DESIGNING A RESILIENT SUPPLY CHAIN NETWORK WITH A DECENTRALIZED STRATEGY UNDER UNCERTAINTY

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Abstract:

This paper investigates the vulnerability of supply chains to unforeseen disruptions and proposes a novel decentralized approach to enhance resilience. Traditional centralized supply chains are prone to risks, and this study introduces a decentralized model where individual entities make decisions based on local information, improving overall performance. The primary aim is to optimize a three-level resilient supply chain using a multi-objective mathematical model to minimize operational costs and promote decentralization. To address this, the study utilizes three optimization algorithms namely NSGA-III, bat, and whale algorithms where NSGA-III proved most effective by providing the highest number of Pareto-optimal solutions. The bat algorithm showed weaker performance across various metrics. A detailed sensitivity analysis was also conducted, revealing that increasing cost parameters, such as construction, ordering, and transportation, enhances decentralization. For example, a 50% rise in construction costs led to a 40% improvement in decentralization. This research highlights the potential of decentralized models in optimizing supply chain resilience.

1 Introduction

In recent years, the critical importance of integrating resilience into supply chain management has become increasingly evident, particularly in light of the growing frequency and severity of disruptions caused by a range of both natural and human-induced events. These disruptions include not only natural disasters, such as earthquakes, floods, and pandemics, but also unnatural disasters like social uprisings, political instability, and economic crises, all of which can severely impact the continuity of supply chains [1]. The concept of resilience in this context extends beyond security; it encompasses the ability of the supply chain to anticipate, prepare for, and adapt to unexpected disruptions, ensuring minimal impact on performance even when certain nodes or segments of the supply chain fail [2]. This approach necessitates proactive planning and robust design, enabling the supply chain to maintain functionality under adverse conditions, thereby reducing the likelihood of complete disconnection or failure during critical situations. The imperative for resilient supply chains has thus become a focal point for businesses and policymakers alike, as they seek to mitigate risks and ensure sustained operations in an increasingly volatile global environment [3]. Introducing resilience into the supply chain has become a critical priority for organizations seeking to navigate an increasingly unpredictable global environment. Supply chain resilience refers to the ability of a supply chain to anticipate, absorb, adapt to, and recover from various disruptions ranging from natural disasters to geopolitical events, economic crises, and unforeseen technological failures [4]. The importance of resilience lies in its capacity to minimize the impact of these disruptions, ensuring continuity of operations, protecting the integrity of supply flows, and ultimately sustaining the competitive advantage of businesses. In a world where disruptions are not just possible but

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inevitable, embedding resilience into the supply chain is essential for reducing vulnerabilities, enhancing agility, and ensuring that organizations can quickly respond to and recover from unexpected challenges.

This proactive approach not only safeguards against potential losses but also enables supply chains to emerge stronger and more adaptive in the face of future uncertainties [5]. Decentralization plays a pivotal role in enhancing the resilience of supply chains by reducing dependence on a single point of failure and spreading risk across multiple locations or entities. By diversifying suppliers, manufacturing sites, and distribution networks, decentralization ensures that disruptions in one region or facility do not cripple the entire supply chain. This approach allows for greater flexibility and agility, as operations can be quickly rerouted or scaled in response to local disruptions, such as natural disasters, political instability, or economic shifts [6]. Moreover, decentralization facilitates faster decision-making and localized responses, enabling supply chains to adapt more swiftly to changing conditions. This not only mitigates the impact of disruptions but also enhances the overall robustness and continuity of supply chain operations, making them more capable of sustaining performance and delivering value even in the face of unforeseen challenges [7]. Resiliency in supply chain network design is increasingly essential in an era marked by frequent disruptions, necessitating a shift from centralized to decentralized models, particularly in multi-level supply chains. Decentralization enhances resiliency by dispersing risk across a broader network, reducing the impact of localized disruptions and enabling more agile responses to unforeseen events [8]. In a decentralized multi-level supply chain, production, distribution, and sourcing activities are strategically dispersed across multiple locations rather than being concentrated in a single hub.

This approach allows for greater flexibility in rerouting processes, maintaining operations, and meeting demand even when parts of the network are compromised. Redesigning supply chains to embrace decentralization also involves leveraging local suppliers, diversifying transportation routes, and adopting digital tools for real-time monitoring and decision-making. Ultimately, decentralization not only mitigates vulnerabilities but also fosters a more adaptive and resilient supply chain capable of withstanding and recovering from disruptions more effectively [9]. Hence, in the current study, we aim to investigate the resilience of supply chains within these industries by focusing on the decentralization of supply chain components as a strategic approach to mitigate the effects of disruptions. Disruptions, whether stemming from natural disasters, geopolitical tensions, or market fluctuations, can have far-reaching impacts on supply chains, leading to delays, increased costs, and, in severe cases, total operational shutdowns [6]. Centralized supply chains, where critical functions and resources are concentrated in specific locations or with a limited number of suppliers, are particularly vulnerable to such disruptions. In contrast, decentralization disperses these critical functions across multiple, geographically dispersed nodes, thereby reducing the risk of a single point of failure. By diversifying production sites, sourcing, and distribution channels, decentralized networks enhance a supply chain's ability to respond to and recover from disruptions [8]. Uncertainty in supply chains, particularly concerning demand and supply fluctuations, plays a critical role in shaping the effectiveness and efficiency of operations. Demand uncertainty arises from unpredictable changes in customer preferences, market conditions, and external factors such as economic shifts or technological advancements, leading to challenges in accurately forecasting demand and aligning inventory levels [10]. Similarly, supply uncertainty is driven by factors such as variability in supplier performance, disruptions in raw material availability, and logistical issues, which can impede the timely delivery of goods and services. To cope with these uncertainties, companies must adopt agile and flexible supply chain strategies that incorporate real-time data analytics, demand sensing technologies, and collaborative planning with suppliers and partners. By enhancing visibility across the supply chain and fostering a responsive, adaptive infrastructure, businesses can better navigate the complexities of uncertainty, ensuring more stable and resilient operations in the face of unpredictable changes in demand and supply [11].

In light of the aforementioned issues, this paper seeks to offer appropriate answers to the following questions:

- How can a multi-level supply chain be effectively designed to mitigate operational and disruption risks, ensuring resilience and continuity in the face of unforeseen challenges?
- How can a supply chain be strategically designed through decentralization to enhance resiliency against disruptions and ensure sustained operational performance?
- How can uncertainty be effectively managed in the design of supply chains to enhance adaptability and ensure consistent operational efficiency?
- What are the most effective methods for solving the proposed mathematical model, given its complexity, and how can these methods be applied to achieve solutions within a reasonable time?

This paper is structured as follows. Section 2 offers a focused review of the problem. Sections 3 and Section 4 explore the mathematical models and solution approaches, respectively. Section 5 discusses the computational results, sensitivity analysis, and key findings of the research. Finally, Section 6 concludes with managerial insights and suggestions for future works.

2 Literature review

This paper concentrates on developing a multi-level supply chain while incorporating resilience measures. In this section, relevant literature is reviewed based on the specific features of this study. Bottani et al. [12] presented a comprehensive framework for designing resilient food supply chains. It integrates resilience measures into the supply chain design process, using a modeling approach combined with a metaheuristic solution to address complex challenges. The study effectively demonstrates the importance of resilience in ensuring the robustness of food supply chains, providing valuable insights into mitigating risks and improving overall supply chain performance. Mohammed et al. [13] developed a hybrid Multi-Criteria Decision Making (MCDM) and fuzzy multi-objective programming approach for designing a green and resilient (G-resilient) supply chain network. It addresses the dual challenge of enhancing supply chain resilience while adhering to green regulations by developing a model that optimizes the number of facilities based on economic, environmental, and resilience criteria. The study uses fuzzy Analytical Hierarchy Process (AHP) to determine the importance of resilience pillars—Robustness, Agility, Leanness, and Flexibility (V-RALF)—and integrates these into a multi-objective model. Through a case study and sensitivity analysis, the research demonstrates the model's effectiveness in achieving a balance between cost, environmental impact, and resilience measures. Sabouhi and Jabalameli [14] rendered a stochastic bi-objective optimization model for designing a resilient supply chain network, focusing on minimizing total costs and reducing non-resiliency under disruption risks. The model addresses key decisions such as the location of manufacturers, warehouses, and distribution centers, as well as the production and transportation of various products across the network. Using the ε-constraint method, the study converts the bi-objective model into a single-objective formulation.

The model's validity is demonstrated through random examples, showcasing its effectiveness in optimizing supply chain design while managing risks and enhancing resilience. Arabsheybani and Arshadi Khasmeh [15] in response to the significant risks and uncertainties in the spice and flavor industry, developed a robust bi-objective multi-product mathematical model for designing a resilient supply chain network. Given the high variability in spice quality due to factors like suppliers, seeds, and climate, the model focuses on maximizing total profits while enhancing resilience across multiple periods and items. Using Fuzzy AHP, the study weights resilience factors and integrates them into the model. It proposes a coordinated approach to production planning, distribution, supplier selection, and order allocation, applying the ε-constraint method to generate Pareto solutions based on a real case in Iran. Abadi et al. [16] explored resilient supplier selection within the SAPCO supply chain using the fuzzy DEMATEL approach combined with the Analytical Network Process (ANP). The study emphasizes the importance of resilience as a competitive advantage in today's risk-laden supply chain environment. By engaging experts from SAPCO company, the research identifies key criteria for resilient supplier selection, highlighting supplier risk, flexibility, and responsiveness as crucial factors. The findings also stress the significance of the technological dimension in supplier evaluation. The paper provides valuable insights and recommendations for SAPCO managers to enhance their supply chain resilience through informed supplier selection. Yavari and Ajalli [17] developed the design of a green-resilient supply chain network using a novel "coalition" risk mitigation strategy among suppliers. The study develops a bi-objective mixed-integer linear programming model aimed at simultaneously minimizing total costs and carbon emissions. The coalition strategy, alongside a multi-sourcing approach for retailers, is compared against traditional risk mitigation strategies in both single-source and multi-source retail scenarios. The findings demonstrate that the green-resilient model significantly reduces total costs and carbon emissions by 14% and 3.6%, respectively, compared to a non-resilient model. Additionally, the study highlights the varying economic and environmental impacts of the resilient model depending on the number of sources used by retailers. Lozano-Diez et al. [18] focused on designing resilient supply chains to mitigate drug shortages during epidemic outbreaks, such as COVID-19. The study highlights the critical challenges that drug supply networks face, including manufacturing issues, infrastructure limitations, and the need for immediate response mechanisms. Using anyLogistix optimization and simulation software, the authors conduct a hypothetical case study to analyze the impact of COVID-19 on a regional drug supply network. The findings provide valuable insights for developing resilient supply chains that can effectively respond to disruptions during public health crises. Piprani et al.[19] focused on identifying and prioritizing resilient capability factors to manage supply chain disruptions in Pakistan's textile industry. Using a two-stage methodology, the researchers first reviewed literature and consulted experts to identify key resilience factors at different disruption stages. They then applied the AHP to rank these factors.

The findings emphasize the importance of building an integrated supply chain and highlight the readiness phase as the most crucial for resilience. Zhao and You [20] presented a robust optimization framework for designing and operating resilient supply chains under uncertain disruptions. The authors introduce a bi-objective two-stage adaptive robust fractional programming model that simultaneously optimizes economic and resilience objectives. A key innovation is the use of a decision-dependent uncertainty set, where uncertain parameters like post-disruption production capacities depend on initial decisions such as facility locations and capacities. This model is enhanced by a data-driven approach that leverages historical data to construct the uncertainty set. Additionally, the model accounts for time delays between disruptions and recovery. To address the computational complexity, the authors propose two solution strategies. The framework's effectiveness is demonstrated through applications to a location-transportation problem and a biofuel supply chain optimization problem. Mari et al. [21] addressed the challenge of supplier selection and order allocation in resilient supply chains, particularly in the face of high-impact, low-probability disruptions. Recognizing that the resilience of individual suppliers is crucial for the overall supply chain, the authors propose a possibilistic fuzzy multi-objective approach to develop quantitative resilience criteria. An interactive fuzzy optimization solution methodology is introduced, enabling organizations to balance cost and resilience effectively. The approach is demonstrated through a case study in a garments manufacturing supply chain, showcasing its practical application and potential to enhance decision-making in complex, uncertain environments. Ward and Hargaden [22] provided an exploratory assessment of risk and resilience in pharmaceutical supply chains, focusing on the downstream section where vulnerabilities often contribute to medicine shortages. Utilizing the Supply Chain Risk Assessment Method, the authors gathered survey data from supply chain managers in the pharmaceutical sector. The findings highlight key areas needing improvement to enhance resilience, particularly in flexibility of sourcing, order fulfillment, visibility, and collaboration. This assessment underscores the critical need for strengthened supply chain capabilities to address and mitigate the growing issue of medicine shortages. Clavijo-Buritica et al. [23] presented a hybrid modeling approach for designing resilient agri-supply networks, with a focus on the Colombian coffee supply chain. Given the increasing challenges posed by global warming and natural disasters, the study emphasizes the importance of resilience in Agri-Food Supply Chains (AFSCs), particularly in emerging countries. The authors address the difficulty of creating efficient and resilient AFSCs while considering perishability constraints. The proposed methodology offers a structured approach to enhance the resilience of AFSCs, ensuring they can effectively manage and mitigate disruptions caused by environmental and human factors. Alikhani et al. [24] addressed the crucial need for supply chain resilience, particularly highlighted by the COVID-19 pandemic, by focusing on the challenges in resilient supply chain network design.

The authors propose a multi-methodological approach combining resource dependence theory and two-stage stochastic programming to select appropriate resilience strategies considering their synergistic effects under resource constraints. This approach emphasizes the importance of understanding the dynamics between different resilience strategies and how their interactions can influence overall supply chain performance. Through a case study in the retail industry, the paper demonstrates the criticality of nodes and network susceptibility to disruptions, showcasing the advantages of applying multiple resilience capabilities simultaneously. Shi and Ni [25] focused on designing resilient supply chain networks in environments characterized by significant uncertainty, such as natural disasters and market fluctuations. The authors use an uncertain programming method to develop models that achieve the desired level of resilience with minimal redundancy, addressing the challenges posed by limited historical data through uncertainty theory. By converting the models into deterministic formulations solvable by CPLEX, they make the approach more practical for real-world applications. The study's sensitivity analysis underscores the importance of incorporating uncertainty in the supply chain network design phase, revealing the effectiveness of resilience constraints and the benefits of controlled redundancy in enhancing service levels. Hosseinzadeh and Taghipour [26] introduced an integrated approach to enhance manufacturing resilience by jointly optimizing product design and supply chain network design within a two-echelon capacitated network. The methodology focuses on simultaneously addressing the critical decisions related to the design of modular products and their corresponding supply chain networks, which include multiple production facilities and product variants. By incorporating redundancy allocation, the approach aims to optimize product reliability within these facilities, thereby strengthening the overall resilience of the manufacturing process. Vali-Siar and Roghanian [27] presented a novel approach to designing a resilient mixed supply chain network that accounts for disruptions and competition between supply chains.

The study develops a two-stage stochastic programming model, where facility location and supplier selection are first-stage decisions, and material and product flows are second-stage decisions. The model incorporates resilience strategies to minimize the expected total cost and maintain market share under uncertain facility capacities. The findings emphasize the critical importance of resilience in supply chain design, demonstrating that incorporating competition and resilience strategies leads to more realistic and effective decisions. Badi et al. [28] introduce a heuristic model for Vendor Managed Inventory that effectively integrates customer clustering, service sequencing, and route optimization to reduce stockouts and transportation costs. The practical case study validates its capacity to enhance supply chain efficiency while keeping the approach simple and accessible. In another study, Mehdiabadi et al. [29] expanded the literature by addressing an underexplored area, service supply chain capabilities in the oil and gas sector, using advanced fuzzy hybrid methodologies (SWARA and fuzzy MABAC). It identifies seven core capabilities and emphasizes the strategic role of information processing in enhancing decision-making and location optimization. Badi et al. [30] presented an integrated vendor-managed inventory and vehicle routing problem model for a three-echelon distribution system, using a three-phase methodology enhanced by an insertion heuristic to optimize vehicle utilization and cost efficiency. Computational experiments on a real-life supply network validated its robustness in reducing transportation and inventory costs. In another related study, Kolahi-Randji et al. [31] utilized a discrete event simulation model via Arena to assess multi-level, multi-commodity supply chain performance in a detergent industry context.

The study integrated multiple echelons with (s, S) inventory control and considers both financial and operational metrics to evaluate different strategic scenarios. Readers interested in exploring how MADM/MCDM techniques can enhance the planning and optimization of supply chains are encouraged to refer to [32-36] for more information. In summary, the existing literature reveals a significant gap in addressing the role of decentralization in achieving supply chain resilience. This lack of focus on resiliency measures in decentralized supply chains is particularly concerning given the increasing complexity and unpredictability of modern supply chain environments. Moreover, the simultaneous impact of uncertainty in supply chain planning has not been adequately integrated with resiliency considerations in previous studies. To address these critical concerns, this research introduces a novel multi-objective optimization approach that not only emphasizes the importance of decentralization in enhancing supply chain resilience but also incorporates the effects of uncertainty into the decision-making process. Therefore, this paper makes the following key contributions to this field:

- Proposing an innovative multi-level supply chain design framework that effectively mitigates both operational and disruption risks, ensuring resilience and continuity in the face of unforeseen challenges;
- Introducing a strategic approach to supply chain decentralization, enhancing resiliency against disruptions and supporting sustained operational performance;
- Applying an appropriate approach for managing uncertainty in supply chain design and planning, which enhances adaptability and maintains consistent operational efficiency;
- Developing and applying advanced metaheuristic algorithms, including NSGA-III, Bat, and Whale algorithms, to efficiently solve the mathematical model for large-scale instances.

3 Problem description and model formulation

In recent years, the critical importance of developing resilient supply chains has gained significant attention in both academic research and industry practices, driven by the increasing frequency and severity of risks that threaten the stability and functionality of supply networks. These risks, ranging from natural disasters to man-made disruptions, have underscored the need for a strategic approach to supply chain management that prioritizes resilience. While various strategies have been proposed to enhance supply chain resilience, one area that has not been thoroughly explored is the concept of decentralization within the supply chain structure. Concentrating supply chain elements within specific, often high-risk geographic areas, exposes the entire system to significant vulnerabilities. These areas are frequently at risk from both terrorist activities and natural disasters such as floods and earthquakes. The clustering of supply chain components in such regions can lead to catastrophic consequences in the event of a disruption, potentially crippling the entire supply chain. Although decentralizing these components may introduce challenges such as increased route risks and higher operational costs, this approach offers a strategic advantage by mitigating the impact of localized disasters. The trade-off between increased logistical complexity and enhanced resilience suggests that dispersing supply chain elements across multiple, lower-risk areas could be a more prudent strategy. Building on these insights, our research aims to develop a resilient supply chain model that emphasizes the decentralization of supply chain elements. We propose a systematic approach to allocate supply chain components across different geographic regions based on a risk assessment framework. By setting thresholds for the number of elements that can be placed in high-risk areas, our model seeks to minimize the exposure of critical supply chain components to potential disruptions. The schematic representation of the decision variables is illustrated in Figure 1. This figure provides a visual overview of the process involved in assigning products to suppliers, factories, warehouses, and wholesalers.

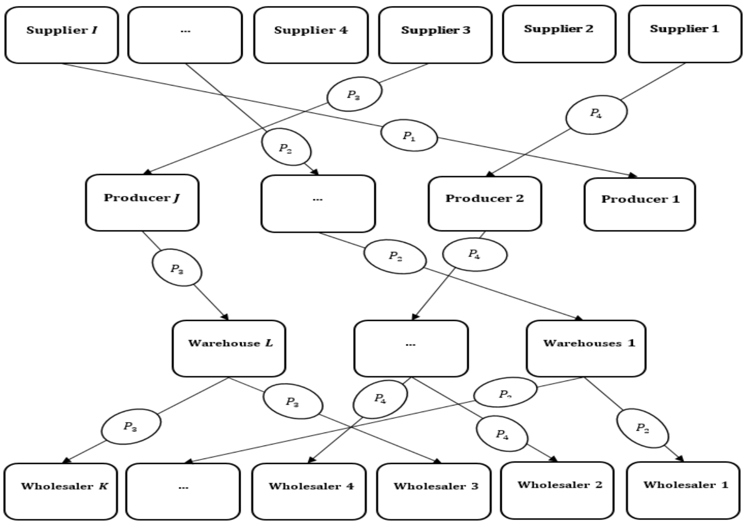


Figure 1. A schematic representation of the product flow between suppliers, producers, wholesalers, and warehouses.

As illustrated in Figure 1, each product follows a pathway from the supplier to the producer, then from the producer to the warehouse, and finally from the warehouse to the wholesalers. An example of this assignment is depicted in Figure 2. In this figure, large white circles represent different regions, while green points indicate the locations of suppliers. Orange points correspond to wholesalers, and red and blue points signify the positions of factories and warehouses, respectively. The placement of each node is strategically designed to maximize decentralization, thereby enhancing the resilience of the supply chain. For instance, in the first region, the optimal decentralization is achieved with two suppliers, two wholesalers, and one producer. In contrast, the second region consists of two wholesalers, one warehouse, one supplier, and one producer. Similar conditions apply to the other two regions.

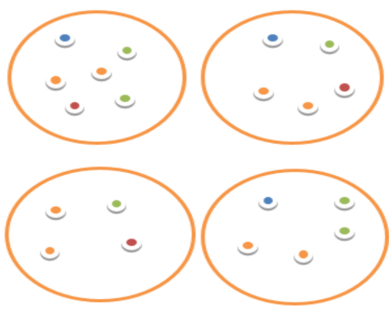


Figure 2. The procedure of assigning nodes to areas.

3.1 Assumptions

This study relies on several assumptions and the most significant ones are outlined as follows:

- The supply chain operates in a multi-product environment, handling multiple product types simultaneously;
- The supply chain structure comprises three distinct layers: suppliers, producers (including warehouses), and wholesalers. Warehouses are integrated within the producer layer, facilitating the storage and distribution of products;
- The supply chain components are distributed across various geographic regions, each with its unique characteristics and constraints;
- Each region is associated with a specific risk level, quantified as a percentage, representing the likelihood and potential impact of disruptions;
- A predefined threshold is established for the allocation of supply chain components, ensuring the decentralization of these elements to enhance resilience and reduce risk exposure;
- The products within the supply chain are categorized as either semi-finished or fully finished goods. Semi-finished products are supplied by the supplier and subsequently processed by the manufacturer to become complete products ready for distribution.

3.2 Notations

Sets

i *Set of all suppliers,* $i \in \{1, \dots, I\}$
j *Set of all producers,* $j \in \{1, \dots, J\}$
l *Set of all warehouses,* $l \in \{1, \dots, L\}$
k *Set of all wholesalers,* $k \in \{1, \dots, K\}$
p *Set of all products,* $p \in \{1, \dots, P\}$
r *Set of all regions,* $r \in \{1, \dots, R\}$

Parameters

FCI_{ir} *The cost associated with establishing supplier i in region r*
FCJ_{jr} *The cost of constructing factory j in region r*
FCL_{lr} *The cost of constructing warehouse l in region r*
FCK_{kr} *The cost of constructing wholesaler k in region r*
TCI_{ij} *The cost of transferring products between supplier i and manufacturer j*
TCJ_{jl} *The cost of transferring products between manufacturer j and warehouse l*
TCL_{lk} *The cost of transferring products between warehouse l and wholesaler k*
OC_{ijp} *The cost of ordering product p from supplier i by factory j*
MC_{jp} *The production cost of product p at factory j*
SC_{lp} *The storage cost of product p at warehouse l*
PC_{kpj} *The cost of purchasing product p by wholesaler k from factory j*
RI_{ir} *The percentage risk associated with supplier i being located in region r*
RJ_{jr} *The percentage risk associated with producer j being located in region r*
RL_{lr} *The percentage risk associated with warehouse l being located in region r*
RK_{kr} *The percentage risk associated with wholesaler k being located in region r*
CI_i *The capacity of supplier i*
CJ_J *The production capacity of factory j*
CL_L *The capacity of warehouse l*
CK_k *The sales capacity of wholesaler k*
TY_{lp} *Binary parameter equals 1 if warehouse l has the capacity to store product p; otherwise, it equals 0*
LM_r *The threshold established for the placement of supply chain elements in region r*
D_{pk} *The demand of product p at wholesaler k*

Binary variables

X_{ijp}	*Binary variable equals 1 if product p is purchased by factory j from supplier i; otherwise, it equals 0*
Y_{jlp}	*Binary variable equals 1 if product p is delivered to warehouse l by factory j; otherwise, it equals 0*
Z_{pj}	*Binary variable equals 1 if product p is produced by factory j; otherwise, it equals 0*
Q_{pl}	*Binary variable equals 1 if product p is stored by warehouse l; otherwise, it equals 0*
V_{plk}	*Binary variable equals 1 if product p is delivered to wholesaler k by warehouse l; otherwise, it equals 0*
W_{pkj}	*Binary variable equals 1 if product p is purchased by wholesaler k from factory j; otherwise, it equals 0*
XI_{ir}	*Binary variable equals 1 if supplier i is located in region r; otherwise, it equals 0*
YJ_{jr}	*Binary variable equals 1 if product j is located in region r; otherwise, it equals 0*
ZL_{lr}	*Binary variable equals 1 if warehouse l is located in area r; otherwise, it equals 0*
UK_{kr}	*Binary variable equals 1 if wholesaler k is located in area r; otherwise, it equals 0*

Positive variables

QI_{ijp}	*The quantity of product p that supplier i delivers to factory j*
QJ_{pjl}	*The quantity of product p that factory j delivers to warehouse l*
QL_{pl}	*The quantity of product p that warehouse l stores*
QK_{pkl}	*The quantity of product p that wholesaler k receives from warehouse l*

3.3 Mathematical formulation

In this section, we present the formulation of the problem as a mixed-integer linear programming model.
Objectives function
In this sub-section, we delineate the objective functions employed in the model. The primary focus of Equation (1) is to reduce the total supply chain cost, encompassing various components such as construction, transfer, maintenance, and product acquisition expenses. Conversely, Equation (2) is dedicated to minimizing the risks associated with the supply chain.

$$\begin{aligned} \min Z_1 = &\sum_i \sum_r FCI_{ir} * XI_{ir} + \sum_j \sum_r FCJ_{jr} * YJ_{jr} + \sum_l \sum_r FCL_{lr} * ZL_{lr} + \sum_k \sum_r FCK_{kr} * UK_{kr} \\ &+ \sum_i \sum_j \sum_p TCI_{ij} * X_{ijp} \\ &+ \sum_j \sum_l \sum_p TCJ_{jl} * Y_{jlp} + \sum_l \sum_k \sum_p TCL_{lk} * V_{plk} + \sum_p \sum_j MC_{jp} * Z_{pj} + \sum_l \sum_p SC_{lp} * Q_{pl} \\ &+ \sum_k \sum_p \sum_j PC_{kpj} * W_{pkj}, \end{aligned} \tag{1}$$

$$\min Z_2 = \sum_i \sum_r RI_{ir} * XI_{ir} + \sum_j \sum_r RJ_{jr} * YJ_{jr} + \sum_l \sum_r RL_{lr} * ZL_{lr} + \sum_k \sum_r RK_{kr} * UK_{kr}, \tag{2}$$

Constraints

$$\sum_j Y_{jlp} = 1, \quad \forall l, p. \tag{3}$$

Equation (3) represents a constraint on supplier selection within the model. Specifically, this equation ensures that each factory l is limited to selecting exactly one supplier j for each product p. The variable Y_{jlp} is a binary indicator, where $Y_{jlp} = 1$ if supplier j is chosen by factory l for product p, and $Y_{jlp} = 0$ otherwise.

$$Q_{pl} = TY_{lp}, \ \ \forall l, p, \tag{4}$$

Equation (4) defines a constraint related to the selection of factories for product delivery by each warehouse. Specifically, this equation stipulates that the quantity Q_{pl} must align with a predefined type or classification TY_{lp} associated with that factory and product combination.

$$\sum_{l} V_{plk} = 1 \ , \quad \forall p,k. \tag{5}$$

Equation (5) specifies a constraint concerning the maintenance of products by each warehouse, taking into account the resilience degree associated with each warehouse.

$$\sum_{r} XI_{ir} = 1, \quad \forall i. \tag{6}$$

Equation (6) enforces a constraint on the allocation of products to wholesalers, ensuring that each wholesaler i sources products from exactly one warehouse r.

$$\sum_{r} YJ_{jr} = 1, \quad \forall i. \tag{7}$$

Equation (7) enforces a constraint on the location of suppliers, stipulating that each supplier j can only be established in a single area r. By enforcing this restriction, the model ensures that each supplier is restricted to a unique geographical area, supporting clear and organized supplier management.

$$\sum_{r} ZL_{lr} = 1, \ \forall l. \tag{8}$$

Equation (8) specifies that each plant l can only be constructed in one area r. In this equation, ZL_{lr} is a binary variable where $ZL_{lr} = 1$ if plant l is situated in area r, and $ZL_{lr} = 0$ otherwise.

$$\sum_{r} UK_{kr} = 1, \quad \forall k. \tag{9}$$

Equation (9) stipulates that each warehouse k can only be constructed in one specific area r. This restriction ensures that the allocation of warehouses is streamlined and unambiguous, thereby supporting efficient supply chain operations and avoiding complications related to multiple-area warehouse configurations.

$$\sum_{i} XI_{ir} + \sum_{j} YJ_{jr} + \sum_{l} ZL_{lr} + \sum_{k} UK_{kr} = LM_r, \ \forall r. \tag{10}$$

Equation (10) imposes a capacity constraint on each area r, ensuring that the total number of facilities built—across wholesalers, suppliers, plants, and warehouses—does not exceed a predefined limit.

$$\sum_{j} \sum_{p} QI_{ijp} \leq CI_i, \ \forall i. \tag{11}$$

Equation (11) establishes a threshold for the total volume of supply chain components located in each area i to promote decentralization within the supply chain network.

$$\sum_{j} \sum_{p} QJ_{pjl} \leq CJ_J, \quad \forall j. \tag{12}$$

Equation (12) establishes a constraint on the capacity of suppliers to provide products to manufacturers. This constraint ensures that no supplier is allocated more products than it can handle.

$$\sum_{p} QL_{pl} \leq CL_{L}, \qquad \forall l. \tag{13}$$

Equation (13) imposes a constraint on the production capacity of each producer l. This constraint is critical for managing production levels effectively, ensuring that no producer is tasked with more production than it can handle.

$$\sum_{l} \sum_{p} QK_{pkl} \leq CK_{k}, \quad \forall k. \tag{14}$$

Equation (14) establishes a constraint on the storage capacity of each warehouse k. This constraint ensures that the total volume of products stored remains within the warehouse's capacity limits.

$$\sum_{i} QI_{ijp} = \sum_{l} QJ_{pjl}, \quad \forall j. \tag{15}$$

$$\sum_{j} QJ_{pjl} = QL_{pl}, \quad \forall l. \tag{16}$$

$$\sum_{l} QL_{pl} = \sum_{l} \sum_{p} QK_{pkl}, \quad \forall k. \tag{17}$$

Equation (15)- (17) establish constraints on the product flow in producers, warehouses, and wholesalers. These constraints ensure that the total amount of inflow and outflow of products are equal in each node and maintaining consistency and preventing discrepancies in product flow within the supply chain.

$$\sum_{l} QK_{pkl} \geq D_{pk}, \quad \forall p, k. \tag{18}$$

Equation (18) enforces a constraint on the demand of products in each wholesaler. This constraint ensures that the total amount products received from warehouses should be satisfied the demand of each product in warehouses.

4 Uncertainty approach and solution methodology

In this section, an uncertainty method, along with three metaheuristic approaches NSGA-III, Bat algorithm, and Whale algorithm are developed to effectively solve the mathematical model.

4.1. Uncertainty approach

Uncertainty is a crucial factor in supply chain planning because it directly influences decision-making and the ability to respond effectively to dynamic market conditions. Supply chains are inherently complex, involving multiple interconnected entities, and are subject to various unpredictable factors such as demand fluctuations, supply disruptions, geopolitical events, and natural disasters. In this section, we address the uncertainty approach in contrast to the deterministic model previously discussed. This approach, as outlined by Mulvey et al. [37], involves robust optimization, which includes two key concepts: robust solutions and robust models. A robust solution is one that remains near-optimal across all possible scenarios, while a robust model is one that remains valid across nearly all scenarios. Based on these definitions, a general model of robust optimization has been developed, specifically designed for problems characterized by scenario-based data. In this context, the data values are represented by a set of scenarios. Mulvey and Shetty [38] highlight that mathematical programming models often encounter volatile and uncertain data, making traditional methods such as sensitivity analysis and scenario planning inadequate. Typically, optimization models are divided into two components: the structural part, which remains constant without fluctuations, and the control part, which is subject to uncertain and variable data. The optimization model is defined accordingly:

$$
\begin{gathered}
min\, C^T x + d^T y, \\
subject\ to \\
Bx + Cy = e, \\
x,y \geq 0, \\
x \in R^{n1}, y \in R^{n2}.
\end{gathered}
\tag{19}
$$

In the aforementioned model:
- x denotes the decision variables associated with deterministic parameters.
- y denotes the decision variables pertaining to the control segment.

The constraints are categorized into two sections:
- Structural constraints, which have fixed coefficients and are considered reliable.
- Control constraints, which involve coefficients that are subject to uncertainty.

The model assumes a finite set of scenarios $\Omega = \{1,2,3, \ldots .S\}$ to account for the uncertain parameters. Additionally, a set $\{d_s, B_s, C_s, e_s\}$ is defined to represent the outcomes of each scenario $s \in \Omega$. P_s indicates the probability of occurrence for each scenario. The general formulation of the robust optimization model, as proposed by Mulvey et al. [38], is presented as follows:

$$
\begin{gathered}
\min \partial(x, y_1, y_2, \ldots, y_s) + \omega \sum_s \rho(\partial_1, \partial_2, \ldots .\partial_s), \\
\text{subject to} \\
Ax = b, \\
B_s x + C_s y_s + Z_s = e_s, \\
x \geq 0, y_s \geq 0.
\end{gathered}
\tag{20}
$$

In the state model, $(y_1, y_2, \ldots, y_s)$ represents the set of control variables corresponding to each scenario $s \in \Omega$. Additionally, $(\partial_1, \partial_2, \ldots .\partial_s)$ denotes a set of error vectors that quantify the permissible deviation in the control constraints under scenario s. The objective function $C^T x + d^T y$ is a random variable, with $C^T x + d_s^T y_s$ representing its value under scenario s, occurring with probability P_s. The balance between solution stability and model robustness is achieved through the application of multi-criteria decision-making concepts. The optimization model presented here is designed to evaluate the extent of this trade-off. The term σ_0 is recognized as a nonlinear expression, and the model is built upon a practical scenario, aligning with the framework of a potential nonlinear programming model. The set $(\partial_1, \partial_2, \ldots .\partial_s)$, as the second term in the objective function, serves as a penalty function designed to enforce compliance with control constraints across different scenarios. This function penalizes violations of these constraints, ensuring that the model adheres to specified limits. By incorporating the weight ω, the model measures and balances the trade-off between solution stability and model robustness, using σ_0 and ρ_0, respectively. This approach can be framed within a multi-criteria decision-making process. For example, when $\omega = 0$, the objective function focuses on minimizing ∂_0, which may result in an ungrounded solution. Conversely, assigning a relatively high value to ω increases the cost but enhances solution stability. The expression $\partial(x,y_1,y_2,\dots,y_s)$ includes the mean value of ∂_0 plus the product of a constant λ and its variance, further refining the model's response to uncertainty.

$$\partial(x,y1,\dots ys) = \sum_{s\in S} P_s \mathcal{E}_s + \lambda \sum_{s\in S} P_s \left(\mathcal{E}_s - \sum_{s\in S} P_s\, \mathcal{E}_s \right), \tag{21}$$

The above expression was reformulated by Yu and Li [30] to include a quadratic term, making it a quadratic form in the modeling process. This transformation allows for a more precise representation of the problem, capturing the non-linearity inherent in the system and enabling a more accurate analysis of the trade-offs between different decision criteria. The inclusion of the quadratic term enhances the model's ability to reflect the complexities of real-world scenarios, leading to more robust and reliable optimization outcomes.

$$\partial(x,y1,\dots ys) = \sum_{s\in S} P_s \mathcal{E}_s + \lambda \left| P_s (\mathcal{E}_s - \sum_{s\in S} P_s\, \mathcal{E}_s) \right|, \tag{22}$$

Although the expression remains nonlinear, it can be transformed into a linear function by introducing two non-negative deviation variables, following the approach proposed by Yu and Li [39]. This method allows for the conversion of the quadratic form into a linear optimization problem. Instead of directly minimizing the absolute deviation from the mean of the two functions mentioned earlier, the model minimizes the two deviation variables, subject to specific constraints. This approach simplifies the problem while maintaining the integrity of the original objective, ensuring that the deviations are minimized effectively within the linearized framework, as demonstrated in the following formulation:

$$\begin{gathered} min \sum_{s\in S} P_s \mathcal{E}_s + \lambda \sum_{s\in S} P_s \left[\left(\mathcal{E}_s - \sum_{s\in S} P_s\, \mathcal{E}_s \right) + 2\theta_s \right], \\ subject\ to \\ \mathcal{E}_s - \sum_{s\in S} P_s\, \mathcal{E}_s + \theta_s \geq 0, \\ \theta_s \geq 0. \end{gathered} \tag{23}$$

In the model presented, s represents a scenario, and P_s denotes the probability of that scenario occurring. Furthermore, the objective function in above models has been updated, replacing with $\mathcal{E}_s$. This substitution reflects the adjustment in the formulation to better capture the desired outcomes or metrics associated with each scenario.

4.2 Solution methodology

In the present study, three meta-heuristic algorithms are employed to solve the aforementioned model. The details of these algorithms are outlined as follows.

4.2.1 NSGA-III algorithm

The NSGA-III metaheuristic algorithm is one of the most widely used and powerful methods for solving multi-objective optimization problems. Its effectiveness has been demonstrated across a wide range of applications. Originally introduced by Deb et al. [40] as the NSGA optimization method, it has since evolved to address the complexities of multi-objective problems. Key aspects of this optimization method are outlined below. In NSGA, a solution that is not outperformed by any other solution receives the highest ranking. Solutions are ranked based on the number of other solutions that dominate them, with eligibility (or fitness) assigned according to their rank and non-dominance. To ensure an optimal distribution of solutions across the search space, an eligibility sharing technique is employed for solutions that are close to one another.

Given that the performance and quality of NSGA algorithm solutions are highly sensitive to the choice of fitness sharing parameters and other variables, Seada and Deb [41] introduced the third version of the NSGA algorithm, known as NSGA-III. This version not only improves upon its predecessors but also serves as a

foundational model for the development of numerous other multi-objective optimization algorithms. The NSGA-III algorithm, with its distinctive approach to solving multi-objective optimization problems, has been widely adopted and has inspired the creation of newer algorithms in this field. It is a key member of the second generation of multi-objective evolutionary optimization algorithms.
The main features of the NSGA-III algorithm are as follows:
- Introduction of a crowding distance measure as an alternative to traditional fitness sharing methods.
- Implementation of binary tournament selection.
- Preservation and archiving of solutions from previous iterations (elitism).

NSGA-III is a multi-objective genetic algorithm that operates based on non-dominated solutions. Unlike a single-objective genetic algorithm, where only one objective function serves as the fitness function, NSGA-III handles multiple objectives. The initial population is generated by encoding decision variables as genes within chromosomes. In this algorithm, solutions are compared across multiple objectives for each chromosome, resulting in the formation of a Pareto front or a Pareto curve. On this curve, the best solutions are considered dominant, as no other solutions outperform them on all objectives. Importantly, all points on this curve are equally optimal with respect to the trade-offs involved. The primary distinction between NSGA-III and traditional genetic algorithms lies in its handling of multi-objective optimization, including non-dominated sorting, Pareto front formation, and the comparison of solutions across multiple objectives. These features are not present in traditional or single-objective genetic algorithms, making NSGA-III uniquely suited for complex optimization tasks.

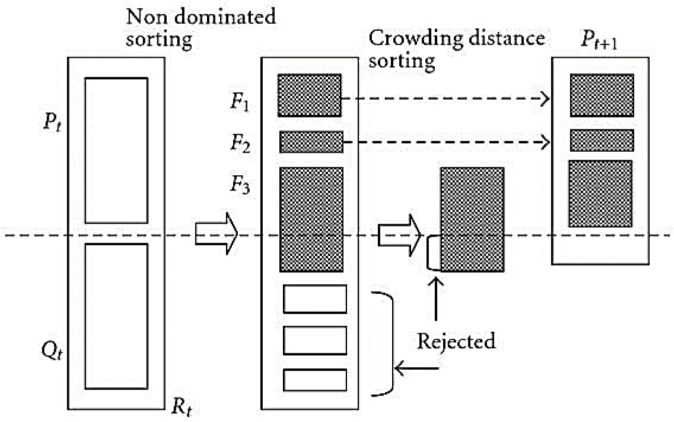


Figure 3. The procedure of NSGA-III algorithm.

4.2.2 Bat algorithm

Bats are a remarkable group of animals, distinguished as the only mammals capable of sustained flight. Additionally, they possess the unique ability to navigate using echolocation. Most bats emit sounds within a specific frequency range to determine their position in space. Among the various species, small bats are particularly well-known for their use of echolocation to locate objects. These bats emit high-intensity sound pulses and listen to the returning echoes as the sound waves bounce off objects in their surroundings (Yang, 2013) [42]. The bat optimization algorithm, first introduced by Yang (2013), is inspired by the echolocation behavior of small bats as they hunt for prey.
The development of this optimization algorithm is based on the following general principles:
Rule 1: All bats perceive distance through echoes and can distinguish between the echoes produced by food and those generated by other objects in their environment.
Rule 2: Bats that pursue their prey move at velocities v_i and positions p_i, with a continuous frequency f_{min}, varying wavelengths, and a volume R. They can automatically adjust their wavelength and the rate of their emitted pulses ($r \in [0,1]$) to track their prey.
Rule 3: While the volume of the emitted sound pulses can vary, it is assumed that these changes are constrained between a maximum value R and a minimum value R_{min}.

4.2.2.1 Formulation of the Bat algorithm

Based on the aforementioned rules, the following equations are employed to mathematically model the movement of each virtual bat i within the search space of dimension d. These equations determine the next position P_i and velocity V_i of the bat in each iteration of the algorithm.

$$f_i = f_{min} + (f_{max} - f_{min})\beta, \tag{24}$$

$$v_i^{\tau+1} = v_i^{\tau} + (p_i^{\tau} - p_*^{\tau})f_{i,} \tag{25}$$

$$p_i^{\tau+1} = p_i^{\tau} + v_i^{\tau}. \tag{26}$$

In this context, τ represents the algorithm's iteration counter, and β is a random variable uniformly distributed between zero and one. The variable p_*^{τ} denotes the best-known position, which is updated in each iteration by comparing it with the new positions of the virtual bats. If no better position is found, a local search is performed using the equation $p_{new} = p_{old} + \varepsilon R^{\tau}$, where a random rotation around the best bat's position is applied. Here, $\varepsilon \in [-1,1]$ constrains the random rotation steps. In this equation, $R^{\tau} = \langle R_i^{\tau} \rangle$ represents the average bandwidth of the sound pulses emitted by all bats after τ iterations. Additionally, the volume R_i and the pulse rate r_i emitted by each bat in every iteration of the algorithm are updated according to the following equations:

$$R_i^{i+1} = \alpha R_i^{\tau}, \quad \forall\, 0 \le \alpha \le 1, \tag{27}$$

$$r_i = [1 - \exp(-\gamma\tau)], \quad \forall \gamma \ge 0. \tag{28}$$

As indicated in the above equation, the range of changes for r spans from zero to one, where zero signifies no pulse transmission and one represents the maximum transmission rate. The standard procedures of the bat optimization algorithm are illustrated in the following figure. It's important to note that the pulse rate r_i is crucial for simulating the bat's natural behavior. As a bat approaches its prey, it increases its pulse emission frequency to better monitor the prey's movements. This behavior is replicated in the bat optimization algorithm by adjusting the parameter r_i. The closer r_i is to one, the higher the likelihood that the local search will focus around the best-known location. According to the algorithm's process depicted in the figure, it is noteworthy that when the variables r_i and R_i are set to zero, the algorithm behaves similarly to a particle swarm optimization algorithm. Additionally, it should be emphasized that the termination of the algorithm is contingent upon reaching a predetermined number of iterations.

4.2.2.2 Steps of bat optimization algorithm

Regardless of the type of algorithm employed, the first step is to select the appropriate cost function. The variable A (one of the rows in the population matrix, representing the weights of the neural network) is defined as a row vector. This vector is used to construct the desired neural network. To achieve this, a function is developed with the primary purpose of creating a network based on the specified number of layers and the neurons within each layer. Next, the evaluation stage begins by testing different values of A. Utilizing the defined weights function, the network's output is simulated by inputting the relevant data. The mean squared error (MSE) is then calculated by comparing the network's output with the actual output. This error is stored as the cost function, which serves as a key metric for assessing the network's performance.

4.2.3 Whale algorithm

The algorithm begins with a set of random initial solutions. During each iteration, the search agents update their positions based on the previously outlined principles. The parameter A is gradually decreased from 2 to 0 to facilitate both exploration and exploitation phases. Two scenarios are considered for updating the search positions of the agents: when $|A| > 1$, a random search agent is selected, whereas when $|A| < 1$, the best-known solution is chosen. The whales alternate between helical and rotational movements, governed by the value of p. The algorithm continues until it meets the predefined satisfaction criteria, at which point it terminates. A pseudo-algorithm illustrating this process is presented below. It is important to note that a, b, c, I, and p are random parameters used to update the solutions. The structures of the bat and whale algorithms are illustrated in Figure 4 and Figure 5, respectively. In this study, the design of the algorithm is centered around a Pareto archive, which serves as the foundation. This archive is updated with each iteration, ensuring that the most optimal solutions are preserved. Additionally, an improvement procedure is applied in every iteration of the algorithm to enhance the quality of the solutions continuously.

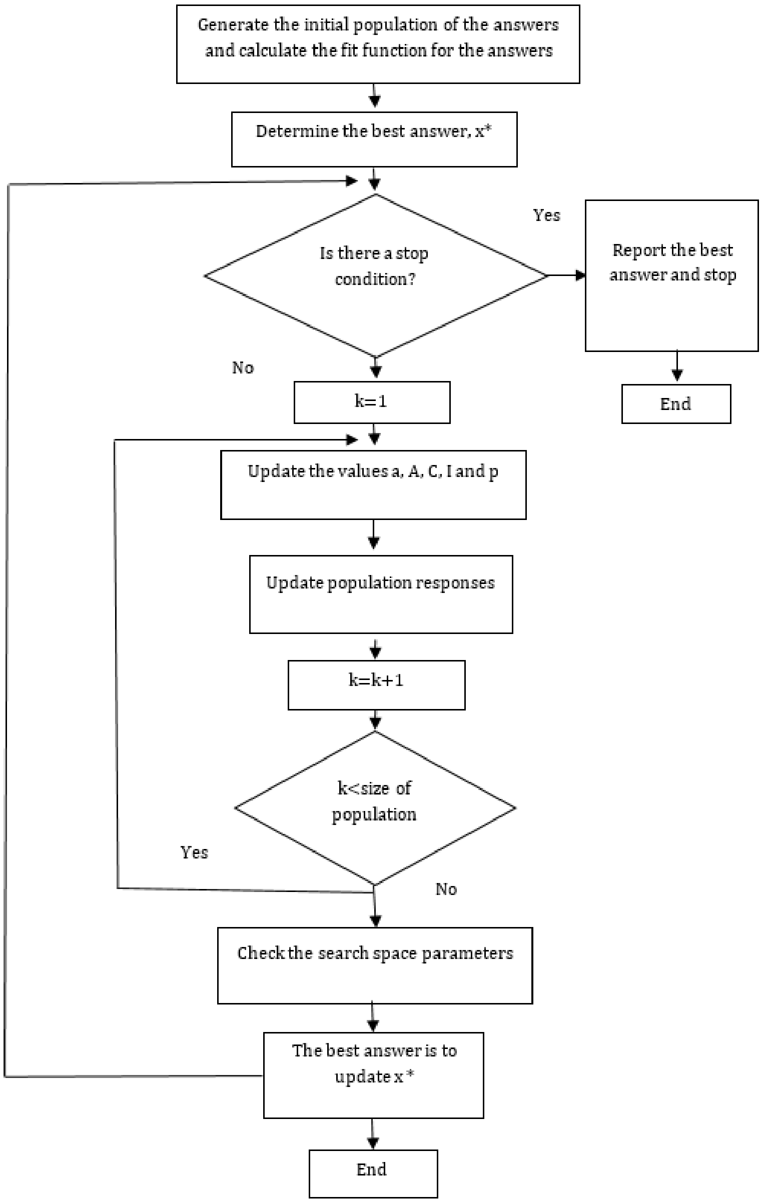


Figure 4. Steps of the Bat algorithm adopted from Yang, 2013 [42].

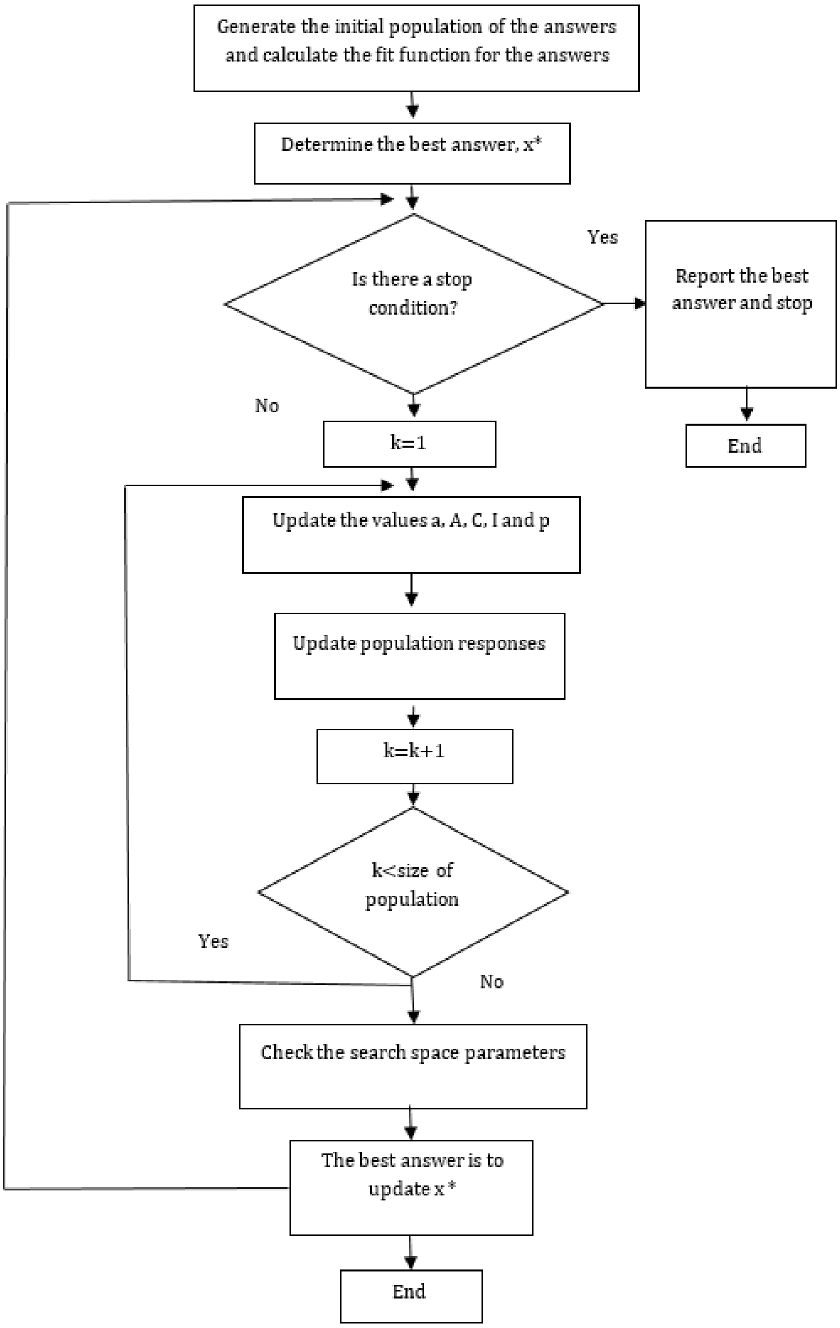


Figure 5. Steps of the whale algorithm adopted from Mirjalili and Lewis [43].

5 Computational result and sensitivity analysis

In this section, meta-heuristic algorithms are employed to optimize the proposed model. The optimization process begins with solving the model on a smaller scale to validate its accuracy and effectiveness. This initial step ensures that the model is functioning correctly and provides a foundation for further analysis. Once the model's validity is confirmed, it is subjected to a comprehensive analysis using three advanced algorithms: NSGA-III, bat, and whale algorithms. The decision variables generated by these algorithms are meticulously recorded, and a detailed sensitivity analysis is conducted on the model. This analysis focuses on evaluating the influence of various parameters on two critical factors: cost and decentralization. The sensitivity analysis is crucial for understanding how changes in different parameters affect the model's outcomes, particularly in terms of cost efficiency and the degree of decentralization. Decentralization is a key aspect that contributes to the resilience of the system, and its impact is thoroughly examined to ensure that the model promotes robustness in the face of uncertainties. All algorithms are implemented in MATLAB software, which provides a robust platform for executing complex computational tasks and analyzing the results. The combination of meta-heuristic optimization and sensitivity analysis offers deep insights into the model's performance and its ability to balance cost with decentralization, ultimately enhancing the system's resilience.

5.1 Validation of mathematical model

In this section, the model is validated on a small scale. Initially, 15 samples are identified and tested across various dimensions to assess the model's performance in different scenarios. The computational time required for solving the model in these small dimensions is also evaluated to understand its efficiency. The details of these 15 examples, including their varying dimensions, are summarized in Table 1.

Table 1. The problem in small dimensions.

Problem Number	Supplier	Producer	Store	Wholesaler	Product	Area
1	3	2	1	1	1	2
2	3	2	1	2	1	2
3	4	2	1	3	1	3
4	4	2	1	4	2	3
5	5	3	2	5	2	3
6	5	3	2	6	2	4
7	6	3	2	7	3	4
8	6	3	2	8	3	4
9	7	4	3	9	3	5
10	7	4	3	10	4	5
11	8	4	3	11	4	5
12	8	4	3	12	4	6
13	9	5	4	13	5	6
14	9	5	4	14	5	6
15	10	5	4	15	5	7

As presented in Table 2, 15 problems of varying dimensions, both small and large, are highlighted. These problems were subsequently solved using GAMS software, and the recorded results are summarized below.

Table 2. Problem-solving in small to large dimensions.

Problem number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Computational time	18	26	33	41	56	68	79	90	97	112	123	137	151	low memory	low memory

As demonstrated in Table 2 and Figure 6, the time required to solve a problem increases as the problem's dimensions expand. Up to example 13, the problems are solvable within the available computational resources. However, for problems 14 and 15, a low memory error is encountered, indicating that these larger-dimensional problems exceed the system's memory capacity and, therefore, cannot be solved using conventional methods. This limitation highlights the necessity of employing meta-heuristic algorithms to tackle problems of this scale effectively. These algorithms are better suited for handling large, complex problems, offering a more scalable and efficient approach to optimization when traditional methods fall short.

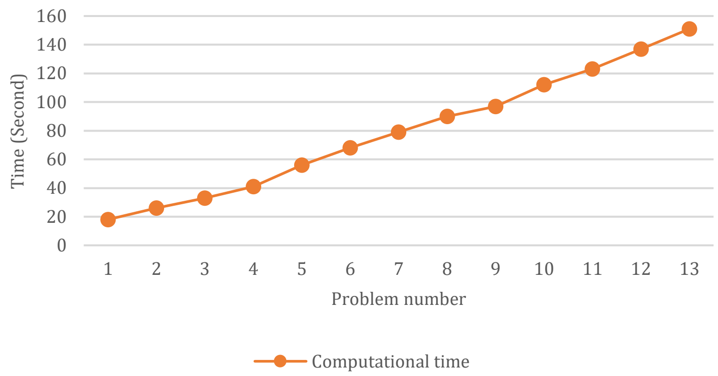


Figure 6. Computational time from small to large dimensions.

5.2 Results on large dimensions

This section presents the results obtained from addressing the problem in large-sized instances. Table 3 outlines the various key parameters involved in the multi-objective model, providing an overview of their respective quantities.

Table 3. The results of large-sized instances.

Problem Number	Supplier	Producer	Store	Wholesaler	Product	Area
1	9	5	4	14	5	6
2	10	5	4	15	5	7
3	10	6	4	15	5	7
4	12	6	5	16	5	7
5	12	7	5	16	6	7
6	14	7	5	17	6	8
7	14	8	6	17	6	8
8	15	8	6	18	6	8
9	15	9	6	18	7	8
10	16	9	7	19	7	9
11	16	10	7	19	7	9
12	17	10	7	20	7	9
13	18	11	8	20	8	10
14	19	12	8	21	8	10
15	20	12	8	22	8	10

The scale of a large-sized problem is defined in the following manner. For instance, in the first problem, the number of suppliers and producers is set at 9 and 5, respectively. In contrast, in the 15th problem, these numbers increase to 20 suppliers and 12 producers. Additionally, the number of products rises from 5 to 8, and the number of regions expands from 6 to 10 in the 15th problem. Subsequently, the performance of the algorithms is assessed based on four criteria: distance to the ideal point, congestion distance, solving time, and the number of Pareto points generated (Table 4).

Table 4. Comparison of algorithm performance.

	NSGA-III				Bat				Whale			
Example	Number of Pareto solutions	Distance to the ideal solutions	Congestion distance	Computational time	Number of Pareto solutions	Distance to the ideal solutions	Congestion distance	Computational time	Number of Pareto solutions	Distance to the ideal solutions	Congestion distance	Computational time
1	8	0.81	33	64	13	0.79	80	71	5	0.82	88	67
2	7	0.82	41	79	5	0.78	74	86	11	0.83	92	82
3	5	0.81	43	102	8	0.78	61	109	14	0.83	43	105
4	13	0.83	40	117	12	0.79	95	124	6	0.81	58	120
5	15	0.84	89	133	10	0.8	94	140	13	0.82	50	136
6	7	0.85	33	158	6	0.81	77	165	9	0.83	86	161
7	15	0.85	92	177	7	0.8	85	184	6	0.84	55	180
8	12	0.86	39	192	13	0.81	59	199	10	0.81	82	195
9	15	0.87	39	210	12	0.82	85	217	9	0.82	59	213
10	11	0.86	77	227	10	0.82	45	234	16	0.81	82	230
11	17	0.82	69	245	7	0.79	79	252	9	0.81	71	248
12	7	0.81	51	263	8	0.8	73	270	12	0.82	88	266
13	12	0.83	48	288	10	0.81	69	295	17	0.83	77	291
14	16	0.84	48	308	10	0.8	71	315	14	0.84	48	311
15	7	0.85	72	327	14	0.82	92	334	5	0.81	42	330

In Figure 7, the horizontal axis represents the different problems, while the vertical axis indicates the number of Pareto points generated. As illustrated in the figure, the Pareto points provide a comparison among the three algorithms. The NSGA-III algorithm produced more Pareto points compared to the Whale and Bat algorithms. Additionally, it appears that the Bat algorithm had the lowest output of Pareto points. Therefore, the NSGA-III algorithm demonstrated superior performance in generating Pareto points.

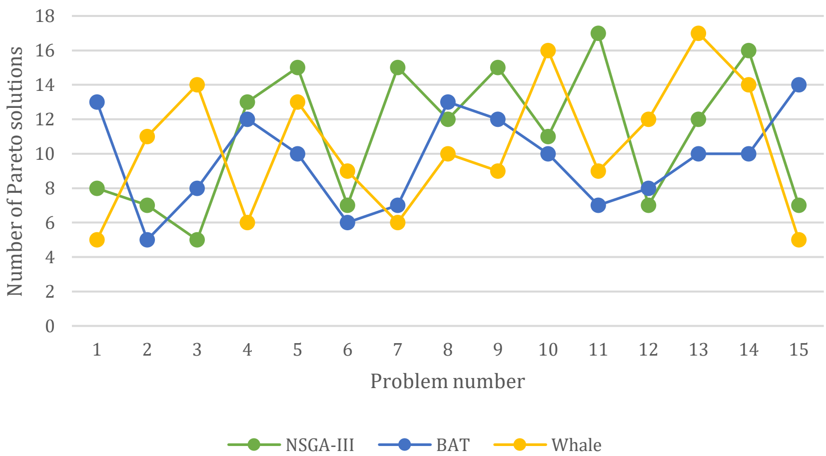


Figure 7. Comparison of Pareto diagrams generated by the tailored algorithms.

In Figure 8, the horizontal axis represents the problem numbers, while the vertical axis displays the distance to the ideal point. The Bat algorithm demonstrated superior efficiency compared to the other two algorithms, with the Whale algorithm following closely behind. The NSGA-III algorithm, on the other hand, exhibited the least efficiency, producing the greatest distance to the ideal point.

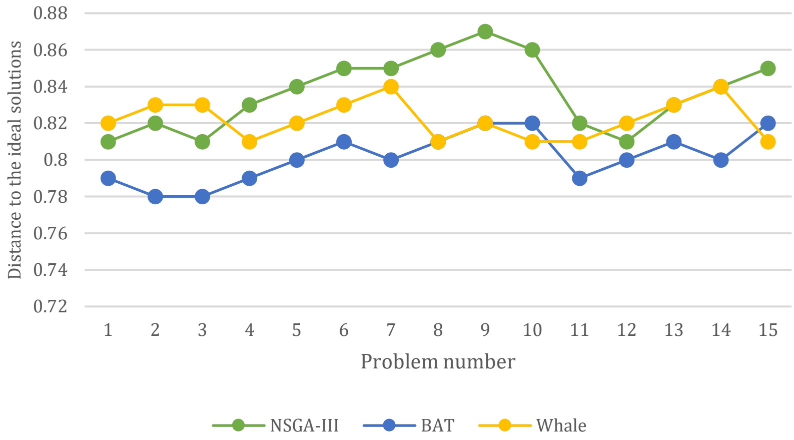


Figure 8. Comparison of the distance to the ideal point.

In Figure 10, the horizontal axis represents the problems, while the vertical axis indicates the congestion distance. As illustrated, the NSGA-III algorithm generated the lowest congestion distance, which signifies its higher efficiency. The lower the congestion distance, the more efficient the algorithm is considered to be. The figure shows that the NSGA-III algorithm consistently resulted in the lowest congestion distance overall, followed by the Whale algorithm. In contrast, the Bat algorithm produced the highest congestion distance, indicating the least efficiency among the three algorithms.

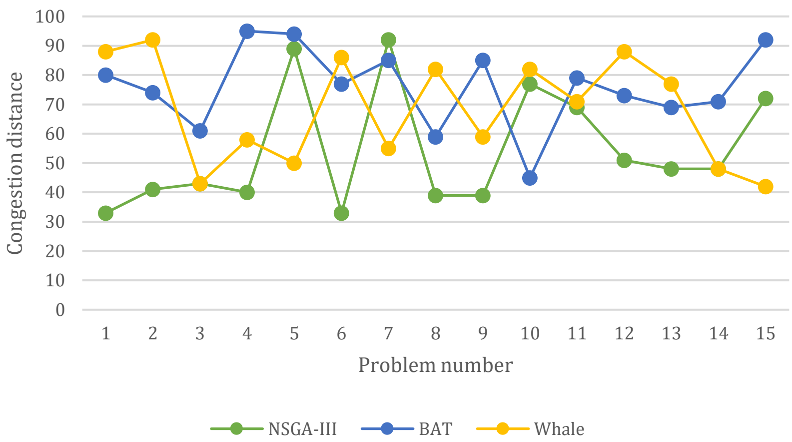


Figure 9. Comparison of congestion distance.

In Figure 10, the horizontal axis represents the problem numbers, while the vertical axis displays the computational time. As shown, there is minimal difference in computational time among the algorithms. However, the NSGA-III algorithm, represented in blue, consistently shows slightly shorter computational times compared to the other two algorithms, while the Bat algorithm exhibits slightly longer times. Overall, although the NSGA-III algorithm demonstrates the shortest computational time, the differences between the algorithms are not significant.

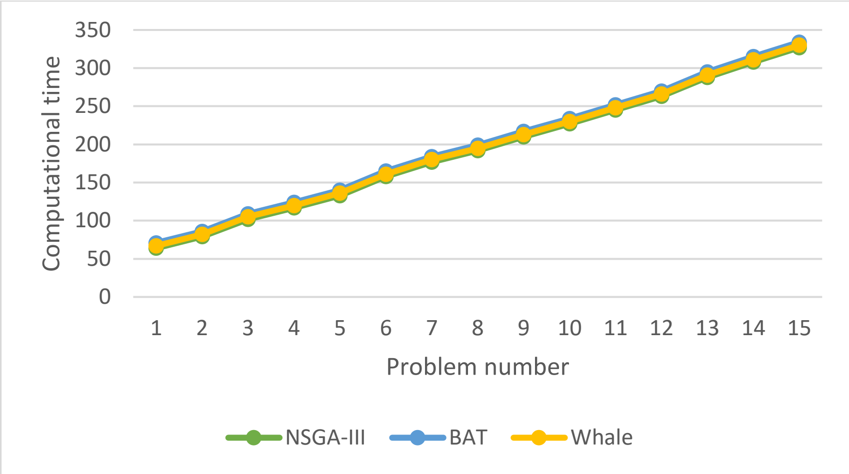


Figure 10. Comparison of computational time.

5.3 Sensitivity analysis

This section presents a sensitivity analysis of the model, examining how fluctuations in key factors impact the results, specifically in terms of costs and decentralization. The sensitivity analysis highlights how the model responds to changes in determining factors, focusing on cost and risk. In other words, the analysis explores how cost and decentralization are affected under various scenarios.

These scenarios include:

- Scenario #1: Increase in fuel prices
- Scenario #2: Path disruption
- Scenario #3: General price level increase
- Scenario #4: Currency rate increase

The analysis reveals that different scenarios can significantly alter the values of the total cost, which is the first objective, and decentralization, which is the second objective. For instance, in Scenario One, where fuel prices increase, the total cost is 14,832. In Scenario Two, which involves path disruption, the total cost rises to 14,981, indicating a higher cost and a negative impact. Regarding decentralization, Scenario Three, which involves a general price level increase, results in a decentralization score of 23. In contrast, Scenario Four, involving a currency rate increase, leads to a decentralization score of 24, suggesting a deterioration in the decentralization objective under this scenario.

Table 5. Sensitivity analysis on construction cost.

Construction cost	Total Cost Scenario				Decentralization Scenario			
	1	2	3	4	1	2	3	4
0%	14832	14981	15096	15202	20	22	23	24
10%	14932	15179	15283	15382	22	23	25	26
20%	15121	15349	15449	15513	23	24	26	27
30%	15240	15454	15584	15668	25	25	28	28
40%	15402	15644	15782	15801	26	27	29	29
50%	15516	15769	15905	15907	28	28	31	31

In Figure 11, the horizontal axis represents the percentage increase in construction costs, while the vertical axis shows the total cost. As depicted in the diagram, under the 1st scenario, the lowest total cost is associated with the construction cost. Conversely, the 4th scenario results in the highest total cost due to construction cost increases, making it the worst-case scenario. The 2nd and 3rd scenarios fall in between, representing an average state in terms of their impact on total cost (as outlined in Table 8).

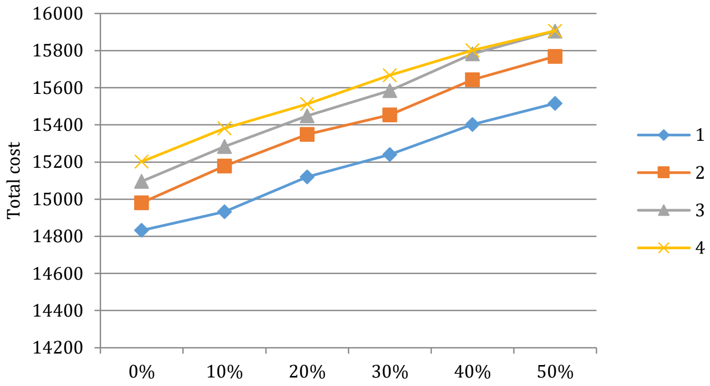


Figure 11. Sensitivity analysis on construction cost parameter and its effect on total cost.

In Figure 12, the horizontal axis represents the percentage increase in construction costs, while the vertical axis indicates the total level of decentralization. From the perspective of decentralization, the 1st and 2nd scenarios demonstrate a relatively better outcome compared to the 3rd and 4th scenarios. Interestingly, the 1st and 2nd scenarios overlap in some instances, as do the 3rd and 4th scenarios. In summary, the 1st scenario shows the most favorable reaction, while the 4th scenario exhibits the worst.

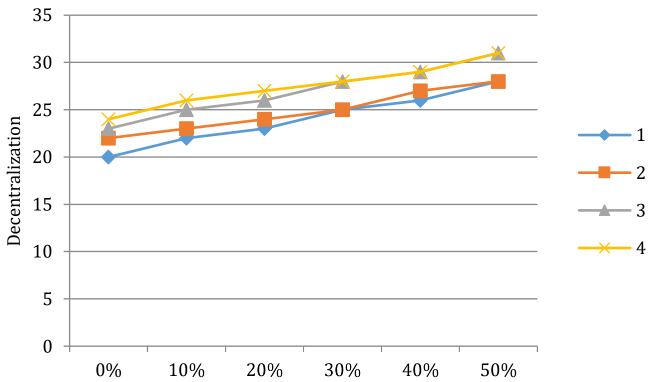


Figure 12. Sensitivity analysis of the construction cost and its effect on decentralization.

In Figure 13, the horizontal axis represents the percentage increase in transportation costs, while the vertical axis displays the total cost. According to this figure, the 1st scenario results in the lowest total cost associated with transportation costs. In contrast, the 4th scenario represents the worst case, with transportation costs leading to the highest total cost. The detail of the results is presented in Table 6.

Table 6. Sensitivity analysis on transportation cost.

Transfer cost	Total cost Scenario				Decentralization Scenario			
	1	2	3	4	1	2	3	4
0%	14832	15020	15210	15337	20	22	24	26
10%	14989	15150	15392	15445	21	23	26	28
20%	15137	15348	15502	15568	23	25	28	30
30%	15237	15508	15699	15753	24	26	30	32
40%	15437	15657	15885	15938	26	27	31	34
50%	15542	15848	16035	16041	27	28	32	36

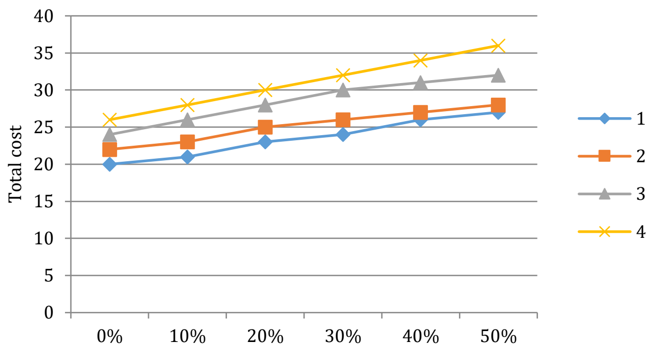


Figure 13. Sensitivity analysis on transportation cost and its effect on total cost.

Figure 14 illustrates the sensitivity analysis of transfer costs in relation to decentralization. In this figure, the horizontal axis represents the percentage increase in transfer costs, while the vertical axis shows the total decentralization. The analysis reveals that increasing transfer costs can lead to a reduction in decentralization. Notably, decentralization is at its lowest level in the 1st scenario, while the 4th scenario exhibits the highest level of decentralization. Among the scenarios, the 2nd scenario has the least impact on decentralization, followed by the 3rd scenario (as shown in Table 6).

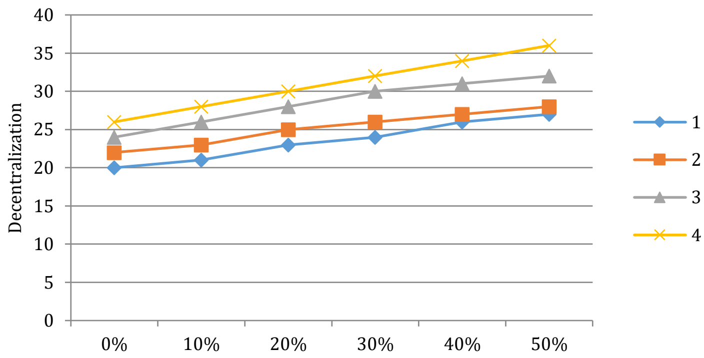


Figure 14. Sensitivity analysis on transportation cost and its effect on decentralization.

As shown in Figure 15, the horizontal axis represents the percentage increase in ordering costs, while the vertical axis displays the total cost. The figure indicates that an increase in ordering costs leads to a corresponding increase in the total cost. However, this increase is minimal in the 1st scenario, while the 4th scenario represents the worst-case scenario, with the most significant impact on ordering costs. It is also noteworthy that the 2nd and 3rd scenarios rank second and third, respectively, in terms of their impact (as detailed in Table 7).

Table 7. Sensitivity analysis of the ordering cost.

Ordering cost	Total cost				Decentralization			
	Scenario				Scenario			
	1	2	3	4	1	2	3	4
0%	14832	15002	15174	15322	20	21	23	24
10%	14951	15113	15362	15487	22	22	24	25
20%	15117	15229	15533	15596	24	23	25	27
30%	15248	15409	15728	15786	26	25	26	28
40%	15438	15565	15837	15912	28	27	27	30
50%	15609	15764	16033	16065	30	28	29	32

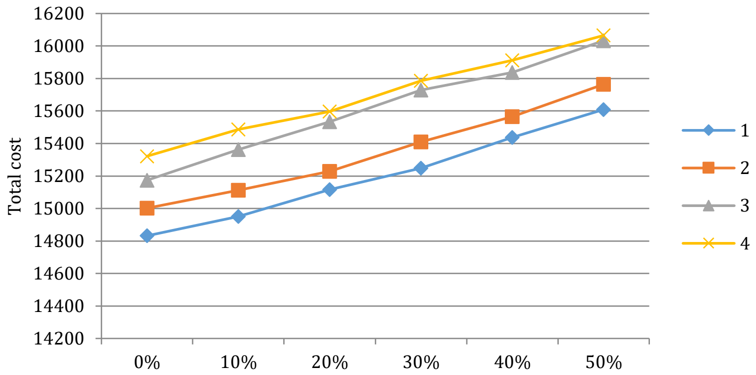


Figure 15. Sensitivity analysis of the ordering cost and its effect on total cost.

In Figure 16, the horizontal axis represents the percentage increase in ordering costs, while the vertical axis displays the total level of decentralization. The figure illustrates that an increase in ordering costs can negatively impact decentralization, leading to a reduction in the overall decentralization. The 2nd scenario represents the best case, with the least negative impact on decentralization. In contrast, the 4th scenario exhibits the worst-case impact. The 1st and 3rd scenarios follow closely behind the 2nd scenario in terms of their effect on decentralization.

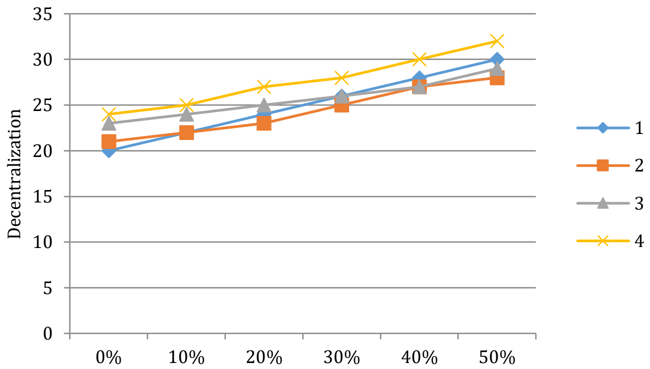


Figure 16. Sensitivity analysis of the ordering cost and its effect on decentralization.

Figure 17 illustrates the relationship between the percentage increase in production costs (horizontal axis) and the total amount of decentralization (vertical axis). The figure shows that as production costs increase, the total decentralization also increases. The best scenario, with the least impact on decentralization, is the 1st scenario, while the 4th scenario represents the worst-case scenario, with the most significant negative effect. The 2nd and 3rd scenarios are ranked second and third, respectively, in terms of their impact on decentralization (as detailed in Table 8).

Table 8. Sensitivity analysis of the production cost.

Production cost	Total cost Scenario				Decentralization Scenario			
	1	2	3	4	1	2	3	4
0%	14832	14983	15152	15334	20	22	23	24
10%	14987	15124	15332	15470	22	23	25	26
20%	15132	15228	15524	15643	23	25	27	27
30%	15261	15366	15717	15764	24	26	29	28
40%	15375	15472	15836	15963	25	27	31	29
50%	15563	15593	16035	16159	26	28	32	31

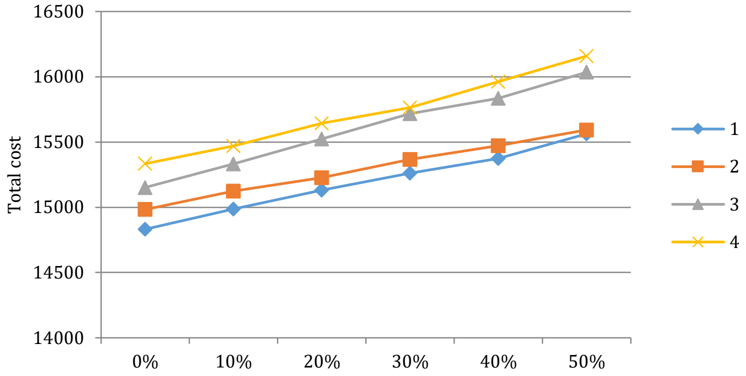


Figure 17. Sensitivity analysis of the production cost and its effect on total cost.

In Figure 18, the horizontal axis represents the percentage increase in production costs, while the vertical axis shows the total amount of decentralization. An increase in production costs can lead to a reduction in decentralization, thereby increasing the need for centralization. It appears that the 3rd scenario, rather than the 4th, represents the worst case in this context. The 2nd scenario remains in the second position in terms of its impact on decentralization.

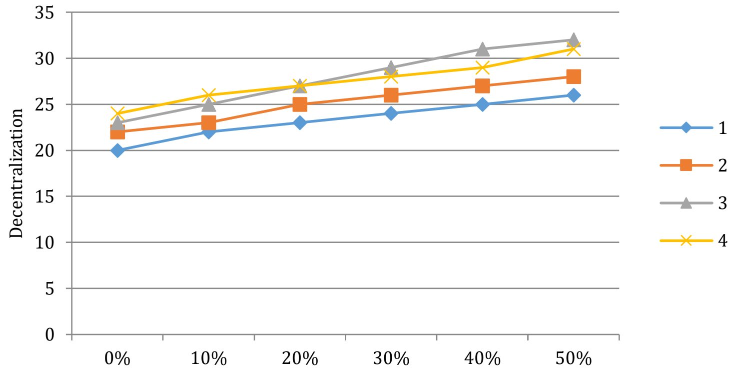


Figure 18. Sensitivity analysis of the production and its effect on decentralization.

As depicted in Figure 19, the horizontal axis represents the percentage increase in warehousing costs, while the vertical axis shows the total cost. The figure demonstrates that an increase in warehousing costs leads to a rise in the total system cost. However, the 1st scenario presents a more favorable outcome compared to the others, while the 4th scenario represents the worst-case situation (as detailed in Table 12).

Table 9. Sensitivity analysis of the warehousing cost.

Decentralization Scenario				Total cost Scenario				Warehousing cost
4	3	2	1	4	3	2	1	
23	22	21	20	15251	15083	14937	14832	0%
24	24	23	21	15397	15205	15112	14958	10%
26	25	25	23	15555	15357	15237	15067	20%
28	27	27	25	15693	15476	15420	15225	30%
29	28	29	27	15804	15585	15540	15352	40%
30	30	30	28	15918	15772	15730	15464	50%

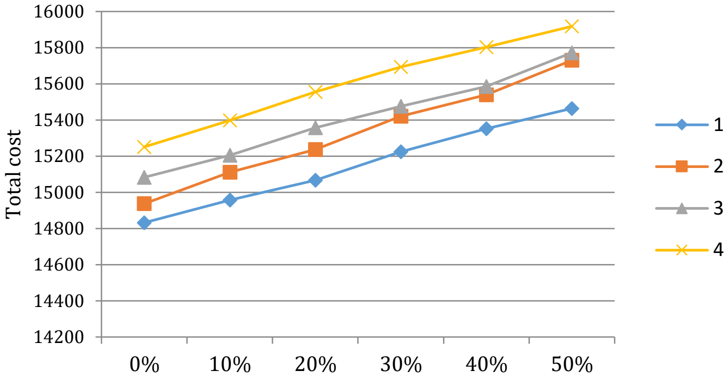


Figure 19. Sensitivity analysis of the warehouse cost and its effect on total cost.

In Figure 20, the horizontal axis represents the percentage increase in warehousing costs, while the vertical axis shows the total rate of decentralization. The data indicate that an increase in warehousing costs tends to strengthen centralization. Although scenarios 2, 3, and 4 appear to overlap to some extent, the 1st scenario represents the best case with the least impact on centralization. Conversely, the 4th scenario exhibits the worst case, with the most significant impact on centralization.

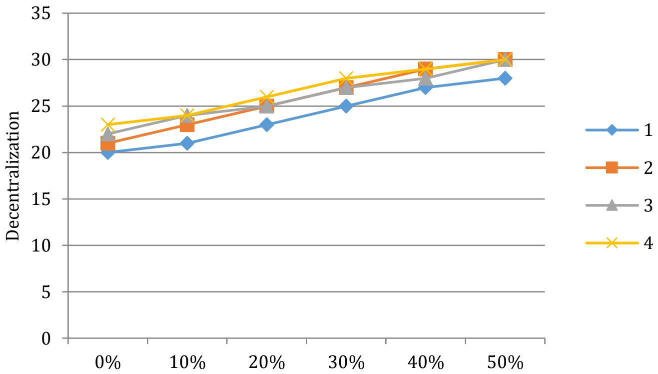


Figure 20. Sensitivity analysis of the warehousing cost and its effect on decentralization.

In Figure 21, the horizontal axis represents the percentage increase in purchase costs, while the vertical axis shows the total cost. The data indicate that, in the 1st scenario, the purchase cost has the lowest impact on the system's total cost. Conversely, the 4th scenario represents the worst case, where the purchase cost has the most significant impact on the total cost (as detailed in Table 10).

Table 10. Sensitivity analysis of the purchase cost.

Purchase cost	Total cost Scenario				Decentralization Scenario			
	1	2	3	4	1	2	3	4
0%	14832	14944	15051	15242	20	22	24	25
10%	14954	15054	15245	15393	21	24	26	26
20%	15114	15181	15396	15592	23	26	28	28
30%	15226	15325	15547	15766	25	27	29	30
40%	15378	15486	15717	15964	26	29	31	31
50%	15566	15628	15845	16136	28	30	32	32

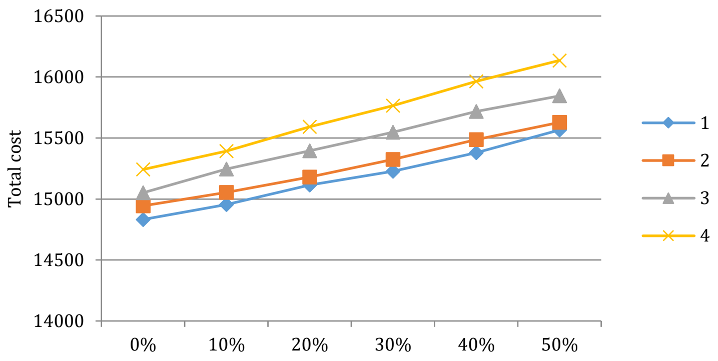


Figure 21. Sensitivity analysis of the purchase cost and its effect on total cost.

As presented in Figure 22, the horizontal axis represents the percentage increase in purchase costs, while the vertical axis shows the total amount of decentralization. It is evident that the purchase costs in the 4th and 3rd scenarios result in the most adverse impact on decentralization. Conversely, the 1st scenario shows the lowest impact on decentralization, indicating a more favorable outcome.

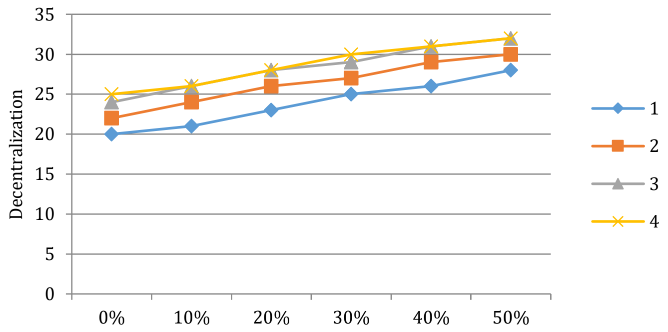


Figure 22. Sensitivity analysis of the purchase cost and its effect on decentralization.

In Figure 23, the horizontal axis represents the percentage increase in the studied parameters, while the vertical axis shows the total cost. According to the diagram, warehousing costs have the lowest impact on the total cost compared to the other parameters. The other costs, however, are nearly equal in their impact and tend to overlap (as shown in Table 11).

Table 11. The comparison of parameters effect on total cost.

Percentage of increase	Construction cost	Transportation cost	Ordering cost	Production cost	Warehousing cost	Purchase cost
0%	14832	14832	14832	14832	14832	14832
10%	14932	14989	14951	14987	14958	14954
20%	15121	15137	15117	15132	15067	15114
30%	15240	15237	15248	15261	15225	15226
40%	15402	15437	15438	15375	15352	15378
50%	15516	15542	15609	15563	15464	15566

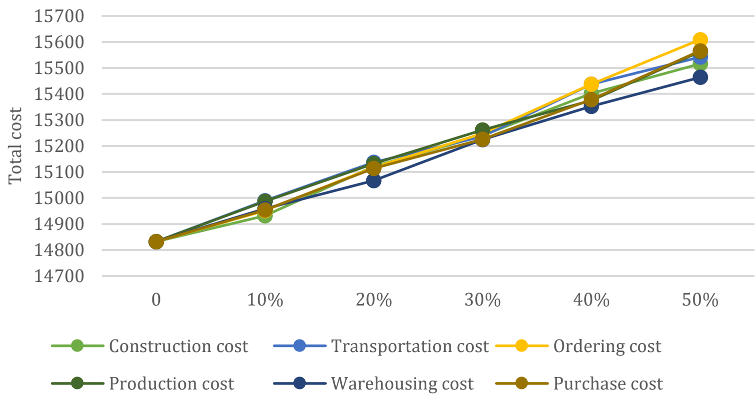


Figure 23. The comparison of parameters effect on total cost.

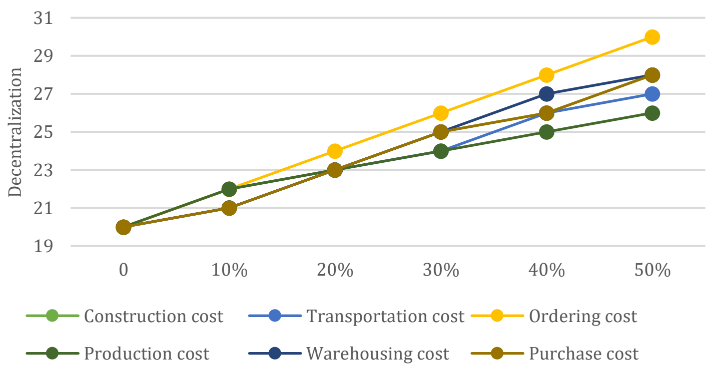
In Figure 24, the horizontal axis represents the percentage increase in the studied parameters, while the vertical axis indicates the total amount of decentralization. The diagram reveals that ordering costs have the most significant impact on decentralization, leading to its worsening and intensification. On the other hand, production costs appear to have the least effect on decentralization, with transfer costs following closely behind (as detailed in Table 12).

Table 12. The comparison of parameters effect on decentralization.

Percentage of increase	Construction cost	Transportation cost	Ordering cost	Production cost	Warehousing cost	Purchase cost
0%	20	20	20	20	20	20
10%	22	21	22	22	21	21
20%	23	23	24	23	23	23
30%	25	24	26	24	25	25
40%	26	26	28	25	27	26
50%	28	27	30	26	28	28

Figure 24. The comparison of parameters effect on decentralization.

6 Conclusion and future suggestions



The results of the sensitivity analysis show that all the evaluated parameters significantly influence both the costs and decentralization of the supply chain. As various cost parameters increase, overall costs rise, leading to greater centralization. In other words, higher costs affect the supply chain's order and centralization strategies, with the effects differing across scenarios. The first scenario consistently produced the most favorable results, showing the smallest increases in both cost and centralization, while the fourth scenario exhibited the most unfavorable conditions, with the largest increases in both metrics. Typically, the second scenario had the second most significant impact, followed by the third scenario. Among the cost parameters, storage costs were found to have a smaller impact compared to others. This is partly due to the minimal differences and overlaps among the other cost parameters, making it difficult to definitively determine whether, for instance, construction costs have a greater effect on overall system costs than transportation costs. However, it is clear that storage costs have a lesser impact on total system costs compared to production costs. When it comes to decentralization, the influence of these parameters varies more across supply chain components than their effect on overall costs. In general, production costs contribute less to increasing centralization and reducing decentralization than other cost parameters. These results highlight the importance of considering these factors to mitigate risks and improve supply chain resilience. Storage costs were found to have the greatest effect on centralization, followed by ordering costs, both of which significantly increase the concentration of supply chain components. Meanwhile, transfer and construction costs have a moderate impact, which, while significant, is less pronounced.

Based on the findings and limitations of this study, the following recommendations are suggested for future research to strengthen the robustness of supply chain modeling:

- Incorporating additional parameters for decentralization: To further refine the analysis of decentralization within resilient supply chains, future studies should investigate the inclusion of additional parameters such as network topology, decision-making autonomy, or resource allocation. These factors could provide deeper insights into how decentralization affects both the flexibility and adaptability of supply chains, contributing to a more nuanced understanding of how decentralized systems respond to disruptions and recover from them.
- Integrating stability constraints into resilience modeling: Incorporating stability constraints into the resilience framework of the supply chain model would enhance its ability to handle unexpected disruptions while maintaining operational continuity. Stability constraints, such as limits on fluctuations in production or inventory levels, would ensure that the supply chain remains operational under stress, contributing to a more resilient system that can recover quickly from shocks without significant loss in efficiency or performance.
- Comparative analysis of meta-heuristic algorithms: A comparative analysis between the algorithms used in the current study (NSGA-III, bat, and whale) and newer meta-heuristic algorithms, such as particle swarm optimization (PSO) or artificial bee colony (ABC) algorithms, could uncover potential improvements in optimization performance. By comparing different algorithmic approaches, researchers could identify methods that offer better accuracy, faster convergence, or greater ability to find global optimal solutions in complex supply chain scenarios, contributing to more efficient supply chain management.
- Applying a fuzzy logic approach to parameters: Future research should consider incorporating a fuzzy logic approach to manage the inherent uncertainty and imprecision in real-world supply chain scenarios. By allowing parameters such as demand forecasts, lead times, or cost estimates to take on fuzzy values, the model would better reflect the variability and ambiguity present in practice. This could result in more robust and adaptable decision-making processes, enabling supply chains to operate effectively even under conditions of uncertainty.
- Transitioning from a three-level to a four-level supply chain: To better represent more complex real-world supply chains, researchers could explore transitioning from a three-level to a four-level supply chain model. Adding an additional level, such as distribution centers or suppliers, would capture more intricate relationships and dependencies, offering a more accurate representation of modern supply chain dynamics. This could improve the model's applicability to industries with more complex logistics networks, such as manufacturing or retail.
- Exploring closed-loop or green supply chain configurations: Finally, it is recommended that future studies explore the application of the current supply chain model within the context of closed-loop or green supply chains. By incorporating sustainability objectives, such as reducing waste, recycling, or minimizing environmental impact, the model could be aligned with the growing demand for environmentally responsible practices. This would ensure that supply chains are not only resilient and decentralized but also sustainable, addressing the rising emphasis on resource efficiency and environmental stewardship in global supply chains.

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