Industry 4.0 technologies assessment: An integrated reverse supply chain model with the whale optimization algorithm

Sharareh Mohajeri[a], Fatemeh Harsej[a,*], Mahboubeh Sadeghpour[b], Jahanfar Khaleghi Nia[c]

[a]*Department of Industrial Engineering, Nour Branch, Islamic Azad University, Nour, Iran*
[b]*Department of Industrial Engineering, Qaemshahr Branch, Islamic Azad University, Qaemshahr, Iran*
[c]*Department of Mechanical Engineering, Nour Branch, Islamic Azad University, Nour, Iran*

(Communicated by Madjid Eshaghi Gordji)

Abstract

In recent years, integrated reverse supply chain practices have been adopted by companies that desire to reduce the negative environmental and social impacts within their supply chains. models and solutions assisted by industry 4.0 technologies have been developed to transform products in the end of their life cycle into new products with different use. There are several methods with different technologies to recycle the wastes, which have been selected and weighted based on the indicators of the industry 4.0 revolution and the wastes sent to recycling centers based on the technology weight. The understudy model is multi-objective, including minimizing transportation costs and environmental effects and maximizing customer response demand. The whale optimization algorithm and the NSGA-II algorithm were also used to solve this model. The results obtained from whale optimization and genetic algorithms have been comprised of each other through comparative indicators of quality, dispersion, uniformity, and solving time. The results showed that the whale algorithm has a higher ability to explore and extract possible points and achieve optimal solutions in all cases. The NSGA-II algorithm was also superior to the whale algorithm in terms of uniformity and solving time. The investigation of changes in solving time with increasing problem size was another confirmation of the NP-hard nature of the understudied problem.

Keywords: Reverse supply chain, Industry 4.0 revolution, whale optimization algorithm, technologies assessment.

*Corresponding author

Email addresses: mohajerisharareh@gmail.com (Sharareh Mohajeri), f_harsej@iaunour.ac.ir (Fatemeh Harsej), Sadeghpoor.ma@gmail.com (Mahboubeh Sadeghpour), J.khaleghinia@gmail.com (Jahanfar Khaleghi Nia)

1. Introduction

A critical success factor that benefits productivity, resource efficiency and waste reduction, is the digitalization of processes and the implementation of practices that use smarter equipment [18]. The concept of reverse logistics has emerged over the past decades due to environmental pollution and the increasing waste of resources, and greenhouse gas emissions. Reverse logistics is defined as all logistics activities for products that have reached the end of their life or require a series of processes to improve. Other definitions of reverse logistics include all supply chain activities that occur in reverse. The most crucial principle in reverse logistics is that many unusable or unused materials of customers are valuable and can be re-introduced into the supply chain with a little modification. Today, an important concept in the environment is urban recycling management. Recycling is to utilize used goods to recycle them into the same good or other usable goods. For example, used paper becomes newspaper and egg combs after recycling. The first point is that resources are limited and non-renewable and eventually will run out. Recycling makes it less likely to use these raw materials. Its second advantage is saving energy and consuming less energy to make a product. The third advantage is that it allows less waste to enter the environment, which has irreparable consequences and creates an ugly view of the environment.

On the other hand, the world also faces technological advances in digitalization and automation in addition to sustainable challenges. A range of new technologies can define the Industry 4.0 Revolution. It is highlighted that empirical investigation of how industry 4.0 solutions and circular economy are applied in practice is needed [15, 20]. The industry 4.0 revolution paradigm promotes the communication of physical items such as sensors, devices, and the connection of organizational assets to each other and the internet. The production process is divided into small value-based units that only share information about sequential process steps, increasing flexibility and possibly decreasing coordination complexity. Considering the importance of using reverse logistics in the waste collection as well as the importance of the 4th industrial revolution, the purpose of the present study was to develop and solve an integrated model of the reverse supply chain of municipal waste under uncertain conditions based on the model of the industry 4.0 revolution. In the present study, a mathematical model for reverse supply of municipal waste has been discussed under uncertain conditions based on the model of the 4th industrial revolution. In this model, wastes (garbage) are collected from customer centers and sent to recycling or disposal centers. Recycled wastes are sent from recycling centers to distribution centers and from distribution centers to customers. The vehicles of transportation for collection and delivery have been considered in electric type based on the 4th industrial revolution.

The remainder of the paper is structured as follows. The research literature is presented in section 2. Section 3 examines the proposed solution method, while section 4 deals with the mathematical model, demonstrating the model components. In Section 5, computational results are reported, and finally, in section 6, conclusions and some recommendations are presented.

2. Literature Review

Over the past decades, environmental issues have become very important, and one of the most critical current concerns is how to decrease waste and dispose of it properly. The disposal rate of goods has been increased with the growth of population and living standards, and many landfill sites have reached their maximum capacity [5]. Numerous studies have been conducted on the reverse supply chain, which is described below.

Koppius, Özdemir-Akyıldırım and Laan [9] investigated the closed-loop supply chain by considering the value of employment and trade as a measure of sustainability. They developed a rule-based

information system to examine the social values of employees and customers. In this system, customers and employees are evaluated based on existing evaluation and information indicators.

Nylén and Holmström [12] investigated innovative digital strategies and developed an organizational framework for improving digital products and service innovation. In the study, factors such as user experience and knowledge, skills, evaluation, and scanning have been utilized to develop this framework. It has been shown that implementation of this framework in companies accelerates the increase of competitive advantages and improves products and services. Kong [8] developed a green mixed-integer linear planning model for optimizing lateral gases to decrease the iron and steel industry's overall costs, i.e., operating costs and environmental costs. In the 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 2.2% of total costs were decreased compared to the previous one.

Kaya and Urek [7] investigated designing a closed-loop supply chain network that integrates production and collection centers. They developed a mixed-integer nonlinear location-inventory-pricing model. They proposed this model to maximize profits and obtain optimal facility locations, optimal inventory values, optimal price of final products, and optimal price of returned products and solved the problem by heuristic methods.

Tosarkani and Amin [19] investigated the multi-product closed-loop supply chain in the battery industry. They developed a multi-objective mathematical model and solved it using the Epsilon restriction method. Wang, Zhao and He [21] investigated reverse logistics optimization for bicycle sharing and bicycle recovery. In this study, logistics costs and reverse customer satisfaction have been observed in significant areas. The model creates a reverse logistics network for defective shared bicycles. A modified genetic simulated algorithm (MGSA) has been used to solve this model. The results confirmed the effectiveness of MGSA. Casper and Sundin [3] reverse logistics in-vehicle reproduction, packaging, and transportation and reverse material flow management. The purpose of their case study was to a framework for reverse material flow management in the automotive industry with an emphasis on reproducing activities. Various methods and techniques were used to obtain and confirm the necessary information of the above problems: 1) related literature on this topic was investigated; 2) data and documents were requested directly from relevant market experts, 3) cluster data were analyzed, and samples were highlighted, and 4) the data were evaluated and suggested practical courses were recommended.

Šomplák et al. [17] evaluated reverse logistics-based waste generators to investigate global warming potential. In the study, a specific problem of network flow has been investigated. Mixed municipal waste as a secondary and somewhat renewable energy carrier from waste producers (municipalities) is transferred to their final treatment sites in waste processing units through pre-processing facilities. The overall goal of this model is flow optimization. The obtained results were of minimum total costs, including treatment and transportation related to the production and storage of a certain amount of CO_2 and other greenhouse gases, described as Global Heating Potential. The share of wastes' GWP in different locations and different technologies varies among waste producers. For this reason, the problem of network flow was proposed to identify the wastes accurately. The model's conceptual framework has been made up of five crucial perspectives on supply chain management, including trade, technology, sustainable development, cooperation, and management strategy. Table 1 shows the summary of the last works in this field.

As shown in Table 1, it can be seen from the literature review, numerous studies have ever been conducted on reverse logistics problems and developed and solved a mathematical model for this problem. A small number of studies have also investigated the reverse logistics model of urban waste

Table 1: Summary of previous studies

Researchers	Research problem		Sustainable dimensions	Waste collection	Location	Routing	Solving method	
	Reverse supply chain	Fourth Industrial Revolution					Mathematical model	Meta-heuristic algorithms
Ramezani et al (2014)[14]	*						*	
Nylén and Holmström (2015)[12]		*			*			
Kong (2015)[8]	*		*				*	
Ruimin et al (2016)[16]	*						*	
Wang et al (2018)[21]	*						*	
Bottani and Casella (2018)[2]	*		*				*	
Tosarkani and Amin (2018)[19]	*						*	
Liu et al (2018)[10]	*	*					*	
Casper and Sundin (2018)[3]	*		*					
Zhou et al (2019)[22]		*						
Šomplák et al (2019)[17]	*							
Manavalan and Jayakrishna (2019) [11]	*	*	*	*				
Present study	*	*	*	*	*	*	*	*

recycling. However, modeling a sustainable reverse supply chain for waste collection and recycling of the municipal waste with the approach of the industry 4.0 revolution has not ever been investigated in previous studies, and the present study is entirely new in this regard, and its innovations are as follow:

- Developing and solving the mathematical model for the reverse supply chain of urban waste recycling with 4th industrial revolution approach.

- Considering the sustainability dimensions in the reverse supply chain of urban waste recycling with industry 4.0 revolution approach.

- Considering the location-routing phase in the reverse supply chain of urban waste recycling with the 4th industrial revolution approach.

3. Methodology

The gray relational analysis method with the fuzzy number and fuzzy VIKOR method was used to weigh the effective technology criteria (main dimensions and sub-components) and technologies, respectively. Also, the archive-based multi-objective whale optimization algorithm was used to solve the mathematical model, and its results were comprised of the results of the NSGA-II algorithm.

3.1. The theory of gray relations with distance fuzzy numbers

Assume that a multi-criteria decision problem has M non-profit options including $A1, A2, ..., Am$ and n criteria including $C1, C2, ..., Cn$. Each option is measured by n criteria. All evaluation/ranking

values are related to the options by considering $\mathcal{X}$'s decision matrix $(= (x_{ij})_{m \times n})$. The technique of gray relational analysis includes the following steps:

Step 1 normalized decision matrix is calculated. The normalized values of r_{ij} are calculated as follows:

$$r_{ij} = \frac{X_{ij}}{\max(X_{ij})}, i = 1, 2, ..., m; j = 1, 2, ..., n, \ for \ j \in I \tag{3.1}$$

$$r_{ij} = \frac{\min(X_{ij})}{X_{ij}}, i = 1, 2, ..., m; j = 1, 2, ..., n, \ for \ j \in J \tag{3.2}$$

Where, I is the set of profit criteria and J is the set of cost criteria.

Step 2 determine R_0 the series.

$$r_{ij} = \frac{X_{ij}}{\max(X_{ij})}, i = 1, 2, ..., m; j = 1, 2, ..., n, \ for \ j \in I \tag{3.3}$$

Where,

$$r_{0j} = \max_{j} r_{ij} \ j1, 2, ..., n \tag{3.4}$$

Step 3 forming a distance table. The distance δ_{ij} between the reference values and the comparison values are calculated as follows:

$$\delta_{ij} = r_{0j} - r_{ij} \tag{3.5}$$

Then, the distance matrix Δ is obtained as follow:

$$\Delta = \begin{bmatrix} \delta_{11} & \delta_{12} & ... & \delta_{1n} \\ \delta_{21} & \delta_{22} & ... & \delta_{2n} \\ \vdots & \vdots & & \vdots \\ \delta_{m1} & \delta_{m2} & ... & \delta_{mn} \end{bmatrix} \tag{3.6}$$

Step 4 calculation of gray relational coefficient. The gray relational coefficient is defined as follow:

$$\xi_{ij} = \frac{\delta_{\min} + \zeta \delta_{\max}}{\delta_{ij} + \zeta \delta_{\max}}, i = 1, 2, ..., m; j = 1, 2, ..., n \tag{3.7}$$

Where, $\delta_{\max}$ and $\delta_{\min}$ are the maximum and minimum values of $\delta_{ij}(i = 1, ..., m; j = 1, ..., n)$, respectively and ζ is a distinct coefficient between 0 and 1. The value of ζ is usually considered equal to 0.5.

Step 5 estimate the degree of gray relation γ_i through the following equation

$$\gamma_i = \sum_{j=1}^{n} w_j \xi_{ij}, i = 1, 2, ..., m \tag{3.8}$$

Where, w_j is the weight of jth criterion and:

$$w_j \geq 0, \sum_{j=1}^{n} w_j = 1 \tag{3.9}$$

Step 6 ranking the options based on their gray relational value so that whatever γ_i is greater A_i is a better option.

3.2. VIKOR method algorithm

Step 1 Forming the decision matrix

The decision matrix or scoring matrix of options is formed based on criteria. The decision matrix is denoted by $\mathcal{X}$, and each of its arrays is denoted by x_{ij}.

Step 2 Data normalizing

The next step is to normalize the decision matrix using Eq. (3.10):

$$n_{ij} = \frac{x_{ij}}{\sum_{1}^{m} x_{ij}} \tag{3.10}$$

Note that the linear normalization method is different from the vector method. The linear method is used in the VIKOR technique, and the vector method is used in the TOPSIS technique [4]. Each $\mathcal{X}_{ij}$ is the value of each criterion for each option: After powering numbers and summing each column, and taking each column's total square root, the numbers appear as a new table.

Step 3 Determine the ideal positive and negative point

The best and worst of all options are determined for each criterion and name f^+ and f^-, respectively. If the criterion is from utility type, then:

$$f_j^* = \max(f_{ij}) \ \forall i = 1, 2, ..., m \tag{3.11}$$

$$f_j^- = \min(f_{ij}) \ \forall j = 1, 2, ..., n \tag{3.12}$$

Step 4 Determining utility (S) and regret (R) Opricovic and Tzeng [13] have proposed two basic concepts of utility (S) and regret (R) in VIKOR's calculations. The utility value (S) indicates the relative distance of the ith option from the ideal point, and the regret value (R) indicates the maximum discomfort of the ith option from the ideal point distance.

$$s_i = \sum_{j=1}^{n} w_j \frac{f_{ij}^* - f_{ij}}{f_{ij}^* - f_{ij}^-} \tag{3.13}$$

$$R_i = maz(w_j \frac{f_{ij}^* - f_{ij}}{f_{ij}^* - f_{ij}^-}) \tag{3.14}$$

Step 5 Calculation of VIKOR Index

The next step is to calculate the VIKOR $(\mathcal{Q})$ index for each option:

$$Q_i = v \left[\frac{s_i - s^*}{s^- - s^*} \right] + (1 - v) \left[\frac{R_i - R^*}{R^- - R^*} \right] \tag{3.15}$$

$$s^* = \min(s_i); s^- = \max(s_i) \tag{3.16}$$

$$R^* = \min(R_i); R^- = \max(R_i) \tag{3.17}$$

- The two final decision-making conditions with the VIKOR technique

Condition one: If options A_1 and A_2 are ranked first and second among m options, the following relation should be established:

$$Q(A_2) - Q(A_1) \geq \frac{1}{m-1} \qquad (3.18)$$

Condition two: option A_1 must be recognized as a top rank in at least one of the R and S groups. If the first condition is not met, both options will be the best option. If the second condition is not met, options A_1 and A_2 are both selected as top options.

After evaluating options according to experts' existing criteria, the expression values are first converted into their equivalent fuzzy, and then, the average opinions of experts are calculated, and the fuzzy decision matrix is formed. The negative and positive criteria were determined after the formation of the fuzzy decision matrix. Then, the normalized cumulative fuzzy decision matrix was formed through the following relations.

For positive criteria:

$$M = \min_i(x_{ij1}, c_j), \quad \tilde{P}_{ij} = \left(\frac{x_{ij1}}{M}, \frac{x_{ij2}}{M}, \frac{x_{ij3}}{M} \right) \qquad (3.19)$$

For negative criteria:

$$N = \max_i(x_{ij3}, c_j), \quad \tilde{P}_{ij} = \left(\frac{N - x_{ij1}}{N}, \frac{N - x_{ij2}}{N}, \frac{N - x_{ij3}}{N} \right) \qquad (3.20)$$

After calculating the above equations, the utility measure $(\tilde{S}_i)$ and regret measure $(\tilde{R}_i)$ of ith option was calculated using the following relations.

$$(\tilde{S}_i) = \sum_{j=1}^{n} c_j \times \tilde{P}_{ij} \qquad (3.21)$$

$$(\tilde{R}_i) = \max_j(c_j \times \tilde{P}_{ij}) \qquad (3.22)$$

In the next step, the value of the VIKOR index $(\tilde{Q}_i)$ was calculated using the below equation.

$$\begin{aligned} \tilde{Q}_i &= \frac{v(s_i - s^*)}{s^- - s^*} + (1-v)\frac{(R_i - R^*)}{R^- - R^*} \\ &= \frac{s^- - s^*}{s^- - s^* + R^- - R^*}\frac{s_i - s^*}{s^- - s^*} + \frac{R^- - R^*}{s^- - s^* + R^- - R^*}\frac{R_i - R^*}{R^- - R^*} \end{aligned} \qquad (3.23)$$

Where,

$$S^* = \min_i S_i, S^- = \max_i S_i, R^* = \min_i R_i, R^- = \max_i R_i \qquad (3.24)$$

After preparing the values of $\tilde{Q}_i$, the next step was to defuzzification these values. There are several formulas for defuzzification of fuzzy numbers, and BNP (Best non-fuzzy performance) formula is one of the formulas that determine the best value for a fuzzy number, which can be calculated from the following relation:

$$BNP = L_{ij} + \frac{[(R_{ij} - L_{ij}) + (M_{ij} - L_{ij})]}{3} \qquad (3.25)$$

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 utilize 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.

1	0	1	1	0	1

Figure 1: Variable a_j representation

1	1	0	1	0

Figure 2: Variable b_k representation

3.3. The Proposed Algorithms Structure

3.3.1. Whale Optimization Algorithm (WOA)

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 provide exploration and exploitation, respectively. Two modes are considered to update the position of search agents. If the variable is $\mid A \mid > 1$, then the random search agent is selected, and if it is $\mid A \mid < 1$, then the best solution is selected. Depending on the value of p, the whale can change the position between two movements of spiral and rotational. Finally, WOA ends with reaching the specified satisfaction criterion.

In all meta-heuristic algorithms, it is necessary to store the solution according to 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, which have been designed according to the outputs of the model. For example, a line matrix (one-dimensional) has been defined for the variable (a_j), in which the number of its arrays equals J. The following matrix shows an example of this part of the solution (assume that the number of potential dismantling plant locations is 6 and the maximum allowable value of this plant is 4). In Figure 1, dismantling plants have been established in locations 1, 3, 4, and 6. A line matrix has also been used to display a variable (b_k) which the number of its arrays equals K. The following matrix shows an example of this part of the solution (assume that the number of potential locations of the processing plant is 5).

As shown in Figure 2, processing plants have been established in locations 1, 2, and 5. A one-dimensional matrix has also been used to display a variable (α_{ij}), in which the number of its arrays equals the number of collection centers, and the values of its cells indicate the number of dismantling plants that the collection center 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 centers is 8, then the following matrix is a way of displaying the solution to this variable, which has been given according to the example of variable (a_j).

In Figure 3, the collection centers No. 1 and 2 have been allocated to dismantling plant No. 1, the collection centers No. 3 and 7 to dismantling plant No. 3, the collection centers No. 4 and 6 to dismantling plant No. 6 and the collection centers No. 5 and 8 to dismantling plant No. 4.

1	1	3	6	4	6	3	4

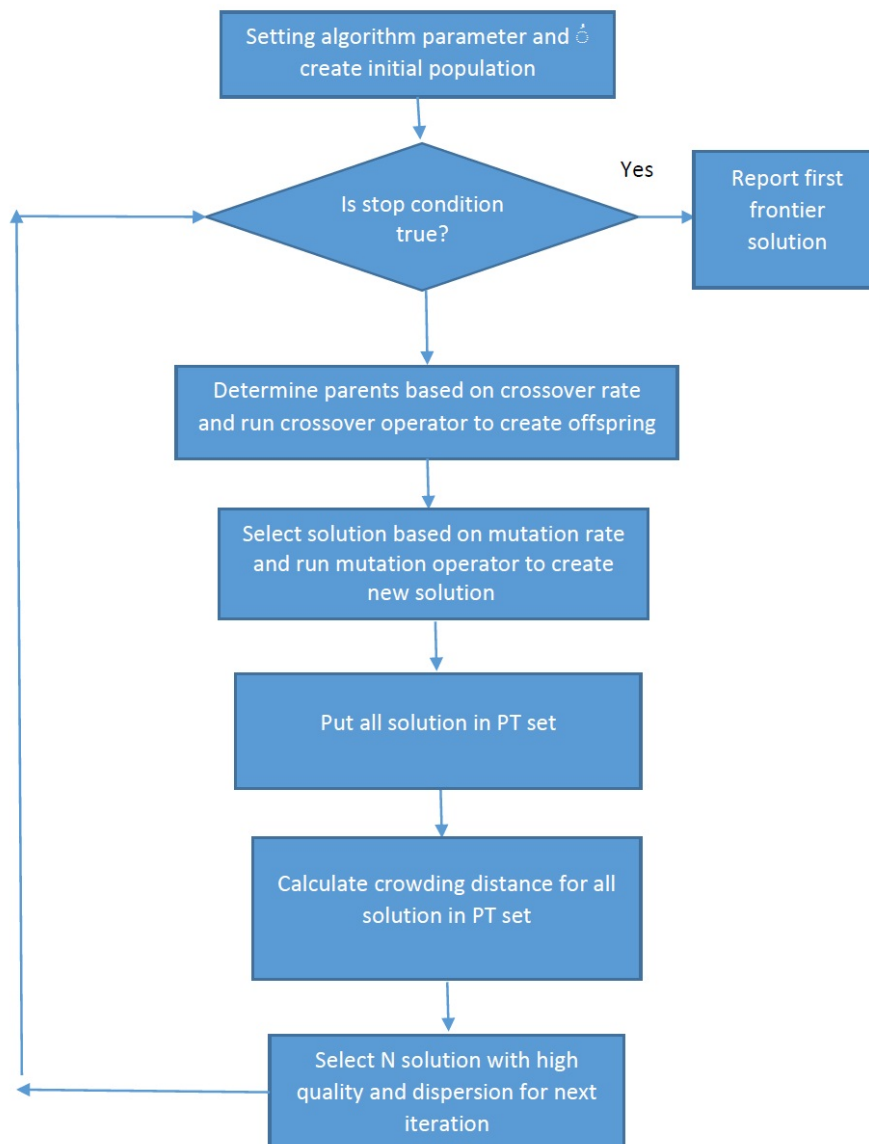Figure 3: Variable α_{ij} representation

Figure 4: NSGA-II Algorithm Flowchart

3.3.2. NSGA II algorithm

The solution method in the NSGA-II algorithm is similar to WOA, but the general structure of the genetic algorithm is as following in Figure 4.

4. Problem Definition

This model's characteristics and capabilities in the supply chain have been used to design a mathematical model based on the industry 4.0 Revolution. In this regard, transportation vehicles for collection and delivery have been considered in electric type based on the 4th industrial revolution. Also, the technology rate has been defined in recycling centers. The influential factors of technology selection for waste collection, disposal, and recycling have been discussed in Table 2.

In this section, a mathematical model for reverse logistics of municipal waste collection has been presented under a fuzzy condition by considering the model of the 4th industrial revolution. The understudy reverse supply chain of the present thesis includes the levels of distribution centers,

Table 2: Effective factors of selecting technology in waste management

Dimension	Sub-component
Information (data)	Gathering data related to product life cycle
	Real-time data analysis
	Data sharing
	Data-based decision making
	Data security and privacy of citizens
Technological	Intelligent & connected devices
	New data acquisition and communication technologies
	Resilient infrastructure
	Technology standards
Economic	Investment costs for technology development and localization
	The effectiveness of selection process in the commercial term
	The cost of technology transfer (the cost of absorbing hardware, software, human and organizational software)
Social	Citizen participation
	Green behavior
	Intelligently collaboration between stakeholders
Environmental	Green collection, disposal and recycling
	The issues related to energy and contamination emissions
	Dangerous effects of the end of technology life
legal	Strategic planning
	Non-governmental parties involvement
	Laws and regulations compatible with circular economy concept

customers, collection centers, recycling centers, and landfill centers. In the proposed model, wastes are collected from customer centers and sent to recycling or landfill centers. Recycled wastes are sent from recycling centers to distribution centers and from distribution centers to customers. There are several methods with different technologies to recycle the wastes, which have been selected and weighted based on the indicators of the industry 4.0 revolution and the wastes sent to recycling centers based on the technology weight.

4.1. Assumptions

In the present study, several assumptions have been considered for mathematical modeling, which is as follows:

- The understudy problem includes routing and locating with minimizing carbon emissions in the reverse supply chain.

- The considered reverse supply chain is multi-waste.

- The number and capacity of electric vehicles are limited and predetermined.

- Vehicle capacity restrictions include the weight limit of transported waste.

- The number of potential places for collection, recycling, and landfill centers is predetermined with limited capacity.

- The number of demand points (customers) is inevitable, and each customer has demand.

- Customer demand is uncertain and fuzzy.

- All points of demand must be visited by vehicles.

- The distance between centers is certain.

- The amount of electricity consumption of vehicles in the distance unit is determined by the vehicle's speed and the weight of cargo.

- The price per unit of charge consumption is certain.

- The amount of carbon dioxide emissions per processing unit in the centers is certain.

4.2. The variables of the model

z_m: If the collection center is established at point m, it is equal to 1 and otherwise equal to 0.
z_p: If the recycling center is established at point m, it is equal to 1 and otherwise equal to 0.
z_n: If the landfill center is established at point m, it is equal to 1 and otherwise equal to 0.
y_{l1l2k}^{tg}: If k^{th} vehicle goes from customer l1 to customer l2 under technology g in period t, it is equal to 11 and otherwise equal to 0.
y_{lk}^{tg}: If the kth vehicle goes from customer l1 to collection centers under technology g in period t, it is equal to 11 and otherwise equal to 0.
y_{mk}^{tg}: If the kth vehicle goes from customer centers to collection and restoration center m under technology g in period t, it is equal to 11 and otherwise equal to 0.
y_{mnk}^{tg}: If the kth vehicle goes from collection and restoration center m to landfill center n under technology g in period t, it is equal to 11 and otherwise equal to 0.
y_{mpk}^{tg}: If the kth vehicle goes from collection and restoration center m to recycling center p under technology g in period t, it is equal to 11 and otherwise equal to 0.
y_{mik}^{tg}: If the kth vehicle goes from collection and restoration center m to reproduction center i under technology g in period t, it is equal to 11 and otherwise equal to 0.
xw_{l1l2k}^{tsg}: The amount of waste s is traveled by k^{th} vehicle under technology g in period t from customer l1 to customer j2 and collected from customer l1.
x_{lk}^{tsg}: The amount of waste s that is received by k^{th} vehicle from customer l under g technology in period t, to be sent to the collection and restoration centers.
x_{mk}^{tsg}: The amount of waste s sent by k^{th} vehicle from customer centers to collection and restoration center m under g technology in period t.
x_{mnk}^{tsg}: The amount of waste s sent by k^{th} vehicle from collection and restoration center m to landfill center n under g technology in period t.
x_{mpk}^{tsg}: The amount of waste s sent by k^{th} vehicle from collection and restoration center m to recycling center p under g technology in period t.
x_{mik}^{tsg}: The amount of waste s sent by k^{th} vehicle from collection and restoration center m to reproduction center i under g technology in period t.
q_{ls}^t: Unanswered demand of lth customer for s waste during period t.

4.3. The proposed mathematical model

$$\min z1 = \sum_{m=1}^{M} \tilde{f}_m z_m + \sum_{p=1}^{P} \tilde{f}_p z_p + \sum_{n=1}^{N} \tilde{f}_n z_n$$
$$+ \sum_{k=1}^{K} \sum_{g=1}^{G} (1 - w_g) [\sum_{s=1}^{S} \sum_{t=1}^{T} [\sum_{l} (w_s C_k c_l^{sg} L_l x_{lk}^{tsg} + c_0 \times L_l (\widetilde{p_0} + \tilde{\alpha} x_{lk}^{tsg}) y_{lk}^{tg})$$

$$
+ \sum_{l1=1}^{L} \sum_{l2=1,l2\neq l1}^{L} (w_s C_k c_{l1l2}^{sg} L_{l1l2} x w_{l1l2k}^{tsg} + c_0 \times L_{l1l2}(\widetilde{p}_0 + \tilde{\alpha} x w_{l1l2k}^{tsg}) y_{l1l2k}^{tg})
$$

$$
+ \sum_{m=1}^{M} [\sum_{i=1}^{I} (w_s C_k c_{mi}^{sg} L_{mi} x_{mik}^{tsg} + c_0 \times L_{mi}(\widetilde{p}_0 + \tilde{\alpha} x_{mik}^{tsg}) y_{mik}^{tg})
$$

$$
+ \sum_{n=1}^{N} (w_s C_k c_{mn}^{sg} L_{mn} x_{mnk}^{tsg} + c_0 \times L_{mn}(\widetilde{p}_0 + \tilde{\alpha} x_{mnk}^{tsg}) y_{mnk}^{tg})
$$

$$
+ \sum_{p=1}^{P} (w_s C_k c_{mp}^{sg} L_{mp} x_{mpk}^{tsg} + c_0 \times L_{mp}(\widetilde{p}_0 + \tilde{\alpha} x_{mpk}^{tsg}) y_{mpk}^{tg})]]]
$$

$$
+ \sum_{t\in T} \sum_{s=1}^{S} \sum_{g=1}^{G} (1 - w_g) [\sum_{k=1}^{K} [\sum_{m=1}^{M} cost_{sg} x_{mk}^{tsg}
$$

$$
+ \sum_{p=1}^{P} (costp_{sg} x_{mpk}^{tsg} - value_{sg} x_{mpk}^{tsg}) + \sum_{n=1}^{N} costn_{sg} x_{mnk}^{tsg}]] \tag{4.1}
$$

Eq. (4.1) represents the first objective function, which includes minimization of the cost of establishing facilities and the cost of electric charging of vehicles, transportation costs, and environmental costs resulting from the emission of polluting gases.

$$
\min z2 = \sum_{t=1}^{T} \sum_{l=1}^{L} \sum_{s=1}^{S} \frac{q_{ls}^{t}}{\tilde{d}_{ls}^{t}} \tag{4.2}
$$

Eq. (4.2) represents the second objective function, which includes the sum of the ratio of unanswered customer demand to the amount of their demand for all periods and waste.
The model constraints are as follow:

$$
\sum_{m} \sum_{k} \sum_{g=1}^{G} y_{lk}^{tg} \geq 1 \qquad \forall l, t \tag{4.3}
$$

Constraint (4.3) ensures that all customers are visited by at least one vehicle at all times.

$$
\sum_{k} y_{mk}^{tg} = \sum_{k} (\sum_{p} y_{mpk}^{tg} + \sum_{n} y_{mnk}^{tg} + \sum_{j} y_{mjk}^{tg} + \sum_{i} y_{mik}^{tg}) \quad \forall m, t, g \tag{4.4}
$$

Constraint (4.4) ensures that vehicles entering customer points and collection and restoration centers must be exited from these points.

$$
\sum_{k} \sum_{g=1}^{G} (x_{lk}^{tsg} + \sum_{l1} x w_{l1lk}^{tsg}) + q_{ls}^{t} = \tilde{d}_{ls}^{t} \quad \forall l, t, s \tag{4.5}
$$

Constraint (4.5) calculates the amount of unanswered customer demand l for waste s in period t.

$$
\sum_{g=1}^{G} \sum_{k} x_{mk}^{tsg} = + \sum_{g=1}^{G} \sum_{k} (\sum_{p} x_{mpk}^{ts} + \sum_{n} x_{mnk}^{ts} + \sum_{i} x_{mik}^{ts}) \quad \forall m, t, s \tag{4.6}
$$

Constraint (4.6) ensures the balance of waste flow in the nodes.

$$xw_{l1l2k}^{tsg} \leq M \times y_{l1l2k}^{tg} \quad \forall l1, l2, k, t, s, g \tag{4.7}$$

$$x_{mk}^{tsg} \leq M \times y_{mk}^{tg} \quad \forall l, m, k, t, s, g \tag{4.8}$$

$$x_{mpk}^{tsg} \leq M \times y_{mpk}^{tg} \quad \forall p, m, k, t, s, g \tag{4.9}$$

$$x_{mnk}^{tsg} \leq M \times y_{mnk}^{tg} \quad \forall n, m, k, t, s, g \tag{4.10}$$

$$x_{mik}^{tsg} \leq M \times y_{mik}^{tg} \quad \forall i, m, k, t, s, g \tag{4.11}$$

$$x_{lk}^{tsg} \leq M \times y_{lk}^{tg} \quad \forall i, m, k, t, s, g \tag{4.12}$$

Constraints (4.7), (4.8), (4.9), (4.10), (4.11), (4.12) ensure that a vehicle is sent from one center to another only when travel has been occurred between them by that vehicle.

$$\sum_{l1 \in N} \sum_{l2 \in N} y_{l1l2k}^{tg} \leq \mid N \mid -1 \quad \forall N \in NL : \mid N \mid \geq 2 \& \quad \forall k, t, g \tag{4.13}$$

Constraint (4.13) prevents the creation of sub-nets when vehicles travel between customer points.

$$\sum_{s} (x_{mpk}^{tsg} \times w_s) \leq QW_k \quad \forall m, p, k, t, g \tag{4.14}$$

$$\sum_{s} (x_{mpk}^{tsg} \times vol_s) \leq QV_k \quad \forall m, p, k, t, g \tag{4.15}$$

$$\sum_{s} (x_{mnk}^{tsg} \times w_s) \leq QW_k \quad \forall m, n, k, t, g \tag{4.16}$$

$$\sum_{s} (x_{mnk}^{tsg} \times vol_s) \leq QV_k \quad \forall m, n, k, t, g \tag{4.17}$$

$$\sum_{s} (x_{mik}^{tsg} \times w_s) \leq QW_k \quad \forall m, i, k, t, g \tag{4.18}$$

$$\sum_{s} (x_{mik}^{tsg} \times vol_s) \leq QV_k \quad \forall m, i, k, t, g \tag{4.19}$$

$$\sum_{s} (\sum_{l} ((xw_{ll1k}^{tsg} \times y_{ll1k}^{tg}) + x_{l1k}^{tsg}) \times w_s) \leq QW_k \quad \forall l1, k, t, g \tag{4.20}$$

$$\sum_{s} (\sum_{l} ((xw_{ll1k}^{tsg} \times y_{ll1k}^{tg}) + x_{l1k}^{tsg}) \times vol_s) \leq QV_k \quad \forall l1, k, t, g \tag{4.21}$$

$$\sum_{s} (x_{mk}^{tsg} \times w_s) \leq QW_k \quad \forall m, k, t, g \tag{4.22}$$

$$\sum_{s} (x_{mk}^{tsg} \times vol_s) \leq QV_k \quad \forall m, k, t, g \tag{4.23}$$

$$\sum_s (x_{lk}^{tsg} \times w_s) \leq QW_k \quad \forall l, k, t, g \tag{4.24}$$

$$\sum_s (x_{lk}^{tsg} \times vol_s) \leq QV_k \quad \forall l, k, t, g \tag{4.25}$$

Constraints (4.14) to (4.25) ensure that the vehicle's waste does not exceed its weight and volume capacities.

$$\sum_m z_m \geq 1 \quad \forall m \tag{4.26}$$

$$\sum_p z_p \geq 1 \quad \forall p \tag{4.27}$$

$$\sum_n z_n \geq 1 \quad \forall n \tag{4.28}$$

Constraints (4.26), (4.27), (4.28) ensure that at least one facility must be established for the collection, landfilling, and recycling.

$$z_n, z_p, z_m, y_{mk}^{tg}, y_{lk}^{tg}, y_{mpk}^{tg}, y_{mnk}^{tg}, y_{mik}^{tg}, y_{l1l2k}^{tg} = \{0, 1\} \tag{4.29}$$

$$x_{mk}^{tsg}, x_{lk}^{tsg}, x_{mpk}^{tsg}, x_{mnk}^{tsg}, x_{mik}^{tsg}, x_{l1l2k}^{tsg} \geq 0 \tag{4.30}$$

Constraints (4.29) and (4.30) represent the binary and integer variables of the problem.

4.4. Model defuzzification

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 Jimenez et al. [6] was used for the defuzzification of the model.

$$\min z = \tilde{c}x$$
$$ax \leq \tilde{b}$$
$$x \geq 0 \tag{4.31}$$

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 5) if $\tilde{A} = L, M, U$:

$$\mu A(x) = \begin{bmatrix} f_A(x) = \frac{X-L}{M-L} & L \leq X \leq M \\ 1 & X = M \\ g_A(x) = \frac{X-L}{M-U} & M \leq X \leq U \end{bmatrix} \tag{4.32}$$

The expected interval of a fuzzy number is defined as follow:

$$EI(\tilde{A}) = [E_1^{\tilde{A}}, E_2^{\tilde{A}}] = \left[\int_{a1}^{a2} x df_A(x) - \int_{a3}^{a4} x dg_A(x) \right] \tag{4.33}$$
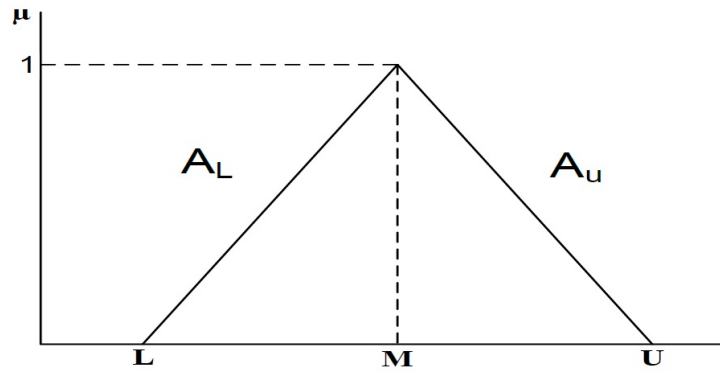
Figure 5: Triangular fuzzy number

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

$$EI(\tilde{A}) = [E_1^{\tilde{A}}, E_2^{\tilde{A}}] = \left[\int_0^1 f_A^{-1}(\alpha)d\alpha - \int_0^1 f_A^{-1}(\alpha)d\alpha \right] \tag{4.34}$$

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:

$$EI(\tilde{A}) = [\frac{1}{2}(L + M), \frac{1}{2}(M + U)] \tag{4.35}$$

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

$$EV(A) = \frac{E_1^{\tilde{A}} + E_2^{\tilde{A}}}{2} \tag{4.36}$$

$$EV(A) = \frac{L + 2M + U}{2} \tag{4.37}$$

Definition 4.1. *for both fuzzy numbers $\tilde{A}$ and $\tilde{B}$ the membership degree $\tilde{A}$ being bigger than $\tilde{B}$ in the following form:*

$$\mu_M(\tilde{A}, \tilde{B}) = \begin{cases} 0, & if\ E_2^a - E_1^b < 0 \\ \frac{E_2^A - E_1^B}{E_2^A - E_1^B - (E_1^A - E_2^B)}, & if\ 0 \in [E_1^A - E_2^B, E_2^A - E_1^B] \\ 1, & if\ E_1^A - E_2^B > 0 \end{cases} \tag{4.38}$$

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 4.2. *suppose the vector $x \in R^n$ is acceptable with degree α if: $\min \mu_M(\tilde{A}x, \tilde{B}) = \alpha$ (which can be displayed as $\tilde{A}x \geq_\alpha \tilde{B}$). Equation (4.34) can be re-written as follow:*

$$[(1 - \alpha)E_2^A + \alpha E_1^A]x \geq \alpha E_2^B + (1 - \alpha)E_1^B \tag{4.39}$$

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

$$\min EV(\widetilde{C})x \quad s.t: \quad x \in \{x \in R^n \mid \tilde{A}x \geq_\alpha \tilde{B}, x \geq 0\} \tag{4.40}$$

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

First objective function:

$$
\begin{aligned}
\min z1 = &\sum_{m=1}^{M} \frac{f_m^1 + 2f_m^2 + f_m^3}{2} z_m + \sum_{p=1}^{P} \frac{f_p^1 + 2f_p^2 + f_p^3}{2} z_p + \sum_{n=1}^{N} \frac{f_n^1 + 2f_n^2 + f_n^3}{2} z_n \\
&+ \sum_{k=1}^{K} \sum_{g=1}^{G} (1 - w_g) [\sum_{s=1}^{S} \sum_{t=1}^{T} [\sum_{l} (w_s C_k c_l^{sg} L_l x_{lk}^{tsg} + c_0 \times L_l (\frac{\rho_0^1 + 2\rho_0^2 + \rho_0^3}{2} + \frac{\alpha_1 + 2\alpha^2 + \alpha^3}{2} x_{lk}^{tsg}) y_{lk}^{tg}) \\
&+ \sum_{l1=1}^{L} \sum_{l2=1,l2\neq l1}^{L} (w_s C_k c_{l1l2}^{sg} L_{l1l2} x w_{l1l2k}^{tsg} + c_0 \times L_{l1l2} (\frac{\rho_0^1 + 2\rho_0^2 + \rho_0^3}{2} + \frac{\alpha_1 + 2\alpha^2 + \alpha^3}{2} x w_{l1l2k}^{tsg}) y_{l1l2k}^{tg}) \\
&+ \sum_{m=1}^{M} [\sum_{i=1}^{I} (w_s C_k c_{mi}^{sg} L_{mi} x_{mik}^{tsg} + c_0 \times L_{mi} (\frac{\rho_0^1 + 2\rho_0^2 + \rho_0^3}{2} + \frac{\alpha_1 + 2\alpha^2 + \alpha^3}{2} x_{mik}^{tsg}) y_{mik}^{tg}) \\
&+ \sum_{n=1}^{N} (w_s C_k c_{mn}^{sg} L_{mn} x_{mnk}^{tsg} + c_0 \times L_{mn} (\frac{\rho_0^1 + 2\rho_0^2 + \rho_0^3}{2} + \frac{\alpha_1 + 2\alpha^2 + \alpha^3}{2} x_{mnk}^{tsg}) y_{mnk}^{tg}) \\
&+ \sum_{p=1}^{P} (w_s C_k c_{mp}^{sg} L_{mp} x_{mpk}^{tsg} + c_0 \times L_{mp} (\frac{\rho_0^1 + 2\rho_0^2 + \rho_0^3}{2} + \frac{\alpha_1 + 2\alpha^2 + \alpha^3}{2} x_{mpk}^{tsg}) y_{mpk}^{tg})]]] \\
&+ \sum_{t \in T} \sum_{s=1}^{S} \sum_{g=1}^{G} (1 - w_g) [\sum_{k=1}^{K} [\sum_{m=1}^{M} cost_{sg} x_{mk}^{tsg} + \sum_{p=1}^{P} (costp_{sg} x_{mpk}^{tsg} - value_{sg} x_{mpk}^{tsg}) \\
&+ \sum_{n=1}^{N} costn_{sg} x_{mnk}^{tsg}]]
\end{aligned}
\tag{4.41}
$$

Second objective function:

$$\min z2 = \sum_{t=1}^{T} \sum_{l=1}^{L} \sum_{s=1}^{S} \frac{q_{ls}^t}{\frac{d_{ls}^{t,1} + 2d_{ls}^{t,2} + d_{ls}^{t,3}}{2}} \tag{4.42}$$

Constraint (4.5) is converted to:

$$\sum_k (\sum_g x_{lk}^{tsg} + \sum_{l1} x w_{l1lk}^{tsg}) + q_{ls}^t = (1 - \alpha) \frac{d_{ls}^{t,1} + d_{ls}^{t,2}}{2} + \alpha \frac{d_{ls}^{t,2} + d_{ls}^{t,3}}{2} \quad \forall l, t, s \tag{4.43}$$

5. Computational results

In the present study, the gray relational analysis method with the fuzzy number and fuzzy VIKOR method was used to weigh the effective technology criteria (main dimensions and sub-components) and technologies, respectively. The ranking results have been presented in this section.
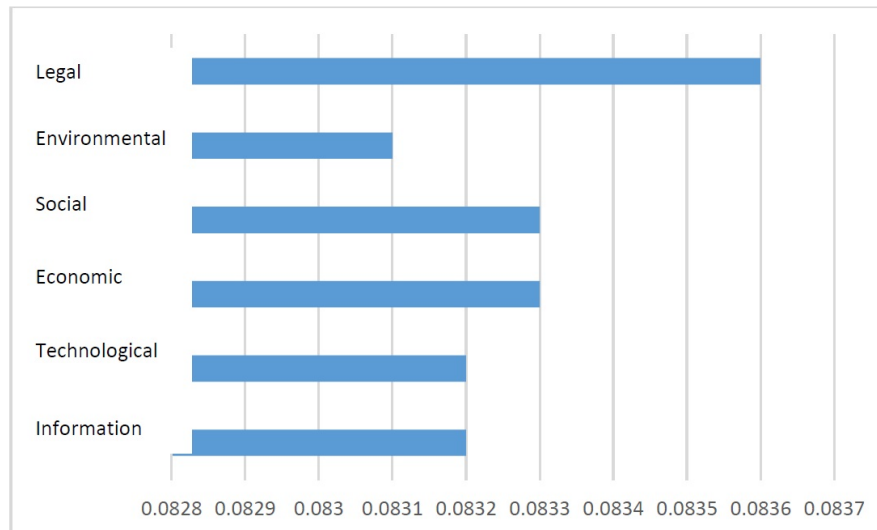
Figure 6: The weight of major factor on technology selection

5.1. Weighting of Criteria

In this section, a questionnaire in the form of a table was provided to 10 statistical sample individuals, the data were gathered, and their mean was calculated. Then, the calculated mean values were converted into integer numbers in the ranges of 1 to 7. Then, the integer numbers were converted into distant fuzzy numbers, and finally, the data analysis method was performed step-by-step. As shown in Figure 6, it can be seen among the effective factors of technology selection, the legal factor is in the first place, the economic and social factors are in the second place, the information and technological factors are in the third place, and the environmental factor is in the fourth place.

5.2. Weighing of waste collection technologies

The purpose of this section was to prioritize existing options through the fuzzy VIKOR method as a multi-criteria group decision-making technique in fuzzy space. Decision-makers evaluated the options for waste collection technologies relative to the effective factors of technology selection. The criteria have positive and negative aspects. For example, the legal dimension has a negative aspect, i.e., a lower legal restriction is better. In contrast, higher positive information is better. After determining the positive and negative criteria, the normalized cumulative fuzzy decision matrix was formed. After calculating the normal fuzzy decision matrix, the size of the utility measure ($\tilde{S}_i$) and regret measure ($\tilde{R}_i$) of ith option was calculated.
In the next step, the value of VIKOR index ($\tilde{Q}_i$) was calculated.

5.3. Sample problems

Several experimental sample problems were designed in small, medium, and large scales in the present study. Since no sample problem in the literature could be following the proposed model of the present study and cover all parts of the model, some of the previous studies were selected to design some experimental problems, and their sample problems were used as far as could be following the proposed model, and some of the parameters that previous studies have not covered were selected randomly. Also, the previous studies were investigated, and experimental problems were designed according to their size range in these studies to determine some other experimental problems.
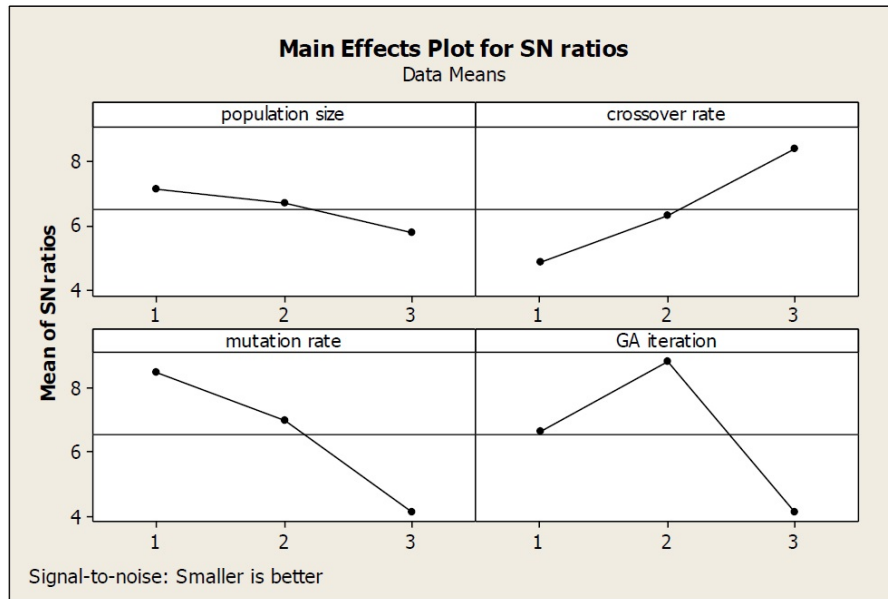
Figure 7: NSGA-II noise signal

5.4. Algorithm parameters tuning

Taguchi experimental design and analysis in the MINITAB software were used to adjust some of the two proposed algorithms' parameters. The parameters included whale population size, the number of repeated neighborhood search variables, the number of repetitions in the whale optimization algorithm, population size, mutation rate, intersection rate, and the number of repetitions in the NSGA-II algorithm. Moreover, to adjust the genetic algorithm's parameters, the values of the two parameters of mutation rate and intersection rate at 3 levels and the population size at three levels have been investigated.

To perform the analysis, a criterion called RPD has been designed, which is the calculation by Eq. (5.1).

$$RPD = (\sum \frac{alg_{sol} - Best_{sol}}{Best_{sol}}) \times 100 \tag{5.1}$$

Alg_{sol}: the value of each obtained objective function for each problem by the desired combination of parameters.

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.

Figure 7 and Figure 8 indicate conducted an analysis using the Taguchi method to adjust the parameters. As shown in Figure 7, mutation rate, cross-rate, algorithm iteration, and population size are more effective at the levels of 1, 3, 2, and 1, respectively. Therefore, values of 150, 300, 0.007, and 0.96 were considered for the parameters of population size, algorithm iteration, mutation rate, and cross rate, respectively.

To quantify the fuzzy parameters, m2 is determined according to Alikhani et al. [1] (if any), and two values of m1 and m3were determined using the MATLAB program. For this reason, only the value of m2 has been presented in the section of parameter adjustment. The following values have been considered in the production of sample problems:

- The amount of customer demand l of the product s in each period, the triangular fuzzy number (m1, 100, m3) was considered the triangular fuzzy number (m1, 30, m3).
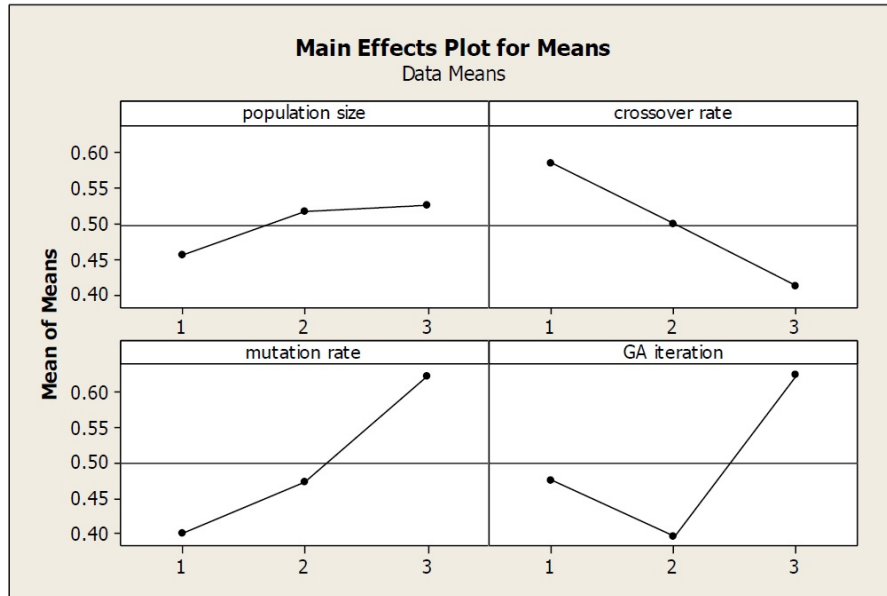
Figure 8: Mean effect of NSGA-II

- The cost of establishing landfill centers was considered equal to fuzzy numbers (m1,5000, m3), the cost of establishing collection/restoration centers equal to fuzzy numbers (m1,10000, m3), and the cost of establishing recycling centers were considered as triangular fuzzy numbers (m1,15000, m3).

- All distances between facilities were randomly generated in a uniform range of [1...50].

- Product weight was considered equal to 5 and its volume equal to 27.

- The electric charge's consumption rate was equal to 0.1, and the load-dependent consumption rate of the electric charge was equal to 0.01.

- The variable cost of using each vehicle depended on the distance and was calculated equal to 10 times of distance.

- The cost of each electric charging unit was considered 100.

- The cut value for fuzzy number rankings was considered 0.8.

5.5. Solving results

In this section, the designed experimental problems have been solved using whale algorithms and a genetic algorithm, and their results have been analyzed. The designed experimental problems have been solved using whale algorithms and a genetic algorithm, and their results have been analyzed. The results of implementing the two algorithms have been presented in Table 3 based on the comparative indexes.

As shown in Figure 9, solving the time of problems for the whale algorithm was more than the genetic algorithm in all cases, and it means that the whale algorithm needs more time to solve these problems than the genetic algorithm. It should be noted that the solving time needed by the algorithm increasingly changes with the increase in problem size, and the solving time of large-scale

Table 3: Solution results of sample problems

|	Prob.	WOA(whales optimization algorithm)					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	85.81	0.89	1257.8	0.061	79	14.64	0.81	782.8	0.032	49
	2	80.13	1.2	1043.1	0.067	86	19.97	0.73	734.2	0.035	51
	3	82.14	1.01	1340.6	0.055	49	17.86	0.76	551.4	0.039	80
	4	90.43	0.75	1450.1	0.077	95	9.57	0.90	604.3	0.047	59
Medium	1	100	1.08	3004. 6	0.11	39	0	0.70	1655.2	0.088	21
	2	76.6	0.97	4913.9	0.10	77	23.4	0.45	1947.5	0.086	22
	3	86.6	0.96	5826.9	0.18	72	13.4	0.52	2181.8	0.094	58
	4	75.7	0.94	5938.2	0.25	81	24.3	0.79	2266.6	0.101	38
	5	91.3	1.13	5994.7	0.25	67	8.7	0.68	2496.8	0.16	33
	6	96.8	1.08	5943.7	0.39	53	3.2	0.74	2686.7	0.19	30
	7	92.01	1.09	6617.7	0. 38	46	7.99	0.44	2842.8	0.18	33
	8	86.3	0.76	6949.4	0.43	39	13.7	0.62	2776.1	0.24	33
	9	79.5	0.91	7184.7	0.56	88	20.5	0.56	2838.2	0.29	62
Large	1	93.6	1.15	6523.1	6.7	58	6.4	0.73	3372.4	3.06	54
	2	92.2	0.94	7921.5	8.04	89	7.8	0.74	4164.9	3.93	51
	3	93.6	1.04	8293.7	10.8	85	6.4	0.79	4327.1	3.95	74
	4	95.2	1.27	7863.6	13.1	97	4.8	0.76	4788.9	4.32	60
	5	87.4	0.93	9873.4	18.2	98	12.6	0.65	4848.2	4.63	71
	6	100	1.29	11721.2	22.3	89	0	0.64	5037.8	4.78	72
	7	89.4	1.03	11953.2	29.6	56	10.6	0.71	5821.6	6.57	69
	8	80.8	0.92	13234.8	27.5	66	19.2	0.77	7363.4	8.45	58
	9	94.3	1.03	17845.8	30.6	61	5.7	0.66	8110.6	13.40	54
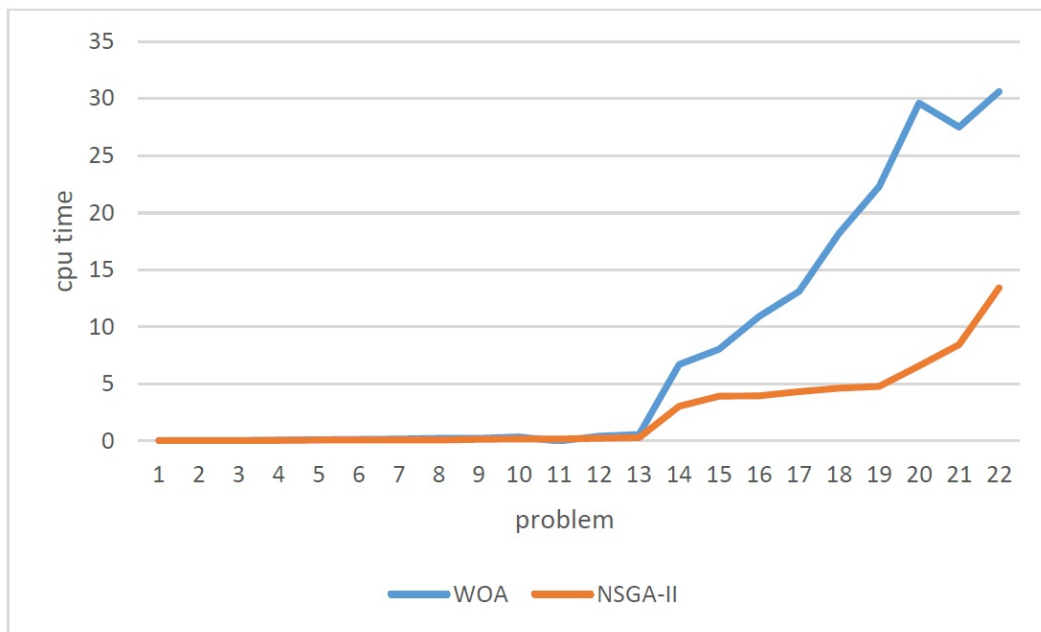
Figure 9: CPU time comparison
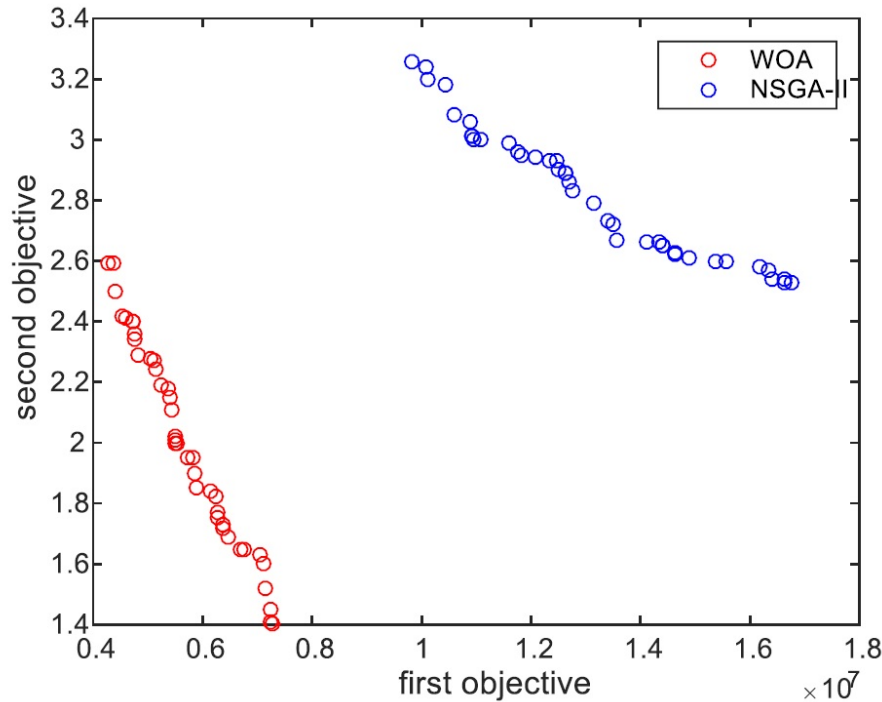
Figure 10: Pareto frontier for sample problem No. 9 in large scale

problems is significantly higher compared to medium and small-scale problems, which the matter indicates the NP-hard nature of problems.

Figure 10 represents the Pareto efficiency of problem NO.9 as one of the significant scale problems. As can be seen, the quality of solutions obtained from the WOA algorithm is better than the GA algorithm. Also, both algorithms' Pareto efficiency shows the value of the first objective function increases with a decrease in the second objective function and vice versa. This matter indicates a contradiction between the objective functions of the proposed mathematical model. Also, comprising the Pareto efficiency of two algorithms shows the whale optimization algorithm's good performance and its convergence toward optimal and near-optimal solutions.

6. Conclusion and Recommendations

Considering the importance of supply chain and reverse logistics, a multi-objective mathematical model of the reverse supply chain was presented in the present study to collect municipal waste under fuzzy conditions and taking into account the industry 4.0 revolution. The proposed model was solved using meta-heuristic algorithms. The present study tried to consider all potential centers in reverse logistics, including collection/restoration centers, recycling centers, and landfills centers, with the assumptions of the limited capacity of centers being multi-product. The output of the model was facility locating and the optimal flow rate between facilities. In the present study, a mixed-integer linear planning model was developed for the understudied problem, which was solved using two meta-heuristic whale and genetic algorithms. The proposed algorithms were implemented in MATLAB software environment, and the results of their implementation in sample experimental problems were comprised of each other in terms of quality, dispersion, uniformity, and solving time. The sample experimental problems were designed in three scales of small, medium, and large. Previous studies were investigated o design medium and large-scale problems, and some medium-scale problems and some large-scale designs were designed according to the considered size range. After

designing the problems with different sizes, algorithms' parameters to solve the model were adjusted. The parameters of the two proposed algorithms of the present study were adjusted in two parts. One part of parameters were adjusted using statistical analysis using MINITAB statistical software (population size number of parameters, neighborhood search iterations and algorithm iterations for whale optimization algorithm and population size of parameters, mutation rate, and cross-rate algorithm iterations in the genetic algorithm). Another part of the parameters was randomly adjusted according to the subject literature. In general, the results of the present study can be categorized as follow:

- Developing a new reverse supply chain network for waste collection with the approach of the industry 4.0 revolution.

- Investigating waste collection technologies and their effective factors.

- Weighting the effective factors waste collection technologies and weighting technologies. The results of investigative and effective technology selection showed that the legal factor is in the first place, economic and social factors are in second place, information and technological factors are in third place, and the environmental factor is in the fourth place. Also, technology rankings showed that mobile-based technologies are in the first place, GIS-based technologies are in the second place, IoT-based technologies are in third place, and Web-GIS-based technologies are in the fourth place.

- The NP-hard nature of the problem and solving it through meta-heuristic algorithms and investigating the performance of these algorithms.

- They are investigating and comprising the solutions of proposed algorithms with each other according to the comparative criteria (quality, dispersion and uniformity, and solving time).

- The better and more acceptable performance of the whale algorithm compared to the genetic algorithm according to the comparative indicators in achieving near-optimal solutions for understudy sample experimental problems of the present study.

- The better performance of the genetic algorithm compared to whale algorithm in the term of execution time for understudy sample experimental problems of the present study.

Following recommendations can be suggested for further studies:

- Considering parameters in probabilistic form.

- Considering other purposes to conduct future studies.

- Utilizing probabilistic and fuzzy parameters to express uncertainty.

- Developing searching models of meta-heuristic methods based on the principles of advanced reaction methods to solve the mathematical model of the problem.

- Utilizing the new fuzzy ideal planning method to optimize the objectives.

- Utilizing real-time problems instead of generating random problems.

- Utilizing other meta-heuristic algorithms to solve problems such as scatter search, ACO, DE, NN.

- Utilizing from robust optimization method to solve the model.

References

[1] P. Alikhani, S. Vesal, P. Kashefi, R.E. Pour, F. Khorvash, G. Askari and R. Meamar, *Application and preventive maintenance of neurology medical equipment in Isfahan Alzahra hospital*, Int. J. Preventive Med., 4(2) (2013) 323.

[2] E. Bottani and G. Casella, *Minimization of the environmental emissions of closed-loop supply chains: A case study of returnable transport assets management*, Sustainability 10 (2018) 329.

[3] R. Casper and E. Sundin, *Reverse logistic transportation and packaging concepts in automotive remanufacturing*, Proc. Manufact. 25 (2018) 154–160.

[4] A. Habibi-Yangjeh, *Artificial neural network prediction of normalized polarity parameter for various solvents with diverse chemical structures*, Bull. Korean Chem. Soc. 28(9) (2007) 1472.

[5] M. Jahre, *Household waste collection as a reverse channel*, Int. J. Phys. Distribution & Logistics Management, (1995).

[6] M. Jiménez, M. Arenas, A. Bilbao and M.V. Rodri, *Linear programming with fuzzy parameters: an interactive method resolution*, European journal of operational research, 177(3) (2007) 1599–1609.

[7] O. Kaya and B. Urek, *A mixed integer nonlinear programming model and heuristic solutions for location, inventory and pricing decisions in a closed loop supply chain*, Comput. Operat. Res. 65 (2016) 93–103.

[8] H.N. Kong, A *green mixed integer linear programming model for optimization of byproduct gases in iron and steel industry*, J. Iron Steel Res. 22(8) (2015) 681–685.

[9] O. Koppius, Ö. Özdemir-Akyıldırım and E.V.D. Laan, *Business value from closed-loop supply chains*, Int. J. Supply Chain Manag. 3(4) (2014) 107–120.

[10] S. Liu, G. Zhang and L. Wang, *IoT-enabled dynamic optimisation for sustainable reverse logistics*, Proc. CIRP 69 (2018) 662–667.

[11] E. Manavalan and K. Jayakrishna, *A review of Internet of Things (IoT) embedded sustainable supply chain for industry 4.0 requirements*, Comput. Indust. Engin. 127 (2019) 925–953.

[12] D. Nylén and J. Holmström, *Digital innovation strategy: A framework for diagnosing and improving digital product and service innovation*, Business Horizons 58(1) (2015) 57–67.

[13] S. Opricovic and G.H. Tzeng, *Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS*, European J. Operat. Res. 156(2) (2004) 445–455.

[14] M. Ramezani, A.M. Kimiagari, B. Karimi and T.H. Hejazi, *Closed-loop supply chain network design under a fuzzy environment*, Knowledge-Based Syst. 59 (2014) 108–120.

[15] P. Rosa, C. Sassanelli, A. Urbinati, D. Chiaroni and S. Terzi, *Assessing relations between Circular Economy and Industry 4.0: a systematic literature review*, Int. J. Prod. Res. 58(6) (2020) 1662–1687.

[16] M.A. Ruimin, Y.A.O. Lifei, J.I.N. Maozhu, R.E.N. Peiyu and L.V. Zhihan, *Robust environmental closed-loop supply chain design under uncertainty*, Chaos, Solitons Fract. 89 (2016) 195–202.

[17] R. Šomplák, M. Pavlas, V. Nevrlý, M. Touš and P. Popela, *Contribution to global warming potential by waste producers: Identification by reverse logistic modelling*, J. Cleaner Product. 208 (2019) 1294–1303.

[18] G.L. Tortorella and D. Fettermann, *Implementation of industry 4.0 and lean production in Brazilian manufacturing companies*, Int. J. Prod. Res. 56(8) (2018) 2975–2987.

[19] B.M. Tosarkani and S.H. Amin, *A possibilistic solution to configure a battery closed-loop supply chain: multi-objective approach*, Expert Syst. Appl. 92 (2018) 12–26.

[20] M.L. Tseng, R.R. Tan, A.S. Chiu, C.F. Chien and T.C. Kuo, *Circular economy meets industry 4.0: can big data drive industrial symbiosis?*, Resour. Conserv. Recycl., 131 (2018) 146e147.

[21] X. Wang, M. Zhao and H. He, *Reverse logistic network optimization research for sharing bikes*, Proc. Comput. Sci. 126 (2018) 1693–1703.

[22] L. Zhou, C. Du, C. Bai and Y. Song, *An Internet of Things based COPD managing system: its development, challenges and first experiences*, Clinical eHealth 2 (2019) 12–15.