GREEN CROSS-DOCK BASED SUPPLY CHAIN NETWORK DESIGN UNDER DEMAND UNCERTAINTY USING NEW METAHEURISTIC ALGORITHMS

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Abstract. This study concerns the optimization of green supply chain network design under demand uncertainty. The issue of demand uncertainty has been addressed using a scenario-based analysis approach. The main contribution of this research is to investigate the optimization of cross-dock based supply chain under uncertainty using scenario-based formulation and metaheuristic algorithms. The problem has been formulated as a two-objective mathematical model with the objectives of minimizing the costs and minimizing the environmental impact of the supply chain. Two metaheuristic algorithms, namely non-dominated sorting genetic algorithm II (NSGA-II) and multi-objective invasive weed optimization (MOIWO), have been developed to optimize this mathematical model. This paper focuses on the use of new metaheuristic algorithms such as MOIWO in green supply chain network design, which has received less attention in previous studies. The performance of the two solution methods has been evaluated in terms of three indices, which measure the quality, spacing, and diversification of solutions. Evaluations indicate that the developed MOIWO algorithm produces more Pareto solutions and solutions of higher quality than NSGA-II. A performance test carried out with 31 problem instances of different sizes shows that the two methods perform similarly in terms of the spread of solutions on the Pareto front, but MOIWO provides higher quality solutions than NSGA-II.

1. Introduction. Today’s world is facing the intensifying consequences of climate change and pollution, which can disrupt and potentially endanger the lives of millions of humans across the globe. Realizing this danger, many businesses have given high priority to the strategies that can minimize the environmental impacts of their activities, treating them as business innovation. To achieve this goal, businesses
must strike a balance between the minimization of unwanted outputs (energy loss, production of greenhouse gases, hazardous chemicals, solid waste, etc.) and their profitability and competitive advantage. The concept of the green supply chain has been introduced to help businesses in this matter. Over the past two decades, with the rising public pressure and the emergence of stricter laws and regulations that force businesses to pay attention to the environmental impacts of their activities, environmental protection studies have become increasingly important, and so has the subject of green supply chains in the area of supply chain management [3].

To become more environment-friendly, a business must adopt environment-friendly strategies for its logistics as well as products and services [21]. For example, it has to plan the procurement of parts and materials from suppliers such that the process can be done with the least possible pollution. Also, the production process itself should be modified to produce the least possible pollution; a goal that falls in the domain of the field known as green manufacturing. The business also has to be mindful of hazardous substances in the raw materials provided by suppliers, which can cause serious environmental impacts further downstream in the supply chain. This highlights the importance of working with reliable green suppliers and the necessity of integrating environmental issues into supplier development decisions for the long-term competitiveness of environment-friendly businesses and their supply chains [33]. In a study by Lamba & Thareja [24], on developing the structural model based on analyzing the relationship between the barriers of green supply chain management (GSCM), 16 barriers related to the GSCM considered and the multi-criteria decision-making approach used to define the ranking of the barriers. [24].

In the supply chain literature, the terms “sustainable supply chain management” and “green supply chain management” are often used interchangeably, but these are two slightly different concepts. While green supply chain management is focused on integrating environmental thinking into supply-chain management, sustainable supply chain management attempts to build a sustainable supply chain not only from an environmental viewpoint but also from economic and social perspectives. Thus, green supply chain management can be considered a branch of sustainable supply chain management [8]. In the past, the product life cycle used to refer to the processes between the design process and the consumption of the final product. But in the environmental management approach, involves the preparation of raw materials and the design, manufacturing, use, recycling, and reuse of the product, which form a closed-loop flow of materials, and the goal is to reduce resource consumption and environmental impacts of this loop.

Empirical research has shown that supply chain integration leads to improved business and operational performance and can be a perfect solution for senior managers who are struggling with the problems of fragmented organizational units.

One of the most inspirations in proposing this research study is the role of the environmental effects of the supply chain. Selecting the best suppliers, eco-friendly production and distribution are the most important decisions in this field of environmental responsibility of the supply chain. On the other hand, using different technologies can change the level of eco-friendly products in the supply chain and it can be considered as an important matter in supply chain network design. In 2019, Tseng et al. [35] presented a literature review on green supply chain management which addresses trends and future challenges. Their study revealed a declining trend on drivers or barriers analysis of green supply chain management while there is a
The growing trend of applying mathematical optimization model and sharp growth of publication on green supply chain management after 2010 [35].

Another noteworthy point in the definition of this research is that the use of cross-docks can improve the distribution process of final products in the supply chain. Cross-docks are centers that can receive a great variety of products and in a short period, turn them into a collection of product packs and then distribute them among customers. By considering the main inspirations and importance of the green supply chain, this paper presents a new model for designing green supply chain networks. In this model, the total cost of the supply chain and the total pollution resulting from manufacturing and distribution processes are minimized simultaneously. The constraints considered in the model formulation include supply constraints, distribution constraints, and supply chain capacity constraints. Accordingly, the main contribution of this research can be summarized as follows:

- Designing a green supply chain by considering the role of cross-dock in the distribution phase.
- Considering uncertainty in the demand parameter and applying scenario-based formulation.
- Using MOIWO as an efficient metaheuristic in the green supply chain optimization.

The rest of the paper is outlined as follows: In Section 2, a literature review is presented. In Section 3, we proposed a mathematical model and the model assumption. In section 4, the structure of the proposed metaheuristic algorithms (MOIWO) and (NSGA-II) are described and the performance evaluation criteria along with the mechanism of parameter setting for the algorithms are elaborated. In Section 5, solutions produced by the developed algorithms are presented and compared. Finally, the paper concludes with the results evaluation and some recommendations for future research in section 6.

2. Literature review.

2.1. Green supply chain. Green supply chain management was introduced by the Manufacturing Research Association of Michigan State University as a new management model for environmental protection. In terms of a product lifecycle, green supply chain management covers all processes involving raw materials, product design and manufacturing, sales and transportation, and use and recycling. By combining supply chain management and green technology, green supply chain management enables businesses to reduce the negative environmental impacts of their activities and make optimum use of their energy and resources [41].

One way to measure the environmental effects of supply chain activities is to consider the effects of products on the environment with a holistic approach (analyzing the effect of products from the beginning to the end of their life). In this approach, all ecological effects of each activity in each stage of the product lifecycle including concept design, design, preparation of raw materials, manufacturing, assembly, storage, packaging, transportation, and use and reuse of the product must be estimated and considered in product design [8].

Considering the rising environmental concerns and emerging environmental regulations, which are forcing industries to take a fresh look at the environmental impact of their supply chain operations, researchers have developed a framework based on mixed-integer linear programming for designing sustainable supply chains, which, in addition to the traditional constraints related to material balance in each
node, also it considers the principles of life cycle assessment. This framework distinguishes between solid and nonsolid wastes (e.g. greenhouse gas emissions) of different production and transportation processes. This framework has been used to analyze a tradeoff between economic and environmental goals at different costs and different strategies in the aluminum industry. To achieve an effective environmental strategy, the study has shown that the current rules of emission trading schemes need to be strengthened and coordinated at the global level. It has also been shown that effective carbon management strategies can help decision-makers achieve sustainability objectives and make continuous progress in this area in a cost-effective manner [32].

The idea of green closed-loop supply chains was first introduced by Guide et al. [20], who discussed the differences between this supply chain and the classic one and also explored the issue of value creation in these chains. The approach of supply chain greenness has been also analyzed by considering the product life cycle [20].

In 2008, Zhu et al. studied the concept of closed-loop green supply chain management in petrochemical, power generation, and automobile supply chains in China. In this study, the authors showed that in each of these chains, the closed-loop structure helps in reducing pollution and improving the environmental impact of the operations [42].

In later studies, Kannan et al. [23] attempted to design a green closed-loop supply chain for battery recycling. These researchers designed a multi-level chain model for decision-making on how to produce and distribute the product by taking into account the environmental factors. This model was solved by a metaheuristic genetic algorithm [23].

In 2012, Amin and Zhang developed a multi-objective mathematical model for designing green closed-loop supply chains. The structure of the chain includes manufacturing plants, assembly centers, collection centers, and recycling centers. They aimed to reduce both costs and damage to the supply chain. They used the model for different numerical examples and analyzed the results [2].

In a survey paper on the subject of the closed-loop supply chain by Govindan et al. [19], authors reviewed some of the studies published between 2007 and 2013 and specifically examined their methodologies to address the problem. In this paper, it was stated that the combination of green supply chain and closed-loop supply chain concepts and the use of quantitative methods to design such chains are among the most attractive new subjects of research in this field [19].

In another study by Talaei et al. [34], a multi-level closed-loop green supply chain model was designed for the electronics industry. The study aimed to design a supply chain with the lowest total cost and the lowest possible carbon production. To design such a supply chain, the problem was formulated as the site location of manufacturing, storage, and recycling facilities under uncertainty using the fuzzy logic [34].

In 2017, Burgess et al. combined the forward and reverse logistics to design a supply chain under demand uncertainty. This model, which was attempting to minimize the total cost of the chain as well as its CO₂ emission, was solved with an ant colony algorithm proposed in [5].

In 2018, Rad et al. developed an integrated multi-objective model for designing green closed-loop supply chain networks by considering the product quality and discounts. The objectives considered in this model were to reduce the costs, reduce environmental pollution, and increase customer satisfaction. The results of this
study showed that reducing environmental pollution improves customer satisfaction [31].

In another study, Ghelichi et al. [15] designed a green supply chain for the production of diesel vehicles. For this purpose, they developed a scenario-dependent multi-objective mathematical model and then optimized it by random mathematical programming. The objectives of this model were to reduce the costs and decrease the environmental pollution of the process [15].

In a study by Liang & Quesada [26] on the fuel supply chain, they identified the reduction of energy costs and the reduction of greenhouse gas emissions as the most important objectives of this chain and tried to optimize these factors. The developed model was implemented in Japan in order to provide an ideal solution for creating a balance between energy costs and environmental pollution [26]. Moreover, in the research by Lotfi et al. [27] a robust model for sustainable closed-loop supply chain network design is optimized.

Gholipour et al. assessed the integrated green supply chain network design and inventory-location problem. In order to optimize it, a fuzzy solution approach is applied for this purpose [16].

2.2. Application of metaheuristic algorithms. In the field of using appropriate metaheuristic algorithms, several related papers dealing with comparing some metaheuristic algorithms to find the best one in the supply chain network design problem.

Garg [13] presented a hybrid PSO-GA algorithm for constrained optimization problems and used particle swarm optimization (PSO) for improving and genetic algorithm (GA) for modifying, then by comparing the results of the PSO-GA method with the results of the previous experiments, the results indicated a better solution to supply chain optimization problem [13].

In 2019, Goli et al. [18] presented a multi-level supply chain network design model, where fuzzy logic was used to address demand uncertainty and fluctuations. The objectives considered in this model were to minimize the total cost and maximize the number of jobs to be created. In this study, the multi-objective forms of the grey wolf optimization algorithm and invasive weed optimization algorithm (IWO) were used for optimization [18].

In 2019, Garg presented a new hybrid GSA-GA algorithm for the constraint non-linear optimization problems by combining the features of GA and GSA algorithms and the solution of the gravitational search algorithm upgraded with the genetic algorithm and the performance of the algorithm was tested on the several problems with different nature and the results of proposed algorithm showed to be very profitable [14].

In 2020, Niroomand et al. presented an intuitionistic fuzzy two-stage supply chain network design problem with multi-mode demand and multi-mode transportation. They considered plants, distribution centers, and customers as a typical supply chain network design problem. A hybrid approach was proposed to convert the fuzzy objective function to a set of the crisp objective function, and the fuzzy constraints are crisped [30].

Gholizadeh and Fazlollahtabar in their research in 2020 provided an improved version of the genetic algorithm for closed-loop supply chain network design. Moreover, robust optimization is applied to deal with uncertainty. This study has been carried out at Melting Imen Tabarestan Company in Iran [17].
In a comprehensive study by Abdi et al., some novel metaheuristic algorithms are proposed for the integrated green supply chain network design and pick-up and split delivery problem. They applied four metaheuristics including GA, GA-PSO, SA, and red deer algorithm (RDA) to evaluate the solutions. Moreover, a case study has been done in order to analyze the effect of different parameters [1].

Table 1 presents a summary of the most notable studies in this domain. A review and comparison of previous research show that in none of the reviewed researches, the cross-dock based supply chain network design has been designed and optimized. Uncertainty in important parameters of the mathematical model, such as demand, has also received less attention. On the other hand, a closer look at Table 1 shows that the use of new and efficient algorithms has been considered by researchers over the last two years and is one of the attractive aspects in the field of supply chain network optimization.

| Authors          | Year of publication | Supply chain network design | Green supply chain | Reducing costs | Reducing environmental impacts | Qualitative analysis | Qualitative analysis | Uncertainty | Metaheuristic algorithms |
|------------------|---------------------|-----------------------------|--------------------|---------------|--------------------------------|---------------------|---------------------|-------------|--------------------------|
| Barros et al.    | 1998                | 0                           | 0                  | 0             | 0                              | 0                   | 0                   |             |                          |
| Lourens et al.   | 1999                | 0                           | 0                  | 0             | -                              | -                   | -                   |             |                          |
| Jayaraman et al. | 1999                | 0                           | 0                  | 0             | -                              | -                   | -                   |             |                          |
| Guo et al.       | 2003                | 0                           | 0                  | 0             | -                              | -                   | -                   |             |                          |
| Zhu et al.       | 2008                | 0                           | 0                  | 0             | -                              | -                   | -                   |             |                          |
| Kanan et al.     | 2010                | 0                           | 0                  | 0             | -                              | -                   | -                   |             |                          |
| Xing et al.      | 2011                | 0                           | 0                  | 0             | -                              | -                   | -                   |             |                          |
| Farahani et al.  | 2011                | 0                           | 0                  | 0             | -                              | -                   | -                   |             |                          |
| Shabani et al.   | 2012                | 0                           | 0                  | 0             | -                              | -                   | -                   |             |                          |
| Amin and Zhang   | 2012                | 0                           | 0                  | 0             | 0                              | 0                   | 0                   | -           |                          |
| Fahimnia et al.  | 2013                | 0                           | 0                  | 0             | 0                              | 0                   | 0                   | -           |                          |
| Taheri et al.    | 2016                | 0                           | 0                  | 0             | 0                              | 0                   | 0                   | -           |                          |
| Garbi et al.     | 2016                | 0                           | 0                  | 0             | -                              | -                   | -                   | -           | PSO-GA                   |
| Farahani et al.  | 2017                | 0                           | 0                  | 0             | 0                              | 0                   | 0                   | -           |                          |
| Rad & Nahavandi  | 2018                | 0                           | 0                  | 0             | 0                              | 0                   | 0                   | -           |                          |
| Ghelichi et al.  | 2018                | 0                           | 0                  | 0             | 0                              | 0                   | 0                   | -           |                          |
| Liang & Qureshi  | 2018                | 0                           | 0                  | 0             | 0                              | 0                   | 0                   | -           |                          |
| Gol et al.       | 2019                | 0                           | 0                  | 0             | -                              | -                   | -                   | IWO         |                          |
| Garbi et al.     | 2019                | 0                           | 0                  | 0             | GSA-GA                         | 0                   | 0                   | -           |                          |
| Lotfi et al.     | 2019                | 0                           | 0                  | 0             | 0                              | 0                   | 0                   | -           |                          |
| Niroomand et al. | 2020                | 0                           | 0                  | 0             | 0                              | 0                   | 0                   | -           |                          |
| Lamba & Barijas  | 2020                | 0                           | 0                  | 0             | 0                              | 0                   | 0                   | -           |                          |
| Ghadimazdeh & Fardighchavar | 2020 | 0       | 0       | 0       | 0                              | 0                   | 0                   | GA          |                          |
| Golipour et al.  | 2020                | 0                           | 0                  | 0             | 0                              | 0                   | 0                   | -           |                          |
| Abdi et al.      | 2020                | 0                           | 0                  | 0             | GA-PSO, RDA                    | 0                   | 0                   | -           |                          |
| Present study    | 2020                | 0                           | 0                  | 0             | MOFIO, NSGA-II                 | 0                   | 0                   | -           |                          |
To address the above-mentioned research gaps, the present study focuses on the quantitative approach to cross-dock based green closed-loop supply chain in the presence of demand uncertainty. The study also contributes to the literature by investigating the use of a new metaheuristic algorithm as the multi-objective invasive weed optimization algorithm in the green supply chain network design, which has received less attention in previous studies.

3. The proposed mathematical model. The supply chain under study consists of 5 echelons. At the first echelon, there is a set of suppliers who are responsible for supplying raw materials for the production phase. At the second echelon, there is a set of potential manufacturers that can meet the needs of customers. At the third echelon, several potential distributors are responsible for receiving final products from manufacturers and distributing them to the next echelon of the supply chain at the appropriate time. At the fourth echelon, there is a set of cross-docks that receive, package, and deliver various products immediately to the next echelon of the supply chain. At the fifth level echelon, there are a certain number of retailers who are responsible for selling products to customers. The structure of the proposed supply chain is illustrated in Figure 1.

**Figure 1.** The structure of the studded supply chain

By designing the network of the desired supply chain, the selection of suppliers, the number of factories to be established, the number of distribution centers and the number of cross-docks to be established are determined. Also, the amount of raw materials purchased, the number of products produced, and the number of products shipped along the supply chain are determined. To find the optimal solution, two objectives are considered. The first goal is to reduce the total costs of the supply chain and the second goal is to reduce the adverse environmental effects of production and distribution.

In order to bring the research problem closer to the real situation, demand uncertainty has been studied. For this purpose, several different scenarios are considered for the demand, and for each scenario, a specific probability is defined. Then, using the scenario-based formulation, this uncertainty is taken into account in the mathematical model. Other research assumptions are as follows.

- Each customer demand must be met in its entirety.
- There is only one type of product.
- Demands are registered according to the available capacity.
• Retails are not allowed.
• The number of facilities required at each level of the supply chain is predetermined.
• There is no flow of product or material between the facilities at the same level of the supply chain.
• Suppliers, plants, distribution centers, and cross-docking warehouses have limited capacity.

Indices

\( G \) : The set of chosen suppliers
\( S_g \) : The set of chosen potential suppliers
\( P \) : The set of potential manufacturing plants
\( D \) : The set of potential distributors
\( C \) : The set of potential cross-docking warehouses
\( R \) : The set of retailers
\( T \) : The set of manufacturing technologies
\( \xi \) : The set of demand scenarios

Parameters

\( TEC_{pt} \) : The cost of using the technology \( t \) in the plant \( p \)
\( OC_p \) : The cost of opening the plant \( p \)
\( OC_d \) : The cost of opening the distribution center \( d \)
\( OC_c \) : The cost of opening the cross-docking warehouse \( c \)
\( FCS_g \) : The fixed cost of a long-term relationship with the supplier \( S_g \)
\( VCD_d \) : The variable cost of moving the product in the distribution center \( d \)
\( VCC_c \) : The variable cost of moving the product in the cross-docking warehouse \( c \)
\( VCS_g \) : The variable cost of moving the product in the supplier \( S_g \)
\( TCS_{sp}d \) : The cost of transporting each unit of product from the supplier to the plant \( p \)
\( TCD_{pd} \) : The cost of transporting each unit of product from the plant \( p \) to the distribution center \( d \)
\( TCD_{dc} \) : The cost of transporting each unit of product from the distribution center \( d \) to the cross-docking warehouse \( c \)
\( TCD_{cr} \) : The cost of transporting each unit of product from the cross-docking warehouse \( c \) to the retailer \( r \)
\( TCD_{dr} \) : The cost of transporting each unit of product from the distribution center \( d \) to the retailer \( r \)
\( MCP_{pt} \) : The cost of manufacturing each unit of product in the plant \( p \) using the technology \( t \)
\( EM_{pt} \) : The greenhouse gas emission cost due to the manufacturing of each unit of product in the plant \( p \) using the technology \( t \)
\( ET_{sp} \) : The environmental impact of transporting each unit of product from the supplier \( S_g \) to the plant \( p \)
\( ET_{pd} \) : The environmental impact of transporting each unit of product from the plant \( p \) to the distribution center \( d \)
\( ET_{dc} \) : The environmental impact of transporting each unit of product from the distribution center \( d \) to the cross-docking warehouse \( c \)
\( ET_{cr} \) : The environmental impact of transporting each unit of product from the cross-docking warehouse \( c \) to the retailer \( r \)
\( ET_{dr} \) : The environmental impact of transporting each unit of product from the distribution center \( d \) to the retailer \( r \)
\( ESS_g \) : The environmental impact of the supplier \( S_g \)
\( EO_{pt} \) : The environmental impact of opening the plant \( p \) using the technology \( t \)
\[ EO_d \]: The environmental impact of opening the distribution center \( d \)
\[ EO_c \]: The environmental impact of opening the cross-docking warehouse \( c \)
\[ \text{Cap}_{S_g} \]: Capacity of the supplier \( S_g \)
\[ \text{Cap}_{pt} \]: Production capacity of the plant \( p \) using technology \( t \)
\[ \text{Cap}_{d} \]: Product transfer capacity at the distribution center \( d \)
\[ \text{Cap}_{d} \]: Product transfer capacity at the cross-docking warehouse \( c \)
\[ S_{Max} \]: The maximum number of suppliers required
\[ P_{Max} \]: The maximum number of plants required
\[ D_{Max} \]: The maximum number of distribution centers required
\[ D_{Max} \]: The maximum number of cross-docking warehouses required
\[ P(\xi) \]: The probability of occurrence of the scenario \( \xi \)
\[ \text{Dem}_{r,}\xi(\xi) \]: Demand of the retailer \( r \) in the scenario \( \xi \)
\[ M \]: A very large number

**Decision variables**

\[ \alpha_{S_g} \]: Equals 1 if the supplier \( S_g \) is chosen and 0 otherwise
\[ \beta_{pt} \]: Equals 1 if the plant \( p \) with the technology \( t \) is opened and 0 otherwise
\[ \gamma_d \]: Equals 1 if the distribution center \( d \) is opened and 0 otherwise
\[ \lambda_c \]: Equals 1 if the cross-docking warehouse \( c \) is opened and 0 otherwise
\[ g_{rc}(\xi) \]: Equals 1 if the demand of the retailer \( r \) in the scenario \( \xi \) is assigned to the cross-docking warehouse \( c \) and 0 otherwise
\[ X_{S_{gp}}(\xi) \]: The flow of product from the supplier \( S_g \) to the plant \( p \) in the scenario \( \xi \)
\[ X_{pd}(\xi) \]: The flow of product from the plant \( p \) to the distribution center \( d \) in the scenario \( \xi \)
\[ X_{dc}(\xi) \]: The flow of product from the distribution center \( d \) to the cross-docking warehouse \( c \) in the scenario \( \xi \)
\[ X_{cr}(\xi) \]: The flow of product from the cross-docking warehouse \( c \) to the retailer \( r \) in the scenario \( \xi \)
\[ h_{pt}(\xi) \]: The amount of product produced in the plant \( p \) using the technology \( t \) in the scenario \( \xi \)
\[ \delta_{S_g} \]: Auxiliary variable used for linearizing the constraint related to the supplier \( S_g \)

**Objective functions**

\[ \text{Min } OB_1 \]
\[ = \sum_{g \in G} \sum_{s \in S_g} FC_{sg} \alpha_{sg} + \sum_{p \in P} \sum_{t \in T} (OC_p + TEC_{pt}) \beta_{pt} + \sum_{d \in D} OC_d \gamma_d \]
\[ + \sum_{c \in C} OC_c \lambda_c + \sum_{\xi \in \Xi} P(\xi) \]
\[ \left\{ \sum_{g \in G} \sum_{s \in S_g} \sum_{p \in P} (VC_{sp} + TC_{sp}) X_{sgp}(\xi) \right. \]
\[ + \sum_{p \in P} \sum_{t \in T} MC_{pt} h_{pt}(\xi) + \sum_{p \in P} \sum_{d \in D} (VC_d + TC_{pd}) X_{pd}(\xi) \right. \]
\[ + \sum_{p \in P} \sum_{c \in C} (VC_c + TC_{dc}) X_{dc}(\xi) + \sum_{c \in C} \sum_{r \in R} TC_c X_{cr}(\xi) \]
\[ \left. + \sum_{d \in D} \sum_{r \in R} TC_{dr} X_{dr}(\xi) \right\} \]
\[ (1) \]

\[ \text{Min } OB_2 \]
\[ = \sum_{g \in G} \sum_{s \in S_g} ES_{sg} \alpha_{sg} + \sum_{p \in P} \sum_{t \in T} EO_{pt} + \beta_{pt} + \sum_{d \in D} EO_d \gamma_d + \sum_{c \in C} EO_c \lambda_c \]
\[ (2) \]
\[ + \sum_{\xi \in \Xi} P(\xi) \left\{ \begin{array}{l}
\sum_{g \in G} \sum_{s_g \in S_g} \sum_{p \in P} (ET_{s_g p} X_{s_g p})(\xi) \\
+ \sum_{p \in P} \sum_{t \in T} EM_{pt} h_{pt}(\xi) + \sum_{p \in P} \sum_{d \in D} ET_{pd} X_{pd}(\xi) \\
+ \sum_{p \in P} \sum_{c \in C} ET_{pc} X_{pc}(\xi) + \sum_{c \in C} \sum_{r \in R} ET_{cr} X_{cr}(\xi) \\
+ \sum_{d \in D} \sum_{r \in R} ET_{dr} X_{dr}(\xi)
\end{array} \right\} \]

The objective function (1) minimizes the cost resulting from the choices made for the supply chain, including both fixed and variable costs. The components of this objective function are the fixed cost of establishing a business relationship with the selected supplier, the fixed cost of opening the selected plant \((p)\), the fixed cost of opening the selected distribution center \((d)\), and the cost of opening the selected cross-docking warehouse \((c)\).

The objective function (2) minimizes the environmental impacts resulting from the choices made for the supply chain. The components of this objective function are the environmental impact of the selected supplier, the environmental impact of opening the selected plant \((p)\) with the selected technology \((t)\), the environmental impact of opening the selected distribution center \((d)\), and the environmental impact of opening the selected cross-docking warehouse \((c)\).

Model constraints

\[ \sum_{g \in G} \sum_{s_g \in S_g} X_{s_g p}(\xi) = \sum_{d \in D} X_{pd}(\xi) \quad \forall p, \xi \]  
(3)

\[ \sum_{c \in C} X_{dc}(\xi) = \sum_{r \in R} X_{dr}(\xi) \quad \forall d, \xi \]  
(4)

\[ \sum_{p \in P} X_{pd}(\xi) = \sum_{c \in C} X_{dc}(\xi) + \sum_{r \in R} X_{dr}(\xi) \quad \forall d, \xi \]  
(5)

\[ \sum_{t \in T} h_{pt}(\xi) = \sum_{p \in P} \sum_{s_g \in S_g} X_{s_g p}(\xi) \quad \forall p, \xi \]  
(6)

\[ \sum_{c \in C} X_{cr}(\xi) + \sum_{d \in D} X_{dr}(\xi) \geq Dem_r(\xi) \quad \forall r, \xi \]  
(7)

\[ \sum_{c \in C} y_{cr}(\xi) \leq 1 \quad \forall r, \xi \]  
(8)

\[ X_{cr}(\xi) \leq Dem_r(\xi) y_{cr} \xi \quad \forall c, r, \xi \]  
(9)

\[ \sum_{s_g \in S_g} X_{s_g p}(\xi) \leq Cap_{s_g} \alpha_{s_g} \quad \forall s_g, \xi \]  
(10)

\[ \sum_{g \in G} \sum_{s_g \in S_g} X_{s_g p}(\xi) \leq Cap_{pt} \beta_{pt} \quad \forall p, t, \xi \]  
(11)

\[ \sum_{d \in D} X_{pd}(\xi) \leq Cap_{pt} \beta_{pt} \quad \forall p, t, \xi \]  
(12)

\[ \sum_{r \in R} X_{cr}(\xi) \leq Cap_c \lambda_c \quad \forall c, \xi \]  
(13)
\[
\sum_{t \in T} \beta_{pt} \leq 1 \quad \forall p
\]

\[
\sum_{g \in G} \sum_{s_g \in S_g} \alpha_{s_g} \leq S_{max}
\]

\[
\sum_{p \in P} \sum_{t \in T} \beta_{pt} \leq P_{max}
\]

\[
\sum_{d \in D} \gamma_d \leq D_{Max}
\]

\[
\sum_{c \in C} \lambda_c \leq C_{Max}
\]

\[
\alpha_{s_g} \geq \sum_{p \in P} X_{s_g p}(\xi) - C_{aps_g} + 1 \quad \forall s_g, \xi
\]

\[
\alpha_{s_g} \geq 0 \quad \forall s_g
\]

\[
\alpha_{s_g} \geq \sum_{p \in P} X_{s_g p}(\xi) - C_{aps_g} + 1 - M \delta_{s_g} \quad \forall s_g, \xi
\]

\[
\alpha_{s_g} \leq \sum_{p \in P} X_{s_g p}(\xi) - C_{aps_g} + 1 - M \delta_{s_g} \quad \forall s_g, \xi
\]

\[
\alpha_{s_g} \leq -M \delta_{s_g} \quad \forall s_g
\]

\[
\alpha_{s_g} \geq -M (1 - \delta_{s_g}) \quad \forall s_g
\]

\[
\gamma_d \in \{0, 1\} \quad \forall d
\]

\[
\lambda_c \in \{0, 1\} \quad \forall c
\]

\[
y_{rc}(\xi) \in \{0, 1\} \quad \forall r, c
\]

\[
X_{s_g p}(\xi) \geq 0 \quad \forall s_g, p
\]

\[
X_{pd}(\xi) \geq 0 \quad \forall p, d
\]

\[
X_{dc}(\xi) \geq 0 \quad \forall d, c
\]

\[
X_{cr}(\xi) \geq 0 \quad \forall c, r
\]

\[
X_{dr}(\xi) \geq 0 \quad \forall d, r
\]

\[
h_{pt}(\xi) \geq 0 \quad \forall p, t
\]

\[
\alpha_{s_g} \leq \text{Max} \left\{ \sum_{g' \in \{g-1,g-2,\ldots,1\}} \sum_{s_g \in S_g} \sum_{p \in P} X_{s_g p}(\xi) - \sum_{g' \in \{g-1,g-2,\ldots,1\}} \sum_{s_g \in S_g} C_{aps_g} + 1 \right\} \quad \forall s_g
\]

Eqs. (3) - (5) guarantee the continuity of the flow of product in the supply chain. Eq. (6) expresses the production or transfer of products from plant \( p \) with the technology \( t \) in the scenario \( \xi \). Eq. (7) ensures that each demand is entirely met in the retailer or the warehouse at which it has been registered. Eq. (8) ensures that the demand of each retailer cannot be assigned to more than one cross-docking warehouse. Eq. (9) states that the cross-docking warehouse can send the product to a retailer only if it has been given the demand for that retailer.

Eq. (10) expresses that the products can only be supplied from the supplier and through the route determined by the demand and that the transported amount
should not exceed the capacity of the supplier. Eqs. (11)-(13) indicate that the products can be supplied by the plants, distribution centers, and cross-docking warehouses defined in the network. These constraints also limit the volume of transport to the capacity of the supply chain facilities.

Eq. (14) guarantees the creation of plants with special technology in the set of potential plants. Eqs. (15)-(18) limit the maximum number of chosen suppliers according to the number of facilities and their capacity based on the company’s overall policy. Eqs. (19)-(24) are the linearized version of Eq. (36). Eq. (36) states that a supplier will be selected only if the supply quantity is exactly equal to its capacity ($\alpha_{sg} = 1$). In other words, if a supplier is selected, its full capacity must be used.

4. The proposed solution methods. In this research, two metaheuristic algorithms are proposed. The reason for choosing these two algorithms can be summarized in the fact that in the literature, the use of the MOIWO algorithm in supply chain network optimization has received less attention. Therefore, this algorithm has been used as a new method in supply chain network design. On the other hand, to evaluate the performance of this algorithm, it is necessary to evaluate its performance by one of the most prominent and powerful meta-heuristic algorithms. For this reason, the NSGA-II algorithm has been used to evaluate the performance of the MOGWO algorithm.

4.1. Multi-objective invasive weed optimization (MOIWO). The invasive weed optimization algorithm (IWO) is a numerical optimization algorithm developed by Mehrabian and Lucas [29], which takes inspiration from the growth of weed plants. Weeds are fast-growing invasive plant species that can threaten the growth of cultivated crops. Weeds are very opportunistic and resilient and highly adaptable to environmental changes; features that make them a good source of inspiration for developing robust optimization algorithms.

Optimization with IWO

Emulating the natural life cycle of weed plants, IWO attempt to improve its output iteratively through the following steps:
Step 1: the seeds are spread over the search space
Step 2: The seeds grow into flowering plants that produce and spread their own seeds based on their fertility (fitness)
Step 3: After several iterations, the seeds with the lowest fitness values will be removed from the process (competitive elimination)
Step 4: The process continues until reaching the best fitness

A detailed description of IWO

Step 1. Random population generation and fitness evaluation.
In this step, each plant produces a certain number of seeds. The number of seeds each plant is allowed to produce depends on its fitness and the maximum and minimum fitness of the weed colony. This number increases linearly with fitness. Naturally, the number of seeds produced by each plant depends on its success in its environment. Since this relationship is considered to be linear, the best solution from the current population gets the highest number of new seeds, the worst solution gets the fewest seeds, and other solutions get a linearly decreasing number of seeds based on these two numbers.
Step 2. Fitness-based reproduction and updating of standard deviation

Depending on the species of a weed plant, it may reproduce with or without the use of sex cells. Sexual reproduction is done using seeds or spores. In this type of reproduction, a plant is born when an egg in the parent plant is fertilized by a pollen grain, thus turning into a seed. The produced seeds are then dispersed by wind, water, animals, etc. (seed dispersal). So that they can find the space and opportunity to grow. Upon reaching suitable conditions, healthy seeds start to germinate and grow. They continue to grow in interaction with other nearby plants until becoming mature. Finally, they turn into flowering plants and produce seeds.

Step 3. Competitive elimination

Since the plants that fail to reproduce must die away, there must be a competition between seeds to limit the maximum number of plants in the colony. For this purpose, once seeds are dispersed around the plants, the algorithm only allows a certain number of seeds with the highest fitness to turn into mature plants. This number, $P_{\text{max}}$, is the predefined maximum number of plants in the colony. The seeds that are given a chance to survive will grow and produce their own seeds and the above process will be then repeated. In this way, the algorithm obtains progressively improving solutions in its iterations. In this mechanism, the plants with low fitness also have a chance to reproduce and possibly create seeds with higher fitness. The algorithm stops upon reaching a predefined maximum number of iterations. The maximum number of plants can be set equal to the size of the initial population, in which case one of the parameters of the algorithm will be eliminated.

Step 4. The termination conditions

One can define multiple types of termination condition for metaheuristic algorithms:

- Obtaining a sufficiently acceptable solution
  
  This type of termination condition is used when, for example, the total expenditure of a company is 1000 monetary units and the management of that company is attempting to reduce this expenditure to 800 units, which it considers to be sufficiently acceptable. It should be noted that 800 units are not the optimal solution and the optimization may yield an even better result if one is required.

- After a certain amount of time elapsed or a certain number of iterations
  
  The algorithm can be instructed to stop after performing the steps a certain number of times and for a certain period. For example, if you know that the results reached at the end of the 100th iteration will be sufficiently good, you can set the algorithm to stop after 100 iterations. However, the optimization may be able to yield an even better result after this iteration.

- After a certain amount of time elapsed or a certain number of iterations passed without significant improvement in the output
  
  The algorithm can be instructed to stop after running for a certain period or a certain number of iterations without achieving any significant improvement in the solution. For example, one can set the algorithm to stop if the improvement achieved in $n$ consecutive iterations is not enough to change an evaluation indicator from $a$ to $b$ or is less than $x\%$.

4.2. Non-dominated sorting genetic algorithm II (NSGA-II). Non-dominated sorting genetic algorithm II is a genetics-inspired elitist multi-objective algorithm
introduced by Deb [6]. In this algorithm, the populations of parents and children (each with N members) are combined and then evaluated by running the following operations: 1) fast non-dominated sorting, 2) an elitist approach, and 3) an efficient population comparison mechanism. When there are more than N members in the archive of the dominant elements, only the elements that have the greatest distance in terms of population distance from their neighboring elements are stored. In this research, the exact expression of the algorithm steps is avoided. However, for more details, please refer to the reference [6]. Continuing his research, Deb has used simulations on a number of difficult problems and concluded that his proposed algorithm NSGA-II outperforms two other contemporary MOEAs: PAES and SPEA. This efficiency is in the form of a much better spread of solution and better convergence near the true Pareto-optimal boundary. Considering the good performance of NSGA-II and the fact that it is commonly used by researchers to evaluate the performance of other algorithms, this study also used NSGA-II for this purpose.

4.3. Performance evaluation criteria for multi-objective metaheuristic algorithms. This section introduces the quantitative and qualitative criteria typically used to measure and compare the performance of metaheuristic algorithms [43].

Spread of the Non-dominated Solutions (SNS) index
SNS is an index used to measure the diversity of Pareto solutions. Larger SNS values are indicative of better algorithm performance. This index is calculated using Eq. (37).

$$SNS = \sqrt{\frac{\sum_{i=1}^{n} (MID - C_i)^2}{n - 1}}$$  \hspace{1cm} (37)

In Eq. (37), $n$ is the number of non-dominated solutions and $C_i$ is given by Eq. (38).

$$C_i = \sqrt{f_{1i}^2 + f_{2i}^2}$$  \hspace{1cm} (38)

where $f_{1i}$ and $f_{2i}$ are the values of the first and second objective functions for the non-dominated solution $i$.

Divergence Metric (DM) index
This index is used to measure the spread of the solutions on the Pareto optimal front. The larger the value of max spread, the better the algorithm performs. This index is calculated by Eq. (39).

$$DM = \sqrt{\sum_{i=1}^{n} (Min f_i - Max f_i)^2}$$  \hspace{1cm} (39)

Where $Min f_i$ and $Max f_i$ are the minimum and maximum values of the objective function in all the non-dominated solutions obtained from the algorithm.

Mean Ideal Distance (MID) index
MID can be used to measure how close the obtained non-dominated solutions are to the ideal point. Smaller MID values indicate better algorithm performance.
This index is calculated using Eq. (40).

\[
MID = \frac{1}{n} \sum_{i=1}^{n} \sqrt{(f_{1i} - f_{1\text{best}})^2 + (f_{2i} - f_{2\text{best}})^2}
\]

In Eq. (40), \(f_{1\text{max}}\) is the largest value and \(f_{1\text{min}}\) is the smallest value among the non-dominated solutions obtained from the algorithm.

5. Numerical results.

5.1. Model validation. To demonstrate the performance of the mathematical model presented in this study, we first examine the results obtained by solving the model with CPLEX solver using GAMS software. For this purpose, we use the problem with the specifications given in Table 2.

Table 2. Information of the problem used for validation

| Indices | Symbol | Value |
|---------|--------|-------|
| Total number of potential suppliers | \(|S|\) | 15 |
| Number of potential manufacturing plants | \(|M|\) | 10 |
| Number of potential distribution centers | \(|D|\) | 20 |
| Number of potential cross-docking warehouses | \(|C|\) | 35 |
| Number of retailers | \(|R|\) | 50 |
| Number of manufacturing technologies | \(|T|\) | 3 |

Based on the dimensions of this problem, the parameters of the mathematical model were set as listed in Table 3.

Table 3: Parameter setting used for the validation problem

| Parameter | Description | Value |
|-----------|-------------|-------|
| TEC_{pt} | The cost of using the technology \(t\) in the plant \(p\) | 15000 |
| OC_{p} | The cost of opening the plant \(p\) | 60000 |
| OC_{d} | The cost of opening the distribution center \(d\) | 20000 |
| OC_{c} | The cost of opening the cross-docking warehouse \(c\) | 7000 |
| FC_{sg} | The fixed cost of a long-term relationship with the supplier \(S_g\) | 1000 |
| VC_{d} | The variable cost of moving the product in the distribution center \(d\) | 100 |
| VC_{c} | The variable cost of moving the product in the cross-docking warehouse \(c\) | 80 |
| TC_{sp} | The cost of transporting each unit of product from the supplier \(S_g\) to the plant \(p\) | 45 |
| TC_{pd} | The cost of transporting each unit of product from the plant \(p\) to the distribution center \(d\) | 50 |
| Parameter   | Description                                         | Value |
|------------|-----------------------------------------------------|-------|
| $TC_{dc}$  | The cost of transporting each unit of product from the distribution center $d$ to the cross-docking warehouse $c$ | 30    |
| $TC_{cr}$  | The cost of transporting each unit of product from the cross-docking warehouse $c$ to the retailer $r$ | 25    |
| $TC_{dr}$  | The cost of transporting each unit of product from the distribution center $d$ to the retailer $r$ | 30    |
| $MC_{pt}$  | The cost of manufacturing each unit of product in the plant $p$ using the technology $t$ | 190   |
| $EM_{pt}$  | The greenhouse gas emission cost due to the manufacturing of each unit of product in the plant $p$ using the technology $t$ | 230   |
| $ET_{sp}$  | The environmental impact of transporting each unit of product from the supplier $S_g$ to the plant $p$ | 70    |
| $ET_{pd}$  | The environmental impact of transporting each unit of product from the plant $p$ to the distribution center $d$ | 60    |
| $ET_{dc}$  | The environmental impact of transporting each unit of product from the distribution center $d$ to the cross-docking warehouse $c$ | 60    |
| $ET_{cr}$  | The environmental impact of transporting each unit of product from the cross-docking warehouse $c$ to the retailer $r$ | 60    |
| $ET_{dr}$  | The environmental impact of transporting each unit of product from the distribution center $d$ to the retailer $r$ | 40    |
| $ES_{sg}$  | The environmental impact of the supplier $S_g$ | 130   |
| $EO_{pt}$  | The environmental impact of opening the plant $p$ using the technology $t$ | 230   |
| $EO_d$     | The environmental impact of opening the distribution center $d$ | 160   |
| $EO_c$     | The environmental impact of opening the cross-docking warehouse $c$ | 150   |
| $Cap_{sg}$ | Capacity of the supplier $S_g$ | 25000 |
| $Cap_{pt}$ | Production capacity of the plant $p$ using technology $t$ | 20000 |
| $Cap_d$    | Product transfer capacity at the distribution center $d$ | 15000 |
| $Cap_c$    | Product transfer capacity at in the cross-docking warehouse $c$ | 10000 |
| $S_{max}$  | The maximum number of suppliers required | 6     |
| $P_{max}$  | The maximum number of plants required | 5     |
| $D_{max}$  | The maximum number of distribution centers required | 10    |
| $C_{max}$  | The maximum number of cross-docking warehouses required | 30    |
| $P(\xi)$   | The probability of occurrence of each scenario | 0.1-0.3-0.6 |
Given the uncertainty of demand, demand values in the scenarios were defined as given in Table 4. This problem information was entered into the software GAMS, where it was solved with the CPLEX solver. The results obtained by solving this model are presented below.

Out of 15 potential suppliers, the model could choose a maximum of 6. The suppliers chosen by the model in the optimal solution are listed below. As seen, the model has selected 4 suppliers. This is because choosing too many suppliers will impose more costs on the system and reduce their efficiency in meeting the needs of the supply chain.

In this problem, there were 10 potential plants, of which a maximum of 5 could be built. In the solution of the model, the plants and their manufacturing technologies were chosen as detailed in Table 6.

As the above table shows, in the optimal solution, the maximum allowed number of plants (five) need to be opened. This is because fewer plants would not be able to cover the demand of retailers under the defined scenarios. The total cost of establishing the plants will be 300,000 monetary units for the plants themselves and 75,000 monetary units for launching the chosen manufacturing technologies. In the optimal solution, the environmental impact of setting up these plants will be 1,150 units.

Out of 20 potential distribution centers, the model could choose a maximum of 10 to be established. The distribution centers chosen in the optimal solution are listed in Table 7.

---

**Table 4.** Demand information in the scenarios

| Scenario No. | 1  | 2  | 3  |
|--------------|----|----|----|
| Probability  | 0.1| 0.6| 0.3|
| Retailer demand | 100| 250| 320|

**Table 5.** The selected suppliers in the optimal solution

| Scenario No. | 2  | 3  | 4  | 5  |
|--------------|----|----|----|----|
| Technology ID | 1  | 1  | 2  | 3  | 2  |

**Table 6.** The selected plants and manufacturing technologies in the optimal solution

| Plant No. | 1  | 5  | 6  | 7  | 9  |
|-----------|----|----|----|----|----|
| Technology ID | 1  | 1  | 2  | 3  | 2  |

**Table 7.** The distribution centers chosen in the optimal solution

| Distribution center No. | 7  | 9  | 14 | 15 | 18 | 19 | 20 |
|--------------------------|----|----|----|----|----|----|----|
In this solution, the total cost of building distribution centers is 140,000 monetary units and their environmental impact is 1,120 units.

In the defined problem, there were 35 potential cross-docking warehouses, of which a maximum of 30 could be established. The cross-docking warehouses chosen to be established in the optimal solution are listed in Table 8.

Table 8. The cross-docking warehouses chosen in the optimal solution

| Cross-docking warehouse No. | 2   | 4   | 9   | 10  | 11  | 14  | 18  | 19  | 26  | 28  | 29  | 30  |
|---------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|

As can be seen, the optimal solution uses only 12 of 30 cross-docking warehouses that can be built. The cost of establishing these warehouses is 84,000 monetary units and their environmental impact is 1,800 units. A summary of the cost and environmental impact of the chosen facilities and technologies in the optimal solution is given in Table 9.

Table 9. Details of the output of the mathematical model for the validation problem

| Items                        | Cost   | Environmental impact |
|------------------------------|--------|----------------------|
| Selecting suppliers          | 4000   | 520                  |
| Establishing manufacturing   | 300000 | 75000                |
| plants                       |        |                      |
| Establishing distribution    | 160000 | 1280                 |
| centers                      |        |                      |
| Establishing warehouses      | 84000  | 1800                 |
| Manufacturing the productb   | 37000  | 960                  |
| Transportation               | 34000  | 1620                 |
| Total                        | 619000 | 81180                |

Figure 2 compares the cost and environmental impact of different supply chain decisions in the optimal solution. As shown in Figure 2, the opening of plants...
accounts for the greatest portion of the cost as well as the environmental impact. From this result, the following can also be concluded:

- In the considered supply chain, the greatest environmental impact in the distribution and retailing facilities is related to cross-docking warehouses and then transportation.
- Overall, the largest environmental impact in the considered supply chain originates from the plants. Therefore, attention to the pollution of the plants can have the greatest effect on the environmental impact of the chain as a whole.
- Combining the above output with managerial approaches for cost-saving and environmental impact mitigation can further reduce the cost and environmental impact of the supply chain from the amounts to be achieved in this solution.

Moreover, the results presented in Figure 2 show that there are the least cost and environmental impact in the selection of suppliers. This is while establishing factories has the greatest cost and environmental impact. Therefore, focusing on improving performance in production units can have a positive effect on economic efficiency and environmental efficiency at the same time. Also, after factories, distribution centers, and cross docks are the most important in terms of cost environmental impact.

5.2. Performance comparison between NSGA II and MOIWO. In this study, the performance comparison was performed in terms of MID, DM, and SNS. The reason is NSGA-II and MOIWO are both multi-objective optimization algorithms and produce multiple solutions (efficient points), therefore they had better to be compared in terms of criteria that are suitable for this purpose.

To compare the algorithms in terms of the considered criteria, we randomly produced 31 problem instances of different sizes. These instances were classified into three groups of small-scale, medium-scale, and large-scale. The specifications of these problem instances are given in Table 10.

Table 10: Information of the numerical problem instances used for performance evaluation

| Instance No. | $|R|$ | $|D|$ | $|C|$ | $|M|$ | $|S|$ | $|T|$ | $|KS|$ |
|--------------|------|------|------|------|------|------|------|
| 1            | 6    | 4    | 2    | 1    | 1    | 1    | 2    |
| 2            | 8    | 5    | 2    | 1    | 2    | 1    | 2    |
| 3            | 10   | 5    | 2    | 1    | 2    | 1    | 3    |
| 4            | 12   | 7    | 2    | 1    | 3    | 2    | 3    |
| 5            | 14   | 8    | 3    | 1    | 3    | 2    | 4    |
| 6            | 16   | 8    | 3    | 1    | 4    | 2    | 4    |
| 7            | 18   | 10   | 3    | 2    | 4    | 3    | 5    |
| 8            | 20   | 12   | 3    | 2    | 5    | 3    | 5    |
| 9            | 22   | 12   | 4    | 2    | 5    | 3    | 6    |
| 10           | 24   | 15   | 4    | 2    | 6    | 4    | 6    |
| 11           | 26   | 16   | 4    | 2    | 6    | 4    | 7    |
| 12           | 28   | 18   | 5    | 2    | 7    | 4    | 7    |
| 13           | 30   | 20   | 6    | 3    | 7    | 5    | 8    |
| 14           | 35   | 24   | 7    | 3    | 8    | 5    | 8    |
| 15           | 40   | 25   | 8    | 3    | 8    | 5    | 9    |
| 16           | 45   | 25   | 9    | 3    | 9    | 6    | 9    |
| 17           | 50   | 30   | 10   | 4    | 9    | 6    | 10   |
| 18           | 55   | 30   | 11   | 4    | 10   | 6    | 10   |
These 31 problems were solved with both algorithms using the optimal parameter setting in each case. The MID, DM, and SNS values of the algorithms were then calculated. It should be noted that the algorithms are run using Matlab R2016 software with a PC CPU Core i5 and 5G Ram. The values of these performance measures for NSGA II and MOIWO are given in Table 11.

Table 11: Performance evaluation of NSGA II and MOIWO

| Test problem | NSGA II | MOIWO | Solution time | Solution time |
|--------------|---------|-------|----------------|---------------|
| Test problem | MID     | DM    | SNS            | Solution time |
| 1            | 2128.402| 388.3026| 337.138       | 19.6          |
| 2            | 17064.71| 1115.375| 630.3547      | 23.5          |
| 3            | 12676.91| 2407.15| 1438.363      | 38.6          |
| 4            | 50760.99| 3411.264| 2778.861      | 42.3          |
| 5            | 172745.8| 3498.732| 2442.37       | 55.3          |
| 6            | 256509.7| 5928.794| 4474.071      | 57.5          |
| 7            | 367442.1| 8144.148| 10614.28      | 74.2          |
| 8            | 13023.62| 5017.187| 2116.804      | 76.5          |
| 9            | 500211   | 5713.979| 7539.665      | 79.9          |
| 10           | 535189.2| 10652.97| 5908.288      | 87.8          |
| 11           | 436215.3| 3333.181| 2116.804      | 76.5          |
| 12           | 500211   | 5713.979| 7539.665      | 79.9          |
| 13           | 535189.2| 10652.97| 5908.288      | 87.8          |
| 14           | 436215.3| 3333.181| 2116.804      | 76.5          |
| 15           | 500211   | 5713.979| 7539.665      | 79.9          |
| 16           | 500211   | 5713.979| 7539.665      | 79.9          |
5.3. **Comparison of the algorithms in terms of MID.** The values of this index for each of the instances are plotted in Figure 3. The average value of the MID index in the MOIWO algorithm is 857186.9 and in the NSGA-II algorithm is 958480.1. This indicator shows the degree of proximity to the ideal points. Therefore, it is concluded that the MOIWO algorithm is less distant from the ideal points of the Pareto boundary. This indicates the high quality of the MOIWO algorithm in optimizing the design of the green supply chain. A closer look at Figure 3 shows that in Problems 13 and 31 a sharp increase in the MID value is reported for the NSGA-II algorithm, indicating a severe weakness of this method in some solved problems.

5.4. **Comparison of the algorithms in terms of DM.** Figure 4 shows the DM values obtained for each of the problem instances. The average value of DM index in the MOIWO algorithm is 16598.15 and in the NSGA-II algorithm is 16465.75. This index indicates the dispersion of the solutions found at the Pareto border.
Therefore, it is concluded that the MOIWO algorithm covers a larger area of the Pareto boundary and it can be claimed that the MOIWO algorithm performs better in optimizing the design of the green supply chain network. Since higher DM values are more desirable, it can be seen that NSGA-II has outperformed MOIWO in instances 5, 7, 9, 10, 11, 12, 13, 14, and 15. On average, however, MOIWO has performed better than NSGA-II.

![Comparison of the algorithms in terms of DM](image_url)

Figure 4. Comparison of the algorithms in terms of DM

5.5. **Comparison of the algorithms in terms of SNS.** Figure 5 shows the value of this index for each of the problem instances. The average obtained SNS value for NSGA II and MOIWO was 5355 and 9989, respectively. Like DM, this index indicates the dispersion of the solutions found at the Pareto border. Therefore, it is concluded that the MOIWO algorithm covers a larger area of the Pareto boundary. As can be seen, in most problem instances, MOIWO has a higher SNS than NSGA-II. Considering the nature of this index (the higher the SNS value, the better), the above chart shows that MOIWO has performed better than NSGA-II.

5.6. **Comparison of the algorithms in terms of solution time.** For the problem instances used in this evaluation, NSGA II had an average Figure 6 shows the comparisons of the algorithms in terms of solution time for these problem instances.

As can be seen, for most instances, the two algorithms have almost the same solution time. Based on this chart, it can be concluded that both algorithms are able to solve the problems in reasonably short times; a capability that is indicative of their good performance.

In order to evaluate the search power of metaheuristic algorithms, a random simulation method has been applied. This method has a certain number of iterations. In each iteration, a set of Pareto solutions is generated randomly. After performing all the iterations, the best solutions are introduced in the form of a superior set of solutions. Then, MID, DM, and SNS indices are calculated. The random simulation method was implemented in 100, 500, and 1000 iterations, and the results.
were compared with MOIWO and NSGA-II algorithms. The results are presented in Table 12.

**Table 12.** Comparison of metaheuristic algorithms with random search

| Method          | Iteration | MID     | DM      | SNS      |
|-----------------|-----------|---------|---------|----------|
| Random simulation 100 | 1347512  | 17541.19| 3421.96 |
| Random simulation 500 | 1296475  | 20047.48| 4343.55 |
| Random simulation 1000 | 1253954 | 22096.37| 5736.47 |
| MOIWO           | 200       | 1124600 | 25030.35| 13380.75 |
| NSGA-II         | 200       | 1252267 | 22662.02| 5907.12  |
| Best method     | -         | MOIWO   | MOIWO   | MOIWO    |

**Figure 5.** Comparison of the algorithms in terms of SNS

**Figure 6.** Comparison of the algorithms in terms of solution time
As can be seen in Table 12, the MOIWO algorithm was superior to other methods in all indicators. Also, the results of the NSGA-II algorithm in all indicators were better than random simulation. In other words, random search, even at very high iterations, could not be better than the smart search methods used in the MOIWO and NSGA-II algorithms. This is while the random search uses a much higher number of iterations but still cannot perform better than the algorithms used in this study.

5.7. **Statistical analysis of the algorithms.** In the previous sections, comparisons between the NSGA-II algorithm and the MOIWO algorithm were performed based on different indicators. In this regard, the average value of each indicator was considered as a measure of the strength and weakness of the algorithms. However, these algorithms have performed differently in solving sample problems. In other words, there are significant fluctuations in the performance of the studied algorithms. For this reason, it is necessary to influence these fluctuations in comparing algorithms.

Accordingly, for a better evaluation of the algorithms, the DM, MID, and SNS values of the algorithms were compared using statistical tests. Since the number of instances was more than 30, according to the central limit theorem, normal distribution and T-test could be used for analysis. Therefore, the DM, MID, and SNS values of the algorithms were compared using the t-test. The results of this test are presented in Tables 13, 14, and 15.

| Table 13: Results of the t-test on the MID values of the algorithms |
|------------------------|--------|-----------------|-----------------|--------|
| Mean       | Std. Deviation | Std. Error Mean | 95% Confidence Interval of the Difference | t | df | Sig. (2-tailed) |
| NSGAII-MID | MOIWO-MID | 101293.165 | 135632.934 | 24360.394 | 151043.727 | 4.158 | 30 | .000 |

| Table 14: Results of the t-test on the SNS values of the algorithms |
|------------------------|--------|-----------------|-----------------|--------|
| Mean       | Std. Deviation | Std. Error Mean | 95% Confidence Interval of the Difference | t | df | Sig. (2-tailed) |
| NSGAII-SNS | MOIWO-SNS | -4634.19 | 7169.486 | 1287.677 | -2004.40 | -3.599 | 30 | .001 |

| Table 15: Results of the t-test on the DM values of the algorithms |
|------------------------|--------|-----------------|-----------------|--------|
| Mean       | Std. Deviation | Std. Error Mean | 95% Confidence Interval of the Difference | t | df | Sig. (2-tailed) |
| NSGAII-DM | MOIWO-DM | -132.401 | 5447.236 | 978.352 | 1865.66 | -1.35 | 30 | .893 |
In the analysis of the MID values of the algorithms, the “sig” value is 0, which means there is a significant difference between NSGAII and MOIWO in terms of MID. The average difference between the two numerical methods is positive, i.e. statistically NSGA-II has higher MID values than MOIWO, which means NSGA-II is weaker than MOIWO. The same interpretation also applies to SNS. The Sig value for SNS is less than 0.05, indicating that there is a significant difference between the two methods in terms of this index. Since the average difference is negative and MOIWO has higher SNS values (higher SNS values are better), it shows that MOIWO has a significant advantage over NSGA-II. In the case of DM, the Sig value is greater than 0.05, which means there is no significant difference between the two methods in terms of this index. Therefore, it can be generally concluded that the two methods performed similarly in terms of spread over the Pareto front, but MOIWO provided higher quality solutions than NSGA-II.

5.8. Sensitivity analysis. In this part of the numerical results, the effect of different parameters of the mathematical model on Pareto solutions is examined and analyzed. A preliminary study of the parameters of the mathematical model shows that among all the parameters, only the customer demand can affect both objective functions simultaneously. For this reason, the effect of changes in this parameter on the set of Pareto solutions is investigated. For this purpose, the numerical example provided in Section 5.1 is used. Then customer demand values fluctuate between $-20\%$ up to $+20\%$. Based on this, the demand change coefficient ($p$) is defined, which will be 0.8 to 1.2. Then, in each case, the set of Pareto solutions is obtained and reported using the MOIWO algorithm. The results are shown in Table 16 and Figure 7.

| $p$       | OB1  | OB2  | OB1  | OB2  | OB1  | OB2  | OB1  | OB2  |
|----------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|
| $p=0.8$  | 575413          | 73608          | 606912         | 78914          | 619000         | 81180          | 621994         | 84252          |
| $p=0.9$  | 596470          | 70029          | 619944         | 74532          | 627820         | 75855          | 655736         | 78734          |
| $p=1.0$  | 605106          | 66585          | 661924         | 69282          | 690996         | 72564          | 703981         | 77182          |
| $p=1.1$  | 616355          | 66387          | 759706         | 65312          | 730679         | 70027          | 728719         | 70189          |
| $p=1.2$  | 639479          | 66268          | 797345         | 61378          | 751322         | 67136          | 880525         | 63570          |
|          | 702385          | 60188          | 826948         | 57410          | 809028         | 64373          | 896155         | 59665          |
|          | 775653          | 56490          | 948546         | 54882          | 879333         | 60945          | 934413         | 56740          |

The results presented in Table 16 and Figure 7 show that in each set of Pareto solutions, a downward trend is observed. As the value of the first objective function (OB1) increases, the value of the second objective function (OB2) decreases. In other words, the two objective functions of the mathematical model have the opposite effect on each other, and this indicates a conflict between the economic objective function and the environmental objective function. Examining the set of Pareto solutions at different $p$ levels shows that increasing the amount of demand shifts the Pareto boundary upwards. The reason for this is that as demand increases, the flow of products through the supply chain increases, and therefore both supply chain costs and supply chain pollution increase.
6. Conclusion. This study focused on the optimization of green supply chain network design under demand uncertainty. A two-objective mathematical model with the objectives of minimizing the costs and minimizing the environmental impact of the supply chain is considered. Two algorithms, MOIWO and NSGA-II, were developed and three indices that measure the quality, spacing, and diversification of solutions were used to evaluate the performance of the two solution methods. The evaluations show that the developed MOIWO produces more Pareto solutions with higher quality than NSGA-II. In other words, this method provides the decision-makers with a better sequence of options to choose from. The results also suggest that the solutions of MOIWO are more spread over the optimality front than those produced by NSGA-II. MOIWO was also found to be more capable of performing consistently (producing uniform solutions) than NSGA-II. In general, MOIWO performed better than NSGA-II.

In terms of research impact and managerial insights, two main points can be indicated. First, the proposed mathematical model and solution methods may be interesting for managers and decision-makers, who concern about pollution resulting from manufacturing and are eager to decrease the amount of pollution and implementation of GSCM. On the other hand, the methods used in this research are able to obtain a set of possible solutions for each supply chain network design problem and provide it as the required result. For example, in the automotive supply chain and food supply chain, a part of the demand is always returned to the supply chain. In addition to reducing costs, reducing environmental pollution is also being considered. Accordingly, the proposed mathematical model, as well as the solution method used, can be efficient tools for such supply chain managers. On the other hand, as the managers need to explore and analyze different solutions, using the MOIWO algorithm can provide several Pareto solutions for the managers to analyze and select the best one for implementation.

Second, the results presented in the validation of the mathematical model show that the location of factories, distribution centers, cross docks are the most important factors in terms of cost and environmental impact in the supply chain, respectively. For this reason, another managerial implication of this research is
that it has been able to identify critical decisions in supply chain network design. Managers can greatly control supply chain costs and reduce the negative environmental impact of the chain by paying more attention to the location of factories, distribution centers, and cross-docks.

In terms of limitation to this study, since preliminary data are not real and produced and solved by software and computer, we propose to use real-world data for better performance and evaluation.

For future studies, it is recommended to expand the model by using other objective functions with the aim of considering other factors besides cost and environmental impact and using real preliminary data. The model can also be expanded by adding new constraints such as budget limits or real cost functions. Using other metaheuristic methods such as monarch butterfly optimization (MBO) [10, 11, 12, 39], particle swarm optimization (PSO), earthworm optimization algorithm (EWA) [36], elephant herding optimization (EHO) [25, 37, 40], and moth search algorithm (MS) [11, 38] to solve the proposed mathematical model is also suggested.

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