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Developing and solving an integrated model for production routing in sustainable closed-loop supply chain

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A R T I C L E I N F O

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A B S T R A C T

Social and environmental sustainability has gained increasing importance in today's complex supply chains. Accordingly, an integrated model for production routing in the sustainable closed-loop supply chain is presented in the current study. A three-objective mathematical model is also proposed to minimize supply chain costs, maximize social responsibility or social benefits, and finally, minimize environmental emissions. Sample trial problems are solved in three groups of the small, medium, and large size using the BCO algorithm. To prove the efficiency of this algorithm, its results are compared with the results using the NSGA-II algorithm in terms of comparative metrics such as quality, diversity, and spacing, as well as the runtime to the solution. According to the results, in all cases, the BCO algorithm outperformed the NSGA-II algorithm as it achieved more qualitative and near-optimal solutions. Also, the diversity metric values showed that the BCO algorithm is stronger in the exploration and extraction of the solution feasible region. The results of the metric of spacing and runtime to solution also showed that the NSGA-II algorithm achieves the solution in lower runtime than the BCO algorithm and searches solutions space in a more uniform manner.

1. Introduction

Sustainable supply chain management is defined as "the management of material, information, and capital flow to establish cooperation among companies involved in the supply chain and has received a lot of attention for the past two decades (Hsueh, 2015). The significance of sustainability in supply chain management, as well as considering the environmental factors and social aspects has increased in recent years (Hussain et al., 2015; Brandenburg et al., 2014). Environmental and social sustainability are relatively complex issues affecting the capability of different supply chain segments by adapting technology, creating a friendly environment and paying attention to the environmental factors (Golini et al., 2014).

Corporate social responsibility is the acceptance of business ethics to achieve sustainability and covers both social and environmental, as well as, economic conditions. Social responsibility c.an be considered from four perspectives: 1) Economic responsibilities: the most basic layer of the social responsibility because of the shareholders' demand for return on investment and improving the economic conditions. 2) Legal responsibilities: The rules should be implemented according to the international standards. 3) Ethical responsibilities: organizations should perform activities, expected by the community. 4) Humanitarian responsibilities: Including issues such as supporting poor people, risks protection, reducing energy consumption, and pollution prevention (Zeng et al., 2015).

It has been more than a decade that social responsibility has become a complex concept with increasing effectiveness in organizational decision-making processes. Respect for social responsibility and sustainability along with cost clarification for accepting more social responsibility and self-confidence can encourage the stakeholders to work in this field with new initiatives. Furthermore, this strategy can remarkably improve supplier status and organizational operations and help in the development of environmental promotions and safe products, technology, and process. Organizations should consider the stakeholders' and workers' viewpoints to identifying their needs which, in turn, will improve the social responsibility implementation plans and working conditions, health, and job security in the long run (Sarmah et al., 2015).

Creating coordination in the supply chain, optimizing social

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supply, and reducing production costs are among the major objectives of social responsibility implementation which can reduce prices, encourage customers to buy more and ultimately, optimize supply chain profits. Through analyzing the impact of social responsibility on 133 Spanish companies, the researchers concluded that, in addition to improving economic conditions, it can also cause non-economic impacts such as organizational reputation, employee motivation, customer satisfaction, innovation, improving organizational performance, energy storage, and develop programs to reduce material, recycling (Reverte et al., 2016). Moreover, scheduling plays an important role in supply chain coordination. Beheshtinia and Ghasemi (2018) considered the integration of supplier and vehicle scheduling problems in terms of vehicle routing determination for transporting raw materials from the suppliers to some manufacturing centers. The shared transportation system in the production scheduling of a multi-site manufacturer was also investigated by Beheshtinia et al. (2018).

Akcali and Cetinkaya (2011) reviewed the current quantitative literature on inventory and production planning for CLSC systems. Based on their review, few articles have used quantitative models for sustainable supply chain management (Reverte et al., 2016). However, no study has addressed production routing in the closed-loop supply chain, considering the economic, social, and environmental aspects. Considering the importance of the issue as well as the mentioned research gap, this paper presents a mathematical model of production routing in the closed-loop supply chain considering simultaneous receiving and delivering with the “economic”, “social” and “environmental” objectives. In the first step, a quantitative three-objective model was proposed to optimize costs and levels of social responsibility implementation and reduce environmental impacts. Given that supply chain planning is an NP-Hard problem (Panda, 2014), the BCO and NSGA-II metaheuristic methods were employed to solve the model.

Under these preconditions for gaps, the authors were motivated to investigate the production routing problem in a multi-echelon, multi-product closed-loop supply chain. In the proposed model, distributors’ locations in direct logistics and facilities location for re-production (e.g. collection, destruction, and recycling) were considered in reverse logistics, green production, and green routing. Given the uncertain nature of the parameters in the real world, in this research, the parameters were considered non-deterministic in the form of fuzzy numbers. In contrast to previous studies, the studied model, in addition to planning some cases in direct logistics, planning of all cases was also discussed in reverse logistics and production routing considering the sustainability dimensions. The other difference of the present research lies in the comprehensive and integrated structure of the network, considering the sustainability and uncertainty conditions as fuzzy numbers. In summary, the main contribution of this paper is presenting a new version of the closed-loop problem considering production routing, social responsibility, and environmental emissions under uncertain conditions. Another contribution of this paper is the introduction of two metaheuristic algorithms to solve the problem.

2. Literature review

The study of the closed-loop supply chains has recently gained increasing popularity. For example, Vahdani (2015) presented a multi-product and multi-period model for designing a closed-loop supply chain network under fuzzy environment. Demirel et al. (2014) provided a multi-product and multi-period hybrid linear planning for a closed-loop supply chain network. Fallah Tafti et al. (2014) also designed the supply chain network in an integrated way. Their proposed network was a multi-level network including assembly, customers, and collection and disposal centers. Ruimin et al. (2016) presented a bi-objective planning model for a closed-loop supply chain under uncertain conditions. Banasik et al. (2017) presented a multi-objective linear planning model of the closed-loop supply chain for mushroom production. Their model only included producer and retailer levels in direct logistics level and other levels were not considered. Moreover, only the collection and rehabilitation centers were considered in reverse logistics. Amin and Baki (2017) introduced the multi-objective facility location model in a closed-loop supply chain under fuzzy conditions.

Some studies have addressed the sustainable supply chain. Carter and Rogers (2008) presented a comprehensive conceptual framework for the sustainable supply chain management. In addition to the economic environmental and social dimensions, four other aspects were considered in their framework which played the supporting role for the three main concepts of sustainability. Teuteberg and Wittstruck (2010) presented a systematic approach for the sustainable supply chain management. They also offered sustainable supply chain houses. In their view, by doing so and taking into account different dimensions, the sustainable supply chain is effectively protected from environmental and social threats and risks.

Pishvaee et al. (2014) designed a drug supply chain using a multi-objective planning model. Their proposed model was a sustainable model including economic, environmental (green), and social goals. They used the accelerated Benders decomposition algorithm to solve the model. Devika et al. (2014) have designed a sustainable closed-loop supply chain and proposed a multi-objective mathematical model considering the environmental, economic, and social dimensions. They then used it to solve imperialist metaheuristic algorithms and Variable Neighborhood Search. Aravendan and Panneerselvam (2014) presented a multi-Echelon multi-product model for a sustainable closed-loop supply chain. They also proposed a mathematical model for minimizing social and environmental costs, considering the capacity constraints of the facility, and solving the model using the Lingo software and an innovative method. Koppius et al. (2015) investigated the closed-loop supply chain, taking into account the criterion of the business and trade value (as a sustainability criterion). They also provided a rule-based information system to examine the social values of the employees and customers.

Bhattacharjee and Cruz (2015) addressed the problem of economic sustainability in a closed-loop supply chain and developed an integrated decision-making system for evaluating economic credit to provide optimal decisions based on product and customer life cycle. Hussain et al. (2015) used a combination of interpretative structure modeling (ISM) and analytic network process (ANP) to evaluate the appropriate alternatives to resources, time and money in line with the economic, environmental and social dimensions of a sustainable supply chain management (Hussain et al., 2015).

Zhalechian et al. (2016) modeled a sustainable closed-loop supply chain considering location, routing, and inventory aspects under uncertainty. They first developed a three-objective mathematical model based on the economic, social, and environmental dimensions, and then solved the model in the GAMS Software space using a metaheuristic algorithm. Battini et al. (2016) designed the closed-loop supply chain problem considering sustainability dimensions and provided a mathematical model based on the scenario considering the facilities and vehicle capacity constraints. Rezaei and Kheirkhah (2018) studied the problem of closed-loop supply chain and presented a three-objective mathematical model with economic, social, and environmental objectives. They also used the Cuckoo Search for solving the model. Research by Coenen et al. (2018) was aimed to fill the knowledge gaps regarding approaches to dynamic complexity and deep uncertainty in a transition towards closed-loop supply chain management. Zhen et al. (2019) presented an integration perspective for developing a green and sustainable closed-loop supply chain (CLSC) network under uncertain demand. They proposed a Lagrangean relaxation method to solve the model. Mardan et al. (2019) developed a comprehensive mathematical model for a multi-period, multi-product, multi-modal, and bi-objective green closed-loop supply chain. The objective of the model was to minimize the total cost and environmental emissions, and an effective accelerated benders decomposition algorithm was employed as the solution approach. Hosseini-Motlagh et al. (2020) contributed to the sustainable CLSC literature by proposing an analytical coordination mechanism to coordinate the dual-function acquisition price as an environmental sustainability and corporate social responsibility as social sustainability.

Some studies have also been conducted on the production routing problem (PRP). For example, Adulyasak et al. (2015) published a deep overview of PRP. They concluded that most researchers have proposed heuristic and metaheuristic methods for this problem, while the use of accurate algorithms, as well as robust optimization for this problem, has not been extensively addressed. Adulyasak et al. (2012) presented a complex integer mathematical model for PRP in the supply chain which was a combination of the size-stock and routing-inventory problems. Emamian et al. (2018) focused on the robust optimization of the production routing problem in a closed-loop supply chain to reduce CO_2 and CO emissions. To this end, they provided a fuzzy multi-objective mathematical model and solved the model using the bee colony algorithm based on the Pareto archive and the GAMS software. Fang et al. (2017) also modeled and solved the problem of sustainable production routing in the closed-loop supply chain with the simultaneous receipt and delivery conditions while only the environmental dimension was considered. Pourmehdi et al. (2020) developed a multi-objective linear mathematical model under uncertainty to optimize a steel sustainable closed-loop supply chain. The existed uncertainty was modeled through a scenario-based method in the stochastic environment, and the proposed multi-objective model was developed following a fuzzy goal programming approach. A real case study was explored in one of the active steel supply chains in Iran to validate the model. Yu and Solvang (2020) formulated a new fuzzy-stochastic multi-objective mathematical model for sustainable Closed-loop supply chain network design. In order to solve the complex optimization problem, the model was first defuzzilized and converted into an equivalent crisp form. The computational results showed, through the incorporation with network flexibility, the proposed mathematical model and solution approach can effectively generate consistent objective values and solutions over different scenario trees and obtain robust strategic decisions on facility locations. Mehrjerdi and Shafiee (2021) considered sustainability and resilience in a closed-loop supply chain simultaneously. Accordingly, a new multi-objective mixed-integer programming model was formulated for a closed-loop supply chain. The real data of a tire industry was used for validating the proposed model, and the model was solved using the improved version of the augmented ε-constraint method. Khalili Nasr et al. (2021) presented a novel two-stage fuzzy supplier selection and order allocation model in a closed-loop supply chain. In Stage 1, they used the fuzzy best-worst method to select the most suitable suppliers according to economic, environmental, social, and circular criteria. In Stage 2, they used a multi-objective mixed-integer linear programming model to design a multi-product, multi-period, closed-loop supply chain network, and inventory-location-routing, vehicle scheduling, and quantity discounts considerations. they presented a case study to demonstrate the applicability of the proposed method in the garment manufacturing and distribution industry.

In this regard, the present paper is focused on an important supply chain problem that combines production routing and sustainability management problems. A large number of variations in the closed-loop problems were previously considered in different studies. The present work, however, is aimed at offering an extension for the previous models considering a vast number of real-world cases. The paper addresses a new version of the closed-loop problem considering production routing, social responsibility, and environmental emissions. Also, as the real-world cases are often associated with vagueness and uncertainty, fuzzy numbers were used to represent the cost of construction and demands of the product to approximate the problem to the real-world situations.

3. Problem statement

The present study was aimed to provide a sustainable closed-loop supply chain model. Fig. 1 illustrates the conceptual model of the problem. As shown in Fig. 1; the goods are produced in production centers and sent from production centers to warehouses or distribution centers. The distribution centers can also receive goods from warehouses of manufacturing centers. From distribution centers, goods are shipped to customers and distributed between them. Now, if goods are returned from the customer due to various reasons, these goods will be received, collected, and sent to the collection and recovery centers. If the goods are recoverable and process in the collection and restoration centers, they will be restored and sent back to the distribution centers for resending to customers. If the goods need to be recycled, they will be sent to the recycling centers and then, re-enter the manufacturing cycle. In the case of unprocessable goods, they will be sent to the disposal centers. Therefore, the surveyed problem includes routing, production, distribution, inventory, and location considering sustainability goals in the multi-echelon, multi-product, and multi-period green supply chain.

Three dimensions of supply chain sustainability (e.g. economic, social, and environmental goals) are considered in the present research. Each of these dimensions is based on various criteria and constraints in the model. To examine the environmental dimension, the impact of the supply chain on the use of non-renewable energies such as fossil fuels, supply chain waste, and recycling rates can be considered. The impact of the supply chain on investment, market share, and revenues from recycling can be considered to examine the economic dimension. The impact of the supply chain on social sustainability, social justice, the number of jobs created, and the damage to workplaces in manufacturing centers can be also taken into account to examine the social dimensions. The environmental pollutants were considered in two parts: 1) the contaminants emission from manufacturing and industrial units; 2) the contamination due to the transportation system.

According to the problem description and previous works, the following items distinguish the present research model from previous studies in the field of production routing in the closed-loop supply chain:

- Considering the three dimensions of sustainability (economic, social, and environmental).
- Consideration of emissions from manufacturing and industrial units and the transportation system, as well as the imposition of fines and discounts based on the pollution level
- Considering all direct and reverse logistics levels.

The proposed mathematical model will be presented in the following sub-sections. First, modeling assumptions, followed by presenting the model indices, parameters, and variables in their

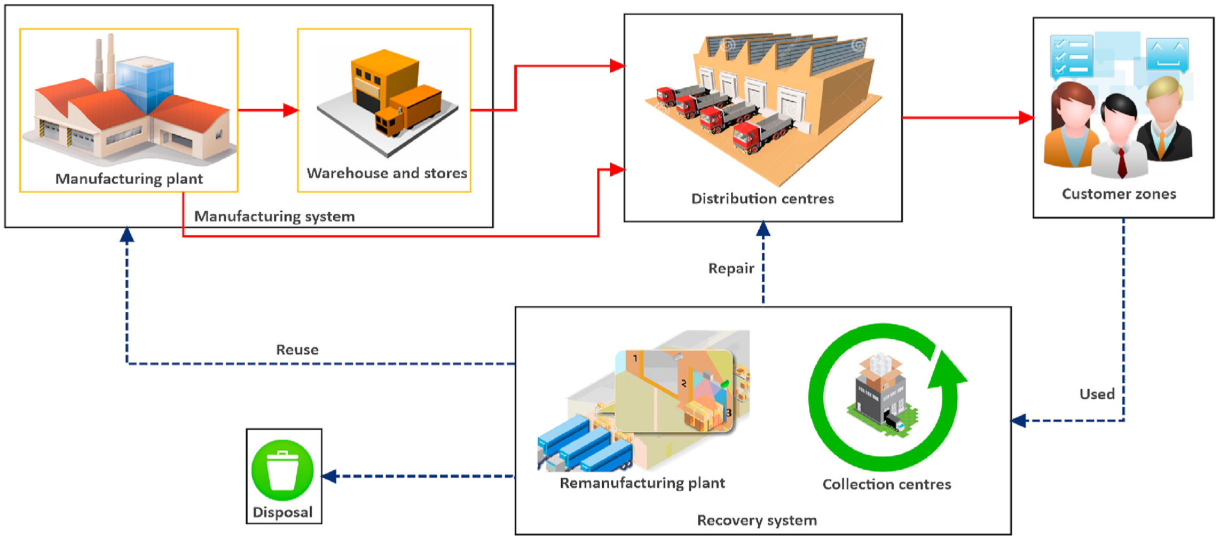

Fig. 1. Remanufacturing and collection centers for the conceptual closed-loop supply chain.

general structure. In the following, using a fuzzy number ranking method, the fuzzy model will be converted into its respective crisp model.

3.1. Modeling assumptions

In this research, the following pre-assumptions were considered for mathematical modeling:

- Commodities are considered solid and single-package containing a certain amount of goods produced.
- The number of vehicles (trucks) is limited and specific. . Also, the vehicles are heterogeneous.
- The capacity of the vehicle is limited in terms of the volume and weight of the goods.
- The number of potential points of distribution centers is predetermined with a limited capacity.
- The number of demand points (customers) is determined and all points of demand must be met by vehicles; the demands from uncertain customers are presented as a triangular fuzzy number.
- Reception from the customer and delivery to the customer occurred simultaneously.
- The fuel consumption of the vehicle per unit of distance is determined by the vehicle speed and cargo weight.
- The distance between the centers as well as the price of each liter of fuel is given.
- The carbon dioxide emission rate is considered as a measure of environmental impacts in the factory, warehouse, and transportation (product delivery) sectors.
- The speed of each vehicle is considered variable for different vehicles.
- The cost of constructing the facility is considered as a triangular fuzzy number.

3.2. Model sets, indices, and parameters

I Set of fixed points for manufacturing centers; $i \varepsilon I$.
J Set of potential points for distribution centers; $j \varepsilon J$.
K Set of vehicles; $k \varepsilon K$.
L Set of fixed points for customers; $l, l1, l2 \varepsilon L$.
M Set of potential points for collection and recovery centers; $m \varepsilon M$.
N Set of potential points for disposal centers; $n \varepsilon N$.
P Set of potential pints for recycling centers; $p \varepsilon P$.
S Set of products; $s \varepsilon S$.
T Set of periods of time; $t \varepsilon T$.
NJ Set of distribution center nodes.
NL Set of demand points.
ca_j The capacity of the distribution center at point j.
p_c Mean price of each unit of emission.
p_f Fuel price per unit of volume.
v_f The volume of fuel consumed per unit of distance and unit of weight; speed and distance.
v_k Speed of vehicle k.
vol_s The volume of product s.
w_c Weight of emissions per liter of consumed fuel.
w_k Weight of vehicle k.
w_s Weight of product s.
α_k Coefficient of speed variation in vehicle k per unit of excessive weight.
α_j The number of job opportunities created at distribution center j.
α_{in_v} The number of job opportunities created in the reverse logistics centers.
α^s_{it} The amount of carbon release to produce a unit of product in the manufacturing center of i in period of t.
L_i Distance between the ith manufacturing center and its corresponding warehouse.
L_{ij} Distance between the ith manufacturing center and distribution center j.
L_{jl} Distance between the jth distribution center and the customer zone of l.
L_{lm} Distance between demand point of l and collection and recovery center of m.
L_{mi} Distance between collection and recovery center of m and manufacturing center of i.
L_{mj} Distance between collection and recovery center of m and distribution center of j.
L_{mn} Distance between collection and recovery center of m and disposal center of n.
L_{mp} Distance between collection and recovery center of m and recycling center of p.

L_{pi} Distance between recycling center of p and the ith manufacturing center.
L_{l1l2} Distance between demand points of $l1$ and $l2$.
LQ_{ij} Distance between the warehouse of the ith manufacturing center and the jth distribution center.
QV_k The cubic capacity of vehicle k.
QW_k Weight capacity of vehicle k.
$\tilde{f}_j$ The fuzzy construction cost of a distribution center at point j.
$\tilde{f}_m$ The fuzzy construction cost of a collection and recovery center at point m.
$\tilde{f}_n$ The fuzzy construction cost of a disposal center at point n.
$\tilde{f}_p$ The fuzzy construction cost of a recycling center at point p.
$\tilde{d}_{ls}^t$ Fuzzy demand for the product s from the demand point of l in the period of t (fuzzy demand for delivery to demand point).
$\tilde{r}_{ls}^t$ Fuzzy value of the return of product s from the demand point of l in the period of t (fuzzy value of customer payment).
λ_{it}^s The amount of carbon released to storing a unit of product in the warehouse of the ith manufacturing center in the period of t.
c_{max} The maximum permissible carbon dioxide emissions in manufacturing and warehouse.
π The fine per unit of emission exceeding the permissible limit of carbon dioxide emission.
dl_i Average lost days of work due to damage to the ith manufacturing center per unit of product.
dp_{is} The average hazardous materials used at the ith manufacturing center per unit of product s.
sp_{is} Average waste generated at the ith manufacturing center per unit of product s.
θ_i work damage weight factor.
θ_w Weight factor of produced waste (weight of waste produced in the objective function).
θ_h Weight factor of hazardous materials (weight of hazardous substances in the objective function).

3.3. Variables

wj_{jk}^{ts} Amount of good s transported by vehicle k in period t before meeting distribution center j.
wl_{lk}^{ts} Amount of good s delivered by vehicle k in period t before meeting demand point l.
x_{ik}^{ts} Amount of good s transported by vehicle k from manufacturing center i to its own warehouse in period t.
x_{ijk}^{ts} Amount of good s transported by vehicle k from manufacturing center i to all distribution centers in period t initially meeting distribution center j.
x_{jlk}^{ts} Amount of good s transported by vehicle k from distribution center j to the demand points in period t and initially meeting customer l.
x_{lmk}^{ts} Amount of good s received from demand point l by vehicle k in period t to be sent to collection and recovery center m, at the same time the replacement product is delivered to the same customer.
x_{mnk}^{ts} Amount of good s transported by vehicle k from collection and recovery center m to disposal center n in period t.
x_{mpk}^{ts} Amount of good s transported by vehicle k from collection and recovery center m to manufacturing center i in period t.
x_{mik}^{ts} Amount of good s transported by vehicle k from collection and recovery center m to manufacturing center i in period t.
x_{mjk}^{ts} Amount of good s transported by vehicle k from collection and recovery center m to distribution center j in period t.
x_{pik}^{ts} Amount of good s transported by vehicle k from recycling center p to manufacturing center i in period t.
xp_i^{ts} Amount of good s produced by manufacturing center i in period t.
xi_{ijk}^{ts} Amount of good s transported by vehicle k from the warehouse of manufacturing center i to all distribution centers in period t and initially meeting distribution center j.
xw_{ijk}^{ts} Amount of good s transported by vehicle k from manufacturing center i to all distribution centers in period t initially meeting distribution center j and being delivered to distribution center j.
xw_{jlk}^{ts} Amount of good s transported by vehicle k from distribution center j to demand points in period t initially meeting demand point l and being delivered to demand point l.
xiw_{ijk}^{ts} Amount of good s transported by vehicle k from the warehouse of manufacturing center i to all distribution centers in period t initially meeting distribution center j and being delivered to distribution center j.
xw_{j1j2k}^{ts} Amount of good s transported by vehicle k from distribution center $j1$ to distribution center $j2$ in period t being delivered to distribution center $j2$.
xw_{l1l2k}^{ts} Amount of good s transported by vehicle k from demand point $l1$ to demand point $l2$ in period t and being delivered to demand point $l2$.
y_{ik}^t If vehicle k leaves manufacturing center i for its own warehouse in period t, it will be equal to 1, and otherwise to 0.
y_{ijk}^t If vehicle k leaves manufacturing center i for distribution center j in period t, it will be equal to 1, and otherwise to 0.
y_{jlk}^t If vehicle k leaves distribution center j for demand point (customer) l in period t, it will be equal to 1, and otherwise to 0.
y_{lmk}^t If vehicle k leaves demand point l for collection and recovery center m in period t, it will be equal to 1, and otherwise to 0.
y_{mik}^t If vehicle k leaves collection and recovery center m for manufacturing center i in period t, it will be equal to 1, and otherwise 0.
y_{mjk}^t If vehicle k leaves collection and recovery center m for distribution center j in period t, it will be equal to 1, and otherwise to 0.
y_{mnk}^t If vehicle k leaves collection and recovery center m for disposal center n in period t, it will be equal to 1, and otherwise to 0.
y_{mpk}^t If vehicle k leaves collection and recovery center m for recycling center p in period t, it will be equal to 1, and otherwise to 0.
y_{pik}^t If vehicle k leaves recycling center p for manufacturing center i in period t, it will be equal to 1, and otherwise to 0.
yi_{ijk}^t If vehicle k leaves the warehouse of manufacturing center i for distribution center j in period t, it will be equal to 1, and otherwise to 0.
y_{j1j2k}^t If vehicle k leaves distribution center $j1$ for distribution center $j2$ in period t, it will be equal to 1, and otherwise to 0.
y_{l1l2k}^t If vehicle k leaves demand point $l1$ for demand point $l2$ in period t, it will be equal to 1, and otherwise to 0.

z_j If distribution center is established at point j, it will be equal to 1, and otherwise to 0.
z_m If collection and recovery center is established at point m, it will be equal to 1, and otherwise to 0.
z_n If disposal center is established at point n, it will be equal to 1, and otherwise to 0.
z_p If recycling center is established at point p, it will be equal to 1, and otherwise to 0.
B equal to 1, if the amount of carbon dioxide emitted exceeds the specified limit; zero, otherwise.

3.4. The main structure of the model

3.4.1. Objective functions

$$cost1 = \sum_{j=1}^{J} \tilde{f}_j z_j + \sum_{m=1}^{M} \tilde{f}_m z_m + \sum_{p=1}^{P} \tilde{f}_p z_p + \sum_{n=1}^{N} \tilde{f}_n z_n$$

The above expression shows the cost of establishing a facility in the supply chain. Costs related to the emission of pollutants can be also calculated as follows:

$$\begin{aligned} cost2 = \Bigg(& \sum_{k=1}^{K} (v_f * \alpha_k * v_k) * \Bigg(\sum_{s=1}^{S} \Bigg(\sum_{t=1}^{T} \Bigg(\sum_{i=1}^{I} \Bigg(x_{ik}^{ts} * L_i + \sum_{j=1}^{J} \Big(xi_{ijk}^{ts} * LQ_{ij} + x_{ijk}^{ts} * L_{ij} \Big) \Bigg) * w_s \Bigg) + \sum_{j=1}^{J} \Bigg(wj_{jk}^{ts} + \sum_{l=1}^{L} x_{jlk}^{ts} * L_{jl} \Bigg) * w_s \\ & + \sum_{l=1}^{L} \Bigg(\Bigg(wl_{lk}^{ts} + \sum_{j=1}^{J} xw_{jlk}^{ts} \Bigg) + \sum_{l1=1}^{L} (xw_{l1lk}^{ts} * L_{l1l}) \Bigg) * w_s + \sum_{m=1}^{M} \Bigg(\sum_{l=1}^{L} x_{lmk}^{ts} * L_{lm} + \sum_{i=1}^{I} x_{mik}^{ts} * L_{mi} + \sum_{j=1}^{J} x_{mjk}^{ts} * L_{mj} \\ & + \sum_{n=1}^{N} x_{mnk}^{ts} * L_{mn} + \sum_{p=1}^{P} x_{mpk}^{ts} * L_{mp} \Bigg) * w_s \Bigg) + \sum_{p=1}^{P} \sum_{i=1}^{I} x_{pik}^{ts} * L_{pi} * w_s + w_k \Bigg) \Bigg) * \Bigg(p_f + w_c * p_c \Bigg) \Bigg) \\ & + \sum_{t=1}^{T} \sum_{s=1}^{S} \sum_{i=1}^{I} \Bigg(\Bigg(xp_i^{ts} * \alpha_{it}^{s} \Bigg) + \Bigg(\sum_{k=1}^{K} x_{ik}^{ts} - \sum_{k=1}^{K} \sum_{j=1}^{J} xi_{ijk}^{ts} \Bigg) * \lambda_{it}^{s} \Bigg) \end{aligned}$$

The difference between the permissible carbon dioxide emission and the estimated total value of the chain is $cost2 - c_{max}$. If $cost2 > c_{max}$, the company must pay a fine for the additional release. If $cost2 < c_{max}$, the company will receive a tax rebate for the difference. The tax rebate is $\rho \le 0$. That is, if the company has the required conditions namely $(cost2 < c_{max})$, it will receive a tax deduction to the amount of $\rho(cost2 - c_{max})$. This discount is considered as a fraction of the cost in the objective function. According to the description, the first objective function will be as follows:

$$\begin{aligned} \min z1 = & \sum_{j=1}^{J} \tilde{f}_j * z_j + \sum_{m=1}^{M} \tilde{f}_m * z_m + \sum_{p=1}^{P} \tilde{f}_p * z_p + \sum_{n=1}^{N} \tilde{f}_n * z_n \\ & + \pi * B * (cost2 - c_{max}) - \rho * (1 - B) * (cost2 - c_{max}) \end{aligned} \tag{1}$$

Equation (1) represents the first objective function aimed to minimize the costs of constructing facilities and fuel as well as the environmental costs due to pollutant emissions.

$$\begin{aligned} \max z2 = & \sum_{t \in T} \left(\sum_{j \in J} \alpha_j * z_j + \sum_{m \in M} \alpha_{inv} * z_m + \sum_{p \in P} \alpha_{inv} * z_p + \sum_{n \in N} \alpha_{inv} * z_n \right) \\ & - \theta_l * \sum_{t \in T} \sum_{i \in I} \sum_{s \in S} dl_i * xp_i^{ts} \end{aligned} \tag{2}$$

Equation (2) represents the second objective function aimed at maximizing social responsibility or social benefits.

$$\min z3 = \theta_w * \sum_{t \in T} \sum_{i \in I} \sum_{s \in S} sp_{is} * xp_i^{ts} + \theta_h * \sum_{t \in T} \sum_{i \in I} \sum_{s \in S} dp_{is} * xp_i^{ts} \tag{3}$$

Equation (3) shows the third objective function aimed to minimize environmental impacts.

3.4.2. Model constraints

The constraints can be briefly described as follows: The constraint ensures that all customers' requests are met. The constraints guarantee the balance of the goods flow in nodes. The constraints prevent the creation of sub tours. The constraints guarantee that the vehicle capacity is not violated. The constraints ensure that at least one center for distribution, collection, recovery, destruction, and recycling facilities is established.

$$\sum_{j} \sum_{k} y_{jlk}^{t} \ge 1 \; \forall l, t \tag{4}$$

$$\sum_{k} y_{ik}^{t} = \sum_{k} \sum_{j} yi_{ijk}^{t} \quad \forall i, t \tag{5}$$

$$\sum_{k} \left(\sum_{i} \left(y_{ijk}^{t} + yi_{ijk}^{t} \right) + \sum_{m} y_{mjk}^{t} \right) = \sum_{k} \left(\sum_{l} y_{jlk}^{t} + \sum_{j1} y_{jj1k}^{t} \right) \quad \forall j, t \tag{6}$$

$$\sum_{k} \sum_{j} y_{jlk}^{t} = \sum_{k} \left(\sum_{m} y_{lmk}^{t} + \sum_{l1} y_{ll1k}^{t} \right) \quad \forall l, t \tag{7}$$

$$\sum_k \sum_l y^t_{lmk} = \sum_k \left(\sum_p y^t_{mpk} + \sum_n y^t_{mnk} + \sum_j y^t_{mjk} + \sum_i y^t_{mik} \right) \quad \forall m, t \tag{8}$$

$$\sum_k \sum_m y^t_{mpk} = \sum_k \sum_i y^t_{pik} \forall p, t \tag{9}$$

$$\sum_k \sum_p y^t_{pik} = \sum_k y^t_{ik} + \sum_k \sum_j y^t_{ijk} \forall i, t \tag{10}$$

$$\sum_k \left(\sum_j xw^{ts}_{jlk} + \sum_{l1} xw^{ts}_{l1lk} \right) = \tilde{d}^t_{ls} \quad \forall l, t, s \tag{11}$$

$$wl^{ts}_{l1k} - wl^{ts}_{l2k} \geq \sum_j \left(xw^{ts}_{jl1k} * y^t_{jl1k} \right) + \sum_l \left(xw^{ts}_{ll1k} * y^t_{ll1k} \right) + \sum_m x^{ts}_{l1mk} - M*(1 - y^t_{l1l2k}) \forall l1, l2 \in L, \ \forall k, t, s \tag{12}$$

$$\sum_k \sum_m x^{ts}_{lmk} = \tilde{r}^t_{ls} \quad \forall l, t, s \tag{13}$$

$$xp^{ts}_i + \sum_k \sum_m x^{ts}_{mik} = \sum_k \left(x^{ts}_{ik} + \sum_j x^{ts}_{ijk} \right) \quad \forall i, t, s \tag{14}$$

$$\sum_k \left(\sum_i \left(xw^{ts}_{ijk} + xiw^{ts}_{ijk} \right) + \sum_m x^{ts}_{mjk} + \sum_{j1} xw^{ts}_{j1jk} \right) = \sum_k \sum_l x^{ts}_{jlk} \quad \forall j, t, s \tag{15}$$

$$\sum_k \sum_l x^{ts}_{lmk} = \sum_k \left(\sum_p x^{ts}_{mpk} + \sum_n x^{ts}_{mnk} + \sum_j x^{ts}_{mjk} + \sum_i x^{ts}_{mik} \right) \quad \forall m, t, s \tag{16}$$

$$wj^{ts}_{j1k} - wj^{ts}_{j2k} \geq \sum_i \left(xw^{ts}_{ij1k} * y^t_{ij1k} + xwi^{ts}_{ij1k} * yi^t_{ij1k} \right) + \sum_j \left(xw^{ts}_{jj1k} * y^t_{jj1k} \right) - M * \left(1 - y^t_{j1j2k} \right) \ \forall (j1, j2) \in J \times J, \ \forall k, t, s \tag{17}$$

$$x^{ts}_{ik} \leq M*y^t_{ik} \quad \forall i, k, t, s \tag{18}$$

$$x^{ts}_{ijk} \leq M*y^t_{ijk} \quad \forall i, j, k, t, s \tag{19}$$

$$xi^{ts}_{ijk} \leq M*yi^t_{ijk} \quad \forall i, j, k, t, s \tag{20}$$

$$xw^{ts}_{ijk} \leq M*y^t_{ijk} \quad \forall i, j, k, t, s \tag{21}$$

$$xiw^{ts}_{ijk} \leq M*yi^t_{ijk} \quad \forall i, j, k, t, s \tag{22}$$

$$xw^{ts}_{j1j2k} \leq M*y^t_{j1j2k} \quad \forall j1, j2, k, t, s \tag{23}$$

$$x^{ts}_{jlk} \leq M*y^t_{jlk} \quad \forall l, j, k, t, s \tag{24}$$

$$xw^{ts}_{jlk} \leq M*y^t_{jlk} \quad \forall l, j, k, t, s \tag{25}$$

$$xw^{ts}_{l1l2k} \leq M*y^t_{l1l2k} \quad \forall l1, l2, k, t, s \tag{26}$$

$$x^{ts}_{lmk} \leq M*y^t_{lmk} \quad \forall l, m, k, t, s \tag{27}$$

$$x^{ts}_{mpk} \leq M*y^t_{mpk} \quad \forall p, m, k, t, s \tag{28}$$

$$x^{ts}_{mnk} \leq M*y^t_{mnk} \quad \forall n, m, k, t, s \tag{29}$$

$$x^{ts}_{mik} \leq M*y^t_{mik} \quad \forall i, m, k, t, s \tag{30}$$

$$x^{ts}_{mjk} \leq M*y^t_{mjk} \quad \forall j, m, k, t, s \tag{31}$$

$$\sum_{j1 \in N} \sum_{j2 \in N} y^t_{j1j2k} \leq |N| - 1 \quad \forall N \in NJ : |N| \geq 2 \ \& \forall k, t \tag{32}$$

$$\sum_{l1 \in N} \sum_{l2 \in N} y^t_{l1l2k} \leq |N| - 1 \forall N \in NL : |N| \geq 2 \ \& \forall k, t \tag{33}$$

$$\sum_i \sum_s \left(x^{ts}_{ik} * w_s \right) \leq QW_k \forall k, t \tag{34}$$

$$\sum_i \sum_s \left(x^{ts}_{ik} * vol_s \right) \leq QV_k \quad \forall k, t \tag{35}$$

$$\sum_i \sum_s \left(xi^{ts}_{ijk} * w_s \right) \leq QW_k \quad \forall j, k, t \tag{36}$$

$$\sum_i \sum_s \left(xi^{ts}_{ijk} * vol_s \right) \leq QV_k \quad \forall j, k, t \tag{37}$$

$$\sum_i \sum_s \left(x^{ts}_{ijk} * w_s \right) \leq QW_k \quad \forall j, k, t \tag{38}$$

$$\sum_i \sum_s \left(x^{ts}_{ijk} * vol_s \right) \leq QV_k \quad \forall j, k, t \tag{39}$$

$$\sum_j \sum_s \left(x^{ts}_{jlk} * w_s \right) \leq QW_k \quad \forall l, k, t \tag{40}$$

$$\sum_j \sum_s \left(x^{ts}_{jlk} * vol_s \right) \leq QV_k \quad \forall l, k, t \tag{41}$$

$$\sum_m \sum_s \left(x^{ts}_{mpk} * w_s \right) \leq QW_k \quad \forall p, k, t \tag{42}$$

$$\sum_m \sum_s \left(x^{ts}_{mpk} * vol_s \right) \leq QV_k \quad \forall p, k, t \tag{43}$$

$$\sum_m \sum_s (x_{mnk}^{ts} * w_s) \le QW_k \quad \forall n, k, t \tag{44}$$

$$\sum_m \sum_s (x_{mnk}^{ts} * vol_s) \le QV_k \quad \forall n, k, t \tag{45}$$

$$\sum_m \sum_s (x_{mik}^{ts} * w_s) \le QW_k \quad \forall i, k, t \tag{45a}$$

$$\sum_m \sum_s (x_{mik}^{ts} * vol_s) \le QV_k \quad \forall i, k, t \tag{46}$$

$$\sum_m \sum_s \left(x_{mjk}^{ts} * w_s\right) \le QW_k \quad \forall j, k, t \tag{47}$$

$$\sum_m \sum_s \left(x_{mjk}^{ts} * vol_s\right). \le QV_k \quad \forall j, k, t \tag{48}$$

$$\sum_s \left(\left(wl_{l1k}^{ts} + \sum_j \left(xw_{jl1k}^{ts} * y_{jl1k}^t \right) + \sum_l (xw_{ll1k}^{ts} * y_{ll1k}^t) + \sum_m x_{l1mk}^{ts} \right) * w_s \right) \le QW_k \quad \forall l1, k, t \tag{50}$$

$$\sum_s \left(\left(wl_{l1k}^{ts} + \sum_j \left(xw_{jl1k}^{ts} * y_{jl1k}^t \right) + \sum_l (xw_{ll1k}^{ts} * y_{ll1k}^t) + \sum_m x_{l1mk}^{ts} \right) * vol_s \right) \le QV_k \quad \forall l1, k, t \tag{51}$$

$$\sum_l \sum_s (x_{lmk}^{ts} * w_s) \le QW_k \quad \forall m, k, t \tag{52}$$

$$\sum_l \sum_s (x_{lmk}^{ts} * vol_s) \le QV_k \quad \forall m, k, t \tag{53}$$

$$\sum_p \sum_s \left(x_{pik}^{ts} * w_s\right) \le QW_k \quad \forall i, k, t \tag{54}$$

$$\sum_p \sum_s \left(x_{pik}^{ts} * vol_s\right) \le QV_k \quad \forall i, k, t \tag{55}$$

$$\sum_s \sum_k \left(\sum_i \left(xiw_{ijk}^{ts} + xw_{ijk}^{ts} \right) + \sum_{j1} xw_{j1jk}^{ts} \right) \le ca_j \quad \forall j, t \tag{56}$$

$$y_{ijk}^t \le z_j \quad \forall i, j, k, t \tag{57}$$

$$yi_{ijk}^t \le z_j \quad \forall i, j, k, t \tag{58}$$

$$y_{j1j2k}^t \le z_{j1} * z_{j2} \quad \forall j1, j2, k, t \tag{59}$$

$$y_{jlk}^t \le z_j \quad \forall l, j, k, t \tag{60}$$

$$y_{lmk}^t \le z_m \quad \forall l, m, k, t \tag{61}$$

$$y_{mpk}^t \le z_m * z_p \quad \forall p, m, k, t \tag{62}$$

$$y_{mnk}^t \le z_m * z_n \quad \forall n, m, k, t \tag{63}$$

$$y_{mik}^t \le z_m \quad \forall i, m, k, t \tag{64}$$

$$y_{mjk}^t \le z_m * z_j \quad \forall j, m, k, t \tag{65}$$

$$y_{pik}^t \le z_p \quad \forall p, i, k, t \tag{67}$$

$$\sum_j z_j \ge 1 \tag{68}$$

$$\sum_m z_m \ge 1 \tag{69}$$

$$\sum_p z_p \ge 1 \tag{70}$$

$$\sum_n z_n \ge 1 \tag{71}$$

$$z_j, z_p, z_m, z_n, y_{ik}^t, y_{ijk}^t, yi_{ijk}^t, y_{jlk}^t, y_{j1j2k}^t, y_{l1l2k}^t, y_{lmk}^t, y_{mnk}^t, y_{mpk}^t, y_{mik}^t, y_{mjk}^t, y_{pik}^t \in \{0, 1\} \tag{72}$$

$$xp_i^{ts}, x_{ijk}^{ts}, x_{ik}^{ts}, xi_{ijk}^{ts}, xw_{ijk}^{ts}, xiw_{ijk}^{ts}, wj_{jk}^{ts}, xw_{j1j2k}^{ts}, x_{jlk}^{ts}, xw_{jlk}^{ts}, xw_{l1l2k}^{ts}, wl_{lk}^{ts}, x_{pik}^{ts}, x_{mnk}^{ts}, x_{mpk}^{ts}, x_{mik}^{ts}, x_{mjk}^{ts} \ge 0 \tag{73}$$

The constraint (4) ensures that all the customers are met at least by a vehicle. The constraints (5) to (10) indicate that vehicles arriving at the centers and warehouses of manufacturers, distributors, customers, collection and recovery centers, and recycling centers should leave these locations. Moreover, vehicles entering to destruction centers reenter the cycle and start from production centers. They go to manufacturing centers based on the production center's needs. While constraint (11) ensures that all customers' requests are met, the constraint (12) is related to the amount of inventory of s in the period of t in the kth vehicle load before meeting the customer centers. The constraint (13) ensures that all returning goods are collected from customer centers in the course of the return. The constraints (14)–(16) guarantee the balance of the goods flow in nodes. The constraint (17) deals with the amount of inventory of s in the period of t in the kth vehicle load before meeting distribution centers. The constraints (18)–(31) guarantee that the good is sent by the vehicle from one center to another if a trip occurs between the two centers. The constraints (32) and (33) prevent the sub tours when vehicles are traveling between distributor points and customer points. The constraints (34) to (55) guarantee that the goods carried by the vehicle k do not exceed the capacity and volume limit. The constraint (56) ensures the capacity constraints of the distribution centers which limit the capacity based on the number of items of goods. The constraints (57)–(66) guarantee that travel occurs between two centers if those centers are established. The constraints (67)–(70) ensure that at least one center for distribution, collection, recovery, destruction, and recycling facilities is established. The constraints (71) and (72) are modeled based on the sign and the allowed values for decision variables.

As can be seen, the proposed model has three-objective and fuzzy parameters. The fuzzy model is transformed into a crisp model based on Jiménez's ranking method (see (Jiménez et al., 2007)).

The definitive form of the first objective function after defuzzification is:

$$\min z1 = \sum_{j=1}^{J}\left(\frac{f_j^1 + 2f_j^2 + f_j^3}{2}\right)z_j + \sum_{m=1}^{M}\left(\frac{f_m^1 + 2f_m^2 + f_m^3}{2}\right)z_m + \sum_{p=1}^{P}\left(\frac{f_p^1 + 2f_p^2 + f_p^3}{2}\right)z_p + \sum_{n=1}^{N}\left(\frac{f_n^1 + 2f_n^2 + f_n^3}{2}\right)z_n + \pi * B * (cost2 - c_{max}) - \rho * (1-B)*(cost2 - c_{max}) \tag{73a}$$

The Constraint (11) after the defuzzification:

$$\sum_k\left(\sum_j xw_{jlk}^{ts} + \sum_{l1} xw_{l1lk}^{ts}\right) = (1-\alpha)\frac{d_{ls}^{t1} + d_{ls}^{t2}}{2} + \alpha\frac{d_{ls}^{t2} + d_{ls}^{t3}}{2} \quad \forall l, t, s \tag{74}$$

The Constraint (13) after the defuzzification:

$$\sum_k x_{lk}^{ts} = (1-\alpha)\frac{r_{ls}^{t1} + r_{ls}^{t2}}{2} + \alpha\frac{r_{ls}^{t2} + r_{ls}^{t3}}{2} \quad \forall l, t, s \tag{75}$$

4. Solving algorithm

Most logistic network design models, including the problem discussed in this paper, are Np-Hard problems (Tibben-Lembke and Rogers, 2002). The problem of designing the logistics network in this study also belongs to the Np-Hard category. Due to the high time complexity of exact methods, they fail in solving such problems at large sizes. Therefore, a bee colony optimization algorithm based on the Pareto archive was employed to solve the problem. The results of this algorithm are compared with the results of the known algorithm of NSGA-II.

4.1. Bee colony algorithm

The Bee's algorithm, presented by Pham et al., in 2006, is an emerging group of algorithms that mimics the behavior of honey bee search. The proposed structure for implementation of the bee colony algorithm for solving the proposed model is as follows:

Purposed Bee colony optimization algorithm.
{Initialization:
Initialize the algorithm parameter.
Generate N feasible solutions as the initial population.
Create an empty set as initial Pareto archive
While criterion is meet,
Calculate the fitness for each solution in the current population.
Select the best bees and their locations as the p1 set.
Select the other bees and their locations as the p2 set.
Apply neighborhood search operator on p1 set,
Apply the feasibility check method on the obtained solutions.
Assign some bees to obtained solutions and calculate their fitness.
Apply random neighborhood search operator on p2.
Apply the feasibility check method on obtained solutions.
Calculate their fitness.
Select the N best bees of each location.
Apply improvement method on selected solutions and take the output of this method as the population of the next generation.
Update Pareto archive
End while
Return the Pareto archive.
}

4.1.1. Displaying the solution

In this research, a matrix was used to represent each solution. Each solution consisted of several matrices based on the model outputs. For example, a row matrix (one-dimensional) whose number of elements is equal to m (m is the number of collection and recovery centers) is defined for the z_m variable; a dimensional matrix with dimensions of I*K*T is defined for the variable y_{ik}^t; a 5-dimensional matrix with dimensions of I*J*K*T*S is defined for the variable x_{ijk}^{ts}. Similarly, the matrix will be defined for the rest of the outputs (Emamian et al., 2018).

4.1.2. Generation of the initial solutions

In this paper, a random approach (solution initialization method) was used to generate the initial solutions. In this regard, the matrices of z_j, z_m, z_p and z_n were first randomly generated; then, the rest of the solution matrixes (model variables) were initialized according to the constraints of the model. For instance, suppose that the location matrices are developed as follows:

Matrix z_j

z_1	z_2	z_3	z_4
1	0	1	0

Matrix z_m

z_1	z_2
1	1

Matrix z_p

z_1	z_2
0	1

Matrix z_n

z_1	z_2
1	0

Now, to determine the value of the variable x_{ijk}^{ts}, only the values of x_{i1k}^{ts}, x_{i3k}^{ts} and x_{i4k}^{ts} from each production center can be greater than 0 and the other indices take the value of 0. Also, the values are randomly specified based on weight and volume capacity in each period. On the other hand, the variable values of y_{ijk}^t are also determined by sending goods (the variable x_{ijk}^{ts}) for possible paths (manufacturers to distribution centers 1, 3, and 4). Received goods by the distributors and the flow balance, capacity and routing constraints are the bases for action to determine the values of the variables of xw_{ijk}^{ts}, xw_{j1j2k}^{ts}, x_{jlk}^{ts} and other variables related to the goods sent from distributors 1, 3, and 4 to other nodes as well as the variables of vehicle routing. Likewise, the goods are sent to the recovery centers of 1 and 2, the recycling center 2 and the disposal facility 1 according to the provided location values and the model constraints; the routing variables are also set based on the delivery variables.

Suppose that population size is equal to N. Every time an answer is generated as described, it will be added to the population if not replicated. This procedure will continue until the number of solutions in the population reaches $\beta \times N$, where β is a number greater than 1.

The method for producing solutions will be stopped after $\beta \times N$ iterations. On the other hand, the number of solutions in each iteration of the algorithm is equal to N. Therefore, N solutions should be selected as the initial generation sequences between $\beta \times N$. In this research, the selection of the initial population of solutions is based on a quick method of arranging non-dominated solutions as described by Deb et al. (2002). This method operates in such a way that $\beta \times N$ solutions, which are designed by the algorithm, are arranged and leveled. The number of each level indicates the quality of the available solutions. For example, the quality of the solutions at the first level is higher than those in the second level. Then, for the solutions at each level, a scale called a Crowding distance is calculated proportionally to the same level. The mentioned scale for the solutions in each level indicates the distribution of the answers of the same level.

In this paper, a criterion called C_s is defined for the selection of initial solutions, which is obtained using the following equation (Emamianet al.,2018; Tavakkoli-Moghaddam et al., 2011):

$$C_s = \frac{rank}{crowding\_dis} \tag{76}$$

The above criterion is calculated for each of the available solutions.

rank: represents the number of solution levels.

crowding_dis: The crowding distance of each solution is proportional to the rank of that solution.

After calculating the above criterion for all solutions, the solutions are arranged in ascending order of C_s, and the first N solution, which has less C_s, will be selected as the initial solution of the algorithm. The use of the C_s criterion is based on this logic that the solutions with higher quality and diversity are selected as the primary population. The solutions produced by the improvement procedure are improved as much as possible. The improvement procedure will be described in the next section.

4.1.3. Improvement procedure

An improvement procedure is designed in the proposed structure of the bees' colony optimization algorithm. This procedure is implemented on the selected solutions of the previous section o improve them. Output solutions of the improvement procedures will be then selected as the population of the next iteration of the algorithm. The implementation of the improvement procedure in this research is based on the variable neighborhood search (VNS). The VNS structure uses four neighborhood search structures (NSS). These structures are used in the form of a VNS (its general structure is given in reference Tavakkoli-Moghaddam et al., 2011). Each solution in the solution population is given to the VNS algorithm and a solution will be received as an output. Then the correction procedure is applied to the rest of the solution matrices and will be perfectly corrected and replaced by the input response. Moreover, the neighborhood search operators used in the VNS structure are as follows (Emamian et al., 2018):

The first neighborhood search operator: In this structure, a distribution facility is randomly selected, and the matrix, relating to its location, will be changed.

The second neighbor search operator: In this structure, one of the collection and recovery centers is randomly selected and the matrix, relating to its location, will be changed.

The third neighborhood operator: In this structure, one of the recycling centers is randomly selected and the matrix, relating to its location, will be changed.

The fourth neighborhood operator: In this structure, one of the disposal centers is randomly selected and the matrix, relating to its location, will be changed.

It should be noted that in the above operators, the location matrices change in such a way that the index of one of the centers is randomly chosen and its associated house turns from 1 to 0 (considering the constraints related to the minimum number of established centers) and is converted to 1 in the case of being 0.

Due to the generation of new algorithms during the algorithm execution, to ensure the feasibility of the solution and, if possible, their conversion into responsive solutions, a procedure is designed to check all the constraints in the generated solution. If one or more of the constraints in the mentioned solution are violated, it will try to turn the solution into a feasible solution. The feasibility function resets the goods flow between facilities taking into account the new location matrices, using the previous or new vehicles (due to the limited capacity and weight of vehicles as well as the capacity constraints of the distribution centers), and the routing variables.

4.1.4. Local search (p1 and p2 bees group)

As shown in the general structure of the algorithm, the bees are divided into two groups: p1 and p2. The guided local search is applied on p1, while the full pseudo-random search is implemented on the p2 group. Neighborhood search applied to p1 is a parallel neighborhood search structure combining the four neighboring search operators described in parallel. Each of the solutions in p1 is given as input to this structure and the algorithm achieves a better solution through it. To perform neighborhood search on any of the solutions in p2, one of the four above-mentioned operators is randomly selected and applied to the solution in this category, and the output of the selected operator (better or worse) will be replaced by the available solution (Emamian et al., 2018).

4.1.5. Selecting the next generation of solutions

In each step of the bees colony optimization algorithm, N (population size) locations will be selected from the previous places and the new places of the bees are determined as the best solutions according to the degree of fitness, the C_s criterion (described in the solution initializing section). For all these places, the C_s value is calculated, and then the locations are sorted according to the upward order of the C_s value; eventually, the first N will be selected [27].

4.1.6. Updating Pareto archive

Due to the contradictions among objectives, there is no single solution for the multi-objective problems in which all objectives are optimal. Therefore, a set of dominant solutions will be presented as optimal (near-optimal) solutions. Here, the Pareto-based archive solution was applied to determine the importance of solutions quality. This archive will be updated in each iteration of the algorithm. For updating, all the solutions in this archive and the newly generated solutions are solved in a pool of solutions and ranked. Then all the first-level answers are selected as the new Pareto's archive solutions (Emamian et al., 2018).

4.2. NSGA-II algorithm

Deb et al. (2002) presented a multi-objective genetic algorithm (NSGA-II) which chooses the solutions according to a leveling system based on non-dominated relations and the calculation of congestion (Pratap et al., 2002). Since the presented model has multi objectives, the genetic algorithm refers to the same NSGA-II algorithm in this study.

The answers representation, generation of the initial answers, updating the Pareto archive, and the improvement procedure were the same as the Bee's optimization algorithm. The parallel neighborhood search model described in the Bee algorithm (P2 Neighborhood Search) was applied to implement the mutation operator. The dual tournament method and single-point intersection operator were also used to select parents and apply the intersection operator, respectively. In this research, the fitness of each solution was determined according to non-dominated relationships due to the parental choice method. Also, the intersection operator was applied to location variables (z_j, z_m, $z_p$and z_n) while the other variables of the model were determined based on the model constraints after determining the location variables of the offsprings.

4.2.1. Sorting and selecting the solution

As stated above, the NSGA-II algorithm addresses the leveling (sorting) of the existing solution based on non-dominated relationships.

The dominant relations were used for sorting and ranking the solutions. First, all the solutions were compared with each other using the dominant relations, and their corresponding non-dominant solutions were considered as the first-level solutions; then, the same procedure was repeated for the set of non-assigned solutions to specify the next levels.

The higher the first level of solution, the more qualitative the solution; therefore, the levels with lower numbers were firstly used to select the solution. In the cases that there is the right to select between two solutions at the same level, the crowding distance criterion was used. The higher this criterion for the available solutions at a level, the higher the priority of that solution will be.

The algorithm requires a population of solutions in each iteration. In this research, for selecting the population of the next iteration, the existent solutions in the population were replicated and the new answers were generated by the algorithm together in a pool and after leveling and calculating the crowding distance for each solution according to its level, N solutions with the highest quality and diversity were selected as the population of the algorithm's next iteration using Deb's rule.

5. Computational results

The model was solved using the bee colony algorithm. In order to test the efficiency of the bee colony algorithms and NSGA-II, they were implemented in the MATLAB software environment and their obtained results were compared in terms of quality, spacing, and diversity comparative metrics, as well as the runtime to the solution. It should be noted that all computations were carried out by a computer with a Core i7 7500U −12GB -1TB-R5 M335 4GB processor.

5.1. Comparative metrics

Numerous indexes can be used to assess the quality and diversity of multi-objective metaheuristic algorithms. In this paper, the following three metrics of quality, spacing, and diversity were considered for comparison purposes (Tavakkoli-Moghaddam et al., 2011):

Quality metric - This metric compares the quality of the Pareto solutions obtained by each method. It indeed levels all of the Pareto solutions obtained by each of the two algorithms (bee colony and genetic) and determines the percent of the first level solutions belonging to each of these methods; the higher the percentage, the better the quality of the algorithm.

Spacing metric- This criterion evaluates the uniformity of the distribution of Pareto solutions obtained at the solutions frontier. This metric is defined as:

$$s = \frac{\sum_{i=1}^{N-1} |d_{mean} - d_i|}{(N-1) \times d_{mean}} \tag{77}$$

In the above relation, $d_i$represents the Euclidean distance between the neighboring non-dominated solutions and d_{mean}denotes the mean of $d_i$values.

Diversity Metric - This metric is used to determine the amount of non-dominant solutions found on the optimal boundary. The definition of the diversity metric is as follows:

$$D = \sqrt{\sum_{i=1}^{N} \max(x_t^i - y_t^i)} \tag{78}$$

where, $x_t^i - y_t^i$ represents the Euclidean distance between two neighboring solutions of $x_t^i$and y_t^i on the optimal boundary.

In addition to the described metrics, the parameters and runtime of the Pareto solution were also considered as follows:

The number of Pareto solutions: This metric includes the number of output solutions for each algorithm.

Runtime: This metric includes the runtime of an iteration for each algorithm in seconds.

5.2. Trial problems

In this paper, several trial problems were designed in small, medium, and large sizes. Since no sample case was found in literature compatible with the presented model which covers all parts of the model, some of the previous studies were selected and their typical problems (relatively conforming with the model) were used; the other parameters, not covered by this research, were randomly selected. Also, to investigate some other trial problems, previous studies were examined and trial problems were designed considering their range of selected problem dimensions.

5.2.1. Trial problems

Small-size problems were selected according to the problems solved by Kannan et al. (2010). Their problems did not cover all of the model parameters. thus, the uncovered parameters were randomly selected. In these problems, the number of products for all the problems was equal to 1; the number of facilities in the forward logistics was equal to 2; the number of inverse logistical facilities varied from 2 to 5; moreover, the number of vehicles was 3.

We studied several problems in literature for designing and producing the test cases of medium to large size. Then, given the size mentioned in the literature, the size of the medium and large problems, as well as several problems with sizes larger than those of the previous research considering the scope of previous research were determined (Pishvaee et al., 2011; Wang and Hsu, 2010; Omidi-Rekavandi et al., 2014).

5.3. Setting the parameters

The parameters of the algorithm were set as follows:

In the bee algorithm, the population size was 200, the number of bees was considered 50% of population size, and the number of iterations in the parallel search algorithm was set to 5.

- In the genetic algorithm, the rates of 0.8 and 0.1 were considered for the intersection and mutation, respectively while the population size was set to 150.

Pouralikhani et al. (2013) determined and initialized the parameters of the model. It is worth noting that because the model presented in this paper did not cover some of the parameters of the model presented in our research, we tried to generate random values that are more reasonable than other values.

To produce triangular numbers related to each of the fuzzy parameters (m1, m2, m3), first, m2 was generated and then, the random number of r was generated in the interval of (0,1). m1 was generated using the relation m2*(1-r) whereas m3 was produced using the relation m2*(1 + r). To set the fuzzy parameter of m2 (according to the referenced article (Kannan et al., 2010) if available), two values of m1 and m3 were determined using the MATLAB software. For this reason, in the section of setting these parameters, we only mention the amount of m2.

In the production of trial problems, the following values were considered:

- In each period, the customer*l*demand of good *s* and the amount of returned good were expressed as triangular fuzzy numbers of (m1, 100, m3) and (m1, 30, m3), respectively.
- The capacity of all distribution centers was 4000.
- The cost of establishing disposal centers was a fuzzy number (m1, 5000, m3), collection and recovery center was (m1, 10000, m3) and the recovery center was considered a fuzzy number (m1, 15000, m3) as well. Also, the cost of establishing distribution centers in a uniform interval was produced in the form of a fuzzy number (m1, 6000, m3).
- All distances between facilities were randomly generated at a uniform interval of [1,50].
- The price of the fuel unit was taken 1000; the fuel consumption per unit distance per vehicle weight was 2; the weight and volume of each unit of the product lied in the uniform interval of [1,20]; the weight of the pollutants emitted per liter of fuel was equal to 2; the average price per unit of gas released was 500; the speed of each vehicle in the uniform interval [70,100]; the weight of each vehicle also ranged within the uniform interval of [1000,1600]; the coefficient of vehicle speed change was produced in the uniform interval of [0.1,0.2].
- The 'α' value for fuzzy numbers ranking was 0.8.
- The average waste generation was 10% of the production value.
- The average production of hazardous materials was 15% of the production.
- The average missed working days was considered in the uniform interval of [5,10].
- The values of the weight factors of the produced waste, hazardous materials, and labor damage were calculated based on the average values defined for the production of waste, hazardous materials, and labor damages. Thus, the sum of the average parameters of waste, hazardous materials, and average missed working days were separately calculated, as well as their total sum. Then, for the calculation of each factor, the numerical division of the total of the corresponding parameter on the sum of all three parameters was used.
- The maximum permissible carbon dioxide emission was 35000.
- The fine per unit of emission was implemented when the CO_2 emission surpassed the limit of 35000.
- The deductible tax per unit of emissions was applied to the cases involving CO_2 emission below the limit of 35000.
- The estimated amount of carbon dioxide released for storing each item (s) in the ith warehouse during the tth period was 0.0081.
- The amount of carbon dioxide released for production in each unit of the product in the ith production center in the tth period was 0.0225.

5.4. Executive results

5.4.1. Comparing the results of the two algorithms

In this section, the designed trial problems were solved using two bee colony algorithms and genetic algorithms and. Tables 1–3 list the results obtained by two algorithms according to comparative metrics.

It should be noted that S/I/J/L/M/P/N has been used to show sample problems in which, S is the number of products, I denotes the number of production centers, J stands for the number of distribution centers, M shows the number of collection and recovery centers, P denotes the number of recycling centers, and N represents the number of disposal centers.

The comparative results of Tables 1–3 along with Figures (2)-(4) indicate that the bee colony algorithm outperformed the NSGA-II algorithm in all cases as it produced more qualitative responses. The BCO algorithm also offered higher-diversity solutions than the NSGA-II algorithm. In other words, this algorithm exhibited higher potentials for exploring and extracting the region of the solution as compared with the NSGA-II algorithm. As suggested by the above tables, the NSGA-II algorithm generated more uniform solutions than the bee colony algorithm.

The runtime values in the above tables and figure (5) also reveal that the BCO algorithm requires a higher runtime as it intelligently searches for many points of the solution space in each iteration based on the design of the proposed method.

To study and compare the results of the two algorithms, Student's T-test was used as implemented in SPSS software. Four hypotheses have been formulated and tested as follows to perform this statistical test.

Hypothesis 1. The quality-metric of the solutions generated by the two algorithms of BCO and NSGA-II shows a significant difference.

Table 1
Results of solving small size problems.

Prob.	BCO					NSGA-II				
S/I/J/L/M/P/N	Quality metric	Spacing metric	Diversity metric	runtime	Number of Pareto solution	Quality metric	Spacing metric	Diversity metric	runtime	Number of Pareto solution
1/2/2/2/2/2/2	70	0.69	177.2	64.5	30	28	0.37	107.9	31.3	29
1/2/2/2/3/3/3	66.7	0.97	208.3	67.2	31	32.6	0.56	131.7	30.6	24
1/2/2/2/4/4/4	77.4	1.27	317.4	70.6	24	22.6	0.95	226.1	37.8	27
1/2/2/2/5/5/5	69.9	0.78	443.5	75.7	35	30.1	0.52	297.9	41.9	19

Table 2
Results of solving medium-sized problems.

Prob.	BCO					NSGA-II				
S/I/J/L/M/P/N	Quality metric	Spacing metric	Diversity metric	runtime	Number of Pareto solution	Quality metric	Spacing metric	Diversity metric	runtime	Number of Pareto solution
1/3/7/7/7/5/4	85.2	0.92	985.2	155.2	80	14.8	0.78	740.7	73.4	30
2/3/7/7/7/5/4	83.5	0.51	1365.9	159.2	99	16.5	0.47	840.9	73.6	79
3/3/7/7/7/5/4	88.1	0.64	1439.9	160.1	53	11.9	0.56	850.2	80.1	47
1/6/8/10/8/6/5	100	1.06	1468.3	162.5	67	0	0.71	1130.6	89.2	31
2/6/8/10/8/6/5	87.7	0.68	1582.2	163.1	98	12.3	0.44	1220.4	85.2	38
3/6/8/10/8/6/5	87.6	0.91	1702.3	171.8	31	12.4	0.78	1261.3	105.7	21
1/7/9/15/9/7/7	83.4	0.71	1708.9	181.8	87	16.6	0.47	1349.1	112.6	49
2/7/9/15/9/7/7	85.8	0.73	1763.2	182.4	45	14.2	0.62	1360.6	124.5	48
3/7/9/15/9/7/7	88.1	1.01	1930.2	184.7	88	11.9	0.49	1218.4	124.9	51

Table 3
Results of solving large-sized problems.

Prob.	BCO					NSGA-II				
S/I/J/L/M/P/N	Quality metric	Spacing metric	Diversity metric	runtime	Number of Pareto solution	Quality metric	Spacing metric	Diversity metric	runtime	Number of Pareto solution
1/10/20/30/16/7/6	90	0.75	2871.6	424.4	99	10	0.74	1901.6	179.2	61
2/10/20/30/16/7/6	85.9	1.72	2685.3	427.8	102	14.1	0.64	1954.2	235.9	89
3/10/20/30/16/7/6	87.6	1.67	3063.5	440.3	121	12.4	0.76	2112.5	354.4	108
1/15/40/70/35/12/10	70.9	0.73	2636.3	459.2	53	29.1	0.65	1901.9	386.5	19
2/15/40/70/35/12/10	89.9	0.71	2816.5	568.8	76	10.1	0.70	2265.1	397.7	83
3/15/40/70/35/12/10	66.8	1.70	3486.3	601.8	92	33.2	0.54	2793.6	429.4	31
1/15/45/90/40/15/13	87.2	1.17	4121.9	614.1	85	12.8	0.65	3278.6	437.9	100
2/15/45/90/40/15/13	100	1.13	4565.9	769.2	93	0	0.64	3397.7	543.4	88
3/15/45/90/40/15/13	88.4	1.04	5054.1	783.6	100	11.6	0.73	4758.7	650.2	87

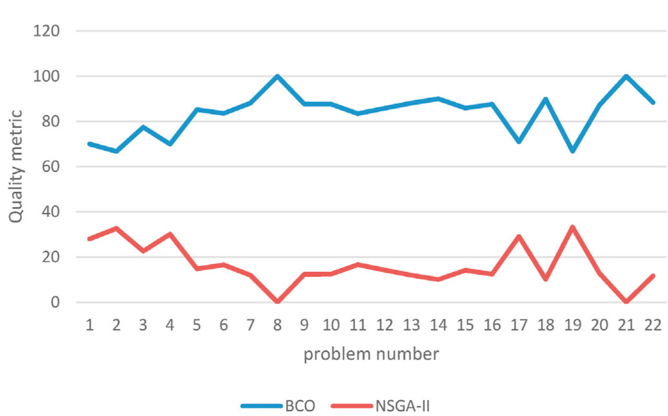

Fig. 2. Comparison of the quality metric of two algorithms for problems with small, medium, and large size.

Hypothesis 2. There is a significant difference between the diversity-metric of the solutions generated by the two algorithms BCO and NSGA-II.

Hypothesis 3. The spacing-metric of the solutions generated by the two algorithms of BCO and NSGA-II significantly differ.

Hypothesis 4. There is a significant difference between the runtime of the solutions generated by the two algorithms of BCO and NSGA-II.

These hypotheses were evaluated as listed in Table 4. This table showed the t-value of 16.603, 7.747, 5.043, and 7.437 for the metrics of quality, diversity, spacing, and runtime, respectively at the significance level of 0.000 (lower than 0.05); moreover, the statistic value was out of confidence interval for all the metrics. Therefore, the research hypotheses were confirmed; it can be said that there is a significant difference between the quality, diversity, and spacing of the solutions generated by the two algorithms BCO and NSGA-II, as well as the runtime in these algorithms.

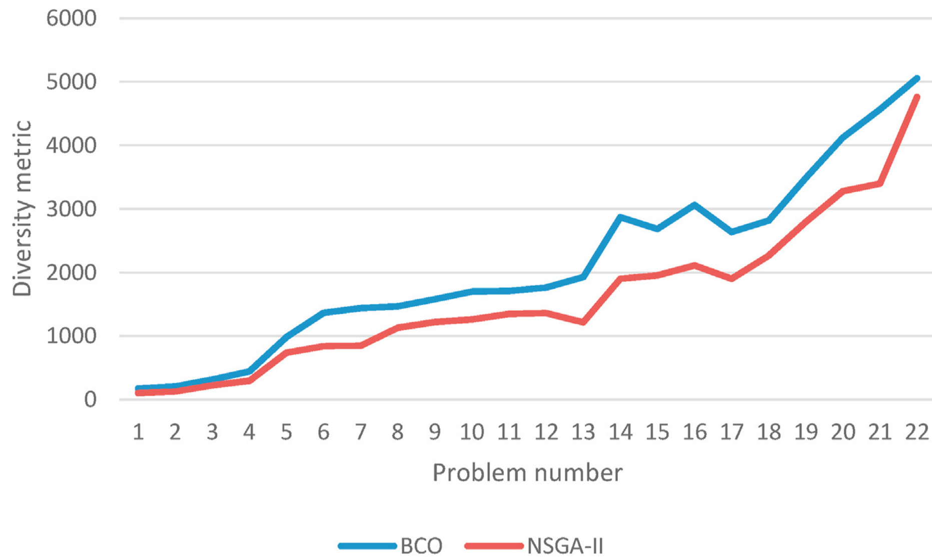

Fig. 3. Comparison of the diversity metric of two algorithms for problems with small, medium, and large size.

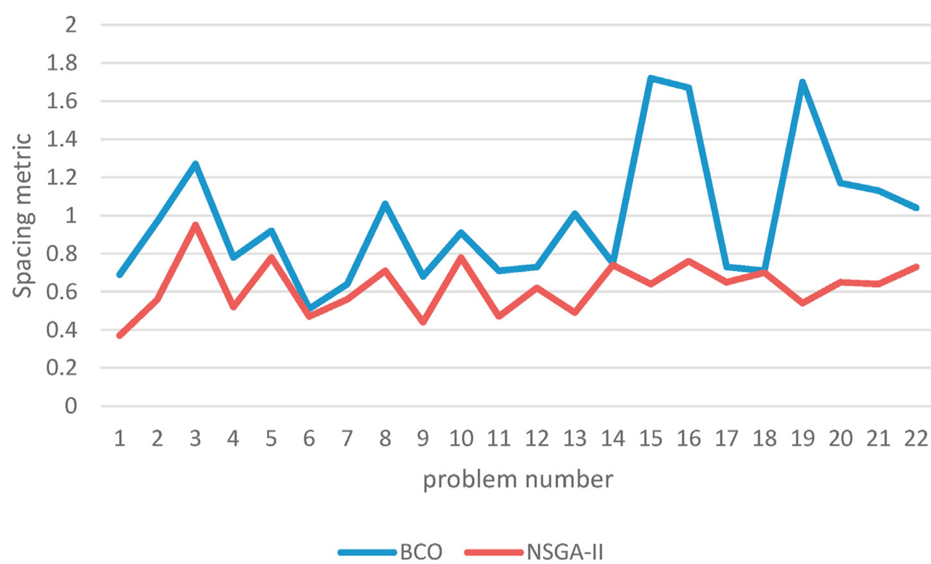

Fig. 4. Comparison of the spacing metric of two algorithms for problems with small, medium, and large size.

5.4.2. Sensitivity analysis

Sensitivity analysis was conducted by changing the demand parameters and the amount of returned goods. To examine changes in objective functions by variation in demand, the amount of demand and returned goods was first reduced to 0.25 and then increased by 1.5, 2, 2.5, 3, 3.5, 4, 4.5, and finally 5 times. The obtained results included the best values of the objective function reported by the bee colony algorithm. The results of this study are shown in Figs. 6 and 7.

As suggested by Fig. 6a, the cost was reduced by a 25% decline in demand. Moreover, the costs incremented by increasing demand. However, the process of cost elevation was 2.5 times slower than that of the demand. It appears that the changes are due to the increase in delivery costs. Due to the production levels increase by demand enhancement, the production costs will be enhanced. Furthermore, the number of shipped goods and hence, their related costs will be augmented to meet the minimum demand level. However, since other parameters were considered constant, the results of the demand effect can't be generalized to the real world condition. In the real-world, an increase in demand will also increment the profit for the cases where the sales price is also increased. On the other hand, if the materials purchase price and sales price are increased simultaneously, the profit behavior can't be easily forecasted.

The total changes in the total ratio of unfulfilled demand to total demand did not uniformly behave with the demand increase or decrease (Fig. 6b).

As can be seen in Fig. 7a, the expense increases with raising the amount of returned goods, which can be due to increased transportation costs and the emission of pollutants in reverse logistics. Also, comparing this figure with Fig. 6a shows that the slope of increased costs versus changes in returned goods is sharper than the same slope versus demand changes.

The total changes in the ratio of unfulfilled demand do not uniformly behave with the increase or decrease in the amount of returned goods (Fig. 7b).

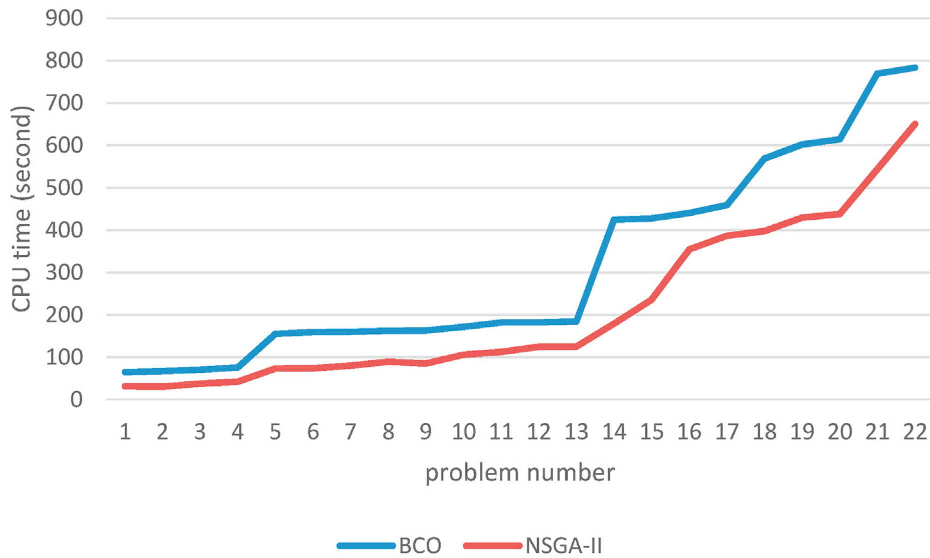

Fig. 5. Comparison of runtime index for two algorithms for problems with small, medium, and large size.

Table 4
The results of the Student's T-Test.

	Average differences	SD.	Sig.	DoF	t-statistics	95% confidence level	
						higher level	Lower level
Quality	67.28	19.01	0.000	21	16.603	75.71	58.85
Diversity	513.37	310.83	0.000	21	7.747	651.18	375.55
Spacing	0.351	0.326	0.000	21	5.043	0.496	0.206
Runtime	102.84	64.86	0.000	21	7.437	131.60	74.09

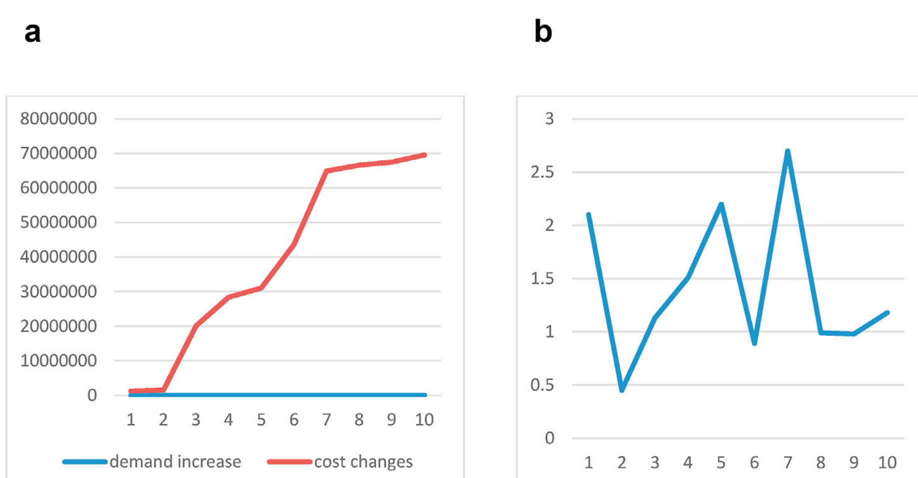

Fig. 6. **a.** Variation in costs versus demand changes. **b.** Variations in the unfulfilled demand ratio versus demand changes.

5.4.3. Managerial insights

In Summary, the findings of the study provided the decision-makers with broader insight. Cost minimization is not the key business objective, and sometimes firms must spend money on social responsibility and sustainability. Broadening the research to the other fields of uncertainty can further enrich the obtained insights. To approximate the problem to the real-world situation, fuzzy numbers were employed to represent some of the parameters to improve the performance of the entire closed-loop system.

6. Conclusion

The optimization of production routing in a sustainable closed-loop supply chain was investigated in the present study. In the studied model, PRP was examined considering the condition of simultaneous receiving and delivery in the product distribution within the supply chain. A three-objective optimization model was proposed in this regard. The main contribution of this study is offering a novel version of the closed-loop problem considering production routing, social responsibility, and environmental

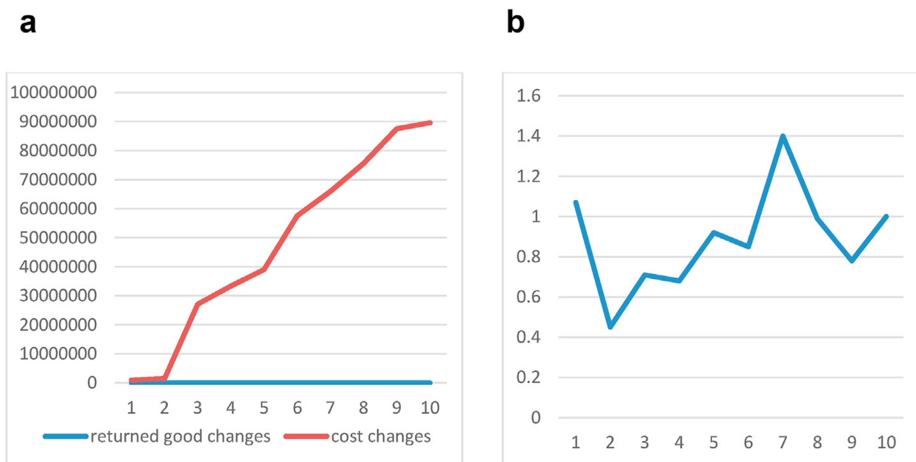

Fig. 7. a. Cost changes versus changes in returned goods. **b.** Changes in the unfulfilled demand ratio versus the variation in the amount of returned goods.

emissions. Moreover, fuzzy numbers were employed to represent the cost of product construction and demand based on the uncertainty situation. Another contribution of this paper is the introduction of two algorithms: bee colony optimization and genetic. To solve the proposed model, trial sample problems were designed in small, medium, and large size considering prior research. The results of bee colony optimization and genetic algorithms were compared in terms of quality, diversity, and spacing metrics, as well as the runtime. The results showed that in all cases, the bee colony algorithm outperformed the other algorithm in exploring and extracting the feasible solutions and achieving near-optimal solutions. In terms of spacing and runtime, the genetic algorithm exhibited superior results compared with the bee colony algorithm. Furthermore, investigation of the variations in the runtime to solution by increasing the problem size is another confirmation of the NP-Hard nature of the studied problem. Certainly, this research had some limitations in data collection for parameters and fine-tuning of algorithms. Future works may involve surveying real cases, designing other meta-heuristic algorithms, handling uncertainty via intuitionistic fuzzy sets, and also considering different forms of vehicle routing (e.g. open tours).

CRediT authorship contribution statement

Yasser Emamian: Methodology, Investigation, Software, Writing – original draft. **Isa Nakhai Kamalabadi:** Conceptualization, Supervision, Visualization. **Alireza Eydi:** Methodology, Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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