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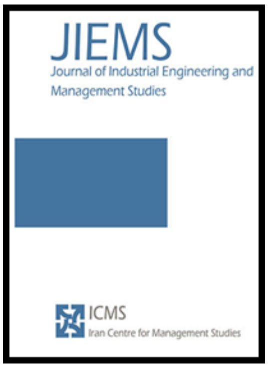

A novel multi-objective model for hub location problem considering dynamic demand and environmental issues

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Abstract
Hubs facilitate aggregation of connection, and switching points of material and people flow to reduce costs as well as environmental pollution. Hub Location Problem (HLP) is a relatively new research field of classical location issues. In this regard, this paper provides a tourist hub location problem to procure essential commodities, which characterized with non-negligible dynamics of demand. Dealing with a high level of change in demand for these goods over time, the possibility of establishment, renovation, or renting the distribution centers have been formulated in the proposed mathematical model. Finding the best location for distribution centers, the model aims to minimize the routing cost between production centers and retailers, along with emitting pollution from vehicles as less as possible. As the proposed model is bi-objective, that is minimizing costs and pollution emission, two Pareto-based solution methodologies, namely the non-dominated sorting genetic algorithm (NSGA-II) and non-dominated ranking genetic algorithm (NRGA), are used. Since the obtained results from these algorithms are highly dependent on the value of parameters, the Taguchi method is adopted to tune the parameters of two solution methodologies. Finally, to verify the proper performance of two solution methodologies, numerical examples in different scales are generated. The obtained results from all scales and solution methodologies indicate that the new modeling approach to the possibility of establishment, renovation, or renting the distribution centers results in lower costs and pollution emission. The results indicate that supply chain costs and environmental impacts increase by increasing the demand. The number of established distribution hubs also increases by increasing the demand.

Keywords: hub location; environmental issues; pollution emission; dynamic demand; mathematical programming.

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1. Introduction

Hubs are special facilities that serve as switching, transshipment and sorting points in many distribution systems (Ghasemi and Babaeinesami, 2020c). Instead of serving each origin-destination pair, the hub facility uses flows to benefit from the resulting economic savings.

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On their route to a hub, flows with the same origin and different destinations and flows with different origins and same destination are combined (Tirkolaee et al. 2020a). Integration occurs on the route from origin to a hub and from a hub to the destination as well as between hubs. Hubs allow a large number of destinations to be connected to each other by a small number of links (Goodarzian et al. 2020, Ghasemi et al. 2020a).

Recently, a large amount of research has been conducted on the hub location problem, as one of the new topics in the field of location problems. The term hub refers to a location or node in a network where people, goods or information are collected from multiple sources and then transferred to other network hubs or destinations. In fact, hubs are generally used to transfer flow between different nodes of a network, especially when direct flow transfer between nodes is difficult or does not stand for economic reasons. Hubs are special facilities that are used as switching, transmission, and classification points in many distribution systems. Rather than serving directly between each source and destination, hub facilities concentrate the flows to gain economic benefits along with reducing the environmental pollution emission. In hub location problems, the number of flows between origins and destinations represent demand and hub facilities act as connecting or integration points. By studying the airline passenger network, Oakley presented the first known mathematical formulation for a hub location problem, which refers to the problem of single hub allocation (Alumur et al., 2008). Alumur et al. (2012) evaluated the hub location problem for a group of workstations and addressed the design of a hub network, including the location of the hub facility, to determine the cost and competitiveness of the transportation and logistics system. Ultimately, they proposed a solution to the hub location problem in the city's transportation network, which is implemented in two steps. Kochel (2007) investigated order optimization for multi-location models with hub structure. To this aim, a location system was examined such that the positions of the warehouses with a high amount of products were determined, and hub locations should estimate the stochastic demand for that product. However, new equilibrium optimization models have been developed for the hub location problem where time travel is specified with random and fuzzy variables. Equilibrium optimization methods have been used to find hub facility locations and demand nodes, aiming to maximize service level at different periods (Karimi and Setak, 2018; Mohammadi et al. 2019; Yang and Li,o 2015, Shafipour-omran et al. 2020). A number of studies have investigated the location problem, which is a combination of the hub location problem and the multi-hub vehicle location problem (Son, 2016; Ghodratnama et al. 2013; Masaeli, 2017).

Generally, environmental conditions vary in the real world over time. For example, the demand for nodes, the amount of transfer cost, set up cost, and the like are not necessarily the same in different periods. In this regard, various approaches are adopted to deal with environmental changes in dynamic location issues can be divided into two categories. In the first approach, the location decision variables can vary depending on the changes in environmental conditions in each period. In the second approach, the location strategy is adopted in the first period so that it partly responses to environmental changes in future periods and remains constant over subsequent periods (Boloori and Farahani, 2012). So far, researchers have dealt with dynamic facility location problems in two ways. The first approach decides which facility should be established or closed while the second approach makes decisions on the opening or closing of facilities at the beginning of the period, and these facilities are open or closed at all periods as in the first period. Joaquin and Hallett (2010) considered two facility location models with dynamic demand. The first model allows establishing a new facility in each period while facilities remain in a fixed location during the second model. Concerning the field of dynamic axis location problem, Taghi Poorian et al. (2012), Ghaderi (2015), and Hurhammer (2014) addressed the location problem with the first approach. Other articles have also analyzed the dynamic facility location problem for various goods and multiple capacity levels (Golareh et al., 2015; Domenik et al. 2018 Khosravi and Akbari joker 2017; Bashiri et al., 2016). Other studies emphasized the hub location problem for air and ground transportation systems as multiple hierarchical models. The main objective of these articles was to create a dynamic network for the transportation system (2016 Torkestani et al. 2018; Zheng et al. 2018; Lopez et al.). Some researchers generalized the multi-objective hub location problem to the perishable food supply chain, in addition to examining the environmental impacts of the transportation fleet and CO_2 emission (Mousavi and Bozorgiamiri, 2017; Dukkanci et al. 2019).

In general, distribution centers play a crucial role in procuring tourist goods and addressing the need for essential commodities in tourist places. Regarding the high demand fluctuations, these areas have a greater amount of demand at certain times of the year compared to the normal days, highlighting the necessity to suggest ways to manage demand in these areas. The dynamic demand in these areas changes the role of distribution centers to be considered as a hub to decide on the construction, rental, and commissioning of these centers in tourist areas while including an optimal way to meet demand in these areas. The amount of demand in tourist areas may vary at different times of the year, depending on the region's tourism aspects. For example, during the New Year holidays, these areas face a significant increase in demand from tourists, which can be covered by forecasting demand. This paper seeks to analyze the issue of demand management in tourist places by creating a hub location problem. In the first stage, the time division of these areas is performed in terms of tourist visits to specify the peak times of need for essential goods in these places, as well as the times when the consumption is at a regular level and when the consumption of essential goods is restricted to indigenous and local people. By identifying different demand levels at different times of the year, it is possible to meet demand by creating hub locations in these areas.

One of the applications of this model is designing supply chain networks with dynamic demand which the amount of these demands changes by passing the time in the seasons. So, the proposed model can be proper for products with seasonal demand such as heaters and air conditioners. The main application of this research is in tourism industry which depends on seasons. Therefore, it can be states that the manufacturers of seasonal products and tourism-related centers such as the tourism organization, etc. benefit from this study. Many of the existing modeling methods for hub location problems are constrained to deterministic conditions. But, the amount of demand in the network and the time needed for processing products in different conditions are different. In other words, the amount of demand cannot be determined deterministically in the real world. Therefore, considering demand as seasonal and dynamic is one of the contributions of this research. Thus, the most important questions of this research are as follows: 1- In what seasons and in which locations are collection and distribution hubs established? 2- What is the number of vehicles used between each of the supply chain levels?

So, the most important objectives of this research are minimizing the total costs of the supply chain, including logistics and hub location costs. Another objective of this study is considering environmental goals such as minimizing fuel consumption. The main contributions of this paper are predict the variable or dynamic demand situation and then, model the hub location based on the demand of each zone in tourist areas, aiming to determine the hub locations with the shortest distance to the highest demand locations as well as minimizing the cost of goods transportation to high-demand areas from an environmental perspective. On the other hand, this issue enables us to meet the maximum demand and increase the speed of goods transportation. To determine hub locations and minimize costs, the state of establishment, rental, and renovating of the hub is considered according to the time and demand situations. Fuel consumption, which includes transportation costs, can be

decreased by finding hub locations and reducing fuel consumption of vehicles, resulting in great benefits to the environment.
The rest of the paper is organized as follows. In section 2, the problem was defined, and then, the mathematical model is presented. Sections 3 and 4 discusses the problem definition and solution methodologies. In section 5, the computational results are analyzed, and the findings of the study are discussed. The sensitivity analysis has been presented in section 6. Finally, the concluding remarks of the current paper and some suggestions for future research are provided.

2. Literature review

Ayough et al. (2020) proposed a three level model for vehicle routing considering the time window. So, routing decisions for capacitated vehicles were determined at first according to customer demand and their soft time windows. Then the decisions made entered the three-dimensional loading problem. Generalized algebraic modeling was used to solve the model in small scale and a hybrid algorithm was used to solve it in large scale. The results indicated the proper performance of the proposed model. Ghasemi et al. (2020b) proposed a stochastic model for minimizing hub location costs and distribution of relief supplies in disaster situations. Because the demand was uncertain, this parameter was estimated by a simulation approach. The main objective of this study was to maximize the demand coverage level along with minimizing the hub allocation and location costs. Their proposed model was solved by the NSGA-II approach and the results showed the efficient performance of their proposed model. Alinaghian et al. (2020) presented a new mathematical model for inventory control and routing between hubs in the Gross Domestic Product supply chain. The main objective of this study was minimizing the fuel costs, driver costs and inventory. Their proposed model was solved by augmented Tabu Search (TS) algorithm and Differential Evolution (DE) algorithm. The results indicated that supply chain costs increase greatly by increasing the demand. Tirkolaee et al. (2020b) presented a multi-objective mathematical model for routing between hubs. Considering traffic along with environmental pollutants was of their research contributions. Multi-Objective Simulated-Annealing Algorithm (MOSA) and Non-dominated Sorting Genetic Algorithm II (NSGA-II) were used to solve their proposed model. The results indicated the superiority of the NSGA-II approach. Tirkolaee et al. (2020c) studied the vehicle routing, hub location, and inventory control in the green supply chain. The main objective of their research was minimizing transportation costs and location of waste disposal centers. Robust optimization was used to solve their proposed model. Finally, the robustness of budget constraints was calculated. Bütün et al. (2020) proposed a mathematical model for hub location and routing considering congestion. The main objective of their research was minimizing the reopening costs of hubs. The Tabu search approach was used to solve their proposed model. The neighborhood search approach was used to increase the precision of the algorithm. The results showed the efficient performance of their proposed model. Shen et al. (2020) investigated the hub location problem in air transport. Considering the reliability for hubs and their failure was of the contributions of their study. Their proposed model was solved for many numerical examples. The examples were solved by two heuristic approaches. Atta and Sen (2020) presented a multiple p-hub location problem for content placement in VoD services. They consider a big data of video records based on the demand patterns of users. The main purpose of this research is to find routes from the Hubs to the demand points with the lowest cost. They determined the location of hubs. The results indicate the appropriate and accurate performance of the proposed model in locating Hub centers. Čvokić and Stanimirović (2020) presented an incapacitated hub location-allocation model in order to maximize profits in supply chain. Considering pricing on goods is one of the contributions of their research. The result of the proposed matheuristic algorithm indicates a low error percentage along with the accuracy of this algorithm. Ghaffarinasab (2020) presented a bi-objective star hub location problem in telecommunications supply chain. Minimizing costs and maximizing service levels are among the most important contributions in their research. The proposed model has been converted to a single-objective model by the weighting method. In order to solve their model, a Tabu Search (TS) heuristic is developed. The results indicate the proper performance of the proposed algorithm.

Maharjan and Hanaoka (2020) presented a hub location-allocation model for disaster relief supply chain. Considering the uncertainty in demand, cost and available relief is one of the innovations of their research. A credibility-based fuzzy chance-constrained programming has been used to deal with the inherent uncertainty of the problem. The findings show when, where, and how many Hubs to open and how to allocate commodities. Osorio-Mora et al. (2020) presented multimodal capacitated Hub location model with multi-commodities. The case study is applied for Latin American country. Their research is presented for 6 different products, 100 demand points and two transportation modes. Results show that only one hub is profitable for the Latin American country, both for the initial and projected scenarios. Fattahi and Shakeri Kebria (2020) presented a bi objective dynamic reliable hub location model considering reliability and importance of flow congestion on hub nodes. Considering traffic and capacity for hubs is one of the contributions of this research. The first objective function involves minimizing transportation costs and hub rental fees. The second objective function involves maximize supply chain reliability. The results indicate the appropriate performance of the proposed model after solving with the Epsilon constraint approach. Ghodratnama et al. (2019) investigated hub location–allocation problems considering congestion in manufacturing plants. The first objective function involves minimizing transportation and hub deployment cost. The second objective function involves minimize the total elapsed time of products in firms. Fuzzy chance constrained programming and expected value approaches have been used to deal with the inherent uncertainty of the problem. Ghasemi et al. (2019) provided a multi-objective mathematical model for locating distribution hubs and allocating vehicles to these hubs in disaster situations. Demand was scenario-based in their proposed multi-period and multi-commodity model. The objective of their research was to minimize the set up costs of hubs along with minimizing the relief time to affected areas. NSGA-II and MMOPSO approaches were used to solve their proposed model. Finally, the city of Tehran was selected to prove the efficiency of their proposed model. Ayough and Khorshidvand (2019) proposed a model for minimizing costs in cellular manufacturing. A limited number of cells were allocated to the workforce in this study. The contributions included model dynamics and demand uncertainty. Two meta-heuristic approaches of Simulated Annealing (SA) and Particle Swarm Optimization (PSO) were used to solve their proposed model. The results indicated that the PSO approach performed better than the SA. Ayough et al. (2017) proposed a mathematical model for locating and allocating suppliers in the supply chain. Considering customer prioritization was one of their contributions. The main objective of their proposed model was to minimize the costs of location and allocation. A genetic algorithm was used to solve their proposed model. The results indicated the proper performance of their proposed algorithm for solving the model.

Table 1. Literature review

Reference	Objective	Green	Hub	Location	Dynamic	Routing	Load	tourist hub
Kara et al. (2007)	**Single**	√				√	√	
Govindan et al. (2014)	**Multi**	√		√		√		
Koc et al. (2016)	**Single**	√		√		√	√	
Niknamfar and Niaki (2016)	**Multi**	√	√	√		√	√	
Khoei et al. (2017)	**Single**	√		√			√	
Dukkanci et al. (2019)	**Multi**	√	√	√		√		
Ghasemi et al. (2020)	**Multi**	√		√		√		
Alinaghian et al. (2020)	**Single**	√				√	√	
Tirkolaee et al. (2020)	**Multi**	√		√			√	
Bütün et al. (2020)	**Single**		√	√		√		
Shen et al. (2020)	**Multi**		√	√	√		√	
Atta and Sen (2020)	**Multi**		√	√				
Čvokić and Stanimirović (2020)	**Single**		√	√			√	
This Paper	**Multi**	√	√	√	√		√	√

Despite conducting various research on the hub location in different optimization models, no research, to the best of our knowledge, has addressed the issue of tourist destinations. Thus, this paper attempts to fill the gap of existing literature on the lack of referring or considering tourist places, due to the dynamic nature of demand. Moreover, focusing on the environmental effects and reducing fuel consumption are other issues that have greatly contributed to the importance of this research. The authors believe that effective management of heavy vehicle loads in tourist places can help to reduce fuel consumption and prevent pollution emission because these trucks naturally produce a high amount of pollutants. Therefore, decreasing the number of these types of vehicles along with increasing their capacity can help to generate fewer pollution. The demand dynamics for essential commodities are another important factor, which needs to be studied in this research. Regarding the mentioned issues, a mathematical optimization model is proposed aimed at reducing the costs and emitted pollutants. As the problem may be in large dimensions in the real world, the solution time exponentially increases, and achieving the exact solution is not possible using Lingo or GAMS software. Therefore, it is necessary to rely on approximate solution methodologies that are meta-heuristic algorithms. As a result, to solve the model, two metaheuristic algorithms, namely non-dominated sorting genetic algorithm (NSGA-II) and non-dominated ranking genetic algorithm (NRGA), for multi-objective problems, are utilized. These two algorithms are considered as widely-used solution methodologies for the multi-objective problem, which seems a suitable option for solving the proposed model.

3. Problem definition

3.1. General issues

This research sought to develop a mathematical optimization model for distribution locations aimed at reducing transportation costs as well as decreasing fuel consumption and pollutant emission. As the current model is proposed for the transportation of essential commodities, they are assumed as perishable items. The objective of the model is to determine the best area for the distribution center, as a hub, by minimizing the transportation costs between production centers and retail stores and emitted pollutants. Additionally, utilization of the distribution centers is investigated in various ways such as establishment, renovation, and renting. As the model is applied for the logistics of perishable products, the location of the collection center is another decision variable to collect the perished and degenerated products.

3.2. Problem assumptions

Given the above-stated matters, the following assumptions are raised:

- Considering goods as perishable items, which cannot be stored for a long time
- Dealing with demand as a dynamic decision variable

The following cases are the assumptions related to the factors considered in the model:

- Fuel consumption is calculated with respect to the traveled distance.
- The amount of fuel consumption of vehicles depends on their load.
- The cost of transportation is based on the traveled distance.
- The depreciation cost of the vehicle is calculated based on the traveled distance.
- Vehicle maintenance costs are based on the traveled distance.
- Vehicles are considered as trucks, Kei trucks, and pick-ups with different useful life.
- Vehicles are loaded from plants to distribution centers with maximum capacity.
- The load of vehicles from distribution center to plants is zero.
- Vehicles are loaded from distribution center to retail stores with maximum capacity.
- The load of vehicles from retail stores to distribution center is zero.
- The load of vehicles from the collection center to retail stores is zero.
- Vehicles are loaded from retail centers to collection center with maximum capacity.
- The distance in round trip between plants to distribution centers are not the same.
- The distance in round trip between distribution centers to retail centers are not the same.
- The distance in round trip between collection centers to retail centers are not the same.

The following section introduces indexes, parameters, and decision variables.

3.3. Sets

Regarding above assumptions, sets of indices, which are used in the formulation, are defined as follows:

D: Number of distribution centers $d = 1,2,3, ..., n$
C: Number of collection centers $c = 1,2,3, ..., n$
P: Number of factories $p=1,2,...n$
R: Number of retailers $r=1,2,3,...,n$
V: Type of vehicle $v=1,2,3,...,n$

S: Seasons set S = {1,2,3,4,5} $s \in S$

3.4. Parameters

By specifying the sets, we introduce the model parameters.

M: A large number

CD_{ds}: The cost of establishing distribution center d in season s

CS_{ds}: The cost of renovating distribution center d in season s

CR_{ds}: The cost of renting distribution center d in season s

MCD_{ds}: The holding cost of goods at distribution center d in season s

$DCVPD_{pd}^{vs}$: The driving cost of vehicle v from plant p to distribution center d in season s

$DepCVPD_{pd}^{vs}$: The depreciation cost of vehicle v from plant p to distribution center d in season s

$RMCVPD_{pd}^{vs}$: The maintenance cost of vehicle v from plant p to distribution center d in season s

$FCVPD_{pd}^{vs}$: The fuel cost of vehicle v from plant p to distribution center d in season s

$DISVPD_{pd}^{v}$: Distance of plant p to distribution center d

$DCVDP_{dP}^{vs}$: The driving cost of vehicle v from distribution center d to plant p in season s

$DepCVDP_{dp}^{vs}$: The depreciation cost of vehicle v from distribution center d to plant p in season s

$RMCVDP_{dp}^{vs}$: The maintenance cost of vehicle v from distribution center d to plant p in season s

$FCVDP_{dp}^{vs}$: The fuel cost of vehicle v from distribution center d to plant p in season s

$DISVDP_{dp}^{v}$: Distance of distribution center d to plant p

$DCVDR_{dr}^{vs}$: The driving cost of vehicle v from distribution center d to retail center r in season s

$DepCVDR_{dr}^{vs}$: The depreciation cost of vehicle v from distribution center d to retail center r in season s

$RMCVDR_{dr}^{vs}$: The maintenance cost of vehicle v from distribution center d to retail center r in season s

$FCVDR_{dr}^{vs}$: The fuel cost of vehicle v from distribution center d to retail center r in season s

$DISVDR_{dr}^{v}$: Distance between distribution center d to retail center r

$DCVRD_{rd}^{vs}$: The driving cost of vehicle v from retail center r to distribution center d in season s

$DepCVRD_{rd}^{vs}$: The depreciation cost of vehicle v from retail center r to distribution center d in season s

$RMCVRD_{rd}^{vs}$: The maintenance cost of vehicle v from retail center r to distribution center d in season s

$FCVRD_{rd}^{vs}$: The fuel cost of vehicle v from retail center r to distribution center d in season s

$DISVRD_{rd}^{v}$: Distance between retail store r to distribution center d

CCC_{cs}: The cost of renovating collection center c in season s

CCR_{cs} : The Cost of renting collection center c in season s

MCC_{cs}: The disposal cost of perishable items at collection center c in season s

$DCVCR_{cr}^{vs}$: The driving cost of vehicle v from collection center c to retail center r in season s

$DepCVCR_{cr}^{vs}$: The depreciation cost of vehicle v from collection center c to retail center r in season s

$RMCVCR_{cr}^{vs}$: The maintenance cost of vehicle v from collection center c to retail center r in season s

$FCVCR_{cr}^{vs}$: The fuel cost of vehicle v from collection center c to retail center r in season s

$DISVCR_{cr}^{v}$: Distance of collection center c to retail center r

$DCVRC_{rc}^{vs}$: Driver cost of vehicle v from retail center r to collection center c in season s

$DepCVRC_{rc}^{vs}$: Depreciation cost of vehicle v from retail center r to collection center c in season s

$RMCVRC_{rc}^{vs}$: Maintenance cost of vehicle v from retail center r to collection center c in season s

$FCVRC_{rc}^{vs}$: Fuel cost of vehicle v from retail center r to collection center c in season s

$DISVRC_{rc}^{v}$: Distance of retail center r to collection center c

$FUELVPD_{pd}^{v}$: Fuel consumption rate of vehicle v to move from plant p to distribution center d

$FUELVDP_{dp}^{v}$: Fuel consumption rate of vehicle v to move from distribution center d to plant p

$FUELVDR_{dr}^{v}$: Fuel consumption rate of vehicle v to move from distribution center d to retail center r

$FUELVRD_{rd}^{v}$: Fuel consumption rate of vehicle v to return from retail center r to distribution center d

$FUELVCR_{cr}^{v}$: Fuel consumption rate of vehicle v to move from collection center c to retail center r

$FUELVRC_{rc}^{v}$: Fuel consumption rate of vehicle v to return from retail center r to collection center c

$POPVPD_{pd}^{v}$: Pollution production rate of vehicle v to move from plant p to distribution center d

$POPVDP_{dp}^{v}$: Pollution production rate of vehicle v to move from distribution center d to plant p

$POPVDR_{dr}^{v}$: Pollution production rate of vehicle v to move from distribution center d to retail center r

$POPVRD_{rd}^{v}$: Pollution production rate of vehicle v to return from retail r to distribution center d

$POPVCR_{cr}^{v}$: Pollution production rate of vehicle v to move from collection center C to retail center r

$POPVRC_{rc}^{v}$: Pollution production rate of vehicle v to return from retail center r to collection center c

$MAXCAPVPD_{v}$: Maximum capacity of vehicle v moving from plant p to distribution center d

$MAXCAPVDR_{v}$: Maximum capacity of vehicle v moving from distribution center d to retailer r

$MAXCAPVRC_{v}$: Maximum capacity of vehicle v moving from collection center r to retailer c

$CAPVPD_{pd}^{v}$: Quantity of goods shipped by vehicle v moving from plant p to distribution center d

$CAPVDR_{dr}^{v}$: Quantity of goods shipped by vehicle v moving from distribution center d to retailer r

$CAPVRC_{rc}^{v}$: Quantity of goods shipped by vehicle v moving from collection center r to retailer c

$DemRS_{rs}$: Demand of retailer r in season s, $s \in S$

RT : Percentage of demand considered in the backward supply chain

.5. Decision variables

This section introduces the model's decision variables and the number of required vehicles. Given that distribution centers are considered as hub locations, these centers are modeled in different seasonal situations under the construction, rent, and commissioning conditions.

XD_{ds} : If the distribution center d is constructed in season s, 1; otherwise zero.

XC_{cs} : If the collection center c is constructed in season s, 1; otherwise zero.

XR_{ds} : If the distribution center d is rented in season s, 1; otherwise zero.

XE_{cs} : If the collection center c is rented in season s, 1; otherwise zero.

XOD_{ds} : If the distribution center d is set up in season s after construction or renting process, 1, otherwise zero.

XOC_{cs} : If the collection center c is set up in season s after construction or renting process, 1, otherwise zero.

XPD_{pd}^{s} : Number of vehicles required from plant p to distribution center d in season s

XDR_{dr}^{s} : Number of vehicles required from distribution center d to retail center r in season s

XCR_{cr}^{s} : Number of vehicles required from collection center c to retailer r in season s

XDP_{dp}^{s} : Number of vehicles required from distribution center d to plant p in season s

XRD_{rd}^{s} : Number of vehicles required from retail center r to distribution center d in season s

XRC_{rc}^{s} : Number of vehicles required from retail center r to collection center c in season s

$XVPD_{pd}^{vs}$: If vehicle v is used to move from plant p to distribution center d in season, 1, otherwise, 0.

$XVDR_{dr}^{vs}$: If vehicle v is used to move from distribution center d to retail center r in season, 1, otherwise, 0.

$XVRC_{cr}^{vs}$: If vehicle v is used to move from collection center c to retail center r in season, 1, otherwise, 0.

3.6. The model formulation

In this research, the investigated problem is formulated as a bi-objective optimization model. The first objective is to minimize the total costs, and the second one aims to minimize fuel consumption and pollutant emissions in line with the environmental observations.

$$\begin{aligned} Min\ Z_1 = {} & \textstyle\sum_{D=1}^{N}\sum_{P=1}^{N}\sum_{V=1}^{N}\sum_{S=1}^{N}\{\{(CD_{ds} + \mathrm{CS}_{ds} + MCD_{ds}).XOD_{ds} + \{(CR_{ds} + \\ & \mathrm{CS}_{ds} + MCD_{ds}).XOD_{ds} + \{(DCVPD_{pd}^{vs} + DepCVPD_{pd}^{vs} + RMCVPD_{pd}^{vs} + \\ & FCVPD_{pd}^{vs}).DISVPD_{pd}^{v}\}.XVPD_{pd}^{vs}\} + (DCVPD_{dp}^{vs} + DepCVDP_{dp}^{vs} + RMCVDP_{dp}^{vs} + \\ & FCVDP_{dp}^{vs}).DISVDP_{dp}^{v}\}.XVPD_{pd}^{vs}\} + \textstyle\sum_{D=1}^{N}\sum_{R=1}^{N}\sum_{V=1}^{N}\sum_{S=1}^{N}\{(DCVDR_{dr}^{vs} + \\ & DepCVDR_{dr}^{vs} + RMCVDR_{dr}^{vs} + FCVDR_{dr}^{vs}).DISVDR_{dr}^{v}\}.XVDR_{dr}^{vs}\} + (DCVRD_{rd}^{vs} + \\ & DepCVRD_{rd}^{vs} + RMCVRD_{rd}^{v} + FCVRD_{rd}^{vs}).DISVRD_{rd}^{v}\}.XVDR_{dr}^{vs}\} + \\ & \textstyle\sum_{C=1}^{N}\sum_{R=1}^{N}\sum_{V=1}^{N}\sum_{S=1}^{N}\{(CCC_{cs} + CCS_{cs} + MCC_{cs}).XOC_{cs} + \{(CCR_{cs} + CCS_{cs} + \\ & MCC_{cs}).XOC_{cs} + \{(DCVRC_{rc}^{vs} + DepCVRC_{rc}^{vs} + RMCVRC_{rc}^{vs} + \\ & FCVRC_{rc}^{vs}).DISVRC_{rc}^{v}\}.XVCR_{rc}^{vs}\} + (DCVCR_{cr}^{vs} + DepCVCR_{cr}^{vs} + RMCVCR_{cr}^{vs} + \\ & FCVCR_{cr}^{vs}).DISVCR_{cr}^{s}\}.XVCR_{rc}^{vs}\} \end{aligned} \qquad (1)$$

$$\begin{aligned}\min Z2 = &\textstyle\sum_{D=1}^{N}\sum_{P=1}^{N}\sum_{V=1}^{N}\sum_{R=1}^{N}\sum_{S=1}^{N}\{FuelVDP_{pd}^{v} . disVPD_{pd}^{v}).XVPD_{pd}^{vs} + \\ &\left(FuelVDP_{dp}^{v}. disVDP_{dp}^{v}\right).XVPD_{pd}^{vs} + (FuelVDR_{dr}^{v}. disVDR_{dr}^{v}).XVDR_{dr}^{vs} + \\ &(FuelVRD_{rd}^{v}. disVRD_{rd}^{v}).XVDR_{dr}^{vs} + (FuelVCR_{cr}^{v}. disVCR_{cr}^{v}).XVCR_{rc}^{vs} + \\ &(FuelVRC_{rc}^{v}. disVRC_{rc}^{v}).XVRC_{rc}^{vs} \left(POPVPD_{pd}^{v}. disVPD_{pd}^{v}\right).XVPD_{pd}^{vs} + \\ &\left(POPVDP_{dp}^{v}. disVDP_{dp}^{v}\right).XVPD_{pd}^{vs} + (POPVDR_{dr}^{v}. disVDR_{dr}^{v}).XVDR_{dr}^{vs} + \\ &(POPVRD_{rd}^{v}. disVRD_{rd}^{v}).XVDR_{dr}^{vs} + \\ &(POPVCR_{cr}^{v}. disVCR_{cr}^{v}).XVCR_{rc+}^{vs}(POPVRC_{rc}^{v}. disVRC_{rc}^{v}).XVRC_{rc}^{vs}\}\end{aligned} \tag{2}$$

Equation (1) reflects the first objective function, which seeks to minimize the logistics costs, including three main parts, the first part considers the cost of traveling from plants to the distribution centers and includes the costs of establishing, renovating, and renting the centers, as well as the holding costs of goods in the centers. The second part denotes the cost of traveling from distribution centers to retail stores, and the third part calculates the cost of traveling from collection centers to retail stores. Equation (2), as the second objective function, addresses environmental issues, and includes two parts. The first part calculates the fuel consumption of vehicles, and the second part represents the amount of pollution produced by transportation vehicles.

subject to

$$\sum_{P=1}^{N}\sum_{D=1}^{N} CAP\,VPD_{pd}^{V}.XVPD_{pd}^{Vs} \leq MAXCAPVPD_{v} \quad , \qquad \forall\, v \in N, s \in S \tag{3}$$

$$\sum_{R=1}^{N}\sum_{D=1}^{N} CAP\,VDR_{dr}^{V}.XVDR_{dr}^{Vs} \leq MAXCAPVDR_{v} \;, \qquad \forall\, v \in N, s \in S \tag{4}$$

$$\sum_{R=1}^{N}\sum_{C=1}^{N} CAP\,VRC_{rc}^{V}.XVRC_{rc}^{Vs} \leq MAXCAPVRC_{v} \;, \qquad \forall\, v \in N, s \in S \tag{5}$$

$$\sum_{V=1}^{N}\sum_{P=1}^{N}(\,CAPVPD_{pd}^{V}.XVPD_{pd}^{Vs}) \geq \sum_{V=1}^{N}\sum_{R=1}^{N}(CAPVDR_{dr}^{V}.XVDR_{dr}^{Vs}) \;, \qquad \forall\, d, s \in N \tag{6}$$

$$\sum_{V=1}^{N}\sum_{D=1}^{N}(\,CAPVDR_{dr}^{V}.XVDR_{dr}^{Vs}) \geq DemDR_{rs} \;, \qquad \forall\, r, s \in N \tag{7}$$

$$\sum_{V=1}^{N}\sum_{C=1}^{N}(\,CAPVRC_{rc}^{V}.XVRC_{rc}^{Vs}) \geq RT.DemDR_{rs} \;, \qquad \forall\, r, s \in N \tag{8}$$

$$XD_{ds} + XR_{ds} \leq 1 \;, \qquad \forall\, d \in N, s \in S \tag{9}$$

$$XC_{cs} + XE_{cs} \leq 1 \;, \qquad \forall\, c \in N, s \in S \tag{10}$$

$$XR_{ds1} \leq 1 - XD_{ds} \;, \qquad \forall\, d \in N, s, s1 \in S \tag{11}$$

$$XE_{cs1} \leq 1 - XC_{cs} \;, \qquad \forall\, c \in N, s, s1 \in S \tag{12}$$

$$XD_{ds} + XR_{ds} \geq XOD_{ds} \;, \qquad \forall\, d \in N, s \in S \tag{13}$$

$$XC_{cs} + XE_{cs} \geq XOC_{cs} \;, \qquad \forall\, c \in N, s \in S \tag{14}$$

$$\sum_{P=1}^{N}\sum_{D=1}^{N} XPD_{pd}^{s} = \sum_{P=1}^{N}\sum_{D=1}^{N} XDP_{dp}^{s} \;, \qquad \forall\, s \in S \tag{15}$$

$$\sum_{R=1}^{N}\sum_{D=1}^{N} XDR_{dr}^{s} = \sum_{R=1}^{N}\sum_{D=1}^{N} XRD_{dr}^{s} \quad , \qquad \forall\, s \in S \tag{16}$$

$$\sum_{R=1}^{N}\sum_{C=1}^{N} XCR_{cr}^{s} = \sum_{R=1}^{N}\sum_{C=1}^{N} XRC_{rc}^{s} \quad , \qquad \forall\, s \in S \tag{17}$$

$$XPD_{pd}^{s} \le M * (XD_{ds} + XR_{ds}), \qquad \forall\, p, d, s \in N \tag{18}$$

$$XDR_{dr}^{s} \le M * (XD_{ds} + XR_{ds}), \qquad \forall\, r, d, s \in N \tag{19}$$

$$XRC_{rc}^{s} \le M * (XC_{cs} + XE_{cs}), \qquad \forall\, r, c, s \in N \tag{20}$$

$$\sum_{V=1}^{N} XVPD_{pd}^{vs} = XPD_{pd}^{s} \quad , \qquad \forall\, p, d, s \in N \tag{21}$$

$$\sum_{V=1}^{N} XVDR_{dr}^{vs} = XDR_{dr}^{s} \quad , \qquad \forall\, d, r, s \in N \tag{22}$$

$$\sum_{V=1}^{N} XVRC_{rc}^{vs} = XRC_{rc}^{s} \quad , \qquad \forall\, r, c, s \in N \tag{23}$$

$$XVPD_{pd}^{vs} \ge XOD_{ds} \quad , \qquad \forall\, p, v, d \in N ، s \in S \tag{24}$$

$$XVDR_{dr}^{vs} \ge XOD_{ds} \, , \qquad \forall\, r, v, d \in N ، s \in S \tag{25}$$

$$XVRC_{rc}^{vs} \ge XOC_{cs} \, , \qquad \forall\, r, v, c \in N ، s \in S \tag{26}$$

$$XD_{ds} \ge 0 \tag{27}$$

$$XC_{cs} \ge 0 \tag{28}$$

$$XR_{ds} \ge 0 \tag{29}$$

$$XE_{cs} \ge 0 \tag{30}$$

$$XOD_{ds} \ge 0 \tag{31}$$

$$XOC_{cs} \ge 0 \tag{32}$$

$$XPD_{pd}^{s} \ge 0 \tag{33}$$

$$XDR_{dr}^{s} \ge 0 \tag{34}$$

$$XCR_{cr}^{s} \ge 0 \tag{35}$$

$$XVPD_{pd}^{vs} \ge 0 \tag{36}$$

$$XVDR_{dr}^{v} \ge 0 \tag{37}$$

$$XVCR_{cr}^{vs} \ge 0 \tag{38}$$

Equations (3) to (5) compute the maximum capacity of vehicles from one center to another one. Equations (6) to (8) consider the flow restriction between different levels of the supply chain based on the number of vehicles and their capacity.

Constraints (9) to (14) show the conditions required for constructing or renting distribution centers and collecting and activating the centers. Concerning the amount of demand in the region, it is decided that the distribution center in the area is to be constructed or rented, and

if it is constructed, what courses may be active and period closed according to seasonal changes in demand. The rental condition is also occurring during the year, in certain periods in some tourist areas, such as historical, forest and mountain regions, and economically, the center is not economical. Therefore, in that period, it can be covered by the rental of the center, the demand for those areas. All of these are aimed at minimizing costs in distribution centers and for the problem of hub location.
Equations (15) to (17) guarantee the conditions required for the correctness of the route, such that the number of vehicles moving from plant to distribution centers should be equal to the number of returned vehicles. In other words, no vehicles should be diverted from the path. Constraints (18) to (20) indicate the limitation of the number of vehicles needed for each facility in the case of renting or construction. Equations (21) to (23) illustrate the number of devices required for each center, which is equal to the number of vehicles used in the process. Equations (24) to (26) guarantee that the model is nonlinear. Equations (27) to (38) ensure that the decision variables are non-negative.

4. Solution method

Nowadays, a large number of real-world application issues are multi-objective optimization problems, in which the goals are in conflict with each other, and the improvement of one objective does not necessarily improve the other objective. In single-objective optimization problems, the algorithm ends by optimizing the objective function of the algorithm. However, the simultaneous optimization of multiple functions is a difficult and time-consuming task in multi-objective problems, resulting in obtaining some acceptable solutions based on undesirable criteria in most issues. Thus, the final solution is in a set of solutions that represent a balance of the various objective functions in the problem. Finally, one of the solutions is selected by the decision-maker as the preferred solution. In order to solve the model proposed in this research, we suggested two Pareto-based multi-objective algorithms, naming non-dominated ranking genetic algorithm and non-dominated sorting genetic algorithm, and compared the results of these two algorithms.

4.1. $\varepsilon -$ constraint Method

Epsilon constraint method is one of the exact methods for obtaining optimal Pareto solutions. The main advantage of this method relative to other multi-objective optimization methods is its use for non-convex solution spaces because methods such as weighted sum of objectives lose their efficiency in non-convex spaces.
One of the objectives is always optimized in this method, provided that the highest acceptable limit is defined for other objectives in the form of constraints, so that:

$$\min f_1(x)$$
$$x \in X$$
$$f_2(x) \le \varepsilon_2$$
$$\vdots$$
$$f_n(x) \le \varepsilon_n$$

The steps of the $\varepsilon - constraint$ method are described in the following:

1. Select one of the objective functions as the main objective function.
2. Solve the problem each time according to one of the objective functions and obtain the optimal values of each objective function.
3. Divide the interval between two optimal values of the secondary objective functions by a pre-determined number and obtain a table of values for $\varepsilon_2, \dots, \varepsilon_n$.

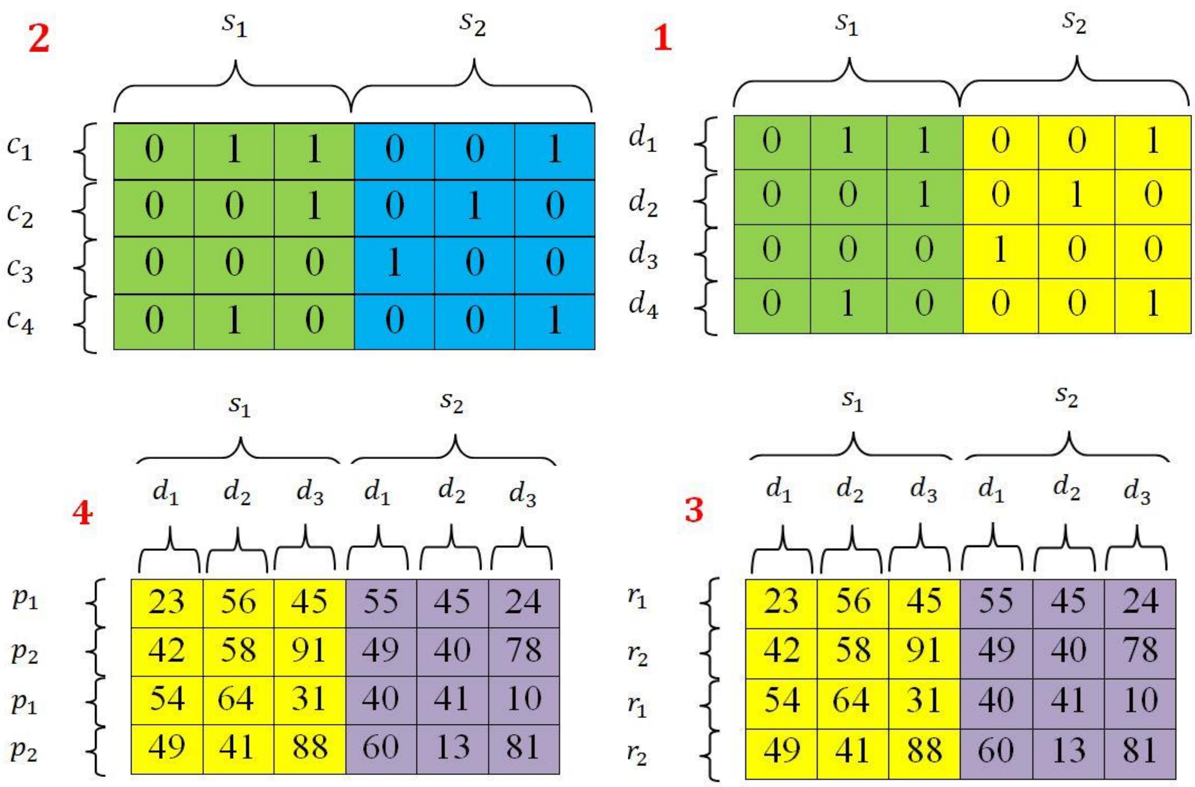
4. Solve the main objective function of the problem each time with one of the values of $\varepsilon_2, \ldots, \varepsilon_n$.
5. Report the obtained Pareto solutions.
6. Obtain the efficient solutions to the problem by changing the right-side values of the constraints (εi).

4.2. Non-Dominated Sorting Genetic Algorithm

The non-dominated sorting genetic algorithm (NSGA-II) is regarded as one of the most efficient and well-known multi-objective optimization algorithms proposed by Deb et al. (2001). This algorithm can converge with the optimal Pareto set and extend the solutions to the whole collection. This method uses a non-dominant classification mechanism to ensure proper convergence. In addition, NSGA-II uses density estimation and comparative congestion operators to cut solutions with poor distributions, aiming to obtain good solutions (Deb et al., 2001). The basic information for implementing the proposed NSGA-II algorithm includes initial population size, probability of mutation operator, probability of intersection operator, and the number of algorithm iterations. It should be noted that the adjusted values of these parameters were obtained by using the Taguchi method.

4.2.1. Chromosome structure

In this section, structural variables are used to design chromosomes in such a way that each of the structures in the created solution determines a characteristic of the solution. Figure 1 illustrates the structure of the problem variables.



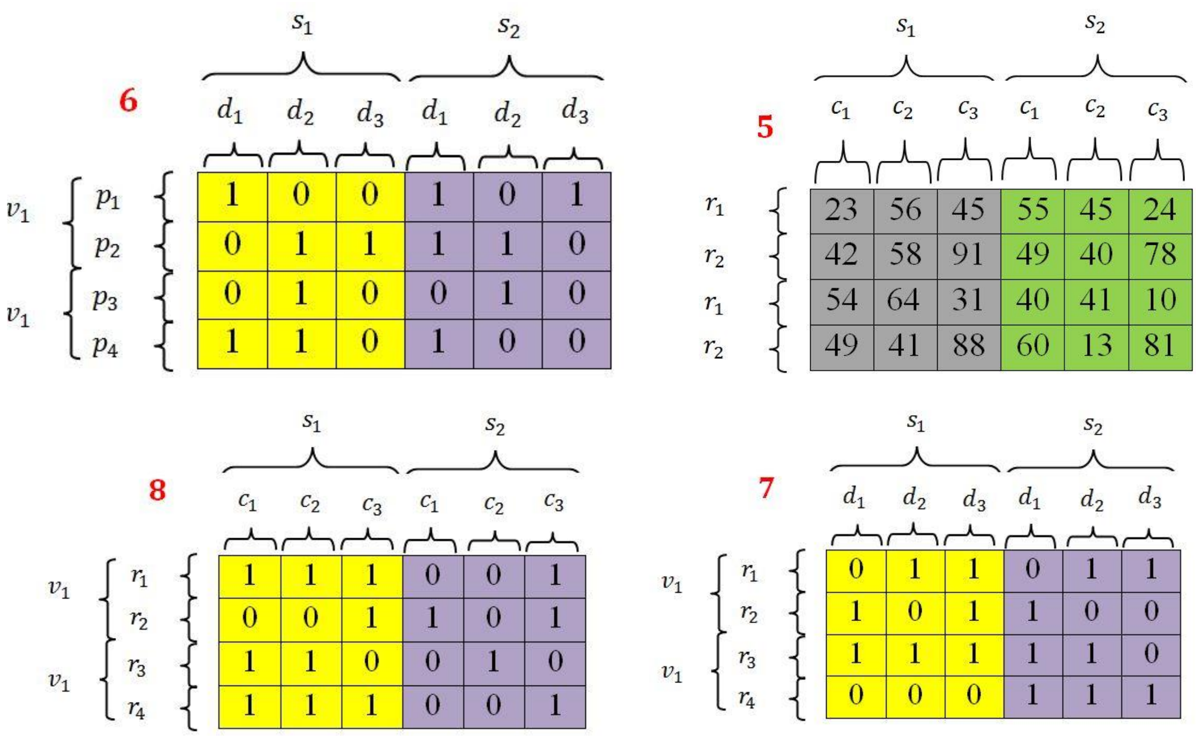


Figure 1. Structure of problem solutions

Regarding the high amount of decision variables in the proposed formulation, the demonstration structure of the chromosome consists of eight parts. In the first part, XD_{ds}, XR_{ds}, and XOD_{ds} , as the first part of the binary variables of the model, are addressed. The second part of binary variables, namely XC_{cs}, XE_{cs}, and XOC_{cs}, are presented in the second section. The third section shows XDR^{s}_{dr} and XRD^{s}_{rd} as integer variables. The rest of the sections are related to (XPD^{s}_{pd} and XDP^{s}_{dp}), (XCR^{s}_{cr} and XRC^{s}_{rc}), and ($XVDR^{vs}_{dr}$), ($XVRC^{vs}_{cr}$), and ($XVPD^{vs}_{pd}$), respectively.

Genetic algorithms benefit from two strong operators: crossover and mutation. As an example, Figure 2 shows the crossover operator for the chromosome of the first section. In this operator, two points in the chromosomes of parents are selected and swapped between the parents' organisms. This operator is called the two-point crossover.

Parent 1	0	1	1	1	0	1
	0	0	1	1	1	0
	0	0	0	0	1	0
	0	1	0	1	0	1
Parent 2	0	1	1	0	1	1
	1	0	1	0	1	0
	1	1	0	1	0	1
	1	1	1	0	1	0
offspring 1	0	1	1	0	0	1
	0	0	1	0	1	0
	0	0	0	1	1	0
	0	1	1	0	0	1
offspring 2	0	1	1	1	1	1
	1	0	1	1	1	0
	1	1	0	0	0	1
	1	1	0	1	1	0

Figure 2. The process of two-point crossover for the first section of chromosome structure

Fig. 3 reflects the mutation operator. In this process, one row is randomly selected and then reversed (the last row in Fig. 3).

Parent	0	1	1	0	0	1
	0	0	1	0	1	0
	0	0	0	1	0	0
	1	1	0	0	0	1
offspring	0	1	1	0	0	1
	0	0	1	0	1	0
	0	0	0	1	0	0
	1	0	0	0	1	1

Figure 3. The process of the mutation operator

4.3. Non-dominated ranking genetic algorithm

Al Jadaan et al., (2007, 8) developed a new population-based multi-objective evolutionary algorithm called NRGA for unconventional, nonlinear, and discrete optimization. In most cases, this algorithm can achieve a better extent of solutions at the Pareto boundary and earlier convergence to the optimal Pareto boundary, compared to other multi-objective evolutionary algorithms. Despite the similar operation process of both proposed algorithms, the only difference between the NRGA and NSGA-II algorithm is in the strategies of selection, population sorting, and selection for the next generation. In the NRGA algorithm, a ranking-based roulette cycle operator is used instead of the swarm tournament operator. Concerning the workflow of these algorithms, all the population responses are first sorted out to the non-dominated boundaries, so that the first border has the best solutions in the population. Therefore, the higher the score, the better the solutions at that boundary will be. After ranking the boundaries, the solutions within each boundary are also ranked based on the congestion distance. By calculating the congestion distance for all solutions at each boundary, the solution with the highest congestion distance has the highest rank, and the rank one is assigned to the solution with the lowest congestion distance. Figure 4 depicts the implementation process of both NSGA-II and NRGA algorithms.

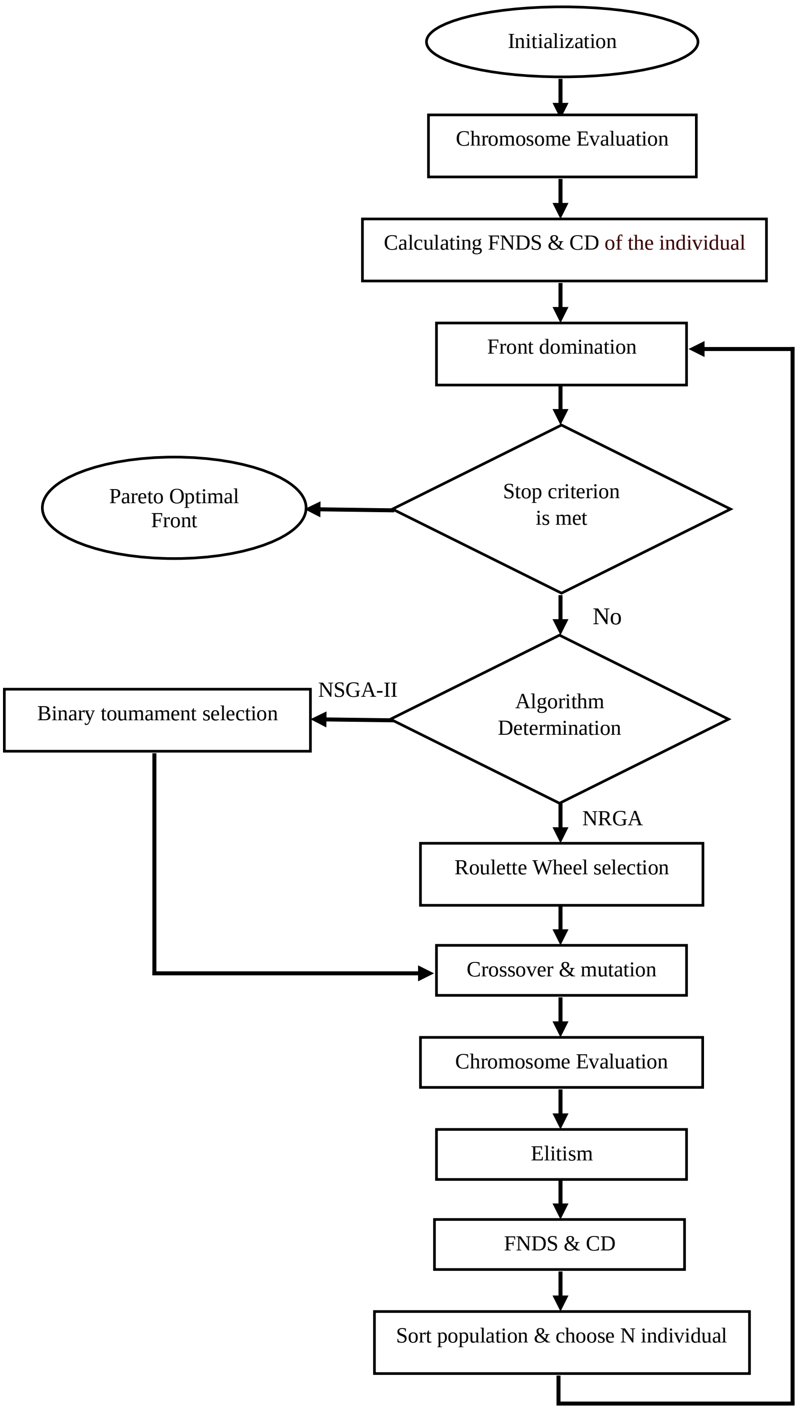


Figure 4. Flowchart of NSGA-II and NRGA algorithms

5. Results analysis

Table 2 is a comparison of the results of the Epsilon constraint approach and metaheuristic approaches. It is worth noting that the first five Pareto points are for small-scale problems and the second five Pareto points are for medium-scale problems. The results of spacing, Diversity, NOS, and MID criteria show that the NRGA approach has performed better than the NSGA-II approach in all problems. Also, the solving time of NRGA approach has been better than the NSGA-II in all problems.

Table 2. Comparing the results with exact approach for small and medium-scale problems

No	NSGA-II					NRGA				
	Spacing	**Diversity**	**NOS**	**MID**	**Time**	**Spacing**	**Diversity**	**NOS**	**MID**	**Time**
1	126.23	86725.56	2	92123.2	31	115.15	87796.50	2	92014.6	26
2	142.15	87430.65	3	92241.4	38	130.85	87540.26	4	921617.5	32
3	150.41	88411.56	4	95710.3	49	141.98	89201.50	4	94934.8	41
4	153.17	88736.41	4	95917.5	53	148.64	89106.46	5	93152.5	49
5	156.78	88860.21	5	96610.6	59	152.36	88990.20	6	965148.0	53
6	160.87	89610.56	6	96829.3	61	155.98	90230.56	7	96635.8	58
7	166.78	91254.10	7	97211.0	63	163.28	91332.19	8	97120.5	60
8	171.47	93140.09	7	98217.5	68	168.09	93140.09	8	97608.9	65
9	183.63	95857.00	8	98896.1	72	180.25	96211.05	9	98505.5	69
10	192.14	96469.01	9	99417.9	79	189.55	96670.06	10	98945.4	75

In order to solve the proposed model, two heuristic algorithms of non-dominated sorting genetic algorithm (NSGA-II) and non-dominated ranking genetic algorithm (NRGA) were provided for solving multi-objective problems based on Pareto approach. This section analyzes the results of implementing the proposed solution methods on the experimental problems. Initially, the parameters of the algorithms were categorized after consecutive runs on the values presented in Table 3 and then adjusted by the Taguchi method. The adjusted levels are shown in Figure 5. Table 4 represents the input parameters provided to implement the problems.

To tune the value of parameters used in solution methods, the Taguchi method is utilized, which considers a statistical measure of performance under the S/N ratio, which includes the mean and variations, and its higher values at any level are more desirable. The corresponding S/N ratio is considered as Equation (39). The proposed heuristic algorithms were implemented for each Taguchi experiment, and then, the S/N ratios were calculated by Minitab16.2 software.

$$ {}^{S}\!/_{N}\ Ratio = -10\log\left[\frac{sum(y^{2})}{n}\right] \tag{39} $$

Table 3. Levels and domains presented for the proposed algorithms

Suggested Algorithm	algorithms Parameters	Parameter ranges	Low(1)	Medium(2)	High(3)
NSGA-II	nPop	50-100	50	75	100
	nIter	50-100	50	75	100
	P_c	0.6-0.99	0.8	0.85	0.9
	P_m	0.05-0.15	0.05	0.1	0.15
NRGA	nPop	50-100	50	75	100
	nIter	50-100	50	75	100
	P_c	0.6-0.99	0.8	0.85	0.9
	P_m	0.05-0.15	0.05	0.1	0.15

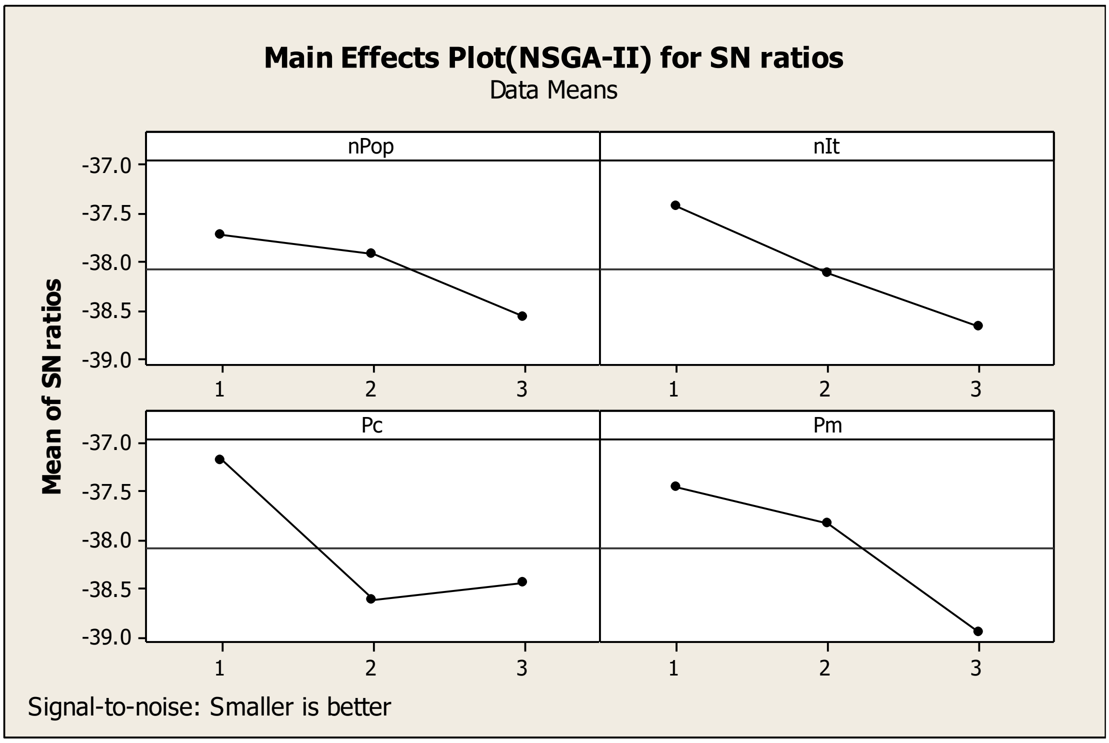


Figure 5.a. Diagram S/N of parameters in NSGA-II

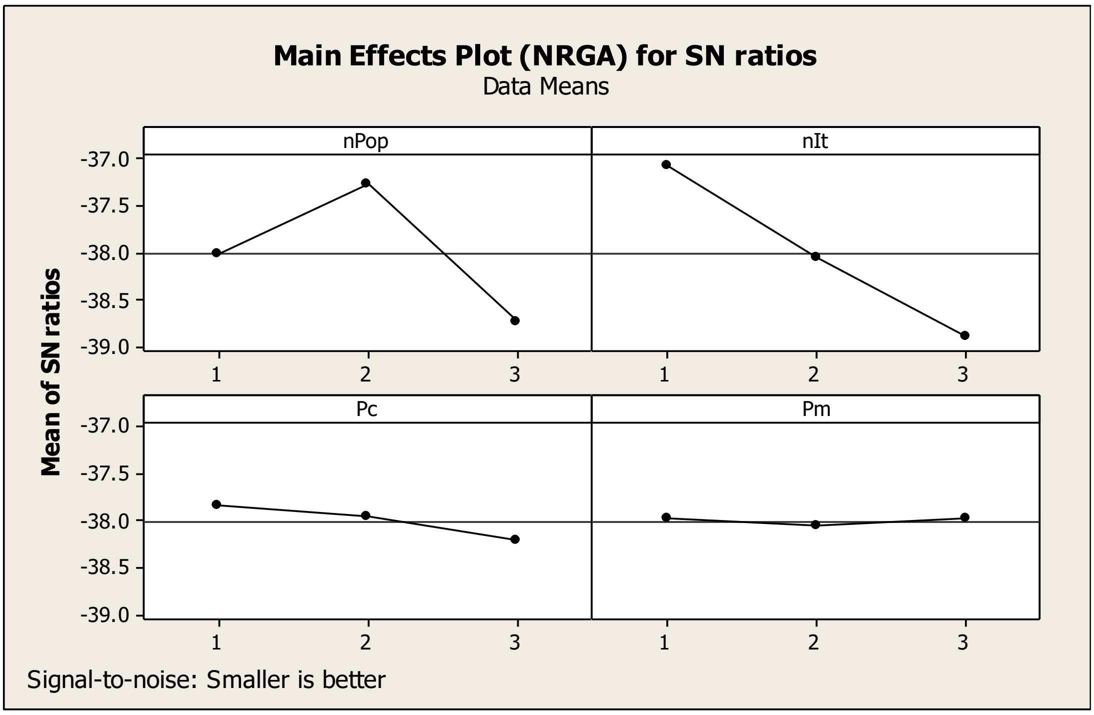


Figure 5.b. Diagram S/N of parameters in NRGA

The value of parameters used in the mathematical formulation is shown in table A (See appendix A).

5.1. Measurement criteria for results comparison

This section reports the standard comparison indices for evaluating multi-objective algorithms with the Pareto approach. Contrary to single-objective optimization, the two main criteria include maintaining diversity between Pareto solutions and convergence to the set of Pareto solutions for multi-objective optimization. In this article, the following indicators are proposed for comparison.

5.1.1. Maximum diversity

This index, which is introduced by Zeitzler, measures the diameter length of the spatial cube used by the endpoints of the targets for the set of non-dominated solutions. Equation (40) shows the computational procedure of this index.

$$D = \sqrt{\sum_{j=1}^{m} (\max f_i^{\,j} - \min f_i^{\,j})^2} \qquad \forall i \tag{40}$$

Equation (40) shows how to calculate the Euclidean distance between two boundary solutions in the target space. Accordingly, the higher values of this criterion indicate the better situation of the result.

5.1.2. Spacing

The spacing index calculates the relative distance of successive solutions using the following equation (41).

$$SM = \frac{\sum_{i=1}^{n-1} \left| d_i - \bar{d} \right|}{(n-1)\bar{d}} \tag{41}$$

So that d_i is the Euclidean distance between two adjacent Pareto solutions and $\bar{d}$ is the average Euclidean distance. The smaller the SM value, the lower the dispersion of Pareto points will be. Also, when SM is closer to zero, the distance between all adjacent answers will be equal.

5.1.3. Number of Pareto solution

The NOS index represents the number of optimal Pareto solutions that can be found in each algorithm. The higher the value of this index, the better the performance of the algorithm would be (Deb, 2000).

5.1.4. Distance from ideal solution

This index is used to measure the proximity to the optimal real Pareto level. The lower values of this index indicate the better status of the set. This index is calculated by Equation (42).

$$MID = \frac{\sum_{i=1}^{n} \sqrt{f_{i1}^2 + f_{i2}^2}}{n} \tag{42}$$

5.1.5. Time

Algorithm run time is one of the most important indicators in the performance of any meta-heuristic algorithm (Deb, 2000).

After defining the standard criteria for comparing Pareto-based multi-objective algorithms, Table 4 presents the criteria for measuring the experimental problems. Figure 6 shows the performance of the proposed algorithms, which are drawn graphically based on the five criteria. According to the outputs, the algorithms are studied statistically through an analysis of variance.

Table 4. Computational results of the measurement criteria for comparing NRGA and NSGA-II algorithms

N	Proposed NSGA-II					Proposed NRGA				
	Spacing	Diversity	NOS	MID	Time	Spacing	Diversity	NOS	MID	Time
1	23604.7	524896.1	5	46586691.2	81.22	29781.6	661781.3	9	66259125.1	61.25
2	75981.9	412697.3	3	58612234.1	89.99	47215.2	510236.2	7	39825473.7	74.33
3	44653.6	498745.2	3	79952312.9	96.25	39647.3	985641.8	4	78925773.4	92.11
4	51468.2	742913.4	7	68912544.6	102.31	78694.2	561327.1	3	48625531.2	98.25
5	59674.1	985674.3	10	41783348.8	115.24	91264.3	1006254.3	5	55631147.1	102.31
6	48213.5	685792.3	4	96784551.3	127.66	69542.8	852364.1	10	110254611.2	109.36
7	89641.1	852369.7	4	107541231.2	139.36	44568.4	598412.1	7	125689315.9	117.20
8	101234.3	1365781.9	5	102368841.2	161.1	86457.1	1219684.6	9	98564231.2	143.56
9	95269.1	596873.2	6	96421289.8	193.2	91236.2	693025.1	4	88956443.3	179.31
10	77226.9	1254690.5	11	131256941.6	211.81	114236.6	1086451.3	4	14236985.2	241.32
11	112697.2	963214.9	3	125641281.2	296.32	101267.4	874596.4	6	102342263.8	256.74
12	109847.3	2641387.3	4	119658371.4	308.21	122367.9	1994588.6	7	133524631.4	289.65
13	134091.5	1985672.2	7	125421369.2	342.8	111289.4	2841174.2	9	115264597.2	306.11
14	158642.4	3629753.9	4	148975162.8	387.58	169874.2	3295412.1	9	139862142.2	338.45
15	146897.2	2845316.1	4	136540877.3	431.05	158964.3	3026541.6	4	128964123.5	364.27
Ave	96888.99	1332385.7	5.34	99097136.57	205.6	90427.13	1347166.9	6.46	89795093.21	184.94

As shown in the Table 5, the mean values of the Spacing, solution time, Diversity, NOS, and MID are more desirable in NRGA algorithm. We also used statistical analysis to examine and compare the results more accurately. As noted, the analysis of variance and t-test were used in this domain, the results of which are provided in Table 5 and Figure 7.

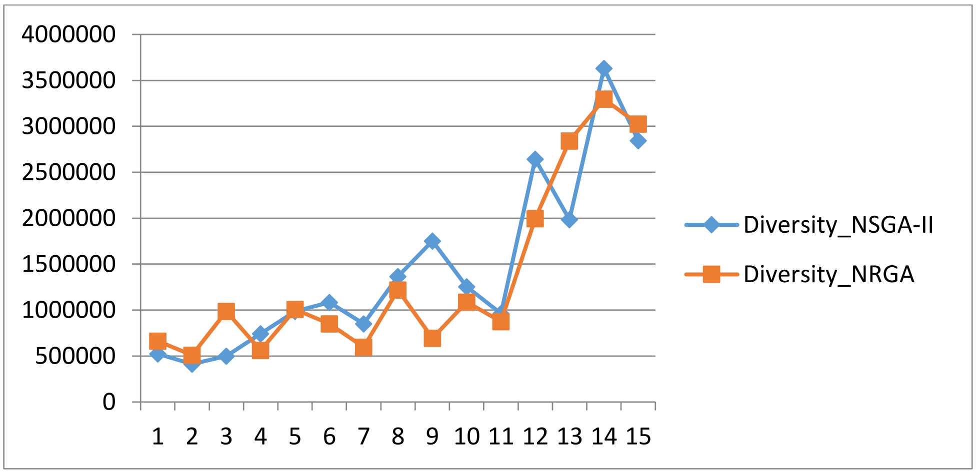


Figure 6.a. The graphical diagram of comparing diversity of NSGA-II and NRGA algorithms

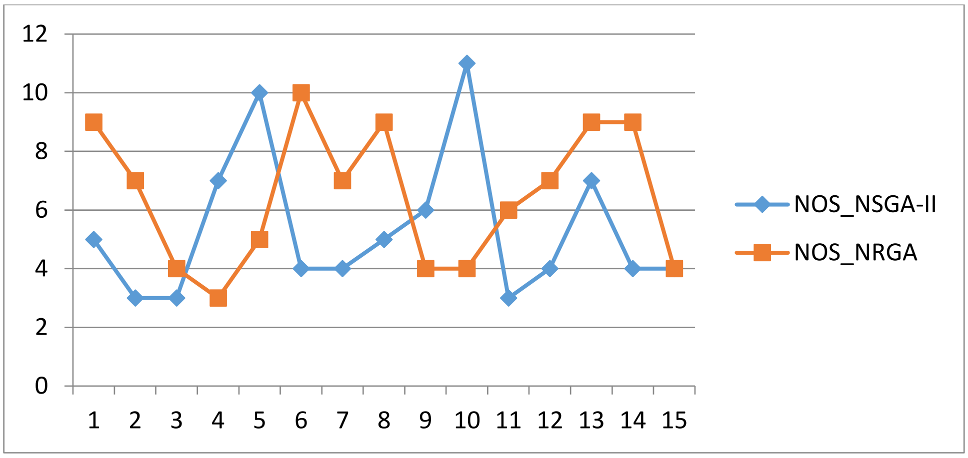


Figure 6.b. The graphical diagram of comparing NOS of NSGA-II and NRGA algorithms

Table 5. Results of analysis of variance on criteria comparison

	P-Value	Results
Spacing	0.818	H0 is not rejected
Diversity	0.967	H0 is not rejected
NOS	0.209	H0 is not rejected
MID	0.484	H0 is not rejected
Time	0.615	H0 is not rejected

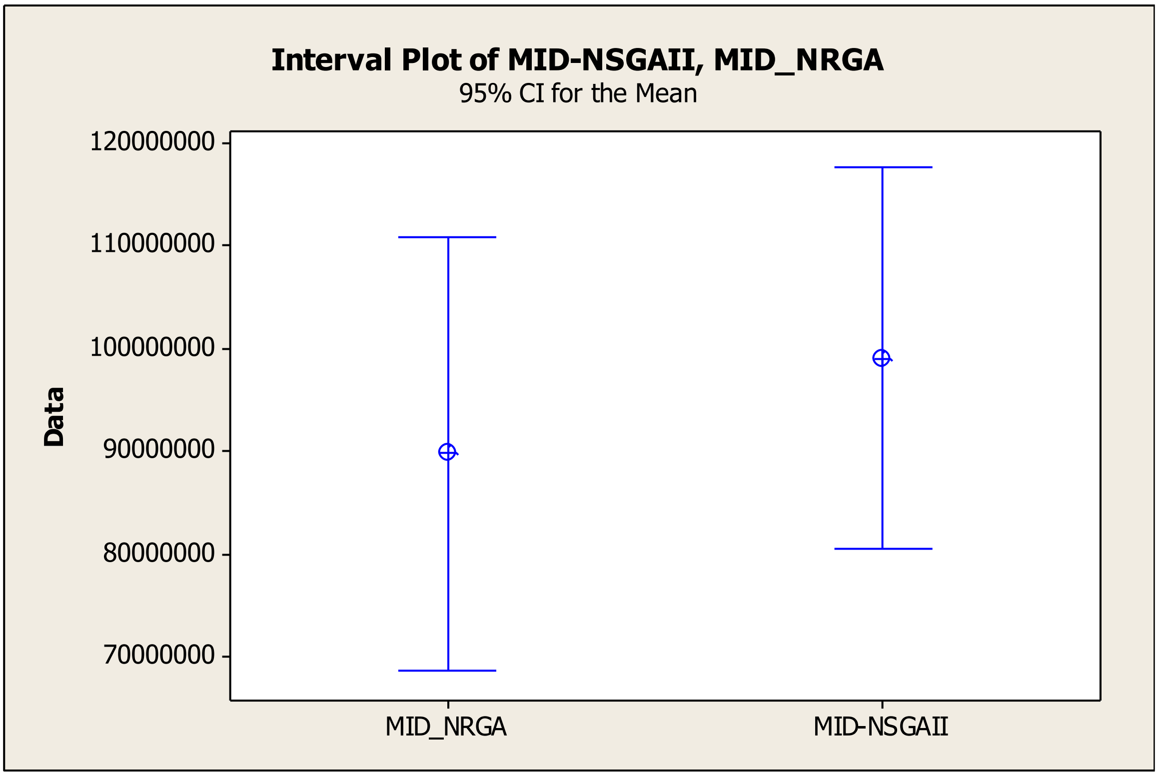


Figure 7.a. Interval Plot of the statistical test on MID metrics

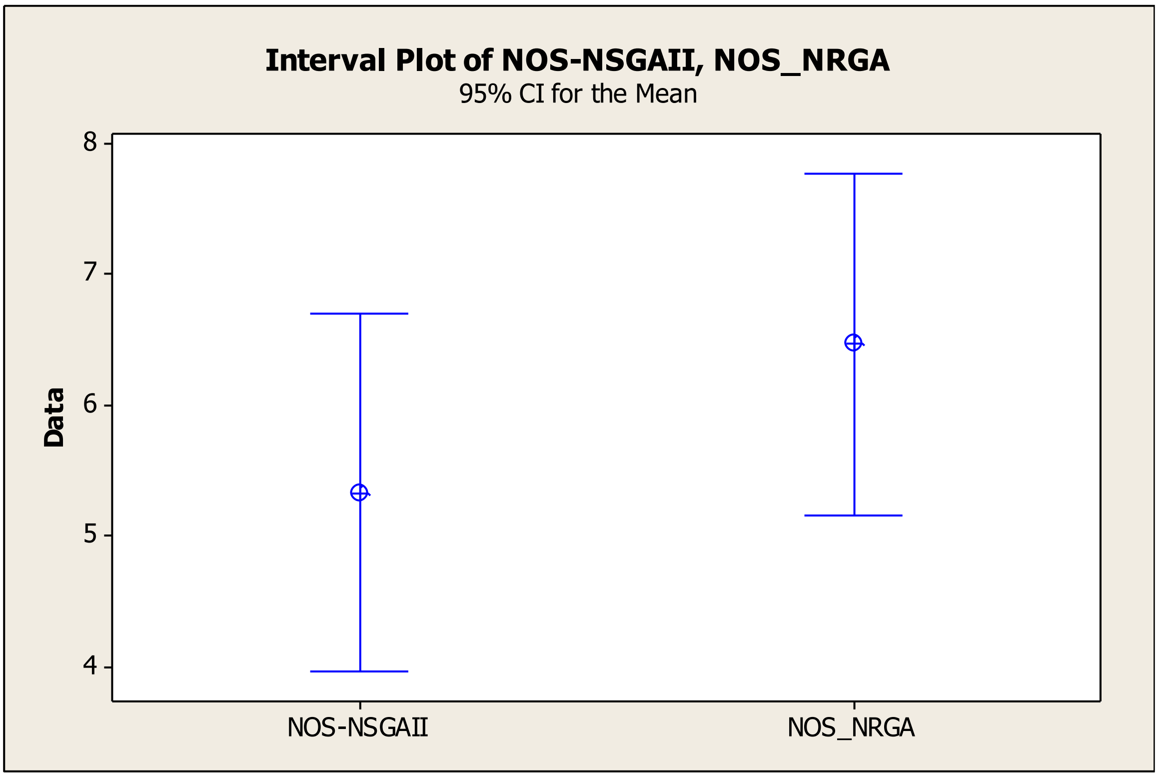


Figure 7.b. Interval Plot of the statistical test on NOS metrics

According to the results, the NRGA algorithm performs better than the NSGA-II algorithm and has a higher utility. Given that in hub locating problems, when problems become larger, then issues enter the problem phase, and mathematical optimization algorithms cannot solve them. Therefore, high-performance meta-heuristic algorithms should be used. It is worth noting that the proposed algorithms in this research can be one of the efficient meta-heuristic algorithms for solving hub location problems.

6. Sensitivity analysis

Because the NRGA approach has performed better than the NSGA-II, it will also be used for sensitivity analysis. Figure 8 shows the sensitivity analysis of the number of distribution centers relative to demand. As it is obvious, the increase in demand results in the establishment of more distribution hubs. For example, a 10 percent increase in demand will result in the establishment of 10 hubs. Also, the number of hubs remains constant for more than 10 percent increase in demand. The reason is the high establishment costs relative to the costs of satisfying the demand. Therefore, the number of established hubs remains constant.

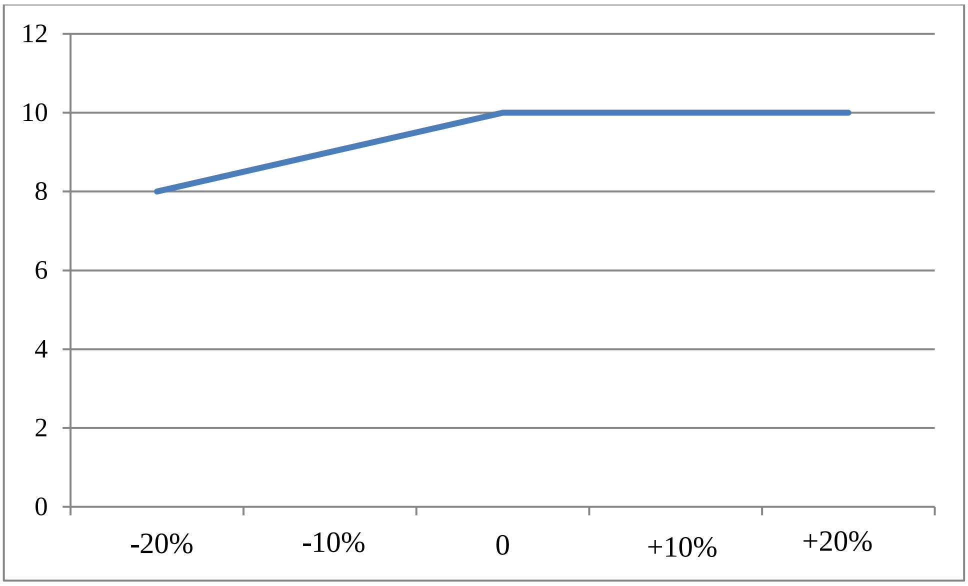


Figure 8. Sensitivity analysis of the number of established distribution centers relative to the demand for products

Figure 9 shows the sensitivity analysis of capacity of vehicles relative to cost. As can be seen, increasing the capacity of vehicles reduces costs. For example, a 20 percent increase in the capacity of vehicles will decrease costs to 3,060 units. Also, a 20 percent decrease in the capacity of vehicles will increase costs to 40,182 units

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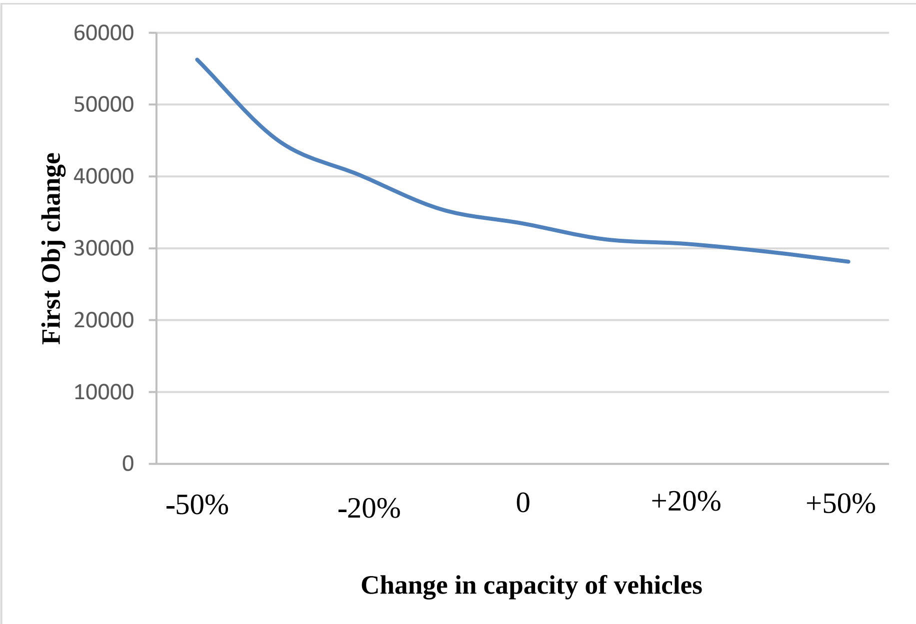

Figure 9. Sensitivity analysis of the objective function relative to the capacity of vehicles

Figure 10 shows the results of demand changes in the second objective function. As is clear, increase in demand results in increase in environmental pollution and higher fuel consumption. For example, a 10 percent increase in demand will increase environmental costs to 244555.2 units. Also, a 20 percent decrease in demand will decrease environmental costs to 241210.5 units

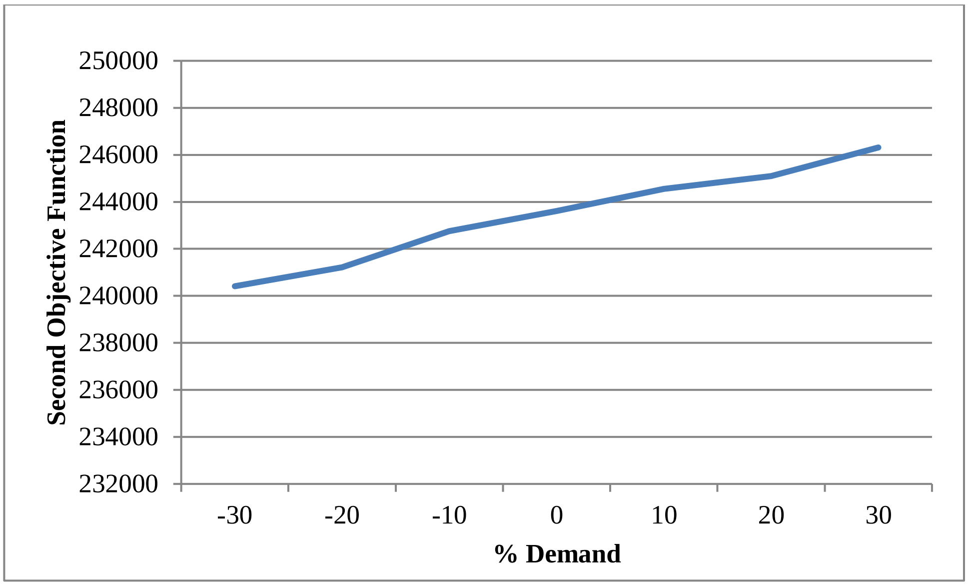

Figure10. Analysis of the effect of demand on the shortage

7. Conclusions and future suggestions

This research sought to provide a hub location model for essential commodities to meet dynamic demand and minimize environmental pollution emissions. As the proposed model contains a vast number of decision variables, two meta-heuristic algorithms were used to solve the model. To this aim, a new model was developed for determining hub points, such that distribution centers were considered as hubs to minimize the cost of the route between production centers and retail centers. Moreover, the distribution centers were studied in different ways such as construction, commissioning, and renting of the center, the results of which formed the basis of the developed model. The second objective function of the model dealt with environmental issues to reduce air pollution by decreasing transportation and fuel consumption. In this research, Pareto-based multi-objective algorithms were applied to solve the proposed model. Given the sensitivity of the parameters during the implementation of solution methods, the Taguchi method was used to adjust the algorithm parameters. Finally, statistical analysis was utilized to select the most efficient solution method for the presented models. According to the results, the NRGA algorithm performs better than the NSGA-II algorithm.

Therefore, the model has been solved in small and medium-scale by the Epsilon constraint approach and the results have been compared with the NSGA-II and NRGA approaches. The Taguchi approach has also been used to adjust the considered parameters. The NRGA approach has performed better than the NSGA-II approach in all criteria, including NOS, MID, SM and solving time. The results of sensitivity analysis indicate that increasing demand will result in the establishment of more distribution hubs. The number of hubs remains constant for more than 10 percent increase in demand. The reason is the high establishment costs relative to the costs of satisfying the demand. Therefore, the number of established hubs remains constant. Increasing the capacity of vehicles reduces costs. Finally, increasing demand will result in increase in environmental pollution and higher fuel consumption. This research, like other researches, is not without limitation and assumptions. Therefore, the limitations of the research are expressed as follows:

1. Meta-heuristic algorithms cannot be the global optimum solution and the local optimum calculated solutions.

2. The final solutions calculated by the NSGA-II and NRGA approaches depend strongly on the ability of the coder to define chromosomes and initial values of parameters.

3. Only numerical examples are examined because there has been a lack of access to real supply chain information in the field under study.

Recommendations for future studies are as follows:
1. Considering routing in the problem under study
2. Considering a cooperative game to minimize costs in cooperative supply chain
3. Considering other meta-heuristic solution approaches such as MOPSO and comparing it with the proposed algorithms
4. Considering other uncertainty approaches such as fuzzy, scenario-based.

Nowadays, ensuring the sustainable development of countries depends on optimal maintenance and use of limited resources and the application of green laws and rules such as using environmentally compatible raw materials in manufacturing and industrial centers, reducing the use of fossil and oil energy resources, reusing waste for public and private organizations and companies. Minimizing environmental costs can help managers and decision makers in making strategic and operational decisions. Thus, speeding up government legislation is recommended to obtain environmental standards and minimize environmental pollution. The results of this research can also be useful for tourism managers. They can satisfy tourists by determining the location of distribution hubs of products needed for tourism and forecasting their demand. This issue can increase the number of tourists in cities. Finally, it is stated that the results of this study are useful for industries with seasonal demand and managers of these industries can use the results of this research.

For future research directions, the proposed model can be included the limits of monuments, epidemics, cultural and religious constraints, and security. It can also be developed based on the two objectives of minimizing costs and reducing environmental issues, in addition to its generalization to other objectives. Finally, the model can be tested with other multi-objective problem-solving algorithms.

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Appendix A.

Table A. The value of parameters used in the mathematical formulation

Parameter	Range	Parameter	Range	Parameter	Range
CD_{ds}	Uniform(1000,2000)	$DepCVRD_{rd}^{vs}$	Uniform(10,20)	$FUELVDR_{dr}^{v}$	Uniform(5,15)
CS_{ds}	Uniform(300,500)	$RMCVRD_{rd}^{vs}$	Uniform(10,20)	$FUELVRD_{rd}^{v}$	Uniform(5,15)
CR_{ds}	Uniform(400,600)	$FCVRD_{rd}^{vs}$	Uniform(10,20)	$FUELVCR_{cr}^{v}$	Uniform(5,15)
MCD_{ds}	Uniform(50,60)	$DISVRD_{rd}^{v}$	Uniform(10,25)	$FUELVRC_{rc}^{v}$	Uniform(5,15)
$DCVPD_{pd}^{vs}$	Uniform(10,20)	CCC_{cs}	Uniform(1000,1500)	$POPVPD_{pd}^{v}$	Uniform(10,30)
$\mathrm{DepCVPD}_{\mathrm{pd}}^{\mathrm{vs}}$	Uniform(10,20)	CCS_{cs}	Uniform(100,300)	$POPVDP_{dp}^{v}$	Uniform(10,30)
$\mathrm{FCVPD}_{\mathrm{pd}}^{\mathrm{vs}}$	Uniform(10,20)	$\mathrm{CC}R_{cs}$	Uniform(400,600)	$POPVDR_{dr}^{v}$	Uniform(10,30)
$DISVPD_{pd}^{v}$	Uniform(10,50)	MCC_{c}^{s}	Uniform(50,100)	$POPVRD_{rd}^{v}$	Uniform(10,30)
$DCVDP_{dP}^{vs}$	Uniform(10,20)	$DCVCR_{cr}^{vs}$	Uniform(10,20)	$POPVCR_{cr}^{v}$	Uniform(10,30)
$DepCVDP_{dp}^{vs}$	Uniform(10,20)	$DepCVCR_{cr}^{vs}$	Uniform(10,20)	$POPVRC_{rc}^{v}$	Uniform(10,30)
$RMCVDP_{dp}^{vs}$	Uniform(10,20)	$RMCVCR_{cr}^{vs}$	Uniform(10,20)	$MAXCAPVPD_{v}$	Uniform(40,60)
$FCVDP_{dp}^{vs}$	Uniform(10,20)	$FCVCR_{cr}^{vs}$	Uniform(10,20)	$MAXCAPVDR_{v}$	Uniform(40,60)
$DISVDP_{dp}^{v}$	Uniform(10,50)	$DISVCR_{cr}^{v}$	Uniform(20,40)	$MAXCAPVRC_{v}$	Uniform(40,60)
$DCVDR_{dr}^{vs}$	Uniform(10,20)	$DCVRC_{rc}^{vs}$	Uniform(10,20)	$CAPVPD_{pd}^{v}$	Uniform(10,30)
$DepCVDR_{dr}^{vs}$	Uniform(10,20)	$DepCVRC_{rc}^{vs}$	Uniform(10,20)	$CAPVDR_{dr}^{V}$	Uniform(10,30)
$RMCVDR_{dr}^{vs}$	Uniform(10,20)	$RMCVRC_{rc}^{vs}$	Uniform(10,20)	$CAPVRC_{rc}^{V}$	Uniform(10,30)
$FCVDR_{dr}^{vs}$	Uniform(10,20)	$FCVRC_{rc}^{vs}$	Uniform(10,20)	$DemRS_{rs}$	Uniform(5,40)
$DISVDR_{dr}^{v}$	Uniform(10,25)	$DISVRC_{rc}^{v}$	Uniform(20,40)		
$DCVRD_{rd}^{vs}$	Uniform(10,20)	$FUELVPD_{pd}^{v}$	Uniform(5,15)		
$RMCVPD_{pd}^{vs}$	Uniform(10,20)	$FUELVDP_{dp}^{v}$	Uniform(5,15)		