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Angaben zur Veröffentlichung / Publication details:

Janinhoff, Lukas, Robert Klein, and Daniel Scholz. 2024. "Multitrip vehicle routing with delivery options: a data-driven application to the parcel industry." *OR Spectrum* 46: 241–94. <https://doi.org/10.1007/s00291-023-00710-6>.

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Multitrip vehicle routing with delivery options: a data-driven application to the parcel industry

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Received: 17 May 2022 / Accepted: 4 February 2023 / Published online: 2 March 2023
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Abstract

To make the last mile of parcel delivery more efficient, service providers offer an increasing number of modes of delivery as alternatives to the traditional and often cost-intensive home delivery service. Parcel lockers and pickup stations can be utilized to reduce the number of stops and avoid costly detours. To design smart delivery networks, service providers must evaluate different business models. In this context, a multitrip vehicle routing problem with delivery options and location-dependent costs arises. We present a data-driven framework to evaluate alternative delivery strategies, formulate a corresponding model and solve the problem heuristically using adaptive large neighborhood search. By examining large, real-life instances from a major European parcel service, we determine the potential and benefits of different delivery options. Specifically, we show that delivery costs can be mitigated by consolidating orders in pickup stations and illustrate how pricing can be applied to steer customer demand toward profitable, eco-friendly products.

Keywords Data-driven decision making · Last-mile delivery · Fulfillment options · Vehicle routing · Adaptive large neighborhood search · Demand management

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1 Introduction

In 2020, more than two billion people purchased goods online (Statista 2020). Exhibiting a global annual growth rate of 8.1%, e-commerce is expected to account for 21.8% of all sales by 2024 (Statista 2020). This growth poses major challenges to all stakeholders in last-mile logistics, particularly in the parcel delivery sector.

Despite handling an ever-increasing parcel volume, delivery service providers struggle to make their businesses more profitable. In the highly competitive market environment, the revenue per parcel is decreasing (PricewaterhouseCoopers 2018). The principal reason for this is a lack of efficiency on the final leg of the delivery process, with approximately 50% of a parcel's delivery cost being attributed to the "last mile" (McKinsey & Company 2016). Further aggravating the need for innovations is the issue of failed deliveries, i.e., the problem that customers are not at home to accept a parcel, which necessitates additional delivery attempts or leaves the customers unsatisfied and hunting for their parcels. Last, in the face of mounting environmental concerns from both the public and regulators, delivery service providers strive to contribute less to pollution and urban congestion.

Both technological (e.g., delivery drones, delivery robots) and infrastructural (e.g., cargo bike delivery, crowdshipping) solutions have been proposed in theory and practice to address the last-mile challenge (cf. Boysen et al. 2020; Savelsbergh and van Woensel 2016). Some of these concepts still seem futuristic, while others are already in use. Among the most applied practices is out-of-home delivery (OOHD). In this infrastructural concept, the delivery service provider drops off parcels at pickup stations where the customers collect them later, i.e., the customers perform the last leg of the delivery process themselves. Typical pickup stations are post offices, gas stations, and small businesses. In the literature, pickup stations are also referred to as PUDOs, transshipment facilities, delivery options, shared delivery locations, or common delivery locations. While the usage of pickup stations varies by country and is most often still only an auxiliary practice, parcel service providers across Europe have been substantially expanding their networks in the past five years (Last Mile Experts 2021).

Compared to home delivery (HD), OOHD offers important advantages to service providers. First, dropping off multiple parcels at a pickup station significantly reduces the number of locations the drivers need to visit. By consolidating orders, the same number of drivers can serve more customers, thereby lowering transportation costs. Furthermore, the consolidation of customer orders helps reduce the service provider's environmental impact since the drivers travel less distance and fewer delivery vehicles are needed. Second, OOHD is not dependent on customers' presence at specific points in time. The handover process is decoupled through the usage of pickup stations: drivers no longer meet customers. Instead, they visit pickup stations, where the customers retrieve the parcels when it is convenient for them. Third, for some customers, both HD and OOHD might be possible. In such cases, the service provider obtains additional (location) flexibility in the planning process.

For these reasons, delivery service providers seek to promote OOHD by introducing new delivery products in addition to the long-established HD product. However, "outsourcing the last mile" to customers also comes with new challenges. Service providers must account for customers' preferences. As most customers prefer home delivery,

simply offering an OOH product will not result in the desired shift toward this product. Generally, incentivizing customers to buy an OOH product poses challenges (PricewaterhouseCoopers 2018; DHL 2018). Therefore, providers must actively steer customers toward selecting OOH products. Possible avenues are charging additional fees to HD customers, rewarding OOH customers with discounts, or branding OOH as eco-friendly. Moreover, current delivery networks and their processes are often not aligned with an OOH strategy. With the adoption of pickup stations, drivers can drop off sizable parts of the entire vehicle load at only a few delivery locations. This results in tours with high truck loads and short durations, especially in densely populated delivery regions close to the depot. To make full use of the vehicles' capacity and the drivers' working hours, multiple trips per vehicle/driver are needed.

In this paper, we address these challenges and contribute to the literature as follows: First, we develop a framework for evaluating and analyzing last-mile business models based on a real-world case study. The framework enables a data-driven approach to determine the potential of delivery networks that rely heavily on OOH in the face of uncertainty. Second, we introduce a VRP with delivery options and multiple trips (MT-VRPDO). In the MT-VRPDO, every customer must be visited by the service provider's fleet of delivery vehicles. In contrast to most other VRPs, there might be multiple possible delivery locations for at least some customers. Each site is associated with location- and customer-specific costs. The vehicles are subject to capacity and time limitations and may each complete multiple trips, with every trip starting and ending at the depot. The service provider chooses the delivery locations, determines route plans, and assigns trips to vehicles to minimize the total operational costs. These encompass routing costs, fixed vehicle costs, and costs depending on the selected delivery locations. Third, we present a solution approach based on adaptive large neighborhood search (ALNS). We utilize both well-known components from the literature adapted to this context and new techniques explicitly developed for large problem sizes. Finally, we show how to apply this approach in a real-world setting to instances with more than 1000 customers and how to derive managerial insights concerning the OOH products' design and pricing using the proposed framework.

The paper is organized as follows. Section 2 introduces the case of GLS, a major European parcel delivery service provider, and demonstrates a data-driven framework for decision support in last-mile delivery. Section 3 gives an overview of the related vehicle routing literature and empirical studies in the context of last-mile delivery with pickup stations. Section 4 provides a mixed-integer programming (MIP) formulation of the multitrip vehicle routing problem with delivery options (MT-VRPDO). Section 5 presents the solution approach. Section 6 provides decision support based on the results of the case study. Section 7 concludes the paper with some final remarks.

2 Data-driven decision support for delivery options in last-mile delivery

This section outlines a data-driven approach to support the decision making of a major European parcel delivery service provider when introducing new business models. Section 2.1 examines the service provider's challenges in detail, introducing different types of possible OOHd products and showcasing the interplay between the products' design, pricing, customer behavior, and vehicle routing. Section 2.2 offers a more abstract view of the service provider's decisions and presents a framework for the data-driven evaluation of delivery options in last-mile delivery.

2.1 Real-world case study

The GLS Group is a European parcel delivery service provider operating in 41 countries. In fiscal year 20/21, the company transported 840 million parcels. The German division of GLS (hereafter referred to as the service provider) currently offers HD as the standard shipping product and markets OOHd at roughly the same price. However, a study by PricewaterhouseCoopers (2018) states that half of the German customers in the business-to-consumer (B2C) segment are willing to accept OOHd to close-by pickup stations as the standard shipping product. The study also reports an average willingness-to-pay for HD of 2.77 € and suggests that offering OOHd as the standard for this segment and surcharging for HD entails considerable potential benefits.

The service provider has already established a network of pickup stations and intends to further tap into this potential. They envision offering a premium and a basic product for B2C customers. The premium product corresponds to HD, i.e., the current standard product, while the yet-to-be-introduced basic product enables OOHd. The service provider is still undecided about the exact nature of the basic (OOHd) product and the possible pricing of the HD product. Specifically, they seek to answer three major questions: "What is the cost-saving potential of different OOHd specifications?", "How will certain combinations of OOHd products and surcharges for the HD product shape demand?", and, ultimately, "What is the most promising combination of an OOHd product and the HD product's surcharge?".

2.1.1 OOHd product design and routing

The first question refers to the eligibility of different delivery locations. There are multiple conceivable specifications of the OOHd product that differ, e.g., in the number of eligible pickup stations and the inclusion or exclusion of home delivery. The service provider has identified four promising basic products and seeks to determine which to offer alongside HD, the existing home delivery product. Two of the proposed basic products (PU1 and PUX) limit the delivery locations to pickup stations, i.e., they exclude home delivery. The other two basic products (FLEX1 and FLEXX) allow delivery both at a home location and

Table 1 Products and delivery locations

Product	Delivery locations
HD	Home location
PU1	One pickup station
PUX	Up to three pickup stations
FLEX1	Home location + one pickup station
FLEXX	Home location + up to three pickup stations

at pickup stations. In the case of PU1 and FLEX1, the pickup station is exactly specified, whereas in the case of PUX and FLEXX, multiple pickup stations may be feasible. Table 1 summarizes the possible delivery locations associated with different products.

By purchasing either the premium product, i.e., HD, or choosing the basic product on offer, the customers select which locations are eligible for their orders. While purchasers of HD and PU1 specify the delivery location exactly, purchasers of PUX, FLEX1, or FLEXX cede the decision on the final delivery location to the service provider. The service provider wants to exploit the potential flexibilities resulting from the location choice during the construction of route plans.

Figure 1 illustrates the effect of different products on the route plan. The first panel shows a depot, four customers, and two pickup stations. The depot (0) is marked by a square, the customers' home locations (1–4) are represented by small circles, and the pickup stations (5–6) are represented by triangles. The large, dashed circles depict the ranges of the pickup stations, i.e., the distance that is acceptable for OOHd. The other three panels show a variety of route plans. In the second (third/fourth) panel, all customers choose HD (PU1/FLEX1). Bold arrows represent the routes of delivery vehicles, and dotted lines represent deliveries to pickup stations. Product selection profoundly impacts the route plan, as exemplified by customer 3. When customer 3 chooses PU1 or FLEX1 and thereby declares location 6 eligible, the resulting route is much shorter.

2.1.2 Pricing and customer choice behavior

The second question addresses the pricing of the HD product and the customers' reaction to this pricing. The service provider is interested in generating additional revenue (from the sale of the premium product) resulting from a multiplication of the surcharge and the number of customers that select the HD product. Clearly, the proportion of customers that opts for the HD product is closely connected to the amount of the surcharge: the higher the surcharge is, the more customers will select OOHd instead. Consequently, it is unclear whether it is more profitable to set a high surcharge (with fewer customers choosing HD) or to steer more customers toward selecting the HD product by charging less.

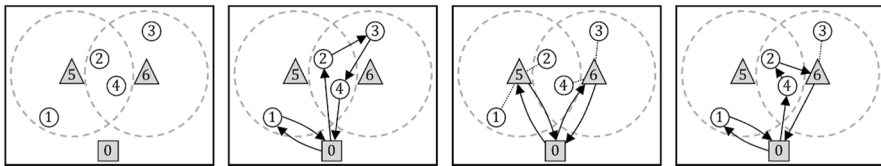


Fig. 1 Different route plans

2.1.3 Data-driven decision support

The last question requires joint consideration of the above effects for decision support. As discussed, the provider wants to select an OOHd product and set a surcharge for the premium HD product. These two problems can hardly be considered separately, as they are tightly interlaced. The price of the HD product influences the customer choice behavior and thereby the proportion of customers selecting OOHd, which in turn impacts the routing problem (the feasible delivery locations for a customer). At the same time, customers' willingness-to-pay for the HD product depends on the "desirability" of the OOHd product on offer. For example, customers might opt for HD if the OOHd product is PUX and their orders can be delivered to *any* pickup station in their vicinity but opt for OOHd if the OOHd is PU1 and the order will be delivered to a *specific* pickup station.

To make a data-driven decision, the service provider must examine different combinations of OOHd products and HD surcharges. On the one hand, they want to gain insights into the potential effects of the four basic products on the vehicle routing problem and to assess the efficiency of the current pickup station network. This includes measurement of the environmental impact of OOHd, quantification of the value of customer flexibility, and an investigation into the importance of multitrip routing (cf. Sect. 6.2). On the other hand, they need to compute revenues and profits to decide which product-surcharge combinations are favorable (cf. Sect. 6.3).

2.2 An evaluation framework for delivery options

The service provider faces an integrated pricing and routing problem. Choosing an OOHd product and setting a surcharge for HD are planning tasks on a strategic or tactical level, whereas the construction of route plans is executed daily, i.e., on the operational level. As discussed above, the tasks are highly intertwined because the pricing and product selection decisions shape the resulting routing problem. Thus, the problem should ideally be handled in an integrated fashion, i.e., in a single optimization model. However, such an approach is unsuitable in this context for two reasons.

First, the service provider's data basis is insufficient for such calculations. While historic customer location data are available and potential network configurations (e.g., the locations of pickup stations) are known, the provider has no data on customer choice behavior, such as customer preferences or price sensitivity. Hence, for a given surcharge, they cannot determine which B2C customers will select the basic OOHd product and which will select the premium HD product. If historic customer choice

data were available, this could be accomplished by estimating a customer choice model (Baur et al. 2014; Berbeglia et al. 2022).

Second, solving the integrated problem is computationally intractable. The service provider does not want to base the selection of an OOH product and the pricing of the HD product on the customers of a single day. Therefore, stochastic variations of the set of customers must be considered, making it exceptionally challenging to obtain accurate results for real-world problem sizes.

For the above reasons, we propose a framework that separates decisions on the strategic and tactical levels from those on the operational level. The basic idea is to leave decisions on the upper levels to the provider's management and generate the data necessary to make these decisions by solving a series of carefully chosen vehicle routing problems. This approach is summarized in our framework for a data-driven evaluation. Figure 2 depicts the framework with oval shapes representing managerial tasks and rectangular shapes depicting tasks centered on the extraction and processing of data. The figure can be read chronologically from top to bottom.

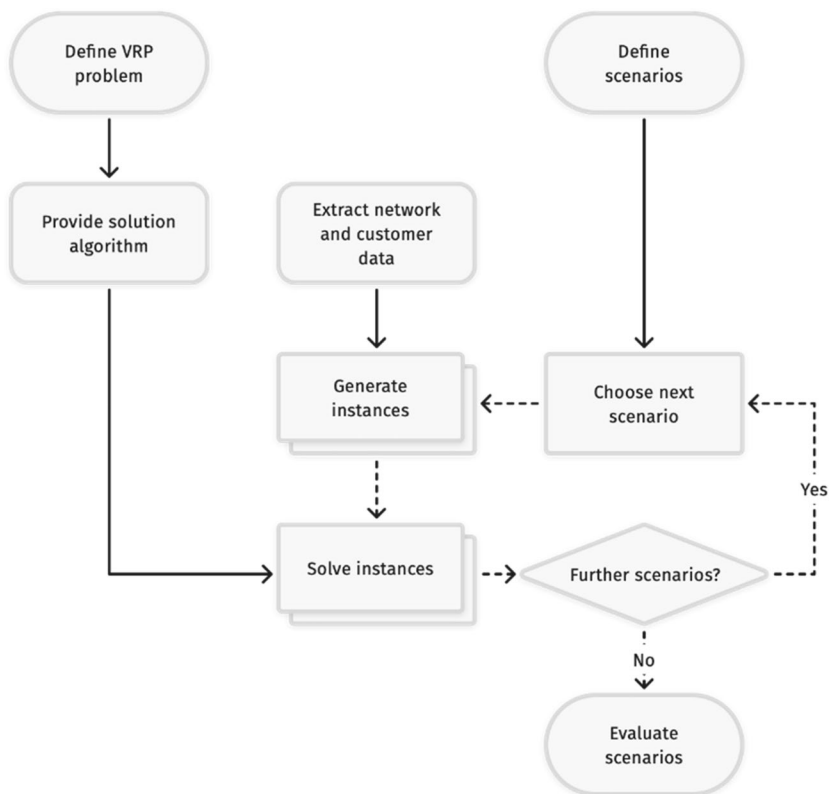


Fig. 2 Data-driven evaluation framework

First, the provider specifies the logistics system and associated delivery processes. For example, they determine whether capacity restrictions at pickup stations are relevant and whether multiple tours per vehicle and shift are possible. Different vehicle routing problems may result from these specifications, and suitable solution algorithms must be deployed. To address the problem of missing data, the provider defines a set of scenarios. A scenario, in this context, is determined by three characteristics: an OOHd product, a surcharge for the HD product, and a proportion of customers choosing the OOHd product. The scenarios should represent a systematic enumeration of possible choice behaviors, i.e., reactions to every product-surcharge combination. The breadth of scenarios to be evaluated may be reduced depending on the provider's knowledge of the customers' perception of the products. For example, it is reasonable to assume that the number of customers selecting the HD product decreases as its surcharge increases.

A sufficient number of instances is generated for each scenario to account for stochastic variation. They differ in the sets of customers selecting OOHd/HD, whereas the proportion of customers is the same for all instances of a scenario. Following a data-driven approach, the provider uses the data available on past customers to make the instances as realistic as possible, e.g., by reflecting that customers located closer to pickup stations are more likely to select an OOHd product. They can uniquely adjust the sampling process to their knowledge and the available data.

The service provider can then tackle the underlying vehicle routing problem (cf. Sect. 4) for each instance of every scenario by applying a solution algorithm (cf. Sect. 5). Once all instances have been solved, evaluations and comparisons of the scenarios can be performed (cf. Sect. 6).

3 Literature review

The multitrip vehicle routing problem with delivery options combines aspects of a wide range of vehicle routing problems. To the best of our knowledge, the use of multiple trips has not been addressed in the context of vehicle routing problems with alternative delivery locations for each customer (order). In this section, we review the optimization problems most closely related to the MT-VRPDO and the methods used to solve them. We divide the routing-related literature into two parts (Sects. 3.1 and 3.2). Section 3.1 discusses problems that explicitly consider OOHd, i.e., the utilization of pickup stations and parcel lockers. Section 3.2 provides a brief overview of some broader problem classes related to the problem at hand, including vehicle routing problems with multiple trips. Furthermore, Sect. 3.3 notes some of the empirical studies conducted in the context of OOHd. Finally, Sect. 3.4 links the routing problem to the research area of demand management.

3.1 Vehicle routing with OOHd

Vehicle routing problems with OOHd have been discussed only recently. The key aspect of these problems is that orders are not necessarily delivered to a customer's home location but may be dropped off at a pickup station or a parcel locker. Since the concepts of pickup stations and parcel lockers are largely interchangeable for routing purposes, we refer

to both types of delivery locations as pickup stations and use the term parcel locker only when the distinction is necessary.

Naturally, not every assignment of a customer's order to a pickup station is reasonable. In all contributions of the literature, the set of possible delivery locations is limited. Most commonly, the proximity of the pickup station to the customer's home location determines feasibility: delivery to a pickup station is feasible if the distance between the customer's home location and the pickup station is below a threshold.

Beyond this preselection of delivery locations, three different ways exist in the literature to handle the assignment of customer orders to delivery locations:

- Location choice with additional consideration of customer preferences: The service provider chooses a delivery location among the set of predetermined delivery locations. The choice is restricted through additional constraints or directly affects the objective function value.
- Free location choice: The service provider chooses a delivery location among the set of predetermined delivery locations.
- Ex ante location: The exact delivery location of every order, be it HD or OOHD, is known ex ante; thus, there is no location choice component.

We present the exponents of these three approaches, starting with the authors who study location choice with additional consideration of customer preferences.

3.1.1 Location choice with customer preferences

In the models of this group, each order is associated with a set of possible delivery locations. This set is determined before the optimization process and may include both home locations and pickup stations.

Most customers prefer some delivery locations over others, e.g., their home location over a pickup station. There are two prevalent methods to handle customer preferences directly within the optimization problem: the preferences are represented by either additional constraints or additional objective function components. Dumez et al. (2021a) describe the vehicle routing problem with delivery options (VRPDO), where each delivery option is a different delivery location with a time window. Furthermore, a customer-specific preference level is associated with every location. Customers rank all delivery locations for their orders. Constraints ensure overall customer satisfaction, e.g., "at least 50% of the orders are delivered to the most preferred delivery locations; at least 75% of the orders are delivered to one of the two most preferred delivery locations." The authors propose a heuristic that periodically solves a set partitioning problem on tours generated through large neighborhood search (LNS). Tilk et al. (2021) similarly construct the solution space. Similar to the VRPDO, their model features preference level, location capacity, and time window constraints. The authors develop a branch-price-and-cut algorithm and present a labeling algorithm to solve the pricing subproblem.

The optimization problem described by Mancini and Gansterer (2021) also considers different delivery locations and customer time windows. However, instead of modeling

customer acceptance of pickup stations through preference levels, the choice of delivery location is reflected in the objective function, i.e., customers receive discounts (compensation) if they are not served at home. The proposed solution method combines iterated local search (ILS) and a matheuristic that fixes the variables associated with the choice of delivery location. Grabenschweiger et al. (2021) investigate a similar problem with location-specific compensation, focusing on different parcel locker sizes. Within their adaptive large neighborhood search (ALNS) application, they heuristically solve a bin-packing problem to assign orders to parcel lockers.

The following publications do not mention discounts explicitly. Nevertheless, the objective functions feature location-specific costs, thereby enabling a seamless integration of customer preferences. Baldacci et al. (2017) define the vehicle routing problem with transshipment facilities (VRPTF) as an edge-flow-based MIP, strengthen the corresponding LP relaxation, derive bounds through dual ascent heuristics, and solve it to optimality using a branch-cut-and-price algorithm. Friedrich and Elbert (2022) extend their model with time windows and develop a heuristic based on ALNS and variable neighborhood descent (VND). Sitek and Wikarek (2019) formulate a binary linear problem that penalizes assignments to pickup stations in the objective function. They solve the problem by first applying different criteria to assign customers to pickup stations and then considering a traveling salesman problem. Additionally, they present an exact approach to obtain optimal solutions for very small instances.

3.1.2 Free location choice

Other works incorporate a location choice between home locations and pickup stations but do not consider customer preferences in the model beyond the initial preselection of feasible locations. In these contributions, the focus is often on another aspect of the optimization problem, e.g., a two-echelon structure. Zhou et al. (2018) formulate the multi-depot two-echelon vehicle routing problem with delivery options. Customers are served from a satellite depot on the second level at either a home location or a pickup station. In contrast to other models, the authors allow for split deliveries at pickup stations. The solution approach uses hybrid genetic search (HGS) with adaptive diversity control (Vidal et al. 2012). Enthoven et al. (2020) also propose a two-echelon distribution scheme and consider the case where orders are fulfilled either through cargo bikes on the second echelon or through trucks delivering to pickup stations on the first level. The problem is solved heuristically using an LNS-based approach.

Dragomir et al. (2022) address a pickup-and-delivery problem wherein the service provider chooses both the pickup and the delivery location. Whereas most locations are only eligible during a given time window, locker boxes function as time-independent delivery alternatives. The authors employ a multi-start ALNS heuristic to assign delivery requests to vehicles and variable neighborhood descent (VND) to determine the locations and the sequence of nodes visited by each vehicle. The problem formulation by Orenstein et al. (2019) permits deliveries to alternative locations as well as the nondelivery of a parcel. While nondeliveries incur penalties in the objective function, there is no distinction regarding location cost or customer preference between the different feasible delivery locations associated with every order. The authors present a multiperiod simulation study and show the value of customer flexibility by solving the problem heuristically using the savings

algorithm, the petal algorithm, and tabu search (TS). Yu et al. (2022) integrate not only alternative locations but also the employment and compensation of occasional drivers, a practice commonly referred to as “crowdshipping,” into their model. Customers belong to different types that signify the feasibility of the different delivery modes. Their solution approach is based on ALNS. Zhou et al. (2016) study a location-routing variant of a VRPDO by including the decision of whether to open a pickup station. Customers may be served at preselected pickup stations without incurring further costs. Furthermore, their model includes a failure probability for home deliveries. The problem is solved with HGS combining a genetic algorithm and local search components.

3.1.3 Ex-ante location

In the third group of papers, the service provider does not decide on the delivery location. All delivery locations are fixed before optimization; i.e., there is only one feasible delivery location for each order. Some orders are assigned to home locations, while others are assigned to pickup stations. As a result, there is no location choice, and the optimization focuses on routing aspects. These contributions highlight the benefits of consolidating orders at pickup stations rather than the advantages of location flexibility.

Employing both ruin-and-recreate and genetic search (GS) paradigms, Heshmati et al. (2019) find that widespread use of pickup stations significantly improves many KPIs, including costs, CO₂ emissions, and the number of vehicles used. In a simulation study based on the Belgian city of Antwerp, Arnold et al. (2018) find that including pickup stations in the delivery network is profitable “even at high pickup costs” compared to traditional home delivery, especially when failed home deliveries are taken into account. The authors first cluster the customers and then apply the savings algorithm to estimate delivery costs.

Zhang and Lee (2016) are among the first to incorporate parcel lockers and multiple depots into the vehicle routing problem. Using ant colony optimization (ACO), they show that both total delivery duration and the distance traveled are significantly reduced when the adoption rate of OOHd increases. He et al. (2019) obtain similar results by applying their two-stage matheuristic to a closely related problem with a single depot while also providing insights into a dynamic variant.

3.1.4 Overview

Table 2 provides an overview of the literature on vehicle routing problems with OOHd. The second column indicates whether the service provider chooses the final delivery location. The third column denotes how customer preferences are considered beyond the initial preselection of feasible delivery locations. P (preference) denotes approaches defining preference levels and ensuring an overall service level through constraints. D (discount) represents problem formulations where the objective function is directly influenced by the location choice, as customers receive a discount if they are served at a pickup station. (D) signifies works that exhibit such location-dependent objective function components without labeling them as discounts or compensation to the customer. C (computational study) denotes papers that extensively investigate the influence of customer preferences in the computational study. Columns 4 and 5 show whether further constraints concerning the

Table 2 Overview of literature dealing with OOHd

	Loc. choice	Pref	Cap	TW	Obj	Solution method
Arnold et al. (2018)	–	–	–	–	T, F, O	Savings
Baldacci et al. (2017)	×	(D)	–	–	T, L	Branch-Price-and-Cut
Dragomir et al. (2022)	×	–	–	×	T	MS-ALNS, VND
Dumez et al. (2021a)	×	P, C	×	×	T	LNS
Enthoven et al. (2020)	×	C	–	–	T, L	ALNS
Friedrich and Elbert (2022)	×	(D)	–	×	T, F, L	ALNS
Grabenschweiger et al. (2021)	×	D	×	×	T, L	ALNS, bin-packing
He et al. (2019)	–	–	–	×	T	LNS
Heshmati et al. (2019)	–	–	–	–	T, F, O	ALNS, GS
Mancini and Gansterer (2021)	×	D, C	×	×	T, F, L	ILS, matheuristic
Orenstein et al. (2019)	×	C	×	–	T, F, O	Savings, Petal, TS, LNS
Sitek and Wikarek (2019)	×	(D)	×	–	T, L	Variable fixing
Tilk et al. (2021)	×	P	×	×	T	Branch-Price-and-Cut
Yu et al. (2022)	×	–	–	×	T, O	ALNS
Zhang and Lee (2016)	–	–	–	×	T	ACO
Zhou et al. (2016)	×	C	×	–	T, F, O	HGS
Zhou et al. (2018)	×	–	–	–	T, F, L	HGS
This paper	×	C, (D)	×	–	T, F, L	ALNS

capacity limits of pickup stations and time windows are included. The sixth column depicts the makeup of the objective function, where T denotes transportation costs (arc-based), F denotes fixed vehicle costs, L denotes location-specific costs, and O denotes other components. Note that both fixed vehicle costs and the emission costs regarded by Heshmati et al. (2019) and Arnold et al. (2018) may be attributed to single arcs and may thus be included in the transportation costs T. The final column shows the proposed solution method.

3.2 Related routing problems

The defining properties of the MT-VRPDO are the choice of delivery location, the location-specific delivery costs, and the multiple uses of vehicles. To the best of our knowledge, these properties have not been examined in combination. When viewed individually, they are not unique to the MT-VRPDO and have been discussed in the context of various other vehicle routing problems. We will now briefly outline further related routing problems that address these aspects without explicitly representing the application area of pickup stations.

3.2.1 Location choice

In the generalized vehicle routing problem (GVRP) introduced by Ghiani and Improta (2000), all locations are parts of mutually exclusive clusters. The GVRP is concerned with finding the shortest routes visiting all clusters exactly once. In the context of parcel delivery, each cluster represents a customer with a set of feasible delivery locations. The GVRP

is seldom solved directly but instead serves as a modeling tool for a wide range of vehicle routing problems, in which the set of locations to be visited is not predetermined (cf., e.g., Baldacci et al. 2010). However, in many of these problems, the clusters are not necessarily mutually exclusive, e.g., multiple customers may have the same feasible pickup station. Among these problems are the GVRPTW (cf., e.g., Yuan et al. 2021; Dumez et al. 2021b), the VRPDO, and the vehicle routing problem with roaming delivery locations (VRPRDL).

The VRPRDL is based on the concept of trunk delivery, i.e., a technology granting the delivery service provider short-term access to the trunk of a customer's car. Associated with every order are multiple locations and corresponding time windows that designate delivery opportunities. This problem was first laid out by Reyes et al. (2017), who present a solution method based on the ruin-and-recreate paradigm. Ozbaygin et al. (2017) provide a branch-and-bound algorithm for the VRPRDL and incorporate the possibility of home delivery during the entire service horizon.

Jungwirth et al. (2022) formulate an optimization problem that applies to the area of hospital scheduling. It features flexible service locations, time windows, time-dependent location capacities, and location- and customer-specific cost components (compensations). They provide a solution approach that utilizes ALNS, guided local search, and a backtracking mechanism to revise prior decisions in the construction phase. Furthermore, they show its benefits compared to manual planning.

3.2.2 Location-specific costs

Due to location-specific costs, e.g., compensation paid to pickup station owners, the MT-VRPDO is also closely related to optimization problems belonging to the class of vehicle routing problems with profits (VRPPs). In these problems, there is no obligation to visit all locations. Instead, locations are associated with profits, and the decision maker selects the most profitable locations with respect to routing constraints, such as vehicle capacity and maximum route duration. Hence, the choice of location often also implies which orders are accepted and which are rejected. Archetti et al. (2014) present a review of VRPPs.

Among VRPPs, the vehicle routing problem with private fleet and common carrier (VRPPC) is the most similar to the MT-VRPDO. First described as the “truckload and less-than-truckload problem” by Chu (2005), the VRPPC allows outsourcing orders. It is concerned with minimizing the total cost, consisting of fixed vehicle costs, travel costs, and fees paid to subcontractors (“common carriers”). Usually, every vertex is assumed to be associated with a specific fee. The VRPPC is a special case of the MT-VRPDO, in which every vehicle can perform only one trip and the subcontractor locations (~pickup stations) are all identical to the depot. Similar to the MT-VRPDO, the VRPPC generalizes the GVRP. Similarly, in the vehicle routing problem with occasional drivers (VRPOD, Archetti et al. 2016), private individuals are utilized and compensated for fulfilling delivery requests, a concept also known as “crowdshipping.”

3.2.3 Multitrip

Finally, in the MT-VRPDO, a vehicle may complete multiple trips, a case first described by Fleischmann (1990). Cattaruzza et al. (2016) provide a comprehensive overview of

mathematical formulations, as well as exact and heuristic solution approaches. To address large instances, both population-based (cf., e.g., Cattaruzza et al. 2014) and ALNS-based algorithms (cf., e.g., François et al. 2019) have been proposed. Azi et al. (2010) combine two characteristics of the MT-VRPDO by including both multiple trips and location-specific cost components. In contrast to the MT-VRPDO and in line with many other VRPPs, each order is associated with only one feasible delivery location and can be rejected. Moreover, the authors propose a branch-and-price algorithm. In further work, the same authors investigate the problem in a dynamic environment (Azi et al. 2012) and present an ALNS heuristic to efficiently solve larger instances (Azi et al. 2014).

3.3 Empirical studies

In addition to the routing literature listed above, OOH concepts have been widely studied on a more aggregated level without explicit routing components. Morganti et al. (2014b) present the alternative delivery modes used in Germany and France, and Morganti et al. (2014a) document the massive growth of pickup station and locker networks in both countries. Durand and Gonzalez-Feliu (2012) compare four last-mile delivery scenarios and find that consolidation in pickup stations leads to significant savings. Edwards et al. (2010) calculate CO₂ emissions in the context of failed delivery attempts and discuss critical success factors for employing a network of pickup stations. Song et al. (2009) also investigate delivery failures and compute considerable potential cost and emissions savings. Lemke et al. (2016) study the usability of parcel lockers in Poland from a customer perspective and contend that their popularity will increase primarily due to environmental aspects. Rohmer and Gendron (2020) provide an overview of different pickup facilities and the corresponding optimization problems and solution methods. Janjevic et al. (2019), Faugère and Montreuil (2020), and Liu et al. (2019) discuss the design of delivery networks concerning the inclusion of pickup stations. Using discrete choice modeling to integrate customer behavior, Lin et al. (2022) aim to optimize parcel locker networks with regard to expected profit from the perspective of a parcel locker company. Vakulenko et al. (2018) conduct a focus group study with an emphasis on customer value. Kawa (2020) presents results from interviews conducted with online retailers and finds that OOH positively impacts customer satisfaction.

3.4 Demand management

Steering customers to select profitable products is a challenge in the research area of demand management. The incorporation of demand management strategies into vehicle routing issues is mostly examined in dynamic and stochastic environments (cf. Fleckenstein et al. 2022; Snoeck et al. 2020). With application areas such as attended home delivery, same-day delivery, and ridesharing, the research focus has also been on vehicle routing problems heavily constrained by time windows. By offering delivery time windows of different lengths at different (static) prices, a concept known as differentiated pricing (Agatz et al. 2013), service providers can exploit heterogeneities in customer flexibility. Gönsch (2020) surveys incompletely specified products (ICSPs, flexible products). For

ICSPs, not all specifics of the product are disclosed to the customer at the moment of purchase. Instead, the seller benefits from an added level of planning flexibility. Customers benefit from the lower price of the ICSP in comparison to a completely specified product. The challenge is to design an ICSP that generates considerable planning flexibility without requiring excessive customer flexibility. Strauss et al. (2021) investigate flexible products in the context of home delivery. Customers may choose products that include multiple possible delivery time windows without specifying the actual time of delivery upon purchase. The actual time window is not revealed to the customers of the flexible product until all customers of a planning period have made their product selection. In this manner, the service provider obtains routing flexibility. Moreover, prices are set dynamically, such that customers are incentivized to select profitable products.

4 The multitrip VRP with delivery options

This section presents a MILP formulation of the multitrip vehicle routing problem with delivery options (MT-VRPDO). Section 4.1 introduces the terminology and the notation; Sect. 4.2 presents the MILP formulation.

4.1 Terminology

Let $\mathcal{G} = (\mathcal{N}, \mathcal{A})$ be a complete directed graph, where the vertex set \mathcal{N} consists of a set of delivery locations and the depot location (0). The set of delivery locations includes both home locations and pickup stations. Each arc $(i, j) \in \mathcal{A}$ is associated with a driving time t_{ij} and a cost coefficient c_{ij} , which depends on the driving time and the driving distance, i.e., it includes fuel consumption costs and the driver's hourly wages.

Let $\mathcal{K} = \{1, \dots, k, \dots, K\}$ be the set of customers. Each customer has an order of weight d_k and a consideration set \mathcal{I}_k of possible delivery locations, where each location corresponds to a different delivery option. The makeup of the set \mathcal{I}_k is determined according to customer k 's product choice (cf. Table 1).

Every delivery location i has a capacity κ_i . The set $\mathcal{K}_i = \{k \in \mathcal{K} : i \in \mathcal{I}_k\}$ denotes the set of customers whose orders may be dropped off at location i . Visiting customer k at location i incurs location-specific cost g_{ki} , which may include compensation paid to pickup station owners and customers. Note that g_{ki} may be negative if customers are charged an extra fee for certain delivery locations, e.g., their home location.

The parcel service provider utilizes a homogeneous fleet, where each vehicle has capacity Q . For every vehicle used, a fixed cost F arises. Additionally, there is a time limit T_{\max} bounding the time on the road for each driver (=vehicle).

A vehicle may complete multiple trips within the time limit, i.e., a vehicle may return to the depot to be reloaded for a second trip. Reloading at the depot takes r time units. Split deliveries are not feasible.

The MT-VRPDO is composed of three closely intertwined decisions. With the aim of minimizing the total costs, the decision maker assigns customers to delivery locations, plans routes, and groups routes for individual drivers.

4.2 Model

The MT-VRPDO can be described as a mixed-integer linear program. The model is based on the MT-VRP formulation by Karaoğlu (2015) and the VRPDO by Dumez et al. (2021a) and adapted to the setting described above. All parameters and decision variables are summarized in Table 3.

$$\text{Min } \sum_{(i,j) \in \mathcal{A}} c_{ij} \cdot x_{ij} + F \cdot \left(\sum_{j \in \mathcal{N} \setminus \{0\}} x_{0j} - \sum_{(i,j) \in \mathcal{A} : i,j \neq 0} z_{ij} \right) + \sum_{k \in \mathcal{K}} \sum_{i \in \mathcal{I}_k} g_{ki} \cdot y_{ki} \quad (1)$$

$$\text{s. t. } \sum_{j \in \mathcal{N}} x_{ij} = \sum_{j \in \mathcal{N}} x_{ji} \quad \forall i \in \mathcal{N} \quad (2)$$

$$\sum_{j \in \mathcal{N}} x_{ij} \leq 1 \quad \forall i \in \mathcal{N} \setminus \{0\} \quad (3)$$

$$\sum_{i \in \mathcal{I}_k} y_{ki} = 1 \quad \forall k \in \mathcal{K} \quad (4)$$

$$y_{ki} \leq \sum_{j \in \mathcal{N}} x_{ji} \quad \forall k \in \mathcal{K}, i \in \mathcal{I}_k \quad (5)$$

$$T_i + s_i + t_{ij} \leq (1 - x_{ij}) T_{\max} + T_j \quad \forall (i,j) \in \mathcal{A} : j \neq 0 \quad (6)$$

$$T_i + s_i + t_{i0} \leq T_{\max} \quad \forall i \in \mathcal{N} \setminus \{0\} \quad (7)$$

$$\sum_{j \in \mathcal{N} \setminus \{0\}} z_{ij} \leq x_{i0} \quad \forall i \in \mathcal{N} \setminus \{0\} \quad (8)$$

$$\sum_{i \in \mathcal{N} \setminus \{0\}} z_{ij} \leq x_{0j} \quad \forall j \in \mathcal{N} \setminus \{0\} \quad (9)$$

$$T_i + s_i + t_{i0} + r + t_{0j} \leq (1 - z_{ij}) T_{\max} + T_j \quad \forall (i,j) \in \mathcal{A} : i,j \neq 0 \quad (10)$$

Table 3 Decision variables and parameters

<i>Decision variables</i>	
x_{ij}	$= \begin{cases} 1 & \text{if any vehicle travels along arc } (i, j) \\ 0 & \text{else} \end{cases}$
y_{ki}	$= \begin{cases} 1 & \text{if customer } k \text{'s order is dropped off at location } i \\ 0 & \text{else} \end{cases}$
z_{ij}	$= \begin{cases} 1 & \text{if } i \text{ and } j \text{ are visited consecutively on different trips by the same vehicle} \\ 0 & \text{else} \end{cases}$
T_i	Point in time when location i is visited
u_i	Accumulated demand already distributed along the trip when leaving location i
ψ_i	Total delivery volume assigned to location i
s_i	Total service time at location i
<i>Sets</i>	
\mathcal{K}	Set of customers
\mathcal{I}_k	Set of possible delivery locations for customer k
\mathcal{K}_i	Set of customers whose orders may be dropped off at location i
\mathcal{N}	Set of vertices ($\mathcal{N} = \bigcup_{k \in \mathcal{K}} \mathcal{I}_k \cup \{0\}$)
\mathcal{A}	Set of arcs
<i>Parameters</i>	
c_{ij}	Transportation cost along arc (i, j)
F	Fixed vehicle/driver cost
g_{ki}	Cost for dropping off customer k 's order at location i
t_{ij}	Transportation time along arc (i, j)
v_i	Service time at location i independent of delivery volume
w_{ki}	Service time at location i for the delivery volume of customer k
T_{\max}	Vehicle/driver time limit
r	Reload time at the depot
d_k	Order weight of customer k
Q	Vehicle capacity
κ_i	Capacity of location i

$$\psi_i = \sum_{k \in \mathcal{K}_i} d_k \cdot y_{ki} \quad \forall i \in \mathcal{N} \setminus \{0\} \quad (11)$$

$$u_i + \psi_j \leq (1 - x_{ij})Q + u_j \quad \forall (i, j) \in \mathcal{A} : i, j \neq 0 \quad (12)$$

$$\psi_i \leq u_i \leq Q \quad \forall i \in \mathcal{N} \setminus \{0\} \quad (13)$$

$$\psi_i \leq \kappa_i \quad \forall i \in \mathcal{N} \setminus \{0\} \quad (14)$$

$$s_i = v_i + \sum_{k \in \mathcal{K}_i} w_{ki} \cdot y_{ki} \quad \forall i \in \mathcal{N} \setminus \{0\} \quad (15)$$

$$x_{ij} \in \{0, 1\} \quad \forall (i, j) \in \mathcal{A} \quad (16)$$

$$y_{ki} \in \{0, 1\} \quad \forall k \in \mathcal{K}, i \in \mathcal{I}_k \quad (17)$$

$$z_{ij} \in \{0, 1\} \quad \forall (i, j) \in \mathcal{A} : i, j \neq 0 \quad (18)$$

$$T_i \geq 0 \quad \forall i \in \mathcal{N} \quad (19)$$

$$u_i \geq 0 \quad \forall i \in \mathcal{N} \setminus \{0\} \quad (20)$$

$$\psi_i \geq 0 \quad \forall i \in \mathcal{N} \setminus \{0\} \quad (21)$$

$$s_i \geq 0 \quad \forall i \in \mathcal{N} \setminus \{0\} \quad (22)$$

The objective function (1) minimizes the total cost, which consists of arc-based transportation costs, fixed vehicle costs, and location-specific delivery costs. Since vehicles may be used on multiple trips, whereas fixed costs are incurred only once per vehicle, the fixed costs cannot simply be incorporated into the transportation cost matrix. $\sum_{j \in \mathcal{N} \setminus \{0\}} x_{0j} - \sum_{(i,j) \in \mathcal{A} : i,j \neq 0} z_{ij}$ is the number of vehicles used, which is calculated by subtracting the number of follow-up trips from the total number of vehicles leaving the depot.

Constraints (2) are flow conservation constraints. Constraints (3) ensure that every non-depot vertex is visited at most once, while constraints (4) guarantee that every customer is served at a feasible location. Constraints (5) state that delivery location i can be selected for customer k only if a vehicle visits location i . Constraints (6) through (10) ensure adherence to the time limit and prevent subtours. Constraints (6) set the points of visit within a trip, and constraints (7) make sure that there is sufficient time for the vehicle to return to the depot after visiting the last customer on a trip. Constraints (8) through (10) incorporate the possibility of multiple trips. The decision variable z_{ij} indicates that a trip starting with vertex j and another trip ending with vertex i are carried out consecutively by the same vehicle (cf. Karaoğlu 2015). It may be set to 1 under the following three conditions: vertex i is the last customer of a trip (i.e., $x_{i0} = 1$), vertex j is the first vertex of a trip (i.e., $x_{0j} = 1$), and the time limit is not exceeded. Constraints (11) through (14) guarantee compliance with the capacity limits of both vehicles and pickup stations. Constraint (15) defines the service time.

5 Solution method

MT-VRPDO instances of realistic size cannot be solved exactly within a reasonable time-frame. Therefore, we employ a matheuristic that combines an adaptive large neighborhood search (ALNS) with the periodical solution of traveling salesman problems (TSP) and bin-packing problems (BPP). ALNS was introduced by Ropke and Pisinger (2006) and relies on the iterative application of the destroy-and-repair principle (also known as ruin and recreate (Shaw 1998)). As it is a concept widely used to address large-scale combinatorial optimization problems, we limit the discussion in this chapter to the adaptations and mechanisms we introduced instead of describing the entire solution procedure in detail.

The newly proposed algorithmic features are motivated by either analyzing the optimization problem (*problem-oriented*) or the real-world application (*application-oriented*). Problem-oriented mechanisms rely on properties of the MT-VRPDO. For example, the above-mentioned TSP component is based on the property that no (implicit) precedence relationships between vertices on the same trip exist, e.g., due to the presence of time windows. In many other last-mile optimization problems, such a component could lead to infeasible solutions (cf. Sect. 3.1). Application-oriented mechanisms factor in the characteristics of real-world instances and the strategic nature of the decisions to be made. For example, the sweep destroy operator presented in Sect. 5.1 exploits the spatial distribution of customers common parcel delivery networks.

The remainder of this section is structured as follows. Sections 5.1 and 5.2 list the utilized destroy-and-repair operators, respectively. Section 5.3 presents selected algorithmic features, which were implemented to either accelerate the solution process or enhance the likelihood of finding very good solutions. A pseudocode overview of the solution procedure is presented in Appendix A.

5.1 Destroy operators

We apply eight different destroy operators. The first group of operators was developed to specifically tackle this routing problem and its large instances. To the best of our knowledge, these operators have not been previously proposed:

- **Sweep:** Customers are deleted if their home locations are in a specified range of polar angles corresponding to a share of $\delta\%$ of all customers. The polar angles are calculated from the location coordinates with the depot at the origin. In the chosen sector, both customers assigned to home locations and customers assigned to pickup stations are removed from the solution. The intuition behind this application-oriented operator is that customers in the “border” region of two or more trips have a higher probability of being in the “wrong” trip. By removing all customers of a certain sector, capacity and time slack is induced in the trips that originally visited customers in the sector. This

process facilitates the insertion of the deleted customers. The value of δ is chosen such that a sector typically includes the locations of two to four trips.

- **Pickup station:** A pickup station is selected at random. All customers that may be assigned to this pickup station are removed from the solution, i.e., if pickup station i is selected, all customers in $\mathcal{K}_i = \{k \in \mathcal{K} : i \in \mathcal{I}_k\}$ are removed. Breaking up the assignment of customers to delivery locations through this problem-oriented operator can alter the solution substantially, as solutions vary considerably depending on which customers are served at a pickup station.
- **Related trips:** A random trip is selected. A second trip is chosen whose average polar coordinate of the visited locations is closest to the average polar coordinate of the first trip. All customers on both trips are removed from the solution. The intention is that the new solution resulting from the repair operator necessitates fewer trips. It is thus especially useful for multitrip vehicle routing problems (problem-oriented).

Figure 3 demonstrates how the novel destroy operators work. The first panel shows the original solution. Black circles represent the home locations of customers who must be visited at their home location. White circles represent the home locations of customers whose orders may be dropped off at the pickup station (triangle) or at the home location. The dotted lines signify that a customer's order is dropped off at the pickup station in the current solution. The other three panels (from left to right) show incomplete solutions after applying sweep destroy, pickup station destroy, and related trips destroy.

The second group of operators are adaptations and slight variations of operators commonly used in a variety of vehicle routing problems (see Appendix B for a detailed description). These are random destroy (Ropke and Pisinger 2006), shortest trip destroy (Nagata and Bräysy 2009), arc cost-based destroy (Ropke and Pisinger 2006), arc width-based destroy (Arnold et al. 2019), and string destroy (Christiaens and Vanden Berghe 2020).

5.2 Repair operators

After the application of a destroy operator, a (reduced) set of trips that meet all trip feasibility requirements remains. To restore the feasibility of the overall solution, the algorithm must reinclude the removed customers. Whenever a customer k is to be reincluded, all possible delivery locations $i \in \mathcal{I}_k$ are examined. k must be assigned to a delivery location, and possibly, the delivery location must be (re)inserted into a trip. We define a reinclusion point

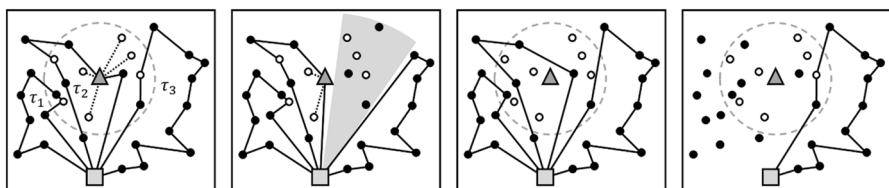


Fig. 3 Destroy operators

as a tuple consisting of a location, a trip, and a position in that trip. We use the term best (re)inclusion point to refer to the reinclusion point leading to the lowest reinclusion costs.

In each iteration, the algorithm chooses one of ten different operators to repair the solution. Nine of these repair operators are extensions of parallel insertion (cf. Solomon 1987), and one is based on regret insertion (cf. Potvin and Rousseau 1993). All ten operators include an assignment decision on top of the routing-focused insertion decision. The nine operators based on parallel insertion are detailed below. They differ in the order in which they reinclude the customers and in the strategy that determines the reinclusion point. Every combination of reinclusion order and reinclusion strategy constitutes a different repair operator.

Prior to the reinclusion of the first customer, the removed customers are sorted in order of nonascending demand, nonascending distance to the depot, or randomly. In real-world instances, there often are large differences between the demand sizes of different customers. As customers with high demand are harder to incorporate into trips close to the capacity limit than are customers with lower demand, it is advantageous to reinclude them early during the repair process. Similarly, customers with a large distance to the depot are more likely to cause a significant detour and an exceedance of the time limit. Hence, an early reinclusion of such customers is preferable. Additionally, the early reinclusion of high-demand and remote customers warranted by this application-oriented mechanism helps in “shaping” a trip. In contrast, customers with low demand in the vicinity of the depot are easily shifted from one trip to another.

Three reinclusion strategies (*best point*, best point with *blinks*, pickup *station*-based) are utilized. In the *best point* insertion strategy, the insertion of the current customer is performed at the reinclusion point of the least cost increase. In the *blinks* variant, every reinclusion point is skipped with a (small) blinking probability (cf. Christiaens and Vanden Berghe 2020) to randomize the reinclusion outcome and in the hope of finding better reinclusion points at a later stage of the repair process. In the proposed *station* variant of parallel insertion, the customer is assigned to a pickup station regardless of whether this corresponds to the best reinclusion point (i.e., the least cost increase) as long as the reinclusion is feasible. While moving a single customer to a pickup station is often detrimental to the objective value, shifting many customers to a pickup station simultaneously (as proposed through this problem-oriented approach) facilitates the exploration of the solution space.

5.3 Enhancements to the solution procedure

In this section, we specify some performance enhancements of the algorithm. They are primarily motivated by the application, as they demonstrate approaches to handling large, real-world instances in the context of strategic decision making. First, we propose pruning the search space to handle large instances more efficiently. Second, we describe the circumstances under which we allow temporary infeasibilities and present a look-ahead mechanism. Both measures aim to prevent the introduction of additional vehicles during the search process, since this is usually tantamount to large increases in the overall costs. Third, we outline an intensification routine. Last, we illustrate how solutions of certain instances are utilized to warm-start the solution of other instances.

5.3.1 Pruning the search space

As described in Sect. 5.2, there are numerous possibilities to reinclude a customer. When addressing large instances, it is, however, not practicable to exhaustively search for the best reinclusion point of customer k , as this would require checking the value of an assignment to each delivery location in the set \mathcal{I}_k and an insertion at any position of any trip. This can easily yield thousands of possible reinclusion points for just a single customer and thus thousands of time-consuming feasibility and profitability checks.

We propose limiting those reinclusions that necessitate an insertion (and not just an assignment) to the θ trips nearest to location $i \in \mathcal{I}_k$. Nearness is calculated as the minimal Manhattan distance to a location on the trip with a heavy penalty for a foreseeable violation of trip capacity. The nearest trips are calculated every η iterations for the upcoming η customers to be reincluded and all pickup stations that are not yet visited in the solution.

5.3.2 Temporary infeasibility

When no feasible reinclusion point is found during the reinclusion loop of customer k , a new trip may be initialized. However, initializing a new trip tends to generate solutions that are neither cost-efficient nor provide a promising start solution for the following ALNS iterations. Therefore, the initialization of a new trip depends on the “degree” of the solution’s incompleteness at this stage of the reinclusion process:

- If there are more than ζ (randomized threshold value) customers not included in the solution, a new trip to one of the delivery locations $i \in \mathcal{I}_k$ is added since it is likely that the remaining noninserted customers will not fit into the existing trips anyway.
- If the number of nonincluded customers is smaller than ζ , k is not reincluded and is instead appended to a list of infeasible customers, *infCusts*.

After all customers have been considered for reinclusion, a second-level process is launched if some customers cannot be feasibly reincluded, i.e., if *infCusts* is nonempty. All customers in *infCusts* are then reincluded at their best reinclusion points. This results in infeasibilities (exceeded time and/or capacity limits).

To restore feasibility, (different) customers are removed from the infeasible trips. Customers are deleted from either end of the trip until the resulting incomplete solution meets all feasibility requirements. These customers are often close to the depot and are thus more likely to fit into other trips. The deleted customers are then reincluded in the solution with a repair operator.

5.3.3 Look-ahead mechanism

Another way to prevent an excessive number of vehicles is to proactively reduce the number of customers added to the list *infCusts*. We propose a look-ahead mechanism that is

invoked during the repair procedure whenever a customer is assigned to a pickup station i not yet visited in the solution. After i is inserted into one of the trips, a removed customer k who can be served at only this pickup station ($\mathcal{I}_k = \{i\}$) is immediately reincluded (i.e., assigned to i).

5.3.4 Intensification routine

Once no improvements have been found in a predetermined number of ALNS iterations, we start an intensification routine to reignite and perturb the search process. The 2-opt*-neighborhood (Potvin and Rousseau 1995), which recombines two trips such that the beginnings of the trips are interchanged, is especially suitable in this application context for several reasons. First, its size is relatively small, making it possible to search the neighborhood exhaustively. Second, multiple trips are involved in every move, which increases the chance that an improvement will lead to further improvements during the ALNS or TSP phase. Last, large parts of the input solution remain untouched by the 2-opt*-moves, such that the likelihood of spending considerable computational effort exploring unpromising areas of the solution space is slim. Once the 2-opt*-neighborhood is searched exhaustively, the best move is performed. The procedure is repeated until no more improving 2-opt*-moves can be found. Appendix A details a proposed reduction of the 2-opt*-neighborhood that does not exclude any feasible solutions.

5.3.5 Warm starts

Finally, we make use of the similarity of different MT-VRPDO instances. For two MT-VRPDO instances, α and β , that differ in only the sets of feasible delivery locations \mathcal{I}_k , every solution to α is feasible for β , if $\mathcal{I}_k^\alpha \subseteq \mathcal{I}_k^\beta \forall k \in \mathcal{K}$. In such cases, the location assignments included in the solution to instance α are necessarily feasible location assignments for instance β . Thus, the best solution to α is used to warm-start the solution process for β . As solving the MT-VRPDO is primarily useful for the evaluation of closely related scenarios (cf. Sect. 6, Appendix A), warm-starting provides another opportunity to reduce the computational effort.

6 Data-driven decision support

In this section, we evaluate and compare the different scenarios of our case study. Section 6.1 describes the data basis and characterizes scenarios and instances. Section 6.2 examines the cost-saving potentials of OOHd, the effect of offering different products, and the importance of multitrip routing. Furthermore, we examine the environmental impact of OOHd. Section 6.3 expands this perspective by means of a demand management component. Through the simulation of scenarios reflecting different customer choice behaviors

and the solution of the corresponding MT-VRPDOs, we derive managerial insights into the profitability of different OOH products and prices for the HD product.

The solution procedure is implemented in Python. We used Gurobi 9.1.2 to solve the TSPs and BPPs. The experiments were performed on an Intel(R) Xeon(R) Gold 5218 CPU @ 2.30 GHz with a time limit of 500 s per instance. For further parameter settings pertaining to the solution procedure, we refer to Appendix B. To keep the focus on data-driven decision support, we omit a discussion of the performance of the proposed solution procedure here. Appendix C compares the performance to the application of Gurobi 9.1.2 leaning on small artificial instances. Appendix D demonstrates how the selected problem-oriented and application-oriented algorithmic features work together to enhance the results on the real-world data set.

6.1 Data, scenarios, and instances

We conduct a computational study on location and demand data from GLS. The data of a typical urban and a typical rural delivery region are provided. In the urban region, there are 18 pickup stations and a set of 892 customers. In the rural region, there are 8 pickup stations and 1101 customers. Distances d_{ij} [km] and transportation times t_{ij} between the locations are calculated based on their positions, local average speeds, and location service times. Following GLS's experience, the service time is 100 seconds for home locations and 200 seconds for pickup stations. These times are independent of the location load, as they are composed of parking and handing over parcels. Therefore, they are not treated as variables, i.e., $s_i = v_i$. The transportation cost c_{ij} equals $0.37 \frac{\text{€}}{\text{km}} \cdot d_{ij} + 10 \frac{\text{€}}{\text{h}} \cdot (t_{ij} + s_i)$, where the first component reflects fuel costs and the second reflects time-dependent driver salary.

In the current pickup station network, the maximum distance of a customer to the closest pickup station corresponds to a travel time of 24(36) minutes in the urban (rural) region. The range of the pickup stations, accordingly, is set to 24(36) minutes; i.e., customers consider only those pickup stations that are reachable within this maximum time. Note that the actual pickup time is usually much shorter, e.g., when the customers visit the pickup station on their way to work. In the regions considered, the capacity of delivery locations is not a limiting factor, i.e., $\kappa_i > Q \forall i \in \mathcal{N} \setminus \{0\}$. Each vehicle of the service provider's fleet has a capacity of $Q = 1150$ kg. The driver time limit T_{\max} is 7.5 hours. The reload time r at the depot is 20 minutes. The location-specific costs g_{ki} represent the pickup station owner compensation of 0.50€ per customer. The fixed cost per vehicle used is 100€.

There are two customer types: B2C and B2B customers. In the urban (rural) region, approximately 43% (56%) of customers are B2C customers. All B2B customers may only be served at home. Every B2C customer selects one of two products: a premium or a basic OOH product. The premium product is guaranteed home delivery (HD), and the basic product enables OOH. We examine four different products that incorporate the possibility of OOH (cf. Table 1). Two of the products (PU1 and PUX) ensure that customers are visited at a pickup station. The other two products (FLEX1 and FLEXX) are more flexible and allow for HD and OOH. For PUX and FLEXX, multiple pickup stations may be feasible, while for PU1 and FLEX1, the pickup station is exactly specified.

We investigate scenarios that differ in the OOHd product on offer and in the percentage of B2C customers that select the OOHd product. Note that we refer to this product as the OOHd product and to customers who select it as OOHd customers, even though some may be visited at home in the case of FLEX1 and FLEXX. The uncertainty about customer choice behavior is reflected in the percentage of B2C customers that select the OOHd product, which is varied from 0 to 100% in 10% increments. In total, there are $4 \cdot 11 = 44$ scenarios.

For each region, we generate thirty random sets of customers to reflect stochastic fluctuations. Any customer is present with a probability of 95% in each customer set. On average, an urban instance has 845 customers (370 B2C customers), and a rural instance has 1045 customers (587 B2C customers). The OOHd customers are chosen with probabilities inversely proportional to the distance to the closest pickup station. Any OOHd customer included in percentage x is also selected for percentage y if $x < y$ (cf. Appendix E for results for instances with fewer customers).

In summary, each instance α is distinguished by four characteristics: region ($R_\alpha \in \{\text{urban, rural}\}$), customer set ($S_\alpha \in \{1, 2, \dots, 30\}$), OOHd product ($O_\alpha \in \{\text{PU1, PUX, FLEX1, FLEXX}\}$), and OOHd percentage ($P_\alpha \in \{0\%, 10\%, 20\%, \dots, 100\%\}$). We examine a total of $2(R) \cdot 30(S) \cdot 4(O) \cdot 11(P) = 2640$ MT-VRPDO instances.

6.2 Cost and environmental impact of out-of-home delivery products

In this section, we quantify the impacts of different OOHd products on the service provider's overall costs and eco-friendliness. In particular, we elaborate on the following main insights:

- OOHd products display substantial cost-saving potential across all product combinations and delivery regions, as the decrease in routing cost outweighs the compensations paid to pickup station owners.
- The savings in rural delivery regions are higher than in urban ones.
- OOHd products enable significant reductions of the service provider's carbon footprint as measured by the number of vehicles used and the number of kilometers driven.
- Multitrip routing is crucial for reaping the benefits of OOHd in urban delivery regions.
- OOHd products that also allow for HD are especially conducive to efficient vehicle routing, as a considerable share of flexible OOHd customers are visited at home.

6.2.1 Total costs and cost structure

Table 4 (urban region) and Table 5 (rural region) summarize the total costs resulting from different OOHd products. These include transportation cost, fixed vehicle cost, and

Table 4 Total cost in urban region (in €)

OOHD product pct	PU1		PUX		FLEX1		FLEXX	
	Cost	Reduc (%)	Cost	Reduc (%)	Cost	Reduc (%)	Cost	Reduc (%)
0%	1762	0.0	1762	0.0	1762	0.0	1762	0.0
10%	1716	2.6	1712	2.8	1701	3.5	1697	3.7
20%	1707	3.1	1706	3.1	1689	4.1	1687	4.2
30%	1714	2.7	1713	2.7	1684	4.4	1682	4.5
40%	1704	3.3	1703	3.3	1666	5.4	1665	5.5
50%	1650	6.4	1646	6.6	1606	8.9	1599	9.2
60%	1629	7.5	1629	7.5	1577	10.5	1573	10.7
70%	1634	7.3	1633	7.3	1567	11.1	1565	11.2
80%	1628	7.6	1628	7.6	1555	11.7	1553	11.9
90%	1557	11.6	1555	11.7	1505	14.6	1493	15.3
100%	1530	13.2	1530	13.2	1465	16.8	1454	17.5

Table 5 Total cost in rural region (in €)

OOHD product pct	PU1		PUX		FLEX1		FLEXX	
	Cost	Reduc (%)	Cost	Reduc (%)	Cost	Reduc (%)	Cost	Reduc (%)
0%	3418	0.0	3418	0.0	3418	0.0	3418	0.0
10%	3303	3.4	3301	3.4	3272	4.3	3266	4.4
20%	3263	4.5	3260	4.6	3226	5.6	3222	5.7
30%	3133	8.4	3122	8.6	3082	9.8	3074	10.1
40%	3114	8.9	3107	9.1	3044	10.9	3043	11.0
50%	2997	12.3	2996	12.3	2946	13.8	2937	14.1
60%	2936	14.1	2935	14.1	2869	16.1	2864	16.2
70%	2848	16.7	2842	16.9	2791	18.3	2779	18.7
80%	2772	18.9	2770	18.9	2697	21.1	2690	21.3
90%	2707	20.8	2694	21.2	2628	23.1	2614	23.5
100%	2618	23.4	2617	23.4	2545	25.5	2534	25.9

compensation paid to pickup station owners. Each row represents the percentage of B2C customers that select the OOHD product. Each block of two columns represents the examined product combination (HD & PU1, HD & PUX, ...), with one column showing the total cost and one column showing the cost reduction compared to serving all customers at home (row 0%). All values are averages over thirty instances.

Across all product combinations and regions, we observe significant cost savings when the number of OOHD customers increases: the cost savings average between 3.6% (urban region, PU1) and 4.4% (rural region, FLEXX) for every 100 B2C customers selecting the OOHD product instead of the HD product (Calculation example for urban region, PU1: $\frac{\text{Total cost } 0\% - \text{Total cost } 100\%}{\text{Total cost } 0\%} \cdot \frac{100}{\text{number of private customers}} = \frac{1762 - 1530}{1762} \cdot \frac{100}{370} = 3.6\%$). Generally, the

savings are larger for rural instances than urban instances, as the geographical demand distribution is much denser in the urban region without OOHd. Therefore, the consolidation provided by OOHd is more beneficial in the rural region.

As mentioned in Sect. 5.3 and detailed in Appendix D, some instances are quite similar and differ in only the sets \mathcal{I}_k . Tables 4 and 5 show some of the effects of this property. First, the costs for product FLEXX are strictly smaller than the costs for any other product when the OOHd percentage is the same. Second, under the same conditions, the costs for FLEX1 and PUX are strictly smaller than the costs for PU1. Third, the costs in columns FLEX1 and FLEXX are nonincreasing when the percentage of OOHd customers increases. This third property is not present in the PU1 and PUX columns because the home location does not remain feasible for the customers switching to the OOHd product. Thus, the solution to an instance with a lower OOHd percentage is generally not feasible for an instance with a higher OOHd percentage for these product combinations.

When comparing costs between the different product types, it becomes evident that the flexibility to choose between OOHd and HD (PU1 vs. FLEX1; PUX vs. FLEXX) has more value for the service provider than does the flexibility to choose among a larger number of pickup stations (PU1 vs. PUX; FLEX1 vs. FLEXX; cf. Tables 4 and 5). The product FLEX1 combines a relatively low level of customer flexibility (discomfort) with a marked increase in location flexibility for the service provider. Consequently, the service provider can let the customers choose the pickup station, i.e., offer FLEX1 instead of FLEXX, without forfeiting much cost-saving potential.

Figure 4 shows how the total cost is composed of fixed vehicle cost, transportation cost, and compensation paid to pickup station owners. The transportation cost is further split into time-dependent (driver salary) and distance-dependent (fuel) costs. Displayed are the averages with OOHd product FLEX1 (cf. Tables 4 and 5). The benefits of OOHd on fixed vehicle cost and transportation cost distinctly outweigh the increase in compensation paid.

6.2.2 Environmental impact and multitrip routing

Figure 5 depicts the development of vehicle kilometers driven and the number of vehicles used. As regulators and customers are becoming more sensitive to environmental issues, these measures directly linked to CO₂ emissions are gaining importance. Heavy usage of pickup stations can significantly reduce the carbon footprint of the service provider. The effect is more pronounced in the rural region, since the detour incurred by a single customer is typically much larger. Whether a higher number of OOHds has positive environmental impacts overall strongly depends on the customers' pickup behavior. For instance, it makes a considerable difference if the customers use dedicated motorized trips to collect the parcels or pick them up on their way to/from work.

Multitrip routing enables the provider to exchange time capacity for vehicle capacity. While the driver's time limit is usually the most restricting factor in the rural region, vehicle capacities are the scarce resource in the densely populated urban region. Thus, the multiple use of vehicles is especially worthwhile in cities and suburbs (close to the depot). Figure 6 shows the differences in the usage of capacity between urban and

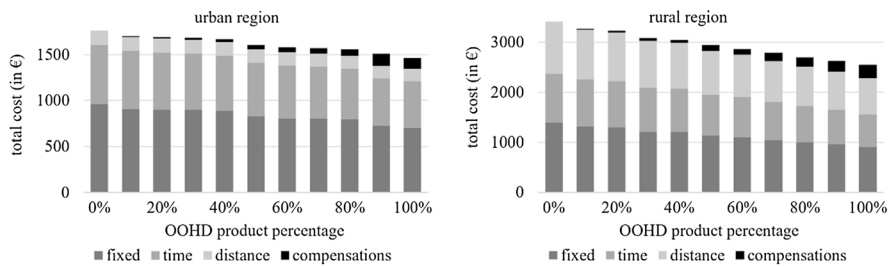


Fig. 4 Cost structure (FLEX1)

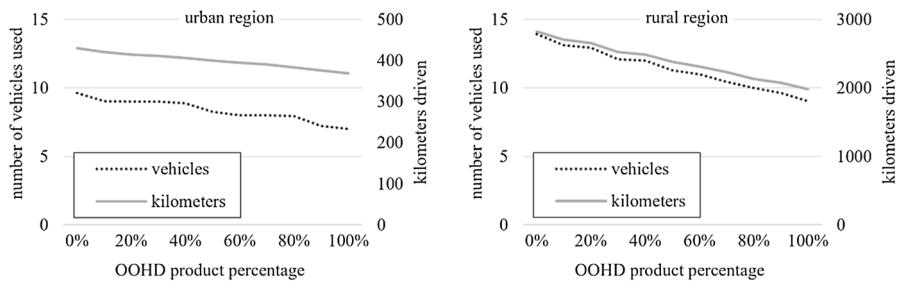


Fig. 5 Environmental impact (FLEX1)

rural instances when FLEX1 is offered. The median usage is reported to avoid outliers caused by multiple trips per vehicle.

When no OOH occurs in the rural region, there is a considerable discrepancy between vehicle capacity usage and driving time usage. With more OOH, this gap diminishes. Because driving time is not as scarce a resource in the urban region, reloading is crucial to use both vehicle capacity and the drivers' working hours efficiently. When reloading is not possible, the driving time limit is not exhausted (Fig. 6). Therefore, more vehicles and drivers are needed, leading to a cost increase (Fig. 7).

6.2.3 Customer flexibility

Figure 8 shows the percentage of customers for whom delivery occurs at a pickup station after selecting a flexible OOH product. The percentage is at times as small as 50%, i.e., only 50% of the orders that could be delivered to a pickup station are dropped off there. The number is especially low in the densely populated urban region and when the overall OOH percentage is small. In such cases, the detour induced by visiting a customer at home is more likely to be short and thus less costly than paying a compensation to the pickup station owner.

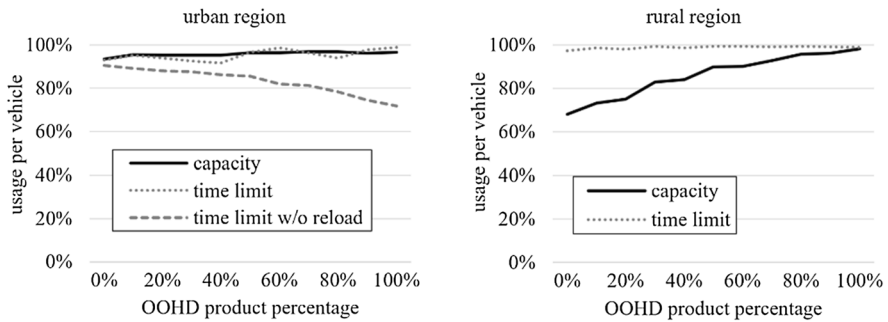
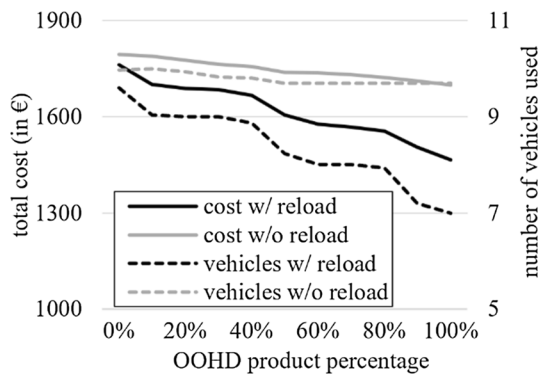


Fig. 6 Median usage of driver time limit and vehicle capacity (FLEX1)

Fig. 7 Impact of reloading in the urban region



However, this does not imply that the delivery service provider should stop expanding their pickup station network. For OOHD to work, it is crucial that customers are satisfied with the pickup experience, which depends mostly on the distance to the pickup station. In urban (rural) instances, where 100% of B2C customers choose the OOHD product, the average pickup distance from the customer's home location is as high as 13 (26) minutes in the current pickup station infrastructure. Since a reasonable pickup distance is indispensable in making OOHD work, this highlights the need for a further increase in the number of pickup stations.

6.3 Controlling customer purchase behavior

In this section, we examine the effect of charging different prices for the HD product with the purpose of controlling customer choice behavior by examining different scenarios as described in Sect. 2.2.

For simplicity, we focus on HD and just one of the OOHD products, namely FLEX1 (delivery to home location or closest pickup station) in this discussion. The results for the

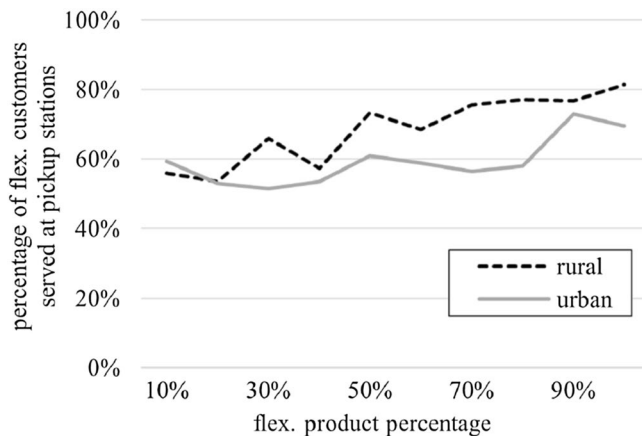


Fig. 8 Percentage of flexible customers served at pickup stations

other product combinations can be found in Appendix F. Based on an average willingness-to-pay for HD of 2.77 € (PricewaterhouseCoopers 2018), we vary the surcharge for HD from 0.00 € to 5.00 € in 0.50 € increments. The percentage of B2C customers selecting OOHd (for each level of surcharge) is varied from 0 to 100%. This leads to 121 different scenarios.

Tables 6 and 7 show the difference between the additional revenues generated by selling HD to some of the B2C customers and the total cost. As the amount of the surcharge does not influence the solution of the routing problem, the entries of Tables 6 and 7 can be computed without solving further MT-VRPDO instances.

The 0.00 € columns correspond to the FLEX1 columns in Tables 4 and 5. The values in all other columns are calculated by adding the additional revenue, i.e., the number of customers choosing HD multiplied with the surcharge. For example, the entry −1429 (Table 6, 60%, 1 €) results from the calculation $-1577\text{€} + 148 \cdot 1\text{€}$, where 1577€ is the total cost (cf. Table 4, FLEX1, 60%), 148 is the number of HD customers (40% of all B2C customers), and 1€ is the surcharge per HD customer. Note that the values in the tables do not represent the overall profit, as they do not include the basic revenues generated by the standard delivery fee.

The tables display the trade-off between the generation of additional HD revenue and the utilization of OOHd cost-saving potential. When looking at a single column from top to bottom, two effects take hold. First, as the percentage of FLEX1 customers increases, the total cost shrinks. Second, the number of HD customers, i.e., the number of B2C customers paying a surcharge, also decreases. For small surcharges, the cost-saving component outweighs the “lost” revenue. In contrast, for high surcharges, the extra revenue from HD customers outweighs the extra (transportation) cost for serving these customers at home. In column 1.50 € of Table 7 (rural region), the values are all roughly equal, signifying that the total profit is largely independent of the number of customers selecting each product. For the urban instance, this surcharge is 0.80 €.

The results of Tables 6 and 7 represent a breadth of scenarios and thereby reflect the uncertainty regarding customer choice behavior. In a next step, the service provider

Table 6 Additional revenues—total cost (urban region, FLEX1)

OOHD percentage	0.00 €	0.50 €	1.00 €	1.50 €	2.00 €	2.50 €	3.00 €	3.50 €	4.00 €	4.50 €	5.00 €
0%	— 1762	— 1577	— 1392	— 1207	— 1022	— 838	— 653	— 468	— 283	— 98	87
10%	— 1703	— 1537	— 1370	— 1204	— 1038	— 872	— 706	— 540	— 374	— 208	— 41
20%	— 1688	— 1540	— 1393	— 1245	— 1097	— 950	— 802	— 654	— 507	— 359	— 211
30%	— 1684	— 1555	— 1426	— 1297	— 1168	— 1038	— 909	— 780	— 651	— 522	— 393
40%	— 1666	— 1556	— 1445	— 1334	— 1224	— 1113	— 1002	— 891	— 781	— 670	— 559
50%	— 1609	— 1517	— 1424	— 1332	— 1240	— 1147	— 1055	— 963	— 871	— 778	— 686
60%	— 1578	— 1504	— 1429	— 1356	— 1283	— 1209	— 1135	— 1061	— 988	— 914	— 840
70%	— 1573	— 1517	— 1462	— 1407	— 1352	— 1296	— 1241	— 1186	— 1131	— 1075	— 1020
80%	— 1558	— 1522	— 1485	— 1448	— 1411	— 1374	— 1338	— 1301	— 1264	— 1227	— 1190
90%	— 1506	— 1488	— 1470	— 1451	— 1433	— 1415	— 1396	— 1378	— 1360	— 1342	— 1323
100%	— 1465	— 1465	— 1465	— 1465	— 1465	— 1465	— 1465	— 1465	— 1465	— 1465	— 1465

Bold print highlights an exemplary price-response function

Table 7 Additional revenues—total cost (rural region, FLEX1)

OOHD percentage	0.00 €	0.50 €	1.00 €	1.50 €	2.00 €	2.50 €	3.00 €	3.50 €	4.00 €	4.50 €	5.00 €
0%	– 3418	– 3125	– 2831	– 2538	– 2244	– 1951	– 1657	– 1364	– 1071	– 777	– 484
10%	– 3272	– 3008	– 2744	– 2480	– 2216	– 1953	– 1689	– 1425	– 1161	– 897	– 633
20%	– 3226	– 2992	– 2757	– 2523	– 2288	– 2053	– 1819	– 1584	– 1350	– 1115	– 881
30%	– 3082	– 2877	– 2672	– 2467	– 2261	– 2056	– 1851	– 1646	– 1441	– 1235	– 1030
40%	– 3044	– 2868	– 2692	– 2516	– 2341	– 2165	– 1989	– 1813	– 1637	– 1461	– 1285
50%	– 2946	– 2800	– 2653	– 2507	– 2360	– 2214	– 2067	– 1920	– 1774	– 1627	– 1481
60%	– 2869	– 2751	– 2634	– 2517	– 2400	– 2283	– 2166	– 2049	– 1932	– 1814	– 1697
70%	– 2791	– 2703	– 2615	– 2528	– 2440	– 2352	– 2264	– 2176	– 2089	– 2001	– 1913
80%	– 2697	– 2639	– 2580	– 2522	– 2463	– 2405	– 2346	– 2288	– 2229	– 2171	– 2113
90%	– 2628	– 2599	– 2570	– 2541	– 2512	– 2482	– 2453	– 2424	– 2395	– 2366	– 2337
100%	– 2545	– 2545	– 2545	– 2545	– 2545	– 2545	– 2545	– 2545	– 2545	– 2545	– 2545

Bold print highlights an exemplary price-response function

can gain insights into profitable pricing schemes by evaluating possible price-response functions for the HD product. Basically, such a function specifies the number of B2C customers choosing the HD product depending on the surcharge. Since in our application no demand data is available, the function could, e.g., be estimated by making reasonable assumptions and by discussions with managers using judgmental forecasting.

The fields in bold print in Table 6 highlight an exemplary price-response function, i.e., a presumed mapping of each surcharge to a percentage of B2C customers selecting OOHd. It can be read as follows: if the surcharge is 0.00 €, all customers select HD; if the surcharge is 0.50 €, 10% of customers select FLEX1 and 90% select HD. This continues until all customers select FLEX1 when the surcharge is 5.00 €. Clearly, the relationship between the FLEX1 percentage and surcharge need not be linear (cf. Table 7 for a different price-response function in the rural region).

Figure 9 shows the difference between the additional revenues and the total cost as a function of price (values correspond to the bold print in Tables 6 and 7). For the price-response function assumed, the data suggest an optimal surcharge in the range of 3.00 € in the urban region and 3.50 € in the rural one. The example also shows that setting different pricing in different regions may be beneficial to the service provider. The regional disparity arises for two reasons. First, the price-response function assumed here implies a higher willingness-to-pay (for HD) for customers in the rural region, as reflected by the lower percentage of customers choosing OOHd at 3.50 €. Second, the detour for visiting a customer at home is usually longer in rural regions, causing HD to be profitable only at higher surcharges.

7 Summary and outlook

In this paper, we introduced a framework for the data-driven evaluation of business models in last-mile logistics based on a real-world case study. We presented a realistic application and a new VRP variant (MT-VRPDO) in which the delivery service provider actively chooses the delivery location. Furthermore, we demonstrated how the introduction of OOHd products

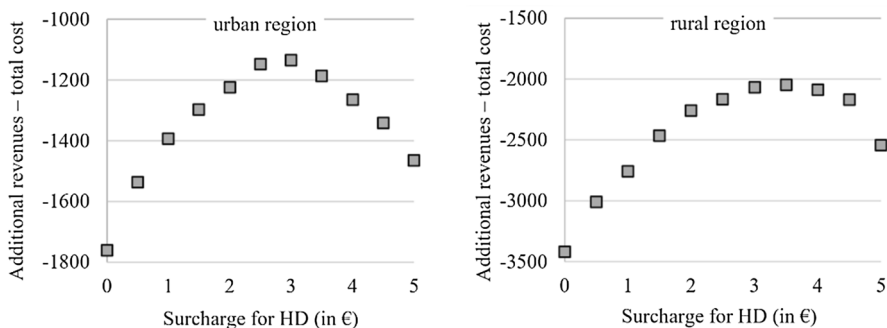


Fig. 9 Impact of surcharge

can pave the way to a more profitable, more efficient, and more eco-friendly future of last-mile delivery services.

The scenario-based approach of the framework and an enhanced ALNS procedure enable the evaluation of network structures and support tactical and strategic decision making under uncertainty. We focused on a delivery network with pickup stations. However, the same framework and a slightly adjusted optimization model can be used to assess a multitude of delivery network infrastructures, delivery modes, and product assortments. These include but are not limited to shipping through subcontractors or crowdshippers, the usage of multiple echelons, the deferral of packages to other delivery days, and the utilization of other alternative delivery locations, e.g., workplaces or cars (cf. Chu 2005; Archetti et al. 2016; Zhou et al. 2018; Laganà et al. 2021; Reyes et al. 2017).

In addition to the variety of application areas, many other interesting research questions related to the MT-VRPDO remain to be investigated. First, it might be sensible to offer more than two products, necessitating a closer look at the underlying problem of assortment optimization (cf. Mackert 2019, for an application to attended home delivery). Moreover, it might be beneficial to take a closer look at the compensation paid to pickup station owners and efficient configurations of pickup station networks, which are still in their infancy in many countries (Last Mile Experts 2021). Furthermore, this paper may underestimate the value of OOH by disregarding failed deliveries that almost exclusively occur with HD. It is also worthwhile to study a dynamic version of the MT-VRPDO and use demand management techniques (Agatz et al. 2013; Klein et al. 2019) to steer customers into selecting profitable products in real time. Last, the multitude of possible application areas warrants a further algorithmic examination, which was out of the scope of this paper.

Appendix

Appendix A: Solution procedure

Overview

Table 8 shows the major steps of the matheuristic. An initial solution is generated by an algorithm based on parallel insertion (line 1, cf. Sect. 5.2). The solution is then alternately subjected to ALNS (lines 3–14) and TSP/BPP optimization (lines 15–16). The search terminates if a time limit is reached, or no improvement has been found (line 2).

During the ALNS phase, the algorithm maintains three solutions. Solution S (current solution) is the solution whose neighborhood is being explored; S^{temp} is a solution in the neighborhood of S ; and S^* is the best solution found thus far. Simulated annealing steers

Table 8 Solution procedure

Input: initial selection probabilities ϕ^D and ϕ^R , ALNS iterations γ	
1	$S^* \leftarrow \text{getInitialSolution}()$
2	while stopping criterion not met do
3	$S \leftarrow S^*$
4	for $j = 1$ to γ do
5	$\text{dest} \leftarrow \text{chooseDestroy}(\phi^D)$
6	$\text{rep} \leftarrow \text{chooseRepair}(\phi^R)$
7	$S^{\text{temp}} \leftarrow \text{repair}(\text{destroy}(S, \text{dest}), \text{rep})$
8	$S, S^*, \phi^D, \phi^R \leftarrow \text{selectSolution}(S^{\text{temp}}, S, S^*)$
9	$\phi^D, \phi^R \leftarrow \text{updateProbabilities}(\phi^D, \phi^R)$
10	if intensification condition is fulfilled then
11	$S^* \leftarrow 2\text{-opt}^*(S^*)$
12	$S \leftarrow S^*$
13	endif
14	endfor
15	$S^* \leftarrow \text{solveTSPs}(S^*)$
16	$S^* \leftarrow \text{solveBPP}(S^*)$
17	endwhile

the search process. The vectors ϕ^D and ϕ^R store the selection probabilities for all operators. In each iteration, the current solution S is destroyed according to the randomly chosen destroy operator dest (line 7). Immediately afterward, a new feasible solution S^{temp} is created by applying the randomly chosen repair operator rep (line 7).

The function *selectSolution* is called next (line 8) to check whether S^{temp} is better than the best solution found thus far (S^*), which would result in assigning S^{temp} to S^* . It also chooses the solution whose neighborhood is to be explored in the next iteration. S^{temp} is chosen and assigned to S :

- if S^{temp} has a better objective value than S **or**
- if a criterion inspired by simulated annealing (cf. Kirkpatrick et al. 1983) is invoked, which allows a temporary reduction in the quality of the solution.

Otherwise, S remains the same and serves as the starting point of the next destroy-and-repair iteration.

Afterward, the function *updateProbabilities* adjusts the selection probabilities ϕ^D and ϕ^R such that the selection of operators leading to solution improvements becomes more likely during the search process, as detailed by Pisinger and Ropke (2010). An intensification routine (lines 10–13; cf., Sect. 5.3) is called after a certain number of iterations without improvement in S^* . It consists of searching the 2-opt* neighborhood (Potvin and Rousseau 1995) in which sequences of locations at the beginnings of two trips are exchanged.

In the TSP optimization phase (line 15), a TSP is solved for each trip. Changing the order of locations within a trip to be TSP-optimal does not lead to infeasible solutions, since there are no time windows and the completion time of a trip decreases with decrease in costs. To avoid spending a disproportionate amount of time in this phase, only trips that have been altered during the previous ALNS phase are subject to the TSP optimization. Also, a time limit is imposed for the solution of each trip. Last, the algorithm solves a bin-packing problem (line 16) to assign the current trips to as few vehicles as possible.

Intensification routine

The 2-opt* intensification routine recombines two trips such that the beginnings of the trips are interchanged. Starting with two trips τ_ρ and τ_σ , two new trips are generated. The first new trip is the combination of the first locations of trip τ_ρ up to and including the location in position l^ρ and the last locations from trip τ_σ starting with the location in position $l^\sigma + 1$. The second new trip is the combination of the first locations of trip τ_σ up to and including the location in position l^σ and the last locations from trip τ_ρ starting with the location in position $l^\rho + 1$. Every pair of trips, τ_ρ and τ_σ , is considered. It is usually not necessary to check every combination of cutoff points. Table 9 shows part of the 2-opt*-neighborhood for an instance with two trips and nine visited locations.

As seen in this example, the second new trip is elongated with every iteration of the loop over l^σ . Thus, once the capacity limit is surpassed, the following iterations cannot result in feasible solutions and are, consequently, expendable. In the example, if the second new trip resulting from a 2-opt*-move with $l^\rho = 3$ and $l^\sigma = 3$ violates the vehicle capacity restriction, it is not necessary to check the trips resulting from $l^\rho = 3$ and $l^\sigma > 3$ since the second trip will only become longer and will carry a higher load. Similarly, if the first trip resulting from a 2-opt*-move

Table 9 2-opt* example

Original trips	$\tau_\rho = [0, 4, 6, 8, 9, 0]$	$\tau_\sigma = [0, 7, 3, 5, 2, 1, 0]$
2-opt* ($l^\rho = 3, l^\sigma = 3$)	[0, 4, 6, 5, 2, 1, 0]	[0, 7, 3, 8, 9, 0]
2-opt* ($l^\rho = 3, l^\sigma = 4$)	[0, 4, 6, 2, 1, 0]	[0, 7, 3, 5, 8, 9, 0]
2-opt* ($l^\rho = 4, l^\sigma = 3$)	[0, 4, 6, 8, 5, 2, 1, 0]	[0, 7, 3, 9, 0]
2-opt* ($l^\rho = 4, l^\sigma = 4$)	[0, 4, 6, 8, 2, 1, 0]	[0, 7, 3, 5, 9, 0]

with $l^p = 3$ and $l^s = 3$ does not meet the capacity restrictions, it is not sensible to check the combinations with $l^p > 3$ and $l^s = 3$, as those moves will yield only infeasible solutions. The 2-opt*-neighborhood also includes trips that do not meet the time limit requirements. The number of necessary combinations to be checked can be reduced in a similar way as shown above. Once the 2-opt*-neighborhood is searched exhaustively, the best move is performed. The procedure is repeated until no more improving 2-opt*-moves can be found.

Warm starts

The solution spaces of two instances, α and β , from the same region and with the same customer set \mathcal{K} (i.e., $R_\alpha = R_\beta$ and $S_\alpha = S_\beta$) differ in only the sets \mathcal{I}_k , i.e., in the set of locations that are feasible for customer k . The sets \mathcal{I}_k are not the same for different OOH products (O_α) and different OOH percentages (P_α), e.g., for $O_\alpha = \text{FLEXX}$, the sets are larger than for $O_\alpha = \text{PU1}$ (cf. Table 1, Table 10). Additionally, the higher P_α is, the more customers can be visited at a pickup station. Listed below are the cases where the solution to instance α is feasible for instance β (cf. Sect. 5.3). We warm-start the process to solve instance β with the best solution to any of the instances α .

- If $O_\beta = \text{PUX}$: instance α with $O_\alpha = \text{PU1}$ and $P_\alpha = P_\beta$. Only one instance yields a feasible starting solution since the OOH product PUX does not have the home location as a possible delivery location. Therefore, all instances with $P_\alpha \neq P_\beta$ or $O_\alpha \in \{\text{FLEX1}, \text{FLEXX}\}$ cannot be utilized.
- If $O_\beta = \text{FLEX1}$: any instance α with $O_\alpha \in \{\text{PU1}, \text{FLEX1}\}$ and $P_\alpha \leq P_\beta$. Instances with $P_\alpha \leq P_\beta$ yield feasible solutions, as the home location is part of the feasible locations for FLEX1 customers. PUX instances cannot be used since the delivery locations of FLEX1 customers include only one pickup station.
- If $O_\beta = \text{FLEXX}$: any instance α with $O_\alpha \in \{\text{PU1}, \text{PUX}, \text{FLEX1}, \text{FLEXX}\}$ and $P_\alpha \leq P_\beta$. As FLEXX has the largest set of feasible delivery locations, almost all other instances yield feasible starting solutions.

Table 10 provides an example of the determination of the feasible delivery locations \mathcal{I}_k based on customers 1 and 2 from Fig. 1 (Sect. 2.1).

Table 10 Products and corresponding sets of delivery locations

Product	Set \mathcal{I}_1	Set \mathcal{I}_2
HD	{1}	{2}
PU1	{5}	{5}
PUX	{5}	{5, 6}
FLEX1	{1, 5}	{2, 5}
FLEXX	{1, 5}	{2, 5, 6}

Appendix B: Parameter settings

Random destroy removes 10% (20%) of all customers. Note that, in the case of a pickup station, the delivery location might not be removed from the trip, as other customers might still be assigned to it (Table 11).

Shortest trip destroy removes one trip, i.e., all customers and pickup stations on this trip. The selection probabilities are inversely proportional to the total demand of the customers on the trip.

Arc cost destroy removes 10% (20%) of all locations, including all customers assigned to these locations. The selection probabilities are inversely proportional to the combined weight of the adjacent edges.

Arc width destroy removes 10% (20%) of all locations, including all customers assigned to these locations. The selection probabilities are inversely proportional to the combined width (as defined by Arnold et al. (2019)) of the adjacent edges.

String destroy removes a random sequence of five to eighteen locations from each trip, including all customers assigned to these locations.

Appendix C: ALNS performance

To compare our solution procedure to a standard solver, two sets of very small instances were generated. The first set contains 30 instances with 15 customers and 3 pickup stations each. The second set contains 30 instances with 25 customers and 5 pickup stations each. The locations of customer home locations, pickup stations, and the depot were generated randomly on a 10×10 grid. The travel time [cost] of arc (i, j) is equal to $1.9 \cdot ed_{ij}$ [$8.55 \cdot ed_{ij}$] where ed_{ij} represents the Euclidean distance between the locations i and j .

Table 11 Parameter settings

Stopping criterion	500 s time limit or no improvement found
γ (destroy-and-repair iterations)	300
Simulated annealing parameters	Initial temperature 200, cooling factor 0.99
ϕ^R, ϕ^D (initial operator selection probabilities)	All equal
Intensification routine criterion	No improvement in last 20 iterations and last improvement not through 2-opt*
δ (destroy percentage)	20%
η (number of next customers nearest trips)	10
β (blinking probability)	1%
θ (number of nearest trips)	3
ζ (new trip initialization threshold)	0, 3, 5, 10, 15, 20 with equal probability
TSP time limit	10 s

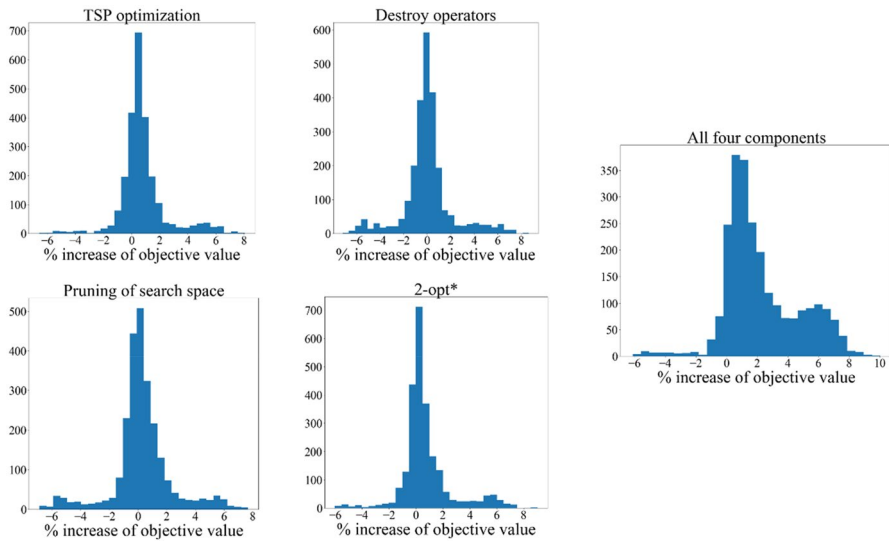
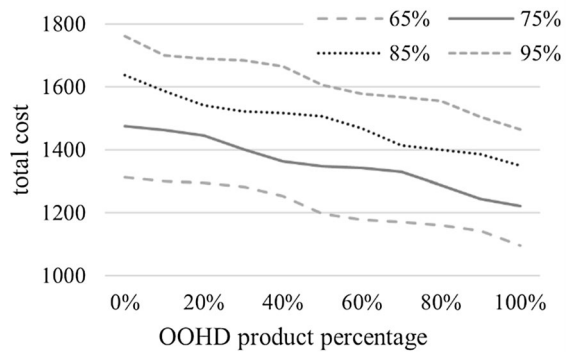


Fig. 10 Performance of selected operators

Fig. 11 Total cost (FLEX1, urban)



Customer i is eligible for OOH (product FLEXX) at pickup station s if $1.9 \cdot ed_{ij} \leq 7$ ($1.9 \cdot ed_{ij} \leq 4$ for the instances with 25 customers). The order weights of the customers were chosen randomly as being 1, 2, 3, 4, or 5 units. The vehicle capacity was set to 13, the fixed vehicle cost was to 50. The vehicle time limit is 75 time units, reloading at the depot takes 10 time units.

Table 12 (instances with 15 customers, 3 pickup stations) and Table 13 (instances with 25 customers, 5 pickup stations) report the results. The first six columns show the progression of the search with a standard solver. They show the objective value of the best solution found after 30 (1800, 3600) seconds, and the gap to the lower bound found at the respective time. The seventh column indicates the objective value of the best solution found by the ALNS after 30 s of computational time. The last three columns display the improvement of the ALNS with respect to the solutions found by the standard solver after 30 (1800, 3600) seconds. Solving the MT-VRPDO to optimality by a standard solver is computationally prohibitive, as evidenced by the progression of the optimality gap. Furthermore, the results indicate that the proposed solution procedure identifies solutions of equal or better

Table 12 Results for instances with 15 customers and 3 pickup stations

	Solver (30 s)		Solver (1800s)		Solver (3600 s)		ALNS (30 s)			ALNS improvement vs.		
	Obj. val	Gap (%)	Obj. val	Gap (%)	Obj. val	Gap (%)	Obj. val		30 s (%)	1800s (%)	3600 s (%)	
1	433.1	44	433.1	30	433.1	28	433.1		0.0	0.0	0.0	
2	629.2	66	629.1	55	629.1	53	629.1		0.0	0.0	0.0	
3	585.2	54	547.2	41	547.2	40	547.2		6.5	0.0	0.0	
4	502.7	50	502.7	40	502.7	38	502.7		0.0	0.0	0.0	
5	752.2	58	743.5	48	732.7	46	732.7		2.6	1.4	0.0	
6	529.5	51	524.0	39	524.0	36	524.0		1.0	0.0	0.0	
7	516.1	56	515.1	44	515.1	43	515.1		0.2	0.0	0.0	
8	766.6	61	744.1	56	744.1	55	744.1		2.9	0.0	0.0	
9	522.4	37	522.4	28	522.4	26	522.4		0.0	0.0	0.0	
10	589.5	60	557.6	48	557.6	46	557.6		5.4	0.0	0.0	
11	520.8	37	520.8	22	520.8	21	520.8		0.0	0.0	0.0	
12	517.3	46	500.0	37	500.0	36	506.8		2.0	− 1.4	− 1.4	
13	362.1	36	362.1	22	362.1	19	362.1		0.0	0.0	0.0	
14	586.8	63	536.6	52	536.6	51	535.9		8.7	0.1	0.1	
15	620.2	46	620.2	38	620.2	37	620.2		0.0	0.0	0.0	
16	500.4	55	500.4	46	500.4	45	500.4		0.0	0.0	0.0	
17	741.9	62	741.7	51	741.7	50	741.7		0.0	0.0	0.0	
18	427.3	49	426.3	33	426.3	31	426.3		0.2	0.0	0.0	
19	675.0	53	656.2	40	656.2	38	656.2		2.8	0.0	0.0	
20	465.2	46	465.2	39	465.2	37	465.2		0.0	0.0	0.0	
21	435.1	48	435.1	36	435.1	34	435.1		0.0	0.0	0.0	
22	593.2	69	591.9	59	591.9	57	591.9		0.2	0.0	0.0	
23	375.3	42	375.3	26	375.3	24	375.3		0.0	0.0	0.0	
24	471.4	48	471.4	38	471.4	37	471.0		0.1	0.1	0.1	

Table 12 (continued)

	Solver (30 s)		Solver (1800s)		Solver (3600 s)		ALNS (30 s)		ALNS improvement vs.	
	Obj. val	Gap (%)	Obj. val	Gap (%)	Obj. val	Gap (%)	Obj. val		30 s (%)	3600 s (%)
25	612.2	67	612.2	59	612.2	58	612.2		0.0	0.0
26	491.6	39	488.3	24	488.3	22	488.3		0.7	0.0
27	662.1	61	662.1	55	662.1	54	662.1		0.0	0.0
28	527.0	52	490.6	41	490.6	40	490.6		6.9	0.0
29	333.8	38	333.8	23	333.8	22	333.8		0.0	0.0
30	501.6	53	501.6	42	501.6	41	501.6		0.0	0.0
Avg		52		40		39			1.34	0.01

Bold print shows averages over all instances

Table 13 Results for instances with 25 customers and 5 pickup stations

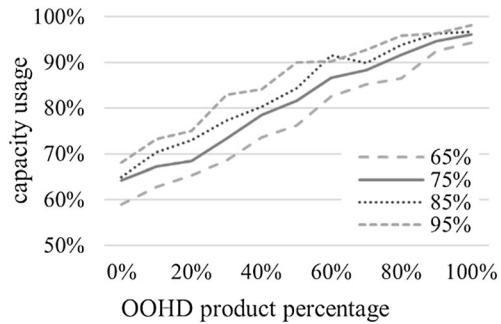
	Solver (30 s)		Solver (1800s)		Solver (3600 s)		ALNS (30 s)		ALNS improvement vs		
	Obj. val	Gap (%)	Obj. val	Gap (%)	Obj. val	Gap (%)	Obj. val		30 s (%)	1800s (%)	3600 s (%)
1	764.97	61	725.4	52	725.4	51	712.067		6.9	1.8	1.8
2	1163.27	75	1145.85	70	1145.85	69	1143.32		1.7	0.2	0.2
3	943.583	63	918.343	58	918.343	58	863.113		8.5	6.0	6.0
4	898.121	64	885.465	56	832.342	52	814.013		9.4	8.1	2.2
5	923.22	66	885.027	61	881.672	60	814.329		11.8	8.0	7.6
6	1052.25	73	1020.37	68	1020.37	67	1018.89		3.2	0.1	0.1
7	953.036	63	932.312	59	929.173	59	913.932		4.1	2.0	1.6
8	873.513	63	806.643	54	806.643	53	806.42		7.7	0.0	0.0
9	789.52	65	711.564	53	703.169	51	700.648		11.3	1.5	0.4
10	897.21	57	888.255	50	888.255	49	888.255		1.0	0.0	0.0
11	1049.14	70	1041.29	66	1041.29	66	1038.77		1.0	0.2	0.2
12	825.76	58	806	53	802.756	52	802.675		2.8	0.4	0.0
13	935.819	64	926.27	59	926.27	58	926.27		1.0	0.0	0.0
14	768.504	54	765.311	50	765.311	49	762.547		0.8	0.4	0.4
15	1058.32	64	1041.27	60	1041.27	59	1002.54		5.3	3.7	3.7
16	989.653	67	950.711	63	950.711	62	940.916		4.9	1.0	1.0
17	903.149	66	888.649	60	888.649	60	888.649		1.6	0.0	0.0
18	918.144	64	918.144	59	918.144	58	917.331		0.1	0.1	0.1
19	917.152	64	782.719	51	782.45	50	777.648		15.2	0.6	0.6
20	955.221	68	922.068	61	907.219	60	903.991		5.4	2.0	0.4
21	776.144	61	750.781	50	750.781	49	749.77		3.4	0.1	0.1
22	760.419	66	732.259	60	722.223	59	725.87		4.5	0.9	-0.5
23	828.122	64	760.701	55	760.701	54	757.591		8.5	0.4	0.4
24	882.231	62	863.915	59	834.407	57	810.581		8.1	6.2	2.9

Table 13 (continued)

	Solver (30 s)		Solver (1800s)		Solver (3600 s)		ALNS (30 s)		ALNS improvement vs		
	Obj. val	Gap (%)	Obj. val	Gap (%)	Obj. val	Gap (%)	Obj. val		30 s (%)	1800s (%)	3600 s (%)
25	974.773	67	967.68	60	967.68	60	928.148		4.8	4.1	4.1
26	1044.26	71	1012.28	65	1012.28	64	1009.65		3.3	0.3	0.3
27	994.199	69	946.258	63	946.258	63	946.258		4.8	0.0	0.0
28	937.72	62	920.64	56	920.64	55	917.06		2.2	0.4	0.4
29	758.917	61	756.297	53	756.297	53	750.554		1.1	0.8	0.8
30	997.4	69	927.56	64	927.56	63	916.145		8.1	1.2	1.2
Avg		65		58		57			5.1	1.7	1.2

Bold print shows averages over all instances

Fig. 12 Capacity usage
(FLEX1, rural)



quality within a much shorter timeframe. The experiments were performed on an Intel(R) Xeon(R) Gold 5218 CPU @ 2.30 GHz using Gurobi 9.1.2.

Appendix D: Operator performance

Figure 10 shows how selected mechanisms contribute in the search procedure and how the largest improvement is achieved when both application-based and problem-oriented techniques are employed. The graphs show the number of instances with a certain percentage increase of the objective value, i.e., a decline in solution quality if the selected components are turned off. (Top left: TSP optimization (problem-oriented), top middle: destroy operators (sweep, pickup station, related trips; problem- and application-oriented), bottom left: pruning of search space (application-oriented), bottom middle: 2-opt* (application-oriented), right: all four components). As is expected from a randomized search procedure on large instances, in rare cases, a better solution is found when the respective operator is turned off.

Appendix E: Reduced instances

The total data set consists of 892 and 1101 customers in the urban and rural region, respectively. The results of Sect. 6 pertain to instances where every customer from the total data set is present in an instance with a selection probability of 95%. This results in instances with an average of 845 (1045) customers in the urban (rural) area. By lowering the selection probability to 65%, 75%, and 85%, we created smaller instances ranging between 555 and 958 customers. As shown in Figs. 11 and 12, the general observations for these instances are quite similar to the ones described in detail in Sect. 6.

Appendix F: Results for other product combinations

See Tables 14, 15, 16, 17, 18, 19.

Table 14 Difference between additional revenue and total cost (urban region, PUI)

	0.00 €	0.50 €	1.00 €	1.50 €	2.00 €	2.50 €	3.00 €	3.50 €	4.00 €	4.50 €	5.00 €
0%	- 1762	- 1577	- 1392	- 1207	- 1022	- 838	- 653	- 468	- 283	- 98	87
10%	- 1716	- 1550	- 1384	- 1218	- 1052	- 886	- 719	- 553	- 387	- 221	- 55
20%	- 1707	- 1559	- 1411	- 1264	- 1116	- 968	- 821	- 673	- 525	- 378	- 230
30%	- 1714	- 1585	- 1456	- 1327	- 1197	- 1068	- 939	- 810	- 681	- 551	- 422
40%	- 1704	- 1593	- 1482	- 1372	- 1261	- 1150	- 1040	- 929	- 818	- 708	- 597
50%	- 1650	- 1558	- 1465	- 1373	- 1281	- 1188	- 1096	- 1004	- 912	- 819	- 727
60%	- 1629	- 1556	- 1482	- 1408	- 1334	- 1261	- 1187	- 1113	- 1039	- 966	- 892
70%	- 1634	- 1578	- 1523	- 1468	- 1413	- 1357	- 1302	- 1247	- 1192	- 1136	- 1081
80%	- 1628	- 1591	- 1555	- 1518	- 1481	- 1444	- 1407	- 1371	- 1334	- 1297	- 1260
90%	- 1557	- 1538	- 1520	- 1502	- 1483	- 1465	- 1447	- 1429	- 1410	- 1392	- 1374
100%	- 1530	- 1530	- 1530	- 1530	- 1530	- 1530	- 1530	- 1530	- 1530	- 1530	- 1530

Table 15 Difference between additional revenue and total cost (rural region, PU1)

	0.00 €	0.50 €	1.00 €	1.50 €	2.00 €	2.50 €	3.00 €	3.50 €	4.00 €	4.50 €	5.00 €
0%	- 3418	- 3125	- 2831	- 2538	- 2244	- 1951	- 1657	- 1364	- 1071	- 777	- 484
10%	- 3303	- 3039	- 2775	- 2511	- 2247	- 1983	- 1719	- 1456	- 1192	- 928	- 664
20%	- 3263	- 3028	- 2794	- 2559	- 2325	- 2090	- 1855	- 1621	- 1386	- 1152	- 917
30%	- 3133	- 2927	- 2722	- 2517	- 2312	- 2107	- 1901	- 1696	- 1491	- 1286	- 1081
40%	- 3114	- 2938	- 2762	- 2586	- 2410	- 2234	- 2058	- 1882	- 1707	- 1531	- 1355
50%	- 2997	- 2851	- 2704	- 2558	- 2411	- 2264	- 2118	- 1971	- 1825	- 1678	- 1531
60%	- 2936	- 2819	- 2702	- 2585	- 2468	- 2350	- 2233	- 2116	- 1999	- 1882	- 1765
70%	- 2848	- 2760	- 2673	- 2585	- 2497	- 2409	- 2321	- 2234	- 2146	- 2058	- 1970
80%	- 2772	- 2714	- 2655	- 2597	- 2539	- 2480	- 2422	- 2363	- 2305	- 2246	- 2188
90%	- 2707	- 2678	- 2648	- 2619	- 2590	- 2561	- 2532	- 2503	- 2474	- 2445	- 2415
100%	- 2618	- 2618	- 2618	- 2618	- 2618	- 2618	- 2618	- 2618	- 2618	- 2618	- 2618

Table 16 Difference between additional revenue and total cost (urban region, PUX)

	0.00 €	0.50 €	1.00 €	1.50 €	2.00 €	2.50 €	3.00 €	3.50 €	4.00 €	4.50 €	5.00 €
0%	- 1762	- 1577	- 1392	- 1207	- 1022	- 838	- 653	- 468	- 283	- 98	87
10%	- 1712	- 1546	- 1380	- 1214	- 1047	- 881	- 715	- 549	- 383	- 217	- 51
20%	- 1706	- 1559	- 1411	- 1263	- 1116	- 968	- 820	- 673	- 525	- 377	- 230
30%	- 1713	- 1584	- 1455	- 1326	- 1197	- 1067	- 938	- 809	- 680	- 551	- 422
40%	- 1703	- 1593	- 1482	- 1371	- 1261	- 1150	- 1039	- 928	- 818	- 707	- 596
50%	- 1646	- 1554	- 1461	- 1369	- 1277	- 1185	- 1092	- 1000	- 908	- 815	- 723
60%	- 1629	- 1555	- 1481	- 1408	- 1334	- 1260	- 1186	- 1112	- 1039	- 965	- 891
70%	- 1633	- 1578	- 1522	- 1467	- 1412	- 1357	- 1301	- 1246	- 1191	- 1136	- 1081
80%	- 1628	- 1591	- 1554	- 1518	- 1481	- 1444	- 1407	- 1370	- 1334	- 1297	- 1260
90%	- 1555	- 1537	- 1519	- 1501	- 1482	- 1464	- 1446	- 1427	- 1409	- 1391	- 1373
100%	- 1530	- 1530	- 1530	- 1530	- 1530	- 1530	- 1530	- 1530	- 1530	- 1530	- 1530

Table 17 Difference between additional revenue and total cost (rural region, PUX)

	0.00 €	0.50 €	1.00 €	1.50 €	2.00 €	2.50 €	3.00 €	3.50 €	4.00 €	4.50 €	5.00 €
0%	- 3418	- 3125	- 2831	- 2538	- 2244	- 1951	- 1657	- 1364	- 1071	- 777	- 484
10%	- 3301	- 3037	- 2774	- 2510	- 2246	- 1982	- 1718	- 1454	- 1190	- 927	- 663
20%	- 3260	- 3025	- 2791	- 2556	- 2322	- 2087	- 1853	- 1618	- 1384	- 1149	- 914
30%	- 3122	- 2917	- 2712	- 2507	- 2302	- 2097	- 1891	- 1686	- 1481	- 1276	- 1071
40%	- 3107	- 2931	- 2755	- 2579	- 2404	- 2228	- 2052	- 1876	- 1700	- 1524	- 1348
50%	- 2996	- 2850	- 2703	- 2556	- 2410	- 2263	- 2117	- 1970	- 1823	- 1677	- 1530
60%	- 2935	- 2818	- 2701	- 2584	- 2467	- 2349	- 2232	- 2115	- 1998	- 1881	- 1764
70%	- 2842	- 2754	- 2666	- 2578	- 2491	- 2403	- 2315	- 2227	- 2139	- 2052	- 1964
80%	- 2770	- 2712	- 2654	- 2595	- 2537	- 2478	- 2420	- 2361	- 2303	- 2244	- 2186
90%	- 2694	- 2665	- 2636	- 2607	- 2578	- 2549	- 2519	- 2490	- 2461	- 2432	- 2403
100%	- 2617	- 2617	- 2617	- 2617	- 2617	- 2617	- 2617	- 2617	- 2617	- 2617	- 2617

Table 18 Difference between additional revenue and total cost (urban region, FLEXX)

	0.00 €	0.50 €	1.00 €	1.50 €	2.00 €	2.50 €	3.00 €	3.50 €	4.00 €	4.50 €	5.00 €
0%	- 1762	- 1577	- 1392	- 1207	- 1022	- 838	- 653	- 468	- 283	- 98	87
10%	- 1697	- 1531	- 1365	- 1199	- 1033	- 867	- 701	- 534	- 368	- 202	- 36
20%	- 1687	- 1540	- 1392	- 1244	- 1097	- 949	- 801	- 654	- 506	- 358	- 211
30%	- 1682	- 1553	- 1424	- 1295	- 1166	- 1036	- 907	- 778	- 649	- 520	- 390
40%	- 1665	- 1554	- 1444	- 1333	- 1222	- 1112	- 1001	- 890	- 779	- 669	- 558
50%	- 1599	- 1507	- 1415	- 1323	- 1230	- 1138	- 1046	- 953	- 861	- 769	- 677
60%	- 1573	- 1499	- 1425	- 1352	- 1278	- 1204	- 1130	- 1057	- 983	- 909	- 835
70%	- 1565	- 1509	- 1454	- 1399	- 1344	- 1289	- 1233	- 1178	- 1123	- 1068	- 1012
80%	- 1553	- 1516	- 1479	- 1442	- 1406	- 1369	- 1332	- 1295	- 1258	- 1222	- 1185
90%	- 1493	- 1474	- 1456	- 1438	- 1419	- 1401	- 1383	- 1365	- 1346	- 1328	- 1310
100%	- 1454	- 1454	- 1454	- 1454	- 1454	- 1454	- 1454	- 1454	- 1454	- 1454	- 1454

Table 19 Difference between additional revenue and total cost (rural region, FLEXX)

	0.00 €	0.50 €	1.00 €	1.50 €	2.00 €	2.50 €	3.00 €	3.50 €	4.00 €	4.50 €	5.00 €
0%	- 3418	- 3125	- 2831	- 2538	- 2244	- 1951	- 1657	- 1364	- 1071	- 777	- 484
10%	- 3266	- 3002	- 2738	- 2475	- 2211	- 1947	- 1683	- 1419	- 1155	- 891	- 628
20%	- 3222	- 2987	- 2753	- 2518	- 2284	- 2049	- 1815	- 1580	- 1346	- 1111	- 876
30%	- 3074	- 2869	- 2664	- 2458	- 2253	- 2048	- 1843	- 1638	- 1433	- 1227	- 1022
40%	- 3043	- 2867	- 2691	- 2515	- 2339	- 2163	- 1988	- 1812	- 1636	- 1460	- 1284
50%	- 2937	- 2790	- 2644	- 2497	- 2350	- 2204	- 2057	- 1911	- 1764	- 1618	- 1471
60%	- 2864	- 2747	- 2630	- 2512	- 2395	- 2278	- 2161	- 2044	- 1927	- 1810	- 1693
70%	- 2779	- 2691	- 2603	- 2515	- 2427	- 2340	- 2252	- 2164	- 2076	- 1988	- 1901
80%	- 2690	- 2632	- 2573	- 2515	- 2456	- 2398	- 2339	- 2281	- 2223	- 2164	- 2106
90%	- 2614	- 2585	- 2556	- 2527	- 2498	- 2469	- 2439	- 2410	- 2381	- 2352	- 2323
100%	- 2534	- 2534	- 2534	- 2534	- 2534	- 2534	- 2534	- 2534	- 2534	- 2534	- 2534

Funding Open Access funding enabled and organized by Projekt DEAL.

Data availability The real-world datasets analyzed during the current study are not publicly available due to confidential company data by General Logistics Systems Germany GmbH & Co. OHG. The datasets generated and analyzed in Appendix C are available from the corresponding author upon request.

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