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CIRRELT-2020-27

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July 2020

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Capacity Planning with Uncertainty on Contract Fulfillment

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Abstract. This paper focuses on the tactical planning problem faced by a shipper which seeks to secure transportation and warehousing capacity, such as containers, vehicles or space in a warehouse, of different sizes, costs, and characteristics, from a carrier or logistics provider, while facing different sources of uncertainty. The uncertainty can be related to the loads to be transported or stored, the cost and availability of ad-hoc capacity on the spot market in the future, and the availability of the contracted capacity in the future, when the shipper needs it. This last source of uncertainty on the capacity loss on the contracted capacity is particularly important in both long-haul transportation and urban distribution applications, but no optimization methodology has been proposed so far. We introduce the Stochastic Variable Cost and Size Bin Packing with Capacity Loss problem and model that directly address this issue, together with a metaheuristic to efficiently address it. We perform a set of extensive numerical experiments on instances related to long-haul transportation and urban distribution contexts, and derive managerial insights on how such capacity planning should be performed.

Keywords: Capacity planning, stochastic programming, City Logistics, last-mile delivery, long-haul freight transportation, supply chain management

Acknowledgements. Partial funding for this work was provided by the Natural Sciences and Engineering Council of Canada (NSERC) through its Discovery Grants Program. While working on this paper, the first author was Adjunct Professor, Department of Computer Science and Operations Research, Université de Montréal, Québec, Canada, and the second author was the head of the Urban Mobility and Logistics Systems (UMLS) initiative of the interdepartmental Center for Automotive Research and Sustainable mobility (CARS) at Politecnico di Torino, Turin, Italy. The authors are grateful to Ms. Diane Larin for her invaluable linguistic and editorial assistance.

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Dépôt légal – Bibliothèque et Archives nationales du Québec
Bibliothèque et Archives Canada, 2020

1 Introduction

Ensuring the reliability and flexibility of supply chains is a great challenge for managers, who are involved in various collaborations with several supply-chain partners and must perform complex planning processes on different decision levels, e.g., operational, tactical, and strategic. In this paper, we address a variant of the l*ogistics capacity planning* problem where specific constraints related to the contracts with external logistics partners are considered and there is uncertainty related to the availability of the contracted capacity.

Generally, manufacturing and distribution firms do business with logistics service providers, bypassing in the process the direct negotiations with carriers. Consequently, for the sake of simplicity of exposition, but without loss of generality, we refer to the *shipper* as a retail firm, a producer or a supplier of goods that requires capacity (e.g., containers, ship or train slots, vans, motor carrier tractors or warehousing space) to either store or transport its raw materials, intermediate or final products to meet customer demands. We identify as the *carrier* a service provider (which could include a third-party logistics company) providing the transportation and warehousing services. Considering the required regularity in the operations conducted in supply chains and their cost-efficiency goals, the shipper often negotiates in advance a tactical plan to secure the needed capacity to perform recurring activities (e.g., monthly) over a given planning horizon (e.g., one year). On the one hand, this tactical plan guarantees both a regular volume of business to the carrier and the availability of the booked capacity to the shipper. On the other hand, the result of this negotiation is a medium-term contract signed in an uncertain environment. In this case, the uncertainty is related to the demand, e.g., number, weight, and volume of freight, on the one hand, and the cost and availability of the contracted and ad-hoc (to be used if needed) capacity.

This paper aims to analyze the possible implications of contractual policies and the effects of considering these sources of uncertainty explicitly in the capacity planning. In doing so, we address this topic from two points of view.

First, a *methodological perspective*. When surveying the literature, one observes that very few studies have addressed capacity planning problems under uncertainty in logistics applications. Furthermore, when the subject of solving capacity planning problems occurring between shippers and carriers has been studied, such studies have mainly focused on the operational decisions, with only a few exceptions dedicated to strategic and tactical planning applications (Crainic et al., 2014, 2016). Moreover, to the best of our knowledge, there are no studies that address all the above-presented issues in a single model, including the different sources of uncertainty, which are relevant to both the long-haul transportation and urban distribution contexts. In particular, the case where there is uncertainty on the availability of the contracted capacity at the moment when operations are to be conducted is completely novel. Consequently, this paper aims to fill this gap by:

1. Presenting an integrated model that considers several stochastic issues affecting capacity planning. In particular, we model the described problem as the *Stochastic Variable Cost and Size Bin Packing* problem with *Capacity Loss,* extending the literature (Crainic et al., 2016) by including the possibility that the contracted capacity turns out to be lower than planned. The proposed model thus explicitly represents the uncertainty affecting the actual volume of the contracted capacity resources.

2. To overcome the computational limitations of standard progressive hedging methods, the model is solved by a specific progressive hedging-based metaheuristic.

3. Conducting an extensive set of computational experiments, using data that reflects the main issues involved in the problem for both the urban distribution and the long-haul transportation contexts, to assess how various sources of uncertainty affect capacity planning (especially the random variability related to contracted capacity).

Second, we also take a *managerial perspective*. The logistics capacity planning problem represents a significant issue in supply chain management (especially when considering transportation and warehousing services), due to its huge impact on the distribution and operating costs of the company involved (Crainic et al., 2016). Moreover, ignoring the stochastic factors could potentially results in poor service quality and high operational costs (Lium et al., 2009). Thus, we show that governing uncertainty in this complex system, using appropriate methods and models, could aid the firms in achieving high performance levels both in terms of service quality and economy efficiency. Thus, thanks to a better operations management, the firms could make profits while containing costs, which still represent one of the major decision factors in the supply chain management, gaining competitive advantage in the long-run.

The tactical capacity planning problem we address is relevant in many contexts, in particular urban distribution and long-haul transportation operations. These two settings are affected by new business models and world-wide economic phenomena. Consider, to illustrate, the case of urban distribution where we observe the continuous growth of e-commerce that is driven by the desires of customers to have their purchased goods delivered both fast and cheap. To answer these needs, enterprises (e.g., the e-commerce giant platforms Alibaba (Alibaba, 2018) and Amazon (Amazon, 2018)) are moving from a push cost-driven supply model to a time and cost pull-driven approach, that is, to demand-driven logistics. To implement such an approach, distribution centres are often built close to urban areas to enable distribution operations to be performed, either through private or, more often, contracted capacity. The latter thus justifies the need to contract in advance the required distribution capacity (Crainic et al., 2016).

Concurrently, globalization and the opening of broad free-trade economic zones have changed logistic chains dramatically. A higher volume of long-haul transportation operations are now required to be planned and performed by organizations everywhere. On the one hand, such operations have been reorganized around the use of bigger warehouses, and the movements of goods are now performed over longer distances involving different modes of transportation (Perboli et al., 2017; Giusti et al., 2018). On the other hand, the liberalization of economies has increased the competition between firms and, in the process, the attention to controlling costs (especially transportation costs).

For example, a North American company that regularly buys its products from various suppliers in China will move the products through a few maritime ports. In such a case, consolidation will be required to perform the intermodal shipments that will ensue. Specifically, such shipments will involve maritime, rail and/or road transportation. Goods will thus be sequentially packed into various containers (ship-containers, wagons and trucks) that are necessary to perform the temporary storage and transportation operations that will bring the goods to their final destination. Therefore, in this context, the company is required to contract and secure both the necessary transportation and warehousing capacities, which are supplied by different carries and logistics providers.

The remainder of this paper is organized as follows. We present the logistics capacity-planning problem we address in Section 2. We then present the two-stage stochastic formulation of the problem and the metaheuristic solution approach to address it in Sections 3 and 4, respectively. Section 5 is dedicated to the experimental plan and the analyses of the computational results with focus on the benefits of considering uncertainty in the capacity-planning process. The structure of the capacity plan under various problem settings and the derived managerial insights are the topic of Section 6. Finally, we provide the concluding remarks in Section 7.

2 Tactical planning to secure capacity of multiple types under uncertainty

This section introduces the logistics capacity planning problem addressed in this paper. We first present the problem setting within two different contexts: *urban distribution* and l*ong-haul transportation*. We provide a compact description of the general problem in the third subsection.

2.1 Urban distribution

Urban distribution refers to the overall process by which freight is transported both to and from dense urban environments. Oftentimes, such a process is performed through a multi-tier urban transportation system, or city logistics system, see (Crainic et al., 2009). 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). City logistics is based on the application of 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. In this case, the use of multiple transportation tiers enables the system to utilize specifically adapted infrastructure and specialized fleets at each tier to better attain the overall goal that is pursued.

In a two-tier system, see (Crainic et al., 2009), the first tier includes a set of City Distribution Centers (CDCs), which are usually located on the outskirts of the city and whose function is to serve as the entry points for the inbound (and outbound) freight. In the following, in an effort to simplify the exposition, we discuss the inbound case only. However, similar arguments can be evoked when considering the outbound freight. In a two-tier system, long-haul transportation vehicles deliver their cargo at the CDCs, where the delivered loads are sequentially sorted and then consolidated into smaller vehicles (i.e., urban trucks). The second tier includes a set of satellites (that serve as transhipment platforms), where the loads coming from the CDCs can be transferred to vehicles that are specifically adapted to perform distribution operations in dense urban zones (i.e., city freighters).

The transportation performed at the first tier will bring the loads located at the CDCs to the satellites. This is done while imposing specific rules on the moves that are performed by the urban trucks to limit their negative impacts (e.g., urban trucks will move along specific paths that are chosen to efficiently reach satellites while minimizing congestion). At the second tier, the loads are distributed from the satellites to their final destination within the city. City freighters, which are significantly smaller vehicles, are then allowed to travel throughout the city's road network to perform the deliveries. Two-tier systems are thus able to distribute freight in urban areas in a more efficient overall way, but the planning of such systems pose important challenges to managers at all decisional levels (strategic, tactical and operational).

As previously mentioned, the principle of consolidation is central to how two-tier city logistics systems operate. In both transportation tiers, loads are consolidated in vehicles (i.e., urban trucks and city freighters) that are then used to move the freight within the city. Tactical capacity planning is thus required to ensure that such consolidation can be efficiently performed. Specifically, managers must secure (through contracts with carriers) the required number and types of vehicles that will be available at each tier to correctly perform the transportation operations. It should be noted that there are now various types of environmental-friendly vehicles, such as cargo-bikes (Perboli et al., 2018), that can be used in city logistics systems. Such vehicles have varying characteristics (e.g., capacity) that must be considered when performing the capacity planning. A further source of complexity for this capacity planning context is the common incidents that occur (e.g., accidents or mechanical failures) and that result in booked vehicles not being available on a given day. Such incidents can significantly disrupt the operations of the system considering that certain loads can remain undelivered for a period of time. In turn, this further compounds the problems associated with not having booked sufficient capacity to perform the required transportation operations. The optimization model that is developed in the present paper enables this type of stochastic capacity loss to be integrated in the capacity planning that is performed.

2.2 Long-haul transportation

Long-haul transportation is another context in which capacity losses can randomly occur. Let us consider the case of a shipper (i.e., a manufacturing firm, wholesaler or retailer) that acquires resources, or products, from a set of suppliers located in distant regions according to their specific global procurement process. In such a case, the shipper must secure in advance the required number of containers (e.g., maritime or intermodal) to perform the long-haul transportation to deliver the resources (or products) to the shipper's warehousing facilities.

In (Crainic et al., 2013), the authors present the specific case of a North American hardware and home-improvement wholesale-retail chain that regularly imports a large variety of products from a set of suppliers located in South-East Asia. The imported products are thus moved in maritime containers that are shipped from a port of origin in South-East Asia to a port of destination located in North America. In this context, the retail chain must negotiate with a carrier a tactical capacity plan to book the needed containers to perform regular shipments for a given time horizon. For example, such a tactical capacity plan will reserve a set of containers to be available on a ship that will travel between the ports of origin and destination on a specific schedule (e.g., once a week) for the next semester. Depending on the details of the contract binding the retail chain and the carrier (e.g., the booked containers are exclusively used by the retail chain, or, they may be shared among multiple clients of the carriers) random changes may be observed regarding the planned capacity. Therefore, on a given week where the carrier is required to move a high volume of freight (aggregating the shipments of multiple clients) the planned capacity may not be fully available for the specific needs of the retail chain. Consequently, stochastic capacity losses must again be considered in the planning process.

2.3 Problem description

As previously stated and observed in the two described applications, capacity planning is a challenge involving tactical decisions in supply chain management. In general terms, the logistics capacity planning problem addressed in this paper concerns a shipper that needs to secure capacity of different types from a carrier, to meet its demand. The capacity types could be transportation modes (e.g., ship or train slots, containers, space in cargo bikes or vans) and carriers or warehousing space, and each type has different characteristics, such as the cost, size and functionalities (e.g., refrigerated containers). The shipper negotiates this capacity of multiple types in advance, and it will use it to perform repeatedly the activities (e.g., every week, every month), over a certain planning horizon (e.g., one semester, one year). The output of this negotiation is a medium-term contract that includes the quantity of capacity and the clauses concerning additional logistics services. Given the time lag that usually exists between the signing of the contract and the logistics operations, there is uncertainty affecting the contract negotiation (Crainic et al., 2016).

The first source of uncertainty is the demand. In fact, whenever the plan is applied, the overall demand can fluctuate and goods with different characteristics than what was predicted may need to be delivered, resulting in insufficient booked capacity on the shipping day (i.e., compromising the fulfillment of the contract). In the present paper we assume that, if the overall demand is lower than estimated, it is not allowed to deploy re-selling strategies of the overcapacity on the market.

Another source of uncertainty is the availability (e.g., number and precise characteristics) and the actual cost of the contracted capacity each time the contract is applied. In fact, due to unfavourable situations (e.g., mechanical failures of vehicles or damage), the capacity may be entirely or partially unavailable at the shipping day and thus lower than what was planned. These situations require the negotiation of additional capacity procured through the spot market, and an adjustment of the plan (e.g., rearrange and realocate loads). However, additional capacity may not be available when required as well, and thus must be considered stochastic. In case of unavailability of the booked capacity, additional costs are incurred to rearrange loads and store goods. These costs depend on the goods to relocate and can thus be considered proportional to the total lost capacity. Therefore, due to its impact on the operational and economic performance of a company, the problem of losses in planned capacity cannot be ignored, and the actual volume of the capacity resource must be considered stochastic.

Most of the research studies that have been conducted on this subject deal only partially with the requirements of capacity planning (only a few have focused on stochastic capacity planning and the different sources of uncertainty involved). The papers by Crainic et al. (2016, 2014) propose first attempts to address capacity planning problem settings found in strategic and tactical applications. In particular, the authors present two versions of the Stochastic Variable Cost and Size Bin Packing Problem (SVCSBPP) in the long-haul transportation context. In these problems, the uncertainty related to the demand (i.e., loads to be transported) and the capacity availability on the spot market was explicitly considered. However, to the best of our knowledge, the uncertainty affecting the availability of booked capacity has not yet been considered in the literature. Moreover, there are no studies addressing all the above-presented issues in a single model, which can be applied and validated in both the long haul transportation and urban distribution applications.

Therefore, we aim to fill this gap by proposing a new optimization model for the capacity planning problem described in this section. This model takes the form of a stochastic bin packing problem, called the *Stochastic Variable Cost and Size Bin Packing with Capacity Loss* (*SVCSBP-LS*) problem, which generalizes prior work on the Stochastic Variable Cost and Size Bin Packing problem proposed by Crainic et al. (2016), which assumes that all the booked capacity is available at the shipping or storage date. However, following the discussion above, such an assumption is unlikely to be observed in the urban distribution and the long-haul transportation contexts. The proposed SVCSBP-LS model will take into account the actual volumes of the contracted resources as stochastic parameters.

3 The SVCSBP-LS model formulation

This section is dedicated to present the SVCSBP-LS model as a two-stage stochastic programming formulation with recourse (Birge and Louveaux, 1997). The first stage concerns the tactical planning decision as the selection *a priori* of the capacity to be made available to move or store the estimated demand of loads, called items. This capacity is expressed in terms of bins characterized by a specific type, volume, and fixed cost defined by the contract (e.g., containers, boxes, vans, etc.). The fixed cost represents a specific price offered by the carrier, and its value is affected by different factors such as bin size and type (e.g., refrigerated bin), additional services, and the time period. The second stage refers to the operational decisions, i.e., the recourse actions that concern the adjustments and thus the acquisition of additional capacity (extra bins) when the actual demand information is revealed. These actions are carried out repeatedly over the planning horizon to cope with unfavorable situations, here defined as random events, which affect the result of the first stage (i.e., booked capacity not sufficient or not available). The extra bins must be purchased at spot-market value, i.e., a higher cost than the fare negotiated initially (Crainic et al., 2016).

Let T be the set of bin types, which are defined according to the volume and fixed cost associated with the bins that are available at the first stage. For $t \in T$, let V^t and f^t be respectively the volume and fixed cost associated with bins of type t. We define

$\mathcal{J}^t$ to be the set of available bins of type t and $\mathcal{J} = \bigcup_t \mathcal{J}^t$ to be the set of available bins at the first stage.

Let set Ω be the sample space of the random event, where $\omega \in \Omega$ defines a particular realization. The vector ξ contains the stochastic parameters defined in the model, and $\xi(\omega)$ represents a given realization of this random vector. Let y_j^t be the first-stage variable, which is equal to 1 if bin $j \in \mathcal{J}^t$ is selected and 0 otherwise.

We define c^t as the extra cost to pay for the loss of a unit of capacity in the first-stage bin of type $t \in T$. This cost is the additional cost required to react to the reduction of the available volume of first-stage bins, rearranging the loads or the storage of goods.

Moreover, let $\mathcal{T}$ be the set of bin types available at the second stage, and V^τ be the volume of bins of type $\tau \in \mathcal{T}$.

We consider the following stochastic parameters in $\xi(\omega)$: $\mathcal{V}_j^t(\omega)$, the actual volume of first-stage bin $j \in \mathcal{J}^t$ of type t, where $0 \leq \mathcal{V}_j^t(\omega) \leq V^t$; $\mathcal{K}^\tau(\omega)$, the set of available bins of type τ at the second stage; $\mathcal{K}(\omega) = \bigcup_\tau \mathcal{K}^\tau(\omega)$, the set of available bins at the second stage; $g^\tau(\omega)$, the cost associated with bins of type $\tau \in \mathcal{T}$; $\mathcal{I}(\omega)$, the set of items to be packed; and $v_i(\omega)$, $i \in \mathcal{I}(\omega)$, the item volumes.

The second-stage variables are defined as follows: $z_k^\tau(\omega) = 1$ if bin $k \in \mathcal{K}^\tau(\omega)$ is selected, 0 otherwise; $x_{ij}(\omega) = 1$ if item $i \in \mathcal{I}(\omega)$ is packed in bin $j \in \mathcal{J}$, 0 otherwise; $x_{ik}(\omega) = 1$ if item $i \in \mathcal{I}(\omega)$ is packed in bin $k \in \mathcal{K}(\omega)$, 0 otherwise.

The two-stage SVCSBP-LS model may then be formulated as:

$$\min_y \sum_{t \in T} \sum_{j \in \mathcal{J}^t} f^t y_j^t + E_\xi \left[Q\left(y, \xi(\omega)\right) \right] \tag{1}$$

$$\text{s.t.} \quad y_j^t \geq y_{j+1}^t, \qquad \forall t \in T, j = 1, \ldots, |\mathcal{J}^t| - 1, \tag{2}$$

$$y_j^t \in \{0, 1\}, \qquad \forall t \in T, j \in \mathcal{J}^t. \tag{3}$$

where

$$Q(y, \xi(\omega)) = \min_{z(\omega), x(\omega)} \sum_{\tau \in \mathcal{T}} \sum_{k \in \mathcal{K}^\tau(\omega)} g^\tau(\omega) z_k^\tau(\omega) + \sum_{t \in T} \sum_{j \in \mathcal{J}^t} c^t (V^t - \mathcal{V}_j^t(\omega)) y_j^t \tag{4}$$

$$\text{s.t.} \quad \sum_{j\in\mathcal{J}} x_{ij}(\omega) + \sum_{k\in\mathcal{K}(\omega)} x_{ik}(\omega) = 1, \qquad \forall i \in \mathcal{I}(\omega), \tag{5}$$

$$\sum_{i\in\mathcal{I}(\omega)} v_i(\omega)x_{ij}(\omega) \le \mathcal{V}_j^t(\omega)y_j^t, \qquad \forall\, t \in T, j \in \mathcal{J}^t, \tag{6}$$

$$\sum_{i\in\mathcal{I}(\omega)} v_i(\omega)x_{ik}(\omega) \le V^\tau z_k^\tau(\omega), \qquad \forall\, \tau \in \mathcal{T}, k \in \mathcal{K}^\tau(\omega), \tag{7}$$

$$x_{ij}(\omega) \in \{0,1\}, \qquad \forall\, i \in \mathcal{I}(\omega), j \in \mathcal{J}, \tag{8}$$

$$x_{ik}(\omega) \in \{0,1\}, \qquad \forall\, i \in \mathcal{I}(\omega), k \in \mathcal{K}(\omega), \tag{9}$$

$$z_k^\tau(\omega) \in \{0,1\}, \qquad \forall\, \tau \in \mathcal{T}, k \in \mathcal{K}^\tau(\omega). \tag{10}$$

The objective function (1) minimizes the sum of the total fixed cost of the tactical capacity plan and the expected cost associated with the extra capacity added during the operation.

Packing problems usually present a strong symmetry in the solution space, and two solutions are considered symmetric (and equivalent) if they involve the same set of first-stage bins in different orders. However, when we consider the available capacity of first-stage bins as a source of uncertainty, this is no longer true. Indeed, each bin of type $t \in T$ may have a different volume, and we need to characterize it properly. We thus introduce constraint (2) to break the symmetry and ensure order in the selection of bins of type $t \in T$, i.e., bin $j \in \mathcal{J}^t$ can be selected at the first stage only if bin $j-1 \in \mathcal{J}^t$ has already been selected. Finally, constraint (3) imposes the integrality requirements on y.

In the second stage, the term $Q\left(y, \xi(\omega)\right)$ represents the extra cost paid for the capacity that is added at the second stage, given the tactical capacity plan y and the vector $\xi(\omega)$. Thus, the objective function (4) minimizes the sum of the cost associated with the extra bins selected at the second stage and the additional cost paid because of the overall lost capacity. Constraint (5) ensures that each item is packed in a single bin. Constraints (6) and (7) ensure that the total volume of items packed in each bin does not exceed the actual volume of the first and second-stage bins. Finally, constraints (8) to (10) impose the integrality requirements on all second-stage variables.

4 Progressive hedging-based metaheuristic

The SVCSBP-LS is a difficult stochastic combinatorial optimization problem that generalizes the SVCSBPP (Correia et al., 2008; Crainic et al., 2016). We thus propose a metaheuristic for the SVCSBP-LS, based on the Progressive Hedging (PH) method (Rockafellar and Wets, 1991). The metaheuristic first applies scenario decomposition through augmented Lagrangian relaxation, which separates the stochastic problem by scenario. The resulting subproblems are much less complex than the complete formulation, which helps addressing more efficiently the overall problem that, otherwise, would require a significant computational effort. A solution to the stochastic model is then obtained through the following steps: (i) at each iteration, the subproblems are first solved separately, obtaining local solutions; (ii) a reference point, indicating the level of consensus among subproblem solutions, is calculated by using the weighted average of subproblem solutions; (iii) the values of the fixed costs of the bin types in the objective function are then adjusted, to promote consensus among the scenario subproblems with respect to the reference point, penalizing their dissimilarity.

Our metaheuristic extends the solution method of Crainic et al. (2016) for the simpler SVCSBPP in two major ways. First, it accounts for the different cost structure, leading to a specific procedure to adjust the costs in order to speed up the consensus process. Second, it efficiently handles the uncertainty on the bin volume, which may generate a huge number of bin types (each bin may have a different volume, leading to single-bin bin types) and scenario subproblems, through a soft variable-fixing strategy.

We re-write the SVCSBP-LS model (1)–(10) using scenario decomposition in Section 4.1, and present our PH-based metaheuristic in Section 4.2.

4.1 Scenario Decomposition

We reformulate the SVCSBP-LS two-stage model by discretizing the value space of the random variables through a set of representative scenarios $\mathcal{S}$, with p_s the probability of scenario $s \in \mathcal{S}$. We then apply scenario decomposition to the resulting multi-scenario deterministic problem.

The notation of the previous section is updated to account for the scenario definition. Thus, $y_j^{ts} = 1$ if bin $j \in \mathcal{J}^t$ of type $t \in T$ is selected in the first stage under scenario $s \in \mathcal{S}$, and 0 otherwise. We then have for the second stage, $\mathcal{K}^s = \bigcup_\tau \mathcal{K}^{\tau s}$, where $\mathcal{K}^{\tau s}$ is the set of extra bins of type $\tau \in \mathcal{T}$ in scenario $s \in \mathcal{S}$, and $\mathcal{I}^s$ the set of items to pack under scenario $s \in \mathcal{S}$. Similarly, $g^{\tau s}$ is the cost associated with bins of type $\tau \in \mathcal{T}$ in scenario $s \in \mathcal{S}$, $\mathcal{V}_j^{ts}$ the volume of first-stage bin $j \in \mathcal{J}^t$ under scenario $s \in \mathcal{S}$, and v_i^s the volume of item $i \in \mathcal{I}^s$ in scenario $s \in \mathcal{S}$. Finally, variable $z_k^{\tau s}$ is equal to 1 if and only if extra bin $k \in \mathcal{K}^{\tau s}$ of type $\tau \in \mathcal{T}$ is selected in scenario $s \in \mathcal{S}$, and x_{ij}^s, and x_{ik}^s are item-to-bin assignment variables for scenario $s \in \mathcal{S}$.

The SVCSBP-LS formulation (1)-(10) can then be approximated by the following deterministic model:

$$\min_{y,z,x} \sum_{s\in\mathcal{S}} p_s \left[\sum_{t\in T} \sum_{j\in\mathcal{J}^t} f^t y_j^{ts} + \sum_{\tau\in\mathcal{T}} \sum_{k\in\mathcal{K}^{\tau s}} g^{\tau s} z_k^{\tau s} + \sum_{t\in T} \sum_{j\in\mathcal{J}^t} c^t (V^t - \mathcal{V}_j^{ts}) y_j^{ts} \right] \quad (11)$$

$$\text{s.t.} \quad y_j^{ts} \geq y_{j+1}^{ts}, \qquad \forall\, t \in T, j = 1, \dots, |\mathcal{J}^t| - 1, s \in \mathcal{S}, \quad (12)$$

$$\sum_{j\in\mathcal{J}} x_{ij}^s + \sum_{k\in\mathcal{K}^s} x_{ik}^s = 1, \qquad \forall\, i \in \mathcal{I}^s, s \in \mathcal{S}, \quad (13)$$

$$\sum_{i\in\mathcal{I}^s} v_i^s x_{ij}^s \leq \mathcal{V}_j^{ts} y_j^{ts}, \qquad \forall\, t \in T, j \in \mathcal{J}^t, s \in \mathcal{S}, \quad (14)$$

$$\sum_{i\in\mathcal{I}^s} v_i^s x_{ik}^s \leq V^\tau z_k^{\tau s}, \qquad \forall\, \tau \in \mathcal{T}, k \in \mathcal{K}^{\tau s}, s \in \mathcal{S}, \quad (15)$$

$$y_j^{ts} = y_j^{ts'}, \qquad \forall\, t \in T, j \in \mathcal{J}^t, s, s' \in \mathcal{S}, \quad (16)$$

$$y_j^{ts} \in \{0, 1\}, \qquad \forall\, t \in T, j \in \mathcal{J}^t, s \in \mathcal{S}, \quad (17)$$

$$z_k^{\tau s} \in \{0, 1\}, \qquad \forall\, \tau \in \mathcal{T}, k \in \mathcal{K}^{\tau s}, s \in \mathcal{S}, \quad (18)$$

$$x_{ij}^s \in \{0, 1\}, \qquad \forall\, i \in \mathcal{I}^s, j \in \mathcal{J}, s \in \mathcal{S}, \quad (19)$$

$$x_{ik}^s \in \{0, 1\}, \qquad \forall\, i \in \mathcal{I}^s, k \in \mathcal{K}^s, s \in \mathcal{S}. \quad (20)$$

The objective function (11) and constraints (12)–(15) and (17)–(20) are self-explanatory (Section 3). Constraints (16) are the non-anticipativity constraints ensuring that the first-stage decisions are not tailored to each scenario in $\mathcal{S}$ and addressing the model yields a single implementable plan. The non-anticipativity constraints link the first-stage variables to the second-stage variables, and make the model not separable.

Applying the augmented Lagrangian-based scenario decomposition scheme proposed by Rockafellar and Wets (1991), the model is decomposed into deterministic VCSBPP subproblems with modified fixed costs $f_b^{\overline{\tau}s}$ and additional constraints (22) that ensure an order in the selection of bins of type $\overline{\tau} \in \overline{\mathcal{T}}$.

For each scenario s, let $\mathcal{B}^{\overline{\tau}s} = \mathcal{J}^{\overline{\tau}} \cup \mathcal{K}^{\overline{\tau}s}$ be the set of available bins of type $\overline{\tau}$ in the subproblem and $\mathcal{B}^s = \bigcup_{\overline{\tau}} \mathcal{B}^{\overline{\tau}s}$ be the whole set of bins available in the subproblem. For $b \in \mathcal{B}^{\overline{\tau}s}$, let $\mathcal{V}_b^{\overline{\tau}s}$ be the actual volume of bin b (for $b \in \mathcal{K}^{\overline{\tau}s}$, $\mathcal{V}_b^{\overline{\tau}s} = V^{\overline{\tau}}$) and let $f_b^{\overline{\tau}s}$ define the fixed cost associated with bin b. The related decision variable becomes $y_b^{\overline{\tau}s} = 1$ if bin $b \in \mathcal{B}^{\overline{\tau}s}$ of type $\overline{\tau} \in \overline{\mathcal{T}}$ is selected, 0 otherwise. Moreover, x_{ib}^s is equal to 1 if item $i \in \mathcal{I}^s$ is packed in bin b, 0 otherwise.

The scenario subproblem for scenario $s \in \mathcal{S}$ becomes:

$$\min_{y,x} \quad \sum_{\overline{\tau} \in \overline{\mathcal{T}}} \sum_{b \in \mathcal{B}^{\overline{\tau}s}} f_b^{\overline{\tau}s} y_b^{\overline{\tau}s} \tag{21}$$

$$\text{s.t.} \quad y_b^{\overline{\tau}s} \geq y_{b+1}^{\overline{\tau}s}, \qquad \forall\, \overline{\tau} \in \overline{\mathcal{T}}, b = 1, \ldots, |\mathcal{B}^{\overline{\tau}s}| - 1, \tag{22}$$

$$\sum_{b \in \mathcal{B}^s} x_{ib}^s = 1, \qquad \forall\, i \in \mathcal{I}^s, \tag{23}$$

$$\sum_{i \in \mathcal{I}^s} v_i^s x_{ib}^s \leq \mathcal{V}_b^{\overline{\tau}s} y_b^{\overline{\tau}s}, \qquad \forall\, \overline{\tau} \in \overline{\mathcal{T}}, b \in \mathcal{B}^{\overline{\tau}s}, \tag{24}$$

$$y_b^{\overline{\tau}s} \in \{0, 1\}, \qquad \forall \overline{\tau} \in \overline{\mathcal{T}}, b \in \mathcal{B}^{\overline{\tau}s}, \tag{25}$$

$$x_{ib}^s \in \{0, 1\}, \qquad \forall\, i \in \mathcal{I}^s, b \in \mathcal{B}^s, \tag{26}$$

4.2 The PH-based heuristic for SVCSBP-LS

We sum up the metaheuristic, displayed in Algorithm 1, and refer to A for a detailed description.

The algorithm starts with the set of scenarios $\mathcal{S}$. It then builds a SVCSBP-LS solution in two phases. The first phase aims for consensus for the first-stage variables generated by the scenarios, consensus being defined as scenario solutions being similar with respect to first-stage bin-selection decisions. Then, if some disagreement among scenario may still be observed, a full solution to the SVCSBP-LS is computed in the second phase by fixing the first-stage variables for which consensus has been reached and solving the restricted formulation with a commercial software.

During Phase I, the scenario subproblems are solved separately and the overall capacity plan is then built combining the bin-selection subproblem solutions. A reference point is thus created through the aggregation of subproblem solutions by applying the expected value operator using the scenario probabilities. This yields a temporary overall capacity plan, which is then used to identify bins for which consensus may be achieved.

The search process is gradually guided toward scenario consensus. To induce consensus among the scenario subproblems, the fixed costs of the bins are adjusted in the objective function. In particular, the fixed costs of bin types of each scenatio are tuned according to the difference between the value of the bin-selection variables at the current iteration and the overall capacity plan. Thus, the fixed cost of a bin type is either increased or reduced depending on whether or not in the current scenario solution the bin type is overused or underused when compared to its usage in the overall capacity plan.

Two strategies are applied to update the fixed costs. The first is based on adjusting the Lagrangian multipliers to penalize the lack of consensus due to the differences in the

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Algorithm 1 PH-based metaheuristic for the VCSBP-LS

Phase 1
$\nu \leftarrow 0$; $\lambda_b^{\overline{\tau}s\nu} \leftarrow 0$; $\rho_b^{\overline{\tau}\nu} \leftarrow f^{\overline{\tau}}/10$;
while Termination criteria not met **do**
  For all $s \in \mathcal{S}$, solve the corresponding VCSBPP subproblem $\rightarrow y_b^{\overline{\tau}s\nu}$;
  Compute temporary global solution
    $\bar{y}_b^{\overline{\tau}\nu} \leftarrow \sum_{s\in\mathcal{S}} p_s y_b^{\overline{\tau}s\nu}$
    $\bar{\delta}^{\overline{\tau}\nu} \leftarrow \sum_{s\in\mathcal{S}} p_s \delta^{\overline{\tau}s\nu}$
  Penalty adjustment
    $\lambda_b^{\overline{\tau}s\nu} = \lambda_b^{\overline{\tau}s(\nu-1)} + \rho_b^{\overline{\tau}(\nu-1)}(y_b^{\overline{\tau}s\nu} - \bar{y}_b^{\overline{\tau}\nu})$
    $\rho_b^{\overline{\tau}\nu} \leftarrow \alpha\rho_b^{\overline{\tau}(\nu-1)}$
  if consensus is at least $\sigma_{\%}$ **then**
    Adjust the fixed costs $f^{\overline{\tau}s\nu}$ (according to (63));
  end if
  Variable fixing
    $\bar{\delta}_m^{\overline{\tau}\nu} \leftarrow \min_{s\in\mathcal{S}} \delta^{\overline{\tau}s\nu}$ and $\bar{\delta}_M^{\overline{\tau}\nu} \leftarrow \max_{s\in\mathcal{S}} \delta^{\overline{\tau}s\nu}$
    Apply variable fixing;
  $\nu \leftarrow \nu + 1$
end while
Phase 2
if consensus not met for a single bin type $\overline{\tau}'$ ($\bar{\delta}_m^{\overline{\tau}'} < \bar{\delta}_M^{\overline{\tau}'}$) **then**
  Identify the consensus number of bins δ of type $\overline{\tau}'$ by enumerating $\delta \in \left[\bar{\delta}_m^{\overline{\tau}'}, \bar{\delta}_M^{\overline{\tau}'}\right]$ (and variable fixing)
else
  Fix consensus variables in model (11)–(20);
  Solve restricted (11)–(20) model using a commercial solver.
end if

---

values of first-stage variables (see Crainic et al., 2016, for details). The second penalty-adjustment strategy is a heuristic, which directly tunes the fixed costs of bins of the same type to accelerate the search process when the overall solution is close to consensus. We introduce a soft variable -ixing scheme to guide the search process, restricting the number of bins of each type that can be used, through lower and upper bounds. This is equivalent to fixing a relevant set of single bin-selection variables, since all bins of a certain type $\overline{\tau}$ are ordered and the selection of bins follows this order. To speed up the algorithm, we stop the search and proceed to Phase 2, either when consensus is achieved for all bin types except one, type $\overline{\tau}'$ for which $\bar{\delta}_m^{\overline{\tau}'} < \bar{\delta}_M^{\overline{\tau}'}$, or when consensus is not achieved within a given maximum number of iterations (200 in our experiments).

Phase II computes the final solution solving a restricted SVCSBP-LS obtained by fixing the first-stage variables for which consensus has been reached (i.e., the bins used in all the scenario subproblems). Moreover, the range of first-stage variables for which consensus is not reached is reduced through the soft variable-fixing strategy. The resulting restricted problem is solved exactly with a commercial solver.

5 Experimental plan

We performed an extensive set of experiments with a threefold aim: 1) Analyze the new logistics capacity planning problem in the contexts of urban distribution and long-haul transportation, in particular, the relevance and impact of the capacity loss phenomenon we introduce and the corresponding uncertainty; 2) Measure the impact of uncertainty and the interest of building a stochastic programming model; 3) Study the relationship between the problem characteristics and parameters and the structure of the capacity plan, drawing managerial insights.

We begin by presenting the instance sets used to qualify our model and the solution procedure (Subsection 5.1). Subsection 5.2 then discusses the potential of considering uncertainty in the planning process, while Subsection 5.3 studies the issue from the point of view we introduce in this paper, the explicit consideration of the loss of capacity on contracted bins. Managerial insights are the object of Section 6.

5.1 Instance set

In this subsection, we provide a set of instances for the SVCSBP-LS and we present the instance generation process. Since, to the best of our knowledge, there is no prior study of the capacity planning problem with uncertainty on the actual volume of the contracted capacity, we generated new test instances for the SVCSBP-LS, based on previous work on bin packing problems (Monaci, 2002; Crainic et al., 2007, 2012, 2011, 2016; Gobbato, 2015).

Table 1 summarizes the parameters of the instances. Most parameters are self explanatory; a few require a bit of explanation.

The *bin availability* is assumed to be different at the time of the contract, the first stage, and when repeatedly executing the contract in the future, the second stage. We define the number of bins of each type $t \in T$ available at the first stage as the minimum number of bins of volume V^t needed to pack all items in the worst-case scenario (Crainic et al., 2016). Three availability classes, *AV1* - *AV3*, are defined for the second stage, representing different levels of variability. The first presents the largest variability, and its worst-case scenario may involve a limited number of extra bins. On the contrary, all the scenarios have the same availability of extra bins in the third class, equal to the first-stage availability. The second class stands for a middle-of-the-road situation.

Characteristic	Value - Parameters for all the problem settings	
Number of items	Uniformly distributed over $[100, 500]$	
Item volume	*Small* (S): uniformly distributed over $[5, 10]$	
	Medium (M): uniformly distributed over $[15, 25]$	
	Big (B): uniformly distributed over $[20, 40]$	
Bin types, with $\mathcal{T}$ is equal set T	Set *T3*: 3 bin types with volumes = 50, 100, 150	
	Set *T5*: 5 bin types with volumes = 50, 80, 100, 120, 150	
Bin availability 1st stage	$\|\mathcal{J}^t\|$ equal to $\lceil \frac{1}{V^t} \max_{s\in\mathcal{S}} \sum_{i\in\mathcal{I}^s} v_i^s \rceil$	
Bin availability 2nd stage	Class 1 (*AV1*): $\|\mathcal{K}^{ts}\|$ uniformly distributed over $[0, \|\mathcal{J}^t\|]$	
	Class 2 (*AV2*): $\|\mathcal{K}^{ts}\|$ uniformly distributed over $[\|\mathcal{J}^t\|/2, \|\mathcal{J}^t\|]$	
	Class 3 (*AV3*): $\|\mathcal{K}^{ts}\|$ equal to $\|\mathcal{J}^t\|$	
Bin costs 1st stage	$f^t = V^t(1 + \gamma^t,\ \gamma^t)$ uniformly distributed over $[-0.3, 0.3]$	
Bin costs 2nd stage	$g^\tau = f^t(1 + \alpha)$, $\alpha \in \{0.3, 0.5, 0.7\}$	
Capacity loss	*SL*: % of scenarios = $20\%, 40\%, 60\%, 80\%$	
	TL - Probability of a bin type = $0.5, 0.75, 1$	
	BL - % of overall loss for all 1st stage bins of a certain type= $20\%, 30\%, 40\%, 50\%, 60\%, 70\%$	
Unit capacity-loss cost	$c^t = \alpha^t f^t / V^t$, same α^t a for g^τ	
Characteristic	**Value - Parameters specific to each problem setting**	
	Long-haul transportation	*Urban distribution*
Capacity loss type	Uniform (U)	Localized (L)

Table 1: Parameters of SVCSBP-LS instances

The fixed costs of bins are assumed higher at the second stage from those at the time of contracting (built based on Correia et al., 2008), by a multiplying factor. Three values were used representing continuously increasing variations in the fixed costs.

Three parameters are used to represent the possible capacity loss on the contracted bins, from the global problem level to the individual bin-type level: 1) the percentage of *scenarios affected by capacity loss* (*SL*); 2) the probability that a *bin type* is affected by capacity loss (TL); 3) the percentage of the *overall capacity loss for all the bins of a certain type* selected in the first-stage (*BL*). Each parameter values represent an increasing level of potential capacity loss. The distributions used to generate these values are different for the two application cases. A *uniform* (U) capacity loss is assumed for long-haul transportation, reflecting the rather wide-spread inability to predict correctly the quality of the service that will be provided by carriers. The situation is different from urban distribution, and even more when city logistics systems are involved, as the relations with the service providers are generally smoother. We identify this type of capacity loss *localized* (L), i.e., only a few randomly-chosen first-stage bins lose their entire capacity and become unusable, while the others are unaffected. Localized capacity losses may be caused by mechanical failure of vehicles or other incidents, e.g., undelivered parcels during the previous operational day that were kept in the vehicle reducing the capacity for new demand to be loaded.

Finally, the unit additional due to capacity loss is set equal to the proportion of the overall loss of capacity among all first-stage bins of type t (BL).

Ten (10) random instances were generated for each combination of parameters, yielding a total of 51 840 instances. All the instances incorporate 100 scenarios. The number of scenarios was tuned in order to guarantee the in-sample and out-of-sample stability conditions and thus, ensures the reliability of the solutions when a different set of scenarios is considered (Crainic et al., 2016).

5.2 Assessment of the SVCSBP-LS model

As stated in Section 2, much of the literature does not consider uncertainty in capacity planning problems. Then, the question we address is whether modeling uncertainty explicitly, through the two-stage SVCSBP-L formulation with recourse, is beneficial compared to solving the deterministic variant of the problem only. Would the shipper gain by considering uncertainty, by the reduction in its overall expenses for the transportation and storage capacity plan? This would be important for the shipping industry where the marginal revenues are already low.

We use two classical and highly relevant measures in the literature (Birge, 1982). The *Expected Value of Perfect Information* (*EVPI*), representing the decision maker's willingness to pay for complete information about the future, and the *Value of the Stochastic Solution* (*VSS*) computing the difference between the solutions obtained by solving the deterministic problem with the expected value of the parameters (the expected value solution - *EEV*) and the stochastic SVCSBP-LS problem (*RP*). Tables 2 and 3 display the average and maximum results for the two measures, respectively, computed as a percentage with respect to the RP for the two instance sets (Column 1), bin-availability class (Column 2), and value of the increase in the future bin cost and capacity loss α (Column 3). Results are displayed for each application type (Columns 4 and 5 for urban distribution, Columns 6 and 7 for long-haul transportation).

Set	Availability	α	Urban distribution		Long-haul transportation	
			$EVPI$[%]	$EVPI_{max}$[%]	$EVPI$[%]	$EVPI_{max}$[%]
T3	**AV1**	**0.3**	13.98	60.76	22.20	77.35
		0.5	18.65	48.07	25.47	75.24
		0.7	21.97	36.69	26.80	74.27
	AV2	**0.3**	9.05	13.85	10.19	20.23
		0.5	15.26	19.12	16.14	29.96
		0.7	19.34	23.71	19.82	35.28
	AV3	**0.3**	9.47	14.52	10.11	20.30
		0.5	15.79	20.38	16.18	29.43
		0.7	19.90	24.61	19.91	35.95
T5	**AV1**	**0.3**	12.13	15.71	13.28	54.26
		0.5	17.73	21.24	19.16	50.83
		0.7	21.44	25.11	22.74	47.86
	AV2	**0.3**	8.09	13.62	9.61	19.27
		0.5	15.23	21.60	16.45	31.17
		0.7	19.59	25.32	20.40	36.60
	AV3	**0.3**	8.97	13.66	9.48	20.72
		0.5	15.84	19.88	16.57	30.17
		0.7	20.20	25.57	21.07	37.25

Table 2: EVPI for SVCSBP-LS with different availability classes, values of α, and types of capacity loss

For the sake of brevity, we discuss the results of these stochastic programming measures at a macro level, analyzing how they vary in long-haul transportation and urban distribution, depending on the availability of second-stage bins and the extra cost due to loss of capacity. The interested reader may refer to B for more detailed results and analysis.

The results show high values for using a stochastic formulation in all cases, i.e., high values for the additional insight about the future. This value increases with the cost of future capacity and the decrease in the availability of future capacity. The higher uncertainty of long-haul transportation is reflected in the higher information values. These results are confirmed by significant VSS values, double-digit gains in expected costs being obtained in most cases by using the stochastic SVCSBP-LS model. In both cases, the look-ahead capability offered by the stochastic formulation would mitigate the impacts of higher operation costs and missed or late deliveries due to loss of contracted capacity, and high costs for limited availability of ad-hoc capacity.

Set	Availability	α	Urban distribution		Long-haul transportation	
			VSS[%]	VSS_{max}[%]	VSS[%]	VSS_{max}[%]
T3	AV1	**0.3**	11.29	23.53	13.79	33.85
		0.5	8.37	20.04	10.58	31.47
		0.7	5.63	15.49	8.47	56.65
	AV2	**0.3**	15.75	44.49	17.57	55.13
		0.5	12.20	30.92	13.95	55.03
		0.7	9.41	38.24	12.59	80.40
	AV3	**0.3**	15.67	43.82	17.02	62.07
		0.5	10.34	35.99	13.52	50.98
		0.7	8.08	29.52	11.90	80.83
T5	AV1	**0.3**	12.00	29.73	14.50	38.40
		0.5	7.79	22.61	12.02	49.84
		0.7	4.93	16.35	9.88	74.71
	AV2	**0.3**	14.12	45.00	16.17	58.54
		0.5	9.95	31.21	12.93	63.77
		0.7	6.70	22.28	11.40	88.36
	AV3	**0.3**	14.54	33.51	17.96	57.93
		0.5	9.07	34.95	14.67	48.97
		0.7	5.34	27.67	11.48	63.08

Table 3: VSS for SVCSBP-LS with different availability classes, values of α, and types of capacity loss

We now examine to what extent the first-stage decisions of the SVCSBP-LS and EV formulation differ. As highlighted in Crainic et al. (2016), the EV problem generally overestimates the future demand, that is, a total item volume larger than the actual volume, and a larger set of available bins in the future. Moreover, when the percentage of scenarios affected by capacity loss and the probability of bin types being affected by capacity loss are low, the EV formulation underestimates the reduction of available capacity, meaning that the total volume of first-stage capacity predicted to be available at operation times is larger than the actual available volume. This behavior can lead to two undesired situations. First, the EV solution may include a set of bins which are not suitable for the set of scenarios considered. The capacity plan is then more expensive than necessary even when the solution is feasible and implementable. Second, the EV solution may include insufficient capacity for certain situations (subset of scenarios) in which the actual availability of bins is limited, yielding an unfeasible capacity plan for those situations.

The importance of the problem and parameter setting was further emphasized as we observed about 10% infeasible instances when the variability in future bin availability and cost is high (AV1), while most instances were feasible in the other settings. Table 4 details this observation, showing that when uniform losses are expected (availability class A1), the number of infeasible instances grows considerably with the variability in availability and cost. The issue is particularly sensitive when only a limited number of bin types is available on the market (up to 30% for sets T5 but 98.75% pour T3). These observations highlight the need for considering uncertainty in capacity planning when the availability of bins may be limited in the future.

5.3 Capacity loss and uncertainty

As stated, the uncertainty on the availability of contracted capacity at operations time is not addressed in the literature. Thus, this subsection is dedicated to studying how considering the possible loss in the planned/contracted capacity as a stochastic parameter is valuable. Table 5 compares the EVPI and VSS obtained for SVCSBP-LS to those of Crainic et al. (2016) where the possible capacity loss and its variability was not considered (the other sources of uncertainty are the same). The table shows for each bin type (Column 1), the average and maximum EVPI and VSS percentages without and with modeling of capacity loss for contracted bins, the latter for the urban distribution and long-haul transportation cases.

The results of both studies emphasize the usefulness of the stochastic formulations for capacity planning. Furthermore, taking into account the uncertainty of the capacity of contracted bins that will be available at operations time increases significantly both the average and maximum values of EVPI and VSS for all instances considered. We can therefore conclude that excluding this source of uncertainty from the stochastic model may lead to underestimate the capacity available at operations time and the additional costs one will have to support, and this, in both urban distribution and long-haul transportation contexts.

α	SL[%]	TL[%]	Set T3 - BL[%]			Set T5 - BL[%]		
			20-30	**40-50**	**60-70**	**20-30**	**40-50**	**60-70**
0.3	**20**	**50**	12.50	10.00	25.00	0.00	0.00	0.00
		75	10.00	20.00	47.50	0.00	0.00	0.00
		100	8.75	43.75	82.50	0.00	0.00	0.00
	40	**50**	12.50	12.50	32.50	0.00	0.00	0.00
		75	10.00	15.00	40.00	0.00	2.50	10.00
		100	6.25	25.00	77.50	0.00	5.00	22.50
	60-80	**50**	12.50	15.00	30.00	0.00	3.75	12.50
		75	10.00	17.50	12.50	1.25	16.25	28.75
		100	8.75	15.00	53.75	6.25	27.5	30.00
0.5	**20**	**50**	12.50	20.00	32.50	0.00	0.00	0.00
		75	10.00	22.50	70.00	0.00	0.00	0.00
		100	15.00	75.00	98.75	0.00	0.00	0.00
	40	**50**	15.00	20.00	32.50	0.00	0.00	0.00
		75	10.00	12.50	50.00	0.00	0.00	2.50
		100	8.75	52.50	98.75	0.00	0.00	25.00
	60-80	**50**	12.50	17.50	25.00	0.00	0.00	15.00
		75	10.00	12.50	35.00	0.00	13.75	26.25
		100	8.75	30.00	85.00	0.00	25.00	30.00
0.7	**20**	**50**	10.00	20.00	40.00	0.00	0.00	0.00
		75	5.00	35.00	100.00	0.00	0.00	0.00
		100	35.00	92.50	98.75	0.00	0.00	0.00
	40	**50**	10.00	20.00	30.00	0.00	0.00	0.00
		75	5.00	15.00	100.00	0.00	0.00	0.00
		100	10.00	77.50	100.00	0.00	0.00	5.00
	60-80	**50**	10.00	20.00	30.00	0.00	0.00	3.75
		75	5.00	15.00	55.00	0.00	2.50	23.75
		100	10.00	65.00	97.50	0.00	12.50	30.00

Table 4: % of infeasible instances for availability class AV1 in the long-haul transportation setting

Set	$EVPI[\%]$	$EVPI_{max}[\%]$	$VSS[\%]$	$VSS_{max}[\%]$
		No capacity loss		
T3	5.40	6.96	5.81	8.19
T5	5.72	7.45	6.74	8.23
		Uncertain capacity loss - urban distribution		
T3	15.93	29.08	10.73	31.34
T5	15.47	20.19	9.38	29.26
		Uncertain capacity loss - long-haul transportation		
T3	18.54	44.22	13.27	56.27
T5	16.53	36.46	13.45	60.40

Table 5: Capacity loss - EVPI and VSS comparison

6 Managerial insights

Having established that incorporating the concept of capacity loss and uncertainty in capacity planning can provide the shipper with competitive advantage through better operations management and reduced costs, we now discuss the structure of the capacity planning solutions. We study, in particular, how solutions vary depending on the attributes of urban distribution and long-haul transportation problem settings, with emphasis on the expected available volumes of contracted bins at operations time.

We base our analysis on comparing the results of SVCSBP-LS and those of Crainic et al. (2016), where the loss of capacity was not considered, on the following performance indicators

- Average number of bin types contracted in the capacity plan N_t;
- Average percentage of the total capacity needed which is booked at the first stage Cap_{FS};
- Average percentage of the objective function value achieved at the first stage Obj_{FS};

computed for all combinations of instance sets, availability classes, and the other characteristics of the sets.

Table 6 summarizes the variation intervals means for the first three measures for each capacity-planning solution according to the number of bin types (Column1) and the availability of extra bins on the spot market (Column 2). When the parameters that determine the actual volumes of first-stage bins are equal, the resulting structures of the capacity-planning solutions are the same for availability classes AV2 and AV3 and we thus present the results of instances with availability classes AV2 and AV3 together. For further details and complete tables concerning the figures and results reported in this section, the interested reader may refer to Lerma (2018).

No capacity loss								
Set	*Availability*	$Cap_{FS}range$	$Cap_{FS}mean$	$Obj_{FS}range$	$Obj_{FS}mean$	$N_t range$	$N_t mean$
T3	AV1	71.82%-83.96%	78.50%	63.38%-72.87%	68.56%	1.10-1.20	1.13
	AV2+AV3	60.81%-81.58%	72.91%	52.64%-70.86%	62.76%	1.00-1.10	1.03
T5	AV1	67.12%-83.61%	76.15%	59.21%-73.17%	66.84%	1.33-1.44	1.37
	AV2+AV3	65.62%-83.14%	74.53%	56.53%-72.56%	64.58%	1.00-1.20	1.03
Uncertain capacity loss - long-haul transportation							
Set	*Availability*	$Cap_{FS}range$	$Cap_{FS}mean$	$Obj_{FS}range$	$Obj_{FS}mean$	$N_t range$	$N_t mean$
T3	AV1	61.19%-82.85%	64.81%	48.45%-73.41%	60.39%	1.20-3.00	1.98
	AV2+AV3	0%-78.62%	42.89%	0%-68.40%	34.99%	0-1.70	0.93
T5	AV1	6.17%-81.12%	49.70%	4.87%-70.99%	40.33 %	0.30-3.00	1.60
	AV2+AV3	0%-81.25%	44.35%	0%-71.71%	36.42%	0-1.90	1.00
Uncertain capacity loss - urban distribution							
Set	*Availability*	$Cap_{FS}range$	$Cap_{FS}mean$	$Obj_{FS}range$	$Obj_{FS}mean$	$N_t range$	$N_t mean$
T3	AV1	66.38%-84.02%	74.39%	59.17%-75.32%	65.92 %	1.00-3.00	1.87
T5	AV1	55.25%-81.62%	72.01%	48.15%-72.14%	63.41%	1.30-3.90	2.18

Table 6: Comparative performance of capacity-planning solutions

When the capacity loss on contracted bins is not accounted for, the shipper books the capacity sufficient to limit the adjustments and costs when the actual demand becomes known. As observed previously (Crainic et al., 2016; Lerma, 2018), this plan tends in this case to mostly include bins of the same type, with only one or two bins of different types. This relates to the cost-orientation of the shipper who uses standardized bins tailored by the carrier to the shipper' needs to avoid the higher loading/unloading and handling costs generated by non-standardized loading schemes. Indeed, results in Table 6 show that, when the availability of second-stage bins is limited, the average number of bin types, N_t, increases slightly, reaching the maximum values of 1.20 for set T3 and 1.44 for set T5. Most capacity is booked (Cap_{FS} around 79%) and paid for (Obj_{FS} around 69%) at contracting time. It is worth noting, however, the large variance of all values.

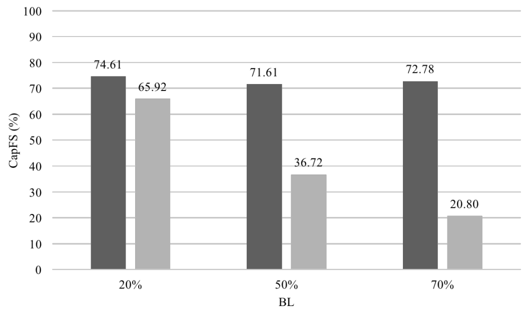
We now turn to examining to what extent and how the structure of the capacity plan changes when the shipping company takes into account the uncertain nature of capacity loss of contracted bins. The percentage of the total capacity needed which is booked at the first stage, Cap_{FS}, characterizes the capacity plan and its variation is a good indication of the structural changes brought by varying the problem definition. Table 7 displays the average Cap_{FS} values for long-haul transportation and urban distribution contexts for each set of bin types (Column 1), bin availability class in the second stage (Column 2), and capacity-lost cost (Column 3).

The results show the sensitivity of the capacity plan to the application context, the availability of extra bins on the spot market, the way capacity is lost and modeled, and the cost of the capacity loss. They thus illustrate the impact of these factors on the managerial decisions concerning how much capacity to contract. The sensitivity and impact are particularly strong in the long-haul transportation context where the capacity the shipper should contract in the first stage changes dramatically with the changes in problem parameters. In particular, when freight demand rises, the supply falls, and the cost of the spot market rates rise, the shipper may suffer from the higher second-stage costs and the methodology proposes to book in advance most of the required capacity. The costs of extra bins and capacity loss at operation time, modeled through the parameter α, impacts strongly the creation of safety buffers in the long-haul transportation context. Thus, the percentage of capacity contracted initially, Cap_{FS}, doubles when $alpha$ increases from 0.3 to 0.7. The situation is different in the urban distribution context, where the shipper should contract more of less the same high-value capacity in all cases. Notice that the percentage of capacity contracted initially is the same for all settings when the possibility of capacity loss is higher, irrespective of the number of bin types.

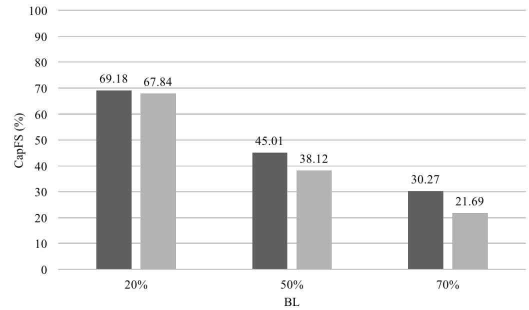
			Long-haul transportation	**Urban distribution**
Set	*Availability*	α	Cap_{FS}	Cap_{FS}
T3	AV1	0.3	35.44%	70.09%
	AV1	0.5	53.36%	78.44%
	AV1	0.7	69.03%	86.78%
	AV2+AV3	0.3	26.49%	61.24%
	AV2+AV3	0.5	42.01%	69.30%
	AV2+AV3	0.7	53.50%	75.01%
T5	AV1	0.3	30.32%	61.96%
	AV1	0.5	45.71%	70.43%
	AV1	0.7	57.01%	75.64%
	AV2+AV3	0.3	26.99%	62.98%
	AV2+AV3	0.5	42.91%	69.99%
	AV2+AV3	0.7	53.66%	76.16%

Table 7: Variation of Cap_{FS}, % of contracted capacity during the 1st stage, with problem parameters

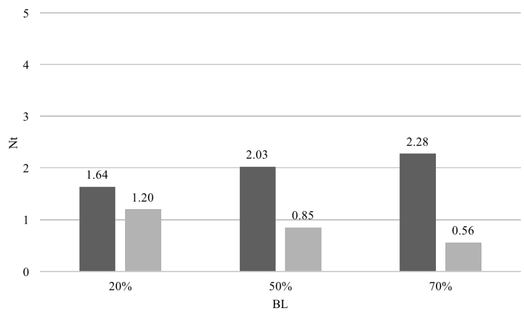
Figure 1 depicts the average values of the percentage of the capacity which is booked at the first stage, Cap_{FS}, and the average number of bin types contracted in the capacity plan, N_t, for the long-haul transportation context (where the capacity loss is uniformly distributed) for the sets T3 and T5, the availability classes AV1, dark gray, and AV2, light gray, and three levels of BL, the % of overall capacity loss for the contracted bins (low = 20%, medium = 50%, and high = 70%). The figure illustrates further the need in this case to book most of the capacity needed in the first stage, irrespective of the possibility of capacity loss at operation time. Moreover, the capacity plan includes several bin types, nearly in all the instances we addressed, the number increasing with the level of possible capacity loss. In practice, such a capacity plan would require, however, that attention be paid to the loading/unloading requirements of the different bin types; the complexity of such requirements should be reflected in the bin type cost.



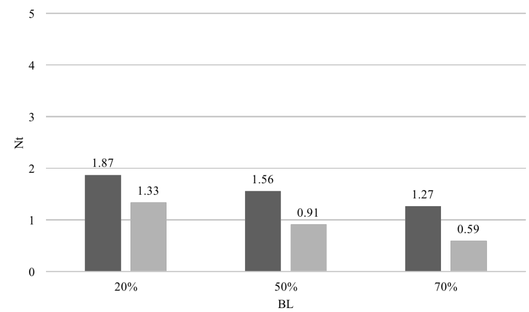
(a) *Cap_{FS} for instance set T3.*



(b) *Cap_{FS} for instance set T5.*



(c) *N_t for instance set T3.*



(d) *N_t for instance set T5.*

Figure 1: Average values of Cap_{FS} and N_t for capacity-loss levels, long-haul transportation setting, availability classes AV1 (dark gray) and AV2 (light gray)

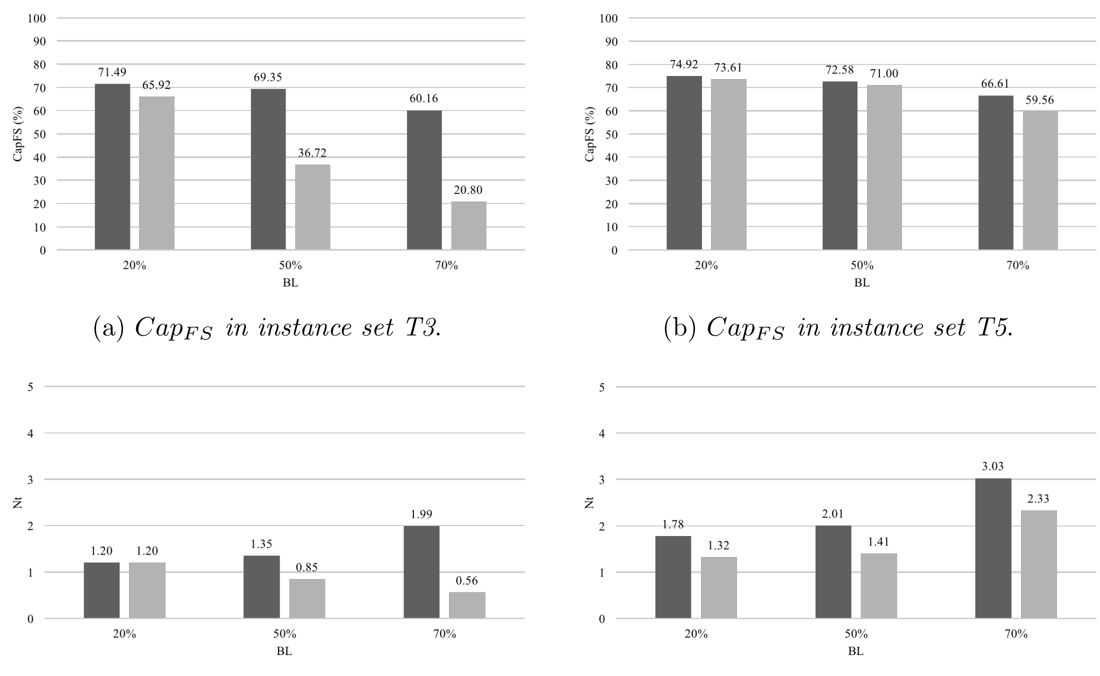
Some cases are of particular interest. First, when there are only three types of bins and the availability of the second-stage bins is limited (AV1), the structure of the capacity-planning solution is always the same, regardless of the likelihood and amplitude of capacity loss and the plan books in advance almost all the capacity needed for the planning horizon.

The second case worthy of interest is when the probability of loosing a large amount of capacity is high. Given the risk of a limited availability of extra bins in the future and the obligation to satisfy the demand, the plan leads in this case to increase the percentage of capacity booked in advance, even though the cost of bins and capacity loss is higher. As illustrated in Figure 1 parts a and b, this increase is much more significant when the number of bin types is low.

The third case concerns the availability of bins in the future as represented through the classes AV1 - AV3. When the predicted level of availability is high, as in class AV2, the capacity plan that is based mainly on the premium cost of extra bins and capacity loss (parameter α), and varies considerably depending on the value of the predicted capacity loss for the contracted bins (parameter BL). The percentage of capacity contracted (first stage) increases with the premium cost and decreases as the BL increases. The latter behaviour corresponds to the realization that there is little value in booking in advance capacity that one will loose for the most part when it will be necessary to use it.

Finally, in the long-haul transportation context, the average number of bin types selected when the contract is established (N_t) increases with α and is particularly sensitive when the number of bin types is relatively low and the predicted future availability is highly uncertain (class AV1). When the latter is not a concern, most of the bins included in the capacity plan are of the same type (the value of N_t is always below 1.9), irrespective of the variations in the other problem parameters.

We now turn to the urban distribution context, where the capacity loss is "localized", that is, it is assumed more predictable and less wide-spread than the long-haul context, with only a few contracted bins losing their entire capacity,while the others remain unaffected. The results are nearly the same for all availability classes in this context, and thus we display the results for the availability class AV1 only in Table 6. To complete those figures, Figure 2 depicts the average values of the percentage of the capacity booked at the first stage, Cap_{FS}, and the average number of bin types contracted in the capacity plan, N_t, for the sets T3 and T5, the availability classes AV1 (dark gray) and AV2 (light gray), and three levels of BL, the % of overall capacity loss for the contracted bins (low = 20%, medium = 50%, and high = 70%).



(a) Cap_{FS} *in instance set T3.*

(b) Cap_{FS} *in instance set T5.*

(c) N_t *in instance set T3.*

(d) N_t *in instance set T5.*

Figure 2: Average Cap_{FS} and N_t for capacity-loss levels, urban distribution setting, availability classes AV1 (dark gray) and AV2 (light gray)

It is noticeable that an increase of accurate information about the capacity loss in the urban distribution, compared to the long-haul transportation, allows the shipper to book in advance the same capacity as for the case with no capacity loss, but with the greater managerial flexibility of being able to select among a larger set of bin types. Thus, the structure of the capacity plan, reflected in Cap_{FS}, the percentage of total capacity contracted at the first stage, does not change in any significant manner with the variation of most parameters. The values observed (Figure 2) for the average number of bin types selected in the capacity plan, N_t, also support this observation, raising from an average of 1.87 when three bin types are available to 2.18 when five types are available (results for the volatile class AV1). Obviously, this number increases with the level of capacity loss (given by the BL parameter). This flexibility would prove beneficial given the availability of new transportation modes, e.g., cargo-bikes and light rail, for city logistics systems.

7 Conclusions

In this paper, we discussed the logistics capacity-planning problem arising in the context of supply-chain management that is relevant in both the long-haul transportation and urban distribution contexts. We addressed the tactical planning problem faced by a shipper that needs, with a carrier, to secure capacity of multiple types, e.g., ship or train slots, containers, vans, cargo bikes, or warehousing space, for moving or storing goods, in order to meet its needs in terms of its procurement or distribution strategy. The shipper thus negotiates in advance a capacity plan to secure the needed capacity and use it repeatedly over the planning horizon. During the negotiation, little information is known regarding the future evolution of both the shipper and carrier environment and thus, the contract is concluded in an uncertain environment.

We introduced for the first time in the literature the issue of the availability of the contracted capacity when it is needed at the operations time. We explicitly addressed and modeled the uncertainty related to this capacity loss, simultaneously with a wide range of other sources of uncertainty, in particular, the future shipments (the demand) and the availability and cost of future capacity to be used in an ad-hoc (spot) manner when needed. We thus introduced the Stochastic Variable Cost and Size Bin Packing with Capacity Loss, SVCSBP-LS, problem, generalizing several bin packing problems of the literature.

We proposed a two-stage stochastic formulation with recourse to address the SVCSBP-LS, where the first stage is dedicated to determining the tactical capacity-plan, selecting bins of multiple types, while the second stage concerns the adjustments to the plan through acquisition of ad-hoc capacity on the spot market and the loading of items into bins, following the revelation of new information on items to ship, the available capacity among the contracted bins, and the characteristics and costs of bins available on the spot market. We then proposed an efficient progressive-hedging-based metaheuristic for the

SVCSBP-LS.

The proposed model and solution method have been validated in both the long-haul transportation and urban distribution contexts, through an extensive experimental campaign on a large set of instances. These two contexts not only qualify the methodology for two broad and important application areas, but also provide a rich experimental ground by the differences in their physical and operational characteristics.

Computational results highlight the need to consider uncertainty in capacity-planning applications explicitly and the usefulness of building a stochastic programming model integrating the uncertainty on the actual volume of contracted capacity that will be available during operations. Indeed, the benefits of using the stochastic programming SVCSBP-LS model compared to solving deterministic formulations assuming knowledge of the future, are significant. Not only the deterministic formulation yield infeasible capacity plans in several relevant situations, but the numerical analysis showed that the stochastic formulation results in improved operations management (prediction of the capacity needed) and economic benefits in terms of lower operating costs.

The solution method also provided the means to explore the different behaviours of the model in the urban distribution and long-haul transportation settings. Managerial insights were drawn specific to each context concerning the impact on the structure of the capacity plan of a wide range of variations in the uncertain parameters describing the context in which the firms operate, including the probability of a reduction of contracted capacity, the type and scope of the capacity loss, and the cost of replacing the lost capacity.

Thus, it is important to note that when uncertainty on future availability of contracted and ad-hoc capacity is high and wide spread, it is good to book most capacity in advance and book more than expected to be needed when there is a high risk of capacity loss. On the contrary, when there is a high probability of losing a large amount of the contracted capacity but the availability of ad-hoc bins is not an issue, no or very little capacity should be booked in advance. The shipper should rather wait until the shipping date to purchase the necessary capacity at that moment price. Finally, when the potential loss of capacity is highly localized, i.e., the loss concerns a few bins only that might be entirely missing, the shipper should contract the capacity in advance paying particular attention to the bin types.

Many interesting developments are still ahead regarding the tactical capacity planning problem under uncertainty. Future work will concern the generalization of the problem to address other issues, such as the selection, and associated contracting, of a limited set of carriers among several carriers proposing different bin types and costs, as well as enjoying different service-quality ratings. We plan to contribute in these areas in the near future.

Acknowledgments

Partial funding for this work was provided by the Canadian Natural Sciences and Engineering Research Council (NSERC) through its Discovery Grants Program. While working on this paper, the first author was Adjunct Professor, Department of Computer Science and Operations Research, Université de Montréal, Montréal, Canada, and the second author was the head of the *Urban Mobility and Logistics Systems* (UMLS) initiative of the interdepartmental *Center for Automotive Research and Sustainable mobility* (CARS) at Politecnico di Torino, Turin, Italy. The authors are grateful to Ms. Diane Larin for her invaluable linguistic and editorial assistance.

References

Alibaba (2018). Alibaba Web Site. http://www.alibaba.com. Last access: 08/09/2019.

Amazon (2018). Amazon Web Site. https://www.amazon.com. Last access: 08/09/2019.

Birge, J. and Louveaux, F. (1997). *Introduction to Stochastic Programming*. Springer Series in Operations Research and Financial Engineering. Springer.

Birge, J. R. (1982). The value of the stochastic solution in stochastic linear programs with fixed recourse. *Mathematical Programming*, 24(1):314–325.

Correia, I., Gouveia, L., and Saldanha-da-Gama, F. (2008). Solving the variable size bin packing problem with discretized formulations. *COR*, 35:2103–2113.

Crainic, T.G., Gobbato, L., Perboli, G., and Rei, W. (2016). Logistics capacity planning: a stochastic bin packing formulation and a progressive hedging meta-heuristic. *European Journal of Operational Research*, 253:404–417.

Crainic, T.G., Gobbato, L., Perboli, G., Rei, W., Watson, J., and Woodruff, D. (2014). Bin packing problems with uncertainty on item characteristics: an application to capacity planning in logistics. *Procedia - Social and Behavioral Sciences*, 111:654–662.

Crainic, T.G., Marcotte, S., Rei, W., and Takouda, P. M. (2013). Proactive order consolidation in global sourcing. In Bookbinder, J. H., editor, *Handbook of Global Logistics: Transportation in International Supply Chains*, pages 501–530, New York, NY. Springer New York.

Crainic, T.G., Perboli, G., Pezzuto, M., and Tadei, R. (2007). New bin packing fast lower bounds. *COR*, 34:3439–3457.

Crainic, T.G., Perboli, G., Rei, W., and Tadei, R. (2011). Efficient lower bounds and heuristics for the variable cost and size bin packing problem. *COR*, 38:1474–1482.

Crainic, T.G., Ricciardi, N., and Storchi, G. (2009). Models for Evaluating and Planning City Logistics Systems. *Transportation Science*, 43(4):432–454.

Crainic, T.G., Tadei, R., Perboli, G., and Baldi, M. M. (2012). The generalized bin packing problem: Models and bounds. In *Odysseus 2012, the 5th International Workshop on Freight Transportation and Logistics, Mykonos (Greece), May 21–25, 2012*, pages 347–350.

Giusti, R., Manerba, D., Perboli, G., Tadei, R., and Yuan, S. (2018). A New Open-source System for Strategic Freight Logistics Planning: The SYNCHRO-NET Optimization Tools. In *Transportation Research Procedia*, volume 30, pages 245–254.

Gobbato, L. (2015). *Stochastic programming for City Logistics: new models and methods.* PhD thesis, Politecnico di Torino.

Lerma, V. (2018). Stochastic bin packing models for capacity planning in logistic application. Models and policy simulations. Publication CIRRELT-2018-25, Centre interuniversitaire de recherche sur les réseaux d'entreprise, la logistique et le transport, Université de Montréal, Montréal, QC, Canada.

Lium, A.-G., Crainic, T.G., and Wallace, S. W. (2009). A study of demand stochasticity in service network design. *Transportation Science*, 43(2):144–157.

Monaci, M. (2002). *Algorithms for packing and scheduling problems.* PhD thesis, Universitá di Bologna, Bologna, Italy.

Morganti, E., Seidel, S., Blanquart, C., Dablanc, L., and Lenz, B. (2014). The impact of e-commerce on final deliveries: Alternative parcel delivery services in france and germany. *Transportation Research Procedia*, 4:178 – 190.

Perboli, G., Musso, S., Rosano, M., Tadei, R., and Godel, M. (2017). Synchro-modality and slow steaming: New business perspectives in freight transportation. *Sustainability (Switzerland)*, 9(10).

Perboli, G. and Rosano, M. (2019). Parcel delivery in urban areas: Opportunities and threats for the mix of traditional and green business models. *Transportation Research Part C: Emerging Technologies*, 99:19 – 36.

Perboli, G., Rosano, M., Saint-Guillain, M., and Rizzo, P. (2018). A simulation-optimization framework for City Logistics. an application on multimodal last-mile delivery. *IET Intelligent Transport Systems*, 12(4):262–269.

Rockafellar, R. T. and Wets, R. J.-B. (1991). Scenarios and policy aggregation in optimization under uncertainty. *Math. Oper. Res.*, 16(1):119–147.

A PH-based meta-heuristic for the SVCSBPP$_L$

Scenario decomposition We first reformulate the SVCSBPP$_L$ stochastic (1)-(10) model using scenario decomposition. Sampling is applied to obtain a set of representative scenarios, namely the set $\mathcal{S}$, and these are used to approximate the expected cost associated with the second stage. For the first stage, let $y_j^{ts} = 1$ if bin $j \in \mathcal{J}^t$ of type $t \in T$ is selected under scenario $s \in \mathcal{S}$ and 0 otherwise. For the second stage, define $\mathcal{K}^s = \bigcup_\tau \mathcal{K}^{\tau s}$, where $\mathcal{K}^{\tau s}$ is the set of extra bins of type $\tau \in \mathcal{T}$ in scenario $s \in \mathcal{S}$, and let $\mathcal{I}^s$ be the set of items to pack under scenario $s \in \mathcal{S}$. Let $g^{\tau s}$ be the cost associated with bins of type $\tau \in \mathcal{T}$ in scenario $s \in \mathcal{S}$, $\mathcal{V}_j^{ts}$ be the actual volume of first-stage bin $j \in \mathcal{J}^t$ under scenario $s \in \mathcal{S}$, and v_i^s be the volume of item $i \in \mathcal{I}^s$ in scenario $s \in \mathcal{S}$. Then, variable $z_k^{\tau s}$ is equal to 1 if and only if extra bin $k \in \mathcal{K}^{\tau s}$ of type $\tau \in \mathcal{T}$ is selected in scenario $s \in \mathcal{S}$, and x_{ij}^s and x_{ik}^s are item-to-bin assignment variable for scenario $s \in \mathcal{S}$.

Given the probability p_s of each scenario $s \in \mathcal{S}$, the SVCSBPP$_L$ problem (1)-(10) can be approximated by the following equivalent deterministic model:

$$\min_{y,z,x} \sum_{s\in\mathcal{S}} p_s \left[\sum_{t\in T}\sum_{j\in\mathcal{J}^t} f^t y_j^{ts} + \sum_{\tau\in\mathcal{T}}\sum_{k\in\mathcal{K}^{\tau s}} g^{\tau s} z_k^{\tau s} + \sum_{t\in T}\sum_{j\in\mathcal{J}^t} c^t (V^t - \mathcal{V}_j^{ts}) y_j^{ts} \right] \quad (27)$$

$$\begin{aligned}
\text{s.t.}\quad & y_j^{ts} \geq y_{j+1}^{ts}, && \forall\, t \in T, j = 1,\ldots,|\mathcal{J}^t|-1, s \in \mathcal{S}, && (28)\\
& \sum_{j\in\mathcal{J}} x_{ij}^s + \sum_{k\in\mathcal{K}^s} x_{ik}^s = 1, && \forall\, i \in \mathcal{I}^s, s \in \mathcal{S}, && (29)\\
& \sum_{i\in\mathcal{I}^s} v_i^s x_{ij}^s \leq \mathcal{V}_j^{ts} y_j^{ts}, && \forall\, t \in T, j \in \mathcal{J}^t, s \in \mathcal{S}, && (30)\\
& \sum_{i\in\mathcal{I}^s} v_i^s x_{ik}^s \leq V^\tau z_k^{\tau s}, && \forall\, \tau \in \mathcal{T}, k \in \mathcal{K}^{\tau s}, s \in \mathcal{S}, && (31)\\
& y_j^{ts} = y_j^{ts'}, && \forall\, t \in T, j \in \mathcal{J}^t, s, s' \in \mathcal{S}, && (32)\\
& y_j^{ts} \in \{0,1\}, && \forall\, t \in T, j \in \mathcal{J}^t, s \in \mathcal{S}, && (33)\\
& z_k^{\tau s} \in \{0,1\}, && \forall\, \tau \in \mathcal{T}, k \in \mathcal{K}^{\tau s}, s \in \mathcal{S}, && (34)\\
& x_{ij}^s \in \{0,1\}, && \forall\, i \in \mathcal{I}^s, j \in \mathcal{J}, s \in \mathcal{S}, && (35)\\
& x_{ik}^s \in \{0,1\}, && \forall\, i \in \mathcal{I}^s, k \in \mathcal{K}^s, s \in \mathcal{S}. && (36)
\end{aligned}$$

Constraints (32) are referred as the non-anticipativity constraints. They ensure that the first-stage decisions are not tailored to the scenarios considered in $\mathcal{S}$. Indeed, all the scenario solutions must be equal to produce a single implementable plan. Thus, the non-anticipativity constraints link the first-stage variables to the second-stage variables, so the model is not separable.

To apply Lagrangean relaxation and make the model separable, we need a different expression of the non-anticipativity constraints. Let $\bar{y}_j^t \in \{0,1\}, \forall\, t \in T, j \in \mathcal{J}^t$, be the *global capacity plan*, i.e., the set of bins selected at the first stage. The following constraints are equivalent to (32):

$$\bar{y}_j^t = y_j^{ts}, \qquad \forall\, t \in T,\; j \in \mathcal{J}^t, s \in \mathcal{S}, \tag{37}$$

$$\bar{y}_j^t \in \{0,1\}, \qquad \forall\, t \in T,\; j \in \mathcal{J}^t. \tag{38}$$

Constraints (37) force the first-stage solution of each scenario to be equal to the global capacity plan. Constraints (38) are simply the integrality conditions on the selection of the bins. With this formulation of the non-anticipativity constraints, when we apply Lagrangean relaxation to (37), we can penalize individually the difference between the scenario solution and the global solution of each bin in the plan.

Following the decomposition scheme proposed by Rockafellar and Wets (1991), we relax constraints (37) using an augmented Lagrangean strategy. We thus obtain the following objective function for the overall problem:

$$\begin{aligned}\min_{y,z,x} \sum_{s\in\mathcal{S}} p_s \Bigg[&\sum_{t\in T}\sum_{j\in\mathcal{J}^t} f^t y_j^{ts} + \sum_{\tau\in\mathcal{T}}\sum_{k\in\mathcal{K}^{\tau s}} g^{\tau s} z_k^{\tau s} + \sum_{t\in T}\sum_{j\in\mathcal{J}^t} c^t(V^t - \mathcal{V}_j^{ts}) y_j^{ts} + \\ &+ \sum_{t\in T}\sum_{j\in\mathcal{J}^t} \lambda_j^{ts}(y_j^{ts} - \bar{y}_j^t) + \frac{1}{2}\sum_{t\in T}\sum_{j\in\mathcal{J}^t} \rho_j^t (y_j^{ts} - \bar{y}_j^t)^2 \Bigg]\end{aligned} \tag{39}$$

where $\lambda_j^{ts}, \forall j \in \mathcal{J}^t, \forall t \in T$, and $\forall s \in \mathcal{S}$, define the Lagrangean multipliers for the relaxed constraints and ρ_j^t is a penalty ratio associated with bin $j \in \mathcal{J}^t$ of type $t \in T$. Within function 39, let us consider the quadratic term. Given the binary requirements of y_j^{ts} and $\bar{y}_j^t$, the term becomes:

$$\sum_{t\in T}\sum_{j\in\mathcal{J}^t} \rho_j^t \left(y_j^{ts} - \bar{y}_j^t\right)^2 = \sum_{t\in T}\sum_{j\in\mathcal{J}^t} \left(\rho_j^t (y_j^{ts})^2 - 2\rho_j^t y_j^{ts} \bar{y}_j^t + \rho_j^t (\bar{y}_j^t)^2\right) = \tag{40}$$

$$= \sum_{t\in T}\sum_{j\in\mathcal{J}^t} \left(\rho_j^t y_j^{ts} - 2\rho_j^t y_j^{ts} \bar{y}_j^t + \rho_j^t \bar{y}_j^t\right). \tag{41}$$

Therefore, the objective function can be formulated as follows:

$$\begin{aligned}\min_{y,z,x} \sum_{s\in\mathcal{S}} p_s \Bigg[&\sum_{t\in T}\sum_{j\in\mathcal{J}^t} \left(f^t + c^{ts}(V^t - \mathcal{V}_j^{ts}) + \lambda_j^{ts} - \rho_j^t \bar{y}_j^t + \frac{\rho_j^t}{2} \right) y_j^{ts} + \\ &+ \sum_{\tau\in\mathcal{T}}\sum_{k\in\mathcal{K}^{\tau s}} g^{\tau s} z_k^{\tau s} - \sum_{t\in T}\sum_{j\in\mathcal{J}^t} \lambda_j^{ts} \bar{y}_j^t + \frac{1}{2}\sum_{t\in T}\sum_{j\in\mathcal{J}^t} \rho_j^t \bar{y}_j^t \Bigg].\end{aligned} \tag{42}$$

Given constraints (28)-(36) and the objective function (42), the relaxed problem is not separable by scenario. However, if the overall plan $\bar{y}_j^t, \forall t \in T$ and $\forall j \in \mathcal{J}^t$, is fixed to a given value vector (i.e., the expected value of the scenario solutions), then the model decomposes according to the scenarios in $\mathcal{S}$ and the scenario subproblems can be expressed as follows:

$$\min_{y,z,x} \quad \sum_{t\in T}\sum_{j\in\mathcal{J}^t}\left(f^t + c^{ts}(V^t - \mathcal{V}_j^{ts}) + \lambda_j^{ts} - \rho_j^t\bar{y}_j^t + \frac{\rho_j^t}{2}\right)y_j^{ts} + \sum_{\tau\in\mathcal{T}}\sum_{k\in\mathcal{K}^{\tau s}} g^{\tau s}z_k^{\tau s} \tag{43}$$

$$\text{s.t.} \quad y_j^{ts} \geq y_{j+1}^{ts}, \qquad \forall\, t \in T, j = 1,\ldots,|\mathcal{J}^t|-1, s \in \mathcal{S}, \tag{44}$$

$$\sum_{j\in\mathcal{J}} x_{ij}^s + \sum_{k\in\mathcal{K}^s} x_{ik}^s = 1, \qquad \forall\, i \in \mathcal{I}^s, s \in \mathcal{S}, \tag{45}$$

$$\sum_{i\in\mathcal{I}^s} v_i^s x_{ij}^s \leq \mathcal{V}_j^{ts} y_j^{ts}, \qquad \forall\, t \in T, j \in \mathcal{J}^t, s \in \mathcal{S}, \tag{46}$$

$$\sum_{i\in\mathcal{I}^s} v_i^s x_{ik}^s \leq V^\tau z_k^{\tau s}, \qquad \forall\, \tau \in \mathcal{T}, k \in \mathcal{K}^{\tau s}, s \in \mathcal{S}, \tag{47}$$

$$y_j^{ts} \in \{0,1\}, \qquad \forall\, t \in T, j \in \mathcal{J}^t, s \in \mathcal{S}, \tag{48}$$

$$z_k^{\tau s} \in \{0,1\}, \qquad \forall\, \tau \in \mathcal{T}, k \in \mathcal{K}^{\tau s}, s \in \mathcal{S}, \tag{49}$$

$$x_{ij}^s \in \{0,1\}, \qquad \forall\, i \in \mathcal{I}^s, j \in \mathcal{J}, s \in \mathcal{S}, \tag{50}$$

$$x_{ik}^s \in \{0,1\}, \qquad \forall\, i \in \mathcal{I}^s, k \in \mathcal{K}^s, s \in \mathcal{S}. \tag{51}$$

Furthermore, by noting that λ_j^{ts} and ρ_j^t are exogenous constants for the model (43)-(51), we can reformulate each scenario subproblem as follows. We define $\overline{\mathcal{T}} = T \cup \mathcal{T}$ to be the overall set of bin types. For each scenario s, let $\mathcal{B}^{\overline{\tau}s} = \mathcal{J}^{\overline{\tau}} \cup \mathcal{K}^{\overline{\tau}s}$ be the set of available bins of type $\overline{\tau}$ in the subproblem and $\mathcal{B}^s = \bigcup_{\overline{\tau}} \mathcal{B}^{\overline{\tau}s}$ be the whole set of bins available in the subproblem. For $b \in \mathcal{B}^{\overline{\tau}s}$, let $\mathcal{V}_b^{\overline{\tau}s}$ be the actual volume of bin b (for $b \in \mathcal{K}^{\overline{\tau}s}$, $\mathcal{V}_b^{\overline{\tau}s} = V^{\overline{\tau}}$) and let $f_b^{\overline{\tau}s}$ define the fixed cost associated with bin b. The value of $f_b^{\overline{\tau}s}$ is given by

$$f_b^{\overline{\tau}s} = \begin{cases} f^{\overline{\tau}} + c^{\overline{\tau}s}(V^{\overline{\tau}} - \mathcal{V}_b^{\overline{\tau}s}) + \lambda_b^{\overline{\tau}s} - \rho_b^{\overline{\tau}}\bar{y}_b^{\overline{\tau}} + \frac{\rho_b^{\overline{\tau}}}{2} & \overline{\tau} \in \overline{\mathcal{T}}, b \in \mathcal{J}^{\overline{\tau}} \\ g^{\overline{\tau}s} & \overline{\tau} \in \overline{\mathcal{T}}, b \in \mathcal{K}^{\overline{\tau}s}. \end{cases} \tag{52}$$

Thus, each scenario subproblem can be reduced to a deterministic VCSBPP with modified fixed costs and an additional constraint that ensures an order in the selection of bins of type $\overline{\tau} \in \overline{\mathcal{T}}$:

$$\min_{y,x} \quad \sum_{\overline{\tau} \in \overline{\mathcal{T}}} \sum_{b \in \mathcal{B}^{\overline{\tau}s}} f_b^{\overline{\tau}s} y_b^{\overline{\tau}s} \tag{53}$$

$$\text{s.t.} \quad y_b^{\overline{\tau}s} \geq y_{b+1}^{\overline{\tau}s}, \qquad \forall\, \overline{\tau} \in \overline{\mathcal{T}}, b = 1, \ldots, |\mathcal{B}^{\overline{\tau}s}| - 1, \tag{54}$$

$$\sum_{b \in \mathcal{B}^s} x_{ib}^s = 1, \qquad \forall\, i \in \mathcal{I}^s, \tag{55}$$

$$\sum_{i \in \mathcal{I}^s} v_i^s x_{ib}^s \leq \mathcal{V}_b^{\overline{\tau}s} y_b^{\overline{\tau}s}, \qquad \forall\, \overline{\tau} \in \overline{\mathcal{T}}, b \in \mathcal{B}^{\overline{\tau}s}, \tag{56}$$

$$y_b^{\overline{\tau}s} \in \{0, 1\}, \qquad \forall \overline{\tau} \in \overline{\mathcal{T}}, b \in \mathcal{B}^{\overline{\tau}s}, \tag{57}$$

$$x_{ib}^s \in \{0, 1\}, \qquad \forall\, i \in \mathcal{I}^s, b \in \mathcal{B}^s, \tag{58}$$

where $y_b^{\overline{\tau}s} = 1$ if bin $b \in \mathcal{B}^{\overline{\tau}s}$ of type $\overline{\tau} \in \overline{\mathcal{T}}$ is selected, 0 otherwise.

Phase 1 of the meta-heuristic

Obtaining consensus among subproblems. At each iteration of the meta-heuristic, the solutions of the scenario subproblems are used to build a temporary global solution (the overall capacity plan). *Consensus* is then defined as scenario solutions being similar with regard to the first-stage decisions with the overall capacity plan and, thus, being similar among themselves. This section describes how the overall plan is computed. Moreover, we introduce strategies for the penalty adjustment when nonconsensus is observed and techniques to guide the search process by bounding the number of bins that can be selected at the first stage.

Defining the overall capacity plan. Let ν be the iteration counter in the PH algorithm. At each iteration, the algorithm solves subproblems (53)–(58), obtaining local solutions $y_b^{\overline{\tau}s\nu}$ $y_j^{\tau s\nu}$, $\forall s \in \mathcal{S}$, $\forall \overline{\tau} \in \overline{\mathcal{T}}$, and $\forall b \in \mathcal{B}^{\overline{\tau}s}$. The subproblem solutions are then combined in the overall capacity plan $\bar{y}_b^{\overline{\tau}\nu}$ by using the expected value operator, as shown in Equation (59). The weight used for each component is the probability p_s associated with the corresponding scenario.

$$\bar{y}_b^{\overline{\tau}\nu} = \sum_{s \in \mathcal{S}} p_s y_b^{\overline{\tau}s\nu}, \quad \forall \overline{\tau} \in \overline{\mathcal{T}}, \forall b \in \mathcal{B}^{\overline{\tau}}. \tag{59}$$

Moreover, we define an overall solution based on the number of bins in the capacity plan. Let $\delta^{\overline{\tau}s\nu} = \sum_{b \in \mathcal{B}^{\overline{\tau}}} y_b^{\overline{\tau}s\nu}$ be the total number of bins of type $\overline{\tau} \in \overline{\mathcal{T}}$ in the capacity plan for scenario subproblem $s \in \mathcal{S}$ at iteration ν. Equivalently to (59), using the expected value operator on $\delta^{\overline{\tau}s\nu}$ $\forall s \in \mathcal{S}$, we can define the overall capacity plan for each bin type $\overline{\tau} \in \mathcal{T}$ as

$$\bar{\delta}^{\overline{\tau}\nu} = \sum_{s\in\mathcal{S}} p_s \delta^{\overline{\tau}s\nu} = \sum_{s\in\mathcal{S}} p_s \sum_{b\in\mathcal{B}^{\overline{\tau}}} y_b^{\overline{\tau}s\nu} = \sum_{b\in\mathcal{J}^{\overline{\tau}}} \sum_{s\in\mathcal{S}} p_s y_b^{\overline{\tau}s\nu} = \sum_{b\in\mathcal{B}^{\overline{\tau}}} \bar{y}_b^{\overline{\tau}\nu}. \tag{60}$$

Equation (60) can be used to define the stopping criterion. Thus, we consider consensus to be achieved when the values of $\delta^{\overline{\tau}s\nu}$, $\forall s \in \mathcal{S}$, are equal to $\bar{\delta}^{\overline{\tau}\nu}$.

It is important to note that (59) and (60) do not necessarily produce a feasible capacity plan. When consensus is not achieved, the overall solution may not satisfy the integrality constraints on the first-stage decision variables. For nonconvex problems such as the SVCSBPP$_L$ using the expected value as an aggregation operator does not guarantee that the algorithm converges to the optimal solution. Moreover, it cannot ensure that a good (feasible) solution will be obtained for the stochastic problem. Therefore, (59) and (60) are used as reference solutions with the goal of helping the search process of the PH algorithm to identify bins for which consensus is possible. Both are used in the penalty adjustment, while (60) is also used in the bounding strategy.

Penalty adjustment strategies. To promote consensus among the scenario subproblems, we adjust the fixed costs of bin types in the objective function at each iteration to penalize a lack of implementability and dissimilarity between local solutions and the overall solution. We propose two different strategies for these adjustments, both working at the local level in the sense that they affect every scenario subproblem separately.

The first strategy was originally proposed by Rockafellar and Wets (1991). Using information on the bin selection (i.e., variable $y_b^{\overline{\tau}s\nu}$), it operates on the fixed costs by changing the Lagrangean multipliers. For a given iteration ν, let $\lambda_b^{\overline{\tau}s\nu}$ be the Lagrangean multiplier associated with bin $b \in \mathcal{B}^{\overline{\tau}s}$ for scenario $s \in \mathcal{S}$, and let $\rho_b^{\overline{\tau}\nu}$ be the penalty deriving from the quadratic term. Note that the value of $\rho_b^{\overline{\tau}\nu}$ is variable-specific. At each iteration, we update the values $\lambda_b^{\overline{\tau}s\nu}$ and $\rho_b^{\overline{\tau}\nu}$, $\forall b \in \mathcal{B}^{\overline{\tau}s}$ and $\forall s \in \mathcal{S}$, as follows:

$$\lambda_b^{\overline{\tau}s\nu} = \lambda_b^{\overline{\tau}s(\nu-1)} + \rho_b^{\overline{\tau}(\nu-1)}(y_b^{\overline{\tau}s\nu} - \bar{y}_b^{\overline{\tau}\nu}) \tag{61}$$

$$\rho_b^{\overline{\tau}\nu} \leftarrow \alpha \rho_b^{\overline{\tau}(\nu-1)}, \tag{62}$$

where $\alpha > 1$ is a given constant and $\rho_b^{\overline{\tau}0}$ is fixed to a positive value to ensure that $\rho_b^{\overline{\tau}\nu} \to \infty$ as the number of iterations ν increases.

We initialize $\lambda_b^{s0} = 0$ for each scenario $s \in \mathcal{S}$. Equation (61) can then reduce, increase, or maintain this contribution according to the difference between the value of the bin-selection variables in the subproblem solutions and the overall capacity plan. The initial choice of $\rho_b^{\overline{\tau}0}$ is important. An inaccurate choice may cause premature convergence to a solution that is far from optimal or cause slow convergence of the search process. To avoid this, we set $\rho_b^{\overline{\tau}0}$ proportional to the fixed cost associated with the bin-selection variable: $\rho_b^{\overline{\tau}0} = max(1, f^{\overline{\tau}}/10)$, $\forall b \in \mathcal{B}^{\overline{\tau}s}$ and $\forall \overline{\tau} \in \overline{\mathcal{T}}$. The value of $\rho_b^{\overline{\tau}0}$ increases according to (62) as the number of iteration grows.

The second penalty adjustment is a heuristic strategy, which directly tunes the fixed costs of bins of the same type. The goal of this strategy is to accelerate the search process when the overall solution is close to consensus. When consensus is close, the difference between the subproblem solution and the overall solution may be small, and adjustments (61) and (62) lose their effectiveness, requiring several iterations to reach consensus.

Let $f^{\overline{\tau}s\nu}$ be the fixed cost of bin $b \in \mathcal{B}^{\overline{\tau}s}$ of type $overline\tau \in \overline{\mathcal{T}}$ for scenario $s \in \mathcal{S}$ at iteration ν. At the beginning of the algorithm ($\nu = 0$), we impose $f^{\overline{\tau}s0} = f^{\tau}$. Then, when at least $\sigma_{\%}$ of the variables have reached consensus, we perturb every subproblem by changing $f^{\overline{\tau}s\nu}$ as follows:

$$f^{\overline{\tau}s\nu} = \begin{cases} f^{\overline{\tau}s(\nu-1)} \cdot M & \text{if } \delta^{\overline{\tau}s(\nu-1)} > \bar{\delta}^{\overline{\tau}(\nu-1)} \\ f^{\overline{\tau}s(\nu-1)} \cdot \frac{1}{M} & \text{if } \delta^{\overline{\tau}s(\nu-1)} < \bar{\delta}^{\overline{\tau}(\nu-1)} \\ f^{\overline{\tau}s(\nu-1)} & otherwise. \end{cases} \tag{63}$$

Here M is a constant greater than 1, while $\sigma_{\%}$ is a constant such that $0.5 \leq \sigma_{\%} \leq 1$. The current implementation of this heuristic strategy uses $\sigma_{\%} = 0.75$ and $M = 1.1$. The rationale for (63) is the following: if $\delta^{\overline{\tau}s(\nu-1)} > \bar{\delta}^{\overline{\tau}(\nu-1)}$, this means that in the previous iteration the number of bins of a given bin type $\overline{\tau}$ in scenario s was larger than the number of bins in the reference solution $\bar{\delta}^{\overline{\tau}(\nu-1)}$. Thus, the use of bins of type $\overline{\tau}$ is penalized by increasing the fixed cost by M. On the other hand, if $\delta^{\overline{\tau}s(\nu-1)} < \bar{\delta}^{\overline{\tau}(\nu-1)}$, we promote bins of type $\overline{\tau}$ by reducing the fixed cost by $1/M$.

Bundle fixing. To guide the search process, we introduce a variable-fixing strategy called bundle fixing.

We restrict the number of bins of each type that can be used, specifying lower and upper bounds. It should be noticed that it is equivalent to fix single bin-selection variables, since all bins of a certain type $\overline{\tau}$ are ordered and constraint 54 ensures that the selection of bins follows this order.

Let $\bar{\delta}_m^{\overline{\tau}\nu}$ and $\bar{\delta}_M^{\overline{\tau}\nu}$ be the minimum and maximum number of bins of type $\overline{\tau}$ involved in the overall solution at iteration ν:

$$\bar{\delta}_m^{\overline{\tau}\nu} \leftarrow \min_{s\in\mathcal{S}} \delta^{\overline{\tau}s\nu}, \tag{64}$$

$$\bar{\delta}_M^{\overline{\tau}\nu} \leftarrow \max_{s\in\mathcal{S}} \delta^{\overline{\tau}s\nu}. \tag{65}$$

At each iteration, the bundle strategy applies two bounds as follows. The lower bound $\bar{\delta}_m^{\overline{\tau}\nu}$ determines a set of compulsory bins that must be used in each subproblem;

to implement this we set the decision variables $y_b^{\overline{\tau}s(\nu+1)}$ to one for $b = 1, ..., \bar{\delta}_m^{\overline{\tau}\nu}$. The upper bound $\bar{\delta}_M^{\overline{\tau}\nu}$ is an estimate of the maximum number of bins of type $\overline{\tau}$ available in the next iteration; this reduces the number of decision variables in the subproblems. To implement this we remove decision variables $y_b^{\overline{\tau}s(\nu+1)}$ for $b = \bar{\delta}_M^{\overline{\tau}\nu} + 1, ..., \|\mathcal{B}^{\overline{\tau}}\|$.

Termination criteria. There are to date no theoretical results on the convergence of the PH algorithm for integer problems. Thus, we implement three stopping criteria for the search phase of the proposed meta-heuristic, based on the level of consensus reached and the number of iterations.

The level of consensus is measured through equations 64 and 65, as consensus is reached when $\bar{\delta}_m^{\overline{\tau}\nu} = \bar{\delta}_M^{\overline{\tau}\nu}, \forall \overline{\tau} \in \overline{\mathcal{T}}$. To speed up the algorithm, we actually stop the search, and proceed to Phase 2, as soon as consensus has been reached for all the bin types except one, type $\overline{\tau}'$, for which $\bar{\delta}_m^{\overline{\tau}'} < \bar{\delta}_M^{\overline{\tau}'}$.

When neither of the preceding conditions has been reached within a maximum number of iterations (200 in our experiments), the search is stopped and the meta-heuristic proceeds to the Phase 2.

Phase 2 of the meta-heuristic Phase 2 is thus invoked either when consensus is not achieved within a given maximum number of iterations, or the search was stopped when all but one bin type were in consensus.

In the first case, there is only one bin type $\overline{\tau}'$ with $\bar{\delta}_m^{\overline{\tau}'} < \bar{\delta}_M^{\overline{\tau}'}$, that is, not in consensus. Given the efficiency of the item-to-bin heuristic, Phase 2 computes the final solution by iteratively examining the possible number of bins for $\overline{\tau}'$ (a consensus solution is always possible because $\bar{\delta}_M^{\overline{\tau}'}$ is feasible in all scenarios):

For all $\delta \in \left[\bar{\delta}_m^{\overline{\tau}'}, \bar{\delta}_M^{\overline{\tau}'}\right]$ **do**

- Set the number of bins of type $\overline{\tau}'$ to δ;
- Solve all the scenario subproblems with the heuristic;
- Check the feasibility of the solutions;
- Update the overall solution if a better solution has been found;

- **Produce** the consensus solution.

When the maximum number of iterations is reached, consensus is less close. Phase 2 of the meta-heuristic then builds a restricted version of the formulation (27)–(36) by fixing the bin-selection first-stage variables for which consensus has been achieved, together with the associated item-to-bin assignment variables. The range of the bin types not in consensus is reduced through bundle fixing, and the resulting MIP is solved exactly.

B Analysis of $EVPI$ and VSS

In this appendix, we evaluate how the values of the $EVPI$ and VSS change depending on the parameters that characterize the actual volume reduction of first-stage bins (i.e., SL, TL and BL).

B.1 Expected value of perfect information

Table 8 reports the average and maximum percentages $EVPI$, showing how different parameters such as the level of the volume reduction, the percentage of scenarios affected by capacity losses and the probability that a bins type has a capacity reduction, affect the $EVPI$. Indeed, the above mentioned aspect is highlighted by the reduction of the average percentage $EVPI$ with an increase of SL and TL. For example, Table 8 highlights that when SL and TL are respectively equal to 20% and 50%, and BL is between 60% and 70%, the average and maximum percentages of $EVPI$ are 17% and 32% for instances with three bin types (set T3), and 16% and 25% for instance with five bin types (set T5).

Finally, the considerable risk of not being able to pack all items affects the decisions of the shipper, whose willingness to pay for the complete information about the future depends on the availability of bin types. Indeed, when the shipper can include in its capacity plan a wide range of bin types (in terms of volumes and types), its decisions are not affected by the availability of the second-stage bins, regardless of the context (long-haul transportation or urban distribution). In this case, at the shipping day, most likely it will be able to pack all the items using different configurations of bins or split them in different bin types. This aspect emerges by the results obtained considering the instances in T5 (see Tables 8 and 10).

On the contrary, the knowledge of the future becomes particularly important when the shipper can use a lower number of bin types and their availability could be limited at the shipping day. In this case, the risk of not being able to pack all items is high and the shipper may not be able to switch to other carrier who supply more capacity, with the consequent risk of unshipped products that turn into a loss of revenues. As highlighted in Table 9, this aspect is particularly relevant in the long-haul transportation, where considering three types of bins (set T3), the impacts of the number of scenarios affected by the uncertainty and the probability that a bin types has a capacity reduction depend on the availability of second-stage bins. For example, the average percentage of $EVPI$

reaches 46% when SL, TL, and BL are equal to 80%, 100%, and 70%, respectively (see Table 9).

SL[%]	TL[%]	BL[%]	Set T3		Set T5	
			$EVPI$[%]	$EVPI_{max}$[%]	$EVPI$[%]	$EVPI_{max}$[%]
20	**50**	**20-30**	16.26	26.62	15.77	23.91
		40-50	16.24	28.09	16.00	23.63
		60-70	16.90	31.99	16.15	24.90
	75	**20-30**	16.30	26.65	15.94	23.90
		40-50	16.33	28.47	15.95	23.31
		60-70	17.06	33.43	16.08	25.32
	100	**20-30**	16.45	26.13	15.93	23.84
		40-50	16.22	28.67	15.80	23.30
		60-70	17.00	33.75	16.00	24.48
40	**50**	**20-30**	16.33	26.54	15.98	23.97
		40-50	16.10	29.08	15.79	23.23
		60-70	17.05	33.93	16.16	25.57
	75	**20-30**	16.32	26.66	15.91	23.94
		40-50	15.99	29.99	15.61	23.16
		60-70	16.66	34.84	15.91	24.34
	100	**20-30**	16.25	26.35	15.92	23.60
		40-50	15.68	30.20	15.20	22.81
		60-70	16.03	35.49	15.40	23.29
60	**50**	**20-30**	16.23	26.70	16.07	23.75
		40-50	15.92	30.10	15.47	23.38
		60-70	16.52	48.07	15.99	24.46
	75	**20-30**	16.22	26.46	15.88	23.85
		40-50	15.47	28.95	15.06	22.81
		60-70	15.75	60.76	15.23	23.27
	100	**20-30**	16.11	26.50	15.79	23.56
		40-50	15.08	28.00	14.54	22.73
		60-70	14.59	50.01	14.21	21.93
80	**50**	**20-30**	16.23	26.55	15.95	23.79
		40-50	15.48	29.18	15.20	23.10
		60-70	15.84	36.60	15.47	23.81
	75	**20-30**	16.05	26.47	15.73	23.83
		40-50	15.04	30.29	14.46	22.61
		60-70	14.76	51.06	14.20	23.17
	100	**20-30**	15.87	25.68	15.48	23.50
		40-50	14.28	26.51	13.90	22.61
		60-70	12.99	28.73	12.81	21.73

Table 8: The impact of SL, TL and BL on $EVPI$ in the urban distribution setting.

SL[%]	TL[%]	BL [%]	AV1		AV2-AV3	
			$EVPI$[%]	$EVPI_{max}$[%]	$EVPI$[%]	$EVPI_{max}$[%]
20	**50**	**20-30**	18.12	25.59	15.61	24.23
		40-50	20.27	34.30	17.28	27.36
		60-70	25.21	63.69	19.79	29.42
	75	**20-30**	17.73	24.95	14.93	23.54
		40-50	20.67	38.63	16.66	24.65
		60-70	26.03	63.14	19.80	29.13
	100	**20-30**	16.58	24.60	13.68	22.41
		40-50	19.01	37.97	15.02	21.84
		60-70	27.83	61.04	18.59	25.83
40	**50**	**20-30**	18.30	25.66	15.67	26.48
		40-50	23.20	40.98	18.45	29.05
		60-70	30.92	63.53	22.30	32.52
	75	**20-30**	17.01	24.10	14.31	22.53
		40-50	22.16	40.79	17.31	26.21
		60-70	32.49	64.40	21.30	31.79
	100	**20-30**	14.75	22.89	11.56	21.09
		40-50	19.43	38.07	13.42	20.23
		60-70	35.60	65.67	16.50	25.29
60	**50**	**20-30**	18.29	29.49	15.44	26.84
		40-50	25.35	50.96	19.16	31.13
		60-70	34.46	74.27	23.01	35.04
	75	**20-30**	17.09	35.24	13.29	22.41
		40-50	24.91	52.88	16.71	27.18
		60-70	40.30	76.84	19.65	30.42
	100	**20-30**	13.85	33.34	8.91	19.27
		40-50	22.10	57.15	9.56	16.96
		60-70	43.53	77.34	10.39	18.53
80	**50**	**20-30**	18.54	34.95	15.02	27.57
		40-50	27.77	56.97	19.09	32.17
		60-70	37.34	75.52	22.34	35.95
	75	**20-30**	16.58	34.37	12.09	22.42
		40-50	25.22	53.94	14.95	25.70
		60-70	42.52	75.24	16.00	28.90
	100	**20-30**	12.09	31.38	6.27	16.55
		40-50	22.20	56.19	3.97	9.24
		60-70	46.16	77.35	4.14	8.15

Table 9: The impact of SL, TL and BL on $EVPI$ for instance set T3 in the long-haul transportation setting.

SL[%]	**TL**[%]	**BL** [%]	$EVPI$[%]	$EVPI_{max}$[%]
20	**50**	**20-30**	16.05	24.71
		40-50	17.93	27.18
		60-70	20.51	31.33
	75	**20-30**	15.39	23.33
		40-50	17.65	27.78
		60-70	20.70	30.36
	100	**20-30**	13.87	22.11
		40-50	15.19	21.97
		60-70	18.51	27.49
40	**50**	**20-30**	16.28	25.73
		40-50	19.47	30.75
		60-70	23.47	35.77
	75	**20-30**	15.03	25.03
		40-50	18.53	28.08
		60-70	22.84	33.54
	100	**20-30**	11.83	19.62
		40-50	13.75	20.66
		60-70	17.41	26.68
60	**50**	**20-30**	16.31	27.08
		40-50	20.49	32.35
		60-70	24.92	36.79
	75	**20-30**	14.29	24.45
		40-50	18.46	31.79
		60-70	22.14	34.89
	100	**20-30**	9.42	18.44
		40-50	10.34	17.39
		60-70	12.04	30.31
80	**50**	**20-30**	16.14	28.30
		40-50	21.23	34.39
		60-70	25.04	43.02
	75	**20-30**	13.32	26.15
		40-50	17.44	32.46
		60-70	19.51	50.83
	100	**20-30**	7.07	16.82
		40-50	5.33	27.16
		60-70	6.61	54.26

Table 10: The impact of SL, TL and BL on $EVPI$ for instance set T5 in the long-haul transportation setting.

B.1.1 Value of the Stochastic Solution (VSS)

In this section, we focus on the VSS. Tables from 11 to 13 report the average and maximum percentages VSS, showing how different parameters such as the level of the volume reduction, the percentage of scenarios affected by capacity losses and the probability that a bins type has a capacity reduction, affect the VSS.

As stated in the Section B.1, in the urban distribution, where the losses are localized, the stochastic approach is more valuable when there is a low probability of losing a large number of entire bins, which is for the example the case of unavailability of vans, when they are modeled as bins. Indeed, given the atomization of parcel flows (Morganti et al., 2014) and the high performance levels required by the contractual schemes in terms of number of delivery per day (Perboli and Rosano, 2019), an event that disrupts the regularity of operations and makes capacity fully unavailable, could have a huge impact on the service and profitability levels.

Indeed, in this case, Table 11 shows that the average VSS decreases as SL increases for both sets T3 and T5. The maximum values of VSS are reached when SL is equal to 20% and BL is 70%. In this case, the average and maximum percentages of VSS are 15% and 44% for T3 and 14% and 45% for T5.

In the case of the long-haul transportation (Table 12), when we consider instance set T3, when the availability of second-stage bins is limited and a considerable amount of capacity is likely to be lost in first-stage bins, the stochastic problem is not worth solving from a pure cost point of view, while the eventual infeasibility may be the real issue. In this case, the experimental tests revealed that when SL and TL are low, VSS increases as BL increases. On the contrary, when all the parameters have high values, VSS drops sharply. In particular, when we consider the availability class AV1 and SL, TL and BL are respectively equal to 80%, 75%, and 70%, and the average VSS percentage falls to 0%.

As in instance set T3, and even in instance set T5 (see Table 13), when SL and TL are low, the value of VSS increases as BL increases. In particular, the average percentage of VSS reaches 22% when SL, TL, and BL are respectively equal to 20%, 100%, and 70%, while the maximum percentage of VSS reaches 88%, with SL, TL, and BL respectively equaling 40%, 100%, and 70%. On the contrary, when SL and TL are high, the value of VSS decreases as BL increases and falls to 2% when SL, TL, and BL are respectively equal to 80%, 75%, and 70%.

SL[%]	**BL**[%]	**Set T3**		**Set T5**	
		VSS[%]	VSS_{max}[%]	VSS[%]	VSS_{max}[%]
20	**20**	9.31	23.61	8.24	22.61
	30	9.21	24.83	7.98	23.48
	40	9.83	28.23	8.25	27.30
	50	12.24	32.97	10.26	32.69
	60	14.03	38.92	12.74	38.68
	70	15.49	44.49	13.82	45.00
40	**20**	9.24	23.61	7.88	22.61
	30	8.86	24.80	7.78	23.15
	40	9.31	29.54	7.95	27.27
	50	11.65	36.34	9.84	34.15
	60	13.11	40.16	11.20	39.31
	70	13.02	42.68	11.28	40.68
60	**20**	9.14	23.61	7.71	22.61
	30	8.71	23.27	7.68	22.44
	40	8.93	22.39	8.04	22.74
	50	11.12	25.71	9.55	23.97
	60	12.49	31.96	10.61	30.59
	70	12.08	38.24	10.42	27.85
80	**20**	9.09	23.61	7.75	22.61
	30	8.70	22.63	7.74	22.44
	40	9.03	22.36	8.09	22.83
	50	11.10	25.71	9.61	24.03
	60	12.39	32.66	10.45	31.22
	70	11.80	30.58	10.29	27.41

Table 11: The impact of SL, TL and BL on VSS in the urban distribution setting.

SL[%]	TL[%]	BL[%]	AV1		AV2-AV3	
			$VSS[\%]$	$VSS_{max}[\%]$	$VSS[\%]$	$VSS_{max}[\%]$
20	**50**	**20-30**	6.41	21.52	10.42	25.14
		40-50	8.32	23.05	13.19	29.33
		60-70	11.65	26.89	17.51	35.35
	75	**20-30**	6.19	19.88	10.41	27.02
		40-50	11.16	23.43	15.84	30.57
		60-70	12.00	25.33	19.47	41.04
	100	**20-30**	8.10	23.15	12.01	26.96
		40-50	12.08	22.68	17.08	32.72
		60-70	13.15	27.41	22.58	43.59
40	**50**	**20-30**	8.31	21.81	11.98	27.75
		40-50	12.02	27.09	17.47	36.46
		60-70	13.14	33.15	22.21	43.40
	75	**20-30**	10.28	22.39	13.57	27.58
		40-50	12.27	25.54	18.86	39.70
		60-70	14.24	31.47	21.90	57.95
	100	**20-30**	10.24	23.03	14.58	32.92
		40-50	11.75	23.87	20.65	47.63
		60-70	15.74	32.00	15.03	62.07
60	**50**	**20-30**	9.92	27.21	14.00	33.47
		40-50	12.41	24.71	19.64	40.68
		60-70	16.17	36.68	19.85	80.83
	75	**20-30**	10.52	24.11	14.74	32.86
		40-50	12.32	26.85	18.68	53.22
		60-70	23.70	31.38	8.00	78.57
	100	**20-30**	10.67	24.83	15.64	36.01
		40-50	11.27	26.44	14.18	62.05
		60-70	0.25	0.75	3.33	8.33
80	**50**	**20-30**	10.18	23.70	15.01	32.25
		40-50	12.44	28.37	19.10	56.13
		60-70	28.13	37.55	8.22	80.40
	75	**20-30**	10.36	23.92	14.96	35.19
		40-50	16.85	56.65	13.11	74.73
		60-70	0.00	0.00	1.95	30.88
	100	**20-30**	9.46	23.52	14.78	44.59
		40-50	8.45	20.00	6.46	52.34
		60-70	-	-	2.92	6.81

Table 12: The impact of SL, TL and BL on VSS for instance set T3 in the long-haul transportation setting.

SL[%]	**TL**[%]	**BL** [%]	VSS[%]	VSS_{max}[%]
20	**50**	**20-30**	8.03	24.23
		40-50	10.12	35.71
		60-70	15.79	41.69
	75	**20-30**	7.94	24.87
		40-50	14.92	37.66
		60-70	19.66	43.39
	100	**20-30**	11.16	35.40
		40-50	17.18	39.62
		60-70	21.95	43.35
40	**50**	**20-30**	10.16	33.00
		40-50	16.80	38.14
		60-70	19.90	43.09
	75	**20-30**	13.56	35.41
		40-50	17.88	37.49
		60-70	20.48	58.54
	100	**20-30**	14.40	35.04
		40-50	18.47	45.31
		60-70	10.66	88.36
60	**50**	**20-30**	13.39	34.73
		40-50	18.10	38.91
		60-70	19.28	57.73
	75	**20-30**	14.51	35.28
		40-50	18.04	78.50
		60-70	7.17	84.46
	100	**20-30**	14.30	34.40
		40-50	11.27	64.27
		60-70	3.11	23.86
80	**50**	**20-30**	14.66	35.38
		40-50	17.49	74.47
		60-70	10.46	85.88
	75	**20-30**	14.41	35.69
		40-50	11.61	63.08
		60-70	1.88	19.62
	100	**20-30**	13.71	55.57
		40-50	4.46	51.44
		60-70	2.68	6.56

Table 13: The impact of SL, TL and BL on VSS for instance set T5 in the long-haul transportation setting.