




Service time window selection for attended home deliveries: a case study for urban and rural areas

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Abstract

Attended home deliveries are one of the most challenging logistics services with different customer expectations and challenges in urban and rural areas. For different demand densities, retailers must strike a balance between providing excellent customer service and optimizing routing efficiency. While customers often expect delivery promises with narrow time windows, research has demonstrated that longer time windows can increase the flexibility and the ability to accept more customers. However, it is not clear how different demand densities impact flexibility and customer acceptance. To serve as many customers as possible with excellent service quality, this paper reviews and expands on ideas for offering short and long time windows in a flexible manner in urban and rural areas. This study proposes different methods for providing customers with time windows of different lengths and investigates their performance based on a case study in Vienna and Upper Austria.

Keywords Delivery area · Routing flexibility · Service planning · Attended home delivery · Vehicle routing with time windows

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1 Introduction

Online grocery sales have been increasing for years.¹ Many e-grocers provide delivery to the customer's door, especially in urban areas. There are many advantages for the customer when using this service, such as fewer trips for shopping and often a higher selection of offered products. However, from the retailer's perspective, delivering groceries presents significant challenges because it requires the presence of the customer at the time of delivery (Campbell and Savelsbergh 2005). This type of delivery is referred to as an attended home delivery. Providing attended home deliveries can be challenging due to the logistical complexities and associated costs, especially for industries with low profit margins such as grocery retail.

Waßmuth et al. (2023) provide a comprehensive review of approaches for demand management and vehicle routing approaches for attended home deliveries. They highlight that a strategic consideration of how to implement these delivery services profitably is still underrepresented in the academic research. In this paper, we will introduce new ideas for the design and implementation of attended home delivery services, with a specific focus on the differences between urban and rural customer locations.

Attended home delivery services are typically offered in urban areas due to the higher demand density which leads to increased efficiency in picking and delivering orders. It is not clear how reduced demand densities as in rural areas affect the performance of such delivery services. The amount of demand that a retailer receives is not only influenced by the available demand in the area, but also by alternative options available to customers, such as the locations of brick-and-mortar stores and the intensity of competition in the service area (Wollenburg et al. 2018). In theory, rural areas might even have greater demand potential because there is less competition and a lower density of supermarkets compared to cities (Hübner et al. 2019). Additionally, the lack of competition in rural areas may allow the retailer to offer a relatively lower quality of service than in urban areas, such as by extending time windows or delivery times.

Thus, our study examines the management of service time windows of varying lengths in urban and rural areas. The goal is to serve as many customers as possible with excellent service quality. We examine the customer acceptance mechanisms proposed in Köhler et al. (2020), investigate their limitations, and consider three additional acceptance methods. The first of these three combines existing methods from Köhler et al. (2020), the second uses a two-stage offering process, and the third implements a bundling idea similar to Strauss et al. (2021). We investigate how these mechanisms enhance the efficiency and service quality of attended home deliveries, particularly in areas characterized by longer average travel distances and lower demand density.

For our experiments, we use real data involving a rural area *Upper Austria* and an urban area *Vienna*. Austria is known for its high density of supermarkets;

¹ <https://bit.ly/3Xewo2M>, 2022-12-27.

however, these supermarkets are not evenly distributed throughout the country. For instance, Billa, one of Austria's leading supermarkets, has a higher concentration of stores in Vienna compared to Upper Austria, despite both areas having a similar population size. Specifically, there are almost 500 Billa supermarkets in Vienna, while in Upper Austria, there are less than half that number.²

We provide valuable insights into the dynamics of attended home deliveries in rural and urban areas. Our findings reveal that rural areas have a lower customer acceptance rate compared to urban areas when assuming equal customer preferences for all time windows. We also emphasize the importance of selecting the appropriate threshold for parameterizing the introduced mechanisms, particularly in urban areas. However, overall, the mechanisms exhibit similar performance in both rural and urban areas. Notably, in a scenario of unequal demand where certain time windows are strongly preferred by customers, which we believe is the most realistic scenario, the discrepancies in customer acceptance rates between rural and urban areas diminish. These insights offer strategic decision-making input for retailers, as they suggest that targeting the less competitive rural market can yield comparable outcomes to urban areas.

The paper is structured as follows. Section 2 provides a comprehensive literature overview. Section 3 describes the problem and emphasizes the new mechanisms that have been added to those presented by Köhler et al. (2020). Section 4 summarizes the computational settings and presents the computational results. In Section 5, we summarize our findings.

2 Literature

In this section, we provide a comprehensive literature review. We first explore the topic of flexible delivery options and examine the efficiency of long and short time windows. Then, we address the specifics of deliveries in rural and urban areas, considering the associated costs and challenges.

2.1 Offering service time windows

The design of attended home delivery services is heavily influenced by the set of time windows offered to customers. While customers often prefer very specific and short time windows as indicators of high service quality, research has shown that these narrow time windows can significantly increase the delivery costs for retailers (Lin and Mahmassani 2002) and limit the number of customers that can be served (Ehmke and Campbell 2014).

To address the challenge of balancing delivery costs and customer service, several studies have explored potential trade-offs in this area to increase delivery flexibility. Table 1 provides a summary of the discussed literature below, categorized

² <https://www.billa.at/maerkte>.

Table 1 Related literature: offering service time windows

Authors	Problem setting	Flexibility design	Area evaluation
Köhler et al. (2020)	Customer acceptance	Length (time window)	Real (urban)
Yildiz and Savelsbergh (2020)	Customer acceptance	Delivery day	Artificial
Agatz et al. (2021)	Customer acceptance	Length (time window)	Artificial
Strauss et al. (2021)	Customer acceptance	Bundles (time window)	Artificial
Klein and Steinhardt (2023)	Customer acceptance	Length (deadline)	Artificial
Köhler et al. (2023b)	Customer acceptance	Length (time window)	Real (urban)
Ulmer et al. (2023)	Customer acceptance	Length (time window)	Real (urban)
This paper	Customer acceptance	Length (time window)	Real (urban, rural)

based on the considered problem setting and the design and control of flexibility. One approach involves managing the time window offers to customers in order to increase routing flexibility. For instance, Köhler et al. (2020) suggest offering short time windows for high-quality service only to selected customers based on factors such as demand uncertainty or proximity to the delivery route, while providing longer time windows to other customers. They demonstrate that selectively assigning short time windows later in the booking process or to customers near the route allows for accepting a larger number of customers overall. Similar findings are reported by Ulmer et al. (2023), who highlight the benefits of this approach. In this paper, we leverage these findings by incorporating temporal and spatial information when deciding on short time window offerings.

In their study, Köhler et al. (2023b) investigate the customer perception of different time window lengths and pricing in the context of choosing a delivery option. They propose a pricing policy that strikes a balance between flexibility and affordability by offering price reductions for short time windows while providing a long time window as a free alternative. This approach allows for the acceptance of a larger customer base and provides customers with a range of choices to align with their preferences. In another study, Yildiz and Savelsbergh (2020) explore the option of offering price reductions to customers who agree to allow for delivery flexibility, such as receiving the delivery earlier or later. Similarly, instead of offering single short time windows, Strauss et al. (2021) suggest offering time window bundles and subsequently narrowing down the time window offered by communicating an updated delivery promise to the customer. We incorporate this idea into one of our approaches as well by asking customers to select multiple time window options. We find similar approaches to price shorter time windows higher also in same-day settings, see, for example, Klein and Steinhardt (2023).

It is worth noting that longer time windows in delivery services not only have the potential to decrease the retailer's costs but are also associated with lower emissions in delivery routes (Agatz and Fleischmann 2023). Hence, they are now also recognized as a way to meet the preferences of environmentally conscious customers. This has led to the emergence of "green time windows" that are marketed as more sustainable options. Agatz et al. (2021) investigate the impact of communicating these

green time windows to customers and find that customers respond positively to this incentivization. However, the study reveals that the effect diminishes as the duration of green time windows increases relative to non-green time windows. In one of our approaches in this paper, we also consider communicating longer time windows as the environmentally-friendly option for delivery.

2.2 Delivering in rural and urban areas

In rural areas, planning challenges arise due to—compared to urban areas—demand being spread across wider geographical areas and factors such as poorer accessibility (e.g., inadequate infrastructure) and longer travel times. An inefficient allocation of resources within these contexts can lead to unused capacities and higher costs. Consequently, services offered for rural residents frequently lag behind those available in urban areas. However, the increase in online shopping options has been widely regarded as a potential solution to bridge the gap and reduce the disparities between rural and urban customers (Yin and Choi 2022).

To the best of our knowledge, in the field of attended home deliveries, no study comparing service offerings for rural and urban deliveries has been conducted. However, for long, vehicle routing research has revealed a relationship between delivery costs and customer location density, which aligns with our study and has been demonstrated by Boyer et al. (2009) and Gevaers et al. (2014). The latter estimate that very low population density incurs higher costs, approximately 5€ per order, due to longer travel times compared to highly populated areas. When capacities are limited, this directly translates into a reduced number of customers that can be serviced overall. Ehmke and Campbell (2014) compare customer acceptance rates between urban and sub-urban areas and find that fewer customers are accepted in the suburban setting. With shorter time windows, this disparity results in a significant 30% fewer customers being accepted. Similar findings are reported by Köhler and Haferkamp (2019), who compare high-density and low-density delivery areas of a German e-grocer with 2-hour time windows, revealing significantly lower customer acceptance rates in the latter region. van der Hagen et al. (2022) introduce a machine learning-based algorithm that considers different spatial demand distributions, highlighting the importance of considering various demand structures for attended home deliveries. While not explicitly considering the density of delivery regions, Köhler et al. (2023a) show that servicing in differently distributed customer locations even in two urban settings can yield different outcomes. To increase efficiency, one possible approach is to increase demand artificially by limiting the delivery options, as suggested by Agatz et al. (2013). Hence, less dense areas are often offered fewer and longer service time windows and higher prices, or, as highlighted by Sousa et al. (2020), experience approximately 70% longer lead times compared to urban areas. As a result, rural customers have limited access to the increasingly popular same-day delivery services. It is worth noting that while there is a substantial body of literature on same-day delivery, the majority of studies primarily focus on urban

Table 2 Related literature: delivering in rural and urban areas

Authors	Problem setting	Area design	Evaluation
Boyer et al. (2009)	Cost simulation	Urban (density)	Delivery costs
Ehmke and Campbell (2014)	Customer acceptance	Urban, sub-urban	Customers accepted
Gevaers et al. (2014)	Cost simulation	Artificial (density)	Delivery costs
Hernandez et al. (2017)	Service distribution	Artificial (density)	Service options offered
Köhler and Haferkamp (2019)	Customer acceptance	Urban	Customers accepted
van der Hagen et al. (2022)	Feasibility check	Artificial (density)	Delivery costs
Chen et al. (2023)	Service distribution	Artificial (utility)	Service options offered
Köhler et al. (2023a)	Customer acceptance	Urban	Customers accepted
This paper	Customer acceptance	Urban, Rural	Customers accepted

settings, leaving a gap in understanding the specific challenges and dynamics associated with same-day delivery in rural areas.

While limited research explicitly focuses on the differences between rural and urban deliveries, a related research stream revolves around the fair distribution of service offerings. In situations where delivery is conducted in both low and highly-populated areas simultaneously, there is often a disadvantage for regions with lower demand. To address this issue, a minimum service requirement is assigned to ensure a more fair allocation of service resources. Relevant examples can be found in Hernandez et al. (2017) and Chen et al. (2023). In this paper, we adopt a broader and more strategic perspective. Rather than focusing on the fair assignment of services within specific regions, we aim to assist retailers in making informed decisions regarding whether to extend their services to rural regions or not. By taking this general perspective, we provide valuable insights to retailers seeking to optimize their delivery operations in both rural and urban settings. Table 2 presents an overview of the cited literature pertaining to customer density and service assignment. The table categorizes the literature based on the problem setting, area design, and the criteria utilized for evaluation.

The differences between rural and urban areas extend beyond population density. Factors such as product availability, accessibility to physical stores, and lead times also play a significant role in shaping customer experiences (Sousa et al. 2020). Hence, it is important to consider these factors when analyzing online shopping behavior in rural areas. Although the operational cost perspective highlights the differences in servicing rural and urban areas, the variation in customer service expectations remains unclear. It is plausible that with less competition in rural areas, customer service expectations may be lower (Sousa et al. 2020). Consequently, lower service expectations may result in reduced costs for the retailer, potentially outweighing or even surpassing the higher delivery costs associated with sparsely populated areas. This aspect will be taken into account when we compare the service expectations of customers in rural and urban areas in our study.

2.3 Service time windows for urban and rural areas

Our study bridges the gap between the two research directions discussed in the preceding sections. We investigate the impact of offering service time windows of varying lengths in urban and rural delivery settings. Our approaches are built on established characteristics from existing literature, incorporating factors such as temporal and spatial information. Additionally, we delve into customer perceptions of service offerings and augment our approaches by enabling the selection of multiple options and considering marketing factors. We put these approaches into practice in two real-world delivery regions, utilizing the actual road networks of both an urban and a rural area. Furthermore, we account for potential variations in service expectations across these areas and model various acceptance levels for long service time windows. As a result, our study provides retailers with valuable insights into formulating strategies for offering service time windows that enhance routing efficiency, align with customer expectations, and facilitate effective service communication across diverse delivery regions.

3 Problem and methodology

We first provide the problem narrative and then discuss the methodology of customer acceptance mechanisms.

3.1 Problem narrative

In the following, we provide the narrative of the problem at hand. We base our description on the formal description of Köhler et al. (2020).

We consider an online grocery retailer that makes delivery promises to customers. The online grocery retailer aims to serve as many customers as possible while providing excellent service. To achieve this goal, the retailer is interested in exploring how to meet demand effectively in different environments, specifically urban versus rural areas. Customers arrive one at a time during the booking process and are each offered a menu of feasible delivery time windows. Choosing a time window out of this offer set immediately confirms their order. We assume the delivery fee is the same for all deliveries, regardless of the length of the time window or the time of day. Demand for service is expected to be imbalanced, with certain time windows being more popular than others. We assume that customers always prefer short time windows over long ones, but service expectations may be higher in urban areas than rural areas, resulting in greater acceptance of longer time windows in rural areas. The retailer decides which time windows to include in the offer set based on the estimated impact on routing flexibility, where the estimates are based on the methods described in Sect. 3.2. The offer set can contain long or short time windows or a combination of both. If the impact on flexibility is minor, the retailer offers short time windows to provide excellent service. If the impact on flexibility is significant, the retailer selects long time windows to maintain flexibility and avoid

overly restricting the acceptance of future customers. However, it should be noted that customers may not agree to the longer time window. The objective is to confirm delivery to the maximum number of customers while offering short time windows to as many customers as possible.

3.2 Methodology

For each incoming request, the retailer creates a request-specific offer set as follows. The offer sets are generated based on a tentative route plan containing the set of already accepted customers (including their locations and confirmed time windows) and the current request. We consider two sets of time windows, non-overlapping and consecutive short time windows in set S , and long time windows in set L .

We perform the following steps for each request to decide which of the time windows from the set S and L are offered to an arriving customer request j within the final offer set O_j .

Check the feasibility of all long and short time windows The retailer determines the feasibility of all time windows that may be offered to a customer. A time window is considered feasible if it is possible to deliver within it without exceeding capacity or violating commitments made to previously accepted customers. We assume a total capacity that results from the number of delivery vehicles $|V|$ and the total time available for servicing customers on a given delivery day T . We do not specify the capacities of the delivery vehicles because time window constraints are often more binding than capacity constraints for attended home deliveries. To determine all time windows that can be offered to a customer, we check all feasible insertion positions within our tentative route plans once a new customer request j has arrived. For each insertion point between positions i and $i + 1$, we compute the earliest and latest arrival time of the new customer request j while considering all time window constraints from already accepted customers, a service time u_i at each customer i , as well as the travel time $t_{i,j}$ from customer i to the request j . Using the earliest and latest arrival times, we can define time spans in which visiting the new request j is feasible. Each time window in which the earliest and latest arrival times are before or after the start and end of a time window is then marked as feasible. For each insertion position and vehicle, all feasible time windows are added to the set $S_{i,i+s}^{iv}$ and $L_{i,i+s}^{iv}$ for short and long time windows, respectively.

For all feasible time windows: decide which ones to include in the offer set The decision on which time windows to include in the offer set is based on evaluating how accepting a request in a particular window impacts the flexibility of the route plan. To this end, we review the acceptance mechanisms LS, SL, and TT as presented by Köhler et al. (2020), and add the three new acceptance mechanisms entitled GW, LS-TT, and MW. Each acceptance mechanism determines the final customer-specific offer set. We will summarize the ideas of the approaches in Sect. 3.3. Each approach determines which time windows to include in the time windows sets $S_{i,i+s}^{iv}$ and $L_{i,i+s}^{iv}$.

Let the customer decide on time window(s) from the offer set The retailer unites all time window sets from the previous step to one final offer set O_j without

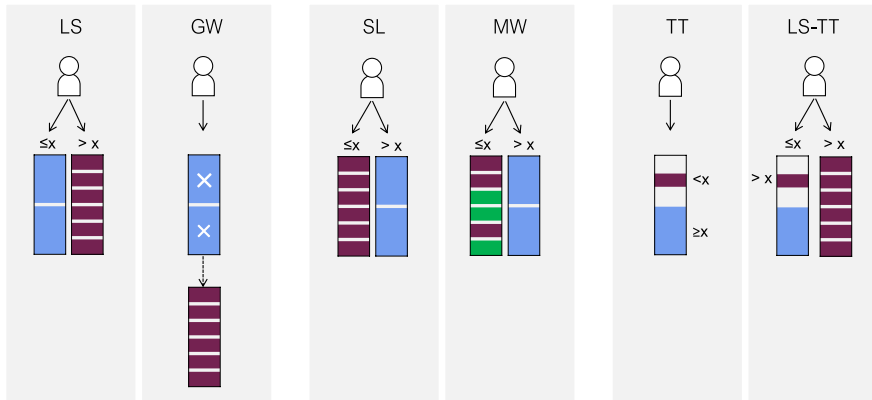


Fig. 1 Overview on flexibility mechanisms and exemplary offer sets presented to a customer request

knowing the customer's preferred delivery time window. Following Köhler et al. (2020), the customer choice behavior is modeled as follows. Generally, customers can choose between all the options provided by their offer set or cancel the booking. We distinguish between customers who would prefer deliveries early or late. Customers who are not offered a long or short time window in their preferred time of the day will cancel. If a short time window is offered, the customer will always prefer this over the long time window. If only a long time window is offered, the customer will accept this with a probability a .

Update route plan Once a request has been confirmed, the tentative routes need to be updated considering time windows and locations of all previously accepted customers and the new request. Customers are always inserted into the cheapest insertion position. Routes are improved with Guided-Local-Search provided by Google OR Tools.³

3.3 Flexibility mechanisms

We will now describe our process for determining whether the offer set O_j of request j contains long, short, or a combination of both time window lengths. This will be followed by a summary of the acceptance mechanisms LS, SL, and TT as described in Köhler et al. (2020). While the efficacy of these mechanisms has been demonstrated, certain scenarios have been identified where they may not be suitable. To address these limitations, we propose the MW, GW, and LS-TT approaches. While all of these approaches have the potential to offer advantages in specific contexts, their effectiveness, especially in urban and rural environments, has not been thoroughly assessed. Figure 1 illustrates an overview of example offer sets generated by each mechanism.

³ See <https://developers.google.com/optimization/routing> for details.

3.3.1 Withhold short time windows in the beginning: LS and GW

The **LS** mechanism (“long-short”) offers only long time windows in the first part of the booking process and only short time windows in the second part of the booking process. The idea is to avoid giving early-arriving customers too many short and constraining time windows. In essence, LS only offers feasible short time windows after a significant portion of the route plan has been defined through accepted customers $q \in R^v$. The point at which LS switches from offering long to short time windows is based on calculating the current utilization of service time capacity $|V| * T$. LS begins offering short time windows when a certain level x^{LS} of the available service time has been used.

As shown in Köhler et al. (2020), the LS mechanism can result in a high number of accepted customers, especially when x^{LS} is set to a high value. However, in situations where customers are seeking short time windows, the LS approach may not be optimal. If customers are only presented with long time windows, those who prefer shorter time windows may cancel their booking, resulting in lower capacity utilization, particularly at higher threshold values. To address this issue, we propose the **GW** (Green Windows) approach, which takes into account that many customers are not willing to accept long time windows. In the first step, the GW mechanism only offers long time windows to all requesting customers. However, if customers reject one of these long time windows because it does not match their preferences, with a probability of x^{GW} , these customers are also offered all feasible short time windows in a second step. By highlighting the increased efficiency and “green impact” of longer time windows during the booking process, GW can nudge customers toward the longer time windows and more flexible options as suggested by Agatz et al. (2021). Hence, an accompanying marketing strategy is required. We note that customers may anticipate this approach and always wait for the short time window options, i.e. they may reject time windows strategically. See the details of this approach in Algorithm 1.

```

CHOOSEWINDOWLENGTH( $\{S'_{i,i+1}, L'_{i,i+1}\}$ )
 $S''_{i,i+1} \leftarrow \emptyset, L''_{i,i+1} \leftarrow \emptyset$  // initialize time window sets
 $L''_{i,i+1} \leftarrow L'_{i,i+1}$ 
return  $\{L''_{i,i+1}\}$ 

// if customer does not accept long time window offer:
if  $x^{GW} \geq \text{random}[0, 100]$  then
  |  $S''_{i,i+1} \leftarrow S'_{i,i+1}$ 
return  $\{S''_{i,i+1}\}$ 

```

Algorithm 1: GW approach

3.3.2 Offer short time windows from the beginning: SL and MW

The **SL** mechanism (“short-long”) exclusively offers short time windows in the first part of the booking process and switches to offering exclusively long time windows for the second part of the booking process. Hence, it mirrors LS. The intuition is to define the basic structures of the route plan with early-arriving customers. In essence, SL offers feasible short time windows from the beginning and only switches to offering feasible long time windows when a large portion of the route plan has been set. The point of switching from long to short time windows is defined by measuring the current utilization of service time capacity T . When a certain level x^{SL} of the available service time has been utilized, SL begins offering short time windows.

As noted in Köhler et al. (2020), SL is easier to communicate to customers compared to LS. However, SL results in a lower number of accepted customers compared to other mechanisms because it applies short time window constraints early on in the booking process. To maintain the idea of offering short time windows at the beginning of the booking process while still increasing flexibility, we propose the **MW** mechanism. The MW mechanism is similar to SL, but customers must choose multiple short-time window options that they consider suitable for delivery. The reasoning goes that if customers can receive a high-quality service offer without an extra fee, they should give the service provider some flexibility by selecting a couple of high-quality service options. This idea is similar to the proposed time window bundles in Strauss et al. (2021). Specifically, at the start of the booking process, only short time windows are available, and the customer must select three of them. If there are fewer short time windows available, the remaining one or two options are automatically selected. When a certain capacity level x^{MW} is reached, only long time windows are available. For more details, see Algorithm 2.

```

CHOOSETIMEWINDOWLENGTH( $\{S_{i,i+1}^v, L_{i,i+1}^v\}, j, v, i$ )
 $S_{i,i+1}^v \leftarrow \emptyset, L_{i,i+1}^v \leftarrow \emptyset$  // initialize sets
if  $x^{MW} \geq (t_{0,1}^v + \sum_{i=1}^{q-1} (t_{i,i+1}^v + u_i) + t_{q,0}^v) / (|V| * T)$  then
  |  $S_{i,i+1}^v \leftarrow S_{i,i+1}^v$ 
else
  |  $L_{i,i+1}^v \leftarrow L_{i,i+1}^v$ 
end
return  $\{S_{i,i+1}^v, L_{i,i+1}^v\}$  // if short time windows are offered, customers have to
accept three

```

Algorithm 2: MW approach

To ensure that each accepted request can be served in at least one time window at the end of the booking process, whenever a new request arrives, MW checks if the offer set of previous requests contains at least one feasible time window. If there is only one option left or if the booking process terminates, unfixed requests are inserted at the cheapest insertion position. Customers are notified of their delivery time window once it has been fixed or the booking process has been completed.

3.3.3 Offer short time windows in the vicinity: TT and LS-TT

The **TT** mechanism (“travel time”) investigates the vicinity of an incoming request. Only for those time windows when the current request is in the vicinity of an already existing customer, TT offers a short time window. The vicinity is defined by the relative travel time from the location of an accepted customer to the location of the current request relative to the total time capacity. If the relative travel time is below the threshold value x^{TT} , the current request is offered a short time window.

As per the findings of Köhler et al. (2020), the TT mechanism is highly efficient in accepting a significant number of customers in short time windows. However, concerning the objective of accepting many customers, overall, the TT mechanism was found to be inferior to LS. Hence, to leverage the benefits of both mechanisms, we propose the introduction of the **LS-TT** (“long-short → travel time”) approach. The **LS-TT** mechanism combines the metrics of LS and TT. The idea is to provide long time windows in the first part of the booking process but allow for short time windows if the request is in the vicinity of an already accepted request, i.e. if the relative travel time is below the threshold value x_{time}^{LS-TT} . Then, at some point in the booking process, when a certain level x_{util}^{LS-TT} has been exceeded, LS-TT switches to only offering short time windows. The intuition is to provide good service also for some early-arriving customers if they are in the vicinity of already accepted customers and do not restrict the flexibility of the route plan too much. Details are shown in Algorithm 3.

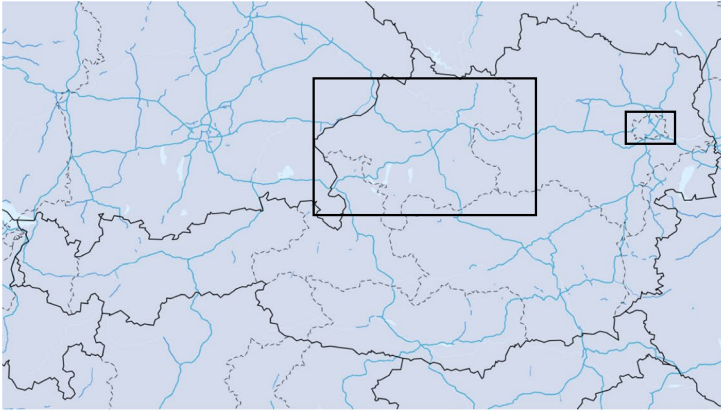
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CHOOSETIMEWINDOWLENGTH( $\{S_{i,i+1}^{''v}, L_{i,i+1}^{''v}\}, j, v, i$ )
 $S_{i,i+1}^{''v} \leftarrow \emptyset, L_{i,i+1}^{''v} \leftarrow \emptyset$  // initialize sets
if  $x_{Utilization}^{LS} < (t_{0,1}^v + \sum_{i=1}^{q-1} (t_{i,i+1}^v + u_i) + t_{q,0}^v) / (|V| * T)$  then
    if  $x_{Travel}^{LS-TT} < t_{i,j}^v / (|V| * T)$  or  $x^{TT} \geq t_{j,i+1}^v / (|V| * T)$  then
        |  $S_{i,i+1}^{''v} \leftarrow S_{i,i+1}^{''v}$ 
        else
        |  $L_{i,i+1}^{''v} \leftarrow L_{i,i+1}^{''v}$ 
        end
    else
    |  $S_{i,i+1}^{''v} \leftarrow S_{i,i+1}^{''v}$ 
    end
return  $\{S_{i,i+1}^{''v}, L_{i,i+1}^{''v}\}$ 

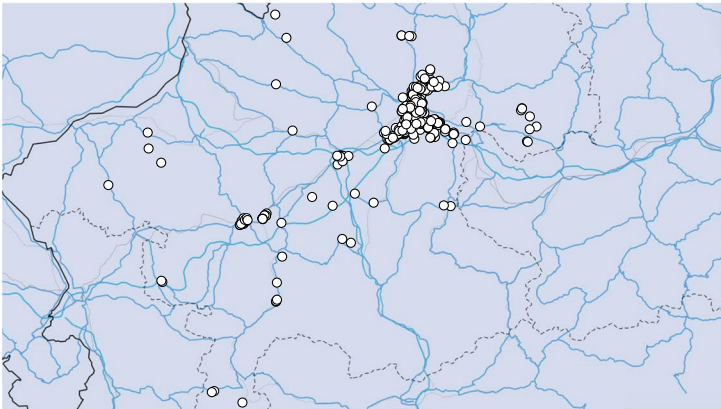
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Algorithm 3: LS-TT approach

(a) Considered Delivery Areas in Austria



(b) Rural: Delivery Locations in Upper Austria



(c) Urban: Delivery Locations in Vienna

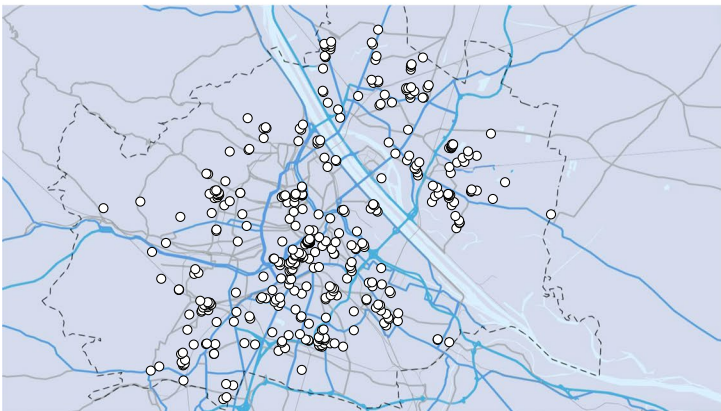


Fig. 2 Overview on delivery areas

Table 3 Overview on the threshold values for x

Flexibility mechanism	Tested thresholds x
Long \Rightarrow Short (LS)	90%, 50%, 10%
Green Window (GW)	10%, 50%, 90%
Short \Rightarrow Long (SL)	10%, 50%, 90%
More Windows (MW)	10%, 50%, 90%
Travel Time (TT)	0.25%, 1.25%, 2.25%
Long \Rightarrow Short—Travel Time (LS-TT)	90% & 2.25%, 50% & 1.25%, 10% & 0.25%

4 Computational experiments

We introduce our experimental settings in Sect. 4.1. Computational results are presented for experiments with equal demand in Sect. 4.2 and unequal demand in Sect. 4.3.

4.1 Experimental settings

For our computational experiments, we consider two different delivery areas: *the City of Vienna*, which represents a metropolitan area with densely concentrated customers, and *Upper Austria*, a state in the northwest of Austria, as an example of a rural delivery area with a central major city and less concentrated customer locations. For each delivery area, we randomly select 400 nodes as potential customer locations that we depict in Fig. 2. We determine travel times between all nodes (as well as nodes to the depot) with the help of the Open Source Routing Machine,⁴ which uses map material from OpenStreetMap. The Vienna delivery area is geographically small and we have average travel times of 15.5 min and a relatively small standard deviation of 6.9 min. Upper Austria, on the other hand, covers a geographically significantly larger area with average travel times of 25.1 min and a standard deviation of 21.1 min. Travel time from the northernmost to the southernmost point in the delivery area takes 121 min in Upper Austria and 34 min in Vienna. From the westernmost to the easternmost point at the edge of the delivery area it takes 143 min in Upper Austria and 30 min in Vienna.

To enable comparability of results, we base the remaining settings on Köhler et al. (2020). We investigate a booking process of 200 requests for a delivery capacity of $|V| = 6$ delivery vehicles and a delivery time of at most $T = 8h$. Each delivery vehicle starts and ends at the depot, but travel times to and from the depot are not included in T . We assume a service time of 12 min and offer long time windows of 4 h and short time windows of 30 min. The time window alternatives are as follows: long time windows = $\{14 : 00 - 18 : 00, 18 : 00 - 22 : 00\}$ and short time windows = $\{14 : 00 - 14 : 30, \dots, 21 : 30 - 22 : 00\}$. We present all thresholds in relation to the total available capacity of $|V| * T$. For the flexibility mechanisms

⁴ <https://github.com/Project-OSRM/osrm-backend>.

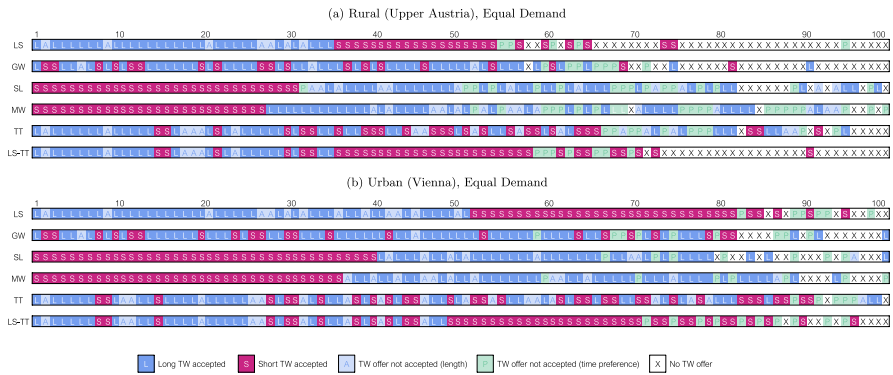


Fig. 3 Example booking processes for equal demand and $a = 75\%$

presented by Köhler et al. (2020), we adopt the values as presented in Table 3. The exception is the values for GW: Here we specify in % the probability with which we offer a short time window after the customer has rejected a long time window.

We consider equally and unequally distributed demand as presented by Köhler et al. (2020). For the former, the probability for early and late time windows is the same, so that $p = 0.5$ as a baseline for equal demand. The booking probability of all included short time windows is equally distributed as well. For the latter, we adopt the strong preference for late time windows observed by many logistics service providers and set $p = 0.1$. The first four early short time windows each have a probability of 1.0%, and the second four early short time windows each have a probability of 1.5%. The first four late short time windows have the highest booking probability of 18.0% each and the last four short time windows 4.5% each. We will conduct experiments using four different acceptance levels for long time windows. The highest acceptance rate, $a = 100\%$, represents that all customers will accept a long time window. The lowest acceptance rate being considered is $a = 25\%$, meaning that only a quarter of customers are willing to accept a long time window.

All results represent averages from five independent runs.

4.2 Computational results for equal demand

In the subsequent sections, we present the results of our analysis for equal demand in three sub chapters, each providing a comparison between rural and urban delivery areas. In Sect. 4.2.1, we visualize the booking process for a small sample instance. In Sect. 4.2.2, we explore suitable thresholds for the acceptance mechanisms. In Sect. 4.2.3, we investigate how the acceptance mechanisms operate when many of the customers are not accepting long time windows. A comprehensive overview of all results can be found in the appendix in Sect. 6.

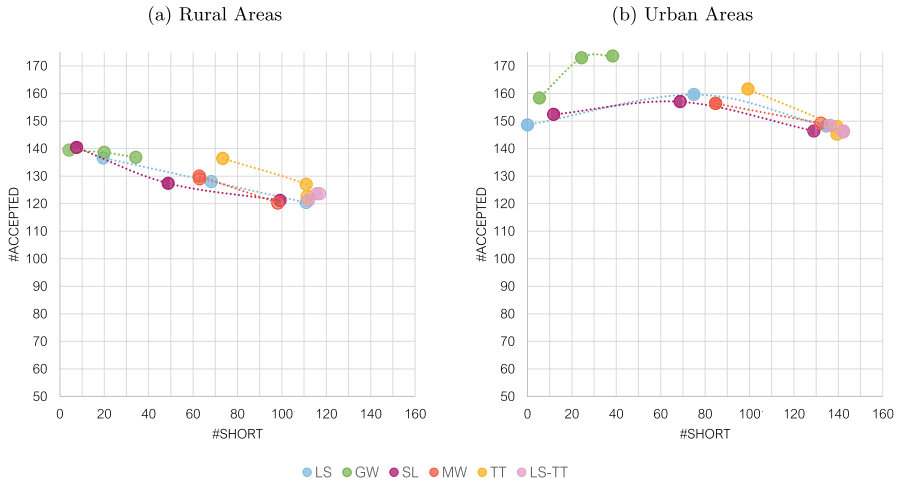


Fig. 4 Overview on results for Rural (left) and Urban (right) with Equal Demand and $a = 75\%$

4.2.1 Booking process illustration

In Fig. 3, we detail the operation of the acceptance mechanisms using a small example booking process with 100 customers for an acceptance level of $a = 75\%$ for long time windows and a threshold for each mechanism such that approximately half of the customers have been accepted in a short time window. In each figure, the incoming customer requests are displayed as numbers from 1 to 100, with a letter denoting whether the customer booked a long (L) or short (S) time window. The booking process is canceled if a suitable time window cannot be offered to the customer. This can occur due to the customer expecting a short time window but only being offered a long time window (A), or due to the customer requesting a time window at a different time (P). If a time window offer cannot be made to the customer at all, the request is marked as (X).

For the equal demand scenarios shown in Fig. 3, we can see that three mechanisms offer customers either long time windows (LS) or only short time windows (SL and MW) at the beginning. With the GW, TT, and LS-TT approaches, time windows are offered more individually, meaning that short or long time windows are offered to customers regardless of when they appear in the booking process and focusing more on the spatio-temporal characteristics of the already accepted customers. For all mechanisms, it can be seen that short time windows are accepted if they fall within the appropriate time period. When long time windows are offered, some of the customers reject them.

Comparing rural and urban settings, for rural, it becomes difficult to meet a customer’s time preferences (P) or offer time windows (X) at all significantly earlier than for urban. In the rural setting, time windows at the appropriate time are no longer available for Customers 32 in SL and 37 in TS. For the urban

setting, with TS, time windows in the correct time period are no longer available for the first time from Customer 55. In the rural setting, time windows cannot be offered at all for the first time with TS and Customer 55. In the urban setting, this occurs much later at Customer 89 and SL. Hence, rural customers face a higher probability of not being offered a short time window or any time window at all because of the lower demand density. However, the overall structure of providing short and long time windows remains similar in rural and urban settings.

4.2.2 Threshold analysis

In this section, we present results for the different acceptance mechanisms across different thresholds for a given acceptance level of long time windows ($a = 75\%$). Figure 4 shows the results for each acceptance mechanism and the three tested thresholds (see Table 3) in rural and urban areas for equal demand. On the y-axis, we display the number of customers accepted in total, while the x-axis denotes the number of customers that can be accommodated within a short time window. To maintain consistency, each grid box in the visualization represents the acceptance of 10 customers, allowing for clear comparisons across different scenarios.

Beginning with the results for the rural setting, we see that the total number accepted ranges from about 120 to 140 customers. The number accepted in a short time window varies significantly, ranging from almost none to 120 customers. Generally, we observe a negative relationship between a large number of customers and customers within a short time window: the more customers we accept in a short time window, the fewer customers we can accept overall. Hence, the importance of selecting the right mechanism and threshold becomes more pronounced when prioritizing good service quality, particularly in accepting customers within shorter time windows. Examining the individual thresholds, TT offers the best compromise between accepting a large number of customers and providing a short time window (up to 136.6 overall/73.4 in a short time window), while SL, on average, performs the worst. No matter what the threshold is, LS-TT provides very service quality: It attains the highest number of customers accepted in a short time window (up to 117.0 customers). LS and SL accept either many customers in total but few customers in a short time window or fewer customers in total but a large number within a short time window. GW is very successful in handling a large number of customers overall, while MW is of intermediate quality.

When examining the results for the urban setting, generally, in contrast to the rural setting, we accept a higher number of customers overall, yielding about 145–175 customers in total. GW again performs best regarding the total number of customers accepted (up to 173.6 customers in total/38.4 short, 90% threshold). Similar to the rural setting, TT and LS-TT provide good compromises between a large number of accepted in total and accepted in short time windows almost independent of the set threshold. However, it is much easier now to keep the total number of customers accepted high and provide many customers with a short time window. With the appropriate thresholds, SL, LS, MW can achieve reasonable outcomes, accepting about 160 customers overall and about 70 in a short time window, while

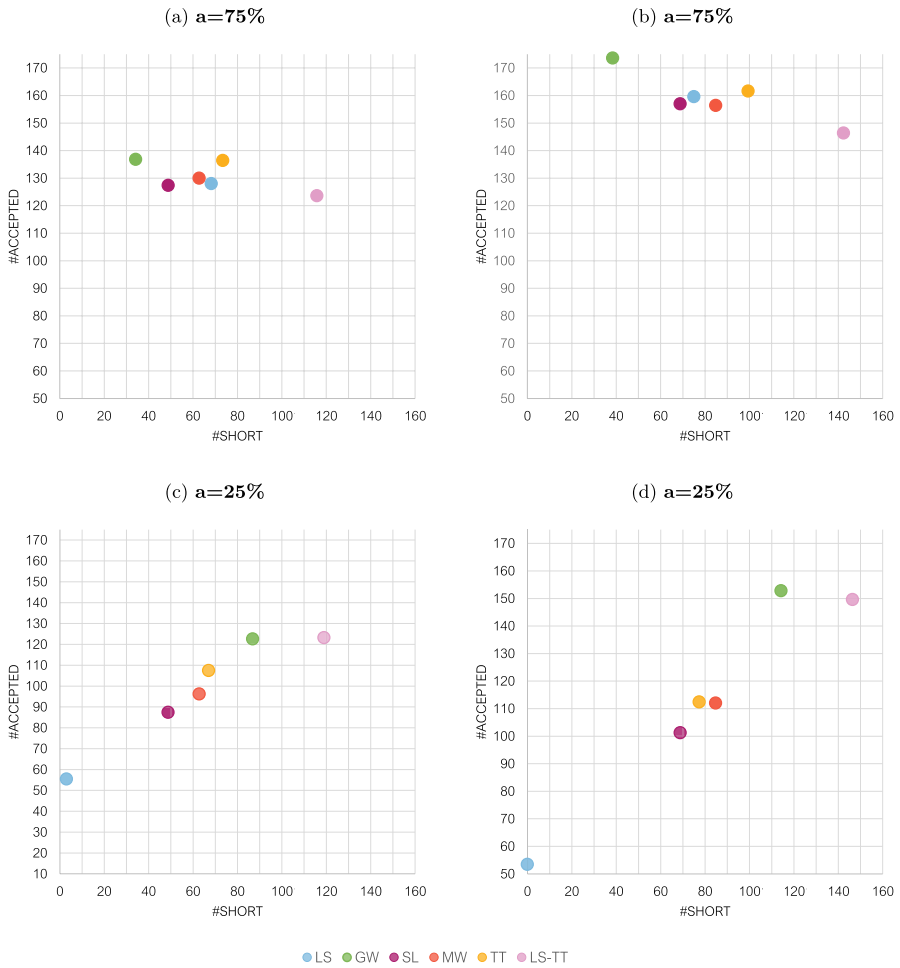


Fig. 5 Results for reduced acceptance of long time windows for Rural (left) and Urban (right) with Equal Demand

the best service quality with a high number of short time windows is provided by LS-TT (up to 142.4). Like in the rural setting, TT provides the best compromise for accepting a large number of customers within a short time window. This implies that the travel-time-based approaches can adapt well to the different demand densities in rural and urban areas. Interestingly, this allows for better compromises than the MW approach. Thus, in the urban setting, keeping the number of customers accepted high while providing short time windows is easier than in rural areas.

In summary, between rural and urban areas, we see a difference in the number and patterns of customers that are accepted. As expected, the longer travel times in the rural setting lead to fewer customers that can be serviced with given

service time constraints. Choosing the right threshold is more challenging in the urban than in the rural setting. In both settings, the LS-TT approach seems to be quite robust across different thresholds and quite stable in achieving good compromises of a high overall acceptance rate and a large number of short time windows. However, GW and TT—when choosing the right threshold—yield the best results for either one or the combination of both our objectives.

4.2.3 Long time window acceptance

A core assumption in our computational analysis is the willingness of customers to accept long delivery time windows to keep route plans flexible. Building upon the results of the previous section, we now analyze lower acceptance rates in conjunction with thresholds that yielded the most similar outcomes in the number of customers being accepted in a short time window among all thresholds, i.e., $x^{LS} = 50\%$, $x^{GW} = 90\%$, $x^{SL} = 50\%$, $x^{MW} = 50\%$, $x^{TT} = 0.25\%$, $x^{LS-TT} = 50\%$. Figure 5 visualizes the results of the different acceptance levels of $a = 75\%$ and $a = 25\%$.

Let us begin by revisiting the results for the rural setting displayed on the left side. For the selected thresholds, we can see a similar outcome in terms of the overall number of customers for $a = 75\%$. However, when the acceptance drops to $a = 25\%$, the results look very different: LS, SL, and MW are now the lowest performers with regard to total number accepted and accepted in a short time window, and, surprisingly, TT, which demonstrated favorable performance previously, now also falls within the middle range in terms of overall customer acceptance. In contrast, mechanisms that predominantly offer short time windows emerge as clear winners now. GW, due to its high proportion of customers receiving short time windows at the displayed threshold of 90%, and LS-TT, which consistently offers short time windows to almost all customers, perform significantly better for low acceptance of long time windows both with regard to total number accepted and accepted in a short time window. Interestingly, we observe identical patterns in the results in the urban setting (see figures on the right). GW and LS-TT reaffirm their effectiveness at the 25% acceptance rate both for the total number accepted and accepted in a short time window.

In summary, when examining a low acceptance rate of only 25% for customers willing to accept a long time window, we observe that several of the tested mechanisms are limited in overall customer acceptance. However, mechanisms that prioritize short time windows demonstrate better outcomes, even in scenarios with lower acceptance rates. Notably, the GW and LS-TT mechanisms continue to accept a similar number of customers as in the higher acceptance rate scenario. The observed patterns highlight the need for tailored approaches based on the specific context, as rural and urban settings may exhibit variations in customer preferences and responses to different acceptance mechanisms. Interestingly, with the lower acceptance rate, the differences in results between rural and urban settings diminish, and we only accept about 30 fewer customers in the rural environment.

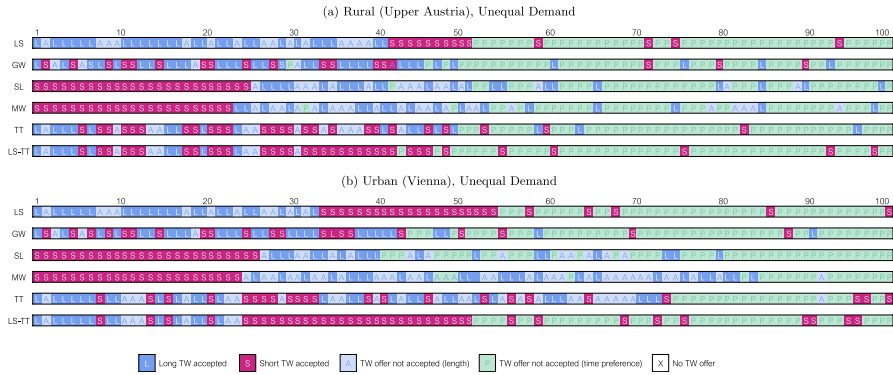


Fig. 6 Example booking processes for unequal demand and $a = 75\%$

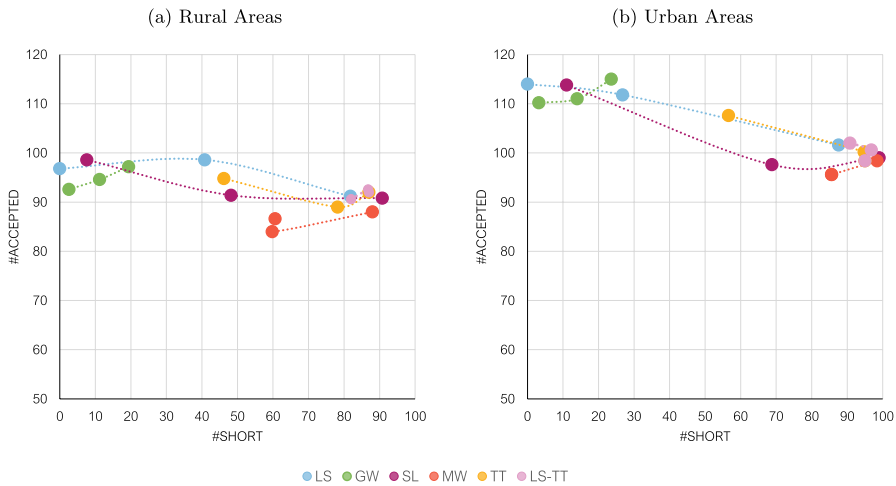


Fig. 7 Overview on results for Rural (left) and Urban (right) with Unequal Demand and $a = 75\%$

4.3 Computational results for unequal demand

In this section, we focus on the analysis of more realistic unequal demand patterns. First, in Sect. 4.3.1, we visualize the booking process for a sample instance. In Sect. 4.3.2, we explore suitable thresholds for the acceptance mechanisms. Finally, we explore in Sect. 4.3.3 what happens for low acceptance rates of long time windows. A comprehensive overview of all results can be found in the appendix in Sect. 6.

4.3.1 Booking process illustration

In Fig. 6, we detail the operation of the acceptance mechanisms using a simple example booking process for an acceptance level of $a = 75\%$ with 100 customers

and a threshold for each mechanism such that approximately half of the customers have been accepted in a short time window as in Sect. 4.2.1.

For unequal demand operations shown in Fig. 6, the booking processes have changed significantly. Fewer customers are being accepted in both rural and urban areas, with almost no customers being accepted after the 50th request. Unlike in the equal demand setting, time window offers are made to all customers until the end of the process. However, there are many time window offers that do not align with the customer's time preferences (P). As a result, there is still capacity available at the end of the booking process, but it cannot be allocated to customers because it does not match their preferences. Interestingly, for LS, GW, TT, and LS-TT, it is also possible to offer a short time window to customers very late in the booking process, although there are only a few of them. While only the first customers in the booking process benefit from a short time window for SL and MW, the other acceptance mechanisms allow even the very last customer in the booking process to be accepted in a short time window. In the unequal demand setting, the probability of not being offered the preferred time window is almost the same for rural and urban customers.

4.3.2 Threshold analysis

In this section, we investigate the influence of unequal demand for specific time windows on customer acceptance results with different thresholds for a given acceptance level of $a = 75\%$. We present the results in Fig. 7.

We observe that the introduction of an unequal demand pattern results in a decrease in the total number of customers accepted. Under the equal demand scenario, the maximum customer acceptance was 139.4 in the rural setting and 173.6 in the urban setting. With the consideration of unequal demand, the maximum acceptance has been reduced to 98.6 customers in the rural setting and 115.0 customers in the urban setting. This indicates a notable change as the disparity in customer acceptance rates between rural and urban settings is less apparent. Previously, distinct differences in acceptance rates were observed due to factors such as longer travel times and limited capacities in the rural setting. However, with the introduction of the highly imbalanced demand pattern associated with unequal demand, we now observe the underutilization of routes in both rural and urban settings. As a result, the discrepancy in the total number of customers accepted has diminished.

In summary, in the rural setting, LS with a threshold of 50% emerges as the top performer, accepting 98.6 customers in total, nearly half of whom are accommodated within a short time window. Surprisingly, previously effective mechanisms like GW, TT, and LS-TT now yield only moderate results. In the urban setting, LS continues to perform well regarding both metrics, while TT and GW also deliver favorable outcomes. Notably, GW achieves the best performance with regard to total customers accepted, yielding a total of 115.0 customers with 23.6 customers accommodated in a short time window. However, it is worth noting that the results for the tested thresholds are not evenly distributed: they cluster either on the left side (high overall customer acceptance) or on the right side (high customer acceptance in a short time window). In this unequal demand scenario in the urban setting, there are

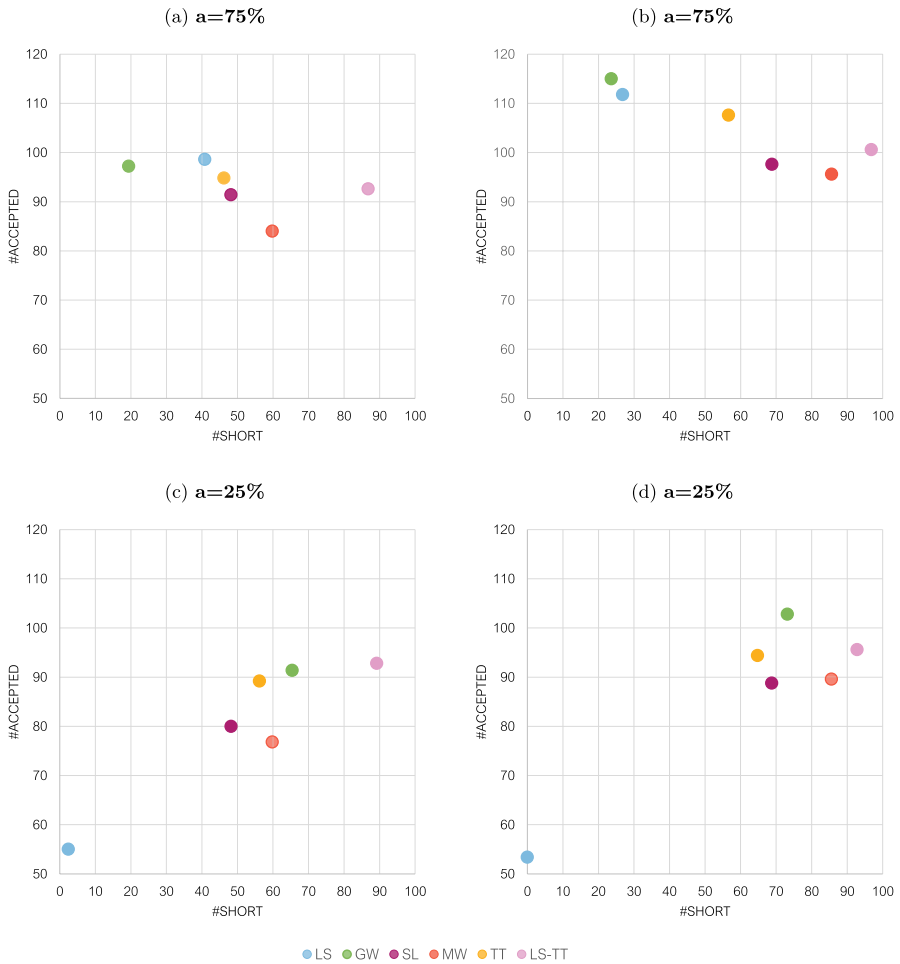


Fig. 8 Results for reduced acceptance of long time windows for Rural (left) and Urban (right) with Unequal Demand

not many compromise options between the two metrics. Instead, the retailer must decide which metric should be prioritized.

4.3.3 Long time window acceptance

In Fig. 8, we analyze the impact of varying acceptance levels ($a = 75%$ and $a = 25%$) on customer acceptance. The results correspond to the same thresholds as discussed in Sect. 4.2.3.

First, focusing on the rural setting, LS performs well in the 75% acceptance scenario for total number accepted. However, in the 25% acceptance scenario, LS exhibits the lowest performance, accepting only 55 customers in total and nearly none in a short time window. This represents the poorest result among all demand

scenarios, mechanisms, and thresholds. In contrast, LS-TT, which offers the highest number of short time windows, displays more consistent performance across the scenarios.

Shifting our attention to the urban setting, we observe a similar pattern. LS accepts even fewer customers in total than in the rural setting, again with no short time windows. Interestingly, all mechanisms yield comparable results in both rural and urban settings. This aligns with the observations from the previous analysis in the equal demand scenario, where we also noticed similar patterns between rural and urban settings in the 25% acceptance scenario. Notably, the differences in customer acceptance among mechanisms are quite small, particularly at the lower acceptance rate. For instance, the difference in total customer acceptance between TT and GW is only 9 customers, emphasizing the convergence of results in both settings.

These findings demonstrate the influence of acceptance levels on customer acceptance rates in both rural and urban settings. LS, while performing sufficiently well in the higher acceptance scenario, struggles to maintain the same level of performance in the lower acceptance scenario. In contrast, LS-TT exhibits more stability across different scenarios regarding both metrics. Furthermore, the similarities in results between rural and urban settings, especially at the lower acceptance rate, highlight the need for careful consideration and decision-making based on specific objectives and customer preferences.

5 Conclusion

In this paper, we investigated the effects of allocating long and short time windows based on six different acceptance mechanisms for a case study of urban and rural instances in Austria. Our mechanisms are designed to be easily implemented in practice. Since they rely on simple and computationally efficient route characteristics, we anticipate that there will be no significant increase in computational time when applying our mechanisms. Based on our study, we have gained the following insights:

- The majority of the approaches exhibit similar performance in both rural and urban settings, which is advantageous for retailers seeking to implement a uniform strategy for presenting time windows to customers in both areas.
- In all scenarios, our new mechanisms demonstrated comparable or improved performance relative to the results of Köhler et al. (2020). Particularly, we found that the two-step approach, where short time window options are only presented to customers in a second step, yielded favorable outcomes by effectively catering to customers willing to accept longer time windows without losing those who expect shorter time windows.
- While deliveries in rural areas generally suffer from the lower demand density and hence lower delivery performance, parameterizing the approaches presents greater challenges in urban settings compared to rural settings, as revealed by our findings.

- As anticipated, the longer travel times in rural areas result in a reduced time capacity to serve customers. However, when more customers are accepted in short time windows and/or with unequal demand, the differences become significantly smaller as unequal demand proves to be very limiting. The more the retailer faces customers who expect high-quality service in the form of short time windows at specific times of the day, the smaller the impact of differences between urban and rural areas.
- Given the lower competition in rural areas, we can assume higher acceptance rates for longer time windows, such as those shown in our experiments with $a = 75\%$, while we expect them to be much lower in urban areas. If this is true, we may actually accept more customers in rural areas than in urban areas, despite the longer average distances.

We have shown that the general assumption of higher efficiency of delivery services in urban areas is not always true, but that the given demand and the service offered must be taken into account in the process. In addition, we believe that offering delivery services in rural areas can create other benefits, such as better coverage in rural areas and also greater sustainability if customers no longer have to make individual trips, especially with longer distances in rural areas.

However, it is important to acknowledge that our results are based on a case study that focused on only two specific delivery regions and a particular delivery setting. Therefore, further testing in additional delivery regions is needed to generalize and validate these findings across a broader range of contexts. This entails exploring additional delivery regions, considering the impact of depot locations on travel times, and investigating the interaction of mixed fleets and varying fleet sizes in urban and rural settings.

For future work, we could envision mechanisms that are specific to the demand structure of the delivery area. For example, there may be more remote customer locations in rural areas than in urban areas. This could be taken into account by, for example, adding a mechanism with density information in the delivery area. In addition, adaptive time-dependent combinations of different mechanisms could be explored, as evidenced by the promising LS-TT results. While our study focused on a single type of vehicle, it is important to acknowledge that different delivery modes, such as bicycles in urban areas and long-distance vehicles in rural areas, can have varying impacts on sustainability. A comparison between rural and urban areas using a heterogeneous fleet would provide valuable insights into the sustainability implications of delivering in remote areas, beyond the scope of customer expectations.

Appendix

In the following, we present a tabular overview of our results. Tables 4 and 5 display the outcomes for the equal demand setting, while Tables 6 and 7 present the results for the unequal demand setting in both rural and urban delivery areas. The

Table 4 Rural (upper Austria), equal demand. $|V| = 6$

x		a = 100%		a = 75%		a = 50%		a = 25%	
		#Accepted	#Short	#Accepted	#Short	#Accepted	#Short	#Accepted	#Short
LS	90%	136.8	19.0	136.6	19.6	100.2	0.0	53.4	0.0
LS	50%	129.2	70.8	128.0	68.2	121.8	61.2	55.4	3.0
LS	10%	121.4	111.6	120.4	111.0	120.2	111.0	120.6	111.6
GW	10%	146.6	0.0	139.4	4.2	114.8	9.2	68.0	14.0
GW	50%	145.8	0.0	138.6	20.0	125.8	42.8	110.2	64.8
GW	90%	146.0	0.0	136.8	34.2	123.4	60.0	122.6	86.8
SL	10%	142.4	7.6	140.4	7.6	104.0	7.6	58.6	7.6
SL	50%	130.0	48.8	127.4	48.8	117.0	48.8	87.4	48.8
SL	90%	122.6	99.2	121.2	99.2	120.0	99.2	111.0	99.2
MW	10%	130.6	63.0	129.0	63.0	120.4	63.0	96.2	63.0
MW	50%	129.2	62.8	130.0	62.8	119.6	62.8	96.2	62.8
MW	90%	121.0	98.2	120.2	98.2	119.6	98.2	117.2	98.2
TT	0.25%	136.8	65.6	136.4	73.4	132.6	77.0	107.4	67.0
TT	1.25%	121.8	101.8	127.0	111.0	130.2	117.8	130.8	121.8
TT	2.25%	121.4	109.6	122.6	111.4	124.6	117.0	119.6	112.8
LS-TT	90%	120.8	113.2	123.6	117.0	124.6	119.8	119.6	114.0
LS-TT	50%	122.4	113.4	123.6	115.8	125.6	119.6	123.2	119.0
LS-TT	10%	120.6	111.0	121.2	112.0	121.2	112.4	118.2	110.0

Table 5 Urban (Vienna), equal demand. $|V| = 6$

x		a = 100%		a = 75%		a = 50%		a = 25%	
		#Accepted	#Short	#Accepted	#Short	#Accepted	#Short	#Accepted	#Short
LS	90%	180.8	18.2	148.6	0.0	100.2	0.0	53.4	0.0
LS	50%	164.2	80.0	159.6	75.0	113.2	29.4	53.4	0.0
LS	10%	147.4	133.6	148.2	134.6	150.0	137.0	147.6	135.0
GW	10%	183.8	0.0	158.4	5.4	114.6	8.2	67.2	12.8
GW	50%	184.0	0.0	173.0	24.4	147.2	51.0	122.0	73.6
GW	90%	184.2	0.0	173.6	38.4	162.2	77.2	152.8	114.2
SL	10%	181.8	11.8	152.4	11.8	104.2	11.8	61.8	11.8
SL	50%	163.2	68.8	157.0	68.8	133.0	68.8	101.2	68.8
SL	90%	147.8	129.0	146.4	129.0	144.6	129.0	140.8	129.0
MW	10%	162.0	84.8	156.4	84.8	137.8	84.8	112.0	84.8
MW	50%	162.0	84.8	156.4	84.8	137.8	84.8	112.0	84.8
MW	90%	150.0	132.2	149.2	132.2	148.0	132.2	143.2	132.2
TT	0.25%	166.6	93.4	161.6	99.4	142.2	94.4	112.4	77.4
TT	1.25%	144.4	135.2	148.0	139.4	147.8	140.2	146.0	140.4
TT	2.25%	146.6	139.0	145.2	139.4	147.4	143.2	149.8	144.6
LS-TT	90%	146.6	142.0	146.0	142.2	148.6	145.4	150.0	146.2
LS-TT	50%	144.0	140.4	146.4	142.4	146.4	142.8	149.6	146.4
LS-TT	10%	148.2	136.4	148.4	136.4	149.0	138.4	147.6	137.4

Table 6 Rural (upper Austria). Unequal demand. $|V| = 6$

	x	a = 100%		a = 75%		a = 50%		a = 25%	
		#Accepted	#Short	#Accepted	#Short	#Accepted	#Short	#Accepted	#Short
LS	90%	102.0	0.0	96.8	0.0	92.2	0.0	53.4	0.0
LS	50%	99.6	42.2	98.6	40.8	90.4	31.8	55.0	2.4
LS	10%	86.6	76.8	91.2	81.8	91.0	81.6	88.6	79.2
GW	10%	103.8	0.0	92.6	2.6	91.2	7.4	67.4	15.0
GW	50%	103.2	0.0	94.6	11.2	86.4	29.8	83.4	47.6
GW	90%	100.6	0.0	97.2	19.4	95.8	47.8	91.4	65.4
SL	10%	104.0	7.6	98.6	7.6	92.2	7.6	56.0	7.6
SL	50%	93.6	48.2	91.4	48.2	87.6	48.2	80.0	48.2
SL	90%	90.8	90.8	90.8	90.8	90.8	90.8	90.8	90.8
MW	10%	87.6	60.6	86.6	60.6	82.8	60.6	77.4	60.6
MW	50%	87.4	59.8	84.0	59.8	79.4	59.8	76.8	59.8
MW	90%	88.0	88.0	88.0	88.0	88.0	88.0	88.0	88.0
TT	0.25%	98.8	44.8	94.8	46.2	94.8	52.4	89.2	56.2
TT	1.25%	93.4	82.6	89.0	78.2	92.6	83.0	93.0	87.6
TT	2.25%	87.4	80.8	92.0	87.0	90.0	84.6	90.2	86.2
LS-TT	90%	87.4	80.8	92.0	87.0	90.0	84.6	90.2	86.2
LS-TT	50%	92.0	85.8	92.6	86.8	91.4	86.8	92.8	89.2
LS-TT	10%	90.6	82.0	90.6	82.0	92.6	84.2	91.4	83.2

Table 7 Urban (Vienna). Unequal demand. $|V| = 6$

	x	a = 100%		a = 75%		a = 50%		a = 25%	
		#Accepted	#Short	#Accepted	#Short	#Accepted	#Short	#Accepted	#Short
LS	90%	117.4	0.0	114.0	0.0	100.2	0.0	53.4	0.0
LS	50%	116.6	32.2	111.8	26.8	101.6	17.0	53.4	0.0
LS	10%	102.8	88.2	101.6	87.6	99.0	85.0	98.4	84.6
GW	10%	117.2	0.0	110.2	3.2	106.4	9.0	68.8	15.4
GW	50%	116.2	0.0	111.0	14.0	103.0	32.6	97.2	54.2
GW	90%	113.8	0.0	115.0	23.6	108.8	50.6	102.8	73.2
SL	10%	115.6	11.0	113.8	11.0	102.4	11.0	58.4	11.0
SL	50%	100.0	68.8	97.6	68.8	93.2	68.8	88.8	68.8
SL	90%	99.0	99.0	99.0	99.0	99.0	99.0	99.0	99.0
MW	10%	98.0	85.6	95.6	85.6	92.8	85.6	89.6	85.6
MW	50%	98.0	85.6	95.6	85.6	92.8	85.6	89.6	85.6
MW	90%	98.4	98.4	98.4	98.4	98.4	98.4	98.4	98.4
TT	0.25%	107.8	52.8	107.6	56.6	99.6	59.6	94.4	64.8
TT	1.25%	98.4	93.0	100.2	94.8	100.0	94.6	95.4	90.4
TT	2.25%	100.8	96.8	98.4	95.0	95.6	92.6	91.6	88.2
LS-TT	90%	100.8	96.8	98.4	95.0	95.6	92.6	91.6	88.2
LS-TT	50%	98.8	94.8	100.6	96.8	100.8	97.2	95.6	92.8
LS-TT	10%	102.0	90.2	102.0	90.8	100.8	91.0	97.4	88.8

two leftmost columns in each table represent the tested flexibility mechanism and the chosen threshold. We compare the results in the right columns for acceptance levels ranging from 100% (where all customers accept long time windows) to 25% (where only few customers are willing to accept offered long time windows). For each setting, we present the average results from five runs, including the number of customers accepted overall and the number of customers accepted within a short time window.

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Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

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