

Simultaneous reduction of emissions (CO₂ and CO) and optimization of production routing problem in a closed-loop supply chain

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Abstract

Environmental pollution and emissions, along with the increasing production and distribution of goods, have placed the future of humanity at stake. Today, measures such as the extensive reduction in emissions, especially of CO₂ and CO, have been emphasized by most researchers as a solution to the problem of environmental protection. This paper sought to explore production routing problem in closed-loop supply chains in order to find a solution to reduce CO₂ and CO emissions using the robust optimization technique in the process of product distribution. The uncertainty in some parameters, such as real-world demand, along with heterogeneous goals, compelled us to develop a fuzzy robust multi-objective model. Given the high complexity of the problem, metaheuristic methods are proposed for solving the model. To this end, the bee optimization method is developed. Some typical problems are solved to evaluate the solutions. In addition, in order to prove the algorithm's efficiency, the results are compared with those of the genetic algorithm in terms of quality, dispersion, uniformity, and runtime. The dispersion index values showed that the bee colony algorithm produces more workable solutions for the exploration and extraction of the feasible region. The uniformity index values and the runtime results also indicate that the genetic algorithm provides shorter runtimes and searches the solution space in a more uniform manner, as compared with the bee colony algorithm.

Keywords: Emissions, production routing, closed-loop supply chain, robust optimization

1- Introduction

Environmental pollution caused by emissions, especially of CO₂ and CO, is one of the major problems whose elimination requires the adoption of appropriate strategies. In December 2015, the United Nations Climate Change Conference was held in Paris. 195 countries from around the world attended the Conference. Based on the statistics released in the Conference, Iran ranks seventh in the production of greenhouse gases (GHGs). According to the Paris Convention, Iran has undertaken to reduce the pollution caused by greenhouse gases by 4% unconditionally and up to 12% conditionally (subject to international aids) in a 20-year period, starting from 2020. The transportation sector, as one of the key components of the supply chain, accounts for a large portion of this pollution. Therefore, exploring the production routing problem can significantly help us reduce CO₂ and CO emissions by motor vehicles.

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A supply chain consists of a sequence of activities involved in the production, lot sizing, distribution, and backflow of goods. Each activity is planned and optimized based on its associated predicted decisions. Transportation is of great importance in economic, manufacturing, and service systems and accounts for a sizeable part of the GDP of each country. Therefore, many researchers have attempted to find ways to improve routes, remove unnecessary trips, and propose alternative shortcuts (Taghavifard et al, 2009). In routing and transportation problems, different objectives such as cost, risk, distance, and response-time minimization or quality, customer satisfaction, profit, and accountability maximization have been taken into account. Cost minimization or at most two of the aforementioned objectives are usually selected as the model's goal by most researchers (Tavakkoli-Moghaddam et al, 2007).

In an attempt to develop new problems, some researchers have combined the Vehicle Routing Problem (VRP) with other problems. For example, some have proposed the Production Routing Problem (PRP). According to PRP, products are routed between different levels of the supply chain including supplier, manufacturer, distributor, and customer. Adulyasak et al. (2015) conducted an in-depth review study on PRP and concluded that most researchers have proposed heuristic and metaheuristic methods for solving this problem, while the use of exact algorithms and robust optimization techniques has been less taken into account. Adulyasak et al. (2014) developed a mathematical model of mixed integer for PRP in the supply chain which is a combination of problems for lot sizing and inventory-routing. Sun & Wang (2015) proposed an approach to the robust optimization technique for the routing problem while taking the uncertainties into consideration.

At the same time, in a transportation system, distributors, who are seeking to maximize their profit, are faced with multiple problems such as traffic congestion, air pollution, loss of time in daily trips, increased fuel consumption, and vehicle depreciation in the process of products distribution and cash earning. This has encouraged researchers to focus on objectives aimed at reducing environmentally polluting emissions, fuel consumption, traffic congestion, etc. For example, considering the conditions of simultaneous product pickup and delivery and the existing uncertainties, Tajik et al. (2014) proposed a robust optimization approach with a limited time window to the routing problem aimed at reducing pollution caused by motor vehicles.

In terms of CO₂ reduction, Bektaş & Laporte (2011) explored PRP as a developed version of VRP. Considering the time window, they proposed a mathematical model for minimizing trip time and emissions. In a study on the allocation of CO₂ reduction to customers in distribution routing, Naber et al. (2015) explained the misunderstanding of logistics service providers (LSPs), both individuals and organizations, of the subject and modeled the problem using the cooperative game theory, while taking into consideration the amount of CO₂ emissions produced in the entire transportation process. Pradenas et al. (2013) solved VRP by taking the return time window into consideration. Their attempt was aimed at reducing trip time and fuel consumption, and ultimately the emission of greenhouse gases. In addition, Talaei et al. (2016) proposed a fuzzy robust optimization model for a closed-loop supply chain, taking into consideration the relevant polluting emissions. First, they converted the fuzzy model into a deterministic model using the Jiménez ranking method, and consequently developed a robust optimization model. Table 1 briefly compares previous studies and shows the framework in this one.

Table 1. Literature summary

Reference	Model description	Robust Optimization	Emissions	Multi-Good	Multi-Period	Inventory	Location	Routing	Simultaneous Pickup and Deliveries	Uncertainty	Solution Method
Adulyasak et al. (2015)	Review study on PRP			*	*	*		*			Review study
Adulyasak et al. (2014)	Mathematical model for PRP			*	*	*					Metaheuristic
Sun & Wang (2015)	Robust optimization technique for the routing problem	*						*		*	Metaheuristic
Tajik et al. (2014)	Robust optimization approach with a limited time window to the routing problem	*	*						*	*	GAMS
Bektaş & Laporte (2011)	Pollution Routing Problem		*				*				CPLEX 12.1
Naber et al. (2015)	Logistics service providers (LSPs)		*					*			Game Theory
Pradenas et al. (2013)	VRP by taking the return time window into consideration		*					*		*	Metaheuristic
Talaei et al. (2016)	A fuzzy robust optimization model for a closed-loop supply chain	*	*		*		*	*		*	E-constraint method
Current paper	A robust optimization of PRP in the closed-loop supply chain to reduce emissions	*	*	*	*	*	*	*	*	*	Metaheuristic

In this study, a mathematical model is proposed for PRP in a closed-loop supply chain in order to reduce CO₂ and CO emissions, while aiming at robust optimization and minimization of carbon emissions. Accordingly, a mathematical model is first developed. This model is based on research studies by Adulyasak et al. (2014) and Tajik et al. (2014) and is widely used in different industries such as the petrochemical industry. Next, metaheuristic algorithms are used for problem-solving.

In the model proposed by Adulyasak et al. (2014), PRP is modeled in the context of a multi-node network. In addition, Tajik et al. (2014) merely modeled a Green Vehicle Routing Problem (G-VRP) by focusing on simultaneous pickup and delivery. However, the model proposed in the present study includes the unified modeling of a closed-loop supply chain focused on different levels of forward and reverse logistics and addresses PRP with regard to conditions of simultaneous pickup and delivery. Simultaneous pickup and delivery means that, in the last layer of direct supply chain logistics, vehicles that deliver goods to customers will also receive their returned goods.

Since this study dealt with routing solutions aimed at reducing CO₂ and CO emissions, carbon emissions minimization is taken as one of the models expected objectives. At the same time, as there is no certainty regarding the supply chain parameters, especially the real-world demand, one of the most important decisions taken in the supply chain concerns the chain's effectiveness and efficiency as combined with uncertain parameters and variables. Uncertainty in the supply chain results in the non-optimal decisions taken based on certainty assumptions. Hence, achieving a robust optimization based on fuzzy demand is taken as one of the proposed model's objectives.

2- Mathematical modeling

The model dealt with location distributor facilities and reverse logistics facilities (collection and recovery, disposal, and recycling). In addition, vehicle routing with limited weight and volume capacity is included in the model. Due to the uncertainty of real-world problems, the robust optimization technique is used to achieve robustness in the face of uncertainty. Figure 1 depicts the conceptual model of the problem. As evident from figure 1, goods are manufactured in manufacturing centers and are then sent to distribution centers. In addition, surplus goods in manufacturing centers are sent to warehouses. Therefore, distribution centers receive the goods they require from manufacturing centers or their warehouses in each period. Goods are then transported from distribution centers to customers and distributed among them. The goods returned by customers for various reasons are received and sent to collection and recovery centers. If possible, the returned goods will be reclaimed and processed at these centers and sent back to distribution centers to be delivered to customers. If the goods need to be recycled, they will be sent to recycling centers to re-enter the production cycle. If goods cannot be processed, they will be sent to disposal centers. Therefore, the problem includes routing, manufacturing, distribution, inventory, and location, all, aimed at minimizing carbon emissions in a multi-level, multi-good, and multi-period green supply chain.

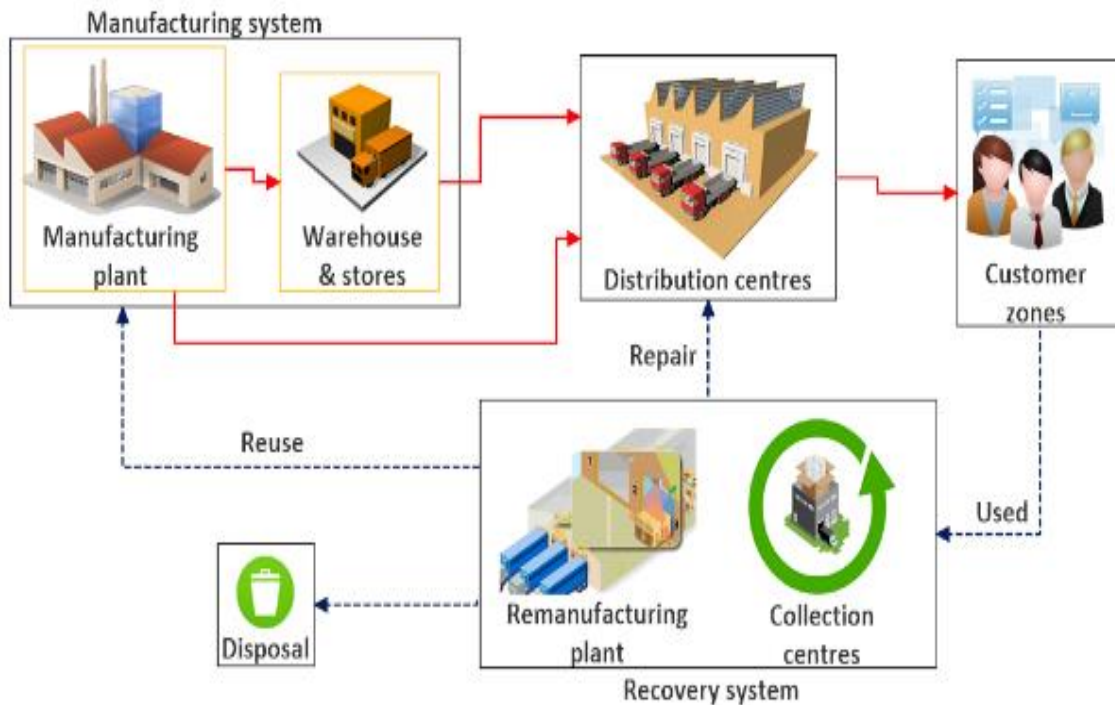


Fig 1. Remanufacturing and collection centers for the conceptual closed loop supply chain.

Modeling assumptions

The mathematical modeling is based on the following assumptions:

- Goods are considered as packages containing a certain amount of a solid produced good.
- Goods are produced in manufacturing centers and sent to distribution centers or warehouses.
- Distribution centers receive the required goods from manufacturing centers or warehouses.
- There number of available vehicles (trucks) is limited and specified. In addition, each vehicle can carry a limited volume of goods.
- A vehicle may carry shipments for several distributors. Hence, after delivering the goods to the distributor $j1$, it may leave for other distributors, for example, $j2$. Therefore, the vehicle also travels between distributors.

- A vehicle may carry shipments for several customers. Hence, following the delivery of the goods to customer $l1$, it may leave for other customers, for example, $l2$. Therefore, the vehicle also travels between customer centers.
- The number of potential points associated with distribution centers is predetermined. These centers have a limited capacity.
- The number of customer (demand) points is predetermined. All these points must be met by vehicles. Customer demand is uncertain and determined as a triangular fuzzy number.
- Delivery and payment are simultaneous.
- Fuel consumption per unit of distance is determined based on the vehicle speed and cargo weight.
- The distance between centers and fuel price per liter are predetermined.
- The speed is considered varying for each vehicle.
- The construction cost is determined as a triangular fuzzy number.

Model indices

I	Set of fixed points for manufacturing centers; $i \in I$
J	Set of potential points for distribution centers; $j \in J$
K	Set of vehicles; $k \in K$
L	Set of fixed points for customers; $l, l1, l2 \in L$
M	Set of potential points for collection and recovery centers; $m \in M$
N	Set of potential points for disposal centers; $n \in N$
P	Set of potential points for recycling centers; $p \in P$
S	Set of products; $s \in S$
T	Set of time periods; $t \in T$
NJ	Set of distribution center nodes
NL	Set of demand points

Model parameters

ca_j	Capacity of distribution center at point j
p_c	Mean price of each unit of emission
p_f	Fuel price per unit of volume
v_f	Volume of fuel consumed per unit of distance and unit of weight; speed and distance
v_k	Speed of vehicle k
vol_s	Volume of product s
w_c	Weight of emissions per a 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
L_i	Distance between manufacturing center i and its own warehouse
L_{ij}	Distance between manufacturing center i and distribution center j
L_{jl}	Distance between the distribution center j and the customer zone l
L_{lm}	Distance between demand point l and collection and recovery center m
L_{mi}	Distance between collection and recovery center m and manufacturing center i
L_{mj}	Distance between collection and recovery center m and distribution center j
L_{mn}	Distance between collection and recovery center m and disposal center n
L_{mp}	Distance between collection and recovery center m and recycling center p
L_{pi}	Distance between recycling center p and manufacturing center i
L_{l1l2}	Distance between demand point $l1$ and demand point $l2$
LQ_{ij}	Distance between the warehouse of manufacturing center i and distribution center j
QV_k	Cubic capacity of vehicle k

QW_k	Weight capacity of vehicle k
\tilde{f}_j	Fuzzy cost of construction of a distribution center at point j
\tilde{f}_m	Fuzzy cost of construction of a collection and recovery center at point m
\tilde{f}_n	Fuzzy cost of construction of a disposal center at point n
\tilde{f}_p	Fuzzy cost of construction of a recycling center at point p
\tilde{d}_{ls}^t	Fuzzy demand for product s from demand point l in period t (fuzzy demand for delivery to demand point)
\tilde{r}_{ls}^t	Fuzzy value of the return of product s from demand point l in period t (fuzzy value of customer payment)

Variables

q_{ls}^t	Unmet demand of customer l for good s in period t
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_{plk}^{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
x_{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
 y_{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 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

2-1- Model

$$\begin{aligned}
\min z1 = & \sum_{j=1}^J \tilde{f}_j z_j + \sum_{m=1}^M \tilde{f}_m z_m + \sum_{p=1}^P \tilde{f}_p z_p + \sum_{n=1}^N \tilde{f}_n z_n + \left(\sum_{k=1}^K (v_f * \alpha_k * v_k) \right. \\
& * \left. \left(\sum_{s=1}^S \left(\sum_{t=1}^T \left(\sum_{i=1}^I \left(x_{ik}^{ts} * L_i + \sum_{j=1}^J (x_{ijk}^{ts} * LQ_{ij} + x_{ijk}^{ts} * L_{ij}) \right) \right) * w_s \right) \right) \right. \\
& + \sum_{j=1}^J (w_{jj}^{ts} + \sum_{l=1}^L x_{jlk}^{ts} * L_{jl}) * w_s + \sum_{l=1}^L ((w_{lk}^{ts} + \sum_{j=1}^J xw_{jlk}^{ts}) + \sum_{l1=1}^L (xw_{l1lk}^{ts} * L_{l1l})) \times w_s \\
& + \sum_{m=1}^M \left(\sum_{l=1}^L x_{lmk}^{ts} * L_{lm} + \sum_{i=1}^I x_{mik}^{ts} * L_{mi} + \sum_{j=1}^J x_{mjk}^{ts} * L_{mj} + \sum_{n=1}^N x_{mnk}^{ts} * L_{mn} \right. \\
& \left. + \sum_{p=1}^P x_{mpk}^{ts} * L_{mp} \right) * w_s + \sum_{p=1}^P \sum_{i=1}^I x_{pik}^{ts} * L_{pi} * w_s + w_k) * (p_f + w_c * p_c) \quad (1)
\end{aligned}$$

$$\min z2 = \sum_{t=1}^T \sum_{l=1}^L \sum_{s=1}^S \frac{q_{ls}^t}{\tilde{a}_{ls}^t} \quad (2)$$

Subject to.

$$\sum_k y_{ik}^t = \sum_k \sum_j y_{ijk}^t \quad \forall i, t \quad (3)$$

$$\sum_k \left(\sum_t (y_{ijk}^t + y_{ijlk}^t) + \sum_m y_{mjk}^t \right) = \sum_k \left(\sum_t y_{jlk}^t + \sum_{j1} y_{j1jk}^t \right) \quad \forall j, t \quad (4)$$

$$\sum_k \sum_j y_{jk}^t = \sum_k \left(\sum_m y_{mk}^t + \sum_{l1} y_{l1k}^t \right) \quad \forall l, t \quad (5)$$

$$\sum_k \sum_l y_{lmk}^t = \sum_k \left(\sum_p y_{mpk}^t + \sum_n y_{mnk}^t + \sum_j y_{mjk}^t + \sum_i y_{mik}^t \right) \quad \forall m, t \quad (6)$$

$$\sum_k \sum_m y_{mpk}^t = \sum_k \sum_i y_{pik}^t \quad \forall p, t \quad (7)$$

$$\sum_k \sum_p y_{pik}^t = \sum_k \sum_i y_{ik}^t + \sum_k \sum_i y_{ijk}^t \quad \forall p, t \quad (8)$$

$$\sum_k \left(\sum_j xw_{jlk}^{ts} + \sum_{l1} xw_{l1k}^{ts} \right) + q_{ls}^t = \tilde{d}_{ls}^t + \tilde{r}_{ls}^t \quad \forall l, t, s \quad (9)$$

$$w_{l1k}^{ts} - w_{l2k}^{ts} \geq \sum_j (xw_{j1k}^{ts} \times y_{j1k}^t) + \sum_l (xw_{l1k}^{ts} \times y_{l1k}^t) + x_{l1mk}^{ts} - M(1 - y_{l12k}^t) \quad \forall l1, l2, l \in L, \forall k, t, s \quad (10)$$

$$xp_i^{ts} + \sum_k \sum_m x_{mik}^{ts} = \sum_k (x_{ik}^{ts} + \sum_j x_{ijk}^{ts}) \quad \forall i, t, s \quad (11)$$

$$\sum_k \left(\sum_i (xw_{ijk}^{ts} + xiw_{ijk}^{ts}) + \sum_m x_{mjk}^{ts} + \sum_{j1} xw_{j1jk}^{ts} \right) = \sum_k \sum_l x_{jlk}^{ts} \quad \forall j, t, s \quad (12)$$

$$\sum_k \sum_l x_{lmk}^{ts} = \sum_k \left(\sum_p x_{mpk}^{ts} + \sum_n x_{mnk}^{ts} + \sum_j x_{mjk}^{ts} + \sum_i x_{mik}^{ts} \right) \quad \forall m, t, s \quad (13)$$

$$wj_{j1k}^{ts} - wj_{j2k}^{ts} \geq \sum_i (xw_{ij1k}^{ts} \times y_{ij1k}^t) + \sum_j (xw_{jj1k}^{ts} \times y_{jj1k}^t) - M(1 - y_{j1j2k}^t) \quad \forall (j1, j2) \in J \times J, \forall k, t, s \quad (14)$$

$$\sum_{j1 \in N} \sum_{j2 \in N} y_{j1j2k}^t \leq |N| - 1 \quad \forall N \in NJ: |N| \geq 2 \ \& \ \forall k, t \quad (15)$$

$$\sum_{l1 \in N} \sum_{l2 \in N} y_{l1l2k}^t \leq |N| - 1 \quad \forall N \in NL: |N| \geq 2 \ \& \ \forall k, t \quad (16)$$

$$\sum_s \sum_k \left(\sum_i (xiw_{ijk}^{ts} + xw_{ijk}^{ts}) + \sum_{j1} xw_{j1jk}^{ts} \right) \leq ca_j \quad \forall j, t \quad (17)$$

$$\sum_s \left((w_{l1k}^{ts} + \sum_j (xw_{j1k}^{ts} \times y_{j1k}^t)) + \sum_l (xw_{l1k}^{ts} \times y_{l1k}^t) + x_{l1k}^{ts} \times w_s \right) \leq QW_k \quad \forall l, k, t \quad (18)$$

$$\sum_s \left((w_{l1k}^{ts} + \sum_j (xw_{j1k}^{ts} \times y_{j1k}^t)) + \sum_l (xw_{l1k}^{ts} \times y_{l1k}^t) + x_{l1k}^{ts} \times vol_s \right) \leq QV_k \quad \forall l, k, t \quad (19)$$

$$\sum_s (x_{ik}^{ts} \times w_s) \leq QW_k \quad \forall i, k, t \quad (20) \quad xi_{ijk}^{ts} \leq M \times yi_{ijk}^t \quad \forall i, j, k, t, s \quad (44)$$

$$\sum_s (x_{ik}^{ts} \times vol_s) \leq QV_k \quad \forall i, k, t \quad (21) \quad xw_{ijk}^{ts} \leq M \times yi_{ijk}^t \quad \forall i, j, k, t, s \quad (45)$$

$$\sum_s (xi_{ijk}^{ts} \times w_s) \leq QW_k \quad \forall i, j, k, t \quad (22) \quad xiw_{ijk}^{ts} \leq M \times yi_{ijk}^t \quad \forall i, j, k, t, s \quad (46)$$

$$\sum_s (xi_{ijk}^{ts} \times vol_s) \leq QV_k \quad \forall i, j, k, t \quad (23) \quad xw_{j1j2k}^{ts} \leq M \times y_{j1j2k}^t \quad \forall j1, j2, k, t, s \quad (47)$$

$$\sum_s (x_{ijk}^{ts} \times w_s) \leq QW_k \quad \forall i, j, k, t \quad (24) \quad x_{jlk}^{ts} \leq M \times y_{jlk}^t \quad \forall l, j, k, t, s \quad (48)$$

$$\sum_s (x_{ijk}^{ts} \times vol_s) \leq QV_k \quad \forall i, j, k, t \quad (25) \quad xw_{jlk}^{ts} \leq M \times y_{jlk}^t \quad \forall l, j, k, t, s \quad (49)$$

$$\sum_s (x_{jlk}^{ts} \times w_s) \leq QW_k \quad \forall j, l, k, t \quad (26) \quad xw_{l1l2k}^{ts} \leq M \times y_{l1l2k}^t \quad \forall l1, l2, k, t, s \quad (50)$$

$$\sum_s (x_{jlk}^{ts} \times vol_s) \leq QV_k \quad \forall j, l, k, t \quad (27) \quad x_{lmk}^{ts} \leq M \times y_{lmk}^t \quad \forall l, m, k, t, s \quad (51)$$

$$\sum_s (x_{mpk}^{ts} \times w_s) \leq QW_k \quad \forall m, p, k, t \quad (28) \quad x_{mpk}^{ts} \leq M \times y_{mpk}^t \quad \forall p, m, k, t, s \quad (52)$$

$$\sum_s (x_{mpk}^{ts} \times vol_s) \leq QV_k \quad \forall m, p, k, t \quad (29) \quad x_{mnk}^{ts} \leq M \times y_{mnk}^t \quad \forall n, m, k, t, s \quad (53)$$

$$\sum_s (x_{mnk}^{ts} \times w_s) \leq QW_k \quad \forall m, n, k, t \quad (30) \quad x_{mik}^{ts} \leq M \times y_{mik}^t \quad \forall i, m, k, t, s \quad (54)$$

$$\sum_s (x_{mnk}^{ts} \times vol_s) \leq QV_k \quad \forall m, n, k, t \quad (31) \quad x_{mjk}^{ts} \leq M \times y_{mjk}^t \quad \forall j, m, k, t, s \quad (55)$$

$$\sum_s (x_{mik}^{ts} \times w_s) \leq QW_k \quad \forall m, i, k, t \quad (32) \quad y_{j_1 j_2 k}^t \leq M \times z_{j_1} \times z_{j_2} \quad \forall j_1, j_2, k, t \quad (56)$$

$$\sum_s (x_{mik}^{ts} \times vol_s) \leq QV_k \quad \forall m, i, k, t \quad (33) \quad y_{jlk}^t \leq M \times z_j \quad \forall l, j, k, t \quad (57)$$

$$\sum_s (x_{mjk}^{ts} \times w_s) \leq QW_k \quad \forall m, j, k, t \quad (34) \quad y_{lmk}^t \leq M \times z_m \quad \forall l, m, k, t \quad (58)$$

$$\sum_s (x_{mjk}^{ts} \times vol_s) \leq QV_k \quad \forall m, j, k, t \quad (35) \quad y_{mpk}^t \leq M \times z_m \times z_p \quad \forall p, m, k, t \quad (59)$$

$$\sum_l \sum_s (x_{lmk}^{ts} \times w_s) \leq QW_k \quad \forall m, k, t \quad (36) \quad y_{mnk}^t \leq M \times z_m \times z_n \quad \forall n, m, k, t \quad (60)$$

$$\sum_l \sum_s (x_{lmk}^{ts} \times vol_s) \leq QV_k \quad \forall m, k, t \quad (37) \quad y_{mik}^t \leq M \times z_m \quad \forall i, m, k, t \quad (61)$$

$$\sum_l \sum_s (x_{pik}^{ts} \times w_s) \leq QW_k \quad \forall m, k, t \quad (38) \quad y_{mjk}^t \leq M \times z_m \quad \forall j, m, k, t \quad (62)$$

$$\sum_l \sum_s (x_{pik}^{ts} \times vol_s) \leq QV_k \quad \forall m, k, t \quad (39) \quad y_{ijk}^t \leq M \times z_j \quad \forall i, j, k, t \quad (63)$$

$$\sum_l \sum_s (x_{pik}^{ts} \times vol_s) \leq QV_k \quad \forall m, k, t \quad (39) \quad y_{ijk}^t \leq M \times z_j \quad \forall i, j, k, t \quad (64)$$

$$\sum_j \sum_k y_{jlk}^t \geq 1 \quad \forall l, t \quad (40) \quad \sum_j z_j \geq 1 \quad \forall j \quad (65)$$

$$\sum_k x_{lk}^{ts} = \tilde{r}_{ls}^t \quad \forall l, t, s \quad (41) \quad \sum_m z_m \geq 1 \quad \forall m \quad (66)$$

$$x_{ik}^{ts} \leq M \times y_{ik}^t \quad \forall i, k, t, s \quad (42) \quad \sum_p z_p \geq 1 \quad \forall p \quad (67)$$

$$x_{ijk}^{ts} \leq M \times y_{ijk}^t \quad \forall i, j, k, t, s \quad (43) \quad \sum_n z_n \geq 1 \quad \forall n \quad (68)$$

$$z_j, z_p, z_m, z_n, y_{ik}^t, y_{ijk}^t, y_{ijk}^t, y_{jlk}^t, y_{j_1 j_2 k}^t, y_{l_1 l_2 k}^t, y_{lmk}^t, y_{mnk}^t, y_{mpk}^t, y_{mik}^t, y_{mjk}^t \in \{0, 1\} \quad (69)$$

$$xp_i^{ts}, x_{ijk}^{ts}, x_{ik}^{ts}, x_{ijk}^{ts}, xw_{ijk}^{ts}, xiw_{ijk}^{ts}, w_{j_1 j_2 k}^{ts}, x_{jlk}^{ts}, xw_{jlk}^{ts}, xw_{l_1 l_2 k}^{ts}, w_{lk}^{ts}, x_{lk}^{ts}, x_{mk}^{ts}, x_{mnk}^{ts}, x_{mpk}^{ts}, x_{mik}^{ts}, x_{mjk}^{ts}, I_{ls}^t, q_{ls}^t \geq 0 \quad (70)$$

Equation (1) shows the first objective function. This function involves minimization of facilities' construction costs, vehicle fuel costs, and environmental costs of emissions. Equation (2) represents the second objective function which involves the total ratio of unmet demands of customers to their total demand for all goods in all periods. Constraints (3) to (8) indicate that the vehicles entering manufacturing centers and their warehouses, distribution centers, demand points, collection and recovery centers, and recycling centers will surely leave these points. In addition, the vehicles entering disposal centers will re-enter the cycle and begin from manufacturing centers. They go to the manufacturing centers as needed. Constraint (9) represents the amount of unmet demands of customer l for good s in period t . Constraint (10) calculates the amount of the inventory of good s in the cargo of vehicle k in period t before meeting

demand points. Constraints (11), (12), and (13) guarantee the balance of goods flow in nodes. Constraint (14) calculates the amount of the inventory of good s in the cargo of vehicle k in period t before meeting distribution centers. Constraints (15) and (16) prevent sub-tours during the trip of vehicles between distribution centers and demand points, respectively. Constraint (17) shows that the capacity of distribution centers is limited in terms of the number of goods they can carry. Constraints (18) to (39) ensure that goods transported by vehicle k do not exceed its weight and cubic capacity. Constraint (40) ensures that all customers are met by at least one of the vehicles in all periods. Constraint (41) ensures that all returned goods from demand points are collected in the backflow. Constraints (42) to (55) ensure that a good is transported from one center to another by a vehicle when the vehicle takes a trip between these two points. Constraints (56) to (64) ensure that a vehicle travels between two centers only when they are already established. Constraints (65) to (68) ensure that at least one center is established for facilities associated with distribution, collection, disposal, and recycling activities. Constraints (69) and (70) are related to symbols and allowed values for the model's decision variables.

2-2- Robust optimization planning model

As can be seen, the proposed model is a dual-objective one with fuzzy parameters. First, the fuzzy model is converted into a corresponding deterministic model using the Jiménez ranking method (Jiménez et al., 2007). Next, the robust optimization planning model is developed.

The final form of objective functions after defuzzification:

$$\begin{aligned} \min z1 = & \sum_{j=1}^J \left(\frac{f_j^1 + 2f_j^2 + f_j^3}{2} \right) z_j + \sum_{m=1}^M \left(\frac{f_m^1 + 2f_m^2 + f_m^3}{2} \right) z_m + \sum_{p=1}^P \left(\frac{f_p^1 + 2f_p^2 + f_p^3}{2} \right) z_p + \sum_{n=1}^N \left(\frac{f_n^1 + 2f_n^2 + f_n^3}{2} \right) z_n + \left(\sum_{k=1}^K (v_f \right. \\ & * \alpha_k * v_k) * \left(\sum_{s=1}^S \left(\sum_{t=1}^T \left(\sum_{i=1}^I \left(x_{ik}^{ts} * L_i + \sum_{j=1}^J (x_{ijk}^{ts} * LQ_{ij} + x_{ijk}^{ts} * L_{ij}) \right) \right) * w_s \right) \right. \\ & + \sum_{j=1}^J (w_{jlk}^{ts} + \sum_{l=1}^L x_{jlk}^{ts} * L_{jl}) * w_s + \sum_{l=1}^L ((w_{lk}^{ts} + \sum_{j=1}^J xw_{jlk}^{ts}) + \sum_{l1=1}^L (xw_{l1lk}^{ts} * L_{l1l})) * w_s \\ & + \sum_{m=1}^M \left(\sum_{l=1}^L x_{lmk}^{ts} * L_{lm} + \sum_{i=1}^I x_{mik}^{ts} * L_{mi} + \sum_{j=1}^J x_{mjk}^{ts} * L_{mj} + \sum_{n=1}^N x_{mnk}^{ts} * L_{mn} + \sum_{p=1}^P x_{mpk}^{ts} * L_{mp} \right) * w_s \\ & \left. \left. + \sum_{p=1}^P \sum_{i=1}^I x_{pik}^{ts} * L_{pi} * w_s + w_k \right) \right) * (p_f + w_c * p_c) \end{aligned} \quad (71)$$

$$\min z2 = \sum_{t=1}^T \sum_{l=1}^L \sum_{s=1}^S \frac{q_{ls}^t}{\left(\frac{d_{ls}^{t1} + 2d_{ls}^{t2} + d_{ls}^{t3}}{2} \right)} \quad (72)$$

Constraint (9) after defuzzification:

$$\begin{aligned} \sum_k \left(\sum_j xw_{jlk}^{ts} + \sum_{l1} xw_{l1lk}^{ts} \right) + q_{ls}^t \\ = (1 - \alpha) \frac{d_{ls}^{t1} + d_{ls}^{t2}}{2} + \alpha \frac{d_{ls}^{t2} + d_{ls}^{t3}}{2} + (1 - \alpha) \frac{r_{ls}^{t1} + r_{ls}^{t2}}{2} + \alpha \frac{r_{ls}^{t2} + r_{ls}^{t3}}{2} \quad \forall l, t, s \end{aligned} \quad (73)$$

Constraint (41) after defuzzification:

$$\sum_k x_{ik}^{ts} = (1 - \alpha) \frac{r_{ls}^{t1} + r_{ls}^{t2}}{2} + \alpha \frac{r_{ls}^{t2} + r_{ls}^{t3}}{2} \quad \forall l, t, s \quad (74)$$

For a robust modeling based on demand, the first objective function remained unchanged. Other changes, assuming the definition of $E(z2)$ being equal to Constraint (75), are as follows:

$$E(z2) = \sum_{t=1}^T \sum_{l=1}^L \sum_{s=1}^S \frac{q_{ls}^t}{d_{ls}^t} \quad (75)$$

Hence, the second objective function is modeled as follows:

$$\begin{aligned}
\min z_2 = E(z_2) + \gamma(z_{max} - E(z_2)) + \varphi_1 & \left[(1 - \alpha) \frac{d_{ls}^{1,1} + d_{ls}^{1,2}}{2} + \alpha \frac{d_{ls}^{1,2} + d_{ls}^{1,3}}{2} + (1 - \alpha) \frac{r_{ls}^{1,1} + r_{ls}^{1,2}}{2} \right. \\
& \left. + \alpha \frac{r_{ls}^{1,2} + r_{ls}^{1,3}}{2} \right] \\
& + \varphi_2 \left[(1 - \alpha) \frac{d_{ls}^{t1} + d_{ls}^{t2}}{2} + \alpha \frac{d_{ls}^{t2} + d_{ls}^{t3}}{2} + (1 - \alpha) \frac{r_{ls}^{t1} + r_{ls}^{t2}}{2} + \alpha \frac{r_{ls}^{t2} + r_{ls}^{t3}}{2} \right] \\
& + \varphi_3 \left[(1 - \alpha) \frac{r_{ls}^{t1} + r_{ls}^{t2}}{2} + \alpha \frac{r_{ls}^{t2} + r_{ls}^{t3}}{2} \right]
\end{aligned} \tag{76}$$

Where all the above constraints exist and z_{max} is calculated as follows:

$$z_{max} = \sum_{t=1}^T \sum_{l=1}^L \sum_{s=1}^S \frac{q_{ls}^t}{d_{ls}^{t3}} \tag{77}$$

In Equation (76), γ represents the weight or importance of relevant statements in the objective function as compared with other objective components. In addition, φ_i denotes the penalty of deviation from equations with fuzzy parameters.

3- Solution methodology

Most of the logistics network design models, including the problem discussed in this study, are among the hard problems. These problems can be reduced to the problem of location facilities with limited capacity, which falls into the category of Np-Complete problems (Tibben-Lembke & Rogers, 2002). Therefore, the problem of logistics network design, discussed in this study, belongs to the category of Np-Hard problems. Due to high time complexity, precise methods cannot be used for solving these problems on a large scale. Thus, in this study, the bee optimization algorithm, which is based on Pareto archive, is used for solving the problem. The results obtained through this algorithm are compared with the results of the well-known *NSGA-II* algorithm.

3-1- Bee colony algorithm

Bee colony algorithm is an emerging group algorithm based on the foraging behavior of honey bees (Pham et al., 2006). The following structure is applied for implementing the bee colony algorithm aimed at solving the proposed model.

3-1-1- Solution representation

In this study, solutions are represented as matrices. Each solution contains several matrices developed according to the model outputs. For example, for Z_m , a row (one-dimensional) matrix is defined whose entries are equal to m (the number of collection centers); for y_{ik}^t , a three-dimensional matrix with dimensions of l , k , and t is defined; and for x_{ijk}^s , a five-dimensional matrix with dimensions i , j , k , t , and s is defined. Similarly, a matrix is defined to test the outputs.

3-1-2- Development of initial solutions

In the present study, a random approach is used for development of initial solutions. To this end, matrices Z_j , Z_m , Z_p , and Z_n are randomly developed and the remaining solution matrices (the model variables) are feasibly initialized while taking the model constraints into consideration. Suppose that the size of the population is equal to N . Each time a solution is developed as explained, it will be added to the population unless it is iterative. This continues until the number of solutions in the population reaches $\alpha \times N$, where α is a number greater than 1.

Development of solutions is stopped after $\alpha \times N$ iteration. At the same time, the number of solutions in each algorithm iteration is equal to N . Therefore, out of $\alpha \times N$ solutions available, N solutions should be selected as the sequence of initial development. In this study, the initial population of solutions is selected based on a rapid method to sort the non-dominant solutions as explained by Deb et al. (2002). In this method, the $\alpha \times N$ solutions available are sorted and ranked. The number of each rank represents the

quality of solutions available in that rank. For instance, the quality of solutions in Rank 1 is higher than those in Rank 2. Then, a scale known as the crowding distance is calculated for solutions available in each rank. This scale indicates the dispersion of available solutions in each rank.

In the present study, an index named C_s is defined for the selection of initial solutions. This index is calculated as follows (Tavakkoli-Moghaddam et al., 2011):

$$C_s = \frac{\text{rank}}{\text{crowding_dis}} \quad (78)$$

This is calculated for each of the available solutions.

rank = number of the rank the available solutions belong to

crowding_dis = crowding distance of each solution commensurate with its rank

After calculating the above index for all solutions, the solutions are ascending sorted in terms of C_s and the N first solutions with lower C_s are selected as the initial algorithm solutions. The use of C_s is premised upon the logic that solutions of higher quality and dispersion should be selected as the initial population. Solutions developed using this procedure, are improved so far as possible. The improvement procedure is described in the following section.

3-1-3- Improvement procedure

In the proposed structure of the bee colony optimization algorithm, an improvement procedure is developed which can be applied to the solutions selected in the previous section. The solutions produced through this procedure are selected as the next iteration population of the algorithm. In this study, the improvement procedure is implemented based on the variable neighborhood search (VNS), which uses four neighborhood search structures (NSS). These structures are in the form of VNS (See Tavakkoli-Moghaddam et al., (2011) for additional information on these structures). Each of the solutions in the population is inserted into the VNS algorithm and one single solution is received as the output. Next, the improvement procedure is applied on the remaining solution matrices to feasibly modify and replace the input solution. In addition, the neighborhood search operators used in the VNS structure are as follows:

- The first neighborhood search operator: In this structure, one of the distribution centers is randomly selected and its location matrix is changed.
- The second neighborhood search operator: In this structure, one of the collection centers is randomly selected and its location matrix is changed.
- The third neighborhood search operator: In this structure, one of the recycling centers is randomly selected and its location matrix is changed.
- The fourth neighborhood search operator: In this structure, one of the disposal centers is randomly selected and its location matrix is changed.

For changing the location matrix in the above-mentioned operators, the index of one of the centers is randomly selected and its corresponding entry is changed to 1 if it is zero, or to zero if it is 1 (with regard to the restrictions on the minimum number of centers established).

Since new solutions may be developed during the execution of the algorithm, a procedure is developed to check the feasibility of solutions and change infeasible solutions into feasible ones. This procedure evaluates the meeting of all constraints in a solution and tries to change them to feasible solutions if one or more constraints are not met. The mechanism of this procedure is as follows: based on new location matrices, the flow of goods between centers using old or new vehicles is established with regard to the cubic and weight capacity constraints of vehicles as well as capacity constraints of distribution centers. Next, the variables pertaining to routing and the flow of goods are re-initialized.

3-1-4- Local search (p1 and p2 groups of bees)

As observed in the overall structure of the algorithm, bees are divided into two groups, namely, p1 and p2. Guided local search and total random local search are applied to p1 and p2, respectively. The neighborhood search applied to p1 is a parallel structure which combines the above-mentioned four neighborhood operators in a parallel manner. Each of the solutions available in p1 is entered into this structure as the input to make it possible for the algorithm to achieve a better solution. To apply the

neighborhood search on each of the solutions available in p2, one of the above-mentioned four neighborhood operators is randomly selected and applied to the group's solutions. The output, whatever it is (better or worse), will replace the existing solution.

3-1-5- Selection of next-generation solutions

At each stage of the bee colony optimization algorithm, N (the population size) locations are selected from among the old and new locations as best solutions while taking their fitness values in to consideration (measured by C_s in this study). Accordingly, C_s value is calculated for all of these locations and they are ascending sorted based on this value. Finally, the first N locations are selected.

3-1-6- Pareto archive upgrading

Due to the conflict between the objectives, there is no single solution to multi-objective problems. In such problems, all the objectives are optimal. Therefore, a set of solutions containing the dominant solutions is provided. These dominant solutions represent the optimal (near-optimal) solutions. Here, a method based on Pareto archive is used for to solve the problem. This method puts much importance on the quality of available solutions. As a result, this archive is upgraded in each iteration of the algorithm. To this end, all solutions available in this archive and the new ones are entered into a solution pool and ranked. Next, all the solutions belonging to the first rank are taken as the solutions to the new Pareto archive.

4- Computational results

In this study, the model is first solved for a small-sized sample problem using GAMS and bee colony optimization (BCO) algorithm in order to validate the model and algorithm, after which the results of GAMS and the proposed algorithm are compared. After this step, in order to assess the efficiency of BCO algorithm and GA, the model and the proposed algorithm are implemented in MATLAB and their results in solving the generated sample problems are compared with respect to comparative indices of quality, uniformity, sparsity, and solution runtime. It should be noted that computations are done using i7 7500U - 12GB -1TB -R5 M335 4GB Core.

4-1- Comparative indices

There are various and varied indices for assessing the quality and dispersion of multi-objective metaheuristic algorithms. In this study, three indices, namely, quality, uniformity, and dispersion (Tavakkoli-Moghaddam et al., 2011), which will be explained below, are used for comparisons.

Quality metric: This metric compares the quality of Pareto solutions obtained from each method. In fact, this metric ranks all Pareto solutions obtained from both bee and genetic algorithms and shows the percentage of solutions included in the first rank belonging to each method. The higher the percentage, the higher the algorithm's quality is.

Spacing metric: This metric examines the spacing of distribution of Pareto solutions on their border. This metric is defined as follows:

$$s = \frac{\sum_{i=1}^{N-1} |d_{mean} - d_i|}{(N-1) \times d_{mean}} \quad (79)$$

Where, d_i and d_{mean} represent the Euclidean distance between two adjacent non-dominant solutions and the mean values of d_i , respectively.

Diversity metric: This metric is used to determining the number of non-dominant solutions found on the optimal border. This metric is defined as follows:

$$D = \sqrt{\sum_{i=1}^N \max(\|x_t^i - y_t^i\|)} \quad (80)$$

Where, $\|x_t^i - y_t^i\|$ denotes the Euclidean distance between the two adjacent solutions of x_t^i and y_t^i on the optimal border.

4-2- Experimental problems

In the present study, several problems are developed in small, medium, and large groups. Since there is no typical problem in the literature to suit the model presented in this study and cover all its components, some of the previous studies are examined to develop the required experimental problems. The typical problems are used, as far as they are consistent with the model, and those parameters not covered by these problems are randomly selected. In addition, in order to determine some additional experimental problems, previous studies are reviewed and experimental problems are developed by taking the size range of selected problem into consideration.

4-2-1- Experimental problems

Small-sized problems are selected based on problems solved by Kannan et al. (2010). Problems solved by these scholars do not cover all the parameters of the present model. The parameters not covered in Kannan et al.'s study are randomly selected. The number of products, forward logistics facilities, reverse logistics facilities, and vehicles is 1, 2, 2-5, and 3, respectively.

For the development of medium- and large-sized problems, a number of problems found in the relevant literature are reviewed. Next, with regard to the sizes mentioned in the literature, the size of medium and large problems and also a number of problems with a size larger than those in the previous studies are determined (Pishvae et al., 2011, Wang & Hsu, 2010, Omidi-Rekavandi et al., 2014). The designed problems are presented in table 2., where S denotes the number of goods, I the number of manufacturing centers, J the number of distribution centers, L the number of customer centers, M the number of collection centers, p the number of recycling centers, and N the number of disposal centers.

Table 2. designed problems

Number of Problem		S	I	J	L	M	P	N	Number of Problem		S	I	J	L	M	P	N	
Small-Sized	1	1	2	2	2	2	2	2	Large-Sized	14	1	10	20	30	16	7	6	
	2	1	2	2	2	3	3	3		15	2	10	20	30	16	7	6	
	3	1	2	2	2	4	4	4		16	3	10	20	30	16	7	6	
	4	1	2	2	2	5	5	5		17	1	15	40	70	35	12	10	
Medium-Sized	5	1	3	7	7	7	5	4		18	2	15	40	70	35	12	10	
	6	2	3	7	7	7	5	4		19	3	15	40	70	35	12	10	
	7	3	3	7	7	7	5	4		20	1	15	45	90	40	15	13	
	8	1	6	8	10	8	6	5		21	2	15	45	90	40	15	13	
	9	2	6	8	10	8	6	5		22	3	15	45	90	40	15	13	
	10	3	6	8	10	8	6	5										
	11	1	7	9	15	9	7	7										
	12	2	7	9	15	9	7	7										
	13	3	7	9	15	9	7	7										

4-3- Parameter setting

The algorithm parameters are set as follows:

- In the bee algorithm, the population size is equal to 200, watch bees accounted for 50% of the population, and the number of iterations in the parallel search algorithm is equal to 5.
- In the genetic algorithm, rates of 0.8 and 0.1 are considered for intersection and mutation, respectively, and the population size is estimated 150.

A study conducted by Pouralikhani et al. (2013) was taken as the basis for setting and initializing the model parameters. Since the model presented in their study did not cover some parameters of the model proposed in the present study, attempts are done to develop random which are logical compared to other values.

In order to develop triangular numbers associated with each fuzzy parameter (m_1 , m_2 , m_3), m_2 is first produced and then random number r is developed in the range of 0 and 1. Parameters m_1 and m_3 are also produced using equations $m_2*(1-r)$ and $m_2*(1+r)$, respectively. To initialize the fuzzy parameters, m_2 is determined based on the aforementioned article [20] and m_1 and m_3 are determined in MATLAB. As a

result, only the value of m2 is mentioned in the development of these parameters. The following values are taken into account in the development of typical problems.

Table 3. Parameter setting

Parameter	Range	Parameter	Range
\tilde{r}_{is}^t	triangular fuzzy numbers of (m1, 10, m3)	w_k	~Uniform (1000,1600)
\tilde{d}_{is}^t	triangular fuzzy numbers of (m1, 100, m3)	w_c	2
ca_j	4000	v_f	2
\tilde{f}_p	triangular fuzzy numbers of(m1, 15000, m3)	v_k	~Uniform (70,100)
\tilde{f}_n	triangular fuzzy numbers of (m1, 5000, m3)	α_k	~Uniform (0.1,0.2)
\tilde{f}_m	triangular fuzzy numbers of(m1, 10000, m3)	vol_s	~Uniform (1,20)
\tilde{f}_j	triangular fuzzy numbers of(m1, 6000, m3)	w_s	~Uniform (1,20)
p_f	1000	p_c	500

- All distances between centers are randomly developed in the same range [1, 50].
- For ranking the fuzzy numbers, α is determined to be equal to 0.8.

4-4- Model validation results

In order to validate the model, the two-objective model is transformed into a single-objective model using the LP-metric method. The resulting single-objective model is then solved in GAMS for small-sized problems.

This study employed the LP-metric method which is popular in the literature study on multi-objective problems. Our goal is to minimize the deviations of the objective functions from their optimal value. In this method, individual solutions are first calculated for each of the objective functions, and then the following objective function is minimized:

$$\min z = [w^*(f_1(x) - f_1(x^*))/f_1(x^*)] + [(1 - w^*)(f_2(x) - f_2(x^*))/f_2(x^*)] \quad (81)$$

where $f_1(x^*)$ is the optimal solution of the first model by considering the first objective function, $f_2(x)$ is the value of the second objective function based on the optimal solution of the model obtained using only the first objective function, $f_2(x^*)$ is the optimal value obtained from the solution of the model by taking into account the second objective function, and $f_1(x)$ is the value of the first objective function based on the optimal solution of the model only using the second objective function. Moreover, w^* is the weight of the objective functions.

The presented model is programmed in GAMS and is solved using the BARON solver. In this method, the value of P is set to 1 and weight of the objectives is all considered 0.5. Small-sized problems are solved using the BCO algorithm and GAMS aiming to optimize the LP-metric method. The solutions of the small-sized problems solved using the proposed algorithms and GAMS are compared in table 4. As shown, the gap between the results of the BCO algorithm and GAMS is very small, indicating the validity of the algorithm and its convergence to the optimal or near-optimal solution.

Table 4. Solution results obtained using GAMS and BCO algorithm.

Number of Problem	BCO	GAMS	GAP
1	1155210000	1036630000	0.103
2	1134960000	1082488000	0.046
3	12377340000	11700220000	0.055
4	17412300000	15699798000	0.098

In the above table, the gap between values is calculated using the following relation:

$$GAP = \frac{Objective\ value_{BCO} - Objective\ value_{GAMS}}{Objective\ value_{BCO}} \quad (82)$$

4-5- Executive results

In this section, the developed experimental problems are solved using the bee colony and genetic algorithms and the results are analyzed. In the following table, the results of the two algorithms are shown in terms of comparative indices.

Table 5. The results of solving small-sized problems

Number of Problem	BCO			GA		
	Quality Metric	S (Spacing Metric)	D (Diversity Metric)	Quality Metric	S (Spacing Metric)	D (Diversity Metric)
1	79.52	1.34	513.7	20.47	0.79	306.6
2	69.73	1.5	510.5	30.27	1.03	313.4
3	83.41	0.84	542.2	16.59	0.51	329.3
4	100	0.97	539.4	0	0.85	343.2

Table 6. The results of solving medium-sized problems.

Number of Problem	BCO			GA		
	Quality Metric	S (Spacing Metric)	D (Diversity Metric)	Quality Metric	S (Spacing Metric)	D (Diversity Metric)
5	76.27	1.35	1399.1	23.73	1.03	969.1
6	87.13	0.98	3167.8	12.87	0.73	1931.4
7	88.76	1.11	4596.9	11.24	0.45	1671.7
8	96.99	1.05	4368.3	3.01	0.71	1857.2
9	81.99	0.81	2436.7	18.01	0.84	1643.7
10	75.79	1.25	3857.3	24.21	0.49	2245.7
11	92.11	0.58	4028.1	7.89	0.83	2784.5
12	91.41	0.84	4464.2	8.59	0.77	3740.5
13	100	1.07	7895.4	0	0.69	4540.7

Table 7. The results of solving large-sized problems

Number of Problem	BCO			GA		
	Quality Metric	S (Spacing Metric)	D (Diversity Metric)	Quality Metric	S (Spacing Metric)	D (Diversity Metric)
14	100	0.96	7678.9	0	0.52	5739.3
15	81.53	1.12	7945.1	18.47	0.71	5858.5
16	100	1.17	8939.5	0	0.74	6619.7
17	100	1.02	8393.8	0	0.66	6941.2
18	93.11	0.98	9116.3	6.89	0.77	8456.2
19	88.61	0.89	9253.7	11.39	0.54	8564.6
20	85.13	1.24	9894.1	14.87	0.67	9391.2
21	86.37	0.71	10291.6	13.89	0.62	9472.9
22	100	0.97	10749.4	0	0.78	9248.8

As can be seen in the above tables, in all small-, medium, and large-sized problems, values of quality and diversity indices obtained for the bee colony algorithm are greater than their corresponding values calculated through the genetic algorithm. This suggests the higher ability and power of the bee colony algorithm in achieving the near-optimal solution and exploring its feasible region. In addition, the spacing metric showed that in most cases, the genetic algorithm searches the solution space in a more uniform manner. Figure 2 indicates that the runtime of problems in the bee colony algorithm is always longer than that of the genetic algorithm. In other words, the bee colony algorithm needs more time for solving these problems. It should be noted that as the size of the problem increases, the runtime increases too. Thus, the runtime of large-sized problems is longer than that of small- and medium-sized ones. This indicates the large-sized problems are hard problems. The following figure shows the comparison between the runtime of problems in the bee colony algorithm and the genetic algorithm.

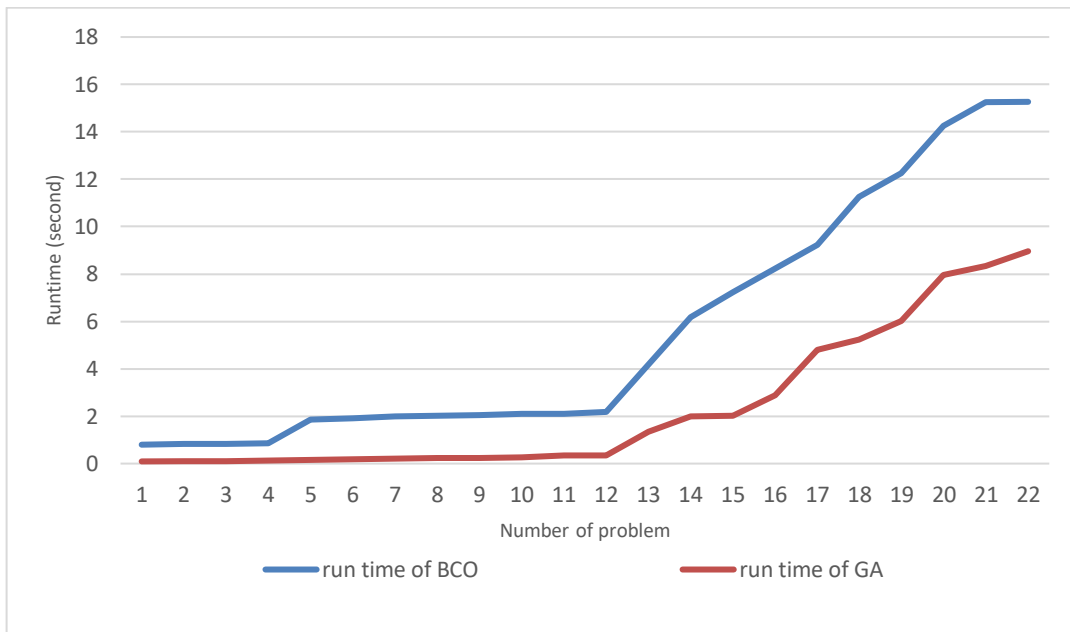


Fig 2. Runtime comparison (seconds)

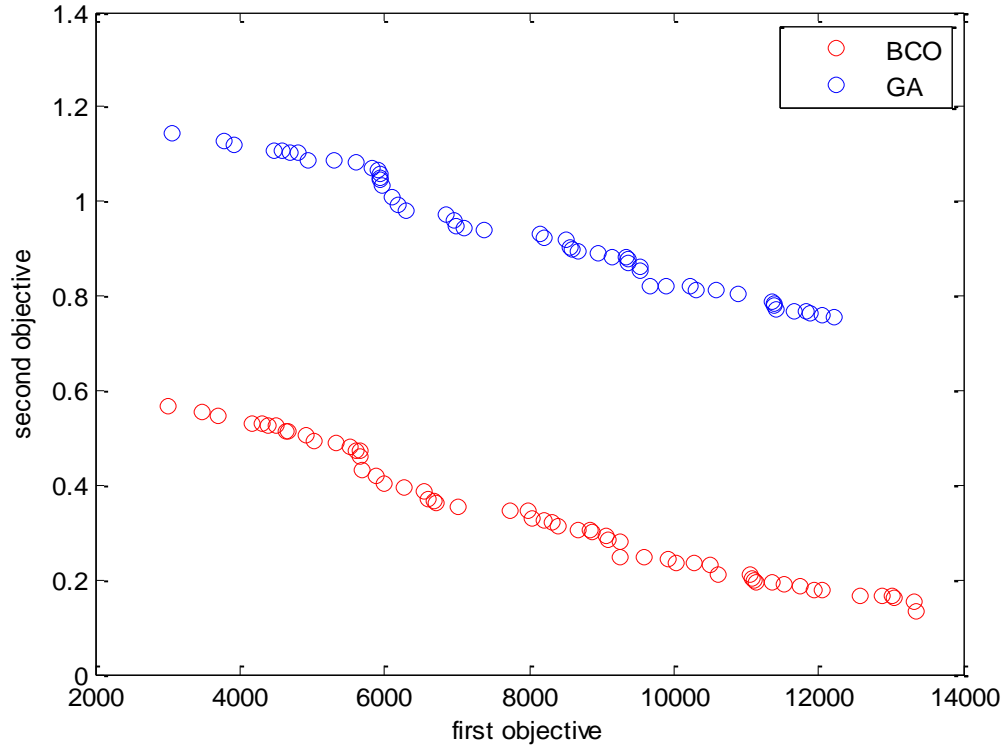


Fig 3. Pareto front for problem number 22 from large-sized problems

As shown in figure 3, the quality of solution obtained from the bee colony optimization (BCO) algorithm is higher than that of the genetic algorithm (GA). It also indicates that by reducing the second objective function, the first objective function increases and vice versa. This suggests the contradiction between the objective functions in the mathematical model proposed. In addition, the comparison between the Pareto front of the two algorithms demonstrates the good performance of BCO and its convergence towards optimal and near-optimal solutions.

5- Conclusion

The present study explored the robust optimization of PRP in a closed-loop supply chain aimed at reducing CO₂ and CO emissions. In other words, this study sought to find a solution to simultaneously achieve robust optimization and carbon emission minimization in a closed-loop supply chain. In the proposed model, PRP is studied by considering the condition of simultaneous pickup and delivery of goods in the supply chain. To this end, a multi-objective robust optimization model is proposed and the bee colony and genetic algorithms are used to solve the model. Abased on the literature review, typical experimental problems are developed in three different sizes, namely, small, medium, and large, and the results obtained through the two algorithms are compared in terms of quality, diversity, spacing, and runtime. The results showed that the bee colony algorithm performs more efficiently in the exploration and extraction of the feasible region and finding near-optimal solutions. In terms of the spacing metric and runtime, the genetic algorithm had a better performance than the bee colony algorithm. In addition, the variations in runtime resulting from the increase in the problem size further confirmed that the studied problem is an NP-HARD problem. It is recommended to develop the present model in future studies by taking various aspects of sustainability into account (environmental, social, and economic). Moreover, uncertain parameters can be considered as combined, fuzzy, or probabilistic parameters. It is also recommended to adopt other approaches to solving the model and compare the results.

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