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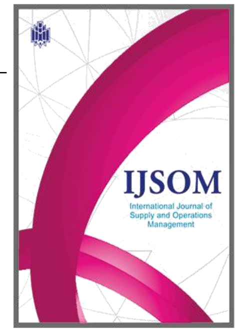

A New Mathematical Model for Designing a Municipal Solid Waste System Considering Environmentally Issues

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Abstract
Nowadays, produced wastes in urban areas are growing exponentially all over the world. Moreover, the environment and natural resources are on the way to destruction. One way to deal with increasing waste generation and protecting the environment is proper management of municipal solid wastes. One aspect of municipal solid waste management is locating the various facilities and the routing between them. In this study, a new mathematical model is developed for the location-routing problem in MSWM system. The integrity of MSWM facilities is the focus of this study. The proposed model meets two objectives including minimization of system costs and environmental impacts. In this model, the location of waste collection centers and reverse logistics centers are determined. In order to improve the efficiency and practicality of the proposed model, a solution method based on the NSGA-II is proposed. Also, a new method based on best-worst approach was developed to parameter tuning of NSGA-II. As a result, it was observed that the total costs of the system increases exponentially as a result of increase in the volume of waste in sources. Numeral experiments indicate the efficiency of the proposed algorithm in achieving approximate optimum solution in an acceptable time.

Keywords: Location-routing, metaheuristic algorithm, multi-objective problem, Municipal solid waste management.

1. Introduction

The increase in urban population will increase waste generated in cities, which has been a major concern for city management authorities. Municipal solid waste management (MSW) is a multidisciplinary field which includes production of waste, the separation of the generated wastes, storage, collection, transfer, transportation, processing, recovery, and disposal (Bovea, Ibáñez-Forés, Gallardo, & Colomer-Mendoza, 2010; Das & Bhattacharyya, 2015; Gallardo, Carlos, Peris, & Colomer, 2015; Ionescu et al., 2013; Minoglou & Komilis, 2013; Rada, 2014). Nowadays, urban waste management is one of the main concerns of the world's health and environment organization (Habibi, Asadi, Sadjadi, & Barzinpour, 2017). Waste production has increased dramatically in recent years, about 3.5 million tons per day are being produced in 2012, and this value will double by 2025 (Hoornweg & Bhada-Tata, 2012). Accordingly, it is necessary to pay attention to the proper management of MSW and provide an approach that can efficiently handle and optimize this system.

In recent years, by increasing the importance of environmental issues, the way of dealing with waste management haschanged and environmental issues are also considered in addition to the cost of the system. In this regard, multi-objective

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optimization models are applied to design appropriate waste management systems that simultaneously consider both economic and environmental factors. For example, some studies in the literature have used this approach like (Asefi & Lim, 2017; Lee et al., 2016; Nema & Gupta, 1999; Rabbani, Saravi, & Farrokhi-Asl, 2017; Yu & Solvang, 2017). Typically, the cost of collecting municipal solid waste is in the range of 80-90% and 80-50% of the waste management budget in low-income and middle-income countries, (Aremu, 2013). therefore, management of cost of the system along with the management of environmental issues in a manner that both goals are met is very critical. Some previous studies have only paid attention to the apparent costs of the system. They proposed models to minimize the costs of the system. For example, Louati (2016) aimed at minimizing system costs and addressed routing between different sections of the municipal solid waste management system. However, what has been more prominent in recent years is environmental issues. For example, Tsai and Chou, (2004) take minimization of environmental impacts into account besides the costs of the system. They locate the various centers of the system including recycling or disposal centers, along with an examination of the flow between them.

In studies which are related to the optimization of municipal waste systems, special attention should be paid to national and international environmentally laws (Lyeme, Mushi, & Nkansah-Gyekye, 2016). MSW management can be divided into different segments consisting of collecting, transferring, and transportation, processing, and ultimately disposing of wastes (Das & Bhattacharyya, 2015). In some studies, such as (Das & Bhattacharyya, 2015), these sections work separately, and separate models are proposed for each section. Often on issues that are individually or hierarchically seen, the local optimal solutions are obtained for each and will not lead to a globally optimal solution. For this reason, the newer models integrated these sections like the one offered by Habibi et al (2007).

MSW management studies can be categorized into three main categories (Rabbani, Heidari, Farrokhi-Asl, & Rahimi, 2018). Due to the importance of routing decisions in this system, the first category relates to studies seeking to find optimal or rational collection routes in this system. For example, Das and Bhattacharyya, (2015) divided routing decisions into four different sections: routing from source or generated nodes to collection centers and from collection centers to transfer centers, then to transportation centers, and then to processing and disposal centers. For each of these sections, they provide a routing mathematical formulation and the problems were solved sequentially. Moreover, Louati (2016) proposes an integrated model for routing among the various components of the municipal solid waste problem considering time window constraint. Time windows is a set of intervals at each site to collect wastes (Louati, 2016). The second category relates to the studies seeking to the location of facilities in the MSW management system. For example, Lyeme, Mushi, and Nkansah-Gyekye (2016) proposed a multi-objective model for locating facilities by considering the flow between these facilities. The purpose of this study was the minimization of costs and amount of waste that finally should be discarded as well as their environmental impacts. The model locates recycling facilities, separators, composting facilities, incinerating facilities and landfills. It also specifies waste flow between these facilities. Combining these two categories, we can find studies that seek to optimize location and routing phases, simultaneously. For example, Asefi and Lim, (2017) developed a multi-objective model for locating and routing between different components of the MSW. More study can be found in (Harijani, Mansour, Karimi, & Lee 2017; Habibi et al., 2017).

Operation research (OR) techniques have been widely used in MSW management issues (Ghiani, Laganà, Manni, Musmanno, & Vigo 2014). A great number of researches in this field can be found in the last two decades. Alumur and Kara (2007) provided a multi-objective model for hazardous wastes location-routing by considering transportation risks and total costs. In this paper, some of the constraints that have not been considered in the previous literature are addressed such as waste-waste, and waste–technology compatibility constraints. Chatzouridis and Komilis (2012) developed a methodology based on geographical information system (GIS) and a mathematical model to locate transfer stations centers and landfills in order to design a user-friendly network. They solved the corresponding model in Excel software. Furthermore, the output of the proposed model is to find the locations and number of transfer stations centers and landfills. Eiselt and Marianov, (2014) developed a two-objective model to locate collection and disposal sites which determined the capacity of each center. To help improve the second objective of the proposed problem (i.e., minimization of pollution), the model considered a constraint to apply legal restrictions on pollution. Xue, Cao, and Li (2015) examined the current status of municipal solid waste routing from its source centers to collection centers in Singapore. The model offered a quantitative and subjective approach to find the optimum amount of waste to be sent from each source center to each incineration plant to minimize overall transportation cost. Generally, Lee, Yeung, Xiong, and Chung (2016) examined municipal solid waste management models. Then, it developed a model for locating collection centers and incinerator and landfills in Hong Kong. It focused on waste flows between collection centers and incinerator and landfills replacement truck warehouses. Taking into account the time window, for moving vehicles between different facilities of the municipal solid waste system, Louati

(2016) focused on routing and allocating vehicles to each of the facilities with the aim of minimizing the distance traveled by each vehicle and the pollution which produce by these facilities and system costs. In (Yildiz, Johnson, & Roehrig 2013), a model was developed for locating the components of the municipal solid waste management system and routing between them. It has developed sustainability indicators for locating components of the system using TOPSIS in the GIS. In addition to costs, its objective was to maximize system stability. Therefore, it provided a multi-objective model and then solved the model with the augmented e-constraint method. Lyeme, Mushi, and Nkansah-Gyekye (2016) developed a model for location-routing, but unlike other researches, its objective was to maximize profits. Revenues are obtained through recycled materials or energy generated from the waste in this model. A summary of the literature review carried out in this study can be seen in Table 1.

Based on the literature review and to the best of our knowledge, the presented models are not fully customized. The model presented in this study is more customized and can include a set of processing centers in the model. These centers are centers for the recycling, disposal, waste to energy or any other centers with regard to organizations which use this model. Therefore, the presented model in the current study can be applicable for different real cases. Furthermore, it cohesively considers the various stage of the waste management system including collection and separation, processing and disposal. This makes the result more efficient than non-integrated approach

Given that the model presented is NP-hard and exact solution approaches are not efficient in large sizes (usually real cases are in large scale), an approach based on a Non-Dominated Sorting Genetic Algorithm II (NSGA-II) is applied which is rarely seen in the literature. Moreover, augmented ε-constraint method is applied to tackle the problems in small scales. However, this method will be inefficient in large size problems.

Parameters tuning is an essential factor in designing meta-heuristic algorithms (Eiben & Smit, 2011). Applying the Taguchi method (Taguchi, 1986) to design experiments and the best worst method (BWM) (Rezaei, 2015) for multi-criteria decision making, a novel method for parameters tuning is presented here. In this method, contrary to existing methods, several criteria are used for parameters tuning and a novel method developed.

As seen in Table 1, some aspects of location-routing models are less noted in municipal solid waste management literature, for instance, location of various process centers, selecting fleet of vehicles and determining number of vehicles for routing and efficient solution approach to tackle the large-sized problem. Given the existing gaps in these studies and by considering real-world assumptions, some features of this study are as follows:

Table 1. A summarized literature review

Study	**Goals**		**Network**		**Collection routes**				
	Economical costs	**Environmental effects**	**Collection Center**	**landfills**	**direct to Landfill**	**To collection centers**	**Select vehicles**	**From collection centers to process centers**	**Determine the number of vehicles**
Badran & El-Haggar, (2006)	✓		✓	✓	✓				
Chatzouridis & Komilis, (2012)	✓		✓	✓	✓				
Eiselt & Marianov, (2014)	✓	✓	✓	✓					
Eiselt & Marianov, (2015)	✓			✓					
Xue et al., (2015)	✓				✓				
Lee et al., (2016)	✓	✓		✓					
Louati, (2016)	✓			✓		✓	✓	✓	✓
Yu & Solvang, (2017)	✓	✓	✓	✓		✓		✓	

Table 1. Continued

Study	**Goals**		**Network**		**Collection routes**				
	Economical costs	**Environmental effects**	**Collection Center**	**landfills**	**direct to Landfill**	**To collection centers**	**Select vehicles**	**From collection centers to process centers**	**Determine the number of vehicles**
Asefi & Lim, (2017)	✓	✓	✓	✓		✓		✓	
Lyeme et al., (2016)	✓	✓	✓	✓					
this study	✓	✓	✓	✓		✓	✓	✓	✓

- Determining the number of vehicles which are needed for each phase of routing.
- Selecting vehicles from a set of vehicles.
- Locating various process centers.
- Providing a solution method based on NSGA-II algorithm to solve large size problems.
- Proposing a new strategy to tune the parameters of algorithms.

The rest of this study is structured as follows: Section 2 describes the problem and its assumptions and presents the mathematical model for the problem and Section 3 addresses the problem-solving approach for the developed model. The presented model is validated in Section 4 and several numerical instances of small and large sizes are solved in this section. Finally, Section 5 deals with results and discussion and some directions for future studies.

2. Problem description

This study aims to develop a new mathematical model based on location-routing problem for municipal solid waste management which involves collecting waste from sources and transferring them to the collection centers and transferring separated wastes to their required processing centers. Wastes are transferred to collection centers after being gathered from sources. Then they are separated in these centers. Afterward, separated wastes are transported to related processing centers. This model is capable of finding locations for collection centers and processing facilities between candidate points considering different types of waste, as well as routing from generation nodes to collection centers and from the collection centers to the processing centers. Given the importance of environmental issues, selecting each candidate points for collection centers and processing facilities different environmental factors are taken into account. Furthermore, for each vehicle, the pollution rate is considered. It is done to simultaneously optimize the impacts of the system on environmental factors along with optimizing costs of the system. The waste generated can be distinguished by the type of waste as follows: 1) Recyclable paper; 2) Recyclable metal; 3) Recyclable plastic; 4) Energy-convertible; 5) Composite; and 6) Other wastes that must be disposed. For each type of waste, a facility is considered that has a specific capacity to respond to the entire volume of that type of waste in the system. In the routing stage from the sources to the collection centers, different vehicles can be used. Each vehicle has different fixed and variable cost and different rates of emissions. Other assumptions of this study are discussed as follows:

- The amount of waste generated from any type of waste is known and deterministic.
- The number of points that collection centers or processing centers can deploy is limited.
- Routing cost is based on traveling distance from each vehicle.
- Vehicles have travel distance restrictions.
- The amount of waste generated per source does not exceed the maximum capacity of vehicles.

The proposed model in this study is able to meet customized type of wastes and environmental factors. Then you can consider your customized type of waste and environmental factors based on your needs. The schematic demonstration of the proposed model is shown in Figure 1.

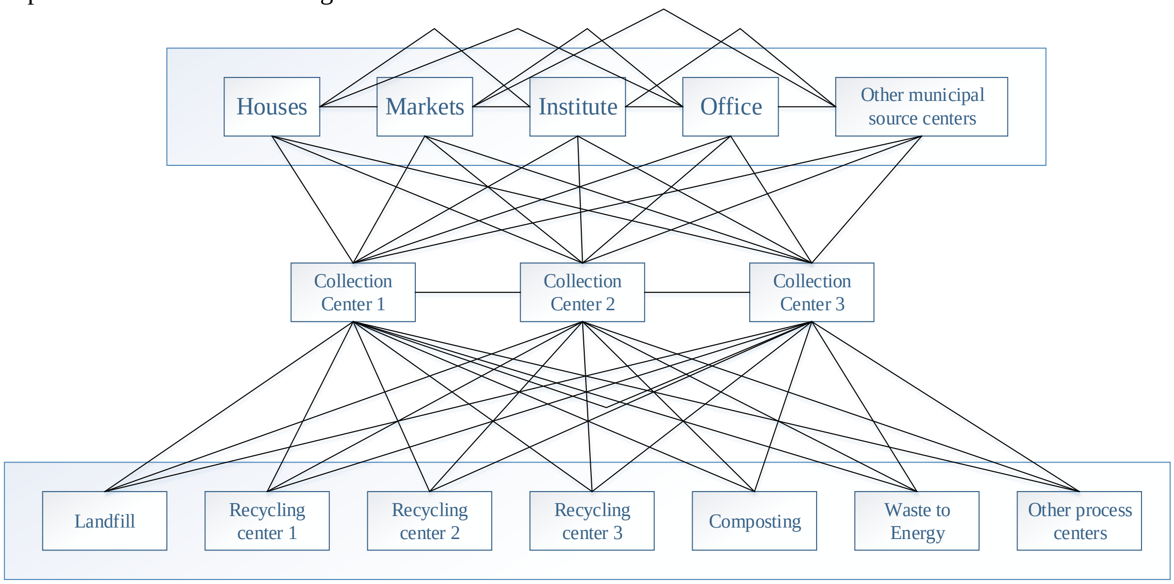

Figure 1. A view of the simple municipal solid waste system

By considering the aforementioned assumptions, we present the mixed-integer programming (MIP) model for managing municipal solid waste. In this model, number, location and capacity of each waste collection center is determined. Collection vehicles are selected from a number of available vehicles and assigned to each collection center. Moreover, routing of vehicles from sources to collection centers and from collection centers to processing centers is determined. Regarding different types of waste, separated wastes in the collection centers are assigned to the suitable processing centers. Moreover, the location of each of these processing centers is determined. All in all, the formulation of this problem is based on the notations of Tables 2-4. The objective functions and problem constraints are given in Equations (1) - (37).

Table 2. Definition of sets

Set:	
I	All potential collection center nodes
J	All source nodes
R	All potential process nodes
K	All vehicles in collection phase
S	All vehicles in process phase for collecting the reminder of different waste in each collection center
N	All environmental factors
L	All process plants

Table 3. Definition of parameters

Parameter:	
O_j	produced waste in source $j \in J$
G_i	Fixed cost of setting up collection center $i \in I$
B_i	Maximum capacity of collection center $i \in I$
UB_i	Minimum capacity of collection center $i \in I$
$H_{r,l}$	Fixed cost of setting up process center $r \in R$ in node $l \in L$
F_k	Fixed cost of using vehicle $k \in K$
P_k	Maximum traveling distance of vehicle $k \in K$
Q_k	Maximum capacity of vehicle $k \in K$

Table 3. Continued

Parameter:	
α_k	Unit vehicle transportation cost in collection phase fore vehicle $k \in K$
β_k	Unit vehicle transportation emissions in collection phase fore vehicle $k \in K$
CA_l	Maximum capacity of vehicle of process plant $l \in L$
CF_l	Fixed cost of using vehicle of process plant $l \in L$
FS_s	Fixed cost of using vehicle $s \in S$ in process phase
ω_l	Unit vehicle transportation cost of process plant $l \in L$
λ_l	Unit vehicle transportation emissions of process plant $l \in L$
δ_s	Unit vehicle transportation cost in process phase for vehicle $s \in S$
ρ_s	Unit vehicle transportation emissions in process phase for vehicle $s \in S$
$\gamma_{j,l}$	percent of waste for process plant $l \in L$ which produced in source node $j \in J$
$d_{i,j}$	Distance between j , i nodes for i , j $\in I \cup J$
$m_{i,r}$	Distance between i , r nodes for i , $r \in I \cup J$
$\tau_{i,n}$	Reduction amount of condition $n \in N$ by setting up collection center $i \in I$
$\pi_{r,n,l}$	Reduction amount of condition $n \in N$ by setting up process plant $l \in L$ in node $r \in R$
$cs_{l,s}$	Is equal to 1 if vehicle $s \in S$ is for process plant $l \in L$; 0 otherwise
A	Number of source center
NL	Number of process plant
AI	Number of collection center
BM	A very large number

Table 4. Definition of variables

Variables:	
y_i	Is equal to 1 if collection center $i \in I$ is established; 0 otherwise
$x_{i,j,k}$	Is equal to 1 if node i immediately precedes node j by vehicle k ; 0 otherwise for $i, j \in I \cup J$ and $k \in K$
$z_{i,j}$	Is equal to 1 if source $j \in J$ allocated to collection center $i \in I$; 0 otherwise
$U_{j,k}$	Auxiliary variable for sub-tour elimination constraints for vehicle $k \in K$ in collection phase
$UR_{i,s,l}$	Auxiliary variable for sub-tour elimination constraints for vehicle $s \in S$ in process phase
$w_{l,r}$	Is equal to 1 if process plant $l \in L$ stablished in process potential node $r \in R$; 0 otherwise
$ws_{l,s}$	Is equal to 1 if process plant $l \in L$ use vehicle $s \in S$ for reminder part of waste
$e_{r,i,s,l}$	Is equal to 1 if node r immediately precedes node j by vehicle s for process plant l ; 0 otherwise for $i, r \in I \cup R$ and $s \in S$
$c_{i,l}$	Auxiliary variable for computing the remainder of waste type $l \in L$ in collection center $i \in I$
$RE_{i,l}$	Auxiliary variable for store the remainder of waste type $l \in L$ in collection center $i \in I$
$v_{r,i,s}$	Is equal to 1 if collection center $i \in I$ allocated to process plant $r \in R$ for process plant $l \in L$; 0 otherwise
$cw_{i,l,r}$	Auxiliary variable for linearization of product of c and w in goal functions for $i \in I, l \in L, r \in R$
$eRE_{r,i,s,l}$	Auxiliary variable for linearization of product of e and RE in vehicle capacity limitations in process phase for $r \in$ R $\in I \cup J, i \in I, s \in S, l \in L$

$$\begin{aligned}\text{Objective 1} = {} & \sum_{i\in I} G_i * y_i + \sum_{i\in I\cup J}\sum_{j\in I\cup J}\sum_{k\in K} d_{i,j} * \alpha_k * x_{i,j,k} + \sum_{k\in K} F_k * \sum_{i\in I}\sum_{j\in J} x_{i,j,k} \\ & + \sum_{r\in R}\sum_{l\in L} H_{r,l} * w_{l,r} + \sum_{l\in L}\sum_{i\in I\cup R}\sum_{r\in I\cup R}\sum_{s\in S} m_{i,r} * \delta_s * e_{r,i,s,l} \\ & + \sum_{l\in L}\sum_{s\in S} FS_s * CS_{l,s} * \sum_{r\in R}\sum_{i\in I} e_{r,i,s,l} + 2 * \sum_{l\in L}\sum_{r\in R}\sum_{i\in I} c_{i,l} * w_{l,r} * m_{r,i} * \omega_l \\ & + \sum_{l\in L}\sum_{i\in I} c_{i,l} * CF_l\end{aligned} \tag{1}$$

$$\begin{aligned}Objective\ 2 = {} & \sum_{i\in I\cup J}\sum_{j\in I\cup J}\sum_{k\in K} d_{i,j} * \beta_k * x_{i,j,k} + \sum_{i\in I}\sum_{n\in N} y_i * \tau_{i,n} + \sum_{l\in L}\sum_{i\in I\cup R}\sum_{r\in I\cup R}\sum_{s\in S} m_{i,r} * \rho_s * e_{r,i,s,l} \\ & + 2 * \sum_{l\in L}\sum_{r\in R}\sum_{i\in I} c_{i,l} * w_{l,r} * m_{r,i} * \lambda_l + \sum_{l\in L}\sum_{r\in R}\sum_{n\in N} \pi_{r,n,l} * w_{l,r}\end{aligned} \tag{2}$$

$S.t.$

$\sum_{K}\sum_{i\in I\cup J} x_{i,j,k} = 1$	$\forall\ j \in J$	(3)
$\sum_{j\in J} O_j * \sum_{i\in I\cup J} x_{i,j,k} \le Q_k$	$\forall\ k \in K$	(4)
$\sum_{j\in I\cup J}\sum_{i\in I\cup J} d_{i,j} * x_{i,j,k} \le P_k$	$\forall\ k \in K$	(5)
$U_{j,k} - U_{u,k} + A * x_{u,j,k} \le A - 1$	$\forall\ j,u \in J, k \in K$	(6)
$\sum_{i\in I,J} x_{j,i,k} - \sum_{i\in I,J} x_{i,j,k} = 0$	$\forall\ j \in I \cup J, k \in K$	(7)
$\sum_{i\in I}\sum_{j\in J} x_{i,j,k} \le 1$	$\forall\ k \in K$	(8)
$\sum_{j\in J} O_j * z_{i,j} - B_i * y_i \le 0$	$\forall\ i \in I$	(9)
$\sum_{j\in J} O_j * z_{i,j} - UB_i * y_i \ge 0$	$\forall\ i \in I$	(10)
$-z_{i,j} + \sum_{u\in I\cup J} (x_{i,u,k} + x_{u,j,k}) \le 1$	$\forall\ i \in I, j \in J, u \in I \cup J, k \in K$	(11)
$\sum_{i\in I} z_{i,j} = 1$	$\forall\ j \in J$	(12)
$\sum_{r\in R} w_{l,r} = 1$	$\forall\ l \in L$	(13)
$\sum_{l\in L} w_{l,r} \le 1$	$\forall\ r \in R$	(14)
$\sum_{r\in I\cup R}\sum_{s\in S}\sum_{l\in L} e_{r,i,s,l} \le BM * y_i$	$\forall\ i \in I$	(15)

$$\sum_{r\in I\cup R}\sum_{s\in S} e_{r,i,s,l} = y_i \qquad \forall\, i \in I, l \in L \qquad (16)$$

$$\sum_{j\in J}\gamma_{j,l} * o_j * z_{i,j} - c_{i,l} * CA_l \ \geq 0 \qquad \forall\, i \in I, l \in L \qquad (17)$$

$$\sum_{j\in J}\gamma_{j,l} * o_j * z_{i,j} - c_{i,l} * CA_l \ \leq CA_l \qquad \forall\, i \in I, l \in L \qquad (18)$$

$$RE_{i,l} - \sum_{j\in J}\gamma_{j,l} * o_j * z_{i,j} + c_{i,l} * CA_l = 0 \qquad \forall\, i \in I, l \in L \qquad (19)$$

$$\sum_{i\in I} RE_{i,l} * \sum_{r\in I\cup R} e_{r,i,s,l} \ \leq CA_l \qquad \forall\, s \in S, l \in L \qquad (20)$$

$$UR_{i,s,l} - UR_{u,s,l} + Al * e_{i,u,s,l} \ \leq Al - 1 \qquad \forall\, i,u \in I, s \in S, l \in L \qquad (21)$$

$$\sum_{i\in I\cup R} e_{r,i,s,l} - \sum_{i\in I\cup R} e_{i,r,s,l} = 0 \qquad \forall\, r \in I \cup R, s \in S, l \in L \qquad (22)$$

$$\sum_{r\in R}\sum_{i\in I} e_{r,i,s,l} \ \leq 1 \qquad \forall\, s \in S, l \in L \qquad (23)$$

$$ws_{l,s} - \sum_{r\in R}\sum_{i\in I} e_{r,i,s,l} = 0 \qquad \forall\, l \in L, s \in S \qquad (24)$$

$$ws_{l,s} \ \leq \ cs_{l,s} \qquad \forall\, l \in L, s \in S \qquad (25)$$

$$-v_{r,i,s} + \sum_{u\in I\cup R}\left(e_{r,u,s,l} + e_{u,i,s,l}\right) \leq 1 \qquad \forall\, i \in I, r \in R, s \in S, l \in L \qquad (26)$$

$$\sum_{i\in I} v_{r,i,s} - BM * w_{l,r} \ \leq 0 \qquad \forall\, r \in R, l \in L \qquad (27)$$

$$\sum_{r\in R} v_{r,i,s} \leq 1 \qquad \forall\, i \in I, l \in L \qquad (28)$$

$$cw_{i,l,r} \leq \ c_{i,l} \qquad \forall\, i \in I, l \in L, r \in R \qquad (29)$$

$$cw_{i,l,r} \leq \ w_{l,r} \qquad \forall\, i \in I, l \in L, r \in R \qquad (30)$$

$$cw_{i,l,r} \geq \ c_{i,l} + \ w_{l,r}\text{-}1 \qquad \forall\, i \in I, l \in L, r \in R \qquad (31)$$

$$eRE_{r,i,s,l} \leq RE_{i,l} \qquad \forall\, r \in \mathrm{R} \ \in I \cup J, i \in I, s \in S, l \in L \qquad (32)$$

$$eRE_{r,i,s,l} \leq \mathrm{BM}{*}e_{r,i,sl} \qquad \forall\, r \in \mathrm{R} \ \in I \cup J, i \in I, s \in S, l \in L \qquad (33)$$

$$eRE_{r,i,s,l} \geq RE_{i,l} \text{ - BM*(1-}e_{r,i,sl}) \qquad \forall\, r \in \mathrm{R} \ \in I \cup J, i \in I, s \in S, l \in L \qquad (34)$$

$$y_i\ , x_{i,j,k}\ , z_{i,j}, w_{l,r}, ws_{l,s}, e_{r,i,s,l}, v_{r,i,s}, cw_{i,l,r} \qquad \in \{0,1\} \qquad (35)$$

$$c_{i,l} \qquad \in Z^+ \qquad (36)$$

$$U_{j,k}, UR_{i,s,l}, RE_{i,l}, eRE_{r,i,s,l} \qquad \in R^+ \qquad (37)$$

$$\sum_{i\in I}\sum_{r\in I\cup R} eRE_{r,i,s,l} \ \leq \ CA_l \qquad \forall\, s \in S, l \in L \qquad (18b)$$

$$2 * \sum_{l\in L}\sum_{r\in R}\sum_{i\in I} cw_{i,l,r} * m_{r,i} * \omega_l \qquad (1.7b)$$

$$2 * \sum_{l\in L}\sum_{r\in R} cw_{i,l,r} * m_{r,i} * \lambda_l \qquad (2.4b)$$

In this model, Equation (1) is the first objective minimizing the overall cost of the system. Equation (2) is the second objective that minimizes total emissions and reduction of environmental impacts. Equation (3) indicates that each source must be allocated to a single route in the collection phase. Equation (4) shows the capacity constraint of vehicles in the collection phase, and Equation (5) indicates maximum traveling distance of vehicles in the collection phase. Equation (6) defines auxiliary constraints for sub-tour elimination in the collection phase (Yildiz et al., 2013). Flow conservation constraints in the collection phase are addressed in Equation (7). Equation (8) states that each vehicle can be used at most once in the collection phase. Equations (9) and (10) indicate the capacity constraint of collection centers in the collection phase. Equation (11) specifies that a source can be assigned to a collection center only if there is a route from that collection center going through that source in the collection phase. Equation (12) guarantees that each source must be allocated just to one collection center. Equations (13) and (14) indicate that each process plant must be allocated once in process phase, Equation (15) specifies that only established collection centers must be routed in process phase, Equation (16) indicates that each collection center must be allocated to a single route for each process plant in process phase. Equation (17), (18) and (19) compute the remainder of any type of waste in each collection center. Equation (20) indicate the capacity constraint of vehicles for collecting reminder of each type of wastes from collection centers in the process phase. Equation (21) indicates auxiliary constraints for sub-tour elimination in the process phase. Equation (22) indicates flow conservation constraints in the process phase. Equation (23) indicates that each vehicle for collecting reminder of each type of wastes can be served at most once in process phase. Equation (24) and (25) indicate that only the vehicles can use for collecting reminder of each type of wastes which are compatible with the process plant. Equations (26), (27) and (28) specify that a collection center can be assigned to a process plant only if there is a route from that process going through that collection center in process phase for each waste type. Equations (29), (30) and (31) linearize product $c \text{ } and \text{ } w$ in objectives. Equations (32), (33) and (34) linearize product $e \text{ } and \text{ } RE$ in vehicle capacity for collecting the remainder of each type of wastes limitations in process phase. Equation (35) must replace Equation (18) because of none linearity of Equation (18). Equation (36) must replace Equation (1) because of none linearity of Equation (1) and at last, Equation (37) must replace Equation (2) because of none linearity of Equation (2).

3. Solution methodology

The location-routing problem belongs to NP-hard problem group (Yildiz et al., 2013). In such cases, finding the optimal solution for the large-scale problem is extremely difficult. Because of the difficulty of solving the problem at large sizes, in this research, an evolutionary algorithm is used to solve the large-size problem. The main advantage of these algorithms is their ability to solve large-size problems in a short time with a fairly acceptable answer (Zhou et al., 2011). Given that the main variables of the proposed problem are discrete, The Non-Dominated Sorting Genetic Algorithm II (NSGA-II) is used which works well for the discrete problem. Also, because the evolutionary algorithms offer close-to-optimal solutions and do not yield absolute optimal solutions, and given that the problem is bi-objective, to solving in small sizes, augmented ε-constraint is used. It is proposed by Chen, Wu, and Lin, (2013) to get non-dominated Pareto's answer set.

In the following, we outline the definitive solution of the model using the augmented ε-constraint. Then, we describe the approximate solution for large-scale problems with Non-Dominated Sorting Genetic Algorithm II.

3.1. Augmented ε-constraint

Augmented ε-constraint is used to present effective solution of presented problem in section 3. This method obtains only efficient Pareto optimal solutions and speeds up the solving process. For this purpose, presented model is programmed in GAMS software with CPLEX solver. Considering the presented model with $\mu = 2$ objectives, the programming is done base on following steps proposed by Chen et al., (2013).

$$\begin{aligned} &\min f_1(x) \\ &\min f_2(x) \\ &s.t. \\ &x \in \beth. \end{aligned}$$

Where x is decision variables $f_1 \text{ } and \text{ } f_2$ are μ objectives and $\beth$ is feasible area.

3.1.1. Making payoff table

To effectively apply the ε-constraint method we must have range of $\mu - 1$ objective used as constraints (Chen et al., 2013). We compute the payoff table by performing the lexicographic optimization of the objective.

3.1.2. Setting up the new constraint base on objectives

After making payoff table, we divide the range of each objective to e_i equal intervals. It produces $e_i + 1$ grid points as the value of e_2 in ε-constraint method. Accordingly, the model II is made as follow.

$$\min f_1(x)$$
$$s.t.$$
$$f_2(x) \leq e_{f_2}$$
$$x \in ℶ.$$

In this model, e_{f_2} is calculated as follow:

$$e_f = \frac{l_f + (j_f * v_f)}{s_f}$$

where l_f is the lower bound of objective 2, v_f is the range of the objective 2, s_f is the number of grid points and j_f is the counter for the objective f_2 from zero to a large enough number of produced effective solution.

3.1.3. Guaranteed efficiency of the result

The point is that the optimal solution of problem (2) is guaranteed to be an effective solution only if all the $(\mu - 1)$ objective's constraints are binding (Mavrotas, 2009). Otherwise, it is a weakly efficient solution (Mavrotas, 2009). For the model only generate optimal solution, the objective constraints must be transformed to equalities by explicitly incorporating the suitable auxiliary variable. These variables are also used as a second term in objective to generate only efficient solutions. So the new model is constructed as follows:

$$\min\left(f_1(x) + \varepsilon\left(-\frac{\varphi f_2}{v_{f_2}}\right)\right)$$
$$S.t.$$
$$f_2(x) + \varphi f_2 = e_{f_2}\ ,$$
$$x \in ℶ.$$
$$\varphi f_2 \in R^+$$

Where in this model ε is a very small number (between$10^{-3} and 10^{-6}$).

3.2. NSGA-II Algorithm

The NSGA-II strategy was suggested by Deb, Agrawal, Pratap, and Meyarivan (2000). it is based on Genetic algorithm that adds features to the selection stage which makes it possible to apply this algorithm to multi-objective problems. In NSGA-II, prior to selecting the set of answers, they are sorted according to the Pareto ranking in a quick procedure. Also, a population gap is obtained based on the density estimate for each of them. A schematic of the NSGA-II algorithm is shown in Fig 2. For more information, see Deb et al., (2000).

This algorithm starts with a bunch of randomly generated initial solution. Then, in each iteration, it initially creates a certain number of crossover children. And then it produces a number of mutation children. Then it calculates fitness of each of these children. At this stage, the total population, which includes the initial population and the children, is arranged based on the non-dominated sorting of the crowding distance, and keeps, as much as the initial population, the top answers that have a higher fitness in the Pareto ranking, and eliminates other answers. The idea behind this selection method is that solution with better rank and less crowded distance is preferred. The algorithm repeats this until one of the end conditions that can be the number of iterations or reach a level that does not make significant changes. In this study, the condition for reaching the end is based on the number of iterations. Eventually sets out Pareto solutions.

3.2.1. Solution representation

The performance of evolutionary algorithms is heavily influenced by how the problem is encoded (Chen et al., 2013). How to choose the encoding of the solution should be in such a way that it can cover all possible scenarios in the solution to the problem. Thus, each chromosome must be defined in a way that can cover all the components of the problem. For this purpose, one of the most popular methods is order-based methods for encoding the problem (Rabbani et al., 2018).

In this research, we define each chromosome as a structure which includes arrays of the following descriptions. The first array is made up of $K+J-1, k$ denotes the number of vehicles in the waste collection phase from its sources, and J is the number of sources. The second array is made up of $K+I-1, k$ denotes the number of vehicles in the waste collection phase from its sources, and I is the number of sources. By this encoding, it is possible to identify all possible scenarios that may occur for vehicle and collection centers in collection phase. The next array includes the R members, where R refers to the number of potential points for establishing processing centers. This array contains L members from one to L and $R-L$ zero members which specify in which of the points R the particular processing center L has been set up. Then a two-dimensional array is defined which contains L rows, each row of which is used for routing one of the processing centers. And each row contains $J+S-1$ members for routing in process phase for each process center. Figure 3 shows an example of this encoding.

3.2.2. NSGA-II operators

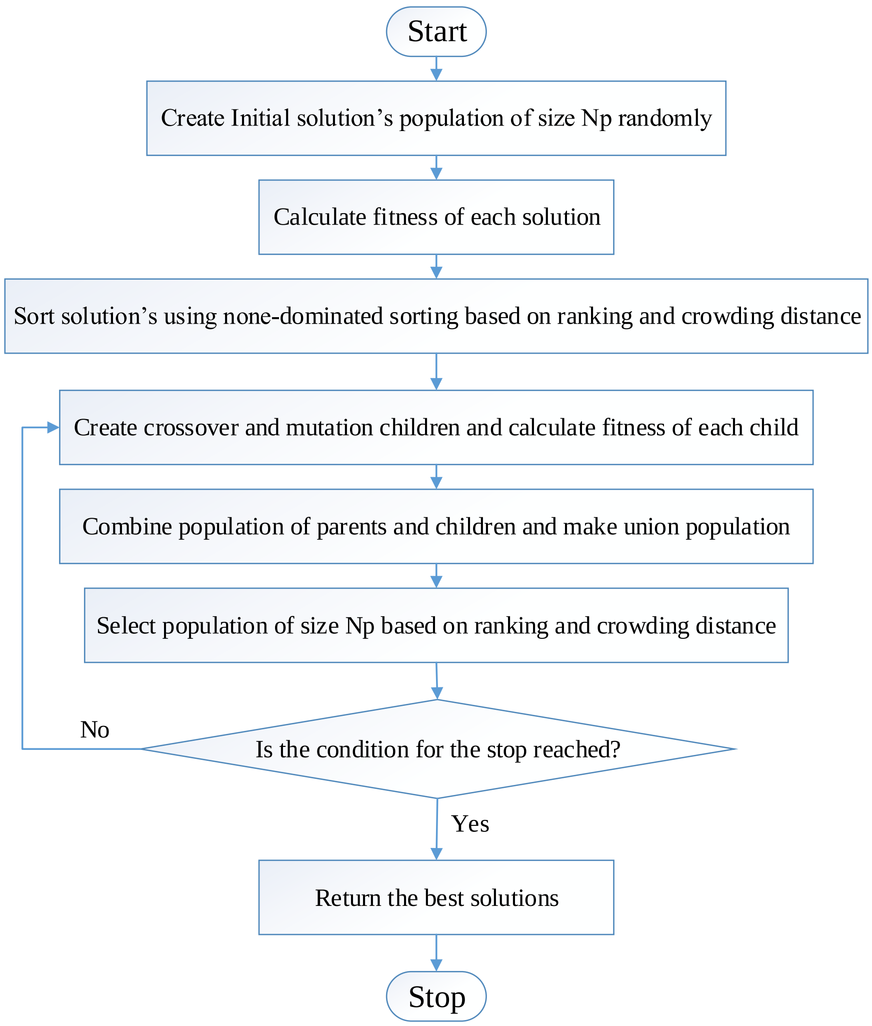

Figure 2. The flowchart of NSGA-II algorithm

To find a solution that is close to the optimal solution, it needs to get the whole space of the answer. To this end, this algorithm produces new solutions in two different approaches from the old ones (primary population). The first is the creation of crossover children which are based on two selective parents. There are various methods for selecting parents, in this research, where random method has been used. This approach seeks to improve the parent's answers and in some ways, one can say that it seeks to improve previous solutions and find optimal local solution. The second approach is to create mutated children based on a selective parent. Like the first approach, the selected parent is chosen randomly in this approach. This approach is used to escape from being trapped in local optimal solution and scrolling through the entire feasible space.

- **Crossover**

Based on the structure of the chromosomes, which is a structure, for each array, a single-point crossover operator is used separately. The operation of this operator is such that it randomly selects a random number from one to n, where n is the length of the array. Then, according to the selected number, the selected parents are divided into two parts. Then it generates two children whose first child consists of the first part of the first parent and the second part of the second parent and second child consists of the second part of the first parent and the first part of the second parent. In this study, since there are $3 + L$ rows, this operator generate$2 * (L + 3)$, child. Figure 4 shows an example of crossover operator on array 1.

- **Mutation**

This operator initially selects the two members from the selected parent and then for generating new child, exchange those two members with each other. In this study, $(L + 3)$ mutant children are produced in each iteration. Figure 5 shows an example of mutation operator on array 2.

3.2.3. Fitness

This function calculates the fitness of solution given by each of these operators. Indeed, this function performs the function of the objectives and after the generation of each child, the amount of solution cost and solution pollution and emissions, which are the objective functions of this study, is compiled as fitness.

3.2.4. Parameters tuning

Since tuning the parameters of the algorithm into fit reduces the runtime and enhances performance and reliability, properly setting these parameters is important (Eiben & Smit, 2011). For this purpose, Taguchi method (Taguchi, 1986) has employed to set up parameters NSGA-II algorithm. By using this method, the most information can be obtained with the least number of possible trials (Hasçalık & Çaydaş, 2008). For this purpose, a four-level Taguchi design is applied to check the parameters affecting this algorithm and select the best combination of these parameters. These parameters are the size of the population (N_p) is considered to be $20, 40, 60$ and 80, the number of iterations (Max_{iter}) is considered to be $50, 75, 100$ and 125, and Crossover rate (C_r), which also affects mutations $(M_r = 1 - C_r)$, is considered to be $0.9, 0.8, .07$ and 0.6. Based on the statistical basis of the Taguchi method, using Minitab software, 16 trials are required. The value of the objectives and execute time of trials have been used as criteria to check the quality of trials. Then, trials were performed by considering a random instance with the following specification: $I = 5, J = 50, K = 10$, $L = 5, R = 10, S = 4$, $N = 5,$. The results of these trials are demonstrated in Table 5.

1	3	8	10	2	5	6	11	4	7	9	12

Array 1. Order of 10 source nodes and 3 vehicles

3	4	2	1	5

Array 1. Order of 3 vehicles and 2 collection centers

0	0	3	0	2	1	0

Array 3. Order of 3 process plants and 7 potential nodes

3	1	2
2	1	3
1	2	3

Array 4. Order of 2 collection centers and 2 vehicles
for each of 3 process plants

Figure 3. An example of solution representation

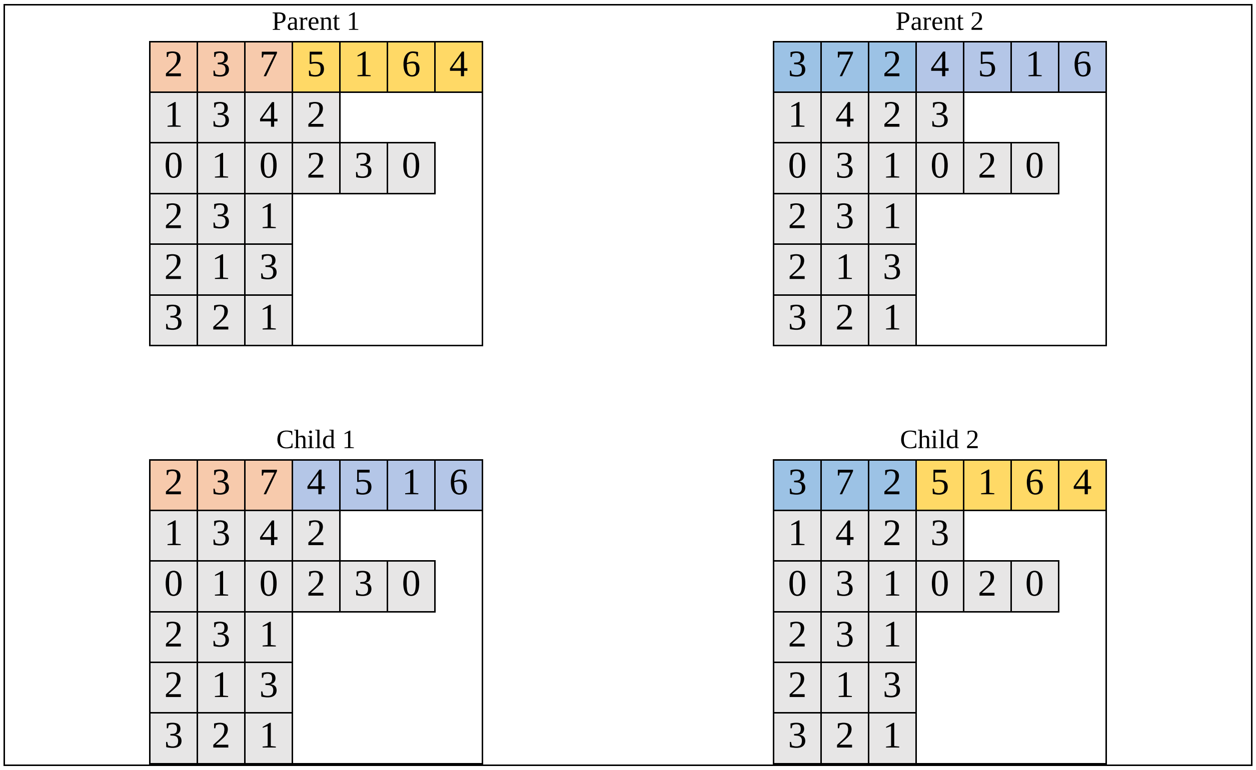

Figure 4. Example of crossover operator

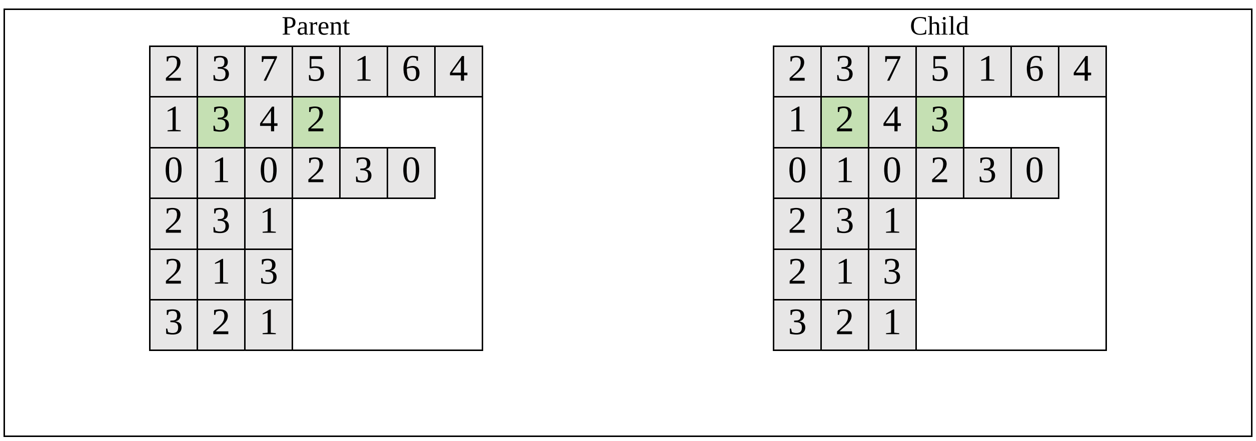

Figure 5. Example of Mutation operator

Table 5. Taguchi trials for selecting the best combination of NSGA-II parameters

No.	Max_{iter}	N_p	C_r	Execute time	Mean of objective 1	Mean of objective 2
1	50	20	0.9	88	4.53E+10	3.24E+10
2	75	20	0.8	140	5.35E+10	4.62E+10
3	100	20	0.7	177	5E+10	4.07E+10
4	125	20	0.6	219	3.74E+10	3.11E+10

Table 5. Continued

No.	Max_{iter}	N_p	C_r	Execute time	Mean of objective 1	Mean of objective 2
5	75	40	0.9	290	3.22E+10	1.57E+10
6	50	40	0.8	205	4.58E+10	2.09E+10
7	125	40	0.7	470	3.65E+10	2.25E+10
8	100	40	0.6	377	3.53E+10	2.00E+10
9	100	60	0.9	611	3.64E+10	2.09E+10
10	125	60	0.8	706	2.52E+10	1.18E+10
11	50	60	0.7	285	2.65E+10	1.51E+10
12	75	60	0.6	444	2.53E+10	1.64E+10
13	125	80	0.9	1037	2.05E+10	5.45E+09
14	100	80	0.8	786	2.61E+10	1.45E+10
15	75	80	0.7	604	2.16E+10	1.46E+10
16	50	80	0.6	425	3.50E+10	1.93E+10

Then, to compare and choose the best combination of parameters, first, the three criteria are considered normalized and dimensionless. For this purpose, each of the criteria was divided in its best value. Second, the Best-Worst Method (BWM) (Rezaei, 2015) was used to weight each criterion. The prominent attribute of BWM is the utilization of a structured way for generating pairwise comparisons which leads to trustworthy results. According to BWM, the best and the worst criteria are primarily specified by the decision-maker. Then, other criteria are compared with the worst and the best criterion using pairwise comparison. Then, a min-max model is formulated in order to obtain the weight of each criterion (Rezaei, 2015).

For this purpose, the most important criterion was specified as objective 2 and the least important criterion was specified as objective 1. Then another criterion (execution time) is compared with the worst and the best criterion using pairwise comparison. This comparison is shown in Table 6.

Table 6. Pairwise comparison of criteria

Criterion	In comparison with the most important Criterion	In comparison with the least important Criterion	Weight
Execution Time	2	3	0.222
Objective 1	1	2	0.222
Objective 2	3	1	0.556

Then, following model has been solved to gain weight of each criterion.

$$
\begin{aligned}
& Min\ \lambda \\
& Subject\ to: \\
& \frac{w_n}{w_j} - a_{Bj} \leq \lambda \quad \forall j \\
& \frac{w_n}{w_j} - a_{Bj} \geq -\lambda \quad \forall j \\
& \frac{w_j}{w_w} - a_{jw} \leq \lambda \quad \forall j \\
& \frac{w_j}{w_w} - a_{jw} \geq -\lambda \quad \forall j \\
& \sum w_j = 1 \\
& w_j \geq 0 \ \forall j
\end{aligned}
$$

Where w_j is the weight of criterion "j", a_{bj} is the amount of superiority of the best criterion in comparison with criterion "j", a_{jw} is the amount of superiority of criterion "j" in comparison with the worst criterion, w_b represents the weight of the best criterion and w_w represents the weight of the worst criterion.
Then, the weighted sum of these three criteria was calculated for each combination of parameters (i) as follows and the results of these calculations are in Table 7.

$$\sum_{j=1}^{5} w_j a_{ij} \quad \forall i$$

Table 7. Weighted sum of each combination of parameters

No.	Execution time	Objective 1	Objective 2	Weighted sum
1	0.2222	0.4910	3.3027	4.0158
2	0.3527	0.5791	4.7094	5.6412
3	0.4452	0.5415	4.1441	5.1308
4	0.5517	0.4055	3.1689	4.1261
5	0.7285	0.3485	1.6012	2.6782
6	0.5150	0.4964	2.1334	3.1447
7	1.1807	0.3953	2.2941	3.8701
8	0.9468	0.3829	2.0394	3.3691
9	1.5352	0.3938	2.1285	4.0575
10	1.7735	0.2733	1.2019	3.2487
11	0.7153	0.2872	1.5386	2.5411
12	1.1164	0.2739	1.6711	3.0614
13	2.6069	0.2222	0.5556	3.3847
14	1.9750	0.2830	1.4762	3.7343
15	1.5181	0.2343	1.4910	3.2434
16	1.0673	0.3790	1.9628	3.4090

Then the combination with the lowest weighted sum were selected as the optimal combination. Based on these calculations, the best combination of these parameters is $N_p = 60$, $Max_{iter} = 50, C_r = 0.7$.

4. Model Validation and Numerical examples

4.1. Model Validation

In order to validate the solution presented by NSGA-II algorithm and ensuring that the presented solution can be at an acceptable level of optimality, we have solved an instance of the problem with the GAMS software and CPLEX solver based on the Epsilon constraint method. Then we compare the result of this method with the result of the NSGA-II algorithm. The problem considered for this purpose is a small size problem. Full details of this problem are available in the following link address:
https://www.dropbox.com/sh/jpo9kjojgnyjtne/AAAdeINObNuIo2DMEk9y1DZ2a?dl=0

The solutions obtained by this method are shown in Table 8 and solutions obtained by NSGA-II are in Table 9 for this problem.

Table 8. Payoff table of solution created by augmented ε-constraint

Solution	Objective 1	Objective 2
1	3042260	342850
2	3255750	338420
3	3462400	335600

Table 9. Obtained solutions using NSGA-II algorithm for validation problem

Solution	Objective 1	Objective 2
1	3152390	423850
2	3432120	416850
3	3668370	397550
4	3752540	383950
5	3807790	382250
6	3892580	371250
7	4121680	359250
8	4321580	358450
9	4408650	344150
10	4498050	341750

4.2. Numerical examples

Due to lack of appropriate data for this problem, 14 sample problems in different sizes were considered. Parameters of these problem were randomly created using the MATLAB software. Main characteristics of these problems are in Table 10 and the full details of these problem are available in the following link address:

https://www.dropbox.com/sh/jpo9kjojgnyjtne/AAAdeINObNuIo2DMEk9y1DZ2a?dl=0

In Table 10, *J* indicates number of source centers, *I* indicates number of potential collection center nodes, *L* indicates number of process plants, *R* indicates potential nodes for establishing process plants, *K* indicates available vehicles in collection phase, *S* indicates available vehicles for collecting reminder of each type of waste in process phase and at last, *N* indicates number of environmental factors. The ranges of creating random parameters of these instances are in Table 11. These instances were solved with the proposed algorithm using MATLAB software. In order to compare and discuss the answers of these instances, Figure 6 and Figure 7 are prepared. More detail about these figures is in Section 6. Spacing metric and diversity metric are used to evaluate quality of solution. Spacing metric gives information about distribution of None-dominated solutions (Suo, Yu, & Li, 2017) which calculated using following equation:

$$d_i = min_j \sum_{t=1}^{T} \left| f_t^j - f_t^i \right| \qquad \forall\, i, j \in \{1, \dots, N\}$$

$$Spacing = \sqrt[2]{\frac{1}{N-1} \sum_{i=1}^{N} (d_i - \widetilde{d})^2}$$

Where N is number of None-dominated solutions, d_i is the minimum distance of pareto optimal solution i from other solutions, $\tilde{d}$ is the average of d_i, and $t \in \{1, \dots, Number\ of\ objectives\}$, and value of each objectives denoted by f_t^i.

Diversity metric calculated as the maximum Euclidean distance between non-dominated solutions (Rabbani et al., 2018). The results of this metrics are in Table 12.

Also, for further discussion on the details of the problem, for instance, one of the solutions for problem instance 2 is schematically shown in Figure 8. None-dominated solutions for this problem instance is shown in Figure 9.

Considering the uncertainty in the amount of waste produced in waste sources, and in order to investigate the effect of waste amount on the objectives, problem instance2 has been solved with different volumes of waste amount. The average of None-dominated solutions of these states is shown in Figure 10 and Figure 11. The ranges of creating random amount of waste for sensitivity analysis is shown in Table 13.

Table 10. Characteristics of instance problems

No.	J	I	L	R	K	S	N
1	10	2	6	10	5	2	5
2	20	5	6	10	5	2	5
3	50	5	6	20	7	3	5
4	75	10	6	25	10	4	5
5	100	10	6	25	10	4	5
6	125	10	6	30	15	4	5
7	150	13	6	30	15	4	5
8	200	13	6	40	20	5	5
9	250	13	6	40	20	5	5
10	500	14	6	50	30	5	5
11	750	14	6	50	40	8	5
12	1000	20	6	50	40	10	5
13	1500	30	6	50	40	10	5
14	2000	50	6	75	50	10	5

Table 11. The ranges of creating random parameters

Parameter	Lower bound	Upper bound
O_j	50	150
G_i	50000000	100000000
B_i	5000	7000
UB_i	1	1000
$H_{r,l}$	50000000	100000000
F_k	40000000	80000000
P_k	50000	100000
Q_k	1000	5000
α_k	1000	2000
β_k	3000	6000
CA_l	5000	10000
CF_l	40000000	80000000
ω_l	5000	10000
λ_l	4000	10000
$d_{i,j}$(between sources)	200	1000
$d_{i,j}$(between potential collection centers)	25000	50000
$d_{i,j}$(between sources and potential collection centers)	2000	10000
$m_{i,r}$(between potential process nodes)	30000	60000
$m_{i,r}$(between collection centers and potential process nodes)	10000	25000
$\tau_{i,n}$	400	800
$\pi_{r,n,l}$	500	1200

Table 12. Results of diversity and spacing metrics

Problem instance	Diversity metric	Spacing metric
1	102540000	1300500
2	93411000	1120700
3	5701300	169110
4	215320000	445480
5	54200000	154580

Table 12. Results of diversity and spacing metrics

Problem instance	Diversity metric	Spacing metric
6	123600000	1437800
7	456250000	3213300
8	285670000	2673100
9	276090000	146900
10	3047500000	4820200
11	1130800000	4958100
12	13226000000	34050000
13	18321000000	17075000
14	18685000000	863230

Table 13. The ranges of creating random amount of waste

Instance	Lower bound of range	Upper bound of range
1	50	150
2	100	300
3	200	400
4	300	500
5	500	700
6	600	800
7	800	1000

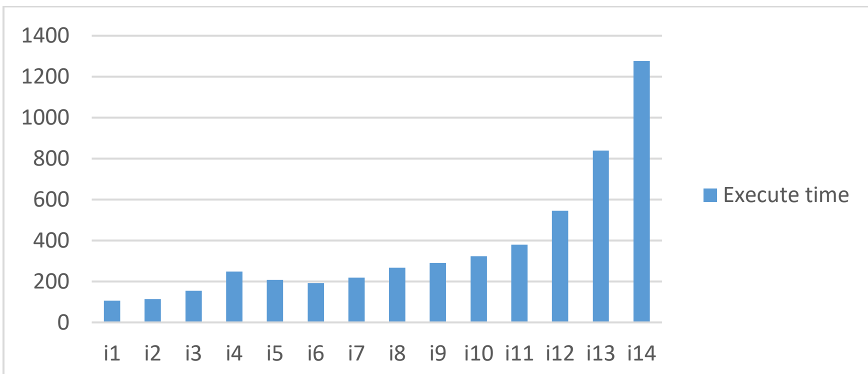

Figure 6. The execution time of each instance

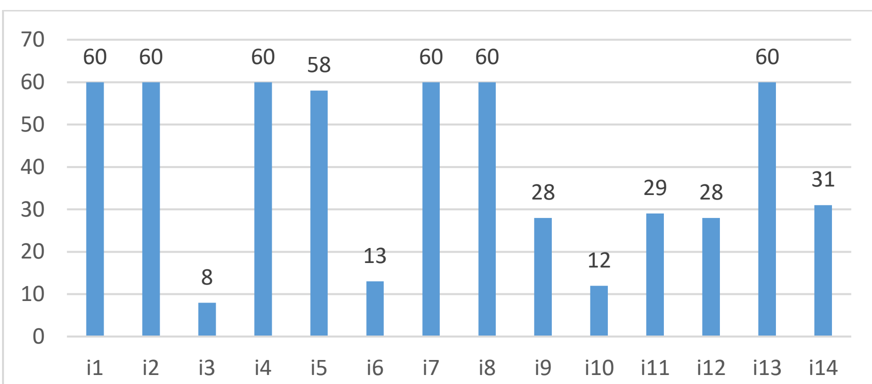

Figure 7. Number of paretor solutions for each instance

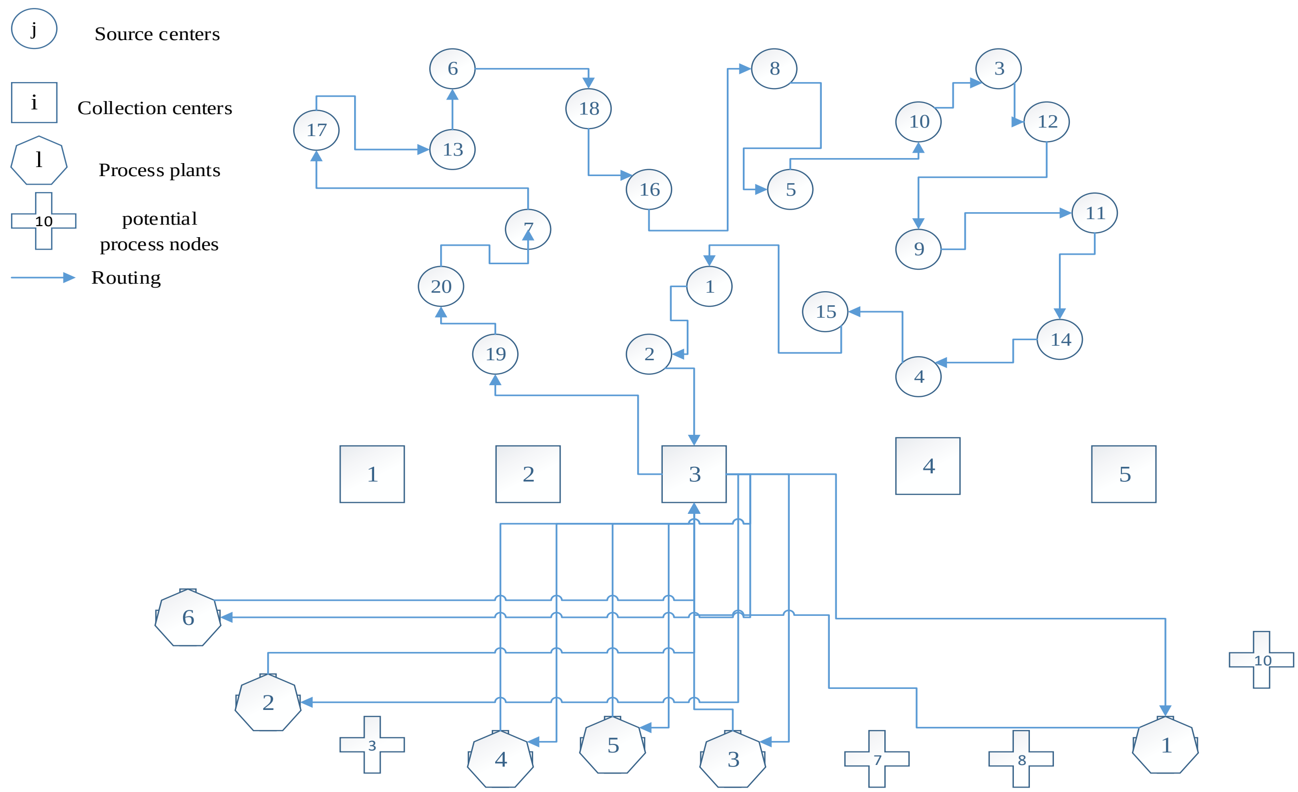

Figure 8. Schematic solution representation for problem instance 2

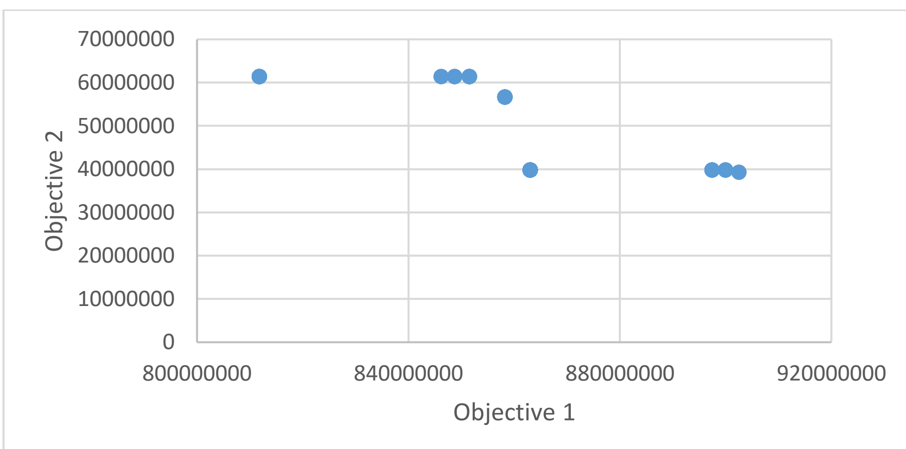

Figure 9. None-dominated solutions for problem instance 2

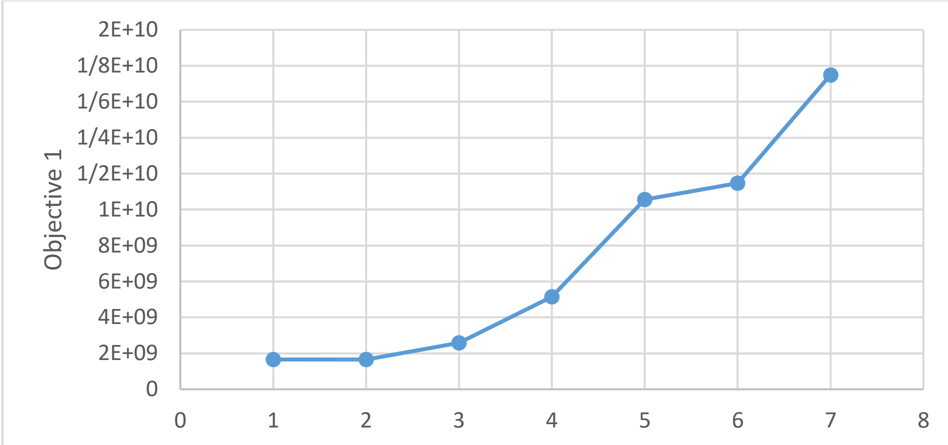

Figure 10. Variations of objective 1

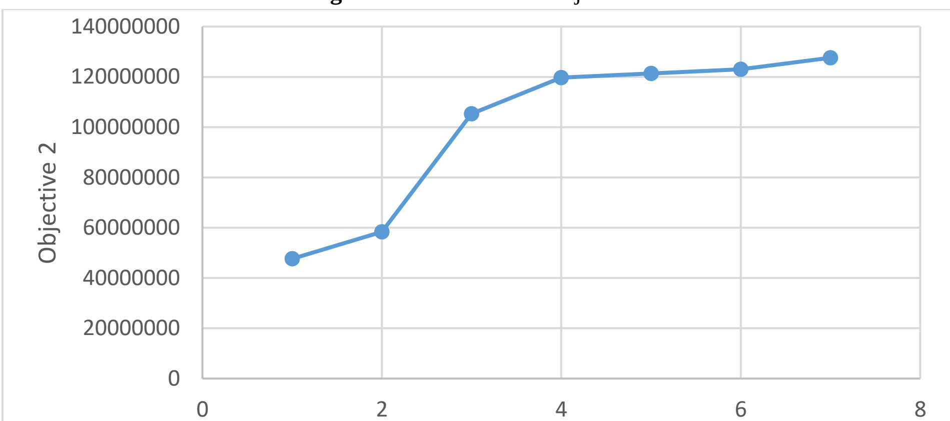

Figure 11. Variations of Objective 2

Throughout, this study has been carried out in a series of studies, some of which are more relevant to the subject of this research and are listed in the literature review. Considering the importance of municipal waste management which is mentioned in section 1, in this study, a model has been developed that simultaneously identifies collection and separation centers for waste and reverse logistics centers, including recycling centers. One of the important findings of this study is the presentation of a solution based on NSGA-II algorithm, which, given the type of problem that is NP-Hard, is very crucial because softwares such as GAM cannot solve such problems. But as shown in Figure 6, the solving time with this solution is more appropriate and more efficient for problems of different sizes. Also, as shown in Figure 7, even in the large sizes, various numbers of Pareto's solutions are presented by this method, which grants the decision-maker more initiative to select different solutions. As shown in Fig. 8, the solution presented by this method is logical and can be relied upon by a high precision. In the parameters tuning and select the best combination of parameters of the evolutionary algorithm that strongly affects the algorithm's performance, a systematic approach based on multi-criteria decision making was presented. Given the uncertainty in the volume of wastes and also the fact that the volume of wastes can vary in different problem, the sensitivity analysis of the objectives based on the amount of waste is presented in Figure 10 and Figure 11. As can be seen, the first objective increases exponentially and the second objective increases logarithmically with increasing wastes volume. As there are limitations in any study, we also encountered some limitations in this research. Including the fact that the real data is uncertain in the real world, but here, in order to avoid the complexity of the problem, we assume the data to be deterministic. And the other limitation was the use of approximate method. Although the solution is close to the optimal solution, sometimes the solution may need to be reviewed by decision maker.

5. Conclusion

In this paper, a model was proposed to minimize waste management system costs and minimize the environmental impacts that arise from setting up a facility or transporting wastes. In order to minimize the environmental impacts, various environmental factors that arise from establishing a center were considered like soil pollution or noise pollution. This article describes the waste management system in two parts, which are integrated together. The first part relates to the location of waste collection centers and the routing of waste production centers, like markets, to these centers. The second part relates to the location of reverse logistics centers, such as waste to energy center or electronic waste recycle center, and routing from collection centers to each of these centers. Then a solution representation is proposed based on the NSGA-II algorithm. In tuning the parameters of the meta-heuristic algorithm, which has a significant effect on the efficiency of these algorithms, using the Taguchi method, first, the number of necessary experiments to select the best combination of parameters was determined. Then, based on the BWM method, which is for multi-criteria decision making the optimal combination was selected. Minimizing the time needed to solve, the first goal of the problem and the second goal of the problem were considered as the criteria choosing the best combination of parameters. In future studies, the model can be developed in a multi-period model, or time window can be considered, helping to make the model more realistic. Also, since real-world data is uncertain, fuzzy approaches can be used to develop the model.

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