INTERNATIONAL TRANSACTIONS IN OPERATIONAL RESEARCH

WILEY

INTERNATIONAL TRANSACTIONS IN OPERATIONAL RESEARCH

Intl. Trans. in Op. Res. 33 (2026) 3825–3854
DOI: 10.1111/itor.70169

The impact of public drop-off boxes and autonomous delivery robots in last-mile delivery

Gianpaolo Ghiani, Emanuela Guerriero, Emanuele Manni* and Deborah Pareo

Department of Engineering for Innovation, University of Salento, Lecce 73100, Italy
E-mail: gianpaolo.ghiani@unisalento.it[Ghiani]; emanuela.guerriero@unisalento.it[Guerriero]; emanuele.manni@unisalento.it[Manni]; deborah.pareo@unisalento.it[Pareo]

Received 8 April 2025; received in revised form 22 January 2026; accepted 23 January 2026

Abstract

The growing concern over emissions from last-mile logistics is motivating the development of innovative delivery models aimed at reducing environmental impact and traffic congestion. To this end, we propose a last-mile delivery scheme based on both public drop-off boxes and autonomous delivery robots. Unlike current practices, we assume that parcels are primarily delivered by a fleet of traditional vehicles to a number of drop-off boxes owned by the municipalities and shared by several logistics providers. Then, citizens must autonomously reach the drop-off point to retrieve their parcels. An exception is made for a small group of customers (like, for instance, elderly or disabled people) whose parcels are loaded on autonomous delivery robots and home-delivered, starting from the drop-off points. To tackle this problem, we devise tailored destroy-and-repair operators to be embedded into a neighborhood-search framework. We then conduct an extensive computational study on a set of realistic instances based on the urban area of Rome (Italy), aimed at assessing the benefits of the proposed last-mile delivery infrastructure, compared to traditional distribution methods. Additionally, we evaluate the environmental and economic advantages of using autonomous delivery robots and drop-off points.

Keywords: last-mile logistics; autonomous delivery robots; parcel lockers; metaheuristics

1. Introduction

The e-commerce sector is facing unprecedented growth, with global sales expected to surpass eight trillion dollars by 2027 (Statista, 2024). This exceptional trend has created significant challenges for the last-mile delivery industry, needing to adapt to such increasing volumes and costs, as well as to enhance efficiency and sustainability. This has led to the development of innovative solutions aimed at reducing costs, as well as health and environmental impacts. To this end, an emerging

*Corresponding author.

© 2026 The Author(s).
International Transactions in Operational Research published by John Wiley & Sons Ltd on behalf of International Federation of Operational Research Societies.
This is an open access article under the terms of the Creative Commons Attribution License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

solution in the last-mile logistics sector is the use of drop-off points, which include parcel lockers (PLs) (Deutsch and Golany, 2018). PLs are typically unmanned facilities where customers can pick up their parcels through locked compartments equipped with technology for securely opening (e.g., secret codes, electronic keys, or mobile apps). This system enables handling more parcels per stop compared to traditional home deliveries. Moreover, it provides additional flexibility for customers, because they do not necessarily need to be at home to wait for the driver to deliver their parcels (Seghezzi et al., 2022; Zhou et al., 2026). Another emerging technology in last-mile logistics is the use of autonomous delivery robots (ADRs), which are small, electric-powered vehicles capable of navigating urban environments (mainly using sidewalks) to deliver parcels to customers. Examples are the robots developed by Starship Technologies (www.starship.xyz), Ottonomy (www.ottonomy.io), or Carteken (www.cartken.com). Recent studies (e.g., Srinivas et al., 2022) review the advantages of employing ADRs for last-mile delivery, highlighting their potential to reduce both emissions and delivery times, especially in densely populated areas. Other studies, such as Koh et al. (2024), discuss several issues about the customer acceptance of autonomous robots in last-mile delivery, emphasizing the aspects which can promote ADR adoption.

Despite the promising results of both PLs and ADRs, very few studies have investigated the combination of these two technologies in a joint last-mile delivery model. Among these, Moradi et al. (2024) study a problem where trucks depart from a central depot and deliver parcels directly to either a subset of customers or PLs. Customers can choose to retrieve their items from these PLs if they prefer the pickup option. Additionally, each truck is equipped with an ADR, which disembarks, serves one or more customers, and returns to the truck for battery replacement and package collection. In this context, the trucks function as mobile satellite depots for the ADRs.

In our work, we tackle this issue from a different perspective by proposing a delivery system that leverages both public drop-off boxes and ADRs, with the aim of reducing costs, emissions, and delivery failures. The primary innovation in our approach lies in imposing the mandatory use of public drop-off points for the majority of customers, with only a selected group of customers with special needs (also referred to as priority customers) allowed to receive their parcels at home, delivered by ADRs. This scheme could be beneficial from several points of view. First, consolidating deliveries at a number of PLs would result in a reduced number of stops for the delivery route, thus reducing the traveled distance and lowering emissions. Moreover, this would also result in cutting logistics costs for companies, effectively eliminating the possibility of unsuccessful first-attempt delivery, which constitutes a serious issue (Lim et al., 2023). In addition, using ADRs would reduce road congestion, given that they primarily use sidewalks to move around the city. As a further positive side-effect, this scheme would encourage citizens to adopt a more active and healthier lifestyle (e.g., the well-known "10,000 steps a day" initiative; see Tudor-Locke and Bassett, 2004).

To solve this problem, we make use of tailored destroy-and-repair operators to be embedded into a neighborhood-search framework. Our approach is tested on a set of realistic instances based on the urban area of Rome (Italy), in which we assess the benefits of the proposed last-mile delivery infrastructure, compared to traditional distribution methods. Additionally, we provide some insights about the environmental and economic advantages of using ADRs and PLs.

The remainder of the paper is organized as follows. In Section 2, we provide an overview of the literature related to our problem. Then, in Section 3, we formally describe the problem, whereas in Section 4 we detail our solution approach. Finally, Section 5 presents the results of our

© 2026 The Author(s).
International Transactions in Operational Research published by John Wiley & Sons Ltd on behalf of International Federation of Operational Research Societies.

14753995, 2026, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/itor.70169 by Universita Del Salento Ser Inf Biblior "La Stecca", Wiley Online Library on [08/06/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

computational experiments, comparing our approach with two traditional scenarios, and Section 6 concludes the paper.

2. Literature

Our paper is mainly related to the research streams involving the use of PLs and ADRs for improving last-mile delivery performance, regarding costs, first-attempt deliveries, and delivery times.

In our study, we assume that the locations of PLs have already been defined. Hence, here we do not review the contributions about locating PLs within the urban area (see, for instance, Kahr, 2022; Zhang et al., 2023). Concerning the usage of PLs as a delivery mode, Iwan et al. (2016) propose an analysis of their usability and efficiency in the context of the Polish company InPost. Zhang and Lee (2016) were among the first to introduce the concept of incorporating visits to both PLs and customers' homes within a single routing plan, demonstrating the potential advantages of this approach. The authors assume that each customer selects their preferred delivery location (either a specific drop-off point or a private address), and the company then optimizes the routing plan to minimize costs. Wen and Li (2016) study a vehicle routing problem (VRP) with soft time windows for last-mile delivery, examining the impact of adding lockers. The goal is to minimize transport costs, soft time window penalties, CO_2 emissions, and labor and vehicle costs. When including the lockers as a delivery alternative, time window constraints are removed, and locker rental and small van acquisition costs are included. In Zhou et al. (2018), the authors propose a multi-depot two-echelon VRP in which customers can choose from various delivery options, enabling them to collect their packages at designated pickup locations. To address this problem, a hybrid multi-population genetic algorithm is proposed. More recently, Mancini and Gansterer (2021) propose a mixed delivery approach, combining home delivery and PLs with time windows. They solve large instances using two matheuristics. In a similar fashion, Carotenuto et al. (2022) compare two different delivery options: traditional home deliveries and locker deliveries. The results, obtained using a matheuristic, show that PLs can significantly reduce pollution. A similar analysis is presented in Pinchasik et al. (2025), where, in addition to substantial potential for CO_2 reductions, decreases in external (societal) damage costs are observed, attributed to reduced traffic. Then, Zang et al. (2023) propose an urban delivery problem aimed at minimizing delivery and self-pickup costs under conflicting time window constraints. To address this, they formulate a mixed-integer linear programming model and provide a branch-and-cut algorithm. A recent contribution is given by Orhan and Wallace (2025), who assess, in cooperation with local authorities in Bergen (Norway), how PLs can improve urban sustainability and liveability through more efficient deliveries. A systematic literature review about the usage of PL solutions for last-mile delivery is reported in Zhang and Demir (2025).

Concerning employing ADRs for last-mile delivery in urban areas, a recent review is due to Srinivas et al. (2022). Given the limited distance that an ADR can cover with a full battery, in the literature, they are typically studied in conjunction with other means of transport. A first alternative is jointly using trucks and robots, for which a notable contribution is due to Boysen et al. (2018), who propose an iterated local search approach for a problem where a truck operates alongside multiple ADRs. In this paradigm, the truck is first loaded with parcels at a central depot and then moves toward the city center, where the ADRs begin their routes, serving a single

© 2026 The Author(s).
International Transactions in Operational Research published by John Wiley & Sons Ltd on behalf of International Federation of Operational Research Societies.

14753995, 2026, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/itor.70169 by Universita Del Salento Ser Inf Biblior "La Stecca", Wiley Online Library on [08/06/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

customer and returning to a designated depot after each delivery. Chen et al. (2021) address a VRP with time windows and delivery robots, developing a two-stage matheuristic using clustering techniques. Alfandari et al. (2022) propose a variant of this problem focusing on minimizing tardiness concerning customer delivery deadlines, using a branch-and-benders-cut algorithm. Other contributions are due to Yu et al. (2022, 2024). In the former, the authors introduce a two-echelon pickup and delivery system involving a van and a robot, in which the van stops at certain nodes to drop off or pick up the robot, replenishing or swapping its battery if needed. To address this, the authors propose a mixed-integer model and an adaptive large neighborhood search (ALNS) algorithm. In Yu et al. (2022), the authors explore a variant where robots can be recharged while on the vans, improving the distribution system's efficiency, again using an ALNS algorithm. In the mixed truck-and-robot delivery model proposed by Heimfarth et al. (2022), trucks also deliver goods to customers. This problem is addressed using a variable neighborhood search. Finally, Ostermeier et al. (2023) extend this problem to include multiple trucks and propose a customized heuristic based on a set improvement neighborhood search.

In a different delivery setting, ADRs make use of a public transportation service as part of their trips. Examples of works in this context are represented by Mourad et al. (2021), Ermağan et al. (2024), and De Maio et al. (2024). In particular, Mourad et al. (2021) consider an integrated system in which a set of freight requests needs to be delivered using a fleet of delivery robots that can use the public transportation system. The availability of space on the public transportation vehicles is not known in advance, so the authors present a sample average approximation method combined with an ALNS to solve the stochastic optimization problem. Subsequently, Ermağan et al. (2024) study a pickup and delivery problem, in which delivery robots serve a set of dynamic requests and are allowed to use more than one public transit vehicle. To optimize real-time operations, the authors propose a rolling-horizon algorithm based on column generation. Finally, De Maio et al. (2024) analyze a similar routing problem in which a fleet of ADRs can travel on the road network, as well as on vehicles of the public transportation system. To build delivery robot routes synchronized with the rides of the public transportation lines, the authors develop a tailored destroy-and-repair mechanism embedded into a neighborhood search algorithm.

The contribution of our paper with respect to the previous literature is twofold. First, we propose a delivery framework in which, apart from some exceptions, home deliveries are not allowed, with PLs as the primary destination for parcels. For priority customers, ADRs are used to bring the parcels from the PLs to their private addresses. To the best of our knowledge, this is the first contribution combining PLs and ADRs. Second, we evaluate the proposed scheme on realistic instances based on the urban area of Rome (Italy) and assess the environmental and economic benefits of employing ADRs and PLs.

3. Problem statement

In our envisaged last-mile delivery framework, we assume that the service territory is an urban area infrastructure with a dense network of public PLs, managed by the municipality. In this smart-city model, direct deliveries to private residences are not allowed, with some exceptions represented by priority customers with specific requisites (e.g., elderly or disabled people), whose parcels are home-delivered by ADRs, initially located at some specialized depots. The PLs are finite in number

© 2026 The Author(s).
International Transactions in Operational Research published by John Wiley & Sons Ltd on behalf of International Federation of Operational Research Societies.

14753995, 2026, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/itor.70169 by Universita Del Salento Ser Inf Biblior "La Stecca", Wiley Online Library on [08/06/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

and have limited capacity. Once loaded with parcels, they remain unavailable until the parcels are retrieved by customers. Two types of vehicles are involved: vans (which may be electric) and ADRs. Starting from a main depot, vans deliver parcels to the PLs, which are accessible both to final recipients, that is, private individuals, and to a fleet of ADRs. All recipients, except for a subset of *priority* customers, are required to collect their items in person from the lockers. More specifically, when placing a delivery request, a customer must specify k PLs in order of preference. On the other hand, priority customers do not choose a subset of PLs, but the k closest to their address are automatically assigned to the request. For both types of customers, if the k selected collection points do not have residual capacity, then the delivery is performed by a van.

To formally describe our problem, let $G = (V, A)$ be a directed graph, in which V denotes the set of vertices and A represents the arc set. Set V is partitioned as $V = \{0\} \cup C \cup P \cup D$, where 0 is the van depot, C is the set of customers, P is the set of PLs, and D is the set of ADR depots. The set of customers C is further divided into two different subsets, C_p and C_{np}, which contain priority and non-priority customers, respectively. We assume that each customer $i \in C$ is characterized by a unit demand. In addition, when placing an order, a customer $i \in C_{np}$ specifies k alternative PLs, associating a preference to each of them. We denote as $L_i \subseteq P$ the list of PLs chosen by customer i. For priority customers $i \in C_p$, L_i is constituted by the k PLs closest to their private address. In both cases, such an address is added to L_i with the lowest preference, to ensure that a feasible solution can always be obtained. Each PL $p \in P$ has a limited capacity Q_p, representing the number of lockers available for hosting parcels. Concerning ADRs, each of them has a capacity Q_d and a maximum distance δ that can be covered with a full battery. At the beginning of the planning horizon, the parcels constituting customers' requests are located at depot 0, from which a fleet of vans moves to take them to the PLs, from which they will be either picked up personally by non-priority customers, or delivered by ADRs to the private addresses of priority customers. As mentioned before, if all the preferred PLs of a request have no residual capacity, then the corresponding parcels are home-delivered by the vans during their routes. The goal is to determine to which PL each request $i \in C$ should be delivered, so that either the preferences expressed by customers are maximized (if $i \in C_{np}$) or the distance traveled by ADRs is minimized (for customers $i \in C_p$).

A solution to our problem consists of (i) assigning each request to either a PL or to a private address, so to favor the assignment of lockers with the highest preference to non-priority customers, and those with the highest proximity to priority customers; (ii) routing the fleet of vans, starting from depot 0, visiting a number of PLs and (if necessary) private addresses, and returning to the depot; (iii) routing the fleet of ADRs, starting from a depot in D, visiting PLs to pick up some parcels to be home-delivered to priority customers, and returning to the depot.

To evaluate the quality of a solution, we consider three different objective functions, defined as follows.

- Minimization of a penalty measure, representing the total inconvenience for not associating a customer $i \in C_{np}$ to their most preferred PL or a customer $i \in C_p$ to the PL closest to their private address. This is expressed by $\sum_{i \in C} \pi_i$, where π_i is the penalty for customer $i \in C$.
- Minimization of CO_2 emissions, obtained as $e_v \Delta_v + e_d \Delta_d$, where Δ_v and Δ_d are the total distance (in kilometers) traveled by vans and ADRs, respectively, and e_v and e_d represent the CO_2 emissions per kilometer for traditional vans and ADRs, respectively.

© 2026 The Author(s).
International Transactions in Operational Research published by John Wiley & Sons Ltd on behalf of International Federation of Operational Research Societies.

14753995, 2026, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/itor.70169 by Universita Del Salento Ser Inf Bibliot "La Stecca", Wiley Online Library on [08/06/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

- Minimization of the overall traveling cost, obtained as $c_v\Delta_v + c_d\Delta_d$. Here, c_v and c_d represent the fuel/energy cost per kilometer for vans and ADRs, respectively.

Details about the values of the coefficients used in our experiments are provided in Section 5.

4. Solution approach

To tackle the problem described in Section 3, we move on from an initial feasible solution and propose tailored destroy-and-repair operators to be embedded into a large-neighborhood-search scheme (Pisinger and Røpke, 2010). In the following, we begin by describing the procedure used to construct the initial feasible solution, based on a two-step approach, in which an integer programming model chooses how each customer should be served; then a black-box solver determines the routes visiting the drop-off points and the customers. After determining the initial solution, we then move on to the core of the methodology: the destroy and repair operators. For each of them, we describe its purpose, the specific portion of the solution it targets, and the mechanisms through which it either removes or reconstructs solution elements. Finally, we show how the destroy-and-repair operators are embedded into a large-neighborhood-search framework.

4.1. Initial solution construction

The basic idea of this phase is to obtain an initial solution by first determining, for each customer, a suitable means of service chosen among ADR/van or PL/van for $i \in C_p$ or $i \in C_{np}$, respectively. Then, the routes for both ADRs and vans are built.

The first step is performed by solving an integer programming model. Given customers $i \in C$ and sets L_i ($i \in C$) as defined in Section 3, we consider decision variables y_{ip} ($i \in C$, $p \in L_i$), equal to 1 if $i \in C$ is associated with drop-off point $p \in L_i$, and 0 otherwise. The mathematical model is as follows:

$$\max \sum_{i \in C} \sum_{p \in L_i} y_{ip} a_{ip}, \tag{1}$$

$$\text{s.t.} \sum_{p \in L_i} y_{ip} \leq 1 \qquad \forall i \in C, \tag{2}$$

$$\sum_{i \in C : p \in L_i} y_{ip} \leq Q_p \qquad \forall p \in P, \tag{3}$$

$$y_{ip} \in \{0, 1\} \qquad \forall i \in C, p \in L_i. \tag{4}$$

The model aims to assign a drop-off point to each customer, taking into account the preferences expressed by standard customers and the distance to the assigned drop-off point for priority customers. To this end, the objective function (1) maximizes the weighted sum of such assignment, where parameters a_{ip} ($i \in C$, $p \in L_i$) represent the weight of assigning customer i to drop-off point p. This weight is set to k if p is the customer's first choice and is decreased by 1 as the preference

© 2026 The Author(s).
International Transactions in Operational Research published by John Wiley & Sons Ltd on behalf of International Federation of Operational Research Societies.

14753995, 2026, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/itor.70169 by Universita Del Salento Ser Inf Bibliot "La Stecca", Wiley Online Library on [08/06/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

ranking decreases, so that it equals 1 if p represents the customer's lowest preference (for customers in C_{np}) or the farthest drop-off point (for customers in C_p). We recall that the cardinality of L_i is k for each $i \in C$. Constraints (2) ensure that each customer is assigned to at most one drop-off point. Constraints (3) impose that the capacity of the PLs is not exceeded, whereas constraint (4) defines the domain of the variables.

We notice that a feasible solution may be such that, for some customers $i \in C$, all the corresponding y_{ip} take value 0. In this case, no PLs are selected and such customers' requests are home-delivered by vans.

After solving model (1)–(4), we define sets $\mathcal{M}[i]$ (for $i \in C$) and $\mathcal{L}[p]$ (for $p \in P$), representing the means of service for customers, and the customers assigned to each PL, respectively. More specifically, for each $i \in C_p$, if there is a PL $p \in L_i$ for which $y_{ip} = 1$, then $\mathcal{M}[i] = \text{adr}$ and i is added to $\mathcal{L}[p]$. On the other hand, if for customers $i \in C_{np}$, there is a PL $p \in L_i$ for which $y_{ip} = 1$, then $\mathcal{M}[i] = \text{pl}$ and i is added to $\mathcal{L}[p]$. Finally, if for some $i \in C$ no y_{ip} variables take value 1, then $\mathcal{M}[i] = \text{van}$.

In the second step, sets $\mathcal{M}$ and $\mathcal{L}$ are used to determine the routes for both types of delivery vehicles, namely ADRs and vans. As far as van routes are concerned, they start from vertex 0 and visit customers $i \in C$ for which $\mathcal{M}[i] = \text{van}$, as well as all the drop-off points $p \in P$ for which the corresponding set $\mathcal{L}[p]$ contains customers $i \in C_p \cup C_{np}$ characterized by $\mathcal{M}[i] = \text{pl}$. On the other hand, each ADR route starts from a depot, visits drop-off points $p \in P$ such that the corresponding set $\mathcal{L}[p]$ contains customers $i \in C_p$ for which $\mathcal{M}[i] = \text{adr}$, services the corresponding customers, and terminates at the same depot.

Determining van routes results in solving a VRP, whereas obtaining the ADR routes consists of finding the solution to a pickup and delivery problem (PDP; see Koç et al., 2020). Since the focus of our work is not on the routing phase, instead of developing ad-hoc procedures, we make use of an off-the-shelf solver. Details about the solvers used for both stages are given in Section 5.

4.2. Destroy operator

The destroy procedure is sketched in Algorithm 1. At each iteration, the goal is to determine a subset C' of customers for which modifying the locker assignment could potentially lead to an improved solution (i.e., a solution with a better objective function value), as well as a subset of lockers P' to which such customers could be reassigned. The basic idea is to identify customers that have some potential PLs in common, so that, by changing their assignments, it is likely to find improved solutions. The procedure takes as inputs a seed customer i_0 and a parameter h controlling the size of the neighborhood to be explored. Let $p(i)$ be the locker assigned to the customer $i \in C$ in the current solution. Starting with i_0, C', and P' are iteratively expanded by considering customers having common drop-off points (Algorithm 1, lines 7–10). By increasing the neighborhood size (Algorithm 1, line 13), we take into account the possibility of exploring wider parts of the solution space. Then, to ensure that a feasible solution can always be obtained, the set P' is further expanded to include all the private addresses of the customers in C' (Algorithm 1, lines 15–17).

In Fig. 1, we report an example of applying the destroy operator of Algorithm 1 with $h = 2$, where, for each value of "size" marked by an horizontal dashed line, we report the composition of sets C' and P', In particular, suppose that, in the current solution, customer i_0 is assigned to $\overline{p}$,

© 2026 The Author(s).
International Transactions in Operational Research published by John Wiley & Sons Ltd on behalf of International Federation of Operational Research Societies.

14753995, 2026, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/itor.70169 by Universita Del Salento Ser Inf Bibliot "La Stecca", Wiley Online Library on [08/06/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Algorithm 1. Destroy operator

```
1:  procedure DESTROY(i_0, h)
2:      size ← 1; C' ← ∅; P' ← ∅; C'' ← {i_0}                    ▷ initialization
3:      while size ≤ h do
4:          C_temp ← ∅                                            ▷ temporary data structure
5:          for i ∈ C'' do
6:              C' ← C' ∪ {i}                                     ▷ update of C'
7:              for p ∈ L_i : p ∉ P' do
8:                  C_temp ← C_temp ∪ {i' ∈ C : p(i') = p}
9:                  P' ← P' ∪ {p}                                 ▷ update of P'
10:             end for
11:         end for
12:         C'' ← C_temp
13:         size ← size + 1                                       ▷ size update
14:     end while
15:     for i ∈ C' do
16:         P' ← P' ∪ {private address of customer i}
17:     end for
18:     return C', P'
19: end procedure
```

customers i_1 and i_2 are assigned to p_1, and customer i_3 is assigned to p_2, that is, $p(i_0) = \overline{p}$, $p(i_1) = p(i_2) = p_1$, and $p(i_3) = p_2$. Moreover, the preferences about the drop-off points are $L_{i_0} = \{\overline{p}, p_1, p_2\}$, $L_{i_1} = \{p_1, p_2, p_3\}$, $L_{i_2} = \{p_1, p_3, p_4\}$, and $L_{i_3} = \{p_2, p_3, p_5\}$. Thus, according to Algorithm 1, for size = 1, $C' = \{i_0\}$ and $P' = \{\overline{p}, p_1, p_2\}$. When size is increased to 2 (the maximum value, in this example), $C' = \{i_0, i_1, i_2, i_3\}$ and $P' = \{\overline{p}, p_1, p_2, p_3, p_4, p_5\}$.

4.2.1. Choice of i_0

The choice of the seed customer i_0 in the destroy step can influence the performance of the solution approach. For this reason, in this section, we propose three alternative strategies for determining i_0.

Random. A first straightforward approach is a random choice in which every customer has the same probability of being selected.

Adaptive. Here, we perform a random choice in which the probabilities that customers are selected dynamically change on the basis of how frequently they have been previously included in C', in the fashion of a softmax function. Specifically, we denote by n_i the number of times customer i has been included in set C'. Initially, $n_i = 0$ for every customer $i \in C$, and the selection probability is set as $\text{Prob}(i) = 1/|C|$. Then, at each iteration, we set $n_i = n_i + 1$ for every $i \in C'$ and let $\bar{n}_i = n_{\text{iter}} - n_i$ denote the number of times i has not been included in C', where n_{iter} is the number of iterations performed. Finally, for each customer $i \in C$, the selection probability is obtained as

$$\text{Prob}(i) = 1 - \frac{e^{(\bar{n}_i - \max_{i \in C}(\bar{n}_i))}}{\sum_{i \in C} e^{(\bar{n}_i - \max_{i \in C}(\bar{n}_i))}},$$

where the term $\max_{i \in C}(\bar{n}_i)$ is added to overcome overflow issues.

© 2026 The Author(s).
International Transactions in Operational Research published by John Wiley & Sons Ltd on behalf of International Federation of Operational Research Societies.

14753995, 2026, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/itor.70169 by Universita Del Salento Ser Inf Bibliot "La Stecca", Wiley Online Library on [08/06/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

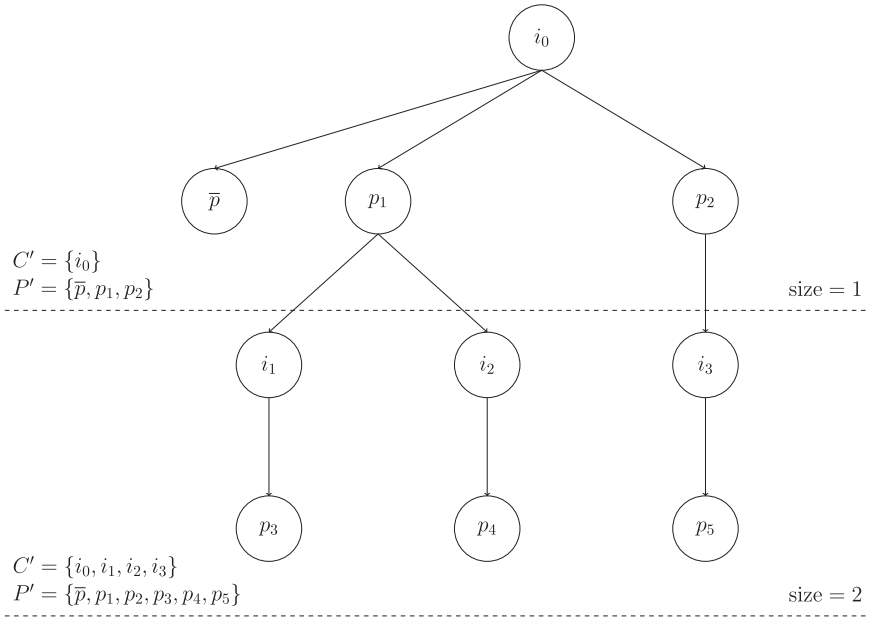


Fig. 1. Example of a destroy operator with $h = 2$.

Restricted. In this strategy, we perform a random choice as in the first alternative, but the candidate customers' list is restricted to contain only those who have never been in C' before. If the candidate list becomes empty (i.e., all the customers have been included at least once in C'), the procedure is re-initialized by assigning the same probability $1/|C|$ to each customer.

4.3. Repair operator

After the destroy phase, the repair operator aims to rebuild the solution by reinserting the elements from C', assigning them to the alternatives in P', possibly enhancing the overall quality of the solution. To this end, we propose the following binary optimization model that assigns each customer to one of the available alternatives:

$$\min \sum_{i \in C'} \sum_{a \in L_i \cap P'} w_{ia} x_{ia}, \tag{5}$$

$$\text{s.t.} \sum_{a \in L_i \cap P'} x_{ia} = 1 \quad \forall i \in C', \tag{6}$$

$$\sum_{i \in C' : a \in L_i} x_{ia} \leq Q'_a \qquad \forall a \in P', \tag{7}$$

$$x_{i_0 p(i_0)} = 0 \tag{8}$$

$$x_{i,a} \in \{0, 1\} \qquad \forall i \in C', a \in P'. \tag{9}$$

© 2026 The Author(s).
International Transactions in Operational Research published by John Wiley & Sons Ltd on behalf of International Federation of Operational Research Societies.

14753995, 2026, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/itor.70169 by Universita Del Salento Ser Inf Biblior "La Stecca", Wiley Online Library on [08/06/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Algorithm 2. Pseudocode of the large-neighborhood-search algorithm

```
1:  procedure LargeNeighborhoodSearch(s_0, h_min, h_max, T_max, z)
2:    current ← s_0
3:    while time < T_max do
4:      h ← h_min
5:      i_0 ← ChooseSeedCustomer()
6:      while h ≤ h_max do
7:        s* ← destroy-and-repair(current, i_0, h)
8:        if z(current) < z(s*) then
9:          current ← s*
10:         h ← h_min
11:       else
12:         h ← h + 1
13:       end if
14:     end while
15:   end while
16:   returncurrent
17: end procedure
```

Here, the decision variable x_{ia} takes value 1 if $i \in C'$ is assigned to alternative $a \in L_i \cap P'$, and 0 otherwise. The objective function aims to minimize a weighted sum of the assignment variables, prioritizing customer satisfaction (i.e., assignment of a customer to the alternative with the highest preference), while penalizing van deliveries. In (5), parameter w_{ia} represents the weight of assigning customer i to alternative a. This weight is set to 0 if a is the customer's first choice, and is increased by 1 as the preference given to an option decreases. If a refers to a delivery by a van at a private address, w_{ia} is set to a reasonably high value. Constraints (6) ensure that each customer is assigned to exactly one alternative. Constraints (7) impose that the capacity of PLs is not exceeded, whereas constraint (8) prohibits reassigning customer i_0 to its original PL. Finally, constraints (9) define the domain of the variables.

After reassigning each element of C' to a feasible alternative, the routing is demanded to an off-the-shelf solver in the fashion of Section 4.1. Again, details about the specific solvers used are provided in Section 5.

4.4. A large neighborhood search procedure

As mentioned before, the sequence of destroy-and-repair operations is repeated until a stopping criterion is met, in a large-neighborhood-search fashion (Shaw, 1998). The pseudocode of the procedure is reported in Algorithm 2 for the sake of completeness. The algorithm takes as inputs: s_0, the initial solution; $h_{\min}$ and $h_{\max}$, the minimum and the maximum level of depth in the destroy phase, respectively; $T_{\max}$, the time limit; $z(\cdot)$, the performance measure according to which a solution is evaluated. Regarding the latter, in this paper, we consider the three different objective functions defined in Section 3, all of which must be minimized.

© 2026 The Author(s).
International Transactions in Operational Research published by John Wiley & Sons Ltd on behalf of International Federation of Operational Research Societies.

14753995, 2026, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/itor.70169 by Universita Del Salento Ser Inf Bibliot "La Stecca", Wiley Online Library on [08/06/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

The procedure is repeated until a maximum time limit is reached (Algorithm 2, line 3). Starting with the lowest value for parameter h for the destroy phase (Algorithm 2, line 4), we first identify the seed customer i_0 (Algorithm 2, line 5), as defined in Section 4.2.1. Then, a destroy and a repair step are performed in sequence on the current solution (Algorithm 2, line 7). If the new solution obtained is better than the current, then the current is updated and h is eventually set back to the initial value (Algorithm 2, lines 8–10). Otherwise, h is increased by 1 to widen the search space to be explored within the destroy-and-repair step (Algorithm 2, line 12).

5. Computational experiments

In this section, we describe the computational results of the analysis we have performed to assess our approach. All the algorithms have been coded in Java, whereas the mathematical models have been coded in OPL and solved using IBM ILOG CPLEX 22.1.0. As an off-the-shelf solver for the VRP and the PDP, when constructing the initial solution and when repairing the solution, we have used the OR-Tools library by Google (https://developers.google.com/optimization). The experiments have been run on a Linux machine with an Intel Core i7 processor clocked at 3 GHz and equipped with 16 GB of RAM. In what follows, we first describe the instances used in our tests and the algorithm setting, and then we present and discuss the results of our experimentation, together with a sensitivity study. Finally, we report some insights of a managerial analysis to show the potential cost and environmental benefits of the proposed delivery framework, in comparison to more conventional approaches.

5.1. Test instances

To test our approach, we have generated instances resembling the distribution of parcels in the urban area of Rome (Italy). By uniformly sampling from a dataset of real addresses extracted from OpenStreetMap (www.openstreetmap.org), we have obtained the customer locations, the drop-off points, the ADR depots, and the van depot. Thus, we have generated three datasets of 10 instances each, characterized by $|C| \in \{500, 700, 900\}$, $|P| = 50$, and $|D| = 25$. Moreover, we have considered: number of priority customers, $|C_p| = 0.3|C|$; number of alternative PLs, $k = 3$; PL capacity, Q_p uniformly selected in $\{3, 4, 5, 6, 7, 8\}$; ADR capacity, $Q_d = 3$; ADR maximum distance that can be covered with a full battery, $\delta = 16$ km.

5.2. Algorithm setting

Our algorithm has been tested with a time limit $T_{\max} = 30$ minutes and the three different strategies for selecting the seed customer i_0 described in Section 4.2.1, namely random, adaptive, and restricted. Moreover, the values of $h_{\min}$ and $h_{\max}$ are 2 and 5, respectively, and we impose a time limit of five minutes for each repair step. Regarding the three performance measures, their parameters are defined as follows.

© 2026 The Author(s).
International Transactions in Operational Research published by John Wiley & Sons Ltd on behalf of International Federation of Operational Research Societies.

14753995, 2026, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/itor.70169 by Universita Del Salento Ser Inf Biblior "La Stecca", Wiley Online Library on [08/06/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

- Total penalty: the penalty associated with each customer $i \in C_{np}$ is $\pi_i = j$, if the assigned PL is the jth among those in L_i, in order of decreasing preference ($j = 1, \ldots, k$). If the customer is served by a van, then $\pi_i = k + 1$. Concerning customers $i \in C_p$, the penalty is $\pi_i = 0$ if the customer is served by an ADR, and $\pi_i = k + 1$ if it is served by a van.
- CO_2 emissions: similarly to De Maio et al. (2024), in our experiments, we have considered $e_v = 0.200$ kg of CO_2/km, and $e_d = 0.001$ kg of CO_2/km.
- Costs: again inspired by De Maio et al. (2024), the fuel cost per kilometer for traditional vans is obtained by considering a cost of 1.90 € /l of diesel fuel and an average consumption of 8.2 l/100 km (mixed driving), leading to $c_v = 0.156$ € /km. Regarding ADRs, the energy cost per kilometer is obtained by multiplying an energy cost of 0.30 € /kWh and an energy consumption of 0.0247 kWh/km, obtaining $c_d = 0.007$ € /km.

Concerning the options used for the routing solver in OR-Tools, to generate the initial solution, we employed PATH_CHEAPEST_ARC for the VRP and PARALLEL_CHEAPEST_INSERTION for the PDP. The former starts from the route's start node and iteratively connects it to the node that yields the cheapest additional segment, extending the route from the most recently added node. The latter incrementally builds a solution by inserting, at each step, the cheapest node in its cheapest feasible position. For the local search phase, in both problems we selected GUIDED_LOCAL_SEARCH, which relies on the guided local search metaheuristic (Voudouris et al., 2025) to escape local minima.

5.3. Results analysis

In this section, we analyze the results obtained by our solution approach with the three strategies for selecting customer i_0 and the three performance measures of Section 3. Tables 1–9 report the results differentiated according to the number of customers and the performance measure. The strategies used to identify the seed customer are labeled as "RANDOM," "ADAPTIVE," and "RESTRICTED." On the other hand, the performance measures are labeled as "PENALTY," "EMISSIONS," and "COST." In the tables, the "INITIAL" columns contain the objective function values of the initial solutions. Moreover, for each seed customer strategy, the column headings are as follows: "z^*," best solution found by the considered strategy, within the given time limit (the bold values are the best among all the three strategies); "DEV," percentage deviation of the performance measure value compared to INITIAL, obtained as DEV $= 100(z^* - \text{INITIAL})/\text{INITIAL}$ (as far as DEV is concerned, a negative value means that the considered result is better than INITIAL); "Time best," time (in seconds) to find the best solution; "Δ_v," total distance (in kilometers) traveled by vans in the best solution; "Δ_d," total distance (in kilometers) traveled by ADRs in the best solution.

Concerning the PENALTY performance measure, it is worth noting that the initial solution obtained by model (1)–(4) is already of very high quality. In fact, this solution matches the best solution found at the time limit in five, eight, and three out of 10 instances for the cases with 500, 700, and 900 customers, respectively. For the remaining instances, the best strategy turns out to be RESTRICTED for the cases with 500 and 700 customers, and RANDOM for those with 900

© 2026 The Author(s).
International Transactions in Operational Research published by John Wiley & Sons Ltd on behalf of International Federation of Operational Research Societies.

14753995, 2026, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/itor.70169 by Universita Del Salento Ser Int Bibliot "La Stecca", Wiley Online Library on [08/06/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table 1
Results for the instances with 500 customers and the PENALTY performance measure

Instance	INITIAL	RANDOM					ADAPTIVE					RESTRICTED				
		z^*	DEV	Time best	Δ_v	Δ_d	z^*	DEV	Time best	Δ_v	Δ_d	z^*	DEV	Time best	Δ_v	Δ_d
500_1	350	347	−0.86%	1527.01	347.50	533.70	347	−0.86%	1818.1	351.00	535.60	**345**	−1.43%	908.45	346.80	535.00
500_2	364	**362**	−0.55%	303.22	327.80	474.10	363	−0.27%	906.0	327.10	485.90	364	0.00%	0.00	326.10	476.70
500_3	**352**	352	0.00%	0.00	342.80	568.60	352	0.00%	0.0	340.90	568.60	352	0.00%	0.00	341.50	568.60
500_4	**349**	349	0.00%	0.00	413.30	524.90	349	0.00%	0.0	413.30	524.90	349	0.00%	0.00	413.30	524.90
500_5	**372**	372	0.00%	0.00	350.60	483.50	372	0.00%	0.0	350.60	483.50	372	0.00%	0.00	350.60	483.50
500_6	**359**	359	0.00%	0.00	241.60	511.10	359	0.00%	0.0	241.60	511.10	359	0.00%	0.00	241.60	511.10
500_7	364	364	0.00%	0.00	324.50	539.70	364	0.00%	0.0	324.50	539.70	**363**	−0.27%	604.25	322.50	538.80
500_8	**375**	375	0.00%	0.00	321.10	469.70	375	0.00%	0.0	321.10	469.70	375	0.00%	0.00	321.10	469.70
500_9	384	384	0.00%	0.00	377.20	472.50	384	0.00%	0.0	377.20	472.50	**383**	−0.26%	903.63	367.60	480.00
500_10	367	367	0.00%	0.00	333.80	508.20	367	0.00%	0.0	333.80	508.20	**365**	−0.54%	1206.65	338.90	522.10
AVERAGE	363.60	363.10	−0.14%	183.02	338.02	508.60	363.20	−0.11%	272.41	338.11	509.97	362.70	−0.25%	362.30	337.00	511.04

© 2026 The Author(s).
International Transactions in Operational Research published by John Wiley & Sons Ltd on behalf of International Federation of Operational Research Societies.

14753995, 2026, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/itor.70169 by Universita Del Salento Ser Inf Biblior "La Stecca", Wiley Online Library on [08/06/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table 2
Results for the instances with 500 customers and the EMISSIONS performance measure

Instance	INITIAL	RANDOM					ADAPTIVE					RESTRICTED				
		z^*	DEV	Time best	Δ_v	Δ_d	z^*	DEV	Time best	Δ_v	Δ_d	z^*	DEV	Time best	Δ_v	Δ_d
500_1	73.79	67.90	−7.99%	1820.60	336.80	537.80	**66.44**	−9.96%	1512.40	329.60	524.30	68.41	−7.30%	1209.79	339.40	527.00
500_2	65.70	**65.62**	−0.12%	301.52	325.70	476.70	65.68	−0.03%	1809.50	326.00	476.70	65.70	0.00%	1205.87	326.10	475.10
500_3	68.87	**68.36**	−0.74%	1212.16	339.00	556.30	68.37	−0.73%	906.77	339.00	568.60	68.41	−0.67%	1510.37	339.20	565.40
500_4	83.18	80.82	−2.84%	1514.65	401.50	524.90	80.17	−3.63%	1815.52	398.20	528.50	**79.54**	−4.38%	907.13	395.10	524.90
500_5	70.60	62.14	−11.98%	302.70	308.30	484.20	62.29	−11.77%	1507.27	309.10	472.30	62.18	−11.93%	1507.01	308.50	477.10
500_6	48.83	48.38	−0.92%	1211.38	239.30	522.90	48.83	0.00%	0.00	241.60	511.10	**48.30**	−1.09%	1209.88	238.90	519.50
500_7	65.44	63.71	−2.64%	1211.04	315.90	530.10	**61.28**	−6.35%	907.63	303.70	543.70	63.90	−2.35%	603.58	316.90	520.80
500_8	64.69	**64.01**	−1.05%	905.23	317.70	469.70	64.35	−0.52%	1205.32	319.40	471.40	64.39	−0.46%	904.26	319.60	469.70
500_9	75.91	**73.99**	−2.53%	1205.61	367.60	472.50	74.50	−1.86%	1205.68	370.10	480.00	74.63	−1.69%	904.36	370.80	472.50
500_10	67.27	58.98	−12.32%	605.36	292.30	524.10	**58.55**	−12.96%	604.82	290.20	507.30	67.26	−0.01%	302.08	333.70	522.80
AVERAGE	68.43	65.39	−4.31%	1029.02	324.41	509.92	65.05	−4.78%	1147.49	322.69	508.39	66.27	−2.99%	1026.43	328.82	507.488

© 2026 The Author(s).
International Transactions in Operational Research published by John Wiley & Sons Ltd on behalf of International Federation of Operational Research Societies.

14753995, 2026, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/itor.70169 by Universita Del Salento Ser Inf Biblior "La Stecca", Wiley Online Library on [08/06/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table 3
Results for the instances with 500 customers and the COST performance measure

Instance	INITIAL	RANDOM					ADAPTIVE					RESTRICTED				
		z^*	DEV	Time best	Δ_v	Δ_d	z^*	DEV	Time best	Δ_v	Δ_d	z^*	DEV	Time best	Δ_v	Δ_d
500_1	60.88	56.64	−6.96%	1208.44	339.40	527.00	**56.30**	−7.52%	302.61	336.70	538.60	56.64	−6.96%	1208.72	339.40	527.00
500_2	54.21	54.19	−0.03%	1508.36	326.10	474.50	**54.17**	−0.08%	301.89	325.80	477.30	54.19	−0.03%	301.89	326.10	474.50
500_3	57.16	56.87	−0.50%	1509.23	339.20	565.40	**56.82**	−0.60%	1207.22	338.70	568.60	56.87	−0.50%	1508.60	339.20	565.40
500_4	68.15	**65.69**	−3.60%	302.15	397.40	528.50	66.01	−3.14%	1813.23	399.20	533.50	**65.69**	−3.60%	1207.22	397.40	528.50
500_5	58.08	51.68	−11.01%	1808.80	309.60	483.50	**51.57**	−11.20%	903.91	308.90	483.50	51.64	−11.09%	1509.89	309.30	484.10
500_6	41.27	**40.90**	−0.88%	1209.28	238.90	519.50	41.05	−0.52%	1508.82	239.90	518.50	**40.90**	−0.88%	1813.23	238.90	519.50
500_7	54.40	**53.08**	−2.42%	603.97	316.90	520.80	53.79	−1.13%	303.12	320.20	547.90	**53.08**	−2.42%	302.78	316.90	520.80
500_8	53.38	53.15	−0.44%	904.56	319.60	469.70	**53.05**	−0.61%	904.57	319.00	469.70	53.15	−0.44%	903.91	319.60	469.70
500_9	62.15	61.15	−1.61%	903.84	370.80	472.50	**60.98**	−1.88%	1203.52	369.70	472.50	61.15	−1.61%	1807.60	370.80	472.50
500_10	55.63	**54.99**	−1.15%	605.23	329.10	521.60	55.11	−0.94%	302.47	329.60	526.80	**54.99**	−1.15%	1508.82	329.10	521.60
AVERAGE	56.53	54.84	−2.86%	1056.39	328.70	508.30	54.88	−2.76%	875.14	328.77	513.69	54.83	−2.87%	1207.27	328.67	508.36

© 2026 The Author(s).
International Transactions in Operational Research published by John Wiley & Sons Ltd on behalf of International Federation of Operational Research Societies.

14753995, 2026, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/itor.70169 by Universita Del Salento Ser Inf Biblior "La Stecca", Wiley Online Library on [08/06/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table 4
Results for the instances with 700 customers and the PENALTY performance measure

Instance	INITIAL	RANDOM					ADAPTIVE					RESTRICTED				
		z^*	DEV	Time best	Δ_v	Δ_d	z^*	DEV	Time best	Δ_v	Δ_d	z^*	DEV	Time best	Δ_v	Δ_d
700_1	**524**	524.00	0.00%	0.00	386.10	629.60	524.00	0.00%	0.00	385.20	629.60	524.00	0.00%	0.00	385.20	629.60
700_2	**558**	558.00	0.00%	0.00	392.60	653.00	558.00	0.00%	0.00	392.60	653.00	558.00	0.00%	0.00	392.60	653.00
700_3	**555**	555.00	0.00%	0.00	379.80	591.40	555.00	0.00%	0.00	379.80	591.40	555.00	0.00%	0.00	379.80	591.40
700_4	**516**	516.00	0.00%	0.00	425.00	611.20	516.00	0.00%	0.00	425.00	611.20	516.00	0.00%	0.00	425.00	611.20
700_5	**516**	516.00	0.00%	0.00	400.60	640.00	516.00	0.00%	0.00	399.80	645.60	516.00	0.00%	0.00	399.80	645.60
700_6	541	541.00	0.00%	0.00	406.50	633.60	**540.00**	−0.18%	1211.53	391.70	638.90	541.00	0.00%	0.00	406.50	633.60
700_7	511	511.00	0.00%	0.00	387.60	695.60	508.00	−0.59%	911.28	387.40	704.70	**506.00**	−0.98%	1213.45	389.60	693.40
700_8	**536**	536.00	0.00%	0.00	414.50	623.80	536.00	0.00%	0.00	414.50	623.80	536.00	0.00%	0.00	414.50	623.80
700_9	**565**	565.00	0.00%	0.00	348.30	679.40	565.00	0.00%	0.00	348.30	679.40	565.00	0.00%	0.00	348.30	679.40
700_10	**550**	550.00	0.00%	0.00	421.00	695.60	550.00	0.00%	0.00	421.00	695.60	550.00	0.00%	0.00	421.00	695.60
AVERAGE	537.20	537.20	0.00%	0.00	396.20	645.32	536.80	−0.08%	212.28	394.53	647.32	536.70	−0.10%	121.34	396.23	645.66

© 2026 The Author(s).
International Transactions in Operational Research published by John Wiley & Sons Ltd on behalf of International Federation of Operational Research Societies.

14753995, 2026, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/itor.70169 by Universita Del Salento Ser Inf Biblior "La Stecca", Wiley Online Library on [08/06/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table 5
Results for the instances with 700 customers and the EMISSIONS performance measure

Instance	INITIAL	RANDOM					ADAPTIVE					RESTRICTED				
		z^*	DEV	Time best	Δ_v	Δ_d	z^*	DEV	Time best	Δ_v	Δ_d	z^*	DEV	Time best	Δ_v	Δ_d
700_1	77.67	**76.82**	−1.09%	1212.28	380.90	644.10	77.02	−0.84%	1513.97	381.90	637.30	77.15	−0.67%	1817.86	382.50	651.80
700_2	79.17	**78.73**	−0.57%	1210.89	390.40	645.50	79.03	−0.17%	1817.75	392.00	634.80	78.75	−0.53%	1513.71	390.50	652.50
700_3	76.55	76.55	0.00%	0.00	379.80	591.40	76.55	0.00%	0.00	379.80	591.40	**76.21**	−0.44%	302.04	378.10	591.40
700_4	85.61	84.94	−0.79%	302.56	421.60	618.50	85.54	−0.08%	908.33	424.60	623.20	**84.42**	−1.39%	1514.58	419.00	619.10
700_5	80.61	80.53	−0.10%	1210.77	399.40	645.60	**80.37**	−0.30%	605.27	398.60	645.60	**80.37**	−0.30%	302.45	398.60	645.60
700_6	81.93	81.93	0.00%	0.00	406.50	633.60	**81.55**	−0.46%	302.67	404.60	633.60	81.93	0.00%	606.60	406.50	631.10
700_7	77.80	77.80	0.00%	0.00	385.50	700.20	**77.76**	−0.05%	1821.36	385.30	697.60	77.80	0.00%	0.00	385.50	700.20
700_8	83.52	83.06	−0.55%	606.54	412.20	620.70	82.64	−1.05%	605.58	410.10	623.80	**80.38**	−3.76%	1513.93	398.80	623.80
700_9	70.34	**70.03**	−0.43%	1815.77	346.80	674.30	70.19	−0.21%	1815.92	347.60	673.50	70.34	0.00%	0.00	348.30	679.40
700_10	84.90	84.90	0.00%	0.00	421.00	695.60	77.82	−8.34%	1515.44	385.60	695.60	**76.50**	−9.89%	1818.67	379.00	695.60
AVERAGE	79.81	79.53	−0.35%	635.88	394.41	646.95	78.85	−1.15%	1090.63	391.01	645.64	78.39	−1.70%	938.98	388.68	649.05

© 2026 The Author(s).
International Transactions in Operational Research published by John Wiley & Sons Ltd on behalf of International Federation of Operational Research Societies.

14753995, 2026, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/itor.70169 by Universita Del Salento Ser Inf Biblior, "La Stecca", Wiley Online Library on [08/06/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table 6
Results for the instances with 700 customers and the COST performance measure

Instance	INITIAL	RANDOM					ADAPTIVE					RESTRICTED				
		z^*	DEV	Time best	Δ_v	Δ_d	z^*	DEV	Time best	Δ_v	Δ_d	z^*	DEV	Time best	Δ_v	Δ_d
700_1	64.50	**63.88**	−0.96%	1211.53	381.10	632.70	63.89	−0.94%	1816.58	381.10	634.40	64.23	−0.41%	1818.31	382.50	651.80
700_2	65.82	65.42	−0.60%	1211.50	390.40	645.50	**63.18**	−4.01%	908.65	376.30	639.40	65.49	−0.50%	1514.22	390.50	652.50
700_3	63.39	63.39	0.00%	0.00	379.80	591.40	63.39	0.00%	0.00	379.80	591.40	**63.12**	−0.42%	301.99	378.10	591.40
700_4	70.58	70.10	−0.68%	302.05	421.60	618.50	**68.59**	−2.82%	1515.54	411.70	623.60	69.70	−1.25%	1514.73	419.00	619.10
700_5	66.89	66.83	−0.09%	1211.37	399.40	645.60	66.89	0.00%	0.00	399.80	645.60	**66.70**	−0.28%	302.58	398.60	645.60
700_6	67.85	67.85	0.00%	0.00	406.50	633.60	**63.19**	−6.87%	1515.78	376.20	643.00	67.83	−0.03%	606.50	406.50	631.10
700_7	65.04	65.03	−0.01%	303.51	385.50	699.30	**64.45**	−0.91%	608.02	381.70	700.20	65.04	0.00%	0.00	385.50	700.20
700_8	69.03	68.65	−0.55%	605.21	412.20	620.70	**65.14**	−5.63%	302.84	389.90	617.00	66.58	−3.55%	1515.08	398.80	623.80
700_9	59.09	58.82	−0.46%	1815.58	346.80	674.30	**58.76**	−0.55%	302.48	346.20	679.40	59.09	0.00%	0.00	348.30	679.40
700_10	70.55	70.55	0.00%	0.00	421.00	695.60	70.20	−0.48%	1818.34	418.60	700.40	**63.95**	−9.35%	1817.64	378.70	695.60
AVERAGE	66.27	66.05	−0.33%	666.07	394.43	645.72	64.77	−2.22%	878.82	386.13	647.44	65.17	−1.58%	939.11	388.65	649.05

© 2026 The Author(s).
International Transactions in Operational Research published by John Wiley & Sons Ltd on behalf of International Federation of Operational Research Societies.

14753995, 2026, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/itor.70169 by Universita Del Salento Ser Inf Biblior, "La Stecca", Wiley Online Library on [08/06/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table 7
Results for the instances with 900 customers and the PENALTY performance measure

Instance	INITIAL	RANDOM					ADAPTIVE					RESTRICTED				
		z^*	DEV	Time best	Δ_v	Δ_d	z^*	DEV	Time best	Δ_v	Δ_d	z^*	DEV	Time best	Δ_v	Δ_d
900_1	874	869.00	−0.57%	305.11	432.60	787.40	**866.00**	−0.92%	1829.47	400.90	793.90	873.00	−0.11%	614.25	423.50	794.50
900_2	740	**732.00**	−1.08%	941.59	394.80	863.40	733.00	−0.95%	620.54	393.20	877.00	735.00	−0.68%	930.21	393.40	857.10
900_3	783	**773.00**	−1.28%	1848.10	481.90	770.10	776.00	−0.89%	307.72	458.80	760.20	779.00	−0.51%	615.59	445.80	763.80
900_4	753	753.00	0.00%	0.00	502.90	735.90	**752.00**	−0.13%	1527.39	497.60	741.20	**752.00**	−0.13%	1526.73	440.80	741.20
900_5	**772**	772.00	0.00%	0.00	453.50	783.10	772.00	0.00%	0.00	453.50	783.10	772.00	0.00%	0.00	453.50	783.10
900_6	**703**	703.00	0.00%	0.00	460.90	764.70	703.00	0.00%	0.00	460.90	764.70	703.00	0.00%	0.00	460.90	764.70
900_7	719	**718.00**	−0.14%	308.23	461.30	770.80	719.00	0.00%	0.00	450.40	789.00	719.00	0.00%	0.00	450.40	789.00
900_8	782	777.00	−0.64%	1845.11	450.60	832.80	**776.00**	−0.77%	615.58	455.80	829.40	778.00	−0.51%	618.31	441.80	821.50
900_9	**784**	784.00	0.00%	0.00	409.90	822.20	784.00	0.00%	0.00	409.90	822.20	784.00	0.00%	0.00	409.90	822.20
900_10	758	755.00	−0.40%	307.10	453.70	823.30	756.00	−0.26%	612.86	454.90	821.10	**753.00**	−0.66%	1230.77	451.70	820.40
AVERAGE	766.80	763.60	−0.41%	555.52	450.21	795.37	763.70	−0.39%	551.36	443.59	798.18	764.80	−0.26%	553.59	437.17	795.75

© 2026 The Author(s).
International Transactions in Operational Research published by John Wiley & Sons Ltd on behalf of International Federation of Operational Research Societies.

14753995, 2026, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/itor.70169 by Universita Del Salento Ser Inf Biblior "La Stecca", Wiley Online Library on [08/06/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table 8
Results for the instances with 900 customers and the EMISSIONS performance measure

Instance	INITIAL	RANDOM					ADAPTIVE					RESTRICTED				
		z^*	DEV	Time best	Δ_v	Δ_d	z^*	DEV	Time best	Δ_v	Δ_d	z^*	DEV	Time best	Δ_v	Δ_d
900_1	80.91	**80.71**	−0.25%	609.05	399.70	769.50	80.75	−0.20%	1826.01	399.90	769.90	80.90	−0.02%	914.05	400.70	756.50
900_2	77.76	**77.36**	−0.51%	306.46	382.60	843.90	77.37	−0.50%	1530.56	382.70	832.30	77.70	−0.08%	919.71	384.30	838.20
900_3	91.86	**86.89**	−5.42%	1219.33	430.60	765.50	91.16	−0.77%	1828.56	452.00	759.80	89.24	−2.85%	610.86	442.40	763.70
900_4	101.32	90.20	−10.97%	1830.58	447.30	739.30	**87.57**	−13.56%	1525.60	434.20	734.60	89.50	−11.67%	1218.60	443.80	735.50
900_5	91.44	**84.52**	−7.57%	1830.36	418.90	739.50	90.83	−0.67%	1834.27	450.30	769.10	91.03	−0.45%	1830.20	451.30	768.90
900_6	92.78	92.78	0.00%	0.00	460.10	764.70	92.60	−0.19%	917.46	459.20	764.70	**91.36**	−1.53%	609.27	453.00	764.70
900_7	90.87	89.81	−1.16%	1835.05	445.10	792.00	**83.95**	−7.62%	1223.84	415.80	789.00	89.95	−1.01%	1528.03	445.80	789.00
900_8	99.01	89.11	−10.00%	1524.13	441.40	827.70	**85.31**	−13.84%	1522.79	422.40	825.10	89.38	−9.72%	1831.17	442.80	824.30
900_9	82.80	**81.99**	−0.98%	916.03	405.80	832.40	82.53	−0.33%	915.91	408.60	810.60	82.80	0.00%	0.00	409.90	822.20
900_10	91.82	85.17	−7.25%	914.97	421.80	805.00	**84.41**	−8.07%	305.54	418.00	811.00	90.41	−1.54%	1221.87	448.00	811.00
AVERAGE	90.06	85.85	−4.41%	1098.59	425.33	787.95	85.65	−4.58%	1343.05	424.31	786.61	87.23	−2.89%	1068.37	432.20	787.40

© 2026 The Author(s).
International Transactions in Operational Research published by John Wiley & Sons Ltd on behalf of International Federation of Operational Research Societies.

14753995, 2026, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/itor.70169 by Universita Del Salento Ser Inf Biblior, "La Stecca", Wiley Online Library on [08/06/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table 9
Results for the instances with 900 customers and the COST performance measure

Instance	INITIAL	RANDOM					ADAPTIVE					RESTRICTED				
		z^*	DEV	Time best	Δ_v	Δ_d	z^*	DEV	Time best	Δ_v	Δ_d	z^*	DEV	Time best	Δ_v	Δ_d
900_1	68.29	**67.65**	−0.94%	1525.35	399.70	756.10	67.90	−0.57%	609.84	400.70	769.90	67.86	−0.63%	1831.02	400.60	766.60
900_2	65.90	**65.59**	−0.48%	1532.48	382.60	843.00	**65.59**	−0.47%	919.83	382.60	843.90	65.82	−0.13%	920.63	384.30	838.20
900_3	76.40	**72.53**	−5.07%	1219.60	430.60	765.50	73.05	−4.39%	303.91	434.00	763.70	74.36	−2.67%	609.48	442.40	763.70
900_4	83.60	74.95	−10.35%	1828.93	447.30	739.30	76.31	−8.72%	608.50	456.30	732.80	**74.38**	−11.03%	1219.50	443.80	735.50
900_5	76.23	75.81	−0.55%	304.92	451.40	769.80	76.22	−0.01%	927.01	454.40	762.20	**71.15**	−6.66%	1833.27	422.30	753.40
900_6	77.13	77.13	0.00%	1834.09	460.10	764.70	77.12	−0.01%	1220.27	460.10	764.10	**76.02**	−1.44%	609.33	453.00	764.70
900_7	75.79	**74.98**	−1.06%	1838.37	445.10	792.00	70.92	−6.42%	919.01	419.20	789.00	75.07	−0.95%	1530.84	445.80	789.00
900_8	82.37	**74.65**	−9.37%	1525.14	441.40	827.70	71.00	−13.81%	306.06	418.00	827.70	74.85	−9.14%	1827.64	442.80	824.30
900_9	69.70	69.13	−0.82%	914.33	405.80	832.40	69.64	−0.09%	913.44	409.40	824.70	**68.87**	−1.19%	1526.61	403.40	848.80
900_10	76.61	71.44	−6.76%	914.33	421.80	805.00	**70.82**	−7.56%	1222.12	417.80	805.80	75.57	−1.37%	1221.45	448.00	811.00
AVERAGE	75.20	72.39	−3.54%	1343.75	428.58	789.55	71.86	−4.20%	795.00	425.25	788.38	72.39	−3.52%	1312.98	428.64	789.52

© 2026 The Author(s).
International Transactions in Operational Research published by John Wiley & Sons Ltd on behalf of International Federation of Operational Research Societies.

14753995, 2026, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/itor.70169 by Universita Del Salento Ser Inf Biblior, "La Stecca", Wiley Online Library on [08/06/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table 10
Results of the sensitivity analysis for k for the instances with 500 customers

Instance	$k = 3$		$k = 5$				$k = 7$			
	Emissions	Cost	Emissions	Cost	DEV emissions	DEV cost	Emissions	Cost	DEV emissions	DEV cost
500_1	66.44	56.30	67.32	52.77	1.32%	−6.26%	69.26	56.77	4.24%	0.85%
500_2	65.68	54.17	66.95	51.05	1.94%	−5.74%	66.48	54.98	1.22%	1.51%
500_3	68.37	56.82	61.76	52.61	−9.66%	−7.40%	64.96	53.17	−4.98%	−6.42%
500_4	80.17	66.01	58.14	48.43	−27.48%	−26.63%	70.27	58.00	−12.35%	−12.13%
500_5	62.29	51.57	60.57	50.38	−2.76%	−2.32%	73.83	60.73	18.52%	17.76%
500_6	48.83	41.05	65.50	54.45	34.14%	32.63%	59.43	49.45	21.71%	20.44%
500_7	61.28	53.79	81.08	66.13	32.31%	22.95%	66.18	54.58	7.99%	1.48%
500_8	64.35	53.05	64.66	53.26	0.48%	0.39%	78.33	64.15	21.72%	20.92%
500_9	74.50	60.98	76.13	58.00	2.19%	−4.89%	74.26	64.35	−0.32%	5.53%
500_10	58.55	55.11	68.40	55.86	16.82%	1.37%	65.63	57.40	12.10%	4.16%
AVERAGE	65.05	54.88	67.05	54.29	4.93%	0.41%	68.86	57.36	6.98%	5.41%

customers. However, the average improvements are minimal, amounting to only a few tenths of a percentage point.

When we consider the other two performance measures, namely EMISSIONS and COST, which are both proportional to the total distance traveled by vans and ADRs, there is no clear strategy outperforming the others. This is probably due to the fact that none of them explicitly bases the choice of the portion of the solution to destroy on the minimization of the traveled distance. More specifically, ADAPTIVE achieves the best results for EMISSIONS with 500 and 900 customers (average improvements of −4.78% and −4.58%, respectively) and for COST with 700 and 900 customers (average improvements of −2.22% and −4.20%, respectively). On the other hand, RESTRICTED yields the best performance for EMISSIONS with 700 customers (−1.70%) and for COST with 500 customers (−2.87%). Overall, however, the approaches that do not achieve the best performance still yield results that remain close to the best observed values.

If we take into account the column "Time best," we observe that all three strategies are typically able to find the best solutions well before the time limit. Across all instances, the best solution is obtained close to the limit only in a very small number of cases.

5.4. Sensitivity analysis

Here, we investigate how the performance of our approach can vary according to some instance parameters. To this end, we study the sensitivity of the solutions to changes in the number of alternative PLs k and the number of priority customers $|C_p|$. In particular, we run the ADAPTIVE algorithm with $|C_p| \in \{0.2|C|, 0.4|C|, 0.5|C|\}$ (in addition to the original value $|C_p| = 0.3|C|$) and $k \in \{5, 7\}$ (in addition to the previous value $k = 3$). The quality of the solutions is evaluated with respect to the emissions and costs objective functions, which are the most relevant to evaluate the impact of the proposed delivery scheme on the community.

The additional computations are reported in Tables 10–15, where a time limit of 30 minutes is considered. More specifically, Tables 10–12 refer to the sensitivity study for k, whereas Tables 13–15

© 2026 The Author(s).
International Transactions in Operational Research published by John Wiley & Sons Ltd on behalf of International Federation of Operational Research Societies.

14753995, 2026, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/itor.70169 by Universita Del Salento Ser Inf Biblior "La Stecca", Wiley Online Library on [08/06/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table 11
Results of the sensitivity analysis for k for the instances with 700 customers

Instance	$k=3$		$k=5$				$k=7$			
	Emissions	Cost	Emissions	Cost	DEV emissions	DEV cost	Emissions	Cost	DEV emissions	DEV cost
700_1	77.02	63.89	77.15	64.49	0.18%	0.94%	76.46	68.83	−0.73%	7.73%
700_2	79.03	63.18	67.60	56.73	−14.46%	−10.21%	74.63	61.56	−5.57%	−2.56%
700_3	76.55	63.39	74.32	66.59	−2.92%	5.05%	87.32	70.54	14.07%	11.29%
700_4	85.54	68.59	81.31	66.38	−4.94%	−3.22%	74.20	62.14	−13.25%	−9.41%
700_5	80.37	66.89	76.35	63.73	−4.99%	−4.72%	76.85	63.99	−4.37%	−4.33%
700_6	81.55	63.19	82.07	68.98	0.63%	9.16%	85.97	67.20	5.41%	6.35%
700_7	77.76	64.45	80.91	67.73	4.05%	5.10%	83.82	69.72	7.80%	8.19%
700_8	82.64	65.14	76.54	63.45	−7.39%	−2.59%	76.21	60.17	−7.79%	−7.64%
700_9	70.19	58.76	76.80	63.85	9.41%	8.66%	82.24	66.24	17.16%	12.72%
700_10	77.82	70.20	83.77	69.63	7.65%	−0.82%	88.84	72.63	14.16%	3.45%
AVERAGE	78.85	64.77	77.68	65.16	−1.28%	0.74%	80.65	66.30	2.69%	2.58%

Table 12
Results of the sensitivity analysis for k for the instances with 900 customers

Instance	$k=3$		$k=5$				$k=7$			
	Emissions	Cost	Emissions	Cost	DEV emissions	DEV cost	Emissions	Cost	DEV emissions	DEV cost
900_1	80.75	67.90	87.82	72.36	8.76%	6.57%	86.19	71.35	6.73%	5.09%
900_2	77.37	65.59	81.67	73.63	5.55%	12.25%	91.48	76.98	18.24%	17.36%
900_3	91.16	73.05	90.54	75.40	−0.68%	3.21%	90.03	74.67	−1.24%	2.22%
900_4	87.57	76.31	94.68	74.66	8.11%	−2.17%	96.83	80.99	10.57%	6.14%
900_5	90.83	76.22	86.41	73.66	−4.87%	−3.36%	90.43	75.45	−0.44%	−1.02%
900_6	92.60	77.12	88.49	73.69	−4.45%	−4.45%	89.62	74.61	−3.23%	−3.26%
900_7	83.95	70.92	89.85	74.47	7.03%	5.00%	79.99	67.32	−4.71%	−5.07%
900_8	85.31	71.00	87.74	72.36	2.85%	1.92%	86.48	72.33	1.37%	1.87%
900_9	82.53	69.64	93.39	69.36	13.16%	−0.40%	91.82	77.31	11.25%	11.02%
900_10	84.41	70.82	82.29	70.27	−2.51%	−0.77%	87.73	72.86	3.93%	2.88%
AVERAGE	85.65	71.86	88.29	72.99	3.30%	1.78%	89.06	74.39	4.25%	3.72%

refer to the analysis for $|C_p|$. The column headings are "Emissions," EMISSIONS performance measure for the reference value (i.e., $k = 3$ for the number of alternative PLs and $|C_p| = 0.3|C|$ for the number of priority customers), obtained as $e_v\Delta_v$; "Cost," COST performance measure for the reference value, obtained as $c_v\Delta_v$; "DEV emissions," percentage deviation of the emissions of the alternative value compared to the reference value; "DEV cost," percentage deviation of the costs of the alternative value compared to the reference value. Both deviations are computed as 100(Alternative value − Reference value)/Reference value, so that a positive value means that the alternative value performs worse than the reference value.

Concerning the sensitivity analysis on k, the tables indicate that the best results are obtained with the original choice $k = 3$ for all the alternatives considered, with the sole exception of the emissions value for 700 customers, where $k = 5$ yields an improvement over the reference value of −1.28%. A closer inspection of Tables 10–12 shows that the overall sensitivity to the parameter k is limited. For the instances with 500 customers (Table 10), both $k = 5$ and $k = 7$ generally lead to

© 2026 The Author(s).
International Transactions in Operational Research published by John Wiley & Sons Ltd on behalf of International Federation of Operational Research Societies.

14753995, 2026, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/itor.70169 by Universita Del Salento Ser Inf Biblior "La Stecca", Wiley Online Library on [08/06/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table 13
Results of the sensitivity analysis for $|C_p|$ for the instances with 500 customers

Instance	$\|C_p\| = 0.3\|C\|$		$\|C_p\| = 0.2\|C\|$				$\|C_p\| = 0.4\|C\|$			
	Emissions	Cost	Emissions	Cost	DEV emissions	DEV cost	Emissions	Cost	DEV emissions	DEV cost
500_1	66.44	56.30	65.51	53.77	−1.41%	−4.49%	78.68	65.45	18.41%	16.26%
500_2	65.68	54.17	69.60	56.61	5.98%	4.52%	74.81	62.16	13.90%	14.75%
500_3	68.37	56.82	70.81	57.51	3.58%	1.22%	84.01	60.90	22.87%	7.19%
500_4	80.17	66.01	69.07	55.44	−13.84%	−16.01%	65.87	55.20	−17.83%	−16.38%
500_5	62.29	51.57	56.10	45.36	−9.94%	−12.05%	69.62	61.99	11.76%	20.21%
500_6	48.83	41.05	61.80	50.96	26.57%	24.12%	78.00	64.65	59.74%	57.47%
500_7	61.28	53.79	51.94	42.89	−15.24%	−20.26%	64.12	53.81	4.62%	0.05%
500_8	64.35	53.05	62.28	47.62	−3.21%	−10.23%	75.05	63.02	16.63%	18.79%
500_9	74.50	60.98	59.04	48.92	−20.75%	−19.77%	71.47	66.70	−4.06%	9.38%
500_10	58.55	55.11	60.90	49.68	4.01%	−9.85%	64.94	54.06	10.92%	−1.90%
AVERAGE	65.05	54.88	62.71	50.88	−2.43%	−6.28%	72.66	60.79	13.70%	12.58%

Table 14
Results of the sensitivity analysis for $|C_p|$ for the instances with 700 customers

Instance	$\|C_p\| = 0.3\|C\|$		$\|C_p\| = 0.2\|C\|$				$\|C_p\| = 0.4\|C\|$			
	Emissions	Cost	Emissions	Cost	DEV emissions	DEV cost	Emissions	Cost	DEV emissions	DEV cost
700_1	77.02	63.89	65.17	54.00	−15.38%	−15.48%	88.46	68.36	14.86%	6.99%
700_2	79.03	63.18	60.98	50.74	−22.84%	−19.69%	87.09	74.19	10.20%	17.42%
700_3	76.55	63.39	64.83	58.30	−15.31%	−8.02%	92.70	78.49	21.10%	23.83%
700_4	85.54	68.59	70.28	58.06	−17.84%	−15.36%	85.38	72.30	−0.19%	5.41%
700_5	80.37	66.89	63.59	52.65	−20.87%	−21.29%	88.35	73.45	9.94%	9.81%
700_6	81.55	63.19	62.91	57.73	−22.87%	−8.63%	78.37	64.45	−3.90%	1.99%
700_7	77.76	64.45	62.49	52.90	−19.64%	−17.92%	84.04	70.26	8.08%	9.03%
700_8	82.64	65.14	69.87	56.71	−15.45%	−12.94%	75.81	73.58	−8.27%	12.95%
700_9	70.19	58.76	66.73	55.52	−4.93%	−5.52%	75.07	71.37	6.95%	21.46%
700_10	77.82	70.20	68.32	52.49	−12.21%	−25.23%	86.84	72.69	11.60%	3.54%
AVERAGE	78.85	64.77	65.52	54.91	−16.73%	−15.01%	84.21	71.91	7.03%	11.24%

positive deviations in EMISSIONS and COST, indicating deteriorations of up to about 7% (for the emissions) with respect to the baseline $k = 3$. For the 700-customer instances (Table 11), as already noticed, $k = 5$ provides a slight marginal improvement in EMISSIONS, while all other deviations, for both EMISSIONS and COST, remain almost null or close to about 2.50%, confirming that $k = 3$ remains the preferable choice. For the instances with 900 customers (Table 12), increasing k generally worsens performance in both objectives, as indicated by positive deviations for most configurations. Overall, these findings confirm that the proposed methodology is robust with respect to the choice of k: the baseline setting $k = 3$ consistently provides strong results, and deviations from this value tend to lead only to modest, most often unfavorable, changes in performance.

Considering the analysis for the variation of $|C_p|$, Tables 13–15 show that the solution quality is more sensitive to the choice of the percentage of priority customers than to the parameter k. In particular, for the instances with 500 customers (Table 13), reducing the proportion of priority

© 2026 The Author(s).
International Transactions in Operational Research published by John Wiley & Sons Ltd on behalf of International Federation of Operational Research Societies.

14753995, 2026, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/itor.70169 by Universita Del Salento Ser Inf Biblior "La Stecca", Wiley Online Library on [08/06/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table 15
Results of the sensitivity analysis for $|C_p|$ for the instances with 900 customers

Instance	$\|C_p\| = 0.3\|C\|$		$\|C_p\| = 0.2\|C\|$				$\|C_p\| = 0.4\|C\|$			
	Emissions	Cost	Emissions	Cost	DEV emissions	DEV cost	Emissions	Cost	DEV emissions	DEV cost
900_1	80.75	67.90	81.15	63.26	0.50%	−6.84%	100.40	84.28	24.33%	24.12%
900_2	77.37	65.59	81.45	67.59	5.27%	3.04%	91.25	77.22	17.94%	17.73%
900_3	91.16	73.05	84.14	64.96	−7.70%	−11.08%	113.82	90.57	24.86%	23.99%
900_4	87.57	76.31	79.48	65.87	−9.24%	−13.68%	97.89	81.82	11.78%	7.21%
900_5	90.83	76.22	80.47	66.30	−11.40%	−13.02%	93.64	80.53	3.10%	5.66%
900_6	92.60	77.12	86.19	70.53	−6.92%	−8.55%	95.37	83.46	2.99%	8.22%
900_7	83.95	70.92	82.50	73.46	−1.73%	3.58%	96.16	81.37	14.54%	14.74%
900_8	85.31	71.00	86.77	65.98	1.72%	−7.07%	92.13	78.52	8.00%	10.59%
900_9	82.53	69.64	81.80	63.48	−0.88%	−8.85%	96.77	79.69	17.26%	14.43%
900_10	84.41	70.82	83.81	68.80	−0.72%	−2.84%	94.88	80.07	12.40%	13.07%
AVERAGE	85.65	71.86	82.78	67.02	−3.11%	−6.53%	97.23	81.75	13.72%	13.98%

customers to $0.2|C|$ leads to moderate average improvements in both EMISSIONS (−2.43%) and COST (−6.28%) with respect to the reference value $0.3|C|$. Conversely, increasing the proportion to $0.4|C|$ systematically degrades performance, with average deviations of 13.70% in EMISSIONS and 12.58% in COST. A similar behavior is observed for the 700-customer dataset (Table 14), where the configuration $|C_p| = 0.2|C|$ yields substantial improvements on average (−16.73% for EMISSIONS and −15.01% for COST), while the choice $|C_p| = 0.4|C|$ results in consistent deteriorations in both objectives, with deviations of 7.03% and 11.24%, respectively. Finally, for the instances with 900 customers (Table 15), the trend remains the same, that is, decreasing the percentage of priority customers to $0.2|C|$ provides slight improvements (average deviations of −3.11% in EMISSIONS and −6.53% in COST), whereas increasing it to $0.4|C|$ leads to marked deterioration, with average deviations of 13.72% for EMISSIONS and 13.98% for COST. Overall, these findings indicate a clear pattern: reducing the proportion of priority customers from the baseline value of $0.3|C|$ tends to improve both EMISSIONS and COST across all instance sizes, while increasing it to $0.4|C|$ systematically worsens performance. This suggests that allowing a smaller proportion of priority customers generally leads to more favorable performance.

5.5. Managerial insights

The goal of this section is to show the potential cost and environmental benefits of the proposed delivery framework, in comparison to more traditional approaches.

We first compare our proposed scheme, in its ADAPTIVE setting, with a baseline in which a conventional delivery method using exclusively vans is employed (BASELINE VANS, in the following). The fleet of vans is routed by using an off-the-shelf solver as in Sections 4.1 and 4.3. As before, a time limit of 30 minutes is given. The results of this analysis are reported in Tables 16, 17, and 18, referring to the instances with 500, 700, and 900 customers, respectively. The column headings are: "Emissions," value of the EMISSIONS performance measure for BASELINE VANS, obtained as $e_v \Delta_v$; "Cost," value of the COST performance measure for

© 2026 The Author(s).
International Transactions in Operational Research published by John Wiley & Sons Ltd on behalf of International Federation of Operational Research Societies.

14753995, 2026, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/itor.70169 by Universita Del Salento Ser Inf Bibliot "La Stecca", Wiley Online Library on [08/06/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table 16
Results provided by BASELINE VANS for the instances with 500 customers

Instance	Emissions	Cost	DEV emissions	DEV cost
500_1	137.42	107.19	106.82%	90.40%
500_2	145.34	113.37	121.30%	109.29%
500_3	150.96	117.75	120.80%	107.24%
500_4	145.48	113.47	81.47%	71.91%
500_5	140.30	109.43	125.23%	112.19%
500_6	146.14	113.99	199.28%	177.66%
500_7	148.86	116.11	142.90%	115.87%
500_8	131.42	102.51	104.22%	93.22%
500_9	149.72	116.78	100.97%	91.51%
500_10	118.10	92.12	101.72%	67.17%
AVERAGE	141.37	110.27	120.47%	103.65%

Table 17
Results provided by BASELINE VANS for the instances with 700 customers

Instance	Emissions	Cost	DEV emissions	DEV cost
700_1	164.32	128.17	113.35%	100.60%
700_2	165.30	128.93	109.15%	104.08%
700_3	164.92	128.64	115.44%	102.93%
700_4	160.38	125.10	87.48%	82.38%
700_5	167.78	130.87	108.77%	95.65%
700_6	155.62	121.38	90.82%	92.10%
700_7	167.00	130.26	114.77%	102.12%
700_8	158.36	123.52	91.62%	89.61%
700_9	166.46	129.57	137.14%	120.50%
700_10	169.82	132.46	118.23%	88.68%
AVERAGE	164.00	127.89	108.68%	97.87%

Table 18
Results provided by BASELINE VANS for the instances with 900 customers

Instance	Emissions	Cost	DEV emissions	DEV cost
900_1	213.46	166.50	164.35%	145.22%
900_2	188.84	147.30	144.07%	124.56%
900_3	202.22	157.73	121.83%	115.92%
900_4	184.02	143.54	110.13%	88.09%
900_5	182.18	142.10	100.57%	86.43%
900_6	203.86	159.01	120.14%	106.17%
900_7	183.68	143.27	118.80%	102.02%
900_8	193.18	150.68	126.46%	112.22%
900_9	203.44	158.68	146.50%	127.86%
900_10	187.74	146.44	122.41%	106.78%
AVERAGE	194.26	151.52	127.53%	111.53%

© 2026 The Author(s).
International Transactions in Operational Research published by John Wiley & Sons Ltd on behalf of International Federation of Operational Research Societies.

14753995, 2026, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/itor.70169 by Universita Del Salento Ser Inf Biblior "La Stecca", Wiley Online Library on [08/06/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table 19
Results provided by BASELINE VANS+PL for the instances with 500 customers

Instance	Emissions	Cost	DEV emissions	DEV cost
500_1	99.44	77.56	49.66%	37.78%
500_2	89.46	68.62	36.21%	26.69%
500_3	114.88	82.57	68.03%	45.33%
500_4	96.20	81.90	20.00%	24.07%
500_5	91.20	71.26	46.41%	38.17%
500_6	74.52	57.88	52.61%	40.98%
500_7	94.20	73.46	53.71%	36.58%
500_8	94.82	73.44	47.35%	38.44%
500_9	86.86	74.60	16.59%	22.33%
500_10	85.66	67.39	46.31%	22.30%
AVERAGE	92.72	72.87	43.69%	33.27%

BASELINE VANS, obtained as $c_v\Delta_v$; "DEV emissions," percentage deviation of the emission value of BASELINE VANS compared to ADAPTIVE; "DEV cost," percentage deviation of the cost value of BASELINE VANS compared to ADAPTIVE. Both deviations are computed as 100(BASELINE VANS − ADAPTIVE)/ADAPTIVE, so that a positive value means that BASELINE VANS performs worse than ADAPTIVE.

The results reported in the tables clearly show that a delivery framework with PLs and ADRs could allow for achieving huge savings in terms of both emissions and operational costs, compared to a traditional approach with only a fleet of vans. Indeed, for the instances with 500 customers (Table 16), the average emissions are 141.37, with an increase of about 120% with respect to the value of 65.05 provided by ADAPTIVE (see Table 2). A similar result is observed for the cost, with an average increase of 103.65% for BASELINE VANS. Similar results are obtained as the number of customers increases to 700 and 900. In particular, for 700 customers (Table 17), the average increases of emissions and cost are about 109% and 98%, respectively, whereas such average increases are about 128% and 111%, respectively, for the instances with 900 customers (Table 18).

In a further comparison, we consider a setting in which, as before, only vans can be used as delivery vehicles, but, in addition to BASELINE VANS, PLs can also be used. This new baseline is termed BASELINE VANS+PL. As before, we impose a time limit of 30 minutes for each instance. The results of this analysis are reported in Tables 19, 20, and 21 for 500, 700, and 900 customers, respectively.

As the tables show, with 500 customers, neglecting the possibility of using ADRs for delivering to priority customers results in an increase in emissions and costs of about 44% and 33%, respectively (Table 19). Similar increases are confirmed for larger instances. In particular, with 700 customers (Table 20), the average percentage deviations for emissions and costs are about 42% and 32%, respectively. Such values are about 48% and 36% for emissions and costs, respectively, when the number of customer requests grows to 900 (Table 21).

All in all, the outcome of this managerial analysis, by considering a delivery framework in which the service territory is an urban area infrastructure with a sufficiently large number of public drop-off points to which all private deliveries should be made (with the exception of customers with special needs), would result in huge reductions in both CO_2 emissions and costs.

© 2026 The Author(s).
International Transactions in Operational Research published by John Wiley & Sons Ltd on behalf of International Federation of Operational Research Societies.

14753995, 2026, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/itor.70169 by Universita Del Salento Ser Inf Biblior "La Stecca", Wiley Online Library on [08/06/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table 20
Results provided by BASELINE VANS+PL for the instances with 700 customers

Instance	Emissions	Cost	DEV emissions	DEV cost
700_1	116.46	90.11	51.21%	41.03%
700_2	103.86	81.54	31.41%	29.06%
700_3	109.08	85.94	42.49%	35.58%
700_4	118.68	83.35	38.74%	21.52%
700_5	113.38	89.15	41.08%	33.29%
700_6	106.40	80.46	30.47%	27.34%
700_7	117.44	83.40	51.03%	29.41%
700_8	100.22	81.84	21.27%	25.63%
700_9	110.26	88.61	57.08%	50.79%
700_10	118.78	90.25	52.64%	28.55%
AVERAGE	111.46	85.46	41.74%	32.22%

Table 21
Results provided by BASELINE VANS+PL for the instances with 900 customers

Instance	Emissions	Cost	DEV emissions	DEV cost
900_1	117.80	91.88	45.88%	35.33%
900_2	122.70	93.91	58.58%	43.17%
900_3	125.46	94.50	37.63%	29.37%
900_4	115.70	99.37	32.12%	30.22%
900_5	126.56	97.50	39.34%	27.92%
900_6	129.94	99.78	40.32%	29.37%
900_7	128.90	102.24	53.55%	44.17%
900_8	129.36	99.70	51.64%	40.42%
900_9	135.08	104.63	63.67%	50.24%
900_10	130.98	88.50	55.17%	24.97%
AVERAGE	126.25	97.20	47.79%	35.52%

6. Conclusions

In this paper, we have proposed a last-mile delivery framework that aims to enhance customer satisfaction and sustainability by reducing operational costs, CO_2 emissions, and delivery failures. In particular, we have assumed that the service territory is an urban area infrastructure with a sufficiently large number of PLs. A fleet of vans delivers parcels to such PLs, from which private citizens are required to retrieve their items. Exceptions are allowed for a (small) subset of customers with special needs. For such customers, home deliveries performed by ADRs are possible. To tackle the problem of deciding to which PL each customer request should be delivered, as well as to determine the routing for the fleets of traditional vehicles and ADRs, we have designed tailored destroy-and-repair operators to be embedded within a neighborhood-search framework. At each iteration of the search process, we identify a subset of customers for which modifying the locker assignment could likely result in an improved solution. In particular, we have proposed three different strategies for determining such customers, as well as an optimization model to repair the solution. The quality of the solutions obtained by the different variants of the proposed approach has been assessed

© 2026 The Author(s).
International Transactions in Operational Research published by John Wiley & Sons Ltd on behalf of International Federation of Operational Research Societies.

14753995, 2026, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/itor.70169 by Universita Del Salento Ser Inf Biblior "La Stecca", Wiley Online Library on [08/06/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

on a number of realistic instances of increasing size, resembling parcel distribution in the urban area of Rome (Italy). Moreover, through a managerial analysis, we have shown that combining PLs with ADRs would allow us to achieve huge benefits with respect to both costs and CO_2 emissions, compared to traditional delivery schemes.

Future work may focus on further improving the solution methodology. A possibility is represented by incorporating additional features—such as, for instance, the distance among customers or PLs—into the destroy-and-repair operators. Another avenue for enhancement is the adoption of a more sophisticated neighborhood-search scheme, such as an ALNS, to enable a more effective exploration of the solution space.

Acknowledgments

This research was partly supported by funds provided by the Ministero dell'Università e della Ricerca (MUR) of Italy, PRIN project "Optimizing sustainable multi-modal and multi-tasking last-mile distribution system with carbon-free autonomous vehicles, ground robots, drones, and public transport," CUP Master H53D23002000006, CUP F53D23002720006. This support is gratefully acknowledged.

Open access publishing facilitated by Universita del Salento, as part of the Wiley - CRUI-CARE agreement.

References

Alfandari, L., Ljubić, I., De Melo da Silva, M., 2022. A tailored Benders decomposition approach for last-mile delivery with autonomous robots. *European Journal of Operational Research* 299, 2, 510–525.

Boysen, N., Schwerdfeger, S., Weidinger, F., 2018. Scheduling last-mile deliveries with truck-based autonomous robots. *European Journal of Operational Research* 271, 3, 1085–1099.

Carotenuto, P., Ceccato, R., Gastaldi, M., Giordani, S., Rossi, R., Salvatore, A., 2022. Comparing home and parcel lockers' delivery systems: a math-heuristic approach. *Transportation Research Procedia* 62, 91–98.

Chen, C., Demir, E., Huang, Y., Qiu, R., 2021. The adoption of self-driving delivery robots in last mile logistics. *Transportation Research Part E: Logistics and Transportation Review* 146, 102214.

De Maio, A., Ghiani, G., Laganà, D., Manni, E., 2024. Sustainable last-mile distribution with autonomous delivery robots and public transportation. *Transportation Research Part C: Emerging Technologies* 163, 104615.

Deutsch, Y., Golany, B., 2018. A parcel locker network as a solution to the logistics last mile problem. *International Journal of Production Research* 56, 1–2, 251–261.

Ermağan, U., Yildiz, B., Salman, F.S., 2024. Express shipments with autonomous robots and public transportation. *Transportation Research Part E: Logistics and Transportation Review* 192, 103782.

Heimfarth, A., Ostermeier, M., Hübner, A., 2022. A mixed truck and robot delivery approach for the daily supply of customers. *European Journal of Operational Research* 303, 1, 401–421.

Iwan, S., Kijewska, K., Lemke, J., 2016. Analysis of parcel lockers' efficiency as the last mile delivery solution—the results of the research in Poland. *Transportation Research Procedia* 12, 644–655.

Kahr, M., 2022. Determining locations and layouts for parcel lockers to support supply chain viability at the last mile. *Omega* 113, 102721.

Koç, Ç., Laporte, G., Tükenmez, İ., 2020. A review of vehicle routing with simultaneous pickup and delivery. *Computers & Operations Research* 122, 104987.

Koh, L.Y., Xia, Z., Yuen, K.F., 2024. Consumer acceptance of the autonomous robot in last-mile delivery: a combined perspective of resource-matching, perceived risk and value theories. *Transportation Research Part A: Policy and Practice* 182, 104008.

© 2026 The Author(s).
International Transactions in Operational Research published by John Wiley & Sons Ltd on behalf of International Federation of Operational Research Societies.

14753995, 2026, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/itor.70169 by Universita Del Salento Ser Inf Bibliot "La Stecca", Wiley Online Library on [08/06/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Lim, S.F.W.T., Wang, Q., Webster, S., 2023. Do it right the first time: vehicle routing with home delivery attempt predictors. *Production and Operations Management* 32, 4, 1262–1284.

Mancini, S., Gansterer, M., 2021. Vehicle routing with private and shared delivery locations. *Computers & Operations Research* 133, 105361.

Moradi, N., Mafakheri, F., Wang, C., 2024. Covering routing problem with robots and parcel lockers: a sustainable last-mile delivery approach. In A. Brown Greer, J.M.F. C. Contardo (eds), *Proceedings of the IISE Annual Conference & Expo 2024*. Curran Associates, Red Hook, NY, pp. 1678–1683.

Mourad, A., Puchinger, J., Van Woensel, T., 2021. Integrating autonomous delivery service into a passenger transportation system. *International Journal of Production Research* 59, 7, 2116–2139.

Orhan, C.C., Wallace, S.W., 2025. E-commerce shipments in an X-minute city: informing authorities on freight transport through parcel lockers. *Transportation Research Part A: Policy and Practice* 199, 104545.

Ostermeier, M., Heimfarth, A., Hübner, A., 2023. The multi-vehicle truck-and-robot routing problem for last-mile delivery. *European Journal of Operational Research* 310, 2, 680–697.

Pinchasik, D.R., Hovi, I.B., Dong, B., 2025. Replacing home deliveries by deliveries to parcel lockers: cost, traffic, emissions, and societal cost effects of locker network expansions in greater Oslo. *International Journal of Logistics Research and Applications* 28, 4, 401–426.

Pisinger, D., Røpke, S., 2010. Large neighborhood search. In Gendreau, M., Potvin, J.Y. (eds), *Handbook of Metaheuristics*. Springer US, Boston, MA, pp. 399–419.

Seghezzi, A., Siragusa, C., Mangiaracina, R., 2022. Parcel lockers vs. home delivery: a model to compare last-mile delivery cost in urban and rural areas. *International Journal of Physical Distribution & Logistics Management* 52, 3, 213–237.

Shaw, P., 1998. Using constraint programming and local search methods to solve vehicle routing problems. In Maher, M., Puget, J.F. (eds), *Principles and Practice of Constraint Programming — CP98*. Springer, Berlin, pp. 417–431.

Srinivas, S., Ramachandiran, S., Rajendran, S., 2022. Autonomous robot-driven deliveries: a review of recent developments and future directions. *Transportation Research Part E: Logistics and Transportation Review* 165, 102834.

Statista, 2024. Retail e-commerce sales worldwide from 2014 to 2027. https://www.statista.com/statistics/379046/worldwide-retail-e-commerce-sales/ (accessed 16 December 2024).

Tudor-Locke, C., Bassett, D.R., 2004. How many steps/day are enough? Preliminary pedometer indices for public health. *Sports Medicine* 34, 1–8.

Voudouris, C., Alsheddy, A., Alhindi, A., 2025. Guided local search. In Martí, R., Pardalos, P.M., Resende, M.G. (eds), *Handbook of Heuristics*. Springer Nature Switzerland, Cham, pp. 427–467.

Wen, J., Li, Y., 2016. Vehicle routing optimization of urban distribution with self-pick-up lockers. In *the 2016 International Conference on Logistics, Informatics and Service Sciences (LISS)*. IEEE, Piscataway, NJ, pp. 1–6.

Yu, S., Puchinger, J., Sun, S., 2022. Van-based robot hybrid pickup and delivery routing problem. *European Journal of Operational Research* 298, 3, 894–914.

Yu, S., Puchinger, J., Sun, S., 2024. Electric van-based robot deliveries with en-route charging. *European Journal of Operational Research* 317, 3, 806–826.

Zang, X., Jiang, L., Liang, C., Fang, X., 2023. Coordinated home and locker deliveries: an exact approach for the urban delivery problem with conflicting time windows. *Transportation Research Part E: Logistics and Transportation Review* 177, 103228.

Zhang, Q., Demir, E., 2025. Parcel locker solutions for last mile delivery: a systematic literature review and future research directions. *Frontiers in Future Transportation* 6, 654621.

Zhang, S., Lee, C., 2016. Flexible vehicle scheduling for urban last mile logistics: the emerging technology of shared reception box. In *2016 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*. IEEE, Piscataway, NJ, pp. 1913–1917.

Zhang, W., Xu, M., Wang, S., 2023. Joint location and pricing optimization of self-service in urban logistics considering customers' choice behavior. *Transportation Research Part E: Logistics and Transportation Review* 174, 103128.

Zhou, L., Baldacci, R., Vigo, D., Wang, X., 2018. A multi-depot two-echelon vehicle routing problem with delivery options arising in the last mile distribution. *European Journal of Operational Research* 265, 2, 765–778.

Zhou, R., Chen, H., Shen, H., 2026. The last mile delivery strategy: relay station service or delivery at home? *International Transactions in Operational Research* 33, 1, 327–358.

© 2026 The Author(s).
International Transactions in Operational Research published by John Wiley & Sons Ltd on behalf of International Federation of Operational Research Societies.

14753995, 2026, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/itor.70169 by Universita Del Salento Ser Inf Biblior "La Stecca", Wiley Online Library on [08/06/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License