Frontiers in Health InformaticsISSN-Online: 2676-7104 www.healthinformaticsjournal.com
2025; Vol 14: Issue 2 Open Access

Modeling the Multi-objective Supplier Selection and Order Allocation with a Risk-Averse Approach and Considering the Impact of Disruption

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Cite this paper as: Danial Daman-Afshan, Rasoul Fili, Omid Veisi (2025), Modeling the Multi-objective Supplier Selection and Order Allocation with a Risk-Averse Approach and Considering the Impact of Disruption. *Frontiers in Health Informatics*, *14(2) 3166-3189*

ABSTRACT

Managing disruption risks in supply chains, particularly in complex and uncertain environments, is a critical concern in industrial engineering and supply chain management. In this study, a mixed-integer nonlinear programming (MINLP) model based on stochastic programming was developed to simultaneously optimize supplier selection and order allocation in a centralized multi-product supply chain. The proposed model accounts for both local disruption risks (e.g., equipment failures) and regional risks (e.g., natural disasters or regional conflicts) and simulates the behavior of a risk-averse decision-maker using Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR) criteria. To solve the model, two multi-objective metaheuristic algorithms—Non-dominated Sorting Genetic Algorithm II (NSGA-II) and Multi-Objective Particle Swarm Optimization (MOPSO)—were employed, with their parameters tuned using the Response Surface Methodology (RSM). The performance of the algorithms was evaluated across 30 test problems using common multi-objective assessment metrics, including NPS, MID, DM, Spacing, computational time, and objective function values. Computational results indicated that NSGA-II outperformed MOPSO in most key metrics, particularly in terms of Pareto front convergence and diversity, achieving the highest overall performance score and ranking first among decision-makers. Meanwhile, MOPSO demonstrated relatively better performance only in terms of computational time and achieving acceptable objective function values.

Key words: Modeling, Supplier selection, Disruption risk, Bi-objective optimization, NSGAII, MOPSO.

INTRODUCTION

In today's competitive environment, organizations must move beyond the sole maximization of individual profit and instead focus on optimizing the performance of the entire supply chain to ensure survival and sustainable growth. Such an approach not only enhances operational efficiency but also mitigates the adverse effects of market fluctuations and strengthens the capability to manage complex and uncertain environments (Gianoccaro, 2018). Close collaboration among supply chain members and the alignment of buyer–supplier decisions are therefore essential. Within this context, supplier selection and order allocation are among the most critical strategic decisions, as they directly influence costs, quality, and the reliability of supply flows (Kuo *et al*., 2010).

With the growing complexity of supply networks, multiple risks have emerged that threaten overall system performance. These risks can be broadly categorized into two groups: operational risks, such as demand fluctuations, changes in transportation costs, or technical failures in the production process (Hosseini & Barker, 2016); and disruption risks, which stem from unpredictable events such as natural disasters or economic crises (Govindan *et al*., 2017; Ivanov, 2020). Past experiences—such as the 2011 earthquake and tsunami in Japan, which caused widespread production shutdowns in companies like Toyota—have clearly highlighted the importance of addressing such risks (Hosseini *et al*., 2019). Consequently, selecting suppliers across different geographical regions and designing flexible ordering policies have become key strategies for organizations (Esmaeili Najafabadi *et al*., 2021).

Managerial responses to risk depend largely on their attitude and tolerance toward uncertainty. Based on utility theory, three main approaches can be identified: risk-averse, risk-seeking, and risk-neutral (Heckmann *et al*., 2015). Evidence shows that in many sensitive industries, managers tend to adopt a risk-averse perspective, since organizations often have limited capacity to endure repeated losses or deal with severe uncertainties (Chahar & Tuff, 2009). This tendency has led to the adoption of quantitative risk assessment measures, such as Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR)—originally introduced in the financial sector (Rockafellar *et al*., 2000)—which are now widely applied in supply chain management. These measures provide effective tools for evaluating worst-case scenarios and developing robust ordering policies resilient to disruptions (Jiange, 2017).

This study primarily focuses on supplier disruptions within a two-tier supply chain comprising multiple domestic and foreign suppliers exposed to two types of disruptions: (i) local disruptions that occur within individual suppliers (*e.g*., production line breakdowns), and (ii) regional disruptions that simultaneously affect all suppliers in a specific geographical area (*e.g*., large-scale natural disasters). The objective of the proposed model is to minimize the total costs of both suppliers and the buyer while enhancing product quality under disruption scenarios. The mathematical model is formulated as a mixed-integer nonlinear programming (MINLP) problem. Given its NP-hard nature, exact methods are inefficient for large-scale problem instances. To address this challenge, two powerful multi-objective metaheuristics are employed: Multi-Objective Particle Swarm Optimization (MOPSO) and the Non-dominated Sorting Genetic Algorithm II (NSGA-II). Both algorithms are well recognized in the literature for their ability to generate diverse Pareto fronts and efficiently solve complex multi-objective decision-making problems. By comparing the results of these two approaches, the study aims to highlight their relative strengths and weaknesses, ultimately identifying a more effective strategy for supplier selection and order allocation under uncertainty.

Accordingly, the primary contribution of this research is the development of a multi-objective model for supplier selection and order allocation that incorporates a risk-averse perspective, accounts for both local and regional disruptions, and evaluates the comparative performance of MOPSO and NSGA-II.

Literature Review

Supplier selection is one of the most critical stages in supply chain management, playing a key role in cost reduction, enhancing flexibility, and improving service quality. This issue has attracted extensive attention from both academic and industrial researchers, leading to the development of diverse decision-making methods and techniques. Weber et al. (1991), in their review of 74 articles published between 1966 and 1990, classified the analytical methods used in supplier selection. Aissaoui et al. (2007) distinguished between single-sourcing and multiple-sourcing models. In single-sourcing models, a single supplier is capable of meeting the entire demand of the supply chain, and the main decision focuses on identifying the best supplier. In contrast, in multiple-sourcing models, capacity constraints require orders to be allocated among several suppliers, making the decision problem a combination of supplier selection and order allocation (Golmohammadi & Malet-Perast, 2012; Sawik, 2014).

Supplier selection approaches are generally categorized into two broad groups: quantitative and qualitative models.

- **Quantitative models** aim to optimize supplier selection and order allocation through techniques such as Linear Programming (LP) (Pan, 1989), Mixed-Integer Linear Programming (MILP) (Hosseini *et al*., 2019), Mixed-Integer Nonlinear Programming (MINLP) (Kamali *et al*., 2011; Esmaeili Najafabadi *et al*., 2019, 2021), Game Theory (GT), Goal Programming (GP) (Buffa & Jackson, 1983), Stochastic Programming (SP) (Sawik, 2015, 2017), Dynamic Programming (DP) (Mendoza, 2008), and Multi-Objective Programming (Lin, 2009; Kucukangul & Susuz, 2009).

- **Qualitative models** include methods such as the Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), Fuzzy Analytic Network Process (FANP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Fuzzy-TOPSIS, and Fuzzy Preference Programming (FPP) (Lin, 2009; Amel Singh, 2014; Gupta & Barua, 2017).

Since supplier selection problems are typically characterized by allocation and integer-based decisions, MINLP models have gained wide application. Additionally, approaches such as the Economic Order Quantity (EOQ) are often used to determine the order quantity from each supplier (Esmaeili Najafabadi *et al.,* 2021).

Uncertainty in parameters such as demand, lead time, and production capacity plays a significant role in many supply chain management problems. Such uncertainty is often modeled using probability distributions, fuzzy sets, or scenario-based approaches. Govindan et al. (2015), for instance, analyzed a five-tier supply chain network—comprising suppliers, factories, distribution centers, and retailers—using hybrid multi-objective metaheuristics, while examining different product shipment strategies.

Supply chain risks, particularly disruptions, constitute one of the most critical challenges in decision-making. These disruptions may be local, regional, or global, each with distinct consequences on supply chain performance (Najafabadi, 2021; Hamdi *et al*., 2018). Risk mitigation strategies include utilizing backup suppliers, maintaining safety stock, and enhancing operational flexibility (Hosseini *et al*., 2019; Esmaeili Najafabadi *et al*., 2019). Furthermore, stochastic MINLP models have been proposed for supplier selection under disruption and risk conditions (Sawik, 2014; Kamal-Hamdi & Perast, 2017).

Recently, multi-objective metaheuristic algorithms have emerged as powerful tools for addressing supplier selection under uncertainty and risk. Studies have demonstrated that evolutionary multi-objective algorithms such as NSGA-II, MOPSO, and MOEA/D—as well as hybrid methods combining Electromagnetism-like Mechanisms with Variable Neighborhood Search—outperform traditional mathematical programming methods, particularly in managing trade-offs among cost, time, and risk criteria (Jovanović *et al*., 2015; Chen *et al*., 2020). For example, NSGA-II has shown effectiveness in providing a well-distributed set of optimal solutions for multi-criteria supplier selection, while MOPSO offers faster convergence in large-scale problems with complex constraints. From a financial and operational risk management perspective, risk measures such as VaR and CVaR have been employed to assess and control risk in supply chains with uncertain demand (Chahar & Tuff, 2009; Madadi *et al*., 2014; Sawik, 2019). These methods facilitate risk-averse or risk-seeking decision-making and can be effectively integrated with multi-objective metaheuristic algorithms.

The significance of this study becomes evident through a critical review of existing research gaps. First, most prior studies have examined supplier selection and order allocation under the assumption of risk-neutral decision-makers, whereas in practice, managers often adopt risk-averse behavior. Accordingly, this research incorporates risk measures such as CVaR and VaR to model risk-averse decision-making. Second, given the crucial role of supplier location in managing operational risks, this study explicitly considers two types of disruptions—local and regional—in order to more realistically simulate supply chain risks, particularly in strategic industries. Third, unlike many studies that primarily focus on single-objective optimization, typically cost minimization, this research develops a multi-objective model that accounts for multiple key dimensions of supply chain performance, thereby enhancing decision-making efficiency in real-world contexts. Fourth, budgetary constraints are modeled as uncertain parameters, reflecting economic fluctuations such as currency exchange rate volatility. As a result, the proposed model exhibits higher adaptability to dynamic and uncertain environments. Finally, this research evaluates different delivery policies, particularly partial shipment strategies, offering a more realistic approach to inventory management when buyers face higher holding costs compared to suppliers. Such a strategy can improve overall efficiency and reduce inventory-related expenses within the supply chain.

On this basis, the central research question of this study is formulated as follows: *Which of the applied multi-objective metaheuristics can achieve superior performance in obtaining optimal solutions and thereby be favored by decision-makers?*

Problem description

In this section, we will first list the notations followed by an outline of the assumptions, and then provide the problem statement for risk-averse decision-maker model.

Notations

Indices:

i: Index for suppliers $\{1, 2,\cdots, n\}$, (Is: set of non-disrupted suppliers under scenario s)

s: Index for disruption scenarios $\{1, 2,\cdots, 2n\}$

j: Index for product types $\{1, 2,\cdots, m\}$

r : Index for geographical regions $\{1, 2\}$

Parameters:

A_{ij}: Fixed ordering cost of the j^{th} product type for the i^{th}supplier

S_{ij}: Setup cost of the j^{th}product type for the i^{th} supplier

C_{ij}: Production cost of the j^{th} product type for the i^{th} supplier

Cap_i: Capacity of the i^{th} supplier

h_i^v: Holding cost per unit of the product for the i^{th}supplier

h_i^b: Buyer's holding cost per unit of the purchased product from the i^{th}supplier

D_j: Market demand for the j^{th} product type

P_j: The selling price of the j^{th} product type in the market

W_{ij}: Wholesale price of the j^{th} product for the i^{th} supplier

a_i: Probability of the local disruption in the i^{th} supplier

a_r^*: Probability of the regional disruption in the region r

β_s: Probability of the s^{th} disruption scenario considering both local and regional disruption risks

B_j: Shortage cost per unit of the j^{th} product type *Decision*

L_{ij}: Number of person-hours for the job per unit of product jth from supplier ith

F_{ij}: Quality level of product jth from supplier ith

$Z_{(\alpha)}$: Confidence coefficient

γ: person-hours coefficient

b_1: Allocated budget for fixed order costs

$\mu_{(b_1)}$: Mean of the allocated budget for fixed order costs

$\sigma^2_{(b_1)}$: Variance of the allocated budget for fixed order costs

b_2: Allocated budget for purchasing cost from the supplier

$\mu_{(b_2)}$: Mean of the allocated budget for purchasing cost from the supplier

$\sigma^2_{(b_2)}$: Variance of the allocated budget for purchasing cost from the supplier

b_3: Allocated budget for buyer's holding cost

$\mu_{(b_3)}$: Mean of the allocated budget for buyer's holding cost

$\sigma^2_{(b_3)}$: Variance of the allocated budget for buyer's holding cost

b_4: Allocated budget for shortage cost

$\mu_{(b_4)}$: Mean of the allocated budget for shortage cost

$\sigma^2_{(b_4)}$: Variance of the allocated budget for shortage cost

b_5: Allocated budget for the production cost of each supplier

$\mu_{(b_5)}$: Mean of the allocated budget for the production cost of each supplier

$\sigma^2_{(b_5)}$: Variance of the allocated budget for the production cost of each supplier

b_6: Allocated budget for setup cost of each supplier

$\mu_{(b_6)}$: Mean of the allocated budget for setup cost of each supplier

$\sigma^2_{(b_6)}$: Variance of the allocated budget for setup cost of each supplier

b_7: Allocated budget for holding cost of each supplier

$\mu_{(b_7)}$: Mean of the allocated budget for holding cost of each supplier

$\sigma^2_{(b_7)}$: Variance of the allocated budget for holding cost of each supplier

Decision variables:

τ_s*:* Tail cost for disruption scenario s^{th}

Q_j: Order quantity of the j^{th} product type $Q_j = \Sigma_{i\in I} Y_{ij}$

$Q_i^{\hat{A}}$: Order quantity from the i^{th} supplier $Q_i^{\acute{\hat{A}}} = \Sigma_{j\in J} Y_{ij}$

X_i: 1 if the i^{th} supplier is selected, otherwise 0

Y_{ij}: Fraction of the demand for the j^{th} product type that is ordered from the i^{th} supplier

U_j^s*:* Unfulfilled demand of the j^{th} product type in the disruption scenario s^{th}

VaR: Value-at-Risk value

CVaR: Conditional Value-at-Risk value

Assumptions

This subsection outlines the assumptions underlying the integrated supplier selection and order allocation problem under supply chain disruption risks.We consider a two-echelon, multi-product centralized supply chain consisting of a single buyer and multiple suppliers. The buyer is able to procure multiple products from different suppliers.

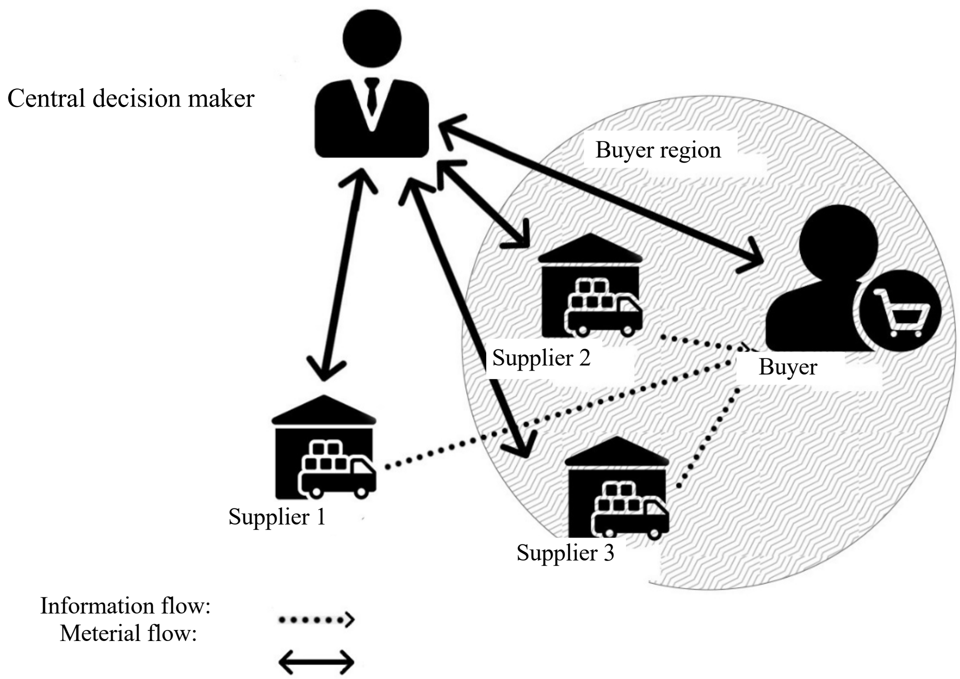

Figure 1. A single-product centralized supply chain with one buyer and multiple suppliers (Gheidar Kheljani et al., 2009).

Figure 1 illustrates the supply chain network. In a centralized supply chain, a central decision-maker, who possesses complete information regarding the supply chain, selects suppliers and allocates orders to satisfy customer demand while accounting for potential disruption risks. It is assumed that suppliers have limited production capacities and that customer demand is deterministic. However, the budgets allocated by the buyer and suppliers for each type of cost within the supply chain are uncertain and modeled probabilistically. The delivery policy from suppliers to the buyer follows a staged delivery approach, as introduced by Kim and Goyal (2009). Similar to their work, it is assumed that in each period, the buyer will not receive order $(i + 1)^{th}$ from a supplier until order i^{th} has been consumed. Under this policy, the economic production quantity of each supplier is fixed and matches the buyer's economic order quantity. Figure 2 depicts this assumption for a supply chain with one buyer, three suppliers, and a single product.

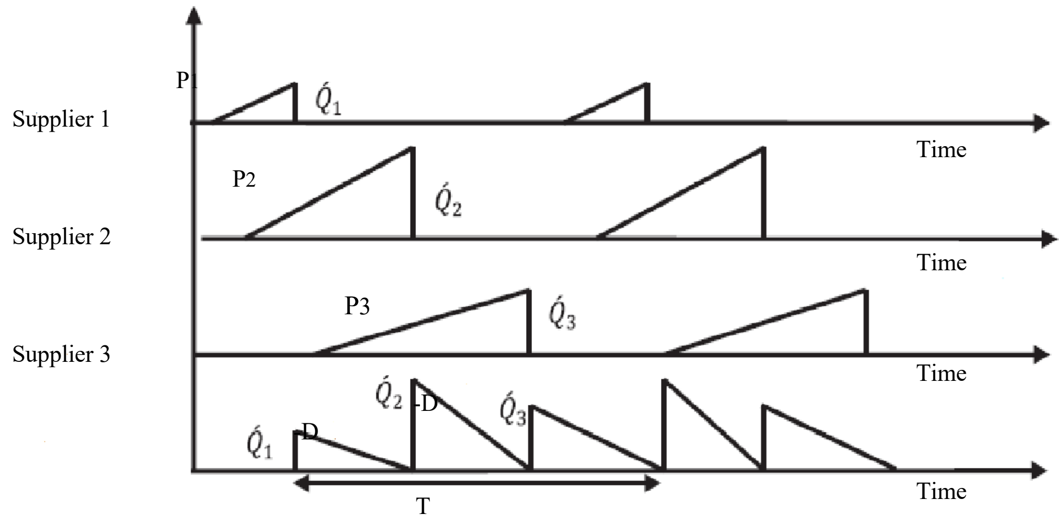

Figure 2. Inventory levels for a single buyer, multi suppliers and one product (Kamali *et al.*, 2011).

Two types of suppliers are considered to account for their geographical characteristics: domestic suppliers, located within the buyer's region, and foreign suppliers, located outside the buyer's region. It is assumed that both domestic suppliers and the buyer operate in a region prone to disruptions (e.g., due to geographical vulnerability or limited technology). As a result, the buyer may seek sourcing options from foreign suppliers located outside the region. Conversely, foreign suppliers are generally more reliable but incur higher costs compared to domestic ones. In addition, A comprehensive scenario for supplier disruption risks, accounting for geographical specifics, is also considered. Disruption risks are categorized into two types: local and regional. Local disruptions, which occur within individual suppliers, include events such as material shortages, labor strikes, and equipment failures. Regional disruptions, which simultaneously impact all suppliers within the same region, include natural disasters like earthquakes, floods, and hurricanes. While regional disruptions are less probable than local disruptions, their impact on the supply chain is more significant (Ray & Jenamani, 2016). We assume that the probability of local disruption for the i^{th} supplier, denoted as α_i, signifies that the supplier i cannot fulfill the buyer's order due to disruptions with probability of α_i. Domestic suppliers, identified as $i \in I^1$, have a higher likelihood of local disruption due to economic instability, technological limitations, and geographical factors. Conversely, foreign suppliers, identified as $i \in I^2$, are less prone to local disruptions but are more expensive. The probability of regional disruption, denoted as a_r^*, represents the simultaneous unavailability of all suppliers in a specific region due to such disruptions. For analytical tractability, we assume that local and regional disruption risks are independent. The probability of disruption scenario s, denoted as β_s, encompasses a subset of suppliers, $I_s \subseteq I$, that remain undisrupted and can fulfill the buyer's order. The number of disruption scenarios, dependent on the number of suppliers, is 2^n. The probability of each disruption scenario s is calculated accordingly, with I^1 and I^2 representing the sets of domestic and foreign suppliers, respectively.

The first term in Eq. (1) investigates the disruption probability when the buyer (he) cannot supply his orders,

$$\beta_s=\begin{cases} a_1^* a_2^* + a_1^*(1-a_2^*)\prod_{i\epsilon I^2} a_i + (1-a_1^*)a_2^*\prod_{i\in I^1} a_i + (1-a_1^*)(1-a_2^*)\prod_{i\in I} a_i \ \ if\ I_s=\emptyset \\ (1-a_1^*)a_2^*\prod_{i\in I_s}(1-a_i)\prod_{i\in I^1/I_s} a_i + (1-a_1^*)(1-a_2^*)\prod_{i\in I_s}(1-a_i)\prod_{i\in I_s} a_i \ \ if\ I_s\subseteq I^1 \\ a_1^*(1-a_2^*)\prod_{i\in I_s}(1-a_i)\prod_{i\in I^2/I_s} a_i + (1-a_1^*)(1-a_2^*)\prod_{i\in I_s}(1-a_i)\prod_{i\in I_s} a_i \ \ if\ I_s\subseteq I^2 \\ (1-a_1^*)(1-a_2^*)\prod_{i\in I_s}(1-a_i)\prod_{i\notin I_s} a_i \ \ I_s\cap I^1\neq\varphi . I_s\cap I^2\neq\varphi \end{cases} \quad (1)$$

which is composed of four parts: (i) domestic and foreign suppliers disrupted due to regional disruptions separately, (ii) domestic suppliers disrupted due to regional disruption and foreign suppliers disrupted due to local disruptions, (iii) foreign suppliers disrupted due to regional disruption and domestic suppliers disrupted due to local disruptions, (iv) all of the domestic and foreign suppliers disrupted due to local disruptions in all of them. The second term is the disruption probability when the domestic suppliers deliver parts without disruptions. The third term is the disruption probability when the foreign suppliers deliver parts without disruptions. The last term shows when no disruption occurs.

Materials and Methods

In the literature of financial risk management and supply chain risk, decision makers have different attitudes towards risk. In this research, similar to Esmaeili-Najafabadi et al. (2021), we investigate a centralized supply chain where the decision maker is risk-averse. We optimize total supply chain costs, including total buyer and supplier costs and manufactured product quality. To calculate the total cost, we consider the average inventory of the buyer, denoted as Ī. As illustrated in Figure 2, the buyer's inventory, based on orders from the i^{th} supplier, fluctuates continuously between zero and $Q_i^{\acute{Â}}$. Additionally, the length of each period is equal to $\frac{Q_j}{D}$. Therefore, the buyer's average inventory for the products ordered from the i^{th} supplier is calculated as follows:

$$\bar{I}_j = \frac{\frac{1}{2}\times \acute{Q_i} \times \acute{Q_i}}{Q_j/_D} = \frac{Q_i^{prime2}}{2Q_j} \quad (2)$$

In addition, we have $Q_i^{\acute{Â}} = Y_{ij} \times Q_j$. The above Equation can be re-written as follows:

$$\bar{I}_j = \frac{\left(Q_i^{\acute{Â}}\right)^2}{2Q_j} = \frac{Y_{ij}{}^2 Q_j{}^2}{2Q_j} = \frac{Q_j Y_{ij}{}^2}{2} \quad (3)$$

The buyer's annual cost can be formulated as follows:

$$\pi^b = \sum_{j\in J}\sum_{i\in I}\frac{D_j}{Q_j}A_{ij}X_i + \sum_{j\in J}\sum_{s\in S}\sum_{i\in I}\beta_s D_j Y_{ij} W_{ij} + \sum_{j\in J}\sum_{s\in S}\sum_{i\in I}\frac{\beta_s Q_j Y_{ij}{}^2 h_i^b}{2} + \sum_{j\in J}\sum_{s\in S}\beta_s D_j B_j U_j^s - \sum_{j\in J}\sum_{s\in S}\sum_{i\in I}\beta_s D_j P_j Y_{ij} \quad (4)$$

Eq. (4) represents five parts, respectively including the fixed ordering cost, purchasing cost of products from the suppliers, holding cost, shortage cost, and finally, revenue from selling the products. The total cost of the ith supplier, $i \in I_s$, will be as follows:

$$\pi^{v} = \sum_{j\in J}\left(Cap_i C_{ij} + \frac{D_j}{Q_j}S_{ij} + \frac{Q_j Cap_i Y_{ij} h_i^{v}}{2D_j} - Cap_i W_{ij}\right)\frac{D_j Y_{ij}}{Cap_i} \quad (5)$$

Similar to (Mohammaditabar et al., 2016), Eq. (5) includes the production cost, setup cost, cost of holding inventory, and the revenue of supplier i^{th}, respectively.

The total cost of the supply chain is the sum of the buyer's annual cost and the expected annual cost of the suppliers, taking into account the probabilities of various disruption scenarios, as follows:

$$\pi_{sc} = \pi^{b} + \sum_{s\in S}\sum_{i\in I_s}\beta_s\pi_i^{v} = \sum_{j\in J}\sum_{i\in I}\frac{D_j}{Q_j}A_{ij}X_i + \sum_{j\in J}\sum_{s\in S}\sum_{i\in I}\beta_s D_j Y_{ij} W_{ij} + \sum_{j\in J}\sum_{s\in S}\sum_{i\in I}\frac{\beta_s Q_j {Y_{ij}}^2 h_i^{b}}{2} + \sum_{j\in J}\sum_{s\in S}\sum_{i\in I}\beta_s D_j B_j U_j^{s} - \sum_{j\in J}\sum_{s\in S}\sum_{i\in I}\beta_s D_j P_j Y_{ij} + \sum_{s\in S}\sum_{i\in I_s}\sum_{j\in J}\beta_s\left(Cap_i C_{ij} + \frac{D_j}{Q_j}S_{ij} + \frac{Q_j Cap_i Y_{ij} h_i^{v}}{2D_j} - Cap_i W_{ij}\right)\frac{D_j Y_{ij}}{Cap_i} \quad (6)$$

We rewrite the total cost of the supply chain as follows:

$$\pi_{sc} = \sum_{j\in J}\sum_{i\in I}\frac{D_j}{Q_j}A_{ij}X_i + \sum_{j\in J}\sum_{s\in S}\sum_{i\in I_s}\beta_s\frac{Q_j}{2}{Y_{ij}}^2\left(h_i^{b} + h_i^{v}\right) + \sum_{j\in J}\sum_{s\in S}\sum_{i\in I_s}\beta_s\frac{D_j^2 S_{ij} Y_{ij}}{Q_j Cap_i} + \sum_{j\in J}\sum_{s\in S}\sum_{i\in I_s}\beta_s D_j C_{ij} Y_{ij} + \sum_{j\in J}\sum_{s\in S}\beta_s D_j B_j U_j^{s} + - \sum_{j\in J}\sum_{s\in S}\sum_{i\in I_s}\beta_s D_j P_j Y_{ij} \quad (7)$$

In this subsection, disruption risks are managed using two widely recognized risk assessment measures in finance literature: Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR). The VaR represents the maximum potential loss within a given confidence level of outcomes. Specifically, it is the probability that the loss of a given portfolio exceeds a certain threshold, referred to as VaR. This measure is used to evaluate the probable loss of a portfolio due to market risk. CVaR, on the other hand, considers the portfolio of outcomes beyond the VaR threshold, capturing the losses that exceed the VaR during the given period. Thus, CVaR at a confidence level of θ is defined as the expected loss of the supply portfolio within the *(1-θ)%* worst-case scenarios. Figure 3 illustrates the relationship between VaR and CVaR. For more detailed information, please refer to Chahar & Taaffe (2009), Madadi et al. (2014), and Merzifonluoglu (2015). CVaR is widely used as an alternative to VaR because VaR complicates the scenario-based optimization model (Merzifonluoglu, 2015). Additionally, CVaR minimization optimizes VaR simultaneously since it is equal to or greater than VaR in the optimization model. Therefore, in the present study, we apply the CVaR measure to control supplier disruption risks.

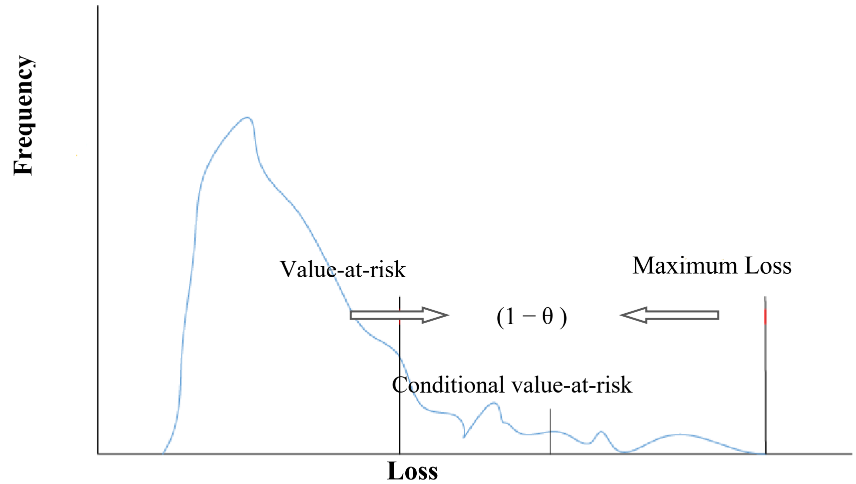

Figure 3. The VaR and CVaR for portfolio management problem minimizing the worst case losses (Chahar & Taaffe, 2009).

In the problem of supplier selection and order allocation under disruption risks, the decision-maker controls the risk associated with significant losses due to supply disruptions by choosing a confidence level θ. The decision-maker only accepts portfolios where the probability of loss is less than the VaR (Value at Risk) amount. Therefore, a higher confidence level indicates a higher risk aversion of the decision-maker. We define τ_s as the tail cost for disruption scenario *s*, representing the cost amount that exceeds the value of VaR in the s^{th} disruption scenario. The supply portfolio is optimized by calculating the VaR and minimizing the CVaR as the first objective function as follows:

$$Min\ CVar_c = VaR_c + \frac{1}{(1-\theta)} \sum_s \beta_s \tau_s \tag{8}$$

$$Max\ \ z = \sum_{j \in J} \sum_{s \in S} \sum_{i \in I_s} \beta_s Y_{ij} D_j f_{ij} \tag{9}$$

s.t:

$$\tau_s \geq \sum_{j \in J} \sum_{i \in I} \frac{D_j}{Q_j} A_{ij} X_i + \sum_{j \in J} \sum_{i \in I_s} \beta_s \frac{Q_j}{2} {Y_{ij}}^2 \left(h_i^b + h_i^v\right) + \sum_{j \in J} \sum_{i \in I_s} \beta_s \frac{D_j^2 S_{ij} Y_{ij}}{Q_j Cap_i} + + \sum_{j \in J} \sum_{i \in I_s} \beta_s D_j C_{ij} Y_{ij} + \sum_{j \in J} \beta_s D_j B_j U_j^s - \sum_{j \in J} \sum_{i \in I_s} \beta_s D_j P_j Y_{ij} - VaR \qquad \forall\ s \tag{10}$$

$$\sum_{i \in I_s} Y_{ij} + U_j^s = 1 \qquad \forall s.j \tag{11}$$

$$\sum_j Y_{ij} D_j \leq X_i\, Cap_i \qquad \forall i \tag{12}$$

$$\sum_j \sum_i \frac{D_j}{Q_j} A_{ij} X_i + Z_{(\alpha)}\, \sigma_{(b_1)} \leq \mu_{(b_1)} \tag{13}$$

$$\sum_j \sum_s \sum_{i \in I_s} \beta_s D_j Y_{ij} W_{ij} + Z_{(\alpha)}\, \sigma_{(b_2)} \leq \mu_{(b_2)} \tag{14}$$

$$\sum_j \sum_s \sum_{i \in I_s} \frac{\beta_s Q_j {Y_{ij}}^2 h_i^b}{2} + Z_{(\alpha)}\, \sigma_{(b_3)} \leq \mu_{(b_3)} \tag{15}$$

$$\sum_s \sum_j \beta_s D_j B_j U_j^s + Z_{(\alpha)}\, \sigma_{(b_4)} \leq \mu_{(b_4)} \tag{16}$$

$$\sum_s \sum_j \beta_s D_j \mathrm{C_{ij}} \mathrm{Y_{ij}} + Z_{(\alpha)}\, \sigma_{(b_5)} \leq \mu_{(b_5)} \quad \forall i \in \mathrm{I_s} \tag{17}$$

$$\sum_s \sum_j \beta_s \frac{D_j^2 S_{ij} Y_{ij}}{Q_j Cap_i} + Z_{(\alpha)}\, \sigma_{(b_6)} \leq \mu_{(b_6)} \quad \forall i \in I_s \tag{18}$$

$$\sum_s \sum_j \beta_s \frac{Q_j}{2} {Y_{ij}}^2 h_i^v + Z_{(\alpha)}\, \sigma_{(b_7)} \leq \mu_{(b_7)} \quad \forall i \in I_s \tag{19}$$

$$\sum_j \sum_{i \in I_s} \beta_s Y_{ij} D_j L_{ij} \geq \gamma \quad \forall s \tag{20}$$

$$X_i \in \{0.1\}. 0 \leq Y_{ij}. U_j^s \leq 1 \qquad \forall i.j.s \tag{21}$$

The second objective function (9) maximizes the quality of manufactured products. Constraint (10) shows the risk constraint. In this constrain total cost of the supply chain which Constraint (11) ensures that the demand for each product is met by the non-disrupted suppliers or is accounted for as unsatisfied demand in each disruption scenario in eq.(7), exceeds the value of VaR in each disruption scenario. Constraint (11) ensures that the demand for each product met by the non-disrupted suppliers or accounted for as unsatisfied demand in each disruption scenario. Constraint (12) addresses the capacity limitations of each supplier in each disruption scenario. The constraints (13) to (19) refer to the budget limitations of the buyer and supplier in the supply chain. As previously mentioned, the Allocated budget values (**b_i**), are uncertain and of type probabilistic. They follow a Gaussian distribution with a mean and variance, denoted as $b_\mathrm{i} \sim N(\mu_{(b_\mathrm{i})}, \sigma^2_{(b_\mathrm{i})})$. In stochastic programming, the concept of a confidence level, denoted as α, is used to manage the randomness of the constraints. For example, if α = 0.95, the constraint holds with a 95% probability and is considered acceptable. For instance, the fixed cost constraint of the buyer in an uncertain state is as follows:

$$\sum_j \sum_i \frac{D_j}{Q_j} A_{ij} X_i \leq b_1 \tag{22}$$

In order to convert this constraint into a deterministic state, we first write it in the form of eq. (23):

$$P\left\{\sum_j \sum_i \frac{D_j}{Q_j} A_{ij} X_i \leq b_1\right\} \geq 0 \cdot 95 \tag{23}$$

Now, this Constraint can be rewritten as as follows:

$$P\left\{\sum_j \sum_i \frac{D_j}{Q_j} A_{ij} X_i - b_1 \leq 0\right\} \geq 0 \cdot 95 \tag{24}$$

Assuming that the values of b_i, are Gaussian distribution, the term $\sum_j \sum_i \frac{D_j}{Q_j} A_{ij} X_i - b_1$ corresponds to a Gaussian distribution with mean and variance $y = \sum_j \sum_i \frac{D_j}{Q_j} A_{ij} X_i - b_1 \sim N(\sum_j \sum_i \frac{D_j}{Q_j} A_{ij} X_i - \mu_{(b_1)}, \sigma^2_{(b_1)})$. Considering this term as y and substituting it into eq. (24), we have:

$$P\{y \leq 0\} \geq 0 \cdot 95 \tag{25}$$

Then, the above term is rewritten in the form of a standard Gaussian distribution:

$$P\left\{Z \leq \frac{0 - \left(\sum_j \sum_i \frac{D_j}{Q_j} A_{ij} X_i - \mu_{(b_1)}\right)}{\sqrt{\sigma^2_{(b_1)}}}\right\} \geq 0 \cdot 95 \tag{26}$$

Finally, in the deterministic case the fixed cost constraint of the buyer is rewritten as eq.(10) in model. Similarly, the other constraints (14) to (19) will be rewritten in their deterministic form. Constraint (20) refers to maximizing the number of person-hours of work per manufactured product in each scenario. And at the end of the constraint (21) states the status of the decision variables.

Solution approach

NP hard problems cannot be solved with the exact method in a reasonable time. In this paper, since the presented model is NP-hard, two meta heuristic algorithms namely NSGAII and MOPSO are proposed to solve the multiobjective SCN model aiming to minimize the Total cost of SCN and maximize the Quality of manufactured products simultaneously, these algorithms described as following subsections.

NSGAII Algorithm

The NSGA-II algorithm is based on non-dominance concepts. In the initial cycle of this algorithm, a population ($p0$) is generated. The populations are then ranked using a non-dominated sorting function, creating Pareto fronts from the ranked solutions. After this initialization step, tournament selection is used for N parent solutions (chromosomes) from the initial population ($p0$). This selection is based on fitness value, rank front, and crowding distance. During the parent selection process, two elements from the population are chosen, and one element is selected as the parent. If the population elements belong to the same Pareto front, the element with the higher crowding distance is selected. However, if the two elements belong to different Pareto fronts, the element with the lower rank is selected as the parent (Babaveisi *et al.*, 2018). Following parent selection, offspring populations (Q) are created using crossover and mutation operators. At this stage, a new population is formed from the initial population and the populations resulting from crossover and mutation. This new population's objective function is calculated, and dominance is determined until the termination criterion is met (Mousavi *et al.*, 2016). Crowding distance helps direct the population toward less crowded regions, indicating the diversity index within the population. It is determined by the adjacent neighbor value and the first and last members of the population. Solutions with a high crowding distance are of better quality. Eq. (27) expresses the crowding distance formula:

$$CD_i = \sum_{j=1}^{M} \frac{\left| f_{j,p}^{(i-1)} - f_{j,p}^{(i+1)} \right|}{f_{j,p}^{max} - f_{j,p}^{min}} \tag{27}$$

In this equation, M is the number of objective functions, $f_j^{(i+1)}$ and $f_j^{(i-1)}$ are j^{th} objective function values $(i+1)^{th}$ and $(i-1)^{th}$ solutions from p^{th} Pareto front. f_j^{max} and f_j^{min} are the maximum and minimum values of j^{th} objective function from the last member of p^{th} Pareto front and first member of the Pareto front, respectively.

MOPSO Algorithm

Particle Swarm Optimization (PSO) operates based on a determined population of candidate solutions called particles. PSO is typically defined for a single objective function, but multi-objective functions are addressed using MOPSO, initially developed by Coello & Lechuga (2002). In MOPSO, each particle explores the solution space and is updated in each iteration based on two factors: position and velocity. During each iteration, particles adjust their positions and velocities according to rules influenced by personal and global experiences. The local best (Lbest) represents each particle's best experience, while the global best (Gbest) identifies the best position overall. Considering these two experiences, particles update their velocities and positions accordingly (Chaudhry *et al.*, 2019). The velocity update is influenced by the local and global coefficients of the particles. A specific mechanism ensures that priority values remain exclusive during updates. In this algorithm, solutions are represented as vectors. The updated velocity reflects changes in the current vector between the current position, the Lbest position, and the Gbest position. Positions are updated using integer-valued velocities.

Performance Evaluation

There are some metrics for evaluating meta-heuristic algorithms, of which four metrics are considered for assessing the algorithm performance.

1) The number of Pareto solutions (NPS): This metric expresses the number of optimal Pareto solutions. Algorithms with more excellent Pareto solutions performed better than the other algorithms.
2) Mean Ideal Distance (MID): This index represents the Pareto optimal solution distance from the ideal solution in each algorithm. The minimum value of the MID has the best performance. Eq. (28) represents the performance index:

$$\mathrm{MID} = \frac{\sum_{i=1}^{n} \sqrt{\left(\frac{f_{1\,i} - f_1^{best}}{f_{1.total}^{max} - f_{1.total}^{min}}\right)^2 + \left(\frac{f_{2\,i} - f_2^{best}}{f_{2.total}^{max} - f_{2.total}^{min}}\right)^2}}{n} \tag{28}$$

In the above expression, n is equal to the number of Pareto points, $f_{i.total}^{max}$ and $f_{i.total}^{min}$ are respectively the highest and lowest values for the objective functions of the algorithm. Moreover, $(f_1^{best}.f_2^{best})$ is coordinates of the ideal point.

3) Divergence Metric (DM): This index measures the distance between the best solutions in pareto front and can be expressed by Eq. (29).

$$d'_i = \max_j \left\{ \sum_{m=1}^{M} \left(f_m^i - f_m^j\right)^2 \right\}$$
$$DM = \sqrt{\sum_{i=1}^{N} d'_i} \tag{29}$$

4) Spacing metric (Spacing): This index evaluates the uniformity of the distribution of solutions on the Pareto front and is calculated according to Eq. (30). $\bar{d}$ is the mean, value of d_i.

$$\text{Spacing} = \frac{\sqrt{\frac{\sum_{i=1}^{n}(d_i - \bar{d})^2}{n}}}{\bar{d}} \tag{30}$$

5) Solution Time: One of the reasons for using metaheuristic algorithms is their high speed in solving high-dimensional problems. Therefore, any algorithm that has a faster convergence rate and reaches a better solution in less time compared to other algorithms is preferable.

6) First Objective Function Value (Obj1): Considering that the first objective function is a minimization type, smaller values of this criterion are more desirable.

7) Second Objective Function Value (Obj2): Considering that the second objective function is a maximization type, larger values of this criterion are more desirable.

Parameters setting

In each algorithm, it is essential to balance between the phases and tune the parameters to enhance the performance of algorithms (Vahdani & Zandieh, 2010). Here, we consider Response Surface Methodology (RSM), which was introduced by Box and Wilson. In this method, we define for each factor (X_i) which is measured at two levels that can be coded as -1 to 1 the low level (x_l) and high level (x_h) of each variable, respectively. The following equation shows the independent variables which are used in our study:

$$X_i = \frac{2x_i - x_h - x_l}{x_h - x_l} \quad i = \{1.2.\ldots.k\} \tag{31}$$

where K is the number of variables. Also, we define y, which is utilized to describe the variation in response variables, as follows:

$$y = \beta_{\circ} + \sum_{j=1}^{k} \beta_j x_j + \sum_{j=1}^{k} \sum_{i<j}^{k} \beta_{ij} x_i x_j + \sum_{j=1}^{k} \beta_{jj} x_{ij}^2 + \varepsilon \tag{32}$$

Where y, $\beta 0$, β_j, β_{ij}, are an estimated response, a constant, the linear coefficient, and the interaction coefficient, respectively. β_{jj} value, linear coefficient, interaction coefficient, and quadratic coefficient. In addition, Equation (32) should be assumed while there is curvature in the system. The factors and their levels and the number of experiments are shown in Table 1. In this table, the lower and upper limits are written on the left and right, respectively.

To analyze by the RSM, this paper develops a MODM model based on fuzzy interactive methods. The model can be formulated as follows:

$$\begin{aligned} & max \sum_{i=1}^{s} w_i \alpha_i \\ & s.t.\ Y_i \leq U_i - \alpha_i (U_i - L_i) \\ & 0 \leq \alpha_i \leq 1 \end{aligned} \tag{33}$$

According to the above equation, s represents the number of objective(s). Y_i, w_i and α_i are the i^{th} goal function (or regression model), its corresponding weight, and its satisfactory level, respectively. U_i and L_i denote the maximum and minimum values of the i^{th} column in the payoff table. The tuned parameter values and the R-squared (R^2) are presented in Table 2.

Table 1. Algorithms and Factor levels with the number of experiments.

Algorithm	Factors and their levels						N.Of Experiment; Total Number= (nf, nax, ncp)
NSGAII	nPop	p_c	p_m				$20=(2^3,6,6)$
	(100,500)	(0.7,0.9)	(0.1,0.3)				
MOPSO	nPop	nGrid	β	α	C_1	C2	$40=(2^4,18,6)$
	(100,500)	(3,15)	(1,6)	(1,6)	(0.2,2)	(0.2,2)	

Table 2. Final values of parameters of algorithms and R-squared (R^2).

Algorithm	Factors and their levels						R^2 objective function1 (%)	R^2 objective function2 (%)
NSGAII	nPop=373	p_c=0.7	p_m=0.1				71	69
MOPSO	nPop=397	nGrid=3.012	β=6	α=5.22	C_1=2	C_2=2	79	72

Results and Discussion

This section presents the numerical analysis of the study to demonstrate the performance of the metaheuristic algorithms. Initially, 30 test problems were generated, and the efficiency of the solution methods was evaluated across seven criteria based on the Pareto-optimal solutions. The input data for the model were randomly generated according to Table 3. As shown in this table, the input values follow a uniform distribution within the specified range. All test problems were executed on a system equipped with a Core i2 processor and 6 GB of RAM in MATLAB R2021b.

Table 3. Range of parameters.

Parameters	Range	Parameters	Range
A_{ij}	U [10,20]	D_j	**U [20,40]**

S_{ij}	U [10,20]	P_j	**U [16,20]**
C_{ij}	U [10,15]	W_{ij}	**U [5,15]**
Cap_i	U [30,50]	F_{ij}	**U [1,5]**
h_i^v	U [10,20]	L_{ij}	**U [10,20]**
h_i^b	U [10,20]	B_j	**U [30,50]**
β_s	U [0,1]	a_i	**U [0,1]**
a_1^*	0.001	a_2^*	**0.01**
γ	10^{-8}	$Z_{(\alpha)}$	**0.01**
$\mu_{(b_1)}$	100×U [10,25]	$\sigma^2_{(b_1)}$	**U [0, 25]**
$\mu_{(b_2)}$	100×U [10,25]	$\sigma^2_{(b_2)}$	**U [0, 25]**
$\mu_{(b_3)}$	100×U [10,25]	$\sigma^2_{(b_3)}$	**U [0, 25]**
$\mu_{(b_4)}$	100×U [10,25]	$\sigma^2_{(b_4)}$	**U [0, 25]**
$\mu_{(b_5)}$	100×U [10,25]	$\sigma^2_{(b_5)}$	**U [0, 25]**
$\mu_{(b_6)}$	100×U [10,25]	$\sigma^2_{(b_6)}$	**U [0,25]**
$\mu_{(b_7)}$	100×U [10,25]	$\sigma^2_{(b_7)}$	**U [0, 25]**
θ	0.7		

The output values were normalized using Equation (34), considering the best solution (Best Sol) for each objective function in every test problem. The distance of each solution from the best solution for each test problem was then calculated. Using Equation (35), these distances were aggregated, where the parameter wiw_iwi represents the weight of each performance criterion as determined by the decision-makers. In this study, the MID criterion was assigned a weight of 2, while all other criteria were given a weight of 1. The best solution indicates the most desirable value, which varies according to the intrinsic nature of each performance measure. Higher values represent better performance for NPS, DM, and Obj2, whereas lower values are preferable for MID, Spacing, Time, and Obj1. The parameter pip_ipi denotes the normalized value of each performance criterion, calculated relative to the best solution. After normalization, lower pip_ipi values are considered more favorable, regardless of the criterion's nature. Table 4 presents the performance evaluation results of the MOPSO and NSGA-II algorithms based on 30 test problems.

$$RPD = \frac{|\text{Present Sol-Best Sol}|}{|\text{Best Sol}|} \tag{34}$$

$$W = \sum_{i=1}^{I} w_i \, p_i \tag{35}$$

w_i: weight of metric performance.

p_i: normalized value of the performance metrics

Table 4 presents a comparative analysis of the results obtained from the NSGA-II and MOPSO algorithms based on the average values of the performance metrics NPS, MID, DM, Spacing, Time, Obj1, Obj2, and W.

According to this table, on average, NSGA-II outperforms MOPSO in terms of NPS, MID, DM, and Spacing. However, the weighted overall performance (W) of NSGA-II is lower than that of MOPSO. Therefore, NSGA-II ranks first from the decision-maker's perspective. This finding is consistent with prior studies; for instance, Deb et al. (2002) demonstrated that NSGA-II, due to its non-dominated sorting mechanism and the use of crowding distance, has superior capabilities in preserving solution diversity and converging toward the Pareto front. On the other hand, MOPSO generally exhibits faster convergence and, in problems with complex search spaces, can achieve acceptable solutions in shorter computational time (Kennedy & Eberhart, 1995).

Moreover, the performance of all criteria was statistically examined using paired t-tests. First, the normality of each criterion was verified through the Anderson-Darling test. The results indicated that the null hypothesis of normality was not rejected at the 0.05 significance level only for Time and Obj2. Conversely, for NPS, MID, DM, Spacing, and Obj1, the null hypothesis was rejected at the 0.05 significance level, indicating a statistically significant difference between the two algorithms. Accordingly, NSGA-II demonstrated superior

Table 4. Performance evaluation results.

	NSGAII								MOPSO							
Run	NPS	MID	DM	Spacing	Time(s)	Obj1	Obj2	W	NPS	MID	DM	Spacing	Time(s)	Obj1	Obj2	W
1	0.333	0.07	0.11	0.22	0.16	0.88	0.21	0.26	0.476	0.24	0.82	1.16	0.13	1.00	0.43	0.56
2	0.437	0.01	0.59	0.30	0.18	0.58	0.57	0.34	0.714	0.47	0.94	1.16	0.10	0.74	0.35	0.62
3	0.583	0.01	0.56	0.08	0.17	0.84	0.39	0.33	0.428	0.00	0.79	0.98	0.16	2.42	0.41	0.65
4	0.166	0.02	0.26	0.22	0.13	0.89	0.23	0.24	0.857	0.47	0.96	0.00	0.31	1.23	0.28	0.57
5	0.104	0.04	0.00	0.35	0.13	0.78	0.21	0.21	0.761	0.34	0.93	0.49	0.22	1.05	0.38	0.56
6	0.770	0.25	0.83	0.36	0.25	0.75	0.00	0.43	0.714	0.02	0.89	0.93	0.03	1.37	0.48	0.56
7	0.291	0.14	0.21	0.28	0.23	0.39	0.20	0.23	0.809	0.43	0.98	0.35	0.04	0.58	0.49	0.51
8	0.604	0.06	0.58	0.37	0.07	0.98	0.24	0.37	0.333	0.14	0.44	1.81	0.09	0.51	0.56	0.50
9	0.458	0.00	0.67	0.32	0.04	0.55	0.65	0.34	0	1.21	0.78	1.28	0.04	0.12	0.37	0.63
10	0.270	0.05	0.53	0.45	0.30	0.52	0.47	0.33	0.619	0.31	0.89	0.76	0.04	1.45	0.24	0.58
11	0	0.05	0.24	0.47	0.24	0.66	0.42	0.27	0.238	0.09	0.44	1.53	0.01	1.27	0.39	0.51
12	0.375	0.02	0.67	0.25	0.22	0.65	0.52	0.34	0.666	0.12	0.95	1.04	0.03	2.58	0.16	0.71
13	0.312	0.00	0.36	0.31	0.20	1.14	0.35	0.33	0.761	0.89	0.98	1.27	0.09	0.64	0.32	0.73
14	0.479	0.10	0.38	0.40	0.20	0.74	0.26	0.33	0.761	0.32	0.96	0.55	0.62	1.31	0.31	0.64
15	0.333	0.07	0.50	0.29	0.29	0.16	0.46	0.27	0.619	0.12	0.93	0.68	0.04	0.88	0.58	0.50
16	0.458	0.04	0.49	0.37	0.11	0.99	0.31	0.35	0.380	0.19	0.85	1.41	0.28	0.78	0.48	0.57
17	0.625	0.12	0.85	0.27	0.13	1.00	0.23	0.42	0.714	0.32	0.93	0.88	0.01	0.00	0.25	0.43
18	0.458	0.20	0.60	0.27	0.10	0.02	0.37	0.28	0.476	0.08	0.82	1.32	0.18	2.26	0.25	0.68
19	0.520	0.02	0.36	0.26	0.00	0.86	0.46	0.31	0.666	0.10	0.93	0.88	0.23	1.51	0.43	0.60
20	0.270	0.02	0.45	0.55	0.18	1.43	0.20	0.39	0.619	0.51	0.89	1.17	0.16	0.62	0.46	0.62
21	0.083	0.16	0.33	0.32	0.10	0.22	0.39	0.22	0.523	0.07	0.80	0.90	0.02	0.80	0.57	0.47
22	0.416	0.06	0.51	0.20	0.28	1.26	0.21	0.37	0.619	0.12	0.80	1.70	0.00	3.02	0.00	0.80
23	0.104	0.12	0.27	0.27	0.23	0.15	0.46	0.22	0.238	0.20	0.00	2.02	0.04	0.50	0.31	0.44
24	0.562	0.06	0.48	0.21	0.03	0.73	0.19	0.29	0.619	0.54	0.86	0.81	0.04	1.04	0.20	0.58
25	0.604	0.10	0.87	0.48	0.28	1.25	0.15	0.48	0.571	0.19	0.91	1.17	0.04	1.64	0.33	0.63
26	0.708	0.14	0.84	0.00	0.12	1.03	0.03	0.38	0	0.02	0.35	1.53	0.16	1.59	0.44	0.51

27	0.520	0.25	0.91	0.32	0.06	0.12	0.42	0.36	0.571	1.10	0.94	1.12	0.32	0.22	0.44	0.73
28	0.541	0.32	0.83	0.24	0.15	0.57	0.10	0.38	0.571	0.01	0.79	1.09	0.23	0.97	0.57	0.53
29	0.770	0.29	0.92	0.21	0.25	0.00	0.40	0.39	0.285	0.21	0.84	1.02	0.20	1.20	0.37	0.54
30	0.437	0.05	0.62	0.15	0.08	0.78	0.43	0.33	0.666	0.04	0.89	0.73	0.07	2.92	0.21	0.70
Average	0.420	0.0942	0.53	0.29	0.16	0.70	0.32	0.33	0.5428	0.295	0.81	1.06	0.13	1.21	0.37	0.59

Table 5. Comparison of algorithms' performance results.

		N	Mean	St Dev	SE Mean	T-Value	DF	P-Value	test result
Nps	Differences	30	-0.1227	0.2112		-2.25	58	0.028	null hypothesis rejected
	NSGAII	30	0.420	0.201	0.037				
	MOPSO	30	0.543	0.221	0.040				
MID	Differences	30	-0.2008	0.2257		-3.45	58	0.001	null hypothesis rejected
	NSGAII	30	0.0942	0.0883	0.016				
	MOPSO	30	0.295	0.307	0.056				
Dm	Differences	30	-0.2836	0.2340		-4.69	58	0.000	null hypothesis rejected
	NSGAII	30	0.527	0.247	0.045				
	MOPSO	30	0.810	0.220	0.040				
Spacing	Differences	30	-0.7642	0.3159		-9.37	58	0.000	null hypothesis rejected
	NSGAII	30	0.293	0.115	0.021				
	MOPSO	30	1.058	0.432	0.079				
Time	Differences	30	0.0318	0.1106		1.11	58	0.270	null hypothesis not rejected
	NSGAII	30	0.1637	0.0832	0.015				
	MOPSO	30	0.132	0.133	0.024				
Obj1	Differences	30	-0.509	0.614		-3.21	58	0.002	null hypothesis rejected
	NSGAII	30	0.698	0.378	0.069				
	MOPSO	30	1.207	0.782	0.14				
Obj2	Differences	30	-0.0496	0.1462		-1.31	58	0.194	null hypothesis not rejected
	NSGAII	30	0.318	0.157	0.029				
	MOPSO	30	0.368	0.135	0.025				

Table 5 reports the results of the paired t-test. The null hypothesis was rejected at the 0.05 significance level for the metrics NPS, Spacing, MID, DM, and Obj1, indicating the superiority of NSGA-II over MOPSO with respect to these criteria. Moreover, based on the values of the standard deviation and the standard error of the mean, NSGA-II demonstrates better performance compared to MOPSO. Overall, it can be concluded that

NSGA-II is more suitable for problems that require a balance between diversity, accuracy, and convergence, whereas MOPSO can serve as a preferable option in scenarios where computational speed and obtaining near-optimal solutions are of primary importance. This analysis is consistent with recent studies on multi-objective optimization algorithms (Li *et al*., 2020; Zhang & Li, 2007). In addition, Figures 4 to 10 illustrate the comparative results of the two algorithms across 30 generated test problems.

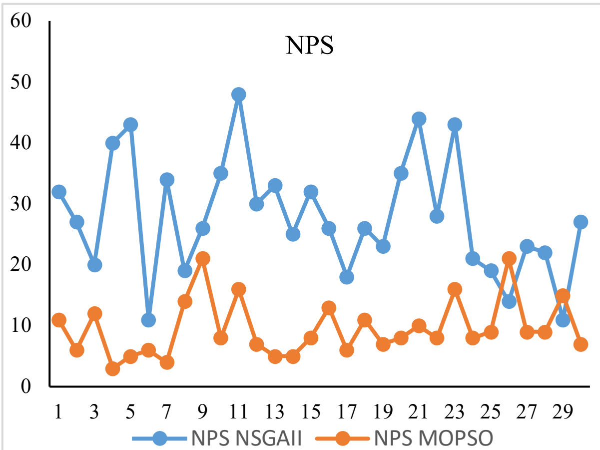

Figure 4. Comparison of algorithms based on NPS

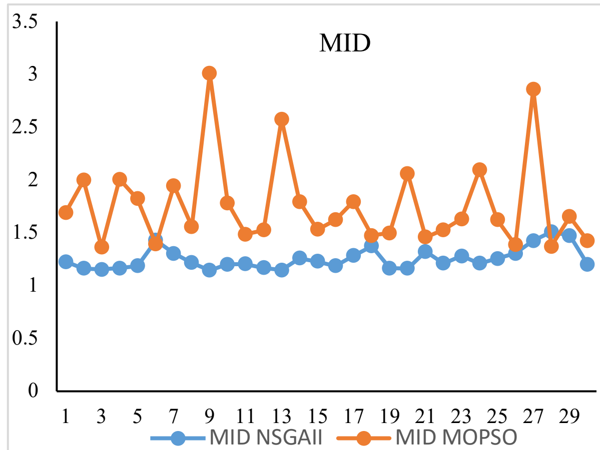

Figure 5. Comparison of algorithms based on MID

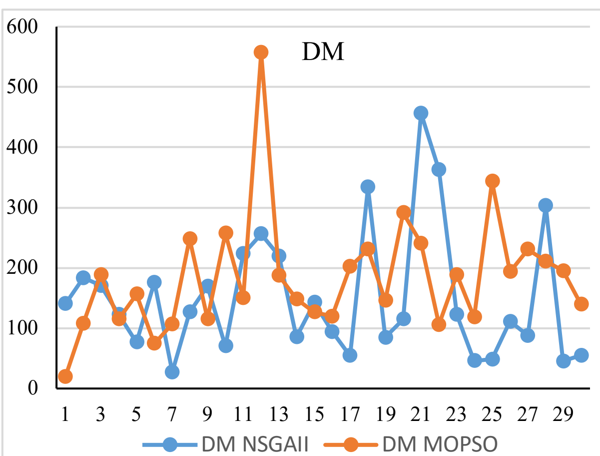

Figure 6. Comparison of algorithms based on DM

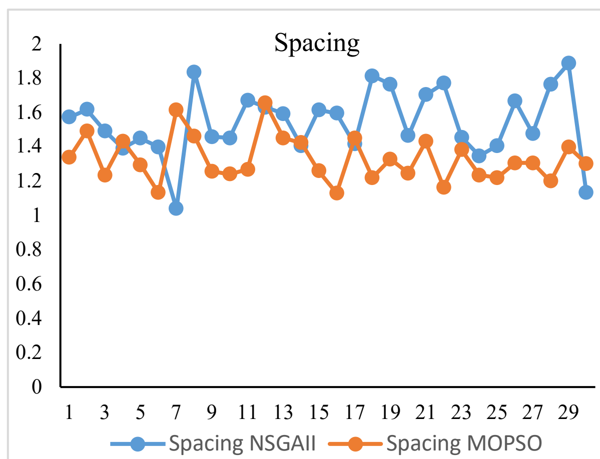

Figure 7. Comparison of algorithms based on Spacing

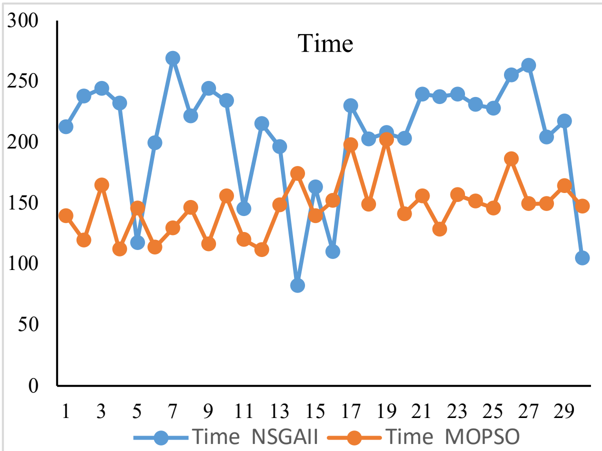

Figure 8. Comparison of algorithms based on Time

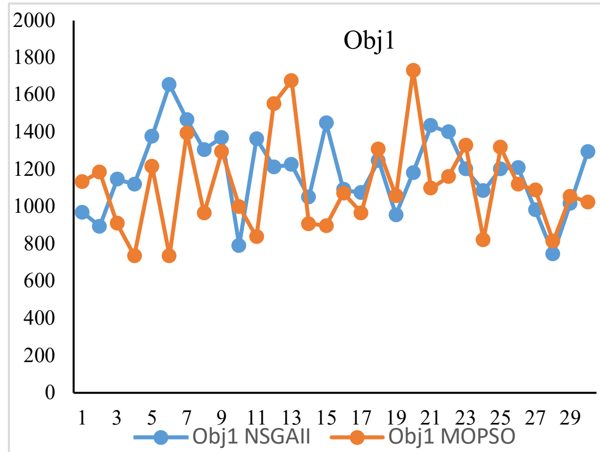

Figure 9. Comparison of algorithms based on Obj1

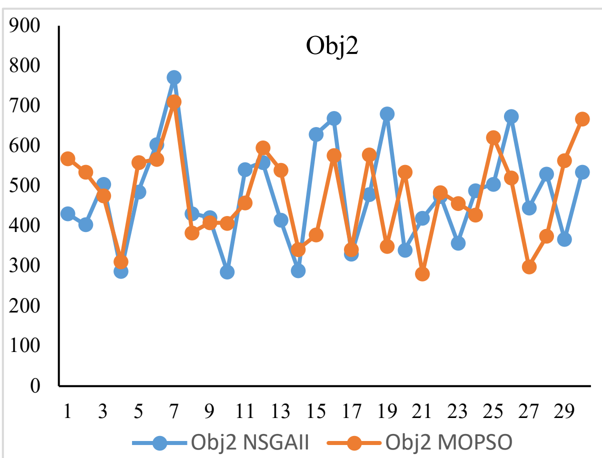

Figure 10. Comparison of algorithms based on Obj2

Conclusion

In this study, a MINLP model was developed to integrate supplier selection and order allocation in a centralized multi-product supply chain under uncertainty, explicitly considering disruption risks. Unlike many previous works that primarily focused on minimizing buyer costs (e.g., Aissaoui *et al*., 2007), the proposed model emphasizes joint optimization for both buyers and suppliers. This collaborative perspective enhances coordination across different tiers of the supply chain, leading to more stable and efficient resource allocation. The decision-maker in the proposed framework adopts a risk-averse approach, modeled through Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR) criteria, which play a significant role in improving supply chain decision-making (Rockafellar & Uryasev, 2000). Moreover, the explicit distinction between local and regional risks increases the accuracy of disruption analysis, whereas many earlier studies (e.g., Kleindorfer & Martel, 2012) have treated such risks in a more aggregated manner. To solve the model, two metaheuristic algorithms—NSGA-II and MOPSO—were employed. Computational results demonstrated that both algorithms are capable of generating diverse sets of Pareto-optimal solutions;

however, NSGA-II outperformed MOPSO in most key performance indicators, including NPS, MID, DM, and Spacing. This indicates the superior ability of NSGA-II to achieve higher-quality Pareto fronts with better convergence, thereby covering a broader range of efficient solutions. On the other hand, MOPSO showed acceptable performance in terms of objective function values and computational time, although it exhibited relative weaknesses in convergence when compared to NSGA-II. Importantly, no significant differences were observed in computational time between the two algorithms, suggesting that both are efficient from a runtime perspective. Overall, the findings highlight that NSGA-II provides a more effective solution approach for tackling complex multi-objective models of supplier selection and order allocation under risk-averse conditions and disruption scenarios. Nevertheless, leveraging the complementary strengths of both algorithms and extending comparisons to other metaheuristic approaches can provide fruitful directions for future research. This study can be further expanded in several ways. Exploring additional forms of uncertainty, such as fuzzy distribution functions, represents a promising avenue for future investigations. Finally, the simultaneous consideration of both supply and demand risks could offer an insightful extension to this line of research.

Acknowledgments: None

Conflict of Interest: None

Financial Support: None

Ethics Statement: None

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