

Collaborative supply chain network design under demand uncertainty: A robust optimization approach

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ABSTRACT

This paper studies a collaborative robust supply chain network design (CRSCND) problem aimed at maximizing economic and social benefits by enabling enterprises to jointly address demand uncertainties. Through strategies including joint inventory replenishment, shared distribution centers (DCs), and pooled transportation resources, the CRSCND problem seeks to optimize plant and DC locations and the allocation of DCs to customers under a collaborative framework. To address this, we develop two robust optimization models incorporating a budget uncertainty set, each model representing a distinct risk-pooling policy. These models are then reformulated into solvable linear programming structures. Results from numerical experiments confirm the cost-reduction benefits of collaboration and robust optimization. Sensitivity analysis reveals that factors like violated probability and high demand volatility minimally impact cost savings enabled by collaboration and robustness. Moreover, each robust model shows distinct suitability depending on specific scenario parameters. Finally, we test three cost-saving allocation mechanisms, finding that only the Shapley value method yields best allocations in cases involving overlapping demand.

1. Introduction

As a popular and enduring topic in supply chain management, supply chain collaboration has received sustained attention and been introduced in many planning problems (Marty and Ruel, 2024). Facing with the various uncertainties and challenges of the modern business environment, collaboration provides an effective method to allow enterprises to surmount these complex problems together, and consequently vie for an enhanced competitiveness. Inspired by this concept, many substantial studies are proposed in different fields, like liner shipping and last-mile delivery (Ergun et al., 2007; Zhang et al., 2022a). In this environment, this research proposes the collaborative robust supply chain network design (CRSCND) problem to improve the efficiency of supply chain.

This research is partially motivated by a development case of supply chain in the western regions of China. Affected by the rapid development of economy and technology, especially the advent of sharing

economy, e-commerce platforms are becoming a major driver of local economic development. Influenced by this circumstance, the demand for agricultural products of the western regions is growing rapidly in the developed regions. In contrast, the less developed and even non-existent supply chain infrastructure in western China makes the transportation of agricultural products expensive and fragile. Particularly, in the presence of promotions, bad weather and other unforeseen events, the fragile supply chain cannot cope with the huge uncertainty of demand. This drives enterprises to build the supply chain network together to meet the growing and uncertain market demand. Another motivating example is the growing cold chain for medicine that requires cold trucks and storage facilities. To overcome the challenges of huge investment and demand uncertainty, Jing-Dong logistics, Derui Medicine, Wanmei Medicine and other enterprises carried out the “cloud cold chain” collaborative program. This program aims to reconfigure the supply chain network by multiple enterprises together

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based on existing infrastructure resources to obtain an efficient and robust network and scale up in the service area.

Collaboration provides a framework that allows multiple enterprises to share their resources such as distribution centers and transportation resources, breaking the capacity limitation of any single enterprise. Through joint designing and constructing a supply chain network, the collaboration model can benefit all stages of the supply chain and effectively mitigate the effects of uncertainty. To enable these benefits, many studies are proposed to investigate the supply chain collaboration (Marty and Ruel, 2024). In the research of supply chain network design (SCND), Hacadiaux and Tancrez (2020) introduced the horizontal collaboration to reduce the carbon emission. Being focused on the environmental benefits, they ignored the joint replenishment of inventory and the impacts of collaboration on the construction of distribution centers. In addition, their model did not consider the negative effects of worse-case scenarios on the supply chain. Another stream of research considering collaboration is the studies introducing the fourth-party logistics (4PL) mode to integrate the logistics resources (Huang et al., 2021; Wang et al., 2022a; Jiang et al., 2024). These papers focused on the collaboration of logistics providers to optimize the network structure and logistics costs. Unlike these studies, Zhang et al. (2023) conducts a thorough and comprehensive analysis of collaborative benefits in SCND, but it assumes that the mean and variance of demand are known.

In this study, the work by Zhang et al. (2023) is extended to the case with demands bounded by an uncertainty set, and the robust optimization framework is utilized to design the collaborative supply chain network that allows multiple enterprises to share the same distribution network to address the risk of demand uncertainty. In this framework, enterprises will collaborate in both strategic and tactical planning decisions, specifically including the sharing of distribution centers, joint inventory replenishment of products from multiple enterprises and the integration of transportation resources. Such collaboration can achieve advantages in efficiency and costs. In efficiency, collaborative design can improve the utilization of distribution centers and transportation resources. In costs, the fixed construction cost is optimized and allocated among enterprises, and the total inventory cost is reduced. Moreover, collaborative design can pool the risk of demand uncertainty of multiple products, which enhances the resilience of supply chain and mitigates effects of demand uncertainty on transportation. Under a reasonable allocation mechanism, the collaboration framework will greatly benefit any enterprise who otherwise needs to design a distribution network on their own with conservatism yet is limited in resources.

Based on these motivations and advantages, our research tries to answer a series of questions about collaborative design of robust supply chain network (SCN):

1. How much benefit can collaborative robust optimization bring to the enterprises?
2. What are the components of the collaboration benefits?
3. What role does robust optimization play in collaborative network design?
4. Can simple allocation mechanisms ensure the stability of the collaboration?

In CRSCND, the interplay of demand uncertainty and collaboration will drastically increase its modeling and computational complexity. First, the integration of strategic decisions including facility location and transportation lines and the tactical decisions including inventory control and resource assignment increases the modeling complexity of the problem. Second, not knowing the probability distribution of the demand leads to the inability to estimate inventory and transportation costs, resulting in a nonlinear mathematical formulation of the model. Third, because the products from different distribution centers and different enterprises are not substitutable, the impact of demand uncertainty on the supply chain cannot be centralized by pooling the risk for

the entire supply chain. Finally, collaborative design of SCN involves more alternative facilities than a single-enterprise model, making the problem size grow geometrically with the number of enterprises. Therefore, the CRSCND problem will be more complex than the traditional robust supply chain network design problem.

This research has the following major contributions:

1. A collaborative robust supply chain network design (CRSCND) problem is defined and formulated as a nominal mathematical model. Through converting its nonlinear terms, a nominal linear mixed-integer programming model is established.
2. The robust optimization method using the budget uncertainty set is applied to deal with the demand uncertainty. Based on different risk-pooling strategies, two robust models are formulated to solve the CRSCND problem.
3. The advantages of collaboration and using robust optimization in designing robust supply chain network are analyzed and verified. The suitable situations of the two robust models are investigated.
4. Three allocation mechanisms are tested to explore the impact of allocation of cost savings on the collaboration incentive of the enterprises.

The remainder of this paper is organized as follows. In Section 2, we review the literature related to this paper. In Section 3, CRSCND is defined. A nominal mathematical model and two robust counterparts are formulated. In Section 4, numerical experiments are conducted, including analysis of the advantages of collaboration, analysis of the robustness, sensitivity analysis experiments, comparison of two robust models, and comparison of three cost saving allocation mechanisms. In Section 5, the managerial insights and practical implications are given. Section 6 concludes this paper.

2. Literature review

This research investigates the collaborative design of robust supply chain networks from the multi-enterprise perspective. There are two literature streams related to this study: (1) the studies integrating inventory control into network design (i.e., the location-inventory problem in SCN research), (2) the SCND problem considering collaboration. Considering the abundance of studies in these domains, this section surveys only the most relevant and the latest research and highlights the research gaps. Readers interested in location-inventory problem (LIP) in SCN can refer to Farahani et al. (2015). Regarding the SCND research considering uncertainty and resilience, readers are referred to Govindan et al. (2017) and Aldrighetti et al. (2021).

2.1. Supply chain network design considering inventory control

Integrating inventory control into the design process of SCN can obtain the benefits of centralized optimization and efficiently reduce the redundancies between different echelons of a supply chain. In this research stream, Daskin et al. (2002) and Shen et al. (2003) are among the first who jointly determine the facility location and inventory control to improve the network performance. Further, Shu et al. (2005) and Atamtürk et al. (2012) extended the solution algorithm and formulation approach for applying to more scenarios. Using the location-inventory model with risk-pooling strategy, these studies verify the advantages of joint optimization of facility location and inventory control decisions. Our study extends this model to the collaborative design of robust SCN considering the joint replenishment of inventory.

Regarding the LIP research, many interesting variants have been proposed and applied to various scenarios in recent years. To investigate the effects of capacity limitation on network structure, Ozsen et al. (2008), Keskin and Üster (2012), Dai et al. (2018) and Jiu et al. (2024) extended the LIP problem to consider the capacity limitation on

distribution centers. Puga and Tancrez (2017) considered the feature of vehicle capacity. The works of Amiri-Aref et al. (2018) and Wang et al. (2020) considered the multi-source and green LIP problem, respectively. Rekabi et al. (2022, 2023, 2024) introduced the design of sustainable SCN for medicine and blood supply. Shahabi et al. (2014) proposed the location-inventory problem with correlated demand. Fathi et al. (2021) considered the case where both customer demand and the replenishment lead time are stochastic. Straubert (2024) focused on exactly solving the “inventory” part. For the potential disruption risk in the supply chain, Saha et al. (2020) and Zhu and Cao (2021) introduced the substitute products and recovery-fund based strategies to solve the LIP problem, respectively. Li et al. (2021, 2023) considered the LIP model on (dis-)economies of scale, and given an inverse S-shaped function to capture the facility cost. Qi et al. (2023) and Jin et al. (2024) proposed the applied LIP model in electric-vehicle battery swapping service and drone-supported humanitarian logistics. Despite that these studies extend LIP research from different perspectives, they all ignore the joint replenishment and management of multi-item inventory. The works of Wang et al. (2022b) and Wang et al. (2023) introduced the joint replenishment policy in their LIP model, which is similar to our research. However, their studies assumed that each retailer sells only one product, with the mean and variance of its demand being known. Their models also ignored the integration of transportation resources in the product transportation from distribution center to retailer.

In the research of closed-loop SCND, there are also some studies considering the joint optimization of location and inventory decisions such as Zhang et al. (2014b), Zhang and Unnikrishnan (2016) and Li et al. (2018). They proposed the LIP variants in closed-loop supply chain from the perspectives of capacitated facility, coordinated inventory management and third-party logistics, respectively. Different from these studies, Guo et al. (2020) conducted a variant that applied to multi-product scenario. Summarizing these research, they all focused on the product returns and improving the performance of the closed-loop supply chain system.

In some research studies, the routing decisions are integrated into the LIP problem to further optimize the network structure of supply chain (Zheng et al., 2019). Ahmadi-Javid and Azad (2010) proposed an integrated model of three-level decisions without any approximation to investigate the advantages of simultaneously optimizing location, inventory and routing decisions. Zhang et al. (2014a) consider the multi-period location-inventory-routing problem. Zhalechian et al. (2016), Liu et al. (2021) and Abbasian et al. (2023) extended the location-inventory-routing model to the sustainable supply chain version. For the applications in special fields, Shang et al. (2022) and Wang and Nie (2023) conducted the research on the emergency supplies and healthcare supply chain, respectively. Like the LIP research, the studies of location-inventory-routing problem focus more on reducing the redundancies among different echelons of a supply chain to improve the performance of supply chain.

2.2. Supply chain network design considering collaboration

Collaboration, as an important topic in supply chain management (Marty and Ruel, 2024), is applied in various planning problems of supply chain, including liner shipping industry and supply chain logistics (Agarwal and Ergun, 2010; Zhang et al., 2022a). In the research of SCND, Hacardiaux and Tancrez (2020) considered the collaboration of multiple companies working at the same level of a supply chain to reduce the carbon emissions. As in our research, horizontal collaboration is considered in their study, but the authors ignored the joint replenishment of multi-product inventory. Their model is not applicable to the design of robust SCN where distribution information of demand is unknown. Another research stream regarding collaboration is the fourth-party logistics (4PL) supply chain network design, which provides a framework to address the collaboration of logistics providers. The 4PL model is introduced by Accenture in 1998 (Gattorna, 1998), in

which the transportation resources, facility and technology of multiple logistics providers are integrated (Huang et al., 2021).

In the 4PL research, the logistics provider is simultaneously determined with facilities. Yin et al. (2021) investigated the design of 4PL supply chain network under demand uncertainty. Later, this work was extended to the uncertain environment (Yin et al., 2022). Jiang et al. (2024) formulated a chance-constrained stochastic programming model to cope with the effects of demand surge. Huang et al. (2021) and Wang et al. (2021) investigated the advantages of 4PL considering the psychological behavior. Zhang et al. (2022b), Yin et al. (2024) and Zhang et al. (2024) examined the multi-period 4PL network design. The limitation of these 4PL studies is that they all ignored the inventory control. In the work of Wang et al. (2022a), the inventory is jointly optimized with the location and 4PL provider. However, they only considered one item and joint replenishment was not implemented. From the viewpoint of collaboration, these existing studies of 4PL focused more on the integration of logistics providers, i.e. the collaboration occurred only on the transportation part. Different from the studies above, our research considers pooling and integrating of all resources of supply chain.

2.3. Research gap

Table 1 gives a summary of related and recent studies in terms of the basic model and some important characteristics. It is obvious from the summarized results that only the works of Hacardiaux and Tancrez (2020) and Wang et al. (2022a) introduced the collaboration in the LIP research. Wang et al. (2022a) focused on the collaboration of logistics providers. Hacardiaux and Tancrez (2020) assessed the environmental benefits of multi-company collaboration in designing the SCN. It is noticeable that there is no LIP research simultaneously considering the collaboration in inventory replenishment, transportation and facilitation location. Another important gap in the literature of collaborative LIP research is the ignorance of scenarios where the distribution information of uncertain parameters is unknown. In this regard, to the best of our knowledge, only Jiu et al. (2024) and Jin et al. (2024) applied the robust optimization in the LIP model without collaboration. In this research, we aim to fill the gaps found in the literature and investigate the benefits of collaborative robust SCN in inventory management, transportation and opening costs. Fig. 1 illustrates the research methodology and describes the steps employed in the research process. In Step 4, two robust programming models are formulated for the CRSCND problem.

The key contributions of our research to the literature can be summarized as follows:

- Collaboration in both strategic and tactical planning is considered, including the joint replenishment, integration of transportation sources and facilities.
- Robust optimization method is applied to solve the location-inventory model under multi-enterprise collaboration.
- A mathematical formulation for the collaborative robust supply chain network design is developed.

3. Collaborative robust supply chain network design

This section gives the formal definition of collaborative robust supply chain network design (CRSCND) problem. The nominal mathematical model is formulated for CRSCND, and then two robust models are proposed.

Table 1
Review of related and recent studies.

Reference	Inventory control	Item	JR	JT	Type of collaboration	Robust optimization
Ozsen et al. (2008)	Y	Single	N	N	–	N
Keskin and İster (2012)	Y	Single	N	N	–	N
Shahabi et al. (2014)	Y	Single	N	N	–	N
Puga and Tancrez (2017)	Y	Single	N	N	–	N
Dai et al. (2018)	Y	Multi	N	N	–	N
Amiri-Aref et al. (2018)	Y	Single	N	N	–	N
Wang et al. (2020)	Y	Single	N	N	–	N
Saha et al. (2020)	Y	Multi	N	N	–	N
Fathi et al. (2021)	Y	Single	N	N	–	N
Zhu and Cao (2021)	Y	Single	N	N	–	N
Li et al. (2021)	Y	Single	N	N	–	N
Wang et al. (2022b)	Y	Multi	Y	N	–	N
Li et al. (2023)	Y	Single	N	N	–	N
Qi et al. (2023)	Y	Single	N	N	–	N
Wang et al. (2023)	Y	Multi	Y	N	–	N
Jiu et al. (2024)	Y	Multi	N	N	–	Y
Straubert (2024)	Y	Single	N	N	–	N
Jin et al. (2024)	Y	Single	N	N	–	Y
Hacardiaux and Tancrez (2020)	Y	Multi	N	Y	Whole supply chain	N
Yin et al. (2021)	N	Single	N	N	Logistics	N
Wang et al. (2021)	N	Single	N	N	Logistics	N
Huang et al. (2021)	N	Single	N	N	Logistics	N
Yin et al. (2022)	N	Single	N	N	Logistics	N
Zhang et al. (2022b)	N	Single	N	N	Logistics	N
Wang et al. (2022a)	Y	Single	N	N	Logistics	N
Yin et al. (2024)	N	Single	N	N	Logistics	N
Zhang et al. (2024)	N	Single	N	N	Logistics	N
This work	Y	Multi	Y	Y	Whole supply chain	Y

The JR and JT denote joint inventory replenishment and joint opening of transportation lines, respectively.

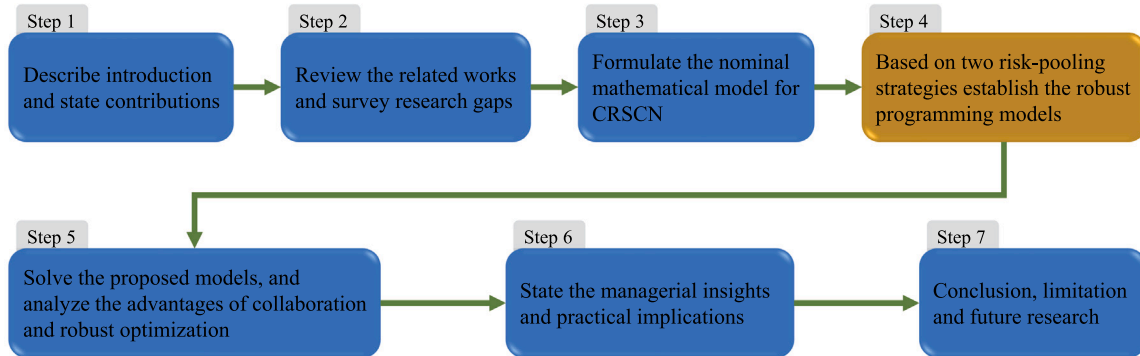


Fig. 1. Research methodology.

3.1. Problem description

Suppose there are multiple enterprises that produce different products, and the products are not substitutable. Let K denote the set of enterprises and $k \in K$ represent the enterprise and its product without causing ambiguity, unless otherwise specified. Each enterprise k has its own candidate plants, denoted by P_k . Candidate plants can only produce the specific product, and different enterprises do not share the candidate plants. The products produced at plants are delivered to customers through the distribution center (DC). DCs can be shared and jointly planned by multiple enterprises. If shared, the inventory of all products at a DC will be replenished aggregately. Let V_D denote the set of candidate DCs. The customer demand for each product is uncertain with limited available information. More specifically, assume only the nominal value of the demand and its deviation are known, but the probability distribution is not. The goal of each enterprise is to obtain a robust network structure, which has good performance at any cases such that the construction cost is minimized.

In this scenario, the enterprises have two options for designing the robust supply chain network. One is to design the supply chain network independently. Another is that the enterprises form an alliance

to pool their resources and integrate the supply chain network. Collaborative design of robust supply chain network, being the second option, will have many advantages. First, through sharing the distribution centers and transportation lines, each enterprise is only responsible for a portion of the cost of opening these facilities. Second, in the shared distribution centers, the inventory of all products is aggregately replenished, which can effectively reduce the total ordering cost. Third, pooling the demand uncertainty risk of all products can efficiently lower the effect of demand fluctuation and decrease the total cost of robust SCND.

Fig. 2 gives an illustrative example of the collaborative robust supply chain network involving two enterprises. As shown in Fig. 2a, two enterprises producing different products, A and B, both have two candidate plants. There are five candidate DCs and three customers who have the demand for two products. The nominal value and deviation of customer demand for each product are known. We need to determine the network configuration fulfilling the distribution tasks for enterprises. When enterprises design their network individually, Fig. 2b shows the result. It can be found that each enterprise opens the DCs according to its own interests. To meet the demand of the customers, enterprises also open the transportation lines independently. In contrast

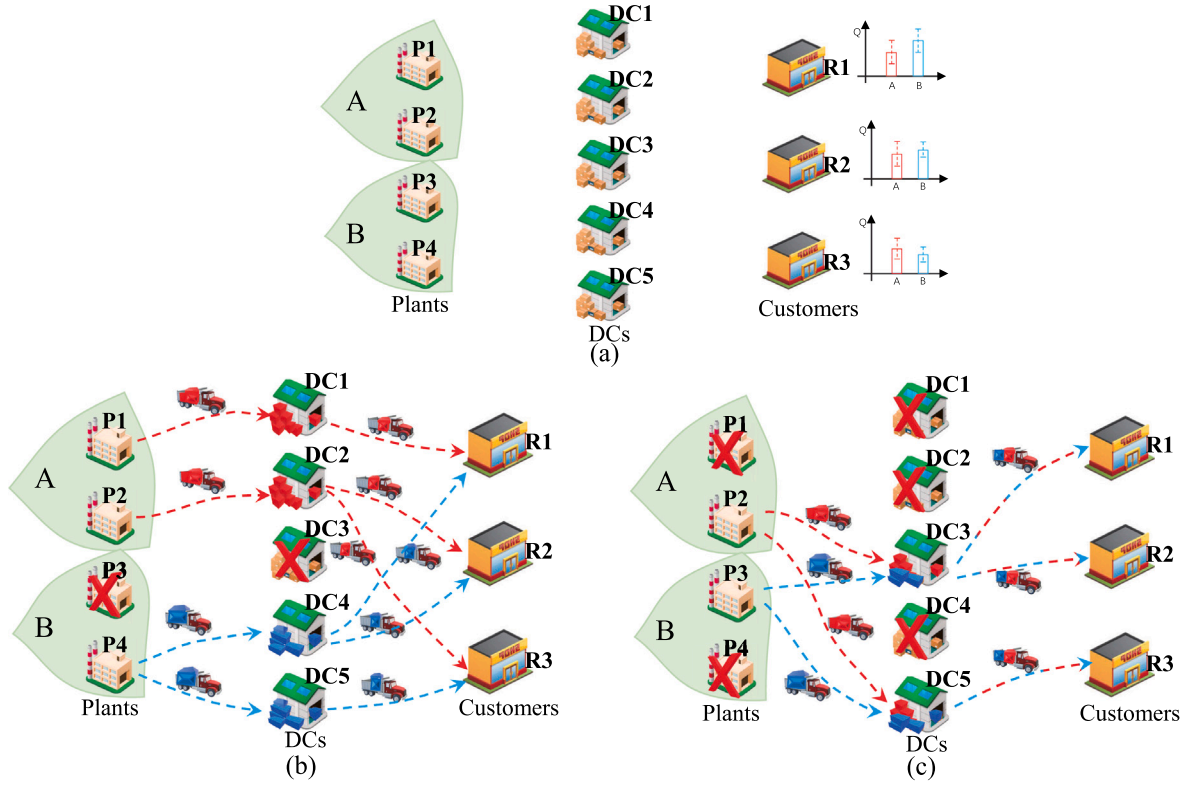


Fig. 2. Example of collaborative robust supply chain network.

to the non-collaborative case, Fig. 2c gives the collaborative design of robust supply chain network where enterprises jointly determine the location of DCs and open the transportation lines for integrating their network. Through sharing DCs and unified inventory control, enterprises can improve the utilization of DCs and reduce the cost. Because demand for different products is met by unified scheduling in integrated network, the impact of demand uncertainty on transportation cost is reduced. Consequently, comparing with the non-collaborative case, the collaborative design of robust SCN is beneficial for enterprises.

Formally, we can define the collaborative robust supply chain network design (CRSCND) problem as follows. Under the demand uncertainty, $|K|$ enterprises form the alliance to jointly design a three-echelon robust supply chain network. Through sharing the distribution centers and transportation lines, aggregately replenishing the inventory of all products, the enterprises will jointly determine the location of plants and DCs, the assignment of DCs to plants, and customers to DCs to minimize the total costs.

In this research, we adopt the following assumptions:

- Each enterprise produces only one kind of product.
- The sets of candidate plants of different enterprises do not overlap.
- DCs can provide transshipment service for all products, and each DC can only be sourced from one plant for any product.
- The customer demands are multi-product and uncertain.
- The distribution information of demand is unknown, and we only know its nominal value and maximum deviation.
- The demand of each customer can only be supplied by one DC.
- Opening any plant, DC, and transportation line will incur a fixed cost.
- The transportation cost per unit shipment, both from plants to DCs and from DCs to customers, is proportional to the Euclidean distance.
- The (T, S) policy is applied to manage the inventory at DCs.

Table 2

Indices (sets).

k	Index of enterprises, $k \in K = \{1, 2, \dots, \bar{k}\}$
i	Index of candidate plants, $i \in P = \bigcup_{k \in K} P_k = \{1, 2, \dots, \bar{i}\}$
j	Index of candidate DCs, $j \in V_D = \{1, 2, \dots, \bar{j}\}$
r	Index of customers, $r \in V_R = \{1, 2, \dots, \bar{r}\}$
v	Index of candidate review intervals, $v \in V = \{5, 10, 15\}$

3.2. Nominal formulation

The indices (sets), parameters and decision variables used in this study are given in Tables 2–4, respectively.

Using these sets, parameters and decision variables, we formulate the nominal mathematical model of the CRSCND problem. In this research, the inventory cost, opening cost of facilities and transportation cost are included in the objective function. The inventory cost, including ordering cost and holding cost, can be formulated as

$$IC = \sum_{j \in V_D} \frac{f_j}{T_j} + \sum_{j \in V_D} \sum_{r \in V_R} \sum_{k \in K} h_j \frac{\mu_r^k w_{jr} T_j}{2} \quad (1)$$

Since $T_j = \sum_{v \in V} v s_{jv}$, we can rewrite the inventory cost as follows.

$$IC = \sum_{j \in V_D} \sum_{v \in V} \frac{f_j}{v} s_{jv} + \sum_{j \in V_D} \sum_{r \in V_R} \sum_{k \in K} \sum_{v \in V} \frac{\mu_r^k v}{2} h_j w_{jr} s_{jv} \quad (2)$$

The opening cost of facilities consists of the fixed cost and variable cost. When the plants, DCs and transportation lines are located, the fixed cost occurs. The variable cost is only incurred at opened DCs. We formulate the fixed cost as:

$$FC = \sum_{k \in K} \sum_{i \in P_k} F_i^p x_i + \sum_{j \in V_D} F_j^D y_j + \sum_{k \in K} \sum_{i \in P_k} \sum_{j \in V_D} F_{ij}^b z_{ij} + \sum_{j \in V_D} \sum_{r \in V_R} F_{jr}^c w_{jr} \quad (3)$$

where the first two terms are the cost of opening plants and DCs, respectively. The last two terms are the opening cost of transportation

Table 3
Parameters.

Parameters	Value for experiments	Unit
μ_0	The base nominal value of customer demand.	10
f_p	The base fixed cost of locating plants.	50
f_d	The base cost of locating DCs.	2
f_0	The base ordering cost of DCs.	10
h_0	The base holding cost at DCs.	3
b_0	The base cost of opening transportation lines from plant to DC.	10
c_0	The base cost of opening transportation lines from DC to customer.	10
r_k	Mark whether customer $r \in V_R$ requests the product $k \in K$	1 indicates customer requests product k , and 0 otherwise.
μ_r^k	Nominal value of customer r 's demand for product k	$\mu_0 U[1, 5]$
$\hat{\mu}_r^k$	Maximum deviation of customer r 's demand for product k	$\min\{\mu_r^k, U[4, 10]\}$
$\bar{\mu}$	The average nominal value of all products demands	$\sum_{k \in K} \sum_{r \in V_R} \mu_r^k / V_D $
$\bar{\mu}_k$	The average nominal value of product k 's demands	$\sum_{r \in V_R} \mu_r^k / P_k $
b_{ij}	The unit cost of transportation between node $i \in P_k$ and node $j \in V_D$, where $k \in K$.	Euclidean distance between two points
c_{jr}	The unit cost of transportation between node $j \in V_D$ and node $r \in V_R$.	Euclidean distance between two points
$\bar{c}$	The average value of all c_{jr} .	$\frac{\sum_{j \in V_D} \sum_{r \in V_R} c_{jr}}{ V_D V_R }$
F_i^p	The fixed cost of opening a plant facility $i \in P_k$, where $k \in K$.	$f_p \bar{\mu}_k (1 + U[-0.5, 0.5])$
F_j^d	The fixed cost of opening a DC facility $j \in V_D$.	$2f_d \bar{\mu} (1 + U[-0.5, 0.5])$
F_j^q	Cost per unit storage capacity of the DC at location j .	$f_d (1 + U[-0.5, 0.5])$
F_{ij}^b	The fixed cost of opening a transportation line from plant $i \in P_k$ to DC $j \in V_D$.	$b_0 \bar{\mu} b_{ij} (1 + U[-0.5, 0.5]) / K $
F_{jr}^c	The fixed cost of opening a transportation line from DC $j \in V_D$ to customer $r \in V_R$.	$c_0 \mu_0 c_{jr} (1 + U[-0.5, 0.5])$
f_j	The fixed cost of placing an order at DC $j \in V_D$.	$f_0 \bar{c} \bar{\mu} (1 + U[-0.5, 0.5])$
h_j	The inventory holding cost per unit per unit time at DC $j \in V_D$.	$h_0 (1 + U[-0.5, 0.5])$

Table 4
Decision variables.

Binary variables:	
x_i	1 if plant $i \in P_k$ is opened, otherwise 0, where $k \in K$.
y_j	1 if DC $j \in V_D$ is opened, otherwise 0.
z_{ij}	1 if the DC $j \in V_D$ is assigned to $i \in P_k$ for sourcing product $k \in K$, otherwise 0.
w_{jr}	1 if customer $r \in V_R$ is assigned to DC $j \in V_D$, otherwise 0.
s_{jv}	1 if DC $j \in V_D$ select review interval v , otherwise 0.
Auxiliary variables:	
T_j	Order cycle of DC $j \in V_D$, $T_j = \sum_{v \in V} v s_{jv}$.

$$x_i, y_j, z_{ij}, w_{jr}, s_{jv} \in \{0, 1\}, \quad \forall k \in K, i \in P_k, j \in V_D, r \in V_R, v \in V \quad (11)$$

lines from plants to DCs and from DCs to customers. At located DCs, the variable cost is proportional to its capacity, which is written as follows.

$$VC = \sum_{j \in V_D} \sum_{r \in V_R} \sum_{k \in K} \sum_{v \in V} F_j^q \mu_r^k v w_{jr} s_{jv} \quad (4)$$

The transportation cost occurs on the process of delivering product from plants to DCs, then to customers, which is approximated by following function.

$$TC = \sum_{k \in K} \sum_{i \in P_k} \sum_{j \in V_D} \sum_{r \in V_R} b_{ij} \mu_r^k z_{ij} w_{jr} + \sum_{j \in V_D} \sum_{r \in V_R} \sum_{k \in K} c_{jr} w_{jr} \mu_r^k \quad (5)$$

We let $G(x, y, z, w, s)$ denote the total cost of CRSCND. Based on the above discussion, the $G(x, y, z, w, s) = IC + FC + VC + TC$. Then, according to the nominal value of demand, we formulate the nominal mathematical model (P1) for CRSCND.

$$P1: \min G(x, y, z, w, s)$$

$$s.t. \sum_{i \in P_k} z_{ij} \leq y_j, \quad \forall j \in V_D, k \in K \quad (6)$$

$$\sum_{j \in V_D} w_{jr} = 1, \quad \forall r \in V_R \quad (7)$$

$$w_{jr} r_k \leq \sum_{i \in P_k} z_{ij}, \quad \forall j \in V_D, r \in V_R, k \in K \quad (8)$$

$$z_{ij} \leq x_i, \quad \forall k \in K, i \in P_k, j \in V_D \quad (9)$$

$$\sum_{v \in V} s_{jv} = 1, \quad \forall j \in V_D \quad (10)$$

The objective function of P1 is to minimize the total cost of CRSCND. Constraints (6) ensure that one product can only be sourced from one plant at each opened DC, which means multiple products will have different sources of supply. Constraints (7) stipulate that the requirement for all products will be met by one DC at each customer. Constraints (8) denote that if there are customers demanding a product at a DC, there must be plants assigned to this DC for providing such product. Constraints (9) mean that only when a plant is opened can it produce the product. Constraints (10) state that each DC can only select one review interval for its inventory.

3.3. Linearization of the nominal model

In the objective function of P1, bilinear terms $w_{jr} s_{jv}$ and $z_{ij} w_{jr}$ exist in IC , VC and TC . This will cause computational difficulties if the problem is directly solved by CPLEX or any other linear programming solver. This paper introduces a linearization scheme to treat the two bilinear terms. This scheme is widely used in existing research (Shahabi et al., 2014). According to this linearization scheme, we first introduce a new nonnegative variable G_{jrv} and three new constraints to linearize the term $w_{jr} s_{jv}$. Three new constraints are as follows.

$$\sum_{v \in V} G_{jrv} = w_{jr}, \quad \forall j \in V_D, r \in V_R \quad (12)$$

$$G_{jrv} \leq s_{jv}, \quad \forall j \in V_D, r \in V_R, v \in V \quad (13)$$

$$G_{jrv} \geq 0, \quad \forall j \in V_D, r \in V_R, v \in V \quad (14)$$

The above three constraints can enforce variable G_{jrv} equal 1 only when variables w_{jr} and s_{jv} both equal 1. Similarly, the nonnegative variable M_{ijr} and three constraints (15)~(17) are introduced to linearize the bilinear term $z_{ij} w_{jr}$.

$$\sum_{i \in P_k} M_{ijr} = w_{jr}, \quad \forall j \in V_D, r \in V_R, k \in K \quad (15)$$

$$M_{ijr} \leq z_{ij}, \quad \forall j \in V_D, r \in V_R, k \in K, i \in P_k \quad (16)$$

$$M_{ijr} \geq 0, \quad \forall j \in V_D, r \in V_R, k \in K, i \in P_k \quad (17)$$

In this research, $M_{ijr} = 1$ means the products produced by plant i are delivered to customer r through DC j . Because the demand of customer is multi-product, $M_{ijr} = 1$ may cover the case where customer r does not require the product of plant i . To avoid this situation, we enhance the constraints (15) as follows.

$$\sum_{i \in P_k} M_{ijr} = w_{jr} r_k, \quad \forall j \in V_D, r \in V_R, k \in K \quad (18)$$

According to the above linearization of the bilinear terms, we reformulate the nominal model P1 as a mixed-integer linear program P2.

$$\begin{aligned} P2 : \quad \min \quad & \sum_{j \in V_D} \sum_{v \in V} \frac{f_j}{v} s_{jv} + \sum_{j \in V_D} \sum_{r \in V_R} \sum_{k \in K} \sum_{v \in V} \frac{\mu_r^k v}{2} h_j G_{jrv} + \sum_{k \in K} \sum_{i \in P_k} F_i^p x_i \\ & + \sum_{j \in V_D} F_j^D y_j \\ & + \sum_{k \in K} \sum_{i \in P_k} \sum_{j \in V_D} F_{ij}^b z_{ij} + \sum_{j \in V_D} \sum_{r \in V_R} F_{jr}^c w_{jr} \\ & + \sum_{j \in V_D} \sum_{r \in V_R} \sum_{k \in K} \sum_{v \in V} F_j^q \mu_r^k v G_{jrv} \\ & + \sum_{k \in K} \sum_{i \in P_k} \sum_{j \in V_D} \sum_{r \in V_R} b_{ij} \mu_r^k M_{ijr} + \sum_{j \in V_D} \sum_{r \in V_R} \sum_{k \in K} c_{jr} \mu_r^k w_{jr} \\ \text{s.t. Constraints } & (6) \sim (14), (16) \sim (18). \end{aligned}$$

Reformulating the model P1 as P2 enables us to directly use the optimization solvers like CPLEX. However, the demand uncertainty may cause the solution found using nominal demand to be meaningless from a practical viewpoint. To reduce the effects of demand uncertainty and find a robust solution, this study gives the robust counterpart of model P2 in the next section.

3.4. Robust formulation

In the research of robust supply chain, some studies adopted robust stochastic programming method to handle uncertainties. For example, Lotfi et al. (2023a,b, 2024a,b) considered robust SCND problem, Lotfi et al. (2022, 2024d) studied the robust supply chain incorporating vendor management inventory, and Lotfi et al. (2024c) introduced robustness and risk-averse into supplier selection with order allocation problem. In these papers, Conditional Value at Risk, Entropic Value at Risk and Weighted Value at Risk are applied to measure risk. However, this approach is not suitable for scenarios where the distribution information of uncertain parameters is unknown.

To obtain a robust supply chain network under distribution information of uncertain demand is unknown, this research adopts robust optimization (RO) approach to solve the CRSCND problem. Regarding the RO approach, Soyster (1973) is among the first to start this research direction. His study proposes a linear optimization model using a rectangular uncertainty set to solve the robust optimization problem, but its solutions are overconservative. To address the over conservatism issue, research developed by Ben-Tal and Nemirovski (1998, 1999, 2000) has promoted the progress of RO approach. Through using an ellipsoidal uncertainty set, these studies develop the conic quadratic programming model to solve the robust linear programming problem, but the nonlinear model will cause the excess computational burden. This research employs the robust optimization approach of Bertsimas and Sim (2004), in which the budget uncertainty is introduced to construct the linear robust counterpart.

The reasons of employing RO approach of Bertsimas and Sim (2004) are fourfold: (1) it does not rely on the distribution information of uncertain demands, like mean and variance. This information is difficult to grasp for enterprises. (2) Based on the minimax principle, this approach focuses on seeking the solutions that show a good performance even in the worst case, which can help enterprises circumvent the effects of worst-case scenarios as much as possible and consequently

avoid the high penalty associating with it. (3) the conservatism level of solutions can be managed by adjusting budget parameters associated with uncertain demand, which gives decision makers the opportunity to make choices. (4) this approach can provide a linear robust counterpart, which is conducive to the subsequent problem solving.

In the robust formulation of CRSCND, we define the random variable $\hat{\mu}_r^k$ to denote the uncertain demand for product k at customer r , which takes value in $[\mu_r^k - \hat{\mu}_r^k, \mu_r^k + \hat{\mu}_r^k]$. Here, μ_r^k is the nominal value and $\hat{\mu}_r^k$ is the maximum deviation of demand from its nominal value. Associated with the variable $\hat{\mu}_r^k$, we let $z_{rk} = (\hat{\mu}_r^k - \mu_r^k) / \hat{\mu}_r^k$. In CRSCND, only the impact of positive deviation in uncertain demand can cause the worst cases, so we stipulate the z_{rk} takes value in $[0, 1]$.

The fluctuation in demand will affect the estimation of variable cost of DCs, inventory cost and transportation cost. On the treatment of first two costs, the uncertainty risk of each product is pooled together at each DC. As for the transportation cost, the effects of uncertainty risk can be pooled together for the entire supply chain network, or separately pooled based on the transportation lines of each product at each DC. According to these different risk-pooling strategies in transportation, two robust optimization models can be constructed for the CRSCND problem. One is the robust model which uses the same risk-pooling strategy to centrally handle the three costs, and another is that the transportation cost is independently handled by pooling the risk for entire network.

Setting inventory at DCs allows the risk-pooling of multiple customers and reduces the impact of demand uncertainty on the capacity and inventory of DCs. However, in the CRSCND, even at the same DC, different products cannot be substituted for each other, so the inventories of different products cannot share the risk. In addition, different DCs cannot collaborate to cope with the impact of demand fluctuations. Based on these reasons, this research establishes a risk pool for each product at each DC to cope with the impact of demand uncertainty on the variable cost of DCs, inventory cost and transportation cost, and constructs a robust model R1 for the CRSCND problem.

$$\begin{aligned} R1 : \quad \min \quad & \sum_{j \in V_D} \sum_{v \in V} \frac{f_j}{v} s_{jv} + \sum_{j \in V_D} \sum_{r \in V_R} \sum_{k \in K} \sum_{v \in V} \frac{\mu_r^k v}{2} h_j G_{jrv} + \sum_{k \in K} \sum_{i \in P_k} F_i^p x_i \\ & + \sum_{j \in V_D} F_j^D y_j \\ & + \sum_{k \in K} \sum_{i \in P_k} \sum_{j \in V_D} F_{ij}^b z_{ij} + \sum_{j \in V_D} \sum_{r \in V_R} F_{jr}^c w_{jr} \\ & + \sum_{j \in V_D} \sum_{r \in V_R} \sum_{k \in K} \sum_{v \in V} F_j^q \mu_r^k v G_{jrv} \\ & + \sum_{k \in K} \sum_{i \in P_k} \sum_{j \in V_D} \sum_{r \in V_R} b_{ij} \mu_r^k M_{ijr} + \sum_{j \in V_D} \sum_{r \in V_R} \sum_{k \in K} c_{jr} \mu_r^k w_{jr} + R \\ \text{s.t. Constraints } & (6) \sim (14), (16) \sim (18). \\ & \sum_{k \in K} \sum_{j \in V_D} z_k \max_{z_k \in U_1(\Gamma_k)} \left\{ \sum_{r \in V_R} \left(\sum_{v \in V} \left(F_j^q + \frac{h_j}{2} \right) v G_{jrv} \sum_{i \in P_k} b_{ij} M_{ijr} \right. \right. \\ & \left. \left. + c_{jr} w_{jr} \right) \hat{\mu}_r^k z_{rk} \right\} \leq R \quad (19) \\ & R \geq 0 \quad (20) \end{aligned}$$

where z_k is the vector comprised of those variables z_{rk} with same index k . $U_1(\Gamma_k)$ is the uncertainty set, and $U_1(\Gamma_k) = \{z_k | \|z_k\|_\infty \leq 1, \|z_k\|_1 \leq \Gamma_k, z_k \geq 0\}$. R is the auxiliary decision variable. The parameter Γ_k provides the protection level against the demand uncertainty of product k , i.e., the maximum number of changed demand for product k . One changed demand refers to the demand for one product at a customer is different from its nominal value. The varying range of Γ_k is in $[0, \sum_{r \in V_R} r_k]$. Specifically, $\Gamma_k = 0$ means the demand uncertainty of product k is not considered in the robust formulation of CRSCND. If $\Gamma_k = \sum_{r \in V_R} r_k$, the robust solutions have the highest conservatism against the demand uncertainty for product k .

Due to the existence of inner optimization problem in constraint (19), the model R1 is a nonlinear program which requires advanced computational power to solve. To obtain a tractable formulation of CRSCND, the duality theory is applied to transform the model R1 to the equivalent linear counterpart R2 as below. The γ^{jk} and ξ_r^{jk} are the corresponding dual variables of the inner problem.

$$\begin{aligned}
 \text{R2 : min } & \sum_{j \in V_D} \sum_{v \in V} \frac{f_j}{v} s_{jv} + \sum_{j \in V_D} \sum_{r \in V_R} \sum_{k \in K} \sum_{v \in V} \frac{\mu_r^k v}{2} h_j G_{jrv} + \sum_{k \in K} \sum_{i \in P_k} F_i^p x_i \\
 & + \sum_{j \in V_D} F_j^D y_j \\
 & + \sum_{k \in K} \sum_{i \in P_k} \sum_{j \in V_D} F_{ij}^b z_{ij} + \sum_{j \in V_D} \sum_{r \in V_R} F_{jr}^c w_{jr} \\
 & + \sum_{j \in V_D} \sum_{r \in V_R} \sum_{k \in K} \sum_{v \in V} F_j^q \mu_r^k v G_{jrv} \\
 & + \sum_{k \in K} \sum_{i \in P_k} \sum_{j \in V_D} \sum_{r \in V_R} b_{ij} \mu_r^k M_{ijr} + \sum_{j \in V_D} \sum_{r \in V_R} \sum_{k \in K} c_{jr} \mu_r^k w_{jr} + R \\
 \text{s.t. Constraints (6)~(14), (16)~(18) and (20),} \\
 & \sum_{j \in V_D} \sum_{k \in K} \left(\gamma^{jk} \Gamma_k + \sum_{r \in V_R} \xi_r^{jk} \right) \leq R \quad (21) \\
 & \gamma^{jk} + \xi_r^{jk} \geq \left(\sum_{v \in V} \left(F_j^q + \frac{h_j}{2} \right) v G_{jrv} \right. \\
 & \quad \left. + \sum_{i \in P_k} b_{ij} M_{ijr} + c_{jr} w_{jr} \right) \hat{\mu}_r^k \quad \forall j \in V_D, r \in V_R, k \in K \quad (22) \\
 & \gamma^{jk} \geq 0 \quad \forall j \in V_D, k \in K \quad (23) \\
 & \xi_r^{jk} \geq 0 \quad \forall j \in V_D, k \in K, r \in V_R \quad (24)
 \end{aligned}$$

In the robust formulation R2, the demand uncertainties are pooled at DCs and separated according to the product type. This risk-pooling strategy can reduce the impact of demand uncertainty and detailly evaluate the effects on the corresponding cost of each DC. However, there is a natural drawback that it does not fully explore the synergies between different products. Although different products are not substitutable, the demand uncertainty can be pooled in calculating the transportation cost. Therefore, we introduce the parameter Γ , which limits the number of changed demand for all products, to formulate the robust model R3 for CRSCND. The varying range of Γ is $[0, \sum_{k \in K} \sum_{r \in V_R} r_k]$. The model R3 is given as below.

$$\begin{aligned}
 \text{R3 : min } & \sum_{j \in V_D} \sum_{v \in V} \frac{f_j}{v} s_{jv} + \sum_{j \in V_D} \sum_{r \in V_R} \sum_{k \in K} \sum_{v \in V} \frac{\mu_r^k v}{2} h_j G_{jrv} + \sum_{k \in K} \sum_{i \in P_k} F_i^p x_i \\
 & + \sum_{j \in V_D} F_j^D y_j \\
 & + \sum_{k \in K} \sum_{i \in P_k} \sum_{j \in V_D} F_{ij}^b z_{ij} + \sum_{j \in V_D} \sum_{r \in V_R} F_{jr}^c w_{jr} \\
 & + \sum_{j \in V_D} \sum_{r \in V_R} \sum_{k \in K} \sum_{v \in V} F_j^q \mu_r^k v G_{jrv} \\
 & + \sum_{k \in K} \sum_{i \in P_k} \sum_{j \in V_D} \sum_{r \in V_R} b_{ij} \mu_r^k M_{ijr} + \sum_{j \in V_D} \sum_{r \in V_R} \sum_{k \in K} c_{jr} \mu_r^k w_{jr} \\
 & + C_1 + C_2 \\
 \text{s.t. Constraints (6)~(14), (16)~(18),} \\
 & \sum_{j \in V_D} \sum_{k \in K} \max_{z_k \in U_1(\Gamma)} \left\{ \sum_{r \in V_R} \sum_{v \in V} \left(F_j^q + \frac{h_j}{2} \right) v \hat{\mu}_r^k G_{jrv} z_{rk} \right\} \leq C_1 \quad (25) \\
 & \max_{z \in U_2(\Gamma)} \left\{ \sum_{j \in V_D} \sum_{k \in K} \sum_{r \in V_R} \left(\sum_{i \in P_k} b_{ij} M_{ijr} + c_{jr} w_{jr} \right) \hat{\mu}_r^k z_{rk} \right\} \leq C_2 \quad (26)
 \end{aligned}$$

$$C_1 \geq 0 \quad (27)$$

$$C_2 \geq 0 \quad (28)$$

where z is the vector of variables z_{rk} . $U_1(\Gamma)$ and $U_2(\Gamma)$ are the uncertainty sets, and $U_1(\Gamma) = \{z_k | \|z_k\|_\infty \leq 1, \|z_k\|_1 \leq \Gamma, z_k \geq 0\}$, $U_2(\Gamma) = \{z | \|z\|_\infty \leq 1, \|z\|_1 \leq \Gamma, z \geq 0\}$. C_1 and C_2 are auxiliary decision variables. In the same manner with R1, we introduce the dual variables α^{jk} , β_r^{jk} , θ and λ_{rk} to transform the nonlinear constraints (25) and (26). α^{jk} and β_r^{jk} correspond to constraint (25), and θ , λ_{rk} correspond to the constraint (26). The linearized formulation (R4) of R3 is as below.

$$\begin{aligned}
 \text{R4 : min } & \sum_{j \in V_D} \sum_{v \in V} \frac{f_j}{v} s_{jv} + \sum_{j \in V_D} \sum_{r \in V_R} \sum_{k \in K} \sum_{v \in V} \frac{\mu_r^k v}{2} h_j G_{jrv} + \sum_{k \in K} \sum_{i \in P_k} F_i^p x_i \\
 & + \sum_{j \in V_D} F_j^D y_j \\
 & + \sum_{k \in K} \sum_{i \in P_k} \sum_{j \in V_D} F_{ij}^b z_{ij} + \sum_{j \in V_D} \sum_{r \in V_R} F_{jr}^c w_{jr} \\
 & + \sum_{j \in V_D} \sum_{r \in V_R} \sum_{k \in K} \sum_{v \in V} F_j^q \mu_r^k v G_{jrv} \\
 & + \sum_{k \in K} \sum_{i \in P_k} \sum_{j \in V_D} \sum_{r \in V_R} b_{ij} \mu_r^k M_{ijr} + \sum_{j \in V_D} \sum_{r \in V_R} \sum_{k \in K} c_{jr} \mu_r^k w_{jr} \\
 & + C_1 + C_2 \\
 \text{s.t. Constraints (6)~(14), (16)~(18), (27) and (28),} \\
 & \sum_{j \in V_D} \sum_{k \in K} \left(\alpha^{jk} \Gamma + \sum_{r \in V_R} \beta_r^{jk} \right) \leq C_1 \quad (29) \\
 & \alpha^{jk} + \beta_r^{jk} \geq \sum_{v \in V} \left(F_j^q + \frac{h_j}{2} \right) v \hat{\mu}_r^k G_{jrv} \quad \forall j \in V_D, r \in V_R, k \in K \quad (30) \\
 & \theta \Gamma + \sum_{r \in V_R} \sum_{k \in K} \lambda_{rk} \leq C_2 \quad (31) \\
 & \theta + \lambda_{rk} \geq \sum_{j \in V_D} \left(\sum_{i \in P_k} b_{ij} M_{ijr} + c_{jr} w_{jr} \right) \hat{\mu}_r^k \quad \forall r \in V_R, k \in K \quad (32) \\
 & \alpha^{jk} \geq 0 \quad \forall j \in V_D, k \in K \quad (33) \\
 & \beta_r^{jk} \geq 0 \quad \forall j \in V_D, r \in V_R, k \in K \quad (34) \\
 & \theta \geq 0 \quad (35) \\
 & \lambda_{rk} \geq 0 \quad \forall r \in V_R, k \in K \quad (36)
 \end{aligned}$$

Based on the different risk-pooling strategies, two robust models R2 and R4 are formulated for CRSCND. We observe that the CPLEX solver shows good performance in solution size and speed. Considering that the purpose of this research is to give a framework of multi-enterprise collaboration and to explore its advantages, the optimization models are solved using CPLEX in this paper.

3.5. Complexity of the model

The problem complexity (CRSCND) is calculated in Eqs. (37) to (42), where the number of binary, positive variables and constraints is given. First three equations correspond to model R2, while the last three are for model R4.

$$\text{BinaryVariables(R2)} = \sum_{k \in K} |P_k| (|V_D| + 1) + |V_D| (1 + |V_R| + |V|) \quad (37)$$

$$\text{PositiveVariables(R2)} = 1 + |V_D| |V_R| \left(|V| + \sum_{k \in K} |P_k| + |K| \right) + |K| |V_D| \quad (38)$$

$$\text{Constraints(R2)} = |V_D| |V_R| \left(3 |K| + \sum_{k \in K} |P_k| + |V| + 1 \right)$$

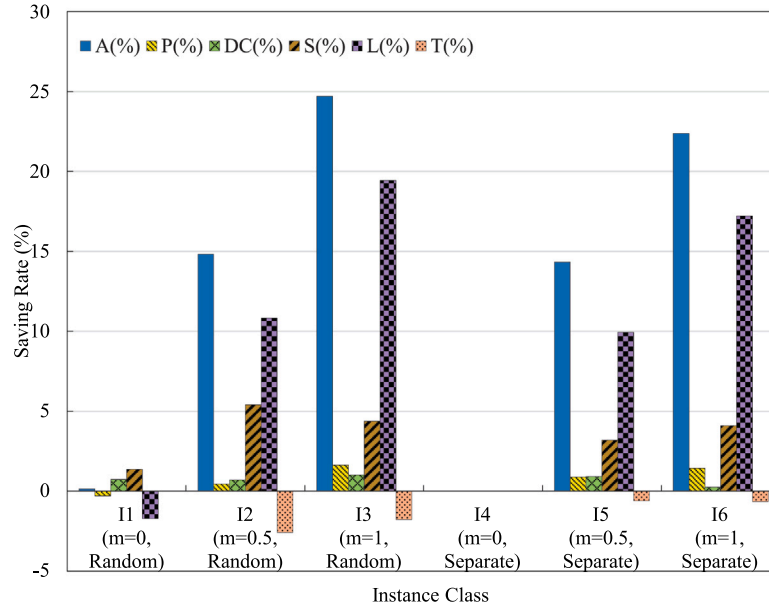


Fig. 3. Cost savings of collaboration using model R2.

$$+ |V_D| \left(|K| + \sum_{k \in K} |P_k| + 1 \right) + |V_R| + 1 \quad (39)$$

$$\text{BinaryVariables}(R4) = \sum_{k \in K} |P_k| (|V_D| + 1) + |V_D| (1 + |V_R| + |V|) \quad (40)$$

$$\text{PositiveVariables}(R4) = 3 + |V_D| |V_R| \left(|V| + \sum_{k \in K} |P_k| |K| \right) + |K| (|V_D| + |V_R|) \quad (41)$$

$$\text{Constraints}(R4) = |V_D| |V_R| \left(3 |K| + \sum_{k \in K} |P_k| + |V| + 1 \right) + |V_D| \left(|K| + \sum_{k \in K} |P_k| + 1 \right) + |V_R| (|K| + 1) + 2 \quad (42)$$

The results indicate that the number of variables and constraints depends not only on the network size, but also on the candidate review intervals. In addition, compared to the model R2, R4 has more variables and constraints, making it more complex. This complexity is related to the number of customers and enterprises.

4. Experiment results and discussion

In this section, the benefits of collaboration in robust supply chain network design are verified through comparing with the no collaboration strategy. The robustness of the optimal results obtained by the two proposed robust models is investigated. The properties of two robust models are analyzed through the sensitivity analysis experiments. Moreover, three cost-saving allocation mechanisms are tested to investigate whether this collaboration is easy to achieve. The computational setup is a desktop with Intel Core i7-10700 2.90 GHz and 16 GB memory, and all experiments are conducted by calling the CPLEX 12.10 in Java.

In the experiments, we create 6 groups of CRSCND instances including 2 enterprises, in which the number of candidate plants of each enterprise, candidate distribution centers (DCs) and customers are set to 5, 10 and 100, respectively. Each group includes 10 instances, and these groups are named as I1, I2, ..., I6. To investigate the effect of relative location between plants, DCs and customers, these nodes are randomly distributed in a square map in groups I1~I3 (called

“Random” distribution), while in groups I4~I6, the candidate plants and DCs are distributed in the left half of the same map, and the customers are distributed in the right half (called “Separate” distribution). To investigate the effect of geographical distribution of demands, the square map is divided into $|K|$ subareas by the evenly separated rays that originate from the map center in groups I1~I3. Each subarea is labeled as k , and the customers located in this subarea must demand the product k and require other products with a probability m which is called “overlap”. In our experiments, the m takes three values. More specifically, in group I1, m equals 0 which means the customer located in subarea only demand the product k . In group I2, m equals 0.5 which means the probability that customers located in subarea k demand any other product is 50%. In group I3, m equals 1 which means every customer has the demand for all products. Similarly, in groups I4~I6, m has the same settings.

In our experiments, all instances are generated in the square of $[1, 50] \times [1, 50]$ in the 2D coordinate system. The assignment of parameter values for generating instances relies on the notation lists (see Tables 2 and 3).

4.1. The advantages of collaboration

In this section, we illustrate the advantages of collaboration in robust supply chain network design by examining the 6 groups of instances. No collaboration strategy, in which each enterprise designs their own robust supply chain network separately, is applied as a baseline to be compared with CRSCND. Figs. 3 and 4 show the average cost savings of CRSCND over no collaboration strategy for robust models R2 and R4, respectively. A (%) is used to denote the total relative cost savings of CRSCND. To unveil how collaboration reduce the total cost, the relative savings of plants construction cost (denoted as P (%)), DCs construction cost (DC (%)), inventory cost (S (%)), opening cost of transportation lines (L (%)) and transportation cost (T (%)) are also showed in Figs. 3 and 4.

Comparing Figs. 3 and 4, we find models R2 and R4 have similar performances in cost saving. When m equals 0 (groups I1 and I4) collaborative construction yields little cost savings. As m increases, the total cost savings by collaboration become significant and show an increasing trend. Looking further into the main sources of total cost savings, we find the followings:

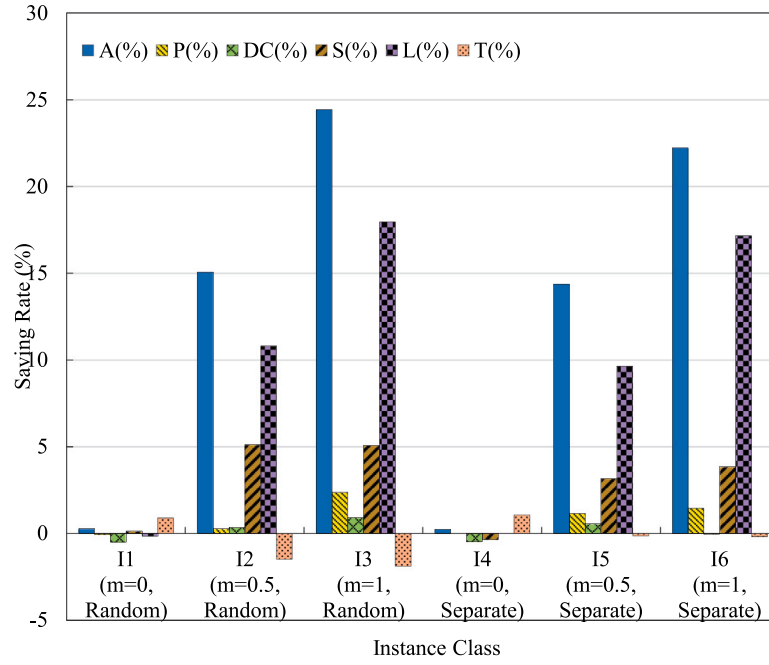


Fig. 4. Cost savings of collaboration using model R4.

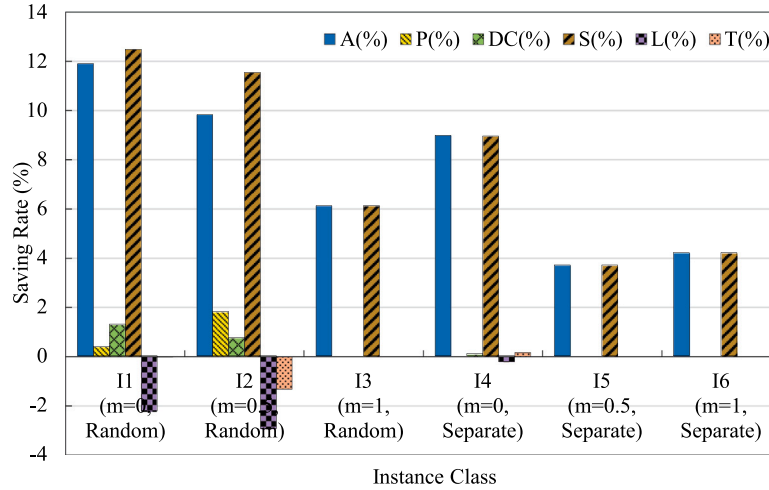


Fig. 5. Comparisons of model R2 and nominal model.

- With the increase of m , the total cost saved by collaboration mainly comes from the reduction of inventory cost and opening cost of transportation lines.
- High overlap of demands will lead to a significant reduction of the plants construction cost.
- Collaboration may bring no cost savings in opening DCs.
- When $m = 0$ transportation cost has a little reduction, but this reduction will change from positive to negative as m increases.

4.2. Analysis of robustness

To evaluate the impact of robust approach on collaborative design of SCN under demand uncertainty, this section investigates the performance difference between the robust models and nominal model in terms of cost.

The total cost of nominal model is calculated by initially solving it with nominal demand then re-evaluating it under demand uncertainty. More specifically, we first solve the nominal model P2 according to

the demand nominal value to obtain a network configuration. Then, based on such configuration, the worst case is acquired with the same violated probability as robust model and the temporary remedial cost for encountering the worst case is calculated. The total cost of nominal model under demand uncertainty is the sum of fixed construction cost of designing network and the remedial cost incurred due to uncertain demand. The remedial cost includes the temporary ordering cost, expanding cost of DCs, temporary inventory cost and transportation cost, when uncertain demand occurs. In our experiments, the temporary ordering cost is 1.5 times that of normal ordering, and other costs are equal to the normal value.

Figs. 5 and 6 show the relative saving rates of the robust models R2 and R4 over the nominal model, respectively. The results demonstrate the robust approach can efficiently alleviate the impacts of uncertain demands on supply chain network and bring economic benefits for enterprises. Moreover, the reduction of inventory cost is the main source of cost-saving brought by the robust approach.

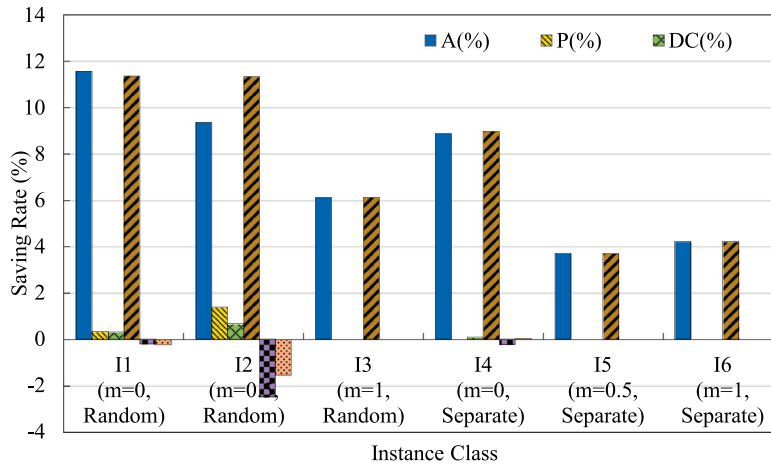


Fig. 6. Comparisons of model R4 and nominal model.

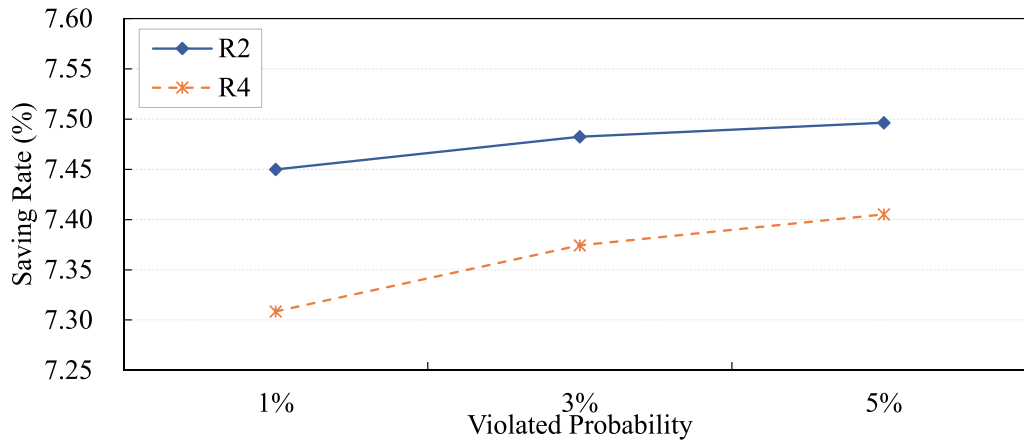


Fig. 7. Advantages of robust approach under changing violated probability.

4.3. Analysis of violated probability

Violated probability is an important parameter in robust approach, which reflects the conservatism of robust solutions. To investigate the effects of violated probability on problem CRSCND, this section conducts the sensitivity analysis of violated probability from two perspectives.

Firstly, we study the effects on advantages of robust approach through comparing the models R2 and R4 with nominal model. Fig. 7 shows the cost-saving curves of models R2 and R4 when the violated probability changes from 1% to 5%. It is observed that the saving rates of two robust models show a same trend, and both have only a slight improvement as the violated probability increases. This indicates the violated probability has no significant effect on advantages of robust approach in problem CRSCND.

Secondly, we study the effects of violated probability on advantages of collaboration. Under different settings of violated probability, Fig. 8 gives the cost-saving curves of collaboration comparing with the no collaboration. The results show the saving rates have a slight increase as violated probability changes. In addition, it is found that models R2 and R4 have no significant gap of saving rate in various violated probabilities.

4.4. Analysis of high volatility demand

In this section, through doubling the maximum deviation of some demands, we examine the effects of high volatility demand in problem

CRSCND. Fig. 9 gives the saving rates brought by collaboration when the proportion of demands with a doubling volatility increases from 0% to 80%. The results show that the saving rates have a slight reduction as the proportion of high volatility demands increases.

Further, we investigate the effects of high volatility demand on the advantages of robust approach. Fig. 10 shows the saving rates of robust approach when some demands double their volatilities. It is noteworthy that the curves of saving rate have no evident change when the number of demands with doubling volatility increases.

4.5. Comparison of two robust models

The above experiments demonstrate that two modeling approaches with different risk-pooling strategies both can bring the considerable cost savings for enterprises in the problem CRSCND. In this section, we compare the two robust models and investigate its applicable scenarios. Fig. 11 shows the relative cost gaps of model R4 with respect to model R2. The results indicate the model R4 has advantages in terms of total cost, opening cost of transportation lines and transportation cost, while model R2 is more beneficial in construction cost of plants and DCs, and inventory cost.

To investigate the applicable scenarios of two robust models, Fig. 12 gives the curves of relative difference of total cost when the weights of variable construction cost of DCs (denoted as w_1), holding cost of inventory (w_2) and transportation cost (w_3) are varied. The results indicate that if the weight of transportation cost is small the model R2

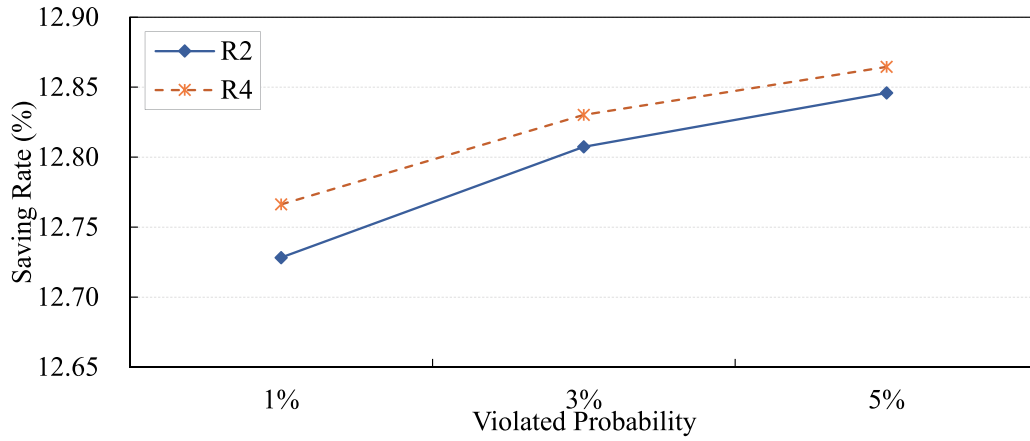


Fig. 8. Advantages of collaboration under changing violated probability.

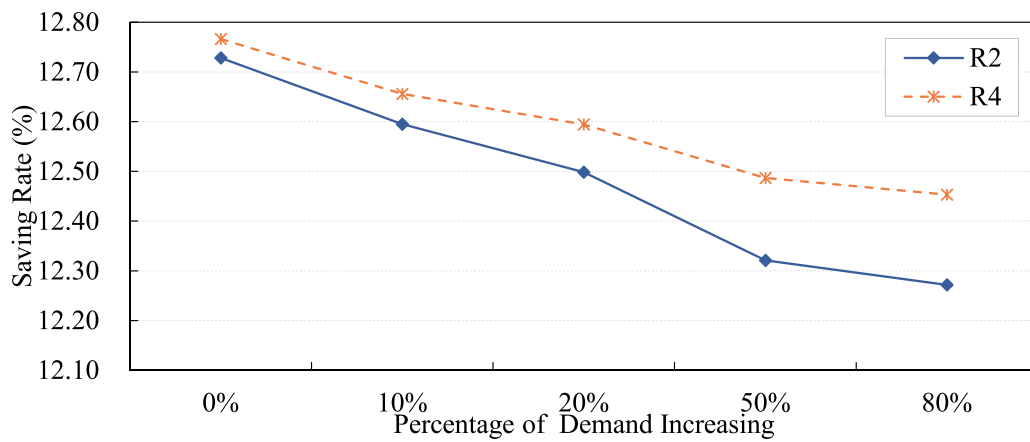


Fig. 9. Advantages of collaboration with high volatility demand.

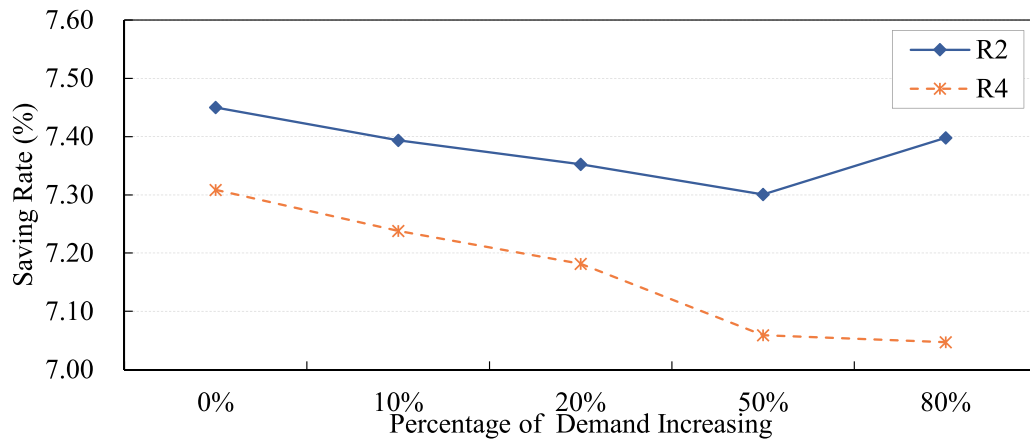


Fig. 10. Advantages of robust approach with high volatility demand.

has the advantages in total cost, while the model R4 is more favorable when weights w_1 and w_2 are low.

4.6. Allocation of cost savings

Collaborative design of robust supply chain network can significantly improve the flexibility of supply chain and reduce the total cost, but enterprises are assumed to be rational, and their primary concern in collaboration is their own benefits, i.e., any enterprise would like to reduce as much of its own total costs as possible. Therefore, how the

cost-saving is distributed will have a direct impact on the willingness of enterprises to participate in collaborative design. When enterprises are unable to derive benefits from collaboration or the benefits are insufficient, enterprises will leave the alliance. Taking the cooperative game-theoretic perspective, any allocation in the core can ensure there is no sub-alliance with higher benefits, and staying in the grand alliance and collaborate with all other enterprises is the most advantageous choice for any enterprise. In this way, the grand alliance is stable.

To ensure that enterprise can have the incentive to participate in collaborative design of robust supply chain network, this paper

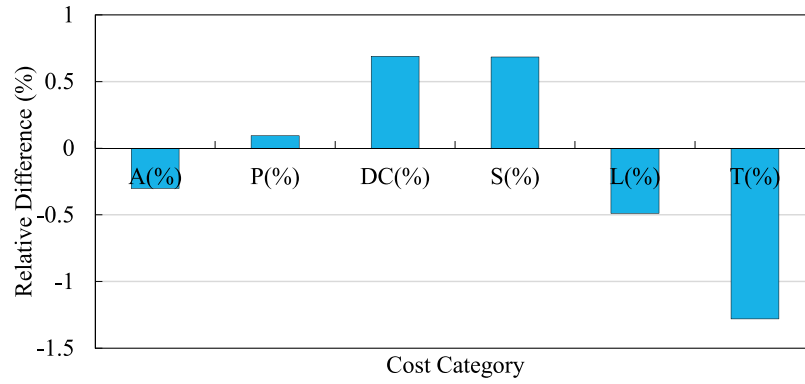


Fig. 11. Relative cost difference between models R2 and R4.

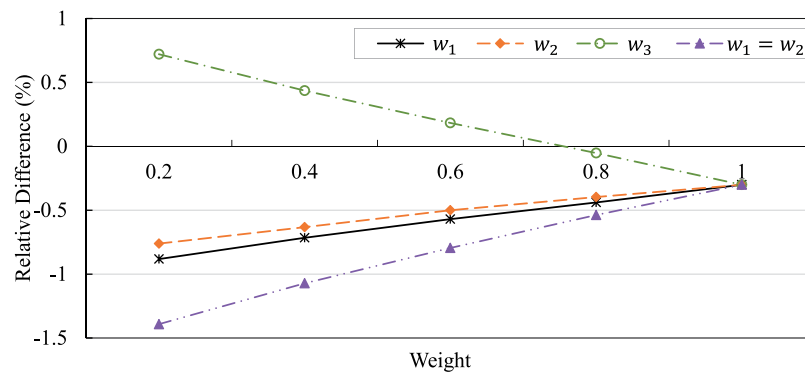


Fig. 12. Relative cost difference under different weight settings.

Table 5

The allocation results under model R2.

	I7	I8	I9	I10	I11	I12
Equal	4	10	10	3	8	9
Utilization	0	4	7	0	1	6
Shapley	9	10	10	5	10	10

Table 6

The allocation results under model R4.

	I7	I8	I9	I10	I11	I12
Equal	1	10	10	2	8	10
Utilization	0	4	7	0	1	7
Shapley	3	10	10	5	10	10

investigates the stability of three allocation mechanisms. We consider the mechanisms formerly studied in Zhang et al. (2023), which are “Equal”, “Utilization” and “Shapley” allocation mechanisms. The Equal mechanism evenly distributes the cost savings to all enterprises, and the Utilization allocates the cost savings such that each enterprise’ actual cost is proportional to the volume of their product. The Shapley mechanism is based on the Shapley values of each enterprise. To carry out the experiments in this section, six groups of CRSCND instances containing three enterprises, named I7, I8, ..., I12, are generated, and each group contains 10 instances. In the generating process, the μ_0 of three different products are set to 10, 20 and 30, respectively, and other parameters are consistent with the settings of instances I1~I6. For each instance, we calculate the allocation results of three mechanisms for total cost savings, and check whether the allocation belongs to the core of the cooperative game. In our experiments, the payoff function is the cost-saving of alliance. Tables 5 and 6 give the results under two robust optimization models, respectively.

The results show that no matter which robust model is used, the Shapley value method can provide a stable allocation for the instances with overlapping demands. When the overlap is 0 or extremely close to 0, the Shapley method can only provide stable allocation for some instances due to the decline of inter-enterprise synergy. The Utilization

mechanism generates the least stable allocations. Especially when the overlap is 0, the Utilization mechanism does not obtain a stable allocation. The Equal method can effectively increase the number of stable allocations, but its results are inferior to the Shapley value method.

4.7. Discussion

This research focuses on the benefits of collaborative design of robust supply chain network and analyzing the components of these benefits. Through comparing with no collaboration strategy, it is found that demand overlap is a key parameter affecting the cost savings of collaborative design. When the overlap is low little sharing of DCs and transportation lines will occur, and consequently the network will remain largely consistent under collaboration and no collaboration. As overlap increases, there are a large number of synergies that can be exploited by enterprises. For example, the joint replenishment of inventory for all products and the collaborative opening and sharing of transportation lines. Based on these synergies, the network structure is optimized and the cost savings of collaboration become significant. To obtain such an optimized and simple network, collaborative design may sacrifice some opening cost of DCs and transportation cost to reduce total number of opened DCs and transportation lines.

Moreover, comparing with the nominal model, using robust approach can avoid the occurrence of temporary orders when dealing with demand uncertainty, thereby efficiently reducing the cost of supply chain. The experiments of sensitivity analysis indicate that the advantages of considering robust approach and collaboration in problem CRSCND will not be significantly affected by violated probability and demand joining with higher volatility.

Analyzing the two risk-pooling strategies, it is found that they have similar saving rate and both can bring considerable cost savings in building collaborative robust SCN. The saving rate gaps between two models R2 and R4 do not exceed 0.35% in the experiments of sensitivity analysis. As the violated probability increases the saving rate gap brought either by collaboration or robust approach show a slight decreasing trend, but such gap has an increasing trend as the demand number with higher volatility increases. Further explore the favorable scenarios of two risk-pooling strategies, we found that when the proportion of transportation cost is high, building the risk-pooling for products transportations of whole supply chain network, i.e. model R4, is more advantageous.

Allocation of cost savings is the key issue in collaborative design of robust supply chain network. This research tests three allocation mechanisms for problem CRSCND and finds that the Shapley value method can fairly measure the contribution of each enterprise. Nevertheless, when there is a large difference in the market size of enterprises and the demand overlap is low, these simple allocation mechanisms may not be able to ensure the stability of alliance. In this case, enterprises need to design a specific allocation mechanism or choose a suitable partner to carry out collaboration.

5. Managerial insights and practical implications

This research advocates for a collaborative approach to designing robust supply chain networks (SCNs) among multiple enterprises, providing a practical framework for modeling and implementing such collaboration. A distinguishing feature of this study is its holistic view, incorporating various integrative strategies to enable a fully collaborative supply chain, including joint inventory replenishment, shared facilities, and pooled transportation resources. Such a collaborative design approach not only lowers total operational costs but also extends market reach for participating enterprises, making it an economically favorable choice for logistics expansion and improvement.

Consideration of Demand Uncertainty: In designing a collaborative SCN, managers must account for demand uncertainties, as neglecting them may result in increased costs when unexpected fluctuations arise. This study offers two risk-pooling strategies to help managers mitigate demand volatility. When transportation costs represent a significant portion of total expenses, managers are advised to apply a comprehensive risk-pooling approach across the entire supply chain; otherwise, Model R2 is recommended. Adjusting the budget value within these models also allows managers to achieve the desired level of conservatism in their solutions.

Partner Selection and Allocation Mechanisms: In implementing the collaborative robust SCN design (CRSCND), the Shapley value method generally provides a stable cost allocation mechanism in cases of overlapping demand, but may be limited when overlap is minimal. Thus, managers should carefully select suitable partners and design an allocation mechanism that ensures stability within the CRSCND. If collaboration is mandatory, where some enterprises incur higher costs to achieve an overall reduction in SCN costs, the parent company may consider subsidizing those enterprises to maintain fairness and stability within the network.

6. Conclusion and discussions

Multi-enterprise collaboration offers a powerful approach to achieving resource integration, enhancing resource utilization, and reducing

individual enterprise investment. Addressing the challenge of unknown demand distribution, this study introduces and resolves the collaborative robust supply chain network design (CRSCND) problem through a robust optimization framework, integrating joint inventory replenishment, shared facilities, and transportation resources. The CRSCND problem was formulated with two robust optimization models based on different risk-pooling strategies, effectively handling demand uncertainty. The numerical experiments support the substantial benefits of collaboration and robust optimization, and three cost-saving allocation mechanisms were analyzed.

The key findings are summarized as follows: (1) **Cost Savings through Collaboration:** Collaborative design of robust SCNs achieves significant cost reductions, mainly by decreasing inventory and transportation line opening costs. (2) **Effectiveness of Robust Optimization:** Applying robust optimization to collaboratively designed SCNs under demand uncertainty reduces total costs, primarily through inventory cost savings. (3) **Cost Savings Resilience:** Cost savings from collaboration and robust optimization are not significantly impacted by changes in violated probability or high demand volatility. (4) **Risk-Pooling Strategy Suitability:** A centralized approach to transportation risk pooling is recommended when transportation costs are high, while independent transportation risk handling is more suitable when distribution center construction and inventory costs dominate. (5) **Shapley Value Allocation Mechanism:** For CRSCND problems with high demand overlap among products, the Shapley value method offers stable cost allocation. For scenarios with low demand overlap, managers should establish a fair allocation or partner selection method.

Limitations and Future Directions: This research focuses on cost factors in the collaborative SCN design. However, in practice, managers' decisions are influenced by psychological preferences and satisfaction, affecting collaboration. Future research could incorporate these behavioral factors into the CRSCND model to analyze potential impacts on network structure. Additionally, exploring scenarios with multiple logistics providers per transportation line could further reduce SCN costs. Finally, considering correlated demand uncertainties may yield insights into how interrelated demands impact the network structure.

CRedit authorship contribution statement

Qihuan Zhang: Writing – review & editing, Writing – original draft, Software, Methodology, Data curation, Conceptualization. **Ziteng Wang:** Writing – review & editing, Writing – original draft, Validation, Methodology, Conceptualization. **Min Huang:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. **Huihui Wang:** Methodology, Conceptualization. **Xingwei Wang:** Software, Conceptualization. **Shu-Cherng Fang:** Writing – review & editing, Methodology.

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Data availability

Data will be made available on request.

References

- Abbasian, M., Sazvar, Z., Mohammadisiahroudi, M., 2023. A hybrid optimization method to design a sustainable resilient supply chain in a perishable food industry. *Environ. Sci. Pollut. Res.* 30 (3), 6080–6103. <http://dx.doi.org/10.1007/s11356-022-22115-8>.

- Agarwal, R., Ergun, Ö., 2010. Network design and allocation mechanisms for carrier alliances in liner shipping. *Oper. Res.* 58 (6), 1726–1742. <http://dx.doi.org/10.1287/opre.1100.0848>.
- Ahmadi-Javid, A., Azad, N., 2010. Incorporating location, routing and inventory decisions in supply chain network design. *Transp. Res. E* 46 (5), 582–597. <http://dx.doi.org/10.1016/j.tre.2009.06.005>.
- Aldridge, R., Battini, D., Ivanov, D., Zennaro, I., 2021. Costs of resilience and disruptions in supply chain network design models: a review and future research directions. *Int. J. Prod. Econ.* 235, 108103. <http://dx.doi.org/10.1016/j.ijpe.2021.108103>.
- Amiri-Aref, M., Klibi, W., Babai, M.Z., 2018. The multi-sourcing location inventory problem with stochastic demand. *European J. Oper. Res.* 266 (1), 72–87. <http://dx.doi.org/10.1016/j.ejor.2017.09.003>.
- Atamtürk, A., Berenguer, G., Shen, Z., 2012. A conic integer programming approach to stochastic joint location-inventory problems. *Oper. Res.* 60 (2), 366–381. <http://dx.doi.org/10.1287/opre.1110.1037>.
- Ben-Tal, A., Nemirovski, A., 1998. Robust convex optimization. *Math. Oper. Res.* 23 (4), 769–805. <http://dx.doi.org/10.1287/moor.23.4.769>.
- Ben-Tal, A., Nemirovski, A., 1999. Robust solutions of uncertain linear programs. *Oper. Res. Lett.* 25 (1), 1–13. [http://dx.doi.org/10.1016/S0167-6377\(99\)00016-4](http://dx.doi.org/10.1016/S0167-6377(99)00016-4).
- Ben-Tal, A., Nemirovski, A., 2000. Robust solutions of linear programming problems contaminated with uncertain data. *Math. Program.* 88 (3), 411–424. <http://dx.doi.org/10.1007/PL00011380>.
- Bertsimas, D., Sim, M., 2004. The price of robustness. *Oper. Res.* 52 (1), 35–53. <http://dx.doi.org/10.1287/opre.1030.0065>.
- Dai, Z., Aqlan, F., Zheng, X., Gao, K., 2018. A location-inventory supply chain network model using two heuristic algorithms for perishable products with fuzzy constraints. *Comput. Ind. Eng.* 119, 338–352. <http://dx.doi.org/10.1016/j.cie.2018.04.007>.
- Daskin, M.S., Coullard, C.R., Shen, Z.-J.M., 2002. An inventory-location model: Formulation, solution algorithm and computational results. *Ann. Oper. Res.* 110 (1), 83–106. <http://dx.doi.org/10.1023/A:1020763400324>.
- Ergun, O., Kuyzu, G., Savelsbergh, M., 2007. Reducing truckload transportation costs through collaboration. *Transp. Sci.* 41 (2), 206–221. <http://dx.doi.org/10.1287/trsc.1060.0169>.
- Farahani, R.Z., Rashidi Bajgan, H., Fahimnia, B., Kaviani, M., 2015. Location-inventory problem in supply chains: a modelling review. *Int. J. Prod. Res.* 53 (12), 3769–3788. <http://dx.doi.org/10.1080/00207543.2014.988889>.
- Fathi, M., Khakifirooz, M., Diabat, A., Chen, H., 2021. An integrated queueing-stochastic optimization hybrid genetic algorithm for a location-inventory supply chain network. *Int. J. Prod. Econ.* 237, 108139. <http://dx.doi.org/10.1016/j.ijpe.2021.108139>.
- Gattorna, J., 1998. *Strategic Supply Chain Alignment: Best Practice in Supply Chain Management*. Gower Publishing Company.
- Govindan, K., Fattahi, M., Keyvanshokoh, E., 2017. Supply chain network design under uncertainty: A comprehensive review and future research directions. *European J. Oper. Res.* 263 (1), 108–141. <http://dx.doi.org/10.1016/j.ejor.2017.04.009>.
- Guo, H., Zhang, Y., Zhang, C., Zhang, Y., Han, Z., 2020. A multi-commodity location-inventory problem in a closed-loop supply chain with commercial product returns. *Int. J. Prod. Res.* 58 (22), 6899–6916. <http://dx.doi.org/10.1080/00207543.2019.1686186>.
- Hacardiaux, T., Tancrez, J.S., 2020. Assessing the environmental benefits of horizontal cooperation using a location-inventory model. *CEJOR Cent. Eur. J. Oper. Res.* 28 (4), 1363–1387. <http://dx.doi.org/10.1007/s10100-018-0599-7>.
- Huang, M., Dong, L., Kuang, H., Jiang, Z.Z., Lee, L.H., Wang, X., 2021. Supply chain network design considering customer psychological behavior—a 4PL perspective. *Comput. Ind. Eng.* 159, 107484. <http://dx.doi.org/10.1016/j.cie.2021.107484>.
- Jiang, S., Huang, M., Zhang, Y., Wang, X., Fang, S.C., 2024. Fourth-party logistics network design with demand surge: A greedy scenario-reduction and scenario-price based decomposition algorithm. *Int. J. Prod. Econ.* 269, 109135. <http://dx.doi.org/10.1016/j.ijpe.2023.109135>.
- Jin, Z., Ng, K.K., Zhang, C., Liu, W., Zhang, F., Xu, G., 2024. A risk-averse distributionally robust optimisation approach for drone-supported relief facility location problem. *Transp. Res. E* 186, 103538. <http://dx.doi.org/10.1016/j.tre.2024.103538>.
- Jiu, S., Wang, D., Ma, Z., 2024. Benders decomposition for robust distribution network design and operations in online retailing. *European J. Oper. Res.* 315 (3), 1069–1082. <http://dx.doi.org/10.1016/j.ejor.2024.01.046>.
- Keskin, B.B., Üster, H., 2012. Production/distribution system design with inventory considerations. *Naval Res. Logist.* 59 (2), 172–195. <http://dx.doi.org/10.1002/nav.21482>.
- Li, Y., Guo, H., Zhang, Y., 2018. An integrated location-inventory problem in a closed-loop supply chain with third-party logistics. *Int. J. Prod. Res.* 56 (10), 3462–3481. <http://dx.doi.org/10.1080/00207543.2017.1338781>.
- Li, Y., Lin, Y., Shu, J., 2021. Location and two-echelon inventory network design with economies and diseconomies of scale in facility operating costs. *Comput. Oper. Res.* 133, 105347. <http://dx.doi.org/10.1016/j.cor.2021.105347>.
- Li, Y., Shu, J., Wang, L., Wu, T., 2023. Joint location-inventory problem with economies and diseconomies of scale: A general model and an efficient column generation algorithm. *Comput. Ind. Eng.* 183, 109537. <http://dx.doi.org/10.1016/j.cie.2023.109537>.
- Liu, A., Zhu, Q., Xu, L., Lu, Q., Fan, Y., 2021. Sustainable supply chain management for perishable products in emerging markets: An integrated location-inventory-routing model. *Transp. Res. E* 150, 102319. <http://dx.doi.org/10.1016/j.tre.2021.102319>.
- Lotfi, R., Hazrati, R., Aghakhani, S., Afshar, M., Amra, M., Ali, S.S., 2024a. A data-driven robust optimization in viable supply chain network design by considering open innovation and blockchain technology. *J. Clean. Prod.* 436, 140369. <http://dx.doi.org/10.1016/j.jclepro.2023.140369>.
- Lotfi, R., Khanbaba, A., Ali, S.S., Afshar, M., Mehrjardi, M.S., Omid, S., 2024b. Net-zero, resilience, and agile closed-loop supply chain network design considering robustness and renewable energy. *Environ. Sci. Pollut. Res.* 1–19. <http://dx.doi.org/10.1007/s11356-024-32661-y>.
- Lotfi, R., Khanbaba, A., Alkhazaleh, H.A., Changizi, M., Kadlubek, M., Aghakhani, S., SamarAli, S., 2024c. A viable supplier selection with order allocation by considering robustness, risk-averse and blockchain technology. *Comput. Ind. Eng.* 110319. <http://dx.doi.org/10.1016/j.cie.2024.110319>.
- Lotfi, R., Mehrjardi, M.S., MohajerAnsari, P., Zolfagari, F., Afshar, M., 2023a. Antifragile, sustainable, and agile supply chain network design by considering resiliency, robustness, risk, and environmental requirements. *Environ. Sci. Pollut. Res.* 30 (48), 106442–106459. <http://dx.doi.org/10.1007/s11356-023-29488-4>.
- Lotfi, R., MohajerAnsari, P., Nevisi, M.M.S., Afshar, M., Davoodi, S.M.R., Ali, S.S., 2024d. A viable supply chain by considering vendor-managed-inventory with a consignment stock policy and learning approach. *Result. Eng.* 21, 101609. <http://dx.doi.org/10.1016/j.rineng.2023.101609>.
- Lotfi, R., Rajabzadeh, M., Zamani, A., Rajabi, M.S., 2022. Viable supply chain with vendor-managed inventory approach by considering blockchain, risk and robustness. *Ann. Oper. Res.* 1–20. <http://dx.doi.org/10.1007/s10479-022-05119-y>.
- Lotfi, R., Shafiei, R.M., Komeleh, M.G., Pasha, F.G., Ferasat, M., 2023b. Vaccine supply chain network design by considering viability, robustness and risk. *J. Eng. Res.* <http://dx.doi.org/10.1016/j.jer.2023.10.007>.
- Marty, J., Ruel, S., 2024. Why is supply chain collaboration still a hot topic? A review of decades of research and a comprehensive framework proposal. *Int. J. Prod. Econ.* 273, 109259. <http://dx.doi.org/10.1016/j.ijpe.2024.109259>.
- Ozsen, L., Coullard, C.R., Daskin, M.S., 2008. Capacitated warehouse location model with risk pooling. *Naval Res. Logist.* 55 (4), 295–312. <http://dx.doi.org/10.1002/nav.20282>.
- Puga, M.S., Tancrez, J., 2017. A heuristic algorithm for solving large location-inventory problems with demand uncertainty. *European J. Oper. Res.* 259, 413–423. <http://dx.doi.org/10.1016/j.ejor.2016.10.037>.
- Qi, W., Zhang, Y., Zhang, N., 2023. Scaling up electric-vehicle battery swapping services in cities: A joint location and repairable-inventory model. *Manage. Sci.* 69 (11), 6855–6875. <http://dx.doi.org/10.1287/mnsc.2023.4731>.
- Rekabi, S., Garjan, H.S., Goodarzi, F., Pamucar, D., Kumar, A., 2024. Designing a responsive-sustainable-resilient blood supply chain network considering congestion by linear regression method. *Expert Syst. Appl.* 245, 122976. <http://dx.doi.org/10.1016/j.eswa.2023.122976>.
- Rekabi, S., Ghodrattama, A., Azaron, A., 2022. Designing pharmaceutical supply chain networks with perishable items considering congestion. *Oper. Res.* 1–61. <http://dx.doi.org/10.1007/s12351-021-00674-x>.
- Rekabi, S., Goodarzi, F., Garjan, H.S., Zare, F., Muñuzuri, J., Ali, I., 2023. A data-driven mathematical model to design a responsive-sustainable pharmaceutical supply chain network: a benders decomposition approach. *Ann. Oper. Res.* 1–42. <http://dx.doi.org/10.1007/s10479-023-05734-3>.
- Saha, A.K., Paul, A., Azeem, A., Paul, S.K., 2020. Mitigating partial-disruption risk: A joint facility location and inventory model considering customers' preferences and the role of substitute products and backorder offers. *Comput. Oper. Res.* 117, 104884. <http://dx.doi.org/10.1016/j.cor.2020.104884>.
- Shahabi, M., Unnikrishnan, A., Jafari-Shirazi, E., Boyles, S.D., 2014. A three level location-inventory problem with correlated demand. *Transp. Res. B* 69, 1–18. <http://dx.doi.org/10.1016/j.trb.2014.07.005>.
- Shang, X., Zhang, G., Jia, B., Almanaseer, M., 2022. The healthcare supply location-inventory-routing problem: A robust approach. *Transp. Res. E* 158, 102588. <http://dx.doi.org/10.1016/j.tre.2021.102588>.
- Shen, Z.-J.M., Coullard, C., Daskin, M.S., 2003. A joint location-inventory model. *Transp. Sci.* 37 (1), 40–55. <http://dx.doi.org/10.1287/trsc.37.1.40.12823>.
- Shu, J., Teo, C., Shen, Z.M., 2005. Stochastic transportation-inventory network design problem. *Oper. Res.* 53 (1), 48–60. <http://dx.doi.org/10.1287/opre.1040.0140>.
- Soyster, A.L., 1973. Convex programming with set-inclusive constraints and applications to inexact linear programming. *Oper. Res.* 21 (5), 1154–1157. <http://dx.doi.org/10.1287/opre.21.5.1154>.
- Straubert, C., 2024. A continuous approximation location-inventory model with exact inventory costs and nonlinear delivery lead time penalties. *Int. J. Prod. Econ.* 268, 109092. <http://dx.doi.org/10.1016/j.ijpe.2023.109092>.
- Wang, H., Fang, S.C., Huang, M., Zhang, Q., Deng, Z., 2022a. A joint model of location, inventory and third-party logistics provider in supply chain network design. *Comput. Ind. Eng.* 174, 108809. <http://dx.doi.org/10.1016/j.cie.2022.108809>.
- Wang, H., Huang, M., Ip, W.H., Wang, X., 2021. Network design for maximizing service satisfaction of suppliers and customers under limited budget for industry innovator fourth-party logistics. *Comput. Ind. Eng.* 158, 107404. <http://dx.doi.org/10.1016/j.cie.2021.107404>.

- Wang, Q., Nie, X., 2023. A location-inventory-routing model for distributing emergency supplies. *Transp. Res. E* 175, 103156. <http://dx.doi.org/10.1016/j.tre.2023.103156>.
- Wang, L., Wang, S., Gong, Y., Peng, L., 2023. Optimizing a multi-echelon location-inventory problem with joint replenishment: A Lipschitz ϵ -optimal approach using Lagrangian relaxation. *Comput. Oper. Res.* 151, 106128. <http://dx.doi.org/10.1016/j.cor.2022.106128>.
- Wang, S., Wang, L., Pi, Y., 2022b. A hybrid differential evolution algorithm for a stochastic location-inventory-delivery problem with joint replenishment. *Data Sci. Manage.* 5 (3), 124–136. <http://dx.doi.org/10.1016/j.dsm.2022.07.003>.
- Wang, M., Wu, J., Kafa, N., Klibi, W., 2020. Carbon emission-compliance green location-inventory problem with demand and carbon price uncertainties. *Transp. Res. E* 142, 102038. <http://dx.doi.org/10.1016/j.tre.2020.102038>.
- Yin, M., Huang, M., Qian, X., Wang, D., Wang, X., Lee, L.H., 2021. Fourth-party logistics network design with service time constraint under stochastic demand. *J. Intell. Manuf.* 1–25. <http://dx.doi.org/10.1007/s10845-021-01843-7>.
- Yin, M., Huang, M., Wang, D., Fang, S.C., Qian, X., Wang, X., 2024. Multi-period fourth-party logistics network design with the temporary outsourcing service under demand uncertainty. *Comput. Oper. Res.* 164, 106564. <http://dx.doi.org/10.1016/j.cor.2024.106564>.
- Yin, M., Huang, M., Wang, X., Lee, L.H., 2022. Fourth-party logistics network design under uncertainty environment. *Comput. Ind. Eng.* 108002. <http://dx.doi.org/10.1016/j.cie.2022.108002>.
- Zhalechian, M., Tavakkoli-Moghaddam, R., Zahiri, B., Mohammadi, M., 2016. Sustainable design of a closed-loop location-routing-inventory supply chain network under mixed uncertainty. *Transp. Res. E* 89, 182–214. <http://dx.doi.org/10.1016/j.tre.2016.02.011>.
- Zhang, Z.-H., Berenguer, G., Shen, Z.-J.M., 2014b. A capacitated facility location model with bidirectional flows. *Transp. Sci.* 49 (1), 114–129. <http://dx.doi.org/10.1287/trsc.2013.0496>.
- Zhang, Y., Gao, Z., Huang, M., Jiang, S., Yin, M., Fang, S.C., 2022b. Multi-period distribution network design with boundedly rational customers for the service-oriented manufacturing supply chain: A 4PL perspective. *Int. J. Prod. Res.* 1–20. <http://dx.doi.org/10.1080/00207543.2022.2140220>.
- Zhang, Y., Huang, M., Gao, Z., Jiang, S., Fang, S.C., Wang, X., 2024. Multi-period fourth-party logistics network design from the viability perspective: a collaborative hyper-heuristic embedded with double-layer Q-learning algorithm. *Int. J. Prod. Res.* 1–31. <http://dx.doi.org/10.1080/00207543.2024.2339530>.
- Zhang, Y., Qi, M., Miao, L., Liu, E., 2014a. Hybrid metaheuristic solutions to inventory location routing problem. *Transp. Res. E* 70, 305–323. <http://dx.doi.org/10.1016/j.tre.2014.07.010>.
- Zhang, Z.-H., Unnikrishnan, A., 2016. A coordinated location-inventory problem in closed-loop supply chain. *Transp. Res. B* 89, 127–148. <http://dx.doi.org/10.1016/j.trb.2016.04.006>.
- Zhang, Q., Wang, Z., Huang, M., Wang, H., Wang, X., Fang, S.C., 2023. Collaborative Supply Chain Network Design Problem. Working Paper.
- Zhang, Q., Wang, Z., Huang, M., Yu, Y., Fang, S.C., 2022a. Heterogeneous multi-depot collaborative vehicle routing problem. *Transp. Res. B* 160, 1–20. <http://dx.doi.org/10.1016/j.trb.2022.03.004>.
- Zheng, X., Yin, M., Zhang, Y., 2019. Integrated optimization of location, inventory and routing in supply chain network design. *Transp. Res. B* 121, 1–20. <http://dx.doi.org/10.1016/j.trb.2019.01.003>.
- Zhu, X., Cao, Y., 2021. The optimal recovery-fund based strategy for uncertain supply chain disruptions: A risk-averse two-stage stochastic programming approach. *Transp. Res. E* 152, 102387. <http://dx.doi.org/10.1016/j.tre.2021.102387>.