A FUZZY CHANCE-CONSTRAINED PROGRAMMING MODEL FOR MATHEMATICAL MODELING-BASED METAHEURISTIC ALGORITHMS IN THE DESIGN OF GREEN LOOP SUPPLY CHAIN NETWORKS FOR POWER PLANTS

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Abstract:

This study introduces a multi-cycle supply chain design model, encompassing crucial executive decisions confronting supply chain management firms. These decisions encompass facility location, the flow of raw material procurement, and investments in diversifying activities within the power plant's supply chain design. A fuzzy chance-constrained programming approach is employed to deal with the uncertainties associated demand and cost, and a service level indicator is incorporated into the performance metric. The model's validation is conducted on a larger scale, employing two metaheuristic algorithms, MOPSO and NSGAII. The results revealed that the MOPSO algorithm exhibited faster computational efficiency than NSGAII and demonstrated superior performance in the first and second objective functions. However, analytical parameters such as NPF, MSI, and SM favored the NSGAII algorithm over MOPSO. This study presents a comprehensive multi-cycle supply chain design model addressing key management decisions, dealing with demand and cost uncertainty, and evaluating performance using a service level indicator. The study's findings underscore the efficiency of the MOPSO algorithm in computational speed but highlight NSGAII's advantages in terms of certain analytical parameters. These insights contribute to enhancing supply chain management strategies in diverse scenarios.

1 Introduction

Iran, a global energy powerhouse, boasts an extensive reservoir of energy resources, positioning it as one of the most influential players in the energy landscape [1]. The nation's impressive portfolio includes over 85 discovered oil fields, solidifying its global prominence [2]. Moreover, Iran stands as the world's second-largest holder of natural gas reserves, with an estimated 2.616 trillion cubic meters still untapped. Beyond these abundant fossil fuels, Iran possesses substantial coal reserves [3].

Recognizing the pivotal role of energy in the production processes of various commodities and the concurrent challenges of its scarcity, the imperative of enhancing energy efficiency has gained prominence among economic stakeholders [4], [5]. Iran faces the predicament of disproportionately high per capita energy consumption, attributed to the reluctance to adopt modern technologies across industries encompassing manufacturing, construction, agriculture, and transportation [6].

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This elevated energy consumption not only exacts an environmental toll but also hinders the trajectory of sustainable development, incurring substantial economic costs for producing nations [7]–[9]. The confluence of these factors underscores the urgency of adopting more efficient energy utilization practices and technologies in Iran, ensuring both economic vitality and environmental sustainability [10], [11].

In recent years, the production of green fuels has seen significant advancements, categorized into distinct generations [12]–[14]. Consequently, a pressing need arises for developing integrated supply chain design models that oversee all phases of green fuel production, from raw material procurement to manufacturing and distribution [15]–[18]. The supply chain encompasses a comprehensive network of facilities, tasks, and operations involved in creating and disseminating services or products, extending from suppliers to end customers [19]. It encompasses the strategic orchestration of supply and demand, material procurement, production, product/service scheduling, storage, inventory management, distribution, delivery, and customer service [20]. Supply chains are pervasive in manufacturing and service-oriented organizations, though their intricacy can vary substantially between industries and individual companies [21]–[23].

The essence of a supply chain lies in its role as an integrative process connecting suppliers, manufacturers, and distributors within an intricate, interdependent framework. In this collaborative ecosystem, the primary objectives are to harmonize with each organization's overarching policies, minimize inventory levels throughout the chain, and meet individual customers' unique demands at the supply chain's conclusion [24]–[27].

Conversely, there exist numerous significant factors contributing to supply chain disruptions, which can be categorized and outlined as follows [28], [29]: adverse weather and climatic conditions, disruptions in telecommunications and Information Technology (IT) networks, challenges within the transportation network, seismic events like earthquakes and tsunamis, and inadequacies in allocating external resources to critical activities. Moreover, the manifestation of varying event dimensions exerts distinct impacts on organizations. These elements underscore the imperative for organizations to cultivate and enhance resilient and adaptable capabilities capable of effectively addressing a spectrum of potential contingencies and events [30].

Hence, applying the supply chain design model within the context of green power plants holds great potential for large-scale fuel production planning. Nonetheless, one of the foremost challenges in designing and optimizing such supply chains pertains to the problem-solving approach [31]. This challenge arises due to the inherent complexity of network design models, often classifying them as intricate matters. Consequently, only a limited subset of supply chain models related to green fuels can be solved with precision using conventional methods. The intricacies of real-world scenarios introduce uncertainties into the foundational parameters of mathematical models, a facet often overlooked in most relevant studies [32]. This research introduces a noteworthy innovation by applying a problem-stabilization approach to address this challenge.

Moreover, supply chain management within natural environments constitutes a multi-objective decision-making process guided by expert oversight [33]. Consequently, developing a multi-objective mathematical model proves indispensable in green fuel supply chains. Accordingly, this paper introduces a multi-objective model aligned with the green supply chain of photovoltaic power plants while accounting for demand and cost uncertainties. Lastly, the mathematical model is fortified using the robustness approach to address uncertainties effectively.

In light of the innovative approach employed to tackle the mathematical model, it is evident that the supply chain model relating to photovoltaic power plants falls within the category of NP-Hard problems. The evaluation of this model is conducted through the utilization of metaheuristic algorithms [34], [35], providing valuable insights into the analysis of the photovoltaic power plant's supply chain.

Assessing the current research landscape on supply chain networks reveals a predominant focus on material flow and financial analysis [22], [36], [37]. However, a significant research gap emerges in the optimization of both material and financial flow within the power plant supply chain. The complexities of power plant supply chains, particularly with regard to demand uncertainty and cost variability, remain underexplored. To address this gap, a comprehensive approach is required that incorporates a multi-objective mathematical model capable of managing these inherent uncertainties [38]. Additionally, the stabilization of such models is crucial for developing robust solutions that can adapt to real-world supply chain complexities. This study introduces a novel solution by combining Fuzzy Chance-Constrained Programming (FCCP) with multi-objective metaheuristic algorithms (MOPSO and NSGAII) for optimizing supply chain networks specific to power plants. Unlike previous works that largely rely on deterministic models or simplified uncertainty handling, our model comprehensively addresses both demand and cost uncertainties through fuzzy logic. Furthermore, this research stands out by integrating environmental sustainability measures, including reverse logistics and green supply chain practices, which are often overlooked in traditional supply chain models. By using two distinct metaheuristic algorithms, this study provides a comparative analysis of computational efficiency and solution quality in large-scale, uncertain supply chain environments. This unique combination of uncertainty management, sustainability considerations, and algorithmic comparison offers a substantial contribution to the advancement of supply chain optimization models in the power plant sector.

This paper is structured as follows. Section 2 presents a detailed literature review, focusing on key areas such as environmental sustainability, economic efficiency, and uncertainty handling in supply chain models. Section 3 defines the problem and introduces the proposed fuzzy chance-constrained programming model to address supply chain uncertainties. Section 4 outlines the research findings, including the performance comparison of the MOPSO and NSGAII metaheuristic algorithms. Finally, Section 5 offers conclusions drawn from the study and provides suggestions for future research directions.

2 Literature Review

In recent years, the importance of environmental sustainability within supply chain management has grown significantly. Studies such as [39], [40] highlight the role of green supply chains in reducing carbon footprints and promoting sustainable energy practices. For instance, Genovese et al. [41] explores the integration of Life Cycle Assessment (LCA) metrics into supply chains, which allows for a more holistic view of environmental impacts from raw material procurement to product end-of-life recycling. Additionally, the concept of a closed-loop supply chain, as discussed in [42], emphasizes the importance of recycling and reusing materials to minimize waste and environmental harm. These studies align with the current research, which incorporates green logistics in power plant supply chains and considers the environmental benefits of implementing reverse flows for recycling.

Economic efficiency in supply chain management remains a central concern, particularly in energy-intensive industries like power plants. Various studies, including [43], [44], examine strategies for minimizing costs across transportation, production, and facility placement. The integration of metaheuristic algorithms, such as the ones used in this study, is commonly explored to address cost minimization in complex supply chain models [45]–[47]. Additionally, [48], [49] discusses the balance between economic efficiency and operational flexibility, highlighting the importance of reducing fixed and variable costs while maintaining service levels. These findings support the current study's focus on minimizing costs through optimization techniques in both forward and reverse logistics.

Effectively managing uncertainty is essential in supply chain optimization, particularly when facing unpredictable factors such as fluctuating demand, variable costs, and supply disruptions. Several studies, including [50], [51], highlight the importance of fuzzy programming and stochastic programming as tools to address these uncertainties. Among these, Fuzzy Chance-Constrained Programming (FCCP), proposed by Liu and Iwamura [52], stands out as a powerful extension of traditional Chance-Constrained Programming (CCP). By integrating fuzzy logic, FCCP allows for a more flexible and adaptive treatment of uncertain parameters like demand, costs, and supply availability. Its theoretical foundation stems from the combination of probabilistic constraints and fuzzy set theory, introduced by Zadeh [53], which models uncertainty not just through probabilities but by degrees of membership in fuzzy sets. In the literature of Supply Chain Management, many scholars have adopted FCCP to tackle uncertainties and imprecise data that are common in supply chains. FCCP is especially valuable in handling unpredictable factors such as fluctuating demand, uncertain lead times, and variable costs. By integrating fuzzy logic into traditional optimization frameworks, FCCP allows for more flexible decision-making under uncertainty, where constraints can be satisfied to varying degrees rather than rigidly.

The application of FCCP in the current study demonstrates its effectiveness in handling uncertainty, particularly with regard to demand and cost variables, leading to more resilient and adaptable supply chain models. In parallel, studies such as [54]–[56] explore stochastic programming as a means of managing external uncertainties, such as fuel price volatility, offering a complementary strategy for mitigating risks in supply chain operations.

Marhamati [57] explore the food cold chain, which preserves perishable food products through refrigeration from farm to consumer, maintaining appropriate temperatures to reduce microbial hazards. Their empirical study of the Australian perishable food industry identifies key impediments and performance indicators of FCC Performance (FCCP), examining how these barriers impact FCCP through factor analysis and structural equation modeling, using data from 292 senior managers in various supply chain roles. Wang et al. [58] develop a Flexible-possibilist Chance Constraints Programming (FCCP) Model to plan low-carbon Energy-Transportation Systems (METS) at a metropolitan scale, addressing multiple uncertainties. Applied to Beijing, the FCCP model reveals increasing reliance on imported power and renewable energy, while the mass adoption of Electric Vehicles (EVs) significantly reduces carbon emissions. The study highlights the need for substantial investment in battery supply facilities and emphasizes the FCCP's ability to manage complexities in power plant planning under uncertain conditions. Fateh et al. [50] highlighted the significant uncertainties introduced by Renewable Energy Sources (RESs) in Virtual Power Plants (VPPs) and the need for advanced modeling techniques. They applied FCCP for addressing such uncertainties by providing a flexible framework that accommodates the variability in RESs. Hanak et al. [59] examined the potential performance of a coal-fired power plant, considering the continued importance of coal as a primary energy source in the foreseeable future while emphasizing the need for an environmentally friendly system. The research examines the use of a stochastic method through probabilistic models to determine the possibility of power plant equipment failure by employing Monte Carlo simulation. This method is an alternative way to assess the power plant's performance and forecast significant performance indicators, such as coal consumption and inlet air rates. The technique also helps to estimate reliability indices (such as the thermal efficiency of the power plant) based on the power plant process model's input uncertainty. Sahin et al. [60] assessed the performance of a combined cycle power plant by conducting an exergy-economic analysis, applying the principles of the first and second laws of thermodynamics. They introduced a comprehensive indicator called the Total Performance Index (OPI) to gauge and analyze the power plant's ideal operation and design. They included some performance indicators: Total Investment cost (TI), Energy Efficiency (ENE), Cost of Electricity (COE), and Exergy Efficiency (EXE). Shen Ho and Lam [61] introduced an innovative optimization method utilizing principal component analysis to address the multi-layer biomass supply chain problem. This approach encompassed technology selection and transportation design, considering economic factors, environmental aspects (including various environmental impacts), and social considerations (such as health, safety, and job creation). Ashtineh and Pishvaee [62] stated that transportation activities that produce greenhouse gases can harm the environment and human health. Therefore, sustainability principles dictate that the burden of environmental problems caused by logistics activities, such as Vehicle Routing Problems (VRP), must be considered. The Pollution Routing Problem (PRP) is an extension of VRP that involves optimizing the routing of several vehicles to serve customers. It also determines their speed on each route segment to minimize fuel consumption, emissions, and driver costs. Saffarian et al. [63] introduced a financial integration and inventory routing model for a closed-loop two-level supply chain. They devised a mathematical model to address smaller-scale problems. Recognizing the complexity of larger scenarios, they employed two meta-heuristic methods—genetic algorithms and particle aggregation optimization—to tackle medium and large-scale problems efficiently.

Wu et al. [64] created a type-2 fuzzy chance-constrained model to optimize water resource management under uncertainty. Applied to Taiyuan, China, the model highlights a shift to diverse industries and increased reliance on external water sources. It also suggests that using reclaimed water can enhance water supply security, supporting sustainable development goals. Huang et al. [65] investigate a decentralized supply chain network with uncertain costs, focusing on optimizing enterprise decisions under this uncertainty. They employ a chance-constrained approach and formulate the problem as a second-order cone-constrained variational inequality model. Their analysis reveals that retailers' and manufacturers' risk attitudes significantly influence their decisions and profits, with high risk tolerance leading to greater impacts on decision-making. Additionally, adopting a chance-constrained method is beneficial when supply chain members can estimate competitors' strategies.

3 Definition of the Problem

This research uses a closed-loop supply chain network of producers (power plant raw materials including fuel oil, etc.), distribution centers and customers (power plants), recycling centers, and recycled product customers to minimize and maximize green logistics costs. It is designed to respond to the demands of two forward and reverse flows of the supply chain of green energy production.

Manufacturers dispatch their products to both distributors and customers, including power plants. Customers also have the option to obtain products from distributors. In this network spanning several periods, a portion of the energy production of raw materials generates waste at these three levels. These waste materials are then routed to a fourth level, the recycling centers, where they undergo reprocessing. After reprocessing, they are further directed to a fifth level, comprising recycling customers. Furthermore, it's worth noting that the first level of this chain can also be viewed as a subset of the fifth-level customers, highlighting the closed-loop nature of this network.

A single-product, dual-objective, and multi-period programming model has been developed to design the power plant logistics network. On the one hand, the developed model aims to minimize network costs, including the fixed cost of establishing distribution centers, transmission, inventory maintenance, and operational costs. On the other hand, it maximizes customer demand response in both the forward and reverse sectors.

As we mentioned above, in this study, the two primary objectives—minimizing costs (OF1) and maximizing responsiveness (OF2)—are central to the design of an efficient closed-loop supply chain network for power plants. However, these objectives often present competing priorities: while cost minimization focuses on reducing expenditures across various aspects of the supply chain (such as transportation, processing, inventory, and operational costs), maximizing responsiveness emphasizes the ability to quickly meet customer demands and adapt to uncertainties in demand and supply. The trade-off between these objectives stems from the fact that increasing responsiveness often incurs higher costs. For example, improving responsiveness may require more frequent shipments, additional inventory holding, or investing in more expensive, faster transportation modes—each of which raises operational expenses. On the other hand, minimizing costs typically involves reducing resource allocation, transportation frequency, or inventory levels, which can slow response times and reduce flexibility in the supply chain.

To address this inherent trade-off, the model uses a multi-objective optimization approach, where the interaction between the two objectives is explicitly modeled. Specifically:

1. The cost minimization objective (OF1) accounts for the fixed costs, transportation, inventory, and operational expenses involved in the supply chain. Reducing these costs is essential to maintaining profitability but must be balanced against maintaining a sufficient service level.
2. The responsiveness maximization objective (OF2), on the other hand, aims to ensure timely fulfillment of customer demand while incorporating the capability to process recycled products efficiently. This is critical for green supply chains that must handle both forward and reverse logistics flows.

To achieve a balanced solution, the epsilon-constraint method is employed, where one objective (typically cost minimization) is incorporated as a constraint while the other objective (maximizing responsiveness) is optimized. By adjusting the bounds on the cost constraint, the model can generate solutions that represent different levels of trade-offs between cost efficiency and responsiveness. Additionally, the MOPSO and NSGA-II algorithms, which are used to solve the model, allow for the exploration of the Pareto front, a set of optimal solutions where no objective can be improved without worsening the other. This enables decision-makers to evaluate different scenarios along the Pareto front and select a solution that best aligns with their priorities—whether it is minimizing costs, maximizing responsiveness, or finding a balanced compromise between the two. By expanding the discussion on these trade-offs, we highlight that the optimization process does not merely seek to improve one objective at the expense of the other. Instead, the model carefully balances both objectives, offering flexible decision-making options depending on the strategic importance of cost savings versus service level performance in a particular context. Therefore, this research has developed a new mixed integer linear programming mathematical model for the power plant logistics network, which we will be described in the next subsection below.

3.1 Problem modelling

In this section, the assumptions of the problem are presented first. Then, in the following, we will describe the novel two-objective model after introducing the parameters, indices, and decision variables.

For better efficiency of the problem and to be close to the real world, the following assumptions are considered:

1. The five-level energy distribution network includes (producers of materials needed by power plants, distributors, customers, recycling centers, and customers of recycled products).
2. Producers' production is not precisely known, and it is considered a decision variable smaller than the maximum production capacity of power plants.

3. The j index for the distributor includes both existing points and potential points.
4. Product transportation cost between network levels is obtained based on the distance between points. It is assumed that a type of transportation equipment with a specific capacity and cost is available.
5. Only distributors can store the raw materials of power plants.
6. To reduce the model complexity, the model has been designed as a single product as raw materials for power plant energy production.
7. It is not possible to transfer raw materials between distributors.
8. It is not possible to move between producers (power plants) or between customers.

3.2 Model symbols

The following symbols are used to develop the proposed mathematical model:

Indexes:

$i=1,2,\ldots,I$	Production sites for raw materials
$j=1,2,\ldots,J$	Candidate and fixed points of distribution locations
$k=1,2,\ldots,K$	Customer locations (power plants)
$l=1,2,\ldots,L$	Candidate and fixed points of recycling places
$t=1,..,T$	Periods
$o=1,2,\ldots,O$	Recycling customer locations

Parameters:

$\widetilde{f_j}$	The j^{th} distribution center's establishing fixed cost.
$\widetilde{f_l}$	The l^{th} recycling center's establishing fixed cost.
$\widetilde{Cx_{ij}}$	Transportation cost from manufacturer i to distributor j.
$\widetilde{Cs_{ik}}$	Transportation cost from manufacturer i to customer k.
$\widetilde{Cu_{jk}}$	Transportation cost from distributor j to customer k.
$\widetilde{Ce_{kl}}$	Transportation cost from customer k to recycling center l.
$\widetilde{Cq_{jl}}$	Transportation cost from distributor j to recycling center l.
$\widetilde{Cv_{il}}$	Transportation cost from producer i to recycling center l.
$\widetilde{Cf_{lo}}$	Transportation cost from recycling center l to compost market o.
$\widetilde{Cg_{li}}$	Transportation cost from recycling center l to producer i.
$\widetilde{Ch_t}$	Product holding cost by distributors in time t.
$\widetilde{Cp_t}$	Product processing and packaging cost in time t.
$\widetilde{Cr_t}$	Recycling centers' production cost in time t.
$\widetilde{Cp'}$	Product production cost by manufacturers.
$\widetilde{d_{kt}}$	The k^{th} customer demand in time t.
λc_{it}	The maximum capacity of producer i in time t.
λh_j	The j^{th} distributor's storage capacity.
λr_l	The l^{th} recycling center's Production and storage capacity.
α_t	The percentage of waste materials produced by the manufacturer in time t according to the parameters of greenness of the raw materials.
θ_t	The percentage of raw materials waste stored by the customer in the time t according to the parameters of greenness of the raw materials.
β_t	The percentage of raw materials waste stored by the distributor in the time t according to the parameters of greenness of the raw materials.
$\tilde{d}'_{ot}$	Demand for reprocessed/recycled products by customers o in time t.
ρ	Weighting factor (importance) to respond in forward flows.
$1-\rho$	Weighting coefficient (importance) to respond in backward flows.
φ	A percentage of waste products that can be sold to customers.
M	A vast positive number.

Decision variables:

X_{ijt}	A quantity of raw materials sent from producer i to distributor j in time t.
λ_{it}	The amount of raw materials produced by producer i in time t.
S_{ikt}	A quantity of raw materials sent from producer i to customer k in time t.
U_{jkt}	A quantity of raw materials sent from distributor j to customer k in time t.
E_{klt}	A quantity of waste raw materials sent from customer k to recycling center l in time t.
Q_{jlt}	A quantity of waste raw materials sent from distributor j to recycling center l in time t.
V_{ilt}	A quantity of waste raw materials sent from producer i to recycling center l in time t.
G_{lit}	A quantity of reproducible raw materials sent from recycling center l to producer i in time t.
Ih_{jt}	A quantity of processed raw materials held in the distributor j's warehouse in time t.
$W_j \begin{cases}1\\0\end{cases}$	One, if the distribution center is established in candidate location j, zero otherwise.
$Y_l \begin{cases}1\\0\end{cases}$	It is one if the recycling center is established at candidate location l, zero otherwise.
F_{lot}	A quantity of recycled raw materials sent from recycling center l to market o in time t.

Also, to better understand the position of decision variables, the network schematic structure, and the used variables are presented in Figure 1.

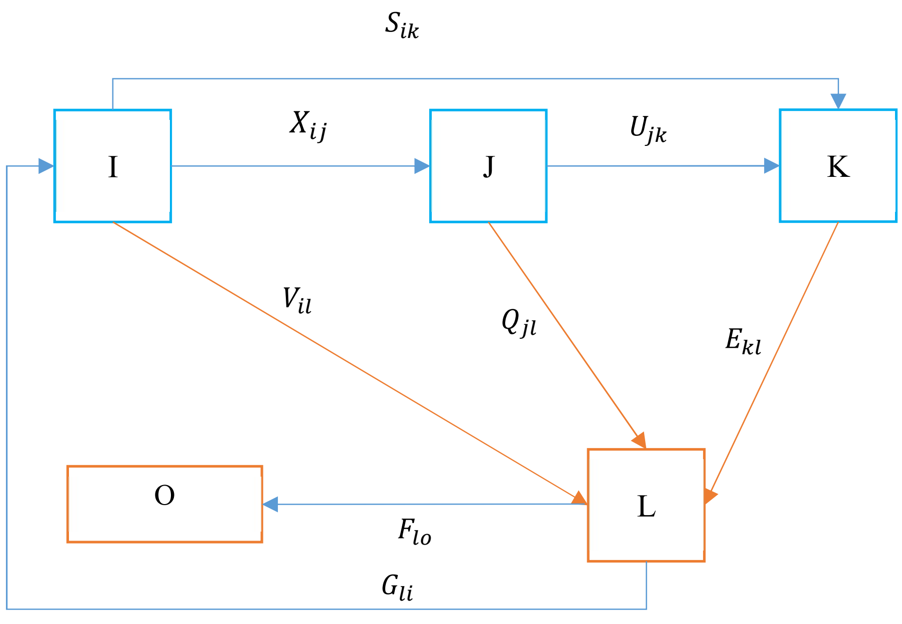

Figure 1. Schematic of the proposed network along with the decision variables.

3.3 Proposed model

According to the problem definition and considering the assumptions, the mathematical model is developed to minimize supply chain costs, including transportation, distribution centers' building potential locations, inventory maintenance and production and processing, and maximizing demand response.

Objective functions

This model consists of two objective functions (OFs): minimizing cost (OF_1) and maximizing responsiveness (OF_2).

$$min\, Z = z_1 + z_2 + z_3 + z_4 \tag{1}$$

$$z_1 = \sum_{j=1}^{J} \tilde{f}_j \times W_j + \sum_{l=1}^{L} \tilde{f}_l \times Y_l \quad (2)$$

$$\begin{aligned} z_2 = & \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{t'} \widetilde{Cx_{ij}} \times X_{ijt} + \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{t=1}^{T} \widetilde{Cu_{jk}} \times U_{jkt} + \sum_{i=1}^{I}\sum_{k=1}^{k}\sum_{t=1}^{t'} \widetilde{Cs_{ik}} \times S_{ikt} + \\ & + \sum_{i=1}^{I}\sum_{l=1}^{L}\sum_{t=1}^{t'} \widetilde{Cv_{il}} \times V_{ilt} + \sum_{j=1}^{J}\sum_{l=1}^{L}\sum_{t=1}^{T} \widetilde{Cq_{jl}} \times Q_{jlt} + \sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{t=1}^{T} \widetilde{Ce_{kl}} \times E_{klt} + \\ & + \sum_{l=1}^{L}\sum_{t=1}^{T}\sum_{o=1}^{O} \widetilde{Cf_{lo}} \times F_{lot} + \sum_{l=1}^{L}\sum_{t=1}^{T}\sum_{i=1}^{I} \widetilde{Cg_{li}} \times G_{lit} \end{aligned} \quad (3)$$

$$z_3 = \sum_{j=1}^{J}\sum_{t=1}^{T} Ih_{jt} * \widetilde{Ch_t} \quad (4)$$

$$z_4 = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{T} X_{ijt} \times \widetilde{Cp_t} + \sum_{l=1}^{L}\sum_{t=1}^{T}\sum_{o=1}^{O} F_{lot} \times \widetilde{Cr_t} + \sum_{i=1}^{I}\sum_{t=1}^{t'} \lambda_{it} \times \widetilde{Cp'} \quad (5)$$

Equation (1) is the cost minimization, which is a total of 4 types of costs presented in relations (2) to (5). Fixed costs of establishing distribution and recycling centers are included in relation (2). It is important to note that existing and potential points can serve as distribution and recycling centers. To achieve this, we consider the construction costs of existing points in zero parameters instead of adding an index. In relation (3) transportation costs, including forward and backward, and in relation (4) the costs of storing processed products are included. In relation (5), operational costs, including processing and packaging and open processing costs, are given.

$$\begin{aligned} max\, Z' = & \rho \times \frac{\left(\sum_{t=1}^{t'}\sum_{k=1}^{K}\sum_{i=1}^{I} S_{ikt} + \sum_{t=1}^{T}\sum_{k=1}^{K}\sum_{j=1}^{J} U_{jkt}\right)}{\left(\sum_{t=1}^{T}\sum_{k=1}^{K} \widetilde{d_{kt}}\right)} + \\ & + (1-\rho) \times \left(\sum_{t=1}^{T}\sum_{l=1}^{L}\sum_{o=1}^{O} F_{lot}\right) / \left(\sum_{t=1}^{T}\sum_{o=1}^{O} \widetilde{d'_{ot}}\right) \end{aligned} \quad (6)$$

Equation (6) describes the second (maximization) objective function OF_2. The response is segmented into two groups: the main product (power plants) and the reprocessed product.

Constraints:

In this mathematical model, there are 18 restrictions as follows.

$$\lambda_{it} \times (1-\alpha_t) = \sum_{j=1}^{J} X_{ijt} + \sum_{k=1}^{K} S_{ikt} - \sum_{l=1}^{L} G_{lit} \qquad \forall\, i \in I, \forall t \in T \quad (7)$$

Equation (7) shows the amount of production by producers with the deduction of waste equal to the amount of transfer from producers to distributors and the target market (power plants).

$$\sum_{i=1}^{I} X_{ijt} \le M \times W_j \qquad \forall j \in J, t \in T \quad (8)$$

Also, relation (8) is a constraint related to relation (7), emphasizing that sending loads to potential distributors is done if that place is built.

$$\lambda_{it} \leq \lambda c_{it} \tag{9}$$

Equation (9) indicates that smaller producers' production equals their maximum capacity.

$$Ih_{j(t-1)} + \sum_{i=1}^{I} X_{ijt} = Ih_{jt} + \sum_{k=1}^{K} U_{jkt} + \sum_{l=1}^{L} Q_{jlt} \qquad \forall\, j \in J, \forall\, t \in T \tag{10}$$

According to Equation (10), the inventory level of the distributors' warehouse in any given period is determined by subtracting the amount of waste from the previous period from the inventory level of the last period and then adding the new products that have entered the warehouse while also subtracting the number of foreign products that have been moved from the warehouse to the processing and packaging line.

$$Ih_{jt} \leq \lambda h_j \times W_j \qquad \forall j \in J,\ \forall t \in T \tag{11}$$

Equation (11) indicates that the smaller distributor's maximum inventory equals the warehouse capacity.

$$\sum_{j=1}^{J} U_{jkt} + \sum_{i=1}^{I} S_{ikt} \leq \widetilde{d_{kt}} \qquad \forall\, k \in K, \forall\, t \in T \tag{12}$$

Equation (12) means that in each more significant period, the market demand equals the products imported from producers and distributors.

$$\sum_{l=1}^{L} V_{ilt} = \alpha_t \times \lambda_{it} \qquad \forall i \in I, \forall t \in T \tag{13}$$

$$\sum_{i=1}^{I} V_{ilt} \leq M \times Y_l \qquad \forall l \in L, t \in T \tag{14}$$

$$\sum_{l=1}^{L} Q_{jlt} = \beta_t \times Ih_{j(t-1)} \qquad \forall j \in J, \forall\, t \in T \tag{15}$$

$$\sum_{j=1}^{J} Q_{jlt} \leq M \times Y_l \qquad \forall l \in L, t \in T \tag{16}$$

$$\sum_{l=1}^{L} E_{klt} = \theta_t \times (\sum_{j=1}^{J} X_{ijt} + \sum_{k=1}^{K} S_{ikt}) \qquad \forall k \in K, \forall\, t \in T \tag{17}$$

$$\sum_{k=1}^{K} E_{klt} \leq M \times Y_l \qquad \forall l \in L, t \in T \tag{18}$$

Equations (13) to (18) specify that in each section, the amount of waste for the reverse flow is shown in the case of the construction of recycling centers.

$$\left(\sum_{i=1}^{I} V_{ilt} + \sum_{j=1}^{J} Q_{ilt} + \sum_{k=1}^{K} E_{ilt}\right) \times \varphi = \sum_{o=1}^{O} F_{lot} \qquad \forall\, l \in L,\ \forall\, t \in T \tag{19}$$

Equation (19) states that the combined amount of waste generated by the producer, distributor, and customer, when multiplied by the waste conversion rate, equals the total recycling sent to recycling markets and customers.

$$\sum_{o=1}^{O} F_{lot} \ \leq\ \lambda r_l \times Y_l \qquad \forall\, l \in L,\ \forall\, t \in T \tag{20}$$

Equation (20) indicates that the total amount of recycled materials sent to the market and smaller customers is equivalent to the recycling centers' production capacity.

$$\sum_{l=1}^{L} F_{lot} \ \leq \widetilde{d'_{ot}} \qquad \forall o \in O,\ t \in T \tag{21}$$

Equation (21) indicates that the total recycled materials sent to the market and smaller customers are equivalent to the recycled customers' demand.

$$\left(\sum_{i=1}^{I} V_{ilt-1} + \sum_{j=1}^{J} Q_{ilt-1} + \sum_{k=1}^{K} E_{ilt-1}\right) \times (1-\varphi) = \sum_{i=1}^{I} G_{lit} \quad \forall\, l \in L,\ \forall\, t \in T \tag{22}$$

Equation (22) indicates that a percentage of waste products that can be reproduced will be sent to the production center in the next period.

$$Y_l\,, W_j \in \{0{,}1\} \qquad \forall l \in L\,, \forall\, j \in J \tag{23}$$

$$X_{ijt}\,,\ S_{ikt},\ U_{jkt},\ V_{ilt},\ Q_{jlt}, E_{klt}, F_{lot}\ \geq 0 \quad \forall o \in O, \forall\, i \in I,\ \forall j \in J,\ \forall k \in K,\ \forall t \in T,\ \forall l \in L \tag{24}$$

$$Ih_{jt} \geq 0 \qquad \forall j \in J,\ \forall t \in T \tag{25}$$

Relations (23) to (25) indicate the sign variables or zero and one variables and their positivity.

3.4 Solution approach

In this study, uncertainty in key parameters such as cost, demand, and transportation are captured using trapezoidal fuzzy numbers. Trapezoidal distributions are selected because they allow for flexibility in modeling uncertainty by defining four critical points: $\tilde{a} = (\tilde{a}_1, \tilde{a}_2, \tilde{a}_3, \tilde{a}_4)$. These points represent the lower limit, lower mode, upper mode, and upper limit of the parameter, respectively, and are particularly suited to situations where precise parameter values are unknown but can be estimated within a bounded range (see Figure 2).

The selection of trapezoidal fuzzy numbers is justified by both the availability of historical data and expert judgment. For instance, in cases where there is incomplete or imprecise data regarding demand or cost, domain experts provide estimates that define the likely range and spread of uncertainty. The use of fuzzy distributions helps incorporate this uncertainty into the model without requiring exact point estimates, making it more robust for real-world applications. To construct the basic fuzzy chance constraints, we employed the Fuzzy Chance-Constrained (FCCP) approach to model the uncertain parameters. The Necessity (Nec) scale is used to transform fuzzy chance constraints into equivalent deterministic equations, ensuring that constraints are satisfied to a specified degree of confidence. Additionally, the expected value approach is applied to manage uncertainty within the objective function, providing a more robust representation of uncertain parameters by averaging their possible values. The expected value approach smooths out variations by averaging the trapezoidal fuzzy numbers, reflecting realistic ranges of costs and demand, while the *Nec* scale transforms fuzzy constraints into deterministic equivalents, ensuring that constraints are satisfied to a predefined confidence level. By clearly defining the fuzzy parameters and their justification, we ensure that the model can handle real-world uncertainties effectively, making the model more reliable for decision-making under uncertainty.to explain the mathematical process To explain the mathematical process of the optimization problem and how fuzzy parameters are incorporated, let's break down the problem. Consider the following optimization problem:

$$\begin{gathered} Min\ Z = fy + cx \\ Subject\ to\text{: } Ax \geq d \\ Bx = d \\ Sx \leq Ny \\ Y \in \{0,1\} \\ x \geq 0 \end{gathered} \tag{25}$$

Suppose the vector f (fixed costs) is a deterministic parameter, while the vectors c (variable costs) and d (demand) and the matrix N are uncertain parameters of the problem. To construct the basic fuzzy programming model with chance constraints, as we mentioned earlier, we used the "expected value" approach to model the uncertain parameters of the objective function and the *Nec* scale to model the chance constraints.

The *Nec* scale can be directly used to convert fuzzy chance constraints into their equivalent deterministic equations (Equation (27)). In this paper, we used a trapezoidal fuzzy distribution in the model because it can define four critical points $\tilde{a} = (\tilde{a}_1, \tilde{a}_2, \tilde{a}_3, \tilde{a}_4)$ (see Figure 2).

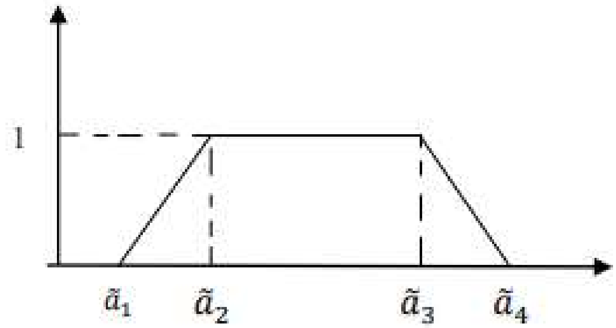

Figure 2. fuzzy parameter $\tilde{a}$.

$$\begin{gathered} Min\ E[Z] = E[f]y + E[\tilde{c}]x \\ Subject\ to\text{: } Nec\{ Ax \geq \tilde{d}\} \geq \alpha_m \quad \forall\, m \in M \\ Nec\{ Bx = \tilde{d}\} \geq \alpha_m \quad \forall\, m \in M \\ Nec\{ Sx \leq \tilde{N}y\} \geq \alpha_m \\ \forall\, m \in M \;\; Y \in \{0,1\} \\ x \geq 0 \end{gathered} \tag{27}$$

Since the objective function and constraints have uncertain parameters and are considered with fuzzy distributions, and given that the constraints with uncertain parameters must be satisfied with at least an α_m satisfaction level, the deterministic model can be defined as Equation (28):

$$\begin{gathered} Min\ E[Z] = fy + \left(\frac{c_1 + c_2 + c_3 + c_4}{4}\right)x \\ Subject\ to\text{: } Ax \geq (1 - \alpha_m)d_3 + \alpha_m d_4 \end{gathered} \tag{28}$$

$$Bx \le (\frac{\alpha_m}{2})\, d_3 + (1 - \frac{\alpha_m}{2})\, d_4$$
$$Bx \ge (\frac{\alpha_m}{2})\, d_2 + (1 - \frac{\alpha_m}{2})\, d_1$$
$$Sx \le [(1-\alpha_m)N_2 + \alpha_m N_1]Y$$
$$Y \in \{0,1\}\; x \ge 0$$

Given the explanations provided above, the crisp equivalent of the proposed multi-objective mixed-integer linear programming model can be expressed as follows:

$$min\, E[Z] = E[z_1] + E[z_2] + E[z_3] + E[z_4] \tag{29}$$

$$E[z_1] = \sum_{j=1}^{J} \frac{(f_{j1}+f_{j2}+f_{j3}+f_{j4})}{4} \times W_j + \sum_{l=1}^{L} \frac{(f_{l1}+f_{l2}+f_{l3}+f_{l4})}{4} \times Y_l \tag{30}$$

$$\begin{aligned} E[z_2] = {} & \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{t'} \frac{(Cx_{ij1}+Cx_{ij2}+Cx_{ij3}+Cx_{ij4})}{4} \times X_{ijt} + \\ & + \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{t=1}^{T} \frac{(Cu_{jk1}+Cu_{jk2}+Cu_{jk}\;\; + Cu_{jk4})}{4} \times U_{jkt} + \\ & + \sum_{i=1}^{I}\sum_{k=1}^{k}\sum_{t=1}^{t'} \frac{(Cs_{ik1}+Cs_{ik}\;\; + Cs_{ik}\;\; + Cs_{ik4})}{4} \times S_{ikt} + \\ & + \sum_{i=1}^{I}\sum_{l=1}^{L}\sum_{t=1}^{t'} \frac{(Cv_{il1}+Cv_{il2}+Cv_{il3}+Cv_{il4})}{4} \times V_{ilt} + \\ & + \sum_{j=1}^{J}\sum_{l=1}^{L}\sum_{t=1}^{T} \frac{(Cq_{jl1}+Cq_{jl2}+Cq_{jl3}+Cq_{jl4})}{4} \times Q_{jlt} + \\ & + \sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{t=1}^{T} \frac{(Ce_{kl1}+Ce_{kl}\;\; + Ce_{kl3}+Ce_{kl4})}{4} \times E_{klt} + \\ & + \sum_{l=1}^{L}\sum_{t=1}^{T}\sum_{o=1}^{O} \frac{(Cf_{lo}\;\; + Cf_{lo2}+Cf_{lo3}+Cf_{lo4})}{4} \times F_{lot} \\ & + \sum_{l=1}^{L}\sum_{t=1}^{T}\sum_{i=1}^{I} \frac{(Cg_{li}\;\; + Cg_{li2}+Cg_{li3}+Cg_{li4})}{4} \times G_{lit} \end{aligned} \tag{31}$$

$$E\,[z_3] = \textstyle\sum_{j=1}^{J}\sum_{t=1}^{T} Ih_{jt} * \frac{(Ch_{t1}+Ch_{t2}+Ch_{t3}+Ch_{t4})}{4} \tag{32}$$

$$\begin{aligned} E[z_4] = {} & \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{T} X_{ijt} \times \frac{(Cp_{t1}+Cp_{t2}+Cp_{t3}+Cp_{t4})}{4} + \\ & + \sum_{l=1}^{L}\sum_{t=1}^{T}\sum_{o=1}^{O} F_{lot} \times \frac{(Cr_{t1}+Cr_{t2}+Cr_{t3}+Cr_{t4})}{4} + \\ & + \sum_{i=1}^{I}\sum_{t=1}^{t'} \lambda_{it} \times \frac{(Cp'_1+Cp'_2+Cp'_3+Cp'_4)}{4} \end{aligned} \tag{33}$$

$$max\ E[Z'] = \rho \times \frac{\left(\sum_{t=1}^{t'}\sum_{k=1}^{K}\sum_{i=1}^{I} S_{ikt} + \sum_{t=1}^{T}\sum_{k=1}^{K}\sum_{j=1}^{J} U_{jkt}\right)}{\left(\sum_{t=1}^{T}\sum_{k=1}^{K}\frac{\left(d_{kt_1}+d_{kt_2}+d_{kt_3}+d_{kt_4}\right)}{4}\right)} + \\ +(1-\rho)\times\left(\sum_{t=1}^{T}\sum_{l=1}^{L}\sum_{o=1}^{O} F_{lot}\right)/\left(\sum_{t=1}^{T}\sum_{o=1}^{O}\frac{(d'_{ot_1}+d'_{ot_2}+d'_{ot_3}+d'_{ot_4})}{4}\right) \tag{34}$$

$$\sum_{j=1}^{J} U_{jkt} + \sum_{i=1}^{I} S_{ikt} \leq \alpha_1\, d_{kt3} + (1-\alpha_1)\, d_{kt4} \qquad \forall\, k \in K, \forall\, t \in T \tag{35}$$

$$\sum_{l=1}^{L} F_{lot} \leq \alpha_2\, d'_{ot3} + (1-\alpha_2)\, d'_{ot4} \qquad \forall o \in O,\ t \in T \tag{36}$$

$$\text{s.t.}\quad \text{constraints 7-11,13-20,22-25} \tag{37}$$

Please note that in this paper, we use a confidence level of 90% for both chance constraints, denoted as $\alpha_1 = \alpha_2 = 0.90$.

4 Research Findings

This article seeks to develop a five-level green closed-loop network of customers (power plants), producers, recycling centers, distributors, and customers of recycled products. The model has been validated by the epsilon constraint method and MOPSO and NSGA II algorithms. In this method, OF_1 is included as a constraint, and the second is considered a constraint. The size of the numerical example in the validation section consists of three producers, four distribution centers, four recycling centers, and two customers of recycled products. The selected cities for each location in this issue are shown in Table 1. Also, the transportation costs used between cities for all matters are taken from Table 2.

Table 1. Selected cities for each index.

o	l	k	j	i
1	3	7	10	14
2	4	8	11	15
	5	9	12	16
	6		13	

Table 2. Transportation cost between cities (dollars/km).

City	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	3.7	4.9	9.0	12.5	12.8	19.4	20.8	17.8	15.2	20.5	19.2	21.3	30.4	34.1	43.7	47.7
2	4.9	3.7	5.3	8.7	9.0	17.3	17.3	30.1	11.4	17.0	17.1	17.8	23.8	30.7	40.3	44.2
3	9.0	5.3	3.7	4.6	4.9	13.1	13.8	11.4	8.0	9.5	13.0	17.2	11.8	26.9	36.5	39.8
4	12.5	8.7	4.6	3.7	7.1	13.1	14.5	7.0	8.5	9.9	13.5	18.3	13.1	24.7	34.3	40.9
5	12.8	9.0	4.9	7.1	3.7	9.4	12.3	8.0	8.2	9.7	12.8	17.3	12.6	23.5	33.4	40.4
6	19.4	17.3	13.1	13.1	9.4	3.7	4.4	16.6	13.1	18.1	18.1	19.1	18.7	31.6	41.2	45.1
7	20.8	17.3	13.8	14.5	12.3	4.4	3.7	17.8	16.4	20.2	19.7	22.0	21.7	33.8	42.5	46.4
8	17.8	30.1	11.4	7.0	8.0	16.6	17.8	3.7	4.6	3.9	7.8	5.9	5.6	19.4	29.0	32.9
9	15.2	11.4	8.0	8.5	8.2	13.1	16.4	4.6	3.7	7.3	6.1	8.9	9.0	20.6	30.1	34.1

City	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
10	20.5	17.0	9.5	9.9	9.7	18.1	20.2	3.9	7.3	3.7	2.9	3.9	4.1	18.1	27.4	28.2
11	19.2	17.1	13.0	13.5	12.8	18.1	19.7	7.8	6.1	2.9	3.7	5.6	5.8	17.4	25.7	29.6
12	21.3	17.8	17.2	18.3	17.3	19.1	22.0	5.9	8.9	3.9	5.6	3.7	3.2	15.2	18.3	27.9
13	30.4	23.8	11.8	13.1	12.6	18.7	21.7	5.6	9.0	4.1	5.8	3.2	3.7	13.3	20.2	29.1
14	34.1	30.7	26.9	24.7	23.5	31.6	33.8	19.4	20.6	18.1	17.4	15.2	13.3	3.7	10.9	15.2
15	43.7	40.3	36.5	34.3	33.4	41.2	42.5	29.0	30.1	27.4	25.7	18.3	20.2	10.9	3.7	5.4
16	47.7	44.2	39.8	40.9	40.4	45.1	46.4	32.9	34.1	28.2	29.6	27.9	29.1	15.2	5.4	3.7

Also, for the first problem, other parameters are shown in Table 3. In addition, φ, ρ, and M are equal to 1.1, 0.6, and 10^{15}, respectively. Also, the value of cp' is assumed equal to 170, and the values of f_j for this problem are equal to 0, 0, 114290, 180000, and the values of f_l This problem is considered equal to 0, 0, 14285, 20000.

Table 3. Parameters related to the first problem.

Parameter	Index	t_1	t_2	t_3	t_4	t_5	t_6	t_7	t_8
ch_t	-	58	58	60	63	63	66	68	72
cp_t	-	86	89	89	91	94	94	100	103
cr_t	-	86	86	100	100	100	115	129	137
d_{kt}	k_1	3	4	3	7	8	5	10	8
	k_2	3	3.5	3.8	6	7.5	4.8	4.8	6.5
	k_3	3	3.2	3.5	5	5.5	4	10	2
λc_{it}	i_1	30	20	70	0	0	0	0	0
	i_2	90	11	45	0	0	0	0	0
	i_3	95	50	80	0	0	0	0	0
λh_{jt}	j_1	10	10	10	0	0	0	0	0
	j_2	20	20	20	0	0	0	0	0
	j_3	10	10	10	0	0	0	0	0
	j_4	30	30	30	0	0	0	0	0
λr_{lt}	l_1	4	4	5	4.3	4.8	5.3	5.2	10
	l_2	5.3	4	4.9	5.3	5.7	4.1	6.9	7.1
	l_3	8.3	4	4.6	7.3	4.5	6.3	4.7	10
	l_4	6.41	4.35	5	6	5.5	10	9.2	8.31
α_t	-	0.1	0.12	0.15	0	0	0	0	0
β_t	-	0.02	0.02	0.03	0.03	0.035	0.04	0.045	0.05
θ_t	-	0.02	0.03	0.04	0.045	0.045	0.048	0.05	0.05
d'_{ot}	o_1	10	20	18	15	14	6	7.9	8.5
	o_2	15	20	16	15.3	14.36	20	6.78	7

After introducing the data related to the first problem, it is time to express the remaining parameters for other problems, as shown in Table 4.

Table 4. The remaining model parameters' values.

Unit	Quantity	Parameter
period (month)	8	T
Percent	[0.1,0.12,0.15,0,0,0,0,0]	αt
Percent	[0.2,0.02,0.03,0.03,0.035,0.04,0.045,0.05]	βt
Percent	[0.02,0.03,0.04,0.045,0.045,0.048,0.05,0.05]	θt
Percent	1.1	φ
Percent	0.6	ρ
Percent	0.4	$1\text{-}\rho$

Unit	Quantity	Parameter
Ton	Uniform ~ [30,100]	λcit
Dollar	Uniform ~ [114290,185715]	fj
Dollar	Uniform ~ [14285,22855]	fl
Dollars/ton	[58,58,60,63,63,66,68,72]	cht
Dollars/ton	[86,89,89,91,94,94,100,103]	cpt
Dollars/ton	[86,86,100,100,100,115,129,137]	crt
Dollars/ton	Uniform ~ [143,172]	cp'
Ton	Uniform ~ [3,10]	dkt
Ton	10 or 20 or 30	λhj
Ton	Uniform ~ [4,10]	λrt
Ton	Uniform ~ [5,20]	$d'ot$

According to the presented mathematical model, MOPSO and NSGAII algorithms have been used to evaluate the given mathematical model using the epsilon limitation method. Therefore, before analyzing numerical examples with NSGA II and MOPSO methods, the problem's initial solution (based on priority) has been defined. Thus, the initial answer is presented at this section's beginning. The meta-heuristic algorithms' parameter setting with the Taguchi method has been discussed at the end of the section.

4.1 Initial solutions

The proposed model used in this article is highly complex, so modified priority-based decoding is employed. This coding is based on a natural numbers' permutation, which corresponds to the number of nodes at each level of two levels of the supply chain network. Figure (2) displays the modified priority-based coding for one of the network levels, which has three central distribution centers and four fixed demand centers. In the Figure, the encoding is shown as (6-1-4-7-3-5-2), where the priorities of (6-1-4-7) are related to fixed demand centers, and (3-5-2) are associated with the central distribution center. To decode the initial answer to the problem, follow these steps:

1. The highest priority can be selected considering the distribution centers/demand points.
2. The distribution center/demand points determine the lowest shipping cost.
3. The selected center's minimum demand and capacity are calculated as the amount of transferred product.
4. Demand quantity and capacity are updated after allocation.
5. If the capacity or demand becomes 0, its priority will be reduced to zero.
6. This action is calculated until all the demand priorities, or the capacity is not reduced to 0.

	Distribution centres			Demand centres (customer)			
Node	1	2	3	1	2	3	4
Priority	2	5	3	7	4	1	6

Figure 2. How to encrypt and decrypt based on priority.

The initial solution provided is only for two levels of a supply chain network; due to the multi-level nature of the closed-loop supply chain network design in this article, the initial solution should be calculated for each level.

4.2 Parameter setting of meta-heuristic algorithms

We use a response variable, a combination of four criteria, to set the parameter. To calculate its value, we use the following formula. Since the requirements have varying levels of importance, we determine the weight coefficients used for them.

$$R_i = \frac{\overline{NPF_1} + \overline{MSI_2} + \overline{SM_3} + \overline{CPU - time}}{w_1 + w_2 + w_3 + w_4} \tag{38}$$

In the above relationship, NPF is the number of effective solutions, MSI is the maximum extent, SM is the distance metric, and CPU-time is the computing time. To adjust the parameter of the NSGA-II algorithm, we defined the factors and their level considering Table 5.

Table 5. Factor levels used for NSGA-II algorithm.

Parameters	Level 1	Level 2	Level 3
nPop	50	70	100
pc	0.2	0.5	0.8
pm	0.2	0.3	0.4

Using Minitab software and the standard Table of orthogonal arrays in the Taguchi method, we selected L9(34) orthogonal arrays as the best design for models three to six. The orthogonal arrays of this design are shown in Table 6.

Table 6. L9(34) orthogonal arrays for NSGA-II algorithm.

Test number	nPop	Pc	Pm
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	2
5	2	2	3
6	2	3	1
7	3	1	3
8	3	2	1
9	3	3	2

Since in each problem, the value of R_i differs and cannot be used directly, the relative percentage deviation (RPD) is applied.

$$RPD = \frac{Alg_{sol} - Min_{sol}}{Min_{sol}} \times 100 \tag{31}$$

In the given relation, Alg_{sol} and Min_{sol} represent the R_i values obtained during each experiment iteration and the best solution obtained, respectively. R_i value is converted to RPD, and the S/N ratio is computed based on RPD, according to the Taguchi parameter design structure. Then, the average S/N ratio of all experiments is computed for each parameter level. The optimal levels of factors result in the minimum ratio of the desired average, i.e., each parameter's best value has the lowest average value of the averages. After running the Taguchi test, the results, average means, and average S/N ratio for each level of factors in the NSGA-II algorithm for the model are shown in Figures 3 and 4.

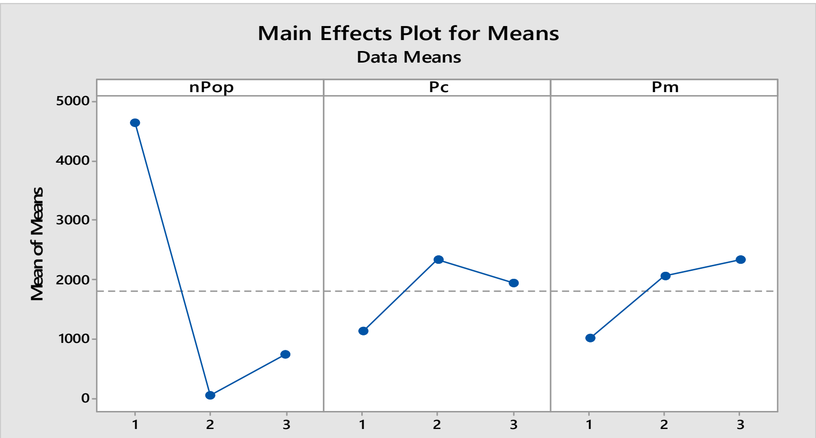

Figure 3. Plot of mean averages for NSGA II algorithm.

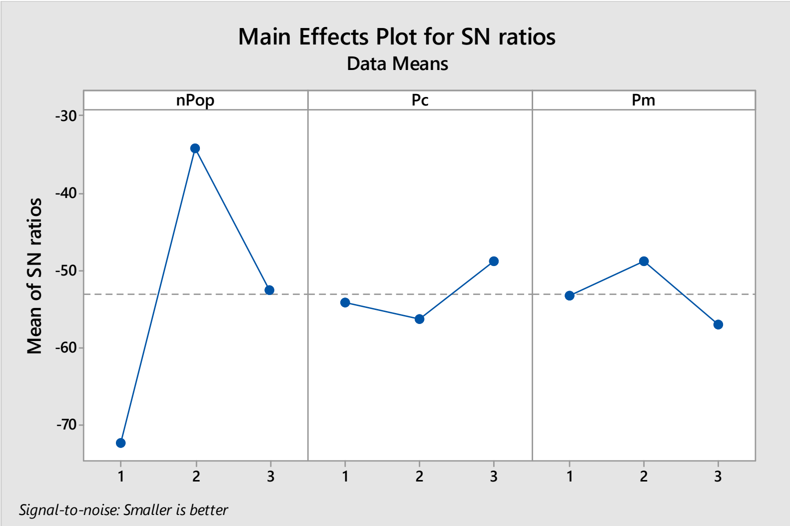

Figure 4. Plot of average S/N ratio for NSGA II algorithm.

Figures 3 and 4 indicate that the NSGA-II algorithm factors optimal level is equal to:

Table 7. Factors optimal levels (NSGA-II)

Levels of factors				Optimum factor level
Parameters	1	2	3	
nPop	50	70	100	70
pc	0.2	0.5	0.8	0.2
pm	0.2	0.3	0.4	0.2

Table 8 defines the factors and their levels for the MOPSO algorithm, and Table 10 defines the orthogonal arrays relating to Table 9.

Table 8. Factor levels used for the MOPSO algorithm.

Parameters	Level 1	Level 2	Level 3
nPop	50	75	100
nRep	70	100	150
W	0.5	0.6	0.7
C1	1	1.25	1.5
C2	1	1.25	1.5

Table 9. L9(3^5) orthogonal arrays for MOPSO algorithm.

Test Number	*nPop*	*nRep*	*W*	*C1*	*C2*
1	1	1	1	1	1
2	1	1	1	1	2
3	1	1	1	1	3
4	1	2	2	2	1
5	1	2	2	2	2
6	1	2	2	2	3
7	1	3	3	3	1
8	1	3	3	3	2
9	1	3	3	3	3
10	2	1	1	1	1
11	2	1	1	1	2
12	2	1	1	1	3

Test Number	*nPop*	*nRep*	*W*	*C1*	*C2*
13	2	2	2	2	1
14	2	2	2	2	2
15	2	2	2	2	3
16	2	3	3	3	1
17	2	3	3	3	2
18	2	3	3	3	3
19	3	1	1	1	1
20	3	1	1	1	2
21	3	1	1	1	3
22	3	2	2	2	1
23	3	2	2	2	2
24	3	2	2	2	3
25	3	3	3	3	1
26	3	3	3	3	2
27	3	3	3	3	3

After conducting the Taguchi test, the results display the average means and S/N ratio for every factor level in the MOPSO algorithm in Figures 5 and 6.

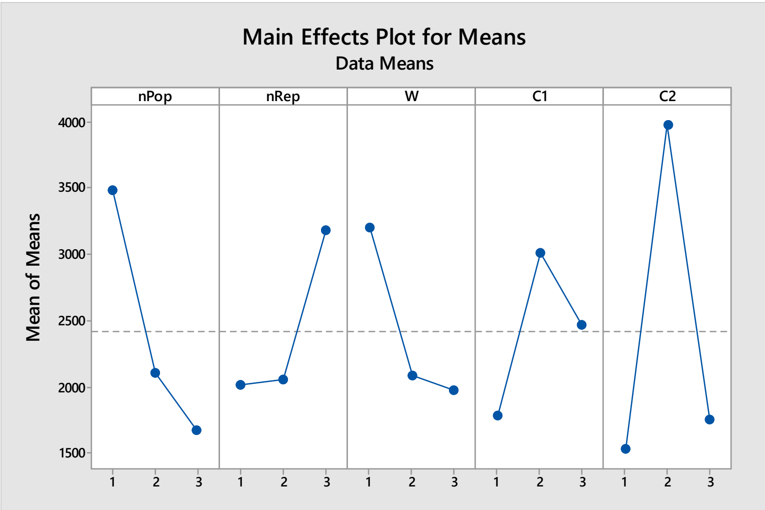

Figure 5. The plot of mean averages for the MOPSO algorithm.

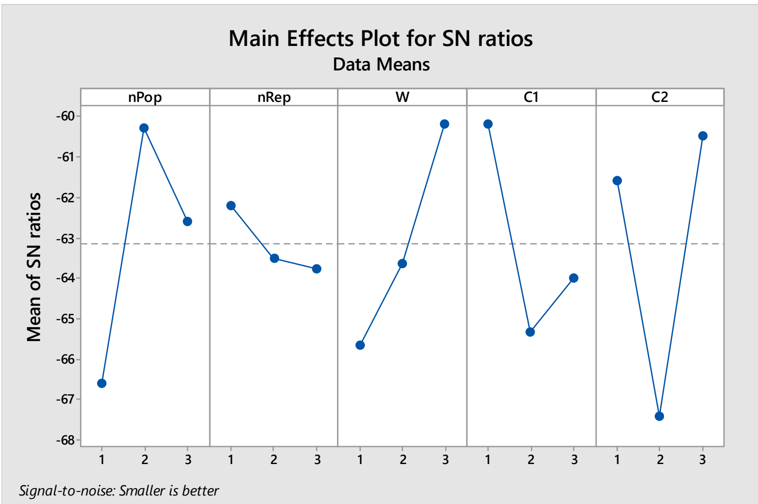

Figure 6. Average S/N ratio plot for MOPSO algorithm.

According to the above graphs, the optimal level of factors has been obtained as described in Table 10:

Table 10. The MOPSO algorithm factor levels.

Levels of factors				Optimum factor level
Parameters	1	2	3	
nPop	50	75	100	100
nRep	70	100	150	70
W	0.5	0.6	0.7	0.7
C1	1	1.25	1.5	1
C2	1	1.25	1.5	1

After designing the initial solution and setting the parameters of the meta-heuristic algorithms, the numerical example has been analyzed. The maximum number of repetitions in meta-heuristic algorithms is equal to 100. Table 11 displays the average and results from NSGA II, MOPSO, and the epsilon method of the limit.

Table 11. Meta-heuristic algorithms compare indices in the sample problem.

Indicator	Epsilon Constraint	NSGA II algorithm	MOPSO algorithm
Computational time	97.68	18.88	6.64
The average of the OF_1	563498.02	573954.21	569563.94
Average of the OF_2	49716.35	49622.11	49371.86
NPF	6	10	9
MSI	35686.25	36643.30	35751.92
SM	0.76	0.476	0.381

Based on the data presented in Table 11, it can be observed that the MOPSO algorithm takes less computational time compared to the NSGA II algorithm and the epsilon constraint method when solving the sample problem. However, the NSGA II algorithm performs better when finding the number of efficient solutions than the MOPSO algorithm and the epsilon method. The results of Table 11 demonstrate the effectiveness of meta-heuristic algorithms in achieving near-optimal solutions quickly without compromising accuracy. The Pareto front obtained from solving the example problem is illustrated in Figure 7.

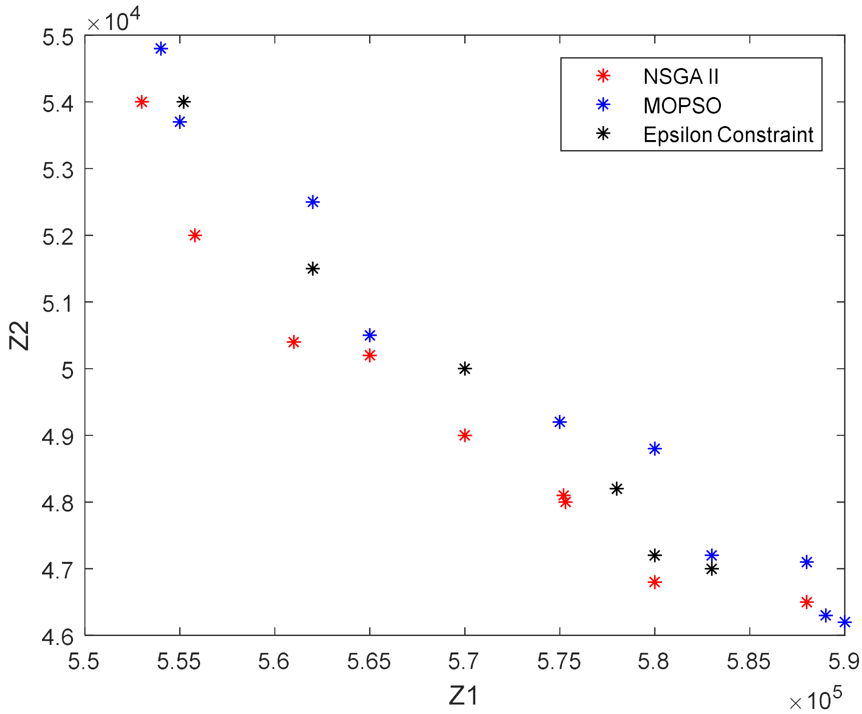

Figure 7. Pareto front of the small-size problem.

4.3 Sample problems (larger sizes) applying NSGA II and MOPSO

To tackle sample problems on a larger scale, a set of 15 sample problems has been created using random data based on a uniform distribution. For each sample problem, five problems of the same size have been created within the defined data range. The averages of each index have been evaluated and compared to provide a basis for comparison. The significance of the difference between the averages of each index has been evaluated using the T-Test statistical test. Finally, the TOPSIS method has been used to determine the most efficient algorithm for solving the problem of the closed-loop supply chain network. The problem sizes were randomly generated using MATLAB software.

Table 12. Dimensions of the problem.

Issue number	I	J	K	L	O
1	3	4	3	4	2
2	5	7	5	7	4
3	7	10	7	10	6
4	9	13	9	13	8
5	15	22	15	22	14
6	17	25	17	25	16
7	19	28	19	28	18
8	25	37	25	37	24
9	35	52	35	52	34
10	37	55	37	55	36
11	39	58	39	58	38
12	41	61	41	61	40
13	45	72	45	65	45
14	50	75	48	68	48
15	53	78	50	70	50

To solve each sample problem to prevent random data generation, five other problems in the same generation and with the problem were solved, and the average of the calculation results was utilized as the evaluation and comparison basis. Tables 13 and 14 show the average OFs and meta-heuristic algorithms comparison indices.

Table 13. Average OFs and comparison indices (NSGA II)

Sample problem	OF_1	OF_2	Number of effective solutions	The index of the greatest expansion	Distance index	Computational time
1	633806.72	62601.70	9	270273.91	0.37	34.46
2	778692.87	78381.54	19	585593.25	0.77	108.00
3	881581.31	85446.74	20	479316.63	0.70	170.30
4	1033814.58	90080.84	14	850298.87	0.57	242.53
5	1674913.50	103382.09	14	1129077.89	0.41	335.50
6	2369557.62	114251.75	22	1508175.51	0.55	434.40
7	2500890.63	125554.34	23	1797128.03	0.53	545.77
8	3416474.10	132080.49	18	2739770.014	0.57	669.07
9	4301935.98	140272.83	21	2529228.60	0.40	819.60
10	4860023.44	159821.22	23	3529017.44	0.75	959.67
11	5040590.70	163061.03	23	3087180.76	0.74	1040.13
12	8540218.42	178342.69	23	4883033.12	0.69	1326.00
13	8887924.17	182872.57	30	3839628.23	0.66	1528.37
14	10361985.83	193154.36	21	4564232.62	0.77	1802.27
15	12608666.41	207290.80	24	5383709.71	0.87	2640.00

Table 14. Average OFs and comparison indices (MOPSO).

Sample problem	OF_1	OF_2	Number of effective solutions	The index of the greatest expansion	Distance index	Computational time
1	635858.69	60567.22	8	109850.13	0.46	34.40
2	776699.89	71074.60	14	329845.53	0.62	39.07
3	871134.25	89693.95	8	370471.43	0.23	51.66
4	1046187.49	94437.00	16	463108.57	0.59	95.93
5	1653146.41	107002.93	18	817523.73	0.35	131.20
6	2353344.2	115415.91	23	1526123.70	0.49	280.50
7	2450251.68	123910.36	16	2008648.76	0.55	349.16
8	3434001.90	136349.08	31	2559860.14	0.75	494.70
9	4334688.39	148225.98	28	3694417.30	0.64	723.16
10	4817592.14	151730.43	19	2215230.18	0.59	980.40
11	5020566.34	165792.57	12	2437807.90	0.76	1328.75
12	8500502.39	175673.57	25	3887334.58	0.44	1834.56
13	8759033.18	187113.32	12	3757576.19	0.72	2337.30
14	10251098.76	192138.59	12	4593286.90	0.66	2983.04
15	12554017.27	207281.68	17	5138916.08	051	3957.90

Tables 13 and 14 display the mean values of OFs and comparison indices of meta-heuristic algorithms for each sample problem using NSGA II and MOPSO algorithms. To compare the results obtained, a T-test was performed at a 95% confidence level to determine the significant difference between the mean values of each index. If the P-test statistic value obtained for each index is less than 0.05, the null hypothesis is rejected, indicating a significant difference between the mean values of that index. Conversely, if the P-test statistic value is greater than 0.95, hypothesis 1 is rejected, indicating no significant difference in the mean values of that index.

Examining the T-Test on the averages of the OF_1

Table 15 displays the T-test output results for the averages. Additionally, Figure 8 presents a box plot for accepting or rejecting the null hypothesis in T-test.

Table 15. T-test results on the averages.

Algorithm	Samples	Average	S.d.	Confidence interval (95%)	T-test	P-test
NSGA II	75	5626072	3852039	(4040*53686)	2.94	0.026
MOPSO	75	4497208	3821250			

Based on Table 15 and the P test statistic value, we can conclude that there is a significant difference between the average values of the OF_1 obtained by using NSGA II and MOPSO algorithms. Based on the minimization mode of the OF_1, it can be inferred that the MOPSO algorithm has performed better than the NSGA II algorithm in this index.

Based on the box diagram shown in Figure 8, it can be concluded that the averages of the OF_1 obtained from the NSGA II and MOPSO algorithms differ significantly because the zero assumption is not included in the obtained interval.

Examining the T-test test (OF_2)

Table 16 displays the T-test results for the averages of the OF_2. Figure 9 depicts the box plot for accepting or rejecting the null hypothesis in the T-test.

Table 16. T-test output results on the averages.

Algorithm	Samples	Average	S.d.	Confidence Interval (95%)	T-test	P-test
NSGA II	75	134440	45240	(-3156*1848)	0.56	0.584
MOPSO	75	135094	45418			

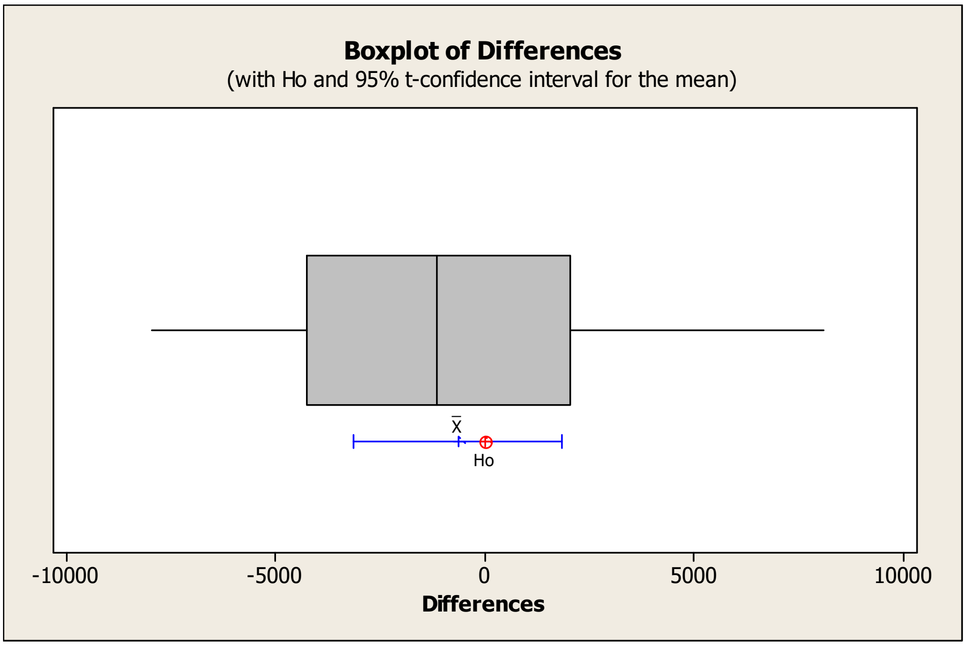

Figure 8. Box plot to confirm or reject the null hypothesis.

According to the P test statistic in Table 16, there is no significant difference between the averages. Therefore, multi-attribute decision-making methods can be applied to compare the most efficient algorithm.

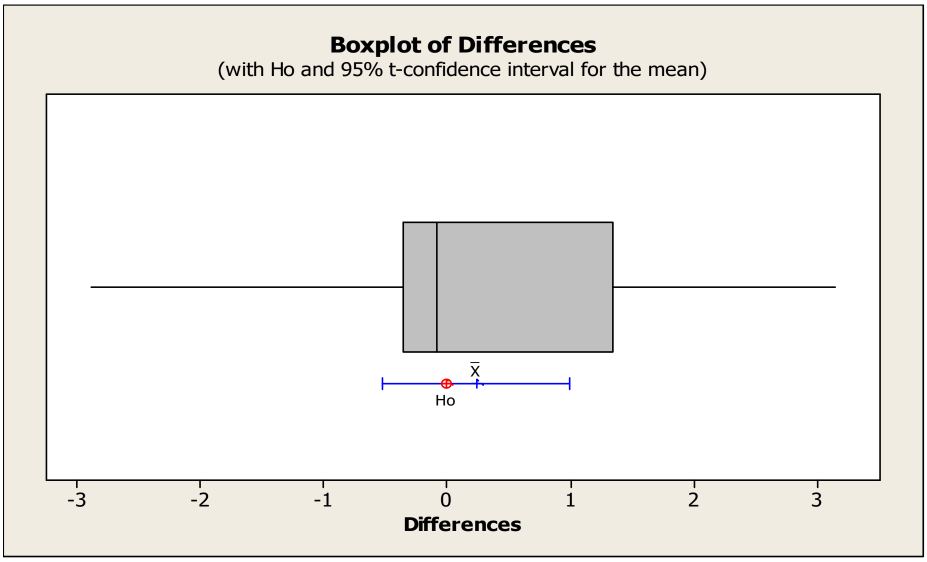

Figure 9. Box plot to confirm or reject the null hypothesis of the OF_2.

The results in Figure 9 reinforce those in Table 16. Based on the null hypothesis falling within the 95% confidence interval, we can argue that there is no significant difference between the averages of the OF_2 obtained by MOPSO and NSGA II algorithms.

Examining the T-test test on the average number of effective answers

Table 17 displays the results of the T-test on meta-heuristic algorithms' comparison indexes for the average number of effective answers at a 95% confidence level.

Table 17. T-test output results on the average number of efficient solutions.

Algorithm	Samples	Average	S.d.	Confidence Interval (95%)	T-test	P-test
NSGA II	75	20.27	5.04	(-1.48*7.48)	1.43	0.173
MOPSO	75	17.27	6.91			

Based on the P-test statistic value being greater than the critical value of 0.05, we can conclude that the null hypothesis of the equality of the difference between the averages of the number of effective answers is accepted. So, there is no significant difference between the averages of efficient solutions obtained from solving with meta-heuristic algorithms.

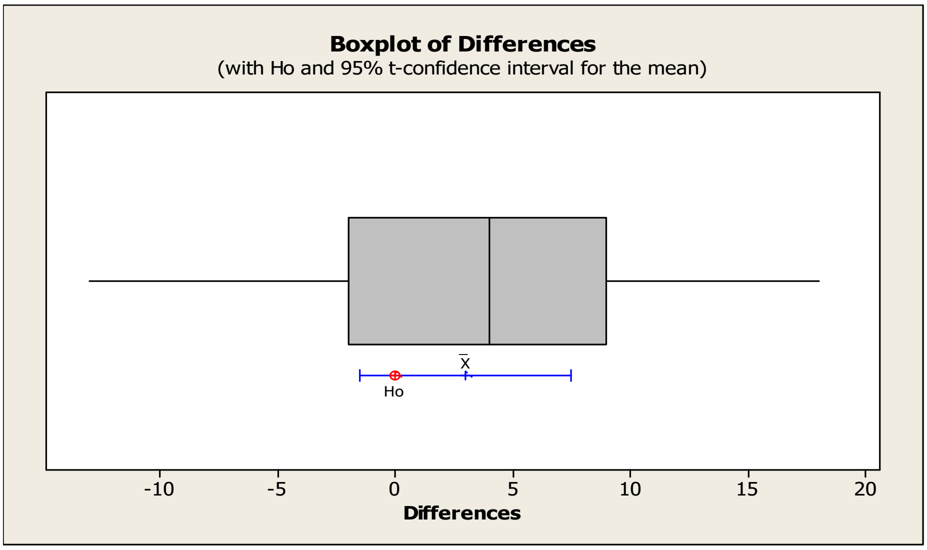

Figure 10. Box plot to confirm or reject the null hypothesis for the average number of effective solutions.

Figure 10 shows a box plot to confirm or reject the null hypothesis for the average number of effective answers, and according to the observations, we can argue that the null hypothesis can be accepted and the one hypothesis is rejected due to being in the confidence interval.

Examining the T-test test on the averages of the most widespread index

Table 18 displays the statistical comparisons of the T-test conducted on the averages of the most commonly used index. Additionally, Figure 11 compares the averages of the most commonly used index in all the sample problems by NSGA II and MOPSO algorithms.

Table 18. Output results of the T-test test on the averages of the most spread index.

Algorithm	Samples	Average	S.d.	Confidence Interval (95%)	T-test	P-test
NSGA II	75	2478417	1496766	(-88459*523960)	1.53	0.149
MOPSO	75	2260667	1661211			

According to the findings in Table 18, the most commonly used index averages obtained by NSGA II and MOPSO algorithms do not differ significantly. This test's P-test statistic value is higher than the confidence level considered.

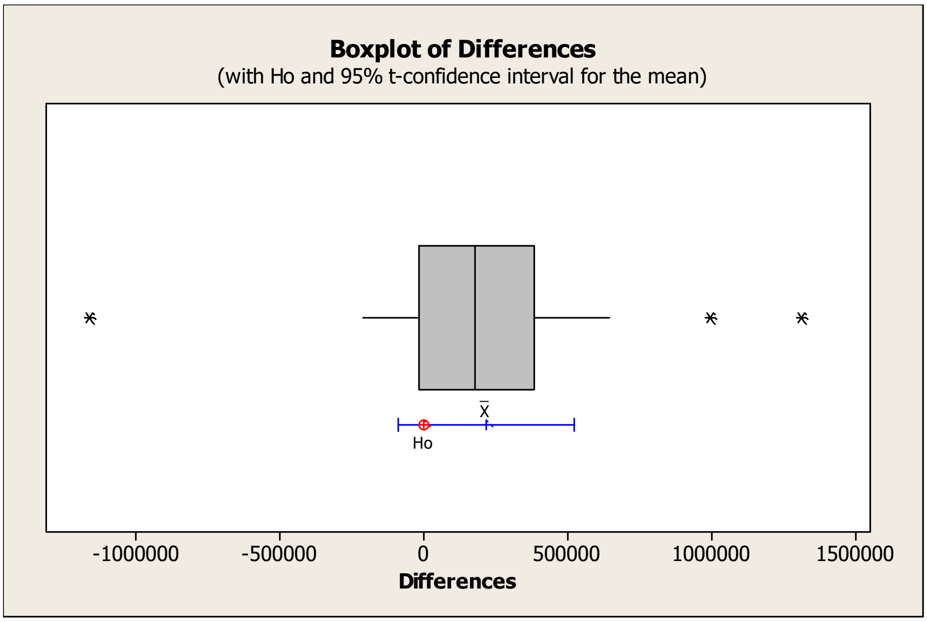

Figure 11. Box plot for the null hypothesis (means of the maximum expansion index).

The graph of Figure 11 shows that for the most widespread index, the assumption values of zero are placed in the confidence interval.

Examining the T-test test on the averages of the distance index

Table 19 displays the statistical comparisons of spacing index averages via T-Test. Additionally, Figure 12 compares the spacing index averages in all sample problems with the NSGA II and MOPSO algorithms.

Table 19. Output results of T-Test on average spacing index.

Algorithm	Samples	Average	S.d.	Confidence Interval (95%)	T-test	P-test
NSGA II	75	0.623	0.152	(-0.0405*0.1725)	1.33	0.205
MOPSO	75	0.557	0.147			

Table 19 results and the P-test statistic (value 0.205) show no significant difference between the distance index averages obtained by NSGA II and MOPSO algorithms.

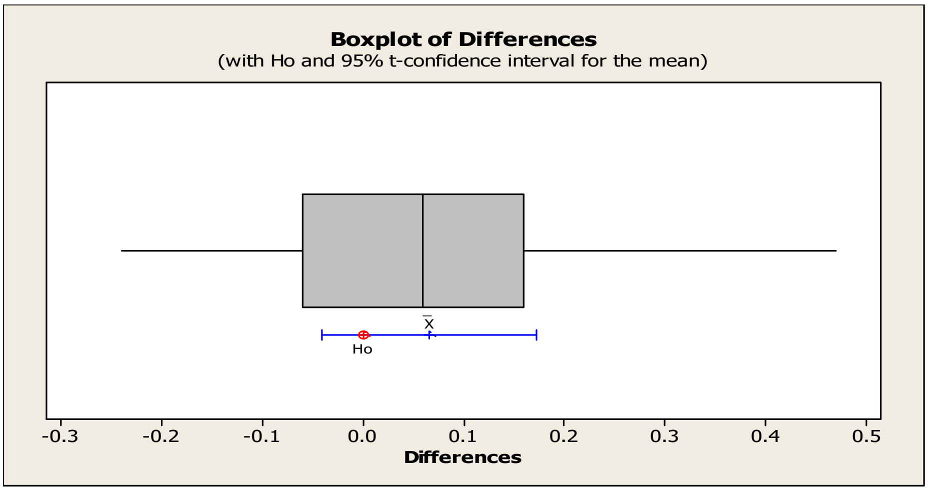

Figure 12. Box plot for the null hypothesis (the averages of distance index).

Figure 12 complements Table 19 by showing rejection of Hypothesis 1 and no significant differences in spacing index averages.

Examining the T-test test on the computing time averages

Table 20 presents the T-test results on average computing time. Also, Figure 13 shows a box diagram for the null hypothesis.

Table 20. The T-test results on average computing time

Algorithm	Samples	Average	S.d	Confidence Interval (95%)	T-test	P-test
NSGA II	75	844	730	(-483*88)	1.48	0.160
MOPSO	75	1041	1220			

According to the value of the P-test statistic, we can conclude that there is no significant difference between the computing time averages with MOPSO and NSGA II algorithms.

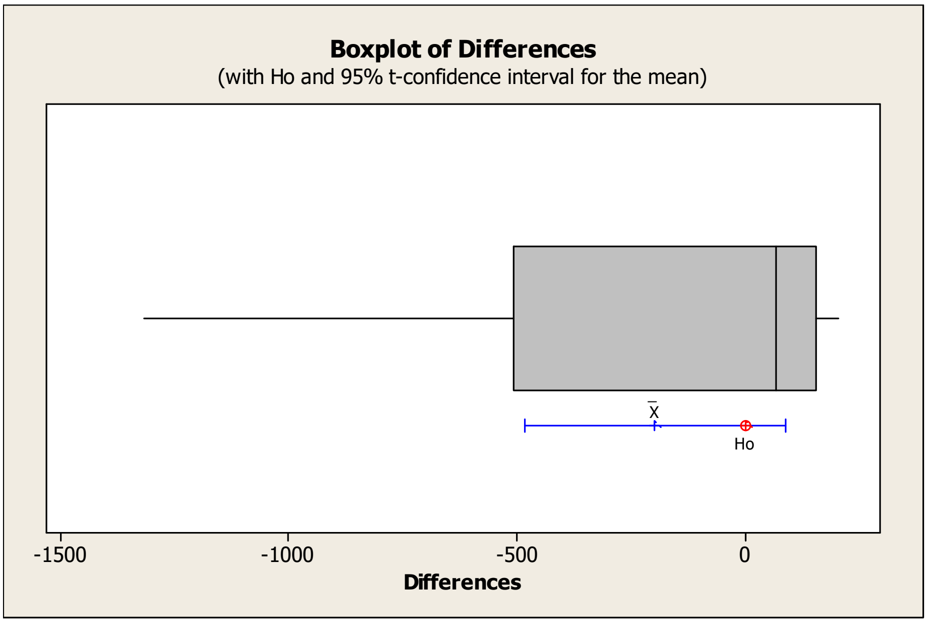

Figure 13. Box plot for the null hypothesis for computing time averages.

Figure 13 displays the null hypothesis, indicating no significant difference between the average computing time of MOPSO and NSGA II algorithms. Additionally, figure 14 compares the averages of the OFs and comparison indices in the numerical examples of large size.

The results of Figure 14 show that with the increase in the size of the problem, the first and OF_2 values have increased, and the time to solve the problem has increased exponentially.

Based on the data presented in Table 21, it is clear that there is only a significant difference between the averages of the OF_1 obtained from solving sample problems with NSGA II and MOPSO algorithms. Other comparison indicators do not show a significant difference.

In the previous section, we made meaningful comparisons between the averages of the computational index obtained from solving sample problems with NSGA II and MOPSO algorithms. We aimed to determine any significant differences between them. The results showed a significant difference only between the averages of the OF_1.

This section aims to select the most efficient algorithm using the TOPSIS multi-criteria decision-making method. To achieve this, we present Table 22, which shows the averages obtained from 75 sample problems.

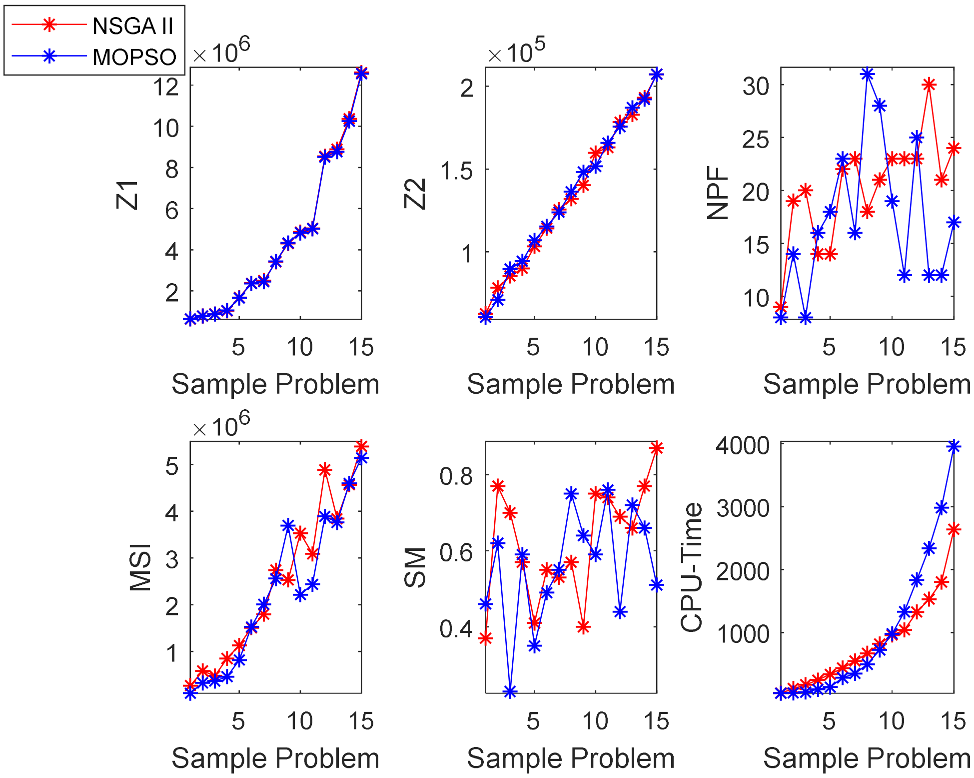

Figure 14. Comparison of averages and comparison indices of effective solutions in large numerical examples.

Table 21. The significant difference between the average comparison indicators.

Indicator	Significant difference
The OF_1 average	Yes
The OF_2 average	no
The number of effective answers	no
The most widespread index	no
Distance index	no
Computational time	no

Table 22. Average indices of meta-heuristic algorithms.

Algorithm	OF_1	OF_2	Effective solutions	The greatest expansion index	Distance index	Computational time
NSGA II	4526072	45240	20.27	2478417	0.623	844
MOPSO	4497208	45418	17.27	2260667	0.557	1041
Weight	0.4	0.4	0.05	0.05	0.05	0.05

After de-scaling Table 22. results, the information was entered into the MCDM engine software. The results showed the NSGA II algorithm efficiency with a weight of 0.6945 compared to the MOPSO algorithm (weight = 0.3055). Therefore, considering all the indicators and results, it is recommended to use the NSGA II algorithm.

5 Conclusion and Future Suggestions

5.1. Key Findings

Numerous endeavors have been dedicated to investigating supply chain network design challenges. This study delves into a multi-round supply chain network design problem, encompassing various real-world intricacies. It scrutinizes the executive decisions tied to energy production within the power plant, which are integral for supply chain management. These decisions include facility placement, procurement of raw materials, and investments in diversifying activities within the power plant's supply chain structure. Additionally, the study addresses the uncertainty associated with demand and cost using fuzzy chance-constrained programming.

The study also incorporates a service level indicator into the performance measurement and goal function. While various investigations have explored power plant supply chain design, the complexities arising from demand uncertainty, along with other inherent risks in the power plant supply chain, present significant challenges. These factors, such as minimizing transportation, construction, and production costs while maximizing supply chain responsiveness, compound the complexity and heighten the supply chain's vulnerability. This necessitates thorough consideration in the decision-making process.

5.2. Metaheuristic Algorithm Comparison

To assess the mathematical model's efficacy on a larger scale, two metaheuristic algorithms—MOPSO and NSGAII—were employed to analyze the model's results. This approach aids in evaluating and validating the model's performance in more extensive scenarios. After analyzing the results of the two algorithms, it was concluded that the MOPSO algorithm has superior computing time compared to the NSGAII algorithm. Additionally, MOPSO exhibited better performance in the first and second objective functions.

However, regarding other analytical parameters such as NPF, MSI, and SM, the NSGAII algorithm outperformed MOPSO. Using the TOPSIS method, it was determined that NSGAII, with a weight of 0.6945, was more favorable than MOPSO. These findings provide valuable insights into the trade-offs between computational efficiency and solution quality across different objective functions and performance metrics.

5.3. Future Research Directions

In addition to exploring new combined metaheuristic algorithms, such as the jumping frog and red deer algorithms, several other potential areas for further research are identified:

1. Stochastic Programming for Uncertainty Management:

Future studies could incorporate stochastic programming to handle other forms of uncertainty, such as fluctuating fuel prices or unforeseen disruptions in supply chains. This could lead to a more dynamic and adaptive model that accounts for sudden market shifts and improves decision-making under uncertainty.

2. Multi-Product Supply Chains:

The current model could be extended to address multi-product supply chains, where power plants rely on various raw materials rather than a single product. While this would increase the complexity of the model, it would make it more applicable to real-world scenarios where multiple energy sources are involved.

3. Real-Time Decision-Making:

Researchers could evaluate the performance of the model in real-time decision-making environments, where rapid adjustments to supply chain disruptions (e.g., natural disasters or geopolitical instability) are required. Integrating real-time data analytics and machine learning techniques could improve the model's responsiveness and accuracy under dynamic conditions.

4. Environmental and Sustainability Impacts:

Future studies could focus on the environmental and sustainability impacts of supply chain decisions, such as minimizing the carbon footprint or optimizing waste management in recycling centers. Incorporating life cycle assessment (LCA) metrics into the model would provide a more holistic view of the environmental benefits and costs of supply chain operations.

Conflict of Interest

The authors claim no conflict of Interest in this article.

Ethical approval

This article contains no studies with human participants or animals performed by authors.

Data Availability

This study was not associated with any third-party data.

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