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A Bi-level Approach for Last-Mile Delivery with Multiple Satellites

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Abstract. Last-mile delivery is regarded as an essential, yet challenging problem in city logistics. One of the most common initiatives, implemented to streamline and support last-mile activities, are satellite depots. These intermediate logistics facilities are used by companies in urban areas to decouple last-mile activities from the rest of the distribution chain. Establishing a business model that considers different stakeholders' interests and balances the economic and operational dimensions, is still a challenge. The aim of this paper is twofold. First, it introduces a novel problem that broadly covers such setting, where the delivery to customers is managed through satellite depots. The interplay and the hierarchical relation between the problem agents are modeled in a bi-level framework. Two mathematical models and an exact solution approach, properly customized for our problem, are presented. To assess the validity of the proposed formulations and the efficiency of the solution approach, we conduct an extensive set of computational experiments on benchmark instances on up to 1000 customers and four satellites. In addition, we present managerial insights for a case study on parcel delivery in Turin, Italy.

Keywords: Last-mile delivery, tariffs, consolidated logistics, bi-level optimization.

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1 Introduction

City logistics systems are at the core of the management of delivery transportation services in urban areas. The expected rapid growth of the number of last-mile deliveries (by 78% worldwide by 2030 [1]) will pose even greater challenges in the next future, for the increased awareness of the need for a sustainable transition of the logistics sector. The pivotal role played by last-mile logistics in the transition is not only due to the evident massive economic impact, but is also related to its socio-environmental dimension. Successful pathways to sustainable last-mile logistics require a strong vision of ways to reduce environmental impact, and foster urban growth, while maintaining the profitability of operations for the logistics sector. The introduction of new technologies and business models that embrace sustainability as a main principle are needed to reshape last-mile logistics in view of the new challenges, with the principle of consolidation playing a central role to how city logistics systems plan and operate.

A particularly promising solution toward a sustainable shift in city logistics is represented by two-tier solutions (Allen et al., 2012; Crainic et al., 2009; Perboli et al., 2011) operated by private or public/private partnerships (ULaaDS, 2020) which uses satellites, transshipment facilities with no or low warehousing capabilities, in the second tier. The main obstacles to a broad and successful adoption of satellite-based logistic systems, remain the lack of a sustainable business model, where stakeholders' interests are properly integrated (Björklund and Johansson, 2018; Crainic et al., 2018; Dreischerf and Buijs, 2022). Considering different stakeholders poses a challenge since they have often different interests, goals, and needs (Ballantyne et al., 2013; de Carvalho et al., 2019). In particular, since logistics initiatives are essentially business driven, a business model should consider financial feasibility for both the owners/initiators and the operators of the system. From the point of view of the initiators (often city administrators) is important a proper definition of tariffs for the usage of the satellite infrastructure (usually volume-based). This is in agreement with the more and more common trend of the usage of dynamic pricing, i.e. time and vehicle-dependent tariffs to access the city, to reduce the congestion in the urban areas and foster more sustainable behaviours of the different actors (Marciani and Cossu, 2014). For the operator of the system, it is vital to reduce costs in order to make the service competitive with traditional carrier-based urban distribution systems and to guarantee the continuation of the initiative (Janjevic and Ndiaye, 2017a,b).

[1] World Economic Forum, 2020

This paper addresses this complicated problem by:

- Presenting an integrated model that explicitly considers the hierarchical and complex relationship between two of the main stakeholders, the satellite-based infrastructure manager (SM) and the satellite operator (SO), presenting a framework where the interests of both stakeholders are embraced and the dynamism, pricing, and costing schemes, as well as operational issues of the system are appropriately considered (Kaspi et al., 2022). Our bi-level formulation, namely the Bi-level Last-Mile Delivery Problem with Multiple Satellites, allows us to explicitly model the hierarchy and the interaction between the SM and the SO: the SM is the leader (upper level decision maker), and the SO is the follower (lower level decision maker). The leader's goal is to maximize revenues, while the follower aims to minimize the total delivery cost, implementing a vertical collaboration between the two agents.

- Contributing to the literature on bi-level last-mile delivery problems presenting two mathematical models solved by an exact solution approach, properly customized for our problem. To the best of our knowledge , this is one of the very few contributions to bi-level last-mile delivery with multiple satellites.

- Conducting an extensive set of computational experiments, using data that reflect the main issues involved in the problem for the urban distribution, to qualify the model and to assess the computational tractability of the proposed model. A thorough analysis of the computational results for a real case study identifies a series of managerial insights with respect to the structure of the tariffs and the fleet mix, given various urban distribution characteristics.

The problem settings come from recent industrial and institutional collaborations of the authors, including work on urban distribution in the metropolitan area of Turin, Italy, as part of the development of the new Logistics and Mobility Plan to be activated in 2025, through the collaboration of CARS@Polito (Automotive and mobility center of Politecnico di Torino), Freight Leaders Council, the think tank supporting the Italian Ministry of Transportation for the logistics policies and regulations (FLC, 2016), and the Regional Government of Piedmont (Perboli et al., 2021a,b).

The remainder of the paper is organized as follows. We give a more detailed description of the problem setting in Section 2. Section 3 provides a review of the relevant literature. Section 4 describes the problem and presents two mathematical formulations. Section 5 is devoted to the description of the exact solution approach. Section 6 discusses the numerical experiments conducted on a set of instances taken from the benchmark test set, appropriately modified to account for the characteristic of the problem. In addition, interesting managerial insights are derived from a real case study on parcel delivery in Turin, Italy in Section 7. Finally, Section 8 summarizes the paper and presents some directions for future research.

2 Urban distribution and satellite depots

Urban distribution refers to the overall process by which freight is transported both to and from dense urban environments. Such environments face increasing challenges of congestion and negative environmental impacts, together with always higher customer expectations to have their purchased goods delivered both fast and cheap. To address these challenges and needs, many firms (e.g., the e-commerce giant platforms Alibaba, 2018; Amazon, 2018) adopt a demand-driven approach to logistics., i.e., they are moving from a cost-driven push supply model to a time and service quality-based pull approach.

Multi-tier smart urban transportation, or *City Logistics*, systems are implementing these approaches (Crainic et al., 2021) by following two general principles: 1) the consolidation of loads originating from different shippers within the same vehicles and 2) the coordination of the distribution operations within the city. New business models, based on the collaboration and the coordination of the activities among the different actors, are required as an answer to the needs for a regulatory effect on the plethora of delivery services asked by the customers (Crainic et al., 2018, 2020, 2021).

The goal of such systems is to reduce the negative impacts (i.e., costs, congestion, noise, etc.) associated with the vehicles transporting freight in urban areas, by more efficiently using their capacity (i.e., increasing the average vehicle fill rate and reducing the number of empty trips that are performed). In all these frameworks, the delivery is based on the use of multiple transportation tiers, which enable the system to utilize specifically adapted infrastructure and specialized fleets at each tier to better attain the overall goal that is pursued. The first tier is generally the same in all contexts and includes a set of terminals, known as Consolidation Distribution Centers, which are usually located on the outskirts of the city, whose main function is to serve as the entry (exit) points and consolidation facilities for the inbound (outbound) freight. Lower tiers are connected to the first tier at transshipment facilities with no or low warehousing capabilities, called satellites through urban trucks. From satellites, freight is then transshipped to city freighters, vehicles specifically adapted to perform distribution operations in dense urban zones. The city freighters deliver freight to their final destination within the city either directly in two-tier systems (for medium-to-large urban areas) or through a series of smaller facilities (e.g., mini hub and lockers) and lower-capacity vehicles (e.g., drones and bicycles) in systems with more than two tiers (for large-to-metropolis size urban areas). Specific access and moving rules constrain activities, to limit their negative impacts (e.g., urban trucks will move along specific paths that are chosen to efficiently reach satellites while minimizing congestion) and contribute toward the goals of economic, social, and environmental efficiency.

Multi-tier systems are able to distribute freight in urban areas in a more efficient way, but the planning of such systems poses important challenges to managers at all decision levels (strategic, tactical, and operational). The overall system is made up of several different actors interacting with each other, including shippers that generate demand for transportation, carriers that provide transportation services, facility and physical infrastructure managers, institutional authorities that regulate the system, and customers and citizens that ask for goods (Crainic et al., 2018; Isa et al., 2021; Quak and Tavasszy, 2011). The aforementioned actors have their own goals, make their own decisions, and are linked with others through many interconnections, interactions, and interdependencies. All contribute to make the system complex Perboli et al. (2014, 2021a) and call for a careful coordination of the system. Figure 1 shows the Social Business Network[2] for a satellite-based multi-tier urban delivery system. Satellites are at the core of the system (Facility and Infrastructure Management) and are directly influenced by the policies of local authorities. This partnership/stakeholdership is often useful to enable a better use of the transport infrastructure: for example, local authorities might concede logistics spaces in strategic locations to set up satellites or limit access to the urban area, to reduce negative last-mile externalities. Concerning satellite management, most part of the literature focuses on the operational and routing part, disregarding the infrastructure managers' view.

In this paper, we particularly focus on the two main types of infrastructure managers in a two-tier urban delivery system: the satellite-based infrastructure

[2] The Social Business Network represents a complex system in a standard visual manner and is part of the GUEST methodology (Perboli, 2016; The GUEST Initiative, 2017)

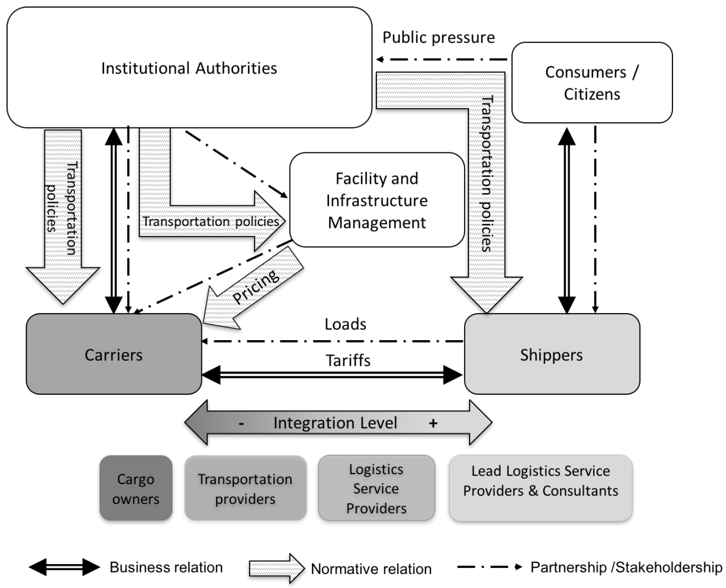

Figure 1: Relationships among the main actors in freight transportation systems (Crainic et al., 2018).

manager (SM) and the satellite operator (SO). The SM can be a private company or a public-private partnership in which local authorities and private stakeholders involved in delivery cooperate. The actual implementation is left to the SO, often private logistic operators, that have to cope with the operational issues, including the integration of different delivery methods, as electric vehicles and cargo bikes (Crainic et al., 2021; Perboli et al., 2018) and whose aim is cost minimization. The total cost of satellite operations can be divided into three separate elements: the cost of the satellite infrastructure (usually volume-based), the cost for the distribution operations and the cost of vehicles and drivers. Minimizing the cost is not only beneficial for the SO, but it has a pivotal role in the sustainability of the urban distribution system as a whole. In fact, since this total cost is used to set the price charged to the carrier for outsourcing its last-mile distribution (Janjevic and Ndiaye, 2017a), it can completely reshape the urban distribution system: carriers will choose whether to use or not satellites mainly on the basis of the price (Isa et al., 2021; Kin et al., 2016), even though another important factor is the corporate social responsibility strategy of the carrier company (Crotti and Maggi, 2022), which can be committed to reducing the environmental impact and noise pollution.

3 Literature review

We analyze the literature along two axes. First, the literature on satellite-based multi-tier urban delivery systems is discussed. Second, the relevant literature on bi-level optimization in last-mile and urban delivery is reviewed.

From the point of view of *satellite-based multi-tier urban delivery systems*, the literature mainly focused on the family of problems known as two-echelon vehicle routing problems (Crainic et al., 2009; Perboli et al., 2011). They have been extended in various forms but always consider the costs and the tariffs as given. Recently, a new direction in the literature used bin-packing problems to tackle the operational and tactical issues in the management of a single satellite depot. In Perboli et al. (2021a) the joint problem of satellite management and urban delivery optimization has been addressed, offering practical insights to manage last-mile delivery and investigating the efficiency and the viability of the underlying business model. The problem has been modeled as a variant of bin packing, which takes into account some specific features of the on-demand economy and e-commerce as, for instance, the time-dependent structure of the costs and the effects of customers' preferences. From a transportation perspective, the more considered issue is tactical capacity planning, arising in many contexts characterizing the new generation of multi-stakeholder systems, e.g., synchromodal (Giusti et al., 2018; Perboli et al., 2017; Qu et al., 2019) and physical-internet-based (Ballot et al., 2014) inter-urban freight transport, data-based 3/4PL activities (Sagliettto, 2013; Skender et al., 2017), and city logistics (Crainic and Montreuil, 2016; Crainic et al., 2021).

From the point of view of *bi-level optimization in last-mile and urban delivery*, the literature is quite limited and mainly focused on bi-level location-routing models. Following this stream, Xu et al. (2018) presented a bi-level programming model for a location-routing problem considering time window, vehicle capacity, and vehicle backhaul cost and proposed a genetic algorithm solution approach. In another paper, Yang et al. (2020) presented a bi-level model to handle the location and demand distribution decisions arising in a parcel locker management problem where a delivery company as the upper level stakeholder minimizes the total cost associated to the locker construction, operation, transportation and parcel delivery to the lockers and the customers as the lower level decision makers minimize the pick-up cost. The model is also solved by a genetic algorithm.

Concerning the integration of pricing plans into bi-level optimization models for last-mile and urban delivery, the literature is still scarce. For the sake of completeness, we mention one of the very few contributions in (Santos et al., 2021) that

investigated an integrated inbound and outbound transportation planning problem in the realm of a bi-level vehicle routing problem with selective backhauls. At the upper level, the shipper decides the minimum cost delivery routes and the set of incentives to offer to the carrier to perform integrated routes. At the lower level, the carrier decides to accept or refuse the offer and optimizes the routes visiting backhaul customers. Of course, the pricing notion in the latter research is on incentives offered by the shipper to the carrier for visiting backhaul customers which is different from the satellite pricing plans addressed in the present paper. In addition, the aforementioned contribution is more focused on operational routing plans and the tactical issues are not addressed.
In Arrieta-Prieto et al. (2022) the authors model the interplay between the policy planners and the carriers in a bi-level framework. The public sector as the leader controls the location and demand coverage decisions for a set of uncapacitated urban micro-consolidation centers, promoting the use of sustainable delivery modes such as bikes and electric vehicles, and aims to minimize the social costs corresponding to the total emission which is, in turn, expressed in terms of the total distance traveled. From the other side, the private carriers control the transportation and fleet assignment decisions to minimize their operational delivery cost which is expressed as a linear function of the carrier tour length. Since the upper level and the lower level objective functions differ only on a multiplicative constant, the problem is reduced to a single level problem that is solved by a greedy heuristic. This research is different from the present paper in many aspects. First of all, the pricing decisions are missing there; secondly, the time-dependent nature of the costs, which is a typical aspect of last-mile operations is not considered. For the sake of completeness we also mention the work of (Ji et al., 2017) studying a problem with an urban consolidation center operator: the urban consolidation center operator is the leader that sets the delivery time windows, whilst a third-party logistics follower delivers the orders to a set of retail stores by considering the time windows set in the upper level. The uncertainty in supply and demand sides are tackled by adopting a risk-averse approach.

It is evident how the literature lacks in terms of models and methods to guide the creation of time and vehicle-dependent tariffs in multi-tier urban systems. We provide the first answer to this need, by proposing a bi-level approach which consider both the multi-tier tariff fixing and the optimization of the operation at the satellites. Assessing and controlling the impact of the tariffs in such complex systems, by using appropriate OR-based methods and models, could support firms to achieve high-performance levels in both quality of service and economic efficiency and, thus, increase profits and gain competitive advantages in the long-run.

4 Problem description and model formulation

The interplay and the hierarchical relation between the two involved stakeholders, in our case the SM and the SO, is a critical problem feature that should be carefully addressed. Obviously, ignoring this hierarchy feature could lead to faulty models that generate invalid and non-applicable decisions. To fill the gap in the literature regarding the existence of models that explicitly consider the hierarchical and complex relationship between SM and SO, we present in this Section a model framework, in the realm of bi-level optimization. Bi-level optimization approach is the suitable framework to address this problem with a hierarchical structure since it accounts for the interplay and the interactions of different agents at two different levels. The origin of bi-level optimization problems dates back to the seminal works of von Stackelberg and Peacock (1952) on game theory and, in particular, leader-follower games. The leader, that has information about the follower's objectives, makes his/her decision first and communicates it to the follower, which reacts to the decision of the leader optimising his/her own objective Colson et al. (2007). As a result, the leader's optimization problem is a nested problem, where the feasible set is partly determined through a second optimization problem (Dempe et al., 2019). This approach has been successfully applied to tackle such hierarchy structure for many real-world problems in various fields such as supply chain, energy sector, transportation network design, revenue management, etc (Kleinert et al., 2021).

Our bi-level formulation allows to explicitly model the hierarchy and the interaction between the SM and the SO. The SM as the upper level decision maker is interested to define time-dependent volume-based tariffs for satellites, in order to maximize the total revenue. Clearly, the SM gain (revenue) varies based on the response/reaction of the lower level decision maker who uses the system and responds to the announced tariffs, that in our particular case is the SO. The tariffs are paid by the SO, which is also responsible for the efficient delivery of the orders to customers with a limited and heterogeneous fleet of vehicles: each vehicle type has a limited and time-dependent capacity and cost [3]. The cost depends on the location of the satellites and the type of vehicle used. To account for the situation in which an order cannot be delivered, the express delivery option is considered.

The SO should take the following decisions: *i*) the selection of a subset of satellite depots from which the deliveries are performed, *ii*) the allocation of ve-

[3]The SO delivery cost could also include environmental costs, congestion, etc. in the spirit of a generalized cost (Baldi et al., 2012).

hicles to selected depots, and *iii*) the delivery schedule. This setting extends the one presented in Perboli et al. (2021a), shifting the focus to a more inclusive analysis, previously restricted to freight and operating costs of the shippers and to one depot (Perboli et al., 2021a).

Before presenting the mathematical formulations, we first provide a brief discussion on tariff setting and address some modeling issues. Let $\mathcal{J}$ and $\mathcal{H}$ be the set of satellites and timeslots indexed by j and h, respectively. Also, let variable T_j^h represent the tariff assigned to satellite j at timeslot h. Tariffs are time-varying for a number of reasons. Cheaper rates can be charged at certain times of day or night, with the aim of smoothing out the utilization of satellites. Tariffs can be also influenced by specific access restrictions set by the local authorities to limit traffic, noise, and pollution in given areas of the cities during specific hours of the day. Hence, the tariffs are required to satisfy some "regulation constraints" expressed as lower and upper bounds ($\underline{T}_j^h \leq T_j^h \leq \overline{T}_j^h,\ \forall j \in \mathcal{J},\ h \in \mathcal{H}$). Moreover, the average tariff for each satellite over all timeslots should be below a pre-specified threshold ($\frac{1}{|\mathcal{H}|} \sum_{h \in \mathcal{H}} T_j^h \leq \Delta_j,\ \forall j \in \mathcal{J}$). Depending on how the thresholds are set, such constraints could also be used to implement public policies like local pollution reduction in specific areas of the city. We should also note that, in practice, the tariffs take discrete values that belong to a set of known and finite realizations as $\{\underline{T}_j^h,\ \underline{T}_j^h + s,\ \underline{T}_j^h + 2s,\ \cdots,\ \underline{T}_j^h + \lfloor \frac{\overline{T}_j^h - \underline{T}_j^h}{s} \rfloor s\}$ where s is the incremental rate. Therefore, we may express tariff T_j^h in terms of binary variables γ_j^{lh} as $T_j^h = \underline{T}_j^h + s \sum_{l \in \Omega_j^h} l \gamma_j^{lh}$ where $\Omega_j^h = \{0, 1, \cdots, \lfloor \frac{\overline{T}_j^h - \underline{T}_j^h}{s} \rfloor\}$ and $\sum_{l \in \Omega_j^h} \gamma_j^{lh} \leq 1\ \ \forall j \in \mathcal{J},\ h \in \mathcal{H}$.

It is clear that by construction, the regulation constraints on the upper and lower bounds are always satisfied.

4.1 First mathematical formulation

By using the notation reported in Table 1, the Bi-level Last-Mile Delivery Problem with Multiple Satellites can be formulated as follows:

Table 1: Notation for the mathematical model

Sets	
I	set of orders indexed by i
$\mathcal{J}$	set of satellite depots indexed by j
$\mathcal{H}$	set of timeslots indexed by h
$\mathcal{K}$	set of vehicles indexed by k
$\mathcal{P}$	set of vehicle types indexed by p
$\mathcal{K}_p \subseteq \mathcal{K}$	set of vehicles of type p where $\cup_{p\in\mathcal{P}}\mathcal{K}_p = \mathcal{K}$
$\Omega_j^h = \{0, 1, \cdots, \lfloor \frac{\overline{T}_j^h - \underline{T}_j^h}{s} \rfloor\}$	set of tariff steps of satellite j at time slot h (indexed by l)
Parameters	
$\underline{T}_j^h$	minimum tariff for satellite depot j at time slot h
$\overline{T}_j^h$	maximum tariff for satellite depot j at timeslot h
Δ_j	average tariff for satellite depot j within the day
s	stepsize for tariff
d_i	demand associated to order i
f_{pj}^h	cost-per-stop for vehicle of type p at timeslot h allocated to satellite depot j
δ_p^h	usage cost for vehicle type p at timeslot h
E	cost for the express delivery
D_j^h	capacity of satellite j at timeslot h
V_p^h	capacity of vehicle type p at timeslot h
Decision variables	
γ_j^{lh}	binary variable which takes value 1 if the l-th discrete tariff is set for satellite j at timeslot h and 0 otherwise; (upper level variable)
x_{ikj}^h	binary variable which takes value 1 if order i is delivered at timeslot h by vehicle k from satellite j and 0 otherwise; (lower level variable)
y_{kj}^h	binary variable which takes value 1 if vehicle k is used to deliver the orders from satellite j at timeslot h and 0 otherwise (lower level variable)
X_i	binary variable which takes value 1 if order i is delivered with express delivery option and 0 otherwise (lower level variable)

$$(M1)\ \max_{\gamma,x,y,X} \sum_{i\in I}\sum_{j\in\mathcal{J}}\sum_{k\in\mathcal{K}}\sum_{h\in\mathcal{H}} (d_i T_j^h) x_{ikj}^h \tag{1}$$

$$T_j^h = \underline{T}_j^h + s\sum_{l\in\Omega_j^h} l\gamma_j^{lh},\ \ \forall j\in\mathcal{J},\ h\in\mathcal{H} \tag{2}$$

$$\frac{1}{|\mathcal{H}|}\sum_{h\in\mathcal{H}} T_j^h \leq \Delta_j,\ \forall j\in\mathcal{J} \tag{3}$$

$$\sum_{l\in\Omega_j^h}\gamma_j^{lh} \leq 1,\ \ \forall j\in\mathcal{J},\ h\in\mathcal{H} \tag{4}$$

$$\gamma_j^{lh}\in\{0,1\},\ \ \forall j\in\mathcal{J},\ h\in\mathcal{H},\ l\in\Omega_j^h \tag{5}$$

The upper level objective function (1) expresses the SM's total revenue. Constraints in (2) set the tariff for each satellite at each timeslot. Constraints (3) are the ”regulation constraints” that require the average of tariffs set for each satellite over all timeslots should be below a defined threshold. Constraints in (4) are logical constraints ensuring that for each satellite j at each timeslot h, only one tariff is set. Finally, constraints in (5) represent the nature of upper level variables.

It is important to note that the SM can control only the variables related to tariffs while the delivery plan decisions are handled by the SO. The lower level problem corresponding to the SO is formulated as follows:

$$\min_{x,y,X} \sum_{j\in\mathcal{J}} \sum_{k\in\mathcal{K}} \sum_{h\in\mathcal{H}} \sum_{i\in I} (d_i T_j^h) x_{ikj}^h + \sum_{j\in\mathcal{J}} \sum_{p\in\mathcal{P}} \sum_{k\in\mathcal{K}_p} \sum_{h\in\mathcal{H}} f_{pj}^h \sum_{i\in I} x_{ikj}^h$$

$$+ \sum_{j\in\mathcal{J}} \sum_{p\in\mathcal{P}} \sum_{k\in\mathcal{K}_p} \sum_{h\in\mathcal{H}} \delta_p^h y_{kj}^h + E \sum_{i\in I} X_i \tag{6}$$

$$\sum_{i\in I} \sum_{k\in\mathcal{K}} d_i x_{ikj}^h \leq D_j^h, \ \forall j \in \mathcal{J},\ h \in \mathcal{H} \tag{7}$$

$$\sum_{i\in I} d_i x_{ikj}^h \leq V_p^h y_{kj}^h, \ \forall j \in \mathcal{J},\ p \in \mathcal{P},\ k \in \mathcal{K}_p,\ \ h \in \mathcal{H} \tag{8}$$

$$\sum_{j\in\mathcal{J}} y_{kj}^h \leq 1, \ \forall k \in \mathcal{K},\ h \in \mathcal{H} \tag{9}$$

$$\sum_{j\in\mathcal{J}} \sum_{k\in\mathcal{K}} \sum_{h\in\mathcal{H}} x_{ikj}^h + X_i = 1, \ \forall i \in I \tag{10}$$

$$x_{ikj}^h \in \{0,1\}, \ \forall i \in I,\ j \in \mathcal{J},\ k \in \mathcal{K},\ h \in \mathcal{H} \tag{11}$$

$$y_{kj}^h \in \{0,1\}, \ \forall j \in \mathcal{J},\ k \in \mathcal{K},\ h \in \mathcal{H} \tag{12}$$

$$X_i \in \{0,1\}, \ \forall i \in I \tag{13}$$

The lower level objective function (6) represents the total cost in terms of the satellite usage, the surrogate routing costs, the vehicle usage costs, and the cost for the express deliveries. Constraints (7) and (8) ensure that at each timeslot, the satellite depot capacity and the vehicle capacity are not exceeded, respectively. Constraints (9) are logical constraints ensuring that each vehicle at each timeslot can be sited in at most one satellite. Constraints (10) ensure that each order is delivered whether as an ordinary or express delivery. Finally, the set of constraints (11)-(13) show the nature of variables.

4.2 Second mathematical formulation

The lower level problem (6)-(13) is a multi-depot extension of the model presented in (Perboli et al., 2021a) and, therefore, is NP-hard. The time-dependent structure of the objective function greatly increases the inherent complexity of the bin packing problem, which lies on the heart of the model. Moreover, the size of the model drastically grows with the increase in the number of orders and brings up serious computational tractability challenges.

To overcome this issue, we derive an aggregated formulation with a lower number of constraints and variables. With this aim, we assume that customers sharing similar characteristics, for example in terms of position location, are grouped into clusters (whose set is denoted by $\mathcal{C}$). We should note that the level of granularity of clusters can be increased to have as many clusters as the number of customers, thus leading back to the first model, and therefore, the aggregated formulation (M2) is a generalization of M1. In the computational results, we will show that even using a coarse-grained clustering, the aggregated model is a good approximation of the non-aggregated one.

We introduce three sets of variables (as reported in Table 2): the aggregated amount of delivered demands in each cluster (from a given satellite, using a given vehicle and in a given timeslot), the number of vehicles of each type dispatched from each satellite during each timeslot, and demand in each cluster delivered by the express delivery.

Table 2: Notation for the aggregated model

Sets	
$\mathcal{C}$	set of clusters indexed by c
Decision variables	
$q^{ch}_{pj} = \sum_{i\in c}\sum_{k\in\mathcal{K}_p} d_i x^h_{ikj}$	aggregated amount of demands in cluster c delivered by vehicles type p from satellite j at timeslot h
$Q^c = \sum_{i\in c} d_i X_i$	demand of cluster c delivered by the express delivery
Parameters	
α_c	average of demands in cluster c ($\alpha_c = \frac{\sum_{i\in c} d_i}{\lvert c\rvert}$)
β^c	total amount of orders in cluster c ($\beta^c = \sum_{i\in c} d_i$)

Following the notations in Table 2, the aggregated model M2 can be written as follows:

$$(M2)\ \max_{\gamma,q,Y,Q} \sum_{c\in\mathcal{C}}\sum_{j\in\mathcal{J}}\sum_{p\in\mathcal{P}}\sum_{h\in\mathcal{H}} T^h_j q^{ch}_{pj} \tag{14}$$

$$(2)-(5)$$

The objective function in (14) displays the total SM's revenue in terms of the aggregated deliveries. It is easy to see that the upper level objective functions (1) and (14) are equal and therefore the upper level problems in M1 and M2 are equivalent. The aggregated lower level problem corresponding to the SO is reformulated as follows:

$$\min_{q,Y,Q} \sum_{c\in\mathcal{C}}\sum_{j\in\mathcal{J}}\sum_{p\in\mathcal{P}}\sum_{h\in\mathcal{H}} T^h_j q^{ch}_{pj} + \sum_{c\in\mathcal{C}}\sum_{j\in\mathcal{J}}\sum_{p\in\mathcal{P}}\sum_{h\in\mathcal{H}} f^h_{pj}\frac{q^{ch}_{pj}}{\alpha_c}$$

$$+\sum_{j\in\mathcal{J}}\sum_{p\in\mathcal{P}}\sum_{h\in\mathcal{H}}\delta_p^h Y_{pj}^h + E\sum_{c\in\mathcal{C}}\frac{Q^c}{\alpha_c} \tag{15}$$

$$\sum_{c\in\mathcal{C}}\sum_{p\in\mathcal{P}} q_{pj}^{ch} \leq D_j^h,\ \forall j\in\mathcal{J},\ h\in\mathcal{H} \tag{16}$$

$$\sum_{c\in\mathcal{C}} q_{pj}^{ch} \leq V_p^h Y_{pj}^h,\ \forall j\in\mathcal{J},\ p\in\mathcal{P},\ h\in\mathcal{H} \tag{17}$$

$$\sum_{j\in\mathcal{J}} Y_{pj}^h \leq |\mathcal{K}_p|,\ \forall p\in\mathcal{P},\ h\in\mathcal{H} \tag{18}$$

$$\sum_{h\in\mathcal{H}}\sum_{j\in\mathcal{J}}\sum_{p\in\mathcal{P}} q_{pj}^{ch} + Q^c = \beta^c,\ \forall c\in\mathcal{C} \tag{19}$$

$$q_{pj}^{ch} \geq 0,\ \forall c\in\mathcal{C},\ j\in\mathcal{J},\ p\in\mathcal{P},\ h\in\mathcal{H} \tag{20}$$

$$Q^c \geq 0,\ \forall c\in\mathcal{C} \tag{21}$$

$$Y_{pj}^h \in \mathbb{Z}^+,\ \forall j\in\mathcal{J},\ p\in\mathcal{P},\ h\in\mathcal{H} \tag{22}$$

The lower level objective function (15) represents the aggregated total costs of the SO. While the satellite usage and the vehicle usage costs are equivalent in M2 and M1 (by the definition of the aggregated variables q_{pj}^{ch} and Y_{pj}^h), the routing and the express delivery costs in (15) are an approximation to their counterparts in M1. In fact, $\frac{q_{pj}^{ch}}{\alpha_c}$ approximates the number of deliveries in cluster c and $\frac{Q^c}{\alpha_c}$ is an estimation to the number of express deliveries in cluster c. Constraints (16) and (17) ensure that the restrictions on the capacity of satellite depots and vehicles are respected, respectively. Constraints (18) require that the total number of vehicles of each type to be deployed at each timeslot should be below the total number of existing vehicles of that type. Constraints (19) guarantee that demand of each cluster should be delivered either with ordinary or express service. Finally, constraints in (20)-(22) show the nature of variables.

We should note that the mathematical formulation M2 has $|\mathcal{H}|(|\mathcal{K}|-|\mathcal{P}|)(|\mathcal{J}|+1)+(|I|-|\mathcal{C}|)$ less variables and $|\mathcal{J}||\mathcal{H}|\left[|\mathcal{K}|(|I|+1)-|\mathcal{P}|(|\mathcal{C}|+1)\right]+(|I|-|\mathcal{C}|)$ less constraints, compared to M1.

5 Solution approach

Despite the large amount of applications fitting the bi-level programming framework, its real-life implementations are quite limited because of the inherent complexity of bi-level problems and the lack of efficient algorithms to handle both the problem complexity and the large size of models. In general, the bi-level problems are neither convex nor differentiable and even the simplest bi-level problems with linear upper and lower level problems are strongly NP-hard (Hansen et al., 1992; Jeroslow, 1985). Therefore, most of contributions on the solution methods for the bi-level models, in particular exact approaches, are based on the exploitation of the problem structure. For instance, in case the optimization problem of the lower level agent, named as the lower level problem, is convex and satisfies a suitable constraint qualification (which, in the convex case, usually is Slater's constraint qualification), a single-level reformulation can easily be derived using the KKT conditions or the strong duality theorem that replaces the lower level problem by a system of equations or inequalities (Dempe et al., 2015; Leyffer et al., 2006). Models M1 and M2 belong to the class of bi-level problems with mixed integer variables. Most of the exact methods for mixed integer bi-level problems are based on the high-point relaxation model and bi-level infeasible solutions are discarded by branching, by adding cutting planes, by approximating the value function, or by a combination of the approaches above mentioned (Kleinert et al., 2021). In our case, the leader's and follower's objective functions contain bilinear terms resulting from the product of upper level and lower level variables. Clearly, the presence of integer variables in the follower's problem prevents the application of standard single level reformulation techniques such as KKT.

To exactly solve the models we apply a value-function-based approach developed by Lozano and Smith (2017) based on sampling a subset of bi-level feasible solutions. The algorithm iteratively finds a bi-level feasible solution representing a lower bound to the original problem; next, the information corresponding to the lower level variables are used to provide an upper bound. This algorithm finally ends with an optimal solution (Köppe et al., 2010). To describe the solution approach, we define the following notation:

Let $\Omega = \{(\mathbf{x}^l, \mathbf{x}^f) | (2)-(5), (7)-(13) \text{ for M1 or } (16)-(22) \text{ for M2}\}$, where $\mathbf{x}^l = (\{\gamma_j^{lh}\})$ and $\mathbf{x}^f = (\{x_{ikj}^h\}, \{y_{kj}^h\}, \{X_i\})$ for M1 or $\mathbf{x}^f = (\{q_{pj}^{ch}\}, \{Y_{pj}^h\}, \{Q^c\})$ for M2, respectively, encode the vector of leader and follower decision variables. We also define $\Omega^l = \{\mathbf{x}^l | (2)-(5)\}$, and $\Omega^f = \{\mathbf{x}^f | (7)-(13) \text{ for M1 or } (16)-(22) \text{ for M2}\}$ as the leader's and the follower's decision spaces.

The follower rational reaction set corresponding to the leader solution $\mathbf{x}^l$ is defined as follows:

$$\Psi(\mathbf{x}^l) = arg\,min_{\mathbf{x}^f}\{Z^f(\mathbf{x}^l, \mathbf{x}^f) | \mathbf{x}^f \in \Omega^f\} \tag{23}$$

where Z^f represents the follower objective function (6) in M1 or (15) in M2. We also refer to (23) as the Lower Level (LL).

Definition 1 *A solution* $(\mathbf{x}^l, \mathbf{x}^f)$ *is called bi-level feasible if* $\mathbf{x}^l \in \Omega^l$ *and* $\mathbf{x}^f \in \Psi(\mathbf{x}^l)$.

Now, we can reformulate the original bi-level model M1 or M2 as

$$(BLM) \quad \max_{(\mathbf{x}^l, \mathbf{x}^f)} \{Z^l(\mathbf{x}^l, \mathbf{x}^f) | \mathbf{x}^l \in \Omega^l, \mathbf{x}^f \in \Psi(\mathbf{x}^l)\} \tag{24}$$

where $Z^l(\mathbf{x}^l, \mathbf{x}^f)$ denotes the leader objective function (1) in M1 or (14) in M2.
It is easy to verify that an optimal solution to the single level problem (25) is a valid an upper bound for model BLM.

$$\max_{(\mathbf{x}^l, \mathbf{x}^f)} \{Z^l(\mathbf{x}^l, \mathbf{x}^f) | \mathbf{x}^l \in \Omega^l, \mathbf{x}^f \in \Omega^f\} \tag{25}$$

The problem in (25) is referred as the High Point Problem (HPP).

Lemma 1 *A solution* $(\mathbf{x}^l, \mathbf{x}^f) \in \Omega$ *is bi-level feasible iff* $Z^f(\mathbf{x}^l, \mathbf{x}^f) \leq Z^f(\mathbf{x}^l, \bar{\mathbf{x}}^f)$ *for every* $\bar{\mathbf{x}}^f \in \Omega^f$.

Proof 1 *The proof is straightforward by the definition of* $\Psi(\mathbf{x}^l)$. ■

Considering the above lemma, the bi-level problem in (24) can be expressed as the single level optimization problem in (26)-(28) where the disjunctive constraints (27) require the bi-level feasibility.

$$\max_{(\mathbf{x}^l, \mathbf{x}^f)} Z^l(\mathbf{x}^l, \mathbf{x}^f) \tag{26}$$

$$\text{s.t.} \quad Z^f(\mathbf{x}^l, \mathbf{x}^f) \leq Z^f(\mathbf{x}^l, \bar{\mathbf{x}}^f), \ \forall \bar{\mathbf{x}}^f \in \Omega^f \tag{27}$$

$$(\mathbf{x}^l, \mathbf{x}^f) \in \Omega \tag{28}$$

The problem in (26)-(28) is called as the Extended High-Point Problem (EHPP).

Theorem 1 *The EHPP is equivalent to the BLM.*

Proof 2 *Since the EHPP and BLM share the same objective function, it is enough to illustrate that* $S_{EHHP} = S_{BLM}$, *where* $S_.$ *denotes the feasible region.*
To show $S_{EHHP} \subseteq S_{BLM}$, *let* $(\mathbf{x}^l, \mathbf{x}^f)$ *be an arbitrary solution in* S_{EHHP}. *Therefore,* $(\mathbf{x}^l, \mathbf{x}^f) \in \Omega$ *(i.e.,* $\mathbf{x}^l \in \Omega^l$, $\mathbf{x}^f \in \Omega^f$*) and* $Z^f(\mathbf{x}^l, \mathbf{x}^f) \leq Z^f(\mathbf{x}^l, \bar{\mathbf{x}}^f)$, $\forall \bar{\mathbf{x}}^f \in \Omega^f$. *The*

latter is equivalent to $\mathbf{x}^f \in \Psi(\mathbf{x}^l)$ *where* $\mathbf{x}^l \in \Omega^l$*. This means* $(\mathbf{x}^l, \mathbf{x}^f) \in S_{BLM}$*.*
To show $S_{BLM} \subseteq S_{EHHP}$*, let* $(\mathbf{x}^l, \mathbf{x}^f)$ *be an arbitrary solution in* S_{BLM}*, by definition we have,* $\mathbf{x}^l \in \Omega^l$ *and* $\mathbf{x}^f \in \Psi(\mathbf{x}^l)$*. The latter is equivalent to* $Z^f(\mathbf{x}^l, \mathbf{x}^f) \leq Z^f(\mathbf{x}^l, \bar{\mathbf{x}}^f)\ \forall \bar{\mathbf{x}}^f \in \Omega^f$ *where* $(\mathbf{x}^l, \mathbf{x}^f) \in \Omega$*. Hence,* $(\mathbf{x}^l, \mathbf{x}^f) \in S_{EHHP}$*.*
From $S_{BLM} \subseteq S_{EHHP}$ *and* $S_{EHHP} \subseteq S_{BLM}$*, we conclude* $S_{EHHP} = S_{BLM}$ *and the proof is complete.* ■

Theorem 1 implies that the BLM in (24) can be solved to optimality by solving the EHHP. This, in turn, requires the enumeration of all feasible follower responses $\bar{\mathbf{x}}^f \in \Omega^f$. Clearly, in case Ω^f is an infinite set or its size is exponentially large, the enumeration approach is not affordable.
To overcome this drawback, we may solve a relaxation of EHHP, named as (REHHP), where Ω^f in (27) is replaced by $\hat{\Omega}^f \subseteq \Omega^f$, including a subset of sampled solutions.

Let $\hat{\Omega}^f \subseteq \Omega^f$ be a finite set which is specified by its elements $\bar{\mathbf{x}}^f_1, \bar{\mathbf{x}}^f_2, \cdots, \bar{\mathbf{x}}^f_K$. The REHHP corresponding to $\hat{\Omega}^f$, denoted by REHHP($\hat{\Omega}^f$), is defined as

$$\max_{(\mathbf{x}^l, \mathbf{x}^f)} Z^l(\mathbf{x}^l, \mathbf{x}^f) \tag{29}$$

$$\text{s.t. } Z^f(\mathbf{x}^l, \mathbf{x}^f) \leq Z^f(\mathbf{x}^l, \bar{\mathbf{x}}^f_\kappa),\ \kappa = 1, \cdots, K \tag{30}$$

$$(\mathbf{x}^l, \mathbf{x}^f) \in \Omega \tag{31}$$

Since $\hat{\Omega}^f \subseteq \Omega^f$, we have $S_{EHHP} \subseteq S_{REHHP}$, that implies $Z^{l*}_{EHHP} \leq Z^{l*}_{REHHP}$. From the equivalency of EHHP and BLM, we conclude $Z^{l*}_{EHHP} = Z^{l*}_{BLM}$ which means that the optimal solution of REHHP provides a valid upper bound to BLM. In addition, the disjunctive constraints in (30) are valid cuts for BLM and do not eliminate any bi-level feasible solution. Therefore, the upper bound provided by the REHHP can be tightened by adding more valid cuts in form of (30) which is equivalent to enlarging the sample set size $\hat{\Omega}^f$.
This idea forms the core of an exact solution approach (Lozano and Smith, 2017). The method iteratively solves the REHHP providing upper bounds to BLM. The response of the follower, corresponding to the optimal upper level variables in REHHP is obtained. This provides us with a bi-level feasible solution (lower bound). By enlarging the current sample set and adding the corresponding cuts to REHHP, tighter upper bounds are obtained. This procedure ends when the global optimality of the current incumbent is verified.
The pseudocode of the exact approach is reported in Algorithm 1, where *LB* and *UB* refer to the BLM lower and upper bounds, respectively. We should also note

that the REHHP without cuts (30) is equivalent to the HPP problem (25). Therefore, in the very beginning of Algorithm 1, when $\kappa = 0$, solving the REHHP is equivalent to solving problem (25).

Algorithm 1: Pseudocode of the exact approach

Initialization ε, $\kappa \leftarrow 0$, $LB \leftarrow -\infty$, $UB \leftarrow \infty$, $\hat{\Omega}^f \leftarrow \emptyset$
Solve REHHP and obtain the optimal upper level variables $\mathbf{x}^{*l}$
Obtain an optimal follower response $\mathbf{x}^{*f} \in \Psi(\mathbf{x}^{*l})$
$(\mathbf{x}^l_\kappa, \mathbf{x}^f_\kappa) \leftarrow (\mathbf{x}^{*l}, \mathbf{x}^{*f})$
$UB \leftarrow Z^l(\mathbf{x}^{*l}, \mathbf{x}^{*f})$
$\hat{\Omega}^f \leftarrow \hat{\Omega}^f \cup \{\mathbf{x}^f_\kappa\}$
while $(UB - LB) \geq \varepsilon)$ **do**
  $\kappa \leftarrow \kappa + 1$
  Solve REHHP($\hat{\Omega}^f$) and obtain an optimal solution $(\mathbf{x}^l_\kappa, \hat{\mathbf{x}}^f_\kappa)$
  $UB \leftarrow Z^l(\mathbf{x}^l_\kappa, \hat{\mathbf{x}}^f_\kappa)$
  Obtain an optimal follower response $\mathbf{x}^f_\kappa \in \Psi(\mathbf{x}^l_\kappa)$
  $\hat{\Omega}^f \leftarrow \hat{\Omega}^f \cup \{\mathbf{x}^f_\kappa\}$
  if $Z^f(\mathbf{x}^l_\kappa, \mathbf{x}^f_\kappa) = Z^l(\mathbf{x}^l_\kappa, \hat{\mathbf{x}}^f_\kappa)$ **then**
    $(\bar{\mathbf{x}}^l, \bar{\mathbf{x}}^f) \leftarrow (\mathbf{x}^l_\kappa, \hat{\mathbf{x}}^f_\kappa)$
    $UB = LB$
  end
  else if $Z^l(\mathbf{x}^l_\kappa, \mathbf{x}^f_\kappa) > LB$ **then**
    $LB \leftarrow Z^l(\mathbf{x}^l_\kappa, \mathbf{x}^f_\kappa)$
    $(\bar{\mathbf{x}}^l, \bar{\mathbf{x}}^f) \leftarrow (\mathbf{x}^l_\kappa, \mathbf{x}^f_\kappa)$
  end
end
return $(\bar{\mathbf{x}}^l, \bar{\mathbf{x}}^f)$

Theorem 2 *Algorithm 1 provides the optimal solution and converges in a finite number of iterations.*

Proof 3 *Since the leader's decision variables do not appear in the follower's constraints, by the same argument presented in Lozano and Smith (2017), the exactness of the algorithm is guaranteed.*

Moreover, since the upper level variables are discrete, and so the solution space Ω^l is finite, the convergence of the algorithm is guaranteed. ■

5.1 How to solve the REHHP efficiently

The upper level objective function (1) in M1 or (14) M2, includes bilinear terms; the same holds for the REHHP, which is a mixed integer problem with bilinear terms $\gamma_j^{lh} x_{ikj}^h$ or $\gamma_j^{lh} q_{pj}^{ch}$, depending on whether model M1 or M2 is considered. Obviously, this nonlinearity exacerbates the computational complexity of the problem. To tackle this issue, we use the McCormick's inequalities, defining the convex envelope of the bilinear term (McCormick (1976)). In our case, since the bilinear terms include binary variables (γ_j^{lh}), the McCormick's reformulation is exact (Costa et al., 2017). To do so, we may introduce an auxiliary binary variable ζ_{ikj}^{lh} which replaces the bilinear term $\gamma_j^{lh} x_{ikj}^h$ in (1) where $\zeta_{ikj}^{lh} \leq x_{ikj}^h$, $\zeta_{ikj}^{lh} \leq \gamma_j^{lh}$, $\zeta_{ikj}^{lh} \geq x_{ikj}^h + \gamma_j^{lh} - 1$. Considering the above discussion, the REHHP can be formulated as an integer model with linear objective function and constraints as presented in (43)-(49) in Appendix 9.1.
In a similar way, the bilinear terms $\gamma_j^{lh} q_{pj}^{ch}$ in (14) can be replaced by an auxiliary continuous variables μ_{pj}^{clh} and the equivalent linear REHHP is cast as (50)-(56) (see Appendix 9.1).

5.2 An efficient procedure to obtain the follower rational reaction

Finding an optimal follower response in Lines 3 and 11 in Algorithm 1 requires solving two single level optimization problems consecutively: *i*) the follower's problem (23) parameterized by the values of leader decisions $\mathbf{x}^{*l}$. *ii*) In case $\Psi(\mathbf{x}^{*l})$ is not a singleton, we follow the "optimistic approach" assuming that the follower always responds in favor of the leader and selects a $\mathbf{x}^f \in \Psi(\mathbf{x}^{*l})$ that maximizes the leader's revenue Z^l. Hence, an auxiliary problem should be solved to ensure that the optimistic approach is adopted. In this way, we assume some form of cooperation between the leader and the follower. Hereafter, we report the auxiliary problem in our case:

$$\max_{\mathbf{x}^f} Z^l(\mathbf{x}^{*l}, \mathbf{x}^f) \tag{32}$$

$$\text{s.t. } Z^f(\mathbf{x}^{*l}, \mathbf{x}^f) \leq Z^{*f} \tag{33}$$

$$\mathbf{x}^f \in \Omega^f \tag{34}$$

where Z^{*f} represents the optimal objective value corresponding to $\Psi(\mathbf{x}^{*l})$ in (23).

Solving problem (32)-(34) imposes an additional computational burden that may be efficiently handled, in our case. In case the customers' demands and, consequently, the delivery variables q^{ch}_{pj} are restricted to be integer, we may design a simple procedure to explore all the multiple alternative solutions of the follower's problem without solving again the auxiliary problem.
Such a procedure is described as follows.
First, the follower's problem (23) corresponding to $\mathbf{x}^l = \mathbf{x}^{*l}$ is solved to optimality. Then, a no-good cut is added to the follower's problem (23) and the model, amended with the constraint which excludes the current optimal solution $\mathbf{x}^{*f} = (x_1^{*f}, x_2^{*f}, \cdots, x_n^{*f})$ from solution space of the follower's problem, is solved again. The no-good cut

$$\sum_{i=1}^{n} |x_i^f - x_i^{*f}| \geq 1$$

can be rewritten as

$$z_i \leq |x_i^f - x_i^{*f}|, \; \sum_{i=1}^{n} z_i \geq 1, \; \forall i = 1, \cdots, n$$

and further reformulated as

$$z_i \leq x_i^f - x_i^{*f} + M_i \delta_i, \forall i = 1, \cdots, n \tag{35}$$

$$z_i \leq -(x_i^f - x_i^{*f}) + M_i (1 - \delta_i), \forall i = 1, \cdots, n \tag{36}$$

$$\sum_{i=1}^{n} z_i \geq 1 \tag{37}$$

$$\delta_i \in \{0, 1\}, \forall i = 1, \cdots, n \tag{38}$$

$$z_i \in \mathbb{Z}^+, \forall i = 1, \cdots, n \tag{39}$$

where M_i is a big-M value set as $M_i = \overline{x}_i^f - \underline{x}_i^f$, $i = 1, \cdots, n$ and $\underline{x}_i^f, \overline{x}_i^f$ are such that $\underline{x}_i^f \leq x_i^f \leq \overline{x}_i^f$.

This provides another optimal solution, if any; otherwise, the optimal objective value deteriorates and the search ends. This process iteratively adds the no-good cuts one at a time until all the optimal solutions are found. Clearly, among the set of solutions found, the one that benefits the leader the most is chosen as the rational response of the follower.

The customized procedure is described in Algorithm 2.

Algorithm 2: Pseudocode of the customized procedure

```
Obtain an optimal follower response x̂^f ∈ Ψ(x*^l)
x*^f ← x̂^f
Z*^l ← Z^l(x*^l, x*^f), Z*^f ← Z^f(x*^l, x*^f)
repeat
    Add cuts (35)-(39) to min_{x^f ∈ Ω^f} Z^f(x*^l, x^f) and get the optimal solution x'^f
    if Z^f(x*^l, x'^f) > Z*^f then
        break
    end
    else if Z^l(x*^l, x'^f) > Z*^l then
        Z*^l ← Z^l(x*^l, x'^f)
        x*^f ← x'^f
    end
return (x*^l, x*^f)
```

6 Computational experiments

In this Section, we first present extensive experimental results performed on a set of benchmark instances to investigate the efficiency of the proposed models and the solution approach. Next, we present a real case study for last-mile parcel delivery in Turin city (Italy) and report the main managerial insights.

6.1 Testing environment

The instances used in this paper are a multi-satellite extension of the instances presented in Perboli et al. (2021a) available in a BitBucked repository[4]. All the parameters have been generated in agreement with the real distribution of the e-commerce parcels in an urban area (Perboli and Rosano, 2019b), then anonymized and normalized. We then present in brief their main characteristics.

The instances consider a number of orders in the set $\{200, 500, 1000\}$. Randomly generated order volumes belong to two sets: small orders, with demand $d_i \in \{1, ..., 15\}$, and medium orders, with demand $d_i \in \{16, ..., 20\}$. Small and medium orders are then mixed in different percentages to better represent the future real mix of volumes in parcel delivery (De Marco et al., 2017). The number of

[4] https://bitbucket.org/orogroup/vcsbpp-td/src/master/

timeslots in one day has been considered equal to three and five. The fleet is composed of three types of vehicles: cargo bikes (with capacity of 100 kg in all the timeslots), electric vans (with capacity of 150 kg in all the timeslots), and fossil-fueled light-duty (with capacity of of 200 kg in all the timeslots). Also the case with a homogeneous fleet has been considered. The cost of the usage of a vehicle δ_p^h is computed as the mean delivery cost obtained from Brotcorne et al. (2019) normalized with respect to the other quantities in the instances for obfuscating industrial data. The time-dependent cost-per-stop f_{pj}^h has been set according to Crainic et al. (2011), and by using a time-dependent cost modifier assuming values $[1.0, 0.3, 0.7]$ when three timeslots are considered and $[1.0, 0.1, 0.3, 0.5, 0.7]$ if the timeslots are five. The number of satellites for instances with 200, 500, and 1000 orders has been set to two, three, and four, respectively. The capacity of each satellite is equal to the capacity of single depot case, as reported in the benchmark, divided by the number of satellites that varies based on the number of orders.

The lower and upper bounds for the satellite tariff are set to $[30, 3, 9, 15, 21]$ and $[45, 18, 24, 30, 36]$, respectively when five timeslots are considered and for the case of three timeslots, the bounds are set as $[30, 9, 21]$ and $[45, 24, 36]$.
All the experiments have been performed on a laptop with CPU Intel Core i7 with 2.60 GHz CPU and 16 GB RAM. The exact method has been coded in AIMMS 4.79.2.5, with Cplex 20.1.0 used as MIP solver. A time limit of 1800 seconds has been imposed on all the instances.

6.2 Models and exact solution approach performance analysis

In the first set of experiments, we perform a comparison between M1 and M2. The question that we want to address here is how much we loose in terms of quality of the solution by solving M2, and if this is worth from a computational viewpoint. Clearly, M2 has less variables and constrains compared to M1, on one hand. On the other hand, M2 provides an approximation of the optimal delivery plans of M1. To compare the performance of the proposed models in terms of solution quality and computational time, we fix the tariffs in the upper level model to the values reported in the benchmark instances. This provides a fair setting to compare the lower level problems in M1 and M2. The comparison is made on the set of instances with 200 orders and two satellite depots. For instances with more than 200 orders, the non-aggregated model M1 cannot be solved within a reasonable solution time while the size of aggregated model M2 is independent of the orders and can be efficiently solved. For the sake of brevity, Table 3 reports the summary of results (detailed results are reported in Appendix 6) in terms of the average of CPU time ($CPU_{(.)}$) for M1 and M2, the average of relative percentage solution gap (Gap_M), where $Gap_M = \frac{|Z^{*f}_{M2} - Z^{f*}_{M1}|}{|Z^{f*}_{M1}|} 100$.

Table 3: Summary of results: comparison of M1 and M2

Instance	$\|\mathcal{H}\|$	$CPU_{M1}(s)$	$CPU_{M2}(s)$	$Gap_M(\%)$
200	3	71.23	0.03	0.86
200	5	131.83	0.03	0.86

The solution time of model M2 is quite stable while M1 is sensitive to the increase in timeslots as its CPU time increases by about 46%. The values of Gap_M are quite small confirming the validity of model M2.

Table 4: Optimal tariffs in the bi-level model versus fixed tariffs ($|\mathcal{J}| = 1$)

Instances	$Gap_{Tariff}(\%)$			$Gap_{CPU}(\%)$
	$h=1$	$h=2$	$h=3$	
200	1.07	0.00	41.66	15.86
500	1.74	0.87	41.67	15.20
1000	1.91	0.00	40.63	9.46

To investigate the quality of the optimal tariffs provided by the bi-level model (M2), we compared them with the suggested tariffs as reported in the benchmark [5]. In fact, this gives us insights on the performance of the bi-level versus the single level approach. Table 4 shows the summary of the results for instances up to 1000 orders and one satellite where Gap_{Tariff} refers to the average relative gap between the optimal tariff and the tariffs in the data set for each timeslot, Gap_{CPU} denotes the average relative gap between the solution time spent in the solution of the bi-level and the single level models. As we can see, the optimal tariffs are higher than the real tariffs for distribution of the e-commerce parcels in urban area (Perboli and Rosano, 2019a) by 41.67%. However, this superiority comes at a price of increase in the solution time which is always below 15.86%. Of course, such increase in CPU time is quite affordable since a bi-level model is clearly more complicated.

Table 5 reports the summary of the computational results gathered by applying Algorithm 1 on the aggregated model M2 (the detailed results are reported in

[5]Municipality of Turin, 2018 Perboli et al., 2018 Torino living lab. http://torinolivinglab.it/en/ (last accessed, 19/12/2020).

Appendix 6). In particular, we report the average values corresponding to the CPU time in the REHHP and the LL problem, the total CPU time, and the relative gap of the best upper and lower bounds, denoted by Opt ($Opt = \frac{|UB-LB|}{|LB|} 100$). The solution approach provides the optimal solution for all the instances but four instances with 1000 orders and five timeslots for which the average relative gap is around 11.43%. All the instances with three timeslots are solved to optimality and the average CPU time is below four seconds. For the instances with 1000 orders and five timeslots, the average CPU time is less than four minutes.

Table 5: Summary of results: exact solution approach

	$\|\mathcal{H}\| = 3$				$\|\mathcal{H}\| = 5$			
Instances	$CPU_{REHHP}\,(s)$	$CPU_{LL}\,(s)$	$CPU\,(s)$	$Opt\,(\%)$	$CPU_{REHHP}\,(s)$	$CPU_{LL}\,(s)$	$CPU\,(s)$	$Opt\,(\%)$
200	0.04	0.03	0.39	0	0.05	0.03	0.61	0
500	0.09	0.05	0.83	0	0.13	0.15	2.33	0
1000	0.31	0.62	3.29	0	7.31	0.04	205.12	11.43

To investigate the effect of the numbers of clusters, we ran a set of experiments for instances with 1000 orders, four satellite depots, three timeslots, and a number of clusters ranging in the set $\{1, 2, 5, 10, 20\}$. Figure 2 shows the average CPU time for such test cases. As expected, the solution time increases considerably with a higher number of clusters: for example going from one to 20 clusters, the average solution time increases 18 times but it is still affordable and around 60 seconds. It is noticeable that the optimal objective function value remains the same.

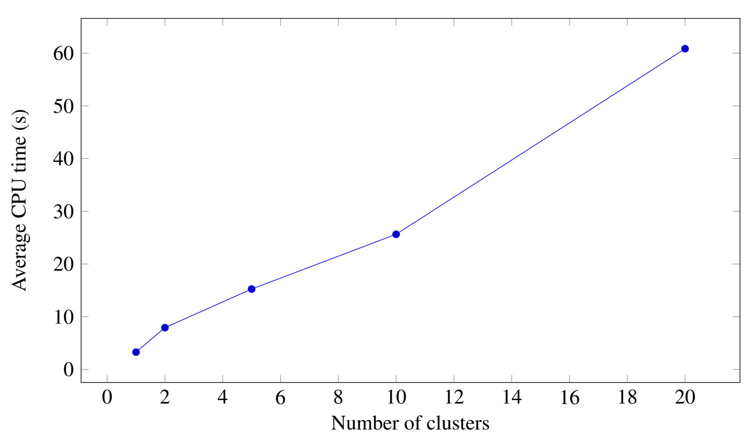

Figure 2: Solution time versus the number of clusters

7 Case study and managerial insights

In this section, we analyze the potential impact of tariff setting via a bi-level paradigm and present the relevant managerial insights on a case study for urban logistics in Turin City, Italy. The case study is a last-mile delivery application to deliver the orders of 1000 customers using a heterogeneous fleet of 45 vehicles composed of three types of vehicles: including Cargo-Bike (CB), Van (VAN), and Electric Vehicle (EV). Each fleet type has the same number of vehicles. The deliveries should be performed within fifteen hours (from 9 AM to 12 PM); five different timeslots with a length of three hours have been considered. There are five satellite depots and the minimum and the maximum tariffs (€ per kg) are the same for each satellite and vary based on the timeslot in the following sets $[0.07, 0.10, 0.13, 0.05, 0.03]$ and $[0.10, 0.13, 0.16, 0.08, 0.06]$. The express delivery cost is set to 5.3 € and the capacity of each vehicle type is set to 45 kg; the satellite capacity is 429 kg. The order volumes have been randomly generated following a discrete uniform distribution $d_i \sim U(0,3]$ (Perboli et al., 2018). Each order can be delivered within a time range (window) that specifies the timeslots in which the customer prefers to receive the order. All customers sharing the same delivery time window are grouped into a specific cluster. Notice that this enables us to implicitly account for the hard time window constraints in an efficient way. In fact, to forbid the delivery of orders outside the required timeslot, we impose the following restrictions as $q_{pj}^{ch} = 0$, $\forall, p \in \mathcal{P}$, $j \in \mathcal{J}$, $c \in \mathcal{C}$, $h \in \mathcal{H} - \{h^c\}$ where h^c denotes the delivery timeslot assigned to orders in cluster c. The assumption is not restrictive, since orders can be further clustered on the basis of other features, as, for instance, the location.
Table 6 reports the input parameters on the cost-per-stop and the vehicle usage cost in the case study.

Table 6: Input parameters

Cost-per-stop						Vehicle usage cost					
	h=1	h=2	h=3	h=4	h=5		h=1	h=2	h=3	h=4	h=5
CB	0.13	0.18	0.23	0.09	0.05	CB	20.16	28.8	37.44	14.4	8.64
VAN	0.38	0.54	0.7	0.27	0.16	VAN	30.24	43.2	56.16	21.6	12.96
EV	0.31	0.44	0.57	0.22	0.13	EV	24.64	35.2	45.76	17.6	10.56

In order to illustrate the effects of customers' preferences, we solved model M2 under three different operational scenarios. We have considered, as a baseline, a scenario where each cluster has a given single-period time window. In the second scenario, we have considered a flexible time window configuration, that mimics a typical situation in which customers place orders to be delivered in a few consecutive timeslots. For example, the delivery is allowed to be made one time period early or one period late (one period before or one period after the preferred period). Only one timeslot will be then assigned for the service of each cluster. In our experimnets, the customers in clusters C1, C2, and C3 can receive the orders in the first three timeslots and the customers in clusters C4 and C5 can be serviced within the last two timeslots. This restriction are specified by the following set of constraints

$$\sum_{j\in\mathcal{J}}\sum_{p\in\mathcal{P}} q_{pj}^{ch} = 0,\ c = 1, 2, 3,\ h = 4, 5 \tag{40}$$

$$\sum_{j\in\mathcal{J}}\sum_{p\in\mathcal{P}} q_{pj}^{ch} = 0,\ \ c = 4, 5,\ h = 1, 2, 3. \tag{41}$$

Finally, the last scenario considers one cluster and does not contemplate any customers' preferences.

First of all, we have investigated the impact of aggregation to have an idea about the quality of optimal solution in model M2 with respect to the extended model M1. With his aim, since the difference only relies on the lower level problem, we have set the tariffs in M1 equal to the optimal values in model M2 (as reported in Table 8). We have also fixed the fleet size by amending the set of constraints (42) to (6)-(13) where $\hat{Y}_{pj}^{h}$ represents the optimal value corresponding to variable Y_{pj}^{h} in model M2.

$$\sum_{k\in\mathcal{K}_p} y_{kj}^{h} = \hat{Y}_{pj}^{h},\ \forall p\in\mathcal{P},\ j\in\mathcal{J},\ h\in\mathcal{H} \tag{42}$$

The corresponding single level model that includes only the assignment variables x_{ikj}^{h} and X_i is solved and the results are reported in Table 7.

Table 7: The comparison of aggregated and non-aggregated models

Model	Leader's revenue	Follower's delivery cost	Satellite usage cost	Routing cost	Vehicle usage cost	Express delivery cost
M1	198.40	1260.16	198.40	139.20	922.56	0.00
M2	198.40	1260.92	198.40	139.96	922.56	0.00

As we can see, model M2 provides a good approximation to M1, since the leader's revenue is the same and the follower's delivery cost is only 0.06% higher, due to the overestimation in the routing cost.

Table 9 reports the optimal solution in terms of number of deployed vehicles of each type, average vehicle fill ratio, and delivery ratio evaluated as the ratio between the demand serviced at that specific timeslot over the total demand.

Table 8: Results: optimal tariffs

Satellite tariff				
h=1	h=2	h=3	h=4	h=5
0.10	0.13	0.16	0.08	0.06

We can observe that in the optimal solution only cargo bikes and electric vehicles are used. This is reasonable since the cost-per-stop of cargo bikes and electric vehicle are lower than the cost of vans. The vehicle fill ratios are always above 93% of the vehicle capacity and in the last timeslot, in which the demands are the highest (about 42% of the total demands), the vehicle fill ratio increases to 1.00 and 0.99 for cargo bikes and electric vehicles, respectively. This shows that the best use of the fleet capacity is made. Finally, based on the delivery ratio values, all the orders within the first four timeslots are handled by cargo bikes and only in the fifth timeslot, the cargo bikes' delivery ratio decreases to 75% and the electric vehicles are deployed to deliver the rest of orders.

Table 9: Results: Case study

	# of deployed vehicles					Average vehicle fill ratio					Delivery ratio				
	h=1	h=2	h=3	h=4	h=5	h=1	h=2	h=3	h=4	h=5	h=1	h=2	h=3	h=4	h=5
CB	8	7	7	8	15	0.95	0.93	0.94	0.95	1.00	1.00	1.00	1.00	1.00	0.75
EV	-	-	-	-	5	-	-	-	-	0.99	-	-	-	-	0.25

Table 10 reports the fill ratio for the satellites. The first satellite (SD1) is only used in the first timeslot and its fill ratio is quite low (10%), the same also holds for SD3 in the fourth timeslot. It is evident that the satellite fill rates are not balanced.

Table 10: Utilization of satellites in different timeslots

Satellite	Satellite fill ratio				
Id	h=1	h=2	h=3	h=4	h=5
SD1	0.10	-	-	-	-
SD2	-	-	-	-	0.52
SD3	-	-	-	0.10	0.94
SD4	-	0.68	-	-	0.63
SD5	0.66	-	0.69	0.66	-

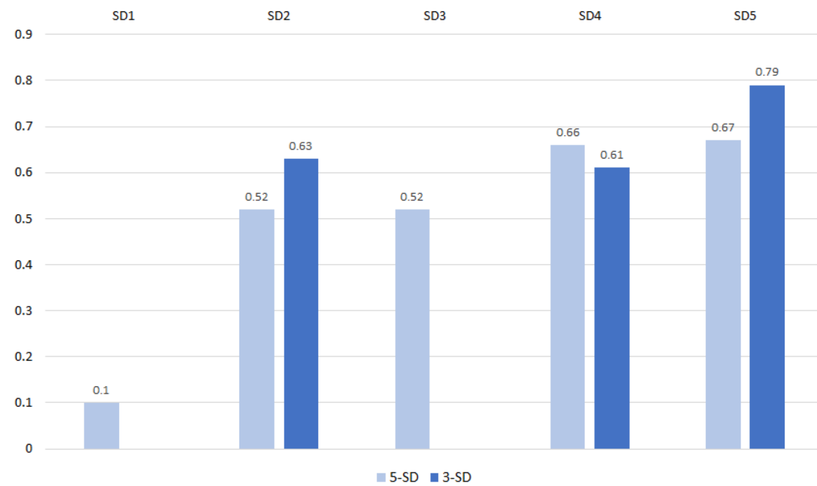

Figure 3: The average of satellite fill ratio under two configurations

It would be interesting to see if, by excluding SD1 a more balanced solution can be obtained. To do so, we re-solved the model excluding SD1 and we observed that only three satellites are used. Neither the optimal objective values nor the number of deployed vehicles are dramatically affected, but the corresponding satellite fill rates are more balanced (see Figure 3 for the new configuration (3-SD), where the first depot is excluded, and the previous configuration 5-SD). This may suggest that the dynamic optimization of the deployment and relocation of satellites should be eventually considered in the first tier of the system, especially acknowledging the dynamic aspects of urban parcel logistics. An attempt in this direction has been recently made by Faugère et al. (2022).

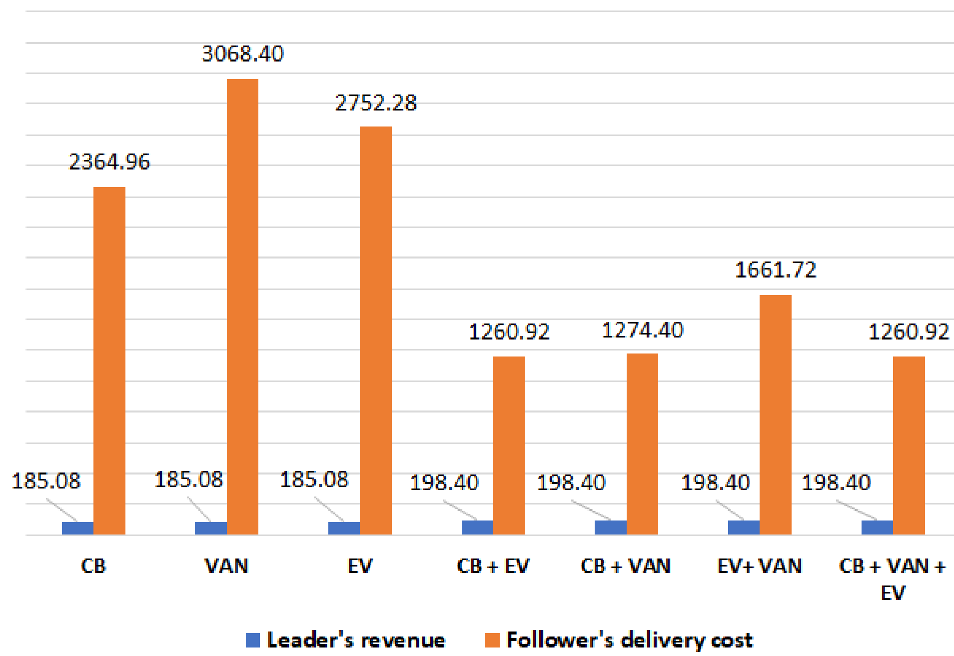

Figure 4: Leader's revenue and follower's delivery cost under different fleet configurations

We also investigated the effects of different fleet mix configurations on the SM's gain and the SO's total cost. Figure 4 displays the leader's revenue and the follower's delivery cost under different fleet mix configurations. The baseline case (EV+CB+VAN) is the rightmost in the figure. In this case we only use EVs and CBs. If we only consider fleets composed by EVs and VANs, we observe an increase in the delivery cost of 24.11%, while the leader revenue is not affected. This means that ensuring efficient operation of CBs should become a priority for urban planners, municipalities, road owners and logistic companies. Increasing the amount of bicycle lanes, and spreading satellites are essential prerequisite for effective operation. Of course, the successful introduction of any policy measure requires adaptation to the local context in terms of needs and specific characteristics. For instance, CBs are becoming a part of city logistics (Perboli and Rosano, 2019a), but still there is a lack of regulation for them. As urban planners are shifting their focus from automobiles to cyclists and pedestrians, an excessive use of cargo bikes could even decrease the sustainability of the city from the viewpoint of citizens. In this respect, it is not clear how the expansion of the cycling network should accommodate the usage of CBs. Nevertheless, forbidding the use of CBs could bring dramatic consequences, not only in terms of local pollution, but also in terms of costs. In fact, having homogeneous fleets, with only CBs, VANs or EVs, increases the delivery cost up to 46.68%, 58.91%, and 54.19%, respectively. This situation is also inconvenient for the leader, since its revenue is 7.20% lower. As a result, it is beneficial to integrate CBs into the logistic system and use them alongside EVs to distribute last-mile deliveries.

In the following, we consider the effect of the customers' preferences and delivery time in terms of tariffs and fleet usage.

Table 11 presents the results for the second scenario, where flexible time windows have been considered. We observe that increasing the flexibility is advantageous, because it may allow consolidations that were previously impossible and can result in reduced delivery costs. In fact, orders are serviced on the first and the fifth timeslots in the early morning and late at night. This is advantageous for SO, since the delivery cost decreases by 19.36%. The SO may offer, on the basis of the sensible reduction of the delivery cost, a discount to customers in exchange for flexibility in the timing of the delivery. However, in the long term, this could make the system financially not viable, since the leader revenue decreases by about 16.69%, given that all the deliveries are scheduled in the cheapest timeslots. Even though this solution is also beneficial for reducing the congestion in rush periods, preferring the early morning and the late evening for performing the last-mile deliveries, the SM would not necessarily consider it fair to be penalized. A third actor must be found who sees the potential of running such a business model. In particular, this motivates the involvement of public authorities in the management of satellites. This has been already observed in Crainic et al. (2004), where the authors argued that increased efficiency in urban freight can only be achieved through new ways of organizing freight activities, requiring public–private collaboration.

Table 11: Results: Flexible delivery time

	# of deployed vehicles					Average vehicle fill ratio					Delivery ratio				
	h=1	h=2	h=3	h=4	h=5	h=1	h=2	h=3	h=4	h=5	h=1	h=2	h=3	h=4	h=5
CB	15	-	-	-	15	1.00	-	-	-	1.00	0.74	-	-	-	0.55
EV	6	-	-	-	13	0.90	-	-	-	0.97	0.26	-	-	-	0.45

In the third scenario (see Table 12), when the customers' preferences are not taken into account, the SO can arrange all the deliveries on the fourth and the fifth timeslots in which both the cost-per-stop and the vehicle usage costs are the lowest, leading to a total delivery cost decrease (with respect to the baseline scenario) by 39.06%. VANs are heavily used in the free delivery time scenario, due to their larger capacity and the increased efficiency in this case. But this solution is viable only in traditional offer-driven logistics. In fact, the presence of the customer's preferences and the need of considering the quality of service as a primary goal makes them not practicable. For this reason, the more flexibility is given to the customers, the more EVs and cargo bikes become an effective delivery option. This effect will become more and more exacerbated in the future, with possible increase of costs of more than 200% for traditional vehicles. Thus, this will force the companies to the usage of swarms of smaller automated vehicles and drones (Perboli et al., 2021a).

Table 12: Results: Free delivery time

	# of deployed vehicles					Average vehicle fill ratio					Delivery ratio				
	h=1	h=2	h=3	h=4	h=5	h=1	h=2	h=3	h=4	h=5	h=1	h=2	h=3	h=4	h=5
CB	-	-	-	3	15	-	-	-	1.00	1.00	-	-	-	0.15	0.23
VAN	-	-	-	-	15	-	-	-		0.97	-	-	-	-	0.31
EV	-	-	-	-	15	-	-	-	-	1.00	-	-	-	-	0.31

8 Conclusions and future research directions

In this paper, driven by a real application in Turin, we have studied a last-mile logistics problem with multiple satellites in the realm of bi-level optimization. We believe that the proposed mathematical model is an important generalization of the single level single depot version proposed in Perboli et al. (2021a) with a great potential for application in practical settings. The model captures the interplay between the SM and the SO as the two most important agents of the system, interacting in a hierarchical fashion. In a notable addition to the traditionally considered costs at the lower level, the model explicitly accounts for the the leader's tariff setting problem. An exact solution approach is also discussed and applied on large sized instances and on a real-world case study that corresponds to actual transport practices in Turin. To increase the realism of our study, we have also incorporated customers' preferences. The computational tests show that the broader consideration of the service quality brings, as expected, a higher cost on the SO (follower). Another important cost-generating factor for the SO is the fleet composition. When the vehicle fleet is heterogeneous, i.e., vehicles differ in their equipment, typical use and capacity, it is preferred to service customers with small and eco-friendly vehicles like EVs and CBs. A homogeneous fleet of only CBs or EVs causes dramatic increases in the delivery cost. As already observed (Perboli et al., 2021a), an appropriate mix of different vehicles gives the flexibility to allocate the capacity according to the customer's varying demand, in a more cost effective way. The use of traditional VANs is not beneficial for any of the actors involved. The modal shift goal to be attained by 2030 is hence necessary for the sustainability of satellite based two-tier systems and should be addressed by stronger political measures.

As a research outlook, this work could be further developed by considering a competition between several SOs. Nevertheless, representing such an aspect requires the development of a multi-follower bilevel program, which is a problem that is significantly more computationally expensive. Along the same line, it would be interesting to represent a multi-level model that could potentially differentiate between the decisions of the main stakeholders: the SM, the SO, and the customers. Alternative interesting avenues for future research concern the development of stochastic or robust variants to incorporate uncertainty into the SO's total cost.

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9 Appendix

9.1 The linearized REHHP

The linearized REHHP corresponding to model M1 is cast as

$$\max \sum_{i\in I}\sum_{j\in \mathcal{J}}\sum_{k\in \mathcal{K}}\sum_{h\in \mathcal{H}} d_i \underline{T}_j^h x_{ikj}^h + s \sum_{i\in I}\sum_{j\in \mathcal{J}}\sum_{k\in \mathcal{K}}\sum_{h\in \mathcal{H}}\sum_{l\in \Omega_j^h} l\, \zeta_{ikj}^{lh} \tag{43}$$

$$(2)-(5),\ (7)-(13) \tag{44}$$

$$\zeta_{ikj}^{lh} \leq x_{ikj}^{h},\ \forall i \in I,\ k \in \mathcal{K},\ j \in \mathcal{J},\ h \in \mathcal{H},\ l \in \Omega_j^h \tag{45}$$

$$\zeta_{ikj}^{lh} \leq \gamma_j^{lh},\ \forall i \in I,\ k \in \mathcal{K},\ j \in \mathcal{J},\ h \in \mathcal{H},\ l \in \Omega_j^h \tag{46}$$

$$\zeta_{ikj}^{lh} \geq x_{ikj}^{h} + \gamma_j^{lh} - 1,\ \forall i \in I,\ k \in \mathcal{K},\ j \in \mathcal{J},\ h \in \mathcal{H},\ l \in \Omega_j^h \tag{47}$$

$$\begin{aligned}
&\sum_{i\in I}\sum_{j\in\mathcal{J}}\sum_{k\in\mathcal{K}}\sum_{h\in\mathcal{H}} d_i \underline{T}_j^h x_{ikj}^h + s\sum_{i\in I}\sum_{j\in\mathcal{J}}\sum_{k\in\mathcal{K}}\sum_{h\in\mathcal{H}}\sum_{l\in\Omega_j^h} l\,\zeta_{ikj}^{lh} + \sum_{j\in\mathcal{J}}\sum_{p\in\mathcal{P}}\sum_{k\in\mathcal{K}_p}\sum_{h\in\mathcal{H}} f_{pj}^h \sum_{i\in I} x_{ikj}^h \\
&+ \sum_{j\in\mathcal{J}}\sum_{p\in\mathcal{P}}\sum_{k\in\mathcal{K}_p}\sum_{h\in\mathcal{H}} \delta_p^h y_{kj}^h + E\sum_{i\in I} X_i \leq \sum_{i\in I}\sum_{j\in\mathcal{J}}\sum_{k\in\mathcal{K}}\sum_{h\in\mathcal{H}} d_i \underline{T}_j^h (x_{ikj}^h)_\kappa + \\
&s\sum_{i\in I}\sum_{j\in\mathcal{J}}\sum_{k\in\mathcal{K}}\sum_{h\in\mathcal{H}}\sum_{l\in\Omega_j^h} l\,(x_{ikj}^h)_\kappa \gamma_j^{lh} + \sum_{j\in\mathcal{J}}\sum_{p\in\mathcal{P}}\sum_{k\in\mathcal{K}_p}\sum_{h\in\mathcal{H}} f_{pj}^h \sum_{i\in I} (x_{ikj}^h)_\kappa \\
&+ \sum_{j\in\mathcal{J}}\sum_{p\in\mathcal{P}}\sum_{k\in\mathcal{K}_p}\sum_{h\in\mathcal{H}} \delta_p^h (y_{kj}^h)_\kappa + E\sum_{i\in I} (X_i)_\kappa,\ \kappa = 1,\cdots,K
\end{aligned} \tag{48}$$

$$\zeta_{ikj}^{lh} \in \{0,1\},\ \forall i \in I,\ k \in \mathcal{K},\ j \in \mathcal{J},\ h \in \mathcal{H},\ l \in \Omega_j^h \tag{49}$$

where $\{(x_{ikj}^h)_\kappa, (y_{kj}^h)_\kappa, (X_i)_\kappa\}$ denote the optimal values of lower level variables $\{x_{ikj}^h, y_{kj}^h, X_i\}$ in the $\kappa-$th bi-level feasible solution of Algorithm 1.
Also, the REHHP corresponding to model M2 is cast as the mixed integer problem (51)-(56) with linear objective (50).

$$\max \sum_{c\in\mathcal{C}}\sum_{j\in\mathcal{J}}\sum_{p\in\mathcal{P}}\sum_{h\in\mathcal{H}} \underline{T}_j^h q_{pj}^{ch} + s\sum_{c\in\mathcal{C}}\sum_{j\in\mathcal{J}}\sum_{p\in\mathcal{P}}\sum_{h\in\mathcal{H}}\sum_{l\in\Omega_j^h} l\,\mu_{pj}^{clh} \tag{50}$$

$$(2)-(5),\ (16)-(22) \tag{51}$$

$$\mu_{pj}^{clh} \leq q_{pj}^{ch},\ \forall c \in \mathcal{C},\ p \in \mathcal{P},\ j \in \mathcal{J},\ h \in \mathcal{H},\ l \in \Omega_j^h \tag{52}$$

$$\mu_{pj}^{clh} \leq \bar{q}_{pj}^{ch}\gamma_j^{lh},\ \forall c \in \mathcal{C},\ p \in \mathcal{P},\ j \in \mathcal{J},\ h \in \mathcal{H},\ l \in \Omega_j^h \tag{53}$$

$$\mu_{pj}^{clh} \geq \bar{q}_{pj}^{ch}(\gamma_j^{lh} - 1) + q_{pj}^{ch},\ \forall c \in \mathcal{C},\ p \in \mathcal{P},\ j \in \mathcal{J},\ h \in \mathcal{H},\ l \in \Omega_j^h \tag{54}$$

$$\begin{aligned}
&\sum_{c\in\mathcal{C}}\sum_{j\in\mathcal{J}}\sum_{p\in\mathcal{P}}\sum_{h\in\mathcal{H}} \underline{T}_j^h q_{pj}^{ch} + s\sum_{c\in\mathcal{C}}\sum_{j\in\mathcal{J}}\sum_{p\in\mathcal{P}}\sum_{h\in\mathcal{H}}\sum_{l\in\Omega_j^h} l\,\mu_{pj}^{clh} + \sum_{c\in\mathcal{C}}\sum_{j\in\mathcal{J}}\sum_{p\in\mathcal{P}}\sum_{h\in\mathcal{H}} \frac{f_{pj}^h}{\alpha_c} q_{pj}^{ch} \\
&+ \sum_{j\in\mathcal{J}}\sum_{p\in\mathcal{P}}\sum_{h\in\mathcal{H}} \delta_p^h Y_{pj}^h + E\sum_{c\in\mathcal{C}} \frac{Q^c}{\alpha_c} \leq \sum_{c\in\mathcal{C}}\sum_{j\in\mathcal{J}}\sum_{p\in\mathcal{P}}\sum_{h\in\mathcal{H}} \underline{T}_j^h (q_{pj}^{ch})_\kappa + \\
&s\sum_{c\in\mathcal{C}}\sum_{j\in\mathcal{J}}\sum_{p\in\mathcal{P}}\sum_{h\in\mathcal{H}}\sum_{l\in\Omega_j^h} l\,\gamma_j^{lh} (q_{pj}^{ch})_\kappa + \sum_{c\in\mathcal{C}}\sum_{j\in\mathcal{J}}\sum_{p\in\mathcal{P}}\sum_{h\in\mathcal{H}} \frac{f_{pj}^h}{\alpha_c} (q_{pj}^{ch})_\kappa + \sum_{j\in\mathcal{J}}\sum_{p\in\mathcal{P}}\sum_{h\in\mathcal{H}} \delta_p^h (Y_{pj}^h)_\kappa
\end{aligned}$$

$$+E\sum_{c\in\mathcal{C}}\frac{(Q^c)_\kappa}{\alpha_c},\ \kappa=1,\cdots,K \tag{55}$$

$$\mu_{pj}^{clh}\geq 0,\ \forall c\in\mathcal{C},\ p\in\mathcal{P},\ j\in\mathcal{J},\ h\in\mathcal{H},\ l\in\Omega_j^h \tag{56}$$

where $\bar{q}_{pj}^{ch}$ is the upper bound on variables q_{pj}^{ch} and $\{(q_{pj}^{ch})_\kappa, (Y_{pj}^h)_\kappa, (Q^c)_\kappa\}$ denote the optimal values of lower level variables $\{q_{pj}^{ch}, Y_{pj}^h, Q^c\}$ in the $\kappa-$th bi-level feasible solution of Algorithm 1.

9.2 The detailed computational results

Here we first report the details results corresponding to the summarized results of Table 3 in Tables 13 and 14. The results include the CPU time for models M1 and M2 (denoted by CPU_{M1} and CPU_{M2}), the relative percentage solution gap (Gap_M), and the speed up rate (Δ) calculated as $\Delta=\frac{CPU_{M2}}{CPU_{M1}}100$. The column with heading "Instance" displays the instance name, for example, 5-200-42-2-3 refers to the fifth test case in the class of instances with 200 orders, 42 vehicles, two satellites, and three timeslots.

Table 13: comparison of models M1 and M2 for $|\mathcal{H}| = 3$

Instance	CPU_{M1} (s)	CPU_{M2} (s)	Gap_M (%)	Δ(%)
1-200-32-2-3	49.36	0.02	0.90	0.04
5-200-42-2-3	82.89	0.03	0.79	0.04
6-200-42-2-3	38.52	0.03	0.79	0.08
7-200-42-2-3	189.92	0.02	0.78	0.01
8-200-42-2-3	25.89	0.03	0.79	0.12
9-200-42-2-3	69.56	0.03	0.79	0.04
10-200-42-2-3	24.69	0.02	0.78	0.08
2-200-32-2-3	31.69	0.02	0.89	0.06
3-200-32-2-3	16.84	0.03	0.90	0.18
1-200-126-2-3	54.52	0.03	0.81	0.06
2-200-126-2-3	59.50	0.03	0.81	0.05
1-200-132-2-3	64.00	0.03	0.80	0.05
3-200-126-2-3	46.64	0.03	0.82	0.06
4-200-126-2-3	62.94	0.03	0.81	0.05
5-200-126-2-3	110.13	0.03	0.82	0.03
6-200-126-2-3	53.42	0.03	0.81	0.06
1-200-96-2-3	48.09	0.05	0.92	0.10
3-200-96-2-3	54.36	0.03	0.92	0.06
4-200-96-2-3	38.86	0.03	0.92	0.08
5-200-96-2-3	34.28	0.03	0.91	0.09
6-200-96-2-3	70.34	0.03	0.92	0.04
7-200-96-2-3	107.08	0.03	0.92	0.03
8-200-96-2-3	35.11	0.03	0.93	0.09
9-200-96-2-3	44.06	0.03	0.91	0.07
7-200-126-2-3	76.06	0.03	0.82	0.04
8-200-126-2-3	143.80	0.05	0.96	0.03
1-200-120-2-3	27.08	0.03	0.83	0.11
1-200-102-2-3	38.27	0.03	0.90	0.08
4-200-32-2-3	38.09	0.02	0.89	0.05
5-200-32-2-3	21.23	0.03	0.90	0.14
1-200-34-2-3	65.70	0.03	0.88	0.05
2-200-34-2-3	105.61	0.02	0.87	0.02
3-200-34-2-3	433.63	0.02	0.87	0.00
4-200-34-2-3	59.00	0.03	0.88	0.05
5-200-34-2-3	61.67	0.02	0.88	0.03
1-200-42-2-3	81.30	0.02	0.79	0.02
Avg.	71.23	0.03	0.86	0.06

Table 14: comparison of models M1 and M2 for $|\mathcal{H}| = 5$

Instance	CPU_{M1} (s)	CPU_{M2} (s)	$Gap_M\,(\%)$	$\Delta(\%)$
1-200-32-2-5	22.73	0.02	0.90	0.09
5-200-42-2-5	179.42	0.02	0.79	0.01
6-200-42-2-5	148.27	0.02	0.79	0.01
7-200-42-2-5	67.58	0.03	0.78	0.04
8-200-42-2-5	244.39	0.03	0.79	0.01
9-200-42-2-5	46.03	0.03	0.79	0.07
10-200-42-2-5	134.33	0.02	0.78	0.01
2-200-32-2-5	27.39	0.02	0.89	0.07
3-200-32-2-5	87.2	0.03	0.90	0.03
1-200-126-2-5	107.33	0.05	0.81	0.05
2-200-126-2-5	92.81	0.03	0.81	0.03
1-200-132-2-5	197.52	0.02	0.80	0.01
3-200-126-2-5	113.17	0.03	0.82	0.03
4-200-126-2-5	83.52	0.03	0.81	0.04
5-200-126-2-5	174.38	0.05	0.82	0.03
6-200-126-2-5	77.17	0.02	0.81	0.03
1-200-96-2-5	92.41	0.05	0.92	0.05
3-200-96-2-5	100.28	0.05	0.92	0.05
4-200-96-2-5	73.66	0.03	0.92	0.04
5-200-96-2-5	73.41	0.03	0.91	0.04
6-200-96-2-5	76.83	0.03	0.92	0.04
7-200-96-2-5	97.55	0.03	0.92	0.03
8-200-96-2-5	34.53	0.02	0.93	0.06
9-200-96-2-5	57.86	0.03	0.91	0.05
7-200-126-2-5	155.66	0.05	0.82	0.03
8-200-126-2-5	157.08	0.03	0.96	0.02
1-200-120-2-5	51.89	0.03	0.83	0.06
1-200-102-2-5	57.48	0.03	0.90	0.05
4-200-32-2-5	17.55	0.02	0.89	0.11
5-200-32-2-5	22.86	0.02	0.90	0.09
1-200-34-2-5	48.47	0.02	0.88	0.04
2-200-34-2-5	38.28	0.03	0.87	0.08
3-200-34-2-5	32.31	0.02	0.87	0.06
4-200-34-2-5	498.73	0.03	0.88	0.01
5-200-34-2-5	37.52	0.02	0.88	0.05
1-200-42-2-5	1218.3	0.02	0.79	0.00
Avg.	131.83	0.03	0.86	0.04

The detailed results corresponding to Table 5 are shown in Tables 15-17 that report the best iteration of the algorithm (denoted by BI), the total CPU time

(CPU) and the average CPU time for the REHHP (CPU_{EHHP}) and LL problem (CPU_{LL}) over all iterations.

For cases in which the time limit is reached, we also have reported the relative gap of the best upper and lower bounds (OPT).

Table 15: Exact solution approach: 200 orders

Instance	BI	$CPU\,(s)$	$CPU_{REHHP}\,(s)$	$CPU_{LL}\,(s)$	Instance	BI	$CPU\,(s)$	$CPU_{REHHP}\,(s)$	$CPU_{LL}\,(s)$
5-200-42-2-3	2	0.25	0.02	0.02	5-200-42-2-5	5	0.75	0.03	0.02
1-200-42-2-3	3	0.29	0.02	0.02	1-200-42-2-5	5	0.64	0.02	0.02
6-200-42-2-3	2	0.28	0.03	0.02	6-200-42-2-5	5	0.77	0.03	0.03
7-200-42-2-3	2	0.24	0.02	0.02	7-200-42-2-5	4	0.55	0.03	0.02
8-200-42-2-3	2	0.24	0.02	0.02	8-200-42-2-5	4	0.62	0.04	0.03
9-200-42-2-3	2	0.48	0.06	0.09	9-200-42-2-5	5	0.70	0.02	0.02
10-200-42-2-3	2	0.21	0.02	0.02	10-200-42-2-5	4	0.80	0.04	0.04
1-200-132-2-3	2	0.40	0.05	0.03	1-200-132-2-5	2	0.43	0.06	0.03
1-200-126-2-3	2	0.43	0.07	0.03	1-200-126-2-5	5	1.17	0.06	0.04
2-200-126-2-3	2	0.38	0.05	0.02	2-200-126-2-5	4	0.86	0.06	0.04
3-200-126-2-3	3	0.46	0.05	0.03	3-200-126-2-5	5	1.14	0.05	0.03
4-200-126-2-3	2	0.35	0.03	0.02	4-200-126-2-5	5	0.93	0.05	0.02
5-200-126-2-3	3	0.67	0.09	0.03	5-200-126-2-5	2	0.65	0.11	0.05
6-200-126-2-3	2	0.34	0.03	0.02	6-200-126-2-5	4	0.88	0.05	0.03
7-200-126-2-3	3	0.61	0.05	0.04	7-200-126-2-5	4	1.16	0.07	0.05
8-200-126-2-3	3	0.96	0.09	0.08	8-200-126-2-5	2	0.66	0.11	0.04
1-200-96-2-3	2	0.37	0.05	0.03	1-200-96-2-5	2	0.56	0.09	0.04
3-200-96-2-3	2	0.40	0.06	0.03	3-200-96-2-5	2	0.58	0.10	0.03
4-200-96-2-3	2	0.40	0.05	0.03	4-200-96-2-5	2	0.64	0.08	0.03
5-200-96-2-3	3	0.55	0.05	0.04	5-200-96-2-5	2	0.51	0.09	0.03
6-200-96-2-3	2	0.45	0.05	0.05	6-200-96-2-5	2	0.52	0.09	0.05
7-200-96-2-3	3	0.57	0.06	0.03	7-200-96-2-5	2	0.68	0.13	0.04
8-200-96-2-3	3	0.67	0.11	0.03	8-200-96-2-5	3	0.44	0.05	0.02
9-200-96-2-3	3	0.49	0.06	0.03	9-200-96-2-5	2	0.50	0.09	0.03
2-200-96-2-3	2	0.41	0.04	0.02	2-200-96-2-5	3	0.45	0.05	0.02
1-200-120-2-3	3	0.51	0.04	0.01	1-200-120-2-5	3	0.48	0.04	0.03
1-200-102-2-3	2	0.98	0.11	0.22	1-200-102-2-5	3	0.59	0.06	0.04
5-200-32-2-3	2	0.24	0.02	0.02	5-200-32-2-5	2	0.29	0.04	0.02
4-200-32-2-3	2	0.22	0.02	0.02	4-200-32-2-5	2	0.29	0.02	0.02
3-200-32-2-3	3	0.30	0.02	0.02	3-200-32-2-5	3	0.37	0.03	0.02
2-200-32-2-3	3	0.29	0.01	0.02	2-200-32-2-5	3	0.38	0.03	0.02
1-200-32-2-3	2	0.22	0.02	0.02	1-200-32-2-5	2	0.52	0.08	0.05
1-200-34-2-3	2	0.22	0.02	0.02	1-200-34-2-5	2	0.36	0.05	0.03
2-200-34-2-3	3	0.29	0.02	0.02	2-200-34-2-5	3	0.37	0.02	0.03
3-200-34-2-3	2	0.21	0.02	0.01	3-200-34-2-5	3	0.37	0.02	0.03
4-200-34-2-3	3	0.29	0.02	0.02	4-200-34-2-5	3	0.39	0.02	0.03
5-200-34-2-3	2	0.25	0.02	0.02	5-200-34-2-5	2	0.31	0.03	0.02
2-200-42-2-3	3	0.30	0.02	0.02	2-200-42-2-5	4	0.61	0.03	0.02
3-200-42-2-3	2	0.24	0.02	0.02	3-200-42-2-5	4	0.63	0.04	0.02
4-200-42-2-3	2	0.25	0.02	0.02	4-200-42-2-5	5	0.74	0.03	0.03
Avg.		0.39	0.04	0.03			0.61	0.05	0.03

Table 16: Exact solution approach: 500 orders

Instance	BI	$CPU\,(s)$	$CPU_{REHHP}\,(s)$	$CPU_{LL}\,(s)$	Instance	BI	$CPU\,(s)$	$CPU_{REHHP}\,(s)$	$CPU_{LL}\,(s)$
1-500-246-3-3	3	0.95	0.11	0.06	1-500-246-3-5	3	1.18	0.15	0.06
2-500-246-3-3	2	1.00	0.16	0.08	2-500-246-3-5	2	1.25	0.24	0.09
3-500-246-3-3	3	1.01	0.14	0.06	3-500-246-3-5	3	1.46	0.21	0.10
4-500-246-3-3	4	0.92	0.06	0.04	4-500-246-3-5	3	0.99	0.12	0.05
1-500-258-3-3	4	1.04	0.09	0.05	1-500-258-3-5	4	1.24	0.12	0.09
1-500-318-3-3	3	0.58	0.04	0.04	1-500-318-3-5	7	3.28	0.06	0.23
2-500-318-3-3	4	0.88	0.08	0.03	2-500-318-3-5	6	3.19	0.09	0.20
3-500-318-3-3	3	0.66	0.08	0.03	3-500-318-3-5	7	1.98	0.08	0.05
4-500-318-3-3	3	0.74	0.08	0.05	4-500-318-3-5	7	2.40	0.08	0.10
5-500-318-3-3	2	0.87	0.15	0.09	5-500-318-3-5	7	3.62	0.14	0.18
6-500-318-3-3	3	1.45	0.24	0.09	6-500-318-3-5	7	9.04	0.75	0.28
1-500-258-3-3	4	0.89	0.08	0.03	1-500-258-3-5	3	1.16	0.16	0.05
1-500-108-3-3	4	0.97	0.11	0.03	1-500-108-3-5	5	6.64	0.19	0.85
2-500-108-3-3	3	1.14	0.17	0.07	2-500-108-3-5	5	6.21	0.21	0.43
3-500-108-3-3	2	0.73	0.14	0.09	3-500-108-3-5	5	8.16	0.16	0.88
4-500-108-3-3	2	0.61	0.06	0.06	4-500-108-3-5	6	3.36	0.15	0.21
1-500-252-3-3	4	0.86	0.08	0.03	1-500-252-3-5	2	0.80	0.16	0.07
2-500-252-3-3	3	0.92	0.10	0.06	2-500-252-3-5	2	0.90	0.20	0.09
3-500-252-3-3	3	1.15	0.15	0.09	3-500-252-3-5	2	1.38	0.29	0.09
4-500-252-3-3	2	0.86	0.15	0.10	4-500-252-3-5	3	1.14	0.16	0.07
1-500-82-3-3	4	0.56	0.02	0.03	1-500-82-3-5	3	0.56	0.05	0.04
2-500-82-3-3	4	0.78	0.04	0.02	2-500-82-3-5	4	0.78	0.05	0.04
3-500-82-3-3	4	0.65	0.04	0.04	3-500-82-3-5	4	0.82	0.07	0.05
4-500-82-3-3	3	0.49	0.05	0.02	4-500-82-3-5	4	0.77	0.06	0.04
5-500-82-3-3	3	0.47	0.03	0.03	5-500-82-3-5	4	0.63	0.04	0.03
1-500-312-3-3	3	1.12	0.16	0.08	1-500-312-3-5	6	5.77	0.17	0.43
1-500-324-3-3	3	1.18	0.14	0.12	1-500-324-3-5	6	4.87	0.16	0.43
2-500-324-3-3	2	0.94	0.18	0.10	2-500-324-3-5	6	3.34	0.16	0.15
3-500-324-3-3	2	0.99	0.19	0.10	3-500-324-3-5	6	2.74	0.17	0.09
1-500-84-3-3	4	0.61	0.05	0.02	1-500-84-3-5	4	0.85	0.06	0.04
2-500-84-3-3	4	0.79	0.04	0.05	2-500-84-3-5	3	0.72	0.05	0.07
3-500-84-3-3	4	1.06	0.06	0.10	3-500-84-3-5	4	1.30	0.07	0.13
1-500-80-3-3	4	0.60	0.04	0.02	1-500-80-3-5	4	0.74	0.05	0.03
1-500-86-3-3	3	0.53	0.06	0.03	1-500-86-3-5	4	1.16	0.06	0.10
1-500-106-3-3	4	0.74	0.05	0.03	1-500-106-3-5	4	0.93	0.07	0.05
2-500-106-3-3	3	0.65	0.05	0.04	2-500-106-3-5	7	1.64	0.05	0.05
3-500-106-3-3	3	0.52	0.03	0.04	3-500-106-3-5	7	1.74	0.03	0.07
4-500-106-3-3	4	0.72	0.05	0.03	4-500-106-3-5	7	2.02	0.05	0.08
5-500-106-3-3	4	0.72	0.03	0.03	5-500-106-3-5	7	1.39	0.03	0.04
6-500-106-3-3	4	0.67	0.03	0.04	6-500-106-3-5	7	1.46	0.03	0.04
7-500-106-3-3	4	0.81	0.05	0.04	7-500-106-3-5	7	2.02	0.05	0.07
Avg.		0.83	0.09	0.05			2.33	0.13	0.15

Table 17: Exact solution approach: 1000 orders

Instance	BI	$CPU\,(s)$	$CPU_{REHHP}\,(s)$	$CPU_{LL}\,(s)$	Instance	BI	$CPU\,(s)$	$CPU_{REHHP}\,(s)$	$CPU_{LL}\,(s)$	$OPT\,(\%)$
1-1000-170-4-3	3	3.70	0.19	0.90	1-1000-168-4-5	3	0.71	0.14	0.03	0.00
2-1000-164-4-3	3	1.91	0.11	0.41	2-1000-168-4-5	3	2.33	0.53	0.06	0.00
3-1000-160-4-3	3	3.06	0.10	0.83	3-1000-168-4-5	3	0.79	0.14	0.02	0.00
4-1000-166-4-3	3	1.30	0.08	0.27	1-1000-218-4-5	5	3.40	0.47	0.06	0.00
5-1000-166-4-3	3	1.35	0.03	0.32	2-1000-216-4-5	7	3.30	0.29	0.05	0.00
6-1000-166-4-3	3	2.20	0.04	0.58	3-1000-214-4-5	7	3.04	0.25	0.04	0.00
7-1000-166-4-3	3	2.88	0.57	0.31	4-1000-214-4-5	7	9.16	1.00	0.05	0.00
1-1000-168-4-3	3	2.19	0.22	0.31	5-1000-214-4-5	8	3.89	0.32	0.03	0.00
2-1000-168-4-3	3	2.76	0.51	0.32	6-1000-214-4-5	6	5.92	0.82	0.03	0.00
3-1000-168-4-3	3	1.75	0.18	0.31	7-1000-214-4-5	8	2.40	0.14	0.02	0.00
1-1000-498-4-3	2	3.47	0.21	1.00	8-1000-214-4-5	6	6.03	0.83	0.04	0.00
2-1000-498-4-3	3	2.03	0.20	0.32	9-1000-212-4-5	8	2.91	0.17	0.03	0.00
3-1000-498-4-3	3	1.28	0.27	0.04	10-1000-212-4-5	6	2.27	0.22	0.03	0.00
4-1000-498-4-3	3	8.46	0.59	2.00	1-1000-170-4-5	4	1.88	0.32	0.02	0.00
5-1000-498-4-3	3	2.28	0.48	0.15	2-1000-164-4-5	3	1.43	0.23	0.07	0.00
6-1000-498-4-3	3	1.69	0.21	0.17	3-1000-160-4-5	3	2.50	0.69	0.03	0.00
7-1000-498-4-3	3	5.10	0.58	0.97	4-1000-166-4-5	3	1.24	0.23	0.03	0.00
8-1000-498-4-3	2	6.97	1.00	2.00	5-1000-166-4-5	3	2.03	0.49	0.03	0.00
9-1000-498-4-3	3	4.26	0.73	0.44	6-1000-166-4-5	3	1.14	0.19	0.04	0.00
10-1000-504-4-3	3	3.32	0.57	0.32	7-1000-166-4-5	3	1.07	0.20	0.03	0.00
1-1000-642-4-3	4	7.91	0.33	1.00	1-1000-498-4-5	2	12.69	6.00	0.05	0.00
2-1000-642-4-3	2	3.70	0.23	1.00	2-1000-498-4-5	3	42.17	10	0.03	0.00
3-1000-642-4-3	2	5.58	0.75	2.00	3-1000-498-4-5	2	1.81	0.65	0.02	0.00
4-1000-642-4-3	3	2.04	0.14	0.33	4-1000-498-4-5	2	103.36	50	0.07	0.00
5-1000-642-4-3	3	3.37	0.53	0.40	5-1000-498-4-5	1	1800	0.63	0.05	114.29
6-1000-642-4-3	3	2.70	0.33	0.27	6-1000-498-4-5	2	7.31	2.00	0.02	0.00
7-1000-636-4-3	2	7.22	0.21	3.00	7-1000-498-4-5	2	11.84	6.00	0.02	0.00
8-1000-654-4-3	4	9.43	0.65	1.00	8-1000-498-4-5	2	1.44	0.52	0.02	0.00
9-1000-648-4-3	4	8.60	0.64	1.00	9-1000-498-4-5	1	1800	0.50	0.02	114.29
10-1000-630-4-3	2	0.58	0.15	0.02	10-1000-504-4-5	3	5.50	0.41	0.01	0.00
1-1000-218-4-3	3	0.89	0.10	0.08	1-1000-642-4-5	4	718	200	0.13	0.00
2-1000-216-4-3	3	1.74	0.03	0.45	2-1000-642-4-5	6	5.21	0.70	0.02	0.00
3-1000-214-4-3	3	3.72	0.88	0.25	3-1000-642-4-5	6	3.14	0.30	0.02	0.00
4-1000-214-4-3	3	1.95	0.11	0.43	4-1000-642-4-5	4	5.87	1.00	0.12	0.00
5-1000-214-4-3	3	1.59	0.18	0.25	5-1000-642-4-5	4	16.23	4.00	0.06	0.00
6-1000-214-4-3	3	1.91	0.08	0.45	6-1000-642-4-5	4	2.55	0.30	0.22	0.00
7-1000-214-4-3	4	1.13	0.07	0.09	7-1000-636-4-5	6	3.60	0.40	0.02	0.00
8-1000-214-4-3	4	1.86	0.09	0.25	8-1000-654-4-5	1	1800	0.52	0.03	114.29
9-1000-212-4-3	4	1.77	0.07	0.25	9-1000-648-4-5	1	1800	0.59	0.05	114.29
10-1000-212-4-3	3	1.92	0.14	0.39	10-1000-630-4-3	9	6.70	0.20	0.02	0.00
Avg.		3.29	0.31	0.62			205.12	7.31	0.04	11.43