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Carrying capacity procurement of rail and shipping services for automobile delivery with uncertain demand

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ABSTRACT

The determination of the optimal carrying capacity procurement of rail and shipping services in the automobile intermodal network with unique characteristics is essential to save automobile delivery cost. In this research we develop a two-stage stochastic programming model for the tactical-level decision problem arising in the special automobile intermodal network. Furthermore, we improve the sample average approximation algorithmic procedure to solve the model. We apply the model and solution method to a case study associated with the Shanghai Automobile Industry Corporation. We believe that this study deals with an emerging new research topic with practical significance for the automobile industry.

1. Introduction

Automobile manufacturers produce automobiles and coordinate the delivery to customers. They have low profit margins nowadays because of the intense market competition in providing low-price automobiles to customers. As a result, the manufacturers have to seek all possible means to cut down costs associated with the production and delivery of automobiles. In particular, there is a large potential for reducing the cost of automobile delivery because as estimated by Automotive Logistics (2013), by 2020 the finished vehicle logistics sector will be worth $4 billion per year.

Automobile delivery in a large country such as China, India and United States is a complex logistics process including different transport modes and their combinations (intermodal transportation). A large automobile manufacturer usually has several automobile production factories in the large country. Each factory has a vehicle distribution center (VDC) for handling the automobiles produced by the factory. The manufacturer also has vehicle storage centers (VSCs), which are located in different cities of the country with high volumes of customers. For example, the automobile delivery network in China operated by Shanghai Automobile Industry Corporation (SAIC) has a total of 7 VDCs and 11 VSCs as shown in Fig. 1. The 7 VDCs are Shenyang (SY), Yantai (YT), Qingdao (QD), Shanghai (SH), Nanjing (NJ), Chongqing (CQ), and Liuzhou (LZ2). The 11 VSCs are Xinjiang (XJ), Beijing (BJ), Tianjin (TJ), Yuci (YC), Lanzhou (LZ1), Xianyang (XY), Zhengzhou (ZZ), Deyang (DY), Wuhan (WH), Kunming (KM), and Dongguan (DG). The automobile delivery network consists of road, rail (Fig. 2) and water transportation (Fig. 3). Automobiles from VDCs are transported to VSCs to serve customers. Automobiles may also be transported from one VDC to another VDC, wherein the latter VDC serves the same function as VSCs. Automobiles can be transported from a VDC to another VDC or a VSC by truck, rail, or ship. Trucks can directly transport automobiles from an

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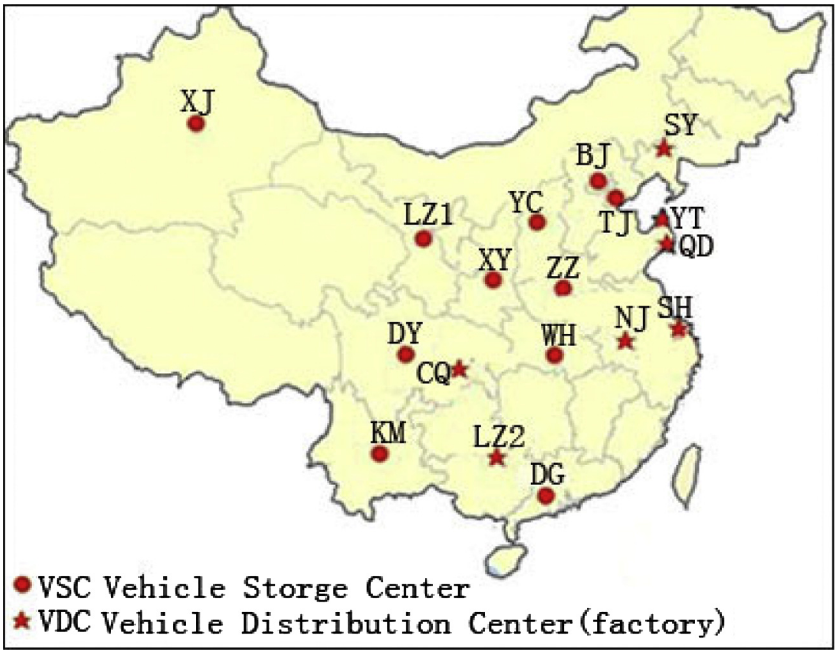

Fig. 1. Distribution of the 7 VDCs and 11 VSCs.

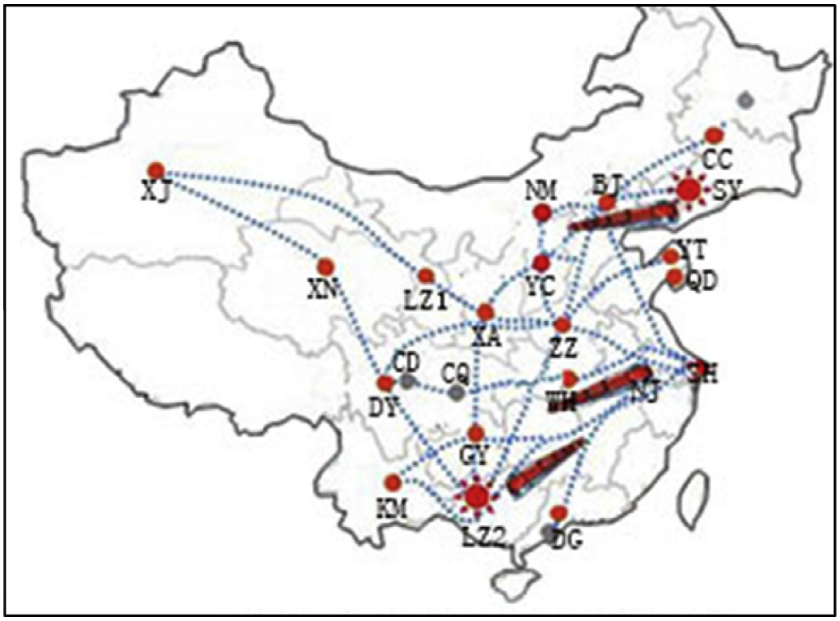

Fig. 2. Rail transportation network.

origin (a VDC) to a destination (another VDC or a VSC). By contrast, trains/ships cannot be that convenient because automobiles have to be transported by truck from the origin VDC to the origin railway station/port, and transported by truck again from the destination railway station/port to the final destination (another VDC or a VSC). Hence, the overall automobile delivery network is an intermodal transportation network that involves road, railway and waterway transportation.

Automobile intermodal networks are different from other general logistics networks in that they have special and complex characteristics. Firstly, on the strategy level planning, the location of the VDCs or VSCs is no longer the decision of a single individual manufacturer, but is the game of decisions between many automobile manufacturers. When the automobile manufacturers locate VDCs or VSCs, they first consider geographical advantages of a city, that is, the city is convenient to

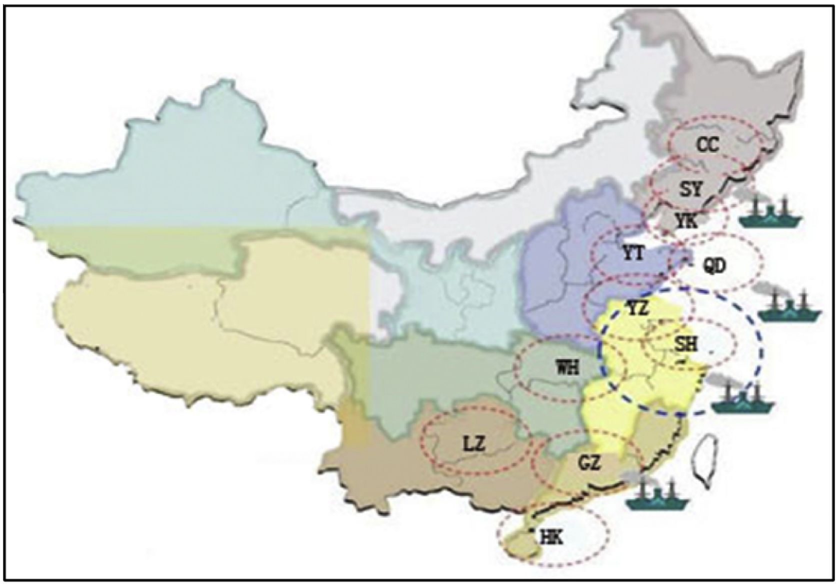

Fig. 3. Water transportation network.

deliver automobiles in transportation conditions; furthermore, the city considered as VDC or VSC is close to consumer market. However, most of the cities which meet the above mentioned two basic conditions are already automobile delivery network nodes of other automobile manufacturers, leading to the fact that the nodes of different automobile delivery networks coincide to a certain degree. Therefore, the automobile delivery network is a composite logistics network composed of multiple automobile manufacturers. It is very difficult and complex for each automobile manufacturer to organize automobiles' delivery on its own, considering the balance relationship between market competition and the full utilization of transportation resources.

Secondly, in the automobile delivery network, the planning on the tactic level needs to consider the service network design problem extended from forward transportation service to reverse transportation service in the near future; furthermore, the integration of transportation services among multiple origin–destination (O–D) pairs is an inevitable tendency, that is, the convective transport among multiple VDCs/VSCs is cost-effective and propitious to energy conservation and environment protection. Thirdly, on the operational layer, automobile intermodal transportation considers either the transfer of different transportation modes or the match of frequencies of different transportation services. For example, trucks can be dispatched any time on each day in a week, and trains/ships have fixed service frequency such as once or twice in a week. The cost of waiting time for trains/ships will influence the flow assignment on different transportation services based on different modes.

In terms of transportation mode, trucking has the advantage of door-to-door services and the disadvantage of high costs for long transportation distances. Rail/waterway has a lower cost compared with trucking in case of long-distance delivery of a large number of automobiles. At the same time, rail/waterway transportation has three disadvantages: (i) Rail/waterway transportation must involve the trucking services to and from the railway stations/ports. (ii) The network of railway/waterway is not as extensive as road network: some cities do not have railway stations and many cities do not have ports. (iii) Train/ship routes have regular schedules. In other words, automobiles transported by truck to a railway station/port may have to wait for the train/ship to come. When the automobiles are stored at the railway station/port, the storage cost cannot be neglected.

To reduce the overall automobile delivery cost, the automobile manufacturers take advantage of the existing intermodal transportation network that consists of road, rail, and waterway. However, the manufacturers must purchase rail and waterway services in advance for a period between a few months and one year. Obviously, if too much train and/or ship carrying capacity is procured, some train/ship slots will be empty, which is a waste of money. On the contrary, if too little carrying capacity is procured, a large proportion of automobiles will have to be transported by the (possibly much more expensive) trucking mode in the delivery stage, which also leads to a high cost. Consequently, it is a realistic decision problem faced by automobile manufacturers to determine the optimal rail and waterway capacity to procure. This problem is further complicated by the fact that the number of automobiles to be delivered in each week cannot be known a priori because it depends on the market. In fact, the delivery demand fluctuates week by week in a random manner, which must be incorporated in the problem of carrying capacity procurement of rail and shipping services. This study aims to determine the optimal train and ship capacity to book from railway companies and shipping companies to minimize the expected automobile delivery cost in an intermodal automobile delivery network by taking into account the uncertain demand. Note that the proposed problem is a realistic decision problem faced by automobile manufacturers such as SAIC.

The proposed carrying capacity procurement problem is related to two research issues: service network design and intermodal freight modeling. We therefore review the relevant studies from these two aspects. The service network design, which was formulated as a mixed integer linear programming model by Magnanti and Wong (1984), is an important freight transportation network planning problem. It arises in the airlines, rail and maritime industries and is further extended to the intermodal freight transportation. There are several review articles on the service network design, including Cordeau et al. (1998) for the rail transportation, Crainic and Kim (2007) for intermodal transportation, Crainic (2000) and Wieberneit (2008) for freight transportation, and Christiansen et al. (2007) for maritime transportation. According to these reviews, it can be concluded that most studies have primarily assumed static and deterministic characteristics in their problem setting. Few studies focus on the service network design under the uncertain environment. Yan et al. (2006) considered passenger choice behaviors and uncertain market demands, and used stochastic and robust optimization and a passenger choice model to develop inter-city bus scheduling models. Yan et al. (2008) proposed a flight scheduling model with stochastic demand and passenger choices for different airlines. Lium et al. (2009) investigated the importance of introducing stochastic elements into the service network design problems. It was extended by Bai et al. (2014) by incorporating the vehicle rerouting options into the stochastic freight service network design problems. Lo et al. (2013) developed a model for ferry service network design with stochastic demand via the notion of service reliability. These studies are inapplicable for the carrying capacity procurement problem proposed in this study because they are unable to deal with the intermodal transport operations arising in the automobile delivery.

There are a number of efforts made for the intermodal freight transportation modeling and optimization. However, to the best of our knowledge, there has been no study that simultaneously investigates the problem of carrying capacity procurement of rail and shipping services in an intermodal transportation network with uncertain demand. Crainic and Rousseau (1986) proposed a general modeling and algorithmic framework for the service network design problem in the multicommodity, multimode freight transportation networks. Bontekoning et al. (2004) contributed an excellent overview on the intermodal freight transportation studies. This review is devoted solely to truck–rail transportation. Caris et al. (2008) conducted an extensive overview of the advancement of research on intermodal freight transportation planning. SteadieSeifi et al. (2014) presented a structured overview of the intermodal transportation studies from 2005 onward. According to this review, no study that is specific to the intermodal automobile delivery is reported. Min (1991), Barnhart and Ratliff (1993), Boardman et al. (1997), Kim et al. (1999), Chang (2008), Gromicho et al. (2011) and Ayar and Yaman (2012) have studied how to route freight in an intermodal transportation network without considering the carrying capacity procurement of railway/waterway services. In fact, freight routing is more of an operational-level problem that occurs when the real demand is known, while carrying capacity procurement is a tactical-level decision that must be made before the future demand is revealed. Meng et al. (2012a) and Liu et al. (2014) have investigated the shipping network design for intermodal container transportation. However, container transportation is different from automobile delivery in that the main focus on container transportation is shipping at sea, while automobile delivery in a country mainly involves land transportation (road and rail) and river or coastal shipping. Moreover, these two studies do not consider carrying capacity procurement of trains.

The above literature review shows that there has not yet been an optimization model that addresses the problem of carrying capacity procurement of rail and shipping services in automobile intermodal networks with unique characteristics that will help automobile manufacturers determine the optimal carrying capacity procurement of rail and shipping services as well as assign flow to the selected routes optimally. As a matter of fact, our study is based on automobile delivery practice initiated by SAIC with automobile delivery network shown in Figs. 1–3, addressing a practical decision problem arising in the automobile industry. We formulate a two-stage stochastic programming model for the special problem. The model is solved by an improved sample average approximation method. We apply the model and method to a case study from SAIC. The results not only demonstrate that the model could help automobile manufacturers to determine the optimal ordering capacity of trains and ships, but also provide a number of useful managerial insights for automobile manufacturers. We believe that this study deals with an emerging new research topic with practical significance for the automobile industry.

The rest of this study is organized as follows. Section 2 states the problem. Section 3 presents a two-stage stochastic programming model. Section 4 describes a sample average approximation solution method. A case study based on the automobile distribution operations of SAIC is reported in Section 5. Conclusions and future work are presented in Section 6. For better readability, the acronyms and notation used are listed in Table 1.

2. Problem description

Consider an automobile manufacturing company such as SAIC. It has a set of VDCs represented by N^D and a set of VSCs represented by N^S. Different VDCs have different types of automobiles. In this study, we use flatbed as the unit of automobiles where a flatbed can load ten automobiles. The automobiles in a distribution center need to be transported to VSCs and other VDCs. We use O–D to differentiate the automobile delivery demand. Therefore, an origin is a node in N^D, and a destination is a node in $N^D \cup N^S$ that is different from the origin.

Denote by N^T the set of railway stations (the superscript T means train), and N^P the set of ports. Consequently, the set of nodes in the transportation network is $N := N^D \cup N^S \cup N^T \cup N^P$.

Table 1
List of acronyms and notation.

Acronym	
O–D	Origin–destination
SAA	Sample average approximation
SAIC	Shanghai Automobile Industry Corporation
VDC	Vehicle distribution center
VSC	Vehicle storage center
LR	Lagrangian relaxation of the SAA problem
LD	Lagrangian dual
EVP	Expected value problem
EEV	Expected value of the EVP solution
Notation	
N^D	Set of VDCs
N^s	Set of VSCs
N^T	Set of railway stations, where T means train
N^P	Set of ports, where P means port
N	Set of nodes in the transportation network, $N = N^D \cup N^S \cup N^T \cup N^P$
R^T	Set of rail services, where T means train
R^P	Set of shipping services, where P means port
E_r	Maximum capacity of the train on service $r \in R^T$
I_r	Number of railway station visited on service $r \in R^T$
n_{ri}	The ith railway station of on service $r \in R^T$
$\boldsymbol{\xi}$	Random weekly demand vector, $\boldsymbol{\xi} = (\xi^{od}, o \in N^D, d \in N^D \cup N^S)$
q^{od}	Demand (flatbeds of vehicles/week) from a VDC $o \in N^D$ to another VDC or a VSC $d \in N^D \cup N^S$
$\mathbf{q}$	Realization of the random vector $\boldsymbol{\xi}$, $\mathbf{q} = (q^{od}, o \in N^D, d \in N^D \cup N^S)$
W	Set of days in a week, $W = \{1, 2, 3, 4, 5, 6, 7\}$
B	Set of fixed batches in a day
$B'(\boldsymbol{\xi})$	Set of additional batches in a day
$Q^{wb}(\boldsymbol{\xi})$	Number of flatbeds in batch $b \in B \cup B'(\boldsymbol{\xi})$ of day $w \in W$
$c_{n_1 n_2}$	Trucking cost of vehicles of a flatbed between two nodes $n_1 \in N, n_2 \in N$
$t_{n_1 n_2}$	Trucking time of a flatbed between two nodes $n_1 \in N, n_2 \in N$
$c_{on_{ri}}$	Trucking cost of vehicles of a flatbed from VDC $o \in N^D$ to railway station n_{ri}
$c_{n_{rj}d}$	Trucking cost of vehicles of a flatbed from railway station n_{rj} to $d \in N^D \cup N^S$
$\tilde{t}_o^{wb}$	Leaving time of vehicles delivered in batch $b \in B \cup B'$ of day $w \in W$ from VDC $o \in N^D$ in a week
$t_{o,ri}^{wb}$	Storage time of vehicles delivered in batch $b \in B \cup B'$ of day $w \in W$ from VDC $o \in N^D$ at railway station $n_{ri} \in N^T$
$t_{on_{ri}}$	Trucking time of a flatbed from VDC $o \in N^D$ to railway station n_{ri}
$\tilde{t}_{ri}$	Train departure time from the ith railway station on rail service $r \in R^T$ in a week
$\hat{c}_{n_{ri}}$	Storage cost of vehicles of per flatbed per hour at railway station n_{ri}
$c_{od,rij}^{wb}$	Storage cost of vehicles of per flatbed in batch $b \in B \cup B'$ of day $w \in W$ at railway station n_{ri}, transported from VDC $o \in N^D$ to $d \in N^D \cup N^S$ via rail service $r \in R^T$ from railway station n_{ri} to railway station n_{rj}, $1 \leqslant i \leqslant j \leqslant I_r$
c_{ri}	Unit weekly booking cost of one flatbed on leg i of rail or shipping service $r \in R^T \cup R^P$, $i = 1, 2, \ldots, I_r - 1$
x_{ri}	Weekly booked capacity on leg i of rail or shipping service $r \in R^T \cup R^P$, $i = 1, 2, \ldots, I_r - 1$
$\mathbf{x}_n$	nth weekly booked capacity vector corresponding to nth realization of the random demand $\boldsymbol{\xi}$
$C(\mathbf{x}, \boldsymbol{\xi})$	Minimum trucking and storage costs with the first-stage decision $\mathbf{x}$ under the uncertain demand $\boldsymbol{\xi}$
c_{od}	Trucking cost of a flatbed from a VDC $o \in N^D$ to another VDC or a VSC $d \in N^D \cup N^S$
$f_{od,rij}^{wb}(\mathbf{q})$	Number of flatbeds in batch $b \in B \cup B'$ of day $w \in W$ transported from VDC $o \in N^D$ to $d \in N^D \cup N^S$ via rail or shipping service $r \in R^T \cup R^P$ from railway station (port) n_{ri} to railway station (port) n_{rj}, $1 \leqslant i \leqslant j \leqslant I_r$
$f_{od}^{wb}(\mathbf{q})$	Number of flatbeds in batch $b \in B \cup B'$ of day $w \in W$ transported from VDC $o \in N^D$ to $d \in N^D \cup N^S$ via only truck
$\mathbf{c}$	Cost vector including the cost coefficients of first-stage problem
$\mathbb{Z}^+$	Set of nonnegative integers
$\overline{N}$	Realization times of random demand $\boldsymbol{\xi}$
$\mathbf{H}_n$	Matrix with $\overline{N} \times \left(\sum_{r \in R^T \cup R^P} (I_r - 1)\right)$ rows and $\sum_{r \in R^T \cup R^P} (I_r - 1)$ columns, $n = 1, 2, \ldots, \overline{N}$
$\mathbf{I}$	Identity matrix of size $\sum_{r \in R^T \cup R^P} (I_r - 1)$
$\mathbf{0}$	Zero matrix of size $\sum_{r \in R^T \cup R^P} (I_r - 1)$
M	Number of independent samples of size $\overline{N}$
$\hat{N}$	Size of a reference sample
$\boldsymbol{\lambda}$	Vector of Lagrangian multipliers associated with the non-anticipativity constraints
$s^{(k)}$	Step size sequence $\left\{s^{(k)} = \frac{1}{k}, k = 1, 2, \ldots, \infty\right\}$
ε	Given tolerance in the subgradient method

Let R^T be the set of rail services that are available for transporting automobiles. Each rail service $r \in R^T$ has a weekly frequency and contains the following information: (i) the maximum capacity of trains on the service denoted by E_r; (ii) the number of railway stations visited, denoted by I_r; (iii) the itinerary of the railway stations denoted by

$$n_{r1} \to n_{r2} \to \cdots \to n_{rI_r} \tag{1}$$

where $n_{ri} \in N^T$, $i = 1, 2, \ldots, I_r$; and (iv) the cut-off time at each railway station. The cut-off time means the latest time that a flatbed must be at the railway station so that it could be transported by the train. For simplicity, we use the departure time $\tilde{t}_{ri}$

from the ith railway station on rail service $r \in R^T$ to represent the cut-off time in a week. Note that $\tilde{t}_{ri} \in [0, 168)$ due to the weekly services where 168 is the number of hours in a week.

Example 1: Suppose that a train visits Shanghai (the first railway station on the service, arrival: 2:00, 8 December 2014; departure: 10:00, 8 December 2014), Wuhan (the second railway station, arrival: 20:00, 11 December 2014; departure: 1:00, 12 December 2014), Chongqing (the last railway station, arrival: 5:00, 14 December 2014; departure: 11:00, 14 December 2014). We have:

$$I_r = 3 \tag{2}$$

$$n_{r1} = \text{Shanghai}, \quad n_{r2} = \text{Wuhan}, \quad n_{rI_r} = \text{Chongqing} \tag{3}$$

$$\tilde{t}_{r1} = 10, \quad \tilde{t}_{r2} = 97, \quad \tilde{t}_{r3} = 155 \tag{4}$$

There is no difference in modeling between rail and water transportation and hence we let R^P be the set of shipping services and a shipping service is also denoted by $r \in R^P$.

2.1. Uncertain automobile delivery demand

The number of automobiles to be transported from a VDC $o \in N^D$ to another VDC or a VSC $d \in N^D \cup N^S$ depends on the market situation. As the market situation fluctuates randomly, it is impossible to know the exact delivery demand in advance. However, based on historical data, the manufacturer could have an estimate of the probability distribution function of the demand. We use ξ^{od} (flatbeds/week) to represent the random weekly demand from $o \in N^D$ to $d \in N^D \cup N^S$, and define the following vector:

$$\boldsymbol{\xi} = (\xi^{od}, o \in N^D, d \in N^D \cup N^S) \tag{5}$$

The probability distribution of the vector $\boldsymbol{\xi}$ is known and is an important input for the planning model.

2.2. Scheduling plan of flatbeds

At the beginning of each week, the manufacturer knows the exact value of the demand $\boldsymbol{\xi}$, denoted by the following vector

$$\mathbf{q} = (q^{od}, o \in N^D, d \in N^D \cup N^S) \tag{6}$$

That is, $\mathbf{q}$ is a realization of the random vector $\boldsymbol{\xi}$.

Based on the realized demand $\mathbf{q}$, the manufacturer makes a scheduling plan of flatbeds for the week. Note that the back-ordering is not allowed in this study and all the delivery demand can be fulfilled because of the unlimited trucking capacity. As a result, the scheduling plans in different periods are independent of each other, and we thus only need to determine the weekly scheduling plan with uncertain demand. The scheduling plan of flatbeds consists of how many batches of automobiles to deliver on each day of the seven days of a week, and how many automobiles a batch has. Since the number of fixed lanes of the warehouse to load automobile products into each flatbed is limited, the assembled automobile products in different times must be assigned to different batches to transport each day. For a stable production plan, we assume that the daily delivery batches of automobile products are fixed and the flatbeds delivering the automobile products in each batch are fully loaded.

For example, the manufacturer has 63 fixed lanes of warehouse. Each fixed lane serves one flatbed for loading automobile products and its service time is 3 h, that is, a flatbed should be fully loaded in 3 h. According to the layout of warehouse, usually, 21 fixed lanes of warehouse are scheduled for loading the assembled automobile products in an hour. Hence, though the loading cycle of each flatbed is 3 h, from the perspective of a day, a total of 21 flatbeds may leave the VDC every hour. If the delivery plan of manufacturer is 1911 flatbeds in a week, and then there are 1911/7 = 273 flatbeds which can leave the VDC every day, furthermore, 273/21 = 13 fixed batches can be assigned from 8:00 to 20:00 in a day, as shown in Fig. 4: the

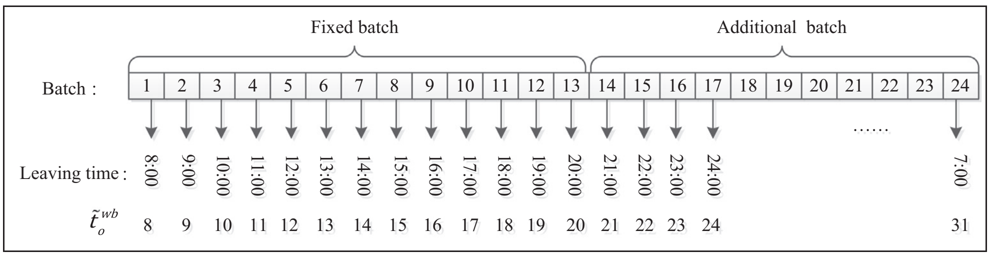

Fig. 4. Batch and leaving time from 8:00 on Monday to 7:00 on Tuesday.

Table 2
Number of flatbeds in each batch of the scheduling plan of flatbeds.

Batches	Leaving time	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Fixed batches 1–13	8:00–20:00	21	21	21	21	21	21	21
Additional batch 1	21:00	21	21	21	21	21	21	21
Additional batch 2	22:00	21	21	21	21	21	21	21
Additional batch 3	23:00	21	21	10	0	0	0	0

first fixed batch leaves the distribution center by trucking at 8:00, the last fixed batch leaves at 20:00, and each batch includes 21 flatbeds. We represent the set of fixed batches in a day by the set B. However, when the demand increases significantly in a week, additional batches need to be provided in a day that leave at 21:00 through to 7:00; furthermore, the capacity of each additional batch is less than or equal to 21 flatbeds. The automobiles delivered in the additional batches come from the warehouses storing some automobiles with respect to the market fluctuations. The company tries to minimize the variation of the numbers of automobiles delivered in different days in a week.

Example 2: Suppose that in a particular week, a VDC o needs to export 2257 flatbeds, i.e., $\sum_{d \in N^D \cup N^S} q^{od} = 2257$. Then, the company needs $2257/21 \approx 107.48$ batches. Hence, each day has $107.48/7 \approx 15.4$ batches. Therefore, the manufacturer first assigns 15 batches to each day, including 13 fixed batches and 2 additional batches. After that, there are $107.48 - 7 \times 15 = 2.48$ batches to be assigned. The manufacturer then assigns one additional batch to Monday, and one additional batch to Tuesday. Then, there are$2257 - 7 \times 15 \times 21 - 21 - 21 = 10$ flatbeds to be assigned. The manufacturer therefore assigns one additional batch to Wednesday, which only produces 10 flatbeds of automobiles rather than 21. The scheduling plan of flatbeds is summarized in Table 2.

In general, the total demand from a VDC is not smaller than the total flatbeds in all the fixed batches, and does not exceed the production capacity of the manufacturer. Denote by $W = \{1,2,3,4,5,6,7\}$ the set of days in a week. We use $B'(\xi)$ to represent the set of additional batches, and $Q^{wb}(\xi)$ to represent the number of flatbeds in additional batch $b \in B'(\xi)$ of day $w \in W$. Both parameters depend on the random variable ξ. To simply the notation, we also use $Q^{wb}(\xi)$ to represent the number of flatbeds in fixed batch $b \in B$ of day $w \in W$ and $Q^{wb}(\xi) = 21$. Finally, we denote by $\tilde{t}_o^{wb}$ the time of a week that the batch $b \in B \cup B'$ of flatbeds leaves the VDC. For instance, Table 2 shows that the time of a week that the second additional batch of flatbeds on Wednesday leaves the VDC is $24 \times 2 + 22 = 70$ h, which corresponds to 22:00 on Wednesday.

2.3. Intermodal automobile delivery

A flatbed can be transported from VDC $o \in N^D$ to another VDC or a VSC $d \in N^D \cup N^S$ by truck. The road transportation cost of a flatbed from node $n_1 \in N$ to node $n_2 \in N$ is denoted by $c_{n_1 n_2}$, and the transportation time is $t_{n_1 n_2}$ (h). There is sufficient trucking capacity to transport the automobiles and trucks are always available for service.

A flatbed can also be transported to a railway station (station i of service r) by truck, and then transported to another railway station (station j of service $r, j > i$) by train, and finally transported to the destination by truck. The total cost comprises: the trucking cost from origin o to railway station n_{ri}, the storage cost at n_{ri}, and the trucking cost from railway station n_{rj} to the destination d (the train booking cost is fixed and hence is not included here). The total trucking cost is $c_{on_{ri}} + c_{n_{rj}d}$.

We now elaborate on how to calculate the storage cost at railway station n_{ri}. This cost depends on the schedules of the rail service and the batches of the automobiles. Recall that the batch $b \in B \cup B'(\xi)$ of flatbeds in day $w \in W$ leaves the VDC at time $\tilde{t}_o^{wb}$. Therefore, it arrives at the railway station n_{ri} at time $(\tilde{t}_o^{wb} + t_{on_{ri}})\mathrm{mod}(168)$ of a week. Since the cut-off time of the train is $\tilde{t}_{ri}$, the storage time is represented by $t_{o,ri}^{wb}$ and can be calculated by

$$t_{o,ri}^{wb} = \begin{cases} \tilde{t}_{ri} - (\tilde{t}_o^{wb} + t_{on_{ri}})\mathrm{mod}(168), & \text{if } \tilde{t}_{ri} - (\tilde{t}_o^{wb} + t_{on_{ri}})\mathrm{mod}168 \geqslant 0 \\ 168 + \tilde{t}_{ri} - (\tilde{t}_o^{wb} + t_{on_{ri}})\mathrm{mod}168, & \text{otherwise} \end{cases} \tag{7}$$

We let $\hat{c}_n$ be the storage cost per flatbed per hour at a railway station or a port $n \in N^T \cup N^P$. As a result, the storage cost at railway station n_{ri} is $\hat{c}_{n_{ri}} t_{o,ri}^{wb}$. Note that the storage cost at a railway station on a rail service and the transportation cost on the

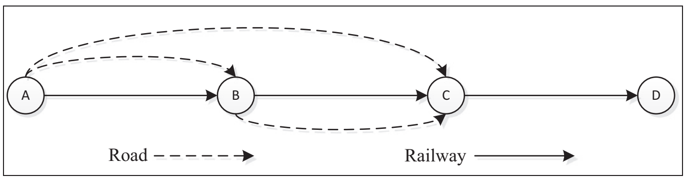

Fig. 5. Optional transportation combinations in a rail service.

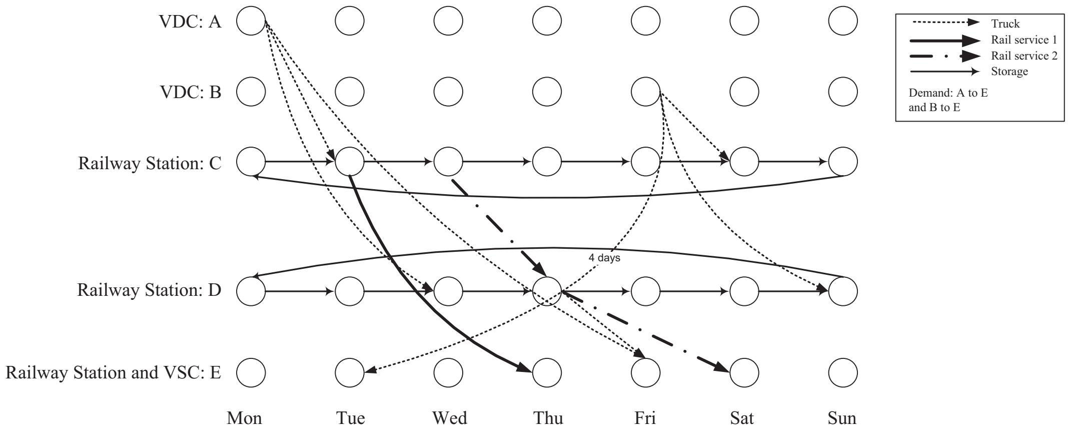

Fig. 6. A space-time network representation of the automotive delivery problem.

service are sort of deterministically linked, that is, when the storage cost at a railway station on a rail service is obviously higher, the total cost including the storage cost and transportation cost on the service must be higher, furthermore, there is no non-trivial trade-off between them that depends on the solution. When the flatbed is transported to railway station n_{rj}, it will immediately be transported by truck to its destination d and hence there is no storage cost at railway station n_{rj}.

It is emphasized that a rail service may include several optional transportation combinations for flexible transportation in terms of some special situations. For example, in Fig. 5, a rail service visits four railway stations A, B, C and D. If the manufacturer wants to deliver their automobiles from a VDC nearby the railway station A to another VSC located beside the railway station D, the following several transportation combinations may be selected: (i) Complete rail transportation from A to D, hence, the storage cost of the automobiles for waiting for train arrival is only incurred at A. (ii) Firstly, road transportation from A to B, and then rail transportation from B to D, therefore, only B has the storage cost. (iii) Road transportation from A to C and rail transportation from C to D, consequently, the storage cost occurs at C. In addition, because railway stations B and C are on the rail service, other VDCs near B or C may also use the rail service to deliver their automobiles to the destination, in this case, the storage cost at railway station B or C is paid for the automobiles from other VDCs. In sum, during the delivery of automobiles between each O–D pair, the storage cost is considered only once. We define the storage cost $c^{wb}_{od,rij} := \hat{c}_{n_{ri}} t^{wb}_{o,ri}$ for the models to be developed later. The computation of the storage cost at ports is similar to that at railway stations.

The automotive delivery problem can also be represented using a space-time network model (Yan et al., 2009). Take Fig. 6 as an example, which uses day rather than hour as the time unit for the purpose of clarity. There are two rail services: service 1 visits C on Tuesday and E on Thursday; service 2 visits C on Wednesday, D on Thursday, and E on Saturday. Some vehicles are to be delivered from A on Monday to E, and the other vehicles are to be delivered from B on Friday to E. We can see that there are five options to deliver the vehicles from A to E: option 1: use trucks only and the vehicles will be delivered to E on Friday of the same week; option 2: use trucks to deliver to C first, and then use rail service 1 (the vehicles will be delivered to E on Thursday, and there is no storage cost); option 3: use trucks to deliver to C first, and then use rail service 2 (the vehicles will be delivered to E on Saturday, and vehicles are stored at C for one day); option 4: use trucks to deliver to C first, then use rail service 2 to deliver to D, and then use trucks (the vehicles will be delivered to E on Friday, and vehicles are stored at C for one day); and option 5: use trucks to deliver to D first, and then use rail service 2 (the vehicles will be delivered to E on Saturday, and vehicles are stored at D for one day). There are also five options to deliver the vehicles from B to E: option 1: use trucks only and the vehicles will be delivered to E on the next Tuesday; option 2: use trucks to deliver to C first, and then use rail service 1 (the vehicles will be delivered to E on the next Thursday, and vehicles are stored at C for three days); option 3: use trucks to deliver to C first, and then use rail service 2 (the vehicles will be delivered to E on the next Saturday, and vehicles are stored at C for four days); option 4: use trucks to deliver to C first, then use rail service 2 to deliver to D, and then use trucks (the vehicles will be delivered to E on the next Friday, and vehicles are stored at C for four days); and option 5: use trucks to deliver to D first, and then use rail service 2 (the vehicles will be delivered to E on the next Saturday, and vehicles are stored at D for four days).

2.4. Carrying capacity procurement

In many cases it is less costly to transport flatbeds by rail or water than by truck. Therefore, the manufacturer books some transport capacities of trains and ships for a period between a few months to one year. We let C_{ri} be the unit weekly procurement cost of one flatbed on leg i of rail or shipping service $r \in R^T \cup R^P$, $i = 1, 2, \ldots, I_r - 1$. The automobile company needs to determine the optimal carrying capacity to book on railway and shipping services to minimize the expected total delivery cost, including the booking cost, the trucking cost, and the storage cost at railway stations and ports.

Determining the optimal capacity to book is no easy task because of the uncertain delivery demand: if not enough capacity is booked, then many flatbeds have to be transported by the more expensive trucking mode; if more capacity is booked, then the total booking cost is too high. Consequently, the manufacturer needs to determine the optimal capacity on each leg of each rail and shipping service to book, to minimize the sum of the booking cost and the expected trucking costs plus the storage costs.

3. Two-stage stochastic optimization model

The carrying capacity ordering problem could be formulated as a two-stage stochastic optimization model. In the first stage, the manufacturer needs to determine the capacity of trains and ships to book, denoted by the following decision vector

$$\mathbf{x} = (x_{ri}, r \in R^T \cup R^P, i = 1, 2, \ldots, I_r - 1) \tag{8}$$

where x_{ri} is the weekly booked capacity on leg i of rail or shipping service $r \in R^T \cup R^P$, $i = 1, 2, \ldots, I_r - 1$. In the second stage, the manufacturer observes the demand in each week, and determines how to transport the automobiles in the most cost-efficient manner.

We let $C(\mathbf{x}, \xi)$ be the minimum trucking and storage costs with the first-stage decision $\mathbf{x}$ under the uncertain demand ξ. $C(\mathbf{x}, \xi)$ is also random due to the randomness of ξ and we will elaborate on how to compute $C(\mathbf{x}, \xi)$ later. The first-stage model minimizes the expected total cost:

$$[\text{First stage}] \quad \min_{\mathbf{x}} \sum_{r \in R^T \cup R^P} \sum_{i=1}^{I_r - 1} C_{ri} x_{ri} + \mathbb{E}_{\xi} C(\mathbf{x}, \xi) \tag{9}$$

subject to:

$$x_{rk} \leqslant E_r, \quad r \in R^T \cup R^P, \quad 1 \leqslant k \leqslant I_r - 1 \tag{10}$$

$$x_{ri} \in \mathbb{Z}^+, \quad r \in R^T \cup R^P, \quad i = 1, 2, \ldots, \quad I_r - 1 \tag{11}$$

The first term in the objective function (9) is the fixed procurement costs, and the second term is the expectation of the total trucking and storage costs. Constraint (10) enforces that the total booked capacity cannot exceed the maximum capacity of trains or ships in the service in a week. Constraint (11) imposes that x_{ri} are nonnegative integers where $\mathbb{Z}^+$ represents the set of nonnegative integers.

Recall that $\mathbf{q}$ is a realization of the random vector ξ. Given $\mathbf{q}$, we define the following second-stage decision variables: $f_{od,rij}^{wb}(\mathbf{q})$ represents the number of flatbeds in batch $b \in B \cup B'(\mathbf{q})$ of day $w \in W$ transported from $o \in N^D$ to $d \in N^D \cup N^S$ via rail or shipping service $r \in R^T \cup R^P$ from railway station (port) n_{ri} to railway station (port) n_{rj}, $1 \leqslant i < j \leqslant I_r$; and $f_{od}^{wb}(\mathbf{q})$ represents the number of flatbeds in batch $b \in B \cup B'(\mathbf{q})$ of day $w \in W$ transported from VDC $o \in N^D$ to $d \in N^D \cup N^S$ by only trucking. The second-stage decision model is:

$$\begin{aligned}[\text{Second stage}] \quad C(\mathbf{x}, \mathbf{q}) = \min_{f_{od,rij}^{wb}(\mathbf{q}), f_{od}^{wb}(\mathbf{q})} & \sum_{o \in N^D} \sum_{d \in N^D \cup N^S} \sum_{w \in W} \sum_{b \in B \cup B'(\mathbf{q})} c_{od} f_{od}^{wb}(\mathbf{q}) \\ & + \sum_{o \in N^D} \sum_{d \in N^D \cup N^S} \sum_{w \in W} \sum_{b \in B \cup B'(\mathbf{q})} \sum_{r \in R^T \cup R^P} \sum_{i=1}^{I_r - 1} \sum_{j=i+1}^{I_r} (c_{on_{ri}} + c_{od,rij}^{wb} + c_{n_{rj}d}) f_{od,rij}^{wb}(\mathbf{q})\end{aligned} \tag{12}$$

subject to:

$$\sum_{w \in W} \sum_{b \in B \cup B'(\mathbf{q})} \left[f_{od}^{wb}(\mathbf{q}) + \sum_{r \in R^T \cup R^P} \sum_{i=1}^{I_r - 1} \sum_{j=i+1}^{I_r} f_{od,rij}^{wb}(\mathbf{q}) \right] = q^{od}, \quad o \in N^D, \quad d \in N^D \cup N^S \tag{13}$$

$$\sum_{o \in N^D} \sum_{d \in N^D \cup N^S} \sum_{w \in W} \sum_{b \in B \cup B'(\mathbf{q})} \sum_{i=1}^{k} \sum_{j=k+1}^{I_r} f_{od,rij}^{wb}(\mathbf{q}) \leqslant x_{rk}, \quad r \in R^T \cup R^P, \quad 1 \leqslant k \leqslant I_r - 1 \tag{14}$$

$$\sum_{d \in N^D \cup N^S} \left[f_{od}^{wb}(\mathbf{q}) + \sum_{r \in R^T \cup R^P} \sum_{i=1}^{I_r - 1} \sum_{j=i+1}^{I_r} f_{od,rij}^{wb}(\mathbf{q}) \right] = Q^{wb}(\mathbf{q}), \quad o \in N^D, \quad w \in W, \quad b \in B \cup B'(\mathbf{q}) \tag{15}$$

$$f_{od,rij}^{wb}(\mathbf{q}) \in \mathbb{Z}^+, \quad o \in N^D, \quad d \in N^D \cup N^S, \quad w \in W, \quad b \in B \cup B'(\mathbf{q}), \quad r \in R^T \cup R^P, \quad 1 \leqslant i < j \leqslant I_r \tag{16}$$

$$f_{od}^{wb}(\mathbf{q}) \in \mathbb{Z}^+, \quad o \in N^D, \quad d \in N^D \cup N^S, \quad w \in W, \quad b \in B \cup B'(\mathbf{q}) \tag{17}$$

The objective function (12) minimizes the sum of two types of costs. The first cost is the trucking costs for flatbed delivery solely by truck, and the second cost is the sum of trucking costs and storage costs for intermodal transportation. Eq. (13) imposes that all the automobile transportation demand is satisfied. Eq. (14) enforces that the number of flatbeds transported on trains or ships cannot exceed the booked capacity, which is determined in the first-stage model. Eq. (15) requires that all batches of flatbeds are transported. Eqs. (16) and (17) define that the variables $f_{od,rij}^{wb}(\mathbf{q})$ and $f_{od}^{wb}(\mathbf{q})$ are nonnegative integers.

4. Solution method

Unless the uncertain delivery demand ξ has a small number of possible realizations (scenarios), it is usually impossible to compute $\mathbb{E}_\xi C(\mathbf{x},\xi)$ in Eq. (9) exactly. One approach for approximately solving the two-stage model is the sample average approximation (SAA) method (see, Kleywegt et al., 2001; Shapiro et al., 2009). The SAA method is an approach for solving stochastic optimization problems using Monte Carlo simulation, and it has been applied for solving the two-stage programming models developed for various decision problems (e.g., Meng et al., 2012b). In this technique the objective function of the stochastic program is approximated by a sample average estimate derived from a random sample. The resulting sample average approximating problem is then solved by deterministic optimization approaches. For example, we might draw $\overline{N}$ (e.g., $\overline{N}=30$) realizations of the random demand ξ, denoted by $\mathbf{q}_1,\mathbf{q}_2,\ldots,\mathbf{q}_{\overline{N}}$, and solve the following deterministic optimization model:

$$[\mathrm{SAA}]\quad \min_{\mathbf{x},f_{od,rij}^{wb}(\mathbf{q}_n),f_{od}^{wb}(\mathbf{q}_n)} \sum_{r\in R^T\cup R^P}\sum_{i=1}^{I_r-1} C_{ri}x_{ri}$$

$$+\frac{1}{\overline{N}}\sum_{n=1}^{\overline{N}}\sum_{o\in N^D}\sum_{d\in N^D\cup N^S}\sum_{w\in W}\sum_{b\in B\cup B'(\mathbf{q}_n)}\left[c_{od}f_{od}^{wb}(\mathbf{q}_n)+\sum_{r\in R^T\cup R^P}\sum_{i=1}^{I_r-1}\sum_{j=i+1}^{I_r}\left(c_{on_{ri}}+c_{od,rij}^{wb}+c_{n_{rj}d}\right)f_{od,rij}^{wb}(\mathbf{q}_n)\right] \tag{18}$$

subject to:

$$x_{rk}\leqslant E_r,\quad r\in R^T\cup R^P,\quad 1\leqslant k\leqslant I_r-1 \tag{19}$$

$$x_{ri}\in\mathbb{Z}^+,\quad r\in R^T\cup R^P,\quad i=1,2,\ldots,I_r-1 \tag{20}$$

$$\sum_{w\in W}\sum_{b\in B\cup B'(\mathbf{q}_n)}\left[f_{od}^{wb}(\mathbf{q}_n)+\sum_{r\in R^T\cup R^P}\sum_{i=1}^{I_r-1}\sum_{j=i+1}^{I_r}f_{od,rij}^{wb}(\mathbf{q}_n)\right]=q_n^{od},\quad o\in N^D,\quad d\in N^D\cup N^S,\quad n=1,2,\ldots,\overline{N} \tag{21}$$

$$\sum_{o\in N^D}\sum_{d\in N^D\cup N^S}\sum_{w\in W}\sum_{b\in B\cup B'(\mathbf{q}_n)}\sum_{i=1}^{k}\sum_{j=k+1}^{I_r}f_{od,rij}^{wb}(\mathbf{q}_n)\leqslant x_{rk},\quad r\in R^T\cup R^P,\quad 1\leqslant k\leqslant I_r-1,\quad n=1,2,\ldots,\overline{N} \tag{22}$$

$$\sum_{d\in N^D\cup N^S}\left[f_{od}^{wb}(\mathbf{q}_n)+\sum_{r\in R^T\cup R^P}\sum_{i=1}^{I_r-1}\sum_{j=i+1}^{I_r}f_{od,rij}^{wb}(\mathbf{q}_n)\right]=Q^{wb}(\mathbf{q}_n),\quad o\in N^D,\quad w\in W,\quad b\in B\cup B'(\mathbf{q}_n),\quad n=1,2,\ldots,\overline{N} \tag{23}$$

$$f_{od,rij}^{wb}(\mathbf{q}_n)\in\mathbb{Z}^+,\quad o\in N^D,\quad d\in N^D\cup N^S,\quad w\in W,\quad b\in B\cup B'(\mathbf{q}_n),\quad r\in R^T\cup R^P,\quad 1\leqslant i<j\leqslant I_r,\quad n=1,2,\ldots,\overline{N} \tag{24}$$

$$f_{od}^{wb}(\mathbf{q}_n)\in\mathbb{Z}^+,\quad o\in N^D,\quad d\in N^D\cup N^S,\quad w\in W,\quad b\in B\cup B'(\mathbf{q}_n),\quad n=1,2,\ldots,\overline{N} \tag{25}$$

4.1. Dual decomposition and lagrangian relaxation

It is difficult to solve the [SAA] model by integer programming solvers because it has a large number of decision variables and constraints caused by the sampling approach. We therefore employ the efficient dual decomposition and Lagrangian relaxation approach proposed by Carøe and Schultz (1999), in which the SAA problem can be divided into $\overline{N}$ sub-problems that match the $\overline{N}$ automobile delivery demand realizations. Correspondingly, the first-stage decision variables are copied $\overline{N}$ times. In order to guarantee that the first-stage decision variables are not influenced by the second-stage decision variables, the following non-anticipativity constraints are added to the original SAA problem to ensure $\mathbf{x}_1=\cdots=\mathbf{x}_n$:

$$\mathbf{x}_n=\mathbf{x}_{n+1},\quad n=1,2,\ldots,\overline{N}-1 \tag{26}$$

$$\mathbf{x}_{\overline{N}}=\mathbf{x}_1 \tag{27}$$

The decomposition form of the original SAA problem is

$$\min_{\mathbf{x}_n} \frac{1}{\overline{N}} \sum_{n=1}^{\overline{N}} \mathbf{c}^{\mathrm{T}} \mathbf{x}_n + \frac{1}{\overline{N}} \sum_{n=1}^{\overline{N}} C(\mathbf{x}_n, \mathbf{q}_n) \tag{28}$$

subject to the constraints (26), (27), and the constraints (19)–(25) associated with each of the nth realization of the random parameters.

Eqs. (26) and (27) can also be written using matrix notation:

$$\sum_{n=1}^{\overline{N}} \mathbf{H}_n \mathbf{x}_n = 0 \tag{29}$$

where $\mathbf{H}_n (n = 1, 2, \ldots, \overline{N})$ is a matrix with $\overline{N} \times \left(\sum_{r \in R^T \cup R^P} (I_r - 1)\right)$ rows and $\sum_{r \in R^T \cup R^P} (I_r - 1)$ columns, $\sum_{r \in R^T \cup R^P} (I_r - 1)$ being the total number of first-stage decision variables x_{ri}. The matrices $\mathbf{H}_n$ are defined as follows:

$$\begin{aligned} &\mathbf{H}_1 = (-\mathbf{I}, \mathbf{I}, \mathbf{0}, \ldots \mathbf{0})^{\mathrm{T}}, \quad \mathbf{H}_2 = (\mathbf{0}, -\mathbf{I}, \mathbf{I}, \mathbf{0}, \ldots, \mathbf{0})^{\mathrm{T}}, \quad \mathbf{H}_3 = (\mathbf{0}, \mathbf{0}, -\mathbf{I}, \mathbf{I}, \ldots, \mathbf{0})^{\mathrm{T}}, \ldots, \quad \mathbf{H}_{\overline{N}-1} = (\mathbf{0}, \mathbf{0}, \ldots, \mathbf{0}, -\mathbf{I}, \mathbf{I})^{\mathrm{T}}, \\ &\mathbf{H}_{\overline{N}} = (\mathbf{I}, \mathbf{0}, \ldots, \mathbf{0}, \mathbf{0}, -\mathbf{I})^{\mathrm{T}} \end{aligned} \tag{30}$$

where $\mathbf{I}$ and $\mathbf{0}$ are the identity matrix and the zero matrix of size $\sum_{r \in R^T \cup R^P} (I_r - 1)$, respectively.

Define $\boldsymbol{\lambda}$ as an $\overline{N} \times (\sum_{r \in R^T \cup R^P} (I_r - 1))$-dimensional vector of Lagrangian multipliers associated with the non-anticipativity constraints shown in Eq. (29). The corresponding Lagrangian relaxation of the SAA problem is as follows:

[LR]

$$LR(\boldsymbol{\lambda}) = \min \sum_{n=1}^{\overline{N}} \left[\frac{1}{\overline{N}} \mathbf{c}^{\mathrm{T}} \mathbf{x}_n + \boldsymbol{\lambda}^{\mathrm{T}} \mathbf{H}_n \mathbf{x}_n + \frac{1}{\overline{N}} C(\mathbf{x}_n, \mathbf{q}_n) \right] \tag{31}$$

subject to the constraints (10), (11), (13)–(17) associated with the nth realization of the random parameters. Note that problem (31) is separable in scenarios. Each scenario n corresponds to a small-scale integer linear programming model that is easier to solve:

$$LR_n(\boldsymbol{\lambda}) = \min \frac{1}{\overline{N}} \mathbf{c}^{\mathrm{T}} \mathbf{x}_n + \lambda^{\mathrm{T}} \mathbf{H}_n \mathbf{x}_n + \frac{1}{\overline{N}} C(\mathbf{x}_n, \mathbf{q}_n) \tag{32}$$

subject to the constraints (10), (11), (13)–(17) associated with the nth vehicle transportation demand realization. The best lower bound for the SAA problem can be found by solving the Lagrangian dual model:

[LD]

$$LD = \max_{\boldsymbol{\lambda}} LR(\boldsymbol{\lambda}) \tag{33}$$

The Lagrangian dual model is a concave maximization problem with non-differentiable objective function $LR(\boldsymbol{\lambda})$. We use the subgradient method to solve the Lagrangian dual model. It is found that $\sum_{n=1}^{\overline{N}} \mathbf{H}_n \mathbf{x}_n^*$ is a subgradient of (33) where $\mathbf{x}_n^*$ is the optimal solution of the nth sub-problem. Therefore, the subgradient method based optimization iterative procedure is designed as follows:

Step 1: Set an initial value for the Lagrangian multiplier vector $\boldsymbol{\lambda}^{(1)}$ and define a step size sequence $\left\{s^{(k)} = \frac{1}{k}, k = 1, 2, \ldots, \infty\right\}$ that could ensure the global convergence of the subgradient method (Shore, 1985). Let the number of iterations $k = 1$.

Step 2: Solve the sub-problem (32) for each scenario with responding constraints and Lagrangian multiplier vector $\boldsymbol{\lambda}^{(k)}$, and then calculate the subgradient $\sum_{n=1}^{\overline{N}} \mathbf{H}_n \mathbf{x}_n^{*(k)}$.

Step 3: Update the Lagrangian multiplier vector using the subgradient information as follows:

$$\boldsymbol{\lambda}^{(k+1)} = \boldsymbol{\lambda}^{(k)} + s^{(k)} \sum_{n=1}^{\overline{N}} \mathbf{H}_n \mathbf{x}_n^{*(k)} \tag{34}$$

Step 4: If the following criterion is met, the algorithm ends.

$$|(LR(\boldsymbol{\lambda}^{(k+1)}) - LR(\boldsymbol{\lambda}^{(k)}))/LR(\boldsymbol{\lambda}^{(k)}))| \leqslant \varepsilon \tag{35}$$

where ε is a given tolerance. Otherwise, set $k = k + 1$ and go to Step 2.

It should be stressed that the automobiles delivery problem is a combination optimization problem. The optimal first-stage solution $\mathbf{x}_n^{*(k)}$ to each sub-problem in Step 2 may be different for different $n = 1, 2, \ldots, \overline{N}$. In the next sub-section, we use the average value of the first-stage solutions for each sub-problem as the solution for estimating an upper bound.

4.2. Sample average approximation

When the uncertain demand has a large number of scenarios, we use the above mentioned SAA method (see Kleywegt et al., 2001) to solve the model (9)–(17). The quality of the solution obtained from the SAA method, depending on the number of samples and the sample size, can be assessed by statistical analysis techniques. The method of sample average approximation is presented below:

Step 1: Generate M independent samples of size $\overline{N}$ and solve the corresponding SAA problem (18) using the abovementioned Dual decomposition and Lagrangian relaxation approach. Denote the optimal objective function value by $\hat{v}^m_{\overline{N}}$. We further represent by $\hat{\boldsymbol{X}}^m_n$ as the optimal solution to sub-problem $n = 1, 2, \ldots, \overline{N}$ in the model for sample $m = 1, \ldots, M$.

Step 2: Compute the average of all optimal objective function values from the SAA problem (18), $\bar{v}_{\overline{N},M}$ and its variance, $\sigma^2_{\bar{v}_{\overline{N},M}}$:

$$\bar{v}_{\overline{N},M} = \frac{1}{M}\sum_{m=1}^{M}\hat{v}^m_{\overline{N}} \tag{36}$$

$$\sigma^2_{\bar{v}_{\overline{N},M}} = \frac{1}{(M-1)M}\sum_{m=1}^{M}\left(\hat{v}^m_{\overline{N}} - \bar{v}_{\overline{N},M}\right)^2 \tag{37}$$

The average objective function value $\bar{v}_{\overline{N},M}$ is a point estimation of a lower bound on the optimal objective function value of the original problem (9)–(17) (Norkin et al., 1998; Mak et al., 1999).

Step 3: Calculate the average of the optimal solutions obtained in Step1, that is, let $\hat{\boldsymbol{X}} = \left[\frac{1}{M\overline{N}}\sum_{m=1}^{M}\sum_{n=1}^{\overline{N}}\hat{\mathbf{X}}^m_n\right]$, where $[\rho]$ represents the nearest integer to number ρ, and then compute the objective function value of the original problem using a reference sample of size $\hat{N}$ ($\hat{N}$ is much larger than $\overline{N}$) as

$$\hat{v}_{\hat{N}}(\hat{\boldsymbol{X}}) = \mathbf{c}^{\mathrm{T}}\hat{\boldsymbol{X}} + \frac{1}{\hat{N}}\sum_{n=1}^{\hat{N}}C(\hat{\boldsymbol{X}}, \mathbf{q}_n) \tag{38}$$

Note that the difference from the traditional SAA method is that we adopt the average of the optimal solutions obtained in Step 1, instead of arbitrarily choosing an optimal solution $\hat{\boldsymbol{X}}^m_n$ obtained in Step 1. As $\hat{\boldsymbol{X}}$ is a feasible solution, $\hat{v}_{\hat{N}}(\hat{\boldsymbol{X}})$ is an unbiased estimation of an upper bound on the optimal objective function value. The variance of $\hat{v}_{\hat{N}}(\hat{\boldsymbol{X}})$ can be estimated as follows:

$$\sigma^2_{\hat{v}_{\hat{N}}} = \frac{1}{\hat{N}(\hat{N}-1)}\sum_{n=1}^{\hat{N}}\left[\mathbf{c}^{\mathrm{T}}\hat{\boldsymbol{X}} + C(\hat{\boldsymbol{X}}, \mathbf{q}_n)\right] \tag{39}$$

Step 4: Estimate the gap between $\bar{v}_{\overline{N},M}$ and $\hat{v}_{\hat{N}}(\hat{\boldsymbol{X}})$ as well as its variance as follows:

$$gap_{\overline{N},M,\hat{N}}(\hat{\boldsymbol{X}}) = \hat{v}_{\hat{N}}(\hat{\boldsymbol{X}}) - \bar{v}_{\overline{N},M} \tag{40}$$

$$\sigma^2_{gap} = \sigma^2_{\hat{v}_{\hat{N}}} + \sigma^2_{\bar{v}_{\overline{N},M}} \tag{41}$$

The $1-\alpha$ confidence interval for the optimality gap can be calculated as

$$\hat{v}_{\hat{N}}(\hat{\boldsymbol{X}}) - \bar{v}_{\overline{N},M} + z_\alpha\left(\sigma^2_{\hat{v}_{\hat{N}}} + \sigma^2_{\bar{v}_{\overline{N},M}}\right)^{1/2} \tag{42}$$

with $z_\alpha = \sigma\phi^{-1}(1-\alpha)$, where $\phi^{-1}(z)$ is the cumulative distribution function of the standard normal distribution.

5. Case study

To assess the applicability of the proposed model and solution algorithm, we perform a case study based on the intermodal automobile delivery network of SAIC. The solution methods are coded in C++, calling CPLEX 12.5 to solve the mixed-integer linear programming formulations. The tests are run on a desktop computer with a CPU of Intel Core 2 Duo Processor 3 GHz and with 8 GB RAM under Microsoft Windows 2007.

Table 3
Railway and shipping routes.

Mode	ID	$\tilde{t}_{r,1}$	Max capacity E_r	Sequence of stations (ports)
Railway	T1	10	58	SH → ZZ → XY → DY
	T2	10	58	SH → WH → CQ → DY
	T3	16	58	SH → ZZ → XY → LZ1 → XJ
	T4	16	58	SH → WH
	T5	24	58	SH → WH → CQ
	T6	24	58	SH → ZZ → XY → LZ1
	T7	57	58	SH → BJ → SY
	T8	57	58	SH → DG
	T9	57	58	SH → ZZ → XY
	T10	57	58	SH → LZ2
	T11	84	58	SH → ZZ → YC
	T12	84	58	SH → ZZ → YT
	T13	84	58	SH → BJ
	T14	112	58	SH → ZZ → QD
	T15	112	58	SH → KM
	T16	112	58	SH → LZ2 → KM
	T17	112	58	SH → TJ
Shipping	S1	38	50	SH → TJ
	S2	38	50	SH → CQ
	S3	38	50	SH → DY
	S4	38	50	SH → DG
	S5	38	50	SH → YT
	S6	134	70	SH → TJ → BJ
	S7	134	70	SH → YT → QD
	S8	134	70	SH → DG → LZ2

Table 4
Alternatives of delivering automobiles from Shanghai VDC to Dongguan VSC.

Alternatives	Detail
1	Solely by road transportation
2	Road transportation to Shanghai railway station, rail transportation on route T8 to DG, and road transportation to DG VSC
3	Road transportation to Shanghai port, ship transportation on route S4 to DG, and road transportation to DG VSC
4	Road transportation to Shanghai port, ship transportation on route S8 to DG, and road transportation to DG VSC

Table 5
Unit transportation cost rate.

Mode	Distance of transportation	Cost rate (RMB/flatbed/km)
Road	⩽100 km	20
	(100-200] km	17
	(200-500] km	15
	(500-1000] km	13
	>1000 km	12
Rail	Any	11
Ship	Any	10

5.1. Model inputs

The automobile intermodal delivery network created from SAIC has a total of 7 VDCs and 11 VSCs as shown in Fig. 1. As aforementioned, automobiles may be delivered from one of the 7 VDCs to another VDC or a VSC. Since all automobiles are transported from Shanghai VDC, the train routes and ship routes all start from Shanghai. In detail, the network has 17 train routes and 8 ship routes, as shown in Table 3, Figs. 2 and 3. Note that in Table 3 we only report the departure time $\tilde{t}_{ri}$ from the first railway station (port), because all automobiles originate from Shanghai. In other words, the departure time from other stations (ports) does not affect the result. Note further that because Shanghai VDC is very close to Shanghai railway station and Shanghai port (less than 1 h by truck), we simply assume that the road transportation time from Shanghai VDC to Shanghai railway station or Shanghai port is 0.

In addition, we assume only one rail service along the same route in one week, as shown in Table 3. For the moment, the development of rail freight transportation is much slower than that of rail passenger transportation in China, which causes difficulties of transport automobiles by train such as the shortage of rail freight carriages, and unpredictable pricing regime.

Table 6
The mean value of delivery demand (flatbeds/week) to VDCs and VSCs.

VDC	SY	YT	QD	NJ	CQ	LZ2					
Mean demand	100	60	70	100	120	80					
VSC	XJ	BJ	TJ	YC	LZ1	XY	ZZ	DY	WH	KM	DG
Mean demand	50	220	135	60	80	80	90	100	150	120	110

Despite this, some manufacturers have to select railway transportation to deliver their automobiles directly to remote areas at low frequency because few road transportation carriers are willing to transport automobiles from VDCs to remote areas due to low profits and transportation safety.

Recently, the market-oriented reforms of rail freight industry are launched in China. Some measures which include adding more freight carriages to match transportation demand, transparent pricing and so on are being implemented. This brings a great deal of encouragement to the delivery of automotives by train. Hence, automobile manufacturers add more rail transportation routes for main VDCs and VSCs and expand previous transportation routes to visit more nodes. For example, the old direct route from SH to XJ is expanded into the new route T3 in Table 3, where SH, ZZ, XY, LZ1 and XJ are visited successively. The assumption that only one rail service along the same route in one week is reasonable based on the current actual situation. However, if there is more than one rail service along the same route in a week, we can simply model each service as an independent route and the proposed model is still applicable.

Table 3 indicates that there may be several alternatives to deliver automobiles from Shanghai VDC to a destination. For example, from Shanghai VDC to Dongguan VSC, four alternatives are possible, as shown in Table 4. Table 3 also demonstrates that the demand from some VDCs or VSCs is met only by road transportation. For example, Nanjing VDC has no shipping routes, and is too close to Shanghai VDC to use the complicated train transportation.

The unit weekly booking cost of one flatbed in trains or ships is confidential. SAIC recommends using the value of the distance multiplied by the unit transport cost as a substitute. SAIC suggests the unit transport costs shown in Table 5 for the models. The storage cost for each flatbed at railway stations or ports is 30 RMB/h.

The random automobile delivery demand from Shanghai VDC to another VDC or a VSC is assumed to follow a normal distribution. The mean value of the delivery demand is shown in Table 6, the sum of which is 1725 flatbeds/week. According to the suggestion of SAIC, the standard deviation of the delivery demand is considered as 30% of the mean value. It should be mentioned that the demand cannot be negative. Hence, we truncate the negative part of the normal distribution and its symmetrical positive part that corresponds to very large demand values. This means that, strictly speaking, the distribution is no longer normal, but a truncated normal distribution. Furthermore, we set stop tolerance $\varepsilon = 10^{-5}$ in the subgradient method, and the number of samples $M = 20$ and the reference sample size $\hat{N} = 1000$ in the SAA method.

It should be pointed out that this case study created from SAIC only considers automobiles delivery from Shanghai VDC to the 11 VSCs and the other 6 VDCs. Other instances with multiple origins are not examined in the case study. This is because we have only the data of Shanghai VDC (one origin) and are lack of the data of other VDCs. It may not be adequate to crate some hypothetical instances with multiple origins and destinations as the resultant results may not provide the useful insights. Nevertheless, the proposed models and methods are applicable to the most general problems with multiple origins and destination in practice.

5.2. Statistical analysis of solution quality

The statistical lower bound, upper bound, estimated gap and 95% confidence interval of the gap for different sample sizes are presented in Table 7. We compare the results of obtained from the SAA problem to those obtained from the expected value problem (EVP), that is, the solution to the problem where the uncertain vehicle transportation demands are replaced by their expected value. Table 7 also gives the upper bound provided by the EEV (see Birge and Louveaux, 1997), the expected value of the EVP solution, by finding the expected value of implementing the EVP first-stage solution for a large number of different scenarios of vehicle transportation demand. From Table 7, we can see that the confidence interval of the optimality gap is getting narrower as the sample size increases. Specially, we also note that the feasible solution from

Table 7
Statistical analysis of solution quality based on $M = 20$ and $\hat{N} = 1000$.

$\overline{N}$	Lower bound ($\times 10^5$)		Upper bound ($\times 10^5$)		Estimated gap ($\times 10^5$)		95% confidence interval ($\times 10^5$)		
	Average	σ_{LB}	Average	σ_{UB}	Average	σ_{gap}	Min	Max	Interval
20	283.853	0.747	286.020	0.414	2.167	0.854	0.493	3.841	3.348
40	283.306	0.562	285.302	0.429	1.996	0.707	0.610	3.381	2.771
60	283.588	0.456	284.534	0.418	0.946	0.619	−0.267	2.159	1.892
EEV			287.475	0.397					

Table 8
The ordering capacity on each route.

ID	Ordering capacity of trains or ships (SAA)	ID	Ordering capacity of trains or ships (EVP)
T1	SH 8 ZZ 6 XY 0 DY	T1	SH 0 ZZ 0 XY 0 DY
T2	SH 34 WH 0 CQ 0 DY	T2	SH 42 WH 0 CQ 0 DY
T3	SH 54 ZZ 52 XY 41 LZ1 41 XJ	T3	SH 58 ZZ 58 XY 50 LZ1 50 XJ
T4	SH 55 WH	T4	SH 58 WH
T5	SH 39 WH 0 CQ	T5	SH 50 WH 0 CQ
T6	SH 12 ZZ 10 XY 0 LZ1	T6	SH 10 ZZ 10 XY 0 LZ1
T7	SH 0 BJ 0 SY	T7	SH 0 BJ 0 SY
T8	SH 0 DG	T8	SH 0 DG
T9	SH 35 ZZ 32 XY	T9	SH 42 ZZ 42 XY
T10	SH 5 LZ2	T10	SH 0 LZ2
T11	SH 29 ZZ 0 YC	T11	SH 26 ZZ 0 YC
T12	SH 33 ZZ 0 YT	T12	SH 58 ZZ 0 YT
T13	SH 0 BJ	T13	SH 0 BJ
T14	SH 16 ZZ 0 QD	T14	SH 6 ZZ 0 QD
T15	SH 0 KM	T15	SH 0 KM
T16	SH 44 LZ2 0 KM	T16	SH 58 LZ2 0 KM
T17	SH 0 TJ	T17	SH 0 TJ
S1	SH 50 TJ	S1	SH 50 TJ
S2	SH 0 CQ	S2	SH 0 CQ
S3	SH 0 DY	S3	SH 0 DY
S4	SH 49 DG	S4	SH 50 DG
S5	SH 47 YT	S5	SH 50 YT
S6	SH 70 TJ 70 BJ	S6	SH 70 TJ 70 BJ
S7	SH 67 YT 55 QD	S7	SH 70 YT 60 QD
S8	SH 68 DG 12 LZ2	S8	SH 70 DG 10 LZ2

Table 9
The comparison between two-stage solutions obtained by different methods.

Method	Mode	The first-stage solution	The average of the second-stage solutions (the sample size $\hat{N} = 1000$)
SAA	Train	364	356
	Ship	351	341
	Truck		1020
EVP	Train	408	391
	Ship	360	346
	Truck		987

Table 10
Delivery pattern from Shanghai VDC to Liuzhou VDC.

Day	Batch	Route	Number of flatbeds
3	1	T10	6
5	6	T16	5
5	7	T16	21
5	8	T16	21
5	9	S8	11
3	1	Road	1
3	3	Road	6

the SAA method gives the upper bound based on sample sizes $\overline{N} = 60$ and $\hat{N} = 1000$ which is lower than the upper bound from the EEV. This shows the superiority of the SAA approach over the conventional deterministic method solving the EVP.

5.3. Solution properties

The above mentioned model includes two types of decision variables that are the booked capacity of trains and ships, and the flow on each feasible route from different transportation modes. We first take a look at the booked capacity. Table 8 shows the ordering capacity on each route from the SAA solution and the EVP solution. The sum of the ordering capacity from trains and those from ships are presented in Table 9. We find that in the EVP the total ordering capacities of both trains and ships are higher than those from the SAA method, however, with the increase of the sample size, the minimal transportation cost obtained by the SAA is always lower than that obtained by the EVP, which is showed in Table 7. The results shown in Tables 7–9 reflect that more ordering capacity does not always cause lower transportation costs. This indicates that, in the

EVP, the choice of the routes might not be optimal and the booked capacity of trains and ships is not the most reasonable. Though the number of flatbeds transported by road is high in the SAA problem, as shown in the last column in Table 9, the optimal combination of transportation modes of road, railway and shipping, as well as the reasonable ordering capacity of trains and ships result in the minimal total transportation cost. Note that the average of second-stage solutions in Table 9 is obtained during computing the upper bound of the optimal objective function value of the SAA problem and of the EVP, respectively.

The results in Table 8 also provide a number of managerial insights. First, we can see that the ordering capacity from the train routes T7, T8, T13, T15 and T17 are all zero, which means that these train routes are not the optimal railway transportation routes. Therefore, the automobile manufacturer may give up these routes and use other cost-effective train routes instead. For the same reason, the ship routes S2 and S3 may also be canceled. Second, we can find that the maximum capacity of some routes such as T3, T4, S1, S4, S5, S6 and S7, is almost completely ordered. Such routes have high potential in reducing the delivery cost of automobiles, and railway transportation companies (shipping companies) should consider enhancing the capacity of trains (ships) on these routes.

Finally, let us examine the impact of the schedules of train and ship routes on the delivery of automobiles, that is, the flow on each feasible route using different transportation mode, which is also significant for the automobile manufacturer to save transportation cost in practice. In a certain week, the number of flatbeds to be delivered from Shanghai VDC to Liuzhou VDC (LZ2) is 71, and the delivery pattern based on the ordering capacity of trains and ships obtained by the SAA problem is shown in Table 10. The result can be explained as follows: the first batch on day 3 leaves Shanghai VDC at time 56 (h), and therefore can catch the train on T10, which leaves Shanghai station at time 57. However, due to the limitation of the ordering capacity of T10, not more than 6 flatbeds can be transported by T10. Therefore, the most cost-effective transportation mode for the remaining one flatbed from the first batch is trucking. The 3rd batch on the same day cannot catch this train and are also transported by truck. The 6th, 7th and 8th batches on day 5 can catch the train on T16 (leaving Shanghai railway station at time 112); however, the 9th batch on day 5 leaves Shanghai VDC at time 113, and hence this batch can only catch the ship on S8, which leaves Shanghai port at time 134. This example clearly shows how the delivery of automobiles is scheduled.

6. Conclusions and future work

This study has addressed a practical carrying capacity procurement problem with uncertain delivery demand arising in the automobile industry. A two-stage stochastic programming model has been formulated for the problem. Furthermore, in the light of the characteristics of combinatory of the proposed problem, the model is solved by an improved sample average approximation method in combination with dual decomposition and Lagrangian relaxation approach. We apply the model and solution method to a case study from SAIC. Comparing the results from the SAA problem and corresponding expected value problem, we see that the first-stage ordering capacity obtained from the SAA problem results in lower transportation cost than the solution of the EVP, which shows that the SAA method is better than the EVP method for this kind of problem. The case studies not only demonstrate that the model could help automobile manufacturers to determine the optimal ordering capacity of trains and ships, but also provide a number of useful management insights for automobile manufacturers. We believe that this study deals with an emerging new research topic with practical significance for the automobile industry.

With the constant improvement of railway/water transportation infrastructure in China, transportation resources like trains/ships in automobile intermodal network will be more effectively utilized, that is, different automobile manufacturers in China are considering to implement convective transportation from their own VDCs/VSCs to other automobile manufactures' VDCs/VSCs because some of their VDCs/VSCs locate in the same city with geographic advantages. Hence, how to implement convective transportation effectively in the different automobile manufacturers is an important tactical decision problem for further research. In addition, the automobile manufacturers may build new VSCs to serve new customers or better serve existing customers. The design of the location and size of the new VSCs is a strategic-level problem because a VSC may operate for 20–30 years. When making such strategic decisions, the setup cost of the VSCs and the delivery cost of automobiles should be examined in a holistic model. Furthermore, in order to faster respond to customer demand, some manufacturers will transport more automobile products to their VSCs than the known customer demand, which means that their VSCs become the warehouses with the function of adjusting inventory. Therefore, how to move automobile products to supplement VSC's inventory among different VSCs is a complex operation problem. These provide interesting future research opportunities.

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