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Bin Packing Problems with uncertainty on item characteristics: an application to capacity planning in logistics

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Abstract

Most modern companies are part of international economic networks, where goods are produced under different strategies, then transported over long distances and stored for variable periods of time at different locations along the considered network. These activities are often performed by first consolidating goods in appropriate bins, which are then stored at warehouses and shipped using multiple vehicles through various transportation modes. Companies thus face the problem of planning for sufficient capacity, e.g., negotiating it with third party logistic firms (3PLs) that specify both the capacity to be used and the logistical services to be performed. Given the time lag that usually exists between the capacity-planning decisions and the operational decisions that define how the planned capacity is used, the common assumption that all information concerning the parameters of the model is known is unlikely to be observed. We therefore propose a new stochastic problem, named the Variable Cost and Size Bin Packing Problem with Stochastic Items. The problem considers a company making a tactical capacity plan by choosing a set of appropriate bins, which are defined according to their specific volume and fixed cost. Bins included in the capacity plan are chosen in advance without the exact knowledge of what items will be available for the dispatching. When, during the operational phase, the planned capacity is not sufficient, extra capacity must be purchased. An extensive experimental plan is used to analyze the impact that diversity in instance structure has on the capacity planning and the effect of considering different levels of variability and correlation of the stochastic parameters related to items.

Keywords: Stochastic Bin Packing; logistics capacity planning; supply chain; third party logistic.

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1. Introduction

Most modern companies are part of international economic networks, where goods are produced under different strategies (made-to-stock or made-to-order), then transported over long distances, and stored for variable periods of time at different locations along the considered network. In this context, having enough capacity to properly perform crucial activities such as the supply, storage and distribution of goods is paramount if a company is to be competitive. It should be noted that these activities are often performed by first consolidating goods in appropriate bins, which are then stored in warehouses and shipped using multiple vehicles through various transportation modes. Thus, companies face the problem of having to plan for sufficient capacity, expressed here in terms of bins, to be available at different locations throughout their network and for different periods of time, in order to satisfy demand, expressed here as a number of items of variable size to be shipped and stored. Given that logistics activities are often subcontracted, capacity planning entails negotiations with third party logistics firms (3PL's) to book the needed capacity. The results of these negotiations often take the form of medium term contracts specifying both the capacity to be used (the quantity and type of the bins) and the additional services to be performed (storage, transportation, bin operations, etc.). Therefore, bin packing models represent important decision support tools for logistics managers, who bear the responsibility for these tactical planning decisions.

Although bin packing optimization problems have been extensively studied, e.g., Martello & Toth (1990) and Wäscher et al. (2007), this research has mainly been conducted under the assumption that all the necessary information concerning the different parameters used to model the problems is known and readily available (i.e., deterministic parameters). Given the time lag that usually exists between the capacity-planning decisions and the operational decisions that define how the planned capacity is used, such an hypothesis in unlikely to be observed. Moreover, when the information becomes really known, an additional negotiation phase becomes necessary, in order to rent additional space and services, normally at a higher price. Therefore, we propose a new stochastic bin packing model, referred to as the *Variable Cost and Size Bin Packing Problem with Stochastic Items* (*VCSBPSI*). The VCSBPSI is an extension of the *Variable Cost and Size Bin Packing Problem* (Crainic et al., 2011) that explicitly takes into account more container types, the uncertainty related to their costs at the time of the full availability of the information, as well as the uncertainty related to the items appearing in capacity planning problems (both in terms of their volume and presence). The model is based on a two-stage stochastic programming formulation with recourse (Birge & Louveaux, 1997) that separates the tactical capacity planning decisions (Monczka et al., 2009) of the first stage, i.e., the *a priori* plan often performed in practice by considering a point estimation of future demand, from the operational decisions, that is, the *recourse* actions, taken repeatedly over the planning horizon, and defining the adjustments that can be made to the plan whenever the information becomes known.

We investigate the use of this model in the context of an international supply chain for a major retail firm (Crainic et al., 2013). We focus, specifically, on the contract between the firm and a 3PL service provider to secure capacity for regular long-haul container shipping. In this context, the contract specifies the numbers of containers of various sizes and costs to be provided by the 3PL at shipping date, for a given planning horizon. On shipping dates, whenever the demand exceeds the planned capacity, additional containers may be secured at premium costs. In this paper, we first examine the impact of problem characteristics on the efficiency of an exact solver. We then analyze the value of explicitly accounting for uncertainty within the tactical plan.

The remainder of this paper is organized as follows. In Section 2, a detailed formulation of the VCSBPSI problem is provided, while Section 3 describes the solution approach proposed and the experimental plan that is conducted. Section 4 presents the computational results and analyses the impact of the different problem characteristics on the problem solutions. Finally, conclusions and future research directions are presented in Section 5.

2. The VCSBPSI problem

The firm is engaged in a continuous procurement process (Aissaoui et al., 2007 and Rizk et al., 2008). Based on current inventories, short-term forecast demand, estimated lead times, and its specific procurement and inventory policies (Bertazzi & Speranza, 2005 and Bertazzi et al., 2007), the firm orders on a regular basis products to suppliers in a given geographical region, e.g., South-East Asia. Suppliers are instructed to deliver their goods to a consolidation center (Crainic & Kim, 2007 and Bertazzi et al., 2008), e.g., a port. The 3PL then consolidates them into containers and ensures their shipping (Crainic et al., 2013 and Chen et al., 2001). The latter is performed by long-haul carriers, e.g., maritime lines, according to a known fixed schedule, e.g., twice a week.

Better fares may be negotiated with the 3PL, and the carriers, when the number of containers and slots on vehicles is negotiated a priori for a given planning horizon (Ford, 2001), e.g., a semester, months or a year. The resulting contract guarantees a regular volume of flow and business to the 3PL (and carrier), e.g., a maritime shipment of a given number of containers every week for the next semester, and the desired level and cost of service to the company. Tactical capacity planning aims to determine these quantities for the firm, given an estimation of the demand, number of items, and their sizes, to be shipped at each selected departure over the planning horizon. The plan thus specifies the set of containers, or *bins*, of particular volumes and (fixed) costs, to be made available at each selected departure to ship the estimated items. Fixed costs are used here to represent the specific rates offered by the 3PL for bins of different sizes. The capacity plan is then repeatedly applied at each selected departure of the planning horizon. Bins included in the capacity plan are thus chosen in advance, without knowing exactly what items will eventually be packed.

Variations in the customer demand for goods in stores and in the delivery of the products to the consolidation center by suppliers may yield, however, numbers and sizes of items different from the estimation used when building the tactical plan. In particular, these variations require an adjustment of the plan when the planned capacity is not sufficient. Extra capacity must then be purchased, generally at a much higher cost than the fare negotiated in the plan, to properly perform the necessary operations. We represent this extra capacity as extra bins of various volumes, provided at a premium by the 3PL (e.g., fixed costs defined according to the spot market).

Including explicitly the uncertainty on the future demand, the number and characteristics of items, into the tactical planning model should reduce the need, and cost, of adjusting the plan and adding capacity. A two-stage stochastic programming formulation is used to model this planning problem, where the a priori planned selection of bins makes up the first stage decisions, the acquisition of extra capacity when actual item information is revealed making up the second stage decisions. This yields the VCSBPSI model.

Let J define the set of available bins in the first stage of the problem where, $\forall j \in J$, f_j and V_j are respectively the fixed cost and volume associated with bin j. Let set Ω be the sample space of the random event, where $\omega \in \Omega$ defines a particular realization. Let vector ξ contain all stochastic parameters defined in the model and $\xi(\omega)$ be a given realization of this random vector. If we define the first stage variables as $y_j = 1$ if bin $j \in J$ is selected, 0 otherwise, the VCSBPSI model may then be formulated as

$$\min \sum_{j \in J} f_j y_j + \mathrm{E}_{\xi}[Q(y, \xi(\omega))] \tag{1}$$

$$\text{s.t. } y_j \in \{0,1\}, \forall j \in J, \tag{2}$$

where $Q(y, \xi(\omega))$ is the extra cost paid for the capacity that is added in the second stage of the problem, given the tactical capacity plan y and the vector $\xi(\omega)$. The objective function (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 operations, while constraints (2) impose the integrality requirements on y.

Let K stand for the set of available bins in the second stage, and $f_k, k \in K$, the associated fixed costs. To formulate $Q(y,\xi(\omega))$, we consider the following stochastic parameters in $\xi(\omega)$: $I(\omega)$, the set of items to be packed, and $v_i, i \in I(\omega)$, the item volumes. The second stage variables are defined as follows: $z_k = 1$ if bin $k \in K$ is selected, 0 otherwise; $x_{ij} = 1$ if item $i \in I(\omega)$ is packed in bin $j \in J$, 0 otherwise; and $x_{ik} = 1$ if item $i \in I(\omega)$ is packed in bin $k \in K$, 0 otherwise. We now define function $Q(y,\xi(\omega))$ as

$$Q(y,\xi(\omega)) = \min \sum_{k \in K(\omega)} f_k z_k \tag{3}$$

$$\text{s.t.} \sum_{j \in J} x_{ij} + \sum_{k \in K} x_{ik} = 1, \forall i \in I(\omega) \tag{4}$$

$$\sum_{i \in I(\omega)} v_i(\omega) x_{ij} \le V_j y_j, \forall j \in J \tag{5}$$

$$\sum_{i \in I(\omega)} v_i(\omega) x_{ik} \le V_k z_k, \forall k \in K \tag{6}$$

$$x_{il} \in \{0,1\}, \forall i \in I(\omega), \forall l \in J \cup K \tag{7}$$

$$z_k \in \{0,1\}, \forall k \in K. \tag{8}$$

The objective function (3) minimizes the cost associated with the extra bins selected. Constraints (4) ensure that each item is packed in a single bin. Constraints (5) and (6) make sure that the total volume of items packed in each bin does not exceed the bin volume. Finally, (7) and (8) impose integrality requirements on all second stage variables.

3. Solution approach and experimental plan

The first step towards solving model (1)-(8) is to obtain a manageable approximation of function $\mathrm{E}_{\xi}[Q(y,\xi(\omega))]$. Sampling is applied to obtain a set of representative scenarios, namely the set S, which are used to approximate the expected cost associated with the second stage:

$$\min \sum_{j \in J} f_j y_j + \sum_{s \in S} p_s \Big(\sum_{k \in K^s} f_k z_k^s \Big) \tag{9}$$

$$\text{s.t.} \sum_{j \in J} x_{ij}^s + \sum_{k \in K} x_{ik}^s = 1, \forall i \in I^s, \forall s \in S \tag{10}$$

$$\sum_{i \in I^S} v_i^s x_{ij}^s \le V_j y_j, \forall j \in J, \forall s \in S \tag{11}$$

$$\sum_{i \in I^S} v_i^s x_{ik}^s \le V_k z_k^s, \forall k \in K \ , \forall s \in S \tag{12}$$

$$x_{il}^s \in \{0,1\}, \forall i \in I^s, \forall l \in J \cup K \ , \forall s \in S \tag{13}$$

$$z_k^s \in \{0,1\}, \forall k \in K \ , \forall s \in S \tag{14}$$

$$y_j \in \{0,1\}, \forall j \in J, \tag{15}$$

where p_s defines the probability associated with scenario $s \in S$; $z_k^s = 1$ if bin $k \in K$ is selected in scenario $s \in S$, 0 otherwise; $x_{ij}^s = 1$ if item $i \in I^s$ is packed in bin $j \in J$ in scenario $s \in S$, 0 otherwise; and $x_{ik}^s = 1$ if item $i \in I^s$ is packed in bin $k \in K$ in scenario $s \in S$, 0 otherwise.

We aim to explore the impact that diversity, in particular regarding 3PL's bins availability, has on capacity planning and the effect of considering different levels of variability and correlation of the stochastic parameters related to the items. Starting from existing instances for BPP and VSBPP (Monaci, 2001 and Crainic et al. 2011) and the extension for the stochastic version of BPP defined by Crainic et al. (2012), a new set of instances was generated. The set considered three types of bins with the following characteristics:

- Volumes 50, 100 and 120;
- Fixed cost correlated to their volumes computed as $\sqrt{V_j}(1+\delta)$, where δ is uniformly distributed in the range [-0.3, 0.3]; According to Correia et al. (2008) these values ensure a spread of the fixed costs which replicates realistic situations;
- The number of bins of volume V_j defined in both stages as the minimum number of bins of volume V_j needed to pack all items;
- The cost f_k for extra bins in the second stage is the original one increased by a fixed percentage factor α (5%, 10%, 20%, and 40%).

Concerning the set of items, it was assumed that the number of items in the second stage was uniformly distributed into the range [25, 50]. The items were organized in the following categories:

- Small (S): volume in the range [5, 10];
- Medium (M): volume in the range [15, 25];
- Big (B): volume in the range [20, 40].

Three classes of item spread were identified, reflecting actual data and transportation cases. The first class (Sp1) included a high percentage of small items (S=60%, M=20%, B=20%). The second class (Sp2) included a high percentage of medium items (S=20%, M=60%, B=20%), while the third class (Sp3) included a high percentage of big items (S=20%, M=20%, B=60%).

For each combination of the parameters mentioned above, 10 instances were randomly created, giving a final set of 360 instances.

Finally, the number of scenarios was set to 25, 50, and 100.

In order to qualify the problem, we use the following experimental plan:

- The scenario-based stochastic problem (9)-(15) is solved by a commercial MIP solver, with a maximum running time of 15 minutes. The obtained stochastic solution is then used as reference for further analysis.
- Expected Value Problem (EVP). This problem is obtained by substituting the stochastic item set in each scenario with a set of deterministic items computed by averaging the number and the volume of big, medium and small items in the scenarios. Then, the associated deterministic problem is solved in order to obtain the tactical plan (i.e., the first stage decision). The corresponding optimal solution of the deterministic problem is then used in a Monte Carlo simulation in order to compute the actual stochastic objective function associated to the first-stage decisions.
- Percentage VSS ($VSS_{\%}$). The Value of the Stochastic Solution (VSS), which gives a measure of how much a decision maker gains by using Stochastic Programming instead of the EVP approach is computed as

$$VSS_{\%} = \frac{|z_{EVP} - z_{2SP}|}{z_{2SP}} \cdot 100 , \tag{16}$$

where z_{EVP} and z_{2SP} are the objective function values of the Monte Carlo simulation of the EVP and of the scenario-based two-stage stochastic problem, respectively.

Additional data is moreover collected in order to qualify the two-stage stochastic model, i.e., the percentage of the objective function value given by the first and the second stages, and the percentage of used volume in each bin loaded in the first and the second stages.

4. Experimental Results

In this section, we report the experimental results and analyze the impact of stochastic parameters on the problem solution. All the computations were carried out on an Intel Core i7-2630 workstation with 6 Gb RAM and 2.0 GHz processors. Gurobi 5.5 was chosen as MIP solver (Gurobi Optimization Inc, 2013). The choice of Gurobi follows from its efficiency in finding good feasible solutions within limited computation time. Notice that, an in-depth experimentation was conducted with CPLEX 12.5 (CPLEX, IBM ILOG, 2012) on a subset of instances. It showed that the solution gaps (i.e., the distance between the incumbent solution and the lower bound) were comparable with those obtained with Gurobi and that, within the same computational time, Gurobi was able to find, in the mean, better integer solutions. A time limit of 15 minutes was imposed to each instance.

Table 1 compares the solutions obtained with the two methodologies described in the experimental plan. Table 1 reports, for each combination of item spread (Column 1), second-stage bin cost increase parameter α (Column 2), and number of scenarios (Row 1), the percentage VSS (Columns 3, 5 and 7) and the average computational time required by the EVP (Columns 4, 6 and 8). The computational time of the two-stage stochastic model is not reported in Table 1 because it reaches the limit of 15 minutes for each instance.

The maximum $VSS_{\%}$ is sufficiently large to justify the two-stage stochastic approach when the values of α are small (5% and 10%). In fact, the $VSS_{\%}$ decreases when the cost of bins in the second stage increases (minimum with α = 40%). For high values of α, the increase in the bin cost of the second stage also makes the EVP reserve extra space in the first stage.

Notice that, in terms of number of scenarios, 25 scenarios are enough for a good approximation of the problem. Also notice that, the $VSS_{\%}$ decreases when the number of scenarios increases. In our opinion, this behavior is related to the usage of the uniform distribution for choosing the items in the second stage scenarios. This issue should be further investigated.

The computational time of the EVP mainly depends on the number of scenarios and the value of α. With the number of scenarios increasing, the computational time reaches the limit of 15 minutes.

Table 1. Comparison of the solutions obtained with the scenario-based stochastic problem and the EVP.

		$\lvert S\rvert = 25$		$\lvert S\rvert = 50$		$\lvert S\rvert = 100$	
	α (%)	$VSS_{\%}$	**Time (s)**	$VSS_{\%}$	**Time (s)**	$VSS_{\%}$	**Time (s)**
Sp1	**5**	3.11	126.49	2.85	334.61	2.41	246.22
	10	2.91	308.51	2.86	813.25	1.76	639.08
	20	2.25	210.21	1.71	813.82	1.28	819.09
	40	1.17	126.86	0.51	162.59	0.64	254.36
Sp2	**5**	2.62	206.24	1.97	777.22	1.83	831.67
	10	2.79	390.10	2.23	738.96	1.44	837.06
	20	1.49	70.10	1.93	248.30	0.67	639.43
	40	1.36	222.37	0.68	579.32	0.32	825.96
Sp3	**5**	3.43	246.66	3.26	846.85	2.31	900.76
	10	2.62	128.16	2.44	139.30	1.47	744.46
	20	1.84	220.44	1.49	795.81	0.37	900.18
	40	0.60	510.99	0.69	900.23	0.34	902.09

For more details on the results of the two-stage stochastic model and the EVP, Table 2 and Table 3 report the optimality gap reached by the MIP solver (Columns 3, 7 and 11) computed as

$$Gap = \frac{z^* - LB}{z^*} \cdot 100 , \tag{17}$$

where z^* is the best integer solution and LB is the lower bound, the percentage of the objective function due to the first stage (Columns 4, 8 and 12) and the average filling levels of bins in the first stage (Columns 5, 9 and 13) and in the second stage (Columns 6, 10 and 14). The values are grouped by classes of item spreads (Column 1), the cost factor of bins in the second stage (Column 2) and the number of scenarios.

The gaps of the scenario-based stochastic problem are quite large (greater than 4%). This is due, in our opinion, to the difficulty of the MIP solver to compute a good lower bound for large-size integer problems that include a lot of symmetry in the solutions, which is unfortunately typical of packing problems. Moreover, the percentage of the objective function achieved in the first stage increases with the cost factor. In fact, when the difference of the cost of the bins in the first and second stages increases, the tactical decisions become more conservative. This is contrary to the filling level of bins, which is decreasing when the cost of the bins in the second stage increases given that the first stage decisions allocate more capacity.

From the point of view of the sources of complexity, the item spread classes do not seem to affect the solution quality. This is mainly due to the unrestricted availability of bins. However, further experimentations (involving possibly different distributions used to generate the number of items) are needed to extend our findings. Obtaining tighter lower bounds would also help in assessing the impact of the spread. Furthermore, it is interesting to note that the results are stable and do not depend on the number of scenarios. This means that 25 scenarios are enough to model the actual transportation case under study.

Table 2. Summary of main experimental results for the two-stage stochastic model.

		$\lvert S \rvert = 25$				$\lvert S \rvert = 50$				$\lvert S \rvert = 100$			
	α (%)	**Gap (%)**	**O_{FS} (%)**	**F_{FS} (%)**	**F_{SS} (%)**	**Gap (%)**	**O_{FS} (%)**	**F_{FS} (%)**	**F_{SS} (%)**	**Gap (%)**	**O_{FS} (%)**	**F_{FS} (%)**	**F_{SS} (%)**
Sp1	**5**	7.21	73.87	89.26	86.47	7.80	67.82	92.03	85.89	8.96	72.84	91.50	85.61
	10	6.95	77.21	89.63	80.77	6.92	74.70	91.41	87.55	7.32	77.06	91.46	86.53
	20	5.68	76.46	89.96	85.07	6.12	77.16	91.16	86.84	7.26	78.67	90.62	84.92
	40	5.15	81.28	87.05	85.87	6.02	85.34	88.16	82.70	6.12	86.92	88.58	80.07
Sp2	**5**	6.12	71.86	90.48	87.71	7.20	73.37	91.49	85.14	7.58	76.80	91.34	86.85
	10	6.16	73.25	90.75	84.34	6.55	76.72	90.98	88.17	7.38	79.84	90.77	87.72
	20	5.99	75.28	89.72	83.75	6.12	79.57	90.08	85.47	7.00	85.33	89.87	84.94
	40	5.16	84.94	87.06	82.44	5.53	84.37	88.81	83.10	5.58	85.15	89.99	85.12
Sp3	**5**	5.38	71.80	91.19	88.68	5.85	73.50	91.69	90.39	6.67	73.63	92.32	89.08
	10	6.31	74.46	89.51	86.14	6.78	75.41	90.64	88.03	7.76	79.62	90.66	88.06
	20	7.78	78.57	87.86	82.79	7.88	80.40	89.08	84.37	8.39	86.53	89.58	87.39
	40	4.46	81.96	88.32	83.88	4.55	85.78	88.79	88.47	4.89	88.08	89.27	84.61

The Monte Carlo simulation shows similar trends. Gaps are tighter than in the stochastic model, supporting our hypothesis that it is the symmetry of the first level that is mainly responsible for the high gaps in Table 2.

Table 3. Summary of main experimental results for the EVP.

		$\|S\| = 25$				$\|S\| = 50$				$\|S\| = 100$			
	α (%)	**Gap (%)**	**O_{FS} (%)**	**F_{FS} (%)**	**F_{SS} (%)**	**Gap (%)**	**O_{FS} (%)**	**F_{FS} (%)**	**F_{SS} (%)**	**Gap (%)**	**O_{FS} (%)**	**F_{FS} (%)**	**F_{SS} (%)**
Sp1	**5**	0.09	90.38	86.55	72.60	0.26	88.94	89.02	77.74	0.22	90.61	88.78	77.94
	10	0.04	90.33	86.38	71.82	0.21	90.26	88.22	77.76	0.28	89.62	88.96	78.93
	20	0.03	90.12	86.09	71.14	0.10	90.18	87.70	78.88	0.17	89.74	88.25	77.58
	40	0.14	89.16	85.23	71.19	0.32	85.52	87.51	78.29	0.37	88.89	88.58	76.43
Sp2	**5**	0.21	90.42	87.73	77.48	0.36	91.61	88.40	81.07	0.64	90.84	89.26	82.37
	10	0.09	91.24	86.83	77.88	0.60	90.31	87.90	81.51	0.56	89.88	89.36	84.10
	20	0.25	91.36	85.77	74.93	0.45	90.33	87.54	79.68	0.53	90.33	88.74	82.64
	40	0.05	89.35	86.22	78.62	0.68	87.68	88.47	82.33	0.95	87.50	89.60	83.53
Sp3	**5**	0.15	91.41	86.29	77.69	0.64	90.62	87.80	83.71	0.77	90.91	88.92	85.56
	10	0.04	91.85	75.49	82.52	0.55	91.49	87.53	82.80	0.56	91.60	88.25	83.86
	20	0.50	91.31	84.79	78.50	0.71	91.66	86.95	83.54	0.75	91.55	88.30	84.86
	40	0.83	89.09	86.02	78.67	1.08	89.58	87.52	82.89	1.45	89.21	90.56	85.73

5. Conclusions

In this paper, we considered a real problem arising in the context of the management of an international supply chain. In particular, we analyzed the process of the contract procurement between a major retail firm and the 3PL service provider, which is ensuring the capacity for the firm's long-haul container shipping. This let us to introduce the *Variable Cost and Size Bin Packing Problem with Stochastic Items*, a new stochastic variant of the Bin Packing problem, explicitly taking into account container types, the uncertainty related to their costs when information becomes fully available, and the uncertainty related to the items (in terms of volume and presence) that are to be moved when the plan is to be implemented. We derived a two-stage stochastic formulation with recourse that assigns the tactical capacity planning decisions to the first stage, yielding the a priori plan, and the operational decisions, taken each period of the planning horizon, to the recourse actions specifying the adjustments that can be made to the plan whenever the information becomes known.

Extensive computational results performed over a large set of instances showed how the usage of the stochastic model brings relevant effects both in terms of economic impact (reduction of costs) and operations management (prediction of the capacity needed by the firm).

Future work will focus on pursuing other sources of uncertainty for capacity planning in logistics (e.g., the availability and cost of bins at shipping date, the volume of the bins chosen in advance, and the selection of the 3PL), and adapt the proposed model to other application fields, e.g., City Logistics, E-grocery, etc.

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