Journal of Cleaner Production 318 (2021) 128577

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

A fuzzy multi-objective optimization model for a sustainable reverse logistics network design of municipal waste-collecting considering the reduction of emissions

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ARTICLE INFO

Handling Editor: Govindan Kannan

Keywords:
Reverse logistics
Municipal waste-collecting
Reduction of emissions
Fuzzy mathematical programming
Multi-objective metaheuristic algorithm
NSGA II
Bee colony algorithm

ABSTRACT

The most important reason for waste collection is the protection of the environment and the health of the population. Reverse logistics is applied in the sustainable management of municipal waste and is used in the collection, recycling and reuse, as well as the reduction of consumables and environmental compatibility. One of the challenges of sustainable management is costs and customer demand must be considered simultaneously. In this paper, we try to address a comprehensive approach by applying fuzzy mathematical programming to design a multi-objective model for a reverse logistics network. To cover all aspects of this system, we tried to minimize the cost of facility construction, vehicle fuel and environmental damage from the emission of polluting gases, as well as minimize the sum of the ratio of unanswered customer demand to the amount of their demand for all periods, as objective functions of the model. In order to obtain solutions on the Pareto front, a customized multi-objective genetic algorithm (NSGAII) and a customized bee colony algorithm (BCO) were applied. The results of the two algorithms according to the indicators of quality comparison, spacing, diversification and solution time have been compared. The results showed that in all cases, the bee colony algorithm was better able to explore and extract the area to a feasible solution and to achieve near-optimal answers. In terms of spacing metric and resolution time, the genetic algorithm performed better than the bee algorithm.

1. Introduction

According to the American Reverse Logistics Executive Council (ARLEC), reverse logistics are defined as; an efficient planning, implementation and control process with the effective cost of raw materials flow, ongoing assets, final products and related information from destination point to origin point with the aim of recovering for the purpose of capturing value, or proper disposal (Zhou and Wang, 2008). Over the past decades, the concept of reverse logistics has emerged due to environmental pollution, increased waste of resources, and greenhouse gas emissions. Reverse logistics is also defined as all logistics activities for products that have reached the end of their life or that require a series of processes for further improvement. Other definitions of reverse logistics include all supply chain activities that occur in reverse. Overall, the most important principle in reverse logistics is that many materials that are so-called unusable or unused by the consumer are valuable and can be re-entered into the supply chain with a little modification and restoration. Reverse logistics application, one of the most essential logistics activities in the present era, is the process of collecting municipal waste. It starts with garbage collection and ends with the waste recycling process (Habibi et al., 2017). Reverse logistics has received a lot of attention due to its ability to recover value from returned and used products and has become a key element in the supply chain. Legal requirements, social responsibilities, environmental concerns, economic benefits, and customer awareness have led manufacturers to not only produce environmentally friendly products, but also to regain and collect returned and used products (Mutha and Pokharel, 2009). When it comes to reverse logistics, we are actually talking about the core component of the overall supply chain. Most people's perception of the supply chain is as a forward-looking network in which raw materials enter and are transformed into products that are distributed among customers. While reverse logistics work in the opposite direction, there are many other differences between the two processes. Among all these differences, the first and most fundamental difference is that reverse logistics depends on the product (Marcotte et al., 2008).

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https://doi.org/10.1016/j.jclepro.2021.128577
Received 10 November 2020; Received in revised form 2 August 2021; Accepted 5 August 2021
Available online 12 August 2021

Table 1
Differences between Forward and Reverse Logistics.

Forward Logistics	Reverse Logistics
1. Forecasting based on demand 2. Uniform product quality 3. Uniform product packaging 4. Clear processing sequence 5. Pricing relatively uniform 6. Forward distribution costs are closely monitored by accounting systems 7. Inventory management consistent 8. Real-time information readily available to track products	1. Forecasting is difficult as quantity of returned products can be hard to predict 2. No uniform product quality 3. No uniform packing due to nonexistent product packaging 4. Processing sequence is unclear until each individual product is tested and sorted and the various disposition options are considered 5. Pricing dependent on many factors 6. Reverse logistics costs are less directly visible and cannot always be planned until products are sorted 7. Inventory management not always consistent 8. Visibility of process less transparent

The underlying principles of reverse and forward logistics systems are also different, and (Tibben-Lembke and Rogers, 2002) have listed them as follows Table 1:

Reverse logistics is the part of sustainable management that ensures proper processing or elimination of waste in a socially responsible way (Coelho and Mateus, 2017) in order to retrieve the economic and ecological value of a product and thus reduce the mass of generated waste (Cruz Netro et al., 2016). The dynamic development of the methods and concepts of management has led to the implementation of environmental activities in the functioning of organizations and to the creation of necessary tools (Mesjasz-Lech, 2019). In effect, a reverse or environmentally oriented concept of logistics. Reverse logistics can be considered one of the key concepts in a supply chain. It reduces the quantity of waste and enables waste recovery (Safaei et al., 2017). Reverse logistic operations can play a significant role in making existing supply chains greener in terms of a reduction in environmental pollution and the implementation of proper waste management practices (Safdar et al., 2020). The applicability of reverse logistic operation is further enhanced by giving customers the option to return products that are either defective or an end-of-life product with a remaining warranty period. Similarly, firms are also shifting their focus towards reverse logistics due to current environmental regulations, shorter product lifecycles, and greater waste generation (Seamus and Anita, 2016). The notion of reverse logistics is gaining attention in both academia and practice, in terms of how environmental and economic perspectives should be incorporated to enhance the performance of reverse logistic operations (John et al., 2017). Also, firms have started realizing that the implementation of reverse logistic operations has a potential for generating a huge amount of revenue or profit while minimizing costs, to remain sustainable and competitive in the market (Morgan et al., 2018). On the other hand, we must also consider education and awareness to reduce emissions can be practiced through the consideration of production, inventory, and routing-related supply chain optimization problems. Recycling and remanufacturing to reduce emissions and to be environmentally friendly are best demonstrated through closed-loop supply chains (Shuang et al., 2019). Due to the rapid growth of technology over the past few decades and the consequent competition between companies due to increasing customer expectations and the beginning of globalization, companies and organizations have become more focused on in-house activities. Create your own efficient supply chain to increase your collaboration with other companies and organizations. Reverse logistics seeks to examine and manage reverse flows in supply chains (Manavizadeh et al., 2020). One of the main applications of reverse logistics is waste management. Waste management is an important and growing industry. The national health, environment, and economic wellbeing are important factors in any society. Hazardous waste refers to those wastes that, as nonfunctional materials, can be harmful to the environment. According to (Alumur and Kara, 2007), waste is considered harmful if it has characteristics such as flammability, corrosion, reactivity, and toxicity. Field and Sroufe (2007), Baumgarten et al. (2004) both noted the importance of proper and efficient waste recycling and reuse in manufacturing and logistics centers. While (Hicks et al., 2004) stated that proper and efficient waste management can reduce costs and create a new supply chain that allows materials to be recycled and reused.

Given the importance of using reverse logistics in trash collection and the importance of vehicle routing in this scope, the present study aims to provide a multi-objective mathematical model for vehicle routing to collect municipal waste in the reverse supply chain. In this regard, a mathematical model was developed, taking into account sustainability, and then multi-objective meta-heuristic algorithms based on the Pareto Archive were used to solve the model.

This paper is organized into six sections. Section 2 provides an overview of the design of logistics networks and the classification and coding using the defined criteria. In Section 3, the assumptions, goals, and outcomes of the problem are precisely defined. Then, the definitions of the parameters and variables of the decision as well as the integrated mathematical model of the reverse supply chain network are presented. Section 4 describes the proposed structure of the metaheuristic algorithms used to solve the problem. Section 5 presents the results of the model solution using the proposed meta-initiative algorithm for several experimental cases, and finally, Section 6 discusses general conclusions and suggestions for future research.

In this research, MATLAB software was used to implement the solution algorithms. To analyze the comparative results, criteria to compare multi-objective problems were first designed and then used to analyze the output results of the algorithms. MINITAB software was used to adjust the parameters of the model to solve the experimental problems.

2. Literature review

In the supply chain, return management is applied in the form of reverse logistics, and for many different reasons, the flow of materials and goods in the opposite direction of the chain is inevitable. With regards to the issue of a reverse logistics network, management and guidance are necessary for it to be effective. Khastoo et al. (2017) studied the profound ongoing changes and developments in the business world as well as the new requirements of production and trade in the current era that provide the basis for the appearance of new attitudes and paradigms that should need to be considered by those involved in the field of production and trade. One of these new trends in logistics management is recovery, recycling, or reuse of products. In this way, products that reach the end of their useful life are repurchased from the end consumer, disassembly, and the parts that can be reused are returned to the product life cycle in the form of scrapped products. In recent years, increasing attention to environmental issues and the growth of opportunities to save on costs and resources or increase revenue through returned products has encouraged researchers to study reverse logistics. Khansalar et al. (2015) researched many activities being done around the world in the design of logistics networks, including various models for optimizing and locating facilities based on integer programming. Reverse logistics is a process consisting of a chain of activities that starts from collecting returned products from the consumers and ends when those returned products are reprocessed and are ready to be sold again (Safdar et al., 2020). Dekker et al. (2013) defined reverse logistics as "complete coordination and control, physical loading and delivery of materials, parts and products, from the place of consumption to the place of operation and recovery or disposal and then subsequent return to the place of use in appropriate cases". The issue of location is related to the selection of a set of candidate points for the establishment of the facility. The term reverse logistics is becoming increasingly associated with waste management, mainly due to increasing social concerns about the environment. In fact, municipal solid waste management can be considered one of the reverse logistics issues in supply chain management (Demirel and Gökçen, 2008). At present, academic circles are engaged in extensive discussion on the resource utilization of municipal solid waste, and research on the reverse logistics of municipal solid waste is gradually being carried out in the continuous extension of logistics studies. Certain developed countries have formed complete management systems for the management of municipal solid waste that integrate the information flow, logistics, and capital chain of municipal solid waste to achieve an efficient operation. Research on reverse logistics has attracted widespread attention, and the main body of research has been carried out in residential areas and operating stations (Hu and Yang, 2020). The relationship between reverse logistics and waste management occurs in activities in the reverse distribution channel such as reusing, recycling, and proper waste treatment (Kinobe et al., 2015). Municipal waste and waste, in general, can be treated as redundant objects that have lost their initial functionality but which present value in terms of their secondary function (Bajdor et al., 2016). Interest in environment preservation has increased during the last decade, and environmental aspects play an important role in strategic and operational policies, especially in urban areas where waste generation is increasing with population growth. Thus, green logistics have arisen, extending the traditional definition of logistics by explicitly considering external factors associated mainly with climate change and air pollution. Waste Collection Vehicle Routing Problems (WCVRP)s are clearly part of green logistics as they reduce environmental impact by optimizing energy usage in reverse logistics activities and by reducing waste and managing its treatment (Sbihi and Eglese, 2007). Several studies have focused on developing mathematical models to aid in different aspects of waste collection vehicles, waste site selection, and bin location. Molina et al. (2019) presented a mathematical model with an environmentally friendly objective function for routing vehicles for garbage collection. The problem is first heuristically solved using a semi-parallel construction algorithm. Then, solutions are improved by a variable neighborhood tabu search algorithm developed for this problem. Lee et al. (2016) developed a mathematical model of integer linear programming for Hong Kong's municipal solid waste management. They used sensitivity analysis to simulate different scenarios. Galvez et al. (2015) designed a network for reverse logistic operations carried out for the management of waste for which they have focused on the economic dimension by minimizing the cost of buying or hiring a vehicle and then using that vehicle for transportation purposes. Li et al. (2017) solved the problem of optimizing the site selection of domestic solid waste stations based on the improved maximum covering location problem (MCLP) model. The purpose is to reduce the operating costs in the logistics process through the optimization of site selection. Ghiani et al. (2012) developed an integer programming model for locating segregated waste collection bins in the city, as well as for determining the capacity of each bin located at each collection center. Other studies took a more integrated approach. Fleischmann et al. (2001) proposed a well-mixed linear integer-programming model for a direct-reverse integrated network design. In their network, they collect the products consumed by the customer and redistribute them after reconstruction. Salema et al. (2009) presented a more comprehensive model for an integrated logistics network design after correcting the weaknesses of (Fleischmann et al., 2001). Other considerations in the network included uncertainty about parameters such as demand, rate of return on products, and variable costs. More recent studies have begun to take a more inclusive look at a reverse or closed-loop supply chain. Ko and Evans (2007) presented a nonlinear integer-programming model for the simultaneous design of a reverse and frontal network. They also developed a genetic algorithm to solve the model. Aras and Aksen (2008) focused on the reverse supply chain and, with the aim of maximizing the profitability of the chain, sought to optimize decisions about returned products. They developed a nonlinear mathematical model of location–allocation to find the optimal location of collection centers and to provide the optimal amount of returned products with different levels of quality. Finally, they solved the model using an innovative method based on the Tabu search algorithm. Kannan et al. (2009) presented a coherent closed-loop multi-level supply chain for built environments based on order. They used genetic algorithms and particle optimization to solve the problem. Kannan et al. (2010) developed a multi-level, multi-period, and multi-product supply chain network for returned products and decisions regarding the supply of materials, production, distribution, recycling, and disposal. The proposed innovative method was based on a genetic algorithm used as a solution-based methodology. Sasikumar et al. (2010) presented a nonlinear mixed-integer programming model for maximizing multi-level reverse logistics network profitability, as well as a real-time case study of truck tire reproduction for the secondary market segment. Lingo software was used to solve the model. Liang (2006) proposed a dynamic reverse logistics network under demand uncertainty. The integration of the sampling method proposed was developed with the refrigeration simulation algorithm as the solution method. El-Sayed et al. (2010) presented a multi-level forward-reverse logistics network design model with uncertain demand and return, with the aim of maximizing the closed-loop supply chain profitability. Ruimin et al. (2016) provided a strong environmental supply chain network that includes manufacturing centers, customer centers, collection centers, and disposal centers. They presented a multi-objective integer nonlinear planning model that considered two conflicting goals simultaneously. The first goal was to minimize economic costs, and the second goal was to minimize the impact of the supply chain on the environment. They solved the model using the LP metric method. Finally, by providing an example, they demonstrated the efficiency of the model. Bottani and Casella (2018) examined the issue of a stable closed-loop supply chain, taking into account the reduction in emissions of environmental pollutants. They provided a model for this problem and then solved the model using a simulation tool for a case study and concluded reverse logistics (RL) and the closed-loop supply chain (CLSC) are integral parts of the holistic waste management process. Several review articles have been written on reverse logistics and closed-loop supply chains. Islam and Huda (2018) selected, classified, and analyzed papers published between 1999 and 2017 in these fields. They described one of the most important study gaps as, "In RL and CLSC network designing, lack of studies considering different modeling objectives, problem formulation and solution approaches are discussed, and future opportunities are advised. Scope of utilizing multi-objective programming considering different uncertainty parameters is highlighted and prescribed for further research". Govindan and Soleimani (2017) selected and reviewed 83 articles accepted as of December 31, 2014. They reviewed the articles based on their content and the categories they developed. Among the articles reviewed, they found only four articles (4.8%) discussed mathematical optimization that considered profit maximization or cost minimization. Tosarkani and Amin (2018) introduced an optimization model consisting of several layers, components and products for different periods for the reverse logistics network. From a linear multi-purpose planning model (MILP) to maximize total profit, green practices and on-time delivery by minimizing defect rate In the proposed reverse logistics network, they have used several purposes. Finally, the multi-objective model is solved to achieve non-dominant solutions between the objectives. Kuşakcı et al. (2019) developed a fuzzy mixed integer location–allocation model for a reverse logistic network of end-of-life vehicles conforming to the existing directives. Zarbakhshnia et al. (2019) proposed a complex integer linear programming model to design and program a forward and reverse green logistics network. This model is used for a multi-stage, multi-product and multi-objective problem. The first goal is to minimize the costs of the institution's operations, processes, transportation, and fixed costs. The second goal is to minimize CO_2 emissions, while the third goal is to optimize the number of machines on the production line. In terms of the solution method, an Epsilon constraint method has been developed as the optimization region in order to achieve a set of Pareto solutions. Yin et al. (2021) proposed an inexact two-stage multi-objective planning (ITMOP) model for supporting municipal solid waste (MSW) management. This model advanced existing optimization methods through integrating interval linear programming and two-stage stochastic programming within the multi-objective programming framework, where various uncertainties expressed as interval value and probability distributions were effectively reflected. Ooi et al. (2021) developed a novel multi-objective mixed-integer linear programming with the augmented ϵ-constraint method to assess the optimum Municipal solid waste (MSW) allocation on seven conventional waste processing facilities, including open landfills, material recycling facility, sanitary landfills, anaerobic digestion, composting, incineration, and plasma gasification. In this study, the avoided emissions of the valuable products valorized from MSW, which have been often neglected in the optimization model, are included in the study to investigate the extent of emissions reduction in the MSW management system. Abdallah et al. (2021) proposed model determines the optimum allocation of the different waste streams to selected waste management facilities, including material recovery facilities (MRFs), incinerators, anaerobic digestion (AD) plants, and sanitary landfills with gas recovery. The waste generated was divided into three streams, namely readily biodegradables, recyclables, and non-recyclables. The model objectives included maximum material and energy recovery, financial profitability, as well as minimum carbon footprint. The optimum hybrid strategy was based on the relative importance of each objective, which was acquired through a Fuzzy Analytic Hierarchy Process (AHP). Lu et al. (2020) address the optimal design of a hybrid assembly-recycling network that simultaneously integrates the forward and reverse logistics among its multi-product multi-echelon superstructure. Various types of uncertainties on return flow and waste flow are investigated. To optimize the dual-system superstructure, the problem is hereby modeled by a fuzzy mixed integer linear programming approach. Further, an interactive fuzzy optimization approach is developed to solve the problem by differentiating the piece-wise sections of satisfactory degrees.

Most articles maximize profits, and there is nothing in the literature that simultaneously examines economic and environmental objective functions such as minimizing costs and minimizing greenhouse gas emissions. Despite the lack of mathematical studies in this field, a multi-objective model with fuzzy parameters that reduce costs (such as vehicle use costs, facility construction costs, and environmental costs) as well as minimizes waste and the ratio of unanswered customer demand to total demand for all periods is provided in this study. The simultaneous use of two meta-heuristic algorithms and comparison of the obtained results studied here was rarely found in the thematic literature.

3. Problem definition and model formulation

First, the problem is defined, then the model assumptions, indices, parameters, and model variables are presented.

3.1. Problem definition

Given the importance of the green supply chain issue, emission of polluting gases, and considering the uncertainty of the parameters of this issue, this section presents a mathematical model for reverse logistics of municipal waste collection considering the reduction of emissions in fuzzy conditions. The proposed model is a fuzzy mixed-integer programming model. The objectives of this model are to minimize costs, including the cost of using vehicles and environmental costs, and to maximize satisfying demand.

3.2. Model assumptions

In this paper, several assumptions are considered for mathematical modeling as follows:

- The issue under consideration involves routing and locating by minimizing the emission of carbon gases in the reverse supply chain.
- The reverse supply chain involves several types of waste.
- The number and capacity of vehicles (trucks) are limited and predetermined.
- Vehicle capacity limitation includes a weight limit of transported waste.
- The number of potential points of collection, recycling, and disposal centers is predetermined, and they have a limited capacity.
- The number of demand points (customers) is certain and each customer has demand.
- Customer demand is uncertain and fuzzy.
- All centers of demand must be met by vehicles.
- The distance between the centers is determined.
- The amount of fuel consumption of vehicles in the distance unit is determined according to the speed of the vehicle and the weight of the cargo.
- The price of each unit of fuel consumption is constant.
- The speed of each vehicle is constant.
- The amount of carbon dioxide emissions is determined per unit of fuel consumption.

3.3. Indices, parameters, and variables of the model

The following notations, parameters, and variables are used in modeling the multi-objective reverse logistics network design:

I Index of collection of reproduction centers
K Index of vehicles $k \in K$
L Index of fixed points for customers (waste producer) $l \in L$
M Index of a collection of potential points for collection and rehabilitation centers $m \in M$
N Index of potential points for a landfill and demolition centers $n \in N$
NL Customer center node collection
P Index of potential points for recycling centres $p \in P$
S Waste collection index $s \in S$
T Period index $t \in T$
$\tilde{d}_{lt}^{s}$ The amount of fuzzy demand of the product s by the customer l in period t (the amount of fuzzy demand of customers to collect the waste produced by them)
$\tilde{f}_m$ Fuzzy cost of constructing a collection and recovery at m center
$\tilde{f}_p$ Fuzzy cost of constructing a recycling at p center
$\tilde{f}_n$ Fuzzy cost of building a landfill and demolition at n location
W_k kth vehicle weight
W_c The weight of pollutant emissions per litter of fuel

P_c The average price of emitted gas unit
P_f Fuel price per volume unit
V_f Volume of fuel consumption per unit distance per unit of weight, speed and distance
α_k The kth vehicle's speed change coefficient for more unit weight
V_k kth vehicle speed
W_s sth product weight
vol_s sth product volume
L_{l1l2} Distance between customer centre l1 and customer center l2
L_l Average distance between customer l and collection and revival centers
L_{mp} The distance between the collection and revival centre (m) and the recovery center (p)
L_{mn} The distance between the centre of collection and restoration (m) and the center of landfill and demolition (n)
L_{mi} The distance between the landfill and demolition centre (m) and the reproduction center (i)
QW_k kth vehicle weight capacity
QV_k kth vehicle volumetric capacity
z_m If the collection center is established at point (m), it is equal to 1, otherwise it is 0.
z_p If the recycling centre is established at point (p), it is equal to 1, otherwise it is 0.
z_n If the landfill and demolition centre is established at point (n), it is equal to 1, otherwise it is 0.
y^t_{l1l2k} If the vehicle kth goes from customer l1 to customer l2 in period t, it is equal to 1, otherwise it is 0.
y^t_{lmk} If the vehicle kth from the customer l goes to the collection and recovery centre m in the period (t) it is equal to 1, otherwise it is 0.
y^t_{mnk} If the vehicle kth goes from the collection and recovery centre m to the landfill and demolition centre n in period t it is equal to 1, otherwise it is 0.
y^t_{mpk} If the vehicle kth goes from the collection and recovery centre m to the recycling center p in period t, it is equal to 1, otherwise it is 0.
y^t_{mik} If the vehicle k goes from the collection and recovery centre m to the reproduction centre i in period t, it is equal to 1, otherwise it is 0.
xw^{ts}_{l1l2k} The amount of waste s sent by the vehicle kth from customer l1 to customer j2 during period t and is collected from customer l1.
x^{ts}_{lk} The amount of waste s that is received by the vehicle kth from the customer l in the period t, to be sent to the collection and rehabilitation centres.
x^{ts}_{mk} The amount of waste s sent by the vehicle kth from the customer centre to the collection and recovery centre m in period t.
x^{ts}_{mnk} The amount of waste s sent by the kth vehicle from the collection and recovery centre m to the landfill and demolition centre n during the t period.
x^{ts}_{mpk} The amount of waste s sent by the kth vehicle from the collection and recovery centre m to the recycling centre p in period t.
x^{ts}_{mik} The amount of waste s sent by the kth vehicle from the collection and recovery centre m to the reproduction centre i in period t.
q^t_{ls} Unsatisfied customer (l) demand for waste (s) in period t.

It is noteworthy that the parameters below the tilde are fuzzy parameters.

3.4. Model formulation

The model has two objective functions and 22 constraints.

3.4.1. Objective functions

$$
\begin{aligned}
MinZ_1 = & \\
& \sum_{m=1}^{M} \tilde{f}_m z_m + \sum_{p=1}^{P} \tilde{f}_p z_p + \sum_{n=1}^{N} \tilde{f}_n z_n \\
& + (\sum_{k=1}^{K} (v_f * a_k * v_k * (\sum_{s=1}^{S} (\sum_{t=1}^{T} \sum_{l} (x^{ts}_{lk} * L_l) \times w_s) \\
& + \sum_{m=1}^{M} (x^{ts}_{mk} + \sum_{i=1}^{I} x^{ts}_{mik} * L_{mi} + \sum_{i=1}^{I} x^{ts}_{mnk} * L_{mn} \\
& + \sum_{p=1}^{P} x^{ts}_{mpk} * L_{mp}) + w_s)) * (p_f + w_c + p_c)
\end{aligned}
\tag{1}
$$

Eq. (1) represents the first objective function to minimize construction, and vehicle fuel costs as well as environmental costs resulting from the emission of polluting gases.

$$MinZ_2 = \sum_{t=1}^{T} \sum_{l=1}^{L} \sum_{s=1}^{S} \frac{q^t_{ls}}{\tilde{d}^t_{ls}} \tag{2}$$

Eq. (2) indicates the second objective function of the model to minimize the sum of the ratio of unanswered customer demand to the amount of their total demand for all periods.

3.4.2. Constraints

The proposed model includes the following 22 constraints:

$$\sum_{m} \sum_{k} y^t_{lmk} \geq 1 \qquad \forall l, t \tag{3}$$

Constraint (3) ensures that all customers meet at least one vehicle in all periods.

$$\sum_{k} \sum_{l} y^t_{lmk} = \sum_{k} (\sum_{p} y^t_{mpk} + \sum_{n} y^t_{mnk} + \sum_{j} y^t_{mjk} + \sum_{i} y^t_{mik}) \qquad \forall m, t \tag{4}$$

Constraint (4) Indicates that vehicles imported to customer points and collection and recovery centers must exit from these points.

$$\sum_{k} (\sum_{m} x^{ts}_{lmk} + \sum_{l1} xw^{ts}_{l1lk}) + q^t_{ls} = \tilde{d}^t_{ls} \qquad \forall l, t, s \tag{5}$$

Constraint (5) calculates the amount of unanswered (l) customer demand for (s) waste s in (t) period.

$$\sum_{k} \sum_{l} x^{ts}_{lmk} = \sum_{k} (\sum_{p} x^{ts}_{mpk} + \sum_{n} x^{ts}_{mnk} + \sum_{i} x^{ts}_{mik}) \qquad \forall m, t, s \tag{6}$$

Constraint (6) ensures the balance of waste flow in the nodes.

$$xw^{ts}_{l1l2k} \leq M \times y^t_{l1l2k} \qquad \forall l1, l2, k, t, s \tag{7}$$

$$x^{ts}_{lmk} \leq M \times y^t_{lmk} \qquad \forall l, m, k, t, s \tag{8}$$

$$x^{ts}_{mpk} \leq M \times y^t_{mpk} \qquad \forall p, m, k, t, s \tag{9}$$

$$x^{ts}_{mnk} \leq M \times y^t_{mnk} \qquad \forall n, m, k, t, s \tag{10}$$

$$x^{ts}_{mik} \leq M \times y^t_{mik} \qquad \forall i, m, k, t, s \tag{11}$$

Constraints (7)–(11) guarantee that trash is sent by a vehicle from one center to another if that vehicle has traveled between the two centers.

$$\sum_{l1 \in N} \sum_{l2 \in N} y^t_{l1l2k} \leq |N| - 1 \quad \forall N \in NL : |N| \geq 2 \quad ς \qquad \forall k, t \tag{12}$$

Constraint (12) prevents the creation of sub-tours when vehicles travel between customer points.

$$\sum_{s} (x^{ts}_{mpk} \times w_s) \leq QW_k \qquad \forall m, p, k, t \tag{13}$$

$$\sum_{s} (xi^{ts}_{mpk} \times vol_s) \leq QV_k \qquad \forall m, p, k, t \tag{14}$$

$$\sum_{s} (x^{ts}_{mnk} \times w_s) \leq QW_k \qquad \forall m, n, k, t \tag{15}$$

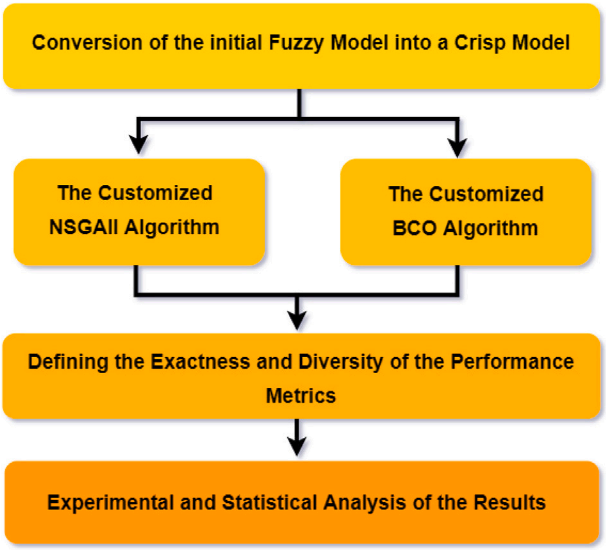

Fig. 1. A schematic view of the proposed approach.

$$\sum_{s}(xi^{ts}_{mnk} \times vol_s) \le QV_k \qquad \forall m,n,k,t \tag{16}$$

$$\sum_{s}(x^{ts}_{mik} \times w_s) \le QW_k \qquad \forall m,i,k,t \tag{17}$$

$$\sum_{s}(xi^{ts}_{mik} \times vol_s) \le QV_k \qquad \forall m,i,k,t \tag{18}$$

$$\sum_{s}\left(\sum_{l}\left((xw^{ts}_{ll1k} \times y^{t}_{ll1k}) + x^{tss}_{l1k}\right) \times w_s\right) \le QW_k \qquad \forall l,k,t \tag{19}$$

$$\sum_{s}\left(\sum_{l}\left((xw^{ts}_{ll1k} \times y^{t}_{ll1k}) + x^{tss}_{l1k}\right) \times vol_s\right) \le Qv_k \qquad \forall l,k,t \tag{20}$$

$$\sum_{s}(x^{ts}_{mk} \times w_s) \le QW_k \qquad \forall m,k,t \tag{21}$$

$$\sum_{s}(xi^{ts}_{mk} \times vol_s) \le QV_k \qquad \forall m,k,t \tag{22}$$

Constraints (13)–(22) ensure that the waste carried by the (k) vehicle does not exceed its weight and volume capacity.

$$\sum_{m=1}^{M} z_m \ge 1 \tag{23}$$

$$\sum_{p=1}^{P} z_p \ge 1 \tag{24}$$

$$\sum_{n=1}^{N} z_n \ge 1 \tag{25}$$

Constraints (23)–(25) ensure that at least one facility will be established for the collection, disposal, and recycling facility.

4. Solving methodology and comparison metrics

Fig. 1 presents a three-step method for solving the model. In the first step, the initial fuzzy model is transformed into an equal crisp model. In the second step, because the problem is NP-hard, the meta-heuristic BCO algorithm is used. Then, the NSGAII algorithm is used to compare the answers. In the third step, the first three comparison metrics (Quality, spacing, and diversification metrics) are defined, and afterward, the solutions obtained by the BCO algorithm and NSGAII algorithm (codified in MATLAB software) are compared based on the three comparison metrics and computational time in MINITAB software.

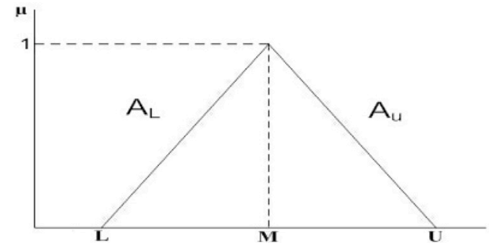

Fig. 2. Triangular fuzzy number.

4.1. The corresponding crisp model

In the development model of the previous section, the demand parameter in the function of the second object and some values in the right hand side are fuzzy numbers. Several methods have been proposed to solve fuzzy mathematical programming problems. In this paper, the ranking method presented by (Jiménez et al., 2007) has been used. They also proposed a method for ranking fuzzy numbers based on comparing their waiting periods.

If the triangular fuzzy number is in the form $\tilde{A} = \{L, M, U\}$, it can be written as follows in Fig. 2:

$$\mu A(x) = \begin{bmatrix} f_A(x) = \frac{X-L}{M-L} & L \le X \le M \\ 1 & X = M \\ g_A(x) = \frac{X-L}{M-U} & M \le X \le U \end{bmatrix} \tag{26}$$

To ensure that the inverse of $f_A^{-1}(x)$ and $g_A^{-1}(x)$ functions are exists, assumed $f_A(x)$ are continuous and ascending and $g_A(x)$ is continuous and descending. The expected phase of a fuzzy number defined as follows:

$$EI(\tilde{A}) = [E_1^{\tilde{A}}, E_2^{\tilde{A}}] = \left[\int_{a1}^{a2} x d f_A(x) - \int_{a3}^{a4} x d g_A(x)\right] \tag{27}$$

By aggregating the components and changing variable:

$$EI(\tilde{A}) = [E_1^{\tilde{A}}, E_2^{\tilde{A}}] = \left[\int_{0}^{1} f_A^{-1}(\alpha)d\alpha - \int_{0}^{1} g_A^{-1}(\alpha)d\alpha\right] \tag{28}$$

If the $f_A^{-1}(x)$ and $g_A^{-1}(x)$ functions be linear and $\tilde{A}$ is triangular fuzzy number, it expecting interval is as follows:

$$EI(\tilde{A}) = [\frac{1}{2}(L+M), \frac{1}{2}(M+U)] \tag{29}$$

In addition, the expecting value of the fuzzy number is half the value of expecting interval.

$$EV(A) = \frac{E_1^{\tilde{A}} + E_2^{\tilde{A}}}{2} \tag{30}$$

and for the triangular fuzzy number of $\tilde{A}$, is as follows:

$$EV(A) = \frac{L + 2M + U}{2} \tag{31}$$

Definitions:

(i) For both fuzzy numbers $\tilde{A}$ and $\tilde{B}$, greater membership degrees of $\tilde{A}$ out of $\tilde{B}$ is as follow:

$$\mu_M(\tilde{A}, \tilde{B}) = \left\{ \begin{matrix} 0 & if\, E_2^a - E_1^b < 0 \\ \frac{E_2^A - E_1^B}{E_2^A - E_2^B - (E_1^A - E_2^B)} & if\, 0 \in [E_1^A - E_2^B, E_2^A - E_1^B] \\ 1 & if\, E_1^A - E_2^B > 0 \end{matrix} \right\} \tag{32}$$

So that $[E_1^A, E_2^A]$ and $[E_1^B, E_2^B]$ are expecting interval of $\tilde{A}$ and $\tilde{B}$.

– if $\mu_M(\tilde{A}, \tilde{B}) = 0.5$, $\tilde{A}$ and $\tilde{B}$ are equal.

– if $\mu_M(\tilde{A},\tilde{B}) \geq \alpha$, $\tilde{A}$ with a minimum degree of α is equal or greater than $\tilde{B}$ and show as: $\tilde{A} \geq_\alpha \tilde{B}$

(ii) Suppose vector $x \in R^n$, it is acceptable with grade α if: $\min\{\mu_M(\tilde{A}x,\tilde{B})\} = \alpha$ (that also it can be shown as $\tilde{A}x \geq_\alpha \tilde{B}$) as a result:

$$[(1-\alpha)E_2^A + \alpha E_1^A]x \geq \alpha E_2^B + (1-\alpha)E_1^B \tag{33}$$

Therefore, according to the above definitions, presented fuzzy model programming can convert to a definite and accurate model as following:

$$MinEV(\tilde{C})x$$
$$s.t:$$
$$x \in \{x \in R^n \mid \tilde{A}x \geq_\alpha \tilde{B}, x \geq 0\}$$

Now, according to the above definitions and using the mentioned method, proposed fuzzy parts of programming model convert to a definite model like it.

Crisp objective functions:

$$\begin{aligned} \min z_1 = &\sum_{m=1}^{M} \frac{f_m^1 + 2f_m^2 + f_m^3}{2} z_m + \sum_{p=1}^{P} \frac{f_p^1 + 2f_p^2 + f_p^3}{2} z_p + \sum_{n=1}^{N} \frac{f_n^1 + 2f_n^2 + f_n^3}{2} z_n \\ &+ \Big(\sum_{k=1}^{K} (v_f * \alpha_k * v_k * \Big(\sum_{s=1}^{S} \Big(\sum_{t=1}^{T} \sum_{l} (x_{lk}^{ts} * L_l) \times w_s\Big) \\ &+ \sum_{m=1}^{M} (x_{mk}^{ts} + \sum_{i=1}^{I} x_{mik}^{ts} * L_{mi} + \sum_{n=1}^{N} x_{mnk}^{ts} * L_{mn} \\ &+ \sum_{p=1}^{P} x_{mpk}^{ts} * L_{mp}) * w_s) + w_k)\Big) * \left(p_f + w_c * p_c\right) \end{aligned} \tag{34}$$

$$\min z_2 = \sum_{t=1}^{T} \sum_{l=1}^{L} \sum_{s=1}^{S} \frac{q_{ls}^t}{\left(\frac{d_{ls}^{t1} + 2d_{ls}^{t2} + d_{ls}^{t3}}{2}\right)_j} \tag{35}$$

Crisp constraint (5):

$$\sum_k \Big(\sum_m x_{lmk}^{ts} + \sum_{l1} xw_{l1lk}^{ts}\Big) + q_{ls}^t = (1-\alpha)\frac{d_{ls}^{t,1} + d_{ls}^{t,2}}{2} + \alpha \frac{d_{ls}^{t,2} + d_{ls}^{t,3}}{2} \qquad \forall l,t,s \tag{36}$$

Due to the conflict between the objective functions in this study, the use of a multi-criteria optimization approach is more appropriate than single-criteria to solve the problem. The fundamental difference between multi-criteria and single-criteria optimization problems is the different and conflicting objective functions in multi-criteria problems. These goals make it impossible to achieve optimal answers using common algorithms for single-criteria optimization problems.

Some Definitions:

1-*Domination relation:*

In multi objective optimization problems, whenever the following two conditions are met, the vector $\vec{x}_1$ dominates the vector $\vec{x}_2$:

(1) $f_i(\vec{x}_1) \leq f_i(\vec{x}_2) \quad i = 1, \ldots, q$

(2) $f_i(\vec{x}_1) < f_i(\vec{x}_2) \quad i = 1, \ldots, q$

Therefore, the main goal in this case is to find a set of points that dominate the other points. The following definitions are given for further clarification.

2-*Local Optimum Points:*

Vector $\vec{x}$ is considered the Local Optimum whenever $\delta > 0$ and another vector like $\vec{x}_1$ cannot be found, so that the vector can overcome the vector $\vec{x}$, in the sphere with a center $\vec{x}$ and radius δ. In this case, the vector $\vec{x}$ is locally named the non-dominate solution. Fig. 3 illustrates the above concept.

3-*Global Optimum Points:*

The vector $\vec{x}$ is considered the Global Optimum whenever another vector like $\vec{x}_1$ cannot be found in the whole solution space, so that can overcome the vector to $\vec{x}$. In this case, the vector $\vec{x}$ is the non-dominated or Pareto solution. According to the concept of domination relation, the solution space can be divided into four parts as seen in Fig. 4:

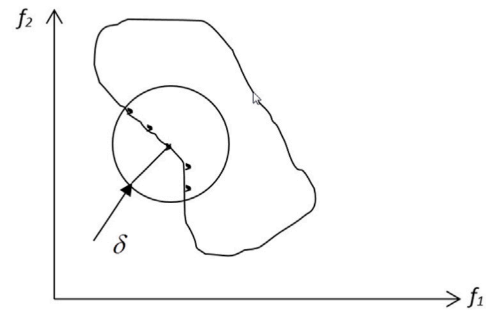

Fig. 3. Local optimum points.

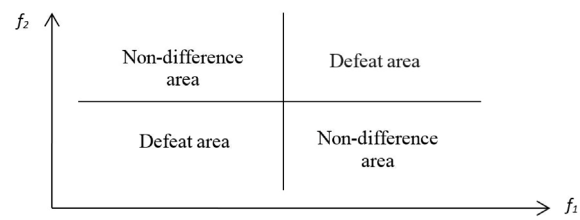

Fig. 4. Relationship between the solution space and the domination relation.

4-*Pareto Front:*

The summation of global optimum or Pareto is the formation of a boundary called the Pareto front. Fig. 5 shows that a Pareto-optimal set of solutions is obtained, which build up the Pareto front (Fig. 6) in the objective space and the front represents the varying impact of the individual objectives (Gollub and de Vivie-Riedle, 2009).

Based on the above, it can be concluded that the main goal of the multi-objective optimization approach is to achieve, as much as possible, the global optimum points (solution) or Pareto.

4.2. Solution algorithm structure

Given that, locating facilities with the limited capacity problem is in the Np-Complete category (Davis and Ray, 1969), designing the logistics network issue studied in this research belongs to the Np-Hard category. Due to the high time complexity, precise methods cannot be used to solve such large-scale problems. Therefore, to solve the problem in this study, we have presented two innovative methods based on the bee colony optimization algorithm and the genetic algorithm and then compared their answers. It should be noted that because the model in this study is multi-objective, non-dominated relations in the form of (Deb et al., 2002) have been used to select the answers in both algorithms. With this method of answer selection, the structure of algorithms is prepared to solve multi-objective problems.

4.2.1. Bee Colony Algorithm (BCO)

The proposed bee algorithm structure based on the Pareto archive:

The proposed bee algorithm structure is based on the Pareto archive. The bee algorithm is an emerging group algorithm that mimics bee food search behavior.

The Artificial Bee Colony (ABC) algorithm is a swarm based meta-heuristic algorithm that was introduced by "Karaboga" in 2005 to optimize numerical problems (Karaboga, 2005). It was inspired by the intelligent foraging behavior of honey bees. The algorithm is specifically based on the model proposed by (Tereshko and Loengarov, 2004) for the foraging behaviour of honey bee colonies. The proposed structure for implementing the bee algorithm to solve the proposed model is as follows:

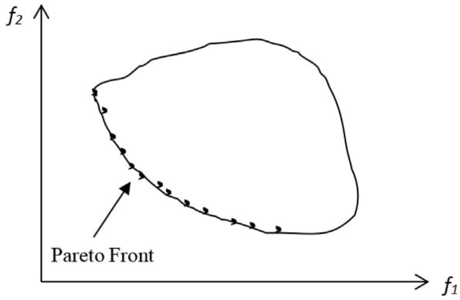

Fig. 5. Pareto front.

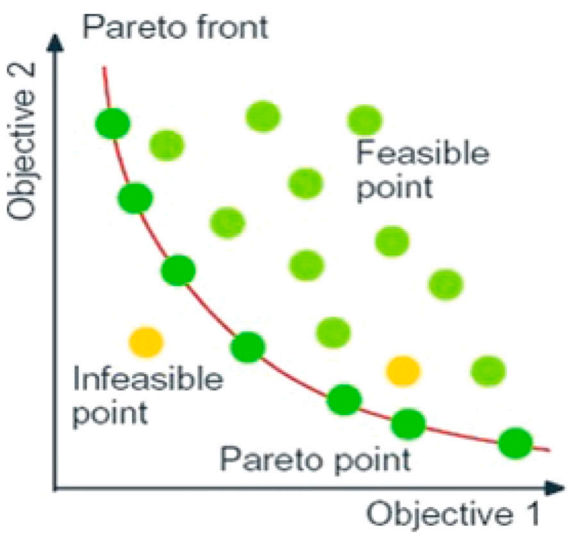

Fig. 6. The two-dimensional-(2D) Pareto front (red line and dark green circles). The light green dots are feasible points and the yellow dots indicate infeasible solutions, with respect to the constraints.

Purposed Bee colony optimization algorithm

{Initialization:

Initialize the algorithm parameter.

Generate N feasible solution as initial population.

Create an empty set as the initial Pareto archive.

While criterion is meet.

Calculate the fitness for each solution in the current population.

Select the best bees and their location as the p1 set.

Select the other bees and their location as the p2 set.

Apply neighborhood search operator on the p1 set.

Apply feasibility check method to the obtained solutions.

Assign some bees to obtained solutions and calculate their fitness.

Apply a random neighborhood search operator on p2.

Apply the feasibility check method to the obtained solutions.

Calculate their fitness.

Select the N best bees of each location.

Apply the improvement method on selected solutions and take the output of this method as the population of next generation.

Update the Pareto archive

End while

Return the Pareto archive.}

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Solution representation. Since an algorithm should be feasible, it is necessary to store the feasible according to a specific structure. In Metaheuristic algorithms, this is the Solution representation. In this research, a matrix is used to display each answer. Each answer consists of several matrices that are designed according to the model outputs. For example, for the variable z_m, a row matrix (one-dimensional) whose number of entries is equal to m (m is the number of collecting centers) is defined. For the variable x_{lk}^{ts}, a four-dimensional matrix with dimensions L*K*T*S and for the variable x_{mnk}^{ts}, a 5-dimensional matrix with dimensions M*N*K*T*S is defined. Similarly, the matrix will be defined for the other outputs.

Solution initialization. In this research, a random approach is used to produce the initial answers. To produce the initial answers, the z_m, z_p and z_n matrices are randomly generated, and then the rest of the answer matrices (model variables) are quantified according to the model constraints. Assume that the population size is N, every time an answer is generated, it is added to the population if it is not repeated. This process will continue until the number of answers in the population reaches $\alpha \times$ N, where α is a number greater than 1.

The method of producing the answers stops after $\alpha \times$ N repetition. On the other hand, the number of solutions in each repetition of the algorithm is equal to N. Therefore, from the existing $\alpha \times$ N solutions, the N solution should be selected as the primary production sequences. In this study, the selection of the primary population of answers is based on a rapid method of arranging non-dominate solution described by K.Deb. This method works in such a way that the existing solutions are aligned with the algorithm designed by (Deb et al., 2002). The number of each level indicates the quality of the solution. For example, the quality of the answers that are in first level is higher than the answers in the second level. Then, for the solutions at each level, a scale as crowding distance is calculated according to the same level. This scale for the solutions of each level shows the scattering of the answers of the same level.

In this paper, in order to select the initial answers, a criterion C_s is defined, which is obtained as follows:

$$C_S = \frac{rank}{crowding\_dis} \tag{37}$$

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

Rank: Indicates the surface number where the solution is located.

Crowding-dis: The distance between each solution, which corresponds to the rank of that solution.

After calculating the above criteria for all the solutions, the solutions are arranged in ascending C_s order, and the first N solutions, which have fewer C_s, are selected as the primary solutions to the algorithm. The use of the C_s criterion is based on the logic that higher quality and responses that are more scattered should be selected as the primary population. After producing the solution, it is improved as much as possible. The improvement procedure is described in the next section.

Improvement procedure. In the proposed structure of the bee colony optimization algorithm, an improvement procedure is designed to be applied to the answers selected in the previous section. The output of the improvement procedure is selected as the next repetition dimension of the algorithm dimension. The implementation of the improvement approach in this research is based on the variable neighborhood search (VNS). The VNS structure uses three neighborhood Search Structures (NSS). These structures are used in the form of VNS (Gholipour Kanani et al., 2011). The VNS algorithm answers each solution in a solution population and one solution is received as output. The Improvement procedure is then applied to the rest of the answer matrices and will be corrected and replaced with the input answer.

In addition, the neighborhood search operators used in the VNS structure are as follows:

– Second Neighbor Search Operator: In this structure, one of the collection centers is randomly selected, and the matrix related to its location is changed.

– Third Neighbor Search Operator: In this structure, one of the recycling centers is randomly selected, and the matrix related to its location is changed.

– Fourth Neighbor Search Operator: In this structure, one of the destruction centers is randomly selected, and the matrix related to its location is changed.

It should be noted that in the above operators, the method of changing location matrices is such that the index of one of the centers is selected randomly and the associated location is changed (if it is 1 change to 0 and If it is 0, becomes 1). Considering the restrictions of the minimum number of established centers.

The new answers are generated during the implementation of the algorithm. In order to check the feasibility of the answers and, if possible, convert the non-feasible answers into feasible answers, a procedure is designed to check the establishment of all constraints in the generated answer, and if one or more constraints are violated, it tries to convert non-feasible answers to feasible ones. The procedure for being feasible with respect to the new location matrices is as follows: Due to the limited capacity of vehicles as well as the limited capacity of centers, the flow of goods between the facilities is established using previous or new vehicles, and the routing variables, as well as the flow of goods, are requantified.

Local search for p1 and p2 bees. As mentioned in the general structure of the algorithm, the bees are divided into two groups, p1 and p2. The are then applied in a directed local search in the p1 category and a completely random local search in the p2 category. In this research, a local search method has been designed to apply a neighborhood search in the p1 category. The input of this method is the population of the answers of the set p1. This method works based on the neighborhood search method. In other words, this method receives a set of answers as input and tries to achieve good neighborly answers by improving the answers.

In this study, the neighborhood search applied to category p1 is a parallel neighborhood search structure that includes a combination of the three neighboring search operators described in parallel. Each of the answers in category p1 is given as an input to this structure, and through it, the algorithm achieves a better answer. In order to apply the neighborhood search on each of the answers in category p2, one of the above 3 operators is randomly selected, the answer in this category is applied, and the output of the selected operator (better or worse) replaces the existing answer.

If we assign the described operators with the symbols ls1, ls2, ls3, the structure of the parallel procedure is as follows:

For each input answer such as s, perform the following operations:

1. Apply the ls1 operator to s and name the output as s1.

2. Check the feasibility of the s1 answer and turn it into a feasible answer if necessary.

3. Apply the ls2 operator to s and name the output as s2.

4. Check the feasibility of the s2 answer and turn it into a feasible answer if necessary.

5. Apply ls3 operator to s and name output as s3.

6. Check the feasibility of the s3 answer and turn it into a feasible answer if necessary.

7. From the input answer and 3 new answers generated, select the answer with the higher quality and distribution.

As can be seen in the above structure, each of the operators is applied separately to each answer in the p1 group, and one answer from the 3 output answers of the operators and the input answer is selected according to the quality level and reported as the output of the described procedure.

Pareto archive update. Since no single answer is obtained when solving multi-objective problems due to the contradiction between goals that all goals are optimal, a set of dominant solutions is ultimately presented as the optimal (nearoptimal) answers. Here, the quality of the answers in the archive is very important because a Paretobased method is used to solve the problem. Therefore, in this research, this archive is updated in each repetition of the algorithm. To update the Pareto Archive, all the existing and newly generated answers are collected and leveled. Then, all the first level answers are selected as the new answers to the Pareto Archive.

Selecting the answers of the next generation. At each step of the bee colony optimization algorithm, the N (population size) location, as the best answers according to the degree of fit (C_s criterion), will be selected from both the previous and new locations of the bees. The method of selection is that for all these places, the value of C_s is calculated, then the places are arranged according to the ascending order of the C_s, and finally, the first N answers are selected.

4.2.2. NSGA-II algorithm

Genetic algorithms (GAs) are a heuristic search and optimization technique inspired by natural evolution. They have been successfully applied to a wide range of real-world problems of significant complexity (McCall, 2005).

Deb et al. (2002) presented a multi-objective version of the genetic algorithm (NSGA-II), which selects responses based on the leveling of answers, non-dominated relationships, and calculating the congestion distance. Since the model in this study has two objectives, the genetic algorithm in the present study is equivalent to an NSGA-II algorithm.

The quasi-code of the combined NSGA-II algorithm is as follows:

{Generate N feasible solutions as initial population.

Apply improvement method on generated solution.

Initialize algorithm parameters.

Create an empty set as Pareto archive.

While algorithm terminated

Apply selection operator for select parents.

Apply crossover operator.

Apply mutation operator.

Combine current population and new solutions generated in current iteration as q.

Apply fast-sort-non dominated method.

Calculate crowding distance for each solution.

Select N solutions with higher quality and higher diversity for next iteration.

Apply improvement method on selected solution.

Update Pareto archive.}

How to display the answer, generate initial answers, update the Pareto archive are procedure of improving the bee optimization algorithm. In order to implement the mutation operator, the parallel variable neighborhood search structure described in the bee algorithm structure (P2 category neighborhood search) is used. Dual tournament method used to select parents. In this research, according to the method of parental selection, the degree of fit of each answer is determined according to non-dominated relation.

Sorting and selecting the answer for the next generation. As mentioned, the NSGA-II algorithm, based on non-dominated relationships, levels the responses in the population. In order to sort and level the answers, the above relation used, so that first all the answers compared with each other using the relationship described in Sections 2–4. In addition, the answers, which no answer prevails, select as the first level answers. Then the same procedure repeated for the set of answers that do not assigned and the next levels are determined.

Due to the fact how much the level number of answer be low, have higher quality, the lower number of levels used to select the answers. If it is possible to choose between two answers at the same level, the crowding distance criterion is used. The higher value of this criterion for the answers on a level can cause the higher priority of that answer for selection.

The algorithm needs a set of solution in each iteration. In this paper, for select the population of the next iteration, the solution in the population repeated and the new solution produced by the algorithm put together in a response pool. After leveling and calculating the crowding distance for each solution according to that level, the solution selected as the population of the repetition dimension of the algorithm, which has the highest quality and the highest scatter.

Intersect operator. Single point intersect: Assume that the 2 opposite matrices and index 3 are the inputs of the single point intersect (One-dimensional parent matrices are provided to facilitate the description of a single point intersection):

0	1	0	1	0	0	1	1

1	1	0	0	1	0	1	0

These two matrices are parent 1 and parent 2 and the two children are created using the following single-point intersection from these two parents. The first 3 houses of the first parent are inherited by the first child and also the first child inherits the last 5 houses from the second parent. The second child formed like the first child, except that he inherits the first three houses from the second parent and the last five houses from the first parent.

The first child will be according to the following matrix.

0	1	0	0	1	0	1	0

Moreover, the second child will be as follows:

1	1	0	1	0	0	1	1

4.3. Comparison metrics

In order to test the performance of the proposed algorithms, the algorithms have been implemented in a MATLAB software environment. The results of implementation in experimental cases are compared with each other according to the indicators of quality comparison, distribution, uniformity, and solution time. There are a number of different indicators to evaluate the quality and dispersion of multifunctional algorithms. In this paper, the following three indicators will be considered for comparison.

4.3.1. Quality metric (QM)

This metric compares the quality of the Pareto answers obtained by each method. It aligns all the Pareto answers obtained by both methods and determines what percentage of level one answers belong to each method, where the higher the percentage, the higher the quality of the algorithm. (Mohammadi et al., 2011)

Table 2
Small issue.

Issue number	Number of reproduction centres	Number of customer centres	Number of collection and inspection centres	Number of rehabilitation centres	Number of destruction centres	Wastes type
1	2	2	2	2	2	1
2	2	2	2	3	3	1
3	2	2	2	4	4	1
4	2	2	2	5	5	1

4.3.2. Spacing metric (SM)

This metric, introduced by (Schott, 1995), shows the relative distance between successive solutions. The metric also shows the uniform distribution of Pareto solutions in the search space. It can be obtained by the following equation:

$$S = \frac{\sum_{i=1}^{N-1} |d_{mean} - d_i|}{(N-1) \times d_{mean}} \tag{38}$$

In this equation, d_i is the Euclidean space between the two sides of the Pareto solutions, d_{mean} is the mean of spaces d_i, and n is the number of Pareto solutions. When the solutions are distributed uniformly, the value of s is small. Therefore, algorithms are better when the spacing values among the final, non-dominated solutions are smalh (Schott, 1995; Chambari et al., 2012).

4.3.3. Diversification metric (DM)

By this metric, diversification among non-dominated solutions is measured. In the following formula, $\|x_t^i - y_t^i\|$ is the Euclidean space between the non-dominated solution x_t^i and the non-dominated solution y_t^i, and n is the number of Pareto solutions. The higher the value of this metric, the better. A high value shows that there are fewer equal solutions and there is more variety among the solutions (Zitzler and Thiele, 1998; Tavana et al., 2013):

$$D = \sqrt{\sum_{i=1}^{N} \max(\|x_t^i - y_t^i\|)} \tag{39}$$

5. Experimental results

In this study, several experimental problems were designed in small, medium, and large group sizes. Although there were no examples in the literature that covered all parts of the model presented in this study, we selected sample problems from previous studies to set up our experiments. Some of the parameters not covered in this research were randomly selected. Also, in order to determine some other experimental problems, the previous researches were reviewed and according to the range of sizes of the selected problems in these researches, experimental problems were designed.

Consider small-sized issues in Table 2:

Consider medium-sized issues in Table 3:

Consider Large-sized issues in Table 4:

5.1. Parameters tuning

This section describes how the parameters were adjusted to run the two algorithms. The parameters of the two proposed algorithms were adjusted in two sections. One section of the parameters was generated using statistical analysis by MINITAB software, and the other was randomly generated according to the values in the literature.

Table 3
Medium issue.

Issue number	Number of reproduction centres	Number of customer centres	Number of collection and inspection centres	Number of rehabilitation centres	Number of destruction centres	Wastes type
1	3	7	7	5	4	1
2	3	7	7	5	4	2
3	3	7	7	5	4	3
4	6	10	8	6	5	1
5	6	10	8	6	5	2
6	6	10	8	6	5	3
7	7	15	9	7	7	1
8	7	15	9	7	7	2
9	7	15	9	7	7	3

Table 4
Large issue.

Issue number	Number of reproduction centres	Number of customer centres	Number of collection and inspection centres	Number of rehabilitation centres	Number of destruction centres	Wastes type
1	10	30	16	7	6	1
2	10	30	16	7	6	2
3	10	30	16	7	6	3
4	15	70	35	12	10	1
5	15	70	35	12	10	2
6	15	70	35	12	10	3
7	15	90	40	15	13	1
8	15	90	40	15	13	2
9	15	90	40	15	13	3

Table 5
BCO parameters level.

Number of scout bees	Population size	Neighborhood search repetitions
0.4N	70	5
0.5N	150	10
0.6N	200	15

Table 6
Genetic algorithm parameters level.

Intersection rate	Mutation rate	Population size
0.1	0.7	70
0.2	0.7	150
0.1	0.8	200

5.1.1. Parameter setting using MINITAB:

MINITAB software was used to adjust some parameters of the two proposed algorithms. These parameters include the number of scout bees, population size, and the number of parallel neighborhood search repetitions in the bee colony optimization algorithm as well as population size, mutation rate and intersection rate in genetic.

To adjust the parameters of the bee algorithm, the values of each parameter are examined in three levels, see Table 5. In this table, N represents the population size.

To adjust the parameters of the genetic algorithm, the values of mutation rate, intersection rate, and population size in three levels have been investigated, see Table 6.

A criterion as **RPD** is designed to perform the analysis, as shown below:

$$RPD = \sum_{obj} \frac{alg_{sol} - \min_{sol}}{\min_{sol}} \times 100 \tag{40}$$

alg_{sol}: The value of the objective function obtained for each problem with the desired combination of parameters.
$\min_{sol}$: The minimum value obtained from all compounds for each problem.

Any problems are executed for each of the above combinations, the **RPD** criterion is calculated, and finally, the related graph is plotted.

- **Diagrams related to the Bee colony algorithm:**

The **RPD** criterion is the amount of gap between the minimum obtained and the existing value. The smaller the gap is, the better the existing value. In the resulting graphs (Figs. 7–9), the vertical axis shows the **RPD** value and the horizontal axis shows the parameter level. (In Table 5, the first level is considered with a, the second level with b, and the third level with c.) At each level, the vertical bar shows the calculated **RPD** values. The closer the vertical bar is to the horizontal axis, the more effective it is. According to the obtained diagrams in the bee algorithm, the population size is equal to 150, the number of scout bees is 50% of the population size, and the number of neighborhood search repetitions is considered equal to 5.

The same is done for the parameters of the genetic algorithm.

- **Diagrams related to the genetic algorithm:**

The following two diagrams for the genetic algorithm (Fig. 10, Fig. 11) allow us to examine the rate of the intersection operator and the mutation operator as well as evaluate the effective population size for the two algorithms.

The three labels in Fig. 10 show the combination rates of the two operators, which are as follows:

– a1 contains 0.7 for the intersection and 0.1 for the mutation
– a2 contains 0.7 for the intersection and 0.2 for the mutation
– a3 contains 0.8 for the intersection and 0.1 for the mutation.

The vertical axis represents the value of the **RPD** criterion.

As can be seen in Fig. 10, the third compound (0.8 for the intersection and 0.1 for the mutation) is more effective and safer. For this reason, this combination was considered for the rates of these operators in this paper.

The second diagram (Fig. 11) is related to the population size. In this study, we examined three population sizes of 70, 150, and 200 (a shows size 70, b: size 150, c: size 200). The vertical axis represents the **RPD** criterion. As can be seen in the diagram, the second level is more effective, and a population size equal to 150 was chosen.

5.1.2. Other parameter tuning

As mentioned at the beginning of the section, the required parameters in the two sections were generated and then adjusted (the first section by MINITAB software and the second section according to the literature). The previous section explained the group setting of the parameters using MINITAB software. This section describes how the other parameters were set.

To generate triangular numbers related to each of the fuzzy parameters (m1, m2, m3), m2 is first generated and then a random number r is generated in the range (0, 1). Next, m1 is generated using the equation m2*(1-r), and m3 will then be generated using the relation m2*(r+1). To quantify the fuzzy parameters, m2 is determined according to the method in (Pouralikhani et al., 2013) and the values of m1 and m3 are determined using the MATLAB program. For this reason, in the section for setting these parameters, we only need to mention the value of m2.

The following values have been considered in the production of the sample problems:

- In each period, the amount of customer demand (l) of product (s), the triangular fuzzy number (m1, 100, m3) is considered as a triangular fuzzy number (m1, 30, m3).

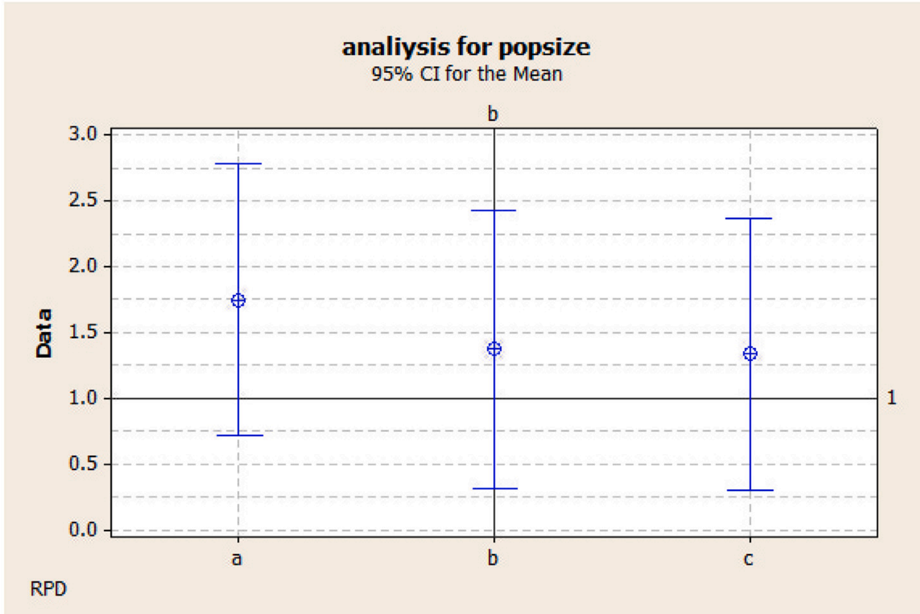

Fig. 7. Diagram of adjust the population size parameter.

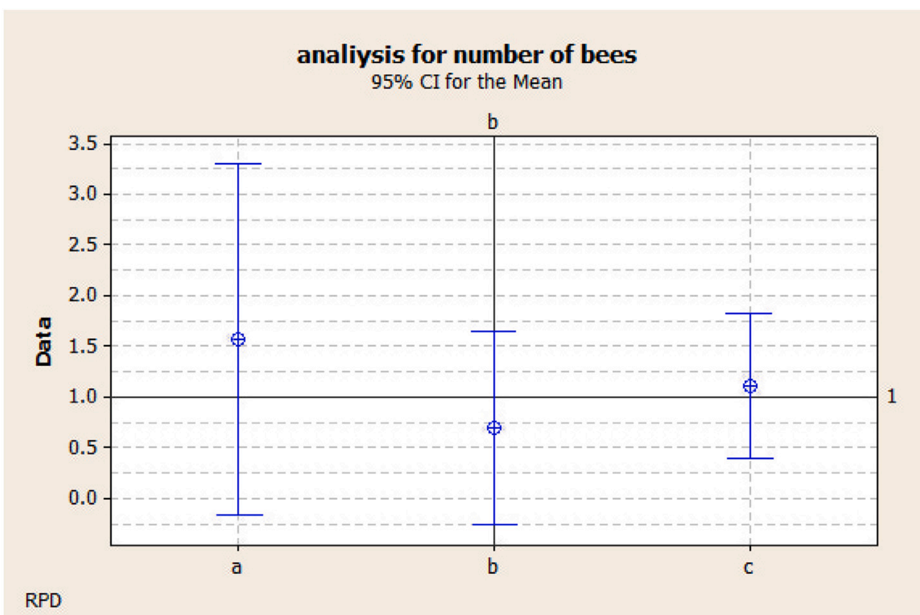

Fig. 8. Diagram of adjust the parameter of the number of scout bees.

- We considered the establishment cost of destruction centers equal to the fuzzy number (m1, 5000, m3), the cost of establishment of collection/rehabilitation centers equal to the fuzzy number (m1,10000, m3), and the recycling centers as the triangular fuzzy number (m1,15000, m3) (Lotfi and Mohaghar, 2015).
- All distances between facilities are randomly generated in a uniform interval [1.50].
- The fuel unit price is 1000.
- The volume of fuel consumption per unit distance per vehicle weight is equal to 2.
- The weight and volume of each product unit is in a uniform range [1.20].
- The weight of pollutant gases emitted per liter of fuel consumption are equal to 2.
- The average price of each unit of emitted gas is equal to 500.
- The speed of each vehicle consider is in a uniform range [70.100].
- The weight of each vehicle is in a uniform range [1000.1600].
- The speed change coefficient of the vehicle is in a uniform range [0.1.0.2].
- For ranking fuzzy numbers the value of α consider 0.8.

5.2. Solving results

In this section, the designed experimental problems were solved using the Bee colony algorithm and NSGAII, and their results were analyzed. It is possible to note that the algorithms were run 20 times by the Core(TM) i5-2430M 2.40 GHz processor, and due to the closeness of the answers, we used the last obtained answers as the final answer. The results of the implementation of the algorithms according to the comparative indicators are shown in Tables 7–9.

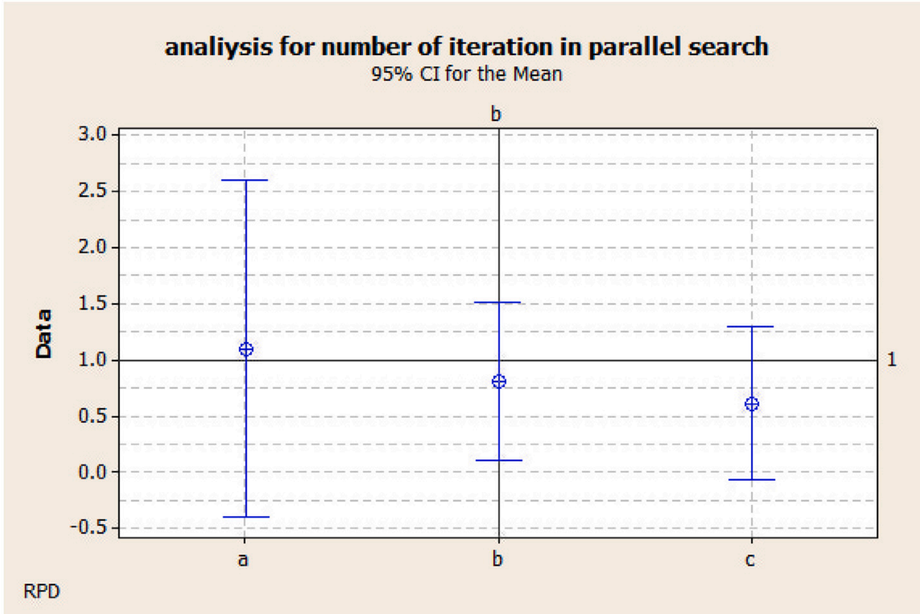

Fig. 9. Diagram of adjust the number of iterations in the parallel neighborhood search procedure.

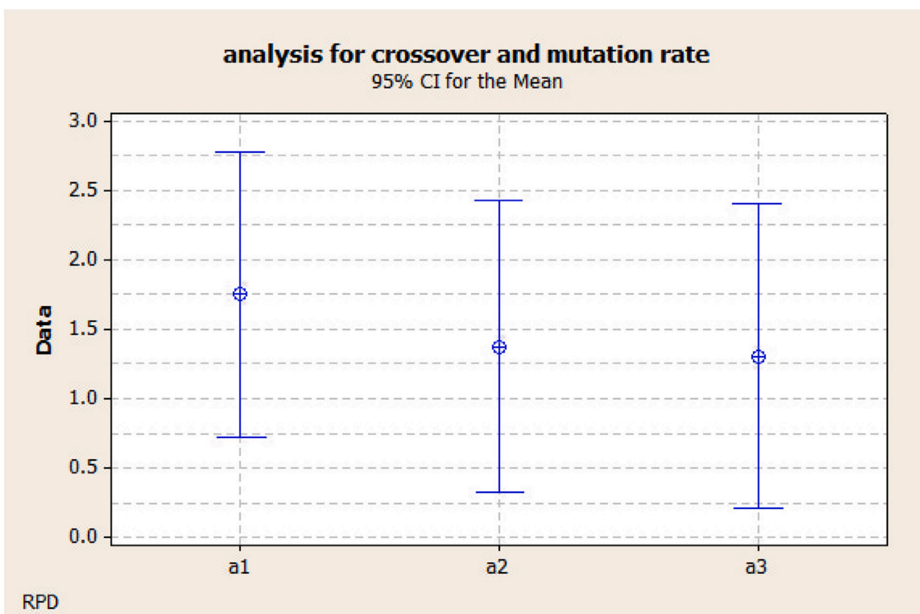

Fig. 10. Diagram of adjust the parameters of mutation and intersection rates.

Table 7
Small size problem solving results.

Probs	BCO				NSGAII			
	Quality metric	Spacing metric	Diversity metric	Time (Min)	Quality metric	Spacing metric	Diversity metric	Time (Min)
1	79.52	1.34	513.7	0.798	20.47	0.79	306.6	0.093
2	69.73	1.5	510.5	0.829	30.27	1.03	313.4	0.094
3	83.41	0.84	542.2	0.843	16.59	0.51	329.3	0.098
4	100	0.97	539.4	0.851	0	0.85	343.2	0.119
Ave.	83.165	1.163	526.45	0.83	16.833	0.795	323.125	0.101
Std. Dev.	10.923	0.268	14.429	0.02	10.922	0.187	14.22	0.011
Max	100	1.5	542.2	0.851	30.27	1.03	343.2	0.119
Min	69.73	0.84	510.5	0.798	0	0.51	306.6	0.093

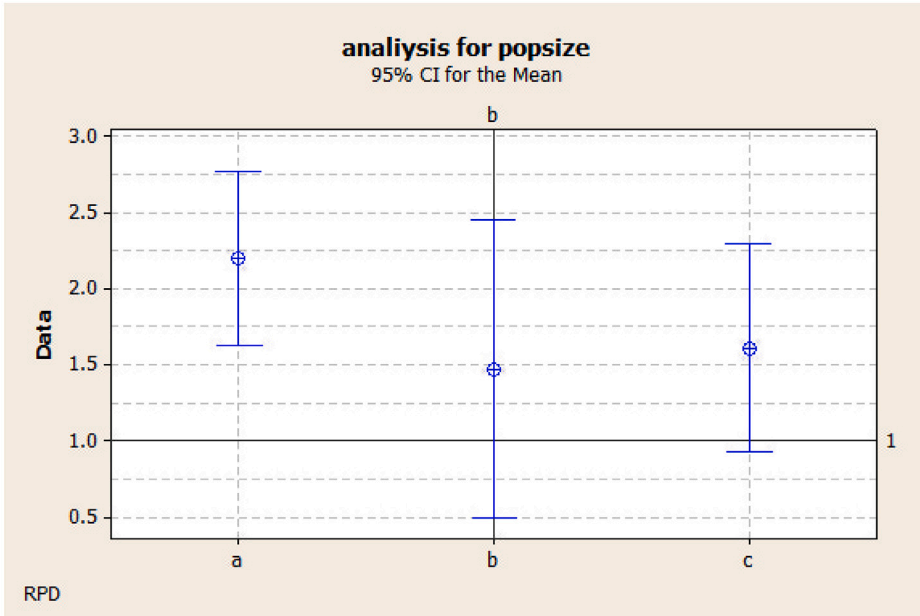

Fig. 11. Diagram of adjust the population size parameter.

Table 8
Medium size problem solving results.

Probs	BCO				NSGAII			
	Quality metric	Spacing metric	Diversity metric	Time (Min)	Quality metric	Spacing metric	Diversity metric	Time (Min)
1	76.27	1.35	1399.1	1.859	23.73	1.03	969.1	0.148
2	87.13	0.98	3167.8	1.919	12.87	0.73	1931.4	0.191
3	88.76	1.11	4596.9	1.991	11.24	0.45	1671.7	0.207
4	96.99	1.05	1368.3	2.023	3.01	0.71	1857.2	0.233
5	81.99	0.81	2436.7	2.053	18.01	0.84	1643.7	0.237
6	75.79	1.25	3857.3	2.096	24.21	0.49	2245.7	0.255
7	92.11	0.58	4028.1	2.108	7.89	0.83	2784.5	0.342
8	91.41	0.84	2464.2	2.176	8.59	0.77	3740.5	0.351
9	100	1.07	7895.4	4.18	0	0.69	4540.7	1.35
Ave.	87.828	1.004	3468.2	2.267	12.172	0.727	2376.056	0.368
Std. Dev.	8.008	0.222	1891.265	0.682	8.008	0.167	1065.11	0.353
Max	100	1.35	7895.4	4.18	24.21	1.03	4540.7	1.35
Min	75.790	0.58	1368.3	1.859	0	0.45	969.1	0.148

Table 9
Large size problem solving results.

Probs	BCO				NSGAII			
	Quality metric	Spacing metric	Diversity metric	Time (Min)	Quality metric	Spacing metric	Diversity metric	Time (Min)
1	100	0.96	7678.9	6.187	0	0.52	5739.3	1.99
2	81.53	1.12	7945.1	7.233	18.47	0.71	5858.5	2.013
3	100	1.17	8939.5	8.237	0	0.74	6619.7	2.86
4	100	1.02	8939.8	9.238	0	0.66	6941.2	4.80
5	93.11	0.98	9116.3	11.26	6.89	0.77	8456.2	5.22
6	88.61	0.89	9253.7	12.26	11.39	0.54	8564.6	6.02
7	85.13	1.24	9894.1	14.26	14.87	0.67	9391.2	7.96
8	86.37	0.71	10291.6	15.26	13.89	0.62	9472.9	8.34
9	100	0.97	10749.4	15.27	0	0.78	9248.8	8.96
Ave.	92.75	1.007	9200.933	11.023	7.279	0.668	7810.267	5.351
Std. Dev.	7.088	0.149	949.15	3.279	7.115	0.089	1437.218	2.542
Max	100	1.24	10749.4	15.27	18.47	0.78	9472.9	8.96
Min	81.53	0.71	7678.9	6.187	0	0.52	5739.3	1.99

As can be seen, quality and dispersion indices values obtained for the bee colony algorithm were greater than the values calculated for the genetic algorithm in all small, medium, and large scale problems, which indicates the higher capability and power of the algorithm. The Bee colony algorithm has an optimum solution compared to the Genetic algorithm, as well as a better ability to explore and extract the feasible area of the solution.

Fig. 12 shows that the solving time of problems in the Bee colony algorithm is longer than the Genetic algorithm in all cases, which means that the Bee colony algorithm needs more time than the genetic

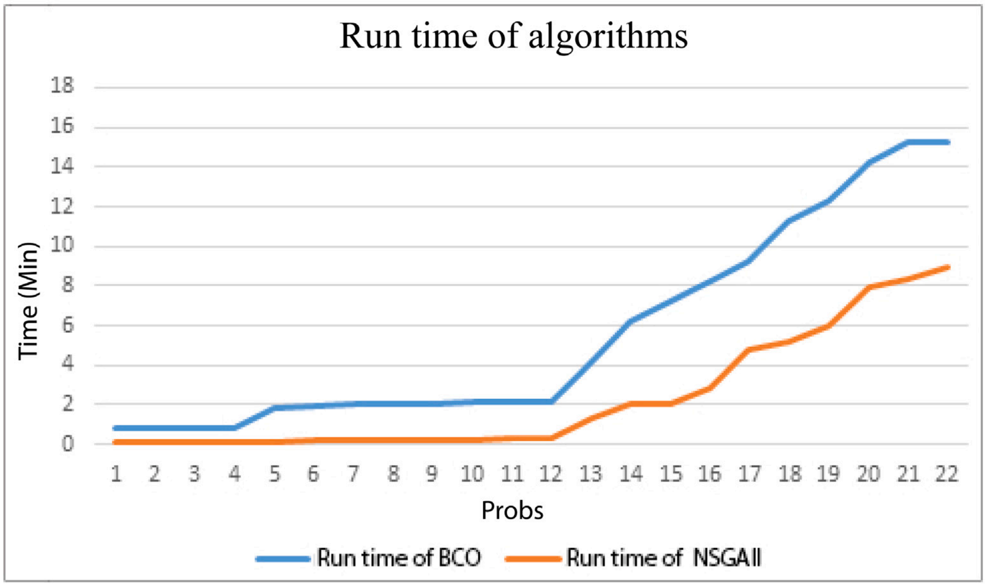

Fig. 12. Comparison of running time.

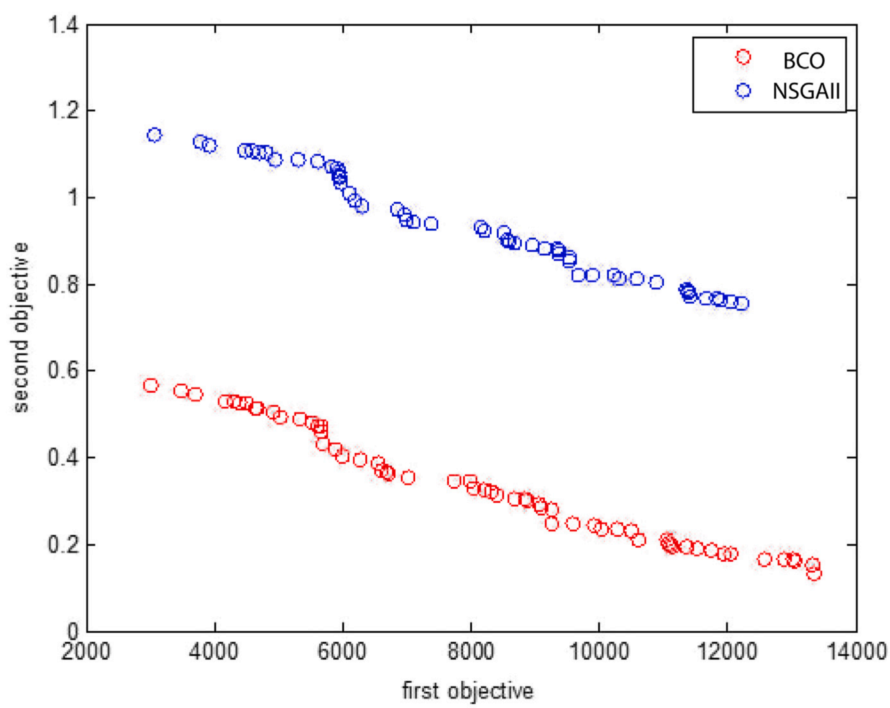

Fig. 13. Pareto front for problem number 9 of large size problems.

algorithm to solve these problems. It should be noted that as the size of the problem increases, the solution time increases, and the time to solve large-scale problems is much higher than for small and medium-sized problems, which indicates that the problem is difficult.

Fig. 13 shows the Pareto front obtained from solving problem No.9 (a large problem). The figure shows the quality of the solution from the Bee colony algorithm is better than the Genetic algorithm. The Pareto front of the algorithms shows that by decreasing the second objective function, the value of the first objective function increases and vice versa, which indicates the contrast between the objective functions in the proposed mathematical model. In addition, the comparison of the Pareto front of the two algorithms also shows the good performance of the Bee colony algorithm and the convergent towards optimal and near-optimal answers.

6. Conclusion and future research

As mentioned before, one of the main activities of supply chain management is logistics management. This field includes all physical activities from raw material production to the final product, including transportation, warehousing, production schedule, etc., and makes up a relatively large portion of supply chain activities. In recent years, the concept of reverse logistics has attracted the attention of many researchers due to the increasing importance of environmental laws and the rise of recycling used goods for reproduction. Due to increasing environmental concerns, declining resources, declining landfilling capacity and increasing pollution from municipal waste in many countries, and the use of reverse logistics in municipal waste collection, reverse logistics has recently attracted more attention. This requires reducing costs and addressing all demands. In this regard, this study presents a multi-objective mathematical model of vehicle routing in the reverse supply chain to collect municipal waste in fuzzy conditions and then solved the model using metaheuristic algorithms. We attempted to have all potential centers, including collection-restoration centers, recycling centers, and landfills with limited capacity assumptions, multi-productivity, etc., in reverse logistics. The output of the model is facility routing and the optimal flow rate between the facilities. A mixed-integer linear programming model was proposed for the problem under consideration. Since the mathematical model presented is classified as an Np-hard problem, meta-heuristic algorithms have been used to solve the model. Genetic algorithm is one of the powerful algorithms in solving such models. But to ensure the accuracy of its operation and the results obtained, we used a Bee colony algorithm that is less used in solving such models. By comparing the results of both algorithms, we were able to measure the performance of the algorithms in such models, and show their accuracy to each other. Experimental sample problems were then designed in three groups of the small, medium, and large size in accordance with previous research. The results of two algorithms, the Bee colony optimization, and the Genetic algorithm, were compared by indicators of quality, comparison, spacing, diversification, and solution time. The results showed that in all cases, the Bee colony algorithm had a better ability to explore and extract the area of a feasible solution and to achieve near-optimal answers. However, in terms of spacing and resolution time, the Genetic algorithm performed better than the Bee algorithm. In addition, examining changes in solution time after increasing the problem size further confirmed the NP-HARD nature of the problem under consideration.

Researchers may consider the following in future studies:

The problems of network design and its models are extensive and different methods should be considered to solve them. It is also possible to further develop existing models by considering new hypotheses to bring them closer to real and practical conditions. Suggestions that can be considered in future research are presented in three groups, as follows:

(A) Suggestions for the structure of the issue under consideration:

- Consider parameters as probabilistic.
- Consider other goals for the issue.
- Use of probabilistic and fuzzy parameters to express uncertainty.

(B) Suggestions for optimization methods:

- To solve the mathematical model of the problem, the search pattern of meta-innovative methods should be based on the principles of advanced reaction methods.
- To optimize the goals, use the new method of fuzzy ideal programming.
- Use a real example, instead of generating random problems.
- Using other meta-heuristic algorithms to solve the problem, such as scatter search, PSO, ACO, DE, etc.
- Use the robust optimization method to solve the model.

(C) Suggestions for the structure of the proposed algorithms:

- Use other innovative algorithms to generate initial solutions.
- The method of improving the answers produced in this paper takes many computational runs. Therefore, the computational time of the algorithm can be reduced by creating a suitable improvement method.
- A guided structure can be used to search for neighborhood answers.

CRediT authorship contribution statement

Seyed Emadedin Hashemi: Writing the article, Including collecting materials and literature, Presenting a mathematical model, Solving a mathematical model with software illustration and data generation.

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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