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RESEARCH ARTICLE

A two-stage stochastic model considering conditional risk in a multi-level multi-product supply chain

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ABSTRACT

This study introduces a novel two-stage stochastic model of mean value exposed to conditional risk to allocate locations and to calculate the flow of materials and manufactured goods in a multi-level, multi-product supply chain. In this model, distributors and suppliers face potential disruptions and could spend money to prevent them. The suggested model considered several sources of uncertainty, such as transportation costs, final customer demand, and the possibility of disruptions at distribution centers and suppliers. The model used the conditional risk-exposed value and the risk-aversion coefficient to control for the risk caused by significant deviations from expected values. The designed model was transformed into a single-level linear programming model using a Monte Carlo simulation. Finally, the model was implemented through a numerical example, and its sensitivity analysis was conducted. The results of the model show that increasing the risk-aversion coefficient led to a decrease of more than 20% in the objective function across all confidence levels for the test problem, indicating the effectiveness of the proposed two-stage stochastic model in proactively mitigating disruptions.

1. Introduction

Managers' attention in supply chain planning has long been focused on the production sector. Today, this issue has been analyzed to some extent, and managers realize that they cannot compete effectively without detailed planning in both the production and distribution sectors. For instance, integrated approaches such as in Ref. 1 have contributed to a better consideration of these aspects. On the other hand, the globalization of economic activities, rapid changes in technology, and limited resources have led to intense competition among companies. Competitive advantages can be achieved by making supply chain management more efficient and effective. [2] In today's highly competitive global markets, competition occurs between supply chains rather than between individual firms. [3] A supply chain includes all steps that contribute to fulfilling customer demand. A typical supply chain delivers raw materials from suppliers to factories. The products manufactured in the factories are then sent to intermediate warehouses and distribution centers, and

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from there, they reach retailers and finally, the end customers. During these steps, the goods require storage and transportation. A supply chain can be considered a collection of warehousing and transportation activities, in addition to production, that work together to distribute a product under appropriate conditions. At the same time, the total cost of the supply chain should be minimized, and the level of service should be increased. [4]

Decision-making in supply chains often faces uncertainty due to inaccuracy, continuous variability, and the inability to forecast future events. Uncertainty in the decision-making process is a major factor that may affect the effectiveness of configuration and coordination throughout the chain. Focusing on optimizing the supply chain under uncertainty can reduce costs and improve quality, and as a result, lead to competitive advantages. [5] Uncertainty can result from various sources, such as changing customer demand and preferences, variable costs of production inputs (e.g., raw materials and labor), the emergence of new technologies, competitive conditions of companies, and macroeconomic situations (e.g., natural disasters, sabotage, changes in laws, and political decisions). [6]

Uncertainty can have destructive effects on the performance of the supply chain and its components and can impose high costs. [7] Therefore, scenarios for uncertainties should be considered in the design of supply chains to reduce their vulnerability. Each scenario corresponds to a probability value that indicates the probability of its occurrence. Considering different scenarios allows the supply chain to operate under changing conditions and provides stability and flexibility. In each scenario, optimal decisions should be made such that the supply chain maintains resilience, robustness, and agility. Facility location in the supply chain is a strategic decision, as it involves high expenditure, and modifying or relocating facilities is costly and complex, affecting all subsequent supply chain functions. Therefore, respective decisions must be made before a specific scenario emerges. These aspects are currently not comprehensively considered in many existing supply chain models.

In our proposed model, we considered the possibility of disruption in the operation of distribution centers using random parameters. We assumed that distribution centers and suppliers can be disrupted and may abandon the expected activity cycle due to various reasons, such as natural disasters, technical and operational problems, and events related to information technology.

In the current study, customer demand in retail stores, transportation costs, and the possibility of disruption (detailed later) depended on the scenario. Under practical conditions, it is not possible to estimate transportation costs for a given demand with certainty due to market fluctuations. Traditional location-allocation problems assume that unit transportation costs from origin to destination are known. However, planned routes may become unavailable under certain conditions, such as natural disasters or construction work, or transportation costs may be affected by traffic congestion or fuel costs. As a result, unit transportation costs from the origin to the destination are uncertain and are treated as random variables. This study addressed the location-allocation problem under random transportation costs.

In the current research, we proposed a multi-level, multi-product supply chain design, as this approach is both more general and of greater practical significance than the simpler models often studied in the literature. The supply chain model was analyzed under uncertain conditions using a combined average-risk approach, where the risk measurement criterion is the conditional risk value (conditional value-at-risk [CVaR]) (see Ref. 8, and further details below).

As decision variables, we considered the allocation of production and distribution centers as strategic choices to address the possibility of disruptions. In addition, we provide an optimal strategy for raw material supply, production, and distribution. Customer demand, transportation costs, and the occurrence of disruptions in distribution centers are treated as random factors in our supply chain model.

In the proposed model, the possibility of disruption in distribution center services was considered, along with the option to equip suppliers to handle such disruptions. The parameters of the supply chain model were not fixed; their values depended on specific scenarios. Under these conditions, the problem of optimal location was investigated. The supply chain under study consisted of suppliers, manufacturers, distributors, and retailers, along with predetermined locations for each entity. The model determined the optimal set of selected locations by minimizing the objective function related to the network costs and considering different scenarios. Given the scenario-based nature of the supply chain, the corresponding optimization problem in this field fell within the scope of stochastic optimization and is formulated as a mixed-integer two-stage stochastic optimization problem. Two sets of decision variables were considered in the two-stage stochastic programming problem. The first stage involved strategic decisions that were independent of specific scenarios (i.e., made before any scenario occurs), while the second stage involved decisions that were dependent on a given scenario. These variables were optimized based on the selection of stage-one variables and possible scenarios. Two-stage stochastic programming problems were discussed in various domains, such as disaster management, [9] process systems, [10] lot-sizing and scheduling, [11] inventory routing, [12] and energy management.

In our model, the second component of the objective function in the two-stage stochastic model was the expected value of system costs. However, relying solely on the expected value may lead to instability. This instability arises from the fact that some scenarios may produce supply chain costs that deviate significantly from the expected value of the cost calculated by the model. In such cases, the actual performance of the supply chain may differ greatly from what is anticipated. A risk factor was also incorporated to enhance model stability, using CVaR as the risk measurement criterion. CVaR (also referred to as the conditional risk value or loss) was calculated for the random variable representing total supply chain costs and was included as a component of the overall objective function. Value-at-risk (VaR) at a given confidence level is the mathematical expectation of supply chain costs if the costs exceed a critical value. Therefore, the overall objective function of the supply chain model comprised: first stage of stochastic planning (costs related to the establishment of centers), second stage of stochastic planning (costs of the operational supply chain after specific location decisions), and the VaR (as a measure of risk). The model was optimized using mixed linear programming, and a sensitivity analysis was performed.

Overall, the innovative aspects of our contribution can be summarized as follows:

(i) Considering the possibility of disruption in distribution centers and suppliers in an average-risk two-stage stochastic planning model (based on CVaR);
(ii) Incorporating the option to equip suppliers to mitigate the effects of disruptions;
(iii) Accounting for uncertainty due to both demand and transportation costs simultaneously;
(iv) Modeling the average-risk model using linear programming.

The remainder of this paper is organized as follows. In the next section, we review the relevant supply chain-related background and related work, and highlight the innovative aspects of our study. Section 3 presents the proposed supply chain model. Section 4 discusses the implementation of the model. Conclusions and recommendations are provided in Section 5.

2. Background and related work

In recent years, various supply chain applications have attracted researchers' attention. The supply chain is a network of value-adding activities with the goal of delivering high-quality products at minimal cost and in the shortest possible time. It typically consists of four components: suppliers, manufacturers, distributors, and customers. [15] A typical supply chain structure can vary significantly in size and complexity from simpler models. These differences include complex company behaviors and interactions among firms. [2] It is worth noting that more complex models are possible, e.g., those considering shortages or inventory capacity constraints, which may require more advanced optimization approaches. [16]

Designing a supply chain network is a strategic-level decision-making problem with a long-term time horizon. Supply chain network design involves decisions related to facility location, capacity determination, and the selection of production technologies for use in production facilities and warehouses. These strategic decisions typically cover a period of several years. The purpose of supply chain management is to plan, execute, and optimally control operations related to the supply chain. The various decisions in supply chain design and management are generally divided into three levels [17]: (i) strategic level which refers to decisions with long-term effects, such as facility locations and infrastructure deployment; (ii) tactical level where medium-term planning is conducted, such as inventory control management policies; (iii) operational level which focuses on short-term decisions with a planning horizon of several weeks, including order fulfillment or routing plans, which are influenced by variability over time.

In recent years, there has been a significant shift toward integrating strategic and tactical decisions through the development of location-allocation models. Integrating different decision levels into the supply chain helps reduce overall costs and improve performance. [18] The location-allocation problem is a classic problem in operations research. The general application of allocation is in production, logistics, services, and military affairs, such as determining the location of factories, warehouses, distribution centers, fire stations, or missile depots. Once a mode of distribution is chosen, it cannot be easily changed, and it directly affects service quality, efficiency, cost, profitability, competitiveness in the market, as well as the survival of companies. Therefore, location planning holds substantial economic and social significance.

Uncertainties in general, and disruptions in particular, have a significant impact on planning activities and their outcomes. The Business Continuity Institute (BCI) has conducted yearly surveys on this topic since 2009, typically involving 500–600 respondents from about 60–70 countries (since 2011). [19] Between 2010 and 2018, approximately 70–85% of companies experienced at least one supply chain disruption per year. During the same period, between 7 and 22% of companies experienced more than 10 disruptions annually. Across the 2009–2018 surveys, 19.7% of companies reported average cumulative losses exceeding €1 million per year due to supply chain disruptions. The 2018 BCI report [19] also noted that more organizations failed to analyze their supply chains to identify the original source of disruption (30.3%) compared to 2011 (23.4%).

Barzegar et al. [20] analyzed disruptions in the operational clothing supply chain of a defense organization using structural interpretive modeling. In this particular research, disruptions related to the supply chain were pinpointed by reviewing the relevant literature. Specific disturbances within the supply chain were then identified through field research and expert interviews. Structural interpretative modeling was used to analyze the degree of dependence and occurrence of disruptions, as well as their internal relationships, in a seven-step process.

Moosavi et al. [21] conducted a series of bibliometric, network, and thematic analyses focusing on influential contributors, major research streams, and disruption management strategies related to supply chain performance in the context of COVID-19. Their findings indicate that resilience and sustainability are primary issues in supply chains. In addition, it was found that the main themes of food-related research include health-related supply chains and technological tools.

Mirhassani and Khaleghi [22] presented a two-stage stochastic programming model to determine the optimal locations of vehicle charging stations. An efficient heuristic algorithm based on Benders decomposition [23] was used to solve the model. The results demonstrated that the heuristic method could quickly find a near-optimal solution within a short computation time.

Eskandari and Saloot [7] designed a sustainable closed-loop supply chain that incorporates economic, social, and environmental aspects, as well as risks arising from uncertain parameters. Stochastic programming was used to model this problem, and risk was assessed using CVaR.

Behzadi and Seifabrghy [24] developed a closed-loop supply chain network that includes foreign suppliers, production/recovery centers, combined distribution/collection centers, disposal centers, and customers. This study assumed uncertainty in parameters such as demand, quantity and quality of returned products, and variable costs. Two approaches, two-stage stochastic optimization and robust optimization, were used to evaluate parameter uncertainty. The results indicated that the robust optimization approach outperformed two-stage stochastic optimization under uncertain conditions. Hasani [4] presented a comprehensive mathematical model for designing a supply chain network, considering both forward and reverse flows of several products over multiple time periods. Uncertainties in demand, return rates, production recovery and disposal, transportation costs, maintenance, and return flow management were addressed using two-stage stochastic programming. The proposed model was solved using an efficient method based on sample mean approximation and an accelerated Bender's analysis algorithm.

Hashemi-Amiri et al. [25] proposed a bi-objective optimization model for a three-tier perishable food supply chain involving multiple products. The model integrated supplier selection, production planning, and vehicle routing. It aimed to reduce demand risk and supply uncertainty while improving distribution decisions by simultaneously optimizing total network costs and supplier reliability. A distributionally robust approach was employed, assuming that the probability distribution of uncertain demand lies within a real-time uncertainty set. This ensured that retailer demand and vehicle capacity constraints were satisfied with high probability. The proposed model was formulated as a mixed-integer linear program using duality and linearization techniques. Multiple objectives were addressed using a weighting approach, and the model was validated through a real-world case study in the poultry industry.

Gholian-Jouybari et al. [26] analyzed an agricultural food supply chain using a stochastic multi-objective programming model to improve environmental, social, and economic goals. A robust convex optimization approach was employed to address uncertainty in farm production capacity and demand. The proposed model was applied to a case study using the linear programming metric method and a metaheuristic method (a modified Keshtel algorithm) to address the considered nondeterministic polynomial time-hard problems. The results confirmed the suitability of the proposed algorithms for solving problems of varying sizes.

Han et al. [27] studied supply chains subjected to uncertain disruptions, incorporating decision-makers' risk attitudes. A bi-objective robust optimization model for a dual-sourcing strategy under outage risk was developed to minimize costs and shortages, considering different risk attitudes. The model was transformed into a single-objective mixed-integer programming formulation using the Îµ-augmented constraint method. The feasibility and effectiveness of the model were validated through organizational case studies. Moreover, analyses were performed on risk attitudes, trade-offs between dual objectives, and procurement strategy superiority analyses. The study also offered managerial insights into decision-making under supply disruption risk.

Ali and Shoaib [28] conducted a literature review on green supply chain management, categorizing the reviewed literature into four areas: practices and functions, mathematical techniques, drivers, and barriers. Their analysis showed that while most publications are theoretical, mathematical techniques are gaining increasing interest among researchers.

Das et al. [29] proposed a multilayer closed-loop supply chain network design for reusable packaging materials (RPMs) made of wood. A deterministic mixed-integer programming model was used to determine the optimal locations for RPM production facilities and distribution centers. In addition, a risk-averse two-stage stochastic programming model was developed to account for uncertainties in demand, initial inventory, and reusability levels of RPMs. CVaR was employed as the risk measure. Beyond the fixed costs of facility setup and capacity installation, the model considered construction, acquisition, renovation, and environmental costs. A sensitivity analysis of the deterministic model, along with experiments using varying CVaR parameters, provided further insights. The study also explored how incorporating a risk measure affects the computational performance of the model.

Wang et al. [30] integrated several practical aspects of disaster relief management, including facility location, pre-positioning and inventory delivery decisions, relief resource prioritization, partial demand probability information, and risk aversion. The problem was presented as a distributionally robust optimization model using mean CVaR. The proposed model demonstrated superior stability compared to a two-stage stochastic programming model. It was implemented in a large-scale, realistic case study involving hurricane threats in the southeastern USA.

Azaron et al. [3] developed a multi-objective, two-stage stochastic planning model that considered warehouse and retailer site selection, along with decisions on production levels, inventory levels, and transportation quantities among supply chain network entities. The first objective was to maximize the overall profit of the supply chain, while the second was to minimize response time. Uncertain parameters were assumed to be distributed as continuous random variables, and a simulation method called the sample mean approximation scheme was applied to compute optimal solutions of the random model under an infinite number of scenarios. Kungwalsong et al. [31] proposed a two-stage stochastic programming model for a four-stage supply chain network design problem, incorporating the possibility of facility disruptions. A modified simulated annealing algorithm was developed to determine first-stage strategic decisions. A comparison with the traditional supply chain network decision-making framework showed that stochastic solutions outperformed conventional methods under disruption scenarios.

Oksuz and Satoglu [32] analyzed the optimal number and locations of temporary medical centers in disaster situations. Using a two-stage stochastic programming model, an optimal solution was derived by considering the location of existing hospitals, the classification of the injured, the capacity of medical centers, and the possibility of damage to roads and hospitals.

Deng et al. [17] developed a stochastic expected-value model for two-stage stochastic modeling of location-allocation with specified capacities in emergency logistics. The decision variables of the model were the number of supply centers and their capacities. Particle swarm optimization was enhanced with a Gaussian cloud operator, a restart strategy, and an adaptive parameter strategy to solve these models.

Liu et al. [18] investigated the problem of optimal location-allocation of factories and distribution centers for a supply chain under uncertain transportation costs. A two-stage mean-risk zero and random mixed-integer optimization model was developed, considering both uncertainty and risk measures in the supply chain. Due to the complexity of the model, the authors proposed a modified hybrid binary particle swarm optimization algorithm to obtain solutions.

Sun et al. [6] addressed two-stage stochastic optimization problems using a risk measure defined as the worst-case expected values within a bounded distribution set. This two-stage quadratic stochastic optimization problem with risk measures is equivalent to a conical optimization problem that can be solved in polynomial time.

Trusevych et al. [33] examined the management of risks associated with accidental equipment failures by optimizing decisions related to the quantity and contracting of critical parts across a network of connected industrial sites. A two-stage random integer programming model with a CVaR criterion was developed to incorporate risk aversion. The computational results demonstrated the advantages of the CVaR approach over a traditional expected-cost minimization approach. The CVaR-based model resulted in fewer harmful policies than the corresponding risk-neutral model.

Another two-stage stochastic programming model using CVaR as a risk measure was proposed by Noyan, [34] who introduced two decomposition algorithms based on the general Benders decomposition framework to solve such problems. A recent analysis of a closed-loop supply chain model focusing on uncertain demand and using a two-stage stochastic programming approach was suggested by Liu et al. [35] Another two-stage stochastic model focusing on disruptions was presented by Ghanei et al. [36] in which three types of resilience strategies were analyzed.

Table 1 presents an overview of areas of contribution in the discussed studies, as well as in our research. Based on our literature review, it can be stated that risks in supply chains are often addressed using relatively simple approaches, such as relying on expected values or worst-case scenarios. In such models, only a single outcome of the random variables is considered, which is not sufficient to capture the full range of possible occurrences. On the other hand, CVaR-based approaches are found only occasionally (in five studies). Moreover, most studies address uncertainty related to a single variable, such as demand, whereas those considering multiple sources of uncertainty (e.g., transportation costs and demand) are rather scarce. Occasionally, two-stage models consider major risks (e.g., disruptions) in the first stage, followed by scenario-based planning in the second stage. However, we do not find models that include decision variables in the first-stage scenario to proactively address such scenarios, such as equipping suppliers to better cope with disruptions. Our proposed model addresses these gaps by incorporating multiple sources of uncertainty, applying a CVaR-based risk measure, and allowing proactive first-stage decisions. The innovative aspects are summarized at the end of Section 1.

3. Supply chain model

The considered supply chain exhibited a multi-level, multi-product structure and consisted of four levels (or layers): suppliers, manufacturers, distribution centers (warehouses), and retailers, as illustrated in Figure 1.

According to Figure 1, the indices and related sets introduced in Table 2 represent the supply chain components, raw materials, and final products.

As shown in Table 2, there are S candidate locations for opening or reopening factories, and J available distribution centers. The optimal manufacturers and distribution centers were selected based on the assumptions and conditions stated below. The parameters used in the model and their definitions are presented in Table 3. Suppliers, such as distribution centers, faced the possibility of disruptions. To mitigate this, the optimal model allowed for equipping these facilities at an additional cost. Transportation costs, customer demand, and the occurrence of disruptions in suppliers were treated as random (probabilistic) variables, dependent on the incidence of a scenario. All scenarios were represented in the set $\{1, \ldots, \Omega\}$.

Table 4 presents the decision variables of the model. The first-level variables correspond to the location-allocation for producers and distributors, as well as the decision to equip suppliers against possible disruptions. The second-level variables represent the amounts of raw materials and final goods transported between supply chain components. The superscript indices refer to the stage in the supply chain, starting from the left (1 for raw materials) to the right (3 for materials distributed to customers).

Conditional risk values are necessary to specify the objective function of the model. Suppose X is a random variable representing cost or loss. Then, the CVaR of X at confidence level

Table 1. Overview of contributions in the literature and in our study

Study	Two-stage model	Conditional risk values	Focus on disruptions	Equipping strategies	Optimization model
Azaron et al. [3]	+	–	–	–	+
Barzegar et al. [20]	–	–	+	–	–
Behzadi and Seifabrghy [24]	+	–	–	–	+
Deng et al. [17]	+	–	+	–	+
Ghanei et al. [36]	+	+	+	–	+
Gholian-Jouybari et al. [26]	–	–	–	–	+
Han et al. [27]	–	–	+	–	+
Hashemi-Amiri et al. [25]	–	–	+	–	+
Eskandari and Saloot [7]	+	+	–	–	+
Kungwalsong et al. [31]	+	–	+	–	+
Mirhassani and Khaleghi [22]	+	–	–	–	+
Liu et al. [18]	+	+	–	–	+
Liu et al. [35]	+	+	+	–	+
Moosavi et al. [21]	–	–	+	–	–
Noyan [34]	+	+	–	–	+
Oksuz and Satoglu [32]	+	–	–	–	+
Sun et al. [6]	+	–	–	–	+
Trusevych et al. [33]	+	+	–	+	+
Wang et al. [30]	+	+	+	–	+
Our study	+	+	+	+	+

Note: "+" indicates the presence, and "–" indicates the absence of a feature.

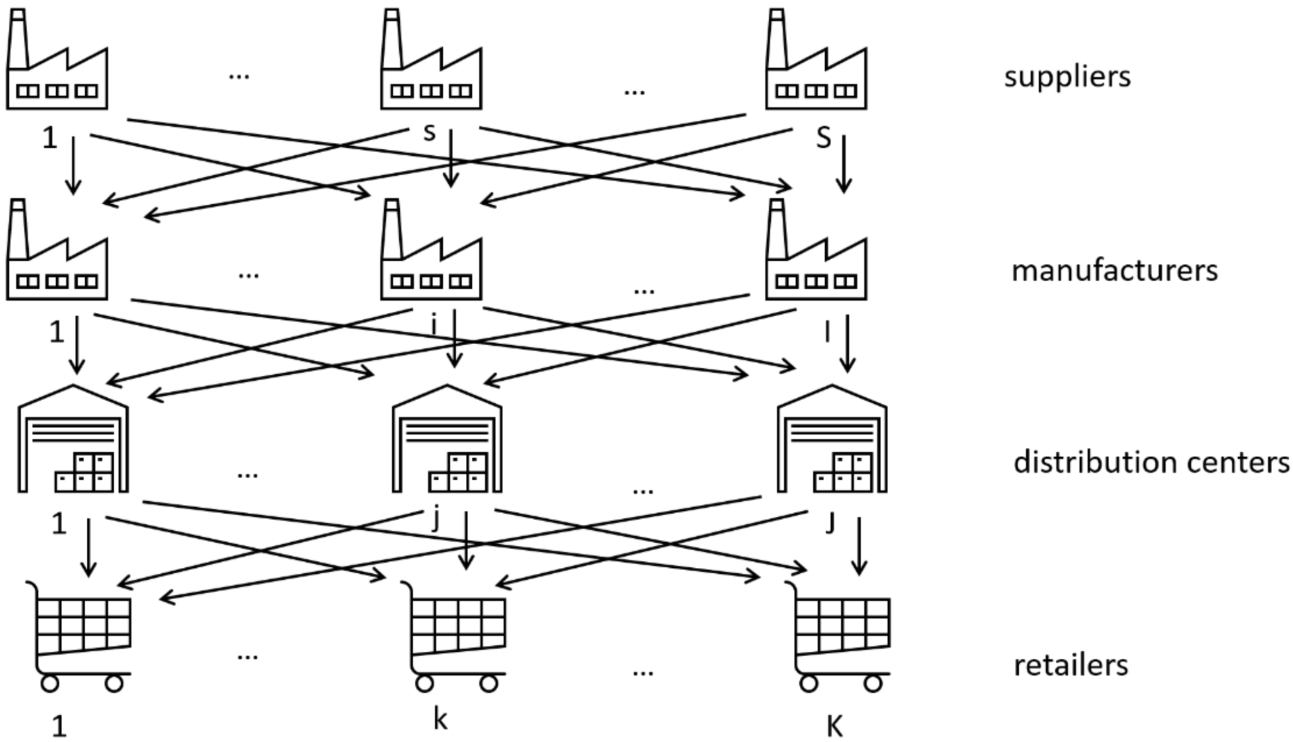

Figure 1. The structure of the multi-level supply chain, including suppliers, manufacturers, distribution centers, and retailers

$\alpha \in (0,1)$ is defined in Equation (1) (see Ref. 37, Equation (9)).

$$CVaR_{\propto}(X) = \min_{\eta\in\mathbb{R}} \left\{ \eta + \frac{1}{1-\alpha} E\left(|X-\eta|_+\right) \right\} \tag{1}$$

where $|x|_+ = \max\{x, 0\}$ and E denotes the expected value. Understanding CVaR requires first understanding $\mathrm{VaR}_\alpha(X)$. VaR measures the maximum cost or loss from variable X at a given confidence level. For example, $VaR_{0.95}(X) = 10\$$ means that, with 95% confidence, the maximum loss due to the random variable will not exceed

Table 2. Indices and sets used in the supply chain model

Indices	**Definition**
$s \in \{1, \ldots, S\}$	The index of suppliers in the set of suppliers
$i \in \{1, \ldots, I\}$	The index of manufacturers in the set of manufacturers
$j \in \{1, \ldots, J\}$	The index of distributors in the set of distributors
$k \in \{1, \ldots, K\}$	The index of retailers in the set of retailers
$v \in \{1, \ldots, V\}$	The index of raw materials in the set of raw materials
$l \in \{1, \ldots, L\}$	The index of products in the set of products
$\omega \in \{1, \ldots, \Omega\}$	The index of scenarios in the set of scenarios

Table 3. Parameters used in the model

Parameters	**Definition**
f_i	The fixed operating cost of the factory i
g_j	The fixed operating cost of the distribution center j
$equip_s$	The cost of equipping supplier s to prevent disruption
a_{vs}	The amount of raw material (capacity) v that supplier s can provide
r_{vs}	The cost of providing the raw material v by supplier s
n_{vl}	The amount of raw material v needed to produce product l
b_{il}	The amount of product l that producer i can manufacture
q_{il}	Manufacturing cost per unit of product l at manufacturer i
τ_{lj}	The amount of product l that center j can store
w_{lj}	The storage cost of each unit of product l in distribution center j
h_l	The wholesale price of product l
$t_{vsi}^{(1)}$	The cost of transporting a unit of raw material v from supplier s to manufacturer i
$t_{lij}^{(2)}$	The cost of transporting a unit of product l from producer i to distribution center j
$t_{ljk}^{(3)}$	The cost of transporting a unit of product l from distributor j to consumer k
D_{lk}	A random vector representing the random parameters of the network, including transportation costs, demand, and disruption in distribution centers and suppliers
λ	Risk aversion factor
$\xi(\omega)$	Binary parameter – takes the value of one if supplier s in the scenario ω is disrupted
$B_s(\omega)$	A random vector representing the random parameters of the network, including transportation costs, demand, and disruption in distribution centers and suppliers

Table 4. Decision variables used in the model

Decision variable	**Definition**
e_i	Binary variable indicating the opening of factory i
c_j	Binary variable indicating the opening of distribution center j
lev_s	Binary variable indicating the equipment of the distribution center s
$x_{vsi}^{(1)}$	The amount of raw material v sent from supplier s to factory i
$x_{lij}^{(2)}$	The amount of product l sent from factory i to distribution center j
$x_{ljk}^{(3)}$	The amount of product l sent from distribution center j to consumer k

\$10. However, this raises the question: What is the expected loss in the remaining 5% of cases? CVaR addresses this by estimating the expected value of losses exceeding the VaR threshold.

The objective function of the model was cost minimization and consisted of two parts or stages. The first stage included costs corresponding to the level-one variables, namely, operating costs of opening factories and distribution centers, as well as the cost of equipping suppliers. The second stage captured the supply chain performance cost after the location-allocation decisions made in the first stage. These costs included transportation and storage costs, from which sales revenue was deducted. The model exhibited four random sources of uncertainty: transportation costs, customer demand, and the possibility of disruptions in both distribution centers and suppliers. The expected value of the overall costs was selected as the objective function of the second part, which aggregated the costs of all scenarios considering their respective probabilities of occurrence. However, it is possible that the cost in one or more scenarios deviates from the expected values. In such cases, the expected cost in the design and optimization stages of the supply chain may differ greatly from the actual cost. To address this, the CVaR was used as the risk assessment criterion. The risk aversion coefficient, $\lambda \in [0,1]$, [38] was used to balance expected return and risk. A value of $\lambda = 0$ corresponds to a fully risk-taking decision-maker, while $\lambda = 1$ represents a risk-averse one. Thus, the objective function of the model is given in Equation (2), with the second-level costs under a given scenario and specific location-allocation decisions from the first stage detailed in Equation (3). The first term of Equation (2) (objective function) represents the transportation costs of raw materials from suppliers to manufacturers, whereas the second term refers to the operating costs of distribution centers. The third term captures the costs of equipping suppliers against disruption, and the final term represents the costs resulting from the second-stage decisions, which are weighted by the risk aversion factor. The second-stage costs in Equation (3) include: raw material costs from suppliers Equation (4), manufacturing costs at the production facilities Equation (5), transportation costs across the supply chain levels under each scenario Equation (6), storage costs at distribution centers Equation (7), and revenues from sales to consumers Equation (8).

$$\min_{e,c,lev} z = \sum_{i\in I} f_i e_i + \sum_{j\in J} g_j c_j + \sum_{s\in S} lev_s\, equip_s + (1-\lambda)E\big(Q(e,c,\omega)\big) + \lambda\, \mathrm{CVaR}_\alpha\big(Q(e,c,\omega)\big) \tag{2}$$

$$\boldsymbol{Q}(\mathbf{e},\mathbf{c},\omega) = \min_{\mathbf{x^{(1)}},\mathbf{x^{(2)}},\mathbf{x^{(3)}}} \Big(\mathbf{rawmatcost}\left(\mathbf{x^{(1)}}\right) + \mathbf{manufacturing\ cost}\left(\mathbf{x^{(2)}}\right) + \mathbf{transportcost}\left(\mathbf{x^{(1)}},\mathbf{x^{(2)}},\mathbf{x^{(3)}},\omega\right) + \mathbf{storagecost}\left(\mathbf{x^{(2)}},\mathbf{x^{(3)}}\right) - \mathbf{revenues}\left(\mathbf{x^{(3)}}\right) \Big) \tag{3}$$

$$rawmatcost\left(x^{(1)}\right) = \sum_{v\epsilon V}\sum_{s\epsilon S}\left(r_{vs}\sum_{i\epsilon I} x^{(1)}_{vsi}\right) \tag{4}$$

$$manufacturing\ cost\left(x^{(2)}\right) = \sum_{i\epsilon I}\sum_{l\epsilon L}\left(q_{il}\sum_{j\epsilon J} x^{(2)}_{lij}\right) \tag{5}$$

$$transportcost\left(x^{(1)},x^{(2)},x^{(3)},\omega\right) = \sum_{v\epsilon V}\sum_{s\epsilon S}\sum_{i\epsilon I} t^{(1)}_{vsi}(\omega)x^{(1)}_{vsi} + \sum_{v\epsilon V}\sum_{s\epsilon S}\sum_{i\epsilon I} t^{(2)}_{lij}(\omega)x^{(2)}_{lij} + \sum_{l\epsilon L}\sum_{j\epsilon J}\sum_{k\epsilon K} t^{(3)}_{ljk}(\omega)x^{(3)}_{ljk} \tag{6}$$

$$storagecost\left(x^{(2)},x^{(3)}\right) = \sum_{l\epsilon L}\sum_{j\epsilon J}\left(w_{lj}\left(\sum_{i\epsilon I} x^{(2)}_{lij} - \sum_{k\epsilon K} x^{(3)}_{ljk}\right)\right) \tag{7}$$

$$revenues\left(x^{(3)}\right) = \sum_{l\epsilon L}\left(h_l\sum_{j\epsilon J}\sum_{k\epsilon K} x^{(3)}_{ljk}\right) \tag{8}$$

The set of constraints of the model is specified in Equations (9)–(15):

$$\sum_{i\in I} x^{(1)}_{vsi} \le \left(B_s(\omega)lev_s + 1 - B_s(\omega)\right)a_{vs} \quad \forall v,s \tag{9}$$

$$\sum_{l\in L}(n_{vl}\sum_{j\in J} x^{(2)}_{lij}) \le \sum_{s\in S} x^{(1)}_{vsi} \quad \forall v,i \tag{10}$$

$$\sum_{j\in J} x^{(2)}_{lij} \le e_i b_{il} \quad \forall i,l \tag{11}$$

$$\sum_{k\in K} x^{(3)}_{ljk} \le \sum_{i\in I} x^{(2)}_{lij} \quad \forall l,j \tag{12}$$

$$\sum_{k\in K} x^{(3)}_{ljk} \le c_j \tau_{lj} \quad \forall l,j \tag{13}$$

$$\sum_{j\in J} x^{(3)}_{ljk} \le d_{lk}(w)\ \forall l,k \tag{14}$$

$$e_i, c_j \in \{0,1\}, x^{(1)}_{vsi}, x^{(2)}_{lij}, x^{(3)}_{ljk} \ge 0 \quad \forall i,j,k,s,l,v \tag{15}$$

The constraints can be explained as follows: Equation (9) limits the maximum amount of raw materials a supplier can provide, considering whether a disruption has occurred and whether the supplier is equipped against this. Equation (10) constrains production at a manufacturer based on the availability of raw materials and specific production coefficients. Equation (11) limits production amounts by the capacity of the factories, factoring in whether the facility is open. Equation (12) ensures that the quantity of goods delivered to customers does not exceed the amount available at each distribution center. Equation (13) enforces the inventory capacity limits of distribution centers, based on whether the distribution center is considered "open". Equation (14) ensures that the customer shipments do not exceed demand. Equation (15) defines the domain of model variables.

Constraint 4, i.e., $\sum_{i\in I} x_{vsi}^{(1)} \leq za_{vs}$, relates to the capacity constraint of suppliers. The binary parameter z depends on the occurrence of a disturbance, $B_s(\omega)$, and whether the supplier has been equipped, denoted by lev_s. Table 5 illustrates how these variables affect z.

Table 5. Effect of disruption and equipment on supplier capacity

z	lev_s	$B_s(\omega)$
1	1	1
0	0	1
1	1	0
1	0	0

These relationships can be expressed using Boolean logic according to Equation (16). In particular, $z = 0$ only when a disruption occurs ($B_s(\omega) = 1$) and the supplier is not equipped (lev_s=0) :

$$z = B_s(\omega)lev_s + 1 - B_s(\omega) \tag{16}$$

The set of random parameters was aggregated in a scenario space $\omega \in \{1, \ldots, \Omega\}$. A scenario ω consisted of the demand at each retailer, the transportation costs, and the disruption status of distribution centers and suppliers. Assuming independence of events, [39] the general probability space was defined as the Cartesian product of the individual probability spaces for demand, transportation cost, and disruptions. Given that demand, transportation costs, and overall disturbance may follow continuous distributions, a Monte Carlo simulation was employed to calculate both the mathematical expectation and CVaR in the objective function, using a combination of continuous and discrete samples. Due to scenario aggregation, the model may face high computational complexity. However, the linear form of the model allowed optimization in high dimensions using existing software.

The probability space Ω was assumed to be finite, enabling the mathematical expectation to be approximated via the sample mean, as shown in Equation (17):

$$E(Q(e,c,\omega)) = \sum_{\omega\in\Omega} p(\omega)Q(e,c,\omega) \tag{17}$$

where $p(\omega)$ is the probability of scenario ω. This transform the expectation into a linear form, suitable for linear programming. If X was a discrete random variable that took values $x_1, x_2, ..., x_n$ with probabilities $p_1, p_2, ..., p_n$, then the CVaR at confidence level α was calculated using Equation (18):

$$\min_{\eta\epsilon\mathbb{R}} \left\{ \eta + \frac{1}{1-\alpha} \sum_{j\in[n]} p_j w_j : w_j \geq x_j - \eta \;\; \forall j \in [n], w \in R_+^n \right\} \tag{18}$$

Given the finite probability space Ω, Equation (18) was used to compute the risk component (CVaR) in the model. This aspect was considered in the model in a linear form because both the objective function and constraint (18) were linear, and the variables were nonnegative real values. Objective function (2) was converted into a linear form, which was solved with the help of linear programming by considering Equations (17) and (18).

4. Model implementation

The numerical example in this section assumed that the supply chain structure comprised three suppliers, three manufacturers, four distributors, and six retailers. In addition, it was assumed that only one product was produced and a single raw material was required. The fixed deterministic parameters used in the model are listed in Table 6.

The final product demand of the retailers was one of the random parameters of the model, which was assumed to follow a uniform distribution, with parameters listed in Table 7.

The transportation costs per kilogram of cargo between different levels of the supply chain were also random parameters of the model. Three scenarios were considered for the transportation costs, as presented in Tables 8–10. In each cell of the tables, the three numbers represent the transportation cost values for each scenario. The probability of the first scenario was 0.60, and the other two scenarios showed probabilities of 0.20 each.

The occurrence of disruptions in the distribution centers was also a random parameter and demonstrated binomial distributions, as shown in Table 11.

Table 6. Parameters used in the model

Index	f_i	g_j	$equip_s$	a_{vs}	b_{il}	τ_{lj}	w_{lj}	q_{il}	r_{vs}	n_{vl}	h_1
1	1000	200	245	900	450	500	2	12	4	1	28
2	1050	202	255	1000	550	400	2	10	3	–	–
3	1020	205	260	800	750	350	2	9	4	–	–
4	–	198	–	–	–	250	2	–	–	–	–

Table 7. Uniform demand distribution parameters in retail stores

Retailer	Demand distribution
1	U(195,225)
2	U(200,235)
3	U(90,120)
4	U(245,260)
5	U(195,230)
6	U(185,215)

Table 8. Transportation costs in three scenarios between supplier s and manufacturer i

i s	1	2	3
1	1/6,1/5,1/2	2/4,2/6,2/8	4,4/5,4/8
2	1/1,1/3,1/5	1/2,1/5,1/6	3/1,3/3,3/8
3	3,3/5,4	1/2,1/3,1/4	1/2,1/4,1/5

Table 9. Transportation cost in three scenarios between manufacturer i and distributor j

j i	1	2	3	4
1	5,5/8,6	4,4/8,5	2,3,3/5	1/2,1/4,1/6
2	3/1,3/3,3/6	1/1,1/4,1/6	4,4/5,4/8	3,3/5,3/8
3	1,1/2,1/4	1/2,1/4,1/6	1/1,1/3,1/5	2/2,2/4,2/6

Table 10. Transportation costs in three scenarios between distributor j and retailer k

j k	1	2	3	4
1	1,1/2,1/4	1,1/2,1/4	3,3/8,4	3,3/6,3/8
2	2,2/5,2/8	4,4/8,5	1/2,1/4,1/6	2/2,2/4,2/6
3	3,3/6,3/8	1/2,1/5,1/8	3,3/8,4	2,2/5,2/8
4	4,4/8,5	4,4/8,5	1,1/6,1/8	1,1/2,1/4
5	2,2/8,3	2,2/5,2/8	1/2,1/5,1/8	1/4,1/6,1/8
6	2,2/5,2/8	1/2,1/4,1/6	4,4/8,5	2/5,2/8,3

Table 11. Disruption probabilities of the suppliers

Center	Disruption probability
1	0.10
2	0.05
3	0.15

Considering the set of scenarios and parameters defined for the supply chain model, it was optimized with a risk factor $\lambda = 0.50$ and confidence level $\alpha = 0.90$. Approximately 1000 scenarios were considered for demand and 100 scenarios for disruptions. Given the three scenarios for transportation costs, the total probability space consisted of 300,000 scenarios. The Pyomo software package (version 5.x, Sandia National Laboratories, USA) was used to implement the linear model. [40] This software, written in Python, supports class-based and flexible modeling. The results of the optimization are listed in Table 12.

According to Table 12, the second and third manufacturers and all four distributors were (re-) opened, and only the third supplier was equipped. Supplier 1 served only Manufacturer 3 with 450 units. Supplier 2 sent 250 units to each of Manufacturers 2 and 3. Supplier 3 supplied only Manufacturer 2 with 200 units. Manufacturer 1, having received no raw material, did not deliver to any distribution center. Manufacturer 2 sent 90 units to Distribution Center 1 and 360 units to Distribution Center 2. Manufacturer 3 sent 210 units to Distribution Center 1, 280 units to Distribution Center 3, and 210 units to Distribution Center 4. Distribution Center 1 delivered 150 units each to Retailers 1 and 3. Distribution Center 2 sent 200 units to Retailer 2 and 160 units to Retailer 4. Distribution Center 3 delivered 40 units to Retailer 1, 60 units to Retailer 4, and 180 units to Retailer 5. Distribution Center 5 sent 210 units to Retailer 6. The optimal value of the objective function was -6.8546, where the negative sign indicates a profit. Subsequently, the supply chain model was optimized to three confidence levels ($\alpha = 0.90, 0.95, 0.98$) and 11 levels of the risk aversion coefficient, as depicted in Figure 2. Given that the values of the objective function were negative for all values shown in Figure 2, the approximate optimal value was interpreted as profit.

As Figure 2 illustrates, with an increase in the risk aversion coefficient, the objective function decreased for all confidence levels. The profit decreased by more than 20% compared to a setting with $\lambda = 0$. This was due to increasing costs associated with greater risk aversion. For a specific value of risk aversion coefficient, the objective function also decreased with higher confidence levels. The decision on whether to equip suppliers in the optimal solution, depending on the risk aversion coefficient, is presented in Figure 3.

According to Figure 3, all suppliers were equipped as the risk-aversion factor increases. While Suppliers 3 and 2 were equipped at $\lambda = 0.5$ and $\lambda = 0.8$, $\lambda = 0.9$ led to all suppliers being equipped. Higher risk aversion led to increased related costs, making it more attractive to invest in equipment to mitigate risks. Table 13 presents the supplier equipment status according to increasing probabilities of supplier disruption.

In Table 13, the optimal model equipped more suppliers as the probability of supplier disruption increased. All centers were equipped once these probabilities reached 25%.

5. Conclusion and recommendations

Parameters in supply chain models, such as demand and transportation costs, are often assumed to be known precisely at the time of decision-making. However, the dynamics of economic, political, legislative, trade, and business conditions; the emergence of new technologies; the policies of competing companies, and natural events all introduce uncertainties that should be considered through different planning scenarios. Without incorporating uncertainties, as we did in our CVaR-based model, a supply chain model fails to reflect the fluctuations commonly observed in real-world operations. In addition, the potential for disruptions affecting key inputs to the supply chain should be accounted for, as such events often pose the most practically relevant risks. Using criteria such as the mathematical expectation to aggregate the outcomes of different scenarios can lead to instability in the results, as these practical results may deviate from the values assumed for the model design, as they do not reflect the full range of possible outcomes. In contrast, the present study utilized CVaR as a risk measure, which considered the variety of uncertain values when searching for an optimal problem. This modeling approach not only offers advantages over simplistic methods such as worst-case or average-case considerations, [41] but it also eliminates extreme solutions, as found in traditional mean-variance optimization, and usually results in more stable solutions, including robustness against data uncertainty. [42]

Building on this, the current research introduced a mean CVaR model that accounted for possible disruptions at suppliers and distributor centers, which can be mitigated through optional equipment investments. This novel feature allows the model to incorporate disruption mitigation strategies and to balance their associated costs and benefits within an optimization framework. The primary application of the model is in the strategic location planning of production and distribution centers under disruption risk. By incorporating CVaR, the optimal solution became more stable and robust against input uncertainty. The results showed that as the risk aversion coefficient increased, the objective function decreased across all confidence levels. Similarly, for a specific risk aversion coefficient, higher confidence levels also led to reduced values of the objective function.

Moreover, the number of equipped suppliers increased with the level of risk aversion. The optimal model equipped all suppliers when the risk

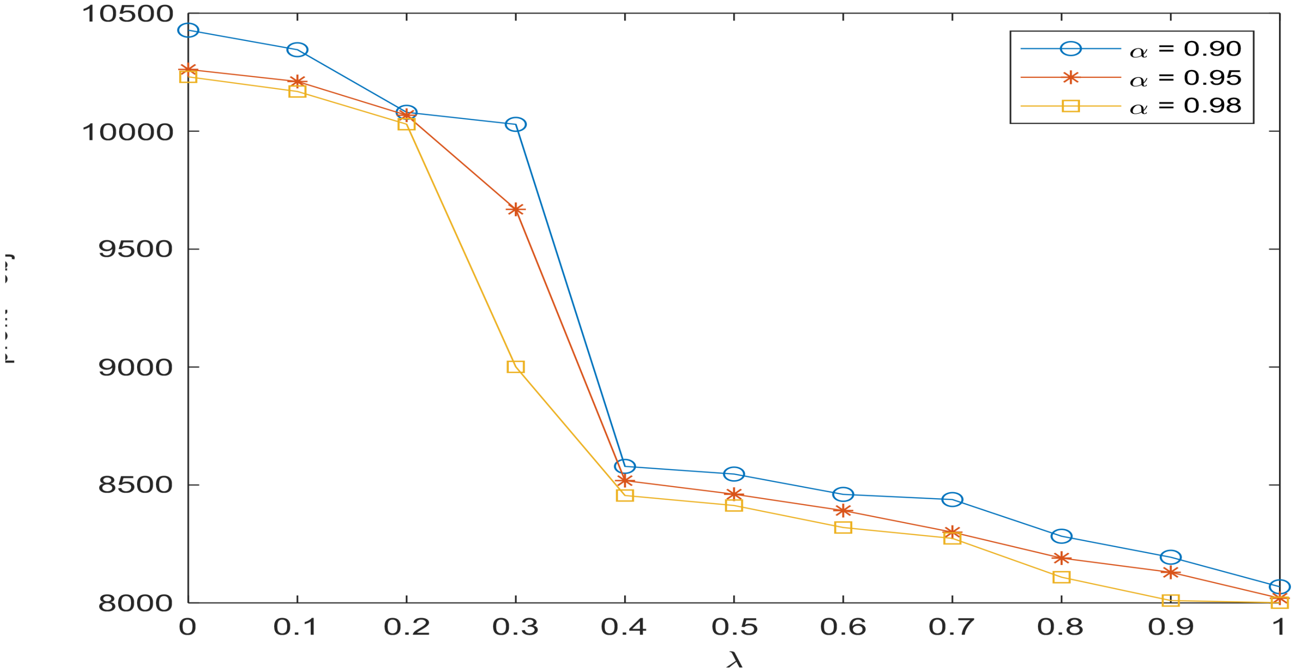

Figure 2. Sensitivity of the objective function to confidence levels α and risk aversion coefficient λ

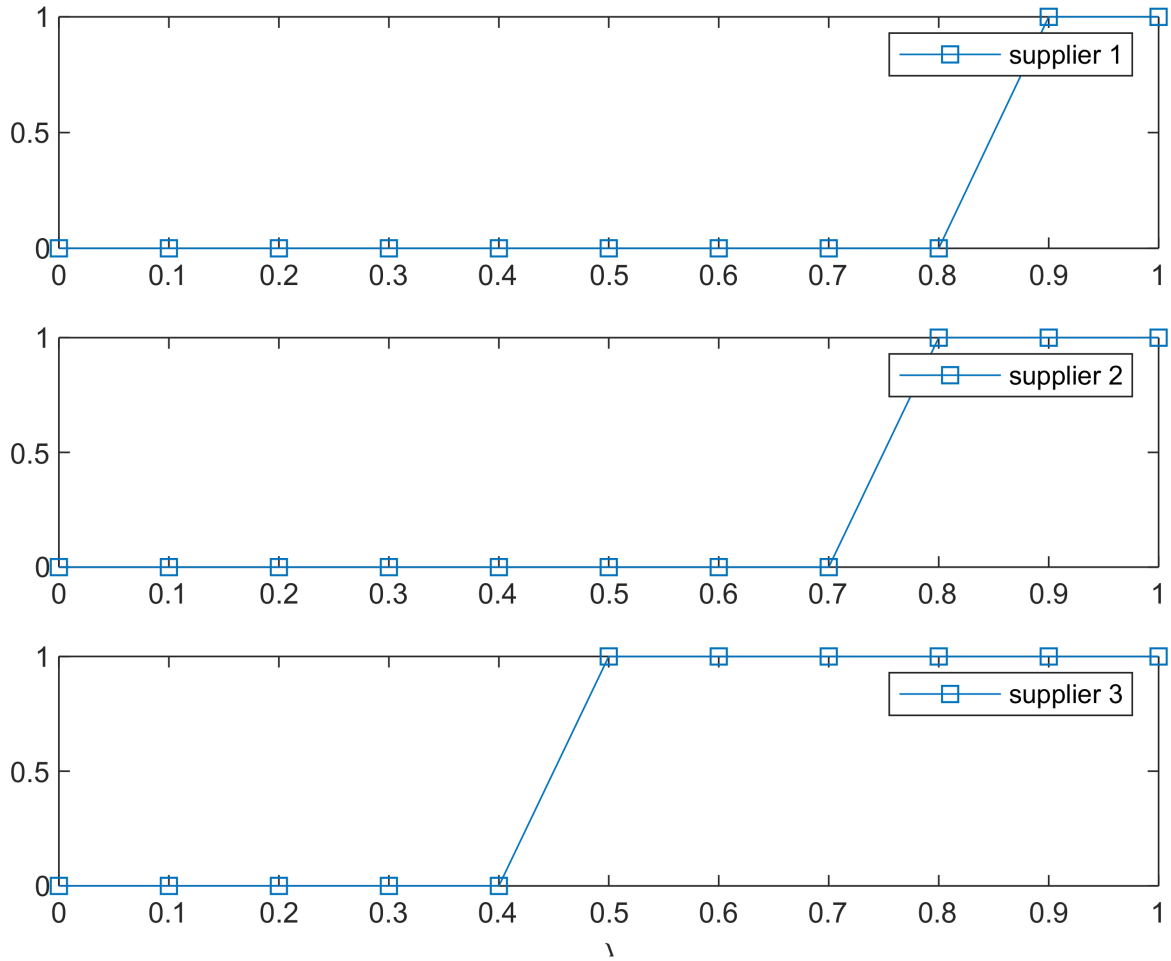

Figure 3. Equipping or not equipping suppliers in the optimal solution, depending on the risk aversion coefficient. Higher risk aversion coefficients λ generally encourage supplier equipment.

Table 12. Optimal values of decision variables and the optimal value of the objective function

Variable	Optimal value
(e_1^*, e_2^*, e_3^*)	$(0, 1, 1)$
$(c_1^*, c_2^*, c_3^*, c_4^*)$	$(1, 1, 1, 1)$
$(\text{level}_1^*, \text{level}_2^*, \text{level}_3^*)$	$(0, 0, 1)$
$(x_{1,1,1}^{(1)*}, x_{1,1,2}^{(1)*}, x_{1,1,3}^{(1)*})$	$(0, 0, 450)$
$(x_{1,2,1}^{(1)*}, x_{1,2,2}^{(1)*}, x_{1,2,3}^{(1)*})$	$(0, 250, 250)$
$(x_{1,3,1}^{(1)*}, x_{1,3,2}^{(1)*}, x_{1,3,3}^{(1)*})$	$(0, 200, 0)$
$(x_{1,1,1}^{(2)*}, x_{1,1,2}^{(2)*}, x_{1,1,3}^{(2)*}, x_{1,1,4}^{(2)*})$	$(0, 0, 0, 0)$
$(x_{1,2,1}^{(2)*}, x_{1,2,2}^{(2)*}, x_{1,2,3}^{(2)*}, x_{1,2,4}^{(2)*})$	$(90, 360, 0, 0)$
$(x_{1,3,1}^{(2)*}, x_{1,3,2}^{(2)*}, x_{1,3,3}^{(2)*}, x_{1,3,4}^{(2)*})$	$(210, 0, 280, 210)$
$(x_{1,1,1}^{(3)*}, x_{1,1,2}^{(3)*}, x_{1,1,3}^{(3)*}, x_{1,1,4}^{(3)*}, x_{1,1,5}^{(3)*}, x_{1,1,6}^{(3)*})$	$(150, 0, 150, 0, 0, 0)$
$(x_{1,2,1}^{(3)*}, x_{1,2,2}^{(3)*}, x_{1,2,3}^{(3)*}, x_{1,2,4}^{(3)*}, x_{1,2,5}^{(3)*}, x_{1,2,6}^{(3)*})$	$(0, 200, 0, 160, 0)$
$(x_{1,3,1}^{(3)*}, x_{1,3,2}^{(3)*}, x_{1,3,3}^{(3)*}, x_{1,3,4}^{(3)*}, x_{1,3,5}^{(3)*}, x_{1,3,6}^{(3)*})$	$(40, 0, 0, 60, 180, 0)$
$(x_{1,4,1}^{(3)*}, x_{1,4,2}^{(3)*}, x_{1,4,3}^{(3)*}, x_{1,4,4}^{(3)*}, x_{1,4,5}^{(3)*}, x_{1,4,6}^{(3)*})$	$(0, 0, 0, 0, 0, 210)$
z^*	-6.8546

Table 13. Equipment status of suppliers according to increasing probabilities of supplier disruption

Equipment status of each supplier			% Increase in the probability of disruption in all units
Supplier 3	Supplier 2	Supplier 1	
1	0	0	5
1	0	0	10
1	0	0	15
1	1	0	20
1	1	1	25 and more

aversion factor or the probability of supplier disruption reached a sufficiently high level. Therefore, for supply chains operating in environments with significant political-economic risk, frequent price volatility, or rapid business changes, we recommend adopting the proposed CVaR-based model. The quality of scenario generation and probability estimation remains an essential factor influencing model outcomes.

Despite its higher complexity compared to simpler models, the proposed model was still solvable using standard optimization tools such as Pyomo. For larger-scale problems involving millions of scenarios, decomposition techniques like Benders decomposition (see Refs. 22 and 34) are well-established and highly effective. Although not implemented in this study, the linear structure of our model makes it readily compatible with such methods, providing a straightforward direction for future work aimed at enhancing scalability.

Future research should apply the model under real-world conditions, which requires careful calibration of model parameters to a specific supply chain context and the elicitation of decision makers' risk preferences. In particular, determining the risk aversion coefficient using input from actual stakeholders would add significant realism. Even without such input, experimenting with the model under varying assumptions (as demonstrated through the sensitivity analysis) can provide valuable insights into risk management strategies. These strategies could also be evaluated on a meta level of the model, e.g., by exploring which activities are most effective for equipping suppliers against the possibility of disruptions (and what the associated costs are). In any case, we argue that a scenario-based analysis as considered in the model is straightforward enough to be applied in practice and beneficial for increasing risk awareness among decision-makers. Moreover, the model could be extended in various directions. Rather than assuming a single objective, a multi-objective version could be explored. Uncertainty could also be handled using alternative approaches, such as hybrid robust-stochastic optimization or fuzzy logic-based models.

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Conflict of interest

The authors declare that they have no competing interests.

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