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Smart routing for municipal solid waste collection: a heuristic approach

Amal Louati[1] · Le Hoang Son[2] · Habib Chabchoub[3]

Abstract

Municipal solid waste (MSW) is considered as one of the primary factors that contribute greatly to the rising of climate change and global warming affecting sustainable development in many different ways. It is indeed necessary to investigate an efficient computerized method for the optimization of MSW collection that minimizes the environmental and other factors according to a given waste collection scenario. In this paper, we propose a heuristic-based smart routing algorithm for MSW collection and implement it by Python scripts in ArcGIS to calculate optimal solutions of the model including routes and total travelling distances and operational time of vehicles. The algorithm will be validated on a case study of Sfax city which is the second largest and among the most polluted cities in Tunisia. A novel optimization model for the MSW collection in Sfax is designed and given to the algorithm for calculation. The achieved results are then compared with those of the current real scenario as well as evaluated by a multi-criteria decision aid method namely PROMETHEE in terms of environment and economic criteria.

Keywords ArcGIS · Dijkstra · Municipal Solid Waste Collection · Optimization models · Sfax city · Vehicle Routing Problem

1 Introduction

Nowadays, the concentration of population in cities has directed influence to increasing quantities of municipal solid waste (MSW) which is one of the primary factors that contribute greatly to the rising of climate change and global warming affecting sustainable development in many different ways (Chang et al. 2009; Son 2014). Road transport of a MSW collection scenario consumes more than 95% of oil, fossil fuels, CO2 emitter, greenhouse gas and burn 1 kg of

gasoline or diesel emits 3.2 kg CO2 (Douaud and Technique 2010). It is indeed recognizable as one of the main sources for environmental pollution in which evidences of pollution can be seen in lung cancer, asthma, allergies, and various breathing problems along with severe and irreparable damage.

Another direct effect is the immediate alterations that the world is witnessing due to global warming affecting increased temperatures, sea levels rise, melting of ice, displacement and loss of habitat (Moisseeva et al. 2016). This raises an alarm of requisition of specific strategies for prevention and precaution of possible disasters that could be foreseen worldwide. For those reasons, the aim of this research is to investigate an efficient computerized method for the optimization of MSW collection that minimizes the environmental and other factors according to a given waste collection scenario.

In this research, we consider a real-world case study for the sake of illustration of a new computerized method for optimization of MSW collection. It is originated from the Sfax city which is the second largest (number of population) city and among the most polluted cities in Tunisia-the Republic located in the North Africa, and resides of 24

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regions. Tunisia contains 10.778 habitats and generated 2.423 million tons in 2012 and 0.815 Kg/day per capita MSW generation in the urban areas in 2014 (Waste 2014) (Fig. 1). Ing et al. (2007) indicated Sfax has high pollution rate and high quantity of population with 272,801 habitats being located in the center city explaining the high average waste quantity (0.702 h kg/hab./day). Waste at Sfax is contained at two types of sources: the first type is a household waste from three main sources namely houses, hotels and streets; the second type is from other sources: markets, offices, restaurants, hospitals, institutions, prisons, etc. These sources are called the *gather sites*.

Current real scenario (called Scenario 0) of SFAX includes a depot (the starting place of vehicles), many gather sites and many collection centers (or transfer stations). The vehicles are responsible for collecting waste to the transfer stations. The agricultural tractor can carry up to 1.6 tons of waste. The dumper truck can transport a 2.3 tons to of waste and the compactor vehicle have the maximal capacity around 7.4 tons of waste. Drivers start the first trip from the depot at the same time. After loading waste at some gather sites, and total load reaches the vehicle's capacity, each vehicle will unload it at a collection center and start a new route. The restricted working times of all vehicles are depended by the boroughs. Inhomogeneous vehicles are used so that different operations are applied to various types of vehicles. The case study contains one depot, 39 gather sites, two transfer stations and 4 vehicles including 2 tractors agricultural, 1 dumper truck and 1 compactor vehicle. An alternative scenario (called Scenario 2) can be applied to Sfax as follows: all the vehicles start their trips from the depot, collect garbage from the gathers sites and unload waste at transfer stations 2, finally return to the depot. Using these scenarios for Sfax, the total travelling distances and operational time of vehicles are attributed to be minimal so that the environmental effects are significantly reduced.

The current MSW collection process (Scenario 0) in Sfax is done manually according to these scenarios which mean that the routes of vehicles are not optimized by any method
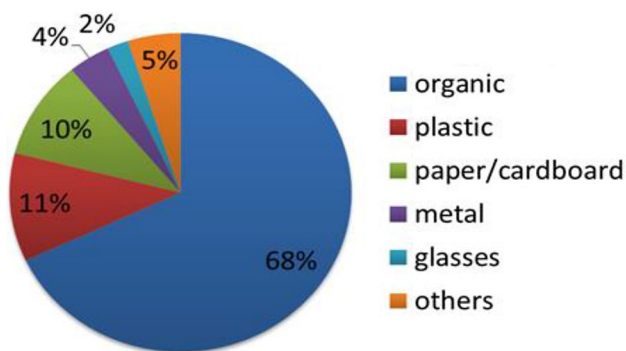

Fig. 1 Variation in MSW composition in Tunisia (Waste 2014)

but based solely on the experience of drivers. Yet, it has been shown that *using computerized methods such as ArcGIS*–a geographic information system to determine optimal routes of vehicles can again reduce the total travelling distances and operational time. Many works done in the past years used a vehicle routing algorithm such as Dijkstra in ArcGIS (ESRI 2006) to derive optimal solutions (Karadimas et al. 2007; Son 2014; Zhang et al. 2015; Zsigraiova et al. 2013; Khan and Samadder 2014). Sanjeevi and Shahabudeen (2015, 2016), Zsigraiova et al. (2013), Tavares et al. (2009), Malakahmad et al. (2014) and Zhang et al. (2015) used ArcGIS Network Analyst to identify the best route for the municipal waste collection of large items. Khan and Samadder (2014) addressed a mini review on various aspects of MSW management using GIS coupled with other tools to know how GIS can help in optimizing solid waste collection. Son and Louati (2016) proposed a generalized vehicle routing model for MSW collection problem including multiple transfer stations. Han (2015) presented a review of waste collection techniques to solve MSW collection. Gallardo et al. (2015) combined the planning methodology with ArcGIS to design an MSW management system in Castellón (Spain). Malakahmad et al. (2014) used ArcView to investigate MSW collection in Poh city aiming to optimize the length of routes and collection time. Santos et al. (2011) utilized GIS to minimize total traveled distances of vehicles with constraints such as shift time a vehicle capacity and network. It has been affirmed that ArcGIS is a good choice for the analysis of MSW collection (Bonomo et al. 2012; Syed et al. 2017; Avila-Torres et al. 2017).

Nonetheless, using ArcGIS for GIS data of Sfax accompanied with the information of waste quantities of all nodes (gather sites, transfer stations, etc.) is not enough to derive a good solution. That is to say, the Network Analyst function (or the vehicle routing function using the Dijkstra algorithm) in ArcGIS ignores the constraints of waste quantity of nodes and vehicles, for instance if a vehicle comes to a gather site, it must check whether its remained capacity is large enough to load (parts of) the waste quantity of that node. Analogously, the total current waste quantities of a vehicle after leaving a node must be less than or equal to capacity of the vehicle. There are also many constraints that were not taken into account in ArcGIS; making the vehicle routing function pays much attention to the map's topology (which means shortest paths between nodes) rather than the waste collection itself. The need of an optimization model for MSW collection at Sfax is indeed inevitable. This model should illustrate all required constraints and include the objectives of minimization of environment expressed through the total travelling distances and operational time of vehicles. On the other hand, an improvement of the vehicle routing function using Dijkstra (or in short the improved Dijkstra algorithm) should be designed to handle the optimization problem.

From the above motivations, the **contributions** of this paper are two folds: *Firstly*, we propose a novel optimization model for the MSW collection based on the current real scenario of waste collection in Sfax; *Secondly*, we propose a novel heuristic-based smart routing algorithm for MSW collection and implement it by Python scripts in ArcGIS to calculate optimal solutions of the model including routes and total travelling distances and operational time of vehicles. The achieved results are then compared with those of the current real scenario (Scenario 0) and Scenario 2 in order to know whether or not using the new model and the smart routing algorithm can have better results than using the current manual scenario (Scenario 0) and Scenario 2 implemented in ArcGIS with classical Dijkstra only (no new model is required herein). The comparison with Scenario 0 is to verify the efficiency of the new optimization model vs. the manual collection process. Analogously, the comparison with Scenario 2 is to validate the capability of the improved Dijkstra algorithm vs. the classical one. All experimental results are then analyzed by a multi-criteria decision aid method namely PROMETHEE in terms of environment and economic criteria.

The rest of the paper is organized as follows. Section 2 presents the optimization model of MSW collection in Sfax, the improved Dijkstra algorithm in ArcGIS and the PROMETHEE tool. Section 3 demonstrates the experimental results and discussions. Section 4 highlights conclusions and further works of this study.

2 Materials and methods

2.1 Modeling waste collection

Firstly, we make following assumptions to the model:

(a) The distance between each pair of nodes is known, constant vehicle speed, hence the travelling time between nodes is also known.
(b) The numbers of node as well as their locations on the map are fixed.
(c) Working time all vehicles is the day shift.
(d) Load and unload time of a vehicle are equal. Partial loads are allowed.
(e) Capacities of each type of vehicles are not equal.
(f) All vehicles need to collect all waste before returning to the depot in a shift.
(g) We assume that the number of trips of all vehicles in a (day) shift is large enough to take all the waste in that shift. This means that waste is always less than the capacities of all vehicles in a (day) shift.
(h) We consider the static waste generation in a (day) shift. This means that waste of all gather sites in a (day) shift

is fixed. If new waste comes (e.g. 2– 3 waste a day), we count it to the next shift.

Secondly, we propose some terms that will be used throughout the model (Table 1).

Thirdly, we propose the optimization model for MSW collection at Sfax city (Table 2).

The MSW collection at Sfax is modeled by the system (N^+, Z, V, Q) taken from a specific map of ArcGIS in the sense that each node in N^+ has a specific location on the map and the distance between two nodes is calculated by the shortest path function in ArcGIS (ESRI 2009). The components Z and Q change dynamically by time. In the first time stamp, the waste quantities of all nodes except those of gather sites are set to zero. But when vehicles in V move to gather sites to load waste and dump them at the transfer station, the waste quantities of those nodes increase. Waste quantities that a vehicle takes from a node are added to the component Q of that vehicle. When dumping waste, Q is reduced by the dumped waste quantity. Partial loads are allowed that means a vehicle can take a part of the total waste quantity in a gather site so that it does not exceed the capacity of the vehicle. Thus, the objective of the MSW collection problem is to minimize the travelling (operational) time which indirectly implies the minimum of total travelling distances of vehicles. Now, we give an example to illustrate the model.

Example 1 Suppose that we have a MSW system (N^+, Z, V, Q) consisting of a depot (ID: 1), a transfer station (ID: 2) and 7 gather sites (IDs from 4 to 10). Waste quantities of all nodes in the first time stamp are shown in the Table 3. In the system, there are 4 vehicles including 2 tractor agricultural (IDs: Ag1 and Ag2), 1 dumper truck (ID: D) and 1 compactor vehicle (ID: C) whose capacities of vehicles are expressed in Table 4. The distance between each pair of nodes is presented in Table 5.

All vehicles started at the same time from the depot, and the results of the first move to nodes of vehicles are presented in Table 6. Those results satisfy constraint (A_1).

The compactor vehicle starts a trip from the depot (constraint A_3), and loads waste from node 9 ($Q^j = 618$) and node 5 ($Q^j = 814$). It cannot load waste from node 7 or 10 because their waste quantities are greater than capacity of the vehicle (constraint A_4). The vehicle loads 1432 kg waste quantity (constraint A_5) and moves to the transfer station for dumping. The vehicle starts the second trip from the transfer station to node 10 to load 1020 kg of waste and return to the transfer station to unload again (Table 7).

After dumping and finishing the shift day, the vehicle goes to the depot (Constraint A_2).

Table 1 Definitions and denotation of variables and terms

Term	Definition and Explanation
num_ts	The number of transfer stations
num_gs	The number of gather sites
$\overline{N} = \{1, 2, 3, 4, .., N^+\}$	An ordered list of nodes representing for the MSW collection system including '1': ID of the depot '2': ID of the first transfer station '2': ID of the second transfer station '4',...,'N$^+$': IDs of the gather sites
$Z = \{Z_1, Z_2, Z_3, Z_4, .., Z_{N^+}\}$	Waste capacity of all nodes $Z_1 = 0$: waste capacity of depot Z_2, Z_3: waste capacities of the first and second transfer stations, respectively $Z_4, .., Z_{N^+}$: waste capacity of gather sites
$V = \{1, 2, 3, 4\}$	An ordered list of vehicles including '1': id of the first Agricultural tractor '2': id of the second Agricultural tractor '3': id of the Dumper truck '4': id of the Compactor vehicle
$C = \{C_1, C_2, C_3, C_4\}$	The capacity of vehicles where C_1, C_2: Capacity of the Agricultural tractor C_3: Capacity of the Dumper truck C_4: Capacity of the Compactor vehicle
$Q = \{Q_k^i\}$	k: id of a vehicle and i: id of a node Q_k^i: Current waste quantities of vehicles k after leaving node i
$X_j^i(k)$	An arc's weight that measures the capability of vehicle k to travel from node i to node j $X_i^i(k) = 1$ if vehicle k is able to travel this arc $X_i^i(k) = 0$ otherwise
$t_{ij}(k)$	Travelling time between nodes i and j of the vehicle k

Table 2 The optimization model

	Objective Function	Explanation
A_0	$\min \sum\limits_{k \in V} \sum\limits_{i,\, j\, \in 2, \overline{N}^+} t_{ij}(k)\, x_j^i(k)$	Minimize the travelling time
Constraints		
Network		
A_1	$\sum\limits_{j=4}^{N^+} x_j^1(k) = 1 \quad (\forall k \in V)$	Each route starts from the depot
A_2	$\sum\limits_{i=2}^{3} x_1^i(k) = 1 \quad (\forall k \in V)$	The last trip from a node in that route should return to the depot
Waste volume		
A_3	$\sum\limits_{i=1,2,3} \sum\limits_{j \in \overline{N}} Q_k^i\, x_j^i(k) = 0 \quad (\forall k \in V)$	Waste volume of each vehicle leaving the depot and the transfer station equals to zero
A_4	$\sum\limits_{\forall i,j \in \overline{N}} Q_k^i\, x_j^i(k) \leqslant C_k \quad (\forall k \in V)$	The total current waste quantities of a vehicle after leaving a node must be less than or equal to the capacity of that vehicle
A_5	$\left(Q_k^j - Q_k^i \right) x_j^i(k) = Z_j \quad ((\forall k \in V,\ \forall i, j \in \overline{N}))$	The waste quantities is load at a node must be less than or equal to the capacity of that node

Table 3 The initial waste quantities of nodes (kilograms)

$\tilde{N}$	1	2	4	5	6	7	8	9	10
R	0	60,000*	735	814	730	828	868	618	1020

*The capacity of a node

Table 4 The capacities of vehicles (kilograms)

V	Ag1	Ag2	D	C
C	800	800	1000	1500

Table 5 Distances between each node in kilometer unit (no. trip)

N^+	1	5	9	2	10
1	0	7.9	11	22.2	33.8
5	7.9	0	3.1	14.3	25.9
9	11	3.1	0	11.2	22.8
2	22.2	14.3	11.2	0	11.6
10	33.8	25.9	22.8	11.6	0

It is obvious that the model allows validating of a possible move of a vehicle from a node to another satisfying the constraints regarding waste quantities and network which cannot be accurately performed by the current Network Analyst function for GIS data only in ArcGIS.

2.2 New smart routing algorithm

In this section, we propose a novel heuristic-based smart routing algorithm for MSW collection. The basic idea of this algorithm is to derive an optimal solution for the model proposed in Tables 1 and 2. In order to do so, a heuristic based method is appropriate to both find the solution and obtain reasonable processing time which is an urgent matter in such the real-world application. The heuristic method considers the objective function and constraints as in Table 2 with real data from the case study. An important note is that it must integrate the final results with the map so that the trips of each vehicle are visually expressed therein. For those reason, we try to integrate the new smart routing algorithm to the ArcGIS software in which the classical Dijkstra algorithm is

replaced with the new method. As a result, the smart routing algorithm is not a trivial improvement of Dijkstra but follow its idea to generate the optimal solutions instead.

ArcGIS Desktop 10.1 (ESRI 2006)- a geographical information system aided method (GIS), provides detailed information of spatially referenced events and phenomena. ArcGIS Network Analyst permits to create and build a network dataset from feature classes stored within a geo-database and perform analyses on a network dataset, with define connectivity rules and network attributes. ArcGIS Network Analyst allows creating a model for finding the fastest collection route. The routing solvers within ArcGIS Network Analyst namely the Route, Closest Facility and OD Cost Matrix are based on the **well-known Dijkstra algorithm** for finding shortest paths. Each of these three solvers implements two types of path-finding algorithms. The first type is the exact shortest path, and the second is a hierarchical path solver for faster performance.

The Dijkstra algorithm solves the single-source, shortest-path problem on a weighted graph. To find a shortest path from a starting location to a destination, Dijkstra maintains a set of junctions, S, whose final shortest path from the starting has already been computed. The algorithm repeatedly finds a junction in the set of junctions that has the minimum shortest-path estimate, adds it to the set of junctions S, and updates the shortest-path estimates of all neighbors of this junction that are not in S. The algorithm continues until the destination junction is added to S (Table 8).

Nonetheless, in order to use Dijkstra within the context of real-world transportation data, it must be modified to represent user settings such as waste quantity and network constraints while minimizing a user-specified cost attribute. In addition, the algorithm needs to be able to model the locations anywhere along an edge, not just on junctions. In what follows, we present a novel heuristic-based smart routing algorithm that mimic the idea of Dijkstra with the constraints of the model and the operation of multiple vehicles

Table 6 The results of the first trip

V	Ag1	C4	Ag2	zd	D	C4	
nodes Q^j	4	5	6	7	8	9	10
	735	814	730	828	828	618	1020
Status	Full	Full	Full	828	Full	Full	1020

Table 7 The results of the second trip

V				D			C4
Nodes	4	5	6	7	8	9	10
Q^jj	0	0	0	828	0	0	1020
Status	Empty	Empty	Empty	Empty	Empty	Empty	Empty

Table 8 The classical Dijkstra algorithm

```
def Dijkstra (G=(V,E) is a undirected graph with V is a set of nodes and E is a set of edges

    For i:= 1 to n

        L(u_i):= ∞          L(a):= 0

        S:= V \ {a}

        u:= a

    End for
     While S ≠ ∅

        For v belonging to S

            If L(u) +m (u,v) < L(v) then L(v) := L(u)+m (u,v)

                u:= a node in S having minimal value of L(u)  where L(u) is the shortest

        length from a to u, and m (u,v) is the weight of edge (u,v)

                S:= S \ {u}

            End if

        End for

    End while

    End
```

being integrated. The algorithm has been implemented in Python script in ArcGIS. Table 9 shows the pseudo-code of the new smart routing algorithm.

In this table, the *Neighbor (a, V)* procedure aims to find gather sites which are neighbors of a node 'a' in the order of closest to farthest. The *Constraint (a, b, i)* procedure checks whether a vehicle 'I' can go from node 'a' to node 'b' by constraints of the model and Dijkstra's strategy (expressed in the condition: $L(b) < L(a) + distance[a][b]$). The *Print (result)* is used to print the optimal routes of a vehicle. Finally, the most important function—*Route*() shows the main idea of the smart routing algorithm in which we iteratively try to find a possible move for a vehicle according to the current waste quantity until the vehicle is full. By this strategy, all vehicles are programmed to collect waste automatically. Finally, the collection system stops working when waste is dumped completely. We can realize that the principle of Dijkstra reflects in the *Constraint* (*a, b, i*) and the *Route*() procedures with major changes of model adaptation. This shows the novelty of the algorithm.

Figure 2 shows the flowchart of the algorithm.

2.3 PROMETHEE

The PROMETHEE (Preference Ranking Organization METHod for the Enrichment of Evaluations) method was developed by Professor Jean-Pierre Brans in 1982. In 1988, GAIA (Graphical Analysis for Interactive Aid) was introduced as a graphical complement to the PROMETHEE rankings. PROMETHEE have successfully been applied to many problems and a number of researchers have used them in decision making problems in solid waste management research (Soltani et al. 2015). In this method, decision makers must define the following information:

(a) *Weights* (w_j) the weight of a criterion measures how much importance to other criteria. The descriptions of criteria and their values are shown in Tables 10 and 11 (Behzadian et al. 2010; Vinodh and Jeya Girubha 2011). The used scale for qualitative criterion is 5-point in Table 12.

(b) *The performance function* defines how pairwise evaluation differences are translated into degrees of prefer-

Table 9 The heuristic-based smart routing algorithm

Input: Capacity waste of the gather sites: Z

Ordered list of the nodes: N

Ordered list of the vehicle: V

Capacity of the vehicle: C

Output: Total time and total distances of vehicles

Class CollectWaste ():

Find gather sites neighbors of node a in the order of closest to farthest

del Neighbor (a, V):

#initialize N(a) is empty

N(a) = {}

For ia in V:

if (ia != a):

Distance(i, a)

N(a) = N(a) ∪ {i}

#ascending sort the neighbor node by distance

Sort(N(a))

Check whether vehicle i can go from node a to node b by constraints of the model and Dijkstra's strategy

del Constraint (a, b, i):

#Current waste quantities of vehicles i after leaving node a: Q[i][a]

a set of labels of nodes: L

capacity of the gather site: G (notation same the model)

While (Q[i][a] != C(i)):

if((C(i)- Q[i][a]) >= Z(b)):   Q[i][b] = Q[i][a] + Z(b)

else:

Q[i][b] = Q[i][a] + (C(i) − Q[i][a])

Z(b) = Z(b) - (C(i) − Q[i][a])

if((L(b) < L(a) + distance[a][b]) & (Q[i][b] <= C(i)) & ((Q[i][b] − Q[i][a]) <= Z(b))):

Table 9 (continued)

```
                                    return true
            else:                   return false
        End while
    # Print optimal routes of a vehicle
    del Print(result):
            for i in len(Math):
                    route += node[i] + "→"
            return result
    # Main algorithm
    del Route():
        Initialize for vehicles at the depot and their current wastes: Q(i) = 0,  (i = 1,K)
        while (∑Z(i) > 0):
            For  each vehicle i  in V:
                while ((Q(i) < C(i)) & (!(Z(i) = 0))):  #Gather sites not empty
                    a = get node of vehicle i          #Find the location of vehicle i
                    Mark = false
                    N(a) = Neighbor(a,V)           #Find its neighbors
                    For b = 1 to N(a) do       #Check the possibility to move to a neighbor
                        if(Constraint (a,b,i) = true) then
                            Node(i) = b                #Mark node b as visited
                            Q(i) = Q[i][b]             #Update current waste of vehicle i
                            Reduce (b)    #Reduce waste quantity of gather site b
                            Mark = true   #Show that the vehicle can continue collecting
                            Break
                        end if
                    end for
                    if(Mark = false)    #If the vehicle cannot go to any node, move it to TS
                        Node(i) = transfer_station;
                        Break
                    end if
                end while
                Print (result)                 # Print optimal routes of the vehicle
            end for                                #Start with another vehicle
        end while                               #End main while
        Print routes of all vehicles and calculate total time and distances
    # Call the application
    if __name == '__main__':
        Route()
```
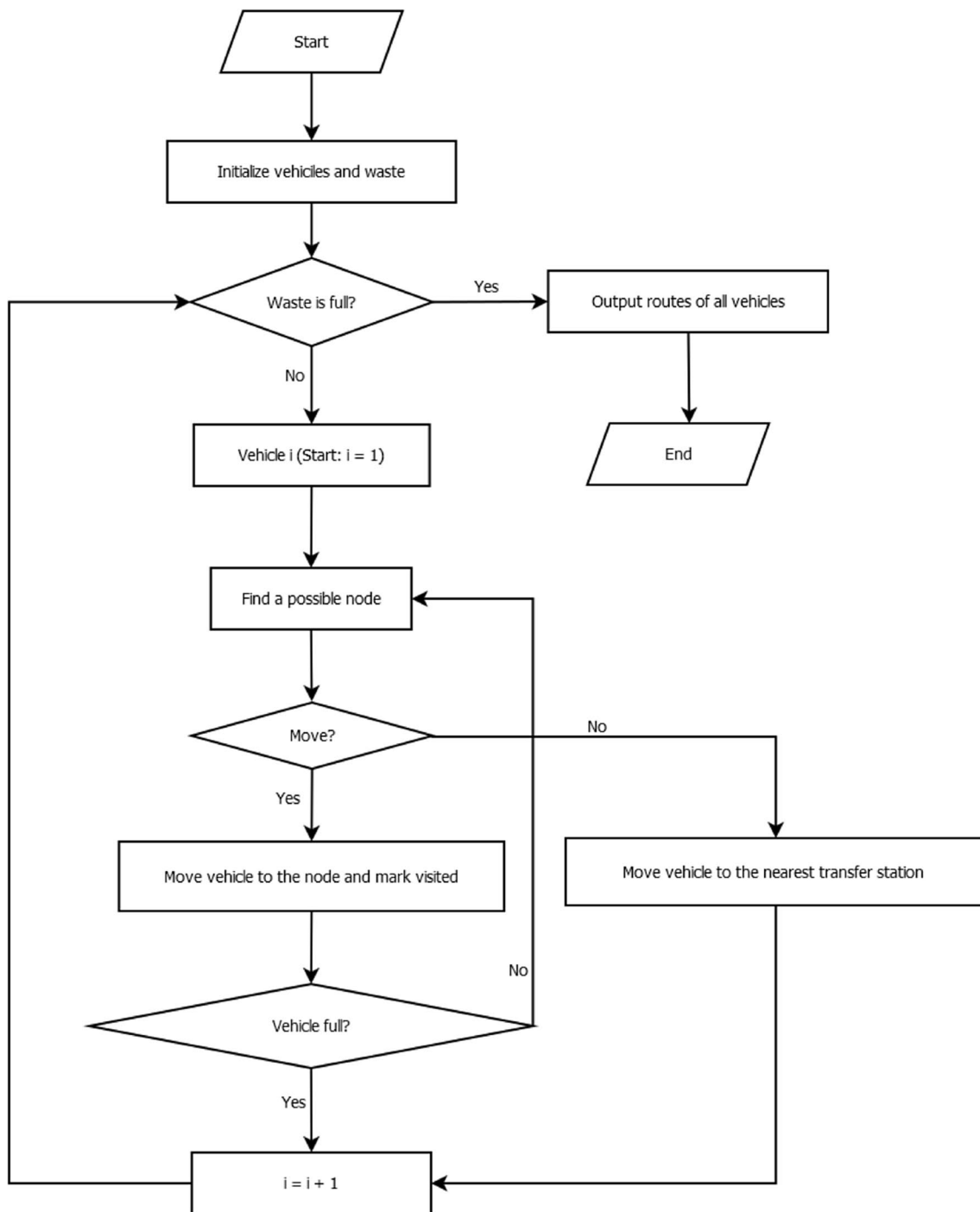
Fig. 2 Flowchart of the smart routing algorithm

ence. It reflects perception of the criterion scale by the decision-maker (Mareschal 2013). Brans and Vincke (1985) proposed six preference functions namely the Usual, U-shape, V-shape, level, Linear and Gaussian. Vinodh and Jeya Girubha (2011) described different preference functions and Behzadian et al. (2010) presented some steps for PROMETHEE as follows.

Step 1 Calculate the deviation value of alternatives a and b:

$$d_j(a, b) = g_j(a) - g_j(b)$$

where $g_j(a)$ is the evaluation of alternative a for criterion j.

Step 2 Calculate the preference function (j = 1..k):

Table 10 The criteria

Criteria	Description
Road length	Capability of routes to minimize the roads lengths
Fuel consumption cost	Capability of routes to minimize fuel cost
Emission gas	Capability of routes to minimize quantity of emission gas
Reliability	Policy may have been only tested in laboratory or only performed in pilot plants, or it could be still improved
Compatibility with the national energy policy objectives	The criterion also takes into account the government's support, the tendency of institutional actors, and the policy of public information
Labor acceptance	Capability of routes to maximize labor satisfaction

Table 11 Recommended values of criteria

Name	Scale	Units	Direction	Preference function	Weight	Thresholds indifference	Preference
Road length	quantitative	Km	Min	Level	20	10	30
Fuel consumption	quantitative	dollars	Min	V-shape	23	0	7
Emission gas	quantitative	g/km	Min	V-shape	17	0	100,30
Reliability	qualitative	5-point	Max	Level	20	1	2
Compatibility with national energy policy objectives	qualitative	5-point	Max	Level	10	1	2
Labor acceptance	qualitative	5-point	Max	Level	10	1	2

Table 12 Evaluations for reliability and compatibility criteria

Level	Value
very bad	1
Bad	2
Average	3
Good	4
very good	5

$$P_j(a,b) = P_j\big[d_j(a,b)\big]$$

Step 3 Calculate the global preference index

$$\pi(a,b) = \sum_{j=1}^{k} w_j P_j(a,b),$$

where w_j is the weight of jth criterion.

Step 4 Calculate the positive and negative outranking flows for each alternative:

$$\Phi^+(a) = \frac{1}{(n-1)} \sum_{x\in A} \prod (a,x)$$

$$\Phi^-(a) = \frac{1}{(n-1)} \sum \prod (x,a)$$

Step 5 Calculate the outranking flow where the best alternative is the one with highest net flow dominance.

$$\Phi(a) = \Phi^+(a) - \Phi^-(a)$$

3 Results and discussions

3.1 Results

Firstly, we present the comparative results of the new method (with the new routing method and the new model) vs. those of the current real scenario (Scenario 0) and Scenario 2 implemented in ArcGIS with classical Dijkstra only (no new model is required herein) (Fig. 3). It is clear that the new method achieves better results than others.

Secondly, the following tables show the details of vehicles of each method (Figs. 4, 5, 6).

Thirdly, the following figures show the route map of each method (Figs. 7, 8, 9).

3.2 Analyzing the results by PROMETHEE

In this section, we analyze the achieved results by PROMETHEE and make a sensitivity analysis with GAIA to discover conflicts among criteria, fix priorities, identify potential compromise and verify the robustness with respect
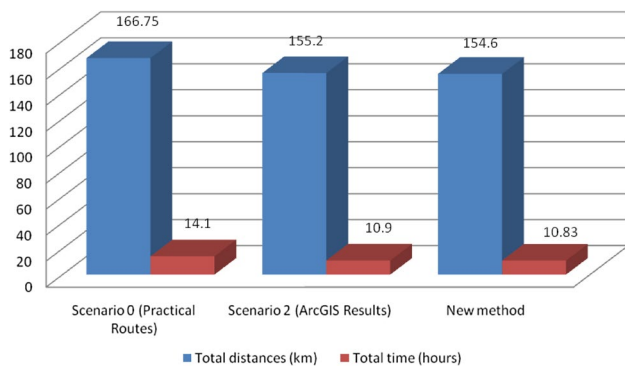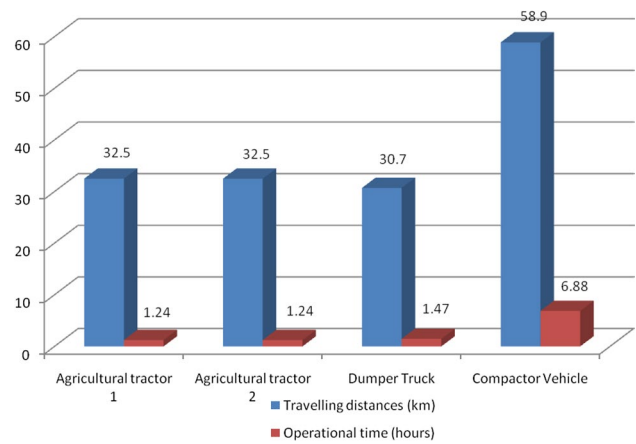
Fig. 3 The comparative results
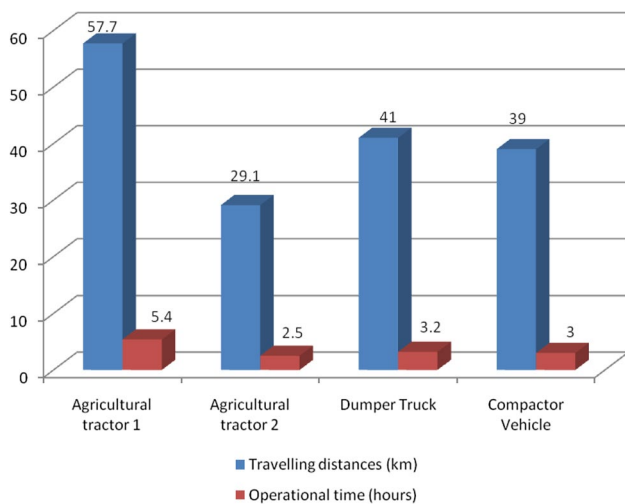

Fig. 6 The results of the new smart routing method
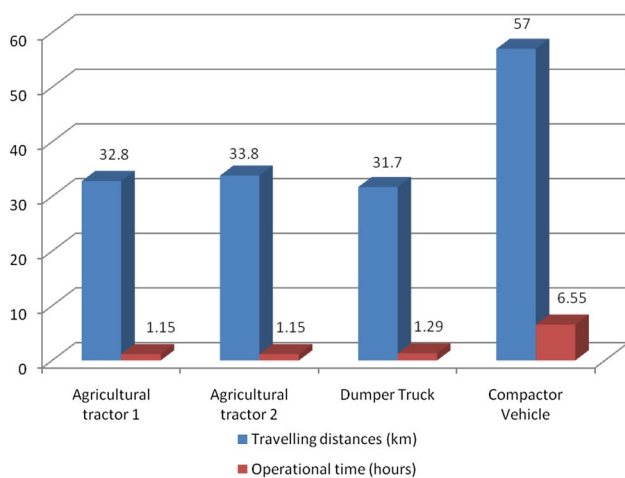

Fig. 4 The results of practical routes in Scenario 0

to weight values. *Firstly*, we present the evaluation for two criteria: reliability and compatibility in Table 13.

3.2.1 Deviation calculation

The deviation show the difference between two alternatives for each criterion (Scenario 0, Scenario 2), (Scenario 2, New method), etc. The total number of deviations in this context is 6. The deviation values are shown in Tables 14 and 15.

3.2.2 Preference function and global preference index

The preference is calculated using the respective preference function formula (Brans and Vincke 1985). To have a common scale of values, non-commensurable criteria should be converted into the dimensionless criteria. In order to normalize the weights of the criterion, relative weight has to be obtained using the following equation with the sum of the relative weights of criteria being equal to one (Vinodh and Jeya Girubha 2011).

$$W_j = \frac{w_j}{\sum_{j=1}^{k} w_j}$$

where w_j the weight of the jth criterion; $\sum w_j$ is the sum of weights of all criteria. The preference function's value and weight of each criterion are shown in Tables 16 and 17. For each couple of actions a, b ϵ A, we first define a preference function for a to b over the criteria (Reliability and Compatibility). The multi-criteria preference index gives a measure of the preference of a over b for the two criteria. The global preference index is calculated from the results in Fig. 3 and Tables 16 and 17.
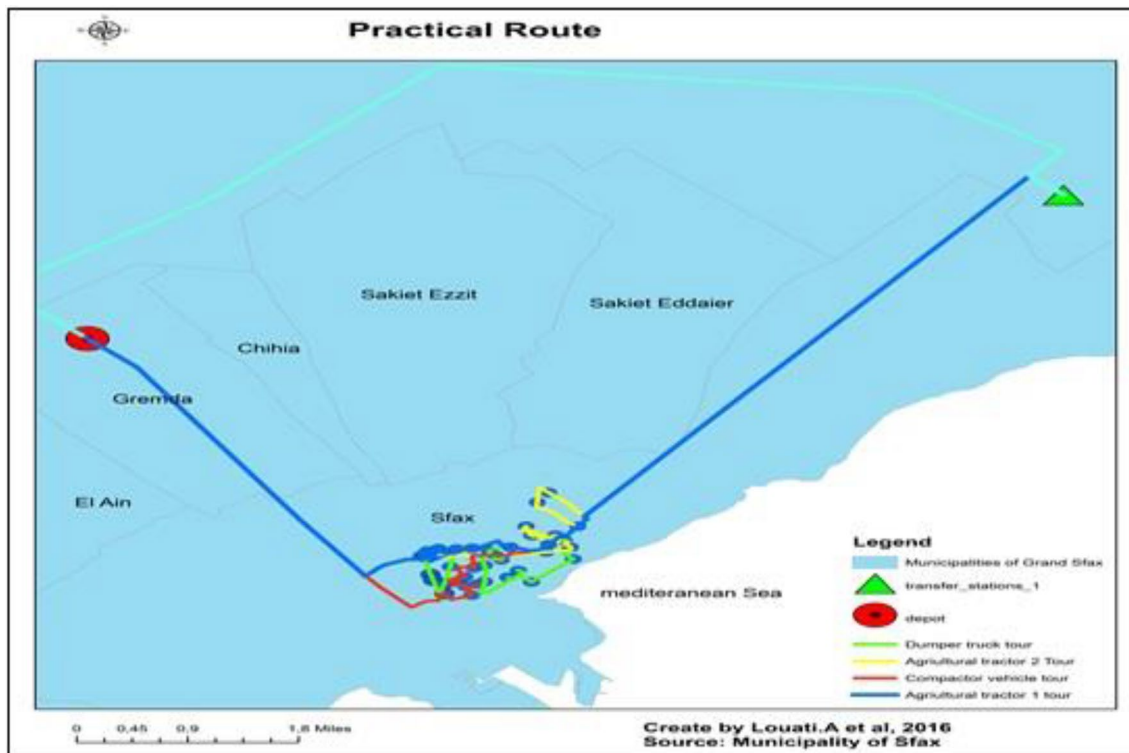

Fig. 5 The results of Scenario 2 using ArcGIS with GIS data

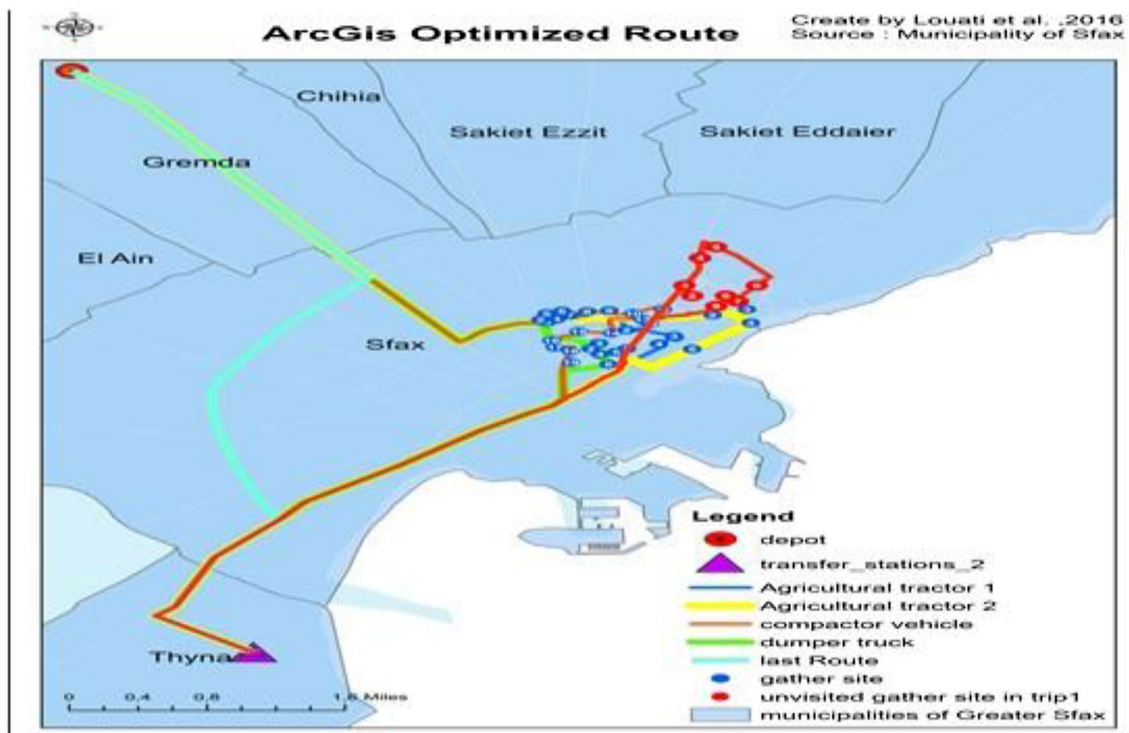**Fig. 7** The route map of Scenario 0 (practical routes)

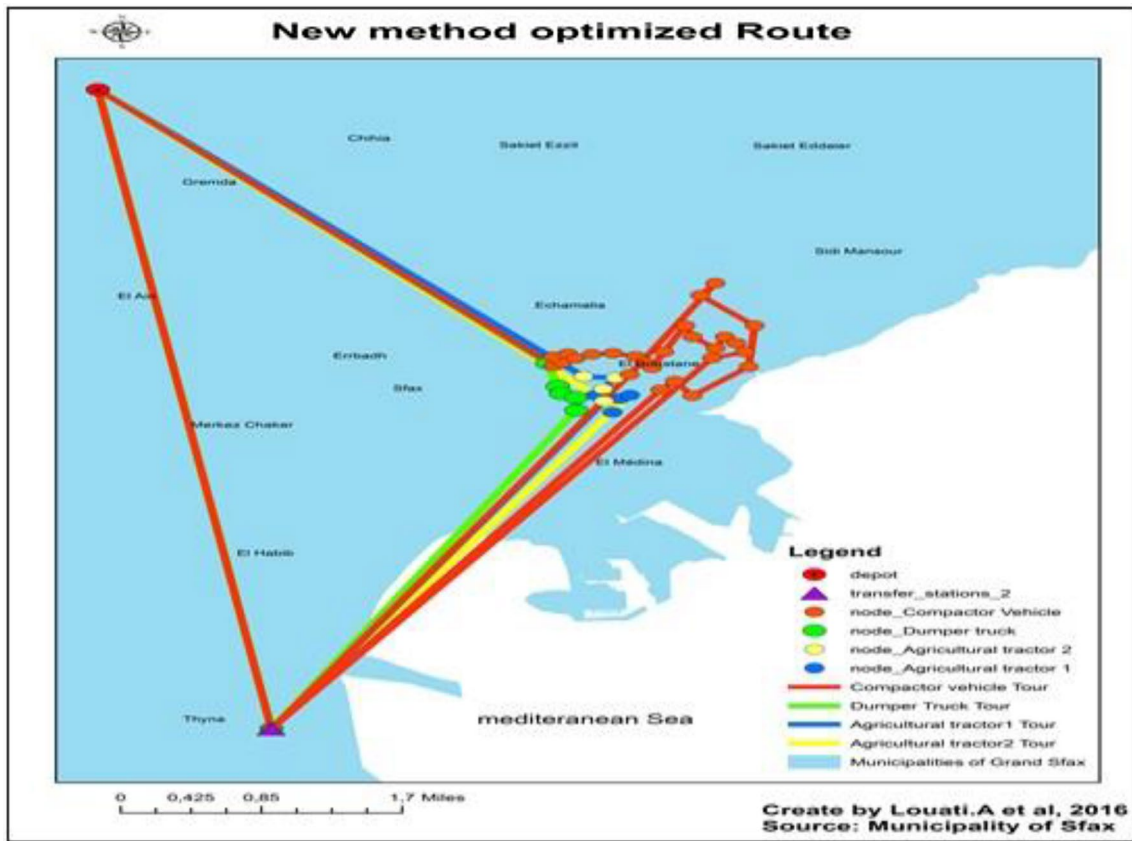**Fig. 8** The route map of Scenario 2 (ArcGIS)

Fig. 9 The route map of the new smart routing method

Table 13 Evaluations for reliability and compatibility criteria

	Reliability	Compatibility
Scenario 0	5	3
Scenario 2	3	4
New method	4	5
Weights	20	10

Table 14 Pair-wise comparison between scenarios on the Reliability criterion

d(a,b)	Scenario 0	Scenario 2	New method
Scenario 0	0	2	1
Scenario 2	− 2	0	− 1
New method	− 1	1	0

Table 15 Pair-wise comparison between scenarios on the Compatibility with the national energy policy objectives criterion

d(a,b)	Scenario 0	Scenario 2	New method
Scenario 0	0	− 1	− 2
Scenario 2	1	0	− 1
New method	2	1	0

Table 16 Preference function for the Reliability criterion

Pj(a, b)	Scenario 0	Scenario 2	New method
Scenario 0	0	0.5	0
Scenario 2	0	0	0
New method	0	0	0

Table 17 Preference function for Compatibility (national energy policy objectives criterion)

Pj(a, b)	Scenario 0	Scenario 2	New method
Scenario 0	0	0	0
Scenario 2	0	0	0
New method	0.5	0	0

Table 18 Flow result for Reliability and Compatibility criteria

Pi(ai,aj)	Scenario 0	Scenario 2	New method	Positive flow (phi+)
Scenario 0	0	10	0	**0.33**
Scenario 2	0	0	0	**0**
New method	5	0	0	**0.16**
Negative flow (phi-)	0.16	0.33	0	
Net flow	0.16	− 0.33	0.16	

Bold values imply that the larger phi+ or the smaller phi−, the better the action

Table 19 Uni-criterion preference flows

	Road length	Fuel consumption	Emission gas	Reliability	Compatibility	Labor acceptance
Scenario 0	−0.5	−0.1729	−1	0.5	−0.5	0
Scenario 2	0.25	0.065	0.3115	−0.5	0	0
New method	0.25	0.1079	0.6885	0	0.5	0

Table 20 PROMETHEE flow

Rank	Action	Net flow	Leaving flow	Entering flow
1	New method	0.2491	0.2419	0
2	Scenario 2	0.0179	0.1532	0.1353
3	Scenario 0	−0.2598	0.1	0.3598

3.2.3 Compute the positive and negative outranking flows (Tables 18, 19)

3.2.4 The final outranking flow (Table 20)

It is clearly that the new method has the highest net flow value. Thus, the new method achieves the best results among all in terms of multiple criteria. In what follows, we perform sensitivity analysis for the results.

3.3 Sensitivity analysis

The Visual Stability Intervals window can be used for to change the weights of the criteria and see the impact of the ranking (Fig. 10).

The visual stability analysis for criterion figure is split into two parts:

The upper part is a bar chart showing the PROMETHEE Complete Ranking and the lower part is a bar chart showing the weights of the criteria. For each active action, a line is drawn to show how the net value changes when the weight of the criterion is modified.
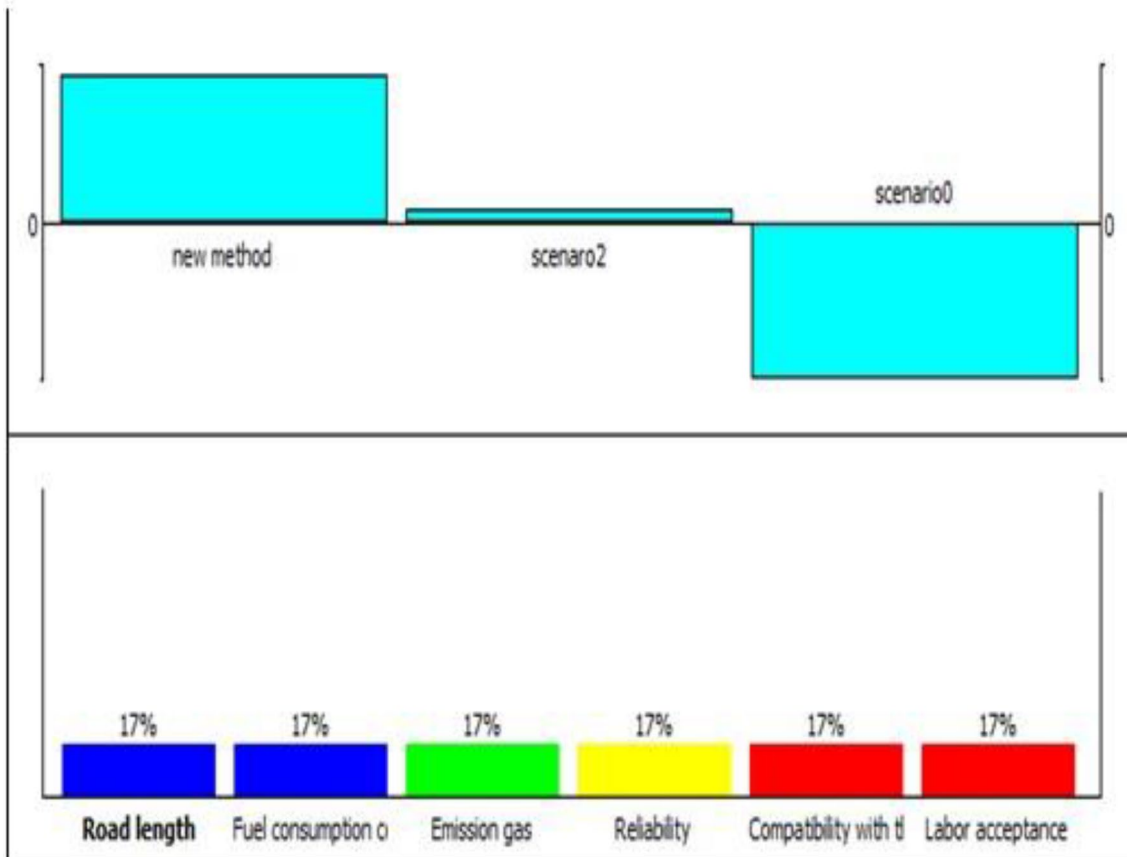
**Fig. 10** The visual stability intervals window

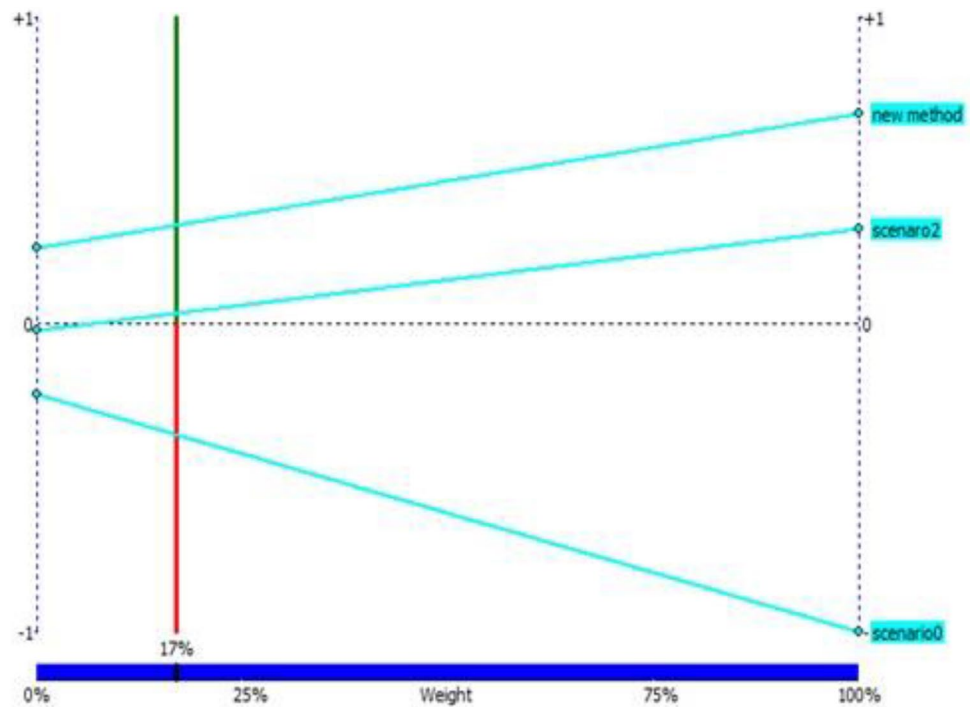**Fig. 11** The weight stability interval for road length criterion
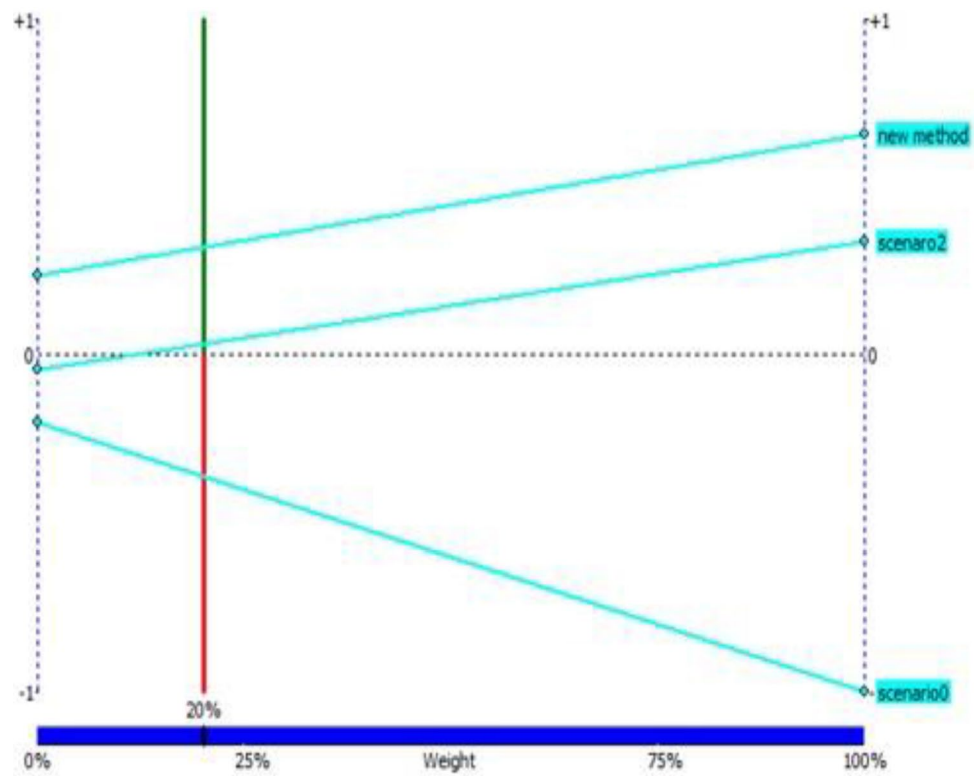
After changing equals weights for each criterion, it can be seen that the new method is at the top of the PROMETHEE ranking. The weight stability interval indicates how the Phi multi-criteria net flow scores change as a function of the weight of a criterion (Figs. 11, 12, 13, 14, 15).
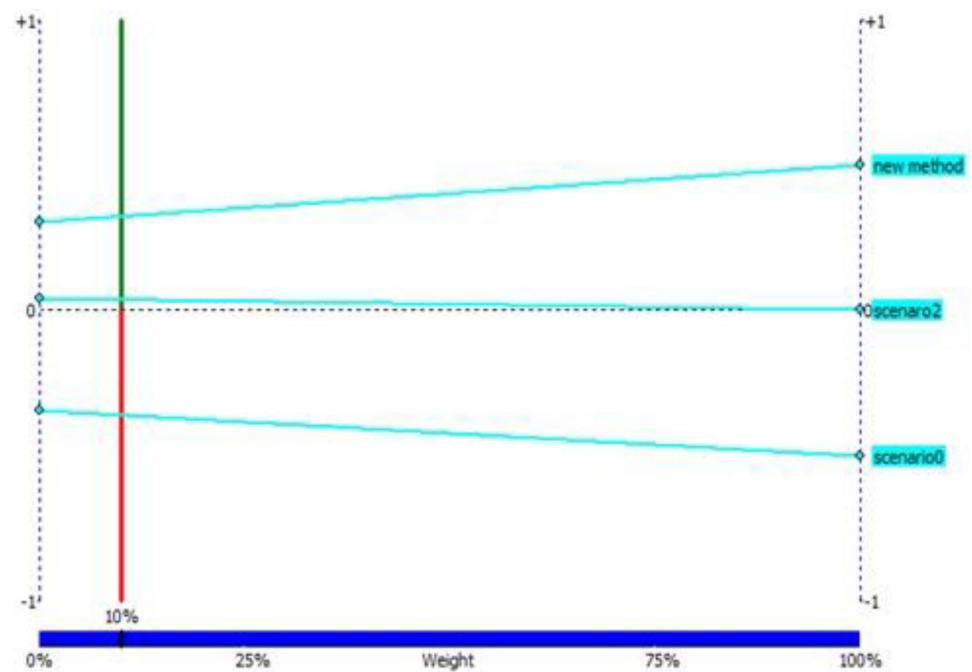
Fig. 12 The weight stability interval for fuel consumption cost
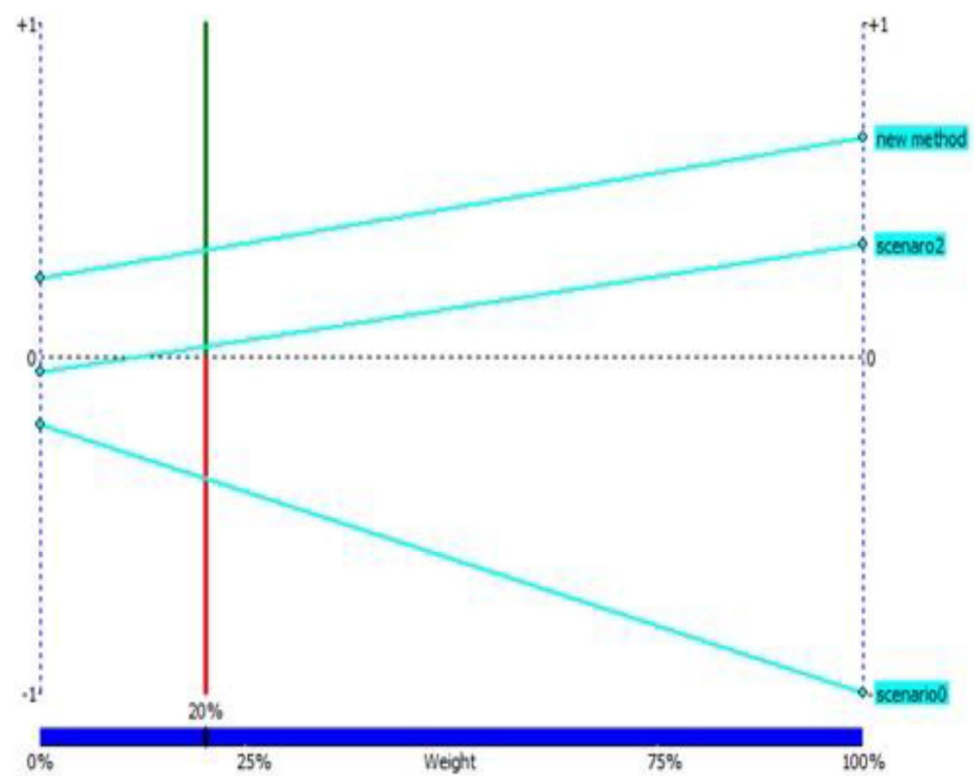
Fig. 13 The weight stability interval for emission gas criterion

Fig. 14 The weight stability interval for Compatibility

The weight stability intervals for criteria: Road length, Fuel consumption cost, Emission gas, Compatibility and Labour acceptance in three scenarios belong to [0%, 100%]. Thus, the PROMETHEE ranking do not change whatever the weight of the Road length criterion and the new method in the top of ranking, but the ranking can change if weight of the Reliability criterion exceeds the weight stability interval [0%, 66.21%] when Scenario 0 dominates Scenario 2

and [0%, 42.68%] when Scenario 0 is in the top of ranking (Figs. 16, 17, 18, 19).

The horizontal dimension corresponds to the weight of the selected criterion, and the vertical dimension corresponds to the Phi net flow score. For each action, a line is drawn that shows the net flow score as a function of weight of the criterion. At the right edge, the weight of criterion is equal to 100% and the actions are ranked according to that

Fig. 15 The weight stability interval for labour acceptance criterion
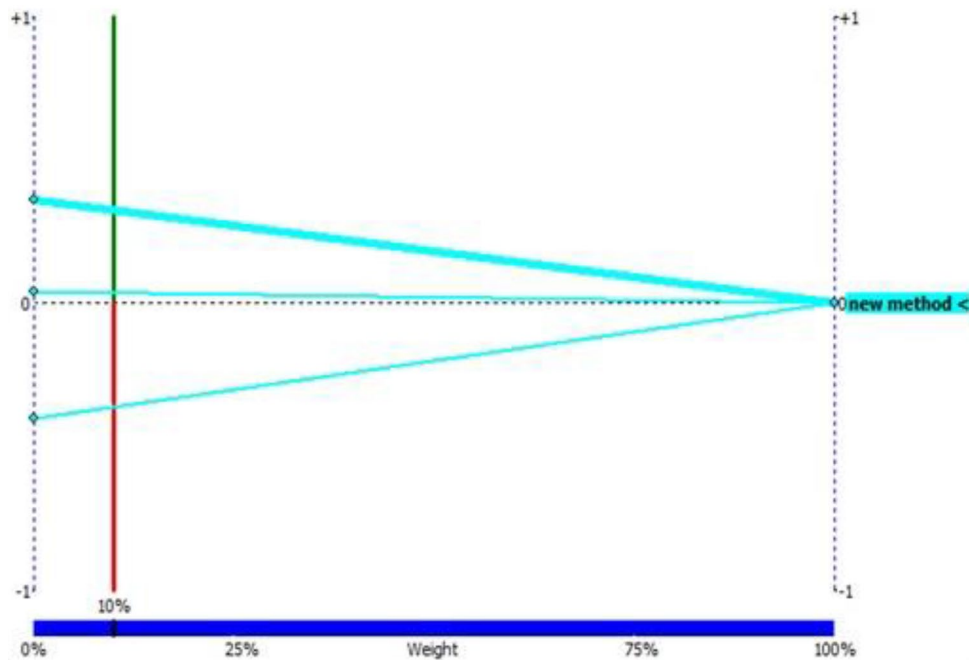
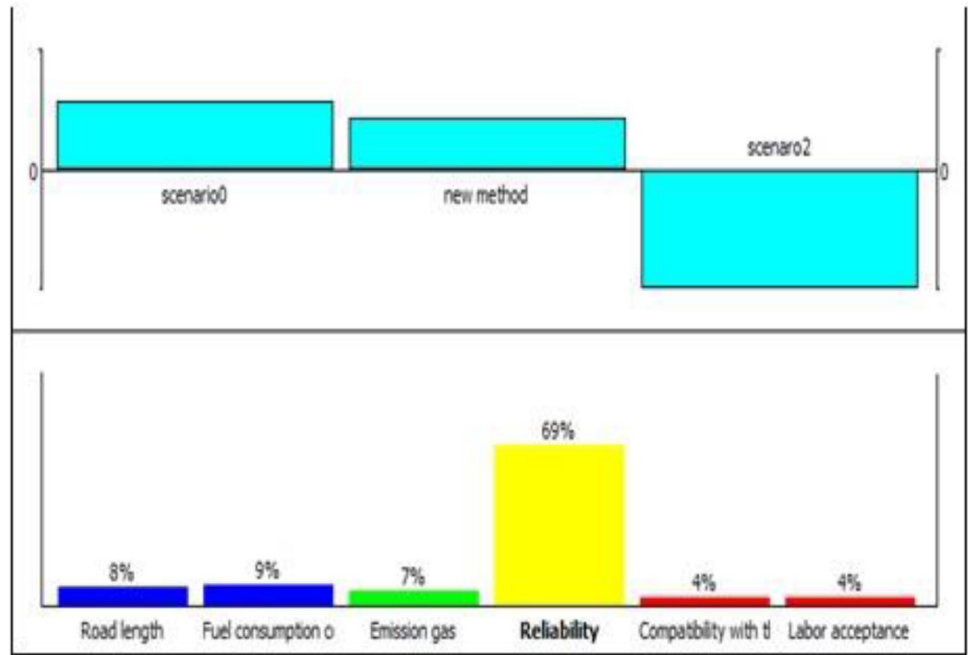**Fig. 16** The weight stability interval for Reliability criterion
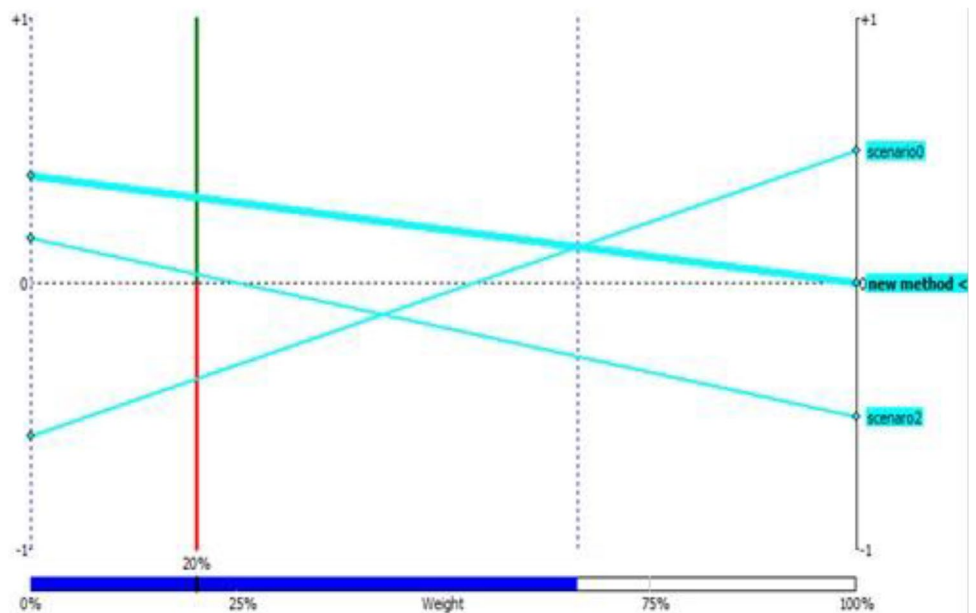
single criterion. At the left edge, the weight of the criterion is equal to 0%. The position of the vertical green and red bar corresponds to the current weight of the criterion. The intersection of the action lines with the vertical bar gives the PROMETHEE complete ranking (see Figs. 16, 17, 18, 19).

It can see that the scores of the Scenario 0 upwards when the weight of the Reliability criterion increases while the scores of Scenario 2 and the new method increase. Again, it affirms that the new method achieves the best results among all.

4 Conclusions

In this paper, we aimed to propose a novel heuristic-based smart routing algorithm for municipal solid waste (MSW) collection. It was implemented in ArcGIS to calculate optimal solutions of the model including routes and total travelling distances and operational time of vehicles. It is capable to represent user settings, such as waste quantity and network constraints, and model locations along an edge, not just on junctions. The new algorithm could take

Fig. 17 The PROMETHEE ranking of scenarios after changing value of Reliability

**Fig. 18** The weight stability interval for the Reliability criterion
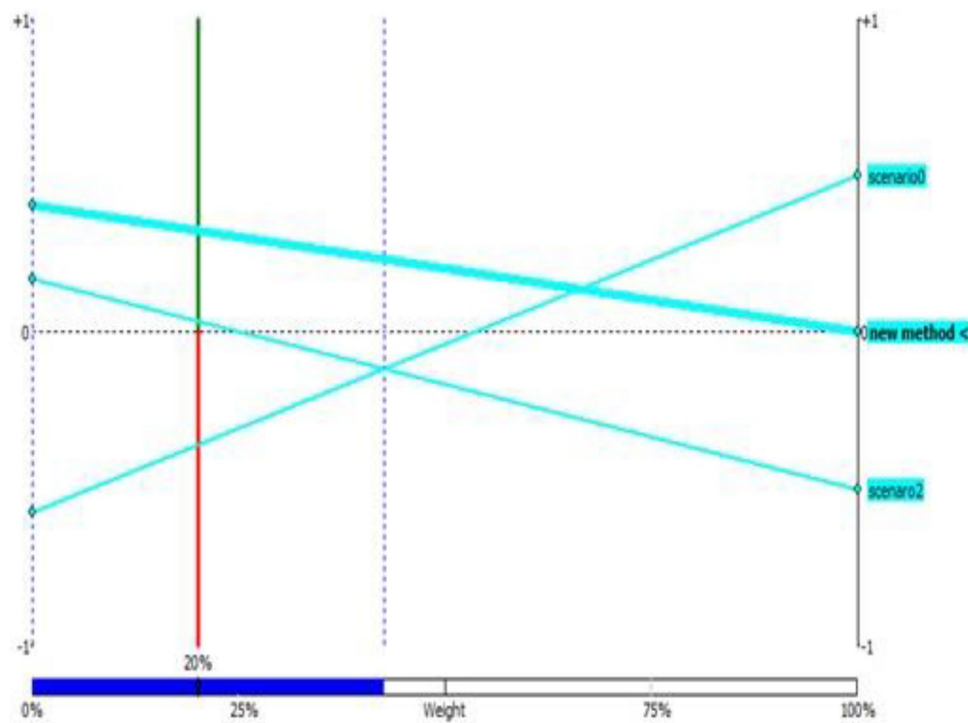
into account constraints of a vehicle routing model and operations of multiple vehicles. The comparison between the original and the new algorithms was given so that one can easily implement it for a specific optimization problem.

In order to illustrate the efficiency of the algorithm, we have investigated a case study of MSW collection in Sfax city, which is the second largest (number of population) city and among the most polluted cities in Tunisia - the Republic located in the North Africa, and resides of 24 regions. Tunisia contains 10.778 habitats and generated 2.423 million tons in 2012 and 0.815 Kg/day per capita MSW generation in the urban areas in 2014. In Tunisia, Sfax has high pollution rate and high quantity of population with 272,801

Fig. 19 The PROMETHEE ranking of scenarios after changing value of Reliability criterion
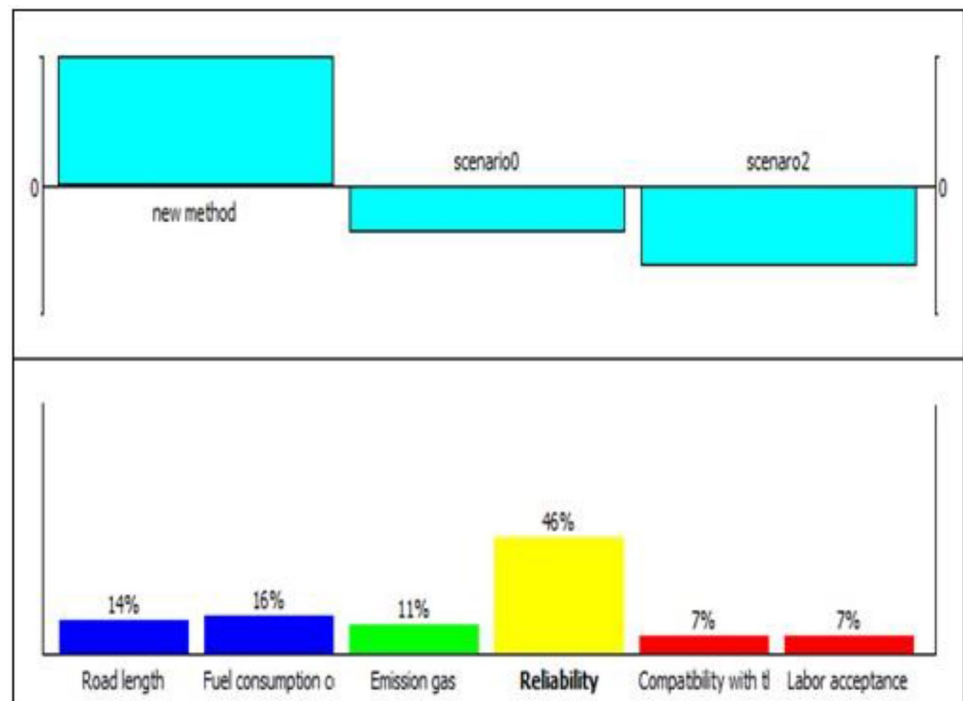
habitats being located in the center city explaining the high average waste quantity (0.702 kg/hab./day). The current MSW collection in Sfax is done manually in the sense that routes of vehicles are not optimized by any method but based solely on the experience of drivers. It was emphasized that using computerized methods to determine optimal routes of vehicles can reduce total travelling distances and operational time. Therefore, we proposed a novel optimization model for the MSW collection based on the current real scenario of waste collection in Sfax, then applied the new smart routing algorithm for MSW collection. All the methodologies have been clearly demonstrated throughout the paper.

The results were compared with those of the practical routes (Scenario 0) and Scenario 2 (implemented in ArcGIS with classical Dijkstra with no new model). They showed that the total distances and operational time of vehicles produced by the new method are 154.6 km and 10.83 h, which are less than those of Scenario 0 (resp. 166.75 km and 14.10 h) and Scenario 2 (resp. 155.2 km and 10.9 h). The experimental results are then analyzed by a multi-criteria decision aid method namely PROMETHEE in terms of environment and economic criteria. PROMETHEE and its graphical complement—GAIA have successfully been applied to many problems in solid waste management research for multi-criteria analysis. It has been demonstrated that the new method has the highest net flow value in PROMETHEE which implies the best results among all in terms of multiple criteria. Sensitivity analysis was performed and affirmed the findings of the paper.

Further works of this study will investigate another improvement of vehicle routing algorithms to get better planning results of the waste collection scenario. The problem of choosing optimal locations of waste bin is also our further direction. Other approaches using information systems (Thanh et al. 2017), picture clustering (Thong and Son 2017; Ngan et al. 2016; Son et al. 2011, 2017; Son and Phong 2016; Phong and Son 2017) are also our target.

Compliance with ethical standards

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