



Solving a multi-objective sustainable waste collection problem considering a new collection network

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Abstract

Waste collection management is considered as one of the important issues in sustainable logistics design which is one of the new concepts in supply chain management. In recent years, researchers' attentions are attracted to apply green and sustainable concepts in their researches. This paper presents a novel multi-objective mathematical model considering a new collection network for waste collection problem. We are interested in the location decisions in design phase of the network and waste collection decisions in operational phase. The problem consists of activities related to collection, treatment, recycling, and disposal of hazardous wastes in multi stage network. Three objective functions including operational cost and social costs are considered, simultaneously. The model is used to evaluate fuel consumption and carbon dioxide emission and its impact on environment. A new hybrid meta-heuristic algorithm is designed to solve the problem and a new way to represent solutions is provided. Finally, experimental results are conducted and the results obtained by proposed algorithm are compared to four well-known meta-heuristic algorithms with respect to five comparison metrics. The results show the efficiency of proposed algorithm in some comparison metrics.

Keywords Metaheuristic algorithm · Multi-objective · Waste collection · Sustainable logistics · Location routing problem (LRP)

Mathematical Subject Classification 90B06 · 90B50 · 90B80

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1 Introduction

Sustainable logistics is one of the novel concepts in supply chain management. In recent years, researchers' attentions are attracted to apply green and satiability in their researches. Some Governments and non-Government organizations oblige logistic companies to address environmental issues in their strategic decisions. Earlier works in Supply Chain Management (SCM) concentrated on economical issues more than other issues, but the trend of researches shows that environmental issues have been considered further in recent years (Sbihi and Eglese 2007).

Sustainability can be defined as the ability of enhancing the quality of human life with simultaneous consideration of activities related to protection of environment (Sbihi and Eglese 2007). According to the world commission on environment and development (termed Brundtland) definition, sustainability is "the potency to meet the present needs of human without disruption and damage to capability of next generations to meet their needs" (Brundtland et al. 1987). Sustainable supply logistic is the logistic system in which economical, social, and environmental objectives are considered simultaneously. In this research, social objectives including minimization of transportation risk and minimization of undesirable sites risks are addressed in addition to the economical costs. Moreover, environmental issues are embedded in the one of the objectives. These terms of objective function aim to reduce destructive impacts of fuel consumption on environment. So, the present paper which considers economical, social, and environmental aspects of logistics management, simultaneously are categorized as a sustainable logistics management.

Green logistics is all activities corresponding to the production and distribution in a way that environmental issues are taken into consideration. The significance of green logistics is derived by the fact that current logistics strategies applied in logistics companies are not sustainable in the long term. Lin et al. (2014) showed that a new branch in vehicle routing problem (VRP) which is one of the typical problems in operations research (OR) has emerged and they called it green vehicle routing problem. They classified this field into the three major categories, i.e., Green-VRP, pollution routing problem, and VRP in reverse logistics. Green-VRP deals with the problems in which the optimization of energy consumption is addressed (Salimifard et al. 2012; Erdoğan and Miller-Hooks 2012; Küçükoğlu et al. 2015). The pollution routing problem (PRP) introduced by Bektas and Laporte (2011) is concerned with reduction of greenhouse gases (GHG) in particular CO₂ emissions. These gases have unfavorable effects on ecosystems and humans' health and efforts to reduce of these gases has increased in recent years (Fagerholt et al. 2010; Demir et al. 2014; Kramer et al. 2015). The third type of green VRP is VRP in reverse logistics (VRPRL). Dekker et al. (2013) proposed the definition for reverse logistics: "The process of planning, implementing and controlling backward flows of raw materials, in process inventory, packaging and finished goods, from a manufacturing, distribution or use point, to a point of recovery or point of proper disposal". According to the Lin et al. (2014), VRPRL is divided into three categories that waste collection management is considered as

one of these categories. Both waste collection management and reduction of CO₂ emission which are two main features of green logistics problems are investigated in this paper. In other words, reduction of CO₂ emission by means of decrease in fuel consumption and applying of the proposed model in waste collection management are green features of the presented model in this paper.

As aforementioned, waste collection problem is categorized as one of the subsets of sustainability (Beamon 2008) and green logistics (Lin et al. 2014). Waste collection problem is one of the most important and crucial applications of vehicle routing problems in real world for the reason that wastes and in particular hazardous wastes influence on human health and have destructive effect on environment. Waste collection management consists of all processes which are related to collect, reuse, dispose and recycle of wastes. These processes are key factors in protecting an environment and conserving resources. Alumur and Kara (2007) presented a new mathematical model for the hazardous waste location routing problem. This paper aimed to minimize total cost and transportation risk. This model was used in real case in central Anatolian region of Turkey. Samanlioglu (2013) extended the collection network presented in Alumur and Kara (2007) and proposed a new network for waste management. This network includes generation, treatment, recycling, disposal nodes and the arcs between them. This network is the most complete network considered in the literature. We improve this network in the paper by adding depots of vehicles to previous network. In addition, the relationship between generation nodes which was neglected in previous network is considered in our research.

Finding an appropriate location for undesirable waste sites and determining of rational routes for collection of wastes from generation nodes are strategic and tactical decisions which should be made with respect to defined goals. Therefore, many of papers in the literature have applied location routing problem (LRP) or VRP models to describe their waste collection network (Alumur and Kara 2007; Samanlioglu 2013; Nambiar et al. 1981; Zhao and Zhao 2010; Zografros and Samara 1989). Martínez-Salazar et al. (2014) introduced a new version of LRP model which combined transportation problem with LRP and called it transportation location routing problem (TLRP). They applied this model in distribution network and two metaheuristic algorithms were used to tackle the problem. Utilizing of TLRP in waste collection network can be interesting subject, so in this paper, waste collection problem is modeled in the format of TLRP.

Metaheuristic algorithms are very common approach for solving optimization problems (Azadeh and Farrokhi-Asl 2017). In recent years, researchers' attention to multi objective problems (MOPs) with Pareto approaches grows more rapidly. Population-based metaheuristics like Non-dominated Sorting Genetic Algorithm (NSGA-II) is an appropriate approach to solve MOPs, because they deal with a set of solutions that allow decision makers to reach several efficient solutions in a single run of the algorithm. In addition, Pareto population-based metaheuristics methods like NSGA-II are less sensitive to the convexity of the Pareto front. For reason of NP-hard nature of the presented problem (Alumur and Kara 2007), exact methods which can find Pareto optimal set are unable to tackle the large sized problems. In this regard, we present a hybrid metaheuristic algorithm to solve the problem presented in this paper. Moreover, the literature of this field are full of papers which

have applied metaheuristics to solve the waste management problem and reached to rational solutions. Especially in recent years researchers have used these approaches (Farrokhi-Asl et al. 2017; Rabbani et al. 2018; Mahmoudsoltani et al. 2018; Gatica 2018).

The paper is structured as follows. In Sect. 2, the problem and its attribute is defined and then, the manner in which the fuel consumption and CO₂ emission is evaluated is described. Also, the mathematical model is presented in this section. The methodologies for solving a problem is introduced in Sect. 3. In Sect. 4, experimental results for evaluating the proposed algorithms are conducted. Finally, conclusion remarks and future research are provided in Sect. 5.

2 Problem description

The problem considered in this paper is about collection of hazardous wastes from generation nodes and transmitting them to the relevant sites such as treatment, recycle, and disposal sites. The graph network of the problem comprises some nodes and arcs between these nodes which includes potential locations for establishing depots, generation nodes, and potential locations for recycling, treatment and disposal facilities. Potential locations for establishing facilities are the locations that a facility can be opened there, but there is no obligation to establish facility at each potential location. There are some vehicles in each opened depot and these depots are capacitated and the capacity of each depot is different from other depots; that is, amount of wastes collected by vehicles of one depot must not trespass from capacity of the depot. There are certain fixed costs to establish a depot in each potential location and this cost is another attribute of each depot which effects on our decisions. It should be noted that the vehicles are heterogeneous and multi-compartment means that they have specific capacity for each type of waste. Also, the method for fuel consumption and CO₂ emission evaluation are described in Fuel consumption rate and CO₂ emission estimation subsections.

Collected wastes from generation nodes are transmitted toward treatment facilities, in order to treat of hazardous wastes and reduce risk level. The locations of these treatment facilities are unknown and should be chosen from potential locations for treatment facilities. The capacity of each established treatment facility is limited. Another assumption addressed in this paper is the limitation about compatibility between wastes and applied technology of treatment facility. Each type of waste can only treated at treatment center which has compatible technology. According to Alumur and Kara (2007), two types of technology (i.e. incineration and chemical treatment) and three types of waste (i.e. compatible wastes with incineration, compatible wastes with chemical treatment, and compatible wastes with both of them) are considered in this problem. The vehicles move between treatment facilities until they unload all wastes.

After treatment process and reduction of wastes risks, waste residues are divided into two groups. First group is the waste residues which are directly transmitted to the disposal facilities. The second group which are recyclable after treatment process are transmitted to recycling centers. According to Samanlioglu (2013), the average

amount of recyclable waste residues after treatment process for chemical technology are 30% and for incineration technology are zero. It should be considered that the volume reduction for chemical treatment facilities are 20% and for incineration treatment facilities are 80%. Transportation cost per unit of waste between each pair of nodes is specified and the location of these undesirable sites should be chosen from potential locations. Also, the capacity of each site is limited and are different from each other. Waste residues which are the result of recycling process are transmitted to disposal centers. A percentage of these waste residues are considered as a 5% of input wastes to recycling centers.

As shown in Fig. 1, the problem of this paper can be seen as an extension to the TLRP which has composed from three stages. At the first stage, wastes are collected from generation nodes and these wastes are transmitted to compatible treatment centers. Finally, the vehicles should return to the depots. The second stage includes transportation of waste residues from treatment facilities to recycling and disposal centers. Eventually, the last stage is related to the transportation of waste residues from recycling centers to disposal centers.

This problem includes three objective functions. The first one is economical cost which comprises routes cost, fuel consumption cost, CO₂ emission cost, sites establishing cost, and transportation costs. The second objective calculates transportation risk in which the population suffered from wastes along routes are minimized. Site risk objective function (i.e., the third objective function) minimizes the total population who lives around undesirable facilities in the presented collection network. The schematic figure for the problem is depicted in Fig. 2 in which opened facilities are shown with solid shapes.

2.1 Fuel consumption rate

Xiao et al. (2012) introduced a factor fuel consumption rate (FCR) which is a function of vehicle's load and vehicle's weight. In their method for evaluating FCR, the statistical data published by Japan Government (<http://www.mlit.go.jp/common/000037099.pdf>) is used. Analysis performed by Xiao et al. (2012) showed that linear regression can be applied with high R-Squared level to represent the relationship between fuel

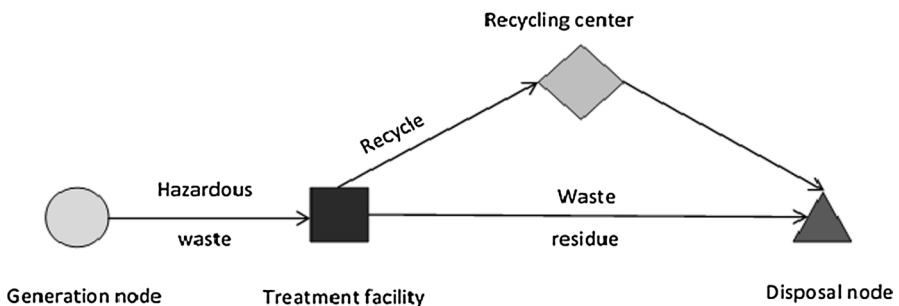


Fig. 1 Waste collection network

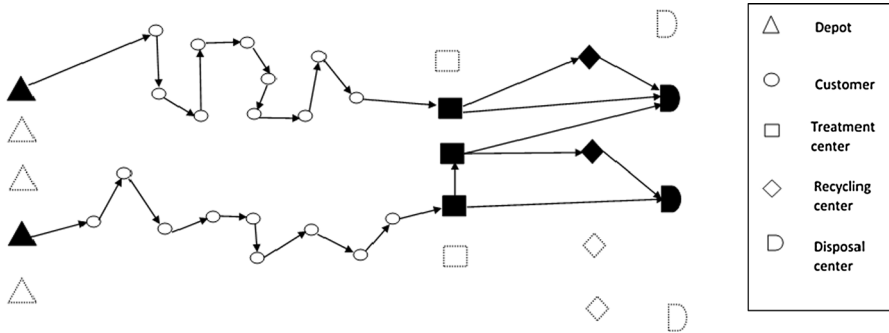


Fig. 2 The schematic figure for waste collection problem

consumption rate and gross weight of vehicles. Given this assumption, the FCR can be calculated by:

$$\rho(F_1) = a(F_0 + F_1) + b \tag{1}$$

where F_1 represents the weight of vehicle’s load, F_0 is the weight of empty vehicle, and $\rho(F_1)$ is the fuel consumption of vehicle with the load weight of F_1 per unit of distance. If the vehicle is full, the formulation is transformed to:

$$\rho^* = a(F_0 + Q) + b \tag{2}$$

where ρ^* shows the FCR a vehicle when the vehicle is full. The capacity of the vehicle is notated by Q . If the vehicle is empty, the FCR calculated as follow:

$$\rho_0 = a(F_0 + 0) + b \tag{3}$$

The FCR in no load condition is represented by ρ_0 . With respect to the Eqs. (1–3) the Eq. (1) can be rewritten as follows:

$$\rho(F_1) = \rho_0 + \frac{\rho^* - \rho_0}{Q} F_1 \tag{4}$$

According to Eq. (4), fuel consumption rate can be evaluated for each amount of vehicle load by knowing fuel consumption rate at the conditions where the vehicle is full of load or the vehicle is empty. The website of “goodyear” company (<http://www.goodyear.com/truck/pdf/commercialtiresystems/FuelEcon.pdf/>) is used for estimating fuel consumption rate in full or empty modes of vehicles.

The load of vehicles are different in arcs between nodes, so FCR for each arc should be evaluated separately with respect to the load transmitted in each arc. For calculation of fuel consumption in each arc the Eq. (5) is applied.

$$C_{fuel}^{ij} = f \rho_{ij} dis_{ij} \tag{5}$$

where C_{fuel}^{ij} denotes fuel consumption cost in arc (i, j) , f is unit cost of fuel, and dis_{ij} denotes the distance between node i and node j .

2.2 CO₂ emission estimation

The cost imposed by carbon dioxide to environment can be estimated by knowing the amount of fuel which is consumed by vehicles. Fuel consumption is one of factors associated with CO₂ emission rate and some of researches have used this factor to estimate the amount of CO₂ emissions (Bektaş and Laporte 2011). The cost of CO₂ is described per gram of it.

Estimation of this cost is very hard task, but some researches have tried to estimate the social cost of CO₂ emission (Tseng and Hung 2014). For example, Forkenbrock (2001) estimated that this cost is between 10\$ and 20\$. Tol (2005) compiled 133 distinguish cost estimation for CO₂ emission from 28 papers. He developed a density function to estimate this cost. This probability is dependent on different situations, but an important deduction was that the mean of this cost is almost \$93/t of CO₂. The Department of Environment, Food and Rural Affairs of United Kingdom (DEFRA) applied a different method named the shadow price of CO₂ and suggested to set it at £27/t of CO₂ for year 2010, and this estimation increases by 2% for each successive year. According to this fact we can set this cost at \$46/t for year 2015. Also, the amount of CO₂ emitted per liter of gasoline is considered as 2.3 kg (Bektaş and Laporte 2011).

2.3 Mathematical formulation

Assumption:

- All facilities have limited capacity.
- Vehicles are multi-compartment; that is, they have different parts for each type of waste.
- The vehicles and facilities capacity is set in the manner that the problem has a feasible solution.
- The wastes of each generation node must be collected by only one vehicle.
- Three types of waste and two types of treatment technology are considered.
- Parameters are deterministic.

Sets and indices:

$D = \{1, 2, 3, \dots, d\}$	Set of potential locations for depots
$N = \{1, 2, 3, \dots, n\}$	Set of generation nodes
$T = \{1, 2, 3, \dots, t\}$	Set of potential locations for treatment facilities
$R = \{1, 2, 3, \dots, r\}$	Set of potential locations for recycling centers
$P = \{1, 2, 3, \dots, p\}$	Set of potential locations for disposal centers
$W = \{1, 2, 3, \dots, w\}$	Set of waste types

$Q = \{1, 2, 3, \dots, q\}$	Set of technologies in treatment facilities
$K = \{1, 2, 3, \dots, k\}$	Set of vehicles
$I = \{1, 2, \dots, i\}$	Set of all nodes
d	Index for depots
n, n_1	Index for generation nodes
t	Index for treatment centers
r	Index for recycling center
p	Index for disposal centers
w	Index for waste type
q	Index for technology
k	Index for vehicles
i, j	Index for all nodes

Parameters:

O_d	Fixed cost of establishing a depot at node d
ot_{tq}	Fixed cost of establishing a treatment facility with technology q at node t
or_r	Fixed cost of establishing a recycling facility at node r
od_p	Fixed cost of establishing a disposal center at node p
cd_d	Capacity of depot d
ct_{tq}	Capacity of treatment facility t with technology q
cr_r	Capacity of recycling facility r
cp_p	Capacity of disposal center p
cv_{wk}	Capacity of vehicle k for waste type w
f	One unit of fuel's cost
e	Cost of CO ₂ emission per consumption of one liter fuel
T_k	Maximum allowable route time for vehicle k
ti_{ij}	Traveling time between node i and node j
dis_{ij}	Distance between node i and node j
$popt_{ij}$	Number of people along the arc between node i and j
$pops_i$	Population size around the facility i
gen_{nw}	Amount of generated wastes type w at node n
fv_k	Fixed cost of using a vehicle k
fd_k	Wage of vehicle k driver per unit of time
com_{wq}	1 if waste type w is compatible with technology q ; 0 otherwise
β_{wq}	Recycle percent of hazardous waste type w treated with technology q
re_{wq}	Mass reduction of waste type w treated with technology q
tr_{tr}	Transportation cost of one unit waste residues between treatment facility t and recycling center r
td_{td}	Transportation cost of one unit waste residues between treatment facility t and disposal center p
rd_{rp}	Transportation cost of one unit waste residues between recycling facility r and disposal center p
γ_r	Recycle percent of waste residue recycled in recycling center r
ρ_{0k}	Fuel consumption rate for empty vehicle k

ρ_k^*	Fuel consumption rate for full loaded vehicle k
Q_k	Maximum allowable load for vehicle k

Decision variables:

y_d	1 if a depot is opened in potential location d ; 0 otherwise
b_{tq}	1 if a treatment facility with technology q is established in potential location t ; 0 otherwise
z_r	1 if a recycling center is opened in potential location r ; 0 otherwise
g_p	1 if a disposal center is opened in potential location p ; 0 otherwise
ki_{tr}	Amount of waste residues transmitted between treatment facility t and recycling center r
a_{tp}	Amount of waste residues transmitted between treatment facility t and disposal center p
v_{rp}	Amount of waste residues transmitted between recycling center r and disposal center p
θ_{tqw}	Amount of waste type w unloaded at treatment facility t with technology q by means of vehicle k
ω_{ijk}	Amount of waste type w transmitted between node i and j
U_{iwk}	Auxiliary variable that represents the amount of waste type w in vehicle k just after leaving node $i \in N$ or the amount of unloaded waste type w by vehicle k just after leaving node $i \in T$
S_{nd}	1 if generation node n is assigned to depot d ; 0 otherwise
e_{ik}	Traveling time of vehicle k just after leaving node i
x_{0nk}^d	1 if generation node n is the first node in the route of vehicle k starting from depot d ; 0 otherwise
x_{ijk}^d	1 if generation node j is visited just after node i in the route of vehicle k starting from depot d ; 0 otherwise
x_{n0k}^d	1 if generation node n is the last node in the route of vehicle k starting from depot d ; 0 otherwise
at_{wqt}	Amount of wastes type w treated in treatment facility t with technology q
ar_r	Amount of waste residues recycled in recycling center r
ad_p	Amount of waste residues disposed in disposal center p

Mathematical model:

$$\begin{aligned}
 \text{Min } Z1 = & \sum_{d \in D} O_d y_d + \sum_{k \in K} f d_k \sum_{d \in D} \sum_{n \in N} t i_{dn} x_{0nk}^d \\
 & + \sum_{k \in K} f d_k \sum_{i \in T} \sum_{d \in D} t i_{id} x_{i0k}^d + \sum_{k \in K} f d_k \sum_{d \in D} \sum_{i \in NUT} \sum_{j \in NUT} t i_{ij} x_{ijk}^d \\
 & + \sum_{q \in Q} \sum_{i \in T} o t_{iq} b_{iq} + \sum_{r \in R} o r_r z_r \\
 & + \sum_{p \in P} o d_p g_p + \sum_{i \in T} \sum_{r \in R} t r_{ir} k i_{ir} \\
 & + \sum_{i \in T} \sum_{p \in P} t d_{ip} a_{ip} + \sum_{r \in R} \sum_{p \in P} r d_{rp} v_{rp} + \sum_{d \in D} \sum_{n \in N} \sum_{k \in K} f v_k x_{0nk}^d \\
 & + \sum_{k \in K} \sum_{d \in D} \sum_{i \in NUT} \sum_{j \in NUT} (f + e) dis_{ij} \left(\rho_{0k} x_{ijk}^d + \frac{\rho_k^* - \rho_{0k}}{Q_k} \omega_{ijk} \right) \\
 & + \sum_{d \in D} \sum_{n \in N} \sum_{k \in K} (f + e) dis_{dn} x_{0nk}^d \rho_{0k} + \sum_{k \in K} \sum_{i \in T} \sum_{d \in D} (f + e) dis_{id} x_{i0k}^d \rho_{0k}
 \end{aligned} \tag{6}$$

$$\text{Min } Z2 = \sum_{d \in D} \sum_{i \in NUT} \sum_{j \in NUT} \sum_{k \in K} pop t_{ij} x_{ijk}^d \tag{7}$$

$$\text{Min } Z3 = \sum_{i \in T} \sum_{q \in Q} pops_i b_{iq} + \sum_{r \in R} pops_r z_r + \sum_{p \in P} pops_p g_p \tag{8}$$

s.t.

$$\sum_{n \in N} \sum_{k \in K} x_{0nk}^d \leq c d y_d \quad \forall d \in D \tag{9}$$

$$\sum_{n \in N} x_{0nk}^d = \sum_{i \in T} x_{i0k}^d \quad \forall d \in D, k \in K \tag{10}$$

$$\sum_{n \in N} \sum_{d \in D} S_{nd} = 1 \tag{11}$$

$$\sum_{i \in N} \sum_{k \in K} x_{ijk}^d + \sum_{k \in K} x_{0nk}^d = S_{nd} \quad \forall j \in N, d \in D, j = n \tag{12}$$

$$\sum_{j \in NUT} \sum_{k \in K} x_{ijk}^d = S_{nd} \quad \forall i \in N, d \in D, i = n \tag{13}$$

$$\sum_{k \in K} \sum_{j \in N} \omega_{ijk} = 0 \quad \forall i \in D \quad (14)$$

$$\sum_{k \in K} \sum_{j \in T \cup N} \omega_{ijk} - \sum_{j \in N \cup D} \sum_{k \in K} \omega_{jik} = \sum_{w \in W} gen_{nw} \quad \forall i \in N, n = i \quad (15)$$

$$\sum_{j \in N \cup T} \omega_{jik} - \sum_{j \in T \cup D} \omega_{ijk} = \sum_{w \in W} \sum_{k \in K} \theta_{iqwk} \quad \forall t \in T, k \in K, i = t \quad (16)$$

$$\omega_{ijk} \leq \left(\sum_{d \in D} x_{ijk}^d \right) \left(\sum_{w \in W} cv_{wk} \right) \quad \forall i, j \in N \cup T, k \in K \quad (17)$$

$$\omega_{ijk} = \sum_{t \in T} \sum_{q \in Q} \sum_{w \in W} \theta_{iqwk} \quad \forall n \in N, t \in T, k \in K, i = n, j = t \quad (18)$$

$$\sum_{w \in W} U_{iwk} = \sum_{j \in N \cup T} \omega_{ijk} \quad \forall k \in K, i \in N \quad (19)$$

$$\sum_{w \in W} U_{iwk} = \sum_{j \in N \cup T} \omega_{jik} \quad \forall k \in K, i \in T \quad (20)$$

$$U_{iwk} - U_{jwk} + cv_{wk} \sum_{d \in D} x_{ijk}^d \leq cv_{wk} - gen_{nw} \quad \forall w \in W, i \in N, j \in N, k \in K, j = n \quad (21)$$

$$gen_{nw} \leq U_{iwk} \leq cv_{wk} \quad \forall i \in N, w \in W, k \in K, n = i \quad (22)$$

$$U_{jwk} - U_{iwk} + cv_{wk} \sum_{d \in D} x_{ijk}^d \leq cv_{wk} - \sum_{q \in Q} \theta_{iqwk} \quad \forall i, j \in T, w \in W, k \in K, i = t \quad (23)$$

$$gen_{nw} \leq U_{iwk} \leq cv_{wk} - (cv_{wk} + gen_{nw}) \sum_{d \in D} x_{0n}^d \quad \forall i \in N, w \in W, k \in K, i = n \quad (24)$$

$$e_{ik} - e_{jk} + (T_k + t_{ij}) \sum_{d \in D} x_{ijk}^d + (T_k - t_{ji}) \sum_{d \in D} x_{jki}^d \leq T_k \quad \forall k \in K, j, i \in N \cup T \cup D \quad (25)$$

$$\sum_{d \in D} t_{ij} x_{0nk}^d \leq e_{ik} \leq T_k + \sum_{d \in D} (t_{ij} - T_k) x_{0n}^d \quad \forall k, \forall i \in N \cup T, i = n \quad (26)$$

$$e_{ik} \leq T_k - \sum_{d \in D} t_{ij} x_{tok}^d \quad \forall i \in T, k \in K, i = t, j = d \quad (27)$$

$$\sum_{i \in D \cup N} \sum_{k \in K} \sum_{d \in D} x_{ijk}^d = 1 \quad \forall j \in N \quad (28)$$

$$\sum_{j \in T \cup N} \sum_{k \in K} \sum_{d \in D} x_{ijk}^d = 1 \quad \forall i \in N \quad (29)$$

$$at_{wqt} = \sum_{k \in K} \theta_{tqwk} \quad \forall w \in W, q \in Q, t \in T \quad (30)$$

$$at_{wqt} \leq ct_{iq} com_{wq} \quad \forall w \in W, q \in Q, t \in T \quad (31)$$

$$\sum_{w \in W} at_{wqt} \leq ct_{iq} b_{tq} \quad \forall q \in Q, t \in T \quad (32)$$

$$\sum_{q \in Q} \sum_{w \in W} at_{wqt} (1 - r_{wq}) \beta_{wq} = \sum_{r \in R} ki_{tr} \quad \forall t \in T \quad (33)$$

$$\sum_{t \in T} ki_{tr} = ar_r \quad \forall r \in R \quad (34)$$

$$ar_r (1 - \gamma_r) = \sum_{p \in P} v_{rp} \quad \forall r \in R \quad (35)$$

$$\sum_{t \in T} v_{tp} + \sum_{r \in R} a_{rp} = ad_p \quad \forall p \in P \quad (36)$$

$$ar_r \leq cr_r z_r \quad \forall r \in R \quad (37)$$

$$ad_p \leq cp_p g_p \quad \forall p \in P \quad (38)$$

$$e_{ik} = 0 \quad \forall i \in D, k \in K \quad (39)$$

$$\sum_{i \in N \cup T} \sum_{d \in D} x_{ijk}^d \leq 1 \quad \forall j \in T, k \in K \quad (40)$$

$$\sum_{i \in N \cup T} \sum_{d \in D} x_{ijk}^d = \sum_{d \in D} \sum_{s \in T} x_{jks}^d + \sum_{d \in D} x_{t0k}^d \quad \forall j \in T, k \in K, j = t \quad (41)$$

$$y_d, b_{tq}, z_r, g_p, S_{nd}, x_{0nk}^d, x_{ijk}^d, x_{t0k}^d = \{0, 1\} \\ \forall d \in D, t \in T, q \in Q, r \in R, p \in P, n \in N, k \in K, \\ i, j \in D \cup N \cup T \quad (42)$$

$$ki_{tr}, a_{tp}, v_{rp}, \theta_{tqwk}, \omega_{iwk}, e_{ik}, at_{wqt}, ar_r, ad_p \geq 0 \\ \forall t \in T, q \in Q, r \in R, p \in P, k \in K, \\ i \in D \cup N \cup T, w \in W \quad (43)$$

The first objective function includes 14 terms. The first Term is related to depots opening cost. Wages of drivers are calculated in terms 2–4. Cost of establishing treatment facilities, recycling centers, and disposal centers are reflected by term 5–7, respectively. Terms 8 and 9 are related to transportation of waste residues from treatment facilities to recycling and disposal centers and term 10 evaluates transportation cost from recycling centers to disposal ones. Fixed cost of applying vehicles are addressed in term 11. The last three terms evaluate fuel and CO₂ emission cost. Objective function two associates with transportation risk in which the number of peoples along the routes are minimized. Also, the third objective function minimizes the sites risk; that is, number of people which are around the undesirable sites is minimized.

Constraint (9) associates with the capacity of each depot, means that a number of vehicles which departs from an opened depot should not trespass from the capacity of the depot. Constraint (10) guarantees that all vehicles return to the depots. Constraint (11) ensures that each generation node is assigned to only one depot. Continuity in each route is guaranteed by constraints (12) and (13). Constraints (14)–(17) specify the load of each vehicle after leaving a node. Constraint (18) determines the relation between two variables and guarantees that all loads of each vehicle should be unloaded at treatment facilities. A relation between two variables in generation nodes and treatment facilities nodes are specified in constraints (19) and (20). Constraints (21)–(24) are the modification of the well-known sub tour elimination constraint called Miller–Tucker–Zemlin (MTZ) for the presented problem (Desrochers and Laporte 1991). These constraints also satisfy the vehicles capacity constraint. Traveling distance limitation is satisfied by means of constraints (25)–(27). Each generation node should be serviced by only one vehicle. This restriction is addressed in constraints (28)

and (29). Constraint (30) evaluates amount of wastes treated in each treatment facility. Constraint (31) associates with compatibility limitation between waste type and technology applied in treatment facility. The next constraint is related to capacity of treatment facility. Constraint (33) specifies the amount of carried waste residues from each treatment facility to recycling center. The amount of recycled waste residues in each recycling center is determined by constraint (34). Constraint (35) calculates the carried waste residues from recycling center to disposal centers. The waste residues which are processed in each disposal center are evaluated in constraint (36). Two subsequent constraints consider the capacity of recycling and disposal centers. The length of each route in the depots' place is set zero by constraint (39). Constraint (40) declares that each vehicle can enter to treatment facility at most once. Constraint (41) guarantees that each vehicle which enters to treatment facility should depart this facility. Constraints (42)–(43) specify the range of decision variables.

3 Methodology

Combination of metaheuristic algorithms can always enhance the performance of each individual algorithm to solve single objective problems. Generally, we can say that hybrid algorithms including other metaheuristics are capable to use advantageous of each constituent algorithm to provide broad space to search (Rabbani et al. 2016). These facts motivate us to introduce a new hybrid algorithm to tackle multi objective problems. The new hybrid multi-objective meta-heuristic is introduced in this section. This algorithm uses the attributes of genetic algorithm (GA) and cultural algorithm (CA) which are the algorithms inspired from biologic and social evolution respectively. This algorithm enhances its ability to reach efficient solutions by combination of methodologies used in GA and CA. This algorithm is population based, so the manner in which the solutions are generated is important. Solution representation is described in next subsection and the steps and operators of this algorithm are explained later. Also, four other well-known metaheuristic algorithms which are applied in this paper to verify the results of proposed metaheuristic algorithm are described briefly.

3.1 Multi-objective optimization

The single objective optimization problems aims to reach the optimum or near optimum value. In this problems comparison and sorting of the solutions existing in solution space is easy; because one objective is available and solutions are sorted regarding the objective function they have. For instance, in minimization problem if $f(x) < f(y)$ we can say that solution x is better than solution y . Nevertheless, in multi objective problems finding a single solution which optimizes all objective functions is difficult and uncommon. In this type of problems, objective function is a vector, so multi-objective optimization is named multi criteria optimization or vector optimization. Hwang and Masud (2012) classified methods for solving multi-objective problems into three categories based on the role of decision maker in the process of solving the problem: The priori methods, the interactive methods and the posteriori or methods. In posteriori

methods (the approach applied in this paper) the efficient solutions of the problem are produced and then the decision maker is asked to specify most preferred solution among them. The multi objective problems aim to find a feasible decision variables that satisfies constraints and optimizes the vector function whose elements represent the objective functions value. These elements of objective function are usually in conflict with each other. Therefore, the term of optimization in this type of optimization problems means that finding the solutions which can satisfy all constraints and give the values of all objective elements acceptable. We can define it mathematically as follows:

If $X = [x_1, \dots, x_N]^T$ is the vector of decision variables, finding the vector such as $X^* = [x_1^*, \dots, x_N^*]^T$ which satisfies all constraints and optimizes the vector of objective function:

$$\begin{aligned} F &= [F_1(x), \dots, F_m(x)]^T \\ g_i(x) &\geq 0, \quad i = 1, 2, \dots, p \\ h_j(x) &= 0, \quad j = 1, 2, \dots, q \end{aligned} \quad (44)$$

So we want to reach the solutions which satisfy (44) and yield to the optimum values of all objective functions. But, as aforementioned, finding the solution which optimizes all objectives and satisfies all constraints is usually impossible; hence, we define the concept of efficient solutions. Let, a general multi objective maximization problem with n decision variable and m objectives ($m > 1$):

$$\begin{aligned} \text{Maximize } F &= [F_1(x), \dots, F_m(x)]^T \\ \text{where } x &\in R^n \text{ and } f(X) \in R^m \end{aligned} \quad (45)$$

We define that solution x dominates the solution y for maximization problem if:

$$\begin{aligned} f_i(X) &\geq f_i(Y), \quad \forall i \in \{1, 2, \dots, m\} \\ f_i(X) &> f_i(Y), \quad \exists i \in \{1, 2, \dots, m\} \end{aligned} \quad (46)$$

If there is any solution that no solution dominates it, this solution is called non-dominated solution. The solutions that are not dominated by any other solution in the feasible space are called Pareto optimal. Their corresponding curve in the objective space are called Pareto frontier.

3.2 Solution representation

The approach in which the solutions are represented has a great effect in reaching to solutions with good quality in acceptable computational time. For this purpose, we use order based representation which has been applied for programming a combinatorial optimization problems (Martínez-Salazar et al. 2014). For coding solutions,

five strings of real or integer numbers are defined that each of these strings specifies some attributes of the solution. These five strings determine assignments of generation nodes to depots and routes, order of treatment facilities, order of recycling centers, order of disposal centers, and technologies developed in treatment facilities respectively. So, the solution representation are composed of following strings:

- Assignment string
- Order of treatment facilities string
- Order of recycling centers string
- Order of disposal centers string
- Technology string

The structure for each of strings can be different with respect to algorithm in which the solution representation is applied. The structure of last four strings are same for all algorithms and composed of the real numbers in the range of [0–1]. Unlike these four strings, the first string's structure is different in proposed algorithms with respect to structure of each algorithm. This string includes real numbers in the range [0–1] for multi-objective particle swarm optimization (MOPSO), multi objective hybrid cultural and genetic algorithm (MOHCGA) and discrete integer numbers for non-dominated sorting genetic algorithm (NSGA-II), strength Pareto evolutionary algorithm (SPEA-II), multi-objective simulated annealing (MOSA).

The problem consists of several stages. The first string is applied for tackling first stage which is location routing problem (LRP). In this stage the assignment of generation nodes to depots, the routes between these nodes, and established depots are specified. First string includes $n + d + k - 1$ integer numbers where n is number of generation nodes, d denotes the number of potential locations for depot, and k is the number of vehicles. Numbers between 1 and n associate with generation nodes, numbers between $n + 1$ and $n + k$ represent vehicles, and numbers between $n + k + 1$ and $n + d + k - 1$ are considered as a delimiter. The generation nodes and vehicles are initially assigned to depots. For this purpose, the locations of numbers associated with depots are marked in the first string. Numbers from first component in the string to the location of the first signed component are allocated to the first depot. Numbers from first signed component to the second one are assigned to the second depot and so forth. If there are not any numbers between two signed components in the string, this means that corresponding depot is not open. Figure 3 illustrates this manner more clearly. In this example, six generation nodes, four vehicles, four potential location for depots are considered. Numbers 11–13 are delimiters and the location of these numbers are marked. Numbers 1, 4, and 5 are assigned to the first depot. Since there is no number between 12 and 11, the second depot will be close. Numbers 3, 6, 7, 8, and 9 are assigned to the third depot and

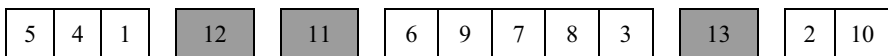


Fig. 3 Example for assignments of generation nodes and vehicles to depots

Customer number	1	2	3	4	5	6
Random real numbers	0.123	0.222	0.809	0.437	0.011	0.943
Numbers rank	5	4	2	3	6	1
Resulted order of customers	6	3	4	2	1	5

Fig. 4 Example of transforming continuous numbers into permutation of integer numbers

number 2 and 10 are assigned to the fourth one. At this point the allocation of vehicles and nodes to depots are specified.

The next step is routes formation in each depot. Numbers in each separated section until the location of component which is associated with vehicle are assigned to this vehicle. The numbers between first vehicle location and the second one are formed the second route and so on. If there is no number corresponding to one vehicle in assigned numbers to the specific depot (i.e. all numbers are between 1 and n) all numbers are assigned to the one free vehicle.

It should be noted that in this solution representation procedure constraints which are related to capacity limitation and route length limitation are not considered. For this reason and simplifying the representation of solutions a virtual objective function called penalty function is considered. This function's value are proportional to the amount of exceeding from these constraints. When this virtual objective function gets value means that the solution is infeasible.

As an aforementioned, for the reason of continuous nature of operators in MOHCGA and MOPSO algorithms, we use the real numbers between zero and one for first string in these two algorithms and then we transform these numbers into discrete integer numbers. The mapping procedure from real numbers to integer ones are performed by the approach shown in Fig. 4. Some studies have used this strategy for applying metaheuristic algorithms and reached to acceptable results (Martínez-Salazar et al. 2014; Rabbani et al. 2017). One integer number is labeled for each real generated number. Then, these real numbers are sorted decently. By relocation of these numbers the attached labels are also relocated and the permutation of numbers are gained.

Thus, the routes and established depots are specified. The next stage is related to unloading the wastes in compatible treatment facilities. Strings 2–5 are real continuous numbers between zero and one. Length of these strings are equal to t , r , p , and t , respectively. We explained that how these numbers can be transformed into the permutation of integer numbers. In each route after servicing to the last generation nodes the vehicle moves to the first treatment facility in the second string which has two necessary conditions: (1) Treatment facility has enough capacity. (2) The loads of vehicle should be compatible with technology of treatment facility. For specifying technology applied in each treatment facility, we multiply corresponding component in fifth string by three and then we round it up. The obtained value specifies the technology implemented in corresponding treatment facility. The vehicle unloads the wastes which are

compatible with the treatment facility. Then, if the vehicle is empty and unloads all of its wastes, the vehicle is free and should come back to the depot; otherwise, the vehicle moves toward the second treatment facility in the second string which has necessary conditions until it depletes all of its load. In this way all wastes of vehicles are unloaded at appropriate treatment facility. It should be noted that the facilities which wastes have not been sent to it do not establish.

The next stage associates with solving a transportation problem between treatment facilities and recycling and disposal centers. Recycle percent and mass reduction percent is determined at each treatment facility. So, the amount of waste residues which should be transported from each treatment facility to recycling and disposal centers can be calculated. We start with the first opened treatment facility specified by second string and send its recyclable waste residues to the first recycling centers specified by third string. The waste residues are transported to first recycling center until it is filled. Then, the second recycling center is selected and waste residues are sent to it until its capacity is filled and so forth. For the transportation stage between treatment facilities and disposal centers and also between recycling and disposal center we perform like above-mentioned with respect to third and fourth strings. By performing all of these steps we can get a solution from five strings.

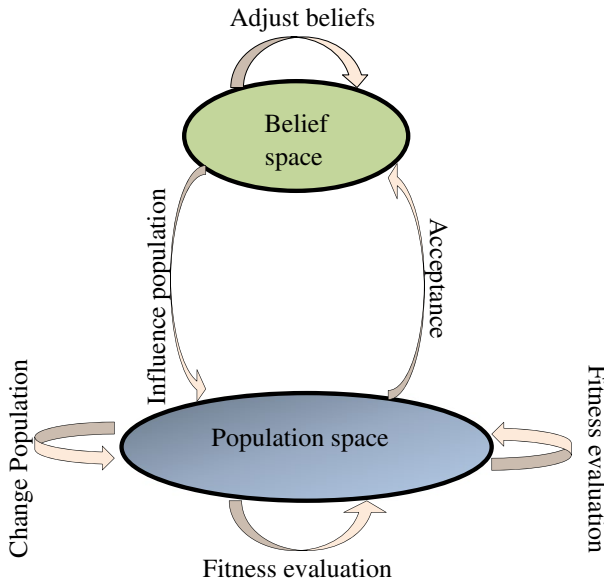


Fig. 5 Single objective CA template

3.3 Proposed algorithm

Cultural algorithm (CA) which was introduced for the first time by Reynolds (1994) can be seen as an extension for genetic algorithm (GA). Cultural algorithm for single objective problems addresses interactions between individuals in the population, but these interactions are not taken into account by GA. Each solution in the population communicate with other solutions to generate a belief space (culture) and belief space records knowledge about the problem and utilizes this knowledge to make better generated solutions. Figure 5 depicts the mechanism of cultural algorithm. Experiences of individuals in the way of problem solving are selected regarding some criteria to produce knowledge about the problem and this knowledge impacts on the belief space. The belief space manipulates the knowledge to effect on the evolution and improvement of the population space.

Best et al. (2010) modified CA framework to handle multi-objective problems. The experimental results conducted in the paper showed that Multi-objective Cultural Algorithm (MOCA) can be applied independently or as a supplementary to other multi-objective algorithms. Another version of cultural algorithm which is used in the current paper is the hybrid version of CA and GA. In the algorithm, knowledge is used to record and transmit knowledge from one generation to the next one. Hybrid Cultural and Genetic Algorithm (HCGA) includes two main spaces: population space and belief space. The population space associates with an extended GA in which crossover and mutation operators are used to improve generations.

Belief space consists of several main components. In CA, knowledge sources includes but not limited to situational knowledge, topographical knowledge, normative knowledge, and historical knowledge. According to the attributes of GA operators in population space, we address only two main components of the algorithm; that is, normative knowledge and situational knowledge. The steps of proposed Multi-objective Hybrid Cultural and Genetic Algorithm (MOHCG) are described as follows:

Step 1 The algorithm is initialized by means of solutions represented according to the previous subsection.

Step 2 The solutions are evaluated with respect to their objective functions and a rank is assigned to each solution regarding the non-domination concept. Level one is the best level, 2 is the next best level, and so forth. For the solutions in the same rank, a crowding distance is calculated as a second criterion to sort solutions. By this criterion, the distribution of solutions goes toward a uniformly spread Pareto front at different iterations of the algorithm. Among two solutions at the same front, the solution located in a low density region is preferred.

Step 3 Specific Operators are used to adjust belief space. The first operator sets the situational knowledge and the second one upgrades the normative knowledge.

Step 4 Cultural space influence on population space. In other words, knowledge about normative solutions and situational solutions impacts on direction of individuals in the population. Population is upgraded with respect to belief space and new generated population is available to keep on the algorithm.

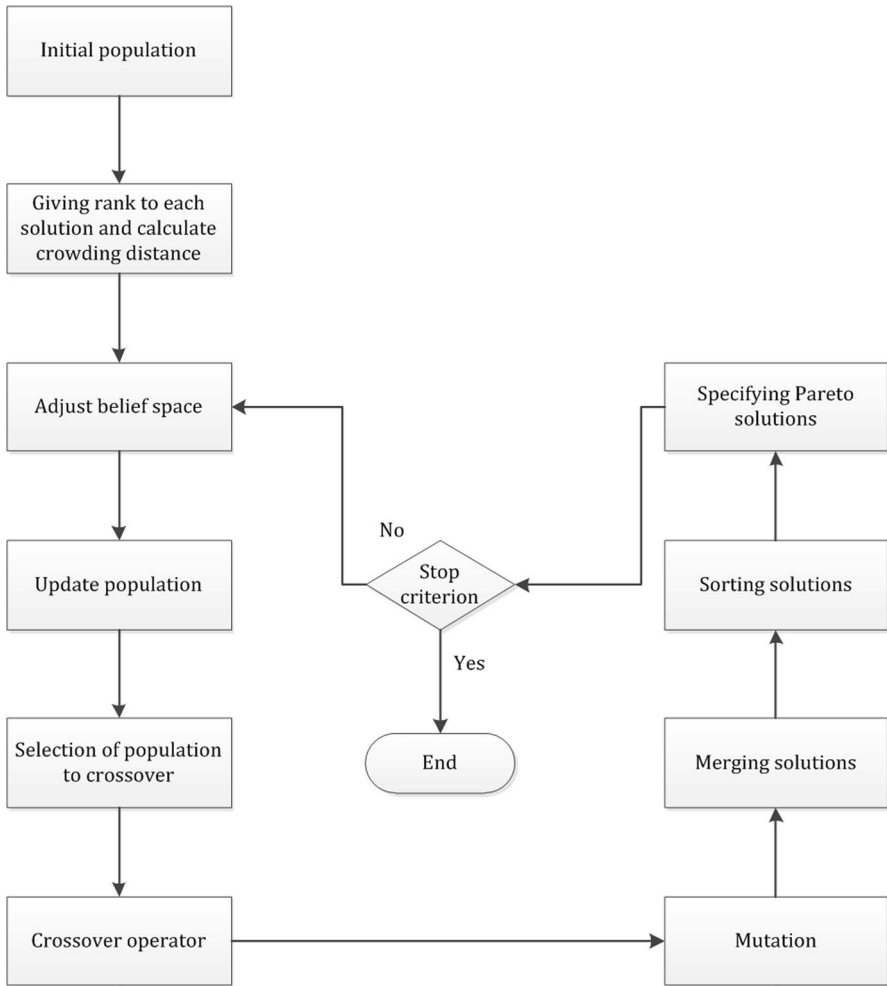


Fig. 6 Flowchart of proposed MOHCG algorithm

Step 5 Genetic operators including crossover and mutation operators are exerted to generate the offsprings from parents.

Step 6 The new generated solutions (offsprings) and the old population are merged with each other.

Step 7 The merged populations are sorted with respect to the rank of solutions and crowding distance.

Step 8 The solutions in the first rank are recorded as Pareto solution.

Step 9 The stop criterion in this algorithm is considered as maximum number of iterations. If the criterion is satisfied the algorithm is stopped; otherwise the steps 3–9 are repeated.

The main structure of proposed MOHCG algorithm is shown in Fig. 6.

3.3.1 Acceptance criterion

It is common that in the society, people who are brilliant and have a specific feature can influence other people or transform the conditions or influence the culture and beliefs. CA which is inspired from this cultural evolution in societies specifies the members of population which are eligible to upgrade belief space. In single objective version of CA, the solutions are sortable regarding their objective functions value. The solutions which have better rank in are accepted to change the belief space. In the proposed algorithm, solutions are sorted with respect to their rank as the first criterion and crowding distance as the second criterion. Therefore, if two solutions have same rank, we refer to crowding distance to determine which one is better.

After sorting the solutions in population space, specific number of solutions is accepted to effect on belief space. In this algorithm, the number of solutions influencing on belief space is dynamic; that is, this number is reduced iteration by iteration. The number of effective members in population is calculated as follow:

$$n_B(t) = \left\lceil \frac{n\gamma}{t} \right\rceil \quad (47)$$

where $n_B(t)$ is the number of effective members in iteration t , n is the population size and γ is the real number value between 0 and 1. In this equation, the number of effective members is decreased gradually.

3.3.2 Adjustment of belief space

Situational knowledge considers the records of the population and good solutions in each iteration are capable to transform the situational knowledge. The operation of this knowledge is similar to the concept of leader in particle swarm optimization (PSO) introduced by Kennedy and Eberhart (1997). The proposed algorithm selects one solution from Pareto solutions randomly and then the selected solution is compared with the solution which is the current situational knowledge. If the selected solution dominates representative solution for situational knowledge, the situational knowledge will be upgraded. If the current solution dominates the selected solution, we do not perform any thing. Finally, if two solutions do not dominate each other, on solution is selected randomly to be situational knowledge. These actions are summarized by following formulation in which $SK(t)$ denotes situational knowledge at iteration t and CS represents selected solution.

$$SK(t+1) = \begin{cases} SK(t) & SK(t) < CS \\ CS & CS < SK(t) \end{cases} \quad (48)$$

Normative knowledge provides a set of promising ranges for variables of solutions. Let $x = (x_1, x_2, \dots, x_n)$ shows the decision variables of each solution. One range for

each variable of solutions are specified by normative knowledge. Each variable's range (I_i) has minimum and maximum value denoted by x_i^{min} and x_i^{max} . These minimum and maximum values are taken from solutions and Corresponding objective functions of these solutions are used to specify lower bound of objective function (L_i) and upper bound of objective function (U_i). Therefore, each solution is shown by three factors as follows:

$$\begin{aligned}
 x_i &= (I_i, L_i, U_i) \\
 I_i &= (x_i^{min}, x_i^{max}) \\
 L_i &= (L_i^1, L_i^2, \dots, L_i^m) \\
 U_i &= (U_i^1, U_i^2, \dots, U_i^m)
 \end{aligned}
 \tag{49}$$

For changing the normative knowledge in each iteration, we use the following formulation:

$$x_j^{min} = \begin{cases} x_{lj}(t), & x_{lj}(t) < x_j^{min}(t) \text{ or} \\ & f(x_i) < (L_j^1, \dots, L_j^m) \\ x_j^{min}(t), & \text{Otherwise;} \end{cases}
 \tag{50}$$

where $x_{lj}(t)$ is the j -th component of the selected solution from Pareto solutions. If the corresponding x_j^{min} value is updated, $L_j^i, \forall i = 1, 2, \dots, m$ will be updated, and new lower bounds replace with older ones. The similar actions are done on the x_j^{max} and $U_j^i, \forall i = 1, 2, \dots, m$.

$$x_j^{max} = \begin{cases} x_{lj}(t), & x_{lj}(t) > x_j^{max}(t) \text{ or} \\ & f(x_i) < (L_j^1, \dots, L_j^m) \\ x_j^{max}(t), & \text{Otherwise;} \end{cases}
 \tag{51}$$

If the corresponding x_j^{max} values is updated, $U_j^i, \forall i = 1, 2, \dots, m$ will be updated, and new upper bounds replace with older ones.

3.3.3 Population space change

After updating the situational and normative knowledge, these changes should influence on the population space and the solutions in the population space should conform themselves with the new belief space. For changing the population space, the solutions and their variables attempt to move into the normative

ranges and become more close to the situational knowledge. In this proposed algorithm, four types of local searches to change a current solution and to search in neighborhoods are considered. In each iteration, one integer random number in the range of [1–4] is generated and one of these methods is selected randomly according to the generated number. These local searches are described as follows:

1. In this neighbor search method, only normative knowledge is used to specify the direction of searching in solution space. The following formulations are used to generate new solutions:

$$\begin{aligned}
 x'_{ij}(t) &= x_{ij}(t) + \sigma_j(t) \times N(0, 1) \\
 \sigma_j(t) &= \left[x_j^{\max}(t) - x_j^{\min}(t) \right] \times \alpha \quad 0 \leq \alpha \leq 1
 \end{aligned}
 \tag{52}$$

2. In the second local search, we apply just situational knowledge for upgrading the solutions. The search aims to approach the solutions to the components of situational knowledge.

$$x'_{ij}(t) = \begin{cases} x_{ij}(t) + \sigma_{ij}|N(0, 1)|, & x_{ij}(t) < y_j(t) \\ x_{ij}(t) - \sigma_{ij}|N(0, 1)|, & x_{ij}(t) > y_j(t) \\ x_{ij}(t) + \sigma_{ij}N(0, 1), & x_{ij}(t) = y_j(t) \end{cases}
 \tag{53}$$

$$\sigma_{ij}(t) = \alpha \times [x_{ij}(t) - y_j(t)] \quad 0 \leq \alpha \leq 1
 \tag{54}$$

where $y_j(t)$ is the j -th component of situational knowledge in iteration t .

3. In the third type of local search, situational knowledge is used to specify the direction of search and normative knowledge for the length of this movement. The formulation is the same with the above formulations, but for specifying the length of movement following formulation is used:

$$\sigma_{ij}(t) = \alpha \times \left[x_j^{\max} - x_j^{\min} \right]
 \tag{55}$$

4. In the fourth type of local search, we use only normative knowledge, but not as the same way in the first method. β denotes one random parameters between 0 and 1. The schematic Figure for this method is shown in Fig. 7.

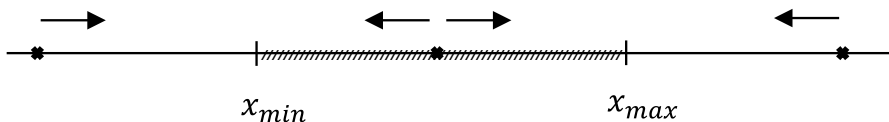


Fig. 7 Schematic Figure of the fourth type of local search

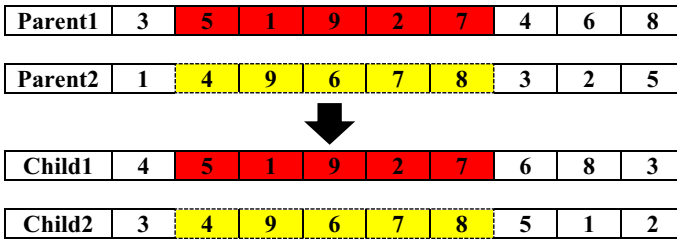


Fig. 8 Illustrative example for OX crossover

$$x'_{ij}(t) = \begin{cases} x_{ij}(t) + \sigma_j|N(0, 1)|, & x_{ij}(t) < x_j^{min}(t) \\ x_{ij}(t) - \sigma_j|N(0, 1)|, & x_{ij}(t) > x_j^{max}(t) \\ x_{ij}(t) + \beta\sigma_{ij}N(0, 1), & \text{Otherwise;} \end{cases} \tag{56}$$

3.4 Crossover and mutation operators

The efficiency of the algorithms applying these two operators are dependent upon the performance of these two operators. These operators help us to search extensively in the space of solutions. There are various types of typical mutation and crossover operators in the literature and we use some of them in this paper according to the structure of strings defined here. If the string is composed of discrete numbers the following steps are performed. Initially two parents are selected using roulette wheel procedure which gives more chance to the better solutions. The order crossover (OX) is selected in this paper to apply on discrete based strings (Oliver et al. 1987). OX crossover choses two components in the string randomly. The components between two selected components in the first parent are inherited to the first offspring. Then, these components are omitted from the second parent and the rest of components are transmitted to the first offspring in the order of appearance in the second parent. Similarly, these steps are performed for generating the second offspring. Figure 8 illustrates the methodology of OX crossover.

For mutation operator and creation of neighborhoods for current solution in permutation based strings, three methods including swap, insertion and reversion are selected (Rabbani et al. 2016). Swap operator selects two components and swaps their locations in the string. Reversion operator selects two components in the string and reverses the components between these two selected components. Insertion operators also selects two components and inserts the first selected component after the second one.

In continuous based strings, the manner is completely different and the following formulation is applied to generate offsprings. y_i^1 and y_i^2 denote i -th component of first and second offsprings respectively. Also, x_i^1 and x_i^2 represent i -th component of first and second parents.

$$\begin{cases} y_i^1 = \alpha x_i^1 + (1 - \alpha)x_i^2 \\ y_i^2 = \alpha x_i^2 + (1 - \alpha)x_i^1 \end{cases} \quad 0 < \alpha < 1 \tag{57}$$

4 Experimental results

Some experiments are conducted in this section and the results obtained from proposed algorithm are compared to four well-known multi-objective metaheuristic algorithms including NSGA-II (Deb et al. 2000), SPEA-II (Laumanns 2001), MOSA (Nam and Park 2000), and MOPSO (Coello and Lechuga 2002). The investigation of these algorithms are not the goal of this paper, so the interested readers can refer to (Coello et al. 2002) which is one of the most complete books on multi-objective evolutionary algorithms. At first the parameters of algorithms are set by means of response surface methodology (RSM), then the comparison metrics will be introduced and finally the numerical results are provided.

4.1 Parameter tuning

Parameters of metaheuristic algorithms have important role in the performance of these algorithms. So, as above-mentioned the RSM method is used to set the parameters. RSM method is applicable in tuning of effective parameters in performance of processes. In this method, regression analysis is used to analyze different levels of parameters. Two common design are beneficial in fitting an appropriate regression model including central composite design (CSD) and Box-Behnken design (BBD). The difference of these two designs are related to the range in which the parameters are defined. The central composite design is used in this paper to tune parameters. Initially, the parameters which are effective on the performance of each algorithm are specified. For each parameter two levels are considered. Lowest level of parameter associates with the -1 and highest level of parameter associates with +1. The manner in which the level of parameters are formulated for CSD method is shown as follows:

$$X_i = \frac{r_i - \left(\frac{h+l}{2}\right)}{\left(\frac{h-l}{2}\right)} \tag{58}$$

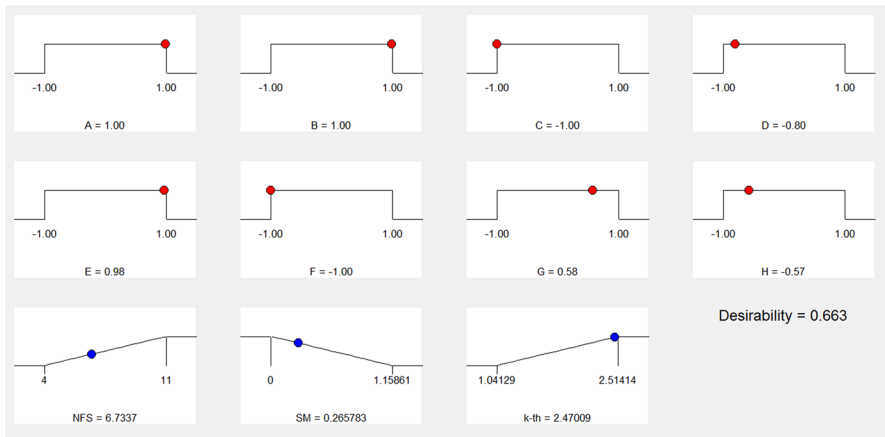


Fig. 9 Outputs of software for parameters tuning of MOHCGA

where h and i are the highest and lowest level of corresponding parameters, respectively. r_i denotes the value of parameter i and X_i specifies the coded value of this parameter (i.e., all parameters are transformed into the real numbers between zero and one). Expert Design software is used to analyze the outputs of algorithms with respect to designed experiments. Figure 9 shows the output of the software for MOHCGA. The results are summarized as follows:

- MOHCGA parameters:
 - Maximum number of iteration is 150.
 - Population size is 200.
 - Crossover rate and mutation rate are 0.3 and 0.22 respectively.
 - Acceptance rate is 0.697.
 - α and β are considered equal to 0.4 and 0.716 respectively.
 - Roulette wheel coefficient is 0.0243.

4.2 Comparison metric

Since the comparison between multi-objective algorithms are different with single objective problems, some comparison metrics are introduced and the obtained results are compared with each other with respect these metrics.

4.2.1 Number of Pareto solutions (NPS)

This metric evaluates number of Pareto solutions obtained by means of each algorithm. The great number for this metrics is desirable for us.

4.2.2 Spacing metric (SM)

This metric shows the uniformity of the gained Pareto solutions in phenotype space. The algorithm which has lowest value of spacing metric has best performance. The following formulation is used to calculate spacing metric:

$$SM = \sqrt{\frac{1}{N-1} \times \sum_{i=1}^n (d_i - \bar{d})^2} \quad (59)$$

where d_i is the Euclidean distance between solution i and the nearest solution belonged to Pareto sets of solutions. \bar{d} is the average value of all d_i . Also, N denotes the number of Pareto solutions.

4.2.3 Mean ideal distance (MID)

This metric specifies the distance between the Pareto solutions and ideal solution. According to the NP-hard nature of proposed problem, each component of ideal point is the best one found by all metaheuristic algorithms. This metric can be calculated by:

$$MID = \frac{\sum_{i=1}^n \sum_{j=1}^4 \sqrt{\left(\frac{f_{ij} - f_j^{best}}{f_j^{max} - f_j^{min}}\right)^2}}{n} \quad (60)$$

n represents the number of Pareto solutions, f_j^{max} and f_j^{min} denote the maximum and minimum value for the j -th objective function obtained by all metaheuristics, and f_{ij} is the j -th objective function of i -th solution in Pareto front. The lower value of this metric is better value.

4.2.4 Coverage metric (CM)

The quality of solutions obtained by each algorithm is evaluated by means of this metric. If x' and x'' are the two sets of Pareto solutions obtained by two different algorithm, the CM function evaluates the quality of these two sets and the output of this function is the number in the range [0–1].

$$CM(x', x'') = \frac{|\{a'' \in x''; \exists a' \in x' : a' \preceq a''\}|}{|x''|} \quad (61)$$

4.2.5 K-th distance metric

In this metric, distance between points and their k -th neighbor are considered. In this paper the k is set three. Higher value for this metric is desirable.

Table 1 Characteristics of small size problems

Problem	d	n	t	r	p	k
Problem 1	2	3	2	2	2	3
Problem 2	3	6	3	3	2	6
Problem 3	4	15	4	4	4	15
Problem 4	5	20	4	4	4	15
Problem 5	5	20	5	5	5	15
Problem 6	6	20	4	4	3	15
Problem 7	6	25	4	4	4	20
Problem 8	6	30	4	4	4	20
Problem 9	8	30	6	6	6	25
Problem 10	10	30	7	6	5	25

Table 2 Characteristics of large size problems

Problem	d	n	t	r	p	k
Problem 11	15	35	15	15	15	25
Problem 12	15	45	12	10	8	30
Problem 13	20	45	15	15	15	35
Problem 14	20	50	15	15	15	30
Problem 15	20	60	15	15	12	35
Problem 16	20	65	20	20	20	35
Problem 17	25	100	25	22	22	45
Problem 18	25	100	25	25	25	50
Problem 19	35	175	50	45	40	70
Problem 20	40	200	60	55	50	80

4.3 Numerical results

Some instances with different sizes are conducted in this section. These instances are divided into two sets. The first set is related to small scaled problem and the second one is large scaled problems. The scale of each problem is specified by attributes of the problem. Characteristics of each problem are shown by $d\#n\#t\#r\#p\#k$ which represent number of potential locations for depots, generation nodes, potential locations for treatment facility, potential location for recycling centers, potential location for disposal centers, and types of vehicles, respectively. Tables 1, 2 show the attribute of each problem in small and large scales. The generated problems can be downloaded at the below link:

<https://www.dropbox.com/sh/7yov1ars5bkq3n0/AACgSyjWX-LvQOGnTQILiwp6a?dl=0>.

Since components and the investigated problem in the current study is different from the studies in the literature, we cannot find similar data set, so we generate a new data set to perform experiments to evaluate performance of presented algorithms. According to the above link, this data set is generated randomly and all values for the parameters in different sizes can be found in this link.

Initially, the NPS and computational time of algorithms are investigated. In each metric student's t-test is applied to specify the best algorithm. Unfamiliar readers with this test can refer to Haynes (2013). In some cases, for hypothesis test for the difference between two population means, we deal with the data collected from two populations which have correlation between them. Student's t-test is appropriate statistical test in this condition. Tables 3, 4 and Fig. 10 summarizes the performance of all algorithms in the NPS and computational metrics. According to the obtained results, we conclude that the SPEA-II have better performance in NPS metric and NSGA-II outperforms other algorithms in computational time. Table 5, 6 perform one sided t-test to evaluate the accuracy of this hypothesis.

It can be concluded that our hypothesis about SPEA-II and NSGA-II are correct. Now, we investigate the SM and the obtained results are summarized in Tables 7, 8. We conclude that SPEA-II achieve better solution in SM with respect

Table 3 Results for NPS and CPU time in small size problems

Prob.	Quantity of Pareto solutions						Computational time(s)					
	NSGA-II	MOPSO	MOSA	SPEA-II	MOHCGA		NSGA-II	MOPSO	MOSA	SPEA-II	MOHCGA	
1	4	6	5	4	3		119	38	992	631	467	
2	39	21	36	51	14		168	23	124	767	364	
3	27	16	39	21	13		91	38	126	554	994	
4	46	63	107	108	26		92	48	671	558	1200	
5	72	54	65	130	23		253	120	390	1358	941	
6	43	30	25	38	11		93	44	94	564	807	
7	18	30	19	71	9		103	58	52	623	436	
8	86	60	74	140	18		382	82	411	890	482	
9	64	107	62	115	30		118	90	234	809	530	
10	114	90	74	272	30		115	92	213	707	538	
Average	51	47	50	95	17		153	63	330	746	675	

Table 4 Results for NPS and CPU time in large size problems

Prob.	Quantity of Pareto solutions						Computational time(s)					
	NSGA-II	MOPSO	MOSA	SPEA-II	MOHCCA		NSGA-II	MOPSO	MOSA	SPEA-II	MOHCCA	
11	120	114	48	230	26		118	112	162	691	575	
12	127	88	93	297	35		121	144	404	969	749	
13	86	99	59	170	32		137	168	247	777	738	
14	107	70	55	178	33		132	161	246	792	1230	
15	131	120	58	244	34		258	705	262	1219	2066	
16	90	133	66	250	38		162	412	381	2585	1494	
17	97	55	40	285	10		241	518	432	1777	1212	
18	130	99	70	291	44		213	356	608	1173	1231	
19	117	98	88	285	22		823	1976	1249	3688	2565	
20	93	71	60	177	52		1450	3390	2311	7263	6050	
Average	110	95	64	240	33		365	794	630	2093	1791	

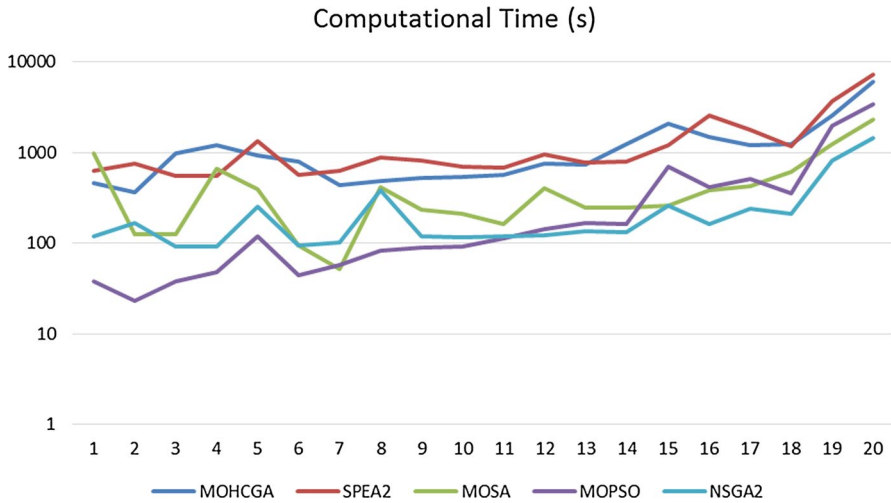


Fig. 10 Comparison between computational times of all algorithms for all problems

Table 5 Pairwise comparison between SPEA-II and other algorithms in NPS metric

H0	\bar{D}	Std.	t0	95% confidence interval of the acceptance area		Result
				Lower bound	Upper bound	
$NPS_{SPEA} > NPS_{NSGA}$	87.3	61.76091	6.321433	-1.72	$+\infty$	✓
$NPS_{SPEA} > NPS_{MOPSO}$	96.65	71.45437	6.049062	-1.72	$+\infty$	✓
$NPS_{SPEA} > NPS_{MOSA}$	110.7	83.94468	5.89752	-1.72	$+\infty$	✓
$NPS_{SPEA} > NPS_{MOHCGA}$	142.7	88.99107	7.171212	-1.72	$+\infty$	✓

Table 6 Pairwise comparison between NSGA-II and other algorithms in CPU time

H0	\bar{D}	Std.	t0	95% confidence interval of the acceptance area		Result
				Lower bound	Upper bound	
$Time_{SPEA} > Time_{NSGA}$	-1160.3	1242.839	-4.17513	$-\infty$	1.72	✓
$Time_{MOPSO} > Time_{NSGA}$	-169.3	501.366742	-1.51013	$-\infty$	1.72	✓
$Time_{MOSA} > Time_{NSGA}$	-221	268.2707587	-3.68412	$-\infty$	1.72	✓
$Time_{MOHCGA} > Time_{NSGA}$	-974	950.4901367	-4.58275	$-\infty$	1.72	✓

to obtained results. The Table 9 shows that our assertion can be true with 95% confidence.

The results of algorithm are compared with each other in Tables 10, 11, 12, 13 with respect to MID and *k*-th distance metric. This results show that MOHCGA

Table 7 Results of SM in small size problems

Prob.	SM				
	NSGA-II	MOPSO	MOSA	SPEA-II	MOHCGA
1	0	0.6438	0.5986	0	0.5640
2	0.4759	0.5665	0.5598	0.3003	0.3916
3	0.6536	0.6267	0.4779	0.9261	0.5486
4	0.4514	0.4991	0.2534	0.2499	0.7061
5	0.4808	0.6345	0.3907	0.2491	0.5777
6	0.4212	0.8222	0.6925	0.3572	0.9844
7	0.4875	1.1082	0.263	0.8949	0.4016
8	0.5095	0.4146	0.4059	0.1802	0.8146
9	0.5698	0.4069	0.5624	0.3884	0.7132
10	0.2967	0.3240	0.4723	0.2762	0.5787
Average	0.4346	0.6045	0.4676	0.3822	0.6280

Table 8 Results of SM in large size problems

Prob.	SM				
	NSGA-II	MOPSO	MOSA	SPEA-II	MOHCGA
11	0.3838	0.4605	0.5667	0.2351	0.5520
12	0.2755	0.2731	0.4069	0.1874	0.4351
13	0.3651	0.3416	0.6114	0.2787	0.6901
14	0.4318	0.3878	0.4032	0.3054	0.5537
15	0.3336	0.7059	0.2945	0.2196	0.4858
16	0.3518	0.3194	0.3505	0.2688	0.5485
17	0.2694	0.3117	0.5610	0.2225	0.6496
18	0.3718	0.2756	0.2753	0.2348	0.4291
19	0.4126	0.2908	0.3364	0.2516	0.6541
20	0.3978	0.3147	0.3952	0.2781	0.4440
Average	0.3593	0.3681	0.4011	0.2482	0.5442

Table 9 Pairwise comparison between SPEA-II and other algorithms in SM

H0	\bar{D}	Std.	t0	95% confidence interval of the acceptance area		Result
				Lower bound	Upper bound	
$SM_{SPEA} < SM_{NSGA}$	-0.081	0.1599	-2.2855	$-\infty$	1.72	✓
$SM_{SPEA} < SM_{MOPSO}$	-0.171	0.2048	-3.736	$-\infty$	1.72	✓
$SM_{SPEA} < SM_{MOSA}$	-0.128	0.2621	-2.194	$-\infty$	1.72	✓
$SM_{SPEA} < SM_{MOHCGA}$	-0.270	0.2743	-4.4168	$-\infty$	1.72	✓

Table 10 Comparison between algorithms with respect to MID and k -th distance metric in small size problems

Prob.	K-distance									
	MID					K-distance				
	NSGA-II	MOPSO	MOSA	SPEA-II	MOHCGA	NSGA-II	MOPSO	MOSA	SPEA-II	MOHCGA
1	0.70	1.15	1.28	0.70	0.384	2.44	1.84	2.16	2.44	2.81
2	0.95	0.42	1.08	1.01	0.36	0.79	1.21	0.82	0.37	1.05
3	0.98	0.59	1.59	0.42	0.43	0.88	1.01	1.07	0.92	1.65
4	0.98	1.57	2.88	1.65	0.53	0.64	0.81	0.63	0.43	1.07
5	1.04	0.61	0.69	0.99	0.29	0.72	0.78	0.78	0.47	1.54
6	1.54	1.21	0.89	0.49	0.31	0.83	0.86	1.16	0.43	1.62
7	1.48	0.79	0.32	1.70	0.09	1.45	0.89	1.30	0.72	1.63
8	1.35	0.76	1.25	1.15	0.25	0.62	0.67	0.61	0.34	1.23
9	0.96	1.65	1.12	1.39	0.48	0.77	0.56	0.60	0.48	0.99
10	1.77	1.71	1.46	3.75	0.51	0.65	0.58	0.73	0.46	1.14
Average	1.17	1.04	1.25	1.32	0.36	0.97	0.92	0.98	0.70	1.47

Table 11 Comparison between algorithms with respect to MID and k -th distance metric in large size problems

Prob.	k-distance									
	MID									
	NSGA-II	MOPSO	MOSA	SPEA-II	MOHCGA	NSGA-II	MOPSO	MOSA	SPEA-II	MOHCGA
11	4.18	4.99	5.58	3.15	4.77	0.68	0.74	0.90	0.45	1.16
12	4.08	3.86	5.83	3.48	4.78	0.69	0.62	0.62	0.41	1.07
13	4.31	4.23	5.23	3.12	5.17	0.72	0.76	0.69	0.49	1.00
14	4.70	4.79	7.16	2.97	5.38	0.70	0.91	0.67	0.48	1.07
15	4.04	3.82	4.46	3.42	4.52	0.60	0.56	0.69	0.43	1.06
16	3.99	4.53	5.20	3.37	4.63	0.72	0.58	0.76	0.46	1.09
17	3.27	4.45	4.38	3.09	3.86	0.68	0.99	0.99	0.40	1.87
18	3.92	4.10	4.16	3.25	4.37	0.63	0.68	0.76	0.39	1.07
19	4.22	4.17	6.83	3.68	5.48	0.72	0.70	0.80	0.44	1.46
20	4.26	3.84	5.60	3.09	5.64	0.76	0.87	0.94	0.47	1.03
Average	4.09	4.27	5.44	3.26	4.86	0.69	0.74	0.78	0.44	1.18

Table 12 Pairwise comparison between MOHCGA and other algorithms in MID

H0	\bar{D}	Std.	t0	95% confidence interval of the acceptance area		Result
				Lower bound	Upper bound	
$MID_{MOHCGA} < MID_{SPEA}$	0.31	1.516	0.938	$-\infty$	1.72	✓
$MID_{MOHCGA} < MID_{MOSA}$	-0.73	0.630	-5.23	$-\infty$	1.72	✓
$MID_{MOHCGA} < MID_{MOPSO}$	-0.05	0.862	-0.26	$-\infty$	1.72	✓
$MID_{MOHCGA} < MID_{NSGA}$	-0.02	0.879	-0.12	$-\infty$	1.72	✓

Table 13 Pairwise comparison between MOHCGA and other algorithms in k-th distance metric

H0	\bar{D}	Std.	t0	95% confidence interval of the acceptance area		Result
				Lower bound	Upper bound	
$K_{MOHCGA} > K_{SPEA}$	0.75	0.263	12.84	-1.72	$+\infty$	✓
$K_{MOHCGA} > K_{MOSA}$	0.44	0.192	10.35	-1.72	$+\infty$	✓
$K_{MOHCGA} < K_{MOPSO}$	0.49	0.278	8.02	-1.72	$+\infty$	✓
$K_{MOHCGA} < K_{NSGA}$	0.49	0.253	8.75	-1.72	$+\infty$	✓

Table 14 Average of pairwise comparison for CM in small size problems

X'/X''	NSGA-II	MOPSO	MOSA	SPEA-II	MOHCGA	Average
NSGA-II	1	0.9612	1	0.764	0.84856	0.9148
MOPSO	0.937	1	1	0.790	0.9	0.9256
MOSA	0.779	0.8534	1	0.612	0.712236	0.7914
SPEA-II	1	0.9980	1	1	0.9	0.9796
MOHCGA	0.943	0.9953	1	0.775	1	0.9428
Average	0.931	0.9616	1	0.788	0.8721	

Table 15 Average of pairwise comparison for CM in large size problems

X'/X''	NSGA-II	MOPSO	MOSA	SPEA-II	MOHCGA	Average
NSGA-II	1	1	1	0.91391	1	0.9827
MOPSO	0.989691	1	1	0.929814	1	0.9839
MOSA	0.921094	0.976965	1	0.689797	0.954779	0.9085
SPEA-II	1	1	1	1	1	1
MOHCGA	0.890434	0.948773	0.953354	0.645357	1	0.8875
Average	0.9602	0.981	0.9906	0.8357	0.9909	

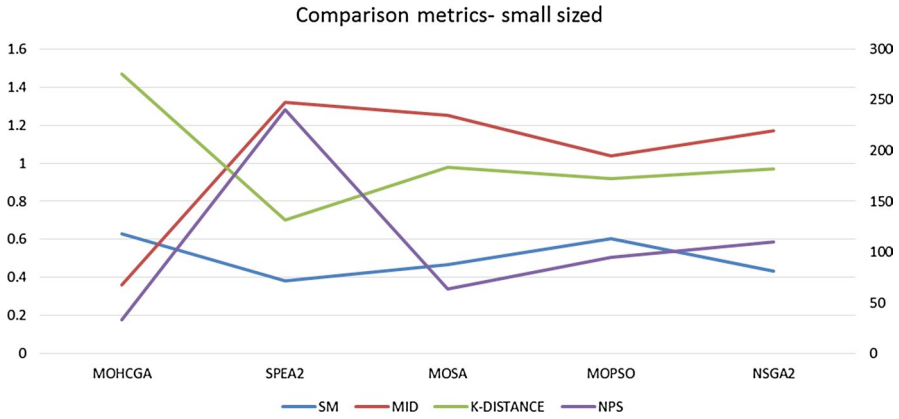


Fig. 11 Comparison between algorithms in small size problems

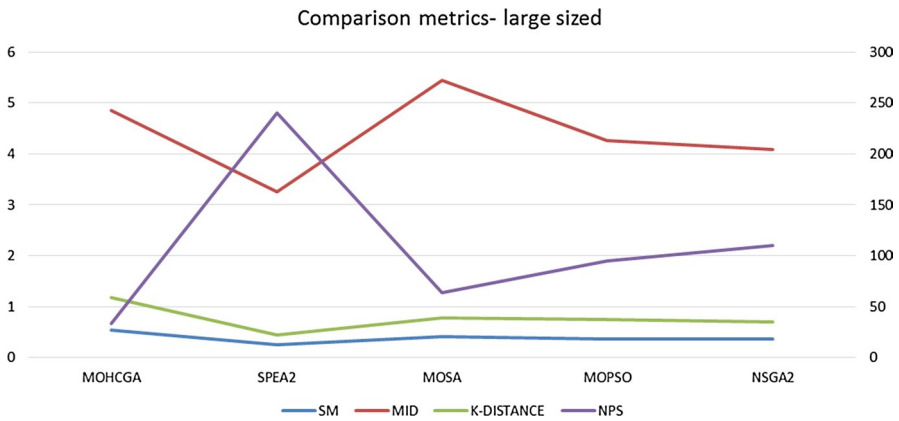


Fig. 12 Comparison between algorithms in large size problems

outperform other algorithms in MID; that is, the solutions obtained by this algorithm has less distance from ideal point. In k -th distance metric also MOHCGA has better results that other algorithms. Therefore, it can be concluded that MOHCGA generates widely speared solutions in phenotype space.

In the following, the comparison between algorithms with respect to CM is provided. The results are summarized in Tables 14, 15. These tables show that SPEA-II have better performance that other algorithms in CM. Figures 11, 12 are presented in order to give graphical perception about the performance of algorithms in small and large size problems.

5 Conclusion

In this work, green concepts and systematic collection of wastes in new presented network were considered, simultaneously. For designing a rational network, some location decisions in design phase of the network and waste collection decisions in operational phase were made in this paper. The problem included activities related to collection, treatment, recycling, and disposal of hazardous wastes in multi stage network. Fuel consumption and CO₂ emission along the collection routes were investigated in this paper for the first time. On other hands, sustainability and reducing social effects of waste were emphasized in this paper. The network presented in this research composed of depots, generation nodes, treatment facilities, recycling centers, and disposal centers, so this makes the networks most complete network investigated in this field. According to general framework for designing a waste management network presented here, it can be applicable in different real collection networks. Also, some risks associated with facilities were considered in this paper. A new mathematical formulation with three objective functions was proposed in which each objective corresponds to one component of sustainability. Five multi-objective metaheuristic algorithms were applied to tackle the problem which one of these algorithms called MOHCGA was proposed in this paper. To the best of our knowledge, MOHCGA and MOSA were applied for the first time in the field of location routing problem. Some experiments were conducted to show the efficiency of proposed algorithm. Also, experiments attribute were provided in an Internet link and interested reads can refer to it. Since the comparison between multi-objective algorithms are different with single objective problems, some comparison metrics were introduced and the obtained results are compared with each other with respect these metrics. According to the obtained results, performance of MOHCGA was competitive with other algorithms performance, specifically in MID and k -th distance metric MOHCGA outperformed other algorithms; that is, MOHCGA can find solutions which are closer to the ideal solution. On the other hand, SPEA-II algorithm can generate more Pareto solutions which are distributed uniformly in Pareto front.

We suggest for the interested researcher in this field to consider the velocity of vehicles as an effective variable on fuel consumption. Also, time windows restriction can be considered in generation nodes or facilities' locations. Using some methods such as epsilon constraint, goal programming, or goal attainment to achieve the exact Pareto frontier and comparison the results of approximate algorithms with these methods could be attractive. Since the model presented in this paper is a general framework for designing a waste management network, applying this model in a real case situation and investigating results are recommended for future researches.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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