offer set containing all feasible short time windows $s \in S'$ can be described as:

$$P_t^S = \frac{exp(\beta_0 + \beta_t + \beta_d * d_t)}{\sum_{s \in S'} exp(\beta_0 + \beta_s + \beta_d * d_s) + 1}, \tag{2}$$

and for choosing a long time window $t \in L'$ out of an offer set containing all feasible long time windows $l \in L'$ (we consider d_t=0 and d_l=0 here):

$$P_t^L = \frac{exp(\beta_0 + \beta_t)}{\sum_{l \in L'} exp(\beta_0 + \beta_l) + 1}. \tag{3}$$

The coherent no-purchase probability for short and long time windows is given by the following formulations:

$$P_0^S = \frac{1}{\sum_{s \in S'} exp(\beta_0 + \beta_s + \beta_d * d_s) + 1}, \tag{4}$$

$$P_0^L = \frac{1}{\sum_{l \in L'} exp(\beta_0 + \beta_l) + 1}. \tag{5}$$

3.4.2 Branch selection

The branch selection of long and short time windows relies on two assumptions, which we justify in this section. These assumptions consider the impact of suitability, prices, and length of the offered alternatives on the customer's decision for a time window length. From a routing perspective, if a feasible insertion position is found, we can always enclose this position with a time window, no matter if short or long. Therefore, we can exclude the availability of time windows in the branch selection, since there is always a feasible long time window if we can find a feasible short time window and vice versa.

Assumption 1. *Customers prefer short over long time windows. The smaller the fee difference between offered short and long time windows is, the more likely customers will choose a short time window.*

The assumption relates the length of time windows to attached delivery fees. As discussed above, customers prefer short and cheap time window offerings. However, we assume that short time windows are more costly for retailers and hence are always offered at higher delivery fees than parallelly offered long time windows. Therefore, customers have to assess their individual cost-benefit-ratio between choosing a more expensive high-quality short time window or a cheap long time window. Consequently, we assume that the smaller the fees for the short time window offerings, the less likely a customer chooses a long time window. Higher delivery fees nudge customers towards booking long delivery time windows. We will include a factor β_w within the branch selection that reflects how sensitive customers are in terms of their booking decision between short and long time window options.

Assumption 2. *Customers consider only suitable time window options out of the offer set for their booking decision. The smaller the fee for a more suitable time window option, the more likely customers choose a short time window.*

Within the second assumption, we incorporate how delivery fees relate to the suitability of time windows. This should reflect that customers do not include all available time window options within an offer set in their booking decision, but only time window options that are suitable for them. Hence, higher or lower delivery fees of suitable time window options should have a higher impact on a customer's branch choice than higher or lower delivery fees of unsuitable time window options. Since we do not know which specific time window option would be the most preferable for each individual customer, we use time window utilities to compute how likely it is that the customers' branch choice is impacted through a high or low delivery fee.

Formula 6 presents the resulting probability of choosing the nest containing the short time windows when the feasible short time windows $s \in S'$ are offered:

$$P_S = \frac{\sum_{s \in S'} exp(\beta_0 + \beta_s + \beta_w * \beta_d * d_s)}{\sum_{s \in S'} exp(\beta_0 + \beta_s)}. \tag{6}$$

We first define a "perfect" short time window offering that we use as a baseline to compare to the customer's short time window options within an offer set. The denominator represents the baseline of offering short time windows at no delivery costs, and only the base utility β_0 and the time window's utility βs need to be included. Within the numerator, we consider the short time windows offered to a customer in terms of delivery fee d_s, price sensitivity β_d and base utility β_0 as well as specific time window utilities β_s. Additionally, we introduce β_w, which reflects the sensitivity of customers regarding time window length. This factor reflects the cost-benefit-ratio of a customer: the higher the value of β_w, the more customers are willing to pay for receiving a more explicit delivery promise, namely a short time window.

Subsequently, the branch probability for long time windows P_L is

$$P_L = 1 - P_S. \tag{7}$$

3.4.3 Illustrative example of nested customer choice

In this section, we illustrate how our NL model works. To this end, Figure 2 shows four exemplary offer sets. Each offer set contains one long and three short time windows. The long time window overlaps with the three short time windows.

We assume an arriving customer to assign a base utility of $\beta_0 = 0$ and a negative price sensitivity of $\beta_d = -0.5$ to all time window options. The short time window options vary in their suitability for the customer. We assume that the short time windows have a utility of $\beta_{S1} = -1.0$, $\beta_{S2} = 0$ as well as $\beta_{S3} = 1$, respectively. For the time window length sensitivity, we assume $\beta_w = 0.5$. Now we can investigate the impact of pricing on the branch probabilities for long and short time windows as presented in Formula 6.

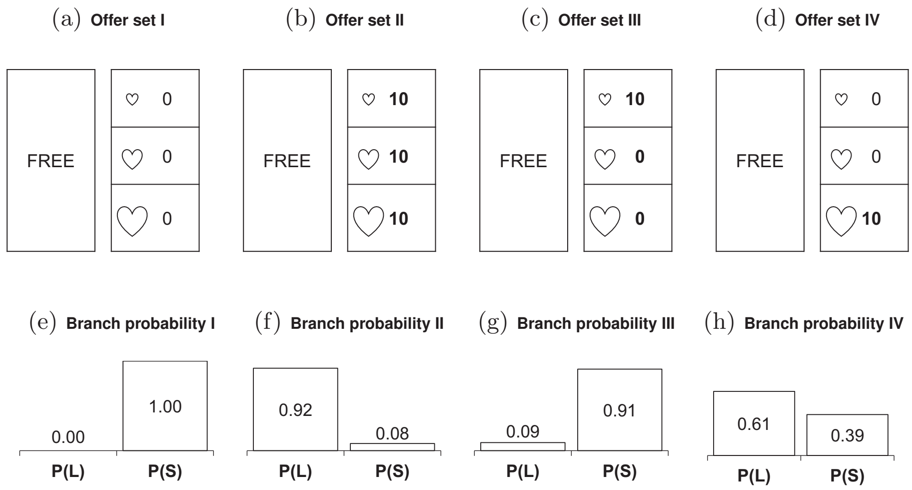


Figure 2: Example for time window offerings and the resulting branch probabilities

Offer sets I and II in Figures 2a and 2b exemplify Assumption 1. In the first offer set, all short time windows are available for free. The short and long time window offering is now equivalent in terms of suitability, availability and price, but the short time window offering is better in terms of length. Hence, customers gain no utility by choosing the long time window, and the resulting branch probability is $P(L) = 0\%$ as depicted in in Figure 2e. In the second offer set, all short time windows are offered at a price of 10. Long and short time window options are now only equivalent in terms of suitability and availability. They differ in terms of price and length. Since the price difference is high and the length sensitivity $\beta_w = 0.5$ implies that customers are not willing to pay much for a short time window, the resulting branch probability for a long time window is now $P(L) = 0.92$ (see Figure 2f).

Offer sets III and IV (see Figures 2c and 2d) consider differentiated pricing of the short time windows. Within offer set III, the least preferred time window is offered at a price of 10, and the other short time windows are provided for free. Options included in the offer set now differ in terms of length, fee, and suitability. Based on the time window utilities, it is more likely that short time window options 2 or 3 are chosen by the customer. As depicted in Figure 2g, the branch probability of long time windows is only $P(L) = 0.09$. Next, in Figure 2d, we can see that only the most preferred time window is offered at a fee of 10 and the less favorable time windows are offered for free. Since it is very likely that the most popular time window would have been the most suitable option to a customer, our model reflects this with an increase in the branch probability for the long time window of $P(L) = 0.61$.

4 Experimental settings

In this section, we introduce the metrics we use to evaluate our flexible dynamic time window pricing policies. We also present our computational setup including assumptions on the customer choice model.

4.1 Metrics

Time window pricing affects two different stakeholders: retailers and customers. While the retailer wants to maximize profit and accept as many customers as possible, customers are looking for inexpensive and short time window options. The following four metrics will be used to show the benefits of flexible dynamic time window pricing from a retailer's as well as a customer's perspective:

- *total number of accepted customers (#accepted):* We assume that each accepted customer adds a value to the retailer's business. This value may be explicit, e.g., the profit margin of a customer's order basket, or implicit, e.g., building a long-term customer relationship. Therefore, we consider accepting as many customers as possible as one of the core retailer's objectives when offering attended home deliveries.
- *fee revenue:* For each customer accepted within a short time window, a particular delivery fee is collected. Although the main purpose of delivery fees here is to nudge customers towards booking a long or short time window, collecting a higher revenue from the charged delivery fee can help cover the operational costs of the retailer. Hence, we will also evaluate the sum of collected fees at the end of the booking process.
- *total number of customers accepted in a short time window (#accepted short):* Customers favor short delivery time windows. Hence, we evaluate the number of customers that we accepted within a short time window.
- *mean fee:* High delivery fees can lead to lower customer satisfaction and loosing customers in the long run. Hence, we report the mean delivery fee that customers had to pay for booking a short time window option. In conjunction with the number of customers accepted in a short time window, this can give interesting insights on the quality of the proposed dynamic flexible time window pricing policy from a customer's perspective.

4.2 Computational setup

We consider an exemplary e-grocer operating in the inner city of Berlin, Germany. We define our delivery area as a rectangle between longitude 13.3-13.5 and latitude 52.45-52.55, which overlays the inner city of Berlin and reflects a dense distribution of customers in an urban area. We use a road network for this area provided by *OpenStreetMap*. From this road network, we randomly select 400 nodes, which serve as potential customer locations, and one fixed location for the depot. The travel times in minutes between these nodes are determined with *OSRM*[1], an OpenStreetMap routing service. During the booking process, whenever further 10 requests have been accepted, the tentative route plans are improved by an Iterated Local Search procedure following Vansteenwegen et al. (2009), which enables fast improvement of existing route plans.

Our time window design contains two long time window options of 4 hour length and 16 short time window options of 30 minutes length. The first long time window starts at the same time as the first short time window ($a_1^S = a_L^n$), and the last long time window ends at the same time as the last short time window ($a_{16}^S = a_2^L$).

[1]https://cran.r-project.org/web/packages/osrm/index.html

Length	t	β_t	$d_t^{FLEX}(\pounds)$	$d_t^B(\pounds)$
Short	s_1	-0.8230	{2, 4, 6, 8, 10}	4
	s_2	-0.7436	{2, 4, 6, 8, 10}	4
	s_3	-0.5746	{2, 4, 6, 8, 10}	4
	s_4	-0.3181	{2, 4, 6, 8, 10}	6
	s_5	0.1529	{2, 4, 6, 8, 10}	8
	s_6	0.1897	{2, 4, 6, 8, 10}	8
	s_7	0.7656	{2, 4, 6, 8, 10}	10
	s_8	0.9941	{2, 4, 6, 8, 10}	10
	s_9	0.4561	{2, 4, 6, 8, 10}	8
	s_{10}	0.9091	{2, 4, 6, 8, 10}	10
	s_{11}	0.1340	{2, 4, 6, 8, 10}	6
	s_{12}	-0.2514	{2, 4, 6, 8, 10}	6
	s_{13}	-1.2908	{2, 4, 6, 8, 10}	2
	s_{14}	-0.3500	{2, 4, 6, 8, 10}	6
	s_{15}	-0.6213	{2, 4, 6, 8, 10}	4
	s_{16}	-0.3435	{2, 4, 6, 8, 10}	6
Long	l_1	-0.0446	0	0
	l_1	-0.1697	0	0

Table 1: Time window related settings, $\beta_0 = -2.8618$, $\beta_d = -0.880$

For the customer choice model, we adapt the values from Yang et al. (2014) with regard to the specification of the base utility β_0, the time window specific utility β_t, and the price sensitivity β_d. Following Yang et al. (2014), we set $\beta_0 = -2.8618$ and $\beta_d = -0.0880$. Since Yang et al. (2014) consider only one time window length, we adapt the time window specific utilities β_t for our short time windows as shown in Table 1. We assign utility values from -1.2908 (s_{13}, least preferred short time window option) to 0.9941 (s_8, most preferred short time window option) to our short time windows (s_1–s_{16}). However, since we also include long time window options, we aggregate the values to match the enclosing long time window options. For the first long time window, we assume a utility of $\beta_{l1} = -0.0446$, which is the mean of the time window utilities s_1–s_8; for the second long time window, we assign a utility value of $\beta_{l2} = -0.1697$, which is the mean of the utilities from s_9–s_{16}. Following the analysis of empirical order data from Yang et al. (2014), we will use pound (£) in the following as monetary unit.

In Figure 3, we present the impact of the base utility as defined by Yang et al. (2014) on the customer choice. We display how the probabilities of time window selection evolve if a customer is being offered all time windows at the same time, but at different delivery fees. In this example, all short time windows are offered for the same delivery fee of either £0, £2, or £10. The y-axis depicts the probabilities for each time window option including the no-purchase option for short and long time windows (NoS, NoL). The x-axis reflects the probability of choosing one alternative. Generally, it can be observed that adopting the negative base utility results in a high non-purchase rate. In the left figure, we can see that although all short time windows are offered for free, there is still a 50% probability that a customer will cancel the booking process. If we increase the delivery fee for the short time windows to £10 (see right figure), the non-purchase probability increases to almost 80%. These high non-purchase probabilities as provided through analysis of empirical order data by Yang et al. (2014) may seem counter-intuitive at first. However, Moe & Fader (2004) state that compared to offline shopping, the base utility for online shopping is usually much smaller. Whereas a customer has to make at least some effort to go to a physical store, in the case of online shopping, customers can search through product offerings with almost no effort at all. Hence, for online shopping, it is more likely that customers cancel the booking process, come back later, or split one purchase into multiple visits of the website, which results in a very low base utility. As a consequence, for our computational setup, we choose a high number of requests, namely 500, resulting in about 60 customers that can be accepted in the end.

We also have to determine the value for β_w reflecting the customers' time window length sensitivity. In

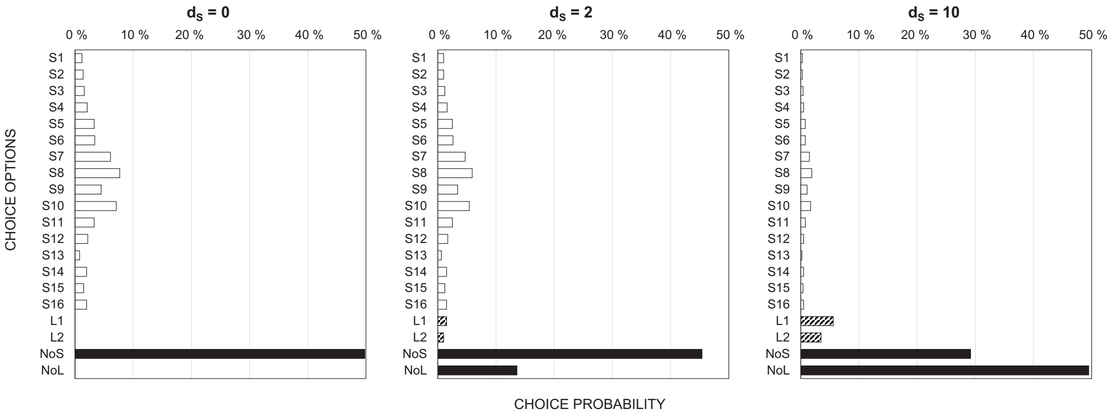


Figure 3: Choice probabilities of a customer when all time windows are available

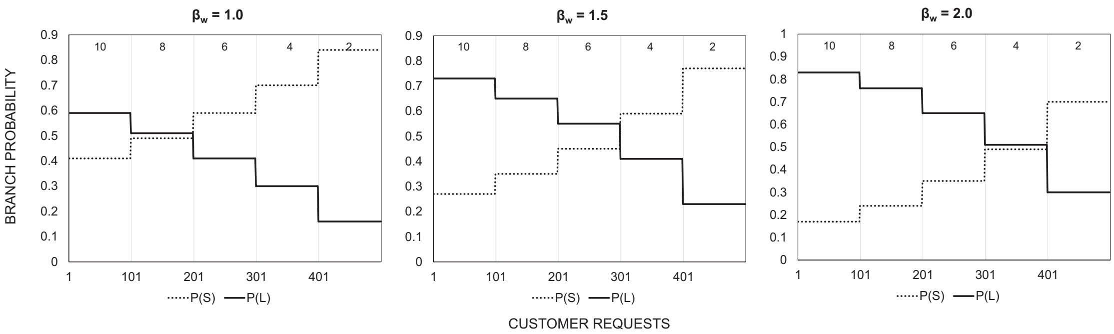


Figure 4: Branch probabilities for varying values of β_w

Figure 4, we show the impact of different values of β_w for the branch probability. The y-axis represents the probability for one of the branches. The x-axis represents a request arriving during the booking process (500 in total). Each continuous line shows the probability for the long time window branch, and each dotted line the probability for the short time window branch. To present the impact of varying levels of β_w, we reduce the delivery fee for short time windows during the booking process. We can see that if short time windows are offered at £10, the probability for choosing a long time window branch is around 60%, and if $\beta_w = 1.0$, the resulting branch for the short time window is approximately 40%. When the delivery fee for short time windows is reduced, the customers' probability of choosing a short time window increases. We assume that based on historical data, a retailer can estimate the value for β_w. For our experiments, we set $\beta_w = 1.5$, which reflects that many customers would be willing to pay around £6 for a short time window offering.

We define $Q = 4$ price points that can be assigned to flexibility stages to categorize the impact of a current request on the route plan's flexibility. The coherent stage boundaries are derived from a computational study and are as follows: $x_q^{ToB} = \{0\%, 25\%, 50\%, 75\%\}$, $x_q^{LoR} = \{0\%, 0.7\%, 1.4\%, 2.1\%\}$, $x_q^{LoR} = \{0\%, 25\%, 50\%, 75\%\}$. We assume a discrete price function P that defines the delivery fee of a short time window according to the measured flexibility within our tentative route plans. We consider five possible delivery fee levels in Pounds (£), which are $d_m = \{2, 4, 6, 8, 10\}$. We will test all price configurations of assigning one of the five price levels to each of the four flexibility stages, with the exception of assigning the same price level to all four stages, since this would reflect a static price assignment. In total, we will test $5^4 - 5 = 620$ different configurations P that reflect all variations of assigning the five

I	II	III	I V
2	2	2	4
2	2	2	6
2	2	2	8
2	2	2	10
2	2	4	2
2	2	4	4
2	2	4	6
2	2	4	8
...	...	...	...
10	10	8	4
10	10	8	6
10	10	8	8
10	10	8	10
10	10	10	2
10	10	10	4
10	10	10	6
10	10	10	8

Table 2: Price configuration variations

different prices to the four flexibility stages. Table 2 summarizes the investigated price configurations.

For the benchmark approach, we use the time window related utilities and also attach prices from £2-10. Time windows with a higher demand will be offered for a higher delivery fee than time windows attached with a lower utilitiy. The attached prices for the benchmark are presented in Table 1 (d_t^B).

5 Computational results

In this chapter, we evaluate many configurations of our flexible dynamic time window pricing policies considering the metrics presented in the previous section. First, we present example configurations and analyze how they affect the corresponding booking processes. Then, we discuss the overall value of our pricing policies and highlight which policies and policy configurations are best in terms of profitability and better customer service. We also provide insights on the distribution of short time windows and set delivery fees.

5.1 Example configurations of policies

Each flexible dynamic pricing policy will shape the sets of time windows offered during the booking process differently. In the following, we present results of one exemplary booking process for each of our policies with a price configuration of 10-8-4-2. Figure 5 shows the time windows offered to each of the 500 requests. The y-axis depicts the available time windows (16 in total), and the x-axis represents the requests as posed in the booking process. For each request, the color represents at which fee an available short time window option was offered (£10: pink, £8: yellow, £4: green, £2: blue) or if a time window was not available for booking (white).

In Figure 5a, with ToB, there is only one price at which short time windows are offered in each request's offer set. For early requests, all short time windows are available, but, in this configuration, only at a high delivery fee of £10. Around request 120, 25% of the route capacity has been assigned, and ToB decreases the delivery fee for short time windows to £8. Around customer 200, especially short time windows 6-9 have sold out for many of the posed requests, which is not surprising since these are among the most popular ones. Around request 220, 50% capacity has been utilized, and the delivery fee is again decreased to £4. From around request 300, most offer sets contain only four short time windows. However, these are offered at a small delivery fee of only £2. As a result, flexibility stages as defined for ToB comprise more than 100 requesting customers in the first stage, less than 100 requests in the middle stages, and more than 200 requests in the last stage. This underlines the importance of considering actual route utilization instead of fixed price patterns during the booking process.

In Figure 5b, the results of the LoR policy are shown, again for a configuration of 10-8-4-2. Since LoR is a multi-price policy, there is no clear pattern for the assignment of delivery fees along the booking process. For some requests, all time windows are offered at the same delivery fee, and for many other requests, delivery fees differ according to the particular time window. Generally, compared to ToB, there are relatively many cheap short time windows offered in the beginning (£2: blue). We can also see that popular time windows are sold out earlier than with ToB. For instance, time windows 7 and 8 are not available as early as around request 80. Late requesting customers can choose from only two time window options on average.

Similar to ToB, the multi-price policy IoR also offers all available short time windows to all early requests at a high delivery fee of £10, as can be seen in Figure 5c. IoR does not withheld popular time windows with a high fee as ToB or the benchmark. However, already around request 30, short time windows 5-8 are offered at a cheaper fee of only £8, and short time windows 9-16 even at £4. Here, we can see that IoR forms "blocks' of delivery fees' of consecutive short time windows. We can also see that time windows 13-16 are offered at a cheap fee of £2 from request 100 until almost request 400. Since these are the more unpopular time window options, even attaching a small fee cannot influence many customer requests to book these.

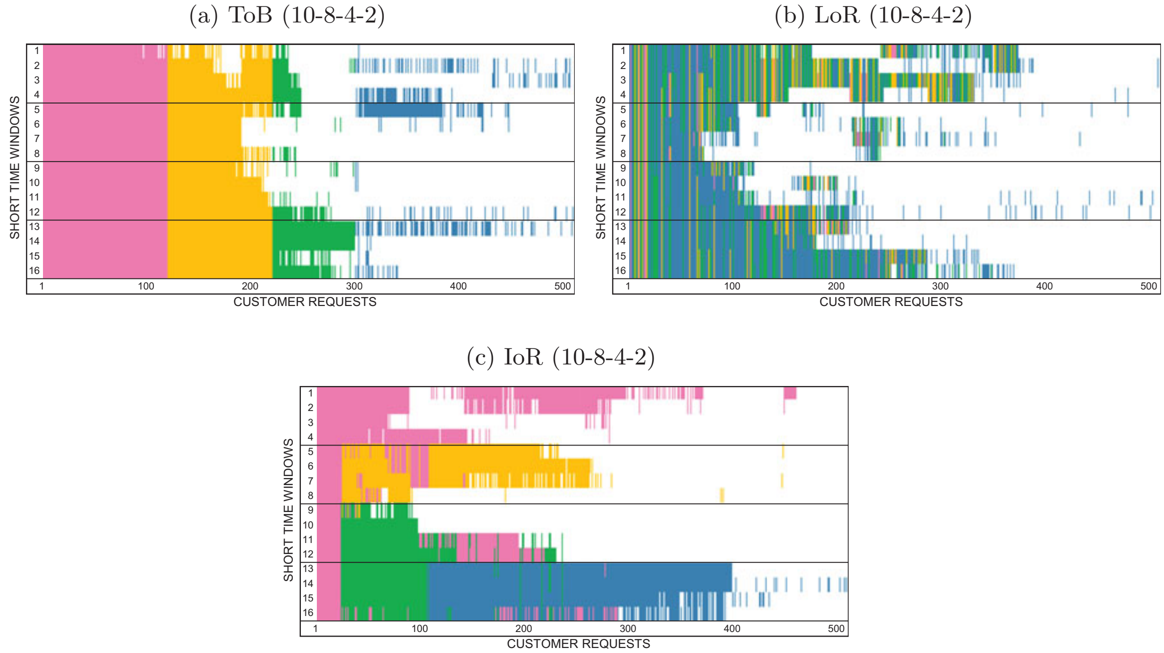


Figure 5: Exemplary booking process: Short time window offering for customer requests (£10: pink, £8: yellow, £4: green, £2: blue, not available for booking: white)

5.2 Overall evaluation of policies

We begin with an evaluation of the performance of all configurations of our flexible dynamic pricing policies and compare them to the performance of simple static pricing policies. The outcomes of all configurations are presented in Figure 6 and in Tables 1-3 in the electronic appendix. Each dot represents the result of one configuration. On the left hand side, in Figures 6a, 6c, 6e, we present *#accepted* and *#accepted short*; on the right hand side, in Figures 6b, 6d, 6f, we consider *mean fee* and *fee revenue*. For example, the dot at the top in Figure 6a represents the results of a policy configuration for ToB with delivery fees of £10 in flexibility stages I and II, and £2 in flexibility stages III and IV. The spline shown in all figures marks the results created by static one-price policies with constant delivery fees of £2, 4, 6, 8 or 10, respectively. Additionally, in each figure, a marked circle represents the results provided by the static multi-price benchmark B, for which delivery fees differ according to the popularity of particular time windows, but remain constant throughout the booking process.

First, we investigate the general structure and value of dynamic flexible pricing considering *#accepted* and *#accepted short* by looking at Figures 6a, 6c, 6e. The outcomes of the different configurations of the static one-price policy indicate that neither constantly offering expensive short time windows for £10 nor constantly offering cheap short time windows for £2 would be a good idea in order to maximize #accepted. When short time windows are offered at a high delivery fee, many customers are not willing to book these and cancel their request. When short time windows are offered at a very low fee, many customers book them. However, these many short time windows reduce the routing flexibility significantly and the ability to accept many customers for the retailer. The best results in terms of #accepted is achieved at a fee of £6.

Generally, for all three flexibility pricing policies, we can find many configurations that clearly outperform the static one-price as well as the static multi-price policies. The static multi-price benchmark results in a total of 58.1 #accepted with 35.7 #accepted short. All flexible pricing configurations highlighted in

#accepted		#accepted short		mean fee		fee rev	
μ	σ	μ	σ	μ	σ	μ	σ
58.1	4.48	35.7	3.66	6.72	0.27	240.32	25.80

Table 3: Benchmark

dark grey are superior to the static one-price policy. They are colored in light grey if they are inferior with regard to #accepted or #accepted short. In particular, with ToB, there are many configurations that achieve the same #accepted short as the static pricing, but ToB can accept more customers in total. Similarly, there are configurations that have the same total #accepted as the static pricing, but are able to accept many more in short time windows. The general acceptance pattern obtained with ToB seems to be a higher #accepted (up to 59.8 in total). Only very few configurations create inferior results than static pricing. For LoR, the performance pattern shifts towards the right side, indicating that many LoR configurations can accept more #accepted short. For IoR, the acceptance pattern is more widely spread. More configurations can be found that show a higher #accepted (between 58.5 and 59.5) compared to ToB. However, there are also more configurations from IoR that produce worse results than ToB; choosing a particular configuration seems to be more challenging for this approach.

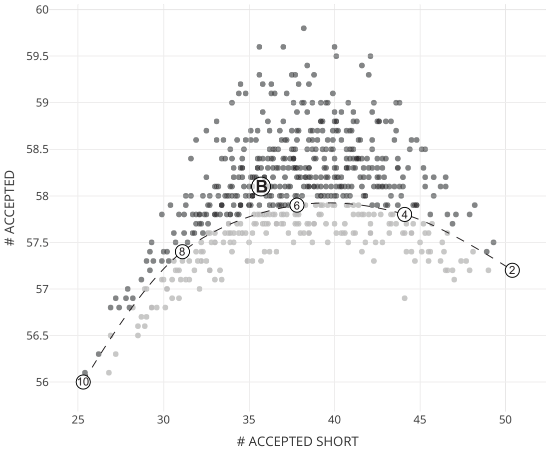
We now want to focus on the metrics *mean fee* and *fee revenue*, see Figures 6b, 6d, and 6f. To enable easy comparison with the results presented above, we mark the same configurations from 6a, 6c, and 6e in dark grey. The spline representing the outcomes of different configurations of the static one-price policy is now growing continuously, indicating that a higher revenue can be achieved when customers are charged more for short time windows and vice versa, which is not surprising. With the benchmark policy, customers have to pay a mean fee of £6.72, and the retailer collects a fee revenue of £240.32. With ToB, many price configurations result in a higher fee revenue than static pricing although the retailer charges customers less (to the right of the spline). For ToB and IoR, many configurations result in a higher fee revenue and lower delivery fees compared to the corresponding configuration of the static one-price policy. For LoR, only a few configurations can outperform static pricing; the most beneficial configuration for LoR has to be defined carefully.

The patterns observed with different configurations of our policies reveal that there is significant value in considering flexible dynamic pricing, especially when compared to simpler static pricing policies. However, interdependencies between the metrics clearly exist, and retailers have to decide on the importance of each metric in the light of their particular business goals before selecting a particular policy and/or policy configuration. We will analyze the trade-off between the metrics in comparison to results from the benchmark policy in detail in the next section.

5.3 The best pricing policies

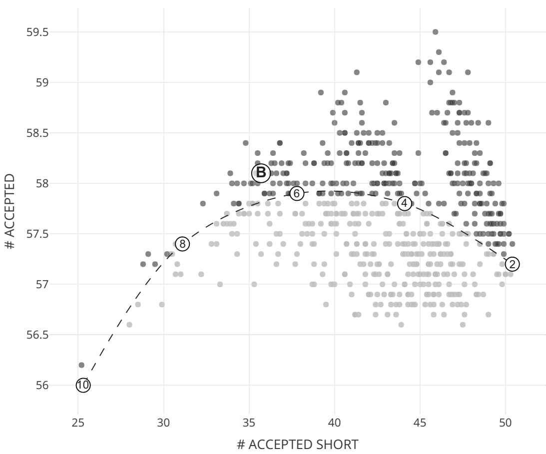
It is unlikely that there is a singular pricing strategy that is equally suitable for all stakeholders. Hence, we will provide managerial insights on the best configurations of our flexible dynamic pricing policies considering different objectives and constraints. We will analyze the trade-offs between the different metrics and compare them to the results of the benchmark policy, which are contained in Table 3. In Tables 4–7, out of all tested policies, we present the configurations that achieve the best results for one metric. We also present configurations that achieve the best results for one metric while at least one other metric does not perform worse than the benchmark. We list the top three price configurations for ToB, LoR, and IoR with regard to finding best compromises. We report the mean results for each metric (μ), the relative difference to the result obtained by the benchmark, and the standard deviation (σ) based on 1000 runs. The remaining four columns denote the configuration, i.e., which delivery fees are assigned to each flexibility stage.

(a) ToB: Accepted Customers



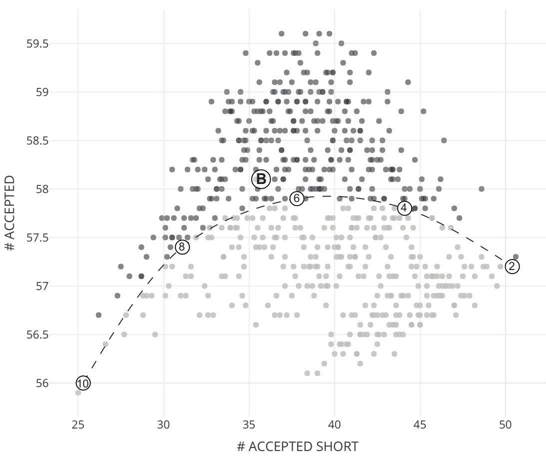
(b) ToB: Delivery Fee

(c) LoR: Accepted Customers



(d) LoR: Delivery Fee

(e) IoR: Accepted Customers



(f) IoR: Delivery Fee

Figure 6: Flexible dynamic pricing policies compared to static one-price and multi-price policies

Maximize profitability: maximize the number of accepted customers. In Table 4, we can see the results of flexible dynamic pricing policies that maximize #accepted. ToB with a price configuration of 10-10-2-2 is the winner and yields a maximum number of #accepted of 59.8. Implementing this configuration would imply to offer expensive short time windows to all customers until about half of the delivery capacity has been utilized, and then switch to low delivery fees of only £2. Compared to the benchmark, this comes with an improvement of 7% #accepted short, mean fees reduced by 13%, but also a loss in fee revenues of 7%. In addition to the winning configuration, we also consider the top three configurations that maximize #accepted while not allowing the other metrics to decrease below the benchmark values. Interestingly, #accepted does not vary much between the reported configurations (all between 2% and 3% more than the benchmark). Therefore, improving the outcome of another metric simply depends on the chosen configuration. We could increase #accepted short up to 12% with ToB and a price configuration of 8-10-2-2, or decrease the mean fee by 28% with IoR and a price configuration of 10-2-2-8 and still increase #accepted by 3%. The standard deviation for IoR is slightly smaller, which indicates that variation in booking streams seems to be handled better with IoR than with ToB.

Maximize service quality: maximize the number of customers accepted in a short time window. The results for maximizing #accepted short are shown in Table 5. For this objective, in general, static pricing works better than dynamic flexibility pricing, i.e., a retailer should simply offer short time windows at low delivery fees. However, this would result in a decrease of #accepted and a huge loss in fee revenues (-58%). ToB can help increasing #accepted short and keeping fee revenue stable. The best ToB price configurations show more accepted customers, smaller delivery fees and/or fee revenues.

If the retailer wants to focus on increasing #accepted short and also achieve good results for #accepted or mean fee, LoR can also provide good results. For instance, with a configuration of 8-8-2-2, LoR can yield the same #accepted as the benchmark and increase #accepted short by 38%, which is analyzed in detail in Figure 7a. We mark each of the 400 customer locations with a dot. The size of a dot represents how often one customer location booked a short time window within 1000 runs. The color of each dot represents the mean delivery fee for booking a short time window at this location. We can clearly identify differences in the sizes of the dots, indicating a higher chance of booking a short time window especially in the center and also in the southwest, which is accompanied by significant differences in the delivers fees. Some locations only have to pay a mean of £2 (blue), whereas others in the outskirts have to pay a mean of £8 (yellow). Apparently, with LoR, smaller detours in the center and southwest lead to a price discrimination of requests located in the northeast. As this is a result of ongoing route planning, we can see how important it is to consider real road networks when implementing dynamic pricing policies that assign delivery fees according to the vicinity of customer location. Following the spatial discrimination of short time windows in the delivery area, #accepted short increases by 41%.

Maximize profitability: maximize fee revenue. Table 6 shows the configurations that are beneficial when a retailer wants to maximize fee revenue. ToB with 10-10-6-6 is the winner and yields a fee revenue that is 8% higher than the benchmark. However, there is a small loss of 1% #accepted. With the same price configuration, IoR is able to keep fee revenue stable, not sacrifice #accepted, and provide more stable results given different bookings streams (#accepted, σ=4.67). In Figure 7b, for this configuration, we show that not only #accepted, but also the spatial distribution of short time window bookings and fees is quite stable. However, small differences in delivery fees can again be seen between northeast and southwest locations with southwest locations being slightly cheaper and having a slightly higher probability of booking a short time window. Again, customers located in the center and in the southwest benefit from the faster travel times with a slightly cheaper time window offering. Locations in the outskirts still have about the same chances to book a short time window, but for a higher fee.

Maximize service quality: minimize delivery fees. The winner for solely minimizing delivery fees is, again, a static pricing of £2. The results reported in Table 7 show the strong relationship between

(a) LoR (8-8-2-2) (b) IoR (10-10-6-6)

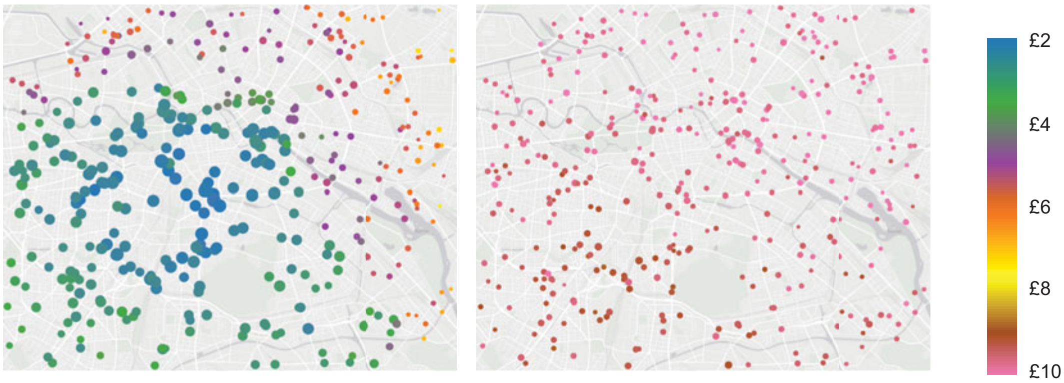


Figure 7: Spatial impact of flexible dynamic pricing policies

mean fee and fee revenue: If we want to charge customers as less as possible, then this limits improvements of fee revenue to only 1% relative to the benchmark. However, with ToB and a configuration of 8-8-6-2, we can increase the fee revenue by 1% while customers even have to pay less than with the benchmark. If the retailer is willing to loose fee revenue to provide better customer service, then LoR with a configuration of 8-8-2-2 prevents sacrificing #accepted (38% more customers accepted and -63% lower fee revenues).

Summarizing, from the above observations, the following managerial insights can be obtained:

- If the objective is increasing #accepted and/or fee revenue, either ToB or IoR create the best results. ToB works slightly better in general, but IoR provides more stable results given different booking streams. However, only ToB is able to create better results in terms of higher fee revenue (as indicated in Figure 6b). If the objective is increasing customer service by means of #accepted short or mean fee while maintaining reasonable results for #accepted or fee revenue, then LoR should be implemented.
- If both #accepted short and mean fee are important and the other metrics are negligible, then flexible dynamic pricing is not effective. These metrics correlate, and a retailer can simply offer cheap time windows throughout the whole booking process. Whenever metrics are considered that have a non-linear or negative correlation with at least one of the other metrics, a trade-off exists, and dynamic flexible pricing can outperform static pricing.
- The benefit of a significant improvement of one metric often goes hand in hand with a significant deterioration of another metric. Hence, retailers have to decide how much improvement of one metric can compensate the loss of another metric (e.g., can accepting one more customer outweigh a loss in fee revenues?). However, we were able to identify many ToB configurations that could relatively outperform the benchmark for all four metrics. We marked these with asterisks in Tables 4–7. For example, ToB with a configuration of 10-8-4-2 (see Figure 5a) is contained in each of the four Tables 4–7.
- For most of the selected superior price configurations, a higher (or at least equal) delivery fee is charged in the first stages of the corresponding policies. We could observe regularly that there is a huge price gap between stages II and III, which indicates that especially in stages I & II, the impact of routing flexibility is high. These stages are hence crucial to keep routing flexibility, and it is important to nudge customers towards booking a long time window for these stages. In conclusion, although we considered many configurations, one general rule helps keeping flexibility: assigning

		#accepted			#accepted short			mean fee			fee revenue			price configuration			
	Policy	μ	ΔB	σ	μ	ΔB	σ	μ	ΔB	σ	μ	ΔB	σ	I	II	III	IV
Best	ToB	**59.8**	**3%**	**4.21**	38.2	7%	4.13	5.84	-13%	0.53	222.54	-7%	25.35	10	10	2	2
	ToB	**59.8**	**3%**	**4.21**	38.2	7%	4.13	5.84	-13%	0.53	222.54	-7%	25.35	10	10	2	2
Best | #accepted short $\geq$ 35.7	ToB	**59.6**	**3%**	**4.15**	40.0	12%	3.91	5.42	-19%	0.43	216.41	-10%	21.77	8	10	2	2
	IoR	**59.6**	**3%**	**4.03**	39.7	11%	3.44	5.11	-24%	0.48	202.83	-16%	25.64	10	2	4	4
	ToB	**59.8**	**3%**	**4.21**	38.2	7%	4.13	5.84	-13%	0.53	222.54	-7%	25.35	10	10	2	2
Best | mean fee $\leq$ 6.72	IoR	**59.6**	**3%**	**4.03**	39.7	11%	3.44	5.11	-24%	0.48	202.83	-16%	25.64	10	2	4	4
	IoR	**59.6**	**3%**	**4.20**	39.1	10%	3.63	4.85	-28%	0.56	189.49	-21%	27.89	10	2	2	8
	ToB	**59.3**	**2%**	**4.74**	35.6	0%	4.44	6.82	1%	0.63	241.32	0%	26.14	10	10	4	2
Best | fee revenue $\geq$ 240.32	ToB*	**59.2**	**2%**	**4.29**	37.9	6%	4.18	6.39	-5%	0.49	241.47	0%	23.08	10	8	4	2
	ToB	**59.2**	**2%**	**4.31**	36.3	2%	3.74	6.76	1%	0.36	245.25	2%	24.17	10	8	4	4

Table 4: Best price configurations for **#accepted**

		#accepted			#accepted short			mean fee			fee revenue			price configuration			
	Policy	μ	ΔB	σ	μ	ΔB	σ	μ	ΔB	σ	μ	ΔB	σ	I	II	III	IV
Best	Static	57.2	-2%	3.83	**50.4**	**41%**	**3.71**	2.00	-70%	0	100.84	-58%	7.41	2	2	2	2
	LoR	58.2	0%	4.17	**49.1**	**38%**	**2.00**	2.47	-63%	0.22	121.00	-50%	13.26	8	8	2	2
Best | #accepted $\geq$ 58.1	LoR	58.2	0%	4.14	**49.1**	**38%**	**3.89**	2.47	-63%	0.24	121.42	-49%	14.07	8	10	2	2
	LoR	58.6	1%	4.06	**49.0**	**37%**	**3.85**	2.49	-63%	0.26	122.09	-49%	14.93	10	10	2	2
	Static	57.2	-2%	3.83	**50.4**	**41%**	**3.71**	2.00	-70%	0	100.84	-58%	7.41	2	2	2	2
Best | mean fee $\leq$ 6.72	LoR	57.4	-1%	4.06	**50.4**	**41%**	**3.81**	2.07	-69%	0.05	104.18	-57%	8.09	4	2	2	2
	LoR	57.5	-1%	4.11	**50.2**	**41%**	**3.92**	2.11	-69%	0.09	105.94	-56%	9.03	6	2	2	2
	ToB*	59.2	2%	4.29	**37.9**	**6%**	**4.18**	6.39	-5%	0.49	241.47	0%	23.08	10	8	4	2
Best | fee revenue $\geq$ 240.32	ToB*	58.6	1%	4.79	**37.1**	**4%**	**4.43**	6.53	-3%	0.5	240.66	0%	23.79	10	6	6	2
	ToB*	58.7	1%	4.97	**36.8**	**3%**	**4.42**	6.65	-1%	0.49	243.45	1%	22.6	8	8	6	2

Table 5: Best price configurations for **#accepted short**

		#accepted			#accepted short			mean fee			fee revenue			price configuration			
	Policy	μ	ΔB	σ	μ	ΔB	σ	μ	ΔB	σ	μ	ΔB	σ	I	II	III	IV
Best	ToB	57.8	-1%	5.36	30.9	-13%	3.83	8.41	25%	0.35	**259.15**	**8%**	**29.26**	10	10	6	6
	ToB	58.6	1%	5.27	31.9	-11%	4.23	8.09	20%	0.50	**256.51**	**7%**	**28.22**	10	10	6	4
Best | #accepted $\geq$ 58.1	ToB	58.5	1%	5.02	33.9	-5%	4.16	7.57	13%	0.39	**255.65**	**6%**	**26.76**	10	8	6	4
	IoR	58.2	0%	4.67	31.4	-12%	3.39	8.01	19%	0.30	**251.86**	**5%**	**29.75**	10	10	6	6
	ToB*	59.2	2%	4.31	36.3	2%	3.74	6.76	1%	0.36	**245.25**	**2%**	**24.17**	10	8	4	4
Best | #accepted short $\geq$ 35.7	ToB*	58.7	1%	4.97	36.8	3%	4.42	6.65	-1%	0.49	**243.45**	**1%**	**22.6**	8	8	6	2
	ToB*	59.2	2%	4.29	37.9	6%	4.18	6.39	-5%	0.49	**241.47**	**0%**	**23.08**	10	8	4	2
	ToB*	58.7	1%	4.97	36.8	3%	4.42	6.65	-1%	0.49	**243.45**	**1%**	**22.6**	8	8	6	2
Best | mean fee $\leq$ 6.72	ToB*	59.2	2%	4.29	37.9	6%	4.18	6.39	-5%	0.49	**241.47**	**0%**	**23.08**	10	8	4	2
	ToB*	58.8	1%	4.57	36.1	1%	4.08	6.70	0%	0.37	**241.33**	**0%**	**25.29**	8	10	4	4

Table 6: Best price configurations **fee revenue**

		#accepted			#accepted short			mean fee			fee revenue			price configuration			
	Policy	μ	ΔB	σ	μ	ΔB	σ	μ	ΔB	σ	μ	ΔB	σ	I	II	III	IV
Best	Static	57.2	-2%	3.83	50.4	41%	3.71	**2.00**	**-70%**	**0**	100.84	-58%	7.41	2	2	2	2
	LoR	58.2	0%	4.17	49.1	38%	2.00	**2.47**	**-63%**	**0.22**	121.00	-50%	13.26	8	8	2	2
Best | #accepted $\geq$ 58.1	LoR	58.2	0%	4.14	49.1	38%	3.89	**2.47**	**-63%**	**0.24**	121.42	-49%	14.07	8	10	2	2
	LoR	58.1	0%	4.07	48.9	37%	3.91	**2.47**	**-63%**	**0.24**	120.58	-50%	14.23	10	8	2	2
	-	57.2	-2%	3.83	50.4	41%	3.71	**2.00**	**-70%**	**0.00**	100.84	-58%	7.41	2	2	2	2
Best | #accepted short $\geq$ 35.7	LoR	57.2	-2%	4.06	50.2	41%	3.78	**2.06**	**-69%**	**0.05**	103.40	-57%	7.93	2	4	2	2
	LoR	57.4	-1%	4.06	50.4	41%	3.81	**2.07**	**-69%**	**0.05**	104.18	-57%	8.09	4	2	2	2
	ToB*	59.2	2%	4.29	37.9	6%	4.18	**6.39**	**-5%**	**0.49**	241.47	0%	23.08	10	8	4	2
Best | fee revenue $\geq$ 240.32	ToB*	58.6	1%	4.79	37.1	4%	4.43	**6.53**	**-3%**	**0.50**	240.66	0%	23.79	10	6	6	2
	ToB*	58.7	1%	4.97	36.8	3%	4.42	**6.65**	**-1%**	**0.49**	243.45	1%	22.6	8	8	6	2

Table 7: Best price configurations **mean fee**

higher delivery fees in the beginning of the booking process or when customers are not in the vicinity of a route plan. Our policies can help to refine this rule in the light of the current booking stream.

- When focusing on optimizing fee revenue or #accepted, the fee level is generally higher than observed for price configurations optimizing the other two metrics. Hence, influencing customer choice and increasing fee revenue is only achievable with charging higher prices for short time windows. In the end, this is only possible if some customers are willing to pay higher delivery fees, which depends on the customers' price sensitivity.

6 Conclusion and future work

In this paper, we presented flexible dynamic pricing policies to allocate standard and premium delivery options during a booking process when overall demand is unknown. We chose offering long and short time window options as an illustrative example for this. We introduced three dynamic multi-price policies that consider temporal and/or spatial characteristics of the evolving route plans to measure current routing flexibility and to set time window fees for the premium delivery options accordingly. To mimic customer choice behavior, we introduced a NL model that includes customer choice with time window options of different lengths. We evaluated our flexible dynamic pricing policies in a real-world setting, considering four metrics that take the perspective of the different stakeholders into account. Since there is no single pricing strategy that is equally suitable for retailers and customers, we tested many price configurations and compared the results to a static benchmark pricing that represents current business practice. We analyzed when our policies can easily outperform the benchmark and presented many managerial insights for different strategies that a retailer could follow. For instance, ToB and IoR achieve good results when we want to maximize the number of accepted customers, whereas LoR provides best results if the focus is on maximizing service quality.

The presented policies are easy to adapt by a retailer. However, each policy sets fees differently in the course of the booking process. This can result in either a temporal or spatial discrimination of customers, which may become a communication challenge for a retailer. For instance, with ToB, particularly early-bird customers have to pay more when booking a short time window. Customers could learn to anticipate cheaper time window offerings as provided by ToB and become strategic in their shopping behavior. However, IoR provides very similar results as ToB, but assigns short time windows more fairly to customers; since the fees charged for short time windows are based on routing mechanisms, this policy is not as easy to learn for customers as ToB. Finally, implementing LoR would lead to a discrimination of customers living in sparsely populated areas. We think that this could be communicated quite easily, because this simply means that the delivery fees are cheap when there is a certain amount of orders being executed in a customer's neighborhood already.

The presented flexible dynamic pricing policies provide significant potential for further extensions. For example, the policies could be extended to consider temporal and spatial flexibility characteristics simultaneously. Additionally, further customer characteristics could be taken into account: for instance, customers that restrict flexibility more but are still favored by a retailer, could receive a discount relative to the measured flexibility impact. Furthermore, in this work, we are assuming there is sufficient time and resources available to pick the orders from a store or warehouse before they are loaded on a truck to be delivered to the customers; the only scarce resource is delivery capacity. In a multi- or omni-channel environment where customers can decide between multiple channels such as picking up their order from a brick-and-mortar store or having their order delivered to the front of their door, the time and resources for preparing the order and making it available to the customers have to be considered more explicitly. For example, if the orders for both pickup and delivery would be picked by the same staff members, there would be a capacity on the time available, which also impacts the flexibility of the booking process. In the end, this could impact the total number of deliveries that can be offered premium options and create new decisions, such as deciding preferences on which types of customers' orders should be prioritized.

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