A fuzzy multi-objective model for a sustainable end of life vehicle reverse logistic network design: two meta-heuristic algorithms

Fatemeh Harsaj* and Yousef Aghaeipour

Department of Industrial Engineering,
Faculty of Engineering Technical Graduate Studies,
Islamic Azad University,
Noor Branch,
Noor, Iran
Email: Harsej88@gmail.com
Email: Yousef.a1359@gmail.com
*Corresponding author

Mahboubeh Sadeghpoor

Department of Industrial Engineering,
Faculty of Engineering Technical Graduate Studies,
Islamic Azad University,
Ghaemshahr Branch,
Ghaemshahr, Iran
Email: Sadeghpoor.ma@gmail.com

Yadollah Rajaee

Department of Economy,
Faculty of Economy Graduate Studies,
Islamic Azad University,
Zanjan Branch,
Zanjan, Iran
Email: yadollahrajaee@yahoo.com

Abstract: In recent years, the concept of reverse logistics has been paid attention by many researchers due to the importance of environmental regulations as well as the importance of utilising from worn-out goods for re-production. The purpose of the present study was to develop a mixed fuzzy integer linear planning model for reverse logistics network of end of life (EOL) vehicles to minimise the cost of establishing and constructing facilities, as well as minimising transportation and material costs between facilities, minimising environmental impacts, and maximising social responsibility with taking into account the uncertainty conditions and the multi-product mode. Due to the NP-HARD nature of the understudied problem, the whale optimisation algorithm (WOA) and NSGA-II algorithm were used to solve the model, which results of these two modes were comprised based on quality indicators, dispersion and uniformity and solution time of the problem.

Keywords: sustainable; reverse logistic; end of life vehicles; multi-objective model; fuzzy theory.

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Biographical notes: Fatemeh Harsaj is an Assistant Professor in Department of Industrial Engineering, Faculty of Engineering Technical Graduate Studies, Islamic Azad University, Noor Branch, Noor, Iran. Her research interests are industrial engineering, evolutionary algorithms in optimisation and supply chain management.

Yousef Aghaeipour is a PhD student in the Department of Industrial Engineering, Faculty of Engineering Technical Graduate Studies, Islamic Azad University, Noor Branch, Noor, Iran. His research interest includes the optimisation and logistic network design.

Mahboubeh Sadeghpoor is an Assistant Professor in Department of Industrial Engineering, Faculty of Engineering Technical Graduate Studies, Islamic Azad University, Ghaemshahr Branch, Ghaemshahr. Her research interests are sustainable development, meta-heuristic algorithms and fuzzy systems.

Yadollah Rajaee is an Associate Professor in Department of Economy, Faculty of Economy Graduate Studies, Islamic Azad University, Zanjan Branch, Zanjan, Iran. His research interests are economy and industry, reverse logistic; and value chain management.

1 Introduction

Nowadays, changes in the economy and industry are happening faster than ever before. On the other hand, organisations are to invest and focus on their logistics systems and reengineering due to the competitive pressure in today's global markets, the introduction of products with short life-cycle, and growing customer expectations. Among these changes and developments, the creation of new institutions and activities along with the development and increase of activities have led to uncontrollable congestions. Meanwhile, there is a need for activities that organise, monitor, and regulate these congestions. One of these activities is to identify the supply chain and manage it and establish a relationship between them. Today closed-loop supply chains or reverse supply chains are among important and vital aspects of any business, which improve the manufacturing, distribution of services, and support for the products of large companies. This technique allows the management of companies to restore the returned goods and raw materials to suppliers and to coordinate inventory production and distribution activities and prevent downtime due to inventory shortages, and reusable items and goods returned by customers (Mirghaderi and Modiri, 2021; Purohit et al., 2020).

In the present study, the reverse logistics model of collecting EOL vehicles has been presented with taking into account the economic, social, and environmental sustainability. In this regard, a mathematical model has been presented for understudy problems, which includes the planning of multi-period and multi-stage reverse logistics networks of EOL vehicles. In this model, the considerations of location, allocation, routing have been considered, and also some of the parameters of the model are fuzzy and the model is multi-objective including minimising costs, minimising environmental impacts, and maximising the social responsibilities. The rest of the study has been organised as follows. The research literature has been reviewed in Section 2. The proposed solution method has been investigated in Section 3. The proposed mathematical model has been developed in Section 4. The computational results have been presented in Section 5 and finally, conclusions and recommendations have been stated in sectiOn 6.

2 Literature review

Vahdani (2015) has proposed a multi-product multi-cycle model of designing a chain network to provide a closed-loop under a fuzzy environment. In the proposed network, the movement of products between two levels of facilities can be performed through different transport models. His proposed model included four layers in the direct direction (supplier, producer, distribution centres, and customers) and three layers in the reverse direction (customers, collection and destruction centres). His model consisted of three objectives: the first objective was to maximise profit, the second objective was to minimise the time of transportation in the direct and reverse directions, and the third objective was to maximise flexibility. He proposed a Fuzzy random mixed planning method to solve the model. Fallah et al (2015) presented a design of a closed-loop single product supply chain network with taking into account the competitive mode under uncertainty conditions. The primary purpose of this study was to investigate the effect of simultaneous competition and Stackelberg between two closed-loop supply chains. The game theory was also used to obtain optimal solutions under uncertainty conditions. Kong (2015) proposed a green mixed-integer planning model for the optimisation of byproduct gases to reduce total costs, i.e., both operating costs and environmental costs of the iron and steel industry. Byproduct gas is an important secondary energy in the iron and steel industry, and its optimisation is critical to decreasing the costs. In his model, operating costs included fines for gas diversion, fuel, and water consumption costs, and booster fines; while environmental costs included fines for discharging direct and indirect pollutants. The case study showed that the proposed model had an optimal solution and decreased the total costs up to 2.2% compared to the previous models.

Behmanesh and Pannek (2016) considered multiple distribution routes in the closed-loop supply chain. In the study, a mathematical model was proposed for the problem and the MAMMOTH algorithm was used to solve the model. Kaya and Urek (2016) investigated the design of a closed-loop supply chain network, which integrates production and collection centres. In the study, a mixed nonlinear integer location-inventory-pricing model was developed. The objectives of this model included maximising profits and finding the optimal location of facilities, optimal inventory values, optimal price of final products, and the optimal price of returned products. The problem was solved using heuristic methods. Ruimin et al (2016) have proposed a strong closed-loop environmental supply chain network that included manufacturing centres, customer centres, collection centres, and disposal centres. They developed a multi-objective integer mixed nonlinear planning model that considered two contradictory goals simultaneously. The first goal was to minimise economic costs and the second goal was to minimise the effect of the supply chain on the environment. They solved the model using LP metric method. Finally, they demonstrated the efficiency of the model by providing an example. Talaei et al (2016) designed a multi-product closed-loop green supply chain network by presenting an integer mixed linear planning model. The proposed network included production/reconstruction centres, collection/inspection, customer and burial, and destruction. The model was introduced to decrease the cost of the entire system. Also, the second-order objective function was based on decreasing carbon dioxide emission rates to consider environmental goals. Moreover, a powerful fuzzy planning method was used to develop the model to investigate the uncertainty effects of variable costs as well as the demand rate in network design. The ε-based constraint method was used to solve this two-objective planning model. A case study was also provided in the copier industry to illustrate the efficiency of the model. The results showed that the model was able to control network uncertainty. Zohal and Soleimani (2016) designed a gold chain supply chain network using a multi-level multi-objective model. They developed an integer linear model to help an experienced Iranian company that had many problems in reverse flow. An ant colony optimisation-based algorithm was proposed to solve the model. To demonstrate the efficiency of e proposed algorithm, several numerical examples based on random data as well as real data were solved. Then, the obtained results were comprised of the results of the Lingo software. Evaluation of studies indicated the capability of model and effectiveness as well as the reliability of the proposed algorithm.

Ene and Öztürk (2017) modelled the reverse logistics problem of EOL vehicles. They proposed a one-way mathematical model to maximise network profits and solved the model using LINGO software. Banasik et al (2017) proposed a multi-objective linear planning model for the closed loop supply chain of mushroom production. Amin and Baki (2017) proposed a multi-objective model for locating facilities in a closed-loop supply chain under fuzzy conditions.

Huang (2018) investigated the problem of the closed-loop supply chain by taking into account the competitive conditions between retailers. In this study, the supply chain included two competitive retailers and one manufacturer where retailers receiving their goods from the manufacturer as well as restoring their returned goods to the manufacturer. In the study, a model has been developed for the competition of two retailers based on competitive strategies. Bottani and Casella (2018) have investigated the problem of a sustainable closed-loop supply chain considering the reduction in emissions. They provided a model for this problem and then solved the model through a simulation tool for a case study. Lin et al (2018) presented a mathematical model for the problem of location-allocation in reverse logistics collection of EOL vehicles to minimise location and allocation costs. They also utilised an improved artificial bee colony (ABC) algorithm to solve the model.

Xiao et al (2019) have investigated the location-allocation problem in the reverse logistics network of EOL vehicles with considering the emission of polluting gases and presented a single-objective model intending to minimise the costs of locating-allocating and emitting pollutant gases. Their model was based on a scenario and used Lingo software to solve it. Kuşakcı et al (2019) developed an optimal reverse logistics planning model for the collection of EOL vehicles and the recycling of their parts by taking into account fuzzy supply. They also presented a single-objective mathematical model to minimise network costs. The summary of previous studies has been presented in Table 1 to explain the research gap and the innovation of the present study.

Table 1 Literature review summary

Author(s)	*Supply chain*		*EOL vehicles*	*Sustainability*			*Location*	*Allocation*	*Routing*	*Uncertainty*	*Method*	
	Forward	*Reverse*		*Economic*	*Social*	*Environmental*					*Multi-objective optimisation*	*Meta heuristic algorithm*
Vahdani (2015)	*	*								*		
Ene and Öztürk (2017)		*	*	*			*					
Behmanesh and Pannek (2016)	*	*					*					*
Kaya an Urek (2016)	*	*					*					*
Banasik et al (2017)	*	*								*		*
Amin and Baki (2017)	*	*								*	*	
Huang (2018)	*	*								*		
Bottani and Casella (2018)	*	*		*		*					*	
Lin et al (2018)		*	*				*	*				*
Xiao et al (2019)		*	*			*	*	*				
Kuşakcı et al (2019)		*	*	*						*		
This study	*	*	*	*	*	*	*	*	*	*	*	*

As shown in Table 1, the number of studies conducted on reverse logistics modelling is very low. Also, the economic, social, and environmental dimensions as well as vehicle routing have not ever been considered in the studies. Therefore, the present study has been defined to fill this gap as well as develop the studies of Xiao et al (2019) and Kuşakcı et al (2019). The dimensions of sustainability and routing have been also considered to develop the proposed models and a multi-objective fuzzy mathematical model has been also proposed and solved. Therefore, the innovation of the present study is due to the following cases:

- proposing a location-allocation-routing model for reverse logistics of EOL vehicles
- taking into account the dimensions of sustainability in reverse logistics of EOL vehicles collection
- proposing and solving a multi-objective fuzzy model for reverse logistics of EOL vehicles collection.

3 Methodology

The whale algorithm has been used to solve the proposed model. Since the nature of meta-heuristic algorithms is random and it is not possible to exactly determine the superior one, it has been tried in the present study to utilise from relatively new algorithms and solve the model and compare them with the well-known NSGA-II algorithm to scientifically and practically evaluate their performance for understudy problem.

3.1 The proposed algorithms structure

3.1.1 Whale optimisation algorithm

This is based on a set of random solutions. For any iteration, search agents update their position according to other agents randomly or with the best solution. The parameter (A) has been decreased from two to zero to enhance exploration and exploitation, respectively. Two modes are considered to update the position of search agents. If the variable is $|A| > 1$, then the random search agent is selected, and if it is $|A| < 1$, then the best solution is selected. Depending on the value of p, the whale can change position between two movements of spiral and rotational. Finally, whale optimisation algorithm (WOA) ends with reaching the specified satisfaction criterion. The flowchart of the WOA algorithm has been presented in Figure 1.

In all meta-heuristic algorithms, it is vital to store the solution based on a specific structure due to the need for a solution at the beginning of the operation, in which the structure is called the solution display method. In the present study, a matrix has been used to display each solution. Each solution consists of several matrices, that have been designed according to the outputs of the model. As an example, a line matrix (one-dimensional) has been defined for variable (a_j), which the number of its arrays equals to J. Figure 2 illustrates a sample of this part of the solution (assume that the number of potential locations of dismantling plant is 6 and the maximum allowable value of this plant is 4).

Figure 1 Whale optimisation algorithm flowchart (see online version for colours)

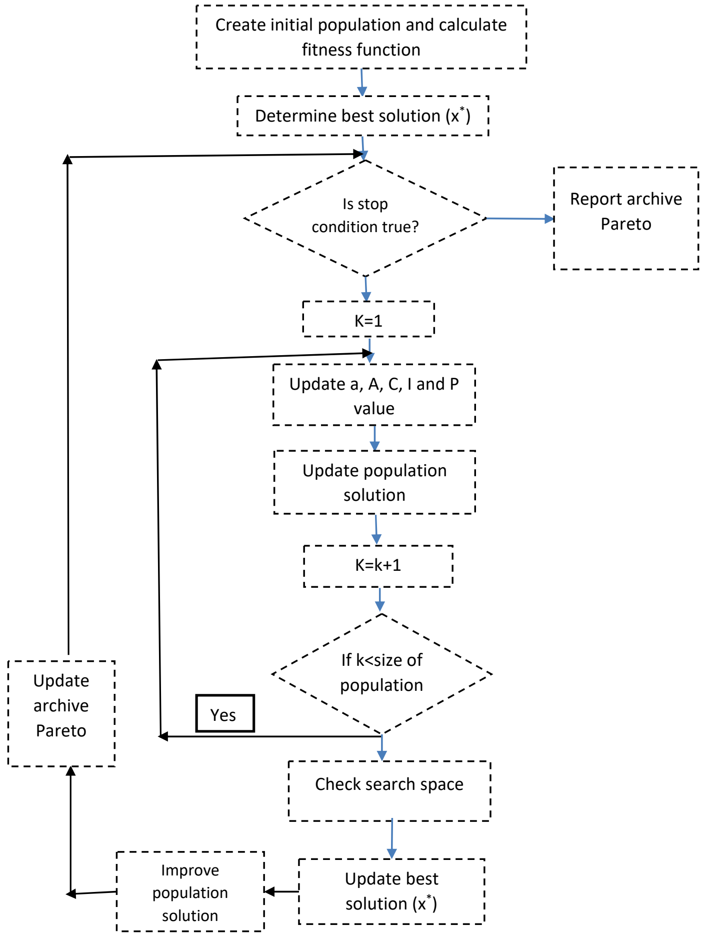


Figure 2 Variable a_j representation

1	0	1	1	0	1

In Figure 2, dismantling plants have been established in locations 1, 3, 4, and 6. A line matrix has been also used to display Variable (b_k), which the number of its arrays equals K. Figure 3 illustrates an example of this part of the solution (assume that the number of potential locations of the processing plant is 5).

Figure 3 Variable b_k representation

1	1	0	1	0

In Figure 3, processing plants have been established in locations 1, 2, and 5. A one-dimensional matrix has been also used to display Variable (α_{ij}), which the number of its arrays equals the number of collection centres and the values of its cells indicate the number of dismantling plants that the collection centre can send the product to it. Assume that the number of potential locations for the establishment of dismantling plant is 6 and the number of collection centres is 8, then Figure 4 is a way of displaying the solution to this variable, which has been given according to the example of variable (a_j).

Figure 4 Variable α_{ij} representation

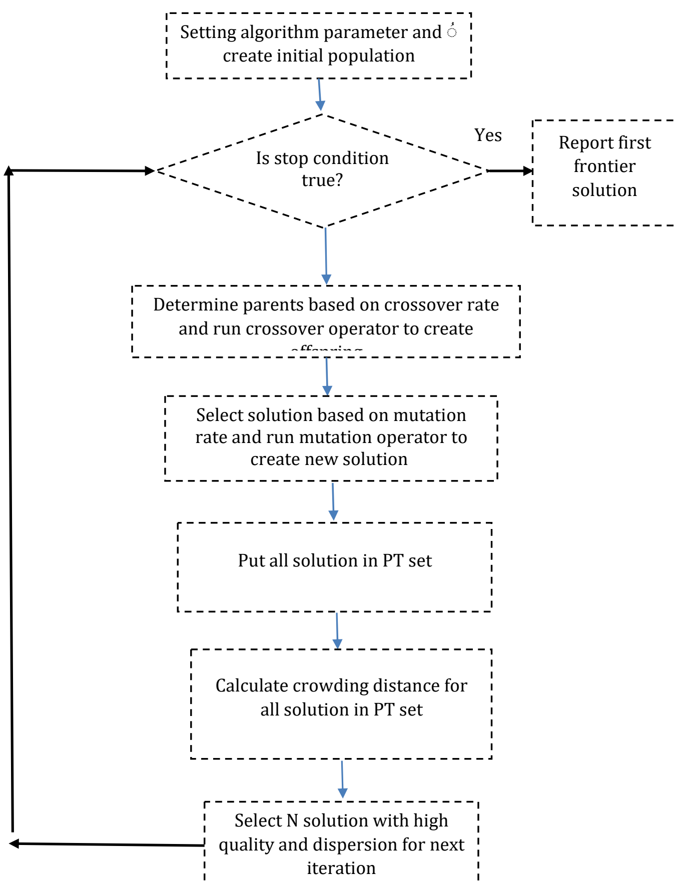
1	1	3	6	4	6	3	4

As shown in Figure 4, the collection centres nos. 1 and 2 have been allocated to dismantling plant no. 1, the collection centres nos. 3 and 7 to dismantling plant no. 3, the collection centres nos. 4 and 6 to dismantling plant no. 6 and the collection centres no. 5 and 8 to dismantling plant no. 4.

3.1.2 NSGAII algorithm

The solution representation in this algorithm is similar to WOA, but the general structure of the genetic algorithm is as following in Figure 5.

Figure 5 NSGA-II algorithm flowchart (see online version for colours)

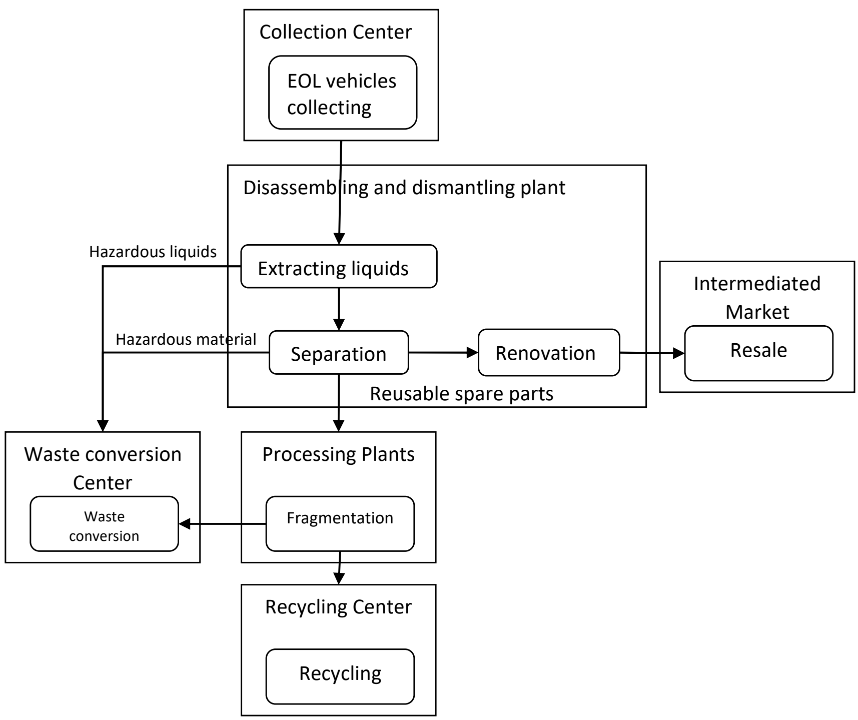


4 The proposed model

4.1 Problem definition

RLO and ND difference is mainly due to the complex structure of the supply chain in the automotive industry. There are several sectors in the supply chain that make it difficult to control and manage the reverse network. Also, high customisation in vehicles makes parts or components different from each other, and hence, it is difficult to predict the recycling of parts or materials. A vehicle includes of various complicated parts and various types of materials such as ferrous/non-ferrous materials, plastics, textiles, and so one and hence, a large number of parts are involved in the supply chain. Also, the operation of isolating EOL vehicles or used vehicles requires large-scale tools and high-level implementation techniques compared to other sectors (Reyhani and Dehnavi, 2020).

Figure 6 The framework of recycling operations for EOL vehicles



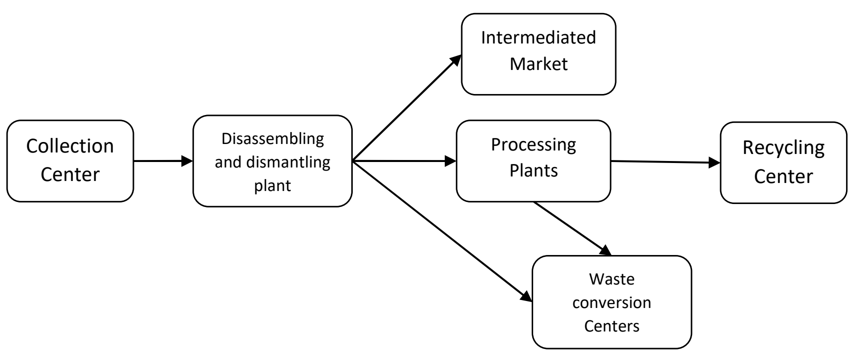
The next step is to transport the returned vehicles to dismantling plants. In dismantling plants, the liquids are extracted and the parts are separated from each other. Car fuel, engine oil, gearbox oil, hydraulic oil, coolant, air conditioning fluid, brake fluid, and steering fluid are extracted from EOL vehicles. Hazardous materials such as accumulators, batteries, airbags), exhaust fumes chemically connected to the exhaust pipe as well as parts including mercury and brake pads including a type of ore are isolated from EOL vehicles. Also, reusable parts such as engines, differentials, gearboxes, body parts (for example, car hoods, car doors, and bumpers), and the wheels are separated and disassembled in these centres. Reusable parts of the vehicle are transported to the intermediary market after renovation operation. Hazardous waste liquids and other hazardous materials are transported to waste conversion centres.

Those non-disassembled vehicles in which their excess fluid has been extracted are transported to processing plants. After fragmentation, scrap ferrous and non-ferrous metals (lead, zinc, copper, and aluminium) and breakable materials are obtained. These materials are transported to recovery centres and converted into waste. The framework of recycling operations for EOL vehicles has been summarised in Figure 6.

In the present study, an integrated integer linear planning model has been used to design a reverse logistics network to maximise the final profit. The critical issue in designing a reverse logistics network is the unknown number of returned products. To overcome this problem, a model has been developed. The proposed model determines the location and number of disassembling, dismantling and processing plants, and allocates the flow of materials between primary/collection centres, disassembling, dismantling and processing plants, intermediate markets, and waste recovery and conversion centres. Since the model maximises the final profit of the entire network, separate maximisation of profits for disassembling plant, dismantling plant, processing plant, and centres of recovery and conversion to waste is outside the scope of the proposed model.

The structure of a multi-time multi-stage reverse logistics network for EOL vehicles has been presented in Figure 7. The decision-making variables set of parameters and constraints used in the model has been defined in follow.

Figure 7 The proposed supply chain network



4.2 Indicators

($\forall i \in I$) where I indicates collection/primary centres

($\forall j \in J$) where J indicates potential locations of disassembling and dismantling plants

($\forall k \in K$) where K indicates potential locations of processing plants

($\forall l \in L$) where L indicates recovery centres

($\forall m \in M$) where M indicates centres of conversion to waste

($\forall n \in N$) where N indicates locations of intermediate market

($\forall t \in T$) where T indicates periods

($\forall p \in P$) where P indicates spare parts of vehicles.

4.3 Parameter

($\tilde{c}_j$)	fuzzy cost of establishing the disassembling and dismantling plant J
($\tilde{c}_k$)	fuzzy cost of establishing the processing plant K
($\widetilde{cap}_j$)	the fuzzy capacity of disassembling and dismantling plant J
($\widetilde{cap}_k$)	fuzzy capacity of processing plant K
($\widetilde{cap}_l$)	fuzzy capacity of the recovery centre l
($\widetilde{cap}_m$)	fuzzy capacity of conversion to waste centre m
(ct_{ij})	transportation cost of each unit from collection/primary centre to disassembling and dismantling plant J
(ct_{jk})	transportation cost of each unit from disassembling and dismantling plant J to processing plant K
(ct_{jn})	transportation cost of each unit from disassembling and dismantling plant J to the location of intermediate market n
(ct_{kl})	transportation cost of each unit from processing plant K to the recovery centre l
(ct_{km})	transportation cost of each unit from processing plant K to the centre of conversion to waste m
(ct_{jm})	transportation cost of each unit from disassembling and dismantling plant J to the centre of conversion to waste m
(cd)	the cost of turning into waste for each unit
(cv)	the cost of incentives to return each vehicle to collection centres
(oc_{jt})	the cost of operating each unit for disassembling and dismantling plant J in the period t
(oc_{kt})	the cost of operating each unit for processing plant K in the period t
(r_p)	the profit of each unit from reusable spare parts
(rr)	the profit of each unit from recovered products
(e_{it})	the number of vehicles admitted by the collection/primary centres in the period t
(k_1)	the amount of material transported from disassembling and dismantling plant to the centre of conversion to waste
(k_2)	the amount of material transported from processing plant to the centre of conversion to waste

(aw_1)	the average weight of the vehicle
(aw_2)	the average weight of the disassembled vehicle
(q_p)	the number of spare parts in each vehicle
(v_p)	the number of reusable spare parts in each vehicle
(EI_j)	Environmental effects of performed operations for each EOL vehicle in disassembling and dismantling plant J
(EI_k)	Environmental effects of performed operations for each EOL vehicle in processing plant k
(EI^T)	Environmental effects of transporting EOL car units per kilometre
(d_{ij})	the distance between collection/primary centre i and disassembling and dismantling plant J
(d_{jk})	the distance between disassembling and dismantling plant J and processing plant k
(d_{jn})	the distance between disassembling and dismantling plant J and the location of intermediate market n
(d_{kl})	the distance between processing plant k and recovery centre l
(d_{jm})	the distance between disassembling and dismantling plant J and the centre of conversion to waste m
(d_{km})	the distance between processing plant k and the centre of conversion to waste m
(W_{em})	the normalised weight of employment
(W_{id})	the normalised weight of local development
(W_{dm})	the normalised weight of high-risk work situation
(W_{pr})	the normalised weight of product risk
(EM_j)	the score for the employment of disassembling and dismantling plant J
(Ld_j)	the score for local development of disassembling and dismantling plant J
(DM_j)	the score for worker's damage in the disassembling and dismantling plant J
(PR_j)	the product risk of disassembling and dismantling plant J
(EM_k)	the score for the employment of processing plant k
(ld_k)	the score for local development of processing plant k
(DM_k)	the score for worker's damage in the processing plant k
(PR_k)	the product risk of processing plant k
F	has been considered as the set of sub-sets j for all sections.
($0 \in F, SD(o)$)	determines the maximum number of disassembling and dismantling plant J for sub-set o.

4.4 Decision-making variables

a_j ={1 if disassembling and dismantling plant J is established 0 otherwise

b_k ={1 if processing plant k is established 0 otherwise

a_{ij} = {1 if there is a flow between the collection centre I and disassembling 0 otherwise

(x_{ijt}) the number of vehicles transported from collection/primary centre I to the disassembling and dismantling plant J during period t

(Y_{jkt}) the number of vehicles transported from disassembling and dismantling plant J to the processing plant k during period t

(Z_{jnpt}) the number of spare parts p transported from disassembling and dismantling plant J to the location of intermediate market n during period t

(w_{klt}) the amount of materials transported from processing plant k to the recovery centre l during period t

(u_{jmt}) the amount of materials transported from disassembling and dismantling plant J to the centre of conversion to waste m during period t

(u_{kmt}) the amount of materials transported from processing plant k to the centre of conversion to waste m during period t.

4.5 The proposed mathematical model

$$\begin{aligned}
Maxz = & \sum_{j=1}^{j}\sum_{n=1}^{N}\sum_{p=1}^{P}\sum_{t=1}^{T} z_{ijnpt} r_p + \sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{t=1}^{T} w_{klt} rr - \sum_{j=1}^{J} a_j \tilde{c}_j - \sum_{k=1}^{k} b_k \tilde{c}_k \\
& - \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{T} x_{ijt} cv - \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{T} x_{ijt} oc_{jt} - \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{t=1}^{T} y_{jkt} oc_{kt} \\
& - \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{T} x_{ijt} ct_{ij} - \sum_{J=1}^{J}\sum_{K=1}^{K}\sum_{t=1}^{T} y_{ikt} ct_{jk} - \sum_{j=i}^{J}\sum_{n-1}^{N}\sum_{p=1}^{P}\sum_{t=1}^{T} z_{jnpt} ct_{jn} \\
& - \sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{t=1}^{T} w_{klt} ct_{kl} - \sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{t=1}^{T} u_{jmt} ct_{jm} - \sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{t=1}^{T} u_{kmt}^2 ct_{km} \\
& - \sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{t=1}^{T} u_{jmt} cd - \sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{t=1}^{T} u_{kmt} cd
\end{aligned} \tag{1}$$

$$\begin{aligned}
Minz_2 = & \sum_j\sum_k\sum_t Y_{jkt} EI_k + \sum_i\sum_j\sum_t X_{ijt} EI_j \\
& + EI^{CT}\Big[\sum_i\sum_j\sum_t X_{ijt} d_{ij} + \sum_j\sum_k\sum_t Y_{jkt} d_{jk} + \sum_j\sum_n\sum_t Z_{jnpt} d_{jn} \\
& + \sum_k\sum_l\sum_t W_{klt} d_{kl} + \sum_j\sum_m\sum_t U_{jmt} d_{jm} + \sum_k\sum_m\sum_t U_{kmt} d_{km}\Big]
\end{aligned} \tag{2}$$

$$Maxz_3 = \sum_j \sum_t \sum \left(W_{em} EM_{jt} + W_{ld} ld_j + W_{dm} DM_j + W_{pr} Pr_j \right)_{aj} + \sum_k \sum_t \sum \left(W_{em} EM_{kt} + W_{ld} ld_k + W_{dm} DM_k + W_{pr} Pr_k \right)_{bk} \tag{3}$$

$$x_{ijt} = e_{ij} \alpha_{ij} \qquad \forall i, j, t \tag{4}$$

$$\sum_{j=1}^{J} \alpha_{ij} = 1 \qquad \forall i \tag{5}$$

$$\sum_{i=1}^{I} x_{ijt} \le \widetilde{cap}_i \quad a_j \forall j, t \tag{6}$$

$$\sum_{j \in O} a_j \le SD(O) \qquad \forall O \in F \tag{7}$$

$$\sum_{j=1}^{J} y_{jkt} \le \widetilde{cap}_k b_k \qquad \forall k, t \tag{8}$$

$$\sum_{k=1}^{K} w_{klt} \le \widetilde{cap}_l \qquad \forall l, t \tag{9}$$

$$\sum_{j=1}^{J} u_{jmt} + \sum_{k=1}^{K} u_{kmt} \le \widetilde{cap}_m \qquad \forall m, t \tag{10}$$

$$\sum_{i=1}^{I} x_{ijt} = \sum_{k=1}^{K} y_{jkt} \qquad \forall j, t \tag{11}$$

$$\sum_{i=1}^{I} x_{ijt} aw_1 k_1 = \sum_{m=1}^{M} u_{jmt} \qquad \forall j, t \tag{12}$$

$$\sum_{i=1}^{I} x_{ijt} q_p v_p = \sum_{n=1}^{N} z_{jnpt} \qquad \forall j, p, t \tag{13}$$

$$\sum_{j=1}^{J} y_{jkt} aw_2 \left(1 - k_2\right) = \sum_{l=1}^{L} w_{klt} \qquad \forall k, t \tag{14}$$

$$\sum_{j=1}^{J} y_{jkt} aw_2 k_2 = \sum_{m=1}^{M} u_{kmt} \qquad \forall k, t \tag{15}$$

$$x_{ijt}, y_{jkt}, z_{jnpt}, w_{klt}, u_{jmt}, u_{kmt} \ge 0 \qquad \forall i, j, k, m, l, n, t \tag{16}$$

$$a_j, b_k, \alpha_{ij} \in \{0, 1\} \qquad \forall j, k \tag{17}$$

The objective function (1) indicates the final profit of the network. The objective function (2) indicates the environmental effects of network and objective function (3) indicate social benefit. Constraint (4) requires that all vehicles admitted by the collection/primary centres must be processed during the period of admission. Constraint (5) ensures the uniqueness of the flow from a collection/primary centre to a disassembling and dismantling plant.

Constraint (6) ensures that the final number of vehicles transported to disassembling and dismantling plant does not exceed their capacity at any time. Constraint (7) limits the number of disassembling and dismantling plants that have been established in each section. Constraint (8) ensures that the final number of vehicles transported to plants does not exceed the capacity of their capacity at any time. Constraints (9) and (10) ensure that the final amount of material transported to recycling centres does not exceed their capacity at any time. Constraints (9) and (10) ensure the compatibility of the amount of disassembled vehicles implemented and materials transported to processing plants and the centres of conversion to waste capacity at any time, respectively. Constraint (13) ensures the compatibility of the number of spare parts transported to the intermediate market at any time. Constraint (14) ensures the amount of material transported from processing plants to recovery centres at any time. Constraint (15) ensures the compatibility of the amount of material transported from processing plants to centres of conversion to waste during period t. Constraint (16) ensures that the value of decision variables X_{ijt}, Y_{jkt}, Z_{jnpt}, u_{kmt}, u_{jmt} and W_{klt} is higher than zero and Constraint (17) determines that the value of decision variables a_j, b_k and α_{ijt} is zero or one.

4.6 Defuzzification of model

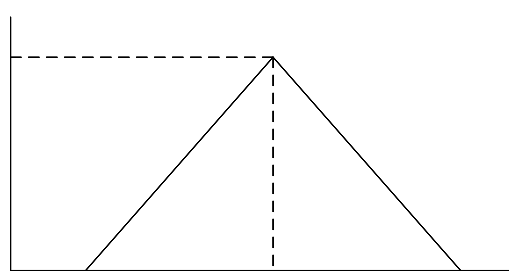
It can be observed from the model that the capacity and cost parameters of facility construction have been considered as fuzzy numbers. The fuzzy number ranking method of Jiménez et al. (2007) was used for the defuzzification of the model.

$$\begin{aligned} &\min z = \tilde{c}x \\ &ax \le \tilde{b} \\ &x \ge 0 \end{aligned} \tag{18}$$

Several methods have been proposed to solve fuzzy mathematical planning problems. In the present study, the ranking method provided by Jimenez was used. Jimenez proposed a method of ranking fuzzy numbers based on comparing their expected interval. The Triangular fuzzy number can be written as following from (Figure 8) if $\tilde{A} = \{L, M, U\}$:

$$\mu A(x) = \begin{bmatrix} f_A(x) = \dfrac{X-L}{M-L} & L \le X \le M1 & x = M \\ g_A(x) = \dfrac{X-L}{M-U} & M \le X \le U & \end{bmatrix} \tag{19}$$

Figure 8 Triangular fuzzy number



It has been assumed that $f_A(x)$ is continuous and ascending and $g_A(x)$ is continuous and descending to ensure the existence of reverse functions $f_A^{-1}(x)$ and $g_A^{-1}(x)$. The expected interval of a fuzzy number is defined as follow:

$$EI(\tilde{A}) = \left[E_1^{\tilde{A}}, E_2^{\tilde{A}}\right] = \left[\int_{a1}^{a2} xdf_A(x) - \int_{a3}^{a4} xdg_A(x)\right] \tag{20}$$

By aggregating the components as well as changing the variable, we will obtain:

$$EI(\tilde{A}) = \left[E_1^{\tilde{A}}, E_2^{\tilde{A}}\right] = \left[\int_0^1 f_A^{-1}(\alpha)d\alpha - \int_0^1 g_A^{-1}(\alpha)d\alpha\right] \tag{21}$$

If the functions $f_A(x)$ and $g_A(x)$ are linear and $\tilde{A}$ is a fuzzy triangular number, its expected interval will be as follow:

$$EI(\tilde{A}) = \left[\frac{1}{2}(L+M), \frac{1}{2}(M+U)\right] \tag{22}$$

Also, the expected value of the fuzzy number $\tilde{A}$ equals to half of the expected interval range and for the fuzzy triangular number $\tilde{A}$ is as follow:

$$EV(A) = \frac{E_1^{\tilde{A}} + E_2^{\tilde{A}}}{2} \tag{23}$$

$$EV(A) = \frac{L+2M+U}{2} \tag{24}$$

Definition 1: for both fuzzy numbers $\tilde{A}$ and $\tilde{B}$ the membership degree $\tilde{A}$ being bigger than $\tilde{B}$ is in the following form:

$$\mu_M\left(\tilde{A}, \tilde{B}\right) = \begin{cases} 0 & \text{if } E_2^a - E_1^b < 0 \\ \dfrac{E_2^A - E_1^B}{E_2^A - E_2^B - \left(E_1^A - E_2^B\right)} & \text{if } 0 \in \left[E_1^A - E_2^B, E_2^A - E_1^B\right] \\ 1 & \text{if } E_1^A - E_2^B > 0 \end{cases} \tag{25}$$

So that, $[E_1^A, E_2^A]$ and $[E_1^B, E_2^B]$ are the expected intervals of $\tilde{A}$ and $\tilde{B}$. When $\mu_M(\tilde{A}, \tilde{B}) = 0.5,$ it can be stated that $\tilde{A}$ and $\tilde{B}$ are equal.

When $\mu_M(\tilde{A}, \tilde{B}) \geq \alpha,$ it can be stated that $\tilde{A}$ is bigger equal to $\tilde{B}$ minimally with the degree α, which is displayed as $\tilde{A} \geq_\alpha \tilde{B}.$

Definition 2: suppose the vector $x \in R^n$, it is acceptable with degree α if: $\min\{\mu_M(\tilde{A}x, \tilde{B})\} = \alpha$ (which can be displayed as $\tilde{A}x \leq_\alpha \tilde{B}$). Equation (21) can be re-written as follow:

$$\left[(1-\alpha)E_2^A + \alpha E_1^A\right]x \geq \alpha E_2^b + (1-\alpha)E_1^B \tag{26}$$

According to the above-mentioned definitions, the fuzzy model can be converted into its equivalent definite and accurate model, which has been shown in follow:

$$\begin{aligned} & MinEV\left(\tilde{C}\right)x \\ & s.t.: x \in \left\{x \in R^n \,|\, \tilde{A}x \geq_{\alpha} \tilde{B},\, x \geq 0\right\} \end{aligned} \tag{27}$$

Now, the fuzzy planning model is converted into its equivalent definite based on the above definition and using the mentioned method.

$$\begin{aligned} Maxz = & \sum_{j=1}^{j}\sum_{n=1}^{N}\sum_{p=1}^{P}\sum_{t=1}^{T} z_{ijnpt} r_p + \sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{t=1}^{T} w_{klt} rr - \sum_{j=1}^{J} a_j \left[\frac{c_j^1 + 2c_j^2 + c_j^3}{4}\right] \\ & - \sum_{k=1}^{k} b_k \left[\frac{c_k^1 + 2c_k^2 + c_k^3}{4}\right] - \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{T} x_{ijt} cv - \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{T} x_{ijt} oc_{jt} \\ & - \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{t=1}^{T} y_{jkt} oc_{kt} - \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{T} x_{ijt} ct_{ij} - \sum_{J=1}^{J}\sum_{K=1}^{K}\sum_{t=1}^{T} y_{ikt} ct_{jk} \\ & - \sum_{j=i}^{J}\sum_{n-1}^{N}\sum_{p=1}^{P}\sum_{t=1}^{T} z_{jnpt} ct_{jn} - \sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{t=1}^{T} w_{klt} ct_{kl} - \sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{t=1}^{T} u_{jmt} ct_{jm} \\ & - \sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{t=1}^{T} u_{kmt}^2 ct_{km} - \sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{t=1}^{T} u_{jmt} cd - \sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{t=1}^{T} u_{kmt} cd \end{aligned} \tag{28}$$

$$\sum_{i=1}^{I} x_{ijt} \leq \left[\alpha \frac{cap_j^1 + cap_j^2}{2} + (1-\alpha)\frac{cap_j^2 + cap_j^3}{2}\right]\alpha_j \qquad \forall j, t \tag{29}$$

$$\sum_{j=1}^{J} y_{jkt} \leq \left[\alpha \frac{cap_k^1 + cap_k^2}{2} + (1-\alpha)\frac{cap_k^2 + cap_k^3}{2}\right] b_k \qquad \forall k, t \tag{30}$$

$$\sum_{k=1}^{K} w_{klt} \leq \left[\alpha \frac{cap_l^1 + cap_l^2}{2} + (1-\alpha)\frac{cap_l^2 + cap_l^3}{2}\right] \qquad \forall l, t \tag{31}$$

$$\sum_{j=1}^{J} u_{jmt} + \sum_{k=1}^{K} u_{kmt} \leq \alpha \frac{cap_m^1 + cap_m^2}{2} + (1-\alpha)\frac{cap_m^2 + cap_m^3}{2} \qquad \forall m, t \tag{32}$$

5 Computational results

The proposed whale algorithm was implemented in MATLAB software environment and the obtained results in a sample problem as a case study were comprised of the results obtained from the NSGA-II algorithm on experimental problems to evaluate its effectiveness. In this section, the computational results have been explained. It should be noted that all calculations have been performed using i7 7500U-12GB-1TB-R5 M335 4GB Core computer.

5.1 Sample problems

In this section, the problem of the case study has been first explained and then, the experimental sample problems have been presented. The case study was the reverse logistics of EOL vehicles in Iran.

5.1.1 Case study

The considered case study included the provinces of Tehran, Kashan, Qazvin, Khorasan, Tabriz, Semnan, and Azerbaijan. These provinces have centres for collecting EOL vehicles as well as potential locations for the establishment of disassembling and dismantling plants and processing plants. According to the above-mentioned explanations, the parameters of the case study's problem were as follow:

- The number of potential locations for the establishment of facilities was equal to 7 and included the provinces of Tehran, Kashan, Qazvin, Khorasan, Tabriz, Semnan, and Azerbaijan.
- The number of periods was considered equal to 12, which indicates 12 months and one year. Planning was done for a year.
- The number of spare parts was equal to 8 and included front and rear doors, trunk lid, engine, hood, differential, gearbox, front console, and front and rear bumpers.
- According to the opinion of experts, the fixed cost of establishing disassembling and dismantling plant in Tehran, Kashan, Qazvin, Khorasan, Tabriz, Semnan, and Azerbaijan provinces was relatively in the ranges of [250–300], [170–200], [220–260], [220–280], [220–280], [160–180] and [130–170] million Tomans, respectively.
- According to the opinion of experts, the fixed cost of establishing processing plant Tehran, Kashan, Qazvin, Khorasan, Tabriz, Semnan, and Azerbaijan was relatively in the ranges of [280–320], [240–280], [260–300], [210–250], [220–260], [180–220] and [200–240] million Tomans, respectively.
- According to the opinion of experts, the capacity of disassembling and dismantling plant was considered 1,800 for all of the cities.
- According to the opinion of experts, the capacity of the processing plant was considered 3,000 for all of the cities.
- According to the opinion of experts, the capacity of recovery centres was considered 1,000 for all of the cities.
- According to the opinion of experts, the capacity of centres of conversion to waste was considered 1,000 for all of the cities.
- Transportation costs between different centres in different cities have been considered as a function of the distance between centres, which equals 10,000 Tomans per 1 km.
- According to the opinion of experts, the cost of conversion to waste was considered 50,000.

- The cost of incentive for returning each unit of vehicle to the collection centres was considered 1,000.
- According to the opinion of experts, the cost of operation of each unit for disassembling and dismantling plants in each period has been generated in a uniform range of [1000–2000].
- According to the opinion of experts, the cost of operation of each unit for processing plants in each period has been generated in a uniform range of [2000–4000].
- The profit per unit of the vehicle's reusable spare parts for the front and rear door parts, trunk lid, engine, hood, differential, gearbox, front console and front, and rear bumpers has been generated in a uniform ranges of [200–500], [200–500], [1000–2500], [150–300], [150–280], [600–850], [200–400] and [50–250], respectively.
- The profit per unit of recovered products has been considered 200,000.
- According to the available geographical information, the distance between centres was considered in kilometres.
- In the present study, life cycle assessment (LCA) and analytic hierarchy process (AHP) methods have been used to calculate the parameters related to environmental and social effects, respectively.

5.1.2 The environmental effects

In the present study, the LCA method was used to calculate the parameters related to environmental effects. LCA is a decision-making tool that assesses the environmental status of products, production activities, and processes throughout their useful life. LCA enjoys a variety of techniques to estimate the economic, social, and environmental value of products, activities, and processes. Nowadays, an increasing number of manufacturers, companies, government agencies, academia, and industry utilise from LCA to assess the long-term effects of their plans and make decisions about them.

In the present study, the criteria of 'human health', 'environmental quality' and 'resource consumption' have been used to measure environmental effects. According to the opinion of experts, the initial weight of these criteria for all facilities was considered equal to 0.4, 0.4, and 0.2, respectively. Also, the stages of vehicle collection, dismantling, processing, and transportation have been analysed to utilise from the LCA method. Measurement of environmental effects by the LCA method has been evaluated in the form of the second-order objective function of the mathematical model.

5.1.3 Social effects

The hierarchical analysis method has been used to determine the social effects, which estimate the level of these effects in the stages of vehicle collection, dismantling, processing and transportation based on the criteria of 'local development', 'product risk', 'damage to the worker' and 'employment'.

The purpose of the hierarchical analysis technique is to select the best option based on different criteria through a paired comparison. This technique is also used to weigh criteria. Since increasing the number of elements in each cluster makes it difficult to comprise pairs, the decision criteria are usually divided into sub-criteria. Utilising this method requires four main steps:

- *Modelling*: the decision elements including decision indicators and options are identified in this step. AHP needs to define the problem hierarchically and the hierarchical tree is specified in this step.
- *Preferential judgment (paired comparisons)*: in this step, the indicators are judged in pairs and the data are collected. This is done by performing two-by-two comparisons between the elements of decision (paired comparison) and assigning numerical scores that indicate the preference or importance between two elements of the decision. For this purpose, i^{th} options or indicators are usually comprised of j^{th} options or indicators. Table 2 shows how the indicators are evaluated relative to each other.

Table 2 Evaluation of indicators relative to each other

Prior value	*Comprising the status of i relative to j*	*Explanation*
1	Equal importance	Option or indicator *i* is equal to *j* or are not superior to each other.
3	Relatively more important	Option or indicator *i* is relatively more important than *j*
5	More important	Option or indicator *i* is more important than *j*
7	Much more important	Option or indicator *i* is very superior to *j*
9	Quite important	Option or indicator *i* is absolutely more important than *j* and cannot be compared to *j*
2, 4, 6, 8	Intermediate values	Indicates the intermediate values between preferential values. As an example, 8 indicate and importance higher than 7 and lower than 9 for *i*.

Relative weight calculations: in this step, the priority of decision elements is determined using numerical calculations. To take this step, the sum of numbers in each column of the paired comparisons matrix is calculated. Then, each element of the column is divided by the sum of numbers in that column. The newly obtained matrix is called the 'normalised comparison matrix'. The average of each row of normalised comparison matrix is then calculated. This average provides the relative weight of decision elements with the matrix lines.

Integration of relative weights: in this step, the relative weight of each element must be multiplied by the weight of higher elements and obtain its final weigh to rank the decision options. The value of the final weight is obtained by taking this step for each option.

In the present study, experts were asked to conduct paired comparisons between the criteria of 'local development', 'employment', 'worker damage' and 'product risk' for the stages of vehicle collection, dismantling, processing, and transportation in each of the provincial centres. Finally, the AHP method was used to determine the weights of social effects in each of the provincial centres for each of the facilities of dismantling and processing after gathering the data obtained from paired comparisons.

According to the results of AHP, the normalised weight for criteria of 'local development', 'employment', 'worker damage' and 'product risk' were obtained equal to

0.231, 0.487, 0.065, and 0.226, respectively. Table 3 represents the weights of each provincial centre for the criteria of 'local development', 'employment', 'worker damage' and 'product risk'.

Table 3 Social effect values

Name of provincial centre		*Local development*	*Employment*	*Worker damage*	*Product risk*
Tehran	dismantling	0.211	0.478	0.264	0.121
	processing	0.278	0.312	0.185	0.143
Kashan	dismantling	0.203	0.426	0.279	0.122
	processing	0.183	0.423	0. 354	0.108
Qazvin	dismantling	0.279	0.337	0.263	0.179
	processing	0.204	0.419	0.284	0.154
Khorasan	dismantling	0.195	0.259	0.247	0.139
	processing	0.230	0.302	0.172	0. 292
Tabriz	dismantling	0.238	0.409	0.272	0. 225
	processing	0.215	0.466	0.281	0.114
Semnan	dismantling	0.252	0.332	0.250	0.127
	processing	0.184	0.496	0.259	0.156
Azerbaijan	dismantling	0.233	0.409	0.255	0.184
	processing	0.244	0.305	0.234	0. 123

5.1.4 How to generate sample problems

In the present article, several experimental sample problems have been randomly generated in addition to the case study and solved by understudy algorithms and the results of their solution comprised of each other. The designed experimental sample problems to be solved by algorithms have been presented in Table 4.

In the sample problems, the model solving parameters have been set as follows. In the presented model, several model parameters were considered fuzzy. The triangular fuzzy number was used to generate fuzzy values. To triangular numbers related to each of the fuzzy parameters (m_1, m_2, m_3), m_2 was firstly generated and then, the random number r was generated in the range (0, 1) and m_1 was generated using Relation ($m_2 * 1 - r$) and m_3 generated using Relation ($m_2 * 1 + r$)). To set the value of fuzzy parameters, m_2 was randomly assigned and the values of m_1 and m_3 were determined using the MATLAB program. For this reason, the value of m_2 has been only mentioned here for the section of setting these parameters.

- The fixed cost of establishing the disassembling and dismantling plant is in the form of a triangular fuzzy number (m_1, m_2, m_3) that m_2 has been considered in the uniform range of [200–500].
- The fixed cost of establishing the processing plant is in the form of a triangular fuzzy number (m_1, m_2, m_3) that m_2 has been considered in the uniform range of [200–500].
- The capacity of disassembling and dismantling plants is in the form of a triangular fuzzy number (m_1, m_2, m_3) that m_2 has been considered in the uniform range of [2000–4000].

Table 4 Sample problems

Size	*Problem number*	*No. of collection centre*	*No. of potential locations for dismantling plant*	*No. of potential locations for processing plant*	*No. of recovery centres*	*No. of centres for conversion to waste*	*No. of intermediate markets*	*No. of spare parts*
Small	1	2	4	2	2	2	1	4
	2	2	4	2	2	2	2	4
	3	2	4	2	2	2	3	4
	4	2	4	2	2	2	4	4
	5	3	5	2	2	2	1	4
	6	3	5	2	2	2	2	4
	7	3	5	2	2	2	3	4
	8	3	5	2	2	2	4	4
	9	5	7	2	2	2	3	4
	10	5	7	2	2	2	4	4
Medium	1	10	5	5	5	10	5	10
	2	10	5	5	5	10	5	10
	3	10	5	5	5	10	5	10
	4	10	5	5	5	10	5	10
Large	1	20	10	5	10	15	5	10
	2	20	10	5	10	15	5	10
	3	20	10	5	10	15	5	10
	4	20	10	5	10	15	5	10
	5	30	15	10	10	15	5	10
	6	30	15	10	10	15	5	10

- The capacity of the processing plant is in the form of a triangular fuzzy number (m_1, m_2, m_3) that m_2 has been considered in the uniform range of [3000–5000].
- The capacity of recovery centres is in the form of a triangular fuzzy number (m_1, m_2, m_3) that m_2 has been considered in the uniform range of [1000–3000].
- The capacity of centres for conversion to waste is in the form of a triangular fuzzy number (m_1, m_2, m_3) that m_2 has been considered in the uniform range of [1000–3000].
- Transportation costs between different centres in different cities have been considered as a function of the distance between centres, which equals 10,000 Tomans per 1 km.
- According to the opinion of experts, the cost of converting to waste has been considered 50,000.
- The cost of incentive for returning each unit of vehicle to the collection centres was considered.
- According to the opinion of experts, the cost of operation of each unit for disassembling and dismantling plants in each period has been generated in a uniform range of [1000–2000].
- According to the opinion of experts, the cost of operation of each unit for processing plants in each period has been generated in a uniform range of [2000–4000].
- The profit per unit of the vehicle's reusable spare parts has been generated in a uniform range of [50–3000].
- The profit per unit of recovered products has been considered 200,000.
- The distance between centres has been considered in the uniform range [200–1000].
- LCA and AHP methods have been used to calculate the parameters related to environmental and social effects, respectively.

5.2 Algorithm setting

Taguchi experimental design and analysis in the MINITAB software were used to adjust some of the parameters of the two proposed algorithms. The parameters included whale population size, the number of repeated neighbourhood search variables, and the number of repetitions in the whale optimisation algorithm, population size, mutation rate, and intersection rate and the number of repetitions in the NSGA-II algorithm.

5.2.1 Parameter tuning

To adjust the parameters of the whale algorithm, the values of each of these parameters have been investigated at three levels shown in Table 5.

Table 5 Whale algorithm parameters

No. of neighbourhood search iteration	*Population size*	*No. of iteration*
5	70	150
10	150	300
15	200	500

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

Table 6 NSGA-II algorithm parameters

Population size	*Crossover rate*	*Mutation rate*	*No. of iteration*
70	0.75	0.006	150
150	0.85	0.009	300
200	0.95	0.01	500

To perform the analysis, a criterion called RPD has been designed, which its calculation has been shown in equation (33).

$$RPD = \left(\sum \frac{a\lg_{sol} - Best_{sol}}{Best_{sol}} \right) \times 100 \tag{33}$$

$a\lg_{sol}$ the value of each obtained objective function for each problem by the desired combination of parameters.

$Best_{sol}$ the best value of objective function obtained from the values of all combinations for each problem.

Each problem was performed for each of the above combinations, and the RPD criterion was calculated for each problem and finally, the corresponding graph was drawn.

To adjust the parameter, Taguchi L9 experimental method was used. The orthogonal value of two algorithms has shown in Table 7 and Table 8.

Table 7 Whale algorithm RPD

Sample no.	*NHS iteration*	*Population size*	*No. iteration*	*value RPD*
1	5	70	150	0.2341
2	5	150	300	0.4367
3	5	200	500	0.3395
4	10	70	300	0.3083
5	10	150	500	0.1285
6	10	200	150	0.2216
7	15	70	500	0.1993
8	15	150	150	0.4643
9	15	200	300	0.2942

Table 8 NSGA-II algorithm RPD

Sample no.	*Population size*	*Crossover rate*	*Mutation rate*	*No. iteration*	*value RPD*
1	70	0.75	0.006	150	0.5032
2	70	0.85	0.009	300	0.1259
3	70	0.95	0.01	500	0.7419
4	150	0.75	0.009	500	0.6635
5	150	0.85	0.01	150	0.4917
6	150	0.95	0.006	300	0.0045
7	200	0.75	0.01	300	0.7124
8	200	0.85	0.006	500	0.7280
9	200	0.95	0.009	300	0.2942

The results obtained from MINITAB software related to the whale optimisation algorithm have been shown in Figure 9 and Figure 10.

Figures 9 and 10 represent the analysis of parameter adjustment by the Taguchi method. As can be seen in Figure 9, the population size, algorithm repetitions, and neighbourhood search are effective at the levels of 2, 2, and 1, respectively. In another word, the population size, number of VNS repetitions and repetitions in the whale optimisation algorithm has been considered equal to 150, 5, and 300, respectively. The diagrams related to the NSGA-II algorithm are depicted in Figure 11 and Figure 12.

Figure 9 Whale algorithm noise signal (see online version for colours)

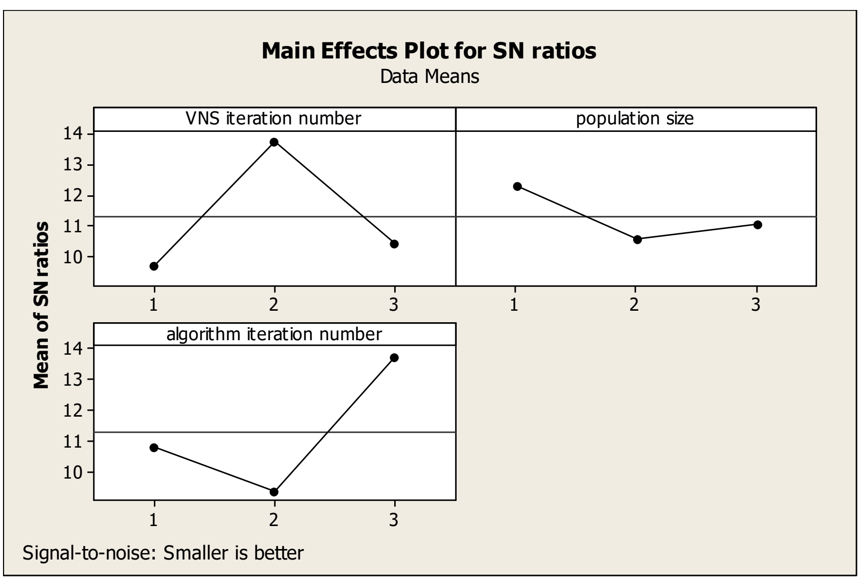
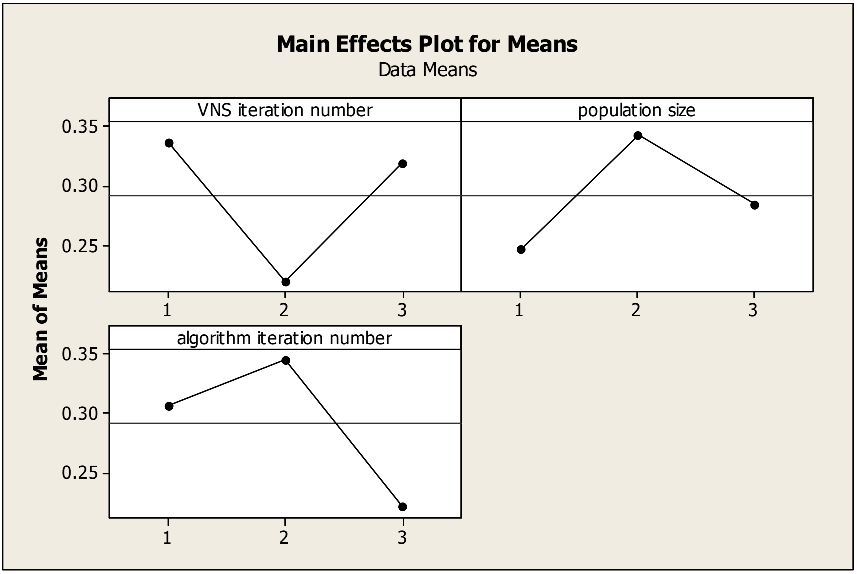


Figure 10 Mean effect of whale algorithm (see online version for colours)



Figures 11 and 12 represent the analysis of parameter adjustment by the Taguchi method. As can be seen from Figure 11, the mutation rate, intersection rate and, algorithm repetitions, and population size are effective at the levels of 3, 1, and 3, respectively. Therefore, the values of 300, 500, 0.01, and 0.75 were considered for population size, algorithm repetitions, mutation rate, and intersection rate, respectively.

Figure 11 NSGA-II noise signal (see online version for colours)

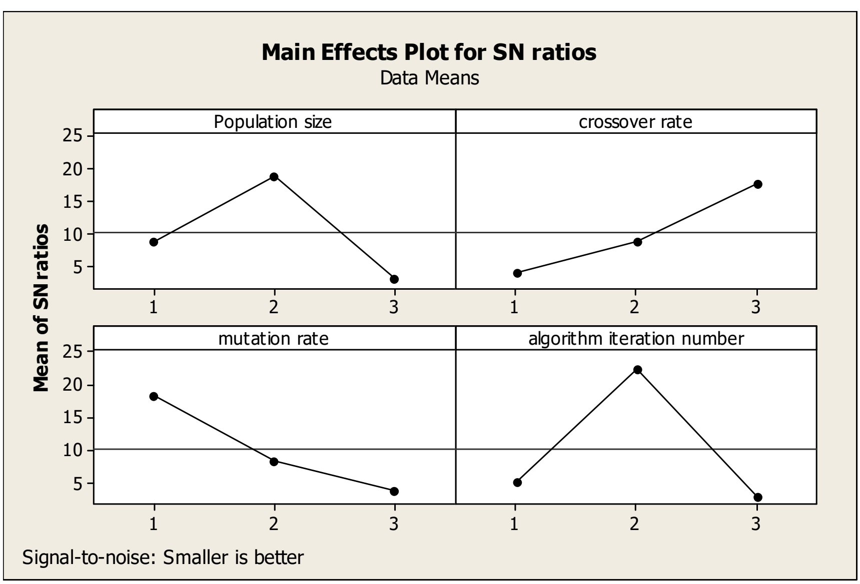
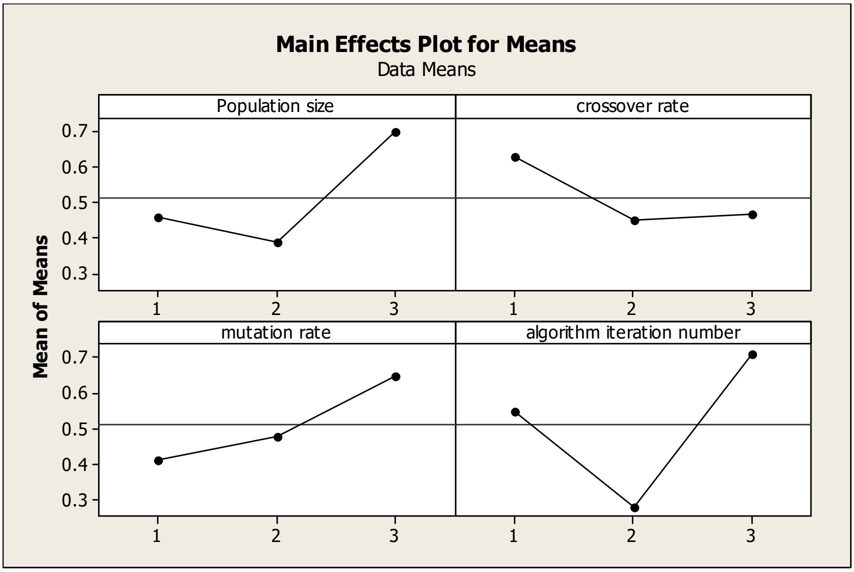


Figure 12 Mean effect of NSGA-II (see online version for colours)



5.2.2 *Comparative indicators*

There are various indicators to evaluate the quality and dispersion of a multi-objective meta-heuristic algorithm. In the present study, three following indicators were used for comparisons.

- *Quality indicator*: This indicator compares the quality of Pareto efficiency solutions obtained by each method. The indicator level all Pareto efficiency solutions obtained from both methods and determine what percentage of level one's solutions belong to each method. Whatever the percentage is higher, the algorithm has higher quality.
- *Spacing indicator*: This criterion tests the uniformity of obtained Pareto efficiency solutions' distribution at the response boundary. The indicator is defined as follows:

$$S = \frac{\sum_{i=1}^{N-1} \left| d_{mean} - d_i \right|}{(N-1) \times d_{mean}} \tag{34}$$

  Where (d_i) indicates the Euclidean distance between two non-dominated adjacent solutions and (d_{mean}) is the mean of d_i values.

- *Dispersion indicator*: this indicator is used to determine the amount of non-dominated solutions on the optimal boundary. The dispersion indicator is defined as follow:

$$D = \sqrt{\sum_{i=1}^{N} \max\left(\left\| x_t^i - y_t^i \right\| \right)} \tag{35}$$

Where $\left(\left\|x_t^i - y_t^i\right\|\right)$ indicates the Euclidean distance between two adjacent solutions of (x_t^i) and (y_t^i) on the optimal boundary.

5.3 Solution results

In this section, the performance of the proposed integrated whale optimisation algorithm and the NSGA-II algorithm has been investigated and analysed for problem-solving related to case study and randomly designed problems.

5.3.1 The results obtained from solving the problem of case study

As was mentioned in the previous section, the presented mathematical model was solved using GAMS Software for a case study including the reverse logistics of EOL vehicles in the provinces of Tehran, Kashan, Qazvin, Tabriz, Azerbaijan, Khorasan, and Semnan. Model solving parameters for the case study as well as algorithm-related parameters were described in previous sections. After solving the problem related to the case study, the values of objective functions were as follows. The Epsilon constraint method was used to solve the model, which has been described below.

As it is known, there are many methods to solve multi-objective problems such as multi-objective solving methods based on the Pareto Archive, goals weighting method, and e-constraint method. In the present thesis, a Pareto Archive-based multi-objective algorithm has been proposed, which described in the next section. To investigate and prove the validity of the model as well as the solution algorithm, the proposed three-objective model was converted to a single-objective model using the e-constraint method and then solved by the solution algorithm and GAMS Software. Finally, the results of solving the single-objective model were comprised of each of the objective functions using a solution algorithm and GAMZ Software. In the following, the e-constraint method has been described. Suppose the multi-objective problem is as follows:

$$\left(f_1(x), f_2(x), \ldots, f_p(x)\right)$$
$$s.t.\ x \in S$$

Where S is the possible space of solution and x is the set of model variables. In the e-constraint method, one of the objective functions is considered and optimised as the target, and the other target functions are considered as constraints. The above multi-objective model can be converted to the following single-objective model through the e-constraint method:

$$f_1(x) : s.t.\ f_2(x) \geq e_2;\ f_3(x) \geq e_p$$

Based on what has been described, the proposed three-objective model of the present research has been converted to a single-objective model as follows.

First objective function optimisation:

$$\max z_1 = \sum_{k=1}^{c}\sum_{i=1}^{n}\sum_{j=1}^{m} c_{ijk} d_{ij} w_{ijk} + \sum_{k=1}^{c}\sum_{i=1}^{n}\sum_{i'=1, i'\neq i}^{n} c'_{ii'k} d_{ii'} w'_{ii'k} + \sum_{k=1}^{c}\sum_{l=1}^{L}\sum_{i=1}^{n} c_{lik} d_{il} w_{lik} \tag{36}$$

s.t.

$$\sum_j \sum_k \sum_t Y_{jkt} EI_k + \sum_i \sum_j \sum_t X_{ijt} EI_j + EI^{CT} \Bigg[\sum_i \sum_j \sum_t x_{ijt} d_{ij} + \sum_j \sum_k \sum_t Y_{jkt} d_{jk} + \sum_j \sum_n \sum_t Z_{jnpt} d_{jn} + \sum_k \sum_l \sum_t W_{klt} d_{kl} + \sum_j \sum_m \sum_t U_{jmt} d_{jm} + \sum_k \sum_m \sum_t U_{kmt} d_{km} \Bigg] \leq \varepsilon_2 \tag{37}$$

$$\sum_j \sum_t \left(W_{em} EM_{jt} + W_{ld} ld_j + W_{dm} DM_j + W_{pr} PR_j \right)_{aj} + \sum_k \sum_t \left(W_{em} EM_{kt} + W_{ld} ld_k + W_{dm} DM_k + W_{pr} PR_j \right)_{bk} \geq \varepsilon_3 \tag{38}$$

Second objective function optimisation:

$$\min z_2 = \sum_j \sum_k \sum_t Y_{jkt} + EI_k + \sum_i \sum_j \sum_t X_{ijt} EI_j + EI^{CT} \Bigg[\sum_i \sum_j \sum_t X_{ijt} d_{ij} + \sum_j \sum_k \sum_t Y_{jkt} d_{jk} + \sum_j \sum_n \sum_t Z_{jnpt} d_{jn} + \sum_k \sum_l \sum_t W_{klt} d_{kl} + \sum_j \sum_m \sum_t U_{jmt} d_{jm} + + \sum_k \sum_m \sum_t U_{kmt} d_{km} \Bigg] \tag{39}$$

s.t.

$$\sum_{k=1}^{c} \sum_{i=1}^{n} \sum_{j=1}^{m} c_{ijk} d_{ij} w_{ijk} + \sum_{k=1}^{c} \sum_{i=1}^{n} \sum_{i'=1, i' \neq i}^{n} c'_{ii'k} d_{ii'} w'_{ii'k} + \sum_{k=1}^{c} \sum_{l=1}^{L} \sum_{i=1}^{n} c_{lik} d_{il} w_{lik} \geq \varepsilon_1 \tag{40}$$

$$\sum_j \sum_t \left(W_{em} EM_{jt} + W_{ld} ld_j + W_{dm} DM_j + W_{pr} PR_j \right)_{aj} + \sum_k \sum_t \left(W_{em} EM_{kt} + W_{ld} ld_k + W_{dm} DM_k + W_{pr} PR_j \right)_{bk} \geq \varepsilon_3 \tag{38}$$

Third objective function optimisation:

$$\max z_3 = \sum_j \sum_t \left(W_{em} EM_{jt} + W_{ld} ld_j + W_{dm} DM_j + W_{pr} PR_j \right)_{aj} + \sum_k \sum_t \left(W_{em} EM_{kt} + W_{ld} ld_k + W_{dm} DM_k + W_{pr} PR_k \right)_{bk} \tag{41}$$

s.t.

$$\sum_{k=1}^{c} \sum_{i=1}^{n} \sum_{j=1}^{m} c_{ijk} d_{ij} w_{ijk} + \sum_{k=1}^{c} \sum_{i=1}^{n} \sum_{i'=1, i' \neq i}^{n} c'_{ii'k} d_{ii'} w'_{ii'k} + \sum_{k=1}^{c} \sum_{l=1}^{L} \sum_{i=1}^{n} c_{lik} d_{il} w_{lik} \geq \varepsilon_1 \tag{40}$$

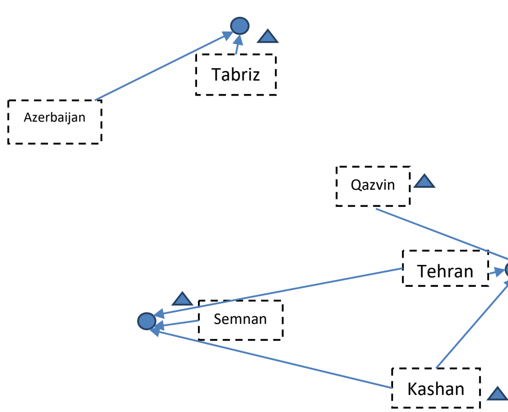
$$\sum_j \sum_k \sum_t Y_{jkt} EI_k + \sum_i \sum_j \sum_t X_{ijt} EI_j + EI^{CT} \Bigg[\sum_i \sum_j \sum_t x_{ijt} d_{ij} + \sum_j \sum_k \sum_t Y_{jkt} d_{jk} + \sum_j \sum_n \sum_t Z_{jnpt} d_{jn} + \sum_k \sum_l \sum_t W_{klt} d_{kl} + \sum_j \sum_m \sum_t U_{jmt} d_{jm} + \sum_k \sum_m \sum_t U_{kmt} d_{km} \Bigg] \leq \varepsilon_2 \tag{37}$$

For example, the model should be solved using GAMS Software without taking into account the mentioned objective function and combing the weights of two other objectives to calculate the e_1, e_2 and e_3 and the related objective function should be calculated using the obtained optimal solution and it value considered as e. Table 9 indicates the value of the first objective function in the proposed algorithm is better than the same value in GAMS Software. On the other hand, the value of the second objective function in GAMS Software is better than its value in the proposed integrated algorithm. Also, the value of the third objective function is the same for both methods.

Table 9 Objective function value of case study

Solution approach	*Objective function value*		
	f_1	f_2	f_3
Whale algorithm	57,432,904	578,425	469
GAMS	49,332,751	552,193	469

Figure 13 Facility location of case study (see online version for colours)



According to the definition of non-dominated relations, the solutions obtained from the two methods are non-dominated to each other and it means that these solutions do not dominate over each other and are on the same level in terms of quality. Figure 13 represents the location of the facility at potential places as well as the relationships between them. It should be noted that it is based on the output of the whale optimisation algorithm. In Figure 13, the provincial centres have been marked. The circle mark indicates the establishment of dismantling plants in these provinces and the triangle mark indicates the establishment of a processing plant. The arrows also indicate the allocation of collection centres to these dismantling plants.

Table 10 Solution results of the small size problem

Size	*Prob.*	*Whales optimisation algorithm (WOA)*					*NSGA-II*				
		Quality metric	*Spacing metric*	*Diversity metric*	*CPU time*	*No. of Pareto solution*	*Quality metric*	*Spacing metric*	*Diversity metric*	*CPU time*	*No. of Pareto solution*
Small	1	85.2	0.92	985.2	155.2	380	14.8	0.78	740.7	73.4	301
	2	83.5	0.51	1,365.9	159.2	299	16.5	0.47	840.9	73.6	79
	3	88.1	0.64	1,439.9	160.1	534	11.9	0.56	850.2	80.1	47
	4	100	1.06	1,468.3	162.5	200	0	0.71	1,130.6	89.2	301
	5	87.7	0.68	1,582.2	163.1	198	12.3	0.44	1,220.4	85.2	217
	6	87.6	0.91	1,702.3	171.8	231	12.4	0.78	1,261.3	105.7	211
	7	83.4	0.71	1,708.9	181.8	187	16.6	0.47	1,349.1	112.6	149
	8	85.8	0.73	1,763.2	182.4	345	14.2	0.62	1,360.6	124.5	348
	9	88.1	1.01	1,930.2	184.7	488	11.9	0.49	1,218.4	124.9	351
	10	88.7	1.32	2,012.9	199.4	529	11.3	0.70	1,495.4	136.7	400
Medium	1	90	0.75	2,871.6	424.4	299	10	0.74	1,901.6	179.2	161
	2	85.9	1.72	2,685.3	427.8	321	14.1	0.64	1,954.2	235.9	208
	3	87.6	1.67	3,063.5	440.3	407	12.4	0.76	2,112.5	354.4	198
	4	70.9	0.73	2,636.3	459.2	513	29.1	0.65	1,901.9	386.5	192
Large	1	89.9	0.71	2,816.5	568.8	376	10.1	0.70	2,265.1	397.7	211
	2	66.8	1.70	3,486.3	601.8	322	33.2	0.54	2,793.6	429.4	319
	3	87.2	1.17	4,121.9	614.1	285	12.8	0.65	3,278.6	437.9	200
	4	100	1.13	4,565.9	769.2	309	0	0.64	3,397.7	543.4	188
	5	88.4	1.04	5,054.1	783.6	300	11.6	0.73	4,758.7	650.2	197
	6	85.1	1.75	6,077.6	808.7	398	14.9	0.56	5,779.7	750.6	320

As shown in Figure 13, the dismantling plant has been established in Tehran, Semnan, Khorasan, and Tabriz provinces. The processing plant has been also established in Kashan, Semnan, Khorasan, and Tabriz provinces. According to the diagram, there is a material flow between collection centre of Tehran and dismantling plants of Tehran and Semnan, between collection centres of Khorasan and dismantling plants of Khorasan and Tehran, between collection centre of Kashan and dismantling plants of Semnan and Tehran, between collection centres and dismantling plant of Tabriz and finally, between collection centre of Azerbaijan and dismantling plant of Tabriz.

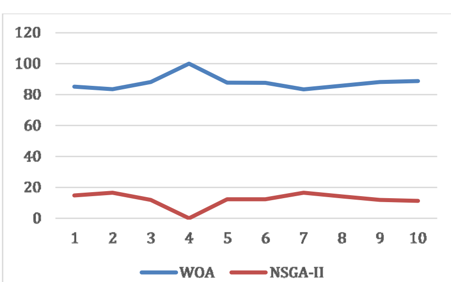
5.3.2 The results obtained from solving the random experimental problems

In the present study, several experimental problems were randomly generated and solved multi-objective whale optimisation and NSGA-II algorithms to more accurately comprise their performance. The comparative results for solving these problems have been presented in Table 10 according to proposed indicators.

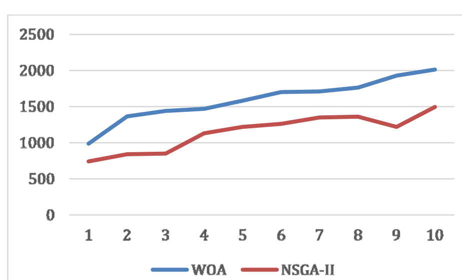
Figures 14 and 15 show that the whale algorithm has a higher ability to produce higher quality responses compared to the NSGA-II algorithm in all cases. The whale algorithm can generate solutions with higher dispersion compared to the NSGA-II algorithm. In other words, the whale algorithm has a greater ability to explore and extract possible space of solutions compared to the NSGA-II algorithm. As can be seen from the above Tables, the NSGA-II algorithm produces solutions with higher uniformity compared to the whale optimisation algorithm.

The execution time of algorithms has been also shown in the above Tables that the values of the execution time and the diagrams of execution time indicate the higher execution time of multi-objective whale optimisation algorithm. Since the proposed method intelligently searches many points of the solution space for iterations due to its designed structure, it is obvious that the method takes more computational time compared to the NSGA-II method.

Figure 14 Comparison of the proposed algorithms in small size problems, (a) quality indicator comparison (b) dispersion indicator comparison (c) spacing indicator comparison (d) CPU time comparison (e) comparison of Pareto solution between two algorithms (see online version for colours)

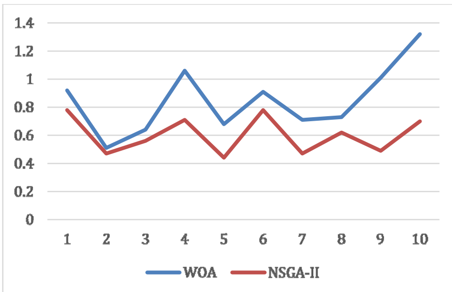


(a)

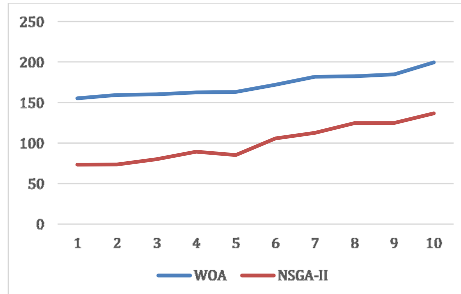


(b)

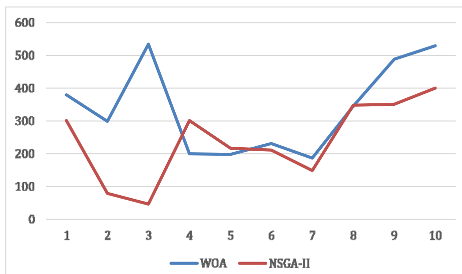
Figure 14 Comparison of the proposed algorithms in small size problems, (a) quality indicator comparison (b) dispersion indicator comparison (c) spacing indicator comparison (d) CPU time comparison (e) comparison of Pareto solution between two algorithms (continued) (see online version for colours)



(c)

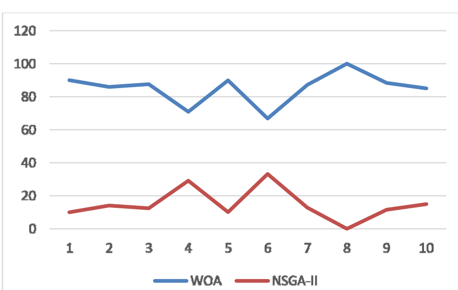


(d)

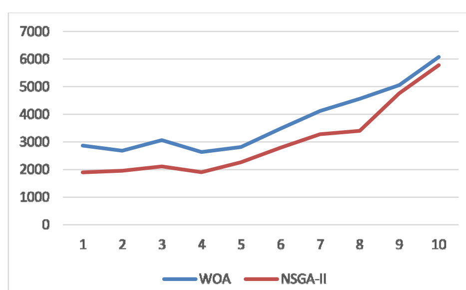


(e)

Figure 15 Comparison of the proposed algorithms in large and medium-size problems, (a) quality indicator comparison (b) dispersion indicator comparison (c) spacing indicator comparison (d) CPU time comparison (e) comparison of Pareto solution between two algorithms (see online version for colours)

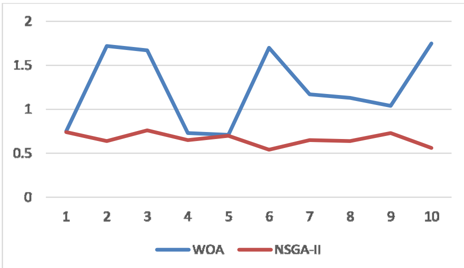


(a)

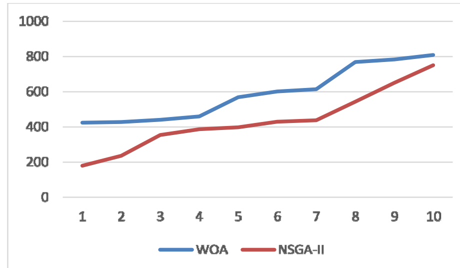


(b)

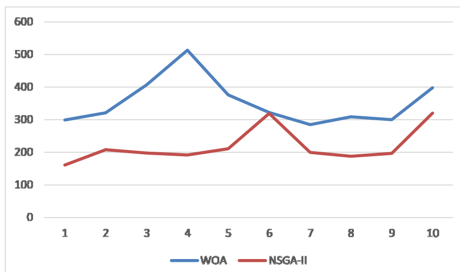
Figure 15 Comparison of the proposed algorithms in large and medium-size problems, (a) quality indicator comparison (b) dispersion indicator comparison (c) spacing indicator comparison (d) CPU time comparison (e) comparison of Pareto solution between two algorithms (continued) (see online version for colours)



(c)



(d)



(e)

5.4 Statistical analysis of comprising two algorithms

The results of solving sample problems with small, medium, and large sizes by two algorithms were based on comparative indicators of quality, dispersion, and uniformity. In this section, the difference between the results of the two algorithms has been investigated based on statistical analysis and developing appropriate hypotheses.

The T-student test was used to investigate the comparative indicators, which have been described in below. It should be noted that each of the hypotheses has been tested separately for problems of small, medium, and large size.

Hypothesis 1 There is a significant difference between the quality indicators of the whale algorithm and genetic algorithm.

Table 11 shows that there is a significant difference between averages of the two groups and the statistical value is beyond the confidence level. Therefore, H0 was rejected and H1 was accepted, which indicates a significant difference between quality indicators of whale algorithm and genetic algorithm for small size problems. According to the results of Table 12, there is a significant difference between averages of the two groups and the statistical value is beyond the confidence level. Therefore, H0 was rejected and H1 was accepted, which indicates a significant difference between quality indicators of whale algorithm and genetic algorithm for medium and large size problems.

Table 11 Result of testing the first hypothesis for small size problems

Sample	*Sample size*		*Mean*	*Standard deviation*	*Mean of error*	
WOA	10		87.8	4.7	1.5	
NSGA-II	10		12.2	4.7	1.5	
	t	*Degrees of freedom*	*Significance level*	*Average difference*	*Confidence level of 95%*	
					Lower	*Upper*
WOA	58.792	9	.000	87.31000	83.9505	90.6695
NSGA-II	7.872	9	.000	11.69000	8.3305	15.0495

Table 12 Result of testing the first hypothesis for medium and large size problems

Sample	*Sample size*		*Mean*	*Standard deviation*	*Mean of error*	
WOA	10		85.2	9.5	3.03	
NSGA-II	10		14.8	9.5	3.03	
	t	*Degrees of freedom*	*Significance level*	*Average difference*	*Confidence level of 95%*	
					Lower	*Upper*
WOA	27.923	9	.000	84.68000	77.8197	91.5403
NSGA-II	4.722	9	.001	14.32000	7.4597	21.1803

Hypothesis 2 There is a significant difference between dispersion indicators of whale algorithm and genetic algorithm.

According to the results of Table 13, there is a significant difference between averages of the two groups and the statistical value is beyond the confidence level. Therefore, H0 was rejected and H2 was accepted, which indicates a significant difference between dispersion indicators of whale algorithm and genetic algorithm for small size problems. Table 14 states that there is a significant difference between averages of the two groups and the statistical value is beyond the confidence level. Therefore, H0 was rejected and H2 was accepted, which indicates a significant difference between dispersion indicators of whale algorithm and genetic algorithm for medium and large size problems.

Table 13 Result of testing the second hypothesis for small size problems

Sample	*Sample size*		*Mean*	*Standard deviation*	*Mean of error*	
WOA	10		1,595.9	298.5	94.5	
NSGA-II	10		1,146.76	253.5	80.1	
	t	*Degrees of freedom*	*Significance level*	*Average difference*	*Confidence level of 95%*	
					Lower	*Upper*
WOA	16.876	9	.000	1,595.40000	1,381.5381	1,809.2619
NSGA-II	14.297	9	.000	1,146.26000	964.8892	1,327.6308

Table 14 Result of testing the second hypothesis for medium and large size problems

Sample	*Sample size*		*Mean*	*Standard deviation*	*Mean of error*	
WOA	10		3,737.9	1,177.5	372.4	
NSGA-II	10		3,014.36	1,330.4	420.7	
	t	*Degrees of freedom*	*Significance level*	*Average difference*	*Confidence level of 95%*	
					Lower	*Upper*
WOA	10.037	9	.000	3,737.40000	2,895.0631	4,579.7369
NSGA-II	7.164	9	.000	3,013.86000	2,062.1450	3,965.5750

Hypothesis 3 There is a significant difference between uniformity indicators of whale algorithm and genetic algorithm.

Table 15 indicates a significant difference between averages of the two groups and the statistical value is beyond the confidence level. Therefore, H0 was rejected and H3 was accepted, which indicates a significant difference between uniformity indicators of whale algorithm and genetic algorithm for small size problems.

Table 15 Result of testing the third hypothesis for small size problems

Sample	*Sample size*		*Mean*	*Standard deviation*	*Mean of error*	
WOA	10		0.84	0.24	0.076	
NSGA-II	10		0.60	0.133	0.042	
	t	*Degrees of freedom*	*Significance level*	*Average difference*	*Confidence level of 95%*	
					Lower	*Upper*
WOA	4.584	9	.001	.34900	.1768	.5212
NSGA-II	2.416	9	.039	.10200	.0065	.1975

According to the results of Table 16, there is a significant difference between averages of the two groups and the statistical value is beyond the confidence level. Therefore, H0 was rejected and H3 was accepted, which indicates a significant difference between uniformity indicators of whale algorithm and genetic algorithm for medium and large size problems.

Table 16 Result of testing the third hypothesis for medium and large size problems

Sample	*Sample size*		*Mean*	*Standard deviation*	*Mean of error*	
WOA	10		1.24	0.44	0.14	
NSGA-II	10		0.66	0.073	0.023	
	t	*Degrees of freedom*	*Significance level*	*Average difference*	*Confidence level of 95%*	
					Lower	*Upper*
WOA	5.323	9	.000	.73700	.4238	1.0502
NSGA-II	6.951	9	.000	.16100	.1086	.2134

Hypothesis 4 There is a significant difference between execution times of whale algorithm and genetic algorithm.

According to the results of Table 17, there is a significant difference between averages of the two groups and the statistical value is beyond the confidence level. Therefore, H0 was rejected and H4 was accepted, which indicates a significant difference between execution times of whale algorithm and genetic algorithm for small size problems. As well, Table 18 states that there is a significant difference between averages of the two groups and the statistical value is beyond the confidence level. Therefore, H0 was rejected and H4 was accepted, which indicates a significant difference between execution times of whale algorithm and genetic algorithm for medium and large size problems.

Table 17 Result of testing the fourth hypothesis for small size problems

Sample	*Sample size*	*Mean*	*Standard deviation*	*Mean of error*
WOA	10	172.02	14.42	4.56
NSGA-II	10	100.59	23.31	7.37

	t	*Degrees of freedom*	*Significance level*	*Average difference*	*Confidence level of 95%*	
					Lower	*Upper*
WOA	37.692	9	.000	171.97000	161.6490	182.2910
NSGA-II	13.638	9	.000	100.54000	83.8635	117.2165

Table 18 Result of testing the fourth hypothesis for medium and large size problems

Sample	*Sample size*	*Mean*	*Standard deviation*	*Mean of error*
WOA	10	589.79	153.42	48.51
NSGA-II	10	436.52	174.16	55.07

	t	*Degrees of freedom*	*Significance level*	*Average difference*	*Confidence level of 95%*	
					Lower	*Upper*
WOA	12.156	9	.000	589.74000	479.9889	699.4911
NSGA-II	7.925	9	.000	436.47000	311.8810	561.0590

Hypothesis 5 There is a significant difference between Pareto solution indicators of whale algorithm and genetic algorithm.

Table 19 depicts that there is a significant difference between averages of the two groups and the statistical value is beyond the confidence level. Therefore, H0 was rejected and H5 was accepted, which indicates a significant difference between Pareto solution indicators of whale algorithm and genetic algorithm for small size problems.

According to the results of Table 20, there is a significant difference between averages of the two groups and the statistical value is beyond the confidence level. Therefore, H0 was rejected and H5 was accepted, which indicates a significant difference between Pareto solution indicators of whale algorithm and genetic algorithm for medium and large size problems.

Table 19 Result of testing the fifth hypothesis for small size problems

Sample	*Sample size*		*Mean*	*Standard deviation*	*Mean of error*	
WOA	10		339.1	138.9	43.9	
NSGA-II	10		240.4	120.1	37.9	
	t	*Degrees of freedom*	*Significance level*	*Average difference*	*Confidence level of 95%*	
					Lower	*Upper*
WOA	7.720	9	.000	339.05000	239.6944	438.4056
NSGA-II	6.328	9	.000	240.35000	154.4256	326.2744

Table 20 Result of testing the fifth hypothesis for medium and large size problems

Sample	*Sample size*		*Mean*	*Standard deviation*	*Mean of error*	
WOA	10		353	70.9	22.4	
NSGA-II	10		219.4	54.5	17.2	
	t	*Degrees of freedom*	*Significance level*	*Average difference*	*Confidence level of 95%*	
					Lower	*Upper*
WOA	15.725	9	.000	352.95000	302.1759	403.7241
NSGA-II	12.729	9	.000	219.35000	180.3688	258.3312

6 Conclusions and further recommendations

In the present study, a problem was first selected as a case study, and the model was solved for the case study. Then, several random experimental problems with different sizes were designed and solved using whale optimisation and NSGA-II algorithms. The case study included provinces of Tehran, Kashan, Qazvin, Khorasan, Tabriz, Semnan, and Azerbaijan. These provinces have centres for collecting EOL vehicles as well as potential locations for the establishment of dismantling and processing plants, a supply chain network, which integrates production and collection centres. The criteria of 'human health', 'environmental quality' and 'resource consumption' have been used to measure environmental effects. According to the opinion of experts, the initial weight of these criteria was considered 0.4, 0.4, and 0.2, respectively, for all facilities. Also, the stages of vehicle collecting, dismantling, processing, and transportation were analysed to utilise from the LCA method. Measurement of environmental effects by the LCA method has been evaluated in the form of the second-order objective function of the mathematical model. Also, the hierarchical analysis method was used to determine the social effects, which estimate the level of these effects at the stages of vehicle collecting, dismantling, processing and transportation according to the criteria of 'local development', 'product risk', ' worker damage ' and 'employment'. In general, the results obtained from solving the model showed that:

- According to AHP results, the normalised weight for the criteria of 'local development', 'employment', 'worker damage' and 'product risk' were calculated equal to 0.231, 0.487, 0.065 and 0.226, respectively.
- According to the results of solving a case study problem, the value of the first objective function in the proposed algorithm is better than the same value in GAMZ Software. On the other hand, the value of the second objective function in GAMZ Software is better than its value in the proposed integrated algorithm. Also, the value of the third objective function is the same for both methods. According to the definition of NON-DOMINATED relations, the solutions obtained from the two methods are non-dominated to each other and it means that these solutions do not dominate over each other and are on the same level in terms of quality.
- According to the results of GAMZ which can find possible solutions for the model, it can be said that the model is possible and valid.
- Comprising the results of the GAMS Software and whale algorithm showed that the whale algorithm is valid for solving the understudy model and is convergent towards the optimal solution.
- According to the results solving case study problem, the dismantling plant has been established in Tehran, Semnan, Khorasan, and Tabriz provinces. The processing plant has been also established in Kashan, Semnan, Khorasan, and Tabriz provinces. According to the diagram, there is a material flow between collection centre of Tehran and dismantling plants of Tehran and Semnan, between collection centres of Khorasan and dismantling plants of Khorasan and Tehran, between collection centre of Kashan and dismantling plants of Semnan and Tehran, between collection centres and dismantling plant of Tabriz and finally, between collection centre of Azerbaijan and dismantling plant of Tabriz.
- The results of solving sample problems in different groups showed that the whale algorithm has a higher ability to produce higher quality responses compared to the NSGA-II algorithm in all cases. The whale algorithm can generate solutions with higher dispersion compared to the NSGA-II algorithm. In other words, the whale algorithm has a greater ability to explore and extract possible space of solutions compared to the NSGA-II algorithm. As can be seen from the above tables, the NSGA-II algorithm produces solutions with higher uniformity compared to the whale optimisation algorithm.
- According to the results of solving sample problems in different groups, the execution time of the whale algorithm for solving sample problems was higher compared to the NSGA-II algorithm. It can be said that the whale algorithm requires more execution time due to the improvement procedure based on the variable neighbourhood search structure.
- Investigating the process of solving time showed that the solving time of the algorithm is increasingly changed with an increase in the size of the problem and the solving time of problem with large size is significantly higher compared to the problems with small and medium sizes, which the matter indicates the difficulty of the problem.

The following recommendations can be provided for future studies:

- considering parameters in the probabilistic form
- considering other purposes for the problem
- utilising from probabilistic and fuzzy parameters to express uncertainty
- considering the inventory control considerations
- considering the cost of shortages as lost orders
- adding direct logistics to the understudy network.

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