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CIRRELT-2025-35

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November 2025

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The Capacity Supplier Selection Problem

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Abstract. An important challenge in the planning and management of supply chains is selecting logistics service providers, which ensures the efficient movement and storage of goods between entities within the chain. In this article, we address this problem from the perspective of a shipper that must plan transportation capacity for a given corridor and, in doing so, must select among multiple suppliers to determine the total transportation capacity to be secured. As suppliers can differ in various ways, including their rates and the quantity of capacity units they offer, this capacity planning problem presents a significant challenge for shippers, who must negotiate such plans in advance. To tackle this problem, we propose a new generalization of the Bin Packing model with variable costs and bin sizes that explicitly incorporates the sourcing decisions, that is, the selection of the suppliers. We conducted a series of computational experiments to investigate the added complexity of explicitly considering supplier selection and to derive insights into how these decision-related aspects influence the resulting capacity plans.

Keywords: Capacity planning, bin packing, supplier selection, integer programming

Acknowledgments: While working on the project, the second author was Adjunct Professor, Department of Computer Science and Operations Research, Université de Montréal, and the fourth held the Canada Research Chair in Stochastic Optimization of Transport and Logistics Systems. We gratefully acknowledge the financial support provided by the Natural Sciences and Engineering Council of Canada (NSERC) through its Discovery Grant program, and the Fonds de recherche du Québec through their CIRRELT infrastructure grants.

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Dépôt légal – Bibliothèque et Archives nationales du Québec
Bibliothèque et Archives Canada, 2025

1 Introduction

In modern logistics and supply chain management, shippers face increasingly complex decisions regarding the procurement of transportation and storage capacity. A shipper must plan its operations to satisfy customer demand while relying on contractor suppliers for the provision of logistics services. These suppliers offer transportation and storage capacity, often under medium-term contracts.

The shipper seeks to secure sufficient capacity for a future period of operations by signing agreements with a set of suppliers. Each agreement involves a fixed fee for engaging the supplier and a variable cost depending on the amount and type of capacity booked. In return, the supplier commits to providing the negotiated level of capacity. However, the capacity supplied by a single supplier may be insufficient to meet demand or, due to external constraints, the shipper may prefer to spread the required capacity over multiple suppliers [7]. Therefore, the shipper's objective is to design a portfolio of supplier contracts that minimizes its total cost, while ensuring the reliability and flexibility required to handle demand.

Despite the extensive literature on supplier selection problems [14, 10], most rely heavily on heuristics and metaheuristics due to the NP-hardness of these problems, leading to solutions that are near-optimal but without guaranteeing optimality. Thus, it is necessary to model the problem and develop the corresponding exact methods [9, 16, 13, 12]. Just a few articles deal with the exact modeling of the Supplier Selection Problem. In this article, we provide a contribution to fill this gap. The problem is formulated as a Mixed-Integer Programming (MIP) model, namely the *Capacity Supplier Selection Problem*. The proposed formulation generalizes the Variable Cost and Size Bin Packing Problem by integrating supplier selection and contractual requirements into the capacity planning process [4]. It captures the operational aspects of logistics procurement, offering a flexible modeling framework for realistic capacity-sourcing decisions.

The remainder of this article is organized as follows. Section 2 discusses the literature. Section 3 presents the Mixed-Integer Programming formulation of the problem, while Section 4 describes the computational experiments and discusses the results obtained.

2 Related work

For the sake of brevity, we focus on the main objective of this article, the modeling of the Supplier Selection problem. Traditional approaches to supplier selection use Analytic Hierarchy Process (AHP) in combination with a mathematical programming approach. Ghodsypour and O'Brien present a non-linear mixed integer programming approach to solve the multiple sourcing problem, considering the total cost of logistics, including net price, storage, transportation, and ordering costs [8]. Ting and Cho [15] propose an integrated methodology that combines AHP with Linear Programming. The approach incorporates tangible and intangible criteria in evaluating suppliers, enabling the selection of the most suitable ones and determining the optimal order quantities. The model aims to maximize the overall purchasing value. Mansini et al. [11] develop an Integer Programming–based solution to the supplier selection problem with quantity discounts and truckload shipping. The experimental results provide valuable insights into how discounts and shipping affect effective sourcing strategies. However, a major limitation of such approaches is that they rely on arbitrarily assigned weights, which are subjective and typically derived from surveys and questionnaires. This subjectivity might lead to inaccuracies, as assigning precise numerical values to preferences is inherently difficult. Moreover, biases in the surveys might affect the results and require additional methods to limit the effects of bias [3], and do not scale well when the number of performance criteria and the size of the model increase.

A different approach, which does not require preferences estimation and related surveys, has recently been introduced by considering extensions of Bin Packing problems. Baldi et al. [1] introduce the Generalized Bin Packing Problem (GBPP), an extension of the classical Bin Packing model that accounts for bins of different sizes and costs while considering the profit due to demand management. This generalization provides a more realistic representation of logistics and transportation applications, where heterogeneous resources and non-uniform cost structures are common. The article presents both theoretical results and computational analyzes, showing the flexibility of the model and its foundational role in subsequent research on capacity allocation and logistics optimization. Crainic et al. [5] propose a multi-period Bin Packing model to support corridor-based logistics capacity planning. The model captures the dynamic nature of logistics operations over multiple time periods, allowing for capacity reuse and time-dependent demand. The authors develop effective constructive heuristics and evaluate their performance on large-scale instances. Their results show that multi-period modeling provides significant advantages in planning efficiency and cost reduction compared to static, single-period approaches. This study establishes a methodological bridge between classical Bin Packing formulations and the temporal dynamics typical of transportation planning. Crainic et al. [6] address the problem of capacity planning under uncertainty in contract fulfillment, where a shipper must determine the amount of capacity to secure from a carrier whose reliability is uncertain. The authors propose a stochastic modeling framework that captures the risk of partial contract fulfillment and analyze how this uncertainty affects procurement decisions and overall operational costs. Their work highlights the importance of considering supplier reliability in medium-term capacity planning and provides a rigorous quantitative approach to managing uncertainty in logistics networks. Building on these developments, Bargetto et al. [2] present an Integer Linear Programming–based exact approach for solving the Variable Cost and Size Bin Packing Problem (VCSBPP) with time-dependent costs, motivated by shared satellite-based last-mile delivery. Their formulation generalizes existing Bin Packing formulations by incorporating cost dynamics that vary over time and operational conditions. The computational experiments demonstrate that the proposed model effectively captures time-sensitive variations in cost and provides exact solutions for medium-sized instances, offering valuable insights into cost–capacity trade-offs in dynamic logistics environments.

While Bin Packing–based models do not require the external tuning of preference parameters, as is the case in AHP-based approaches, they still lack an explicit integration of supplier selection decisions. Conversely, Bin Packing formulations demonstrate strong performance in handling large-sized instances and offer flexibility for incorporating dynamic and stochastic parameters. In this article, we address this gap by modeling supplier selection and effects on costs and operational decisions, leading to what we define as the Capacity Supplier Selection Problem.

3 The Capacity Supplier Selection Problem & Model

The model determines which suppliers to engage and which capacity units (bins) to book from each, while ensuring that all items (representing estimated customer demand) are packed into the selected capacity without exceeding their limits. A fixed cost is incurred for each contracted supplier and a variable cost for each booked capacity unit. Additional constraints ensure that at least a minimum number of suppliers are selected, and that at least the promised minimum capacity is baught from each contracted supplier. The latter represents the desire of the shipper in order to foster business relationships with all selected providers, as well as to distribute the booked capacity so as to limit the risk of over-reliance on a single supplier. The objective is to minimize the total contracting and capacity-booking cost subject to these structural and packing constraints.

Let $\mathcal{M}$ be the set of logistics service providers identified as potentially suitable to contract. The shipper is required to select a minimum of N providers. Let $\mathcal{T}_m$ be the set of bin types that supplier $m \in \mathcal{M}$ can provide, $\mathcal{J}_m^t$ the set of bins of type $t \in \mathcal{T}_m$ made available by supplier m, V_m^t the volume of a bin of type t from supplier m. We also define $\mathcal{J} = \{\bigcup_{m \in \mathcal{M}, t \in T} \mathcal{J}_m^t\}$ as the collection of all bins of all types from all suppliers. Let also f_m be the fixed cost incurred when the shipper contracts supplier $m \in \mathcal{M}$, f_m^t the cost of each bin of type $t \in \mathcal{T}_m$ supplied by that supplier. The needs of the shipper are captured through the set $\mathcal{I}$ of specific items to be packed, each characterized by a volume v_i, for all $i \in \mathcal{I}$. finally, let ν be the minimum fraction of the total capacity offered by each contracted supplier that the shipper promises to pay for.

The decision variables are:

- z_m, Binary variable that takes the value 1 if the shipper selects the supplier $m \in \mathcal{M}$;

0 otherwise.

- y^t_{jm}, Binary variable that takes the value 1 if the transporter secures the bin $j \in \mathcal{J}^t_m$ of type $t \in \mathcal{T}_m$ from the supplier $m \in \mathcal{M}$; 0 otherwise.
- x_{ij}, Binary variable that takes the value 1 if the item $i \in \mathcal{I}$ is packed into the bin $j \in \mathcal{J}^t_m$ such that $t \in \mathcal{T}_m$ and $m \in \mathcal{M}$; 0 otherwise.

The integer programming problem formulation reads as follows:

$$\min_{y,z} \sum_{m \in \mathcal{M}} f_m z_m + \sum_{\substack{m \in \mathcal{M}, \\ t \in T, \\ j \in \mathcal{J}^t_m}} f^t_m y^t_{jm} \tag{1}$$

subject to

$$\sum_{m \in \mathcal{M}} z_m \geq N, \tag{2}$$

$$y^t_{jm} \leq z_m, \qquad \forall m \in \mathcal{M}, t \in T, j \in \mathcal{J}^t_m, \tag{3}$$

$$y^t_{(j+1)m} \leq y^t_{jm}, \qquad \forall m \in \mathcal{M}, t \in T, j \in \{\mathcal{J}^t_m \setminus \sigma(\mathcal{J}^t_m)\}, \tag{4}$$

$$\sum_{\substack{t \in T, \\ j \in \mathcal{J}^t_m}} V^t_m \; y^t_{jm} \geq \nu \sum_{\substack{t \in T, \\ j \in \mathcal{J}^t_m}} V^t_m \; z_m, \qquad \forall m \in \mathcal{M}, \tag{5}$$

$$\sum_{i \in \mathcal{I}} v_i x_{ij} \leq V^t_{jm} y^t_{jm}, \qquad \forall\, t \in T, m \in \mathcal{M}, j \in \mathcal{J}^t_m, \tag{6}$$

$$\sum_{j \in \mathcal{J}} x_{ij} = 1, \qquad \forall i \in \mathcal{I}, \tag{7}$$

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

$$y^t_{jm} \in \{0,1\}, \qquad \forall t \in T, m \in \mathcal{M}, j \in \mathcal{J}^t_m, \tag{9}$$

$$z_m \in \{0,1\}, \qquad \forall m \in \mathcal{M}. \tag{10}$$

The objective function (1) aims to minimize the total cost incurred through the selection of suppliers and bins. Constraints (2) require that at least N suppliers be selected in the solution. Constraints (3) state that the bins offered by each supplier can only be accessed if the corresponding supplier is selected. Constraints (4) break the problem's symmetry, enforcing that identical bins (same type and supplier) are selected according to their lexicographic order, given $\sigma(\mathcal{J}^t_m)$ the last element of the lexicographic order of bins $\mathcal{J}^t_m$. Constraints (5) enforce that the shipper must book the minimum required amount of capacity from each selected supplier. Constraints (6) impose that the total volume of items packed into each selected bin must not exceed the bin's capacity. Regarding constraints (7), they guarantee that each item is assigned to exactly one bin. Lastly, constraints (9)-(8) define the domains of the decision variables.

4 Computational Results

To assess the effectiveness of the proposed integer linear programming (ILP) formulation, we conducted a series of computational experiments on a set of generated instances. With these experiments, our objective was to evaluate the performance of the model in terms of solution quality and computational effort. The test instances were designed to reflect realistic problem settings while varying the number of available suppliers and the minimum number of suppliers to contract with. A summary of the main characteristics of the generated instances is provided in Table 1 (10 instances for each combination of parameters for a total of 320 instances).

Characteristic	Expression	Domain
Nr. of suppliers	$\|\mathcal{M}\|$	{ 3, 4, 5, 6 }
Min. contracts	$\mathcal{N}$	{ 2, 3, 4 }
Min. per cent vol. per supplier	ν	{ 0.05 }
Bin volumes, set *T3*, $\|T\| = 3$	V_t	{ 50, 100, 150 }
Contract cost	$f_m = \zeta_m \cdot \nu \cdot \sum_{i \in I} v_i$	with $\zeta_m \sim U(0.1, 0.5)$
Contract rate of bins	$f_m^t = V_m^t(1 + \gamma_m^t)$	with $\gamma_m^t \sim U(-0.25, 0.25)$
Nr. of items	$\|I\|$	{ 100, 200, 500, 1000 }
Item volume	$v_i : i \in I$	$[5, 40]$

Table 1: Instance characteristics

Computational experiments were carried out using the commercial solver Gurobi 11.0.2, with the ILP model implemented through the C++ Gurobi API. The experiments were performed on a workstation equipped with an Intel Core i5-8500 processor running at 3.0 GHz, with 16 GB of RAM, and operating under Ubuntu 22.04 LTS. The time limit for solving each instance was set to 3600 seconds.

Table 2 summarizes the computational performance of the solver when addressing the Capacity Supplier Selection Problem instances. Each row aggregates the results of a set of 10 instances varying in problem size. The key parameters are the total number of suppliers available (1st column), the minimum number of suppliers that must be selected (2nd column), and the number of items (3rd column). The metrics reported are the number of instances solved to optimality (column *# Opt.*), the average upper and lower bounds (columns *UB* and *LB*), the optimality gap for unsolved instances (column *Gap [%]*) and the computation time for those that were solved to optimality (column *Time [s]*).

The results indicate that problem difficulty increases with the number of items, as seen by the rising computation times and optimality gaps for larger instances (e.g., 1000 items). For smaller problems (100 items), all instances across all configurations were solved to optimality with a limited computational effort. The minimum number of sup-

$\lvert M\rvert$	N	$\lvert I\rvert$	# Opt.	UB	LB	Gap [%]	Time [s]
3	2	100	10	1443.1	1443.1		
		200	8	2833.3	2841.8	1.42	136.3
		500	5	7010.5	7031.6	0.61	66.2
		1000	4	13734.5	13770.6	0.44	868.4
4	2	100	10	1321.5	1321.5		
		200	10	2633.0	2633.0		
		500	4	6835.9	6863.1	0.67	278.2
		1000	5	13562.0	13600.9	0.57	437.3
4	3	100	10	1422.0	1422.0		
		200	9	2915.0	2919.6	1.43	50.4
		500	5	6934.1	6953.5	0.55	32.5
		1000	3	14160.5	14198.6	0.38	164.6
5	2	100	10	1425.0	1425.0		
		200	10	2609.2	2609.2		
		500	7	6770.0	6781.6	0.58	97.3
		1000	5	13473.0	13501.2	0.40	859.8
5	3	100	10	1431.9	1431.9		
		200	10	2820.5	2820.5		
		500	8	6984.0	6991.8	0.56	269.6
		1000	3	13899.8	13932.4	0.34	137.7
6	2	100	10	1380.2	1380.2		
		200	10	2701.5	2701.5		
		500	6	6601.9	6621.1	0.72	442.1
		1000	6	13364.3	13382.6	0.33	526.3
6	3	100	10	1427.5	1427.5		
		200	9	2773.9	2778.2	1.49	186.6
		500	8	6870.1	6876.2	0.43	211.7
		1000	4	13741.9	13773.6	0.38	1030.5
6	4	100	10	1432.9	1432.9		
		200	10	2879.2	2879.2		
		500	6	7242.7	7255.7	0.46	162.1
		1000	2	14263.3	14303.4	0.35	848.4

Table 2: Numerical results

pliers to select (N) also affects performance, with $N = 3$ generally presenting a greater difficulty than $N = 2$ for the same number of total suppliers and items, leading to higher times and gaps. Notably, the solver consistently finds high-quality solutions, as evidenced by the very small optimality gaps (always below 1.5%), even for instances that were not solved to provable optimality within the time limit (1 hour).

By analyzing the solver behavior, we also observe that the primal simplex method, when combined with the proposed symmetry-breaking constraints, provided the most efficient performance as an LP solver for this problem. The effectiveness of symmetry-breaking constraints in improving computational efficiency is consistent with the findings of [2], where such constraints were successfully applied to a Variable Cost and Size Bin Packing problem modeling last-mile delivery operational planning.

The next analysis examines optimal packing solution patterns through two complementary views. Table 3 summarizes the main indicators characterizing the optimal solutions of the Capacity Supplier Selection Problem. It combines two perspectives: supplier concentration and capacity utilization. The columns DSS (Dominant Supplier Share) and S-HH (Supplier Herfindahl–Hirschman Index) describe the concentration of capacity allocation among suppliers. The column BTs (Bin Types Used) reports the number of different bin types employed in the solution, while DBTS (Dominant Bin Type Share) measures the share of total capacity associated with the most frequently used bin type. The indicator I-DBT (Items in Dominant Bins) quantifies the percentage of items packed into the dominant bin type, and BT-HH (Bin Type Herfindahl–Hirschman Index) measures the concentration across bin types. Finally, DS-is-DB specifies the percentage of instances where the dominant supplier is also the provider of the dominant bin type. All values are mean values calculated over 10 instances of 1000 items. We also recall that the Herfindahl–Hirschman Index measures market concentration, ranging from 0 (perfect diversification) to 1 (complete concentration).

The results in Table 3 show that while N increases ($N = 3$), both the DSS and the S-HH indicators decrease (DSS $\approx 65 - 70\%$, S-HH ≈ 0.5), reflecting greater diversification in supplier selection. Regarding bin utilization, most solutions use two to three bin types, with one type consistently dominating (DBTS $\approx 70 - 90\%$). The I-DBT and BT-HH indices confirm that the majority of items are allocated to this dominant bin type, emphasizing the model's tendency to favor cost-efficient capacity configurations. According to our analysis, the dominant bin type is one of the largest available (100 or 150 volume units). In nearly all cases, the DS-is-DB indicator equals 100%, meaning that the dominant supplier also provides the dominant bin type, and the dominant bin utilization rate I-DBT/DBTS consistently approaches or exceeds 1.0 (i.e., the dominant bin type is used more efficiently). This highlights further the model's underlying cost-minimizing logic. Overall, the table highlights the trade-off between diversification and efficiency: increasing supplier diversity reduces concentration but slightly decreases the utilization efficiency of the most cost-effective bins.

5 Conclusion

This article introduced the Capacity Supplier Selection Problem (CSSP), a MIP model that integrates supplier selection and contractual commitments into a flexible Cost and

$\lvert M \rvert$	N	DSS	S-HH	BTs	DBTS	I-DBT	BT-HH	DS-is-DB
3	2	85%	0.74	1.9	89%	91%	0.82	100%
4	2	85%	0.74	1.8	89%	91%	0.82	100%
4	3	69%	0.53	2.5	78%	81%	0.66	100%
5	2	84%	0.74	2.2	88%	88%	0.79	100%
5	3	67%	0.52	2.2	73%	73%	0.61	100%
6	2	83%	0.72	1.9	92%	92%	0.86	100%
6	3	66%	0.51	2.2	78%	78%	0.69	90%
6	4	53%	0.36	2.3	72%	73%	0.61	100%

Table 3: Managerial insight analysis

Size Bin Packing framework. Our preliminary results show that the deterministic CSSP can be solved effectively, yielding non-trivial capacity portfolios where a dominant supplier typically provides the dominant, efficiently utilized bin type.

Building on this exact approach for the deterministic case, the natural next step is to incorporate uncertainty into the model. Future research will extend the CSSP to account for uncertainties in supplier reliability and demand, developing a stochastic programming framework for robust capacity planning.

Acknowledgments

While working on the project, the second author was Adjunct Professor, Department of Computer Science and Operations Research, Université de Montréal, and the fourth held the Canada Research Chair in Stochastic Optimization of Transport and Logistics Systems. We gratefully acknowledge the financial support provided by the Natural Sciences and Engineering Council of Canada (NSERC) through its Discovery Grant program, and the Fonds de recherche du Québec through their CIRRELT infrastructure grants.

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