A new model for Last-Mile Delivery and Satellite Depots management: The impact of the on-demand economy

# A new model for Last-Mile Delivery and Satellite Depots management: the impact of the on-demand economy

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**Abstract**

Two-tier city logistics systems are playing a very important role nowadays in the management of urban freight activities. Although several city authorities have promoted different measures to foster the implementation of small urban consolidation centers in a two-tier system, only a few authors have addressed the joint problem of operating these facilities and providing services to customers. We show how the problem can be modeled as a new variant of the bin packing, for which we provide a mixed integer programming formulation and two heuristics that are shown to be quite effective in solving efficiently and to near optimality the problem. The application of our approach on real data from the city of Turin puts into highlight the superiority of the consolidation approach, including the bundle of goods from different providers, stockholding and other value-added logistics services, over the classical single-tier approach. In addition, the paper provides a thorough analysis of some emerging aspects of the on-demand economy, as the consideration of customers' preferences and the integration of multiple delivery options. The managerial insights coming from this work will be part of the new Logistics and Mobility Plan to be activated in 2022 in the Piedmont region.

*Keywords:* Last-Mile delivery, Urban Delivery, Bin Packing, On-Demand Economy

## 1. Introduction

The paradigms of the on-demand economy and e-commerce let emerge new business models, challenging the success of non-digital native companies. This shift has dramatically affected several business processes, from marketing to production. The logistic sector has been completely reshaped by this change: the delivery options are no longer driven by the supplier, but more and more influenced by the customers' preferences, with a consequent disruptive impact on the delivery process, and the urban distribution in particular (Perboli and Rosano, 2019). Customers have become increasingly connected, informed and empowered, continually demanding more choice and flexibility in delivery options, raising their expectations for fast

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(usually within very limited timeslots as 2 hours), and cheap deliveries of purchased goods. To address their needs and provide a faster service, enterprises and e-commerce giant platforms are moving from a push-driven supply to a pull-driven approach (i.e., demand-driven logistics), completely reshaping the logistic chain and in particular, its last leg, known as the last-mile.

The last-mile delivery is currently regarded as the most expensive, least efficient and most challenging section of the entire logistic chain. Bad design and management of the last-mile freight distribution may bring negative effects, threatening the quality of life, triggering traffic jams and increasing the level of emissions of associated pollutants. In the last few years, in the field of city logistics, a growing number of studies have investigated the competitiveness of alternative distribution systems architectures. A particularly promising solution is the adoption of a two-tier system. In the first level of this two-layered distribution network, trucks perform deliveries from distribution centers (generally logistic platforms located in a strategic node of the city) to Urban Consolidation Centers (UCCs), also called satellites (generally transshipment points situated in the proximity of a city center). At the second level, customers' orders are consolidated into small vehicles (also called city-freighters) that can travel along any street in the city center area such as minivans, electric vans and cargo bikes, and delivered to the final customers. Each city freighter performs the route serving the designated customers and then travels back to the satellite for its next cycle of operations.

Although in principle satellite-based consolidation approaches aim at enhancing the efficiency of last-mile distribution, still operational issues remain to be addressed. The limited capacity of city freighters and the presence of regulatory measures to reduce traffic during peak hours, like restrictions on the times when freight activity can take place, are some noteworthy examples. The promotion of these more and more popular initiatives is a promising strategy for offsetting the traffic impacts of urban freights, but prompts the inclusion of time-dependent parameters into the system optimization, raising significant challenges to policy and decision-makers. Setting up the coordination of this complex system, that involves multiple stakeholders, such as the courier company, the satellite manager and the local authority, is not a trivial task.

To the best of our knowledge, the literature lacks in terms of joint models for satellite management in last-mile and urban delivery. Moreover, one of the distinguishing aspects of the problem is the time-dependent structure of the costs. The latter aspect becomes more and more influential due to the increasing importance of on-demand economy and e-commerce, that fostered the switch from the offer-driven logistics to the demand-driven one.

This paper provides a broad perspective on the problem, namely the Shared Satellite-based Last-Mile Delivery problem (SS-LM-D), tackling the tactical issues involved in last-mile delivery with heterogeneous vehicle fleet and investigating the efficiency and the viability of the underlying business model. The SS-LM-D is modeled as a new variant of the Bin Packing Problem (BPP) with time-dependent costs, namely the Variable Costs and Size Bin Packing Problem with Time-Dependent Costs (*VCSBPP-TD*), enriching the vast literature on variants of the BPP. Our approach can guide the decision-maker strategies to reduce the costs and to better control the whole process, offering practical insights to manage the last-mile delivery, while taking into account some specific features of the on-demand economy and e-commerce as, for instance, the effects of the customers' preferences. The problem setting and the data used in the paper come directly from the analysis of a real case study of the city Turin conducted by

CARS@Polito[1], and the ICELab@polito [2], with the collaboration of the Torino Living Lab project and the Amazon Innovation Award, while the managerial insights coming from this work will be part of the new Logistics and Mobility Plan to be activated in 2022 in the Piedmont region.

The paper is organized as follows. The relevant literature is analyzed in section 2. The problem setting and the model are defined in section 3, where two constructive heuristics, able to tackle large-sized instances, are also described. The heuristic performance is discussed in section 4. In section 5 an analysis of the impact of the application of the *VCSBPP-TD* to the on-demand economy, and e-commerce in particular, is performed and managerial insights are thoroughly discussed. Finally, section 6 concludes the paper and sheds light on possible future research directions.

## 2. Literature review

In recent years, with the increasing interest in Last-mile Logistics and City Logistics, different linear programming models have been proposed to deal with several issues and inefficiencies in the last-mile segment of the supply chain. These models do not consider, or only partially, the usage of shared spaces (e.g., shared satellites). The reason lies in the current practices in this industry imposing the adoption of proprietary warehouses and consolidation centers. However, changes in the regulatory assets at the national and international level, are moving toward the sharing of logistics resources. Also, new and recent paradigms, as crowdsourcing and dynamic access policies, are emerging to deal with the complexities of the sharing economy (Fadda et al., 2019; Rosano et al., 2018). These two factors combined with the double-digit growth of e-commerce make needed some simplifications of routing and the complex functional costs. In this direction, several attempts have been proposed in the literature, belonging in two main categories: BBPs and service network design. The latter is unsuitable for the large-scale problems that characterize the urban context. The former is gaining interest in describing logistics processes, showing how complex real situations can be modeled as BPPs (Baldi et al., 2019; Crainic et al., 2016; Hemmelmayr et al., 2012). However, to the best of our knowledge, no bin packing model has been formulated to address our problem. We choose a bin packing formulation because it maintains the complex functional costs related to the business model with a compact mathematical structure able to efficiently work with realistic instances in urban parcel delivery. Following this literature trend, we propose to model the SS-LM-D as a new variant of the BPP with time-dependent costs. Friesen and Langston first introduced the Variable Sized Bin Packing (VSBPP), i.e., a variant of the BPP where several bin types are present and the bin cost is directly proportional (or equal) to the bin volume (Friesen and Langston, 1986). They introduced the model and one online and two off-line algorithms with their worst-case ratios. An algorithm with upper bounds for some fixed size bin is presented in Seiden et al. (2003) and Monaci (2002). Heuristic and exact solution methods are designed for the case of correlated bin volume and cost. The variant of the problem where bin cost is not directly correlated to the bin volume is introduced by (Crainic et al., 2011), namely the Variable Cost and Size Bin Packing (VCSBPP). The authors introduce both lower and upper bounds and can solve realistic instances. Several studies have been dedicated to the VCSBPP, assuming that the cost of the unit size of each bin does not increase linearly as the bin size increases (see for instance Hemmelmayr et al. (2012)), but no one considered the time-dependent case. A variant

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of the BPP in which bins of different types have different costs and capacities and each bin has to be filled at least to a certain level, depending on the bin size, is discussed in Bettinelli et al. (2010). In this paper, the authors consider an additional constraint named the minimum filling constraint, which imposes that the volume of each bin is at least equal to a certain percentage of the total volume. For the sake of brevity, we omit the details of this constraint, but the interested reader can refer to Bettinelli et al. (2010). Fazi et al. (2012) considered time constraints related to the availability of the bins as well as service deadlines. Crainic et al. (2016) introduced a stochastic formulation considering the unavailability of the orders over time and presented a first study of the impact of some time-dependent demand distributions on long-haul transportation. Other related problems in the literature to SS-LM-D are the variants of the BPP with delay, and the batch scheduling problem. In the BPP with delay, the costs for the bins are reduced whenever some delay occurs. The batch scheduling problem is quite similar in its structure to the BPP with delay. Indeed, the cost for the batch is reduced with respect to time delays. Moreover, the setting is online (the items arrive with no knowledge of the future) and the cost is unique for all the batches (Dobson and Nambimadom, 2001; Li et al., 2019). Another important stream related to our setting is the on-line version of the BPP (Dosa et al., 2013; Epstein, 2019). In an online setting, no information about the item arrivals is available meaning that the management is done when the event occurs (Ahlroth et al., 2013; Epstein, 2019). Conversely, in our case, the delivery timeslots of the customers are known before the starting of the daily operations. Moreover, in our case, the cost structure is much more complex, differing the bins both in costs and sizes. This prevents a straightforward adaptation of the results of the online counterparts of (Dosa et al., 2013), as already proven for the basic variable costs and size BPP (Baldi et al., 2013). In addition, from an industrial point of view, using an on-line approach might not be a good modeling approach, since the information on the delivery timeslots is known in advance and can be incorporated in the decision process for deriving better solutions.

The literature on urban logistics problems is vast, but the great part of contributions is focused on the operational models (e.g., the routing), while few papers deal with the sharing of satellites. Indeed, our problem setting is quite new and no specific model or method of the literature copes with it. However, due to the adoption of multiple delivery modes and non-professional drivers, the costs structure of this system becomes complex enough that our problem setting cannot be ignored.

## 3. Problem setting, model formulation and heuristics algorithms

In this section, we describe the SS-LM-D problem, formally define the mathematical model, and propose heuristic methods able to solve large size instances within a limited computational time. We focus our attention on the problem of a decision-maker represented by a courier company operating a satellite-based consolidation policy in the second layer of a two-tier distribution system. This courier company has to perform a set of customers' deliveries with a limited and heterogeneous fleet of vehicles within one day. Even if order consolidation can be cost-efficient (since it increases the vehicle loafing factor and reduces the number of deliveries to be made) it challenges an efficient use of the satellite storage capacity. Satellites are usually located in existing urban areas and are characterized by different available space, yielding different capacities. In this paper, we assume that the location of the satellites, which is a strategic decision, is pre-defined. The satellites can offer a wide range of value-added logistics activities, including off-site stockholding, inventory management, unpacking, and waste collection services. To offer these services the satellite operator requires a payment (in the foregoing called tariff), typically related to the volume of the stocks. As the satellite capacity can be freed up for other more profitable activities, such as retailing, during the day, it is important to smooth out the demand accordingly. One way to reach this goal is to define incentives like time-varying tariffs. More precisely cheaper rates can be charged at certain times of day or night, when demand is low, and higher rates can be defined at peak times. Peak and off-peak timeslots may be a few hours long, but typically not too short. The fleet is composed of private or, more often, contracted couriers using a mix of traditional vehicles and low-environmental vehicles (i.e., electric vans and cargo bikes). A vehicle (or an entire vehicle type) may be unavailable in certain hours due to access restrictions in some city areas. Moreover, due to the possible unavailability of the driver, a vehicle type can be used only in a specific timeslot of a day. The driver's unavailability is mainly due to crowdsourced delivery. Crowdsourcing, also called Uberization of the last-mile, is an emerging application in the urban context that outsources the parcels delivery to crowd drivers. They are a network of local and non-professional drivers who are willing to temporarily work for delivery companies and to provide their own assets (e.g., the vehicle) to perform the parcel delivery (Arslan et al., 2018) Thus, this emerging method leverages networks of crowd drivers to manage deliveries, sometimes in less than an hour. The orders arrive the day before the planning process; indeed, customers might express time delivery restrictions, requiring parcel delivery in a particular timeslot of the day. Since vehicle and satellite capacities cannot be exceeded, and all the orders must be delivered, reflecting the current practices in the market, we assume that if needed, additional capacity can be bought on the spot market at a higher price (Crainic et al., 2016; De Marco et al., 2017).

### *3.1. Model formulation*

The management of the SS-LM-D logistic system, with shared satellites, limited vehicle capacities and explicit time-related decisions exhibits inherent complexity. In this section, we model it as a new variant of the bin packing problem with time-dependent costs, namely the *VCSBPP-TD*. Let $\mathcal{I}$ be the set of orders. We denote by $d_i$ the demand associated to the order $i \in \mathcal{I}$. A fleet $\mathcal{K}$ of different vehicles is available. The time horizon is split in different timeslots, where a specific timeslot is $h \in \mathcal{H}$. We assume that the operations related to the loading, unloading and handling of the freight can be ended in one timeslot. This is a classical assumption made by time-sensitive delivery services (e.g., Amazon Prime Now, Uber Freight, e-grocery). Let $\Xi$ be the set of pairs $(i, h)$ such that the order $i$ cannot be delivered in timeslot $h$ and $\Upsilon$ the set of pairs $(k, h)$ such that the vehicle $k$ is unavailable in timeslot $h$. While the set $\Upsilon$ depends on the mix of vehicles available to the courier, $\Xi$ is affected by the customers' choices. For each vehicle $k \in \mathcal{K}$, let $V_k^h$ and $\delta_k^h$ be, respectively, the capacity and the cost of the vehicle $k$ at the timeslot $h$ and $c_e$ be the cost for the express delivery in the spot market. The capacity of the satellite and the unitary tariff at time slot $h$ are denoted by $D^h$, $T^h$, respectively. While it is possible to quantify the costs associated with the satellite and vehicle use (accounting for renting, environmental impact (Perboli et al., 2018b)) in different timeslots (accounting for driver availability and working hours), considerably more difficult is the quantification of routing cost. Moreover, in this tactical problem, the routing becomes less relevant (Tadei et al., 2016) and the adoption of simplified approaches is beneficial to retain the computational tractability of the optimization problem. Considering these aspects, we surrogate the routing cost of each delivery of vehicle $k$ at the timeslot $h$ between the satellite and the customers in the surrounding area with a generalized cost-per-stop $c_k^h$. Although this might seem a limiting assumption, we remark that this costing scheme is adopted in practice by parcel delivery companies to evaluate their performances and to plan their activities (Brotcorne et al., 2019;

Perboli and Rosano, 2019). Moreover, if the route size is limited and a proper process of route evaluation is performed, the cost-per-stop can to a great extent approximate the real routing cost (Rosano et al., 2018; Tadei et al., 2016).

We assume that the customers' locations, their orders, the vehicles, and the drivers' availability are known, while other sources of uncertainty (e.g., the traveling and the service times) can be properly approximated with a deterministic counterpart (Baldi et al., 2012; Tadei et al., 2017). The last assumption is motivated by the behaviour of several e-commerce and green logistics companies, that have, up to now, quite limited knowledge of the single customer's behaviours. Moreover, before considering a stochastic model it is important to analyze the structure of its deterministic counterpart.

Defining the decision variables as:

- $x_{ik}^h$ is equal to 1 if an order $i \in \mathcal{I}$ is delivered at timeslot $h \in \mathcal{H}$ by vehicle $k \in \mathcal{K}$, and 0 otherwise;
- $y_k^h$ is equal to 1 if vehicle $k \in \mathcal{K}$ is used at timeslot $h \in \mathcal{H}$, and 0 otherwise;
- $X_i$ is equal to 1 if order $i \in \mathcal{I}$ is delivered as express delivery, and 0 otherwise

the *VCSBPP-TD* can be formulated as follows:

$$\min \quad \sum_{k\in K}\sum_{i\in I}\sum_{h\in H}(d_i T^h)x_{ik}^h + \sum_{k\in K}\sum_{i\in I}\sum_{h\in H}(c_k^h x_{ik}^h) + \sum_{k\in K}\sum_{h\in H}(\delta_k^h y_k^h) + \sum_{i\in I}(c_e X_i) \tag{1}$$

$$\text{s.t.} \quad \sum_{i\in\mathcal{I}}\sum_{k\in\mathcal{K}}(d_i x_{ik}^h) \le D^h, \qquad \forall\, h \in \mathcal{H}, \tag{2}$$

$$\sum_{i\in\mathcal{I}}(d_i x_{ik}^h) \le V_k^h y_k^h \qquad \forall\, h \in \mathcal{H}, k \in \mathcal{K}, \tag{3}$$

$$\sum_{k\in\mathcal{K}}\sum_{h\in\mathcal{H}} x_{ik}^h + X_i = 1 \qquad \forall\, i \in \mathcal{I}, \tag{4}$$

$$\sum_{k\in\mathcal{K}} x_{ik}^h = 0 \qquad \forall (i,h) \in \Xi, \tag{5}$$

$$y_k^h = 0 \qquad \forall (k,h) \in \Upsilon, \tag{6}$$

$$x_{ik}^h \in \{0,1\} \qquad \forall\, i \in \mathcal{I}, h \in \mathcal{H}, k \in \mathcal{K}, \tag{7}$$

$$y_k^h \in \{0,1\} \qquad \forall\, h \in \mathcal{H}, k \in \mathcal{K}, \tag{8}$$

$$X_i \in \{0,1\} \qquad \forall\, i \in \mathcal{I}. \tag{9}$$

We consider the satellite manager's objective function. According to the literature on synchromodality (Giusti et al., 2019), it considers both the costs for the satellite management and the cost of delivery. More in detail, the objective function (1) minimizes the total cost as the sum of the tariff for using the satellite, the surrogate routing costs, the cost of the vehicles, and the cost of the express delivery. This objective function is suitable for the industrial settings in urban parcel delivery that have the following features: (i) surrogate part of the routing between the satellite and the customers; (ii) costs affected by time-dependency (e.g., in case of air drones or land drones); (iii) usage of two-levels fleets managed, even partially, with crowdsourcing contracts, increasingly adopted in current business models. Constraints (2) and (3) ensure that at each timeslot, the capacity of the depot and the vehicle, respectively, are not exceeded. Constraint (4) ensures that each order is delivered. Notice that, the decision variable $x_{ik}^h$ combined with constraint (4) generates inter-dependency among timeslots, making them not separable. It means that we do not know *a priori* the assignment order-timeslot and thus, a certain order could be delivered in any timeslot. Constraints (5) and (6) fix to 0 the variables $x_{ik}^h$ and $y_k^h$ belonging to the sets $\Xi$ and $\Upsilon$, respectively. Indeed, by properly fixing the pairs $(i, h)$ and $(k, h)$, we can model several situations including time windows restrictions to the delivery, desiderata of the customers, as well as unavailability of certain vehicles (single vehicle or group of them) due to policies or accidents. Finally, constraints (7) to (9) are the integrality requirements.

### *3.2. Heuristics*

The *VCSBPP-TD* is NP-hard. It can be trivially shown that the bin packing problem (which is a well-known NP-hard problem) is a special case of this problem. The piecewise time-dependent structure of the objective function greatly increases the complexity of this difficult combinatorial optimization model. To efficiently solve the problem, we propose to extend the well-known First Fit Decreasing ($FFD$) and Best Fit Decreasing ($BFD$) heuristics taking into account the specificity of *VCSBPP-TD*. In addition to the orders and the vehicles' characteristics, we also consider the time dimension, which brings additional complexity not only in the cost structure but also in the satellite and vehicles capacity constraints.

In the classical $FFD$ and $BFD$ heuristics, the orders are sorted by their volume and are loaded in the first available vehicles ($FFD$) or the best available vehicle ($BFD$) with smallest sufficient residual capacity (see Algorithm 1 and 2 for the pseudocode of the two algorithms). For the *VCSBPP-TD* the orders are assigned to timeslots and then to a vehicle if it is possible (feasible). The orders, the timeslots and the vehicles are sorted according to specific ordering criteria: (i) the orders are sorted in non-increasing order of size (breaking ties by first considering orders that can be delivered in fewer timeslots) ; (ii) timeslots are sorted in ascending order of the sum of cost per stop of the vehicles; (iii) vehicles are ordered in each timeslot, by non-decreasing order of their unit cost per capacity ratio ($\delta_k^h/V_k$), breaking ties considering $\sum_{h\in\mathcal{H}} c_k^h$. Each order is assigned to a timeslot, if enough satellite capacity is available and if in that timeslot vehicles have enough residual capacity. If one of the two conditions above is not satisfied, the next timeslot or the next vehicle, respectively, is selected and the process is repeated. The order is assigned to the first vehicle with enough residual capacity, in the $FFD$, or to the vehicle with the smallest non-negative residual capacity after assigning the order, in the $BFD$.

If it is not possible to deliver the order, it is assigned to the express delivery service.

To further improve the solution, a simple iterative local search procedure is applied (see Algorithm 3). In particular, the local search aims to relocate the entire content of a bin in a different bin whose volume allows to load all items. In more detail, adapting the iterative procedure proposed in Baldi et al. (2012), the content of the bin is placed in a bin of a different type (same or different timeslot) or the same bin type, but in a different timeslot and the objective function is updated. If the new solution is improving in terms of the objective function and it is feasible for all the other constraints (capacity of the satellite in the given timeslot, bins of a certain bin type availability, constraints on the delivery of an order in a given timeslot), the bin swap is applied. The *First-improving policy* is considered (the *Best-improving* one was considered too, but no relevant improvements of the solution quality were found)(Gendreau and Potvin, 2019). The local search stops when no improving solution is found.

**Algorithm 1:** FFD-based heuristic

**Input:** Set of orders $\mathcal{I}$ sorted in descending order by $d_i$, breaking ties by first considering orders that can be delivered in less timeslots
Set of timeslots $\mathcal{H}$ sorted by $\sum_{k \in \mathcal{K}} c_k^h$
Set of vehicles $\mathcal{K}$ sorted for each $h \in \mathcal{H}$ by $(\delta^{\mathbf{h}}/\mathbf{V}^{\mathbf{h}})$ and breaking ties considering $\sum_{h \in \mathcal{H}} c_k^h$
**Initialization:** $Satcap_h := D^h \ \forall h \in \mathcal{H},\ Vehcap_k^h := V_k^h, \forall k \in \mathcal{K}, \forall h \in H, BestOF := 0.$
**for** $i \in \mathcal{I}$ **do**
  $\tilde{h} := -1, \tilde{k} := -1$
  **for** $h \in \mathcal{H}$ **do**
    **if** $Satcap_h \geq d_i$ *and* $\{(i, h)\} \notin \Xi$ **then**
      **for** $k \in K$ **do**
        **if** $\{(k, h)\} \notin \Upsilon$ *and* $Vehcap_k^h - d_i \geq 0$ **then**
          $\tilde{k} := k, \tilde{h} := h$
          $BestOF+ = d_i T^{\tilde{h}} + c_{\tilde{k}}^{\tilde{h}}$
          **if** $Vehcap_{\tilde{k}}^{\tilde{h}} = V_{\tilde{k}}^{\tilde{h}}$ **then**
            $BestOF+ = \delta_{\tilde{k}}^{\tilde{h}}$
          **end**
          $Vehcap_{\tilde{k}}^{\tilde{h}} - = d_i$
          $Satcap_{\tilde{h}} - = d_i$
        **end**
      **end**
    **end**
  **end**
  **if** $\tilde{h} = -1$ *and* $\tilde{k} = -1$ **then**
    $BestOF+ = c_e$
  **end**
**end**
Call *Local Search* on the current solution (see Algorithm 3)
**return** *BestOF*

**Algorithm 2:** BFD-based heuristic

**Input:** Set of orders $\mathcal{I}$ sorted in descending order by $d_i$, breaking ties by first considering orders that can be delivered in less timeslots
Set of timeslots $\mathcal{H}$ sorted by $\sum_{k \in \mathcal{K}} c_k^h$
Set of vehicles $\mathcal{K}$ sorted for each $h \in \mathcal{H}$ by $(\delta^{\mathbf{h}}/\mathbf{V^h})$ and breaking ties considering $\sum_{h \in \mathcal{H}} c_k^h$
**Initialization:** $Satcap_h := D^h \; \forall h \in \mathcal{H},\ Vehcap_k^h := V_k^h, \forall k \in \mathcal{K}, \forall h \in H, BestOF := 0.$
**for** $i \in \mathcal{I}$ **do**
  H*:= -1 ,K*:= -1
  **for** $h \in \mathcal{H}$ **do**
    $Min := \infty$ **if** $Satcap_h > d_i$ *and* $\{(i,h)\} \notin \Xi$ **then**
      **for** $k \in K$ **do**
        **if** $\{(k,h)\} \notin \Upsilon$ *and* $Vehcap_k^h - d_i < Min$ **then**
          $Min := Vehcap_k^h - d_i, K* = k, H* := h$
        **end**
      **end**
    **end**
  **end**
  **if** $K* \neq -1$ *and* $H* \neq -1$ **then**
    $BestOF+ = d_i T^{H*} + c_{K*}^{H*}$
    **if** $Vehcap_{K*}^{H*} = V_{K*}^{H*}$ **then**
      $BestOF+ = \delta_{K*}^{H*}$
    **end**
    $Vehcap_{K*}^{H*} - = d_i$
    $Satcap_{H*} - = d_i$
  **else**
    $BestOF+ = c_e$
  **end**
**end**
Call *Local Search* on the current solution (see Algorithm 3)
**return** *BestOF*

## 4. Computational results

In the previous section 3, we presented the model and the heuristics. In this section, we conduct an experimental campaign to assess and validate our model and solution strategy in a realistic parcel delivery application, characterized by the adoption of satellites and by multiple delivery options. In particular, we highlight that the proposed model can be used to support the decision-makers in the last-mile in reducing the costs and in better controlling the whole process, providing useful practical insights.
Since the existing data sets for the BPP in the literature are not suitable to represent a City Logistics setting, we generated new test sets from several real case studies, arising from the analysis of the city of Turin conducted by CARS@Polito (CARS@Polito, 2017; ICELAb@Polito, 2017; Municipality of Turin, 2018). These data are gathered from and the

**Algorithm 3:** Local Search

**Input:** Set of orders $\mathcal{I}$
Set of timeslots $\mathcal{H}$
Set of vehicles $\mathcal{K}$
Current Solution with the objective function equal to $BestOF$
Continue = true
**while** *Continue* **do**
    Continue = false
    **for** $k_1 \in \mathcal{K}$ *in use in the current solution* **do**
        **for** $k_2 \in \mathcal{K}$ *of different type than* $k1$ **do**
            **for** $h \in \mathcal{H}$ **do**
                $V_{k_1}^h = \sum_i d_i$ where $i$ is loaded into $k_1$
                **if** $V_{k_2}^h \geq V_{k_1}^h$ *and* $\delta_{k_2}^h \leq \delta_{k_1}^h$ **then**
                    Move all the items from $k_1$ to $k_2$
                    $BestOF = BestOF - \delta_{k_1}^h + \delta_{k_2}^h$
                    Continue = true
                **end**
            **end**
        **end**
    **end**
    **for** $k_1 \in \mathcal{K}$ *in use in the current solution* **do**
        Let be $h(k_1)$ the slot to which $k_1$ is assigned in the current solution
        **for** $h \in \mathcal{H} \mid h \neq h(k_1)$ **do**
            **if** $\delta_{k_1}^h \leq \delta_{k_1}^{h(k_1)}$ **then**
                Move the bin $k_1$ to slot $h$
                $BestOF = BestOF - \delta_{k_1}^{h(k_1)} + \delta_{k_1}^h$
                Continue = True
            **end**
        **end**
    **end**
**end**
**return** Updated solution and $BestOF$

analysis of the costs of the different vehicles presented in Perboli and Rosano (2019) and Perboli et al. (2018b).

### *4.1. Experimental setting*

With the aim of deriving instances with different characteristics from real data, we have considered different ranges for the problem parameters. We would like to note that all the parameters have been generated in agreement with the real distribution of the e-commerce parcels in an urban area (Perboli and Rosano, 2019). More precisely, the instances are generated according to the following parameters:

- The number of orders has been considered in the set $200, 500, 1000, 2000$. We do not consider larger instances since in practice the maximum number of orders per satellite lies between 1000 and 2000 (Perboli et al., 2018b). The number of orders that fit into a bin can vary, depending on the different parameters considered in the instance generation. According to (Brotcorne et al., 2019; Perboli and Rosano, 2019), the most relevant parameters are the bin type (e.g., bike or van) and the capacity (Brotcorne et al., 2019; Perboli and Rosano, 2019).

- Order volumes have been randomly generated according to a discrete uniform distribution in the range $\{1, ..., 20\}$. More precisely, they are split into two sets: small orders, with demand $d_i \in \{1, ..., 15\}$, and medium orders, with demand $d_i \in \{16, ..., 20\}$. We disregard larger size as not common in the considered industrial application (Perboli et al., 2018b). Small and medium orders are then mixed in the following combinations: T1: 50% Orders are small and 50% are medium; T2: 75% are small and 25% medium. These combinations represent the present and the near future real mix of volumes in parcel delivery (De Marco et al., 2017). The maximum size of the orders demand, the vehicles demand, and the vehicles costs are normalized such that they respect the real distribution of the e-commerce parcels in an urban area (Perboli and Rosano, 2019).

- The number of timeslots in one day has been considered equal to three and five. More than five timeslots are unlikely to be used. In fact, the standard for timeslots in time-sensitive urban delivery is presently two hours in many services (e.g., Amazon Prime Now, Uber Freight, e-grocery services by Brick&Mortar companies as Carrefour, Startup as Supermercato24). Moreover, we noticed that even using higher values, the results were similar to the five timeslots ones.

- The fleet is composed of three types of vehicles: cargo bikes (with capacity 100 in all the timeslots), electric vans (with capacity 200 in all the timeslots), and fossil-fueled light-duty (with capacity 300 in all the timeslots) Perboli et al. (2018b). Also the case with a homogeneous fleet of cargo bikes has been considered.

- The cost of the usage of a vehicle $\delta_k^h$ 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 Cost-per-stop $c_k^h$ has been set to $\overline{c}_k \rho_h$, where $\overline{c}_k$ is obtained, following Crainic et al. (2011), by multiplying by 100 the square root of the vehicle capacity, and $\rho_h$ is 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 oscillation of the cost function of the satellite would be justified by the willingness of the municipality to push the freight transportation out of the rush hours.

- The satellite tariff $T^h$ has been set to $\overline{T}\phi_h$, where $\overline{T} = max_h T^h$ and $\phi_h$ is a time-dependent parameter. In details, $\phi_h = [0.7, 1.0, 0.3]$ for three timeslots and $\phi_h = [0.7, 0.8, 1.0, 0.5, 0.3]$ for five timeslots.

  Notice that, some data being confidential, all the values have been anonymized and normalized.

The model (1)-(9) is solved by Cplex 12.8, while the heuristics are coded in Java. All the tests were performed on an Intel I7700 workstation with 16 Gb of RAM. The instances are publicly available in a BitBucked repository (Perboli, 2019).

*4.2. Model and heuristic performance analysis*

This section is devoted to the discussion of the computational results carried out to qualify the model (1)-(9) and the heuristic presented in section 3.2.

In Table 1 columns 1, 2, and 3 report the number of customers orders (header ORD), the number of vehicle types (header VT), and the number of timeslots (header TS), respectively. Notice that, given a combination of the three parameters, a total of 20 instances are considered (two different orders volume mix, namely T1 and T2, and the generation of 10 randomly generated instances). The statistics of the solutions found by Cplex after 180 and 3600 seconds of computation time are reported. Columns 4-6 and 7-9 report the number of instances solved to optimality (#OPT) the MIP optimality gap in percentage (% Gap) and the average computational time in seconds (Time). Finally, columns 10-13 report the percentage deviation ($\Delta$%) from the best-known solution (which might not be the optimal one in case the column Gap reports a percentage greater than zero) for the FFD and the BFD heuristics without the Local Search (FFD and BFD) and when the local search procedure is applied (FFD+LS and BFD+LS), respectively. We do not report the computational time of the heuristics, since it can be considered negligible (less than 0.1 seconds for the constructive heuristics and less than 1 second for the versions incorporating the local search in the largest instances) for each instance.

The results highlight that Cplex can optimally solve all the instances with 200 orders within 180 seconds. If at least one hour of computational time is given, also all the instances with 500 orders can be solved. In this case, the average computational time is around 530 seconds. Even if Cplex fails to solve to optimality larger instances, the MIP optimality gap of the best solutions found within the allotted time limit is still limited and up to 5%. The instances with five timeslots are the hardest to solve. This is confirmed by both the optimality gaps and the time to find the best solution. In fact, for these instances, the best solution provided by Cplex is generally found after 1800 seconds, resulting in a larger computational time to reach a good optimality gap. We do not report the results of instances with more than 2000 orders because Cplex goes out of memory for a large part of them.

Concerning the performance of the heuristics, the $BFD$ performs much better than the $FFD$. Even if the results are quite satisfactory, we should mention that the heuristics are unable to find the optimal solution in several small-sized instances. As for the solution of the MIP with Cplex, the instances with five timeslots appear to be more challenging, presenting a higher percentage deviation. The very short computational effort, as well as the good performances of the $BFD$ make the latter quite interesting whenever implementable solutions should be obtained fairly quickly. This enables the usage of the model for short-term planning or when the process must be repeated several times, as in the setting of the heuristic solution of stochastic programming models by a progressive hedging algorithm (Crainic et al., 2016) or in dynamic tariff creation by heuristic bilevel programming (Brotcorne et al., 2012). We also observe that $BFD + LS$ and $FFD + LS$ perform better than $BFD$ and $FFD$. Indeed, even if the results for both $BFD$ and $FFD$ are satisfactory in small-sized instances (with and without the local search), applying the improvement procedure, we find solutions very close to the optimal ones, for instances up to 500 orders, particularly for $BFD + LS$. When we consider instances with 500 orders, the percentage deviation $\Delta\%$ becomes less than or equal to 2%. Finally, we notice that for several larger instances the optimality gap is reduced by about half, particularly for $FFD + LS$. For example, when we consider instances with 2000 orders, three vehicles and five timeslots, the $FFD$ the percentage deviation drops from 5.38 to 3.62, while for the $BFD$ it goes from 2.62 to 1.63, applying the local search.

Concerning the solution structure, 30% of the cost can be imputed to the satellite, 50% to the delivery cost, and finally about 20% to the vehicle cost (we do not report the results, being quite stable on all the instances). This cost split reflects the cost structure highlighted in different papers (Manerba et al., 2018; Perboli and Rosano, 2019). Another important point is related to the structure of the solution itself. Bin Packing problems, even in their classical generalized and variable-sized versions, are affected by the symmetry property of the solutions (Baldi et al., 2012; Crainic et al., 2011). Thus, we might have solutions with very similar (or even equal) objective functions with a different structure in terms of vehicle types and timeslots distribution. This aspect becomes more relevant when considering the usage of the heuristics to replace the MIP model. If we have to make decisions or validate policies, we must check that the MIP solver and the heuristics are giving a solution with an equivalent structure in terms of the tactical decisions, i.e., the type of vehicles in use and their distribution in terms of vehicle number per type per timeslot. We summarize this information in Table 2. The table reports, for each size of the order set, the ratio of similarity of the best solution of the MIP model and the best heuristic, i.e., the BFD+LS. In details, we give the ratio of vehicles types in use both in the MIP and the heuristic solutions per timeslot (column 2) and the ratio of the number of vehicles in use for each vehicle type in a timeslot, computed as the ratio between the difference of the number of vehicles in use for each vehicle type in each timeslot between the two solutions and the number of vehicles in use for each vehicle type in a timeslot in the MIP solution only (column 3). The reported values are the mean over all the instances with the same number of orders. According to the numerical results, the two solutions are equal in vehicle type usage, while they differ slightly in the number of vehicles per vehicle type per timeslot. This gap can be attributed simply to the optimality gap of the heuristic. Thus, the heuristic can be used in substitution of the MIP model to obtain accurate results in a very short time.

Table 3 reports, for the instances with three vehicle types and for each combination of order number and timeslots number, the average number of used vehicle types (Used VT) and the average vehicle fill ratio (FR), expressed as a value between 0 (empty) and 1.0 (fully filled). Generally speaking, the model tends to use between one and two vehicle types: the cargo bikes, that are smaller but can be easily fully filled, and the small electric vans. In case the model chooses to use only one vehicle type, the small electric vans are selected. In some instances (and in the five timeslots case, in particular), the model has to use also the light-duty vehicles, mainly due to their larger loading capacity.

| ORD | VT | TS | MIP 180 ss | | | MIP 3600 ss | | | FFD | BFD | FFD+LS | BFD+LS |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | # OPT | % Gap | Time | # OPT | % Gap | Time | Δ% | Δ% | Δ% | Δ% |
| 200 | 1 | 3 | 20 | 0.00 | 9.94 | 20 | 0.00 | 9.94 | 0.00 | 0.00 | 0.00 | 0.00 |
| 200 | 1 | 5 | 20 | 0.00 | 3.66 | 20 | 0.00 | 3.66 | 0.12 | 0.00 | 0.08 | 0.00 |
| 200 | 3 | 3 | 20 | 0.00 | 14.41 | 20 | 0.00 | 14.41 | 0.41 | 0.23 | 0.21 | 0.00 |
| 200 | 3 | 5 | 20 | 0.00 | 16.28 | 20 | 0.00 | 16.28 | 0.65 | 0.23 | 0.30 | 0.07 |
| 500 | 1 | 3 | 9 | 0.12 | 124.14 | 20 | 0.00 | 236.89 | 1.43 | 0.00 | 0.91 | 0.00 |
| 500 | 1 | 5 | 15 | 0.23 | 95.96 | 20 | 0.00 | 537.34 | 2.76 | 0.00 | 2.53 | 0.00 |
| 500 | 3 | 3 | 4 | 0.10 | 169.93 | 20 | 0.00 | 412.30 | 1.83 | 0.06 | 1.31 | 0.06 |
| 500 | 3 | 5 | 2 | 0.56 | 178.80 | 20 | 0.00 | 912.63 | 2.88 | 0.06 | 1.74 | 0.06 |
| 1000 | 1 | 3 | 0 | 0.45 | 180.00 | 5 | 0.06 | 2916.13 | 1.69 | 0.08 | 1.35 | 0.08 |
| 1000 | 1 | 5 | 0 | 2.03 | 180.00 | 16 | 0.04 | 2398.00 | 2.34 | 0.60 | 1.88 | 0.32 |
| 1000 | 3 | 3 | 0 | 1.84 | 180.00 | 12 | 0.01 | 2563.58 | 1.65 | 0.02 | 0.78 | 0.02 |
| 1000 | 3 | 5 | 0 | 43.07 | 180.00 | 17 | 0.20 | 3484.10 | 2.81 | 0.34 | 1.12 | 0.23 |
| 2000 | 1 | 3 | 0 | 54.01 | 180.00 | 3 | 0.05 | 3387.80 | 3.61 | 0.05 | 1.96 | 1.05 |
| 2000 | 1 | 5 | 0 | 85.70 | 180.00 | 0 | 0.23 | 3600.00 | 5.23 | 0.25 | 3.65 | 2.25 |
| 2000 | 3 | 3 | 0 | 69.52 | 180.00 | 0 | 0.91 | 3600.00 | 4.19 | 1.36 | 3.36 | 2.52 |
| 2000 | 3 | 5 | 0 | N/A | 180.00 | 0 | 4.78 | 3600.00 | 5.38 | 2.62 | 3.62 | 1.63 |

Table 1: Computational results of the model after 180 seconds, 3600 seconds, and the heuristics. For the computational time and the gap, reported values are obtained as the mean over the instances with two order volumes mixes (namely T1 ad T2) and 10 randomly generated instances, for a total of 20 instances

| | Similarity | |
|---|---|---|
| ORD | VT | TS |
| 200 | 1.00 | 1.00 |
| 500 | 1.00 | 1.00 |
| 1000 | 1.00 | 0.99 |
| 2000 | 1.00 | 0.98 |

Table 2: Comparison of the solution structure between the MIP solver and the BFD+LS

| ORD | TS | Used VT | FR |
|---|---|---|---|
| 200 | 3 | 1.75 | 0.98 |
| 200 | 5 | 1.9 | 0.97 |
| 500 | 3 | 1.6 | 0.99 |
| 500 | 5 | 1.9 | 0.99 |
| 1000 | 3 | 1.45 | 0.98 |
| 1000 | 5 | 1.55 | 0.99 |
| 2000 | 3 | 1.15 | 0.94 |
| 2000 | 5 | 1.5 | 0.92 |

Table 3: Vehicle types usage (based on the best-known solution)

## 5. *VCSBPP-TD* and on-demand economy

In this section, we first compare the satellite consolidation strategy with a more traditional single-echelon approach, analyzing the operational costs in both settings. Then, we present an analysis of the impact of the customers' choices on the sustainability of the delivery from the operational, economic and environmental points of view. For the satellite consolidation policy, we use the *VCSBPP-TD*, while the single-echelon approach is solved with the state-of-the-art approach in Saint-Guillain et al. (2015), where a dynamic vehicle routing problem with time windows and stochastic customers is considered. Following this approach customers may request services online, even if vehicles have already started their tours. In the evaluation of the impact of the satellite consolidation policy, we consider that the tariffs paid for stocking the freight in the satellite and the delivery itself incorporate also the costs for the management of the facility. The two settings are then integrated into a Monte Carlo based simulation-optimization framework. The present version of the simulator implements a Monte Carlo method, a module for georeferencing the data and a post-optimization software for simulating the given routes with real traffic data from the network of sensors and the crowdsensing data of the Municipality of Turin with a precision of 15 minutes provided by the Municipality company 5T (5T Web Site, 2019).

Concerning the data and to reach a compromise between computational time and instance size, we consider daily delivery instances with 500 orders. This number is compatible with the average number of orders to deliver in a working day in the urban context, according to the real practices (De Marco et al., 2017). Moreover, this number of orders allows us to use the MIP as a solution method, avoiding the very limited, but present, optimality gap that affects the heuristic. Concerning the cost per stop, we use the values from Brotcorne et al. (2019). Fleets with one and three vehicle types are generated as before. In the instances with one vehicle type, we suppose to use the electric vans. A set of 80 instances with 500 orders, one or three vehicle types, three or five timeslots, two order volumes mix and 15 repetitions are randomly generated by a Data-Fusion process (see more details on the data sources in Table 4). Concerning the satellite location, we used a pericentral location given by the Municipality of Turin (Municipality of Turin, 2018). The cost of the usage of a vehicle $\delta_k^h$ needs to incorporate the cost related to the routing and the service delivery time. Thus, it is computed by 100 simulations mixing the different sources of data and using the algorithm for the dynamic and stochastic vehicle routing problem with time windows by Saint-Guillain et al. (2015) with the city of Turin as the road network. The 100 simulations are performed for each type of vehicle and each timeslot separately by integrating the data from Maggioni et al. (2014) for the time-dependent travel times (see Figure 1) and then an empirical distribution of the costs is obtained. Following Maggioni et al. (2014), we approximated the given experimental distribution with a deterministic approximation derived from the Extreme Value theory, which leads to a good approximation of the underlying distribution of probability. Even if anonymized, the data for these instances come from real settings in parcel delivery and have been collected from different projects (see Table 4).

To incorporate the process of customers' choice of the delivery timeslot, given one of the 120 instances, the simulator generates a series of additional instances where a percentage of the orders are affected by the customers' preferences on the timeslot. In more detail, being $\alpha$ the percentage of the orders affected by the customers' choices, it takes the values 10%, 30%, 50%, 70%, and 100%. For each instance and each value of $\alpha$, 10 random instances are created, by choosing randomly the timeslot in which the delivery must be completed. The timeslot is chosen according to a Uniform distribution. This setting is suitable to model the case in which

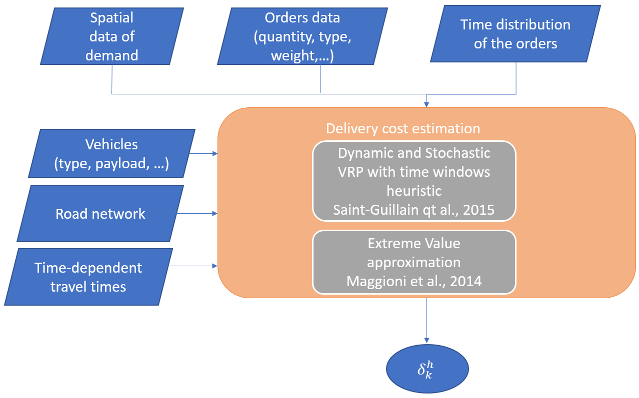


Figure 1: Generation of $\delta_k^h$

no analytic or profiling was performed on the customers' performances.

Thus, our Monte Carlo-based simulation-optimization algorithm follows the following steps (see Figure 2 for a depiction of the overall system):

- The Monte Carlo simulation module repeats the following process for a given number $|I|$ of iterations.
  - Given the different data of the operational context as well as eventual distributions of the data themselves, the simulator generates a series of delivery instances, each one corresponding to a full day of deliveries as previously discussed.
  - Each instance is solved by one of the two policies, i.e., the single-echelon approach optimized by dynamic and stochastic vehicle routing problem by Saint-Guillain et al. (2015) and the satellite consolidation optimized by our *VCSBPP-TD* solved by the BFS+LS. We are adopting the heuristic because it is able to provide high quality solutions with a negligible computational time. Both in the satellite-based and in the single-echelon policy, even if the delivery demand is known, the time period during which it occurs results from a customer's decision taken in a second step. This is modeled as a random-chosen event between the start of the day (beginning of the first timeslot) and the end of the timeslot before the delivery deadline defined by the user. In the satellite-based policy, we do not make use of any information concerning the probability distribution of the customers' choices. Conversely, the single-echelon model explicitly considers the uncertainty in the timeslot chosen by the customer for the freight delivery, by means of the stochastic dynamic approach. In this way, we compare the case of limited knowledge of the customers' behaviors of the satellite-based policy with a more standard single-echelon approach, but with a short-term knowledge of the timeslots choices. To make a more accurate definition of the delivery costs and the travel times and cost matrices, the georeference module is used. The georeference feature is implemented by means of Google Earth APIs and it is also used to graphically represent the results of the simulation itself.
- The distribution of the simulation-based optimization solutions is computed and statistical

| Data type | Source |
|---|---|
| Satellite localization | Municipality of Turin (2018); Perboli et al. (2018b) |
| Satellite operational costs and tariffs | Municipality of Turin (2018); Perboli et al. (2018b) |
| Orders data | Brotcorne et al. (2019); Crainic et al. (2011) |
| Spatial data of demand | De Marco et al. (2017) |
| Time distribution of the orders | De Marco et al. (2017) |
| Vehicles characteristics | Perboli and Rosano (2019); Perboli et al. (2018b) |
| Road network | OpenStreet, 5T Road Sensors' data (5T Web Site, 2019) |
| Time-dependent travel times | Maggioni et al. (2014) |
| Delivery cost estimation | Delivery cost estimator, see Figure 1 |
| Environmental costs | Brotcorne et al. (2019); Giusti et al. (2019) |

Table 4: Sources of data for the Data-Fusion phase

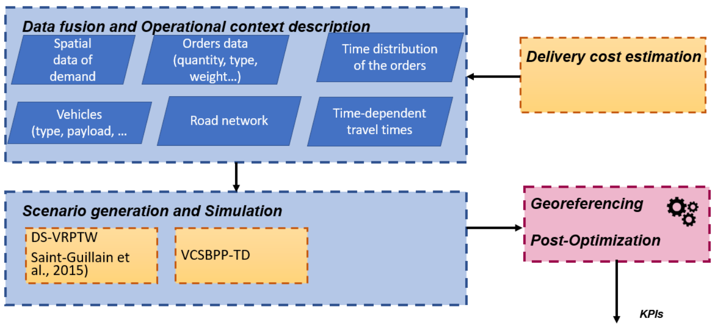


Figure 2: Monte Carlo simulation-optimization

data are collected.

- A post-optimization software module is devoted for the computation of additional Key Performance Indicators (e.g., vehicle usage, CO2 and NOx emissions, stop per working hour, service and travel times) (Brotcorne et al., 2019; Giusti et al., 2019). Concerning the externalities evaluation, we follow the ISO/TS 14067 regulation "Greenhouse gases — Carbon footprint of products" Brotcorne et al. (2019); Perboli et al. (2018b).

Considering the computational effort, each run of the Monte Carlo (120 instances for every single value of $\alpha$) requires about 32 minutes when we are solving the optimization problem by the dynamic and stochastic vehicle routing algorithm by Saint-Guillain et al. (2015), while 5 days of computations in the case of the MIP instead and about 3 minutes of the BFD+LS. Notice that in the computational time it is considered also the overhead for the data fusion and the post-optimization. Thus, there is a big advantage in using our heuristic both compared to the MIP model and the dynamic and stochastic vehicle routing problem, an issue becoming more relevant if larger instances would be considered.

Table 5 reports the gap in percentage between the objective functions of the single-echelon policy versus the satellite consolidation defined by $(OF(SE) - OF(SAT))/OF(SE)$, where $OF(SE)$ is the optimal objective function of the single-echelon policy and $OF(SAT)$ the optimal objective function of the satellite consolidation. Thus, a positive value means a gain in

| VT | TS | 10% | 30% | 50% | 70% | 100% |
|---|---|---|---|---|---|---|
| 1 | 3 | 17.37 | 16.69 | 18.38 | 19.77 | 18.93 |
| | 5 | 19.27 | 20.62 | 22.52 | 21.35 | 22.25 |
| 3 | 3 | 26.02 | 24.85 | 28.42 | 30.51 | 31.32 |
| | 5 | 35.19 | 44.74 | 42.58 | 52.49 | 57.26 |

Table 5: Percentage gain of the satellite consolidation policy with respect to the single-echelon one

| VT | TS | 10% | 30% | 50% | 70% | 100% |
|---|---|---|---|---|---|---|
| 1 | 3 | 6.53 | 20.51 | 33.99 | 46.27 | 65.34 |
| | 5 | 24.63 | 72.40 | 114.85 | 161.61 | 252.93 |
| 3 | 3 | 6.76 | 21.54 | 35.76 | 48.47 | 70.03 |
| | 5 | 29.47 | 84.22 | 132.63 | 187.13 | 295.34 |

Table 6: Cost increase due to a lack of customers' preferences analysis

the percentage of the satellite-based policy on the single-echelon one. Column 1 reports the number of vehicle types ($VT$) and Column 2 the number of timeslots ($TS$) considered. The remaining columns give the results according to the different values of $\alpha$, i.e., the percentage of orders with delivery time restrictions. It is worth noting that a satellite consolidation policy has always better performances than the single-echelon one. As expected, the gain is more limited in the case of the adoption of a single vehicle type, while a satellite consolidation policy gives sensibly better results (up to 57% of cost saving) than the single-echelon setup, proving the effectiveness of the satellite-based paradigm. The gaps show how a proper policy might give benefits even in an early stage, in which the limited knowledge of the customer's preferences might prevent a stochastic programming approach. Moreover, being the *VCSBPP-TD* still deterministic, we would expect that a stochastic variant of the *VCSBPP-TD* model would increase the gap, making the adoption of this approach more interesting. Even if the operational costs of the satellite management can be incorporated in the tariff, there are infrastructure costs due to the creation of the satellite which can be amortized with proper planning (see, for example, Tadei et al. (2012)) and to the usage of industrial areas or unused public facilities.

Table 6 illustrates the dramatic effects that a lack of customers' preferences or marketing policies analysis may have on costs. With this aim, we have simulated the behaviour of the model, solved without considering any customers' preference ($\alpha = 0$), under different operational scenarios. In each row, we report the average increase of the objective function with respect to the case with $\alpha = 0$ computed in percentage. The base case reflects that a poor analysis of the customers' preferences may lead to an increase of the delivery costs up to 300% (three vehicle types, 5 timeslots, $\alpha = 100\%$). In any case, even with a rather limited impact of the customers' choices ($\alpha = 30\%$), the cost increase can be sufficiently high to require a specific redesign of the business model toward the integration of big data and prescriptive analytics. As shown in (Perboli and Rosano, 2019), allowing full freedom to the customers without any prevision on the customers' preferences may cost the e-commerce company between 0.5 and 2 millions of euros per year in the case of a medium-sized city as Turin. While such inefficiency can still be accepted in the present situation, in which the e-commerce market is growing of two digits per year, this becomes unacceptable in a more saturated market situation, where the innovation curve moves towards the full competition phase.

| VT | TS | 10% | | | 30% | | | 50% | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | CB | EV | LD | CB | EV | LD | CB | EV | LD |
| 3 | 3 | 2.37 | 28.10 | 0.03 | 7.47 | 24.70 | 0.00 | 11.43 | 22.33 | 0.00 |
| | 5 | 4.22 | 2.52 | 18.91 | 7.38 | 1.81 | 17.62 | 10.05 | 2.81 | 15.05 |

| VT | TS | 70% | | | 100% | | |
|---|---|---|---|---|---|---|---|
| | | CB | EV | LD | CB | EV | LD |
| 3 | 3 | 15.03 | 19.77 | 0.00 | 36.50 | 5.43 | 0.00 |
| | 5 | 13.86 | 3.43 | 12.90 | 26.86 | 5.67 | 5.00 |

Table 7: Effect of the customers' choices over vehicle usage

Table 7 shows the usage of the vehicle in the delivery. Each row reports the average number of vehicles for each type, i.e., CB for Cargo Bikes, EV for Electric Vans, and LD for Light Duty. Notice that, being the values an average, they can be fractional. It is interesting to highlight two aspects. First, when the customers can choose their timeslot, a small portion of vans might be necessary to serve larger quantities of customers' orders. Second, while the percentage of on-demand deliveries increases, there is a strong shift towards the usage of cargo bikes. This is not due to the unitary cost per volume (which is larger for the greater impact of the freight dispersion and the consequent under-usage of the volume), but to their flexibility, able to better answer to the erratic decisions of the customers. Thus, the strong investment of Venture Capital on alternative and small-sized delivery options, as drones and small robots swarms, cargo-bikes and other similar options are driven by the need of having more flexibility as an answer to the partial knowledge of the customers' behaviour. Moreover, the results show what might be the main effect of the sharing of logistics resources as satellites and local delivery fleets. A joint usage of the resources may allow the logistics provider to acquire the knowledge base to perform customers' preferences analysis. The main obstacles to this process are the e-commerce companies themselves, and their unwillingness to share their information. For this reason, it is important to highlight and remark the potential risks of this lack of sharing. The companies should define a proper mechanism able to disclose the smallest amount of data that enables the interaction of all the actors in the urban system. Examples of this mechanism can be found in recent synchromodality platforms (Giusti et al., 2019; Perboli et al., 2017) and Blockchain-based supply-chain management systems (Perboli et al., 2018a).

We finally analyze the satellite-based paradigm versus the single-echelon approach, in terms of sustainability. The sustainability of the service is computed as a mix of environmental, social, and operational impact. In particular, we show the changes in the solutions with respect to the operational cost, the quality of service (in terms of the number of parcels per hour (nD/h)) and the environmental cost. In this respect, we consider the CO2 emissions and costs of the overall last-mile chain. According to the latest regulation, the ISO/TS 14067:2013 "Greenhouse gases - Carbon footprint of product - Requirements and guidelines for quantification and communication", we consider three types of emissions: direct emissions from the fuel combustion process, indirect emissions, emitted by the fuel production process and the long-haul shipment of the fuel, CO2 equivalent to include other pollutants (e.g., NOx).

We consider the case of five timeslots and three vehicles types and, concerning the customers' behaviour, three different scenarios, according to the Moore technology adoption curve (Moore, 2014):

Table 8: Sustainability analysis

| Market condition | $\alpha$ = 15% | | |
|---|---|---|---|
| | **Costs [Euro]** | **CO2 savings [ton]** | **nD/h [%]** |
| Current situation | 155747 (-37%) | 16.56 (-26%) | 13% |
| Downturn | 97943 (-24%) | 15.48 (-24%) | 8% |
| Growth | 112489 (-24%) | 19.8 (-32%) | 18% |
| **Market condition** | $\alpha$ = 50% | | |
| | **Costs [Euro]** | **CO2 savings [ton]** | **nD/h [%]** |
| Current situation | 204129 (-45%) | 20.88 (-31%) | 11% |
| Downturn | 1745294 (-36%) | 18.36 (-26%) | 10% |
| Growth | 2231202 (-36%) | 23.04 (-37%) | 15% |
| **Market condition** | $\alpha$ = 85% | | |
| | **Costs [Euro]** | **CO2 savings [ton]** | **nD/h [%]** |
| Current situation | 224480 (-51%) | 25.92 (-29%) | 14% |
| Downturn | 201675 (-43%) | 24.12 (-23%) | 9% |
| Growth | 250611 (-55%) | 33.48 (-38%) | 21% |

- Early phase of the penetration of the timeslot free choice service. It corresponds to the middle of the "scale-up" phase of the innovation sigmoid, which corresponds to $\alpha = 15\%$;
- Market penetration of the timeslot free choice service. It corresponds to the beginning of the "compete" phase of the innovation sigmoid, which corresponds to $\alpha = 50\%$;
- Maturity of the timeslot free choice service. It corresponds to the end of the "compete" phase of the innovation sigmoid, which corresponds to $\alpha = 85\%$.

Table 8 reports the results of the sustainability analysis: the savings of the total cost (Column 3), CO2 savings (Column 4), and nD/h (Column 5). All the savings are reported in terms of percentage gap with respect to the single-echelon scenario. For the total cost, the savings are computed for the satellite by considering 360 working days. For CO2 we also report the ton gained by the usage of the green vehicles compared to the fossil-fueled ones. As for the total costs, the CO2 saving is computed per year with 360 working days.
From a pure cost point of view, there is a reduction of the gain in the case of a downturn of the e-commerce, due to the relative reduction of the number of small orders. This led to a reduced number of cargo bikes, and thus an increase in CO2 emissions. The e-commerce market growth increases the number of cargo bikes needed to cope with the higher flows of mailers and small orders, with a consequent increase in the operative costs. Generally speaking, the adoption of the shared satellite with crowdsourced delivery leads to a consistent decrease of the operational costs compared to the traditional delivery, with a gain up to the 55% in the case of the largest diffusion of the service. Notice that, being this phase associated with the "compete" phase of the technological penetration sigmoid, this reduction becomes more crucial. It gives the companies adopting such a scheme in the early phase of their life a competitive advantage in terms of cost structure and know-how. The nD/h increases, in line with the results by Perboli and Rosano (2019), with an efficiency gain which is quite constant. Finally, we can notice how the need for

more flexible solutions is in line with the increasing adoption of more eco-friendly solutions, as cargo bikes and electric vans in the present, and drones, small automatic vehicles and automated mobile lockers in the near future.

## 6. Conclusions and future research directions

In this paper, we addressed a new emerging problem in urban delivery and city logistics, namely the joint management of satellite and the delivery process. The process is modeled as a novel variant of the bin packing problem. The model introduced can be solved to optimality for instances with limited size. For larger instances, with up to 2000 orders, efficient heuristics have been proposed and tested. The paper has also provided a detailed analysis of the impact of the emerging aspects of the on-demand economy, focusing in particular on the customers' choices of the delivery timeslots, highlighting the potential benefits of understanding the customers' choice behavior patterns. The analysis of findings indicates the compelling need for an accurate consumer's preference structure analysis. The managerial insights coming from this work will be part of the new Logistics and Mobility Plan to be activated in 2022 in the Piedmont region.

Future research directions come along different axes. First, we would like to investigate the impact of having multiple timeslots in a more general problem, e.g., the generalized bin packing problem. This problem is strictly related to the revenue management aspect, and thus to the business modeling (Baldi et al., 2012). The second direction is related to the stochastic nature of some parameters when the model is used as a strategic tool. They include the delivery costs, as well as the customers' preferences. Third, different methodological improvements might be investigated. Promising directions are the usage of Constraint Programming, which might be useful in very constrained settings, as well as Column Generation and Branch & Price approaches. Finally, the impact of the tariff definition process should be explored. That might be done by a combinatorial bilevel programming approach to model the hierarchical decision-making process.

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