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Park-and-multi-loop with autonomous delivery robots in last-mile logistics

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Abstract

This paper deals with the park-and-multi-loop routing problem, in the context of last-mile logistics, in which a fleet of traditional vehicles equipped with several autonomous delivery robots leaves from a depot to service a set of customer requests. Each delivery route involves a main tour of a traditional vehicle (subject to time-dependent travel times), which may stop at one or more parking locations, from which one or more walking sub-tours are carried out by the driver and the delivery robots on the pedestrian network. The goal is to minimize the overall cost of both van and walking routes. An alternative objective aims to minimize the CO_2 emissions. A peculiarity of the problem is that the walking distance covered by drivers and delivery robots must not exceed given thresholds. For this problem, we propose a tailored destroy-and-repair mechanism embedded into a neighborhood search algorithm. The destroy-and-repair operators are parameterized, and the most appropriate parameter setting is chosen based on some performance measures of the solution. Computational results on a set of instances of varying size, derived from real data of two major Italian cities, certify the quality of the approach, compared to classic destroy-and-repair operators. Moreover, we also show the benefits of the proposed delivery scheme in terms of CO_2 emissions when compared to a traditional delivery paradigm.

Keywords: last-mile delivery; autonomous delivery robots; park-and-loop; neighborhood search; destroy-and-repair

1. Introduction

The recent rapid expansion of the e-commerce sector and the ever-growing demand for express deliveries have significantly increased the need for efficient last-mile delivery solutions, representing the final and often most complex segment of the supply chain. As cities become more and more

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crowded and consumer expectations for rapid delivery rise, innovative solutions are essential to enhance efficiency and sustainability (Kunze, 2016). Indeed, traditionally, last-mile delivery involves vehicles transporting packages directly to each recipient's address (Zhou et al., 2026). However, this method is frequently challenged by several aspects, such as urban congestion and environmental concerns. In particular, a significant source of congestion and pollution in urban areas is represented by parking cruising, given the limited parking space typically available (Dalla Chiara and Goodchild, 2020). On the other hand, as Reed et al. (2024) observe, "parking is a necessary component of last-mile delivery practices, and finding a parking spot takes time."

To face this issue, a recent trend in the literature is to combine driving and walking for last-mile delivery, in that an alternative option is to allow delivery vehicles to be strategically parked in centralized locations, from which couriers complete the final leg of the delivery on foot. This approach is known as *park-and-loop* (Cabrera et al., 2023). In recent years, a few pilot initiatives have been launched to exploring the usage of designated parking areas or micro-distribution hubs. For example, the New York City Department of Transportation has introduced the "Local Delivery Hub" pilot program, which designates curbside areas for trucks to unload goods that are then delivered via alternative modes such as cargo bikes or on foot (New York City Department of Transportation, 2023). Similarly, the city of Oslo is implementing the CodeZERO project, which aims to reduce emissions and congestion in urban logistics by using consolidation hubs and coordinated delivery systems (City of Oslo, 2024).

In this paper, we extend the park-and-loop approach and envision a delivery framework in which each delivery vehicle is equipped with a small fleet of autonomous delivery robots (ADRs) that are used to perform the final leg of the delivery, in addition to the walking trips of the courier. ADRs are becoming more and more popular for deliveries in highly congested urban areas because of their ability to deliver small packages reaching the customer doors using sidewalks, while traveling at relatively low speeds to satisfy safety requirements (De Maio et al., 2024; Chen et al., 2021; Ghiani et al., 2026). In contrast, the usage of other types of autonomous vehicles, such as aerial drones (see, e.g., Babaee Tirkolaee et al., 2025; Kumar et al., 2025), is more suited for rural areas (Ulmer and Thomas, 2018). Thus, in our problem, each delivery route involves a main tour of a traditional vehicle, which, in addition to visiting customers, may stop at one or more parking locations, from which one or more walking sub-tours are carried out by the driver and the ADRs on the pedestrian network (in the following, the terms "parking location" and "parking spot" are used interchangeably to denote a physical space where a vehicle is parked to enable walking sub-tours.). We consider that the parking locations can be occupied by the vehicles for a given amount of time. Moreover, to consider a more realistic setting accounting for road congestion, we consider time-dependent travel times for the vans. We refer to this problem as the *park-and-multi-loop routing problem with autonomous delivery robots* (PMLRP-ADR). A classical application involves delivering small- to medium-sized parcels to shops or private citizens. As in Le Colleter et al. (2023), we consider potential parking locations to be specific loading/unloading zones designated by local authorities.

The problem studied in this paper reflects a prospective scenario, incorporating elements such as parking spot utilization and robot-based deliveries, which—although not yet common practice—align with trends observed in pilot programs and smart mobility initiatives. While the aforementioned initiatives do not yet take into account such novel elements, they demonstrate growing institutional interest in structured approaches to managing last-mile logistics through designated urban infrastructure.

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Our main contributions can be summarized as follows. First, we extend the park-and-loop framework by introducing the possibility that the walking trips are performed by ADRs, in addition to drivers. Second, we design a heuristic solution strategy in which destroy-and-repair operations are parameterized and, at each iteration, the most appropriate setting of the parameters is determined by evaluating the current solution according to some performance measures. Third, we perform extensive computational experiments on instances of varying size, obtained from real data of two major Italian cities, to assess the quality of the approach. Finally, to show the benefits of the proposed delivery scheme in terms of CO_2 emissions, we benchmark it with a traditional delivery paradigm from current industry practice.

The remainder of the paper is organized as follows. In Section 2, we report an overview of the related literature. In Section 3, we give the details of the problem we study, and in Section 4 we describe our solution approach. Then, in Section 5, we report the results of our computational experiments, followed by conclusions in Section 6.

2. Literature review

The standard park-and-loop approach for delivery routing was first discussed by Bodin and Levy (2000), in the context of mail delivery for the United States Postal Service. The problem was modeled as a *location arc routing problem* to decide the locations of parking lots and determine the corresponding walking trips. Several variants of the problem have been afterwards studied in the literature. For instance, among the most recent contributions, Martinez-Sykora et al. (2020) studied a two-echelon last-mile delivery system explicitly considering driving and walking decisions in an integrated way, aiming to minimize a weighted sum of the total driving and walking times. The solution approach was a branch-and-cut algorithm, tested on instances from London with up to 30 customers. Another contribution is due to Cabrera et al. (2022), who introduced the *doubly open park-and- loop routing problem*, for which three types of routes are possible: routes involving customers served by driving only, routes where the customers are served by walking only, and routes with park-and-loop, in which vehicles can be parked at customer locations. For this problem, the authors proposed a matheuristic. Subsequently, in Cabrera et al. (2023), the same authors proposed, for the park-and-loop routing problem, an exact solution method based on the branch-price-and-cut framework.

It is worth noting that all the previous contributions deal with the case in which a single walking trip can be performed from a parking location (typically, in front of a customer). An extension in which more than one walking trip is performed from a parking spot is known as the *vehicle routing problem with time windows and multiple deliverymen* (VRPTWMD), studied by Pureza et al. (2012). In this version of the problem, a vehicle travels carrying more than one deliveryman and, after parking, the deliverymen walk to serve their respective customers. In this problem modeling, the nodes of the network typically represent clusters of customers that are defined in advance. This choice has a consequence on the service time at a cluster, which is influenced by the number of deliverymen servicing it. For the VRPTWMD, Pureza et al. (2012) presented a mathematical programming formulation, as well as two heuristics based on tabu search and ant colony optimization. Other contributions are due to Álvarez and Munari (2016), Munari and Morabito (2018), and De La Vega et al. (2020). Very recently, Senna et al. (2024) have extended the VRPTWMD by also including the decision of properly evaluating and optimizing the routes of the deliverymen inside

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each cluster, instead of simply considering round-trips. In their problem, every cluster is served by exactly one vehicle, and every customer inside a cluster is served by exactly one deliveryman.

To the best of our knowledge, there are no contributions in which delivery robots are employed in tandem with drivers in a park-and-loop framework. A typical usage of ADRs is the *truck-and-robot* concept with robot depots, in which the delivery trucks are specialized vans acting as a mothership for the transportation of parcels and robots. Examples are reported in Boysen et al. (2018) and Ostermeier et al. (2022). In this problem, only one truck is available to transport robots and goods, and the decisions include both truck routing and robot scheduling. Moreover, the robots have a capacity for a single shipment. An extension to this approach is discussed in Ostermeier et al. (2023), who introduced the *multi-vehicle truck-and-robot routing problem* with robot depot, to determine the simultaneous routing of multiple trucks, as well as the corresponding clustering decisions while choosing the optimal drop-off points for robots and their delivery. Multiple vehicles are also considered in Yu et al. (2022), who studied a pickup and delivery problem involving a fleet of trucks, each equipped with a robot. The robot can be released from the truck to perform several deliveries and later rendezvous with the same truck at a different location, or at the same point. Recently, Ghiani et al. (2025) study a last-mile delivery problem, where a heterogeneous fleet—comprising conventional delivery vehicles and ADRs—is employed to fulfill a high volume of customer demands. In their framework, the delivery robots operate using public transportation stations as temporary depots.

2.1. Contributions to the literature

Our work presents several differences with respect to the existing literature. In particular, our contributions are as follows:

- we consider a park-and-multi-loop framework, in which, after parking the vehicle at a selected parking location, both the vehicle driver and ADRs are used to perform the walking trips. Drivers and delivery robots have different characteristics in terms of capacity and range, thus resulting in a heterogeneous sub-fleet;
- we allow more than one ADR per vehicle, with each of them having the ability to carry more than one package in a single delivery tour;
- we consider time-dependent travel times for the vans to account for realistic traffic conditions in urban environments;
- we assume that a parking location can be used several times during the working day;
- we design a tailored destroy-and-repair mechanism embedded into a neighborhood search algorithm, in which the destroy-and-repair operators are parameterized, and the most appropriate parameter setting is selected after evaluating the solutions based on specific performance criteria;
- we perform an analysis to show the benefits of the proposed delivery scheme in terms of CO_2 emissions, when compared to a traditional delivery paradigm.

3. Problem definition

In the *PMLRP-ADRs*, a fleet of vans, each of which is equipped with a sub-fleet of ADRs, must deliver small parcels to a set of customers. Deliveries can be made by either visiting the customer

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Table 1
Overview of the notation used throughout the paper

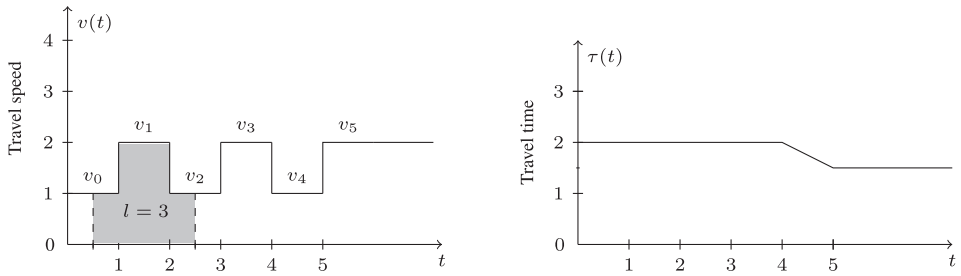
Symbol	Description
$\mathcal{V}$	Set of vertices
$\mathcal{A}$	Set of arcs
$\mathcal{C}$	Set of customers
$\mathcal{P}$	Set of available parking locations
T	Length of the planning horizon
$[e_p, l_p]$	Availability window of parking location $p \in \mathcal{P}$
Λ	Set of time intervals (for parking spots utilization) into which the time horizon is divided
$(i, j)^d$ and $(i, j)^w$	Arcs traversed by a van (driving arc) and by a driver or an ADR (walking arc), respectively, for each pair $i, j \in \mathcal{V}$
L_{ij}	Length of arc (i, j) for each pair $i, j \in \mathcal{V}$
v^D and v^A	Constant average speed for drivers and ADRs, respectively
t_{ij}^D and t_{ij}^A	Walking arcs travel times for drivers and ADRs, respectively
H	Number of time periods into which the time horizon is divided, to account for time-dependent travel times of driving arcs
v_{ijh}	Constant vehicle speed for arc $(i, j)^d$ during time period $h = 0, \ldots, H-1$
$\tau_{ij}(t)$	Travel time for traversing driving arc $(i, j)^d$, when leaving vertex i at time t
$\mathcal{K}$	Fleet of homogeneous vehicles
Q^V	Capacity of vehicles $k \in \mathcal{K}$
$\mathcal{N}_k$	Sub-fleet of ADRs onboard vehicle $k \in \mathcal{K}$
Q^A	Capacity of ADRs
L^A	Maximum distance range that an ADR can travel daily with a full charge
Q^D	Capacity of drivers, referring to the maximum number of parcels that they can carry during a single walking trip
L^D	Maximum daily walking range for drivers
γ_f^V and γ_v	Fixed and variable costs for vans, respectively
γ_f^D and γ_f^A	Fixed costs for drivers and ADRs, respectively
ϵ^V and ϵ^A	CO_2 emissions per km for vans and ADRs, respectively

location with the van (driving route) or by parking the vehicle at specific locations. If the customer is not directly served by the vehicle and instead from such parking spots, the final leg of the delivery can be completed either by the vehicle driver on foot or by one of the ADRs loaded on the van (in both cases, we refer to such tours as walking routes or walking trips). Once released, robots can move autonomously on sidewalks at pedestrian speed and deliver parcels to customer doors.

To formalize the PMLRP-ADR, we refer to the notation reported in Table 1, which is used throughout the paper. Formally, the PMLRP-ADR is defined on a directed multigraph $\mathcal{G} = (\mathcal{V}, \mathcal{A})$, where $\mathcal{V}$ and $\mathcal{A}$ are the vertex set and the arc set, respectively. Moreover, the vertex set is partitioned as $\mathcal{V} = \{0\} \cup \mathcal{P} \cup \mathcal{C}$, with 0 representing the van depot, $\mathcal{P}$ denoting the set of available parking locations, and $\mathcal{C}$ comprising the set of customers who must be serviced during a planning horizon of length T. The depot 0 is characterized by a time window $[0, T]$, whereas, concerning the parking spots $\mathcal{P}$, each $p \in \mathcal{P}$ can be occupied by vehicles for a given amount of time. Although in our solution approach each parking spot $p \in \mathcal{P}$ has an associated availability window $[e_p, l_p]$ during which vehicles can occupy it for an arbitrary amount of time, in this section, for the sake of modeling simplicity, we assume that the time horizon is divided into a given set Λ of time intervals $[T_\lambda, T_{\lambda+1}]$

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(a) Speed function (b) Travel time function

Fig. 1. A constant step-wise speed function (a) and the associated continuous piecewise linear arc travel time function (b). Example adapted from Calogiuri et al. (2021).

($\lambda = 0, \ldots, |\Lambda| - 1$), with $T_0 = 0$ and $T_{|\Lambda|} = T$. Then, each $p \in \mathcal{P}$ can be occupied during such time intervals λ by one vehicle at a time. As a consequence, a parking spot may be visited by more than one vehicle during the same working day, in different time slots. Regarding customers, with each $c \in \mathcal{C}$ is associated a demand q_c, expressed as the number of (small) parcels that must be delivered to them, and a service time s_c. We assume zero parking time at customer locations; thus, vans, drivers, and ADRs can start service immediately upon arrival, and the time spent at customer nodes is equal to s_c only.

For each pair of vertices $i, j \in \mathcal{V}$, set $\mathcal{A}$ contains two arcs, denoted as $(i, j)^d$ and $(i, j)^w$, where the superscripts d and w indicate an arc traversed by the van (driving arc) and a walking arc (traversed by drivers and ADRs), respectively. Each arc (both driving and walking) has an associated length L_{ij}, whereas the value of the travel time is obtained as follows. For walking arcs, we assume that drivers and ADRs traverse them at a constant average speed, denoted as v^{D} and v^{A} for drivers and delivery robots, respectively, so that the corresponding travel times for arc $(i, j)^w$ are $t_{ij}^{\mathrm{D}} = L_{ij}/v^{\mathrm{D}}$ and $t_{ij}^{\mathrm{A}} = L_{ij}/v^{\mathrm{A}}$, respectively. Concerning driving arcs, as briefly mentioned previously, we consider that—as happens in the real world — speed is not necessarily constant over the entire arc length and, thus, the time needed to traverse them depends on the time instant the vehicle starts traveling through the arc. While the effect of incorporating time-dependent travel times is not evaluated experimentally in this study, we consider this assumption essential to capture realistic traffic dynamics in urban delivery contexts. For a recent comprehensive review on time-dependent vehicle routing, we refer the reader to Adamo et al. (2024). In particular, as most of the current literature on time-dependent routing does, we rely on the travel time model proposed by Ichoua et al. (2003) (IGP model), in which the planning horizon $[0, T]$ is partitioned into a finite number H of time slots $[T_h, T_{h+1}]$ ($h = 0, \ldots, H - 1$), with $T_0 = 0$ and $T_H = T$. Vehicle speed for arc $(i, j)^d$ is assumed to be equal to a constant level v_{ijh} during time period h. Then, the corresponding travel time $\tau_{ij}(t)$ needed to traverse arc $(i, j)^d$, of length L_{ij}, with a constant step-wise speed $v_{ij}(t) = v_{ijh}$, $t \in [T_h, T_{h+1}]$, $h = 0, \ldots, H - 1$, if the vehicle leaves node i at time t, is obtained according to the procedure described in Adamo et al. (2024), not reported here for the sake of brevity (see Adamo et al., 2024, Algorithm 1, p. 2). We observe that travel times $\tau_{ij}(t)$ satisfy the First In First Out (FIFO) property. Figure 1 reports an example of a travel speed function and its associated travel time function for an arc of length 3, with a start time equal to $t = 0.5$.

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Customer requests must be satisfied by a fleet $\mathcal{K}$ of homogeneous vans, where each $k \in \mathcal{K}$ has a capacity Q^{V}, and is equipped with a sub-fleet $\mathcal{N}_k$ of ADRs. ADRs are characterized by a capacity Q^{A}, defined in terms of storage compartments, and a maximum distance range L^{A} that they can travel daily with a full charge (we do not consider the possibility of battery swapping or recharging). Analogously, drivers, who can also be used to perform deliveries on foot after parking the van, have a capacity per walking trip equal to Q^{D} (i.e., the number of parcels that they can carry, for instance, by using a small trolley), and a maximum daily walking distance range equal to L^{D}. Regarding the cost structure, each van has a daily fixed cost γ_f^{V} and a variable cost per km γ_v, whereas drivers and ADRs have daily fixed costs γ_f^{D} and γ_f^{A}, respectively. The PMLRP-ADR consists of finding a set of least cost van routes (starting and ending at the depot, possibly visiting the parking spots) and walking routes (by drivers and ADRs) ensuring that: each customer is visited once (either directly by a van or within a walking route by a driver or an ADR), vans return to the depot before the end of the working day, capacity constraints are met, and the maximum distances walked by drivers and ADRs do not exceed the relative thresholds. An alternative is to evaluate the solutions in terms of CO_2 emissions, by multiplying the distance traveled by vans and ADRs for the corresponding values of CO_2 in kg/km, denoted as ε^{V} and ε^{A}, respectively. When assessing the performance of our approach in Section 5, we consider both objective functions.

We observe that, being a generalization of the well-known vehicle routing problem, which is NP-hard, the PMLRP-ADR is NP-hard as well. Thus, instead of developing exact solution approaches which are unlikely to provide results in a reasonable amount of time, we focus our attention on heuristics, as described in Section 4. However, even though our solution methodology is heuristic, in the following, we provide a mathematical formulation of the PMLRP-ADR with the intent of formally stating the problem.

Following Vu et al. (2024), to account for the time-dependency component, we model the van routing sub-problem on a time-expanded network. Such a network contains multiple occurrences of the same physical node (corresponding to different temporal realizations), and a feasible solution will visit only one temporal realization of the same physical node. More specifically, the vertex set in the time-expanded network is denoted as $\mathcal{V}' = \{(i, t) : i \in \mathcal{V},\ t \in [0, T]\}$. Then, the corresponding time-expanded arc set is $\mathcal{A}' = \{((i, t), (j, \Gamma_{ij}(t))) : i \in \mathcal{V},\ j \in \mathcal{V},\ t \in [0, T]\}$, where $\Gamma_{ij}(t) = t + \tau_{ij}(t)$ represents the earliest arrival time at node j when traveling from node i along a path starting at time t. Moreover, $\Gamma_{ij}^{-1}(t)$ is the latest departure time from node i to reach node j at time instant t.

The decision variables are as follows:

- $y_k \in \{0, 1\}$, equal to 1 if vehicle $k \in \mathcal{K}$ and its associated driver are used, and 0 otherwise;
- $y_{kn} \in \{0, 1\}$, equal to 1 if ADR $n \in \mathcal{N}_k$ of vehicle $k \in \mathcal{K}$ is used, and 0 otherwise;
- $y_k^{p\lambda} \in \{0, 1\}$, equal to 1 if the driver of vehicle $k \in \mathcal{K}$ performs a walking trip during time interval $\lambda \in \Lambda$ starting from parking spot $p \in \mathcal{P}$, and 0 otherwise;
- $y_{kn}^{p\lambda} \in \{0, 1\}$, equal to 1 if ADR $n \in \mathcal{N}_k$ of vehicle $k \in \mathcal{K}$ performs a walking trip during time slot $\lambda \in \Lambda$ starting from parking spot $p \in \mathcal{P}$, and 0 otherwise;
- $\sigma_k^{p\lambda} \in \{0, 1\}$, equal to 1 if vehicle $k \in \mathcal{K}$ has occupied parking spot $p \in \mathcal{P}$ during time interval $\lambda \in \Lambda$, and 0 otherwise;
- $\varphi_{kr} \in \{0, 1\}$, equal to 1 if vertex $r = (i, t) \in \mathcal{V}'$ is visited by van $k \in \mathcal{K}$ (i.e., if a customer or a parking spot is visited by van $k \in \mathcal{K}$ (driving route) at time instant $t \in [0, T]$), and 0 otherwise;

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- $\chi_{kc}^{p\lambda} \in \{0, 1\}$, equal to 1 if customer $c \in \mathcal{C}$ is served by the driver of vehicle $k \in \mathcal{K}$ (within a walking route) starting from parking spot $p \in \mathcal{P}$ during time interval $\lambda \in \Lambda$, and 0 otherwise;
- $\beta_{knc}^{p\lambda} \in \{0, 1\}$, equal to 1 if customer $c \in \mathcal{C}$ is served by ADR $n \in \mathcal{N}_k$ of vehicle $k \in \mathcal{K}$ (within a walking route) starting from parking spot $p \in \mathcal{P}$ during time interval $\lambda \in \Lambda$, and 0 otherwise;
- $a_{ki}^{p\lambda} \geq 0$, equal to the time instant when the driver of vehicle $k \in \mathcal{K}$ starts visiting vertex $i \in \mathcal{V} \setminus \{0\}$, within a walking route started from parking spot $p \in \mathcal{P}$ during time interval $\lambda \in \Lambda$;
- $b_{kni}^{p\lambda} \geq 0$, equal to the time instant when the ADR $n \in \mathcal{N}_k$ of vehicle $k \in \mathcal{K}$ starts visiting vertex $i \in \mathcal{V} \setminus \{0\}$, within a walking route started from parking spot $p \in \mathcal{P}$ during time interval $\lambda \in \Lambda$;
- $x_{ijk}^{p\lambda} \in \{0, 1\}$, equal to 1 if the driver of vehicle $k \in \mathcal{K}$ utilizes arc $(i, j)^w \in \mathcal{A}$, during a walking route started from parking spot $p \in \mathcal{P}$ during time interval $\lambda \in \Lambda$, and 0 otherwise;
- $x_{ijkn}^{p\lambda} \in \{0, 1\}$, equal to 1 if the ADR $n \in \mathcal{N}_k$ of vehicle $k \in \mathcal{K}$ utilizes arc $(i, j)^w \in \mathcal{A}$, during a walking route started from parking spot $p \in \mathcal{P}$ during time interval $\lambda \in \Lambda$, and 0 otherwise;
- $u_{ka} \in \{0, 1\}$, equal to 1 if vehicle $k \in \mathcal{K}$ utilizes the time expanded arc $a = ((i, t); (j, \Gamma_{ij}(t + s_i))) \in \mathcal{A}'$ (with $i \in \mathcal{V}$, $j \in \mathcal{V}$, $t \in [0, T]$), and 0 otherwise;
- $d_{ki} \geq 0$, representing (a lower bound on) the load in vehicle $k \in \mathcal{K}$ directly before reaching $i \in \mathcal{V}$.

Then, a mathematical formulation minimizing the overall cost is as follows:

$$\min \quad \sum_{k\in\mathcal{K}} \left[(\gamma_f^{\mathrm{V}} + \gamma_f^{\mathrm{D}}) y_k + \sum_{n\in\mathcal{N}_k} \gamma_f^{\mathrm{A}} y_{kn} \right] + \sum_{k\in\mathcal{K}} \sum_{a\in\mathcal{A}'} L_{ij} \gamma_v u_{ka} \tag{1}$$

$$\text{s.t.} \quad \sum_{k\in\mathcal{K}} \sigma_k^{p\lambda} \leq 1 \qquad \forall p \in \mathcal{P},\ \lambda \in \Lambda, \tag{2}$$

$$\sum_{p\in\mathcal{P}} \sigma_k^{p\lambda} \leq 1 \qquad \forall k \in \mathcal{K},\ \lambda \in \Lambda, \tag{3}$$

$$\sum_{\lambda\in\Lambda} \sigma_k^{p\lambda} \leq 1 \qquad \forall k \in \mathcal{K},\ p \in \mathcal{P}, \tag{4}$$

$$y_k^{p\lambda} \leq \sigma_k^{p\lambda} \qquad \forall k \in \mathcal{K},\ p \in \mathcal{P},\ \lambda \in \Lambda, \tag{5}$$

$$y_{kn}^{p\lambda} \leq \sigma_k^{p\lambda} \qquad \forall k \in \mathcal{K},\ n \in \mathcal{N}_k,\ p \in \mathcal{P},\ \lambda \in \Lambda, \tag{6}$$

$$y_{kn} \geq \frac{1}{|\Lambda|} \sum_{p\in\mathcal{P}} \sum_{\lambda\in\Lambda} y_{kn}^{p\lambda} \qquad \forall k \in \mathcal{K},\ n \in \mathcal{N}_k, \tag{7}$$

$$\sum_{k\in\mathcal{K}} \sum_{r=(c,t)\in\mathcal{V}'} \varphi_{kr} + \sum_{k\in\mathcal{K}} \sum_{p\in\mathcal{P}} \sum_{\lambda\in\Lambda} \chi_{kc}^{p\lambda} + \sum_{k\in\mathcal{K}} \sum_{n\in\mathcal{N}_k} \sum_{p\in\mathcal{P}} \sum_{\lambda\in\Lambda} \beta_{knc}^{p\lambda} = 1 \qquad \forall c \in \mathcal{C}, \tag{8}$$

$$\sum_{c\in\mathcal{C}} x_{pck}^{p\lambda} = y_k^{p\lambda} \qquad \forall k \in \mathcal{K},\ p \in \mathcal{P},\ \lambda \in \Lambda, \tag{9}$$

$$\sum_{c\in\mathcal{C}} x_{cpk}^{p\lambda} = y_k^{p\lambda} \qquad \forall k \in \mathcal{K},\ p \in \mathcal{P},\ \lambda \in \Lambda, \tag{10}$$

$$x_{pck}^{p\lambda} \leq \chi_{kc}^{p\lambda} \qquad \forall k \in \mathcal{K},\ c \in \mathcal{C},\ p \in \mathcal{P},\ \lambda \in \Lambda, \tag{11}$$

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$$x_{cpk}^{p\lambda} \le \chi_{kc}^{p\lambda} \qquad \forall k \in \mathcal{K},\ c \in \mathcal{C},\ p \in \mathcal{P},\ \lambda \in \Lambda, \tag{12}$$

$$\sum_{j \in \mathcal{C}\cup\mathcal{P}} x_{cjk}^{p\lambda} = \chi_{kc}^{p\lambda} \qquad \forall c \in \mathcal{C},\ k \in \mathcal{K},\ p \in \mathcal{P}, \lambda \in \Lambda, \tag{13}$$

$$\sum_{i \in \mathcal{C}\cup\mathcal{P}} x_{ick}^{p\lambda} - \sum_{j \in \mathcal{C}\cup\mathcal{P}} x_{cjk}^{p\lambda} = 0 \qquad \forall c \in \mathcal{C},\ k \in \mathcal{K},\ p \in \mathcal{P}, \lambda \in \Lambda, \tag{14}$$

$$T_\lambda y_k^{p\lambda} \le a_{kp}^{p\lambda} \le T_{\lambda+1} y_k^{p\lambda} \qquad \forall k \in \mathcal{K},\ p \in \mathcal{P}, \lambda \in \Lambda, \tag{15}$$

$$T_\lambda \chi_{kc}^{p\lambda} \le a_{kc}^{p\lambda} \le (T_{\lambda+1} - t_{cp}^{\mathrm{D}} - s_c)\chi_{kc}^{p\lambda} \qquad \forall k \in \mathcal{K},\ c \in \mathcal{C}\ p \in \mathcal{P}, \lambda \in \Lambda, \tag{16}$$

$$a_{ki}^{p\lambda} + t_{ij}^{\mathrm{D}} + s_i - M(1 - x_{ijk}^{p\lambda}) \le a_{kj}^{p\lambda} \qquad \forall i, j \in \mathcal{C} \cup \mathcal{P},\ k \in \mathcal{K},\ p \in \mathcal{P},\ \lambda \in \Lambda, \tag{17}$$

$$\sum_{c \in \mathcal{C}} x_{pckn}^{p\lambda} = y_{kn}^{p\lambda} \qquad \forall k \in \mathcal{K},\ n \in \mathcal{N}_k,\ p \in \mathcal{P},\ \lambda \in \Lambda, \tag{18}$$

$$\sum_{c \in \mathcal{C}} x_{cpkn}^{p\lambda} = y_{kn}^{p\lambda} \qquad \forall k \in \mathcal{K},\ n \in \mathcal{N}_k,\ p \in \mathcal{P},\ \lambda \in \Lambda, \tag{19}$$

$$x_{pckn}^{p\lambda} \le \beta_{knc}^{p\lambda} \qquad \forall k \in \mathcal{K},\ n \in \mathcal{N}_k,\ c \in \mathcal{C},\ p \in \mathcal{P},\ \lambda \in \Lambda, \tag{20}$$

$$x_{cpkn}^{p\lambda} \le \beta_{knc}^{p\lambda} \qquad \forall k \in \mathcal{K},\ n \in \mathcal{N}_k,\ c \in \mathcal{C},\ p \in \mathcal{P},\ \lambda \in \Lambda, \tag{21}$$

$$\sum_{j \in \mathcal{C}\cup\mathcal{P}} x_{cjkn}^{p\lambda} = \beta_{knc}^{p\lambda} \qquad \forall k \in \mathcal{K},\ n \in \mathcal{N}_k,\ c \in \mathcal{C},\ p \in \mathcal{P},\ \lambda \in \Lambda,, \tag{22}$$

$$\sum_{i \in \mathcal{C}\cup\mathcal{P}} x_{ickn}^{p\lambda} - \sum_{j \in \mathcal{C}\cup\mathcal{P}} x_{cjkn}^{p\lambda} = 0 \qquad \forall c \in \mathcal{C},\ k \in \mathcal{K},\ n \in \mathcal{N}_k,\ p \in \mathcal{P}, \lambda \in \Lambda, \tag{23}$$

$$T_\lambda y_{kn}^{p\lambda} \le b_{knp}^{p\lambda} \le T_{\lambda+1} y_{kn}^{p\lambda} \qquad \forall k \in \mathcal{K},\ n \in \mathcal{N}_k,\ p \in \mathcal{P}, \lambda \in \Lambda, \tag{24}$$

$$T_\lambda \beta_{knc}^{p\lambda} \le b_{knc}^{p\lambda} \le (T_{\lambda+1} - t_{cp}^{\mathrm{A}} - s_c)\beta_{knc}^{p\lambda} \qquad \forall k \in \mathcal{K},\ n \in \mathcal{N}_k,\ c \in \mathcal{C}\ p \in \mathcal{P}, \lambda \in \Lambda, \tag{25}$$

$$b_{kni}^{p\lambda} + t_{ij}^{\mathrm{A}} + s_i - M(1 - x_{ijkn}^{p\lambda}) \le b_{knj}^{p\lambda} \qquad \forall i, j \in \mathcal{C} \cup \mathcal{P},\ k \in \mathcal{K},\ n \in \mathcal{N}_k,\ p \in \mathcal{P},\ \lambda \in \Lambda, \tag{26}$$

$$\sum_{c \in \mathcal{C}} q_c \chi_{kc}^{p\lambda} \le Q^{\mathrm{D}} \qquad \forall k \in \mathcal{K},\ p \in \mathcal{P}, \lambda \in \Lambda, \tag{27}$$

$$\sum_{c \in \mathcal{C}} q_c \beta_{knc}^{p\lambda} \le Q^{\mathrm{A}} \qquad \forall k \in \mathcal{K},\ n \in \mathcal{N}_k,\ p \in \mathcal{P}, \lambda \in \Lambda, \tag{28}$$

$$\sum_{p \in \mathcal{P}} \sum_{\lambda \in \Lambda} \sum_{(i,j)^w \in \mathcal{A}} L_{ij} x_{ijk}^{p\lambda} \le L^{\mathrm{D}} \qquad \forall k \in \mathcal{K}, \tag{29}$$

$$\sum_{p \in \mathcal{P}} \sum_{\lambda \in \Lambda} \sum_{(i,j)^w \in \mathcal{A}} L_{ij} x_{ijkn}^{p\lambda} \le L^{\mathrm{A}} \qquad \forall k \in \mathcal{K},\ n \in \mathcal{N}_k, \tag{30}$$

$$\sum_{j \in \mathcal{V}} \sum_{a=((0,0),(j,\Gamma_{0j}(0))) \in \mathcal{A}'} u_{ka} \le y_k \qquad \forall k \in \mathcal{K}, \tag{31}$$

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$$\sum_{j\in\mathcal{V}} \sum_{a=(r,(j,\Gamma_{ij}(t+s_i)))\in\mathcal{A}'} u_{ka} - \sum_{j\in\mathcal{V}} \sum_{a=((j,\Gamma_{ji}^{-1}(t)-s_j),r)\in\mathcal{A}'} u_{ka} = 0 \quad \forall i \in \mathcal{V}\setminus\{0\},\ r=(i,t)\in\mathcal{V}',\ k\in\mathcal{K}, \tag{32}$$

$$\sum_{j\in\mathcal{V}} \sum_{a=(r,(j,\Gamma_{ij}(t+s_i)))\in\mathcal{A}'} u_{ka} = \varphi_{kr} \qquad \forall i \in \mathcal{V}\setminus\{0\},\ r=(i,t)\in\mathcal{V}',\ k\in\mathcal{K}, \tag{33}$$

$$d_{ki} - d_{kj} + Q^{\mathrm{V}} u_{ka} \le Q^{\mathrm{V}} - q_j u_{ka} \qquad \forall a=((i,t),(j,\Gamma_{ij}(t+s_i)))\in\mathcal{A}',\ k\in\mathcal{K}, \tag{34}$$

$$q_i \le d_{ki} \le Q^{\mathrm{V}} \qquad \forall k\in\mathcal{K},\ i\in\mathcal{V}, \tag{35}$$

$$y_k \in \{0,1\} \qquad \forall k\in\mathcal{K}, \tag{36}$$

$$y_{kn} \in \{0,1\} \qquad \forall k\in\mathcal{K},\ n\in\mathcal{N}_k, \tag{37}$$

$$y_k^{p\lambda} \in \{0,1\} \qquad \forall k\in\mathcal{K},\ p\in\mathcal{P},\ \lambda\in\Lambda, \tag{38}$$

$$y_{kn}^{p\lambda} \in \{0,1\} \qquad \forall k\in\mathcal{K},\ n\in\mathcal{N}_k\ p\in\mathcal{P},\ \lambda\in\Lambda, \tag{39}$$

$$\sigma_k^{p\lambda} \in \{0,1\} \qquad \forall k\in\mathcal{K},\ p\in\mathcal{P},\ \lambda\in\Lambda, \tag{40}$$

$$\varphi_{kr} \in \{0,1\} \qquad \forall k\in\mathcal{K},\ r=(c,t)\in\mathcal{V}' : c\in\mathcal{C}, t\in[0,T], \tag{41}$$

$$\chi_{kc}^{p\lambda} \in \{0,1\} \qquad \forall k\in\mathcal{K},\ c\in\mathcal{C}\ p\in\mathcal{P},\ \lambda\in\Lambda, \tag{42}$$

$$\beta_{knc}^{p\lambda} \in \{0,1\} \qquad \forall k\in\mathcal{K},\ n\in\mathcal{N}_k\ c\in\mathcal{C},\ p\in\mathcal{P},\ \lambda\in\Lambda, \tag{43}$$

$$a_{ki}^{p\lambda} \ge 0 \qquad \forall k\in\mathcal{K},\ i\in\mathcal{V}\ p\in\mathcal{P},\ \lambda\in\Lambda, \tag{44}$$

$$b_{kni}^{p\lambda} \ge 0 \qquad \forall k\in\mathcal{K},\ n\in\mathcal{N}_k\ i\in\mathcal{V},\ p\in\mathcal{P},\ \lambda\in\Lambda, \tag{45}$$

$$x_{ijk}^{p\lambda} \in \{0,1\} \qquad \forall (i,j)^w\in\mathcal{A},\ \forall k\in\mathcal{K},\ p\in\mathcal{P},\ \lambda\in\Lambda, \tag{46}$$

$$x_{ijkn}^{p\lambda} \in \{0,1\} \qquad \forall (i,j)^w\in\mathcal{A},\ \forall k\in\mathcal{K},\ n\in\mathcal{N}_k\ p\in\mathcal{P},\ \lambda\in\Lambda, \tag{47}$$

$$u_{ka} \in \{0,1\} \qquad \forall a=((i,t),(j,\Gamma_{ij}(t+s_i)))\in\mathcal{A}' : i,j\in\mathcal{V}, t\in[0,T], k\in\mathcal{K}, \tag{48}$$

$$d_{ki} \ge 0 \qquad \forall k\in\mathcal{K},\ i\in\mathcal{V}. \tag{49}$$

In this formulation, objective function (1) aims to minimize the overall cost, which consists of two components: the fixed costs associated with vans, drivers, and ADRs, and the variable costs for vans, calculated by multiplying a unit cost per kilometer by the distance traveled. Constraints (2) impose that at most one vehicle can occupy a parking spot during a given time interval, whereas constraints (3) state that each vehicle can occupy at most one parking location for every time interval, and relationships (4) prescribe that a given vehicle can occupy a given parking location at most once during the working day. Then, constraints (5) indicate that the driver of a given vehicle k can be used to perform a walking route starting from a parking spot p in a certain time interval λ only if the vehicle have occupied the parking spot for the same time interval. Constraints (6) extend the previous condition to the ADRs of a given vehicle, whereas relationships (7) tie variables y_{kn} to variables $y_{kn}^{p\lambda}$, by ensuring that an ADR associated with a vehicle is activated whenever it is used in at least one parking location and time interval. Constraints (8) impose that a customer is served either by a driving route of a van, or by a walking route of a driver or of an ADR. Constraints

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(9)–(17) are related to drivers' walking routes. In particular, (9) and (10) state that the driver of a vehicle starts/ends their walking trip from a parking spot p in a time interval λ, only if p has been occupied by their vehicle for such a time interval. Then, (11)–(13) tie variables $x^{p\lambda}_{pck}$ and $x^{p\lambda}_{cpk}$ to variables $\chi^{p\lambda}_{kc}$, to ensure consistency between customer assignment to drivers' walking trips and routing decisions for such sub-routes. Flow conservation for drivers performing walking trips is expressed by Equations (14), whereas constraints (15) and (16) impose that, for vertices to be visited in a given time interval, service must occur within the interval's start and end times, s as sub-tour elimination constraints for drivers' walking routes, with M being a sufficiently large constant. Such sub-tour elimination constraints, as well as the ones reported in the following, are of the Miller–Tucker–Zemlin type (Kara et al., 2004). Constraints (18)–(26) have the same meaning of (9)–(17), but refer to the walking routes of ADRs. Relationships (27) and (28) are capacity constraints for drivers and ADRs, respectively, whereas (29) and (30) impose a limit on the maximum distance that can be covered in an entire working day by drivers and ADRs, respectively. Constraints (31)–(35) are related to vans' driving routes. In particular, (31) guarantee that, for a given vehicle, at most one arc (of the time-expanded network) leaving the depot at the beginning of the working day (assumed to happen at time $t = 0$) can be activated, if the vehicle is selected. (32) and (33) are flow conservation constraints, whereas relationships (34) and (35) are sub-tour elimination and capacity constraints. Finally, constraints (36)–(49) enforce the domain of the variables.

An alternative performance measure, according to which the solutions can be evaluated, aims to minimize the CO_2 emissions. In this case, the objective function (1) can be replaced by

$$\min \sum_{k\in\mathcal{K}} \sum_{a\in\mathcal{A}'} \varepsilon^{\mathrm{V}} L_{ij} u_{ka} + \sum_{k\in\mathcal{K}} \sum_{n\in\mathcal{N}_k} \sum_{p\in\mathcal{P}} \sum_{\lambda\in\Lambda} \sum_{(i,j)^w\in\mathcal{A}} \varepsilon^{\mathrm{A}} L_{ij} x^{p\lambda}_{ijkn}. \tag{50}$$

4. An adaptive destroy-and-repair neighborhood search heuristic for the PMLRP-ADR

In this section, we present the details of our approach to solve the PMLRP-ADR. The basic idea is starting from a feasible solution and iteratively improving it by means of a neighborhood-search approach based on the destroy-and-repair paradigm (Pisinger and Ropke, 2010). At each iteration, a neighborhood of the current solution is explored by employing a mechanism dubbed *adaptive destroy-and-repair* (ADAR). Basically, the rationale behind ADAR is to identify the portions of the current solution to destroy according to some performance measures. Then, the repair phase is driven by a parameter $\alpha \in [0, 1]$, whose value is allowed to change at each iteration, depending on the characteristics of the reference solution. The goal of this parameter is to define the width of the time period for which a parking location is occupied by a given vehicle. The choice of α represents a critical issue, because if α is close to 1, then such a window is wide, resulting in the possibility of potentially serving a greater number of customers from the parking spot, but leaving less time for the parking spot to be visited by other vehicles. On the other hand, if α is close to 0, the occupation window is tight, thus limiting the number of customers that can be associated with the parking spot, but potentially allowing more time for visits by other vehicles.

The general structure of our *ADAR* heuristic is depicted in Algorithm 1. The algorithm inputs are the problem instance I and a time limit $T_{\max}$. Let $\mathbf{x}$ represent a solution to the PMLRP-ADR, constituted by the routes of the vans, starting/ending from/at a depot and made up of a sequence of

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Algorithm 1. Pseudocode of the adaptive destroy-and-repair heuristic

```
1:  procedure AdaptiveDestroyandRepair I, T_max, α̲, ᾱ, max_iter
2:    x* ← InitialSolution(I)
3:    while time ≤ T_max do
4:      f ← ExtractFeatures(x*) ▷ f is a vector of features of x
5:      (x_partial, C', P') ← Destroy(x*, f)
6:      x' ← Repair(x_partial, C', P', α̲, ᾱ, max_iter)
7:      if z(x') < z(x*) then ▷ z(·) denotes the cost of a solution
8:        x* ← x'
9:      end if
10:   end while
11:   returnx*
12: end procedure
```

visits at customer locations and parking spots, as well as the walking routes for drivers and delivery robots. The procedure starts by determining an initial solution (Algorithm 1, line 2). Then, until the time limit is not exceeded, the current solution is analyzed and a set of its representative features is extracted (Algorithm 1, line 4). Subsequently, the portions of the current solution to destroy are identified (Algorithm 1, line 5), resulting in a partial solution $\mathbf{x}_{\text{partial}}$, as well as in a subset of parking spots $\mathcal{P}'$ and customers $\mathcal{C}'$ to be reallocated. The output of the destroy step constitutes the input for the repair phase, during which the value of the parameter α is determined (Algorithm 1, line 6). If the repaired solution improves the current best solution, the latter is updated (Algorithm 1, lines 7-9). Finally, the best solution is returned. In the following, we detail the different components of our solution approach.

4.1. Initial solution construction

To quickly obtain an initial feasible solution $\mathbf{x}$, we iteratively open new van routes and fill them with a sequence of parking spots and associated walking trips. Before giving the details of how the routes are constructed, we need to add the following additional notation. If we denote as a_p the arrival time of a vehicle at $p \in \mathcal{P}$, then the waiting time before the vehicle can make use of the parking spot is defined as $w_p = \max(e_p - a_p, 0)$.

At each iteration, we choose a parking spot $p^* \in \mathcal{P}$ to be appended to the current van route (between the last visited parking spot and the return to the depot 0) and decide for how long it should be occupied, by defining a latest departure time from p^*, denoted as $LDT_{p^*} = \max(e_{p^*}, a_{p^*}) + \alpha[\min(\Gamma^{-1}_{p^*0}(T), l_{p^*}) - \max(e_{p^*}, a_{p^*})]$. The parking spot p^* is chosen as $p^* = \arg\min_{p \in \mathcal{P}}(\tau_{p'p}(LDT_{p'}) + w_p)$, where p' is the last parking spot visited by the current van route. In words, p^* represents the parking spot minimizing the sum of the time-dependent travel time from the last stop of the route and the possible waiting time at p^*. Of course, the value of $\tau_{p'p^*}(l_{p'}) + w_{p^*}$ must be lower than l_{p^*}.

As briefly mentioned before, the value of α influences the width of the occupation window. For the sake of determining the initial solution, α is fixed to a given value, whereas in the repair phase it is allowed to change at each iteration (see Section 4.2). After identifying p^* and setting LDT_{p^*}, we build at most $|\mathcal{N}_k| + 1$ (time-invariant) walking routes (i.e., one driver and $|\mathcal{N}_k|$ ADRs, where

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$k \in \mathcal{K}$ is the index of the current vehicle) to service as many customers as possible starting from p^*. To this purpose, we employ a straightforward cheapest insertion approach (Rosenkrantz et al., 1977). When no more parking locations can be feasibly added to the current van route, we open a new route. If no more parking locations are available, and there are still customers to be serviced, the initial solution is finalized by letting such customers to be visited by dedicated van routes. We assume that the fleet is finite, but sufficiently large to guarantee that all customer requests can be assigned to a vehicle. In the case of dedicated van routes—used as an option to guarantee feasibility when no additional parking spots are available—deliveries are carried out directly from the vehicle to the customers, without involving walking trips by the driver or by ADRs. As a consequence, these routes do not require the use of parking spots.

4.2. Adaptive destroy-and-repair

The destroy-and-repair phase starts with the extraction of a number of features characterizing the current solution. In particular, we derive both general features of the solution and specific features of each van route. Concerning the former, we compute the number of van routes and walking routes, as well as the total length and duration of van and walking routes. We specify that the walking routes are differentiated between those made by a driver and those made by a delivery robot. On the other hand, the route-specific features are the number of visited parking spots; total number of customers served, length and duration of the route; total number of walking trips, for both drivers and ADRs; demand served directly by the van, the driver, or an ADR; average percentage of distance range used for drivers and ADRs; average percentage of capacity used for vans, drivers, and ADRs.

Subsequently, we determine the parts of the solution to be destroyed. Typically, in many metaheuristics that utilize the destroy-and-repair paradigm, repair operators are applied to portions of the current solution randomly selected during the destroy phase. On the other hand, in this work, we propose a mechanism that leverages the characteristics of the current solution to guide the destroy action.

4.2.1. Destroying the current solution

To determine the parts of the current solution to be destroyed, van routes are first ranked by computing for each of them the ratio between the contribution of the route to the overall objective function and the number of customers served with it. Afterwards, we randomly choose a seed route i^* among the top k' maximizing the previous ratio and determine the k'' routes most similar to i^* according to a distance metric. In particular, we assume that the distance between two routes is the minimum distance between any two customers in the routes.

Then, the seed route and the k'' ones most similar to it are removed from the current solution, resulting in a partial solution $\mathbf{x}_{\text{partial}}$. Finally, all the parking locations visited by such routes, as well as all their served customers, become unserved, and constitute sets $\mathcal{P}'$ and $\mathcal{C}'$, which will be inputs for the repair phase.

4.2.2. Repairing the solution

The goal of the repair phase is to reallocate all the elements of $\mathcal{P}'$ and $\mathcal{C}'$ to $\mathbf{x}_{\text{partial}}$, possibly improving the previous solution. As anticipated before, the outcome of this step depends on the value of

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Algorithm 2. Pseudocode of the repair step

procedure REPAIR $\mathbf{x}_{\text{partial}}, \mathcal{C}', \mathcal{P}', \underline{\alpha}, \overline{\alpha}$, max_iter
  $\alpha_a \leftarrow 0; \alpha_b \leftarrow 1; \alpha_1 \leftarrow \underline{\alpha}; \alpha_2 \leftarrow \overline{\alpha} \triangleright \underline{\alpha} < \overline{\alpha}$
  iter $\leftarrow 1$
  while iter $\leq$ max_iter **do**
    $\mathbf{x_1} \leftarrow$ ALLOCATE($\mathbf{x}_{\text{partial}}, \mathcal{C}', \mathcal{P}', \alpha_1$)
    $\mathbf{x_2} \leftarrow$ ALLOCATE($\mathbf{x}_{\text{partial}}, \mathcal{C}', \mathcal{P}', \alpha_2$)
    if $z(\mathbf{x_1}) < z(\mathbf{x_2})$ **then**
      $\alpha_b \leftarrow \alpha_2$
    else if $z(\mathbf{x_1}) > z(\mathbf{x_2})$ **then**
      $\alpha_a \leftarrow \alpha_1$
    else $\triangleright z(\mathbf{x_1}) == z(\mathbf{x_2})$
      $\alpha_a \leftarrow \alpha_1; \alpha_b \leftarrow \alpha_2$
    end if
    $\alpha_1 \leftarrow \alpha_a + (\alpha_b - \alpha_a)/4; \alpha_2 \leftarrow \alpha_a + 3(\alpha_b - \alpha_a)/4 \triangleright \alpha_1$ and α_2 update
    iter $\leftarrow$ iter $+ 1$
  end while
  $\mathbf{x_a} \leftarrow$ ALLOCATE($\mathbf{x}_{\text{partial}}, \mathcal{C}', \mathcal{P}', \alpha_a$)
  $\mathbf{x_b} \leftarrow$ ALLOCATE($\mathbf{x}_{\text{partial}}, \mathcal{C}', \mathcal{P}', \alpha_b$)
  if $z(\mathbf{x_a}) < z(\mathbf{x_b})$ **then**
    return $\mathbf{x_a}$
  else
    return $\mathbf{x_b}$
  end if
end procedure

a parameter α, influencing the width of the time period for which a parking spot is occupied exclusively by a given vehicle. Similarly to the initial construction step, when we insert a new parking spot $p \in \mathcal{P}'$ into the partial solution, we set the latest departure time from it as

$$LDT_p = \max(e_p, a_p) + \alpha[\min(\Gamma^{-1}_{pp'}(LDT_{p'}), l_p) - \max(e_p, a_p)], \tag{51}$$

where p' is the parking spot before which we try to insert p. Of course, if the insertion position is just before returning to the depot, in (51) we must replace p' with 0, and $LDT_{p'}$ with T.

The choice of α is the result of a procedure in which the value of the parameter is determined by searching in intervals of increasingly reduced size. The pseudocode of the repair step, including the search procedure for determining α, is reported in Algorithm 2. Here, with the ALLOCATE function, we aim to reinsert the elements in $\mathcal{P}'$ and $\mathcal{C}'$ into $\mathbf{x}_{\text{partial}}$ according to the following actions, for which the insertion step is made using the same logic as the procedure used to obtain the initial solution.

1. An attempt is made to insert each $p \in \mathcal{P}'$ into an existing route of a vehicle $k \in \mathcal{K}$, by choosing, among all feasible insertion positions, the one causing the least shift for the points already on the route. The corresponding time period during which p is occupied is chosen by setting the value of the latest departure time according to (51). Then, at most $|\mathcal{N}_k| + 1$ walking trips are created to visit customers in $\mathcal{C}'$, obviously maintaining the feasibility regarding drivers and ADRs capacity, and maximum walking distance.

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2. An attempt is made to feasibly insert the customers from $\mathcal{C}'$ not allocated during step 1 into walking trips from parking locations already present in $\mathbf{x}_{\text{partial}}$. To this purpose, insertions into both already existing and new walking trips are considered, and the minimum-cost insertion is chosen.
3. If there are still customers in $\mathcal{C}'$, a service by a van with an existing route is evaluated.
4. Finally, the remaining customers are serviced by opening new van routes.

We observe that steps 3 and 4 rely on the same feasibility assumptions described at the end of Section 4.1, particularly regarding the adequacy of fleet size and the absence of parking spots in the dedicated van routes.

5. Computational results

This section presents the results of our computational study, which evaluates the solutions provided by our approach, as well as the impact of the ADAR mechanism on the solution quality. We implemented all algorithms in Java and conducted the experiments on a computer equipped with an Intel Core i7 processor clocked at 2.5 GHz and 16 GB of RAM. First, we describe the test instances used in our experiments, followed by a presentation and discussion of the computational results. Finally, we analyze the potential environmental advantages of our proposed delivery scheme, comparing it to a traditional delivery method.

5.1. Test instances

The test instances have been generated based on the real travel time functions (concerning the time-dependent aspect) and pedestrian networks of two major Italian cities: Naples and Rome. These two cities were selected due to their different characteristics in terms of population and residential density—Rome being more populous, and Naples having a higher population density—with the aim to evaluate the performance of the delivery framework and the proposed solution approach across different real-world urban settings. The travel time functions have been approximated as described in Ghiani et al. (2020), whereas the data on the pedestrian networks have been extracted from OpenStreetMap (www.openstreetmap.org). The delivery locations for customers, as well as the parking locations, have been randomly extracted from real locations of the two cities. Moreover, we considered a single depot from which van start their routes.

Based on this data, we have randomly generated six different datasets for both Naples and Rome, with 10 instances each, characterized by a different number of customers and of available parking spots, with number of customers $|\mathcal{C}| \in \{500, 750, 1000\}$, and number of available parking spots $|\mathcal{P}| \in \{0.05|\mathcal{C}|, 0.10|\mathcal{C}|\}$. Moreover, we have considered: customers' demand $q_c = 1$ and service time $s_c = 60$ seconds for each $c \in \mathcal{C}$, and cardinality of the ADR sub-fleet $|\mathcal{N}_k| = 4, \forall k \in \mathcal{K}$. For the sake of notation simplicity, given that the size of the ADR sub-fleet is the same for each vehicle, in the following, we refer to such a value as m. Concerning the van parameters, we have considered: capacity $Q^{\text{V}} = 200$, fixed cost $\gamma_f^{\text{V}} = 30$ €, and variable cost $\gamma_v = 0.08$ l/km $\cdot 1.80$ € /l $= 0.144$ € /km. Regarding drivers, we have: capacity $Q^{\text{D}} = 10$, maximum daily walking distance $L^{\text{D}} = 6.5$ km, fixed cost $\gamma_f^{\text{D}} = 200$ €, and speed $v^{\text{D}} = 6$ km/h. The parameters of the ADRs are capacity $Q^{\text{A}} = 6$,

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maximum distance with a full charge $L^{\mathrm{A}} = 16$ km, fixed cost $\gamma_f^{\mathrm{A}} = 5$ €, and speed $v^{\mathrm{A}} = 6$ km/h. The fixed and variable costs, as well as the ADR parameters, are taken from De Maio et al. (2024). Concerning driver's capacity, maximum distance, and speed, the two former parameters have been set to reasonable values of packages to be carried per trip and walking distance per day, whereas the latter has been set equal to the ADR speed, which is also similar to a typical pedestrian speed. All the data of our test instances are available from https://github.com/emamanni/PMLRP-ADR.

5.2. Benchmark heuristic

The quality of the solutions generated by the ADAR mechanism is assessed in comparison with a similar heuristic scheme following a classic destroy-and-repair approach, in which, at each iteration, in the destroy phase, the seed route is chosen randomly, whereas in the repair phase, the value of α is chosen randomly among a set of alternatives, according to probabilities that are updated at each iteration in the fashion of an adaptive large neighborhood search (ALNS) (Ropke and Pisinger, 2006). In the following, this benchmark approach is abbreviated as RDAR (random destroy-and-repair). We observe that, to achieve a fair comparison, the initial solution construction, as well as the insertion criterion in the repair phase of RDAR, are the same as for ADAR.

5.3. Analysis of the results

The performances of our approach and of RDAR are evaluated by testing each instance with a time limit of 1800 seconds, and using the two different objective functions (1) and (50), as reported in Section 3. The first objective function concerns the overall cost of a solution in terms of daily fixed costs for vans, drivers, and ADRs, as well as variable costs related to the distance covered by the vans. The second objective function involves the minimization of the CO_2 emissions. To this purpose, we have considered emission values of $\varepsilon^{\mathrm{V}} = 0.200$ and $\varepsilon^{\mathrm{A}} = 0.001$ kg of CO_2 per km for vans and ADRs, respectively (such values have been obtained as in De Maio et al. (2024)).

The quality of the solutions obtained by ADAR and RDAR is assessed by computing the average percentage deviation of the objective function value of ADAR compared to RDAR, denoted as $\mathrm{DEV}_{\mathrm{RDAR}}$, and obtained as:

$$\mathrm{DEV}_{\mathrm{RDAR}} = \frac{\text{ADAR obj. value} - \text{RDAR obj. value}}{\text{RDAR obj. value}}.$$

The results of the experiments are reported in Tables 2–5, which show the average results obtained for Naples (Tables 2 and 3) and Rome (Tables 4 and 5) with respect to the two objective functions. The column headings are as follows. Columns "$|\mathcal{C}|$" and "$\frac{|\mathcal{P}|}{|\mathcal{C}|}$" identify the dataset in terms of number of customers and of parking spots, column "z_{I}" reports the objective function value of the initial solution, whereas columns "z" and "$\mathrm{DEV}_{\mathrm{I}}$" show the best objective function value of RDAR or ADAR, and the percentage deviation of the best objective function value of RDAR or ADAR, compared to z_{I}, respectively. In the tables, the best result for each dataset is reported in bold.

Concerning the Naples instances, when the objective is the minimization of the overall cost (Table 2) ADAR always outperforms RDAR, except for the case with 500 customers and a number

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Table 2
Results for the Naples instances minimizing the overall cost

			RDAR		ADAR		
$\lvert\mathcal{C}\rvert$	$\frac{\lvert\mathcal{P}\rvert}{\lvert\mathcal{C}\rvert}$	z_I	z	DEV_I	z	DEV_I	DEV_{RDAR}
500	0.05	25,254.00	**24,436.07**	−0.03	24,851.83	−0.02	0.02
	0.10	27,013.83	25,625.58	−0.05	**23,739.96**	−0.12	−0.07
750	0.05	33,703.71	33,247.70	−0.01	**32,327.17**	−0.04	−0.03
	0.10	35,623.21	34,892.32	−0.02	**32,252.92**	−0.09	−0.08
1000	0.05	39,716.05	39,406.58	−0.01	**38,865.16**	−0.02	−0.01
	0.10	45,245.52	43,321.45	−0.04	**40,955.09**	−0.09	−0.05

Table 3
Results for the Naples instances minimizing the CO_2 emissions

			RDAR		ADAR		
$\lvert\mathcal{C}\rvert$	$\frac{\lvert\mathcal{P}\rvert}{\lvert\mathcal{C}\rvert}$	z_I	z	DEV_I	z	DEV_I	DEV_{RDAR}
500	0.05	32.51	32.25	−0.01	**30.94**	−0.05	−0.04
	0.10	35.55	33.51	−0.06	**32.89**	−0.07	−0.02
750	0.05	44.08	43.12	−0.02	**42.73**	−0.03	−0.01
	0.10	46.87	46.20	−0.01	**42.89**	−0.08	−0.07
1000	0.05	51.76	51.50	−0.01	**50.41**	−0.03	−0.02
	0.10	59.34	57.56	−0.03	**52.99**	−0.11	−0.08

Table 4
Results for the Rome instances minimizing the overall cost

			RDAR		ADAR		
$\lvert\mathcal{C}\rvert$	$\frac{\lvert\mathcal{P}\rvert}{\lvert\mathcal{C}\rvert}$	z_I	z	DEV_I	z	DEV_I	DEV_{RDAR}
500	0.05	18,098.35	18,098.35	0.00	**17,914.80**	−0.01	−0.01
	0.10	20,993.02	20,315.79	−0.03	**19,649.36**	−0.06	−0.03
750	0.05	25,549.82	25,417.55	−0.01	**25,306.48**	−0.01	0.00
	0.10	30,795.27	30,129.66	−0.02	**27,089.26**	−0.12	−0.10
1000	0.05	30,842.32	30,814.13	0.00	**30,425.50**	−0.01	−0.01
	0.10	38,123.26	36,954.66	−0.03	**34,987.51**	−0.08	−0.05

Table 5
Results for the Rome instances minimizing the CO_2 emissions

			RDAR		ADAR		
$\lvert\mathcal{C}\rvert$	$\frac{\lvert\mathcal{P}\rvert}{\lvert\mathcal{C}\rvert}$	z_I	z	DEV_I	z	DEV_I	DEV_{RDAR}
500	0.05	23.44	**23.26**	−0.01	23.41	0.00	0.01
	0.10	27.47	26.12	−0.05	**24.70**	−0.10	−0.05
750	0.05	33.06	**32.84**	−0.01	33.05	0.00	0.01
	0.10	40.38	38.89	−0.04	**35.88**	−0.11	−0.08
1000	0.05	39.61	39.59	0.00	**39.44**	0.00	0.00
	0.10	49.88	49.09	−0.02	**44.42**	−0.11	−0.10

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Table 6
Results for the Rome instances minimizing the overall cost with a varying number of ADRs

		$m = 0$	$m = 2$	$m = 4$		
$\lvert\mathcal{C}\rvert$	$\frac{\lvert\mathcal{P}\rvert}{\lvert\mathcal{C}\rvert}$	z	z	z	$\text{DEV}_{m=0}$	$\text{DEV}_{m=2}$
500	0.05	29,000.55	26,180.19	**17,914.80**	−0.38	−0.32
	0.10	29,486.77	26,325.26	**19,649.36**	−0.33	−0.25
750	0.05	40,357.38	35,432.61	**25,306.48**	−0.37	−0.29
	0.10	41,835.96	36,518.21	**27,089.26**	−0.35	−0.26
1000	0.05	52,445.47	43,525.31	**30,425.50**	−0.42	−0.30
	0.10	52,128.09	47,631.84	**34,987.51**	−0.33	−0.27

of parking spots equal to the 5% of the number of customers. In all the other datasets, the adaptive approach allows for achieving improvements with respect to RDAR ranging between 1% and 8%, with the best results obtained when the number of available parking locations is larger. When we consider the minimization of the CO_2 emissions as the main driver (Table 3), the trend is the same, but there are no situations in which RDAR is better than ADAR. Again, the best results are achieved for the instances with a larger number of parking spots, with an average percentage improvement of 2%, 7%, and 8%, when the number of customers is 500, 750, and 1000, respectively.

As far as the results for the Rome instances are concerned, when we aim to minimize the overall cost (Table 4), we observe that ADAR consistently provides the best results over all the datasets. The improvements are limited to at most 1% with a limited number of available parking spots, whereas when the cardinality of $\mathcal{P}$ is greater, the average deviations range between −0.03 and −0.10. When the objective function is the minimization of the emissions (Table 5), the two approaches show approximately the same behavior when $\frac{|\mathcal{P}|}{|\mathcal{C}|} = 0.05$, with RDAR slightly better than ADAR with 500 and 750 customers. Similarly to the previous cases, when $\frac{|\mathcal{P}|}{|\mathcal{C}|} = 0.10$ ADAR outperforms RDAR with deviation values between −0.05 and −0.10.

In general, we observe similar results and trends for the two case studies of Naples and Rome, and for the two objective functions, with the best results for ADAR obtained when the availability of parking spots is increased.

5.3.1. Sensitivity analysis

Here, we investigate how the performance of our approach can vary according to the presence and numerousness of ADRs, as well as to some of their characteristics. To this end, we study the sensitivity of the solutions to changes in the number of ADRs onboard each vehicle, and to a technological parameter of the delivery robots, namely the maximum distance covered with a full battery L^{A}. In particular, we run ADAR on the same Rome instances (the corresponding experiments on the Naples instances are reported in Appendix A) as in Tables 4 and 5 and considering: (i) a varying number of ADRs, that is, $m = 0$ (only the drivers perform deliveries by walking), $m = 2$, and $m = 4$ (the case considered previously); varying values for the maximum distance with a full charge, that is, $L^{\text{A}} = 12$ km, $L^{\text{A}} = 16$ km (the case considered previously), and $L^{\text{A}} = 20$ km.

The additional computations are reported in Tables 6–9, in which we compare the best alternative (highlighted in bold) with the others, by computing the average percentage deviation, similarly to

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Table 7
Results for the Rome instances minimizing the CO_2 emissions with a varying number of ADRs

		$m = 0$	$m = 2$	$m = 4$		
$\lvert\mathcal{C}\rvert$	$\frac{\lvert\mathcal{P}\rvert}{\lvert\mathcal{C}\rvert}$	z	z	z	$\text{DEV}_{m=0}$	$\text{DEV}_{m=2}$
500	0.05	39.33	34.58	**23.41**	−0.40	−0.32
	0.10	39.67	35.00	**24.70**	−0.38	−0.29
750	0.05	53.91	46.62	**33.05**	−0.39	−0.29
	0.10	72.70	55.41	**35.88**	−0.51	−0.35
1000	0.05	67.87	56.39	**39.44**	−0.42	−0.30
	0.10	74.88	59.57	**44.42**	−0.41	−0.25

Table 8
Results for the Rome instances minimizing the overall cost with varying values for the maximum distance with a full charge for ADRs

		$L^{\text{A}} = 12$ km	$L^{\text{A}} = 16$ km	$L^{\text{A}} = 20$ km		
$\lvert\mathcal{C}\rvert$	$\frac{\lvert\mathcal{P}\rvert}{\lvert\mathcal{C}\rvert}$	z	z	z	$\text{DEV}_{L^{\text{A}}=12\text{ km}}$	$\text{DEV}_{L^{\text{A}}=16\text{ km}}$
500	0.05	21,458.88	17,914.80	**16,366.77**	−0.24	−0.09
	0.10	23,239.66	19,649.36	**18,297.26**	−0.21	−0.07
750	0.05	27,412.55	25,306.48	**24,124.10**	−0.12	−0.05
	0.10	31,169.59	27,089.26	**26,158.85**	−0.16	−0.03
1000	0.05	33,028.17	30,425.50	**29,700.49**	−0.10	−0.02
	0.10	37,625.43	34,987.51	**33,909.51**	−0.10	−0.03

Table 9
Results for the Rome instances minimizing the CO_2 emissions with varying values for the maximum distance with a full charge for ADRs

		$L^{\text{A}} = 12$ km	$L^{\text{A}} = 16$ km	$L^{\text{A}} = 20$ km		
$\lvert\mathcal{C}\rvert$	$\frac{\lvert\mathcal{P}\rvert}{\lvert\mathcal{C}\rvert}$	z	z	z	$\text{DEV}_{L^{\text{A}}=12\text{ km}}$	$\text{DEV}_{L^{\text{A}}=16\text{ km}}$
500	0.05	27.50	23.41	**21.06**	−0.23	−0.10
	0.10	29.83	24.70	**23.99**	−0.20	−0.03
750	0.05	35.61	33.05	**31.10**	−0.13	−0.06
	0.10	39.40	35.88	**34.10**	−0.13	−0.05
1000	0.05	42.60	39.44	**38.75**	−0.09	−0.02
	0.10	48.72	44.42	**43.03**	−0.12	−0.03

the comparison between ADAR and RDAR. More specifically, Tables 6 and 7 refer to the case in which m varies, for the objectives of minimizing costs and emissions, respectively. Then, for the same two objective functions, Tables 8 and 9 consider different values for L^{A}.

Concerning the results obtained by varying the value of m (Table 6), the best results are achieved with $m = 4$. In particular, the overall cost reduction ranges between about 33% and 42% with respect to the case with no ADRs, and it is still very significant even when comparing with $m = 2$. In this latter case, the minimum and maximum percentage cost reductions are 25% and 32%, respectively. When considering the CO_2 emissions, we observe a similar trend. As before, the largest

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Table 10
Evaluation of the route-specific attributes for the Rome instances minimizing the overall cost with a varying number of ADRs

		$m = 0$				$m = 2$						$m = 4$					
$\lvert\mathcal{C}\rvert$	$\frac{\lvert\mathcal{P}\rvert}{\lvert\mathcal{C}\rvert}$	$\overline{\mathcal{C}^{\mathrm{D}}}$	$\overline{L^{\mathrm{D}}}$	$\overline{\mathrm{WR}}$	$\overline{\mathrm{PS}}$	$\overline{\mathcal{C}^{\mathrm{A}}}$	$\overline{\mathcal{C}^{\mathrm{D}}}$	$\overline{L^{\mathrm{A}}}$	$\overline{L^{\mathrm{D}}}$	$\overline{\mathrm{WR}}$	$\overline{\mathrm{PS}}$	$\overline{\mathcal{C}^{\mathrm{A}}}$	$\overline{\mathcal{C}^{\mathrm{D}}}$	$\overline{L^{\mathrm{A}}}$	$\overline{L^{\mathrm{D}}}$	$\overline{\mathrm{WR}}$	$\overline{\mathrm{PS}}$
500	0.05	1.12	0.49	0.90	0.15	194.95	60.00	9.90	4.28	47.60	3.13	397.43	88.44	11.10	5.70	87.30	3.77
	0.10	0.62	0.42	0.50	0.08	130.48	45.09	7.87	3.37	32.90	2.43	316.51	65.50	9.76	4.67	70.80	3.15
750	0.05	3.45	1.22	3.90	0.44	266.00	108.84	8.41	3.83	65.70	3.23	566.70	160.82	10.10	5.67	123.30	3.77
	0.10	4.08	1.73	5.80	0.68	173.76	66.39	5.13	2.48	42.86	2.47	465.99	106.21	9.39	4.93	100.60	3.03
1000	0.05	4.21	1.52	6.60	0.56	398.63	179.13	9.03	4.34	98.90	3.69	693.98	211.05	9.33	5.42	151.30	3.45
	0.10	5.14	1.61	7.70	0.66	254.41	95.10	5.71	2.71	61.40	2.53	640.24	155.69	8.89	4.92	137.40	3.31

deviation values are with respect to $m = 0$, with values up to -0.51. On the other hand, $\mathrm{DEV}_{m=2}$ ranges between -0.25 and -0.35. In general, we observe that increasing the number of ADRs onboard each van allows us to achieve considerable cost savings, regardless of the instance size or the number of parking spots.

Regarding the setting in which we vary the maximum distance that an ADR can travel with a full battery, the best results are obtained for the largest tested value, that is, $L^{\mathrm{A}} = 20$ km. In general, we observe that the performance of the algorithm improves significantly when L^{A} is increased from 12 to 16 km, with similar results for both objective functions. Specifically, the improvement varies between 10% and 24% in the case of cost minimization (Table 8) and between 9% and 23% in the case of emission minimization (Table 9). When the parameter is further increased from 16 to 20 km, there is still an improvement, but a smaller one than in the previous case. In fact, the minimum and maximum values of the average percentage deviation are -0.02 and -0.09 in the case of Table 8 and -0.02 and -0.10 in the case of Table 9. This smaller percentage improvement can be justified by the fact that, since ADRs have a limited capacity, increasing the value of L^{A} beyond a certain limit does not allow a substantial improvement compared to the previous ones.

We now evaluate whether increasing the number of ADRs per vehicle or extending their maximum travel range yields tangible benefits in route composition, based on some of the route-specific features introduced in Section 4.2, as well as the impact on drivers' work—particularly whether they undertake shorter or longer walking tours, or serve a different number of customers. To this end, in Tables 10 (varying the number of ADRs per vehicle) and 11 (varying the ADRs' maximum range for the initial case with $m = 4$), we consider the Rome instances with the cost-minimization objective function (the corresponding experiments on the Naples instances are reported in Appendix A). For each dataset, we report the average values (over the 10 instances) of the following attributes:

- number of customers served by delivery robots ($\overline{\mathcal{C}^{\mathrm{A}}}$);
- number of customers served by drivers with walking trips ($\overline{\mathcal{C}^{\mathrm{D}}}$);
- average length of delivery robot walking routes in kilometers ($\overline{L^{\mathrm{A}}}$);
- average length of driver walking routes in kilometers ($\overline{L^{\mathrm{D}}}$);
- number of walking routes ($\overline{\mathrm{WR}}$);
- parking spots used per van route ($\overline{\mathrm{PS}}$).

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Table 11
Evaluation of the route-specific attributes for the Rome instances minimizing the overall cost with varying values for the maximum distance with a full charge for ADRs

		$L^A = 12$ km						$L^A = 16$ km						$L^A = 20$ km					
$\lvert\mathcal{C}\rvert$	$\frac{\lvert\mathcal{P}\rvert}{\lvert\mathcal{C}\rvert}$	$\overline{\mathcal{C}^A}$	$\overline{\mathcal{C}^D}$	$\overline{L^A}$	$\overline{L^D}$	$\overline{WR}$	$\overline{PS}$	$\overline{\mathcal{C}^A}$	$\overline{\mathcal{C}^D}$	$\overline{L^A}$	$\overline{L^D}$	$\overline{WR}$	$\overline{PS}$	$\overline{\mathcal{C}^A}$	$\overline{\mathcal{C}^D}$	$\overline{L^A}$	$\overline{L^D}$	$\overline{WR}$	$\overline{PS}$
500	0.05	287.09	76.79	8.48	4.85	69.30	3.22	397.43	88.44	11.10	5.70	87.30	3.77	411.10	88.90	12.30	5.97	87.60	3.73
	0.10	193.21	49.89	5.82	3.39	44.30	2.20	316.51	65.50	9.76	4.67	70.80	3.15	370.72	71.85	12.48	5.36	81.10	3.63
750	0.05	522.86	154.68	9.03	5.60	120.30	3.82	566.70	160.82	10.10	5.67	123.30	3.77	557.04	150.28	11.18	5.70	119.20	3.83
	0.10	377.32	100.53	6.99	4.18	86.60	2.99	465.99	106.21	9.39	4.93	100.60	3.03	545.59	113.35	11.35	5.40	115.80	3.61
1000	0.05	682.11	218.19	8.24	5.27	153.70	3.43	693.98	211.05	9.33	5.42	151.30	3.45	703.99	207.06	9.78	5.25	152.44	3.42
	0.10	506.62	145.26	6.47	4.05	113.20	2.80	640.24	155.69	8.89	4.92	137.40	3.31	689.64	142.96	10.98	5.12	147.00	3.54

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We observe that columns $\overline{C^{\mathrm{A}}}$ and $\overline{L^{\mathrm{A}}}$ are not reported in Table 10 for $m = 0$, as their values are obviously equal to zero.

Concerning Table 10, as m increases, the average number of customers served by delivery robots rises significantly, while the number of customers served by drivers with walking trips rises, but with a much lower ratio, suggesting an offloading effect of ADRs on driver workload. Moreover, both drivers' and ADRs' walking route lengths tend to increase with higher m, as a consequence of the increased number of customers served. In addition, the number of walking routes also grows significantly with increasing values of m, whereas the parking spots used by each van do not vary significantly between $m = 2$ and $m = 4$. In general, the observed trends among the feature values remain consistent, showing the scalability and robustness of the proposed delivery framework.

When we analyze the same features with respect to an increase in the maximum range of ADRs (Table 11), we observe that the average number of customers served by ADRs increases more significantly than the corresponding value for drivers, which in several cases remains stable. This suggests that longer ADR ranges enable the system to reassign deliveries from drivers to robots, thereby reducing the drivers' workload. A similar pattern is observed for both the average ADR route length and the average walking route length for drivers. The average number of walking routes shows a more pronounced increase when the range is extended from 12 to 16 km, compared with the extension from 16 to 20 km. As in the previous case, changing this ADR technological parameter does not significantly affect the number of parking locations visited per van route. Overall, the results seem to confirm the findings from Tables 8 and 9, that is, that increasing the value of L^{A} beyond a certain threshold (16 km in our experiments) does not lead to a substantial performance improvement.

5.4. *Influence of route features on the destroy step*

In this section, we perform some additional computational experiments to evaluate the influence that the different route features involved in the destroy phase have on the quality of the solutions. To this end, instead of considering a single destroy operator as before, we embed several destroy and repair operators—exploiting different route features—into a classical ALNS framework (Ropke and Pisinger, 2006). As is well known, ALNS iteratively destroys and repairs parts of a given solution. At each iteration, a destroy operator is first applied to partially remove elements from the current solution, which are then reinserted by a repair operator, possibly leading to an improving solution. A key feature is the adaptive mechanism for selecting destroy and repair operators, based on their past performance, according to a roulette wheel principle, with the selection probability p_i of operator i given by $p_i = \omega_i / \sum_j \omega_j$, where ω_i is the current weight of operator i. The value of such weights is adapted over segments of iterations. Within a segment, each operator accumulates a score based on its contribution to improving the solution. A typical scoring rule awards: a high score when the operator produces a new global best solution; a moderate score when it produces an improving solution; a small score when it produces an accepted but non-improving solution. At the end of each segment, the weights are updated according to

$$\omega_i = (1 - \rho)\omega_i^{\mathrm{old}} + \rho \, \frac{\mathrm{score}_i}{\mathrm{count}_i},$$

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Table 12
Destroy and repair operators used in the ALNS

Operator type	Description	Abbreviation
Destroy	The κ shortest routes (including drivers' and delivery robots' walking trips) are destroyed.	$\mathcal{D}_1$
Destroy	The κ longest routes (including drivers' and delivery robots' walking trips) are destroyed.	$\mathcal{D}_2$
Destroy	The κ routes with the shortest duration are destroyed.	$\mathcal{D}_3$
Destroy	The κ routes with the longest duration are destroyed.	$\mathcal{D}_4$
Destroy	The κ routes serving the fewest customers are destroyed.	$\mathcal{D}_5$
Destroy	The κ routes with the fewest visited parking spots are destroyed.	$\mathcal{D}_6$
Destroy	The κ routes with the highest cost are destroyed.	$\mathcal{D}_7$
Destroy	The κ routes with the fewest number of walking routes are destroyed.	$\mathcal{D}_8$
Destroy	The κ routes with the greatest number of walking routes are destroyed.	$\mathcal{D}_9$
Destroy	The κ routes with the lowest utilization of the delivery robots' capacity are destroyed.	$\mathcal{D}_{10}$
Destroy	The κ routes with the minimum total walking route length are destroyed.	$\mathcal{D}_{11}$
Destroy	The κ routes with the maximum total walking route length are destroyed.	$\mathcal{D}_{12}$
Destroy	The κ shortest van routes are destroyed.	$\mathcal{D}_{13}$
Destroy	The κ longest van routes are destroyed.	$\mathcal{D}_{14}$
Repair	Only the unused parking spots are inserted in an attempt to open new walking routes. For the customers that remain unserved, new dedicated van routes are then opened.	$\mathcal{R}_1$
Repair	Unserved customers are first inserted into the existing walking routes and subsequently into new van routes.	$\mathcal{R}_2$
Repair	Unserved customers are first inserted into existing van routes and subsequently into new van routes.	$\mathcal{R}_3$
Repair	The solution is repaired by first inserting unused parking spots in an attempt to open new walking routes. Next, unserved customers are inserted into existing walking routes. Customers still unserved are then inserted into existing van routes, and, finally, new dedicated van routes are opened if necessary.	$\mathcal{R}_4$

where $\rho \in [0, 1]$ is a reaction factor controlling how quickly the weight adjustment reacts to changes in the effectiveness of the operators, score_i is the accumulated reward of operator i in the segment, and count_i is the number of times it was used.

The acceptance of new solutions (possibly non-improving ones) is typically based on the simulated-annealing principle (Kirkpatrick et al., 1983).

Based on this framework, to assess which feature involved in the destroy phase has the greatest influence on the solution, we consider an ALNS with the destroy and repair operators listed in Table 12.

Concerning the other parameters of the ALNS, we consider: segment length set to 10 iterations; reward equal to 25 when the operator produces a new global best solution; reward equal to 10 when it produces an improving solution; reward equal to 0 when it produces an accepted but non-improving solution; reaction factor $\rho = 0.3$, which represents a conservative choice.

The results of these experiments are reported in Table 13, which considers the Rome instances under the cost-minimization objective, with $\kappa = 3$ for all destroy operators (a similar analysis is reported in Appendix B for the Naples instances). For each dataset and for each destroy operator, we report the average reward obtained over all instances in the dataset during the execution of

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Table 13
Average rewards achieved by the destroy operators for the Rome instances

$\lvert\mathcal{C}\rvert$	$\frac{\lvert\mathcal{P}\rvert}{\lvert\mathcal{C}\rvert}$	$\mathcal{D}_1$	$\mathcal{D}_2$	$\mathcal{D}_3$	$\mathcal{D}_4$	$\mathcal{D}_5$	$\mathcal{D}_6$	$\mathcal{D}_7$	$\mathcal{D}_8$	$\mathcal{D}_9$	$\mathcal{D}_{10}$	$\mathcal{D}_{11}$	$\mathcal{D}_{12}$	$\mathcal{D}_{13}$	$\mathcal{D}_{14}$
500	0.05	13.20	19.80	13.20	19.73	20.90	23.29	23.15	19.80	19.80	19.96	6.60	16.50	**25.30**	19.80
	0.10	20.90	16.43	**23.10**	16.37	17.60	16.38	18.13	13.20	16.20	16.81	13.43	20.31	**23.10**	19.80
750	0.05	15.51	23.30	16.50	**29.40**	24.05	23.10	13.80	13.20	6.60	16.50	19.80	9.90	13.20	26.40
	0.10	6.71	**41.80**	25.44	22.31	19.80	6.51	5.85	9.91	19.80	9.90	13.61	17.03	9.98	15.40
1000	0.05	16.48	9.90	12.10	13.20	22.00	16.50	13.20	9.90	6.76	16.70	14.66	**24.20**	6.60	11.00
	0.10	13.20	18.61	19.80	19.92	13.20	13.27	11.60	17.45	17.60	7.70	13.54	25.36	8.80	**26.90**

the algorithm, with the best result highlighted in bold. As the table shows, the performance of the destroy operators varies across datasets. With 500 customers, the route feature having the greatest influence appears to be the length of the van component (operator $\mathcal{D}_{13}$), although considering the number of visited parking spots (operator $\mathcal{D}_6$) and the routes' duration (operator $\mathcal{D}_3$) also yield good results. When the number of customers increases to 750, the highest rewards are again achieved by operators related to the routes' spatial and temporal characteristics, such as operators $\mathcal{D}_2$, $\mathcal{D}_4$, and $\mathcal{D}_{14}$. Finally, with 1000 customers, a relevant feature to consider is the total length of walking routes, as shown by the average reward achieved by operator $\mathcal{D}_{12}$ for both values of $|\mathcal{P}|/|\mathcal{C}|$. Regarding the features associated with the lowest rewards, we note the ADRs' capacity ($\mathcal{D}_{10}$) and the number of walking routes ($\mathcal{D}_8$ and $\mathcal{D}_9$).

5.5. *Comparison with a traditional delivery scheme*

In this section, we derive some insights related to the potential environmental and cost benefits of using the proposed delivery scheme of park-and-loop with a heterogeneous sub-fleet (driver and ADRs), compared to a traditional delivery scheme in which the customers can be serviced by traditional vans only. To this aim, the problem could be considered as the PMLRP-ADR, where $\mathcal{P} = \emptyset$ and $\mathcal{N}_k = \emptyset$ for each $k \in \mathcal{K}$. To derive such insights, we consider the ADAR results from Tables 3 and 5 and compare them with the results obtained by running the same approach, removing the parking locations, so that the customer requests can be serviced only by the vans. Moreover, for the solutions minimizing the CO_2 emissions, we also compute the corresponding costs for both the traditional delivery scheme and the scheme we are proposing in this paper. Such information are reported under the "Costs" columns. The columns "Deviations" report the corresponding average relative deviations—for both emissions and costs—of ADAR compared to the traditional scheme. The results are reported in Table 14 for the instances related to the Naples data, and in Table 15 for Rome.

As the tables show, the possible environmental benefits are huge, with average deviations between −0.18 and −0.29 for the Naples instances (Table 14) and between −0.18 and −0.43 for the Rome instances (Table 15). We observe that the advantages are typically lower (even if they are still consistent) when the number of customers is larger, probably because in these cases the constraints about the capacity and maximum walking distance of drivers and ADRs impose that a non-negligible fraction of customers must be serviced by vans. Concerning the costs, the deviations show a trend

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Table 14
Results of the analysis of the possible emissions and cost reduction for the Naples instances

		Emissions		Costs		Deviations	
$\lvert\mathcal{C}\rvert$	$\frac{\lvert\mathcal{P}\rvert}{\lvert\mathcal{C}\rvert}$	$z_{\text{traditional}}$	z_{ADAR}	$z_{\text{traditional}}$	z_{ADAR}	$\text{DEV}_{\text{emissions}}$	$\text{DEV}_{\text{costs}}$
500	0.05	43.61	**30.94**	32,549.73	**23,613.17**	−0.29	−0.27
	0.10	43.63	**32.89**	32,606.38	**25,089.08**	−0.25	−0.23
750	0.05	56.22	**42.73**	42,315.53	**32,737.32**	−0.24	−0.23
	0.10	56.65	**42.89**	42,628.96	**32,725.76**	−0.24	−0.23
1000	0.05	64.59	**50.41**	48,801.36	**38,797.05**	−0.22	−0.21
	0.10	64.95	**52.99**	49,110.37	**40,492.06**	−0.18	−0.18

Table 15
Results of the analysis of the possible emissions and cost reduction for the Rome instances

		Emissions		Costs		Deviations	
$\lvert\mathcal{C}\rvert$	$\frac{\lvert\mathcal{P}\rvert}{\lvert\mathcal{C}\rvert}$	$z_{\text{traditional}}$	z_{ADAR}	$z_{\text{traditional}}$	z_{ADAR}	$\text{DEV}_{\text{emissions}}$	$\text{DEV}_{\text{costs}}$
500	0.05	36.51	**23.41**	27,439.66	**18,156.90**	−0.36	−0.34
	0.10	43.63	**24.70**	27,708.20	**19,037.04**	−0.43	−0.31
750	0.05	46.35	**33.05**	35,208.79	**25,615.40**	−0.29	−0.27
	0.10	46.86	**35.88**	35,578.42	**27,589.20**	−0.23	−0.22
1000	0.05	53.75	**39.44**	41,048.29	**30,770.05**	−0.27	−0.25
	0.10	53.95	**44.42**	41,146.86	**34,332.15**	−0.18	−0.17

similar to $\text{DEV}_{\text{emissions}}$, with average values ranging between −0.18 and −0.27 for the Naples instances and between −0.17 and −0.34 for the Rome instances. Overall, these results indicate that optimizing the emission-based objective does not lead to a deterioration in operational costs. On the contrary, the ADAR solutions consistently provide cost reductions as well, showing that, in the considered scenarios, the two objectives are aligned and no significant trade-off between emissions and costs emerges.

6. Conclusions

In this paper, we have introduced the *PMLRP-ADR*, which extends the park-and-loop framework by allowing customers to be serviced by drivers and delivery robots with walking trips starting from given areas designated as parking locations, in addition to a classic van delivery service. To address this problem, we introduced a tailored parameterized destroy-and-repair mechanism, able to exploit the characteristics of the current solution to determine the appropriate parameter setting. This approach was embedded into a neighborhood-search algorithm and compared with a traditional random destroy approach. We have tested the proposed method on instances with up to 1000 customers obtained from real data of two major Italian cities, and we have shown that our approach can provide important improvements, in terms of both costs and CO_2 emissions minimization, especially when the number of available parking locations grows. Moreover, we have shown that the proposed delivery scheme can provide huge benefits in terms of emission reductions compared with a traditional delivery paradigm, with reductions of over 50% in several scenarios.

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Future research should investigate potential negative externalities associated with this prospective delivery paradigm, such as additional waiting times for drivers at parking locations while ADRs complete their routes, synchronization issues among vans, drivers, and ADRs, and possible operational constraints that may arise in real-world implementations.

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Appendix A

In this appendix, we report the results on the Naples instances for the sensitivity analysis of Section 5.3.1. In particular, Tables A1 and A2 refer to the case with a varying number of ADRs, whereas Tables A3 and A4 take into account the case where parameter L^A varies.

Concerning the results with a varying number of ADRs obtained for the Naples instances (Tables A1 and A2), we observe a trend fully consistent with the one discussed for Rome. In particular, the best results are always achieved with $m = 4$, with overall cost reductions ranging between about 28% and 40% with respect to the case with no ADRs, and still significant when compared with $m = 2$, where reductions range between 23% and 29%. When considering the CO_2 emissions, the same pattern emerges, with $DEV_{m=0}$ values reaching up to -0.45, while $DEV_{m=2}$ ranges between -0.21 and -0.30. Overall, also for the Naples instances, increasing the number of ADRs onboard each van leads to substantial improvements in both cost and emissions reductions, regardless of the instance size and the number of parking locations.

Table A1
Results for the Naples instances minimizing the overall cost with a varying number of ADRs

		$m = 0$	$m = 2$	$m = 4$		
$\lvert\mathcal{C}\rvert$	$\frac{\lvert\mathcal{P}\rvert}{\lvert\mathcal{C}\rvert}$	z	z	z	$DEV_{m=0}$	$DEV_{m=2}$
500	0.05	34,438.72	32,347.64	**24,851.83**	−0.28	−0.23
	0.10	33,818.40	31,530.05	**23,739.96**	−0.30	−0.25
750	0.05	47,771.42	42,854.38	**32,327.17**	−0.32	−0.25
	0.10	52,367.76	43,902.64	**32,252.92**	−0.38	−0.27
1000	0.05	63,243.67	54,680.63	**38,865.16**	−0.39	−0.29
	0.10	67,897.38	53,520.29	**40,955.09**	−0.40	−0.23

Regarding the setting in which we vary the maximum distance that an ADR can travel with a full battery (Tables A3 and A4), the best results are consistently obtained for the largest tested value, that is, $L^{\mathrm{A}} = 20$ km. As in the Rome instances, we observe that the most significant improvement occurs when increasing L^{A} from 12 to 16 km. In particular, in the case of cost minimization, the percentage improvement ranges between 8% and 22%, while for the emission minimization it ranges between 12% and 21%. When further increasing L^{A} from 16 to 20 km, the improvement is still

Table A2
Results for the Naples instances minimizing the CO_2 emissions with a varying number of ADRs

		$m = 0$	$m = 2$	$m = 4$		
$\lvert\mathcal{C}\rvert$	$\frac{\lvert\mathcal{P}\rvert}{\lvert\mathcal{C}\rvert}$	z	z	z	$DEV_{m=0}$	$DEV_{m=2}$
500	0.05	45.70	42.01	**30.94**	−0.32	−0.26
	0.10	45.32	41.73	**32.89**	−0.27	−0.21
750	0.05	63.82	57.26	**42.73**	−0.33	−0.25
	0.10	68.71	58.93	**42.89**	−0.38	−0.27
1000	0.05	83.70	72.17	**50.41**	−0.40	−0.30
	0.10	96.34	70.82	**52.99**	−0.45	−0.25

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Table A3
Results for the Naples instances minimizing the overall cost with varying values for the maximum distance with a full charge for ADRs

		$L^A = 12$ km	$L^A = 16$ km	$L^A = 20$ km		
$\lvert\mathcal{C}\rvert$	$\frac{\lvert\mathcal{P}\rvert}{\lvert\mathcal{C}\rvert}$	z	z	z	$\text{DEV}_{L^A=12\text{ km}}$	$\text{DEV}_{L^A=16\text{ km}}$
500	0.05	27,568.88	24,851.83	**21,822.33**	−0.21	−0.12
	0.10	27,852.81	23,739.96	**23,048.09**	−0.17	−0.03
750	0.05	36,292.24	32,327.17	**28,368.01**	−0.22	−0.12
	0.10	36,366.09	32,252.92	**29,383.86**	−0.19	−0.09
1000	0.05	44,743.30	38,865.16	**35,772.30**	−0.20	−0.08
	0.10	43,042.42	40,955.09	**39,536.23**	−0.08	−0.03

Table A4
Results for the Naples instances minimizing the CO_2 emissions with varying values for the maximum distance with a full charge for ADRs

		$L^A = 12$ km	$L^A = 16$ km	$L^A = 20$ km		
$\lvert\mathcal{C}\rvert$	$\frac{\lvert\mathcal{P}\rvert}{\lvert\mathcal{C}\rvert}$	z	z	z	$\text{DEV}_{L^A=12\text{ km}}$	$\text{DEV}_{L^A=16\text{ km}}$
500	0.05	35.62	30.94	**28.56**	−0.20	−0.08
	0.10	37.94	32.89	**30.59**	−0.19	−0.07
750	0.05	46.25	42.73	**36.64**	−0.21	−0.14
	0.10	47.73	42.89	**38.52**	−0.19	−0.10
1000	0.05	56.37	50.41	**46.72**	−0.17	−0.07
	0.10	58.07	52.99	**50.82**	−0.12	−0.04

Table A5
Evaluation of the route-specific attributes for the Naples instances minimizing the overall cost with a varying number of ADRs

		$m = 0$				$m = 2$						$m = 4$					
$\lvert\mathcal{C}\rvert$	$\frac{\lvert\mathcal{P}\rvert}{\lvert\mathcal{C}\rvert}$	$\overline{\mathcal{C}^D}$	$\overline{L^D}$	$\overline{\text{WR}}$	$\overline{\text{PS}}$	$\overline{\mathcal{C}^A}$	$\overline{\mathcal{C}^D}$	$\overline{L^A}$	$\overline{L^D}$	$\overline{\text{WR}}$	$\overline{\text{PS}}$	$\overline{\mathcal{C}^A}$	$\overline{\mathcal{C}^D}$	$\overline{L^A}$	$\overline{L^D}$	$\overline{\text{WR}}$	$\overline{\text{PS}}$
500	0.05	0.38	0.28	0.40	0.10	20.39	7.24	6.09	2.80	25.60	1.80	69.95	14.95	11.39	5.16	87.30	3.59
	0.10	0.52	0.32	0.50	0.08	23.03	6.88	7.20	3.16	29.80	2.16	61.46	13.28	10.57	4.80	71.00	2.99
750	0.05	1.53	0.67	2.20	0.26	22.96	8.08	6.54	2.92	42.00	2.07	61.98	14.99	9.90	4.86	104.10	3.02
	0.10	4.85	2.17	7.20	0.71	20.35	7.24	5.55	2.47	38.10	2.01	65.65	13.83	10.91	5.19	110.70	3.71
1000	0.05	4.53	1.44	6.80	0.51	22.68	9.53	6.25	2.84	57.10	2.07	70.93	16.44	10.15	5.28	156.70	3.56
	0.10	9.90	4.55	22.00	1.44	23.90	9.63	6.39	2.87	60.70	2.38	60.02	15.62	8.87	4.73	134.50	3.28

present but more limited, with $\text{DEV}_{L^A=16\text{ km}}$ values ranging between −0.03 and −0.12 for costs and between −0.04 and −0.14 for emissions. This behavior confirms that, due to the limited capacity of ADRs, increasing their maximum range beyond a certain threshold yields diminishing returns, as also observed for the Rome instances.

Then, Tables A5 and A6 contain—for the Naples instances—an analysis of the same route-specific features reported at the end of Section 5.3.1 for the Rome instances. In particular, Table A5

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Table A6
Evaluation of the route-specific attributes for the Naples instances minimizing the overall cost with varying values for the maximum distance with a full charge for ADRs

		$L^A = 12$ km						$L^A = 16$ km						$L^A = 20$ km					
$\lvert\mathcal{C}\rvert$	$\frac{\lvert\mathcal{P}\rvert}{\lvert\mathcal{C}\rvert}$	$\overline{\mathcal{C}^A}$	$\overline{\mathcal{C}^D}$	$\overline{L^A}$	$\overline{L^D}$	$\overline{WR}$	$\overline{PS}$	$\overline{\mathcal{C}^A}$	$\overline{\mathcal{C}^D}$	$\overline{L^A}$	$\overline{L^D}$	$\overline{WR}$	$\overline{PS}$	$\overline{\mathcal{C}^A}$	$\overline{\mathcal{C}^D}$	$\overline{L^A}$	$\overline{L^D}$	$\overline{WR}$	$\overline{PS}$
500	0.05	49.33	10.37	8.32	4.64	62.20	2.84	69.95	14.95	11.39	5.16	87.30	3.59	77.74	16.30	13.66	5.71	87.30	3.92
	0.10	39.28	9.35	6.48	3.75	47.50	2.23	61.46	13.28	10.57	4.80	71.00	2.99	70.44	12.86	12.85	5.16	78.20	3.77
750	0.05	48.00	12.64	7.26	4.21	85.40	2.66	61.98	14.99	9.90	4.86	104.10	3.02	80.32	17.32	13.51	5.74	131.80	4.10
	0.10	45.60	11.90	6.64	3.93	78.20	2.57	65.65	13.83	10.91	5.19	110.70	3.71	76.97	14.94	13.68	5.89	128.30	4.39
1000	0.05	59.07	15.17	8.21	4.96	136.80	3.43	70.93	16.44	10.15	5.28	156.70	3.56	76.87	17.69	11.93	5.54	165.50	3.87
	0.10	49.58	14.38	7.04	4.32	114.80	2.85	60.02	15.62	8.87	4.73	134.50	3.28	81.15	18.18	12.33	5.74	180.20	4.45

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refers to the case of a varying number of ADRs per vehicle, whereas Table A6 shows the results when the ADRs' maximum range changes.

Concerning Table A5, increasing the value of m leads to a marked growth in the average number of customers handled by ADRs, while the contribution of drivers through walking deliveries increases at a slower rate. Furthermore, both the average distance traveled by ADRs and the walking distance covered by drivers tend to rise as m increases, reflecting the larger share of customers served through decentralized operations. The number of walking routes expands significantly, particularly when moving to $m = 4$, whereas the number of parking locations visited along van routes remains relatively stable. Overall, these patterns confirm the effectiveness of leveraging multiple ADRs per vehicle in enhancing the system performance.

When considering the impact of different values of L^{A} (Table A6), we observe that larger ranges enable ADRs to serve a greater number of customers, while the role of drivers remains nearly unchanged or exhibits only minor variations. This indicates that extending the operational capability of ADRs promotes a redistribution of delivery tasks in favor of robots. In addition, the average distance covered by ADRs increases with L^{A}, whereas the variation in drivers' walking distance is more contained. The number of walking routes grows more noticeably when increasing the range from 12 to 16 km, with a less pronounced increment beyond this threshold. As in the previous analysis, the number of parking locations used per van route is only marginally influenced by changes in this parameter. These results suggest that the marginal benefit of enlarging the ADR range progressively decreases.

Appendix B

In this appendix, we report the results on the Naples instances for the analysis to evaluate the influence of the different route features involved in the destroy phase on the solution quality, as reported in Section 5.4 for the Rome instances. The results are shown in Table B1.

Table B1
Average rewards achieved by the destroy operators for the Naples instances

$\lvert\mathcal{C}\rvert$	$\frac{\lvert\mathcal{P}\rvert}{\lvert\mathcal{C}\rvert}$	$\mathcal{D}_1$	$\mathcal{D}_2$	$\mathcal{D}_3$	$\mathcal{D}_4$	$\mathcal{D}_5$	$\mathcal{D}_6$	$\mathcal{D}_7$	$\mathcal{D}_8$	$\mathcal{D}_9$	$\mathcal{D}_{10}$	$\mathcal{D}_{11}$	$\mathcal{D}_{12}$	$\mathcal{D}_{13}$	$\mathcal{D}_{14}$
500	0.05	28.38	**29.70**	26.40	16.41	6.60	19.80	18.33	24.20	23.10	19.80	15.40	23.05	6.60	13.20
	0.10	15.70	9.89	19.80	19.80	22.00	16.50	22.85	16.50	**30.80**	19.85	9.90	25.30	19.80	16.45
750	0.05	23.32	**27.64**	9.90	16.50	13.20	16.81	19.10	17.60	24.20	23.10	19.80	13.00	26.40	12.74
	0.10	**28.00**	6.60	13.20	16.54	13.38	9.90	7.25	16.44	25.47	6.60	25.16	27.50	26.19	16.50
1000	0.05	16.50	20.90	15.40	13.20	18.70	**35.33**	7.80	24.07	19.79	9.83	20.00	9.90	18.70	13.19
	0.10	10.25	13.93	**39.60**	3.30	8.80	16.50	18.80	7.09	9.90	9.77	12.82	10.12	15.40	21.99

As shown in Table B1, the effectiveness of the destroy operators varies across instance sizes and configurations, with different route characteristics playing a key role. For instance, with 500 customers, the best-performing operators are $\mathcal{D}_2$ and $\mathcal{D}_9$, which target, respectively, the longest routes and the routes with the highest number of walking trips, suggesting that removing structurally complex routes can be particularly beneficial. When the number of customers increases to 750, operators focusing on route length and structure (e.g., $\mathcal{D}_1$ and $\mathcal{D}_2$), as well as those acting on van-related

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components (e.g., $\mathcal{D}_{13}$), tend to achieve higher rewards. For the largest instances (1000 customers), the most effective operators are $\mathcal{D}_6$ and $\mathcal{D}_3$, indicating that removing routes with few visited parking locations or short duration can better guide the search in more complex settings. Conversely, operators related to ADR capacity utilization or to the number of walking routes (e.g., $\mathcal{D}_{10}$ and, in some cases, $\mathcal{D}_8$) generally yield lower rewards. Overall, these results highlight that operators targeting structurally critical or highly unbalanced routes tend to be more effective in improving solution quality.

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