Resilient supply chain network design under disruption and operational risks

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Abstract Nowadays, supply chain resilience has drawn widespread attention from academics and practitioners due to the high likelihood of operational risk and the destructive consequence of disruption risk. However, the studies on resilient supply chain design considering these two types of risks are limited. Furthermore, how to quantify the uncertainty arising from the lack of historical data in the planning stage is not sufficiently studied. Aiming at these problems, this paper presents two uncertain programming models that optimize the strategic decisions before disruptions and supply chain operations after disruptions. The presented models introduce $p$-robustness measure to bound the cost in disruption scenarios. Besides, uncertainty theory is adopted to handle parameter uncertainty in the absence of historical data. Later, these two programming models are converted into their corresponding deterministic equivalents, which can be solved by Cplex. Finally, we illustrate the validity and feasibility of the proposed models and explore the impact of critical parameters on the optimal solution by implementing a series of randomly generated instances and a practical case. The observations may provide some interesting managerial insights for decision-making in reality.

Keywords Uncertainty theory · Resilience · Supply chain · Disruption risk · Operational risk

1 Introduction

Today’s supply chain operates in a more uncertain environment (Merzifonluglu, 2015; Scheibe and Blackhurst, 2018; Tang and Tomlin, 2018). This is because of many things, such as economic globalization, complicated international situation, new regulatory policy, highly volatile market, the strong correlation among companies in the supply chain. Consequently, the modern supply chain is more vulnerable than ever to various threats caused by natural and human-made attacks, and simultaneously more possible to be disturbed by potential risks (Hasani and Khosrojerdi, 2016; Snyder et al., 2016; Namdar et al., 2017; Ivanov and Dolgui, 2019; Dixit et al., 2020).

As mentioned in Tang (2006); Goh et al. (2007); Zhalechian et al. (2018), these risks during supply chain operation can be classified into two categories. One is disruption risk caused by unpredictable external events such as natural disasters, human-made attacks, unofficial strike action. This kind of risk happens infrequently but usually gives rise to halt production for a certain period (maybe few weeks or months), resulting in severe economic loss and social impact (Torabi et al., 2016; Hosseini et al., 2019). For example, the sudden outbreak and rapid spread of coronavirus have exerted a devastating influence on supply chains around the globe (Ivanov, 2020; Queiroz et al., 2020). Moreover, 94% companies listed in Fortune 1000 list have suffered from supply chain disruptions, as Fortune reports on February 21, 2020 (Fortune, 2020). The other one is the operational risk which is usually caused by high variability of internal parameters such as demand, supply and cost. Despite the lower adverse effect on the supply chain, this risk happens with a relatively high frequency. The modern supply chain has an increased...
possibility of operation risk, due to personalized service and customer requirements, the shorter life cycle of products, and new technological innovations.

High likelihood of operational risk and destructive consequence of disruption risk have been enforcing academics and practitioners to pay more attention to equip supply chain with the ability to prevent effectively, responding timely to and recovering quickly from adverse events (Sadghiani et al., 2015; Dixit et al., 2016; Kamalahmadi and Parast, 2016; Dixit et al., 2020). This ability is identified as the resilience of supply chain (Ponomarov and Holcomb, 2009; Blackhurst et al., 2011; Ponis and Koronis, 2012; Hohenstein et al., 2015; Hosseini et al., 2019). Until now, many scholars attempt to define supply chain resilience from different perspectives (Brusset and Teller, 2017; Ribeiro and Barbosa-Povoa, 2018; Hosseini et al., 2019), but there is no consensus on a precise definition (Kamalahmadi and Parast, 2016). Despite this fact, introducing resilience into supply chain design is essential to reduce the unexpected consequences. Moreover, studies Peng et al. (2011); Jabbarzadeh et al. (2016); Ghavamifar et al. (2018); Sabouhi et al. (2018) also highlight the need to take resilience into account in the planning stages since supply chain configuration is costly and hard to reverse once being built.

To enhance the planned supply chain’s resilience, incorporating disruption risk into supply chain design problem has been widely studied in the literature. As for operational risk, stochastic programming, fuzzy programming and robust optimization are most commonly used to quantify the interruption caused by parameter variations, such as demand (Zhalechian et al., 2018). While most studies identify the optimal supply chain resilient to disruption risk, the works that simultaneously take facility disruptions and parameter variations into consideration are limited. Besides, in the supply chain designing stage, parameters (fixed cost, transportation cost and capacity) related to new opened facilities (to be identified in the models) are usually unknown and indeterminate, since the historical data is nonexistent. However, few studies have considered this situation. To fill these challenges, we present uncertain programming models to design a three-tier supply chain resilient to disruption and operational risks. The problem is formulated as an expected value model (EVM) under the risk-neutral assumption and a chance-constraint programming (CCP) model which introducing confidence level $\alpha$ to measure the degree of risk-aversion. These models introduce scenario-based approach to model facility disruptions. And, the influence of disruption risks on the supply chain is reflected by the capacity loss of facilities. Besides, irregular changes in the market during supply chain operation are quantified as the uncertain demand. Uncertain parameters such as demand, cost and capacity are treated as uncertain variables using uncertainty theory, which is an appropriate approach to deal with parameter uncertainty in the absence of historical data. This study may contribute to the resilient supply chain management literature by the following ways,

- First, this paper takes the risks of facility disruptions and parameter uncertainties into account, simultaneously.
- Second, most studies introduce facility fortification strategy to hedge against disruption risk in which reliable facility with more investment that never fails is assumed. To be more realistic, we relax this assumption by considering relatively reliable facility which may lose smaller capacity when it is disrupted.
- Third, we consider the uncertainty of more parameters, such as demand, cost and capacity. These parameters are modeled as uncertain variables by using uncertainty theory since their historical data is nonexistent.
- Finally, confidence level $\alpha$ is adopted to quantify decision-makers’ risk performance, and a larger $\alpha$ means a high-risk solution. By this way, decision-maker can adjust its value subjectively in accordance with their conservativeness level.

The remainder of this paper is organized as follows. Section 2 reviews the optimization models related to resilient supply chain design problem. Section 3 first explains the assumptions, parameters, variables and then proposes expected value model and chance-constrained programming model, followed by their equivalent crisp programming models in Section 4. Later Section 5 and Section 6 illustrate the feasibility and practicability of the proposed models and conduct the sensitivity analysis about main parameters, ended with the conclusion and future research directions in Section 7.

2 Literature review

In the literature of this context, the most commonly used approach to deal with disruption risk is the scenario-based approach. Using this approach, two-stage mathematical programming models are proposed to investigate the effect of disruption risk on decisions of supply chain configuration. The strategic decisions include optimal number and location of facilities which are determined in the first stages, and the second stage identifies the plans including material purchase, production, distribution, and so on under all or concerned disruption scenarios. Thus, the designed supply chain
is equipped with the ability to hedge against disruption risk.

Besides, scenario-based approach is also utilized to deal with operational risk. For example, Fattahi et al. (2017) investigated a three-tier supply chain (production plants, warehouses, and customer) design problem and proposed a mixed-integer, non-linear model. This model assumed random demand and warehouses’ capacity and generated a scenario tree to represent the stochastic process for such parameters. Using the same approach, Fattahi and Govindan (2018) modeled uncertainties of feedstock supply and available capacity in their multi-stage stochastic program model for biofuel supply chain networks. Tolooei et al. (2020) formulated a reliable capacitated supply chain problem as a two-stage stochastic mixed-integer model. The proposed model adopted the scenario-based approach to model the uncertainty caused by facility disruptions and indeterministic demand.

There were also studies modeled the uncertain parameter as the random variable with a specified distribution. Aryanazhad et al. (2010) and Zhang et al. (2016) presented a nonlinear integer programming model respectively for a two-tier supply chain comprising distribution centers (DC) and customers. The model assumed that each DC might fail with an independent probability and customers have random demands. Atoei et al. (2013) investigated a three-tier supply chain design problem including suppliers, DCs and retailers in which both suppliers and DCs were possible to be disrupted. In the presented model, customer demands were indeterminate and treated as normal random variables. Likely, Baghalian et al. (2013) considered random demands and multi-disruptions in manufacturers, DCs and their connecting links in a multi-product, multi-tier supply chain. For such a problem, a stochastic mathematical formulation is proposed to identify the optimal location of DCs, retailers and optimal network distributions. All these models only assume facility may be disrupted, but ignore the recovery plans after disruptions. Zhao and You (2019) take facility disruptions and recovery time into account and propose a bi-objective two-stage adaptive robust mixed-integer fractional programming model for a three-tier supply chain (supplier, manufacturing facilities, and customers). The mathematical model identifies the optimal strategic decision variables of the supply chain before disruptions and operations during and after disruptions while minimizing total nominal cost and maximizing worst-case resilience. The distribution of uncertain demand is obtained from historical data using kernel density estimation (KDE) technique.

However, it is hard to estimate the probability distribution in some cases. To address this challenge, Bertsimas and Sim (2004) presented a robust optimization approach, which later was adopted by many scholars. For example, Hatefi and Jolai (2014) tackled uncertain demand by using robust optimization approach in a forward-reverse logistics network design problem. Hasani and Khosrojerdi (2016) considered demand and procurement cost uncertainties which were tracked using the same approach in a global supply chain design problem. To mitigate the impact of facility disruptions on the designed supply chain, the researchers introduced multiple strategies, including multiple sourcing, facility dispersion and fortification and extra inventory. Dehghani et al. (2018) addressed a solar photovoltaic supply chain network design problem considering the uncertainty arising from business-as-usual and hazard. To this end, they proposed a hybrid, robust-scenario based optimization model. The presented model introduced facility fortification, multi-sourcing, and alternative material to mitigate the adverse consequence caused by hazard uncertainty. Furthermore, uncertain demand and cost parameter was dealt with robust programming approach. Gholamia et al. (2019) presented a multi-objective mixed-integer linear programming for a four-tier supply chain. In the presented model, robust optimization approach was used to deal with the uncertainty of demand and supply cost. The researchers also discussed the advantage of three methods solving multi-objective problems: goal programming method, weighted-sum method, and LP-metric method. Using robust approach, Fazli-Khalaf et al. (2019) addressed the uncertainty of demand, cost, capacity, and return rate in a closed-loop supply chain network design problem.

There are also studies that adopt fuzzy programming approach to deal with the epistemic uncertainty due to the lack of historical data. For example, Hatefi et al. (2015) proposed a fuzzy possibilistic programming model to design a forward-reverse logistics network resilient to facility disruptions and parameter uncertainties. In the presented model, imprecise parameters such as various cost, demand, facility capacity, returned product were treated as fuzzy triangular variables. Apart from these inherent parameters, Torabi et al. (2016) investigated the uncertainties of various cost, demand, return rate, average disposal fraction and available capacity which were modeled as triangular fuzzy numbers in their mixed-integer possibilistic linear programming model. Moreover, Mari et al. (2016) presented a possibilistic fuzzy multi-objective programming model for a forward-reverse supply chain in the garment industry. This model assumed uncertain de-
mand, cost, return rates, capacity and disruption probability.

Besides, Jabbarzadeh et al. (2016) integrated two programming approach to presented a hybrid robust-stochastic model for a two-echelon supply chain network. This model assumed uncertain demand, disruption probability and available capacity after disruptions. Khalili et al. (2017) modeled cost, demand and available capacity as triangular fuzzy numbers in their two-stage mixed stochastic-possibilistic programming model for a two-echelon supply chain. This model adopted conditional value at risk (CVaR) to measure the risk attitude of decision-makers. To ensure the continuous production and distribution after disruptions, backup inventory, emergency inventory and additional production capacity were developed. Mohammaddust et al. (2017) take disruption and operation risks into account and firstly develop a single-objective model maximizing supply chain profit for four-tier (suppliers, manufacturers, DCs and retail) supply chain. In the model, emergency stock, excess capacity and substitute supplier or facility are introduced to enhance the planned supply chain’s resilience. Moreover, random customer demands were assumed. Later, based on this model, they considered uncertain transportation time and handling time to propose a bi-objective model which min lead time and non-responded demand simultaneously. The latter model adopted robust optimization approach to deal with time uncertainty. Samani and Hosseini-Motlagh (2019) considered a blood supply chain network design problem under uncertain environment. The researchers integrated fuzzy analytic hierarchy process and grey rational analysis to deal with facility disruptions. And robust possibilistic programming approach was proposed to tackle the uncertainty of supply, demand, and cost. Ahranjani et al. (2020) combined stochastic, possibilistic, and robust programming approach to address a resilient bioethanol supply chain design problem. In their works, drought was considered the source of the disruption of biomass feedstock yield. And demand, price, cost, and yield are indeterministic from the limited available data due to various factors, such as market fluctuations, horrible weather conditions, and production environment. Haieri et al. (2020) formulated blood supply chain network design under uncertainty as a multi-objective integrated resilient-efficient model. The model identified the optimal locations and assignments while minimizing the total cost and maximizing efficiency and resilience.

In summary, there are two main sources of uncertainty in the literature. One is randomness with certain regularity in nature which can be mathematically defined as probability distribution. Usually, uncertain parameters are modeled as random variables in existing models. And scholars utilize stochastic programming to formulate mathematical problems if distributional information can be captured according to enough historical data. On the contrary, in the absence of probability distribution, robust optimization approach is adopted to describe random variable with a specific interval. The other one is non-randomness or fuzziness arising from the lack of enough data. In this case, fuzzy or possibilistic programming models are presented by treating uncertain parameters as fuzzy variables based on expert’s opinions and adjustments.

In this paper, we attempt to investigate the impact of disruption risk and operation risk on the strategic decisions of supply chain. The capacity loss of facilities is introduced to quantify the consequence caused by facility disruptions. And irregular changes in the market during supply chain operation are quantified as the fluctuant demand. However, supply chain usually operates in a highly uncertain environment, and direct data of these parameters are nonexistent before risk events happening, especially for unforeseen disruption risk. Moreover, the parameters (fixed cost, transportation cost and capacity) related to new opened facilities (to be identified in the models) are also unknown and indeterminate in the planning stage, which is ignored in the literature. We can not obtain their actual data until the new facility is completed. So, treating these uncertain parameters as random variables is inaccurate in nature. In this case, fuzzy set theory is, seemingly, the remaining alternative in the resilient supply chain management literature. However, it does not emphasize the law of the excluded middle and the law of contradiction theoretically. To address this challenge, Liu proposed uncertainty theory to deal with parameter uncertainty in the absence of historical theory (Liu, 2007), which later is improved in 2010 (Liu, 2010).

Compared with the methods mentioned above, uncertainty theory is a more rational and rigorous mathematical tool. And its effectiveness in modelling uncertain parameters without historical data has been proved by many works Yang and Gao (2016); Wang et al. (2018); Shi et al. (2020); Song et al. (2020). So, this paper adopts uncertainty theory to tackle with uncertainty arising from the limited historical data. Besides, the existing references considering the risk-aversion attitude of decision-makers are even less (only in (Baghalian et al., 2013; Torabi et al., 2016; Khalili et al., 2017)), while most models are formulated based on the assumption of risk-neutral. To fill this gap, we adopt a confidence level $\alpha$ to capture the risk preference of decision-maker in CCP model while modelling the resilient sup-
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3 Problem description and mathematical formulation

This section first elaborates the background and main assumptions of the resilient supply chain design problem, and all parameters, variables of mathematical models. Then excepted value model which minimizes the expected value of nominal cost and chance-constrained programming model which minimizes the optimism value of nominal cost are developed, subjecting to $p$-robustness, capacity, demand satisfaction, and facility location constraints.

3.1 Problem description

The three-tier supply chain network, including production plants, warehouses and customers, is depicted in Figure 1. In the first layer, several existing plants characterized by the limited production capacity produce a single product in accordance with orders and transmit products to warehouses.

In the second layer, a set of potential locations are considered to establish new warehouses with the limited capacity for holding products. Taking disruption risk into account, we assume that the opened warehouses may be disrupted under the threats of various unexpected events. Thus there exist two states for each warehouse: failure or normal. The combinations of every warehouse state define all possible disruption scenarios, such as $n$ warehouses mean $2^n$ disruption scenarios. A disrupted warehouse usually loses its part capacity, which may result in unmet customer demands. To hedge against the risk of facility disruptions, we introduce facility fortification strategy and preset optional fortification level for each warehouse. Moreover, more facility investment is assumed to reduce the adverse consequence of disruption with a less reduced capacity.

In the last layer, customers are distributed in various geographical regions. Moreover, multi-sourcing for customers is assumed, meaning several open warehouses are allowed to supply products for every customer, simultaneously. Meanwhile, unmet demand for the customer is punished with comparatively high penalty under facility disruptions.

Now, we aim to design such a three-tier supply chain resilient to the risks of facility disruption and parameter uncertainty at the lowest possible cost, which has been most studied in the literature related to resilient supply chain design. In this respect, a series of strategic and tactical decisions are identified under the facility location, $p$-robustness, demand satisfaction, facility capacity and resources equilibrium constraints. These decisions include: (1) the optimal number, location, fortification level of warehouses, (2) the optimal production plans of production plants, and (3) the optimal allocation among production plants, warehouses and customers.

3.2 Problem formulation

Here, to better inform the mathematical formulations, we first list all sets, parameters, and decision variables throughout the models.

- **Sets**
  
i: Index of existing production plants, $i = 1, ..., I$.
  
j: Index of potential location for warehouses to be established, $j = 1, ..., J$.
  
k: Index of customer zone, $k = 1, ..., K$.
  
s: Index of disruption scenario, $s = 0, ..., S$.
  
n: Index of fortification levels for warehouses, $n = 1, ..., N$.

- **Parameters**
  
  $pc_i$: Unit production cost in production plant $i$.
  
  $uc_k$: Unit penalty cost for unsatisfied demand in customer $k$.
  
  $C_i$: Capacity of production plant $i$.
  
  $z_{js}$: The state of warehouse $j$. If warehouse $j$ is disrupted, $z_{js}=1$; otherwise, $z_{js}=0$.
  
  $ps$: Desired robustness level in scenario $s$.
  
  $rs_s$: Desired satisfaction rate in scenario $s$.
  
  $w_k$: Weight factor of customer $k$.
  
  $f_{jn}$: Fixed cost of opening warehouse $j$ with fortification level $n$.
  
  $C_j$: Capacity of warehouse $j$. 

\(a_{jn}\): Percentage of capacity loss of a disrupted warehouse \(j\) with fortification level \(n\).

\(D_k\): Demand of customer \(k\).

\(d_{ij}^{pi}\): Unit transportation cost from production plant \(i\) to warehouse \(j\).

\(c_{jk}^{\text{rec}}\): Unit transportation cost of from warehouse \(j\) to customer \(k\).

- Decision variables

\(x_{jn}\): 1 if a warehouse is opened at candidate location \(j\) with fortification level \(n\).

\(Q_{ij}s\): Quantity of products shipped from production plant \(i\) to warehouse \(j\) under scenario \(s\).

\(Q_{jks}\): Quantity of products shipped from warehouse \(j\) to customer \(k\) under scenario \(s\).

\(\bar{tc}\): The optimistic value of total cost.

The parameters distinguished with the tilde sign (\(\sim\)) are modeled as uncertain variables since the related historical data of these parameters is nonexistent. Thus, we cannot obtain their actual values or estimate their probability distribution. In this case, consulting experts to acquire personal belief degree is also an alternative way to quantify these uncertain parameters. Considering that uncertainty theory is a useful tool to deal with belief degree, we adopt this theory to set \(f_{jn}\), \(\tilde{C}_j\), \(a_{jn}\), \(\bar{D}_k\), \(c_{jk}^{\text{rec}}\) and \(c_{jk}^{\text{rec}}\) as uncertain variables with uncertainty distributions \(\Phi_{jn}^{f}, \Phi_{ij}^{C}, \Phi_{jn}^{a}, \Phi_{k}^{c}, \Phi_{ij}^{d}f, \Phi_{jk}^{c}\) and \(\Phi_{jk}^{d}f\), respectively.

In this section, we place more emphasis on minimizing the total cost of nominal scenario with no disruption \(tc_0\) while limiting the cost of disruption scenarios by introducing \(p\) robustness criterion into the constraint.

The total cost under disruption scenario \(s\) is described by the following mathematical function:

\[
tc_s = \sum_{j=1}^{J} \sum_{n=1}^{N} \tilde{f}_{jn} x_{jn} + \sum_{i=1}^{I} \sum_{j=1}^{J} p_{ci} Q_{ij}s + \sum_{j=1}^{J} \sum_{k=1}^{K} \tilde{c}_{ij}^{di} Q_{ij}s + \sum_{j=1}^{J} \sum_{k=1}^{K} c_{jk}^{\text{rec}} Q_{jks} + \sum_{k=1}^{K} u_{ck} (\bar{D}_k - \sum_{j=1}^{J} Q_{jks}).
\]

The first term of this equation is the fixed cost of opening warehouses. The second term is the total production cost in production plants. The third and fourth term is the total transportation cost among nodes. Finally, the penalty of unmet demand is described in the fifth term. Since uncertain variables are considered in the cost function and cannot be directly minimized, we may minimize its expected value. Then we propose the following expected value model (EVM).

\[
\min \ E [tc_0] \quad (1)
\]

\[
s.t. \quad M \left\{ \sum_{k=1}^{K} Q_{jks} \leq \sum_{n=1}^{N} (1 - \tilde{a}_{jn} z_j) \bar{C}_j x_{jn} \right\} \geq \gamma_s, \quad j = 1, ..., J, s = 0, ..., S, \quad (3)
\]

\[
M \left\{ \sum_{k=1}^{K} \frac{\sum_{j=1}^{J} Q_{jks}}{D_k} \geq \theta_s, \quad s = 0, ..., S, \quad (4)
\]

\[
M \left\{ \sum_{j=1}^{J} Q_{jks} \leq \bar{D}_k \right\} \geq \delta_s, \quad k = 1, ..., K, \quad s = 0, ..., S, \quad (5)
\]

\[
\sum_{j=1}^{J} Q_{jks} = \sum_{i=1}^{I} Q_{ij}s, \quad j = 1, ..., J, s = 0, ..., S, \quad (6)
\]

\[
\sum_{j=1}^{J} Q_{ij}s \leq C_i, \quad i = 1, ..., I, s = 0, ..., S, \quad (7)
\]

\[
\sum_{j=1}^{J} x_{jn} \leq 1, \quad j = 1, ..., J, \quad (8)
\]

\[
x_{jn} \in \{0,1\}, \quad j = 1, ..., J, n = 1, ..., N, \quad (9)
\]

\[
Q_{ij}s \geq 0, \quad i = 1, ..., I, j = 1, ..., J, s = 0, ..., S, \quad (10)
\]

\[
Q_{jks} \geq 0, \quad j = 1, ..., J, k = 1, ..., K, s = 0, ..., S. \quad (11)
\]

The objective function (1) attempts to minimize the excepted nominal cost. Besides, it is difficult to define a crisp feasible set since some constraints contain uncertain variables. So we introduce predetermined confidence levels which take value from interval \([0,1]\) to relax these constraints. The higher the confidence level is, the higher possibility the uncertain constraint holds. The constraint (2) introduces \(p\)-robustness criterion, namely, the total cost of each disruption scenario \(tc_s\) can not be greater than \((1 + p_s)\%\) of its optimal cost \(tc_0^\ast\). The constraint (3) expresses the capacity restriction of warehouses. The constraints (4) expressed demand satisfaction criterion which refers to the weighted sum of the ratio between supply quantity for every customer and its demand should be more than \(r_s\%\) with a confidence level \(\theta_s\). The constraint (5) assures all supply quantities from warehouses to one customer can not exceed its demand with a confidence level \(\delta_s\). The constraint (6) stresses the balance of products in warehouses, that is to say, the product quantities shipped from one warehouse to customers should be equal to the product quantities shipped to that warehouse. The constraint (7) expresses that product quantities leaving from one production plant should not be greater than its production capacity. The constraint (8) guarantees that only one warehouse with a fortification level is allowed in each potential location. The constraint (9) is binary constraints. Moreover, the rest of the constraints
are nonnegativity constraints. For simplicity, we assume \( p_s=p, r_s=r, \eta_s=\eta, \gamma_s=\gamma, \theta_s=\theta \) and \( \delta_s=\delta \) for all scenarios in later numerical examples.

The optimal cost \( tc^*_s \) under each disruption scenario in the first constraint derives from following sub-model.

\[
tc^*_s = \min E [tc_s]
\]

**s.t.**

\[
M \left\{ \sum_{k=1}^{K} Q_{jks} \leq \sum_{n=1}^{N} (1 - a_{jna}z_j)\bar{C}_{jnxjn} \right\} \geq \gamma_s, \quad j = 1, ..., J,
\]

\[
M \left\{ \sum_{k=1}^{K} \frac{J Q_{jks}}{D_k} \geq r_s \right\} \geq \theta_s,
\]

\[
M \left\{ \sum_{j=1}^{J} Q_{jks} \leq \bar{D}_k \right\} \geq \delta_s, \quad k = 1, ..., K,
\]

\[
\sum_{j=1}^{J} Q_{jjs} = \sum_{i=1}^{I} Q_{ijs}, \quad j = 1, ..., J,
\]

\[
\sum_{j=1}^{J} Q_{ijs} \leq C_i, \quad i = 1, ..., I,
\]

\[
\sum_{n=1}^{N} x_{jn} \leq 1, \quad j = 1, ..., J,
\]

\[
x_{jn} \in \{0, 1\}, \quad j = 1, ..., J, n = 1, ..., N,
\]

\[
Q_{ijs} \geq 0, \quad i = 1, ..., I, j = 1, ..., J,
\]

\[
Q_{jks} \geq 0, \quad j = 1, ..., J, k = 1, ..., K.
\]

Similarly, we assume \( \hat{\eta}_s=\hat{\eta}, \hat{\gamma}_s=\hat{\gamma}, \hat{\theta}_s=\hat{\theta} \) and \( \hat{\delta}_s=\hat{\delta} \) for all scenarios in this sub-problem in order to simplify calculation.

In the above EVM, we give attention to the expected value of total cost under the normal scenario, since cost function includes uncertain variables which cannot be minimized directly. Sometimes, decision-makers who have a positive attitude more concern the optimistic value of total cost, rather than excepted cost. To this end, we introduce a predetermined confidence level \( \beta \) and optimistic cost \( \bar{tc} \) to propose **chance-constrained programming model (CCP)** as follows.

\[
\min \bar{tc}
\]

**s.t.**

\[
M \{ tc_0 \leq \bar{tc} \} \geq \beta,
\]

Eqs. (2) to (11).

In this model, the optimistic value of total cost under the normal scenario is minimized. The first constraint guarantees the nominal cost can not exceed optimistic cost with a given confidence level \( \alpha \). As for confidence levels, \( p_s=p, r_s=r, \eta_s=\eta, \gamma_s=\gamma, \theta_s=\theta \) and \( \delta_s=\delta \) are also assumed in section 6.

### 4 Solution procedure

The presented models are difficult to solve since chance constraints and uncertain variables are included. This section first converts two models into their deterministic programming models using operational laws in uncertainty theory. Then, more concretely mathematical formulations are presented under the assumption of normal uncertainty distribution.

Let \( \Phi_{j^m}^{-1}, \Phi_{j^w}^{-1}, \Phi_{j^n}^{-1}, \Phi_{j_k}^{-1}, \Phi_{j^w_k}^{-1} \) be the uncertainty distributions of \( \bar{f}_{jn}, \bar{C}_j, a_{jna}, C_{jk}, \) and \( \bar{D}_{jk} \), respectively. Since these uncertain variables are all independent uncertain variables, the total cost under each disruption scenario is also an uncertain variable. We denote the inverse uncertainty distribution of \( tc_s \) by \( \Phi_{tc_s}^{-1}(\alpha) \). Using the operational laws for calculating inverse uncertainty distribution (more details are referred to Appendix, \( \Phi_{tc_s}^{-1}(\alpha) \) can be represented by the following equation,

\[
\Phi_{tc_s}^{-1}(\alpha) = \frac{1}{\alpha} \sum_{i=1}^{I} \sum_{j=1}^{J} x_{jn} \left( \Phi_{j^m}^{-1}(\alpha) + \sum_{i=1}^{I} \sum_{j=1}^{J} p_{ij} Q_{ijs} \right)
\]

\[
+ \sum_{i=1}^{I} \sum_{j=1}^{J} Q_{ijs} \left( \Phi_{j^w}^{-1}(\alpha) + \sum_{i=1}^{I} \sum_{j=1}^{J} p_{ij} Q_{ijs} \right)
\]

\[
+ \sum_{k=1}^{K} w_k \left( \Phi_{j_k}^{-1}(\alpha) - \sum_{j=1}^{J} Q_{jks} \right).
\]

The expected value is the definite integral of inverse distribution from 0 to 1. Thus, the objective function (1) can be converted into the following equivalent formulation,

\[
E [tc_0] = \int_0^1 \Phi_{tc_0}^{-1}(\alpha) d\alpha.
\]

Besides, chance constraint (2) also contains uncertain variable. It can be rewritten as follows,

\[
\Phi_{tc_s}^{-1}(\eta_s) = (1 + p_s)tc^*_s \geq \eta_s.
\]

Using inverse uncertainty distribution, the above equation can be rewritten as follows,

\[
\Phi_{tc_s}^{-1}(\eta_s) \leq \Phi_{tc_s}^{-1}(\eta_s).
\]

\[
\Phi_{tc_s}^{-1}(\eta_s) \leq \Phi_{tc_s}^{-1}(\eta_s).
\]
Similarly, other chance constraints can be converted into their deterministic formulations. Thus, we can present the following deterministic programming model of EVM,

$$\min \int_0^1 \Phi_0^{-1}(\alpha) d\alpha$$

subject to

$$\Phi_s^{-1}(\eta_s) \leq (1 + p_s) t c_s^*$$  \hspace{1cm} \text{for } s = 1, \ldots, S,$$

$$K \sum_{k=1}^N Q_{kjs} \leq \sum_{n=1}^N \left(1 - \left(\Phi_{jn}^w\right)^{-1}(\gamma_s) \right) \left(\Phi_{jn}^d\right)^{-1}$$

$$\times \left(1 - (1 - \eta_s) x_{jn}, j = 1, \ldots, J, s = 0, \ldots, S,$$

$$r_s \leq \sum_{k=1}^K \sum_{j=1}^J Q_{kjs}$$

$$s = 0, \ldots, S, \tag{27}$$

$$\sum_{j=1}^J Q_{kjs} \leq \left(\Phi_k\right)^{-1}(1 - \delta_s), \quad k = 1, \ldots, K, \tag{28}$$

Eqs. (6) to (11).

In the same way, CCP is equivalent to the following deterministic programming model,

$$\min \overline{t c}$$

subject to

$$\Phi_0^{-1}(\beta) \leq \overline{t c},$$

Eqs. (27) to (30),

Eqs. (6) to (11).

In the deterministic programming models, uncertain variables are eliminated by using inverse uncertainty distributions. The inverse uncertainty distribution of a normal uncertain variable $\xi \sim \mathcal{N}(c, \sigma)$ is $\Phi^{-1}(\alpha) = c + \frac{\sqrt{2\pi}}{\sigma} \ln \frac{\alpha}{1 - \alpha}$. And its expected value is $E[\xi] = c$. Assume that all uncertain variables in this paper are independent normal uncertain variables, denoted by $f_{jn} \sim \mathcal{N}(e_{jn}^f, \sigma_{jn}^f), C_j \sim \mathcal{N}(e_j^c, \sigma_j^c), a_{jn} \sim \mathcal{N}(e_{jn}^a, \sigma_{jn}^a), D_k \sim \mathcal{N}(e_k^d, \sigma_k^d), c_{ij}^w \sim \mathcal{N}(e_{ij}^w, \sigma_{ij}^w)$ and $c_{ij}^w \sim \mathcal{N}(e_{ij}^w, \sigma_{ij}^w)$, respectively. Thus the inverse of uncertainty distribution of $t c_s$ can be rewritten as the following formula,

$$\left(\Phi_s^{-1}(\alpha)\right)' = \sum_{j=1}^J \sum_{n=1}^N \left(e_{jn}^f + \frac{\sqrt{3}\sigma_{jn}^f}{\pi} \ln \frac{\alpha}{1 - \alpha}\right) x_{jn}$$

$$+ \sum_{i=1}^I \sum_{j=1}^J p_{ci} Q_{ij}$$

$$+ \sum_{i=1}^I \sum_{j=1}^J \left(e_{ij}^w + \frac{\sqrt{3}\sigma_{ij}^w}{\pi} \ln \frac{\alpha}{1 - \alpha}\right) Q_{ij}$$

$$+ \sum_{j=1}^J \sum_{k=1}^K \left(e_{jk}^w + \frac{\sqrt{3}\sigma_{jk}^w}{\pi} \ln \frac{\alpha}{1 - \alpha}\right) Q_{kjs}$$

$$\geq \sum_{k=1}^K \sum_{j=1}^J u_{ck} \left(e_{k}^c + \frac{\sqrt{3}\sigma_{k}}{\pi} \ln \frac{\alpha}{1 - \alpha} - \sum_{j=1}^J Q_{kjs}\right).$$

And the expected value of total cost under normal scenario is as follows,

$$E \left[\Phi_0^{-1}(\alpha)\right]' = \sum_{j=1}^J \sum_{n=1}^N e_{jn}^f x_{jn} + \sum_{i=1}^I \sum_{j=1}^J p_{ci} Q_{ij}$$

$$+ \sum_{i=1}^I \sum_{j=1}^J e_{ij}^w Q_{ij} + \sum_{j=1}^J \sum_{k=1}^K e_{jk}^w Q_{kjs}$$

$$+ \sum_{k=1}^K u_{ck} \left(e_{k}^c - \sum_{j=1}^J Q_{kjs}\right).$$

Thus, the equivalent formulation of EVM under the assumption of normal uncertain variables can be obtained as follows,

$$\min E \left[\Phi_0^{-1}(\alpha)\right]'$$

subject to

$$\Phi_0^{-1}(\eta_s) \leq (1 + p_s) t c_s^*, \quad s = 1, \ldots, S,$$

$$K \sum_{k=1}^N Q_{kjs} \leq \sum_{n=1}^N \left(e_{jn}^w - \frac{\sqrt{3}\sigma_{jn}^w}{\pi} \ln \frac{\alpha}{1 - \alpha}\right)$$

$$\times \left(1 - \left(\Phi_{jn}^d\right)^{-1}(\gamma_s) \right)$$

$$\times \left(1 - (1 - \eta_s) x_{jn}, j = 1, \ldots, J, s = 0, \ldots, S,$$

$$r_s \leq \sum_{k=1}^K \sum_{j=1}^J Q_{kjs}$$

$$s = 0, \ldots, S, \tag{30}$$

$$\sum_{j=1}^J Q_{kjs} \leq \left(\Phi_k\right)^{-1}(1 - \delta_s), \quad k = 1, \ldots, K, \tag{31}$$

Eqs. (6) to (11).

And CCP can be rewritten by the following mathematical description,

$$\min \overline{t c}$$

subject to

$$\Phi_0^{-1}(\beta) \leq \overline{t c}, \tag{32}$$

Eqs. (33) to (36),

Eqs. (6) to (11).

5 Numerical experiments

In this section, we implement a series of simulation examples to illustrate the feasibility and validity of the
proposed models in section 3. Moreover, sensitivity analysis about critical parameters such as robustness and satisfaction criteria and confidence levels are performed, and some noteworthy observations for practical application are presented. All examples are coded and executed in cplex 12.8.

5.1 Experimental design

We first generate 50 points randomly representing 5 existing production plants, 15 potential locations for new warehouses and 30 customer zones to simulate a three-tier supply chain described in section 4. Here, several necessary data sets are generated as follows. For existing production plants, the production capacity $C_i$ and unit production cost $pc_i$ are drawn uniformly from [1000,10000] and [0,50], respectively. Besides, we assume all uncertain variables in the presented models are normal variables. Therefore, for warehouses, the excepted value $e_C^w$ of holding capacity $C_j$ is drawn uniformly from [1000,3000]. Besides, we set the fortification level $N = 3$. For different fortification level, the excepted value $e_{jn}^w$ of fixed cost for opening a warehouse $f_{jn}$ is drawn uniformly from $[5e_j^w, 10e_j^w], [10e_j^w, 15e_j^w]$ and $[15e_j^w, 20e_j^w]$, respectively. In terms of lose capacity under disruptions $\bar{\sigma}_{j}^{w}$, its excepted value $e_{jn}^{w}$ is drawn uniformly from $[0.4, 1], [0.2, 0.4]$ and $[0, 0.2]$ respectively. With regard to unit transportation cost $c_{ij}^w$ and $c_{jk}^w$, their excepted values $e_{ij}^{pw}$ and $e_{jk}^{wc}$ are set equal to 2, and $\sigma_{ij}^{w} = 5$, $\sigma_{jn}^{w} = 0.02$. Other key parameters are set as $p=0.4$, $r=0.8$, $\eta=0.9$, $\gamma=0.9$, $\theta=0.9$ and $\delta =0.9$. In addition, we set $\eta_1=0.9$, $\gamma_1=0.9$, $\theta_1=0.9$ and $\delta_1 =0.9$ for all sub-problems.

5.2 Sensitivity analysis of disruption scenario

As mentioned earlier, the combinations of warehouses’ state specify all possible disruption scenarios, each of which defines a collection of warehouses that are disrupted at the same time. As the number of warehouses increases, both scenario number and model size grows exponentially, resulting in increased computational burden. However, the possibility of more than two warehouses to be disrupted simultaneously in practice is relatively small. For this reason, decision-makers may focus exclusively on a much smaller part of scenarios which are more likely to happen, rather than all possible scenarios. Meanwhile, to the best of our knowledge, most academic studies in which the scenario-based approach is adopted usually identify a fraction of scenarios to test presented models’ performance. To choose the appropriate scenario number to conduct sensitivity analysis, we design a series of experiments to test how the number of scenarios can influence the optimal solutions and run time.

Table 1 and Table 2 conclude the results of numerical experiments from four aspects. The "see" column gives the number of considered disruption scenarios. In this respect, we prefer to consider scenarios where only one warehouse is disrupted at the beginning, then two, and then three warehouses to be disrupted simultaneously. For each model, four columns report the objective value ("cost"), optimal number, location and fortification level for warehouses ("location"), percent difference between the objective value and the former one ("diff(%)"), and run time ("time(s)"). It’s worth noting that marking "2" in top right corner of locations in column "location" means the facility is opened with fortification level 2. Otherwise, lower fortification level is chosen.

Not surprisingly, we can see that it spends more time getting an optimal solution while disruption scenario increases. However, the objective value is less sensitive to the number of scenarios, while run time increases sharply. Especially when the number of scenarios is more than 60, the objective value changes slightly with no more than 0.10% cost difference in the first model and no more than 0.24% cost difference in the latter, as scenario number becomes larger. For this reason, we set the number of scenarios $S=60$ in the following experiments to conduct sensitivity analysis. Similarly, decision-maker can choose scenarios that they concern more in practice to obtain strategic and tactical decisions regardless of obvious change in the nominal cost.

In these tables, scenario 1 is identified as the normal scenario, which means no warehouses is disrupted. When we take facility disruption into account, it can be seen that disruption scenarios influence the optimal location and fortification level for warehouses. This finding verifies the necessary to consider disruption risk during supply chain planning stage. Besides, we also find that the optimal solutions are different in two models under some disruption scenarios, such as $S=30$, 60, etc. This indicates that the decision criteria of decision-maker may exert an influence on strategic decisions in our study.
Table 1 The results of EVM under different scenarios

| sce  | cost          | location                  | diff(%) | time(s) |
|------|---------------|---------------------------|---------|---------|
| 1    | 833579        | 1,3,5,9,10,12,13          | 0       | 0.20    |
| 10   | 837209        | 1,3,5,7,9,10,12,13        | 0.44    | 4.26    |
| 20   | 840746        | 1,2,3,5,7,9,12,13         | 0.42    | 11.08   |
| 30   | 842350        | 1,3,5,7,9,12,13           | 0.19    | 27.45   |
| 40   | 842350        | 1,3,5,7,9,12,13           | 0       | 31.45   |
| 50   | 842350        | 1,3,5,7,9,12,13           | 0       | 55.33   |
| 60   | 845769        | 1,3,5,2,7,9,12,13,14     | 0.41    | 74.97   |
| 70   | 845769        | 1,3,5,2,7,9,12,13,14     | 0       | 205.67  |
| 140  | 845769        | 1,3,5,2,7,9,12,13,14     | 0       | 126.11  |
| 150  | 846623        | 1,2,3,5,2,7,9,12,13      | 0.10    | 431.05  |
| 160  | 846623        | 1,2,3,5,2,7,9,12,13      | 0       | 562.42  |
| 200  | 846623        | 1,2,3,5,2,7,9,12,13      | 0       | 958.52  |

Table 2 The results of CCP under different scenarios

| sce  | cost          | location                  | diff(%) | time(s) |
|------|---------------|---------------------------|---------|---------|
| 1    | 912468        | 1,3,5,9,10,12,13          | 0       | 0.19    |
| 10   | 916098        | 1,3,5,9,10,12,13          | 0       | 6.30    |
| 20   | 916542        | 1,2,3,5,2,9,12,13         | 0.05    | 12.23   |
| 30   | 921993        | 1,2,3,5,2,9,12,13,14     | 0.60    | 54.70   |
| 40   | 921993        | 1,2,3,5,2,9,12,13,14     | 0       | 46.67   |
| 50   | 921993        | 1,2,3,5,2,9,12,13,14     | 0       | 74.31   |
| 60   | 924099        | 1,2,3,5,2,9,12,13,14     | 0.23    | 117.97  |
| 70   | 924099        | 1,2,3,5,2,9,12,13        | 0       | 262.30  |
| 130  | 924099        | 1,2,3,5,2,9,12,13        | 0       | 297.94  |
| 140  | 926323        | 1,2,3,5,2,9,12,13,14     | 0.24    | 1843.08 |
| 150  | 927177        | 1,2,3,5,2,7,9,12,13      | 0.09    | 472.88  |
| 160  | 927177        | 1,2,3,5,2,7,9,12,13      | 0       | 835.66  |
| 200  | 927177        | 1,2,3,5,2,7,9,12,13      | 0       | 1202.64 |

5.3 Sensitivity analysis of decision criteria

In the presented models, EVM assumes that decision-maker is a risk-neutral, while CCP considers the risk preference by introducing confidence level $\alpha$. A larger $\alpha$ means decision-maker is more risk-averse. In this section, we test the performance of two models under different risk attitude, and the sensitivity analysis results are reported in Figure 2 and Figure 3.

Fig. 2 The objective value at different $\alpha$ when $S=30$

Fig. 3 The objective value at different $\alpha$ when $S=60$

5.4 Sensitivity analysis of robustness and satisfaction criterion

In this section, we conduct a series of numerical examples to test how the subjective value $p$ and $r$ can influence the optimal objective value. The default value of confidence levels in two models are set as $\eta=0.9$, $\gamma=0.9$, $\theta=0.9$, $\delta=0.9$ and $\alpha=0.9$. And only one parameter value is changed in each experiment. Table 3 and Table 4 show the detailed sensitivity analysis results.

It can be seen that the objective value decreases first and then does not change anymore for each column in two tables as $p$ increases. The constant is the one when $p=\infty$, which means the $p$-robustness constraint is inoperative. These observations indicate that decision-makers may attempt to mitigate disruption risk at the expense of more cost. In practice, this operation can be implemented by adjusting and choosing $p$ value subjec-
May every year. To ensure continuous supply, the time of picking this kind of tea is between March to May every year. To ensure continuous supply annually, the company needs available warehouses or distribution centers to store processed tea due to its seasonality. There are three plants in Hangzhou and 11 potential demand nodes (11 main cities in Zhejiang province). Now, what company needs to do is to identify optimal locations for distribution centers in three potential cities: Hangzhou, Shaoxing and Jiaxing. To design a resilient supply chain network, we take disruption risk into account and generate 2^3 = 8 disruption scenarios. Some critical data such as demand of 11 potential markets, penalty cost for unmet demand, the production capacity of three plants and fixed cost of opening distribution centers (level 1) are given by reference Qiu and Wang (2016). The unit transportation cost is obtained from the web site (http://www.chinawutong.com/), which is a professional logistics information platform. In this paper, we introduce the facility fortification concept, and level 3 means the highest prevention system. The excepted value of the fixed cost of locating distribution centers with fortification level 2, 3 is the 1.2, 1.3 times of the above one, respectively. The excepted value of percentage of capacity lose is set to 0.7, 1/2*0.7, 1/3*0.7 for three fortification level, respectively. The excepted value of storage capacity is set to 5000. Moreover, unit production costs for three plant are set to 50, 45, 40. The variances of uncertain variables are set as \( \sigma^u_{ij} = \sigma^k_{w} = 2 \), and \( \sigma^f_{jn} = 5, \sigma^p_{ij} = \sigma^w_{jk} = 0.02, \sigma^v_{jw} = 0.002 \). Other key parameters are set as \( p=0.15, r=0.95, \eta, \gamma, \theta, \delta = 0.9 \).

### 6.2 Sensitivity analysis of maximum capacity limitation

In this case study, reference Qiu and Wang (2016) gives the fixed cost of locating distribution centers but do not provide data related to storage capacity. For convenience, we set the default value to 5000. Thus unit construction cost is the fixed cost dived by 5000. To investigate how maximum capacity limitation influences the solution, we conduct a series of experiments. And the optimal locations and fortification levels for distribution centers and objective values are reported in Figure 4 and 5, respectively.

Figure 4 shows that three distribution centers are established with fortification level 2, 3, 3 (3 means the highest level), respectively, when maximum capacity is 2000. As this limit increases to 3000, the distribution centre 1 (Hangzhou) is not available, and another two with level 3 are the optimal scheme. The fortification level reduces gradually as the maximum limitation enlarges. While capacity is equal or greater than 6000, locating distribution center in Jiaxing is sufficient to satisfy 95% tea demands from 11 markets, even though the company needs available warehouses or distribution centers to store processed tea due to its seasonality.

### Table 3

| p   | r=0 | r=0.6 | r=0.7 | r=0.8 | r=0.9 |
|-----|-----|-------|-------|-------|-------|
| 0.2 | 846623 | 846623 | 846623 | 864716 | 872412 |
| 0.3 | 842350 | 842350 | 842350 | 846623 | 852068 |
| 0.4 | 840746 | 840746 | 840746 | 845769 | 852068 |
| 0.5 | 840746 | 840746 | 840746 | 845769 | 846623 |
| 0.6 | 840746 | 840746 | 840746 | 842350 | 846623 |
| 0.7 | 840746 | 840746 | 840746 | 842350 | 846623 |
| 0.8 | 840746 | 840746 | 840746 | 842350 | 846623 |
| 0.9 | 840746 | 840746 | 840746 | 840746 | 846623 |
| ∞   | 840746 | 840746 | 840746 | 840746 | 846623 |

### Table 4

| p   | r=0  | r=0.6 | r=0.7 | r=0.8 | r=0.9 |
|-----|------|-------|-------|-------|-------|
| 0.2 | 927177 | 927177 | 927177 | 945270 | 952972 |
| 0.3 | 922400 | 922400 | 922400 | 926583 | 932626 |
| 0.4 | 916542 | 916542 | 916542 | 924099 | 932484 |
| 0.5 | 916542 | 916542 | 916542 | 921993 | 927177 |
| 0.6 | 916542 | 916542 | 916542 | 921993 | 927177 |
| 0.7 | 916542 | 916542 | 916542 | 921993 | 927177 |
| 0.8 | 916542 | 916542 | 916542 | 921993 | 927177 |
| 0.9 | 916542 | 916542 | 916542 | 916542 | 927177 |
| ∞   | 916542 | 916542 | 916542 | 916542 | 927177 |
all three centers are disrupted. For this reason, overcapacity (the maximum limitation is 15000 in this case) is also not necessary. Besides, we can find that center 3 (Jiaxing) is always the best option for decision-maker, regardless of the variation of maximum capacity.

Corresponding to these observations, the objective value of the two models decreases as capacity increases from 2000 to 3000, 5000 to 6000, 14000 to 15000, respectively, in figure 5. In other cases, locating distribution centers with larger storage capacity always leads to a higher construction cost, and total cost from a global perspective, especially when capacity increases from 6000 to 14000. This is mainly because the optimal location for distribution center changes in key points 3000, 5000 and fortification level for distribution center 3 downgrades from 2 to 1 in point 15000. Among all cases, it is the most economical scheme for decision-makers to open a distribution center in Jiaxing with fortification level 3 when the maximum capacity limitation is equal to 6000. This finding indicates that overinvestment will lead to extravagant storage capacity in the distribution center, resulting in an increased cost. Moreover, more distribution centers are suggested to be opened under the limited storage capacity, which also costs more sometimes.

6.3 Sensitivity analysis of facility disruptions

In the presented models, we introduce uncertain variable $\delta_{jn}$ to quantify the capacity loss of a disrupted distribution center. More fortification investment means more robust defence capability and lower capacity loss after disruptions. Here, we investigate how the impact of disruption risk can influence the optimal location and fortification level. The optimal strategic schemes and objective value are shown in Figure 6 and 7.

It can be seen from Figure 6 that locating distribution center in Jiaxing with fortification level 1 is optimal and capable of meeting customer demands to some extent when the capacity loss is relatively small. As this value gets larger, the facility is suggested to be fortified with higher level to hedge against disruption risk. The location for distribution center changes in point 0.4 and distribution center Shaoxing is opened. Similarly, while damage is more severe, fortifying facility with more investment is advisable. Jiaxing is always a preferred location for decision-maker in all these cases, whereas Hangzhou is not a right choice.
adverse impact of facility disruption is becoming more severe. In this respect, as this value increases from 0.3 to 0.4, the total cost increases sharply. This change is attributed to the changed location for the distribution center, corresponding to the observation of Figure 6.

The expected value indicates the average cost while optimistic value reports the maximum possible cost. Two criteria may provide decision scale of supply cost for enterprises in application.

Managers should take precautions against disruption risks, such as fortifying facilities with more robust defence capability. Naturally, these actions may incur more investment. As a result, managers may face a classic trade-off between more spending or higher risks.

Under the limited land resources, managers are advised to open more facilities and fortify facilities with more investment to mitigate the disruption risks. If there is no limit, expanding storage capacity may be more economical. However, over-expanding will leads to an extravagant storage capacity sometimes. So, managers should balance capacity utilization and expenditure.

Fortifying facilities with more investment is superior to opening more facilities when the capacity loss caused by disruption risks is more severe. So, managers should adopt proactive strategies in advance to hedge against any disruption risks.

To cope with facility disruptions, we adopt the multi-source strategy and facility fortification strategy to improve the supply chain’s resilience in this study. Future research will consider more proactive strategies, such as back-up facility, emergency stock and excess capacity. Besides, responsive strategies are also under consideration to improve the resilience of the designed supply chain in future. It may be interesting and meaningful to investigate the performance of these measures on mitigating the disruption risks, and compare and discuss the advantages and disadvantages of these two kinds of strategies. The other possible extension is quantifying the supply chain’s resilience by identifying some appropriate metric, such as service time or demand satisfaction, or performance level. We can set it as one of the objectives or incorporate them into constraints to ensure the product’s continuous supply after facility disruption. Moreover, the trade off between cost and resilience may be a good direction for further research.

Appendix: Background of Uncertainty Theory

Let $\Gamma$ be a nonempty set, and $\mathcal{L}$ be a $\sigma$-algebra over $\Gamma$. Each element $A \in \mathcal{L}$ is called an event. A number $M(A)$ indicates the possibility that $A$ will occur. Uncertain measure $M$ is introduced as a set function satisfying the following axioms (Liu, 2007):

Axiom 1 (Normality Axiom) $M(\Gamma) = 1$ for the universal set $\Gamma$. 
Axiom 2 (Duality Axiom) \(\mathcal{M}\{A\}+\mathcal{M}\{A^c\} = 1\) for any event \(A\).

Axiom 3 (Subadditivity Axiom) For every countable sequence of events \(\{A_i\}\), we have
\[
\mathcal{M}\left(\bigcup_{i=1}^{\infty} A_i\right) \leq \sum_{i=1}^{\infty} \mathcal{M}\{A_i\}.
\]

The triplet \((\Gamma, \mathcal{L}, \mathcal{M})\) is called an uncertainty space. In addition, the product uncertain measure \((\mathcal{L}, \mathcal{M})\) was defined as following.

Axiom 4 (Product Axiom) Let \((\Gamma_k, \mathcal{L}_k, \mathcal{M}_k)\) be uncertainty spaces for \(k = 1, 2, \ldots\). The product uncertain measure \(\mathcal{M}\) is an uncertain measure satisfying
\[
\mathcal{M}\left(\bigotimes_{k=1}^{\infty} A_k\right) = \bigwedge_{k=1}^{\infty} \mathcal{M}_k\{A_k\}.
\]

Definition 1 (Liu, 2007) An uncertain variables is a function \(\xi\) from an uncertainty space \((\Gamma, \mathcal{L}, \mathcal{M})\) to the set of real numbers such that \(\xi \in B\) is an event for any Borel set \(B\).

Definition 2 (Liu, 2007) The uncertainty distribution \(\Phi\) of an uncertain variable \(\xi\) is defined by
\[
\Phi(x) = \mathcal{M}\{\xi \leq x\}, \forall x \in \mathbb{R}
\]
for any real number \(x\).

Definition 3 (Liu, 2007) An uncertain variable \(\xi\) is normal if it has a normal uncertainty distribution
\[
\Phi(x) = \left(1 + \exp\left(-\frac{\pi(x-\gamma)}{\sqrt{3}\sigma}\right)\right)^{-1}, \quad x \in \mathbb{R}
\]
denoted by \(\mathcal{N}(\gamma, \sigma)\) where \(\gamma\) and \(\sigma\) are real numbers with \(\sigma > 0\).

Definition 4 (Liu, 2010) An uncertainty distribution \(\Phi(x)\) is said to be regular if it is a continuous and strictly increasing function with respect to \(x\) at which \(0 < \Phi(x) < 1\), and
\[
\lim_{x \to -\infty} \Phi(x) = 0, \quad \lim_{x \to +\infty} \Phi(x) = 1.
\]

Definition 5 (Liu, 2010) Let \(\xi\) be an uncertain variable with regular uncertainty distribution \(\Phi(x)\). Then the inverse function \(\Phi^{-1}(\alpha)\) is called the inverse uncertainty distribution of \(\xi\).

Theorem 1 (Liu, 2010) Let \(\xi_1, \xi_2, \ldots, \xi_n\) be independent uncertain variables with regular uncertainty distributions \(\Phi_1, \Phi_2, \ldots, \Phi_n\), respectively. If \(f(\xi_1, \xi_2, \ldots, \xi_n)\) is strictly increasing with respect to \(\xi_1, \xi_2, \ldots, \xi_m\) and strictly decreasing with respect to \(\xi_{m+1}, \xi_{m+2}, \ldots, \xi_n\), then
\[
\xi = f(\xi_1, \xi_2, \ldots, \xi_n)
\]
has an inverse uncertainty distribution
\[
\psi^{-1}(\alpha) = f\left(\phi_1^{-1}(\alpha), \phi_2^{-1}(\alpha), \phi_3^{-1}(1-\alpha), \ldots, \phi_n^{-1}(1-\alpha)\right)\]

Theorem 2 (Liu, 2010) Let \(\xi_1, \xi_2, \ldots, \xi_n\) are independent uncertain variables with regular uncertainty distributions \(\Phi_1, \Phi_2, \ldots, \Phi_n\), respectively. If \(f(\xi_1, \xi_2, \ldots, \xi_n)\) is strictly increasing with respect to \(\xi_1, \xi_2, \ldots, \xi_m\) and strictly decreasing with respect to \(\xi_{m+1}, \xi_{m+2}, \ldots, \xi_n\), then
\[
\mathcal{M}\{f(\xi_1, \xi_2, \ldots, \xi_n) \leq 0\}
\]
is the root of the equation
\[
f\left(\Phi_1^{-1}(\alpha), \ldots, \Phi_m^{-1}(\alpha), \Phi_{m+1}^{-1}(1-\alpha), \ldots, \Phi_n^{-1}(1-\alpha)\right) = 0.
\]

Theorem 3 (Liu, 2010) Let \(\xi\) be an uncertain variable with regular uncertainty distribution \(\Phi\). Then
\[
E[\xi] = \int_0^1 \Phi^{-1}(\alpha)d\alpha.
\]

Compliance with Ethical Standards

Ethical approval This article does not contain any studies with human participants performed by any of the authors.

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