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2-echelon lastmile delivery with lockers and occasional couriers

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ABSTRACT

We propose a new approach for the lastmile delivery problem where, besides serving as collecting points of orders for customers, parcel lockers are also used as transshipment nodes in a 2-echelon delivery system. Moreover, we consider that a customer (occasional courier) visiting a locker may accept a compensation to make a delivery to another customer on their regular traveling path.

The proposed shared use of the locker facilities – by customers that prefer to self-pick up their orders, and also as a transfer deposit for customers that prefer home delivery – will contribute to better usage of an already available storage capacity. Furthermore, the use of occasional couriers (OCs) brings an extra layer of flexibility to the delivery process and may positively contribute to achieving some environmental goals: although non-consolidation of deliveries may, at first sight, seem negative, by only considering OCs that would go to the locker independently of making or not a delivery on their way home, and their selection being constrained by a maximum detour, the carbon footprint can be potentially reduced when compared to that of dedicated vehicles.

We present a mixed-integer linear programming formulation for the problem that integrates three delivery options – depot to locker, depot to locker followed by final delivery by a professional fleet, and depot to locker followed by final delivery by an OC. Furthermore, to assess the impact of OCs' no show on the delivery process, we extend the formulation to re-schedule the delivery of previous undelivered parcels, and analyze the impact of different no-show rates.

Thorough computational experiments show that the use of OCs has a positive impact both on the delivery cost and on the total distance traveled by the dedicated fleets. Experiments also show that the negative impact of no-shows may be reduced by using lockers with higher capacities.

1. Introduction

Retail e-commerce sales amounted to US$ 4.28 trillion worldwide in 2020, a growth of 27.6% compared to the previous year. A similar growth is expected from 2020 to 2022 (Statista Digital Market Outlook — www.statista.com). The reported amount represents 18% of global retail sales. Congestion in some of the largest cities in the United States, like New York and Los Angeles, has increased between 20 and 35% in the past decade, to a great extent due to the increase of e-commerce (Deloison et al., 2020). In large

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European cities, between 20 to 30% of vehicle kilometer of transport activities are performed by delivery vehicles (Dablanc, 2007). Furthermore, cities are responsible for 70% of global emissions and delivery vehicles contribute with excessively higher amounts of the air pollutant emissions than passenger cars (Deloison et al., 2020), demanding environmentally sustainable solutions (Thompson, 2015).

Traditionally, the delivery of parcels is made through intermediate facilities, where goods are stored and consolidated for further distribution. This implies that from its origin to its final destination a parcel may be transported by multiple vehicles and couriers. In a two-echelon distribution system, for example, goods are firstly transferred from the origin to distribution centers, and later from there to the final destination. The last echelon corresponds to the final leg of the delivery and is often referred to as the lastmile delivery. There are many variations of this system; we refer to Cuda et al. (2015) for an overview of the literature.

That dramatic growth of e-commerce and the consequent pressure put on delivery urgently request for innovation on flexible and reliable delivery models. For example, several carriers have extended their delivery network by installing facilities that allow customers to self-pick up orders at their convenience. These pick-up stations are usually parcel lockers with several slots where orders can be stored by the carrier for a later collection by the customer. These are currently used by national post services, like CTT in Portugal (CTT, 2020), Correos in Spain (Correos, 2017), La Poste in France (LaPoste, 2016), Australia (AustraliaPost, 2021) and Hong Kong Post (HongKongPost, 2017), and by international carriers, like DHL (DHL, 2018). Some non-carrier parties, from international e-business companies like Amazon (AMAZON, 2013), to supermarkets like SPAR in the UK (SPAR, 2016), also operate their own network of lockers. Examples of scientific publications addressing the integration of lockers in the delivery system are Janjevic et al. (2019), Veenstra et al. (2018) and Iwan et al. (2016). The use of parcel lockers may contribute to a reduction in delivery costs and also in gas emissions (Lemke et al., 2016; Song et al., 2013), especially when located according to the users' preferences (Lin et al., 2020; Lyu and Teo, 2019; Yuen et al., 2018).

Other measures that have been considered to adapt to market request are associated with the social phenomenon of *crowdsourcing*: "the practice of obtaining needed services, ideas, or content by soliciting contributions from a large group of people and especially from the online community rather than from traditional employees or suppliers" (Merriam-Webster, 2020). In 2013, DHL tested a pilot service in Stockholm called MyWays (DHL, 2013). The users of the service had access to a list of packages available at DHL's collection locations with time and destination for the delivery, and the delivery fee offered by the company in case the user volunteers to make the delivery. This allowed some users to perform deliveries to other users. Most of the deliveries were made by students that chose the ones that fit in their regular routes in the city. In the same year Walmart announced (but did not implement) a crowdsourcing plan (Barr and Wohl, 2013): a small compensation would be offered to in-store customers willing to perform some deliveries on the way to their destination, i.e., some deliveries ordered by online customers would be outsourced to customers shopping in the store. In 2015, Amazon launched the AmazonFlex service (Bensinger, 2015), giving drivers non-employed by the company the opportunity to register in the service and perform deliveries according to their free time and convenience. The drivers receive offers that match their time preferences or check the deliveries available in a period of interest. An interesting benefit of the DHL and Walmart proposals is that they are environment and traffic-friendly, as deliveries should be made by people already traveling along the delivery path, avoiding dedicated trips. These occasional couriers, as we call them along this text, may be using any transportation mode (car, bike, public transportation, or traveling on foot), and just add a small detour in their route to perform the requested delivery. Such differs from services like AmazonFlex that may at the end substitute a limited number of vehicles of a professional carrier by a large number of dedicated vehicles performing few deliveries each.

In this study, we propose a lastmile delivery framework based on crowdsourcing, under the following setting:

1. There are two types of clients: those that want to collect their orders from a locker and those that request door-to-door service;
2. The distribution network is comprised of a professional fleet (PF) that delivers parcels from a depot to door-to-door clients, of supply vehicles that bring parcels to lockers, of local (professional) fleets (LF) that make deliveries from lockers to door-to-door clients, and of a special set of customers, hereby referred to as occasional couriers (OCs), that visit lockers to collect their own orders and that voluntarily (or in exchange for a small compensation) accept to make a delivery to other customers on their way back home;
3. Lockers are used not only as a pickup point for customers that prefer to self collect their orders but also as intermediary points for transshipment to local fleet delivery and to occasional couriers.

Fig. 1 illustrates how the different players interact in the proposed framework (the professional fleet is not shown; it delivers directly from the warehouse to customers not served by other couriers).

This strategy encompasses a large number of practical situations and may result in significant advantages to all parts: customers requiring home delivery will have their orders delivered at home with no extra cost; customers requiring self pick up in a locker will have the opportunity to get some compensation by making a delivery in their neighborhood; lockers occupancy may be optimized, using the free storage capacity unused by locker customers to temporarily store the parcels of door-to-door customers; delivery costs may be reduced by carefully deciding among the available options which one is the most suitable for each customer requiring home delivery. Moreover, the overall traffic and gas emission may be reduced by using smaller more ecological vehicles at the local delivery and mostly by assigning some deliveries to customers that are already on the way to the final delivery point from the lockers. It may however give rise to unforeseen problems: deliveries outsourced to occasional couriers may remain undelivered because customers using the locker may postpone collecting their own orders to the following days.

We handle the problem as follows. In a first approach, we consider that all customers are known in advance, i.e., the company already has the orders of all customers and knows which ones require home delivery and which ones require a delivery to a locker. We do not analyze no-shows. Based on the transportation costs, on the capacity of the lockers and vehicles, and on the willingness

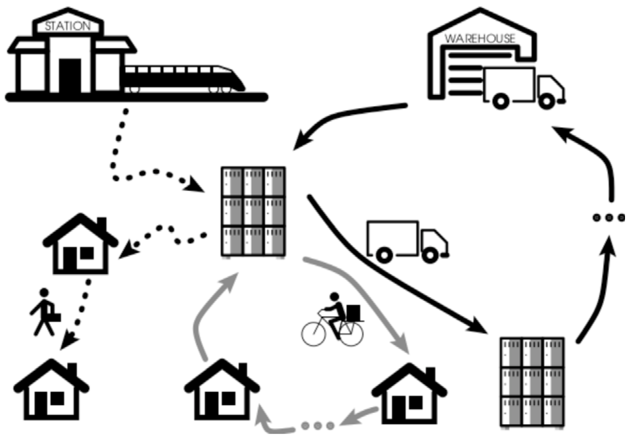

Fig. 1. General representation of lastmile delivery with lockers and occasional couriers: distribution is made from the warehouse to lockers by the supply vehicles (truck), and from the lockers to the recipients by occasional couriers (people that are on their way home) or by the local fleet (e.g. a cyclist).

of locker customers to act as OCs, the company optimizes the costs of the delivery for the known customers. In a second approach, we consider the possibility of no-shows, in a multi-period analysis. We still optimize the delivery, expecting that all locker customers visit the locker when the parcel becomes available, but evaluate this situation considering no-shows at the end of each period. In the event of no-shows, i.e., locker customers not fulfilling the role of an occasional courier within the expected period, the company must re-plan the delivery for the non-served door-to-door customers. Therefore, customers that remain unserved due to no-shows are considered again in the following period. For door-to-door customers that were not served and that are reaching the expected delivery deadline, we guarantee that they will be served by the local (professional) fleet.

1.1. Our contribution

Main contributions of this paper are:

- a novel 2-echelon Vehicle Routing Problem (VRP) Integer Programming (IP) model for lastmile delivery;
- the consideration of lockers that act both as collecting points for customers and as intermediate delivery points;
- the consideration of Occasional Couriers, as a subset of clients that have to pick their own order(s) from a locker, but can also deliver to other clients;
- the proposal of a policy to handle OCs' no-shows, by developing a multi-period model that re-schedules the delivery of previous undelivered parcels.

The 2-echelon VRP has been used for decades in multi-modal transportation where the last echelon corresponds to the lastmile delivery. Recently it has also been used for the whole lastmile delivery when both the first and second echelon are parts of the lastmile delivery process (Enthoven et al., 2020). In this paper, we further explore the concept by considering occasional couriers as an option in the second echelon.

Lockers have become more and more popular, the number of companies using them having considerably increased. Such is not restricted to national and international carriers, with many companies whose primary activity is not transportation, from international e-commerce companies to regional supermarkets and grocery stores (see, e.g., Rohmer and Gendron, 2020), having installed such facilities. We extend the literature on this topic by having multipurpose lockers that are not only collecting points for the final client but can also act as transshipment points. This shared use of locker facilities contributes to a challenging open issue in locker network services (Rohmer and Gendron, 2020) which is to utilize unused capacity at the locker facilities as intermediary consolidation points for further direct delivery to customers.

The third contribution emerges from the growing popularity of crowdsourcing and collaborative consumption services that connect customers to service providers that are not directly employed by the company. Uber Eats (Uber, 2019) and Amazon-Flex (Bensinger, 2015) are examples of this concept in the context of the lastmile delivery. Our proposal does however differ from their business models since we only consider as potential OCs other clients that have also ordered a parcel but did not go for a door-to-door delivery option.

For this integrated approach, we propose an Integer Programming model and study it on small and medium-size instances for different input parameters.

Later we extend the work to address OCs no-shows i.e., no-shows of customers that would pick their parcel(s) from the locker and simultaneously deliver a parcel from there to another customer. So far, such possibility has been discarded from most of the work in the literature (e.g. Archetti et al., 2016; Arslan et al., 2019; Dayarian and Savelsbergh, 2020; Kafle et al., 2017; Macrina et al., 2020), where the optimization is done considering that OCs will accept and make the delivery. In our approach, we consider that if the deadline to serve a customer is reached and if that client was to be served by an OC that did not show up, it can be served in the next period by an alternative OC if the client's delivery due-date has not been reached. Otherwise, it will have to be served by the local fleet. To analyze the impact of such policy, we include in the formulation previous customers yet to be served and study the impact in the overall cost, in the locker occupancy, and in the quality of service for different no-show rates.

1.2. Related literature

Crowd shipping, also referred to as crowdsourcing delivery and crowd logistics, has been explored in different ways and at different levels of users' commitment by several companies. Rai et al. (2017) give a very interesting overview of several crowd shipping platforms and present a categorization of their characteristics and impacts. At a more exploratory level, Archetti et al. (2016) introduced the Vehicle Routing Problem with Occasional Drivers, considering that the company has a fleet of vehicles able to perform the delivery to the customers requesting home delivery, but may also rely on customers that visit the store. The in-store customers are available to make a single delivery to another customer whose delivery address is not far away from their regular path from the store to the destination, in exchange for a small compensation. They presented a mixed-integer linear programming formulation for the problem and a multi-start heuristic to decide assignments of customers to the occasional drivers and routes for the fleet to serve the non-outsourced customers. Gdowska et al. (2018) consider a stochastic version of this problem, where each customer's delivery has a probability to be outsourced to an occasional courier or not, but without keeping track of who is the occasional courier of each delivery. Their objective is to decide which subset of deliveries to propose to occasional couriers in order to minimize the expected cost. They solve the problem by a bi-level stochastic approach where a subset (initially empty) of customers to be outsourced is heuristically increased until no further gain is obtained by adding a customer to this subset. They also test a reverse approach, that starts from a set of customers and removes one-by-one heuristically until no improvement is reached, and a hybrid one that adds/removes customers.

In a non-deterministic setting, Dayarian and Savelsbergh (2020) consider a dynamic version of the problem in which not all in-store and online customers are known a priori; the assignments are to be made upon the arrival of the in-store customers. They also study a stochastic version where predictions may be made about future arrivals and online orders. Dahle et al. (2017) consider a dynamic optimization where occasional couriers become available during a period of time. Based on a prediction about their arrivals, the company decides to outsource the delivery of a customer, wait for another occasional courier, or promptly include the customer in a home delivery route of the company's own vehicles to avoid future delays.

Some studies consider third-party agents acting as occasional couriers, instead of in-store customers. Kafle et al. (2017) study a delivery system where goods are transferred from trucks that depart from the company to occasional couriers that perform the last leg of the delivery. The occasional couriers are bikers and pedestrians that submit bids to the carrier expressing their interest, which may contain a single or multiple deliveries. The carrier selects the bids and defines a meeting point and time to transfer the goods to each selected courier. It is a 2-echelon delivery problem whose transshipment nodes are to be decided but do not have any storage capacity, as the transfer is done directly from the truck to the couriers. Mousavi et al. (2020) consider mobile depots: instead of visiting all transshipment nodes, trucks deliver goods to mobile depots that later move to other points to meet occasional couriers that perform home delivery. As in the work of Kafle et al. (2017), occasional couriers have a limited period of time to pick up the parcels, which is part of the decision problem, but mobile depots allow a larger time window, not only an instant of time. Macrina et al. (2020) consider intermediate depots from where an occasional courier may pick up a parcel for delivery. Customers not served by occasional couriers are to be served by the company's fleet, which also visits the intermediate depots. As these depots are used as capacitated transshipment nodes, their role is similar to the parcel lockers used in our model but they are not used for customers to self-pick up.

The use of parcel lockers in the lastmile delivery has a growing interest in the logistics, transportation, and optimization literature. Several studies focus on the location-routing problem to decide where to locate the lockers so that delivery costs, as a sum of transportation costs to supply the lockers plus the cost of serving customers not covered by the lockers, is minimized (Deutsch and Golany, 2018; Iwan et al., 2016; Janjevic et al., 2019; Veenstra et al., 2018). Some studies consider that customers let the company decide whether to deliver their orders to pick-up stations or to their home address (Zhou et al., 2018), but this may not be the case in several applications. More recent studies include customers' preferences and behavior analysis in order to foresee locker usage, as more customers doing self-pick up at lockers decrease the visits required for home delivery (Lin et al., 2020). This includes adding lockers to an already existent network and closing non used ones (Lyu and Teo, 2019; Wang et al., 2017), and also the use of mobile lockers (Schwerdfeger and Boysen, 2020), a concept similar to the mobile depots studied by Marujo et al. (2018) and Mousavi et al. (2020), to increase customers coverage.

Among the challenges and opportunities of research in the use of parcel lockers for lastmile delivery, Rohmer and Gendron (2020) refers to the shared use of the available capacity of lockers, and the utilization of unused capacity as intermediary consolidation points for further direct delivery to customers. Both are explored in our study, as the lockers are used as transshipment points for a local fleet delivery, and also as a facility that allows locker customers to become occasional couriers. In this sense, our proposal is more general than the classic 2-echelon vehicle routing problem, as the transshipment nodes (in our case, the parcel lockers) are not used merely to connect the first echelon (departing from the depot) to the second one (towards customers).

An extension of the 2-echelon vehicle routing problem was recently proposed by Enthoven et al. (2020), in a problem that they call 2E-VRP-CO – two-echelon vehicle routing problem with coverage options. In the first echelon, trucks depart from the depot to two kinds of supply points: satellites and covering locations. The satellite locations are transshipment points connecting the first to the second echelon where cargo bikers collect parcels for door-to-door delivery. The covering locations are places, e.g. parcel

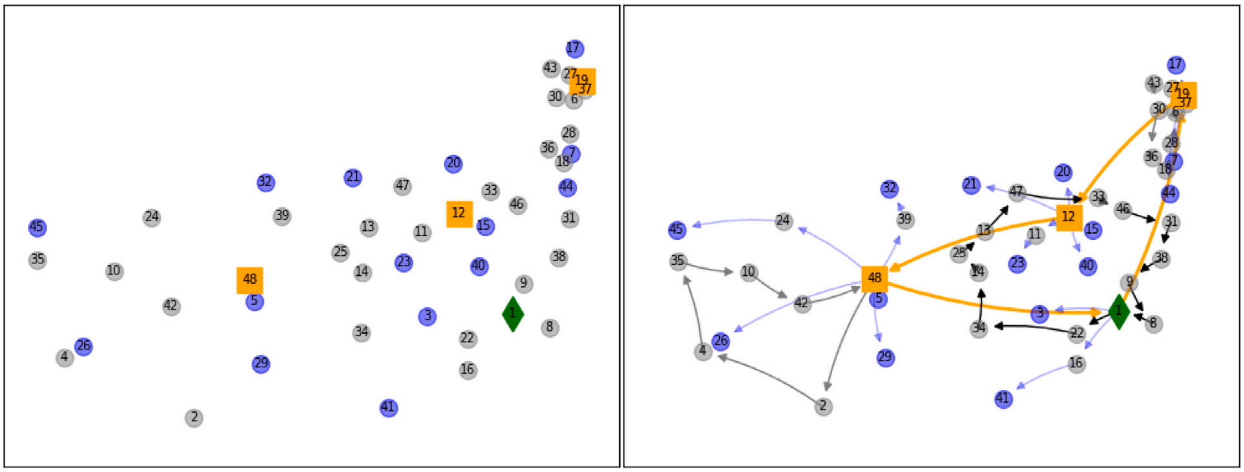

Fig. 2. Left: example of instance: warehouse (green diamond), lockers (orange squares) and customers (circles), divided into door-to-door customers (gray) and locker customers (blue). Right: example of a solution: (i) routes to supply the lockers, in orange; (ii) assignment of customers to OCs, in blue (the door-to-door customer visited on the way from the locker, otherwise no assignment); (iii) door-to-door routes, departing from the warehouse (PF, black) and from lockers (LF, gray).

lockers, where customers go for self-pick up. Their proposal generalizes both the 2E-VRP problem and a case of the facility location and routing problem. In our proposal, a parcel locker is used for both purposes, as satellite and as covering location. We also include occasional couriers that simultaneously pick up their own parcel at the locker and deliver another one to a customer. Moreover, contrasting with Enthoven et al. (2020) where such decision is made by the company, the decision on self collecting the order or receiving it at home is left to the customer. We consider this approach to be more aligned to real contexts, which tend to be more and more customer-oriented.

1.3. Layout of the paper

The remainder of this paper is organized as follows. Section 2 presents an overall description of the problem, our assumptions, and consequent limitations. In Section 3 we present mixed-integer linear programming (MILP) formulations that formally define the problem. Section 4 discusses the compensation strategies and the assumptions on transportation costs considered in this work. Finally, Section 5 presents the experimental results and discussions, followed by the main conclusions and directions for future work on Section 6.

2. Problem definition

In this work, we consider that we are given the location of the company's warehouse (O) from where all parcels depart, the location of the lockers (set L), and the location of the customers (set C) to where, in the end, all parcels must arrive. Lockers have the double purpose of acting as self-collecting points and as transfer deposits to serve customers that request home delivery. When making the order each customer in C decides where to receive the parcel: at home or at a locker.

Let $C_D \subseteq C$ be the set of customers requiring door-to-door delivery and $C_L \subseteq C$, with $C_L \cap C_D = \emptyset$, be the set of customers that require delivery to a locker (see Fig. 2 left). Each customer $k \in C_L$ selects the specific locker $a_k \in (L \cup O)$ to where their parcel must be delivered. Since customers may choose to pick up their parcels directly from the company's warehouse, the warehouse itself acts as a locker. Customers in C_L may act as occasional couriers and, for each $k \in C_L$, there is a subset $S_k \subseteq C_D$ of door-to-door customers that may be served by k on their way back home. These subsets are not necessarily disjoint and may be empty. As they are input to the model, they can be used to model several special cases. For example: if a locker customer $k \in C_L$ is not available for a delivery, $S_k = \emptyset$; if a customer $c \in C_D$ is a prime customer and the company decides that it should not be served by an occasional courier, $c \notin S_k, \forall k \in C_L$.

A solution for our problem comprises three parts (see Fig. 2 right): (i) the selection of the routes to supply the lockers; (ii) the assignment of customers to OCs; (iii) the definition of the door-to-door routes to supply the remaining customers. Notice that door-to-door routes may depart from the warehouse or from the lockers, provided that the parcels were previously delivered there. We call them respectively routes of the professional fleet (PF) and of the local fleet (LF).

The objective is to minimize total delivery costs given by the sum of: (i) the cost of the routes to supply the lockers (with c^L_{ij} being the cost of traversing arc (i,j)); (ii) the sum of the compensations paid to OCs (with p_{ck} being the compensation paid to OC k for serving customer c); (iii) the costs incurred by the door-to-door routes (where c_{ij} is the cost of each arc traversed by the PF departing from the warehouse and c^l_{ij} of each arc traversed by the LF departing from locker l).

2.1. Assumptions and limitations

We consider that the company knows in advance the set of orders to deliver and does not consider future orders. Uncertainty about OCs' no-show is not considered during the optimization; it is handled in the next period, once the absence of the OC is revealed by simulation.

Under the previous assumptions, we consider that the company has enough vehicle capacity to serve all customers: although vehicles have a limited capacity, we do not impose a limit on the number of routes. Such means that more than one route departing from the same place may in fact represent more than one vehicle or more than one route performed by the same vehicle sequentially.

We also assume that a locker has enough capacity to receive the parcels of all locker customers that have chosen that locker, as the company agreed to deliver those parcels there. Such assumption is reasonable because in a real setting companies offer lockers as an option only when there is space available.

Furthermore, we consider separate routes to supply the lockers and for door-to-door delivery for two main reasons: (1) door-to-door delivery is usually made during business hours, while lockers supply should avoid business hours due to traffic congestion, as lockers should be located in points visited by many people during the day, e.g. train stations; (2) a locker supply should be made on time, as a delay would affect a large number of customers, while home delivery requires interaction with customers, which are susceptible to (difficult to predict) delays. Studies in applied contexts follow the same line (Veenstra et al., 2018; Zhou et al., 2019; Ulmer and Streng, 2019; Huang et al., 2019).

Finally, we consider that each OC makes at most one delivery. Here, OCs are regular customers, making a delivery for just a small compensation, as opposed to third-party agents willing to earn extra money in their free time, and justifying several deliveries per OC (e.g. Enthoven et al., 2020; Kafle et al., 2017). Considering multiple deliveries in our context would increase the complexity of defining values of compensation and routes to OCs, which are beyond the intended scope. Moreover, following several works dealing with OCs (Archetti et al., 2016; Dahle et al., 2017; Dayarian and Savelsbergh, 2020; Macrina et al., 2017, 2020), we consider that they do not refuse an assigned delivery. By the time OCs make an order, they inform the system about a (possibly empty) coverage area near their original path to where they accept to make a delivery. The company has then enough information to compute the set of customers that may be assigned to each OC and choose one of them, if profitable.

3. MILP formulation

Let $D = (V, A)$ denote a complete directed graph. The vertex set V is composed of the depot O and two subsets: the set of available lockers L and the set of customers C. C is divided into door-to-door and locker customers, C_D and C_L, respectively (with $C = C_D \cup C_L$ and $C_D \cap C_L = \emptyset$). Consider also the following problem parameters:

- Customers' demand and preferences
  - q_c: demand of customer $c \in C$
  - $S_k \subseteq C_D$: subset of customers that OC $k \in C_L$ may serve
  - $a_k \in (L \cup O)$: locker chosen by customer $k \in C_L$
- Capacities
  - Q: capacity of the PF for door-to-door delivery
  - Q^L: capacity of the vehicles that supply the lockers
  - Q^l: capacity of the LF from locker $l \in L$
  - W_l: storage capacity of locker $l \in L$
- Costs
  - p_{ck}: compensation for OC $k \in C_L$ to deliver to $c \in S_k$
  - c_{ij}: cost for the PF to traverse arc $(i, j) \in A$
  - c^L_{ij}: cost for supply vehicles to traverse arc $(i, j) \in A$
  - c^l_{ij}: cost for LF from locker l to traverse arc $(i, j) \in A$

The following decision variables are used:

- $x_{ij}, x^L_{ij}, x^l_{ij}$: 1, if arc (i, j) is traversed by the PF, the locker supplying vehicles or the LF associated to locker l, respectively; 0, otherwise.
- $y_{ij}, y^L_{ij}, y^l_{ij}$: load on each type of vehicle when traversing arc (i, j).
- z_c: 1, if customer c is served by the PF; 0, otherwise.
- z^l_c: 1, if customer c is served by the LF associated to locker l; 0, otherwise.
- z^L_l: 1, if locker l is served by a supply route; 0, otherwise.
- w_{ck}: 1, if customer c is outsourced to OC k; 0, otherwise.

The 2-echelon lastmile delivery with lockers (2E-LMDLOC) problem can be written as follows:

$$\min \sum_{i,j\in O\cup L} c^L_{ij}x^L_{ij} + \sum_{k\in C_L}\sum_{c\in S_k} p_{ck}w_{ck} + \sum_{i,j\in O\cup C_D} c_{ij}x_{ij} + \sum_{l\in L}\sum_{i,j\in\{l\}\cup C_D} c^l_{ij}x^l_{ij} \tag{1}$$

Subject to:

Customers' service

$$z_c + \sum_{k\in C_L|c\in S_k} w_{ck} + \sum_{l\in L} z^l_c = 1, \qquad \forall c\in C_D \tag{2}$$

$$\sum_{c\in S_k} w_{ck} \le 1, \qquad \forall k\in C_L \tag{3}$$

$$\sum_{k\in C_L|a_k=l}\left(q_k + \sum_{c\in S_k} q_c w_{ck}\right) + \sum_{c\in C_D} q_c z^l_c \le W_l z^L_l, \qquad \forall l\in L \tag{4}$$

Professional fleet constraints

$$\sum_{j\in C_D\cup O} x_{ij} = \sum_{j\in C_D\cup O} x_{ji} = z_i, \qquad \forall i\in C_D \tag{5}$$

$$\sum_{j\in C_D} x_{oj} - \sum_{j\in C_D} x_{jo} = 0 \tag{6}$$

$$\sum_{j\in C_D\cup O} y_{ji} - \sum_{j\in C_D\cup O} y_{ij} = q_i z_i, \qquad \forall i\in C_D \tag{7}$$

$$\sum_{j\in C_D} y_{jo} - \sum_{j\in C_D} y_{oj} = \sum_{i\in C_D} -q_i z_i \tag{8}$$

$$y_{ij} \le Q x_{ij}, \qquad \forall i,j\in C_D\cup O \tag{9}$$

$$y_{io} = 0, \qquad \forall i\in C_D \tag{10}$$

Supply routes constraints

$$\sum_{j\in L\cup O} x^L_{ij} = \sum_{j\in L\cup O} x^L_{ji} = z^L_i, \qquad \forall i\in L \tag{11}$$

$$\sum_{j\in L} x^L_{oj} - \sum_{j\in L} x^L_{jo} = 0 \tag{12}$$

$$\sum_{j\in L\cup O} y^L_{ji} - \sum_{j\in L\cup O} y^L_{ij} = \sum_{k|a_k=i}\left(q_k + \sum_{c\in S_k} q_c w_{ck}\right) + \sum_{c\in C_D} q_c z^i_c, \qquad \forall i\in L \tag{13}$$

$$\sum_{j\in L} y^L_{jo} - \sum_{j\in L} y^L_{oj} = -\sum_{i\in L}\left(\sum_{k|a_k=i}\left(q_k + \sum_{c\in S_k} q_c w_{ck}\right) + \sum_{c\in C_D} q_c z^i_c\right) \tag{14}$$

$$y^L_{ij} \le Q^L x^L_{ij}, \qquad \forall i,j\in L\cup O \tag{15}$$

$$y^L_{io} = 0, \qquad \forall i\in L \tag{16}$$

Local fleet constraints ($\forall l\in L$)

$$\sum_{j\in C_D\cup\{l\}} x^l_{ij} = \sum_{j\in C_D\cup\{l\}} x^l_{ji} = z^l_i, \qquad \forall i\in C_D \tag{17}$$

$$\sum_{j\in C_D} x^l_{lj} - \sum_{j\in C_D} x^l_{jl} = 0 \tag{18}$$

$$\sum_{j\in C_D\cup\{l\}} y^l_{ji} - \sum_{j\in C_D\cup\{l\}} y^l_{ij} = q_i z^l_i, \qquad \forall i\in C_D \tag{19}$$

$$\sum_{j\in C_D} y^l_{jl} - \sum_{j\in C_D} y^l_{lj} = \sum_{i\in C_D} -q_i z^l_i \tag{20}$$

$$y^l_{ij} \le Q^l x^l_{ij}, \qquad \forall i,j\in C_D\cup\{l\} \tag{21}$$

$$y^l_{il} = 0, \qquad \forall i\in C_D \tag{22}$$

Variables domain

$$x_{ij}, x^L_{ij}, x^l_{ij}, z_i, z^L_i, z^l_i, w_{ck} \in \{0,1\} \qquad \forall l,c,k,i,(i,j) \tag{23}$$

$$y_{ij}, y^L_{ij}, y^l_{ij} \ge 0 \qquad \forall l,(i,j) \tag{24}$$

The objective function (1) aims to minimize the overall delivery cost given by the sum of the transportation costs associated with lockers' supplying, of the compensations given to OCs, and of transportation costs associated with door-to-door routes (either departing from the warehouse (PF), or from lockers (LF)).

The set of constraints (2) guarantees that all door-to-door customers are served, either by the PF, by OCs, or by the local fleet, and the set of constraints (3) guarantees that each OC may serve at most one door-to-door customer. By constraints (4), the capacity of a locker is not surpassed: if the locker is used, its storage capacity should be enough to store the demand of locker customers who chose that locker (this is an input to the problem; not part of the decision), of customers served by them, and of customers served by an LF departing from that locker. If no parcel is requested at a locker, then there may be no supply route visiting the locker and the corresponding z_l^L variable may be set to zero.

The set of constraints (5)–(10) controls the PF routes: (5) and (6) are flow conservation constraints; (7) and (8) ensure that the demand of visited customers is satisfied and that sub-tours are avoided; (9) ensures that the vehicle capacity is respected and (10) that the vehicle returns empty to the depot.

The set of constraints (11)–(16) does the same for the supply routes, and the set of constraints (17)–(22) replicates the PF constraints to the local fleet departing from each locker to serve door-to-door customers by transshipment.

3.1. Multi-period version

The previous formulation assumes that OCs collect their parcels from the lockers once they are available. However, in practice, customers may delay their visit to the lockers according to their convenience and to a time frame agreed with companies. Such behavior may bring some problems to the model previously proposed: if no backup plan is implemented, door-to-door customers outsourced to locker customers that do not show up are not served as planned, and the company has to deliver their parcels in another day and/or by other means.

To handle this situation we now propose some modifications to the previous formulation that can be used in a multi-period version of the problem to optimize deliveries in a planning horizon period-by-period. A period may be a day, if deliveries are to be planed day-by-day, or multiple time frames on the same day, for example, morning and afternoon. The main difference between the two models is that the parcels from the previous period/day that are still in the lockers are considered again.

We use the following additional sets:

- C_L^l: set of locker customers of locker $l \in (L \cup O)$ that did not show up;
- C_D^l: set of door-to-door customers whose parcels remained in locker $l \in L \cup O$ (due to no-show of OCs); notice that C_D^o is the set of door-to-door customers that in a previous period were assigned to an OC associated to the warehouse that did not show-up;
- $\hat{C}_D^l \subseteq C_D^l$: subset of door-to-door customers that must be served in that period;

To accommodate the new setting, objective function (1) is changed to (1'):

$$\min \sum_{i,j\in O\cup L} c_{ij}^L x_{ij}^L + \sum_{k\in C_L\cup C_L^*} \sum_{c\in S_k} p_{ck} w_{ck} + \sum_{i,j\in O\cup C_D\cup C_D^o} c_{ij} x_{ij} + \sum_{l\in L} \sum_{i,j\in\{l\}\cup C_D\cup C_D^o\cup C_D^l} c_{ij}^l x_{ij}^l \tag{1'}$$

The first term remains the same and computes the cost of the supply routes. The second term includes as potential OCs the locker customers of the previous period that did not show up yet, where C_L^* is $\bigcup_{l\in L\cup O} C_L^l$. Moreover, the third and fourth terms (cost of the PF and LFs respectively) include previous door-to-door customers still to be served. Notice that each LF is associated to a locker and cannot deliver to customers whose parcels are in different lockers. A special case is for customers in C_D^o: as their parcels are still in the warehouse, they can still be served by the PF or be transferred to a locker by a locker supply vehicle for further delivery by the LF.

Constraints (2) are changed to (2') to include: (i) locker customers that did not show up in the previous period, as they can act as OCs in this period, to serve the new door-to-door customers; and (ii) the undelivered parcels of customers in C_D^o, as they are still in the warehouse. New constraints are added: customers in C_D^l may be served only from locker l (as their parcels are already there). More specifically, they can be served only by an LF from that locker or by OCs whose parcels are already there or will be delivered there (2.1). Moreover, customers whose delivery cannot be postponed for another period must be immediately served by a PF/LF, as OCs may not show up. Such is guaranteed by constraints (2.2)–(2.3).

$$z_c + \sum_{k\in C_L\cup C_L^* | c\in S_k} w_{ck} + \sum_{l\in L} z_c^l = 1, \qquad \forall c \in C_D \cup C_D^o \tag{2'}$$

$$\sum_{k\in(C_L|a_k=l)\cup C_L^l | c\in S_k} w_{ck} + z_c^l = 1, \qquad \forall l \in L, c \in C_D^l \tag{2.1}$$

$$z_c^l = 1, \qquad \forall l \in L, c \in \hat{C}_D^l \tag{2.2}$$

$$z_c + \sum_{l\in L} z_c^l = 1, \qquad \forall c \in \hat{C}_D^o \tag{2.3}$$

Constraints (3) are changed to (3') to include previous locker customers, and constraints (4) are changed to (4'), as parcels from previous periods that are still in the lockers reduce their current storage capacity.

$$\sum_{c \in S_k} w_{ck} \leq 1, \qquad \forall k \in C_L \cup C_L^* \tag{3'}$$

$$\sum_{k \in C_L | a_k = l} \left(q_k + \sum_{c \in S_k} q_c w_{ck} \right) + \sum_{c \in C_D} q_c z_c^l + \sum_{k \in C_L^l} \sum_{c \in S_k} q_c w_{ck} \leq \left(W_l - \sum_{k \in C_L^l} q_k - \sum_{c \in C_D^l} q_c \right) z_l^L, \qquad \forall l \in L \tag{4'}$$

Constraints associated to the supply routes, (11)–(16), remain unchanged. In the constraints associated to the PF routes, (5)–(10), C_D is replaced by $C_D \cup C_D^o$ to include parcels not delivered in the previous period. Finally, for the constraints associated to the local routes, (17)–(22), C_D is replaced by $C_D \cup C_D^o \cup C_D^l$.

4. Compensation strategies and costs

The compensation p_{ck} to pay to OC k for delivering to door-to-door customer c may be defined using several strategies. A basic strategy is to pay a fixed amount for all OCs independently of the customers being served. Archetti et al. (2016) used two other strategies: (1) pay an amount that depends on the customer to be served; or (2) pay an amount that depends both on the customer to be served and on the OC. In the first case, the compensation is proportional to the distance of the customer to the depot. In the second case, it is proportional to the distance of the detour the OC has to take from their original path to serve the customer.

Let d_{ij} be the distance between locations i and j, and ρ a parameter. Recall that a_k is the locker where OC k collects the parcel of customer c for delivery. In this work we consider the three strategies above:

- (F)ixed: $p_{ck} = \rho$
- (L)ocker-based: $p_{ck} = \rho \times d_{a_k c}$
- (D)etour-based: $p_{ck} = \rho \times (d_{a_k c} + d_{ck} - d_{a_k k})$

We may view the L strategy as reflecting the company's viewpoint: pay more to have customers that are more distant served by OCs, trying to reduce costs associated with PF/LF door-to-door delivery. On the other hand, the D strategy reflects the OC's viewpoint: the longer the detour, the higher the compensation. The D strategy is also used by Arslan et al. (2019), Dahle et al. (2017), Macrina et al. (2020) and others. However, Archetti et al. (2016) point out that this may be too theoretical because to implement it the company must know the OC's destination. OC's destinations may differ depending on the time the delivery is made (home, office, etc.) and there is the risk that OCs provide a different destination to earn more. For the L strategy, the company only needs to know the location of the door-to-door customer, which for sure is known as the customer had to provide the address for the home delivery.

We consider transportation costs to be proportional to the distance traveled by the vehicles. Enthoven et al. (2020) consider the same cost for trucks (PF) and cargo bikers (LF), but we allow different vehicles to have different costs. Compared to the PF, which usually serves many customers, the LFs are expected to be composed of smaller vehicles that deliver to few customers in the neighborhood of the lockers. Although consolidation of parcels is less in LFs, fuel consumption should also be significantly lower, implying lower transportation costs. Regarding the vehicles that supply the lockers, we could consider a diverse set: some vehicles should be bigger than those of the LF, to visit several lockers in a route; others smaller or at the same size if lockers are located in areas that restrict the size of vehicles that can circulate. Despite that, in this work, we consider that the transportation costs per unit distance associated with the locker supply fleet are cheaper than those of the PF because several deliveries are made at each stop and there is no delay due to customers interaction.

5. Computational experiments

In this section we present computational results for validation and comparison of the models proposed in Sections 3 and 3.1. All formulations were implemented using IBM ILOG OPL and solved by CPLEX 12.10 on a 3.2 GHz Intel Core i7 machine with 64 GB 2667 MHz DDR4 memory running macOS 10.14.3.

We study the influence of the parameters of the problem – namely capacities, costs, and OCs' coverage – on the decision to be made, by experimenting with different values for each parameter. Whenever they are not specified, we use the default values listed in Tables 1–3. Capacities were set to values that avoid trivial solutions, e.g., guarantee that the PF is used by setting the total storage capacity of lockers to a value that is not enough to serve all customers and that the PF cannot serve all door-to-door customers in a single route. Therefore, even if the delivery costs and locations of customers are considerably more favorable to OCs and LFs than to the PF (or vice-versa), a non-obvious decision must be made about which customer shall be served by which means.

Following Archetti et al. (2016) and Dayarian and Savelsbergh (2020), and regarding OCs coverage, OC k accepts a delivery to customer c if the extra distance the OC has to take compared to a direct path is below a given threshold, i.e., $c \in S_k$ if and only if $d_{a_k c} + d_{ck} \leq \delta \times d_{a_k k}$, where δ is a parameter that reflects the flexibility of the OC.

Table 1
Default delivery costs, proportional to the distance d_{ij} associated to arc (i,j).

Type	Symbol	Standard cost
PF	c_{ij}	$\pi \times d_{ij}$, where $\pi = 1.00$
LF	c^l_{ij}	$\pi^l \times d_{ij}$, where $\pi^l = 0.85$
Supply	c^L_{ij}	$\pi^L \times d_{ij}$, where $\pi^L = 0.75$
Compensation	p_{ck}	$\rho \times d_{a_k,c}$, where $\rho = 0.50$

Table 2
Default capacity values for vehicles and lockers.

Parameter	Symbol	Standard capacity
PF vehicles	Q	$\lceil 0.5 \times \lvert C_D \rvert \rceil$
LF vehicles	Q^l	$\lceil 0.6 W_l \rceil$
Supply vehicles	Q^L	$\lceil 0.8 \times \sum_l W_l \rceil$
Storage	W_l	$\lceil 0.8 \times \lvert C \rvert / \lvert L \rvert \rceil$

Table 3
Default values for customers' characterization.

Parameter	Symbol	Standard value
Demand	q_i	1
Locker	a_k	The closest to customer k
OC's coverage	δ	1.5, i.e., a max detour of 50%

5.1. Test instances

In our analysis we use test instances[1] generated from TSPLIB (Reinelt, 1991), truncating each original instance to the first $n+1$ points: the warehouse plus n points distributed among customers and lockers ($n = |L| + |C|$). An instance named base-L-CL-CD refers to:

- base: instance from TSPLIB, e.g., att48, pr76, dsj1000;
- L: number of lockers, randomly chosen from the n points;
- CL: number of locker customers, randomly chosen from the remaining n - L points;
- CD: number of door-to-door customers (remaining ones).

For the multi-period formulation, customers are evenly distributed by D periods but the number and location of the lockers are the same for all periods.

5.2. Results for the single-period model

The formulation proposed in Section 3 was tested in different instances under different parameters. Table 4 lists the characteristics of the instances used, in terms of number of lockers, number of customers, and capacities of vehicles and lockers. Capacities were calculated according to the parameters defined in Table 1.

The results obtained, using a time limit of 10 min, are shown in Table 5. For each instance, we report the gap and the runtime returned by the solver, the number of door-to-door customers served by OCs, PF, and LF, and the number of routes performed by the PF and LFs. The solver is able to solve to optimality the smaller instances in a few seconds, but when the number of door-to-door customers is beyond 50, after 10 min there is no indication that the optimal solution has been reached, with reported gaps[2] ranging from 2 to 43%. The optimum of two of these larger instances was found using additional time.

Through analysis of the results presented in Table 5 one can note that: (i) the capacity Q was reached only in two instances (rat195-3-10-27 and dsj1000-5-20-75), where more than half of the customers are served by the PF; (ii) around 20 to 55% of locker customers act as OCs; (iii) the LF of at least one locker is not used in the optimal solution of almost all instances; (iv) the use of LF seems to be the primary source of difficulty in the optimization of larger instances, since the main change in the solutions obtained with additional CPU time is a significant reduction in the number of routes and deliveries made by LFs.

Table 6 lists the results for different values of δ. The aim is to study the impact of OC's coverage on the decision process. The following values were considered: $\delta = 1.25$, 1.5 and 2.0 (i.e., OCs accept a detour of 25,50, and 100%), for a maximum of 10 min of execution time for the smaller instances, and of 10 h for the larger instances (below the dashed line in the table). The results reported, for each of the 3 values of δ, are: the linear gap of the solution found within the time limit (a '-' means that the gap is 0), the execution time, and the number of OCs used in the solution. The last three columns in the table show the percentage improvement in the objective value when compared to a solution where OCs are not available.

[1] All instances available at: http://www.dpi.ufv.br/goal/instances/2e-lmdloc.

[2] Relative gaps reported by CPLEX given by $gap = (\mathrm{UB} - \mathrm{LB})/(|\mathrm{UB}| + 10^{-10})$, where UB and LB are upper and lower bound respectively.

Table 4
Instances size and capacities (default values as per Table 2).

Base	N	L	C_L	C_D	Q	Q^L	Q^l	W_l
rat195	40	3	10	27	14	24	6	10
eil101	40	3	10	27	14	24	6	10
att48	47	3	15	29	15	29	8	12
dsj1000	50	3	12	35	18	32	8	13
pr76	75	4	20	51	26	48	9	15
eil101	100	5	20	75	38	64	10	16
dsj1000	100	5	20	75	38	64	10	16
pr107	106	4	25	77	39	68	13	21

Table 5
Results for default parameters, time limit of 10 min. For instances not solved in 10 min, results for a time limit of 10h are reported below the dashed line.

	Solver		#deliveries			#routes	
Instance	gap	time	OC	PF	LF	PF	LF
rat195-3-10-27	—	17	2	14	11	1	2
eil101-3-10-27	—	16	4	12	11	1	2
att48-3-15-29	—	9	6	12	11	1	2
dsj1000-3-12-35	—	13	3	16	16	1	3
pr76-4-20-51	2.0	600	7	26	18	1	3
eil101-5-20-75	24.1	600	7	22	46	1	9
dsj1000-5-20-75	42.7	600	11	28	36	2	10
pr107-4-25-77	30.4	600	8	34	45	1	4
pr76-4-20-51	—	732	8	25	18	1	3
eil101-5-20-75	—	13700	6	30	39	1	4
dsj1000-5-20-75	0.9	36000	11	38	26	1	3
pr107-4-25-77	13.4	36000	14	36	27	1	4

Table 6
Results for different values of OCs' coverage (δ = 1.25, 1.5 and 2.0), with a time limit of 10 min (above) and 10 h (below dashed line).

Instance	Gap			Time (sec.)			#OC			%Cost improvement		
	1.25	1.5	2.0	1.25	1.5	2.0	1.25	1.5	2.0	1.25	1.5	2.0
rat195-3-10-27	—	—	—	12	17	31	2	2	7	2.8	2.8	4.2
eil101-3-10-27	—	—	—	13	16	24	2	4	7	2.1	4.9	6.4
att48-3-15-29	—	—	—	9	9	34	4	6	7	3.0	4.7	6.2
dsj1000-3-12-35	—	—	—	12	13	25	3	3	6	1.1	1.1	3.0
pr76-4-20-51	3.1	2.0	7.9	600	600	600	7	7	11	6.4	6.7	3.5
eil101-5-20-75	19.2	24.1	9.4	600	600	600	4	7	7	−17.7	−24.1	−2.7
dsj1000-5-20-75	16.0	42.7	16.5	600	600	600	6	11	8	−6.3	−52.8	−3.4
pr107-4-25-77	31.9	30.4	22.0	600	600	600	7	8	12	−18.5	−13.9	−0.6
pr76-4-20-51	—	—	—	822	732	878	7	8	8	7.1	7.5	7.5
eil101-5-20-75	0.8	—	—	36000	13700	17947	4	6	11	2.1	3.8	4.1
dsj1000-5-20-75	2.1	0.9	3.4	36000	36000	36000	7	11	10	0.7	2.2	2.3
pr107-4-25-77	14.8	13.4	14.3	36000	36000	36000	5	14	14	0.4	1.4	1.4

As expected, the number of OC deliveries generally increases as δ increases, as the percentage of locker customers used as OCs increases, on average, from 25% to 38% and then to 54%. The cost decreases when OCs accept larger detours. A result that could seem unexpected at first sight is the negative improvement in the 3 larger instances. This is because the optimal solution was not found within 10 min. In fact, if we increase the time limit (see results reported below the dashed line) the cost indeed decreases. This suggests that one needs a more efficient way to solve the model, or allows more time to the solver when considering many customers (in our case, 75 customers or more). The optimal solutions for instances pr76 and eil101, reported below the dashed line, were found within shorter execution times for δ = 1.5 than for δ = 1.25 and 2.0. For the other two larger instances, the optimal solution was not found, but the gap was smaller for δ = 1.5. This may be because larger values of δ increase the number of alternatives available, hence increasing the search space and the difficulty to solve the problem. On the other hand, for smaller values of δ, the number of door-to-door customers that the vehicles must visit increases, increasing the difficulty in optimizing the routes in the two-echelon CVRP component.

Table 7 shows the impact of the use of OCs and LF in these instances. In particular, it shows the increase in cost and in the number of deliveries performed by the PF and LF when no OCs are available, and the impact on OCs and on the PF when there is no LF. The solution without OCs is compared to the solutions when OCs accept a detour of at most 25%, i.e., δ = 1.25, and the solutions without LF are compared to the case where the accepted detour is 100%, i.e., δ = 2.0. These detours were chosen to compare each case to the one where the missing courier (OC or LF) is less frequently used. If an improvement occurs in those cases,

Table 7
Increase in cost (%) and in number of deliveries when there are no OCs or no LF; the asterisk (*) signals that one additional route is used.

	No OC vs. $\delta = 1.25$			No LF vs. $\delta = 2.0$		
	cost	PF	LF	cost	PF	OC
rat195-3-10-27	2.9	0	2*	13.3	5*	1
eil101-3-10-27	2.1	0	2*	6.1	5*	1
att48-3-15-29	3.1	2	2	16.0	10*	1
dsj1000-3-12-35	1.1	3*	0	20.6	11*	2
pr76-4-20-51	7.6	−2	9*	11.5	13*	5
eil101-5-20-75	2.1	3	1*	4.4	27*	2
dsj1000-5-20-75	0.7	2	5	9.1	27*	2
pr107-4-25-77	0.4	2	3	9.5	18*	9

Table 8
Instances' size: total and per period.

ID	Base	Total				Days	Per day	
		N	L	C_L	C_D	D	C_L^d	C_D^d
R2	rat575	575	2	150	422	20	7–8	21–22
R3	rat575	575	3	180	391	20	9	19–20
D2	dsj1000	1000	2	200	797	30	6–7	26–27
D4	dsj1000	1000	4	240	755	30	8	25–26
N3	nrw1379	1379	3	375	1000	40	9–10	25
N4	nrw1379	1379	4	450	924	40	11–12	23–24

it should be even more impactful in the other cases. Results show that the cost of the solution without OCs increases in all cases (more than 7% in one instance). Some of the customers previously served by OCs would now be served by the PF and some by the LF, increasing the number of routes of the vehicles in most of the cases. For the case with no LF, a few more locker customers are chosen to be OCs, and several more customers are to be served by the PF, increasing also the number of routes in all instances. The combination of these factors increases the cost from 4 to 20%. This is the case for $\delta = 2.0$, which means that OCs accept a detour that turns the route twice as long as their original direct route from the locker. Some authors consider the OCs less flexible. For example Archetti et al. (2016) consider $\delta = 1.1 \dots 1.5$ and Enthoven et al. (2020) consider $\delta = 1.25$. The impact of LFs for these values of δ would be even higher.

Fig. 3 shows the relation between the distances covered by the different fleets. For each instance, the first column shows the percentage of the total distance used in the delivery that is covered by the PF to deliver directly from the warehouse, by the vehicles used to supply the lockers, and by the LF to deliver from the lockers, when no OCs are used. The locker supply vehicles cover from 19 to 40% of the distance, which represents a contribution to reducing transit congestion, as the locker supply may be made during non-business hours. LFs cover from 22 to 40% of the distance, which may be a contribution to the environment: they usually serve fewer customers, which are in the neighborhood of a locker, so more environmentally friendly vehicles can be used, like electrical vehicles or cargo-bikes. The second and third columns show the same information when OCs are considered, respectively with $\delta = 1.5$ and 2.0, taking as a baseline the total distance covered in the first column. The numbers above the columns are the percentage of reduction in the total distance covered by the fleets, while negative numbers below the columns show an increase (this occurs only in instances based on dsj1000). The use of OCs reduces up to 9% the distance covered. Since OCs are locker customers already traveling from the locker to their destination after collecting their parcels, the distance they added to the distribution network is only the detour they make on their paths. There does not seem to be a clear relation between δ and the reduction in the total distance used for delivery. Bigger δ means that OCs are more flexible and accept larger detours, which increase the number of customers that can be served by OCs, potentially making the total distance traveled bigger in the presence of OCs (which occurs in the smaller instances). On the other hand, OCs doing larger detours may end up increasing the total distance: this occurs in two instances for $\delta = 2.0$ and in one instance for $\delta = 1.5$, while in two other cases the total distance is the same (reduction 0%). Nevertheless, even in these few cases where the use of OCs increases the total distance considering all carriers, the distance traveled by the dedicated fleets (PF, LF, and supply vehicles) is reduced, as expected.

5.3. Results for the multi-period version

Table 8 lists the characteristics of the instances used to test the formulation in Section 3.1. We consider each period to be one day but conclusions can be generalized for periods of any length.

The problem is solved sequentially, period-by-period, and, for each period (day), considers the customers of that day together with the ones of previous days whose parcels are still in lockers. In these instances we have considered that a door-to-door customer has 2 days to be served. Hence, if a delivery is outsourced and the OC does not show up, the company must deliver it in the following day by PF or LF.

To analyze different locker customers' behavior, we use a parameter γ that reflects the probability that a locker customer comes to the locker in each day of the time frame the parcel is available in the locker. From the solution of day d, we simulate, using γ,

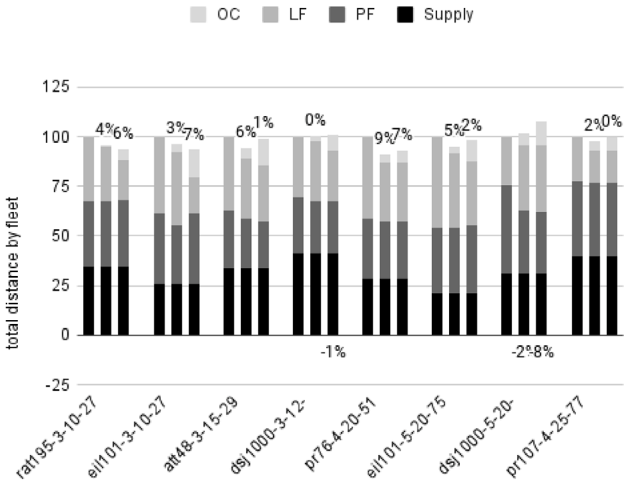

Fig. 3. For each instance, the first column is the percentage of the total distance covered by each fleet when no OCs are used; the second column shows the reduction in the total distance when OCs are used with $\delta = 1.5$, as well as the percentage covered by each fleet in this scenario, while the third column shows the same information for $\delta = 2.0$.

which locker customers came or not to the locker, and we have the carry-over input for day $d + 1$. The process is repeated for the whole time horizon, from period 1 to D. As the no-shows are stochastic, the whole process is simulated five times and averaged for a given γ in order to have a better estimate of the expected accumulated cost over the time horizon.

Fig. 4 shows a typical example. At the top, we can visualize the customers of day 1 and the solution for these customers. If the probability of attendance of locker customers is $\gamma = 50\%$, around half of them do not visit the locker. The parcels of these customers and of those outsourced to them remain in the locker; both are represented by triangles, to differentiate from regular customers of day 2 (middle left). The solution for day 2 (middle right) shows the PF visiting customers located around one of the lockers. This happens because this locker has no space to serve those customers by OCs or transshipment, as several parcels are still there from day 1 (due to no-shows) and new parcels have to be stored there for day 2 locker customers. At the bottom of the figure, we depict the solution of day 2 if all locker customers of day 1 had visited the locker ($\gamma = 100\%$). The PF would have served only the customers around the depot, as all lockers would have space to serve customers nearby.

As seen in the example, in general a customer no-show influences negatively the result by occupying space in the locker, preventing other customers from being served by transshipment or outsourced to OCs. But in some cases, they may have a positive influence by increasing the number of potential OCs in the following day. In the example, some customers of day 2 near the warehouse could be outsourced to OCs that did not show up on day 1.

In the following, we analyze how γ influences the costs along the time horizon, as well as the occupancy of the locker and the quality of service. Later we analyze the impact of other parameters, namely the capacity of lockers and types of compensation fees.

5.3.1. *Influence of no-shows*

The cost of a planned solution comprises the transportation costs and the compensation to OCs. OCs that do not come to the locker cannot perform the planned delivery and do not receive the compensation, which is discounted in the cost of the next day. We compare results for different γ to a baseline of $\gamma = 100\%$, i.e., we analyze the deviation from the costs without no-shows, for different probabilities of locker attendance.

Fig. 5 shows the daily and the accumulated relative deviation for $\gamma = 45, 50, 60$, and 80% of customers showing-up for a particular instance (D4). When locker customers choose to come to the locker later, the cost is higher in several days. See for example the thick dashed curve on the left chart of Fig. 5, which represents the daily cost for $\gamma = 80\%$, i.e., most of the customers come to the locker on a given day, but some do not. The ones that do not come, as well as the door-to-door customers they should serve, keep occupying space in the locker for the following day. Less space in the locker reduces the availability for serving customers by OCs and for transshipment through that locker. As a result, the delivery may need to be done through more costly routes. In some days, however, the cost decreases below the one associated to 100% attendance as the company has a chance to use these delayed locker customers to outsource later customers for which there would not be available OCs in the same day. The deviation oscillates along the time horizon.

Although the cost for a given day may increase or decrease due to no-shows of the previous day, what is more important to the company is the overall cost in the time horizon. The right chart of Fig. 5 shows how the deviation of the cost with different γ accumulates over the days, compared to the case without no-shows. It oscillates in the first days and then tends to stabilize. The lower is γ, the later the cost stabilizes and the higher is its final value. After 30 days, the accumulated costs are 2.3, 4.9, 8.0 and 8.7 higher for $\gamma = 80$, 60, 50 and 45% respectively.

Fig. 6 shows, for different instances, how the accumulated cost over the time horizon using different γ deviates from the solution when all customers come to the locker on the same day ($\gamma = 100\%$). The behavior is very similar to the one discussed before: the

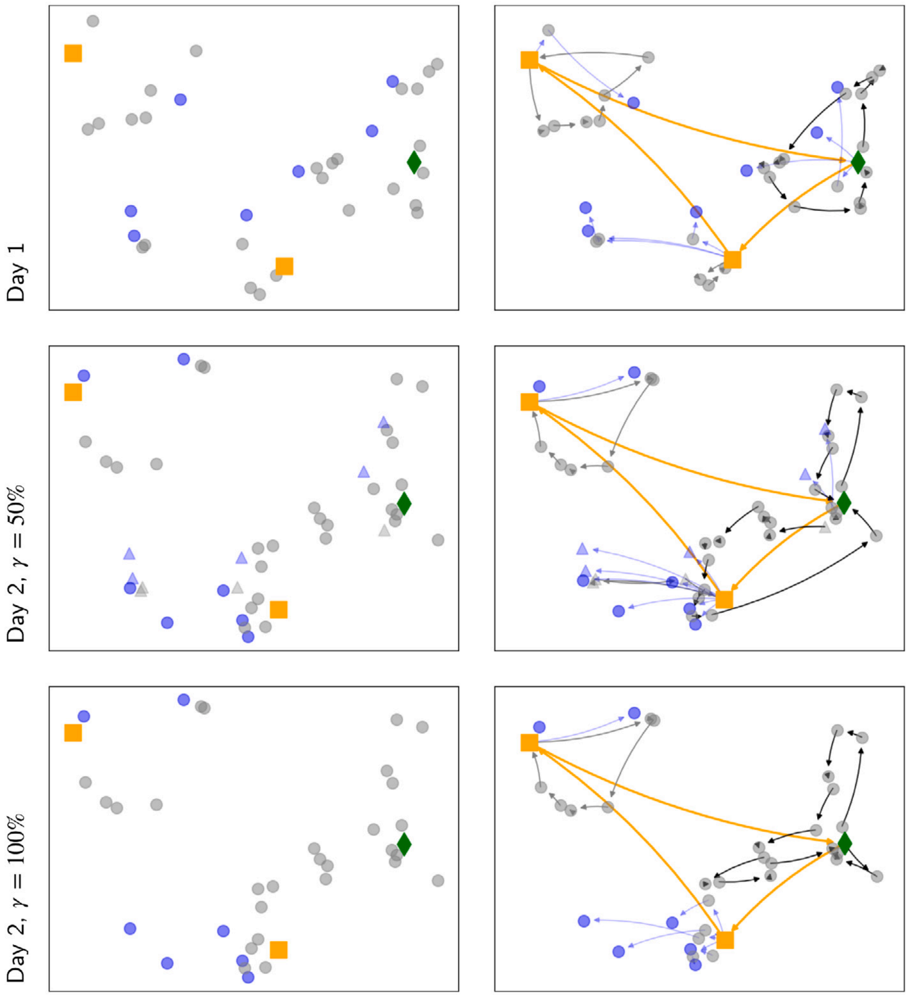

Fig. 4. Results for days 1 and 2 for instance D2 with different probabilities of locker attendance. At the top, the customers of day 1 and the corresponding solution. In the middle, customers of day 2 and the solution for this day, considering that around half of the locker customers of day 1 did not show up ($\gamma = 50\%$); the triangles are customers from day 1: blue's did not show up and gray's are door-to-door customers assigned to locker customers that did not show up. At the bottom, the customers of day 2 and the solution for this day, if all locker customers of day 1 would have visited the locker ($\gamma = 100\%$).

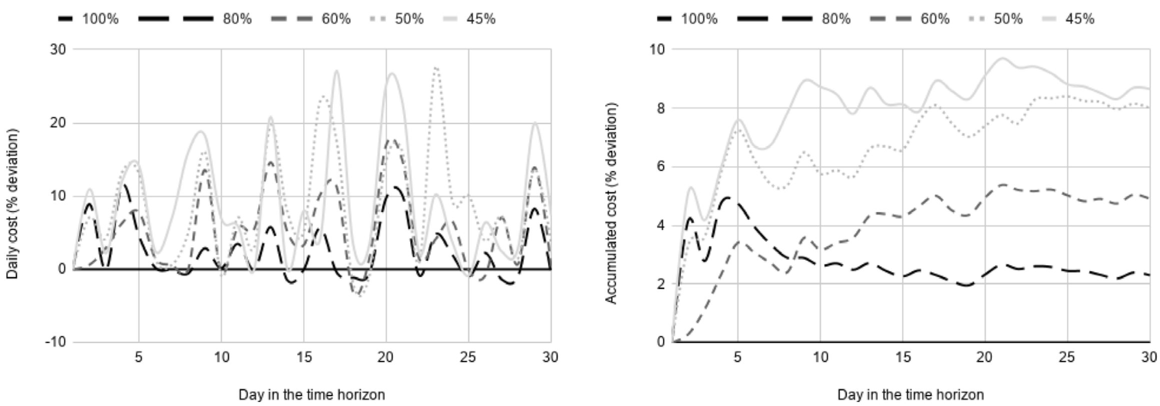

Fig. 5. Percentage deviation from the costs without no-show ($\gamma = 100\%$) in each day of the time horizon for instance D4 for different probabilities of attendance ($\gamma = 80, 60, 50, 45\%$): cost per day (left) and accumulated cost (right).

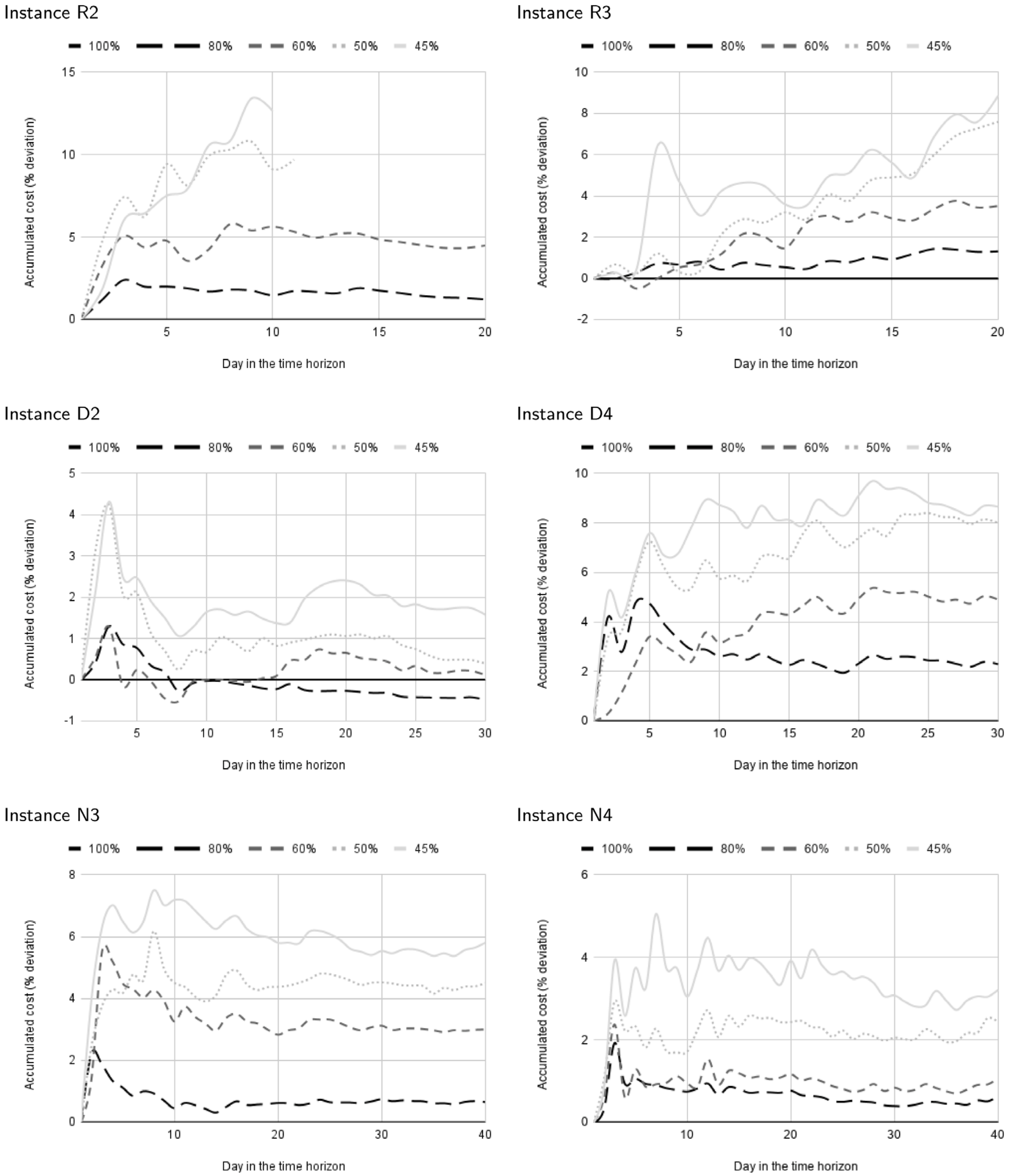

Fig. 6. Deviation of the accumulated cost for different locker attendance rates ($\gamma = 80, 60, 50, 45\%$) compared to the ones without no-show ($\gamma = 100\%$) for all the instances.

lower the probability of any OC coming to the locker, the higher the deviation. A non-typical behavior was observed in instance D2 (middle left chart): the accumulated cost for $\gamma = 80\%$ remains slightly lower than for $\gamma = 100\%$ in most of the days, being the final cost 0.5% lower. This indicates that the flexibility given to locker customers can be beneficial in some cases: it may allow some locker customers to be assigned to a better door-to-door customer, i.e., the outsourced customers of the day when they actually come to the locker were more advantageous to the company. Such may happen on any day of the time horizon and with any probability of attendance, but it is usually overtaken by the negative impact of having less space in the locker to serve new customers. That is

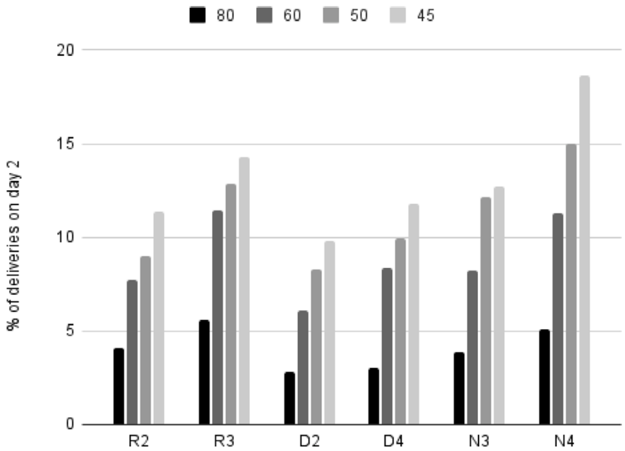

Fig. 7. Delayed delivery to door-to-door customers due to no-show of assigned OC, by instance for each γ.

more patent for lower γ, as more customers postpone the visit to the locker. Noteworthy is that even when there is a positive impact on the cost, as in the case mentioned above, there is a reduction in the quality of the service provided to door-to-door customers. Such is achieved by considering that door-to-door customers have 2 days to be served and that if a delivery is outsourced and the OC does not show up the company must deliver it in the following day by PF or LF. Fig. 7 shows the increasing number of door-to-door customers served on the 2nd day due to the no-show of locker customers. It goes, in average, from 4% when $\gamma = 80\%$ to 13% when $\gamma = 45\%$.

For $\gamma = 45$ and 50%, locker customers most or equally likely do not come to the locker and, for instance R2 at day 10 and 11 respectively (where the lines abruptly end), there was not enough space in one of the lockers to store the parcels of its customers of the day. The problem becomes infeasible, as the company cannot serve all the customers of the day in the way they have chosen to. In this simulation we just indicate that this happened and do not solve for the following days. In a real context the company may, for example, impose a limit on the number of days a parcel is available in the locker and pick up non collected parcels to free space.

Fig. 8 presents some information about locker's occupancy. The gray boxes show the variation in the occupancy of the locker with fewer parcels on each day and the white ones the variation in the occupancy of the locker with more parcels. The least and most occupied locker may change from day to day. As expected, as the attendance to lockers (γ) decreases, the occupancy generally increases. Exceptions occur on instances R3, D4 and N4 when γ goes from 100 to 80%, as the median of the maximum occupancy is higher for $\gamma = 100\%$. Notice that for instance R2 the maximum occupancy of a locker is 100% in almost all days for $\gamma = 50$ and 45%, and the minimum occupancy is also approaching 100%. This explains why the problem becomes infeasible halfway the time horizon (as seen in Fig. 6).

In terms of the difficulty of the problem, Fig. 9 shows that, as more customers postpone their visit to the locker (γ decreases), the average execution time typically increases, and the number of days an optimal solution is found within a time limit of 10 min decreases. This happens because the number of customers to be considered on each day increases, as customers not served due to no-shows must be considered again. For most of the instances the average number of optimal solutions within 10 min slightly decreases, as γ decreases. Instance R3 is the easiest one: optimal solutions were found for all days in all runs for all probabilities of attendance considered in the simulations. The average solution time, however, increases from 6s for $\gamma = 100\%$ to 45s for $\gamma = 45\%$. Instance D4 has the biggest variation: the average execution time ranges from 123s for $\gamma = 100\%$ to 299s for $\gamma = 45\%$, and the average number of days the optimal solution is found drops from 93 to 56%. This may impact the quality of the solution as γ decreases, but is not the source of the significant difference in the delivery costs presented before (Fig. 5) as the average linear gap is smaller than the percentage deviation calculated (going from 0.1, when $\gamma = 100\%$, to 1.4, when $\gamma = 45\%$).

5.3.2. Influence of storage capacity and compensations

We have seen that if many customers postpone their visit to the locker the accumulated cost tends to increase, as more customers have to be served by vehicles: by the PF when no or little space is available in the locker, and by an LF in case of successive no-shows. All these facts are influenced by the value of the compensation fee considered: for a lower value, there is a higher chance that outsourcing is advantageous for the company and a higher number of locker customers chosen to be OCs. We run the simulation using the three different types of compensation proposed: (L)ocker, when the compensation is proportional to the distance of the outsourced customer to the locker; (D)etour based, when the compensation is proportional to the detour the OC has to make (usually much smaller than the previous one); and (F)ixed, when the compensation has a fixed value whatever the customers are. In this simulation the fixed compensation was set to 50% of the average value of the detour-based compensation, and is the cheapest compensation for the company. The lowest accumulated cost was observed for $\gamma = 100\%$ and compensation type F and is used as the baseline cost.

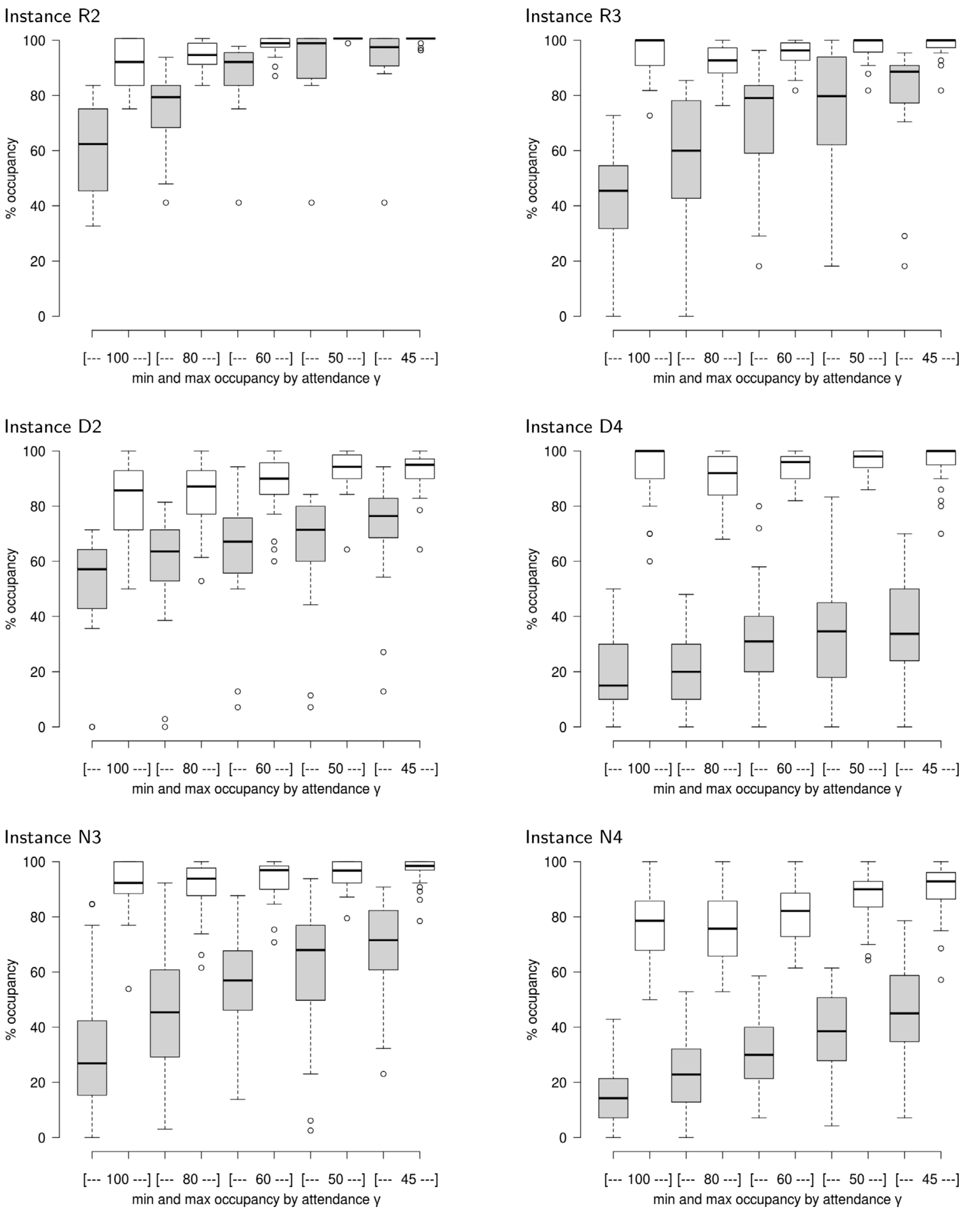

Fig. 8. Boxplot of the occupancy of the locker with min (gray) and max (white) occupancy over the time horizon.

Fig. 10 shows the percentage increase in the accumulated cost for different γ and compensation strategies, i.e., how the cost increases when more customers postpone their visit to the locker, for the different types of compensation. For $\gamma = 100\%$, the accumulated cost is higher for higher compensations: the lowest cost occurs for type F compensation and the highest for type

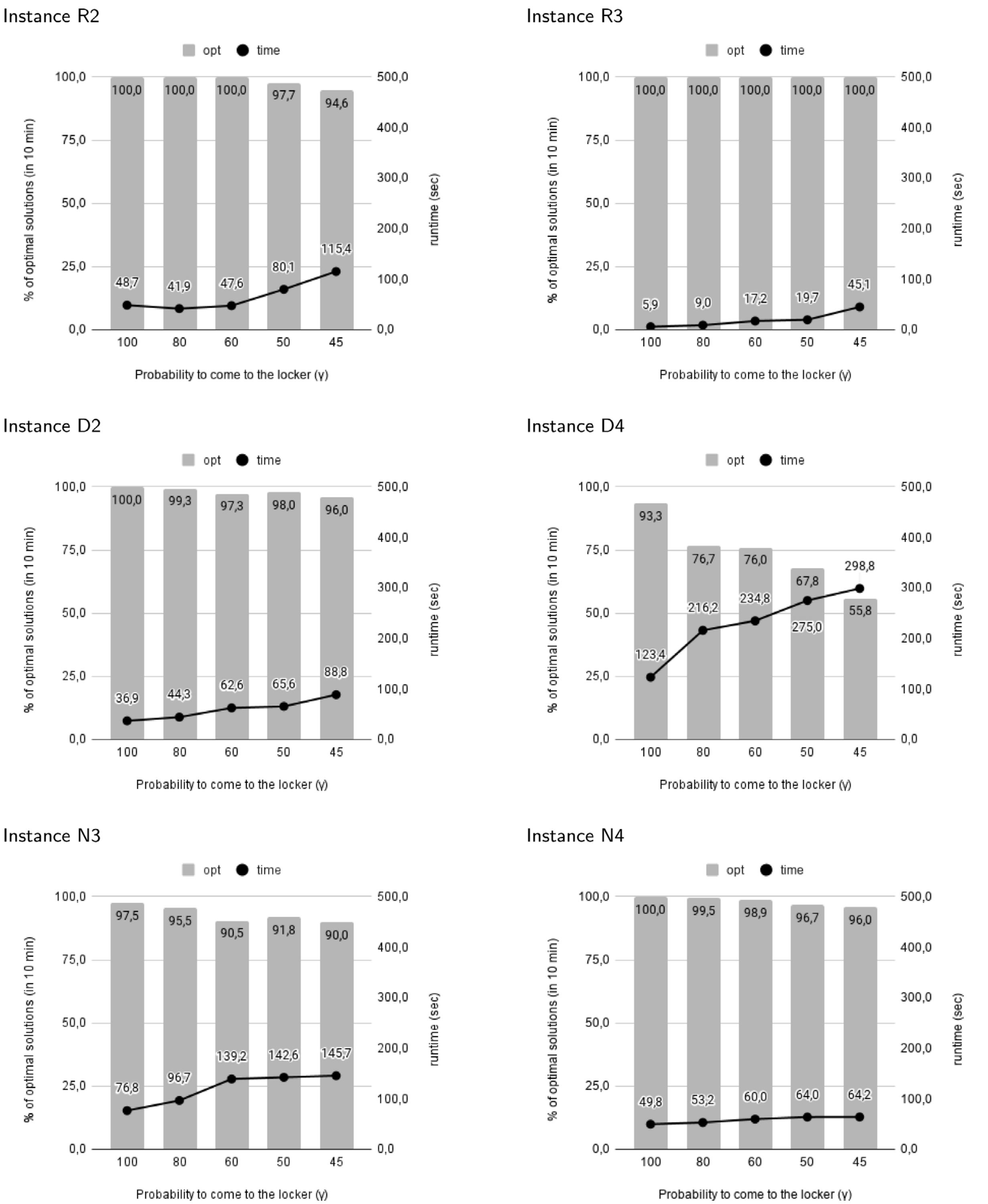

Fig. 9. Performance of the solver for different values of γ. The bars show the average percentage of optimal solutions among all D days in 5 runs, in a time limit of 10 min per day. The line shows the average execution time per day.

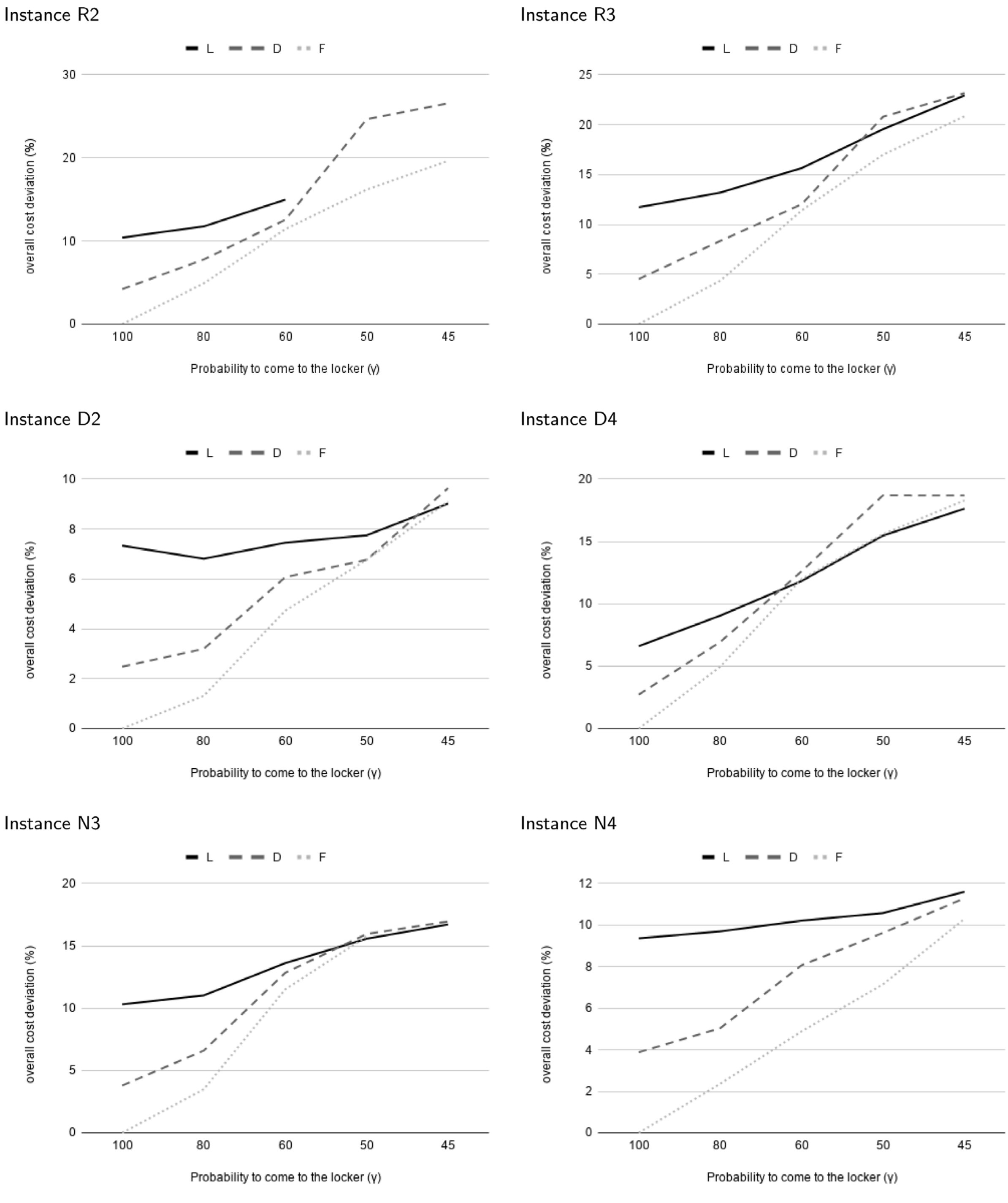

Fig. 10. Relative costs for different γ and different types of compensation fee, using $\gamma = 100\%$ and compensation type F as the baseline. Line L in instance R2 is not complete because of infeasibility for lower values of γ.

L. Notice that for $\gamma = 100\%$ the overall cost for strategy D is around 3 to 4% higher than for strategy F, and around 8 to 10% higher for strategy L. But, as γ decreases (more and more customers postpone their visit to the locker), the difference in the final cost decreases, and for the lowest γ the result may be quite the opposite: the highest accumulated cost may happen for type F or D and the lowest for type L. The reason is that the lower the compensation fee the higher the benefit for the company of using OC, when compared to a door-to-door vehicle service, and then the higher the number of deliveries assigned to OCs. However, as γ decreases, the higher number of no-shows implies a higher occupancy of the locker, which must hold both the parcels of the OCs that do not show and those of the outsourced customers. This explains why a lower compensation fee may end up meaning more customers served by vehicles, consequently a higher overall cost.

As no-shows affect the availability to use a locker as a transshipment point, we analyze in Fig. 11 the impact of increasing the storage capacity of the lockers. For each instance the capacity of the lockers was incremented in steps of 2 (for example, for instance R2, besides capacity 12 we did experiments using capacities 14 and 16). We consider as a baseline (cost deviation of 0%) the overall cost delivery in the time horizon if locker customers do not act as OCs and the lockers are uncapacitated. Continuous gray lines correspond to uncapacitated lockers and black lines to the lowest capacity, without OCs. Notice that the former has the lowest cost among all experiments and the latter the highest cost.

As expected, the overall cost decreases as the storage capacity increases, since more deliveries may be assigned to OCs and LF. For the lowest capacities, the cost increases when γ increases (the lines have a positive slope), as more no-shows prevent the locker from being used as transshipment points. Some lines even cross the baseline, reaching a positive deviation. That means that for a limited storage capacity and a high rate of no-shows it is better not to rely on the OCs. The opposite occurs for the highest capacities: if the locker has enough storage capacity, it can be used as a transshipment point even after successive no-shows. Deliveries assigned to OCs that did not show up promptly are delivered by LFs, but for increasing no-shows the larger number of delayed deliveries made by LF decreases the cost per delivery. This can be seen in Fig. 12, which shows the deviation on the cost per delivery made by the LF for two instances (N3 and D4) and explains why some lines for higher capacities on Fig. 11 have a negative slope as γ decreases. It should be pointed out that the reduction on cost comes with an increase in the number of customers having their delivery delayed. Fig. 13 shows the increasing number of door-to-door customers served on the 2nd day due to the no-show of locker customers. This can be seen as a reduction of the quality of service provided to door-to-door customers, inherent to this setting. The percentage of customers not served on day 1 increases with γ and W_l, reaching 13.4% for $\gamma = 45\%$ for a limited storage capacity of $W_l = 11$, and almost 20% for uncapacitated lockers.

6. Conclusions and future work

In this paper we propose a 2-echelon lastmile delivery Mixed Integer Linear Programming (MILP) model where, for the first time in the literature, three options of delivery are considered: parcel lockers, occasional couriers and dedicated local fleet. Parcel lockers are used to reduce delivery cost of parcels of clients willing to pick up their orders at a location and time that are more convenient for them. They are also used as transshipment nodes to transfer parcels to a cheaper and more environmentally friendly local fleet delivery. Occasional couriers are company's customers that may accept to perform home delivery to another client on the way to their destination, after collecting their own parcels from the lockers or the warehouse. Each of these options has already been studied separately, presented in the literature and experimented in real life by several companies. Furthermore, the integration of 2-echelon distribution with occasional couriers has also been studied, though mainly using third party agents. Similarly, the integration of 2-echelon distribution and lockers has also been addressed, but mostly not mixing the options in the same facility, i.e., lockers are not used as intermediary points for further delivery. In this work we integrate the three different options in a single model.

There is an intrinsic synergy in the proposed integration. Lockers may be accessed at any time of the day, which is convenient for customers that cannot or do not want to wait for a delivery at a specific address. They can be used as intermediary nodes in the 2-echelon distribution system, exempting the carrier agents to schedule a fixed time to meet, as parcels may be transported there on non-business hours to avoid traffic congestion and may be collected at any time during the day. Lockers also enlarge the network of occasional couriers by allowing locker customers to make a delivery, besides customers visiting the warehouse. Furthermore, the shared use of lockers contributes to a more efficient use of its storage capacity, which is relevant to cover the installation and maintenance costs of these facilities.

The MILP model was tested in a set of instances adapted from the literature, results showing that the inclusion of locker customers as occasional couriers contributes to a reduction in delivery costs, even if those customers only accept to make a small detour of no more than 25% of their route. They also contribute to a reduction in the total distance traveled by the vehicles. Furthermore, the use of a local fleet to make door-to-door delivery starting from the lockers contributes to a further decrease in the delivery cost, as this allows the usage of smaller, energy efficient vehicles in the lastmile.

The local fleet can also be used as a backup in the event of a no-show (or delay) of the OC, allowing concerned deliveries to meet a pre-defined dead-line. Such setting is studied by simulation of a multi-period optimization. Results show that, as the number of locker customers postponing their visit to the locker increases, the overall cost of delivery in a time horizon increases, mainly because the storage capacity of the lockers becomes more restrictive preventing the locker from acting as a transshipment point. A natural result is that if the locker customers are given more days to collect the parcels, lockers should have a larger capacity, to reduce the impact of postponed visits.

When applied in a real-life delivery context, the model can be easily extended to include additional characteristics of the couriers. Two cases that should be investigated in future work are: (1) OCs may specify the maximum number of deliveries they are willing to make instead of limiting it to one delivery (such would be interesting as long as orders may be served on the route that the OCs should follow to reach their destination); (2) customers served by LFs may be constrained to the region or neighborhood of the locker to limit the distance traveled by those couriers, specially in the case of cargo bikers (such allows only a subset of the customers to be served from each locker and may reduce the computational effort to solve the problem). Still, when it comes to real-life applications, the number of customers will probably be higher than the ones used in the experiments. To handle a higher number of customers, it may be necessary to develop heuristics for finding good solutions in a reasonable amount of time.

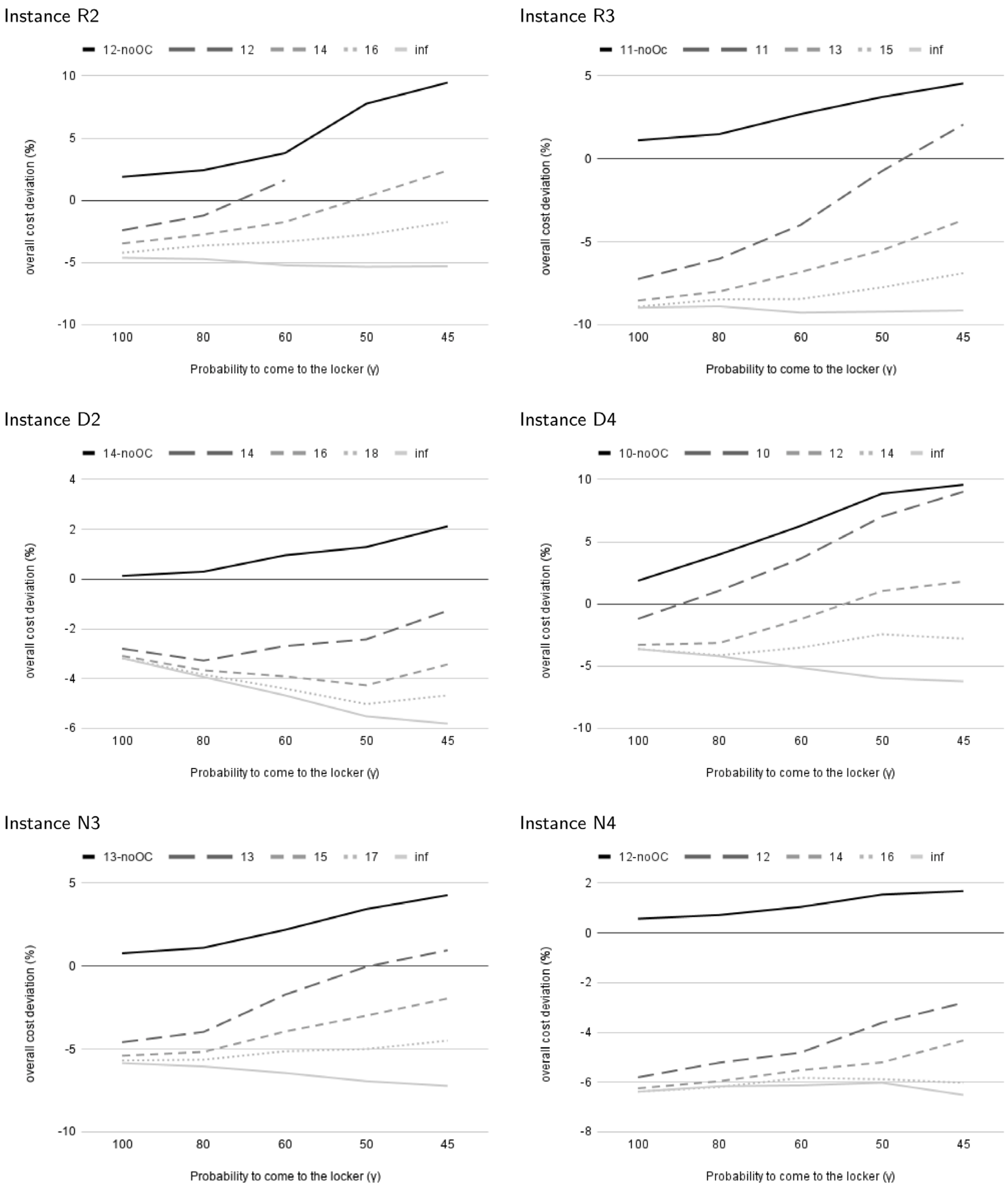

Fig. 11. Relative costs for different γ and different storage capacities of lockers, using as the baseline the cost without using OCs and with uncapacitated lockers.

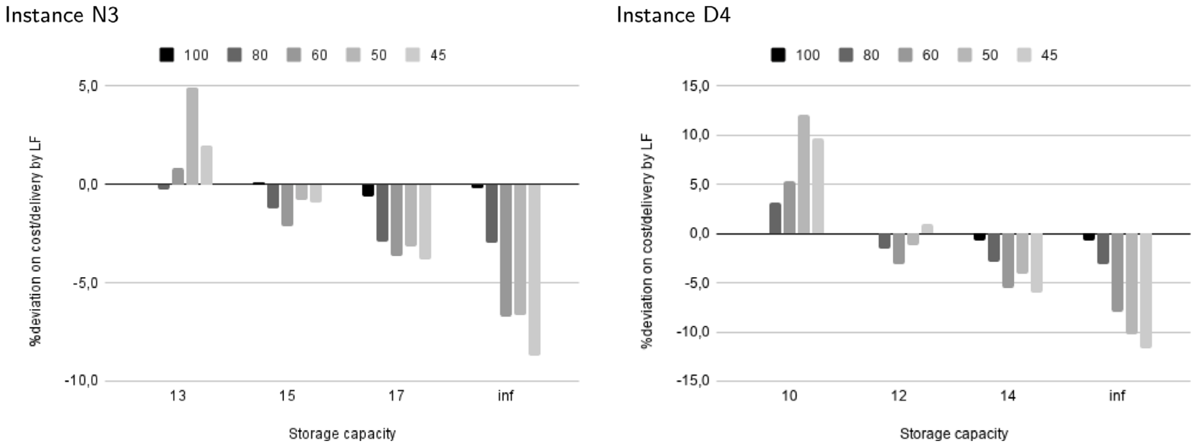

Fig. 12. Relative costs per delivery by LF for different γ and storage capacities of lockers, using $\gamma = 100\%$ and the lowest capacity as the baseline, for instances N3 and D4.

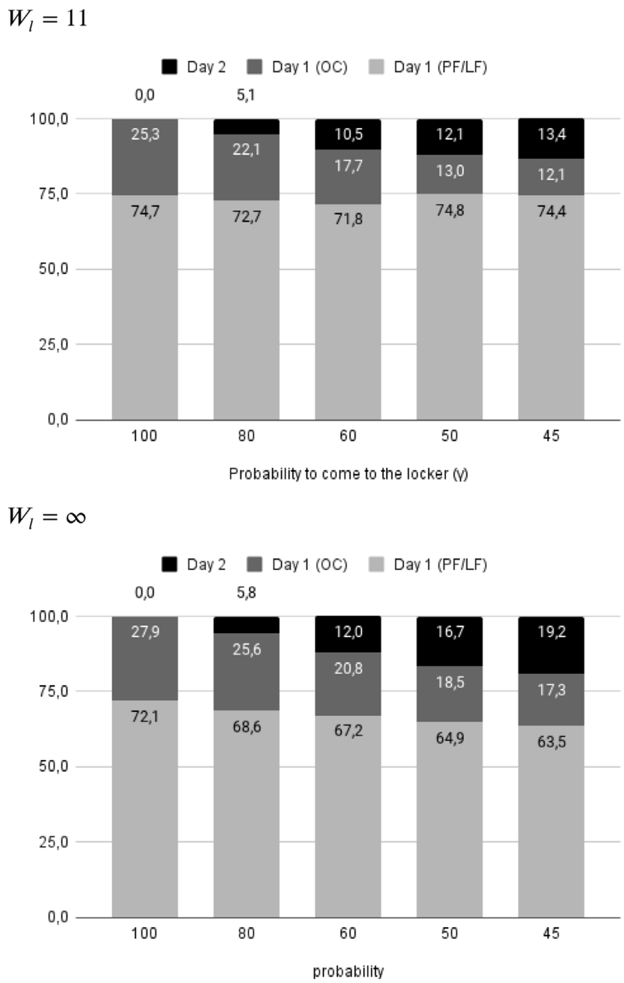

Fig. 13. Distribution of door-to-door customers into the different services and date, for instance R3, with a limited storage capacity ($W_l = 11$) and uncapacitated ($W_l = \infty$).

Future research should also address the different types of uncertainty present in this problem. In particular, it is important to forecast the location (and type) of new customers entering the system, the time a locker customer (potential OC) comes to the locker and their willingness to accept a delivery. Dealing with these issues will allow fine tuning policies for OC assignment and compensation, giving rise to further reductions in costs, emissions and traffic congestion.

CRediT authorship contribution statement

André Gustavo dos Santos: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – reviewing and editing. **Ana Viana:** Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – reviewing and editing, Supervision. **João Pedro Pedroso:** Conceptualization, Methodology, Writing – original draft, Writing – reviewing and editing, Supervision, Project administration, Funding acquisition.

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