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Stochastic Bin Packing Models for Capacity Planning in Logistic Applications

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Stochastic bin packing models for capacity planning in logistic applications

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Chapter 1

Introduction

The need for mobility that emerged in the last decades led to an impressive increase in the number of vehicles, as well as to a saturation of transportation infrastructures. This is particularly true in urban areas, whose population has been steadily growing since the 50s. Consequently, traffic congestion, accidents, transportation delays, and polluting emissions are some of the most recurrent concerns transportation and city managers have to deal with them (Dimitrakopoulos and Demestichas, 2010). However, just building new infrastructures, as new roads or high capacity highways, might be not sustainable because of their cost, the land usage, which usually lacks in metropolitan regions, and their negative impact on the environment (Crainic et al., 2009b). Therefore, a different way of improving the performance of transportation systems, while enhancing travel safety, has to be found in order to make people and good transportation operations more efficient and cost effective and support their key role in the economic development of either a city or a whole country.

The concept of City Logistics (CL) (Taniguchi et al., 2001) is being developed to answer to this need. Indeed, CL focus on reducing the number of vehicles operating in the city, controlling their dimension and characteristics, and reducing the number of empty vehicles (Benjelloun and Crainic, 2008). CL solutions do not only improve the transportation system but the whole logistics system within an urban area, trying to integrate interests of the several stakeholders (e.g., carriers, shippers, public authorities and citizens) of the Supply Chain (SC).

Similarly to any complex transportation system, CL systems require planning decisions at strategic, tactical and operational levels (Benjelloun and Crainic, 2008). In particular, strategic decisions have a long term effect, tactical decisions have an effect over the medium term (monthly or quarterly), and operational decisions have an immediate short-term effect.

Capacity planning is a major challenge involving tactical planning decisions in urban freight supply chain management. Capacity planning addresses the needs for sufficient capacity, expressed in terms of vehicles, containers or space in a warehouse, to satisfy the demand in the next cycle of activities. Thus companies, that want to be competitive in the market and fulfil customers' requirements in a cost-efficient and flexible manner, outsource the logistics activities to third-party logistic providers (3PLs), signing a medium-term contract with a 3PL that ensures sufficient capacity for the planning horizon.

Given the time lag that usually exists between the signing of the contracts and the logistics operations, the negotiations are performed under uncertainty, without all the necessary information concerning the future demand and thus the real needs in terms of loads to be moved or stored, as well as the availability and costs of capacity at the shipping date available. Thus, at each application of the plan, when the booked capacity is not sufficient, further negotiations with the 3PL and an adjustment of the plan are required.

Moreover, although the 3PL should ensure the planned capacity for the firm, this does not always happen. In effect, the capacity actually available for shipping and storage may be lower than the planned capacity. As regards the shipping of freight, vehicle booked in advance may contain several leftovers from previous days, due to delays or setbacks in the delivery of goods. This situation is particularly common in parcel delivery applications in urban and inter-city contexts, where the first attempt to deliver goods often fails. The leftovers cannot be unloaded from the vehicles and therefore only a part of the containers is actually available to load new goods. The problem of leftovers is also typical of warehouses, where it is mainly due to delays in the collection of the products currently stored. In addition, another risk concerns the mechanical failure of vehicles which leads to a loss of available capacity equal to the volume of the vehicle.

The Stochastic Variable Cost and Size Bin Packing Problem (SVCSBPP) (Crainic et al., 2014a) is a stochastic problem that focuses on the relation between a company and its logistics capacity provider. The SVCSBPP is the first attempt to introduce a stochastic variant of the variable cost and size bin packing problem (VCSBPP), considering not only the uncertainty on the demand to deliver (Crainic et al., 2014b), but also on the renting cost of the different bins and their availability. Although also the actual volumes of bins should be considered stochastic, the SVCSBPP is based on the hypothesis that the capacity is completely available at the shipping day.

This work contributes in filling this gap in the literature. In particular, we propose a new stochastic bin packing model, referred to as the Stochastic Variable Cost and Size Bin Packing Problem with Loss of Available Capacity (**SVCSBPP**$_L$), that explicitly takes into account the uncertainty related to the costs, the availabilities and the volumes of bins at the time of the full availability of the information, as well as the uncertainty related to the items, both in terms of their volume and presence. This planning problem is formulated as a two-stage integer stochastic program with recourse (Birge and Louveaux, 1997). Discretization methods are usually applied to approximate the probability distribution of the random parameters, using a finite-dimension scenario tree (Mayer, 1998). The resulting approximated program becomes a deterministic linear program with integer decision variables of generally very large dimensions, beyond the reach of exact methods. Therefore, we introduce an effective and accurate heuristic based on the Progressive Hedging (PH) ideas, initially proposed by Rockafellar and Wets (1991) for stochastic convex programs. The PH mitigates the computational difficulty associated with large problem instances by decomposing the stochastic program by scenario. When effective heuristic techniques exist for solving individual scenario, that is the case of the $\mathbf{SVCSBPP}_L$, the PH further reduces the computational effort of solving scenario subproblems to optimality by means of a commercial solver. In particular, we propose a series of specific strategies to accelerate the search, including an aggregated consensual solution, heuristic penalty adjustments, and a bundle fixing technique.

With the aim to make a complete analysis of the problem proposed, we perform extensive numerical experiments on a large set of instances of various dimensions and combinations of different levels of variability in the stochastic parameters. The goals of the experimental campaign are to measure the impact of uncertainty, determine whether building a stochastic programming model is really useful, and determine whether basic structure for the capacity planning exists and the dependence of the plan on attributes of the problem setting.

The tests show the benefits of using the two-stage model with recourse compared to the perfect information problem (the so-called wait and see approach, WS) and the expected value problem (EV). In particular, the numerical analysis indicates that the stochastic program has significant effects in terms of both the economic impact (i.e., cost reduction) and the operations management (i.e., prediction of the capacity needed by the firm). Moreover, the results indicate that the structure of the capacity planning solutions depends on the availability of bins on the spot market, the type of the reductions of capacity (uniform among all bins or localized), and the percentage of lost capacity. This confirms the need to take into account the reductions of available planned capacity in capacity planning applications.

This thesis is organized as follows. The Chapter 2 describes the concept of CL, introducing the economic and social aspects considered and the urban freight supply chain. In particular, we present the main CL initiative that have been proposed in order to enhance urban freight operations and we explore the main planning issues related to CL system, which challenge researchers to develop appropriate models that incorporate the sources of uncertainty of the urban context.

In Chapter 3, we present a capacity planning application in freight transportation and introduce the $\mathbf{SVCSBPP}_L$. After describing the process of contract procurement between a major retail firm and a third-party logistics service provider (3PL), we report the literature review. Then, we propose a two-stage stochastic formulation that explicitly takes into account several sources of uncertainty arising in capacity planning problems.

In Chapter 4, we present an heuristic for the $\mathbf{SVCSBPP}_L$ based on the PH algorithm. In particular, we show how the model can be decompose in deterministic subproblems and describe the strategies adopted in the algorithm to deal with the lack of implementability due to differences in the first-stage variable values among scenario subproblems.

In Chapter 5, we present new instance sets for tackling the problem and extensive computational results. In particular, we analyse the impact of the uncertainty and we introduce the concept of infeasibility. Then, solutions of the capacity planning are presented with the aim of determining whether basic structure for the capacity planning exists and analysing the dependence of the plan on attributes of the problem setting.

Conclusions and future developments of the research activity are reported in Chapter 6.

Chapter 2

City Logistics

City logistics aims to reduce the nuisances associated to freight transportation in urban areas, while supporting the economic and social development of the cities. The fundamental idea is to view individual stakeholders and decisions as components of an integrated logistics system. This implies the coordination of shippers, carriers, and movements as well as the consolidation of loads of several customers and carriers into the same environment-friendly vehicles. City logistics explicitly aims to optimize such advanced urban transportation systems.

In this chapter we present an overview of City Logistics concepts and ideas. In particular, Section 2.1 examines economic, social and environmental aspects relating to urban freight transportation, defines the concept of City Logistics and describes the urban freight supply chain. Section 2.2 presents the main City Logistics initiatives that have been proposed in order to enhance urban freight operations. Finally, Section 2.3 explores the main planning issues related to City Logistics system, which challenges researchers to develop appropriate models that incorporate the sources of uncertainty of the urban context.

2.1 Concepts of City Logistics

Nowadays, the continuous developments of the urban area, such as growth in population, increase of urbanization and living standards as well as expansion of Just-In-Time delivery and growth of home delivery services, are changing the living conditions. Due to the combination of these factors, the urban area, on one side, requires large quantities of goods and services for commercial and domestic use, but, on the other side, is affected by a deterioration of the quality of life caused by increasing congestion and pollution. In fact, while freight transportation system is fundamental to support economy and activities in urban areas, it also represents a major disturbing factor to urban viability and air pollution. These issues become even more critical if we consider that the global proportion of urban population increased from 13% in 1900, to 29% in 1950, 49% in 2005, and 58% in 2013. 70% of the global population is expected to live in urban areas by 2050 (OECD, 2012). Moreover, the global proportion of people over 65 years old was 7.6% in 2010 and is predicted to become 18.3% in 2060. Under such demographic conditions, urban freight transport issues have become more important for supporting a better life for people as well as an economic growth and a better environment in urban areas (Taniguchi, 2014).

However, just building new infrastructures, as new roads or high capacity highways, might not be sustainable because of their cost, the land usage, which usually lacks in metropolitan regions, and their negative impact on the environment (Crainic et al., 2009a). Therefore, a different way of improving the performance of transportation system, while enhancing travel safety, has to be found in order to make people and good transportation operations more efficient and cost effective and support their key role in economic development of either a city or a whole country. In addition, as we face higher risks of disasters due to global climate change and aging societies, urban freight transport should incorporate these risks for creating more sustainable and liveable cities.

In the last decades the concept of City Logistics (CL) has emerged to answer to these needs. Taniguchi et al. (2001) define CL as "the process for totally optimizing the logistics and transport activities by private companies in urban areas while considering the traffic environment, the traffic congestion and energy consumption within the framework of a market economy". This definition highlights the total optimisation of logistics activities of private companies rather than local optimisation. It also incorporates the social issues of the environment, congestion and energy savings as well as economic issues relating to urban freight transport within the framework of a market economy (Taniguchi, 2014). In particular, CL studies focus on reducing the number of vehicles operating in the city, controlling their dimension and characteristics, and reducing the number of empty vehicles (Benjelloun and Crainic, 2008). Therefore, CL aims to improve the efficiency of urban freight transportation and enhance the urban environment without penalizing the city social and economic activities. As indicated in most of the City Logistics literature, significant gains can only be achieved through a streaming of distribution activities resulting in less freight vehicles travelling within the city. The consolidation of loads of different shippers and carriers within the same vehicles, associated to some form of coordination of operations within the city are among the most important means to achieve the rationalization of distribution activities. The utilization of so-called green vehicles and the integration of public-transport infrastructures may enhance these systems and further reduce truck movements and related emissions in the city. However, consolidation and coordination are the fundamental concepts of CL (Crainic, 2008). Therefore, CL initiatives consider the transportation system as a whole and try to integrate interests of several stakeholders (e.g., carriers, shippers) of the Supply Chain (SC).

Taniguchi et al. (2001) identify four groups of key stakeholders of the city: shippers, carriers, citizens and public authorities. All these stakeholders follow different goals and have therefore different perspectives. Public authorities and citizens share some problems regarding externalities like accidents, congestion, noise, and air pollution caused by freight vehicles. These impacts are felt to reduce the quality of life and of the urban environment substantially. Shippers and carries have a completely different point of view. They have the goal to deliver/receive goods in the cheapest possible way to maximize their own profits within a given regulatory framework and a given transport infrastructure. Their priorities are therefore to remove costly obstacles, which hinder them to deliver faster and cheaper, without taking into consideration externalities.

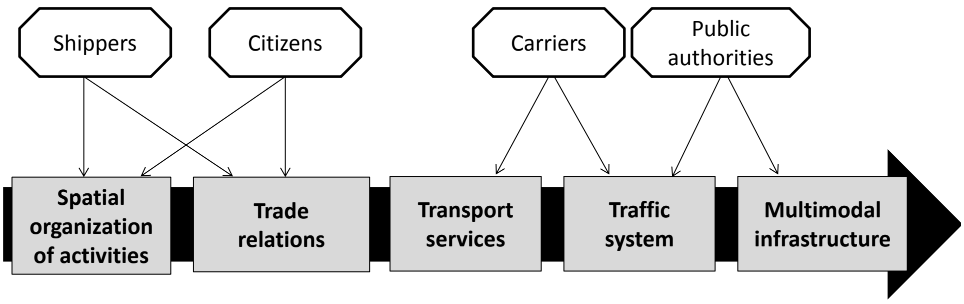

Figure 2.1: Urban freight supply chain model and relationships with stakeholders.

Figure 2.1 shows the urban freight supply chain model and the relationships with the stakeholders (Boerkamps et al., 2000). It can be seen that the stakeholders belong to different parts of the city logistics domain: they are closely connected to at least one component, but are loosely connected to the whole SC. In particular, although actions by one stakeholder affect the whole domain, a stakeholder can influence only the part of the SC to which it is closely connected. For example, a carrier can use a different strategy for routing and avoid congestion, but it cannot influence traffic flow in the city. Similarly, public authorities (i.e., municipality) can impose route restrictions but cannot directly impose a specific route choice. In general, shippers and citizens represent the demand for urban freight transport.

Thus, they are strictly related to the spatial organization (e.g., where people live and work, where facilities are located, and where freight are produced and consumed) and trade activities. On the contrary, carriers and public authorities are involved only in the transportation components of the SC.

The following section describes the main City Logistics initiatives that have been proposed and actually implemented in several cities by stakeholders in order to enhance urban freight operations.

2.2 City Logistics Initiatives

In attempting to reduce the scale of negative impacts and to optimize the decisions at each level of the urban freight SC, a range of initiatives of CL have been proposed. Some of these initiatives address only a single impact, while others address several impacts at the same time. In general, several CL solutions focuses on the consolidation of freight in urban consolidation centers (UCCs) (Benjelloun and Crainic, 2008; McKinnon et al., 2010), which are logistic platforms located in a strategic node of the city (e.g., close to the access of the city or ring highways), with the functions of collecting and dispatching goods. UCCs link the city to regional, national and international hubs and thus must be easily accessible and integrated with other logistics platforms. Regarding the urban freight supply chain model, UCCs affect the "Transport services" and the "Traffic system" blocks of the SC (see Figure 2.1).

Urban consolidation centers are thus facilities where shipments are consolidated prior to distribution. In particular, they receive large trucks of logistics companies and smaller vehicles. Logistic companies drop their loads and avoid the need to enter congested urban areas, saving time and costs. At UCCs, the freight to deliver to the city is stored, sorted, and consolidated (de-consolidated) in an integrated-way. Then, the local distribution is performed by often using environmental-friendly vehicles such as electric and gas powered light vehicles. The UCCs may therefore be viewed as an intermodal centralized platform with enhanced functionality that efficiently coordinates the supply and the demand to and from the city.

UCCs represent the first step toward a better CL organization and a more efficient freight movement (Crainic, 2008). By improving the lading factor of vehicles making final deliveries in congested locations, UCCs reduce the total distance travelled by delivery vehicles in urban areas, as well as reducing GHG emissions and local air quality pollutants associated with these journeys (Browne et al., 2011). Example of the realization of UCCs can be Padova one in Italy or Brema one in Germany. According to a study done by Gonzalez-Feliu et al. (2010), emissions of GHG in 2008 were reduced of 68% respect to 2003 thanks to the installation of a UCC called Cityporto.

When a single level of consolidation is considered and the freight distribution starts at an UCC and arrives directly to customers in the urban area, the system is called single-tier CL system. The first CL projects in Europe and Japan involved some form of single-tier system, mostly considering a single UCC and a limited number of shippers and carriers. Such approaches have not been successful for large cities, however, in particular when the large areas, usually identified as the city center, display high levels of population density as well as commercial, administrative, and cultural activities. Another characteristic of large cities that plays against single-tier systems is the rather lengthy distance a vehicle must travel from the UCC on the outskirts of the city until the city center where the delivery tour begins. One of the trends is to substitute traditional single-tier systems with two-tier ones for such cities.

Crainic et al. (2004) propose an extension of UCCs with a net of smaller facilities called satellite platforms and located closer to the city center respect to UCCs. Figure 2.2 represents a two-tier distribution system. UCCs (black squares in the figure) form the first level of the system and are located on the outskirts of the urban zone (black circles in the figure). The second tier of the system is constituted of satellites (green triangles in the figure), where the freight coming from the UCCs and, eventually, other external points, may be transferred to and consolidated into vehicles adapted for utilization in dense city zones. Existing facilities, e.g., underground parking lots or municipal bus garages, could thus be used for satellite activities. Indeed, satellites offer limited logistics services and storing of freight.

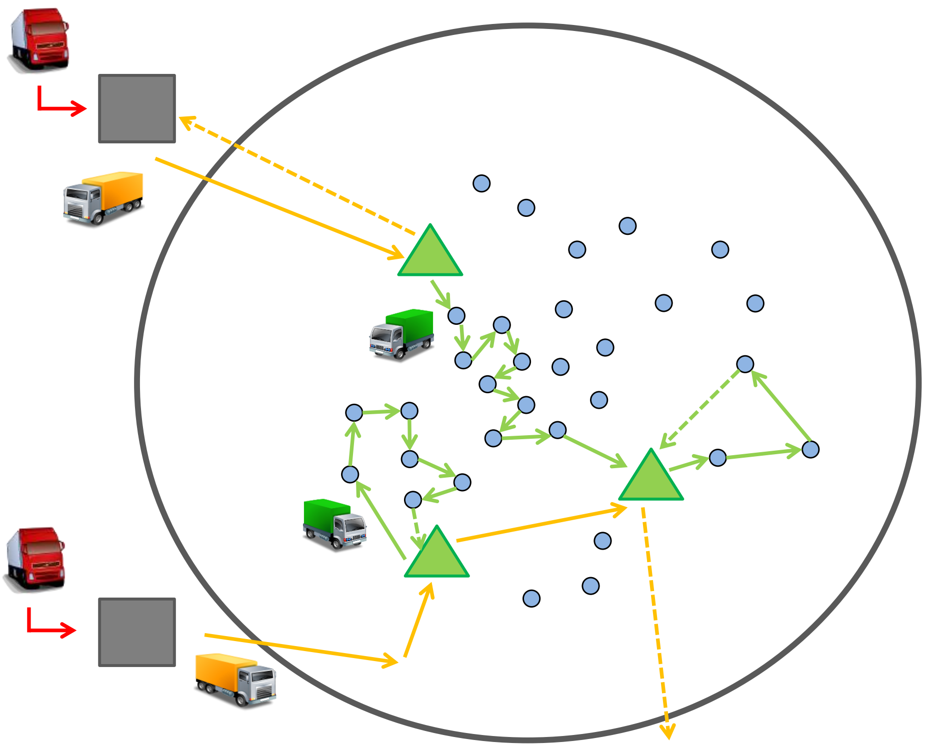

Figure 2.2: A representation of a two-tier distribution system. Urban-trucks (yellow vehicles) move freight from UCCs (black squares) to satellite facilities (green triangles). City-freighters (green vehicles) distribute freight in the city-center area. Dotted lines represent empty vehicles.

Two types of vehicles are involved in a two-tier distribution system: urban-trucks (yellow trucks in the figure) and city freighters (green trucks in the figure). Urban-trucks move freight from UCCs to satellites, possibly by using streets specially selected to facilitate access to satellites and reduce the impact on traffic congestion and environment. Moreover, since the goal is to minimize the truck movements within the city, rules may be imposed to have them travel as much as possible around the city, on the ring highways surrounding the city, and enter the city center as close to destination as possible. Urban-trucks may visit more than one satellite during a trip. Their routes and departures have to be optimized and coordinated with satellites and city-freighters access and availability. City-freighters are vehicles of relatively small capacity that can travel along any street in the city-center area to perform the required distribution activities. City-freighters may be of several types in terms of functionality (e.g., refrigerated or not), box design, loading/unloading technology, capacity and so on. Efficient operations require a certain standardization, however, so the number of different city-freighter types within a given CL system is thus assumed to be small.

Two-tier CL system allow more benefits in terms of congestion and emissions, in particular when small and environmental-friendly vehicles are used inside the city. Van Mierlo et al. (2003) report that electric vehicles, in average, have more than three times lower environmental impact compared to diesel trucks and twice as low impact compared to liquefied petroleum gas trucks. Moreover, the costs due to additional transshipment operations are compensated by the consolidation of freight, the decrease of empty trips (i.e., reverse logistics) and the economy of scale. However, two-tier distribution needs more complex cooperation and planning decisions. Indeed, the transshipment needs integration of different companies requirements and a reliable planning of vehicle routing to deliver shipments on time.

From a physical point of view, the system operates according to the following sequence: freight arrives at an external zone where it is consolidated into urban-trucks; each urban-truck receives a departure time and route and travels to one or several satellites; at a satellite, freight is transferred to city-freighters; each city-freighter performs a route to serve the designed customers, and then travels to a satellite (or a depot) for its next cycle of operations. On the other hand, from an informational and decision point of view, it all starts with the demand for loads to be distributed within the urban zone. The corresponding freight will be consolidated at external zones yielding the actual demand for the urban-truck transportation and the satellite transdock transfer activities. These, in turn, generate the input to the city-freighter circulation, which provides the last leg of the distribution chain as well as the timely availability of empty city-freighters at satellites. The objective is to have urban-trucks and city-freighters on the city streets and at satellites on a "needs-to-be-there" basis only, while providing timely delivery of loads to customers and economically and environmentally efficient operations.

The following section describes several planning and operative problems that arise in two-tier context. In particular, we present the different levels of CL decision processes, the main sources of uncertainty that can affect the transportation system, and an overview of Stochastic Programming methods that can be used to model optimization problems involving uncertainty.

2.3 Planning Issues

The main problems that stakeholders and decision makers of a two-tier CL system must address concern satellite location, two-echelon vehicle routing, capacity and fleet management, handling operators management, and satellite and vehicle replenishment. In particular, the introduction of satellites as additional block in the urban freight SP makes capacity and fleet management a very challenging issue.

Indeed, since storage space of UCCs is limited and, in the case of satellites, even not available (or available only for a very short time), a strict compliance of logistics service providers is needed. Moreover, city-freighters can travel along any street in the city-center area to perform the required distribution activities, but they are vehicles of relatively small capacity. Efficient freight distribution thus requires the management of the capacity within warehouses of UCCs and satellites, as well as the design of different city freighter types (e.g., capacity, power-train, functionality) within a given CL system and the planning of the fleet of vehicles available for the next period of activity. When logistic operations are outsourced to logistic providers, this process becomes even more critical and results in a medium-term contract that ensures sufficient capacity for the planning horizon and a cost-effective logistics service. Chapter 3 describes in more detail the procurement process for logistics capacity planning and its mathematical formulation.

Similarly to any complex transportation system, two-tier CL systems require planning decision at strategic, tactical and operational levels (Benjelloun and Crainic, 2008). Strategic decisions have a long term effect, tactical decisions have an effect over the medium term (monthly or quarterly), and operational decisions have an immediate short-term effect. One more level assumes a key role in the urban system: the real-time. Individual levels differ by the impact they have on future activities:

Strategic level involves the highest level of management and requires large capital investments over a long term horizon. Strategic decisions determine infrastructure aspects (e.g., location of UCCs), freight distribution networks, and general development policies and strategies. Corresponding decisions are complex and of high risk and uncertainty. These decisions have a key role in the planning process: they constrain the activities and the decisions made at tactical and operational levels.

Tactical level defines, over a medium term horizon, the usage of the available resources in order to improve the system's performance. In particular, it concerns the efficient and effective use of transportation infrastructure and the alignment of operations according to strategic objectives. For example, tactical planning addresses the need of sufficient capacity to store (i.e., space in a warehouse) and move (i.e., dimension of the fleet of vehicles) freight to meet demand in the next cycle of activities. Other tactical decisions include the definition of periodic tours used for the entire planning horizon and costs and performance analysis. On one side, tactical level controls and evidences the strengths and the weakness of the strategic decisions while, on the other side, tactical decisions limit the activities of operational and real-time-management level.

Operational level concerns short term decisions, day-to-day operations and the plan of next day activities. The time factor and the detailed representation of the system are essential at this level. The decisions are made in a very dynamic environment. Thus, anticipate the future (e.g., the congestion, the transportation demand) is fundamental. Operational decisions determine the routing, assigning the transportation request to the transportation resources, and the handling operations.

Real-time level reacts on differences between information known at the moment of planning decision and the actual state of the transportation system. Here, the activities are directly related to operational decisions and aims to mitigate the effects of poor quality and reliability of operational planning. Errors in the forecasting of the future may lead to inferior customer service or higher cost to adjust the planning (e.g., rent one more vehicle at a premium cost).

In general, planning implies a certain level of look-ahead skills. The variation of the demand to be shipped or the costs of operations over the planning horizon, as well as the reduction of the actual capacity available within warehouses of UCCs and satellites due to delays in the collection of goods, are only some examples of the uncertainty sources in the urban context. The forecasting of random events thus assume a key role in the planning process. In particular, it may have a strong impact on decisions and on the efficiency of the urban freight transportation service. Random events, however, are usually unknown at the initial planning stage and we only gain knowledge about them during the plan execution. Therefore these events must be included in the decision process at all levels.

Stochastic programming (SP) (Birge, 1982) can be used to model optimization problems that involve uncertainty. Its goal is to find some policy that is feasible for all (or almost all) the possible data instances and maximizes the expectation of some function of the decisions and the random variables. More generally, such models are formulated, solved analytically or numerically, and analyzed in order to provide useful information to a decision-maker.

The most widely applied and studied SP models are two-stage linear programs. The basic idea of two-stage stochastic programming is that optimal decisions should be based on data available at the time the decisions are made and should not depend on future observations. In particular, the decision maker takes some action under uncertainty in the first stage, after which a random event occurs affecting the outcome of the first stage decision. A recourse decision can then be made in the second stage that compensates for any bad effects that might have been experienced as a result of the first-stage decision. This formulation assumes that the second-stage data can be modelled as a random vector with a known probability distribution. The optimal policy from such a model is a single first-stage solution and a collection of recourse decisions defining which second-stage action should be taken in response to each random outcome.

Solutions approaches to SP models are driven by the type of probability distributions governing the random parameters. A common approach to handling uncertainty is to define a small number of scenarios to represent the future. In this case it is possible to compute a solution to the SP problem by solving a deterministic equivalent linear program. These problems are typically very large scale problems, and so, much research effort in the SP community has been devoted to developing algorithms that exploit the problem structure, in particular in the hope of decomposing large problems into smaller more tractable components (Ruszczynski, 1997).

Chapter 3

Capacity Planning Problem under Uncertainty

Capacity planning is a major challenge involving tactical planning decisions in urban freight supply chain management. When tactical decisions are made, no detailed knowledge on the future demand and thus the real needs in terms of loads to be moved or stored, as well as the availability and costs of capacity is available. Capacity planning addresses the needs for sufficient capacity to store and move freight to meet demand in the next cycle of its activities. When logistic operations are outsourced to logistics providers, this process becomes more critical and results in a medium-term contract that ensures sufficient capacity for the planning horizon and a cost-effective logistics service.

This chapter is organized as follows. In Section 3.1 we analyse the process of contract procurement between a major retail firm and a third-party logistics service provider (3PL) and its relevance to the capacity planning problem. Section 3.2 reports the literature review. Finally, in Section 3.3 we propose the two-stage stochastic formulation of the $\mathbf{SVCSBPP}_L$, that explicitly takes into account several sources of uncertainty arising in capacity planning problems.

3.1 Problem description

The tactical capacity planning problem is relevant in many contexts, e.g., manufacturing firms desiring to secure transportation capacity to bring in their resources or to distribute their products, wholesalers and retailers planning for transportation and storage capacity to support their procurement and sales processes, and logistics service providers securing capacity contracts with carriers for long-distance, regular shipments. Manufacturing and whole/retail distribution firms may negotiate directly with carriers and owners/managers of storage space but, very often, they do business with a logistic service provider. Consequently, in order to simplify the presentation, but without loss of generality, we describe the problem within the context of the process of contract procurement between a major retail firm and a third-party logistics (capacity) service provider (3PL).

In the contemporary economic and business environment, firms are engaged in a continuous procurement process (Aissaoui et al., 2007; Rizk et al., 2008), and engage in various collaborations with its supply-chain partners. Such inter-firm alliances yield several benefits, including a reduction in inefficiencies, total cost, and financial risks. The greatest advantages result from the outsourcing of logistics activities to a 3PL (Marasco, 2008). The overall supply-chain process may then be summarized as follows. The firm regularly orders products from suppliers in a given geographical region, according to current inventories, short-term forecast demand, estimated lead times, and specific procurement and inventory policies (Bertazzi and Speranza, 2005; Bertazzi et al., 2007) The suppliers are instructed to deliver their goods to a consolidation center (Crainic and Kim, 2007; Bertazzi and Speranza, 2012). The 3PL then consolidates the goods into containers and ensures their shipping, by consolidating these containers with those of other customers into the slots it secured on long-haul cariers, e.g., ships and trains (Chen et al., 2001; Crainic et al., 2013), which generally operate according to a fixed schedule, e.g., twice a week. Finally the 3PL manages the storing of goods into warehouses.

A key factor in this process is the procurement of sufficient transportation and storage capacity, that we express in the following in terms of bins, at different locations in the network and for varying periods of time, to satisfy the demand. This entails negotiations with the 3PL to book the necessary capacity a priori, before operations start, at the best rate (Ford, 2001). The results of these negotiations often take the form of medium-term contracts specifying both the capacity to be used, the quantity and the type of bins, and the additional services to be performed (e.g., storage, transportation, bin operations) for a given planning horizon, e.g., a semester or a year. These contracts guarantee a regular volume of business to the 3PL (e.g., a fixed number of containers to ship every week for the next semester), which ensures a cost-effective service to the firm.

We refer to the costs of bins selected in advance as fixed costs because they are fixed by the contract and thus represent the specific rates offered by the 3PL for bins of different sizes. The values of the fixed costs are in practice influenced by several factors, including bin size, bin type (e.g., thermal or refrigerated containers), physical handling operations required, the time period for which the bin is to be used, and the economic characteristics of the departure location (e.g., access rules and costs). The result of negotiations and the scope of the capacity planning problem then is a tactical plan defining these quantities for the firm at each location, given the proposed bin types and costs and an estimation of the demand over the planning horizon. The plan thus specifies the set of bins of particular volumes and fixed costs to be made available at each location to ship and store the estimated items.

Given the time lag that usually exists between the signing of the contracts and the logistics operations, the negotiations are performed under uncertainty, without all the necessary information concerning the demand, expressed as a number of items of variable sizes to be shipped or stored at the particular locations. At each application of the plan, variations in the demand may thus yield numbers and sizes of items that differ from the estimation used at negotiation. These variations then require further negotiations with the 3PL and an adjustment of the plan when the booked capacity is not sufficient. Extra capacity (additional bins available at the shipping date) must then be purchased, generally at a much higher cost (the so-called spot - market value) than the fare negotiated initially. The extra capacity may not be available when needed and must therefore be considered stochastic.

Although the 3PL should ensure the planned capacity for the firm, this does not always happen. In effect, the capacity actually available for shipping and storage may be lower than the planned capacity. As regards the shipping of freight, vehicles booked in advance may contain several leftovers from previous days, due to delays or setbacks in the delivery. This situation is particularly common in parcel delivery applications in urban and inter-city contexts, where the first attempt to deliver goods often fails. The leftovers cannot be unloaded from the vehicles and therefore only a part of the containers is actually available to load new goods. The problem of leftovers is also typical of warehouses, where it is mainly due to delays in the collection of the products currently stored. It is particularly important to take this fact into account because it involves the loss of a great percentage of capacity. In addition, in the context of the delivery of goods, another risk concerns the mechanical failure of a vehicle which leads to a loss of available capacity equal to the volume of the vehicle.

Moreover, when the actually available capacity is lower than the planned volume, additional costs must be paid to rearrange loads and storage of goods. These costs depend on the amount of goods that must be relocated and thus can be considered proportional to the total lost capacity. Therefore the problem of the loss of planned capacity cannot be neglected and the actual volume of bins must be considered stochastic.

3.2 Literature review

Bin packing models offer important decision tools for transportation and logistics (Perboli et al., 2014a). In bin packing problems, various items must be packed into bins with the goal of minimizing the overall cost. The particular characteristics of items and bins in terms of capacities and costs generate a rich set of problem settings and formulation. The packing formulations currently proposed in the literature deal only partially, however, with the requirements of capacity planning, as most research has explored operational issues only. Thus, most of the literature addressing bin packing and uncertainty, focuses on modeling uncertainty in item arrival, leading to the so-called on-line packing problem (Seiden, 2002), i.e. the variant of the bin packing where the items come one after the other and no knowledge (or a limited one) on the volume of the next items is given to the decision maker. The researchers studied policies for loading the items in different bins, giving results on their absolute or asymptotic behaviour.

Studies focusing on stochastic versions of bin packing problems for strategic and tactical planning applications are few and recent. Perboli et al. (2012, 2014b) introduced stochastic costs and profits into a bin packing and a knapsack problems. While, Crainic et al. (2014b) proposed a stochastic extensions of the Variable Cost and Size Bin Packing Problem (VCSBPP) (Crainic et al., 2011b), refereed to as the Stochastic Variable Cost and Size Bin Packing Problem (SVCSBPP). The VCSBPP considers bins with different costs and capacities, while the SVCSBPP introduces uncertainty in both the bins, in terms of the number of available bins and their costs, and the demand, in terms of the number of items and their volumes.

Even if the SVCSBPP considers several sources of uncertainty that characterize the capacity planning, it supposes that all the planned capacity is actually available for the shipping and the storage. As we have seen before, this is not always true and therefore we propose a new stochastic bin packing model, referred to as the Stochastic Variable Cost and Size Bin Packing Problem with Loss of Available Capacity (**SVCSBPP**$_L$) that explicitly takes into account the actual volumes of bins.

Regarding the solving strategy, numerous algorithms for solving stochastic mixed-integer programs (SMIPs) (Kall and Wallace, 1994) are based on decomposition of the scenario tree by time stages (i.e., vertical decomposition) or by complete scenarios (i.e., horizontal decomposition). PH algorithm is a horizontal decomposition approach and has emerged as an effective method for solving stochastic linear, non-linear, and linear SMIPs (Silva and Abramson, 1994; Crainic et al., 2011a; Ryan et al., 2013; Watson et al., 2014).

PH is a natural algorithm for solving large-scale SMIPs. By decomposing the Recourse Problem (RP) according to scenarios, and iteratively solving penalized versions of the sub-problems, the PH gradually enforces implementability. However, non-convergence of solution is possible in the case of non-convex optimization problems such as the SVCSBPP and the **SVCSBPP**$_L$. Integer decision variables render SP problems non-convex and significantly increase the difficulty of solution. For some smaller problem instances, standard MIP solvers can be used (Crainic et al., 2014b) to directly solve the RP. However, standard MIP solvers fail to consistently solve even individual scenario sub-problems in realistic applications in the context of CL. In fact, solving scenario problems separately, PH is particularly appropriate when there exist good, fast heuristics for generating solutions of individual scenarios.

3.3 Model formulation

We propose a two-stage stochastic programming formulation of the **SVCSBPP**$_L$, where the first stage concerns the selection of bins, and the second stage concerns the acquisition of extra capacity when the actual demand information is revealed.

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. Let vector ξ contain the stochastic parameters defined in the model, and $\xi(\omega)$ be a given realization of this random vector. Let the first-stage variables be $y_j^t = 1$ if bin $j \in \mathcal{J}^t$ is selected and 0 otherwise. The two-stage model of the $\mathbf{SVCSBPP}_L$ may then be formulated as

$$\min_y \sum_{t \in T} \sum_{j \in \mathcal{J}^t} f^t y_j^t + E_\xi \left[Q\left(y, \xi(\omega)\right) \right] \tag{3.1}$$

$$\text{s.t.} \quad y_j^t \geq y_{j+1}^t, \qquad \forall t \in T, j = 1, \ldots, |\mathcal{J}^t| - 1, \tag{3.2}$$

$$y_j^t \in \{0, 1\}, \qquad \forall t \in T, j \in \mathcal{J}^t, \tag{3.3}$$

where $Q\left(y, \xi(\omega)\right)$ is the extra cost paid for the capacity that is added at the second stage, given the tactical capacity plan y and the vector $\xi(\omega)$. The objective function (3.1) then 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. Usually, packing problems 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. But, when we consider the available capacity of first-stage bins as a source of uncertainty, this is no more true. In effect, each bin of type $t \in T$ may have a different actual volume and we need to characterize it properly. We thus introduce constraints (3.2) to break the symmetry and ensure an 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, constraints (3.3) impose the integrality requirements on y.

To formulate $Q\left(y, \xi(\omega)\right)$, let c^t be the extra cost to pay for the loss of a unit of capacity in a 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.

We now define the function $Q\left(y, \xi(\omega)\right)$ as

$$Q(y, \xi(\omega)) = \min_{y, z(\omega), x(\omega)} \sum_{\tau \in \mathcal{T}} \sum_{k \in \mathcal{K}^\tau(\omega)} g^\tau(\omega) z_k^\tau(\omega) + \sum_{t \in T} \sum_{j \in \mathcal{J}^t} c^t (V^t - \mathcal{V}_j^t(\omega)) y_j^t \tag{3.4}$$

$$\begin{aligned}
\text{s.t.} \quad & \sum_{j \in \mathcal{J}} x_{ij}(\omega) + \sum_{k \in \mathcal{K}(\omega)} x_{ik}(\omega) = 1, && \forall i \in \mathcal{I}(\omega), && (3.5) \\
& \sum_{i \in \mathcal{I}(\omega)} v_i(\omega) x_{ij}(\omega) \leq \mathcal{V}_j^t(\omega) y_j^t, && \forall\, t \in T, j \in \mathcal{J}^t, && (3.6) \\
& \sum_{i \in \mathcal{I}(\omega)} v_i(\omega) x_{ik}(\omega) \leq V^\tau z_k^\tau(\omega), && \forall\, \tau \in \mathcal{T}, k \in \mathcal{K}^\tau(\omega), && (3.7) \\
& x_{ij}(\omega) \in \{0,1\}, && \forall\, i \in \mathcal{I}(\omega), j \in \mathcal{J}, && (3.8) \\
& x_{ik}(\omega) \in \{0,1\}, && \forall\, i \in \mathcal{I}(\omega), k \in \mathcal{K}(\omega), && (3.9) \\
& z_k^\tau(\omega) \in \{0,1\}, && \forall\, \tau \in \mathcal{T}, k \in \mathcal{K}^\tau(\omega). && (3.10)
\end{aligned}$$

The objective function (3.4) 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. Constraints (3.5) ensure that each item is packed in a single bin. Constraints (3.6) and (3.7) ensure that the total volume of items packed in each bin does not exceed the actual volume of the bin. Finally, constraints (3.8) to (3.10) impose the integrality requirements on all second-stage variables.

Chapter 4

Heuristic based on progressive hedging

In this chapter, we present an heuristic for the $\mathbf{SVCSBPP}_L$ based on the PH algorithm. The method first applies a scenario decomposition (SD) technique based on the augmented Lagrangian relaxation, which separates the stochastic problem by scenario. Here, the Lagrangian multipliers are used to penalize a lack of implementability due to differences in the first-stage variable values among scenario subproblems. Algorithm 1 describes the proposed heuristic for the $\mathbf{SVCSBPP}_L$. Section 4.1 describes how the $\mathbf{SVCSBPP}_L$ can be decomposed into deterministic VCSBPP subproblems with modified fixed costs and an additional constraint that ensures an order in the selection of bins of a certain type. Then, the method proceeds in two phases. Part 1 aims to obtain consensus among the subproblems. At each iteration, the subproblems are first solved separately. Their solutions are then aggregated into a temporary overall solution, as defined in Section 4.2. The search process is gradually guided toward scenario consensus by adjusting the Lagrangian multipliers and the subproblem penalties (Section 4.2.2), based on the deviations of the scenario solutions from the overall solution, and by a variable bundle-fixing strategy (Section 4.2.3). This search process continues until the consensus is achieved or one of the termination criteria is met (Section 4.3). When consensus is not achieved in the first phase, Phase 2 (see Section 4.4) solves the restricted $\mathbf{SVCSBPP}_L$ obtained by fixing the first-stage variables for which consensus has been reached, i.e., the bins used in all the scenario subproblems.

4.1 Scenario decomposition

We first reformulate the $\mathbf{SVCSBPP}_L$ stochastic (3.1)-(3.10) 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 $\mathbf{SVCSBPP}_L$ problem (3.1)-(3.10) can be approximated by the following equivalent deterministic model:

$$\min_{y,z,x} \sum_{s \in \mathcal{S}} p_s \left[\sum_{t \in T} \sum_{j \in \mathcal{J}^t} f^t y_j^{ts} + \sum_{\tau \in \mathcal{T}} \sum_{k \in \mathcal{K}^{\tau s}} g^{\tau s} z_k^{\tau s} + \sum_{t \in T} \sum_{j \in \mathcal{J}^t} c^t (V^t - \mathcal{V}_j^{ts}) y_j^{ts} \right] \tag{4.1}$$

Algorithm 1 PH-based meta-heuristic for the **SVCSBPP**$_L$

Scenario decomposition
Generate a set of scenarios $\mathcal{S}$;
Decompose the resulting deterministic model (4.1)–(4.10) by scenario using augmented Lagrangian relaxation;

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 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 (4.37);
  Bundle fixing
    $\bar{\delta}_m^{\overline{\tau}\nu} \leftarrow \min_{s\in\mathcal{S}} \delta^{\overline{\tau}s\nu}$
    $\bar{\delta}_M^{\overline{\tau}\nu} \leftarrow \max_{s\in\mathcal{S}} \delta^{\overline{\tau}s\nu}$
    Apply variable fixing;
  $\nu \leftarrow \nu + 1$

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 (4.1)–(4.10);
  Solve restricted (4.1)–(4.10) model using a MIP solver.

$$
\begin{aligned}
\text{s.t.}\quad & y_j^{ts} \geq y_{j+1}^{ts}, && \forall\, t \in T, j = 1, \ldots, |\mathcal{J}^t| - 1, s \in \mathcal{S}, && (4.2)\\
& \sum_{j \in \mathcal{J}} x_{ij}^s + \sum_{k \in \mathcal{K}^s} x_{ik}^s = 1, && \forall\, i \in \mathcal{I}^s, s \in \mathcal{S}, && (4.3)\\
& \sum_{i \in \mathcal{I}^s} v_i^s x_{ij}^s \leq \mathcal{V}_j^{ts} y_j^{ts}, && \forall\, t \in T, j \in \mathcal{J}^t, s \in \mathcal{S}, && (4.4)\\
& \sum_{i \in \mathcal{I}^s} v_i^s x_{ik}^s \leq V^\tau z_k^{\tau s}, && \forall\, \tau \in \mathcal{T}, k \in \mathcal{K}^{\tau s}, s \in \mathcal{S}, && (4.5)\\
& y_j^{ts} = y_j^{ts'}, && \forall\, t \in T, j \in \mathcal{J}^t, s, s' \in \mathcal{S}, && (4.6)\\
& y_j^{ts} \in \{0, 1\}, && \forall\, t \in T, j \in \mathcal{J}^t, s \in \mathcal{S}, && (4.7)\\
& z_k^{\tau s} \in \{0, 1\}, && \forall\, \tau \in \mathcal{T}, k \in \mathcal{K}^{\tau s}, s \in \mathcal{S}, && (4.8)\\
& x_{ij}^s \in \{0, 1\}, && \forall\, i \in \mathcal{I}^s, j \in \mathcal{J}, s \in \mathcal{S}, && (4.9)\\
& x_{ik}^s \in \{0, 1\}, && \forall\, i \in \mathcal{I}^s, k \in \mathcal{K}^s, s \in \mathcal{S}. && (4.10)
\end{aligned}
$$

Constraints (4.6) are referred as the non-anticipativity constraints. They ensure that the first-stage decisions are not tailored according 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, and 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 (4.6):

$$
\begin{aligned}
& \bar{y}_j^t = y_j^{ts}, && \forall\, t \in T,\ j \in \mathcal{J}^t, s \in \mathcal{S}, && (4.11)\\
& \bar{y}_j^t \in \{0, 1\}, && \forall\, t \in T,\ j \in \mathcal{J}^t. && (4.12)
\end{aligned}
$$

Constraints (4.11) force the first-stage solution of each scenario to be equal to the global capacity plan. Constraints (4.12) 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 (4.11), 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 (4.11) using an augmented Lagrangean strategy. We thus obtain the following objective function for the overall problem:

$$\min_{y,z,x} \sum_{s \in \mathcal{S}} p_s \Bigg[\sum_{t \in T} \sum_{j \in \mathcal{J}^t} f^t y_j^{ts} + \sum_{\tau \in \mathcal{T}} \sum_{k \in \mathcal{K}^{\tau s}} g^{\tau s} z_k^{\tau s} + \sum_{t \in T} \sum_{j \in \mathcal{J}^t} c^t (V^t - \mathcal{V}_j^{ts}) y_j^{ts} + \\ + \sum_{t \in T} \sum_{j \in \mathcal{J}^t} \lambda_j^{ts} (y_j^{ts} - \bar{y}_j^t) + \frac{1}{2} \sum_{t \in T} \sum_{j \in \mathcal{J}^t} \rho_j^t (y_j^{ts} - \bar{y}_j^t)^2 \Bigg] \tag{4.13}$$

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 4.13, let us consider the quadratic term. Given the binary requirements of y_j^{ts} and $\bar{y}_j^t$, the term becomes:

$$\sum_{t \in T} \sum_{j \in \mathcal{J}^t} \rho_j^t \left(y_j^{ts} - \bar{y}_j^t \right)^2 = \sum_{t \in T} \sum_{j \in \mathcal{J}^t} \left(\rho_j^t (y_j^{ts})^2 - 2\rho_j^t y_j^{ts} \bar{y}_j^t + \rho_j^t (\bar{y}_j^t)^2 \right) = \tag{4.14}$$

$$= \sum_{t \in T} \sum_{j \in \mathcal{J}^t} \left(\rho_j^t y_j^{ts} - 2\rho_j^t y_j^{ts} \bar{y}_j^t + \rho_j^t \bar{y}_j^t \right). \tag{4.15}$$

Therefore, the objective function can be formulated as follows:

$$\min_{y,z,x} \sum_{s \in \mathcal{S}} p_s \Bigg[\sum_{t \in T} \sum_{j \in \mathcal{J}^t} \left(f^t + c^{ts} (V^t - \mathcal{V}_j^{ts}) + \lambda_j^{ts} - \rho_j^t \bar{y}_j^t + \frac{\rho_j^t}{2} \right) y_j^{ts} + \\ + \sum_{\tau \in \mathcal{T}} \sum_{k \in \mathcal{K}^{\tau s}} g^{\tau s} z_k^{\tau s} - \sum_{t \in T} \sum_{j \in \mathcal{J}^t} \lambda_j^{ts} \bar{y}_j^t + \frac{1}{2} \sum_{t \in T} \sum_{j \in \mathcal{J}^t} \rho_j^t \bar{y}_j^t \Bigg]. \tag{4.16}$$

Given constraints (4.2)-(4.10) and the objective function (4.16), 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:

$$\min_{y,z,x} \quad \sum_{t\in T}\sum_{j\in\mathcal{J}^t}\left(f^t + c^{ts}(V^t - \mathcal{V}_j^{ts}) + \lambda_j^{ts} - \rho_j^t\bar{y}_j^t + \frac{\rho_j^t}{2}\right)y_j^{ts} + \sum_{\tau\in\mathcal{T}}\sum_{k\in\mathcal{K}^{\tau s}} g^{\tau s}z_k^{\tau s} \tag{4.17}$$

$$\text{s.t.} \quad y_j^{ts} \geq y_{j+1}^{ts}, \qquad \forall\, t \in T, j = 1,\dots,|\mathcal{J}^t|-1, s\in\mathcal{S}, \tag{4.18}$$

$$\sum_{j\in\mathcal{J}} x_{ij}^s + \sum_{k\in\mathcal{K}^s} x_{ik}^s = 1, \qquad \forall\, i\in\mathcal{I}^s, s\in\mathcal{S}, \tag{4.19}$$

$$\sum_{i\in\mathcal{I}^s} v_i^s x_{ij}^s \leq \mathcal{V}_j^{ts}y_j^{ts}, \qquad \forall\, t\in T, j\in\mathcal{J}^t, s\in\mathcal{S}, \tag{4.20}$$

$$\sum_{i\in\mathcal{I}^s} v_i^s x_{ik}^s \leq V^\tau z_k^{\tau s}, \qquad \forall\, \tau\in\mathcal{T}, k\in\mathcal{K}^{\tau s}, s\in\mathcal{S}, \tag{4.21}$$

$$y_j^{ts} \in \{0,1\}, \qquad \forall\, t\in T, j\in\mathcal{J}^t, s\in\mathcal{S}, \tag{4.22}$$

$$z_k^{\tau s} \in \{0,1\}, \qquad \forall\, \tau\in\mathcal{T}, k\in\mathcal{K}^{\tau s}, s\in\mathcal{S}, \tag{4.23}$$

$$x_{ij}^s \in \{0,1\}, \qquad \forall\, i\in\mathcal{I}^s, j\in\mathcal{J}, s\in\mathcal{S}, \tag{4.24}$$

$$x_{ik}^s \in \{0,1\}, \qquad \forall\, i\in\mathcal{I}^s, k\in\mathcal{K}^s, s\in\mathcal{S}. \tag{4.25}$$

Furthermore, by noting that λ_j^{ts} and ρ_j^t are exogenous constants for the model (4.17)-(4.25), 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

$$f_b^{\overline{\tau}s} = \begin{cases} f^{\overline{\tau}} + c^{\overline{\tau}s}(V^{\overline{\tau}} - \mathcal{V}_b^{\overline{\tau}s}) + \lambda_b^{\overline{\tau}s} - \rho_b^{\overline{\tau}}\bar{y}_b^{\overline{\tau}} + \frac{\rho_b^{\overline{\tau}}}{2} & \overline{\tau} \in \overline{\mathcal{T}}, b \in \mathcal{J}^{\overline{\tau}} \\ g^{\overline{\tau}s} & \overline{\tau} \in \overline{\mathcal{T}}, b \in \mathcal{K}^{\overline{\tau}s}. \end{cases} \tag{4.26}$$

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 $\overline{\tau} \in \overline{\mathcal{T}}$:

$$\min_{y,x} \quad \sum_{\overline{\tau} \in \overline{\mathcal{T}}} \sum_{b \in \mathcal{B}^{\overline{\tau}s}} f_b^{\overline{\tau}s} y_b^{\overline{\tau}s} \tag{4.27}$$

$$\text{s.t.} \quad y_b^{\overline{\tau}s} \geq y_{b+1}^{\overline{\tau}s}, \qquad \forall\, \overline{\tau} \in \overline{\mathcal{T}}, b = 1, \ldots, |\mathcal{B}^{\overline{\tau}s}| - 1, \tag{4.28}$$

$$\sum_{b \in \mathcal{B}^s} x_{ib}^s = 1, \qquad \forall\, i \in \mathcal{I}^s, \tag{4.29}$$

$$\sum_{i \in \mathcal{I}^s} v_i^s x_{ib}^s \leq \mathcal{V}_b^{\overline{\tau}s} y_b^{\overline{\tau}s}, \qquad \forall\, \overline{\tau} \in \overline{\mathcal{T}}, b \in \mathcal{B}^{\overline{\tau}s}, \tag{4.30}$$

$$y_b^{\overline{\tau}s} \in \{0, 1\}, \qquad \forall \overline{\tau} \in \overline{\mathcal{T}}, b \in \mathcal{B}^{\overline{\tau}s}, \tag{4.31}$$

$$x_{ib}^s \in \{0, 1\}, \qquad \forall\, i \in \mathcal{I}^s, b \in \mathcal{B}^s, \tag{4.32}$$

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.

It is time-consuming to solve a large VCSBPP to optimality using a commercial MIP solver (Correia et al. (2008)). Thus, several effective algorithms have been developed for the VCSBPP (Crainic et al., 2007; Baldi et al., 2011; Crainic et al., 2011b). The heuristic proposed by Crainic et al. (2011b) is particularly interesting, because of its efficiency on instances with up to 1000 items. The algorithm implements an adapted best-first decreasing strategy that sorts items and bins by nonincreasing order of volume and unit cost, respectively. Then, for each item, the heuristic first attempts to load it into the best already-selected bin, which is the bin with the maximum free space once the item is loaded. If the item cannot be loaded into an already-selected bin, a new bin is selected and the item is loaded into it.

However, we cannot use this algorithm to solve subproblems because of the additional constraint 4.28 that imposes an order in the selection of bins of a certain type. We have thus modified the heuristic proposed by Crainic et al. (2011b), taking into account the order of bins among the set of bins of the same type during their sort.

4.2 Obtaining consensum 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.

4.2.1 Defining the overall capacity plan

Let ν be the iteration counter in the PH algorithm. At each iteration, the algorithm solves subproblems (4.27)–(4.32), 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 (4.33). The weight used for each component is the probability p_s associated with the corresponding scenario.

$$\bar{y}_b^{\overline{\tau}\nu} = \sum_{s\in\mathcal{S}} p_s y_b^{\overline{\tau}s\nu}, \quad \forall \overline{\tau} \in \overline{\mathcal{T}}, \forall b \in \mathcal{B}^{\overline{\tau}}. \tag{4.33}$$

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 (4.33), 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

$$\overline{\delta}^{\overline{\tau}\nu} = \sum_{s\in\mathcal{S}} p_s \delta^{\overline{\tau}s\nu} = \sum_{s\in\mathcal{S}} p_s \sum_{b\in\mathcal{B}^{\overline{\tau}}} y_b^{\overline{\tau}s\nu} = \sum_{b\in\mathcal{J}^{\overline{\tau}}} \sum_{s\in\mathcal{S}} p_s y_b^{\overline{\tau}s\nu} = \sum_{b\in\mathcal{B}^{\overline{\tau}}} \overline{y}_b^{\overline{\tau}\nu}. \tag{4.34}$$

Equation (4.34) 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 $\overline{\delta}^{\overline{\tau}\nu}$.

It is important to note that (4.33) and (4.34) 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, (4.33) and (4.34) 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 (4.34) is also used in the bounding strategy.

4.2.2 Penalty adjustment strategies

To induce consensus among the scenario subproblems, we adjust the penalties 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. This approach outperforms scalar ρ strategies and guarantees faster convergence of the algorithm (Watson and Woodruff, 2011). 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:

$$\lambda_b^{\overline{\tau}s\nu} = \lambda_b^{\overline{\tau}s(\nu-1)} + \rho_b^{\overline{\tau}(\nu-1)}(y_b^{\overline{\tau}s\nu} - \bar{y}_b^{\overline{\tau}\nu}) \tag{4.35}$$

$$\rho_b^{\overline{\tau}\nu} \leftarrow \alpha\rho_b^{\overline{\tau}(\nu-1)}, \tag{4.36}$$

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 (4.35) 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 (4.36) 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 (4.35) and (4.36) 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:

$$f^{\overline{\tau}s\nu} = \begin{cases} f^{\overline{\tau}s(\nu-1)} \cdot M & \text{if } \delta^{\overline{\tau}s(\nu-1)} > \bar{\delta}^{\overline{\tau}(\nu-1)} \\ f^{\overline{\tau}s(\nu-1)} \cdot \frac{1}{M} & \text{if } \delta^{\overline{\tau}s(\nu-1)} < \bar{\delta}^{\overline{\tau}(\nu-1)} \\ f^{\overline{\tau}s(\nu-1)} & otherwise. \end{cases} \tag{4.37}$$

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 (4.37) 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 $1/M$.

4.2.3 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 4.28 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:

$$\bar{\delta}_m^{\overline{\tau}\nu} \leftarrow \min_{s \in \mathcal{S}} \delta^{\overline{\tau}s\nu}, \tag{4.38}$$

$$\bar{\delta}_M^{\overline{\tau}\nu} \leftarrow \max_{s \in \mathcal{S}} \delta^{\overline{\tau}s\nu}. \tag{4.39}$$

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 $b = \bar{\delta}_M^{\overline{\tau}\nu} + 1, ..., \|\mathcal{B}^{\overline{\tau}}\|$.

4.3 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 4.38 and 4.39, 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.

4.4 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 (4.1)–(4.10) 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.

Chapter 5

Computational results

We have performed an extensive set of experiments. The goals of the experimental campaign were to:

- measure the impact of uncertainty and determine whether building a stochastic programming model is really useful;
- determine whether basic structure for the capacity planning exists and the dependence of the plan on attributes of the problem setting.

We start by introducing the test instances generated for the numerical experiments (Section 5.1). We then proceed with the analysis of the impact of the uncertainty (Section 5.2). The tests show the benefits of using the two-stage model with recourse compared to the perfect information problem (the so-called wait and see approach, WS) and the expected value problem (EV). In Section 5.3 we study the solutions of the logistics capacity plan under various problem settings. We first present the structure of the capacity-planning solutions of the basic problem (Section 5.3.1) and then we discuss to what extent the structure of the solution changes when we take into account the actual volume of first-stage bins (Section 5.3.2).

5.1 Instance set

We have developed a new set of instances in two steps. First of all, we have generated a set of basic instances, denoted B, based on existing instances for different BPP problem variants (Monaci, 2002; Crainic et al., 2007, 2011b, 2012, 2014b; Gobbato, 2015). Set B represents standard cases, without reduction of the available capacity booked at the first stage. These instances are characterized by the number of bin types, the availability and the cost of the bins, and the number and volume of the items. Starting from these basic instances, we have then developed a new set of instances, denoted T. Set T represents test cases where the actual volume of first-stage bins plays a key role. In particular, the percentages of scenarios and bin types affected by losses of capacity, as well as the size and the type (uniform or localized) of volume reduction, characterize these instances. Another feature of test instances is the extra cost that must be paid to compensate for the loss of capacity in first-stage bins. Set T aims to analyse which parameters related to the reduction of available capacity impact more on the capacity planning solution.

The basic instances of set B have the following characteristics:

- **Number of types**. We have assumed that $\mathcal{T}$, the set of bin types available at the second stage, is equal to the first-stage set T. We thus consider instances with 3 (T3) and 5 (T5) bin types. The volumes are:
  - 50, 100, 150 for T3;
  - 50, 80, 100, 120, 150 for T5.
- **Availability of bins**. The availabilities of first-stage bins and extra bins are different.
  - **First stage**. The number of bins of type $t \in T$ available at the first stage, $\|\mathcal{J}^t\|$, is the minimum number of bins of volume V^t needed to pack all

items in the worst case scenario (i.e., the scenario with the highest number of items). The availability of bins is thus formulated as

$$\|\mathcal{J}^t\| = \left\lceil \frac{1}{V^t} \max_{s \in \mathcal{S}} \sum_{i \in \mathcal{I}^s} v_i^s \right\rceil . \tag{5.1}$$

- **Second stage**. The number of extra bins of type $t \in T$ available in scenario $s \in \mathcal{S}$, $\|\mathcal{K}^{ts}\|$, varies according to three availability classes:
  * in AV1 $\|\mathcal{K}^{ts}\|$ is uniformly distributed in the range $[0, \|\mathcal{J}^t\|]$;
  * in AV2 $\|\mathcal{K}^{ts}\|$ is uniformly distributed in the range $[\frac{\|\mathcal{J}^t\|}{2}, \|\mathcal{J}^t\|]$;
  * in AV3 $\|\mathcal{K}^{ts}\|$ is equal to $\|\mathcal{J}^t\|$.

  These availability classes are characterized by different levels of variability. In particular, the first class presents the largest variability and its worst-case scenario may involve a limited number of extra bins. On the contrary, when we consider the last class, all the scenarios have the same availability of extra bins, equal to the first-stage availability.

- **Cost of bins**. The costs of bins at the first and the second stage are different.
  - **First stage**. For the set of bins of type $t \in T$ available in advance the fixed cost is

    $$f^t = V^t(1 + \gamma^t), \tag{5.2}$$

    where γ^t is uniformly distributed in the range $[-0.3, 0.3]$. According to Correia et al. (2008) this range replicates realistic situations.
  - **Second stage**. The cost for extra bins of type $t \in T$ in scenario $s \in \mathcal{S}$, g^{ts}, is the original fixed cost f^t multiplied by a factor $(1 + \alpha)$, where α belongs to the set $\{0.3, 0.5, 0.7\}$.

- **Number of items**. The number of items at the second stage is uniformly distributed in the range $[100, 500]$.

- **Volume of items**. The items are organized as follows:
  - Small item (S): volume in the range [5, 10];
  - Medium item (M): volume in the range [15, 25];
  - Big item (B): volume in the range [20, 40].

  These categories are then combined into a volume-spread class without any restriction on the maximum number of items in each category.

- **Number of instances**. For each combination of the parameters mentioned above we have defined 10 instances with 100 scenarios each. This gives us a final set of 180 instances.

For each instance of set B we have developed several instances of set T. The new instances differ from the corresponding basic instance for the actual volume of first-stage bins and the introduction of the extra cost to be paid due to the reduction of a unit of capacity in first-stage bins. The additional characteristics of set T instances are:

- **Actual volume of first-stage bins**.

  The parameters that determine the actual volume of first-stage bins are:
  - the percentage of scenarios affected by capacity losses, SL: 20%, 40%, 60% and 80%;
  - the probability that a bin type is affected by a capacity reduction, TL: 50%, 75% and 100%;
  - the percentage of the overall loss of capacity among all the first-stage bins of a certain type, BL: 20%, 30%, 40%, 50%, 60% and 70%;

- the type of the capacity loss: uniform (U) or localized (L). When the reduction of capacity is uniform, every first-stage bin loses a percentage of its volume equal to BL. Uniform capacity losses represent the case of leftovers from previous days, both in vehicles and warehouses. When the loss of volume is localized, on the other hand, only few first-stage bins lose their entire capacity and become unusable, while the others are unaffected. The overall reduction of capacity among all the bins of a certain type is however equal to a percentage of the overall volume equal to BL. Localized capacity losses represent the case of mechanical failures or other setbacks that lead to a loss of available capacity equal to the volume of the vehicle.

- **Extra cost due to the reduction of a unit of capacity**. The extra cost that must be paid to compensate for the reduction of a unit of capacity in a first-stage bin of type $t \in T$, c^t, is set equal to zero or to the proportion of the overall loss of capacity among all first-stage bins of type t (BL).
- **Number of instances**. For each basic instance we have defined 288 test instances. This gives us a final set of 51840 instances.

5.2 Impact of uncertainty

In this section, we show the benefits of using the two-stage model with recourse for the **SVCSBPP**$_L$. We do this by considering the most important measures in stochastic programming: the expected value of perfect information ($EVPI$) and the value of the stochastic solution (VSS).

The $EVPI$ measures the maximum amount a decision maker would be ready to pay in return for complete information about the future. The $EVPI$ is defined by the difference between the here-and-now solution corresponding to the recourse problem

(RP) and the expected value of the optimal solutions, known in the literature as the wait-and-see solutions (WS) and obtained when the realizations of all the random parameters are known at the first stage:

$$EVPI := RP - WS. \tag{5.3}$$

The VSS indicates the expected gain from solving the stochastic problem rather than the expected value problem (EV), which is its deterministic counterpart obtained by replacing all random variables with their expected values. The VSS is thus defined by:

$$VSS := EEV - RP \tag{5.4}$$

where the EEV is the expected result of using the expected value solution, which is obtained by fixing the first-stage variables at the optimal values of the EV and solving the second-stage problem over all possible scenarios.

In the following we present the values of $EVPI$ and VSS for our problem. We show the results in an aggregated form and we discuss how different parameters, such as the availability of second-stage bins, the entity of the volume reduction, and the extra cost due to lost capacity affect the $EVPI$ and the VSS. First of all we consider the $EVPI$ measure. Then we discuss to what extent the first-stage decisions of the recourse problem and of the expected value problem differ and we introduce the concept of infeasibility. Finally, we take into account the VSS measure.

Tables from 5.1 to 5.5 report, for different groups of instances, the average and maximum percentage $EVPI$, computed as $EVPI/RP \cdot 100$. We first analyze the impact of different availabilities and costs of second-stage bins on the $EVPI$. Table 5.1 reports, for each combination of instance set (Column 1), availability class (Column 2) and value of alpha (Column 3), the average and maximum percentage $EVPI$ (Columns 4 and 5 for localized losses, and Columns 6 and 7 for uniform losses). The

Set	**Availability**	**Alpha**	**Localized Losses** $EVPI[\%]$	**Localized Losses** $EVPI_{max}[\%]$	**Uniform Losses** $EVPI[\%]$	**Uniform Losses** $EVPI_{max}[\%]$
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 5.1: $EVPI$ for different availability classes, values of alpha and types of losses.

average percentage $EVPI$ is always greater than 8%, showing the benefit of having information about the future in advance. When the loss of volume is uniform (i.e., all bins of a certain type lose some capacity) the percentage $EVPI$ is higher than when the reduction of volume is localized (i.e., only some first-stage bins lose their entire capacity and become thus unusable). Moreover, the values of average and maximum $EVPI$ are quite similar when the availability classes are $AV2$ and $AV3$, while are higher when we consider AV1. The most critical availability class is thus AV1, which represents the situation where the worst case scenario may involve a very limited number of extra bins. Regarding the costs of second-stage bins, the average and maximum values of the $EVPI$ increase as alpha increases. Instance set T3 generally show higher values of percentage $EVPI$ than instance set T5. When the losses are uniform and the availability class is AV1, this gap is quite high and reaches 8%, while in all other cases it is around 1%. The highest average percentage $EVPI$, 27%, is obtained for instance set T3 with uniform losses, availability class AV1 and alpha equal to 0.7. This means that it would be particularly important to have complete information about the future when a lot of first-stage bins are likely to lose part of their available capacity and at the same time second-stage bins are quite expensive and may not be available in sufficient numbers to pack all items. In this situation the maximum percentage $EVPI$ exceeds 75%. When we consider the instance set T5, the highest average and maximum percentage $EVPI$, respectively equal to 23% and 54%, are obtained for uniform losses and availability class AV1. Smaller values of $EVPI$ in this case are due to the fact that in instance set T5 we consider more bin types and thus the limited availability of extra bins of a certain type has less impact on the solution structure. When the losses are localized, the highest values of average percentage $EVPI$ are almost 22% for both $T3$ and $T5$, while the maximum values are 61% for T3 and 26% for T5.

Set	**BL [%]**	**No Extra Cost**		**Extra Cost**	
		$EVPI$ [%]	$EVPI_{max}$ [%]	$EVPI$ [%]	$EVPI_{max}$ [%]
T3	**20**	12.27	27.68	12.24	27.09
	30	13.75	33.35	15.21	35.24
	40	16.33	41.47	19.93	44.34
	50	20.72	51.16	25.82	57.15
	60	25.93	63.93	32.44	69.13
	70	31.87	71.71	39.91	77.35
T5	**20**	10.21	15.06	9.96	15.31
	30	10.46	16.83	11.62	18.34
	40	11.79	18.14	13.23	20.66
	50	12.68	19.75	15.11	28.11
	60	14.40	28.10	16.43	39.88
	70	15.66	38.23	17.80	54.26

Table 5.2: Impact of the extra cost on $EVPI$ in instances with AV1, alpha equal to 0.3 and uniform losses.

We now consider the impact of the extra cost needed to react to the lost of available capacity in first-stage bins. When the losses are localized, the addition of the extra cost has no impact on the $EVPI$. This is due to the fact that, when we consider localized losses, usually on average a little amount of capacity is actually lost and so the additional cost is low. On the contrary, when the losses are uniform, the addition of the extra cost increases the average $EVPI$. The gap between the percentage $EVPI$ with or without the extra cost increases as the percentage of loss increases. The reason is twofold: on the one hand the cost is proportional to the capacity lost and on the other the unit cost increases with the percentage of lost volume. The difference is larger when the availability of second-stage bins is limited and the premium cost is low. This means that when the losses are uniform and the availability of second-stage bins is limited, having information about the future in advance is even more valuable if we consider the additional cost required to react to the reduction of volume of first-stage bins. Table 5.2 reports, for each combination of instance set (Column 1) and level of loss (Column 2), the average and maximum percentage $EVPI$ (Columns 3 and 4 without extra cost, and Columns 5 and 6 with extra cost) when the availability class is AV1 and alpha is equal to 0.3. Table 5.2 shows that the biggest gap for the average percentage $EVPI$ is equal to 8% and is reached with the instance set T3, while the biggest difference for the maximum percentage $EVPI$ is equal to 14% and is reached with T5.

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 5.3: The impact of SL, TL and BL on $EVPI$ when the losses are localized.

We now analyze the impact of the parameters that determine the actual volumes of first-stage bins on the $EVPI$. At first we consider instances with localized losses and then we discuss instances with uniform losses. Table 5.3 reports, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction TL (Column 2) and percentage of reduction of bin volume BL (Column 3), the average and maximum percentage $EVPI$ (Columns 4 and 5 for set T3, and Columns 6 and 7 for set T5) when we consider localized losses. Table 5.3 shows that the average percentage $EVPI$ decreases with the increase of SL and TL. This means that on average, having information about the future in advance is more valuable when the reductions of actual volume are less likely. The impact of the parameter BL on the $EVPI$ is not clear. When the percentage of scenarios affected by capacity losses is equal to 20%, the average percentage $EVPI$ increases as BL increases, but when SL is equal to 80%, the average percentage $EVPI$ decreases as BL increases. For medium values of SL, the minimum average percentage $EVPI$ is obtained when BL is equal to 0.4 and 0.5. The average percentage $EVPI$ for instance set T3 reaches 17% when SL is equal to 20% and the percentage of reduction of bin volume is high. On the contrary, the overall maximum percentage $EVPI$ is obtained in set T3 when SL is 60%, TL is 75% and BL is maximum and it is equal to almost 61%.

SL[%]	TL[%]	BL [%]	AV1		AV2-AV3	
			$EVPI$[%]	$EVPI_{max}$[%]	$EVPI$[%]	$EVPI_{max}$[%]
20	50	**0.2-0.3**	18.12	25.59	15.61	24.23
		0.4-0.5	20.27	34.30	17.28	27.36
		0.6-0.7	25.21	63.69	19.79	29.42
	75	**0.2-0.3**	17.73	24.95	14.93	23.54
		0.4-0.5	20.67	38.63	16.66	24.65
		0.6-0.7	26.03	63.14	19.80	29.13
	100	**0.2-0.3**	16.58	24.60	13.68	22.41
		0.4-0.5	19.01	37.97	15.02	21.84
		0.6-0.7	27.83	61.04	18.59	25.83
40	50	**0.2-0.3**	18.30	25.66	15.67	26.48
		0.4-0.5	23.20	40.98	18.45	29.05
		0.6-0.7	30.92	63.53	22.30	32.52
	75	**0.2-0.3**	17.01	24.10	14.31	22.53
		0.4-0.5	22.16	40.79	17.31	26.21
		0.6-0.7	32.49	64.40	21.30	31.79
	100	**0.2-0.3**	14.75	22.89	11.56	21.09
		0.4-0.5	19.43	38.07	13.42	20.23
		0.6-0.7	35.60	65.67	16.50	25.29
60	50	**0.2-0.3**	18.29	29.49	15.44	26.84
		0.4-0.5	25.35	50.96	19.16	31.13
		0.6-0.7	34.46	74.27	23.01	35.04
	75	**0.2-0.3**	17.09	35.24	13.29	22.41
		0.4-0.5	24.91	52.88	16.71	27.18
		0.6-0.7	40.30	76.84	19.65	30.42
	100	**0.2-0.3**	13.85	33.34	8.91	19.27
		0.4-0.5	22.10	57.15	9.56	16.96
		0.6-0.7	43.53	77.34	10.39	18.53
80	50	**0.2-0.3**	18.54	34.95	15.02	27.57
		0.4-0.5	27.77	56.97	19.09	32.17
		0.6-0.7	37.34	75.52	22.34	35.95
	75	**0.2-0.3**	16.58	34.37	12.09	22.42
		0.4-0.5	25.22	53.94	14.95	25.70
		0.6-0.7	42.52	75.24	16.00	28.90
	100	**0.2-0.3**	12.09	31.38	6.27	16.55
		0.4-0.5	22.20	56.19	3.97	9.24
		0.6-0.7	46.16	77.35	4.14	8.15

Table 5.4: The impact of SL, TL and BL on $EVPI$ for instance set T3 and uniform losses.

SL[%]	**TL**[%]	**BL** [%]	$EVPI$[%]	$EVPI_{max}$[%]
20	**50**	**0.2-0.3**	16.05	24.71
		0.4-0.5	17.93	27.18
		0.6-0.7	20.51	31.33
	75	**0.2-0.3**	15.39	23.33
		0.4-0.5	17.65	27.78
		0.6-0.7	20.70	30.36
	100	**0.2-0.3**	13.87	22.11
		0.4-0.5	15.19	21.97
		0.6-0.7	18.51	27.49
40	**50**	**0.2-0.3**	16.28	25.73
		0.4-0.5	19.47	30.75
		0.6-0.7	23.47	35.77
	75	**0.2-0.3**	15.03	25.03
		0.4-0.5	18.53	28.08
		0.6-0.7	22.84	33.54
	100	**0.2-0.3**	11.83	19.62
		0.4-0.5	13.75	20.66
		0.6-0.7	17.41	26.68
60	**50**	**0.2-0.3**	16.31	27.08
		0.4-0.5	20.49	32.35
		0.6-0.7	24.92	36.79
	75	**0.2-0.3**	14.29	24.45
		0.4-0.5	18.46	31.79
		0.6-0.7	22.14	34.89
	100	**0.2-0.3**	9.42	18.44
		0.4-0.5	10.34	17.39
		0.6-0.7	12.04	30.31
80	**50**	**0.2-0.3**	16.14	28.30
		0.4-0.5	21.23	34.39
		0.6-0.7	25.04	43.02
	75	**0.2-0.3**	13.32	26.15
		0.4-0.5	17.44	32.46
		0.6-0.7	19.51	50.83
	100	**0.2-0.3**	7.07	16.82
		0.4-0.5	5.33	27.16
		0.6-0.7	6.61	54.26

Table 5.5: The impact of SL, TL and BL on $EVPI$ for instance set T5 and uniform losses.

We now discuss the impact of the parameters that determine the actual volumes of first-stage bins on the $EVPI$ for instances with uniform losses. Table 5.4 reports, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction TL (Column 2) and percentage of reduction of bin volume BL (Column 3), the average and maximum percentage $EVPI$ (Columns 4 and 5 for availability class AV1, and Columns 6 and 7 for availability class AV2-AV3) when we consider the instance set T3 and uniform losses. As we noticed before, the percentage $EVPI$ is higher if the availability of second-stage bins is limited. The values of average and maximum $EVPI$ increase as the level of loss BL increases. This is true for all classes of availability. On the contrary, the impact of SL and TL on the $EVPI$ depends on the availability of second-stage bins. When we consider AV1, the average and maximum percentage $EVPI$ increase as SL increases. Moreover, they increase as TL increase when BL is low, but decrease as TL increase when BL is above 60%. For AV1 thus the maximum average percentage $EVPI$ reaches 46% when SL, TL and BL are respectively equal to 80%, 100% and 70%. The corresponding maximum percentage $EVPI$ is equal to 77%. For instance set T3 with uniform losses and a limited availability of second-stage bins, the knowledge of the future in advance is really important when all the parameters that determine the actual volumes of first-stage bins are high because of the not negligible risk of not being able to pack all items. When we consider AV2 and AV3, the average and maximum percentage $EVPI$ decrease as TL increases. In addition, if TL is high, they decrease as SL increases. The maximum average percentage $EVPI$ for AV2 and AV3 is equal to 23% and is obtained when SL, TL and BL are respectively equal to 60%, 50% and 70%. The corresponding maximum percentage $EVPI$ is equal to 35%. For instance set T3 with uniform losses and a sufficient availability of second-stage bins, having information about the future is thus particularly important if few bin types are affected by considerable reductions of volume. The reason is that if we know in advance which bin types will be affected by losses, we can avoid them.

We now consider the relation between SL, TL and BL and the $EVPI$ in instance set T5 with uniform losses. In this case, the impact of SL, TL and BL on the $EVPI$ is almost the same for all availability classes and so we present the results in an aggregated form. Table 5.5 reports, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction TL (Column 2) and percentage of reduction of bin volume BL (Column 3), the average and maximum percentage $EVPI$ (Columns 4 and 5) when we consider instance set T5 and uniform losses. Table 5.5 shows that the values of average and maximum $EVPI$ increase as LL increases. On the contrary, the average percentage $EVPI$ decreases as TL increases. Moreover, it increases as SL increases when TL is low, but it decreases as SL increases when TL is high. The maximum average percentage $EVPI$ is equal to 25% and is obtained when SL, TL and BL are respectively equal to 80%, 50% and 70%. The maximum percentage $EVPI$ exceeds 54% when all the parameters are at their maximum. For instance set T5 with uniform losses, having information in advance is thus particularly valuable when it is very likely that few bin types will be affected by strong reductions in the available capacity.

We now consider to what extent the first-stage decisions of the recourse problem and of the expected value problem differ. On average, the EV problem overestimates the demand to be loaded (the total volume of the items is larger than the actual volume) and the availability of extra bins (a larger set of bins is available for the recourse action). Moreover, when the percentage of scenarios affected by capacity losses and the probability that a bin type is affected by a capacity reduction are low, the EV problem on average underestimates the reduction of available capacity (the total volume of first-stage bins available to load items is larger than the actually available volume). This can lead to two situations. First, EV may plan to use a set of bins that is not actually required for the set of scenarios considered. Although the capacity plan is more expensive, the solution is feasible and thus implementable. Second, EV may plan an insufficient capacity for a subset of scenarios in which the actual availability of bins is very limited. This situation is even worse if for these scenarios the reduction of available capacity of first-stage bins is considerable. The capacity plan is infeasible for these scenarios.

For the basic problem without reduction of available capacity in first-stage bins, the percentage of infeasible instances is equal to 10% for set T3 and availability class AV1, while it is equal to 0% for all other groups of instances. When we take into account the losses of volume, the percentage of infeasible instances depends on different parameters. There are no infeasible instances for both T3 and T5 when the availability class is AV2 or AV3. The overall percentage of infeasible instances for set T3 with availability class AV1 and localized losses is equal to 10.7%, slightly higher than the corresponding percentage for the basic problem. This gap is due to the fact that when SL is equal to 20% and TL and BL are high, the percentage of infeasible instances reaches 20%. On the contrary, set T5 with availability class AV1 and localized losses has no infeasible instances. When we consider the availability class AV1 and uniform losses, the number of infeasible instances grows considerably. In this situation the overall percentages of infeasible instances for set T3 and T5 are respectively equal to 37.5% and 6.4%. Table 5.6 reports, for each combination of alpha (Column 1), percentage of scenarios affected by capacity losses SL (Column 2), probability that a bin type is affected by a capacity reduction TL (Column 3) and percentage of reduction of bin volume BL (Row 1), the percentage of infeasible instances (Columns 4, 5 and 6 for set T3, and Columns 7, 8 and 9 for set T5) when we consider uniform losses. For set T3, the percentage of infeasible instances is always greater than 5%. Generally, excluding when alpha is equal to 0.3, the

Alpha	SL[%]	TL[%]	Set T3 BL[%] 20-30	40-50	60-70	Set T5 BL[%] 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 5.6: Percentage of infeasible instances when the availability class is AV1 and the losses are uniform.

number of infeasible instances increases as BL increases. Moreover, when the value of BL is high, the percentage of infeasible instances decreases as SL increases. This is reasonable because the more scenarios are affected by reduction of capacity, the more the expected value problem takes into account this risk.

Set	Availability	Alpha	Localized Losses $VSS[\%]$	Localized Losses $VSS_{max}[\%]$	Uniform Losses $VSS[\%]$	Uniform Losses $VSS_{max}[\%]$
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 5.7: VSS for different availability classes, values of alpha and types of losses.

When the premium cost of second-stage bins is great (i.e., alpha is equal to 0.7), the percentage of scenarios with reduction of capacity is around 20%-40%, almost all bin types are affected by losses and the level of loss is 60%-70%, all the instances are infeasible. For set T5, on the contrary, there are no infeasible instances when the percentage of scenarios affected by reduction of capacity is 20%. Moreover, the percentage of infeasible instances increases as SL, TL and BL increase. When all the parameters that determine the actual volumes of first-stage bins are at their maximum values, the percentage of infeasible instances reaches 30%. These results clearly show the need to explicitly consider uncertainty in capacity-planning applications when the availability of second-stage bins can be limited.

We now present the results concerning the VSS, which represents the expected gain from solving the stochastic problem rather than its deterministic counterpart obtained by replacing all random variables with their expected values. Tables from 5.7 to 5.10 report, for different groups of instances, the average and maximum percentage VSS, computed as $VSS/RP \cdot 100$. We first analyze the impact of different availabilities and costs of second-stage bins on the VSS. Table 5.7 reports, for each combination of instance set (Column 1), availability class (Column 2) and value of alpha (Column 3), the average and maximum percentage VSS (Columns 4 and 5 for localized losses, and Columns 6 and 7 for uniform losses). Table 5.7 shows that the average percentage VSS is always greater than 5% and reaches 17%. The gap between the expected-value solution and the stochastic solution is thus always significant. For both localized and uniform losses, the average VSS decreases as alpha increases. The average and maximum values of the VSS are greater when the reduction of volume is uniform rather than when it is localized. When we consider instance set T3 with localized losses, alpha equal to 0.3 and a high availability of second-stage bins, the average and maximum values of the VSS reach 15% and 44% respectively. Table 5.7 shows similar values also for set T5 when the losses are localized. When the reduction of volume is uniform, the average percentage VSS for set T5 increases as the availability of second-stage bins increases. In particular, when the availability class is AV3, it reaches almost 18%. On the contrary, the maximum value of average percentage VSS for set T3 and uniform losses, equal to 17.50%, is reached when the availability class is $AV2$. When the losses are uniform, the maximum value of VSS increases as the cost and the availability of second-stage bins increase. The maximum value of percentage VSS is indeed equal to 88% and is reached for set T5, alpha equal to 0.7 and availability class AV3. The maximum value of percentage VSS for the instance set T3 is equal to almost 81%.

We now discuss the impact on the VSS of the parameters that determine the actual volumes of first-stage bins. At first we consider instances with localized

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 5.8: The impact of SL, TL and BL on VSS when the losses are localized.

losses and then we discuss instances with uniform losses. Table 5.8 reports, for each combination of percentage of scenarios affected by capacity losses SL (Column 1) and percentage of reduction of bin volume BL (Column 3), the average and maximum percentage VSS (Columns 4 and 5 for set T3, and Columns 6 and 7 for set T5) when we consider localized losses. The probability that a bin type is affected by a capacity reduction has no impact on the VSS when the losses are localized. Table 5.8 shows that, both for set T3 that for the set T5, the average VSS decreases with the increase of SL.

SL[%]	**TL**[%]	**BL**[%]	**AV1** VSS[%]	**AV1** VSS_{max}[%]	**AV2-AV3** VSS[%]	**AV2-AV3** VSS_{max}[%]
20	**50**	**0.2-0.3**	6.41	21.52	10.42	25.14
		0.4-0.5	8.32	23.05	13.19	29.33
		0.6-0.7	11.65	26.89	17.51	35.35
	75	**0.2-0.3**	6.19	19.88	10.41	27.02
		0.4-0.5	11.16	23.43	15.84	30.57
		0.6-0.7	12.00	25.33	19.47	41.04
	100	**0.2-0.3**	8.10	23.15	12.01	26.96
		0.4-0.5	12.08	22.68	17.08	32.72
		0.6-0.7	13.15	27.41	22.58	43.59
40	**50**	**0.2-0.3**	8.31	21.81	11.98	27.75
		0.4-0.5	12.02	27.09	17.47	36.46
		0.6-0.7	13.14	33.15	22.21	43.40
	75	**0.2-0.3**	10.28	22.39	13.57	27.58
		0.4-0.5	12.27	25.54	18.86	39.70
		0.6-0.7	14.24	31.47	21.90	57.95
	100	**0.2-0.3**	10.24	23.03	14.58	32.92
		0.4-0.5	11.75	23.87	20.65	47.63
		0.6-0.7	15.74	32.00	15.03	62.07
60	**50**	**0.2-0.3**	9.92	27.21	14.00	33.47
		0.4-0.5	12.41	24.71	19.64	40.68
		0.6-0.7	16.17	36.68	19.85	80.83
	75	**0.2-0.3**	10.52	24.11	14.74	32.86
		0.4-0.5	12.32	26.85	18.68	53.22
		0.6-0.7	23.70	31.38	8.00	78.57
	100	**0.2-0.3**	10.67	24.83	15.64	36.01
		0.4-0.5	11.27	26.44	14.18	62.05
		0.6-0.7	0.25	0.75	3.33	8.33
80	**50**	**0.2-0.3**	10.18	23.70	15.01	32.25
		0.4-0.5	12.44	28.37	19.10	56.13
		0.6-0.7	28.13	37.55	8.22	80.40
	75	**0.2-0.3**	10.36	23.92	14.96	35.19
		0.4-0.5	16.85	56.65	13.11	74.73
		0.6-0.7	0.00	0.00	1.95	30.88
	100	**0.2-0.3**	9.46	23.52	14.78	44.59
		0.4-0.5	8.45	20.00	6.46	52.34
		0.6-0.7	-	-	2.92	6.81

Table 5.9: The impact of SL, TL and BL on VSS for instance set T3 and uniform losses.

SL[%]	**TL**[%]	**BL** [%]	VSS[%]	VSS_{max}[%]
20	**50**	**0.2-0.3**	8.03	24.23
		0.4-0.5	10.12	35.71
		0.6-0.7	15.79	41.69
	75	**0.2-0.3**	7.94	24.87
		0.4-0.5	14.92	37.66
		0.6-0.7	19.66	43.39
	100	**0.2-0.3**	11.16	35.40
		0.4-0.5	17.18	39.62
		0.6-0.7	21.95	43.35
40	**50**	**0.2-0.3**	10.16	33.00
		0.4-0.5	16.80	38.14
		0.6-0.7	19.90	43.09
	75	**0.2-0.3**	13.56	35.41
		0.4-0.5	17.88	37.49
		0.6-0.7	20.48	58.54
	100	**0.2-0.3**	14.40	35.04
		0.4-0.5	18.47	45.31
		0.6-0.7	10.66	88.36
60	**50**	**0.2-0.3**	13.39	34.73
		0.4-0.5	18.10	38.91
		0.6-0.7	19.28	57.73
	75	**0.2-0.3**	14.51	35.28
		0.4-0.5	18.04	78.50
		0.6-0.7	7.17	84.46
	100	**0.2-0.3**	14.30	34.40
		0.4-0.5	11.27	64.27
		0.6-0.7	3.11	23.86
80	**50**	**0.2-0.3**	14.66	35.38
		0.4-0.5	17.49	74.47
		0.6-0.7	10.46	85.88
	75	**0.2-0.3**	14.41	35.69
		0.4-0.5	11.61	63.08
		0.6-0.7	1.88	19.62
	100	**0.2-0.3**	13.71	55.57
		0.4-0.5	4.46	51.44
		0.6-0.7	2.68	6.56

Table 5.10: The impact of SL, TL and BL on VSS for instance set T5 and uniform losses.

Generally, the average and maximum VSS increases as LL increases. However, when the value of SL is high and LL is equal to 0.3 or 0.7, the values of average and maximum VSS are lower than expected. The maximum values of VSS are reached when SL and LL are equal to 20% and 0.7 respectively. The average percentage VSS reaches 15.5% for set T3 and 13.8% for set T5, while the maximum percentage VSS reaches almost 45% for both the sets. These results show that when the losses are localized, the stochastic approach is more valuable when there is a low probability of losing a huge number of entire bins.

We now discuss the impact of SL, TL and BL for instances with uniform losses. Table 5.9 reports, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction TL (Column 2) and percentage of reduction of bin volume BL (Column 3), the average and maximum percentage VSS (Columns 4 and 5 for availability class AV1, and Columns 6 and 7 for for availability class AV2-AV3) when we consider instance set T3 and uniform losses. Table 5.9 shows that, when SL and TL are low, the average and maximum VSS increase as the value of BL increases. On the contrary, when all the parameters assume high values, the 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%, the average percentage VSS falls to 0%. This behaviour might suggest that when the availability of second-stage bins is limited and it is likely to lose a lot of capacity in first-stage bins, it is not worth solving the stochastic problem. In fact, in the situation described is particularly important to explicitly consider uncertainty because of the number of infeasible instances. When the availability class is AV0, and SL, TL and BL are at their maximum, it is impossible to compute the VSS because all instances are infeasible. When the availability class is AV2 or AV3, on the contrary, there are no infeasible instances and the average percentage VSS falls to 2%. Apart from these cases, the value of percentage VSS is always above 8% and it reaches 28% when the availability class is AV1 and SL, TL and BL are equal to respectively 80%, 50%, 70%. However, when the availability class is AV2 or AV3, the maximum value of percentage VSS is equal to 22.5% and is obtained with SL and TL equal to 20% and 100%. In addition, when the number of second-stage bins is not limited and is likely to lose a lot of capacity in few types of bin, the maximum value of VSS reaches 80%.

We now consider instance set T5 with uniform losses. Table 5.10 reports, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction TL (Column 2) and percentage of reduction of bin volume BL (Column 3), the average and maximum percentage VSS (Columns 4 and 5) when we consider instance set T5 and uniform losses. As in instance set T3, even in set T5, when SL and TL are low, the value of VSS increases as BL increases. In particular, the average percentage VSS reaches 22% when SL, TL and BL are respectively equal to 20%, 100% and 70%, while the maximum percentage VSS reaches 88% with SL, TL and BL respectively equal to 40%, 100% and 70%. On the contrary, when SL and TL are high, the value of VSS decreases as BL increases and falls to 1.9% when SL, TL and BL are respectively equal to 80%, 100% and 70%. For this combination of parameters, when the availability class is AV1, the percentage of infeasible instances is equal to 30%. When SL and TL take medium values, the maximum percentage VSS is reached with BL equals to 40% or 50%. These results show that when the losses are uniform and the second-stage bins are available in sufficient numbers (set T5 or set T3 with availability classes AV2 and AV3), the stochastic approach is more valuable when there is a low probability of losing a big amount of capacity.

5.3 Solution analysis

The goal of this analysis is to determine whether basic structure for the capacity planning exists and the dependence of the plan on attributes of the problem setting (e.g., availabilities and costs of second-stage bins, actual volumes of first-stage bins, and the extra cost due to the lost capacity). We first present the structure of the capacity-planning solutions of the basic problem (Section 5.3.1) and then we discuss to what extent the structure of the solution changes when we take into account the actual volume of first-stage bins (Section 5.3.2).

5.3.1 Solution analysis of the basic problem

This section analyses the structure of the capacity-planning solutions of the basic problem and in particular the use of bins in the plan. Table 5.11 reports, for each combination of instance set (Column 1), availability class (Column 2), and value of alpha (Column 3), the average number of bin types N_t used in the capacity plan (Column 4), the average percentage of the capacity booked at the first stage Cap_{FS} (Column 5), the average percentage of the objective function value achieved at the first stage Obj_{FS} (Column 6), and the average percentage fill level of the bins at the first stage f_{FS} (Columns 7). Only a few bin types are used in the plan. The number is close to 1 for both T3 and T5, which have three and five bin types, respectively. When the availability of second-stage bins is limited, the average number of bin types is slightly greater: the percentage of instances that book more than one bin type at the first stage in instance sets T3 and T5 is respectively equal to 15% and 25%. Furthermore, the number of bins is not evenly distributed among the types. Almost all the bins included in the capacity plan are of the same type; only one or two bins are of different types.

Set	Availability	Alpha	N_t[%]	Cap_{FS}[%]	Obj_{FS}[%]	f_{FS}[%]
T3	**AV1**	**0.3**	1.10	71.82	63.38	88.74
		0.5	1.20	79.71	69.44	86.29
		0.7	1.10	83.96	72.87	82.70
	AV2	**0.3**	1.00	64.26	55.58	91.99
		0.5	1.10	73.31	62.11	87.45
		0.7	1.00	80.89	69.61	84.78
	AV3	**0.3**	1.00	60.81	52.64	93.40
		0.5	1.00	76.62	65.75	86.63
		0.7	1.10	81.58	70.86	85.16
T3	**AV1**	**0.3**	1.33	67.12	59.21	92.10
		0.5	1.33	77.71	68.13	88.65
		0.7	1.44	83.61	73.17	85.31
	AV2	**0.3**	1.00	65.62	56.53	91.68
		0.5	1.00	76.14	65.73	87.82
		0.7	1.00	83.14	72.56	84.30
	AV3	**0.3**	1.00	65.83	57.27	91.70
		0.5	1.00	75.85	65.62	87.75
		0.7	1.20	80.60	69.76	85.20

Table 5.11: Structure of solutions of the basic problem.

This is, in our opinion, a result compatible with the rules used in practice, i.e., the larger the number of bin types used, the higher the loading/unloading costs because it becomes impossible to use standardized loading schemes. The percentage of the capacity bookend in advance is about 75%. It decreases as the availability of second-stage bins increases and strongly increases with alpha and thus with the cost of second-stage bins. When alpha is equal to 0.7, the percentage of the capacity bookend in advance exceeds 80%. The percentage of the objective function achieved in advance is about 65%, reaching 70% when alpha is equal to 0.7. These results show that the tactical decisions should be conservative when there is no loss of volume in first-stage bins: the company should book sufficient capacity in advance to limit the adjustment necessary when the actual demand becomes known. Moreover, they indicate that 30% of recourse is a good compromise between cost reduction and uncertainty management. Finally, the average percentage fill level of the bins selected at the first stage is equal to 87%. The fill level decreases as alpha increases and reaches 93% when the availability of second-stage bins is high. This indicates the effectiveness of the capacity plan, which requires only targeted adjustments at the second stage.

5.3.2 Impact of losses of available volume

When we take into account the actual volume of first-stage bins, the changes in the structure of the capacity plan depend on the type of capacity losses and on the availability of extra bins. In this section we first present the structure of the capacity-planning solutions of instances with uniform reductions of capacity and then of instances with localized losses of volume. Since the structure of the solutions depends only slightly on the additional cost required to react to the reduction of capacity in first-stage bins, we present the results of instances where an extra cost must be paid and then we briefly discuss what changes when this cost is set equal to zero.

Uniform losses of capacity

We first present the structure of the capacity-planning solutions of instances with three bin types, uniform losses of volume and availability class AV1. When there are only three types of bins and the availability of second-stage bins is limited, the structure of the capacity-planning solution is always the same, regardless of the likelihood of losses and the percentage of lost capacity. This situation occurs especially when logistic operations require customized treatments and are thus outsourced to a logistics provider that has specialized equipment. The number of bins available at the second stage can be very limited because the company cannot turn to other 3PLs. Therefore the firm is forced to buy a great portion of capacity at the first stage although it is very likely that the bought capacity will not be fully available.

Figure 5.1: Percentage of capacity bookend at the first stage for instance set T3, availability class AV1 and uniform losses.

Figure 5.1 shows, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction TL (Row 1), and value of alpha (blue, red and green bars represent instances with alpha respectively equal to 0.3, 0.5 and 0.7), the average percentage of capacity booked at the first stage Cap_{FS} as a function of the percentage of lost volume in each bin BL. The percentage of capacity rescued at the first stage is always between 60% and 83%. This means that the risk of having a limited availability of extra bins and the need to load all items lead to book much of the capacity in advance, although most likely the actual available capacity will be lower than planned. When the percentage of lost volume is low, the percentage of capacity booked at the first stage depends on the value of alpha. In particular, the capacity booked in advance is greater when the premium cost of extra bins is high. On the contrary, when the values of BL, SL and TL are high, the percentage of first-stage capacity is always the same, whatever the cost of second-stage bins. When the probability that a bin type is affected by a capacity reduction is equal to 50%, the capacity booked in advance decreases as BL increases. The lowest values, equal to 61%, are reached when the percentage of scenarios affected by reductions of available volume is greater than 60% and the level of loss is 70%. While, when all the bin types are affected by losses of volume, the percentage of capacity booked in advance increases with the level of loss BL. In particular, when all the parameters that determine the losses of volume take their highest value, the percentage of capacity booked in advance is equal to 76%.

The percentage of objective function value paid at the first stage is always between 48% and 73%. Figure 5.2 shows, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction TL (Row 1), and value of alpha (blue, red and green bars represent instances with alpha respectively equal to 0.3, 0.5 and 0.7), the average percentage of the objective function value achieved at the first stage Obj_{FS} as a function of the percentage of lost volume in each bin BL. When the values of BL, SL and TL are high, the percentage Obj_{FS} decreases slightly with alpha, even if the corresponding first-stage capacity is stable (see Figure 5.1). This happens because the higher the cost of extra bins, the lower is the percentage of the objective function value achieved at the first stage. When SL is greater than 40%, the percentage

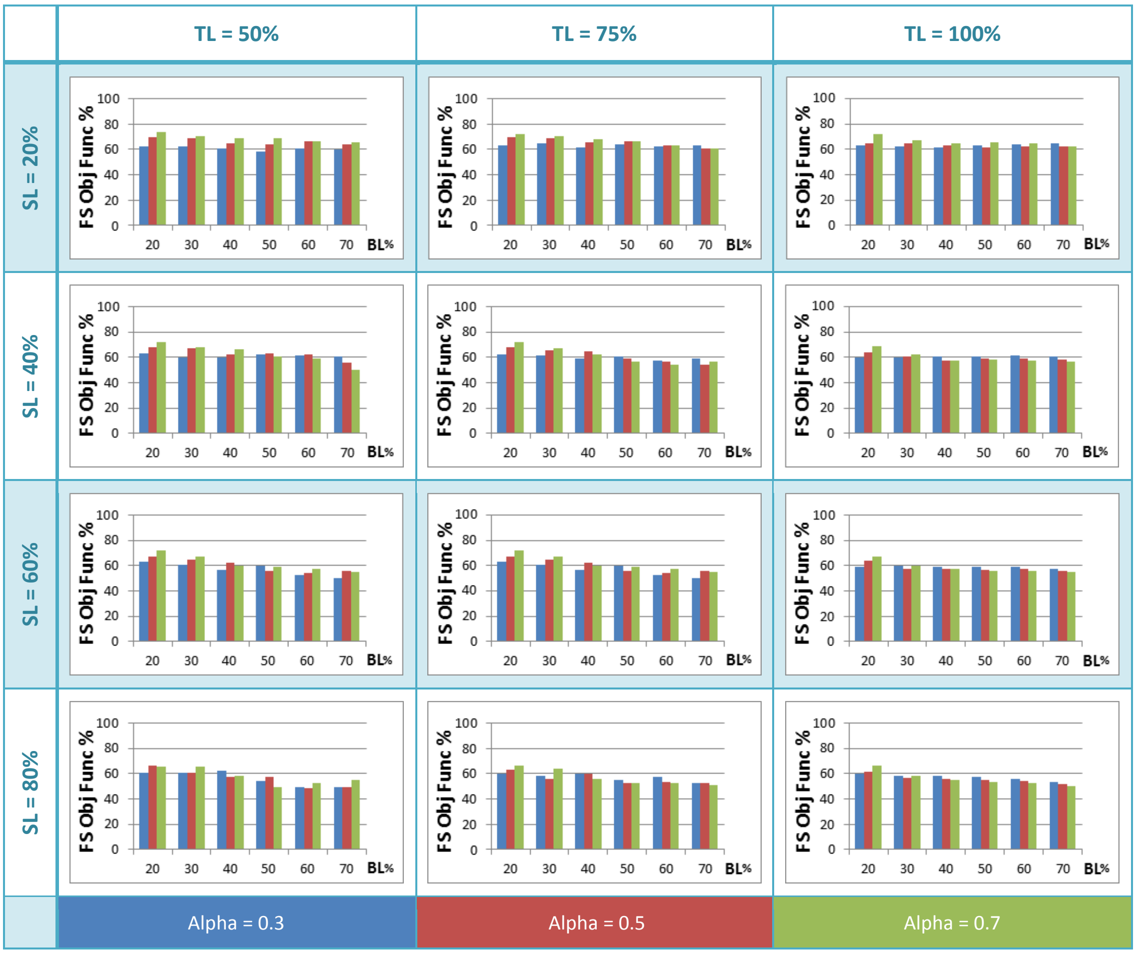

Figure 5.2: Percentage of objective function value achieved at the first stage for instance set T3, availability class AV1 and uniform losses.

Obj_{FS} decreases as the percentage of lost volume in each bin increases. The lowest value of average percentage Obj_{FS}, equal to 48.4%, is reached with alpha, SL, TL and BL respectively equal to 0.5, 80%, 50%, and 70%.

The average N_t used in the capacity plan is always greater than 1.2 and its maximum value is equal to 3. Figure 5.3 shows, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction TL (Row 1), and value of alpha (blue, red and

Figure 5.3: Number of bin types used in the capacity plan for instance set T3, availability class AV1 and uniform losses.

green bars represent instances with alpha respectively equal to 0.3, 0.5 and 0.7), the average number of bin types N_t used in the capacity plan as a function of the percentage of lost volume in each bin BL. The average number of first-stage bin types used in the plan increases with the percentage of lost volume and with the percentage of scenarios affected by capacity losses. Moreover, the highest values of average N_t are obtained when the probability that a bin type is affected by a capacity reduction is equal to 75%. In particular, when SL, TL and BL are respectively equal to 60%, 75% and 60%-70%, the number of bin types included in the plan is always greater than 2.7. This means that when a lot of scenarios are suffering from large reductions of volume which, however, do not affect all types of vehicles, almost all types of bin are included in the capacity plan. The downside of this capacity plan is the raising of loading/unloading costs because it becomes impossible to use standardized loading schemes.

Figure 5.4: Percentage fill level of first-stage bins for instance set T3, availability class AV1 and uniform losses.

The percentage fill level related to the actual volume of first-stage bins is always between 71% and 95%. Figure 5.4 shows, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction TL (Row 1), and value of alpha (blue, red and green bars represent instances with alpha respectively equal to 0.3, 0.5 and 0.7), the average percentage fill level of the bins at the first stage f_{FS} as a function of the percentage of lost volume in each bin BL. When the probability that a bin type is affected by a loss of available volume is 50% or 75%, the average percentage f_{FS} is greater than 80%. Whereas, if all bin types suffer from reduction of capacity and the percentage of lost volume is greater than 60%, the percentage fill level of first-stage bins decreases up to 71%. The reason for this behaviour is that, when TL is equal to 100%, the capacity plan includes several large bins that are not completely filled. On the other hand, the percentage fill level of second-stage bins f_{SS} is always greater than 80%. In particular, the percentage f_{SS} remains stable regardless of the probability and the level of losses and its average value is equal to 85%.

Figure 5.5 shows, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction TL (Row 1), and value of alpha (blue, red and green bars represent instances with alpha respectively equal to 0.3, 0.5 and 0.7), the average percentage lost capacity in first-stage bins $LostCap_{FS}$ as a function of the percentage of lost volume in each bin BL. The percentage $LostCap_{FS}$ is the same whatever the value of alpha and thus does not depend on the cost of second-stage bins. Moreover, the average percentage lost capacity increases as SL, TL and BL increase and reaches 56% when all the parameters are set to their highest values.

These results show that if there are only three types of bins on the market and the availability of second-stage bins can be limited, the firm should book sufficient capacity in advance although it is very likely that part of this capacity will not actually be available. It is important to notice that the firm, given an estimation

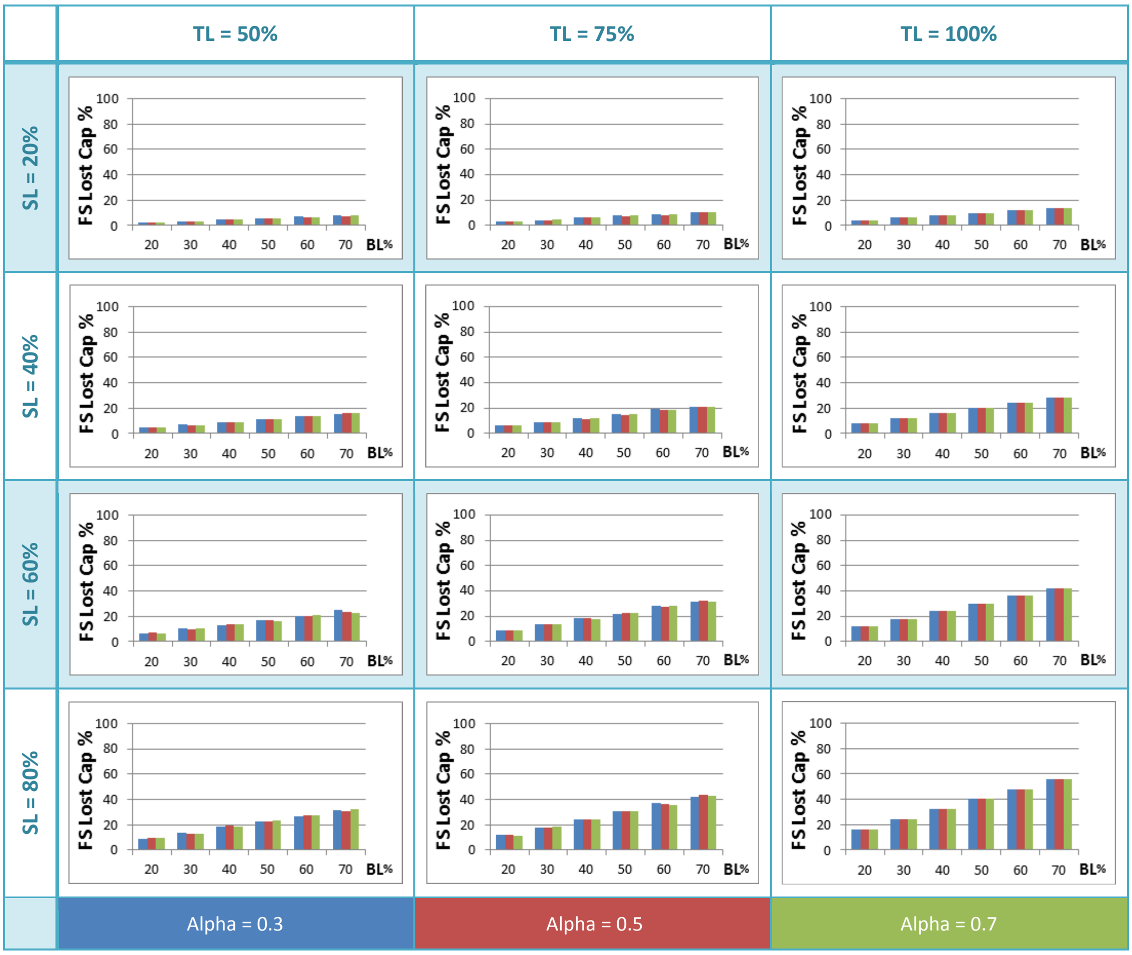

Figure 5.5: Percentage of lost capacity for instance set T3, availability class AV1 and uniform losses.

of the total volume of items to ship or store, should book a percentage of expected volume greater than Cap_{FS}, to take into account the losses of available volume.

Figure 5.6 shows, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction TL (Row 1), and value of alpha (blue, red and green bars represent instances with alpha respectively equal to 0.3, 0.5 and 0.7), the average percentage of the estimation of the needed capacity the firm should book in advance $CapBook_{FS}$

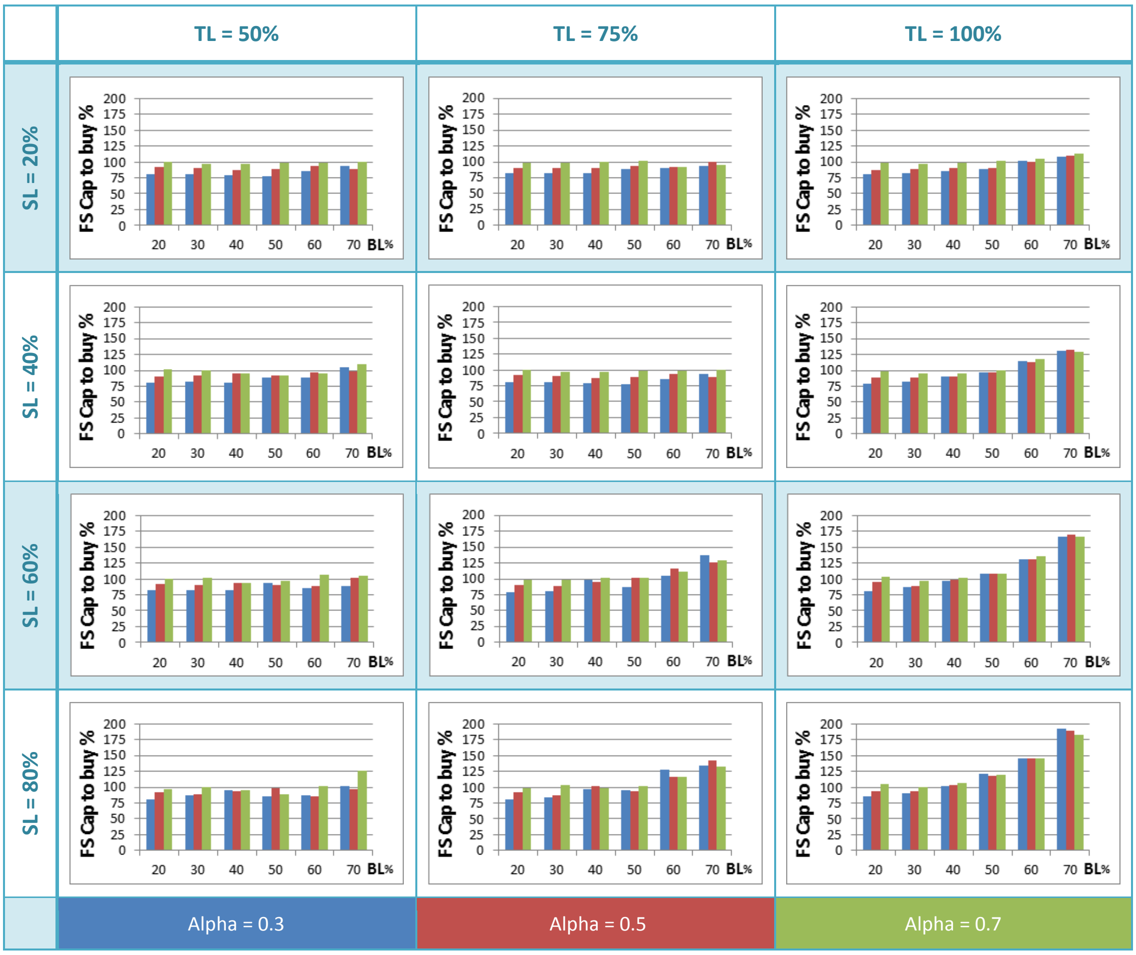

Figure 5.6: Percentage of estimated capacity that should be booked at the first stage for instance set T3, availability class AV1 and uniform losses.

as a function of the percentage of lost volume in each bin BL. When the probabilities that a scenario and a bin type are affected by losses are low, the average percentage of estimated capacity the company should book at the first stage depends on the value of alpha. Obviously the percentage $CapBook_{FS}$ is greater when the premium cost of second-stage bins is higher. Moreover, the average percentage $CapBook_{FS}$ increases as BL increases, with a different slop depending on the values of the other parameters. If the probability that a bin type is affected by a capacity reduction is less than 50%, the percentage of estimated capacity the firm should book in advance is about 90%, whatever the values of SL and BL. The average $CapBook_{FS}$ is stable when TL is equal to 75% and SL is lower than 40% and more in general when the level of loss is up to 40%. When SL, TL and BL are respectively greater than 60%, 75% and 50%, the capacity that should be booked at the first stage is greater than the estimated total volume of items and does not depend on the cost of second-stage bins. In particular, the average $CapBook_{FS}$ reaches 121%, 146%, 192% when the percentage of lost volume is respectively equal to 50%, 60% and 70%.

When we consider instances without the additional cost required to react to the reduction of the available volume of first-stage bins, the structure of the capacity-planning solutions does not change. In particular, the capacity plans are identical when all bin types are affected by losses and the premium cost of second-stage bins is high. While, when the premium cost is low, the average percentage capacity booked in advance is slightly higher (up to 12% more) for instances where the extra cost is set equal to zero. However, the percentage of loss of capacity is the same regardless of the extra cost.

We now discuss the structure of the capacity-planning solutions of instances with three bin types, uniform losses of volume and a high availability of second-stage bins. The structures of the capacity-planning solutions, when all the parameters that determine the actual volume of first-stage bins are equal, are the same for availability classes AV2 and AV3. We thus present the results of instances with availability class AV2 because they represent the most common case in practice. The availability class AV2 indeed implies that the number of bins of a certain type available at the second stage is, in the worst case, equal to half the number of bins of that type available in advance.

The structure of the capacity-planning solution for instance set T3 with availability class AV2 and uniform losses varies considerably depending on the values

Figure 5.7: Percentage of capacity bookend at the first stage for instance set T3, availability class AV2 and uniform losses.

assumed by the parameters SL, TL and BL. Figure 5.7 shows, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction TL (Row 1), and value of alpha (blue, red and green bars represent instances with alpha respectively equal to 0.3, 0.5 and 0.7), the average percentage of capacity booked at the first stage Cap_{FS} as a function of the percentage of lost volume in each bin BL. The percentage of capacity booked at the first stage is greater when alpha is high and thus when the premium cost of extra bins is high. Moreover, the percentage Cap_{FS} is always below 79%, decreases as the parameters SL, TL and BL increase and reaches 0% when the level of loss is sufficiently high. When the percentage of scenarios affected by capacity losses is equal to 20%, the average percentage Cap_{FS} is always greater than 31%. But, when the percentage of scenarios affected by capacity losses is high and the level of loss is greater than 40%, the structure of the capacity plan is completely different. In particular, when SL is equal to 40% and all bin types are affected by losses or when SL and TL are respectively equal to 80% and 50%, no capacity is booked in advance if alpha is equal to 0.3 or 0.5 and the level of loss is maximum. When SL and TL are both high, the percentage Cap_{FS} is equal to 0% even if alpha is 0.7. Moreover, when SL and TL are set at their maximum values, no capacity is booked at the first stage if the percentage of lost volume is greater than or equal to 50%, whatever the cost of second-stage bins.

Figure 5.8 shows, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction TL (Row 1), and value of alpha (blue, red and green bars represent instances with alpha respectively equal to 0.3, 0.5 and 0.7), the average percentage of the objective function value achieved at the first stage Obj_{FS} as a function of the percentage of lost volume in each bin BL. Figure 5.8 confirms the structures of the capacity-planning solutions shown by Figure 5.7. In particular, the percentage Obj_{FS} increases as the cost of second-stage bins increases and decreases as SL, TL and BL increase. When the percentage of scenarios affected by capacity losses is equal to 20%, the average percentage Obj_{FS} is always between 25% and 61%. Moreover, when the percentage of lost volume is equal to 20%, the average percentage Obj_{FS} is always around 57%. On the contrary, when all the parameters that determine the actual volume of first-stage bins are high, the objective function value achieved at the first stage is equal to 0%.

Figure 5.8: Percentage of objective function value achieved at the first stage for instance set T3, availability class AV2 and uniform losses.

The average number of bin types used in the plan is always below 1.7. Figure 5.9 shows, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction TL (Row 1), and value of alpha (blue, red and green bars represent instances with alpha respectively equal to 0.3, 0.5 and 0.7), the average number of bin types N_t used in the capacity plan as a function of the percentage of lost volume in each bin BL. The average number of first-stage bin types used in the plan increases with alpha.

Figure 5.9: Number of bin types used in the capacity plan for instance set T3, availability class AV2 and uniform losses.

The low values of average N_t show that, when the number of extra bins is not limited, almost all the bins included in the capacity plan are the same type and if in more than half of the scenarios all bin types lose a big amount of capacity, no bins are booked in advance. These values of average N_t lead to obtain an average percentage fill level of first stage bins higher than 79%. This fill level refers of to the actual volume of first-stage bins. While, the overall average percentage fill level of second-stage bins f_{SS} is equal to 82%.

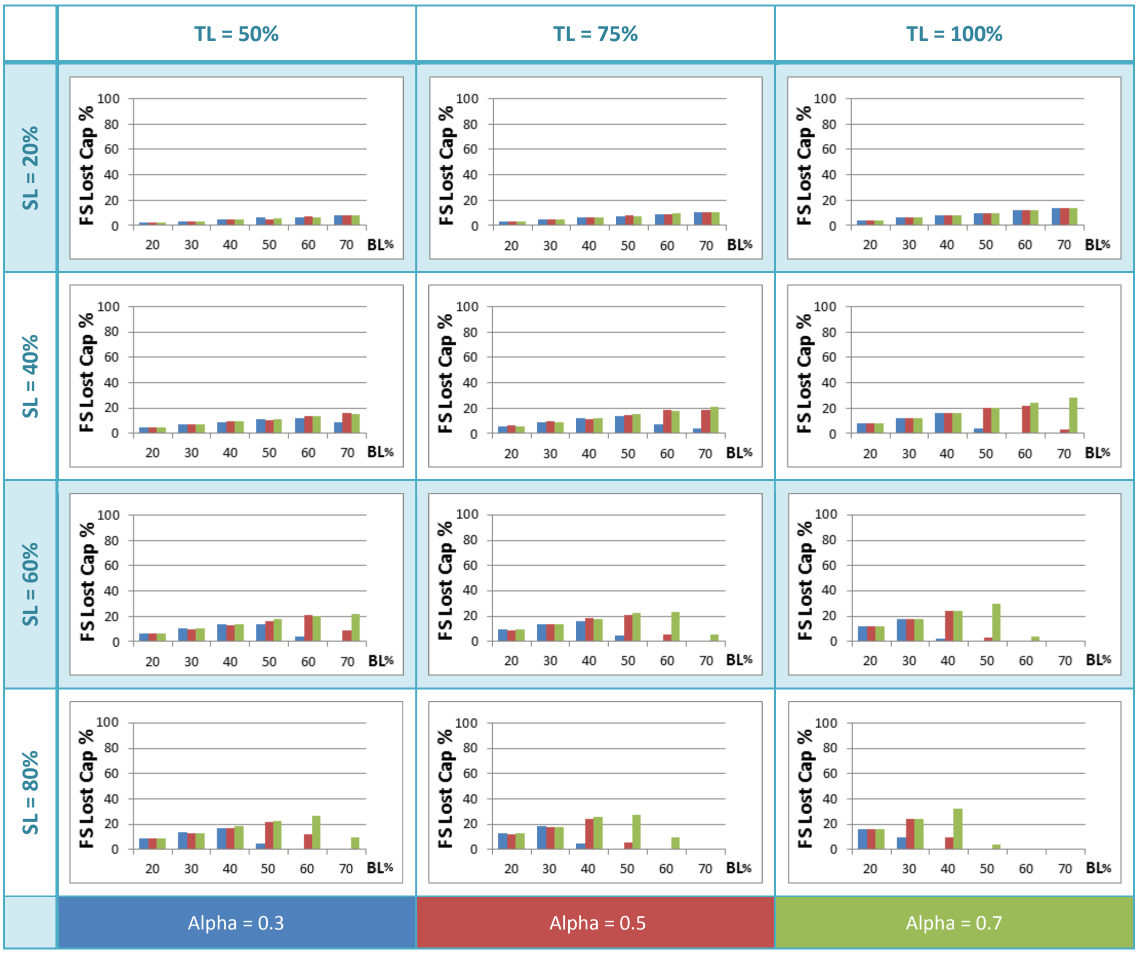

Figure 5.10: Percentage of lost capacity for instance set T3, availability class AV2 and uniform losses.

For this set of instances, the average percentage lost capacity reaches 32%. Figure 5.10 shows, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction TL (Row 1), and value of alpha (blue, red and green bars represent instances with alpha respectively equal to 0.3, 0.5 and 0.7), the average percentage lost capacity in first-stage bins $LostCap_{FS}$ as a function of the percentage of lost volume in each bin BL. When some bins are booked in advance, the average percentage lost capacity increases as SL, TL and BL increase. This means that, when the probability of losing capacity is low or when the percentage of lost volume is less than 40%, the firm should book several bins in advance and then run the risk of losing a percentage of capacity and thus of paying an extra cost. It is important to notice that this structure of the capacity-planning solution is due to a convenience in terms of cost and not to a limited availability of second-stage bins.

Figure 5.11: Percentage of estimated capacity that should be booked at the first stage for instance set T3, availability class AV2 and uniform losses.

Figure 5.11 shows, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction TL (Row 1), and value of alpha (blue, red and green bars represent instances with alpha respectively equal to 0.3, 0.5 and 0.7), the average percentage of the estimation of the needed capacity the firm should book in advance $CapBook_{FS}$ as a function of the percentage of lost volume in each bin BL. The average percentage of estimated capacity the company should book at the first stage increases with the premium cost of second-stage bins. Here, the trend of $CapBook_{FS}$ as a function of the parameters that determine the actual volume of first-stage bins coincides with that of Cap_{FS}. This is due to the fact that the percentage $LostCap_{FS}$ is quite low. In particular, the percentage of expected capacity the firm should book in advance is approximately 25% greater than the corresponding Cap_{FS}.

When we consider instances without the additional cost required to react to the reduction of the available volume of first-stage bins, the structure of the capacity-planning solutions does not change. In particular, the capacity plans are identical when all bin types are affected by losses and the premium cost of second-stage bins is high. For the other combinations of parameters, the percentage of capacity booked in advance is slightly higher in instances where there is not an extra cost needed to deal with losses. The additional cost is therefore a disincentive to book bins in advance. For example, the percentage of capacity booked in advance in instances without the additional cost reaches 22%, while no capacity is booked at the first-stage in the corresponding instances with the extra cost. This happens in particular when the premium cost of second-stage bins and the probability that a bin type is affected by losses are low, while the percentage of lost capacity is high. In this situation, the percentage of loss capacity is up to 20%. Anyway, the overall maximum percentage $LostCap_{FS}$ is equal to 32%, regardless of the additional cost.

We now discuss the structure of the capacity-planning solutions of instances with five bin types and uniform losses. The structure of the solutions depends on the availability of second-stage bins and varies with the values assumed by the parameters SL, TL and BL. We first present the results of instances with availability class AV1 and then those related to AV2.

Figure 5.12: Percentage of capacity bookend at the first stage for instance set T5, availability class AV1 and uniform losses.

When we consider instances with five bin types and a limited availability of extra bins, the percentage of capacity booked in advance is between 6% and 81%. Figure 5.12 shows, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction

TL (Row 1), and value of alpha (blue, red and green bars represent instances with alpha respectively equal to 0.3, 0.5 and 0.7), the average percentage of capacity booked at the first stage Cap_{FS} as a function of the percentage of lost volume in each bin BL. The minimum value, equal to 6%, is reached when SL, TL, BL and alpha are respectively equal to 80%, 75%, 60%-70% and 0.3. Moreover, when the percentage of scenarios affected by capacity losses is 20%, the percentage Cap_{FS} is always greater than 37%. In general, the percentage Cap_{FS} increases with alpha and decreases as the parameters SL, TL and BL increase. But, when the main portion of scenarios are characterized by reductions of available capacity and all bin types are affected by huge losses, the percentage Cap_{FS} is always the same, whatever the cost of extra bins. Moreover, in this situation, the percentage of capacity booked in advance increases with the percentage of loss. This trend is due to the limited availability of second-stage bins: when it is very likely that there will be high losses, the risk of not having enough extra bins and thus of not being able to load all items, leads to book capacity at the first stage. For example, when all the parameters that determine the actual volume of first-stage bins are set at their maximum values, the average percentage Cap_{FS} is equal to 14%.

Figure 5.13 shows, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction TL (Row 1), and value of alpha (blue, red and green bars represent instances with alpha respectively equal to 0.3, 0.5 and 0.7), the average percentage of the objective function value achieved at the first stage Obj_{FS} as a function of the percentage of lost volume in each bin BL. The percentage of objective function value paid at the first stage is between 5% and 71%. Figure 5.13 confirms the structures of the capacity-planning solutions shown by Figure 5.12. In particular, the minimum values of Obj_{FS} are reached when 80% of scenarios are characterized by capacity losses, not all bin types are affected by reductions of volume and the percentage of

Figure 5.13: Percentage of objective function value achieved at the first stage for instance set T5, availability class AV1 and uniform losses.

loss is greater than 60%. Moreover, when SL, TL and BL reach their maximum values, the average percentage Obj_{FS} is equal to 9%.

Figure 5.14 shows, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction TL (Row 1), and value of alpha (blue, red and green bars represent instances with alpha respectively equal to 0.3, 0.5 and 0.7), the average number of bin types N_t used in the capacity plan as a function of the percentage of lost volume in

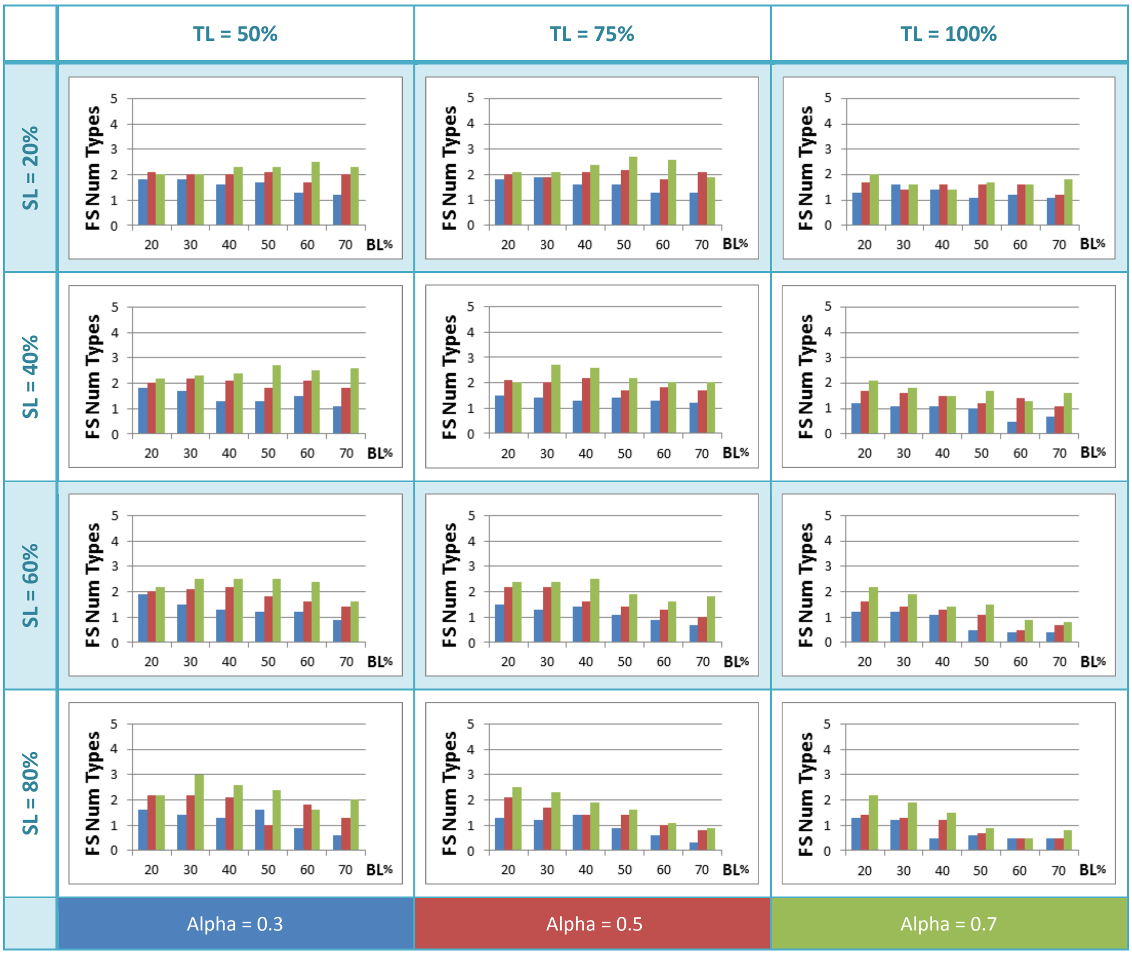

Figure 5.14: Number of bin types used in the capacity plan for instance set T5, availability class AV1 and uniform losses.

each bin BL. The average number of first-stage bin types reaches 3 when SL, TL, BL and alpha are respectively equal to 80%, 50%, 30% and 0.7. However, the overall average N_t is equal to 1.6. Moreover, when all the parameters that determine the actual volume of first-stage bins are high, the average N_t drops below 1. Therefore in those cases, even if the average Cap_{FS} is not equal to 0%, in some instances no bins are booked in advance. The minimum value of average N_t, equal to 0.3, is reached when the premium cost of extra bins is low and SL, TL, BL are respectively equal to 80%, 75%, 70%. Moverover, the average percentage fill level related to the actual volume of first-stage bins is always between 84% and 98%. The average percentage fill level of second-stage bins is instead around 86%.

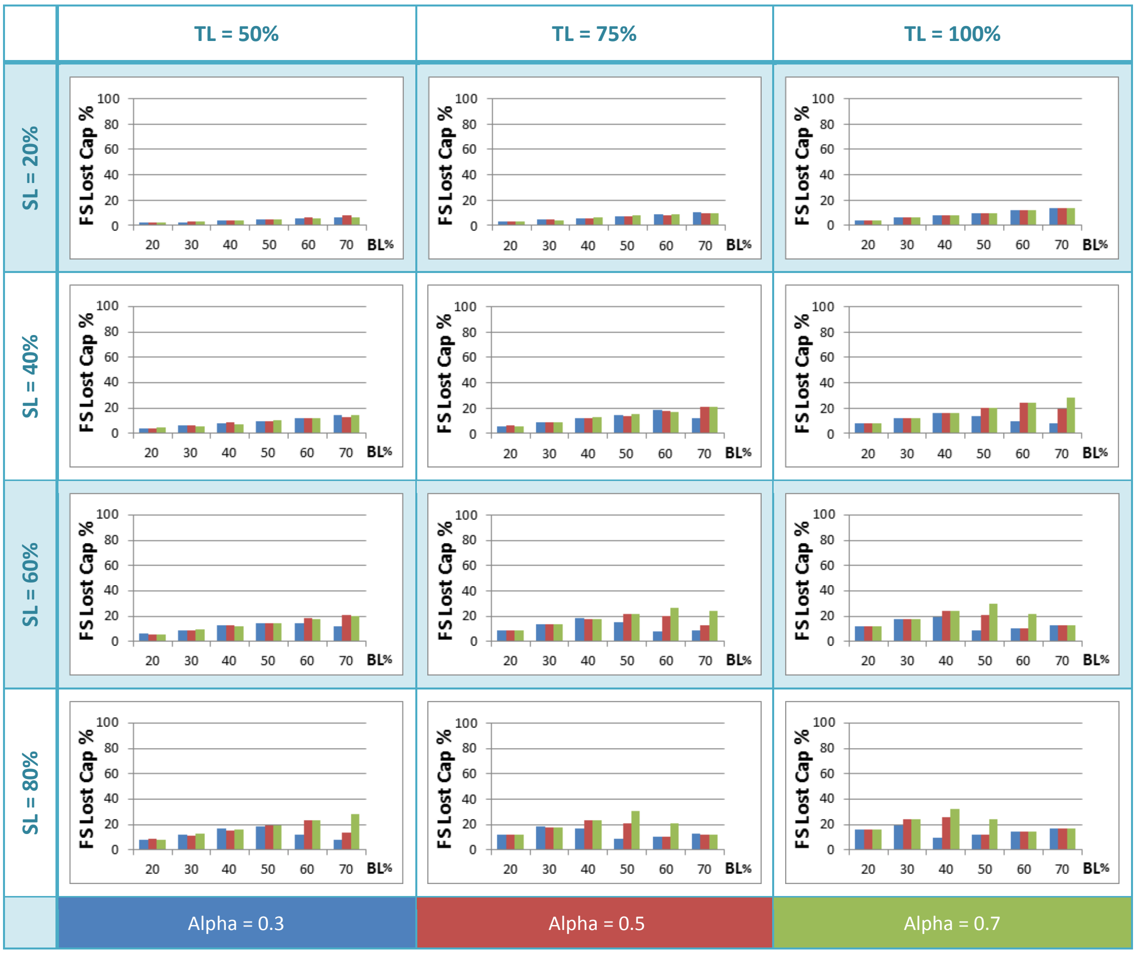

Figure 5.15: Percentage of lost capacity for instance set T5, availability class AV1 and uniform losses.

The maximum value of average percentage $LostCap_{FS}$ is equal to 32%. Figure 5.15 shows, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction TL (Row 1), and value of alpha (blue, red and green bars represent instances with alpha respectively equal to 0.3, 0.5 and 0.7), the average percentage lost capacity in first-stage bins $LostCap_{FS}$ as a function of the percentage of lost volume in each bin BL. In general, when the percentage of loss is lower than 40%, the percentage $LostCap_{FS}$ increases as SL, TL and BL increase and does not depend on the premium cost of second-stage bins. When the percentage of scenarios affected by capacity losses is equal to 20%, this behaviour occurs even for larger values of BL and the average percentage $LostCap_{FS}$ reaches 14%. But, when SL and BL are respectively greater than 40% and 50%, there is not this trend and in addition $LostCap_{FS}$ varies with alpha. The maximum value of average percentage $LostCap_{FS}$ is reached when SL, TL, BL and alpha are respectively equal to 80%, 100%, 40% and 0.7.

The firm, given the estimation of the total volume of items to ship or store, should book a percentage of estimated volume greater than Cap_{FS}, to take into account the losses of available volume. Figure 5.16 shows, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction TL (Row 1), and value of alpha (blue, red and green bars represent instances with alpha respectively equal to 0.3, 0.5 and 0.7), the average percentage of the estimation of the needed capacity the firm should book in advance $CapBook_{FS}$ as a function of the percentage of lost volume in each bin BL. Figure 5.16 confirms the structure of the capacity-planning solutions shown by Figure 5.12. But, the firm should book on average 23% more than the value of Cap_{FS}. In particular, when all the parameters that determine the actual volume of first-stage bins are set at their maximum value, the percentage of estimated capacity that the firm should book in advance is 25%, double the corresponding average percentage Cap_{FS}.

When the additional cost needed to deal with the losses of volume in first-stage bins is set equal to zero, the structure of the capacity plan remains almost the same. In particular, the average values of Cap_{FS} and $LostCap_{FS}$ are really close

Figure 5.16: Percentage of estimated capacity that should be booked at the first stage for instance set T5, availability class AV1 and uniform losses.

when alpha is equal to 0.5 or 0.7. On the contrary, if alpha is equal to 0.3, the percentage of capacity booked in advance is greater in instances where there is not an additional cost that must be paid. This difference grows with the parameters SL, TL and BL. In particular, when SL, TL and BL are respectively equal to 80%, 50% and 60%, the percentage Cap_{FS} in instances without the additional cost is four times the percentage Cap_{FS} in instances with the additional cost. This leads to higher values of the corresponding $LostCap_{FS}$. However, the overall maximum percentage $LostCap_{FS}$ is equal to 32%, as in instances where there is an extra cost.

We now present the structure of the capacity-planning solutions of instances with five bin types, uniform losses of volume and a high availability of second-stage bins. The structures of the capacity-planning solutions, when all the parameters that determine the actual volume of first-stage bins are equal, are the same for availability classes AV2 and AV3. We thus present the results of instances with availability class AV2 because they represent the most common case in practice.

Figure 5.17: Percentage of capacity bookend at the first stage for instance set T5, availability class AV2 and uniform losses.

When we consider the instance set T5 with availability class AV2, the percentage of capacity booked at the first stage varies between 0% and 81%. Figure 5.17 shows, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction TL (Row 1), and value of alpha (blue, red and green bars represent instances with alpha respectively equal to 0.3, 0.5 and 0.7), the average percentage of capacity booked at the first stage Cap_{FS} as a function of the percentage of lost volume in each bin BL. The percentage Cap_{FS} increases with the premium cost of extra bins and decreases as the parameters SL, TL and BL increase. When the percentage of scenarios affected by capacity losses is equal to 20%, the average percentage Cap_{FS} is always greater than 29%. But, when at least one between SL and TL is high, the percentage Cap_{FS} reaches 0% for high levels of loss. In particular, when SL and TL are set at their maximum values, no capacity is booked at the first stage if the percentage of lost volume is greater than or equal to 50%, whatever the cost of second-stage bins.

The values of the average percentage of the objective function value achieved at the first stage confirm the structure of the capacity-planning solutions shown by Figure 5.17. In particular, figure 5.18 shows, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction TL (Row 1), and value of alpha (blue, red and green bars represent instances with alpha respectively equal to 0.3, 0.5 and 0.7), the average percentage of the objective function value achieved at the first stage Obj_{FS} as a function of the percentage of lost volume in each bin BL. The average percentage Obj_{FS} varies between 0% and 72%. In particular, the percentage Obj_{FS} increases as the cost of second-stage bins increases and decreases as SL, TL and BL increase. When the percentage of scenarios affected by capacity losses is equal to 20%, the average percentage Obj_{FS} is always between 23% and 72%. Instead,

Figure 5.18: Percentage of objective function value achieved at the first stage for instance set T5, availability class AV2 and uniform losses.

when the percentage of lost volume is equal to 20%, the average percentage Obj_{FS} is always about 59%. On the contrary, when all the parameters that determine the actual volume of first-stage bins are high, the objective function value achieved at the first stage is equal to 0%.

Figure 5.19 shows, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction TL (Row 1), and value of alpha (blue, red and green bars represent

Figure 5.19: Number of bin types used in the capacity plan for instance set T5, availability class AV2 and uniform losses.

instances with alpha respectively equal to 0.3, 0.5 and 0.7), the average number of bin types N_t used in the capacity plan as a function of the percentage of lost volume in each bin BL. The average number of first-stage bin types used in the plan increases with alpha. Moreover, the average number of bin types N_t is always below 1.9. This means that almost all the bins included in the capacity plan are the same type, whatever the probability and the entity of the volume losses. Furthermore, the percentage fill level related to the actual volume of first-stage bins varies between

87% and 99%. While the average percentage fill level of second-stage bins is around 83%. These values indicate the effectiveness of the capacity plan.

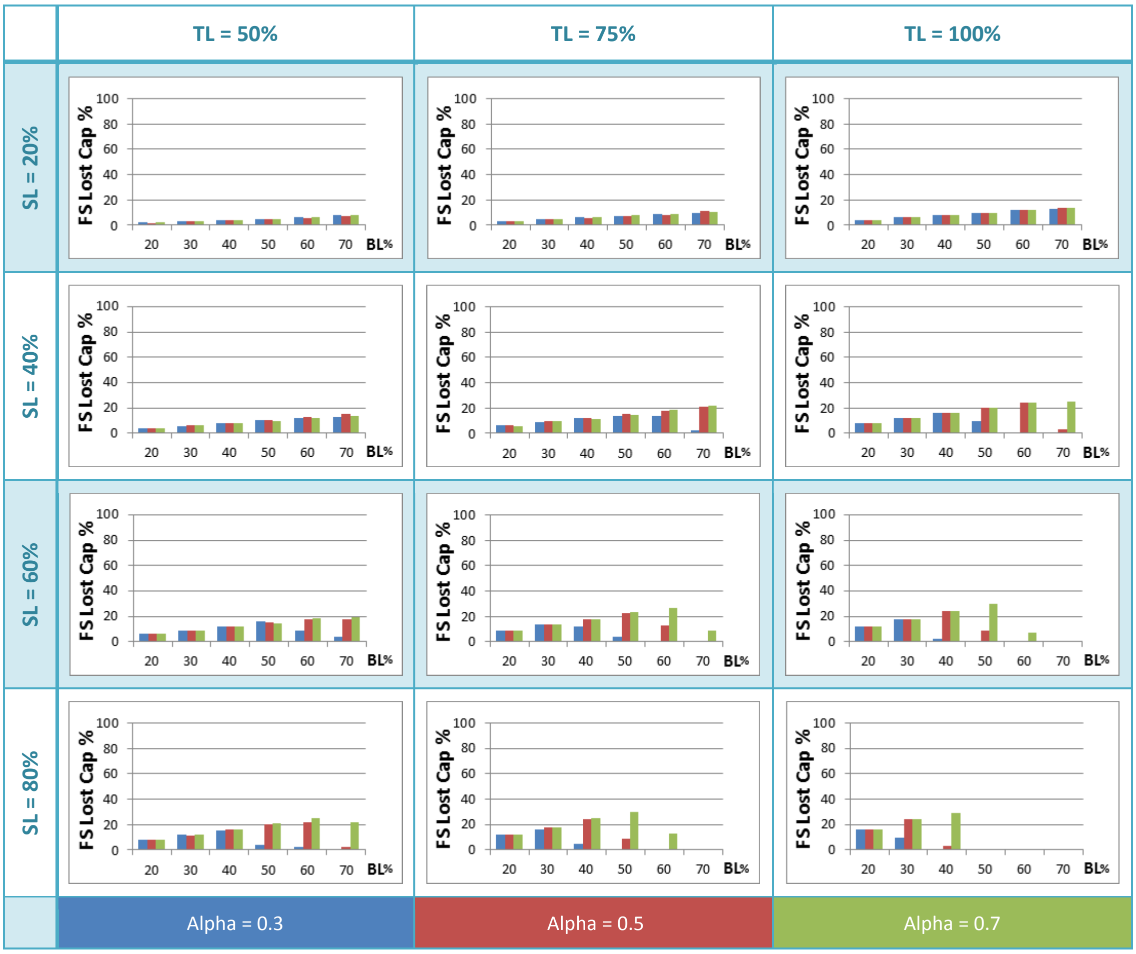

Figure 5.20: Percentage of lost capacity for instance set T5, availability class AV2 and uniform losses.

In this set of instances, the maximum average percentage lost capacity in first-stage bins is equal to 30% Figure 5.20 shows, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction TL (Row 1), and value of alpha (blue, red and green bars represent instances with alpha respectively equal to 0.3, 0.5 and 0.7), the average percentage lost capacity in first-stage bins $LostCap_{FS}$ as a function of the percentage of lost volume in each bin BL. When SL and TL assume low values, the percentage $LostCap_{FS}$ does not depend on alpha. The same happens, more generally, when the level of loss is low. The maximum value of $LostCap_{FS}$ is reached when SL, TL, BL and alpha are respectively equal to 60%, 100%, 50% and 0.7. Moreover, when the percentage $LostCap_{FS}$ exceeds 25%, then it drops significantly for higher values of BL.

Figure 5.21: Percentage of estimated capacity that should be booked at the first stage for instance set T5, availability class AV2 and uniform losses.

Figure 5.21 shows, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction TL (Row 1), and value of alpha (blue, red and green bars represent instances with alpha respectively equal to 0.3, 0.5 and 0.7), the average percentage of the estimation of the needed capacity the firm should book in advance $CapBook_{FS}$ as a function of the percentage of lost volume in each bin BL. Figure 5.21 confirms the structure of the capacity-planning solutions shown by Figure 5.17. This means that, when the probability of losing capacity is low or, more in general, when the percentage of lost volume is less than 40%, the firm should book several bins in advance and then run the risk of losing a percentage of capacity and paying an extra cost. In particular, the firm should book in advance on average 20% more than the value of Cap_{FS}. This gap is due mainly to the loss of available volume in first-stage bins and slightly to the fill level of bins.

When we consider instances without the additional cost required to react to the reduction of the available volume of first-stage bins, the structure of the capacity-planning solutions does not change. In particular, the average values of Cap_{FS} and $LostCap_{FS}$ are really close when alpha is equal to 0.5 or 0.7. On the contrary, if alpha is equal to 0.3, the percentage of capacity booked in advance is greater in instances where there is not an additional cost to pay to deal with losses. This difference grows with the parameters SL, TL and BL. In particular, if there is not an additional cost, the percentage Cap_{FS} reaches 0% for higher levels of loss. For example, when SL, TL and BL are respectively equal to 40%, 75% and 70%, the average percentage Cap_{FS} is equal to 32%, while it is 0% when we consider the extra cost. In this situation, the percentage $LostCap_{FS}$ is obviously higher but the maximum percentage $LostCap_{FS}$ is still not exceeding 30%.

Localized losses of capacity

We now discuss the structure of the capacity-planning solutions of instances with three bin types and localized losses of volume. The structures of the capacity plan, when all the parameters that determine the actual volume of first-stage bins are equal, are almost the same for all the availability classes. We thus present the results of instances with availability class AV1 and then we briefly describe what changes with an higher availability of extra bins.

Figure 5.22: Percentage of capacity bookend at the first stage for instance set T3, availability class AV1 and localized losses.

In instances with three bin types, localized losses and availability class AV1, the percentage of capacity booked at the first stage varies between 66% and 84%. Figure 5.22 shows, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction TL (Row 1), and value of alpha (blue, red and green bars represent instances with alpha respectively equal to 0.3, 0.5 and 0.7), the average percentage of capacity booked at the first stage Cap_{FS} as a function of the percentage of lost volume in each bin BL. The percentage Cap_{FS} increases with alpha and thus with the premium cost of extra bins. Moreover, the average percentage Cap_{FS} decreases slightly as the level of loss increases, while it remains the same whatever the parameters SL and TL. This means that the capacity booked at the first stage does not depend on the probability of being affected by losses. In addition, even if the percentage of lost volume in each bin is equal to 70%, at least 66% of the capacity is booked in advance.

Figure 5.23 shows, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction TL (Row 1), and value of alpha (blue, red and green bars represent instances with alpha respectively equal to 0.3, 0.5 and 0.7), the average percentage of the objective function value achieved at the first stage Obj_{FS} as a function of the percentage of lost volume in each bin BL. The percentage Obj_{FS} varies between 59% and 75%. Moreover, when BL is less than or equal to 50%, the average percentage Obj_{FS} increases with alpha and decreases slightly as the level of loss increases. While, when the percentage of lost volume is greater than 60%, it is the same whatever the values of alpha and BL. Figure 5.23 confirms that the probability of having losses does not affect the structure of the capacity plan.

Figure 5.24 shows, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity

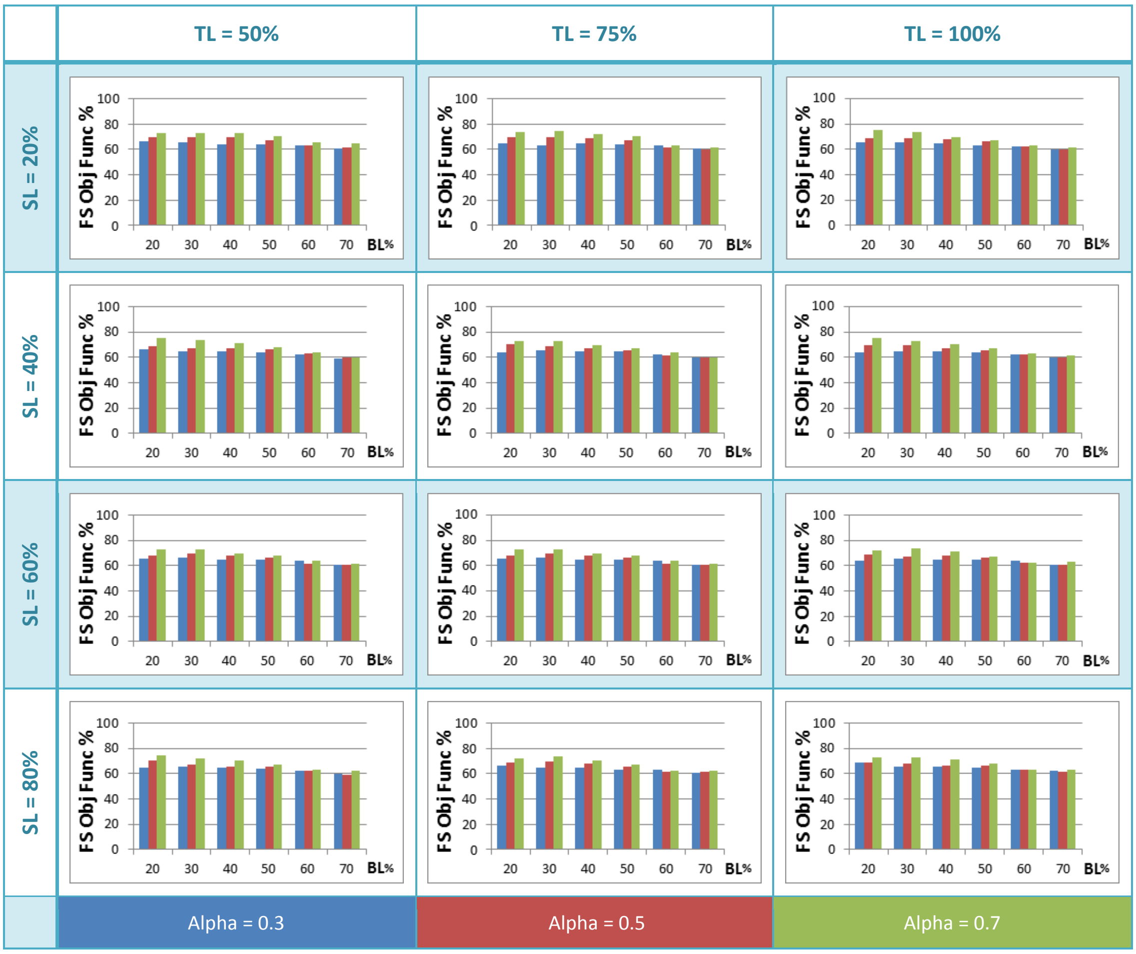

Figure 5.23: Percentage of objective function value achieved at the first stage for instance set T3, availability class AV1 and localized losses.

reduction TL (Row 1), and value of alpha (blue, red and green bars represent instances with alpha respectively equal to 0.3, 0.5 and 0.7), the average number of bin types N_t used in the capacity plan as a function of the percentage of lost volume in each bin BL. The average number of bin types N_t used in the capacity plan increases as the level of loss increases and reaches 3. In particular, the average number of bin types used is equal to 2.50 when LL is greater than 60%. Thus, when the percentage of lost volume is high, the capacity booked at the first stage decreases slightly and

Figure 5.24: Number of bin types used in the capacity plan for instance set T3, availability class AV1 and localized losses.

almost all types of bins are included in the capacity plan.

Moreover, the average percentage fill level related to the actual volume of first-stage bins is always between 80% and 93%. In particular, when the percentage of lost volume is greater than or equal to 50%, the average percentage fill level is greater than 84%. When LL is higher, the percentage f_{FS} decreases slightly, especially for high values of TL and SL. This happens because usually, to try to avoid bins that probably will have problems of availability, larger bins are included in the capacity plan. As a result, in this situation the fill level is slightly lower. The average percentage fill level of second-stage bins varies instead between 79% and 86%.

In this set of instances, the overall average percentage of lost capacity in first-stage bins is lower than 0.5%. The percentage lost capacity increases with the level of loss and is higher when alpha is equal to 0.3. However, the maximum average percentage of lost capacity is equal to 3.4%. Low values of lost capacity show that the choice of booking in advance at least 66% of capacity is not due to a limited availability of extra bins but it is a cost-effective strategy. This is confirmed by the structure of the capacity plan that remains the same regardless of the probability of losses.

Figure 5.25 shows, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction TL (Row 1), and value of alpha (blue, red and green bars represent instances with alpha respectively equal to 0.3, 0.5 and 0.7), the average percentage of the estimation of the needed capacity the firm should book in advance $CapBook_{FS}$ as a function of the percentage of lost volume in each bin BL. Figure 5.25 confirms the structure of the capacity plan described before. In particular, the firm should book in advance a percentage of estimated capacity between 75% and 103%, on average 15% more than the value of Cap_{FS}.

When we consider instances with the additional cost needed to deal with the losses of volume in first-stage bins equal to zero, the structure of the capacity plan does not change. While, when we consider instances with availability classes AV2 or AV3, instead of AV1, the structure of the capacity plan remains the same but the capacity booked at the first stage is slightly lower. This gap grows with the percentage of lost volume. In particular, when BL is equal to 70% and the availability of extra bins in high, the percentage Cap_{FS} is approximately 17% lower than the

Figure 5.25: Percentage of estimated capacity that should be booked at the first stage for instance set T3, availability class AV1 and localized losses.

corresponding percentage Cap_{FS} for instances with availability class AV1. While, when BL is lower, the percentage Cap_{FS} is approximately 8% lower when we consider availability classes AV2 or AV3, instead of AV1. As a result, when the availability of extra bins in high, the average percentage of lost capacity is lower and its maximum value is 0.7%.

We now consider instances with five bin types and localized losses of volume. As for instances of set T3, the structures of the capacity plan are almost the same for all the availability classes. We thus present the results of instances with availability class AV1 and then we briefly discuss what changes with an higher availability of extra bins.

Figure 5.26: Percentage of capacity bookend at the first stage for instance set T5, availability class AV1 and localized losses.

For instances with five bin types and availability class AV1, the percentage of capacity booked at the first stage varies between 55% and 81%. Figure 5.26 shows, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction TL (Row 1), and value of alpha (blue, red and green bars represent instances with alpha respectively equal to 0.3, 0.5 and 0.7), the average percentage of capacity booked at the first stage Cap_{FS} as a function of the percentage of lost volume in each bin BL. The percentage Cap_{FS} increases with alpha and thus with the premium cost of extra bins. Moreover, the average percentage Cap_{FS} decreases with the level of loss. In particular, it decreases faster when LL is higher. As for instance set T3, it seems that the probability of being affected by losses has no impact on the capacity booked at the first stage.

Figure 5.27 shows, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction TL (Row 1), and value of alpha (blue, red and green bars represent instances with alpha respectively equal to 0.3, 0.5 and 0.7), the average percentage of the objective function value achieved at the first stage Obj_{FS} as a function of the percentage of lost volume in each bin BL. Figure 5.27 confirms the structure of the capacity plan shown by Figure 5.26. In particular, the percentage of objective function value achieved at the first stage varies between 48% and 72%.

Figure 5.24 shows, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction TL (Row 1), and value of alpha (blue, red and green bars represent instances with alpha respectively equal to 0.3, 0.5 and 0.7), the average number of bin types N_t used in the capacity plan as a function of the percentage of lost volume in each bin BL. The average number of bin types depends on the value of BL. In particular, the average N_t is around 1.9 when the level of loss is lower than 40%, while, when the level of loss is higher, it increases with BL and reaches 3.9. Thus, when the percentage of lost capacity is high, several types of bins are included in the capacity plan.

The average percentage fill level related to the actual volume of first-stage bins

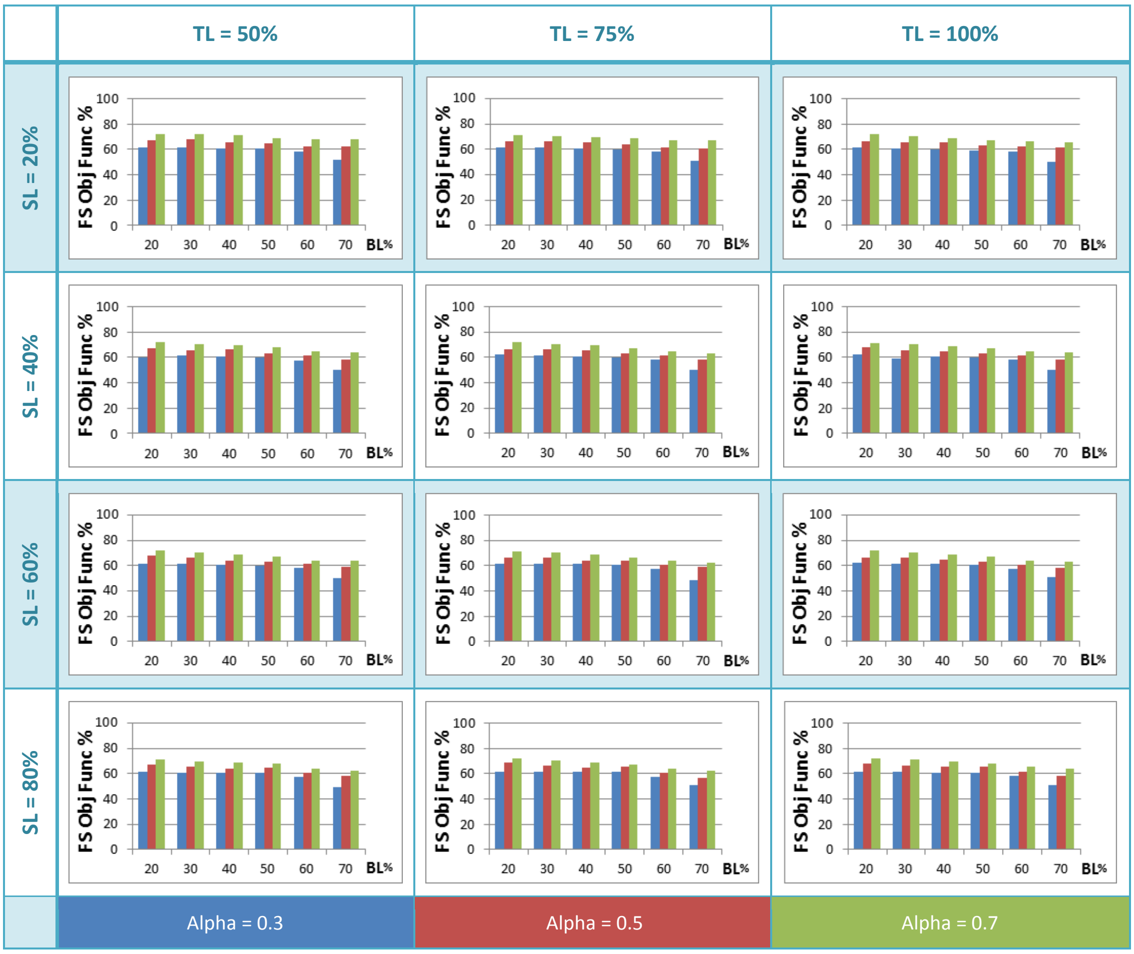

Figure 5.27: Percentage of objective function value achieved at the first stage for instance set T5, availability class AV1 and localized losses.

varies between 83% and 95%. The percentage f_{FS} does not depend on the parameters SL, TL and BL but it decreases with the value of alpha. In particular, the average percentage fill level of first stage bins is 93%, 90% and 87%, when alpha is respectively equal to 0.3, 0.5 and 0.7. On the other hand, the average percentage fill level of second-stage bins is always around 85%. This indicates the effectiveness of the capacity plan, which requires only targeted adjustments at the second stage. Moreover, for this set of instances, the lost capacity in first-stage is almost always

Figure 5.28: Number of bin types used in the capacity plan for instance set T5, availability class AV1 and localized losses.

zero. In particular, the maximum average lost capacity is lower than 0.3%.

Figure 5.29 shows, for each combination of percentage of scenarios affected by capacity losses SL (Column 1), probability that a bin type is affected by a capacity reduction TL (Row 1), and value of alpha (blue, red and green bars represent instances with alpha respectively equal to 0.3, 0.5 and 0.7), the average percentage of the estimation of the needed capacity the firm should book in advance $CapBook_{FS}$ as a function of the percentage of lost volume in each bin BL. Figure 5.29 confirms

Figure 5.29: Percentage of estimated capacity that should be booked at the first stage for instance set T5, availability class AV1 and localized losses.

that, even if the probability of loosing capacity and the level of loss are high, a great part of the needed capacity should be booked at the first stage. In particular, the firm should book in advance a percentage of estimated capacity between 60% and 96%. These values are, on average, 13% higher than the corresponding values of Cap_{FS}.

When we consider instances without the additional cost required to react to the reduction of the available volume of first-stage bins, the structure of the capacity-planning solutions does not change. While, when we consider instances with availability classes AV2 or AV3, instead of AV1, the structure of the capacity plan remains the same but the capacity booked at the first stage is slightly lower. In particular, when BL is equal to 70% and the availability of extra bins in high, the percentage Cap_{FS} is approximately 10% lower than the corresponding percentage Cap_{FS} for instances with availability class AV1. While, when BL is lower, the percentage Cap_{FS} is approximately 3% lower when we consider availability classes AV2 or AV3, instead of AV1. Moreover, the number of bin types used in the capacity plan is lower when the availability of extra bins in high. In particular, the overall average N_t is around 1.6 and the average N_t is always lower than 3.4.

Chapter 6

Conclusions

In this thesis, we have introduced and studied a new planning problem arising in City Logistic applications, where the design and the optimization of the freight transportation process is essential. This problem is the Stochastic Variable Cost and Size Bin Packing Problem with Loss of Available Capacity ($\mathbf{SVCSBPP}_L$), which explicitly takes into account the presence of uncertainty on parameters that characterize the system of urban areas and strongly affect the long and medium term decisions. In particular, for the first time, the actual availability of the capacity booked in advance is considered stochastic.

The trend in City Logistics solutions is to substitute traditional single-echelon routing structures with two-echelon ones and to introduce satellites and the use of environmental friendly vehicles. The $\mathbf{SVCSBPP}_L$ may thus be used to plan the capacity of the fleet and of the transshipment satellites.

We have addressed this new problem in order to overcome a portion of the gap in the literature concerning the development of models for City Logistics solutions in terms of comprehensive study of the sources of uncertainty and methodologies. In particular, to mitigate the computational difficulty associated with this stochastic problem, we have proposed an heuristic strategy based on the Progressive Hedging algorithm. This heuristic uses specialized solving strategies to solve the deterministic subproblems obtained from the scenario decomposition of the stochastic model. Moreover, we have implemented advanced strategies that directly operate on the data of the problem (e.g., cost of the bins) in order to accelerate the convergence. We have also developed a large set of instances of various dimensions and combinations of different levels of variability in the stochastic parameters. Finally, extensive computational tests have been performed with the aim to measure the impact of uncertainty, determine whether building a stochastic programming model is really useful, and determine whether basic structure for the capacity planning exists and the dependence of the plan on attributes of the problem setting.

The results show the need to explicitly consider uncertainty in capacity-planning applications. In particular, the gap between the stochastic solution and the expected-value solution, obtained solving the deterministic problem with all the random variables replaced by their expected values, is always significant. Moreover, when the availability of bins at the shipping day is limited and there is a low probability of loosing a great amount of planned capacity, the expected-value solutions lead to infeasible capacity plans.

The numerical results show that the structure of the capacity plan depends on the probability of suffering from reductions of available capacity and on the type and the entity of these losses. This confirms the importance of considering the actual availability of the planned capacity stochastic. If only few types of bins are available on the market, the availability of extra bins at the shipping day may be limited and the losses of available volume are uniformly distributed among the bins, the firm should book in advance almost all the capacity that it will need for the planning horizon. In particular, if there is a high probability of loosing a great amount of capacity, the firm should book in advance more capacity than needed. On the contrary, if there is a high probability of loosing a great amount of capacity but the availability of extra bins is not limited, no capacity should be booked in advance. In this situation, the firm, instead of making a capacity plan, should wait the shipping date to purchase the necessary capacity at a premium price. Finally, if the reductions of capacity are localized (i.e., the losses concern only few bins that become completely unusable), the firm should book in advance the same capacity that it would buy if there were no losses of capacity, but using more different types of bins.

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