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SOFT COMPUTING IN DECISION MAKING AND IN MODELING IN ECONOMICS

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 has not been sufficiently studied. Aiming at these problems, this paper presents two uncertain programming models that optimize strategic decisions before disruptions and supply chain operations after disruptions. The proposed models introduce p-robustness measure to control the cost in disruption scenarios. Besides, uncertainty theory is adopted to handle parameter uncertainty without 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 (Merzifonluoglu 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, and 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 (Ivanov and Dolgui 2019; Dixit et al. 2020; Aldrighetti et al. 2021; Sawik 2022, 2023).

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, and unofficial strike action. This kind of risk happens infrequently but usually gives rise to halt production for a certain period (maybe a 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 devastatingly influenced supply chains around the globe (Ivanov 2020; Queiroz et al. 2020). Moreover, 94% companies listed in the 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, 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 relatively frequently. 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.

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High likelihood of operational risk and destructive consequence of disruption risk have been enforcing academics and practitioners to pay more attention to equipping the supply chain with the ability to prevent effectively, respond timely to, and recover quickly from adverse events (Dixit et al. 2020; Katsaliaki et al. 2021; Spieske and Birkel 2021; Maharjan and Kato 2022). This ability is identified as the resilience of the supply chain (Ambulkar et al. 2015; Hosseini et al. 2019; Ivanov and Dolgui 2019; Zhao et al. 2023). Only now, many scholars have attempted to define supply chain resilience from different perspectives, but there is no consensus on a precise definition (Kamalahmadi and Parast 2016). Despite this, introducing resilience into supply chain design is essential to reduce the unexpected consequences. Moreover, studies such as Ghavamifar et al. (2018); Sabouhi et al. (2018); Vali-Siar et al. (2022); Ghanei et al. (2023) 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' resilience, incorporating disruption risk into the 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 consider facility disruptions and parameter variations are limited. Besides, in the supply chain designing stage, parameters (fixed cost, transportation cost, and capacity) related to newly opened facilities (to be identified in the models) are usually unknown and indeterminate since the historical data is nonexistent. However, only some studies have considered this situation. We present uncertain programming models to fill these challenges 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 introduces confidence level α to measure the degree of risk aversion. These models present a 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 operations are quantified as 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 without historical data. This study may contribute to the resilient supply chain management literature in the following ways:

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

The remainder of this paper is organized as follows. Section 2 reviews the optimization models related to the resilient supply chain design problem. Section 3 first explains the assumptions, parameters, and variables and then proposes the expected value and chance-constrained programming models, followed by their equivalent crisp programming models in Sect. 4. Later, Sects. 5 and 6 illustrate the feasibility and practicability of the proposed models and conduct the sensitivity analysis of main parameters, ended with the conclusion and future research directions in Sect. 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 the 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, the 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, nonlinear 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. Tolooie 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 that modeled the uncertain parameter as the random variable with a specified distribution. Aryanezhad 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 that 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 could 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 the facility may be disrupted but ignore the recovery plans after disruptions. Zhao and You (2019) took facility disruptions and recovery time into account and proposed 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 identified the optimal strategic decisions 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 was obtained from historical data using the kernel density estimation (KDE) technique. Vali-Siar et al. (2022) considered uncertain customer demand and the percentage of facilities' capacity decrease due to disruptions and proposed a two-stage stochastic programming model to address the problem of resilient mixed open and closed-loop supply chain network design. Masruroh et al. (2023) developed a multi-objective model to design a three-echelon supply chain network under demand uncertainty and limited production capacity after disruptions. The presented model considered and assumed uncertain demand as the normal random variable.

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 was later adopted by many scholars. For example, Hatefi and Jolai (2014) tackled uncertain demand by using the 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 consequences caused by hazard uncertainty. Furthermore, uncertain demand and cost parameter was dealt with the robust programming approach. Gholamia et al. (2019) presented a multi-objective mixed-integer linear programming for a four-tier supply chain. The presented model used the robust optimization approach to deal with the uncertainty of demand and supply costs. The researchers also discussed the advantages of three methods of solving multi-objective problems: goal programming, weighted sum, and LP-metric. Using the 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. Cheng et al. (2021) proposed a robust model for a fixed-charge location problem under uncertain demand and facility disruptions.

There are also studies that adopt the 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 costs, demand, facility capacity, and returned product were treated as fuzzy triangular variables. Apart from these inherent parameters, Torabi et al. (2016) investigated the uncertainties of various costs, 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 demand, cost, return rates, capacity, and disruption probability. Seyfi et al. (2021) formulated the problem of an efficient blood supply chain network under uncertainty and disruption as a fuzzy optimization model. The demand for blood, the amount of the blood supply, the percentage of usable blood, failure rates of the network's components, and network costs were represented by trapezoidal fuzzy numbers. Mohammed et al. (2023) considered the uncertainty of purchasing and transportation costs, demand, and supply capacity and proposed a fuzzy optimization model towards a sustainable and resilient two-tier supply chain network design problem.

Besides, Jabbarzadeh et al. (2016) integrated two programming approaches to present 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. Mohammaddust et al. (2017) took disruption and operation risks into account and first developed a single-objective model maximizing supply chain profit for a four-tier (suppliers, manufacturers, DCs, and retail) supply chain. In the model, random customer demands were assumed. Later, based on this model, they considered uncertain transportation time and handling time to propose a bi-objective model that simultaneously minimizes lead time and non-responded demand. The latter model adopted the robust optimization approach to deal with time uncertainty. Samani and Hosseini-Motlagh (2019) considered a blood supply chain network design problem under an uncertain environment. The researchers integrated the fuzzy analytic hierarchy process and grey rational analysis to deal with facility disruptions. A robust possibilistic programming approach was proposed to tackle supply, demand, and cost uncertainty. Ahranjani et al. (2020) combined stochastic, possibilistic, and robust programming approaches to address a resilient bioethanol supply chain design problem. In their works, drought was considered the source of the disruption of biomass feedstock yield. Demand, price, cost, and yield were indeterministic from the limited available data due to various factors, such as market fluctuations, horrible weather conditions, and the production environment. Namdar et al. (2021) developed a two-stage mixed possibilistic-stochastic programming model for a multi-echelon, multi-product resilient supply chain design that considered the uncertainty of imprecise input parameters and random disruption scenarios. Habib et al. (2022) addressed the biodiesel supply chain network design problem under mixed uncertainty by combining flexible, possibilistic, and robust programming. To deal with disruption risk, a scenario-based p-measure approach was employed, and possibilistic programming and robust programming were utilized to deal with operational uncertainty. Tafakkori et al. (2023) proposed a robust-stochastic optimization method to design a resilient supply chain. In the presented models, the available time to recover and the impact and occurrence of disruptions were modeled as interval numbers using robust optimization due to the lack of information around the distribution.

In summary, there are two primary sources of uncertainty in the literature. One is randomness with a certain regularity in nature, which can be mathematically defined as a probability distribution. Usually, uncertain parameters are modeled as random variables in existing models. Scholars utilize stochastic programming to formulate mathematical problems if distributional information can be captured using enough historical data. On the contrary, in the absence of probability distribution, the robust optimization approach is adopted to describe random variables with a specific interval. The other one is non-randomness or fuzziness arising from insufficient 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 the supply chain. The capacity loss of facilities is introduced to quantify the consequence caused by facility disruptions. Irregular changes in the market during supply chain operation are quantified as the fluctuant demand. However, the supply chain usually operates in a highly uncertain environment, and direct data of these parameters are nonexistent before risk events happen, especially for unforeseen disruption risks. Moreover, the parameters (fixed cost, transportation cost, and capacity) related to newly opened facilities (to be identified in the models) are also unknown and indeterminate in the planning stage, which needs to be addressed in the literature. We can only obtain their actual data once the new facility is completed. Therefore, treating these uncertain parameters as random variables is inaccurate. 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 without historical theory (Liu 2007), which later 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 modeling uncertain parameters without historical data has been proved by many works (Shi et al. 2020; Song et al. 2020; Shi and Ni 2021; Yang et al. 2022). Therefore, this paper adopts uncertainty theory to tackle 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 α to capture the risk preference of the decision-makers in the CCP model while modeling the resilient supply chain design problem under operational and disruption risks.

3 Problem description and mathematical formulation

This section first elaborates on the background and main assumptions of the resilient supply chain design problem, all parameters, and variables of mathematical models. Then, the expected value model, which minimizes the expected value of nominal cost, and the chance-constrained programming model, which minimizes the optimistic 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 Fig. 1. In the first layer, several existing plants characterized by 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 is considered to establish new warehouses with a limited capacity for holding products. Considering disruption risk, we assume that the opened warehouses may be disrupted under the threat 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 the 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.

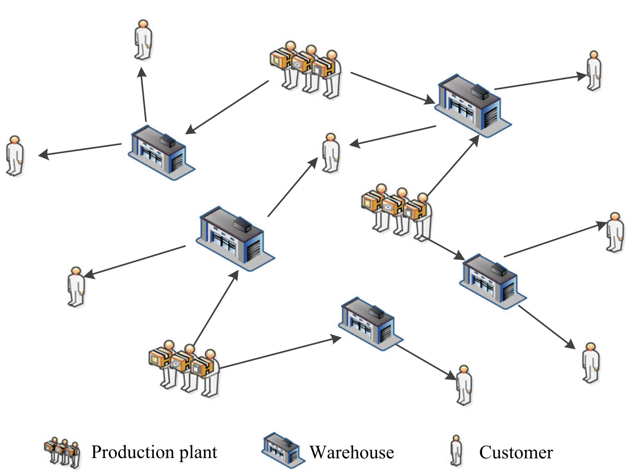

Fig. 1 The supply chain network

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 from the customer is punished with comparatively high penalties under facility disruptions.

The main assumptions of the mathematical models are as follows: (1) the supply chain network is a three-tier, single-product, and single-period supply chain. (2) Candidate locations to establish new warehouses are predetermined. (3) Disruptions can lead to partial or complete loss in the capacity of warehouses. (4) Various levels of warehouse fortification are considered to increase supply chain resilience. A high fortification level means less capacity loss in the case of disruptions but usually leads to more costs. (5) Cost parameters related to warehouses are indeterministic in the designing stage since the direct data is nonexistent. (6) The capacity decrease after unexpected disruptions is also uncertain. (7) Unmet demand is allowed, which can incur higher penalty costs after disruptions.

Now, we aim to design 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, strategic and tactical decisions are identified under the facility location, p-robustness, demand satisfaction, facility capacity, and resource equilibrium constraints. These decisions include (1) the optimal number, location, and 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, we first list all sets, parameters, and decision variables throughout the models to better inform the mathematical formulations.

- 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, $s = 0, ..., S$ (Denote s = 0 as the nominal scenario, i.e., the scenario with no disruptions).
  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.
p_s: Desired robustness level in scenario s.
r_s: Desired satisfaction rate in scenario s.
w_k: Weight factor of customer k.
$\widetilde{f_{jn}}$: Fixed cost of opening warehouse j with fortification level n.
$\widetilde{C_j}$: Capacity of warehouse j.
$\widetilde{a_{jn}}$: Percentage of capacity loss of a disrupted warehouse j with fortification level n.
$\widetilde{D_k}$: Demand of customer k.
$\widetilde{c_{ij}^{pw}}$: Unit transportation cost from production plant i to warehouse j.
$\widetilde{c_{jk}^{wc}}$: 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_{ijs}: 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.
  $\overline{tc}$: 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 can not obtain their actual values or estimate their probability distribution. In this case, consulting experts to acquire a 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 $\widetilde{f_{jn}}$, $\widetilde{C_j}$, $\widetilde{a_{jn}}$, $\widetilde{D_k}$, $\widetilde{c_{ij}^{fw}}$ and $\widetilde{c_{jk}^{wc}}$ as uncertain variables with uncertainty distributions Φ_{jn}^f, Φ_j^w, Φ_{jn}^w, Φ_k^c, Φ_{ij}^{pw} and Φ_{jk}^{wc}, respectively.

In this section, we place more emphasis on minimizing the total cost of the nominal scenario (no warehouses are disrupted) 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:

$$\begin{aligned} tc_s = & \sum_{j\in J}\sum_{n\in N}\widetilde{f_{jn}}x_{jn} + \sum_{i\in I}\sum_{j\in J} pc_i Q_{ijs} \\ & + \sum_{i\in I}\sum_{j\in J}\widetilde{c_{ij}^{pw}}Q_{ijs} + \sum_{j\in J}\sum_{k\in K}\widetilde{c_{jk}^{wc}}Q_{jks} \\ & + \sum_{k\in K} uc_k\left(\widetilde{D_k} - \sum_{j\in J} Q_{jks}\right). \end{aligned}$$

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 for unmet demand is described in the fifth term. We may minimize the expected value since uncertain variables are considered in the cost function and cannot be directly minimized. Then, we propose the following expected value model (EVM):

$$\min \ E\left[tc_0\right] \tag{1}$$

s.t.

$$\mathcal{M}\left\{tc_s - (1+p_s)tc_s^* \le 0\right\} \ge \eta_s, \forall s \in S \setminus 0, \tag{2}$$

$$\mathcal{M}\left\{\sum_{k\in K} Q_{jks} \le \sum_{n\in N}(1-\widetilde{a_{jn}}z_j)\widetilde{C_j}x_{jn}\right\} \ge \gamma_s, \quad \forall j \in J, \forall s \in S, \tag{3}$$

$$\mathcal{M}\left\{\sum_{k\in K} w_k \frac{\sum_{j\in J} Q_{jks}}{\widetilde{D_k}} \ge r_s\right\} \ge \theta_s, \forall s \in S, \tag{4}$$

$$\mathcal{M}\left\{\sum_{j\in J} Q_{jks} \le \widetilde{D_k}\right\} \ge \delta_s, \forall k \in K, \forall s \in S, \tag{5}$$

$$\sum_{k\in K} Q_{jks} = \sum_{i\in I} Q_{ijs}, \forall j \in J, \forall s \in S, \tag{6}$$

$$\sum_{j\in J} Q_{ijs} \le C_i, \forall i \in I, \forall s \in S, \tag{7}$$

$$\sum_{n\in N} x_{jn} \le 1, \forall j \in J, \tag{8}$$

$$x_{jn} \in \{0,1\}, \forall j \in J, \forall n \in N, \tag{9}$$

$$Q_{ijs} \ge 0, \forall i \in I, \forall j \in J, \forall s \in S, \tag{10}$$

$$Q_{jks} \ge 0, \forall j \in J, \forall k \in K, \forall s \in S. \tag{11}$$

The objective function (1) attempts to minimize the expected nominal cost. Besides, defining a crisp feasible set is difficult since some constraints contain uncertain variables. Therefore, we introduce predetermined confidence levels, which take value from interval [0,1] to relax these constraints. The higher the confidence level is, the higher the possibility of 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_s^*. The constraint (3) expresses the capacity restriction of warehouses. The constraint (4) expressed the 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 θ_s. Constraint (5) assures all supply quantities from warehouses to one customer can not exceed its demand with a confidence level δ_s. Constraint (6) stresses the balance of products in warehouses. That is to say, the product quantities shipped from one warehouse to customers should equal the ones sent to that warehouse. Constraint (7) expresses that product quantities from one production plant should not exceed its production capacity. Constraint (8) guarantees that only one warehouse with a fortification level is allowed in each potential location. Constraint (9) is the binary constraint. 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 the following sub-model:

$$tc_s^* = \min \ E\left[tc_s\right] \tag{12}$$

s.t.

$$\mathcal{M}\left\{\sum_{k\in K} Q_{jks} \le \sum_{n\in N}(1-\widetilde{a_{jn}}z_j)\widetilde{C}_j x_{jn}\right\} \ge \gamma_s, \quad \forall j\in J, \tag{13}$$

$$\mathcal{M}\left\{\sum_{k\in K} w_k \frac{\sum_{j\in J} Q_{jks}}{\widetilde{D_k}} \ge r_s\right\} \ge \theta_s, \tag{14}$$

$$\mathcal{M}\left\{\sum_{j\in J} Q_{jks} \le \widetilde{D_k}\right\} \ge \delta_s, \forall k\in K, \tag{15}$$

$$\sum_{k\in K} Q_{jks} = \sum_{i=1}^{I} Q_{ijs}, \forall j\in J, , \tag{16}$$

$$\sum_{j\in J} Q_{ijs} \le C_i, \forall i\in I, \tag{17}$$

$$\sum_{n\in N} x_{jn} \le 1, \forall j\in J, \tag{18}$$

$$x_{jn}\in\{0,1\}, \forall j\in J, \forall n\in N, \tag{19}$$

$$Q_{ijs}\ge 0, \forall i\in I, \forall j\in J, \tag{20}$$

$$Q_{jks}\ge 0, \forall j\in J, \forall k\in K. \tag{21}$$

Similarly, we assume $\eta_s=\eta_1$, $\gamma_s=\gamma_1$, $\theta_s=\theta_1$ and $\delta_s=\delta_1$ for all scenarios in this sub-problem to simplify the calculation.

In the above EVM, we give attention to the expected value of total cost under the normal scenario since the cost function includes uncertain variables that can not be minimized directly. Sometimes, decision-makers with a positive attitude are more concerned about the optimistic value of total cost rather than the expected cost. To this end, we introduce a predetermined confidence level β and optimistic cost $\overline{tc}$ to propose chance-constrained programming model (CCP) as follows:

$$\min \overline{tc} \tag{22}$$

s.t.

$$\mathcal{M}\left\{tc_0 \le \overline{tc}\right\} \ge \beta, \tag{23}$$

$$\text{Eqs. (2) to (11).} \tag{24}$$

This model minimizes the optimistic value of total cost under the normal scenario. The first constraint guarantees the nominal cost can not exceed the optimistic cost with a given confidence level α. 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 Sect. 5 and 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 deterministic programming models using operational laws in uncertainty theory. Then, more concrete mathematical formulations are presented under the assumption of normal uncertainty distribution.

Let $\left(\Phi_{jn}^{f}\right)^{-1}$, $\left(\Phi_{j}^{w}\right)^{-1}$, $\left(\Phi_{jn}^{w}\right)^{-1}$, $\left(\Phi_{k}^{c}\right)^{-1}$, $\left(\Phi_{ij}^{pw}\right)^{-1}$ and $\left(\Phi_{jk}^{wc}\right)^{-1}$ be the uncertainty distributions of $\widetilde{f_{jn}}, \widetilde{C_j}, \widetilde{a_{jn}}$, $\widetilde{D_k}$, $\widetilde{c_{ij}^{fw}}$ and $\widetilde{c_{jk}^{wc}}$, respectively. Since these uncertain variables are all independent, the total cost under each disruption scenario is also uncertain. We denote the inverse uncertainty distribution of tc_s by $\Phi_s^{-1}(\alpha)$. Using the operational laws for calculating inverse uncertainty distribution (more details are referred to Appendix A, $\Phi_s^{-1}(\alpha)$ can be represented by the following equation:

$$\begin{aligned}\Phi_s^{-1}(\alpha) = &\sum_{j\in J}\sum_{n\in N} x_{jn}\left(\Phi_{jn}^{f}\right)^{-1}(\alpha)\\ &+\sum_{i\in I}\sum_{j\in J} pc_i Q_{ijs}\\ &+\sum_{i\in I}\sum_{j\in J} Q_{ijs}\left(\Phi_{ij}^{pw}\right)^{-1}(\alpha)\\ &+\sum_{j\in J}\sum_{k\in K} Q_{jks}\left(\Phi_{jk}^{wc}\right)^{-1}(\alpha)\\ &+\sum_{k\in K} uc_k\left(\left(\Phi_{k}^{c}\right)^{-1}(\alpha)-\sum_{j\in J} Q_{jks}\right).\end{aligned}$$

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:

$$E\left[tc_0\right] = \int_0^1 \Phi_0^{-1}(\alpha)d\alpha.$$

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

$$\Phi_s((1+p_s)tc_s^*) \ge \eta_s.$$

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

$$\Phi_s^{-1}(\eta_s) \le ((1+p_s)tc_s^*).$$

Similarly, other chance constraints can be converted into their deterministic formulations. Thus, we can present the following deterministic programming model of EVM:

$$\min \int_0^1 \Phi_0^{-1}(\alpha)d\alpha \tag{25}$$

s.t.

$$\Phi_s^{-1}(\eta_s) \le (1+p_s)tc_s^*, \forall s \in S \setminus 0, \tag{26}$$

$$\sum_{k\in K} Q_{jks} \le \sum_{n\in N}\left(1-\left(\Phi_{jn}^{w}\right)^{-1}(\gamma_s)z_j\right)\left(\Phi_j^{w}\right)^{-1} * (1-\gamma_s)x_{jn}, \forall j \in J, \forall s \in S, \tag{27}$$

$$r_s \le \sum_{k\in K} w_k \frac{\sum_{j\in J} Q_{jks}}{(\Phi_k^c)^{-1}(\theta_s)}, \forall s \in S, \tag{28}$$

$$\sum_{j\in J} Q_{jks} \le (\Phi_k^c)^{-1}(1-\delta_s), \forall k \in K, \forall s \in S,$$

Eqs. (6) to (11). (29)

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

$$\min \overline{tc}$$

s.t.

$$\Phi_0^{-1}(\beta) \le \overline{tc}, \tag{30}$$

Eqs. (26) to (29),

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 $\xi \sim \mathcal{N}(e,\sigma)$ is $\Phi^{-1}(\alpha) = e + \frac{\sigma\sqrt{3}}{\pi}\ln\frac{\alpha}{1-\alpha}$. And its expected value is $E[\xi] = e$. Assume that all uncertain variables in this paper are independent normal uncertain variables, denoted by $\widetilde{f_{jn}} \sim \mathcal{N}\left(e_{jn}^f, \sigma_{jn}^f\right)$, $\widetilde{C_j} \sim \mathcal{N}\left(e_j^w, \sigma_j^w\right)$, $\widetilde{a_{jn}} \sim \mathcal{N}\left(e_{jn}^w, \sigma_{jn}^w\right)$, $\widetilde{D_k} \sim \mathcal{N}\left(e_k^c, \sigma_k^c\right)$, $\widetilde{c_{ij}^{pw}} \sim \mathcal{N}\left(e_{ij}^{pw}, \sigma_{ij}^{pw}\right)$ and $\widetilde{c_{jk}^{wc}} \sim \mathcal{N}\left(e_{jk}^{wc}, \sigma_{jk}^{wc}\right)$, respectively. Thus, the inverse of the uncertainty distribution of tc_s can be rewritten as the following formula:

$$\begin{aligned}(\Phi_s^{-1}(\alpha))' = &\sum_{j\in J}\sum_{n\in N}\left(e_{jn}^f + \frac{\sqrt{3}\sigma_{jn}^f}{\pi}\ln\frac{\alpha}{1-\alpha}\right)x_{jn} \\ &+ \sum_{i\in I}\sum_{j\in J} pc_i Q_{ijs} \\ &+ \sum_{i\in I}\sum_{j\in J}\left(e_{ij}^{pw} + \frac{\sqrt{3}\sigma_{ij}^{pw}}{\pi}\ln\frac{\alpha}{1-\alpha}\right)Q_{ijs} \\ &+ \sum_{j\in J}\sum_{k\in K}\left(e_{jk}^{wc} + \frac{\sqrt{3}\sigma_{jk}^{wc}}{\pi}\ln\frac{\alpha}{1-\alpha}\right)Q_{jks} \\ &+ \sum_{k\in K} uc_k\left(e_k^c + \frac{\sqrt{3}\sigma_k^c}{\pi}\ln\frac{\alpha}{1-\alpha} - \sum_{j\in J} Q_{jks}\right).\end{aligned}$$

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

$$\begin{aligned}E\left[(\Phi_0^{-1}(\alpha))'\right] = &\sum_{j\in J}\sum_{n\in N} e_{jn}^f x_{jn} \\ &+ \sum_{i\in I}\sum_{j\in J} pc_i Q_{ijs} \\ &+ \sum_{i\in I}\sum_{j\in J} e_{ij}^{pw} Q_{ijs} \\ &+ \sum_{j\in J}\sum_{k\in K} e_{ij}^{wc} Q_{jks} \\ &+ \sum_{k\in K} uc_k\left(e_k^c - \sum_{j\in J} Q_{jks}\right).\end{aligned}$$

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

$$\min\ E\left[(\Phi_0^{-1}(\alpha))'\right] \tag{31}$$

s.t.

$$(\Phi_s^{-1}(\eta_s))' \le (1+p_s)tc_s^*, \forall s \in S \setminus 0, \tag{32}$$

$$\sum_{k\in K} Q_{jks} \le \sum_{n\in N}\left(e_j^w - \frac{\sqrt{3}\sigma_j^w}{\pi}\ln\frac{\gamma_s}{1-\gamma_s}\right) * \left(1-\left(e_{jn}^w + \frac{\sqrt{3}\sigma_{jn}^w}{\pi}\ln\frac{\gamma_s}{1-\gamma_s}\right)z_j\right)x_{jn}, \quad \forall j \in J, \forall s \in S, \tag{33}$$

$$r_s \le \sum_{k\in K} Q_{jks} w_k \frac{\sum_{j\in J} Q_{jks}}{\left(e_k^c + \frac{\sqrt{3}\sigma_k^c}{\pi}\ln\frac{\theta_s}{1-\theta_s}\right)}, \quad \forall s \in S, \tag{34}$$

$$\sum_{j\in J} Q_{jks} \le \left(e_k^c - \frac{\sqrt{3}\sigma_k^c}{\pi}\ln\frac{\delta_s}{1-\delta_s}\right), \quad \forall k \in K, \forall s \in S,$$

Eqs. (6) to (11). (35)

And CCP can be rewritten by the following mathematical description:

$$\begin{aligned}
&\min \overline{tc} \\
&\text{s.t.} \\
&(\Phi_0^{-1}(\beta))' \le \overline{tc}, \qquad (36)\\
&\text{Eqs. (32) to (35),} \\
&\text{Eqs. (6) to (11).}
\end{aligned}$$

5 Numerical experiments

In this section, we implement a series of simulation examples to illustrate the feasibility and validity of the proposed models in Sect. 3. Moreover, sensitivity analysis about critical parameters such as robustness, 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 Sect. 3. 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 [1000,10,000] and [0,50], respectively. Besides, we assume all uncertain variables in the presented models are normal variables. Therefore, for warehouses, the excepted value e_j^w of holding capacity $\widetilde{C_j}$ is drawn uniformly from [1000,3000]. Besides, we set the fortification level $N = 3$. For different fortification level, the excepted value e_{jn}^f of fixed cost for opening a warehouse $\widetilde{f_{jn}}$ 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 $\widetilde{a_{jn}}$, 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 $\widetilde{c_{ij}^{pw}}$ and $\widetilde{c_{jk}^{wc}}$, their excepted values e_{ij}^{pw} and e_{jk}^{wc} are set to the Euclidean distance between two locations. For customers, the excepted value e_k^c of demand $\widetilde{D_k}$ is drawn uniformly from [0,1000] and penalty cost uc_k is drawn uniformly from [100,500]. As for standard deviation of these uncertain variables, σ_j^w, σ_{ij}^{pw}, σ_{jk}^{wc}, σ_k^c are set equal to 2, and $\sigma_{jn}^f = 5$, $\sigma_{jn}^w = 0.02$. Other key parameters are set as p=0.4, r=0.8, η=0.9, γ=0.9, θ=0.9 and δ =0.9. In addition, we set η_1=0.9, γ_1=0.9, θ_1=0.9 and δ_1 =0.9 for all sub-problems.

5.2 Sensitivity analysis of disruption scenario

As mentioned, the combinations of warehouses' states specify all possible disruption scenarios, each defining a collection of warehouses that are disrupted simultaneously. As the number of warehouses increases, scenario number and model size grow exponentially, increasing computational burden. However, the possibility of more than two warehouses being disrupted simultaneously in practice is relatively small. For this reason, decision-makers may focus exclusively on a much smaller part of scenarios that 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.

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

Not surprisingly, it spends more time getting an optimal solution while the 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-makers can choose scenarios that they concern more in practice to obtain strategic and tactical decisions regardless of apparent changes in the nominal cost.

In these tables, scenario 1 is identified as the normal scenario, which means no warehouses are 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 necessity to consider disruption risk during the supply chain planning stage. Besides, we also find that the optimal solutions are different in the two models under some disruption scenarios,

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	1,3,5^2,9,10,12,13	0.44	4.26
20	840746	1,2,3,5^2,9,12,13	0.42	11.08
30	842350	1,3,5^2,7,9,12,13	0.19	27.45
40	842350	1,3,5^2,7,9,12,13	0	31.45
50	842350	1,3,5^2,7,9,12,13	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	1,3,5^2,9,10,12,13	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	1,2,3,5^2,8,9,12,13	0.23	117.97
70	924099	1,2,3,5^2,8,9,12,13	0	262.30
130	924099	1,2,3,5^2,8,9,12,13	0	297.94
140	926323	1,3,5^2,7,9,12,13,14	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

such as $S = 30$, 60, etc. This indicates that the decision criteria of decision-makers may exert an influence on strategic decisions in our study.

The above observations indicate the influence of considering disruption risks on strategic and resilience decisions. It is suggested to fortify facilities with higher levels or equip the supply chain with more facilities with sufficient capacity under disruption scenarios. In other words, the decisions obtained under normal scenario in which no warehouses are disrupted are impractical and valid when unexpected disruptions occur, which may result in more severe consequences, such as a decrease in service level and market share. In reality, decision-makers should include disruption risks in the planning stage to ensure the resilience and competitiveness of the designed supply chain. The determination of critical facilities in the decision-making process is also advised in practice since superabundant disruption scenarios generated from the failure possibility of all facilities may increase the difficulty and time of decision-making.

5.3 Sensitivity analysis of decision criteria

In the presented models, EVM assumes that decision-makers are risk-neutral, while CCP considers the risk preference by introducing confidence level α. A larger α means decision-makers are more risk-averse. In this section, we test the performance of two models under different risk attitudes, and the sensitivity analysis results are reported in Figs. 2 and 3.

EVM minimizes the excepted value of total nominal cost, which is not influenced by the variation of α. Even so, we also describe its objective value in Figs. 2 and 3 to investigate the performance of two presented models. It can be seen that the optimistic value of total cost increases as α gets larger. This means a decision-maker who is more risk-averse prefers

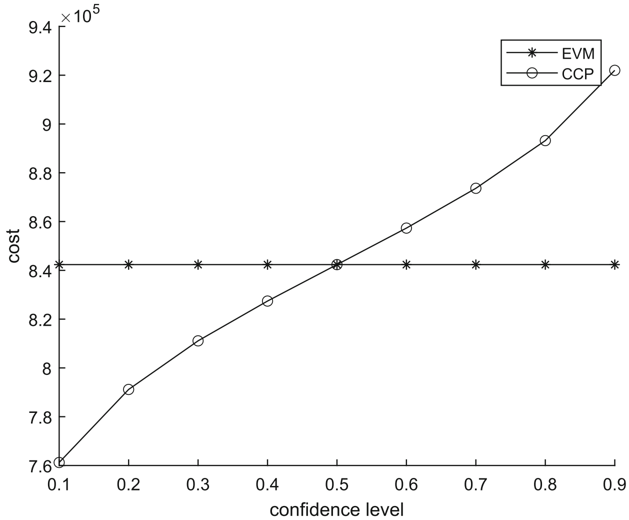

Fig. 2 The objective value at different α when S = 30

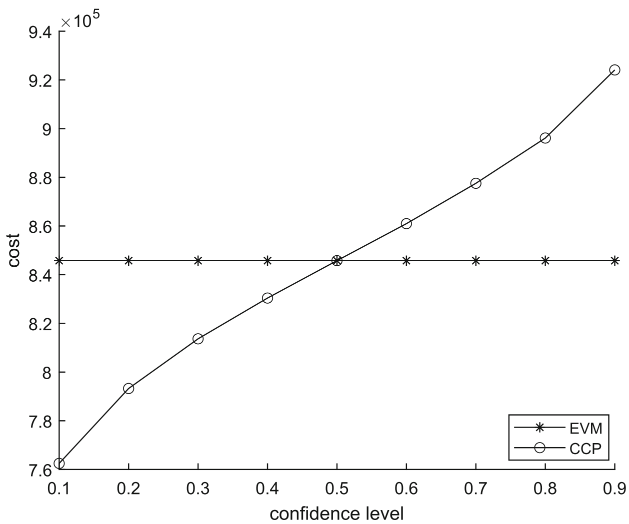

Fig. 3 The objective value at different α when S = 60

to mitigate risk at a higher cost. In addition to this, we also find that the optimistic value of CCP is always greater than the excepted value of EVM when $\alpha > 0.5$. The conclusion is just the opposite while $\alpha < 0.5$. The optimistic and excepted values are the same as $\alpha = 0.5$, representing a neutral attitude to risk.

EVM indicates the average value of nominal cost, while CCP reports the maximum possible cost with a higher confidence level. Two values may identify the interval of nominal cost for enterprises to design supply chain in application.

5.4 Sensitivity analysis of robustness and satisfaction criterion

In this section, we conduct a series of numerical examples to test how the subjective values p and r can influence the optimal objective value. The two models' default value of confidence levels are set as $\eta = 0.9$, $\gamma = 0.9$, $\theta = 0.9$, $\delta = 0.9$ and $\alpha = 0.9$. Only one parameter value is changed in each experiment. Tables 3 and 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 the two tables as p increases. When $p = \infty$, 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 subjectively, which depends on decision-makers attitudes to risk. Moreover, Tables 3 and 4 show that the objective value remains a constant first, followed by an increase when r becomes larger for each row. It means decision-makers may afford more cost in return for higher demand satisfaction to maintain the well-deserved reputation and promote long-term development. We also observe the objective values change irregularly (no increasing trend or downward trend) in each diagonal line by increasing p and r simultaneously. This finding indicates no priority between the binding effects of the p-robustness criterion and the satisfaction criterion.

6 Case example

Here, a tea supply chain from the real world, discussed in reference Qiu and Wang (2016), is further considered to investigate the application of the mathematical models in Sect. 3.

6.1 Study area and data

A company in Hangzhou City, China, produces and supplies superior Longjing for tea markets. The best time to pick this kind of tea is between March to May every year. To ensure continuous supply annually, the company needs 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, the company needs to identify optimal locations for distribution centers in three potential cities: Hangzhou, Shaoxing, and Jiaxing. To design a resilient supply chain network, we consider disruption risk and generate $2^3 = 8$ disruption scenarios. Some critical data such as the 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 Qiu and Wang (2016). The unit transportation cost is obtained from the website (http://www.chinawutong.com/), a professional logistics information platform. In this paper, we introduce the facility fortification concept, and level 3 means the highest preven-

Table 3 Excepted value under different robustness and satisfaction criterions

	$r = 0$	$r = 0.6$	$r = 0.7$	$r = 0.8$	$r = 0.9$
$p = 0.2$	846623	846623	846623	864716	872412
$p = 0.3$	842350	842350	842350	846623	852068
$p = 0.4$	840746	840746	840746	845769	852068
$p = 0.5$	840746	840746	840746	845769	846623
$p = 0.6$	840746	840746	840746	842350	846623
$p = 0.7$	840746	840746	840746	842350	846623
$p = 0.8$	840746	840746	840746	842350	846623
$p = 0.9$	840746	840746	840746	840746	846623
$p = \infty$	840746	840746	840746	840746	846623

Table 4 Optimistic value under different robustness and satisfaction criterions

	$r = 0$	$r = 0.6$	$r = 0.7$	$r = 0.8$	$r = 0.9$
$p = 0.2$	927177	927177	927177	945270	952972
$p = 0.3$	922400	922400	922400	926583	932628
$p = 0.4$	916542	916542	916542	924099	932484
$p = 0.5$	916542	916542	916542	921993	927177
$p = 0.6$	916542	916542	916542	921993	927177
$p = 0.7$	916542	916542	916542	921993	927177
$p = 0.8$	916542	916542	916542	921993	927177
$p = 0.9$	916542	916542	916542	916542	927177
$p = \infty$	916542	916542	916542	916542	927177

tion system. The expected value of the fixed cost of locating distribution centers with fortification levels 2 and 3 is 1.2 and 1.3 times of the above one, respectively. The expected value of the percentage of capacity loss is set to 0.7, 1/2*0.7, and 1/3*0.7 for three fortification levels, respectively. The expected value of storage capacity is set to 5000. Moreover, unit production costs for the three plants are set to 50, 45, 40. The variances of uncertain variables are set as $\sigma_j^w = \sigma_k^c$=2, and $\sigma_{jn}^f = 5$, $\sigma_{ij}^{pw} = \sigma_{jk}^{wc} = 0.02$, $\sigma_{jn}^w = 0.002$. Other key parameters are set as p=0.15, r=0.95, η, γ, θ, δ =0.9.

6.2 Sensitivity analysis of maximum capacity limitation

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

Figure 4 shows that three distribution centers are established with fortification levels 2, 3, and 3 (3 means the highest level), respectively, when the maximum capacity is 2000. As this limit increases to 3000, distribution center 1 (Hangzhou) is unavailable, and another two with level 3 are the optimal scheme. The fortification level reduces gradually as the maximum limitation enlarges. While capacity is equal to or greater than 6000, locating a distribution center in Jiaxing is sufficient to satisfy 95% tea demands from 11 markets, even though all three centers are disrupted. For this reason, overcapacity (the maximum limitation is 15,000 in this case) is also not necessary. Besides, we can find that center 3 (Jiaxing) is always the best option for decision-makers, 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– 6000, and 14,000—15,000, respectively, in Fig. 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 the distribution center changes in key points 3000 and 5000, and the 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.

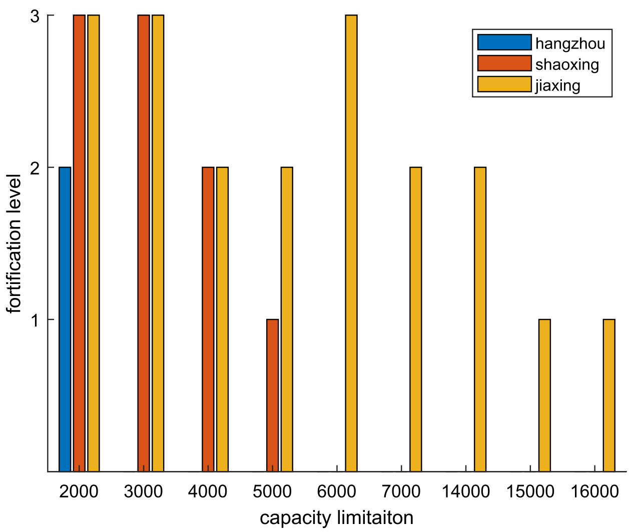

Fig. 4 Optimal locations under different capacity limitation

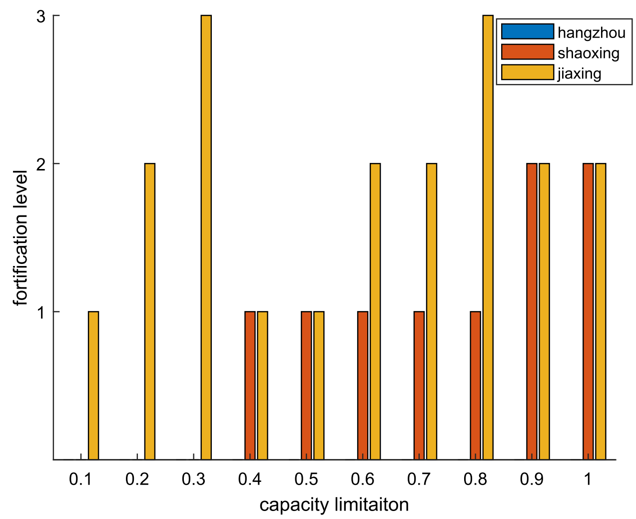

Fig. 6 Optimal locations under different extent of damage

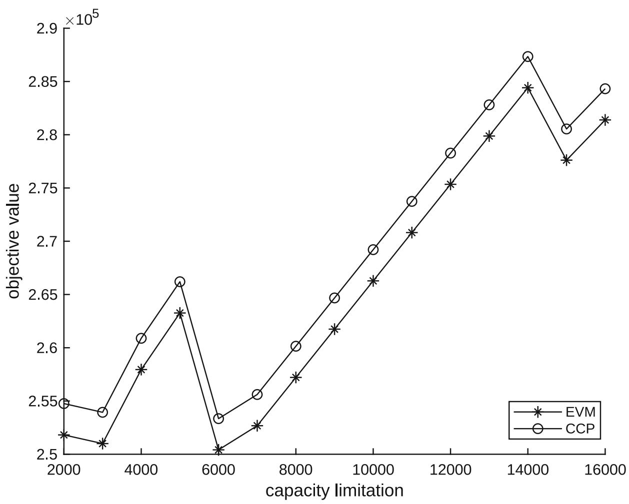

Fig. 5 The objective value under different capacity limitation

These findings indicate that more distribution centers and higher fortification levels are suggested for decision-makers in the planning stage when the predicted capacity of distribution centers is very limited. In some cases, relaxing this capacity limitation is conducive to reducing cost due to less capacity redundancy. That is to say, expanding storage capacity is more economical compared to opening more distribution centers in practice. However, it should be noted that over-investment will lead to extravagant storage capacity in the distribution center, resulting in an increased cost.

6.3 Sensitivity analysis of facility disruptions

In the presented models, we introduce uncertain variable $\widetilde{a_{jn}}$ to quantify the capacity loss of a disrupted distribution center. More fortification investment means more robust defense 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 Figs. 6 and 7.

It can be seen from Fig. 6 that locating a 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 a higher level to hedge against disruption risk. The location for the distribution center changes at point 0.4, and the distribution center Shaoxing is opened. Similarly, while damage is more severe, fortifying the facility with more investment is advisable. Jiaxing is always a preferred location for decision-makers in all these cases, whereas Hangzhou is not the right choice.

Besides, what is apparent is that the objective value of the two proposed models gets larger when the adverse impact of facility disruption becomes 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 of the distribution center, corresponding to the observation of Fig. 7.

Considering severe disruptions, decision-makers are advised to fortify facilities with higher levels at the expense of more investment in the designing stage. And fortification strategy is superior to opening more facilities when the capacity loss caused by disruption risks is more severe.

7 Conclusions and future research

This study formulates the resilient supply chain design problem as uncertain programming models using uncertainty theory, which considers both partial facility failure and the

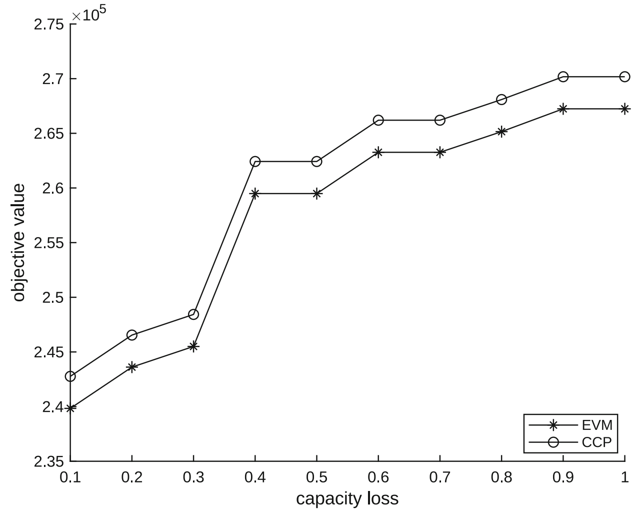

Fig. 7 The objective value under different extent of damage

uncertainty arising from critical parameters such as demand, cost, and capacity. The proposed models aim to minimize the excepted value and optimistic value of the total cost under the normal scenario (no disruption) while bounding cost under disruption scenarios by introducing the p-robustness approach into constraints. Later, we transform the presented models into their crisp equivalent models with inverse uncertainty distribution, which can easily be solved by cplex 12.8. Finally, we implement a series of simulation examples to illustrate the feasibility and validity of these models. Moreover, the sensitivity analysis about critical parameters such as p-robustness criterion, satisfaction criterion, and confidence levels arrive at some noteworthy observations. The practical application of the presented models is investigated by a case example of the tea supply chain from the real world. From the obtained results, we can conclude the following managerial insights:

- It is necessary to consider facility disruption during the supply chain planning stage since the optimal strategic decisions (location decisions in this paper) are affected by disruption scenarios. And neglecting to include disruption risk can lead to unrealistic and impractical decisions. Besides, proactive strategies such as fortification strategy in advance are advised for decision-makers to hedge against disruption risks. Naturally, these actions may incur more investment. As a result, managers may face a classic trade-off between more investment or higher risks in the planning stage of the supply chain.
- 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 compared to opening more facilities in practice. However, over-expanding will lead to an extravagant storage capacity sometimes. Therefore, managers should pay special attention to the redundancy of the designed supply chain when considering disruption risks in the designing stage.
- Confidence level β introduced in cost function in CCP and p-robustness criterion are utilized to measure the risk preference of decision-makers in practice. For a minimization problem, a higher value of confidence level and a stricter p-robustness constraint are suggested for risk-averse decision-makers.

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 backup facilities, emergency stock, and excess capacity. Besides responsive strategies are also under consideration to improve the resilience of the designed supply chain in the future. It may be interesting and meaningful to investigate the performance of these measures in 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, demand satisfaction, or performance level. We can set it as one of the objectives or incorporate it into constraint 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.

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Data availability All data generated or used during the study appear in the submitted article.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Appendix A background of uncertainty theory

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

Axiom 1 *(Normality Axiom) $\mathcal{M}\{\Gamma\} = 1$ for the universal set Γ.*

Axiom 2 *(Duality Axiom) $\mathcal{M}\{\Lambda\}+\mathcal{M}\{\Lambda^c\} = 1$ for any event Λ.*

Axiom 3 *(Subadditivity Axiom) For every countable sequence of events $\{\Lambda_i\}$, we have*

$$\mathcal{M}\left\{\bigcup_{i=1}^{\infty} \Lambda_i\right\} \leq \sum_{i=1}^{\infty} \mathcal{M}\{\Lambda_i\}.$$

The triplet $(\Gamma, \mathcal{L}, \mathcal{M})$ is called an uncertainty space. In addition, the product uncertain measure (Liu 2009). was defined as following.

Axiom 4 *(Product Axiom) Let $(\Gamma_k, \mathcal{L}_k, \mathcal{M}_k)$ be uncertainty spaces for $k = 1, 2, \cdots$. The product uncertain measure $\mathcal{M}$ is an uncertain measure satisfying*

$$\mathcal{M}\left\{\prod_{k=1}^{\infty} \Lambda_k\right\} = \bigwedge_{k=1}^{\infty} \mathcal{M}_k\{\Lambda_k\}.$$

Definition 1 (Liu 2007) An uncertain variables is a function ξ 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 Φ of an uncertain variable ξ is defined by

$$\Phi(x) = \mathcal{M}\{\xi \leq x\},\ \forall x \in \Re$$

for any real number x.

Definition 3 (Liu 2007) An uncertain variable ξ is normal if it has a normal uncertainty distribution

$$\Phi(x) = \left(1 + exp\left(\frac{\pi(e-x)}{\sqrt{3}\sigma}\right)\right)^{-1},\ x \in \Re$$

denoted by $\mathcal{N}(e, \sigma)$ where e and σ 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

$$\lim_{x\to-\infty} \Phi(x) = 0, \qquad \lim_{x\to+\infty} \Phi(x) = 1.$$

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

Theorem 1 *(Liu 2010) Let $\xi_1, \xi_2, \cdots, \xi_n$ are independent uncertain variables with regular uncertainty distributions $\Phi_1, \Phi_2, \cdots, \Phi_n$, respectively. If $f(\xi_1, \xi_2, \cdots, \xi_n)$is strictly increasing with respect to $\xi_1, \xi_2, \cdots, \xi_m$ and strictly decreasing with respect to $\xi_{m+1}, \xi_{m+2}, \cdots, \xi_n$, then*

$$\xi = f(\xi_1, \xi_2, \cdots, \xi_n)$$

has an inverse uncertainty distribution

$$\Psi^{-1}(\alpha) = f\left(\Phi_1^{-1}(\alpha), \cdots, \Phi_m^{-1}(\alpha), \Phi_{m+1}^{-1}(1-\alpha), \cdots, \Phi_n^{-1}(1-\alpha)\right).$$

Theorem 2 *(Liu 2010) Let $\xi_1, \xi_2, \cdots, \xi_n$ are independent uncertain variables with regular uncertainty distributions $\Phi_1, \Phi_2, \cdots, \Phi_n$, respectively. If $f(\xi_1, \xi_2, \cdots, \xi_n)$ is strictly increasing with respect to $\xi_1, \xi_2, \cdots, \xi_m$ and strictly decreasing with respect to $\xi_{m+1}, \xi_{m+2}, \cdots, \xi_n$, then*

$$\mathcal{M}\{f(\xi_1, \xi_2, \cdots, \xi_n) \leq 0\}$$

is the root of the equation

$$f\left(\Phi_1^{-1}(\alpha), \cdots, \Phi_m^{-1}(\alpha), \Phi_{m+1}^{-1}(1-\alpha), \cdots, \Phi_n^{-1}(1-\alpha)\right) = 0.$$

Theorem 3 *(Liu 2010) Let ξ be an uncertain variable with regular uncertainty distribution Φ. Then,*

$$E[\xi] = \int_0^1 \Phi^{-1}(\alpha)d\alpha.$$

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