International Journal of Industrial Engineering & Production Research (2018)

March 2019, Volume 30, Number 1
pp. 117- 134

DOI: 10.22068/ijiepr.30.1.117 http://ijiepr.iust.ac.ir/

A Bi-Objective Vehicle Routing Problem with Time Windows Considering Fuel Consumption and Co2 Emission

Hossein Jandaghi, Ali Divsalar* & Mohammad Mahdi Paydar

Hossein Jandaghi, *Department of Industrial Engineering, Babol Noshirvani University of Technology, Babol, Iran.*
Ali Divsalar*, Department of Industrial Engineering, Babol Noshirvani University of Technology, Babol, Iran.*
Mohammad Mahdi Paydar, *Department of Industrial Engineering, Babol Noshirvani University of Technology, Babol, Iran.*

KEYWORDS

Vehicle routing problem;
Time windows;
Fuel consumption;
Co2 emission; ε-constraint;
Environmental impacts.

ABSTRACT

In this research, a new bi-objective routing problem is developed in which a conventional vehicle routing problem with time windows (VRPTW) along with its environmental impacts and heterogeneous vehicles is considered. In this problem, minimization of fuel consumption (liter) as well as reduction of the length of the routes (meter) are the main objectives of this study. Therefore, a mathematical bi-objective model is solved to create Pareto's solutions. The objectives of the proposed mathematical model are to minimize the sum of distance costs as well as fuel consumption and Co2 emission. Then, the proposed Mixed-Integer Linear Program (MILP) is solved using the ε-constraint approach. Furthermore, numerical tests are performed to quantify the benefits of using a comprehensive goal function with two different objectives. Managerial insights and sensitivity analysis are also performed to show how different parameters of the problem affect the computational speed and the solutions' quality.

1. Introduction

Due to the high importance of fuel consumption in transportation costs as well as environmental problems such as air pollution and global warming, in general, transportation companies study several methods to optimize their fuel consumption. Therefore, researchers have also focused on green aspects of routing problems in mathematical modeling. In the literature, various types of vehicle routing problems (VRP) have been studied (Beheshti & Hejazi, 2008; Mehrjerdi, 2008; Yang & Chu, 2013) including the VRP with time windows (VRPTW) (Karimi & Seifi, 2012).

This problem is one of the most popular problems in the field of operation research, which has received much attention in recent years. In the classic model of VRP problem, there is one depot and several points for delivering products to them. There are also several vehicles with different capacity that should deliver products to customers. There is also a time budget limit for VRP problem. The objective function in this problem is to minimize the total distance visited by all vehicles. The VRPTW is a variant of the VRP in which each customer is assigned one or more time windows, and products should be delivered within the customer's corresponding time windows.

However, to the best of our knowledge, this is the first research that studies a bi-objective green VRPTW and considers both travel costs and fuel consumption (CO2 emission) separately in two distinguished objectives. Moreover, in this research, a heterogeneous fleet of vehicles is taken into account. In fact, each vehicle type differs in terms of its speed, capacity, and fuel

* **Corresponding author:** ***Ali Divsalar***

Email: Ali.Divsalar@nit.ac.ir

Received 16 January 2019; revised 03 March 2019; accepted 10 March 2019

consumption properties based on the transported load weight. In the investigated problem, vehicles are assigned to each route according to their load capacity and fuel consumption in different situations (low load, average load, and heavy load).

Sbihi & Eglese (2007) proposed some research directions that link the VRP with green logistics issues, such as the application of the time-dependent VRP as an approach to the minimization of emissions during traveling. Salimifard et al. (2012) reported several publications in which the environmental impacts of transportation were directly taken as an objective function. In their review, they stated that this research topic was still in its beginning phase and, thus, was rather attractive. A survey of the green vehicle routing problem was studied by Lin, Choy et al. (2013). As a result, those papers published after 2014 have been reviewed here. Salimifard & Raeesi (2015) presented a modeling approach to investigate both fuel consumption levels and the utilization of an alternative fuel for the vehicle.

Dabiri, J. et al. (2017) presented a mathematical model for the bi-objective inventory routing problem with a step cost function and developed a multi-objective particle swarm (MOPSO) optimization solution approach to solve instances of this problem. In their study, they presented a new transport cost calculation pattern for the IRP based on some real cases. In this pattern, the transportation cost was calculated as a function of the load carried and the distance traveled by the vehicle based on a step cost function. Furthermore, previous methods usually aggregate the inventory and transportation costs to formulate them as a single-objective function; however, in non-cooperative real-life cases, the inventory-holding costs are paid by retailers, whereas the transportation-related costs are paid by the distributor. In this study, these two cost elements are separated, and a bi-objective IRP formulation is introduced where the first objective is to minimize the inventory-holding cost and the second is to minimize the transportation cost. Wang et al. (2017) presented a bi-objective vehicle routing problem for transportation of hazardous materials, and a two-stage exact algorithm was developed based on the ϵ-constraint method. Their model aims to simultaneously minimize the maximum risk of each vehicle and the transportation cost. Alinaghian et al. (2017) developed a new bi-objective periodic vehicle routing problem with maximization of market share in an uncertain competitive environment. In addition, a multi-objective particle swarm and local MOPSO algorithms were applied to evaluate the algorithm performance, and some samples were generated. They presented a new variant of periodic vehicle routing problem in which the reaching time to the customers affected market share. Thus, there is a competition between distributors to achieve more market share by reaching out to the customers earlier than others; moreover, travel time between every two pairs of customers is uncertain. This situation is called an uncertain competitive environment. For the given problem, a new bi-objective mathematical model, including minimization of total traveled time and maximization of the market share, was presented. Abad et al. (2018) presented a bi-objective model for pickup and delivery pollution-routing problem with integration and consolidation shipments in the cross-docking system. In addition, three multi-objective meta-heuristic algorithms were developed, i.e., non-dominated ranking genetic algorithm (NRGA), non-dominated sorting genetic algorithm (NSGA-II), and multi-objective particle swarm optimization (MOPSO). Hooshmand & MirHassani (2018) presented a novel extension of the vehicle routing problem considering alternative green-fuel powered vehicles in the presence of congestion with the aim of minimizing CO2 emissions, and a hybrid heuristic algorithm, consisting of two phases, was proposed to solve large instances. The first phase decomposes the problem into clustering and routing stages, and the second phase is a simulated annealing framework that attempts to improve the solution obtained by the first phase.

Yi & Bortfeldt (2018) presented the capacitated vehicle routing problem with three-dimensional loading constraints and split delivery. They consider a logistics company that repeatedly has to pick up goods at different sites. Often, the load of one site exceeds the volume capacity of a vehicle. Often, the load of one site exceeds the volume capacity of a vehicle. Therefore, they focus on the 3L-CVRP with split delivery and propose a hybrid algorithm for this problem. It consists of a Tabu search procedure for routing and some packing heuristics with different tasks. One packing heuristic generates packing plans for shuttle tours involving special sites with large-volume sets of goods. Another heuristic cares for packing plans for tours with numerous sites. Behnke et al. (2018) developed an emission-minimizing vehicle routing problem with heterogeneous vehicles and pathway selection. In their article, besides the total distance covered by a transport process, the modal split, payload, traveling speed as well as vehicle type and other specifications are identified as the most influential planning parameters. (De Bruecker, Beliën, De Boeck, De Jaeger & Demeulemeester, 2018) developed a model enhancement approach to optimize the integrated shift scheduling and vehicle routing problem in waste collection, and the solutions not only resulted in considerable saving, but were also proven to be (near-) optimal in comparison with a practical lower bound based on flexible routes. (Affi, Derbel & Jarboui, 2018) presented a variable neighborhood search algorithm for solving the green vehicle routing problem. (Belgin, Karaoglan & Altiparmak, n.d.) presented a two-echelon vehicle routing problem with simultaneous pickup and delivery and developed a heuristic approach. They consider the two-echelon vehicle routing problem with simultaneous pickup and delivery (2E-VRPSPD), which is a variant of the vehicle routing problem. In the 2E-VRPSPD, the pickup and delivery activities are performed simultaneously by the same vehicles through depot to satellites in the first echelon and from satellites to customers in the second echelon. (Hojabri, Gendreau, Potvin & Rousseau, 2018) developed a large neighborhood search with constraint programming for a vehicle routing problem with synchronization constraints, which is an extension of the vehicle routing problem with time windows, where the arrival of two vehicles at different customer locations must be synchronized. A constraint programming-based adaptive large neighborhood search was proposed to solve this problem.

(Liu, Qi & Cheng, 2018) is the closest publication to the current research. They studied a vehicle routing problem in which multiple optional paths were considered between each pair of customers (VRPTW-PF). They proposed a mathematical model for the green VRPTW-PF that took into account the fuel consumption of acceleration and waiting on traffic lights. Their proposed model aims to determine the routes for a heterogeneous fleet of vehicles so that the sum of driver's wage, fuel consumption cost, and emission cost is minimized.

In this research, a bi-objective Green VRPTW with a heterogeneous fleet of vehicles is proposed. To the best of our knowledge, this is the first research in which the green aspects are considered in a multi-objective VRPTW with a heterogeneous fleet of vehicles. Since there are several incompatible goals in most real problems, the green VRPTW is mathematically modeled as a multi-objective mixed integer problem. Some interesting applications can be seen for the proposed problem. For instance, on the one side, imagine a transportation company that is looking for high-capacity vehicles to reduce its cost of transportation. On the other side, the environmental constraints imposed on companies over the years by governments are necessary to follow. This means that a vehicle with less fuel consumption and fewer emissions should be selected. Modeling the problem in a bi-objective way may be a proper option to tackle this situation.

In the following sections, first, a mathematical model for the bi-objective green VRPTW with heterogeneous fleet of vehicles (BO-GVRPTW-HV) is presented. Then, this model is implemented in CPLEX. The Epsilon-constraints method is used to solve the bi-objective model. Afterwards, new benchmark instances are generated, and the solution method is applied to these instances. Various sensitivity analyses are performed, and management insights are presented based on the results.

2. Problem Definition and Mathematical Formulation

In the green bi-objective vehicle routing problem with time windows, the first objective function minimizes travel costs, and the second objective function minimizes both vehicle fuel consumption and CO2 emissions.

The VRPTW is defined on an undirected graph G = (V, A), where V = {0, 1, …, n+1} is the vertex set and A is the arcs set. Both Vertex 0 and Vertex n+1 correspond to the depot, and the set of vertices $N = \{1, 2, ..., n\}$ corresponds to customers. In this graph, a distance c_{ij} is associated with each arc (i, j) ∈ A. Each customer i ∈ N is assigned a service time st_i, a demand d_i, and a time window $[a_i, b_i]$, where a_i and b_i are the earliest time and the latest time to start the service at customer *i*. Thus, a vehicle must wait if it arrives before a_i at customer i. In the case of the depot, $d_0 = 0$, $st_0 = 0$, $a_0 = 0$, and $b_0 = T$, where T is the latest time that a vehicle may return to the depot. A fleet of m vehicles, each with a capacity q_m, is considered. t_{ij} is the travel time between nodes i and j for i,j ∈ V and is equal to $c_{ij} + st_i$. Let s_i be the departure time at customer *i*. x_{ijm} is defined a binary variable and is equal to 1 if the arc (i, j) is traveled in a route by vehicle *m*, and 0 otherwise. v_{ijm} represents the speed of vehicle m when traveling from customer i to customer j. y_{im} represents the load delivered by vehicle m at customer i. It is assumed that the lower and upper bounds of the vehicle speed on each arc are l and u, respectively, and a discrete set of speed levels is defined in between.

2-1. Fuel consumption and Co2 emission

Based on a model by (Barth & Boriboonsomsin, 2009), the fuel consumption for a vehicle of type m and with distance *d* at a speed of v can be calculated using Equation (1).

$$F_m = \lambda\left(\frac{k_m N_m V_m d}{v} + M_m \gamma_m \alpha d + \beta_m \gamma_m d v^2\right) \quad (1)$$

and $\lambda = \varepsilon / (k\psi), \gamma_m = 1/(1000 n_{mtf}\eta), \alpha = \tau + g\sin\theta + gC_r\cos\theta, \beta_m = 0.5C_{dm}\rho A_m$

where M_m is the sum of curb weight and payload (in kg). Other common and special vehicle parameters and description of parameters are mentioned in Tables 1 and 2. Common parameters imply that these parameters are common for all light, medium, and heavy vehicles. However, the special parameters are different for each vehicle type (light, medium, and heavy).

Tab. 1. Common vehicle parameters (Cheng, Yang, Qi & Rousseau, 2017)

Notation	Description	Typical values
ε	Fuel-to-air mass ratio	1
G	Gravitational constant (m/s^2)	9.81
ρ	Air density (kg/m^3)	1.2041
C_r	Coefficient of rolling resistance	0.01
η	Efficiency parameter for diesel engines	0.45
σ	CO2 Emitted by unit fuel consumption (kg/L)	2.669
κ	Heating value of a typical diesel fuel (kj/g)	44
v	Speed (m/s)	--
Ψ	Conversion factor (g/s to L/s)	737
θ	Road angle	0
τ	Acceleration (m/s^2)	0
d	Travel distance (m)	--

Tab. 2. Special vehicle parameters (Cheng et al., 2017)

Notation	Description	Light duty	Medium duty	Heavy duty
w_m	Curb weight (kg)	4672	6328	13154
Q_m	Maximum payload (kg)	2585	5080	17236
k_m	Engine friction factor (kJ/rev/L)	0.25	0.20	0.15
N_m	Engine speed (rev/s)	39	33	30.2
V_m	Engine displacement (L)	2.77	5.00	6.66
A_m	Coefficient of aerodynamics drag	0.6	0.6	0.7
Cd_m	Frontal surface area (m^2)	9.0	9.0	9.8
ntf_m	Vehicle drive train efficiency	0.40	0.45	0.50

2-2. Mathematical formulation

The described problem is formulated as a multi-objective Mixed Integer Problem (MIP). The first objective function minimizes the distance traveled by each vehicle in each path. The second objective function consists of three parts. The first part is related to the engine type and its fuel consumption at different speeds. The second part relates to the weight of the vehicle so that the amount of fuel consumption that depends on the weight of the vehicle is minimized. The third part of the first objective function minimizes fuel consumption based on the engine speed level (See Fig. 1). In this figure, for different speed levels, fuel consumption is shown. As it is shown in this figure, fuel consumption is appropriate for the speed between 20 to 80.

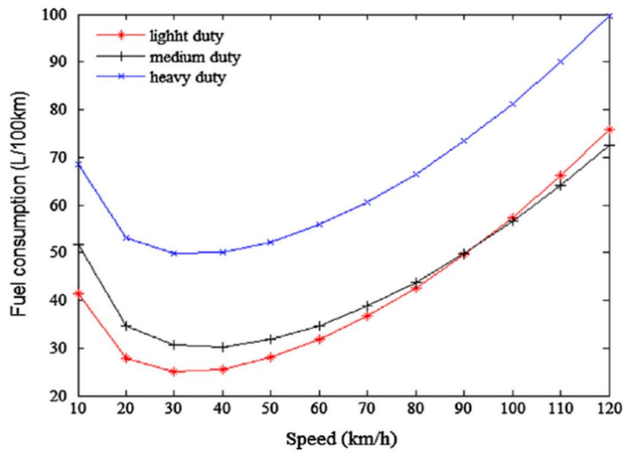


Fig. 1. The fuel consumption of each type of vehicles at different speeds

$$f_1 = \sum_{m\in M}\sum_{i\in V}\sum_{j\in V} c_{ij} x_{ijm} \tag{2.a}$$

$$f_2 = \sum_{i\in V}\sum_{j\in V}\sum_{m\in M} \lambda\left(\frac{x_{ijm} k_m N_m V_m c_{ij}}{v_{ijm}} + (w_m x_{ijm} + \sum_{i\in N} y_{im})\gamma_m \alpha c_{ij} + x_{ijm}\beta_m \gamma_m c_{ij} (v_{ijm})^2\right) \tag{2.b}$$

$$\sum_{j\in N}\sum_{m\in V} x_{ijm} = 1 \;\; \forall i \in N, i \neq 0 \tag{3}$$

$$\sum_{j\in N} x_{ijm} - \sum_{j\in N} x_{jim} = 0 \;\; \forall i \in N, m \in V, i \neq 0 \tag{4}$$

$$s_i + t_{ij} - s_j \leq M(1 - x_{ijm}) \;\; \forall i, j \in N, m \in V, j \neq 0, i \neq j \tag{5}$$

$$a_i \leq s_i \leq b_i \;\; \forall i \in N, m \in V \tag{6}$$

$$y_{im} + d_i - y_{jm} \leq M(1 - x_{ijm}) \;\; \forall i, j \in N, m \in V, i \neq 0, j \neq 0, i \neq j \tag{7}$$

$$y_{im} \leq q_m \;\; \forall i \in N, m \in V \tag{8}$$

$$\sum_{i\in N}\sum_{m\in V} y_{im} \leq \sum_{i\in N} d_i \tag{9}$$

$$y_{im} \leq M \sum_{j\in N} x_{0jm} \;\; \forall i \in N, m \in V \tag{10}$$

$$\sum_{r\in R} z_{ijmr} = x_{ijm} \;\; \forall i, j \in N, m \in V \tag{11}$$

$$x_{iim} = 0 \;\; \forall i \in N, m \in V \tag{12}$$

$$x_{ijm} \in \{0,1\}, \; \forall i, j \in N, m \in V \tag{13}$$

$$z_{ijmr} \in \{0,1\}, \; \forall i, j \in N, m \in V, r \in R \tag{14}$$

$$s_i \geq 0, \; \forall i \in N \tag{15}$$

$$y_{im} \geq 0, \; \forall i \in N, m \in V \tag{16}$$

In this mathematical model, the first objective function (2.a) minimizes the total distance. The objective function (2.b) minimizes he fuel consumption and CO2 emission. Constraints (3) guarantee that each customer is served by exactly one vehicle. Constraints (4) are flow conservation equations that enforce route continuity so that the constructed routes are tours (loops) rather than open paths. Constraints (5) and (6) are time windows constraints, and ensure that the vehicle reaches out to a customer at the pre-defined time windows of that customer. Constraints (7) ensure that the load delivered to customers does not exceed customer demand. Constraints (8) are vehicle capacity constraints. Constraint (9) ensures that the total delivered load is less than the total demand. Constraints (10) ensure that if only a tour starts from depot point, then load can be delivered to customers. Constraints (11) have the role of correlations between x_{ijm} and z_{ij}^{mr} used for linearization. Constraints (12) ensure that no point is connected to itself. Constraints (13) to (16) are variables' definition.

2-3. Linearization

The second objective function (2.b) includes a nonlinear term. The linearization procedure proposed by (Demir, Bektaş & Laporte, 2012) is used to linearize the equation through the discretization of the speed variable, v_{ijm}. It is assumed that the lower and upper bounds of the speed of a vehicle on each arc are l and u, respectively. Then, a set of speed levels $R = \{1,..,r\}$ is defined in which r is the number of speed levels. Each $r \in R$ for a given arc (i,j) corresponds to a speed interval $[l_r, u_r]$ with $l_l = 1$ and $u_{|R|} = u$. Next, the average speed is computed as $\bar{v}_r = (l_r + u_r)/2$ for each speed level $r \in R$. A binary variable z_{ijmr} has been introduced. z_{ijmr} equals 1 if vehicle type m travels at speed level r on arc (i,j), and 0 otherwise. Therefore, z_{ijmr} and x_{ijm} are linked using Equation (11). The linear function is as follows:

$$f_2 = \sum_{i \in V} \sum_{j \in V} \sum_{m \in M} \sum_{t \in T} \lambda \left(\sum_{r \in \Re} \frac{k_m N_m V_m c_{ij}}{\bar{v}_r} + (w_m x_{ijm} + \sum_{i \in N} y_{im}) \gamma_m \alpha c_{ij} + \beta_m \gamma_m c_{ij} (\sum_{r \in \Re} (\bar{v}_r)^2 z_{ijmr}) \right) \tag{17}$$

3. Solution Approach

For the proposed bi-objective model, the ε -constraint approach is applied to solve the instances of the problem. In this method, the goal is to minimize one objective, say $f_i(x)$, subject to additional constraints $f_i(x) \le \varepsilon_j$ for all $j \ne i$ and some $\varepsilon_j \ge 0$. ε_j represents the `worst' value that f_j may take. This method is known for its simple implementation. It has been shown that if the solution to the ε -constraint is unique, then it is efficient (Marler & Arora, 2004). One issue with this approach is that it is necessary to pre-select ε_j values and, also, which objective to minimize. This is problematic since there will be no feasible solution for many values of ε. The solution space concept is shown in Fig. 2. In this figure, the ideal point is the intersection of the best value for the first function and the best value for the second function. The worst point is the intersection of the worst value for the first function and the worst value for the second function. Nadir points are feasible points in which either of the first or second objective function is optimal. Pareto optimal front is a state that is impossible to reallocate so as to make any one individual or preference criterion better off without making at least one individual or preference criterion worse off.

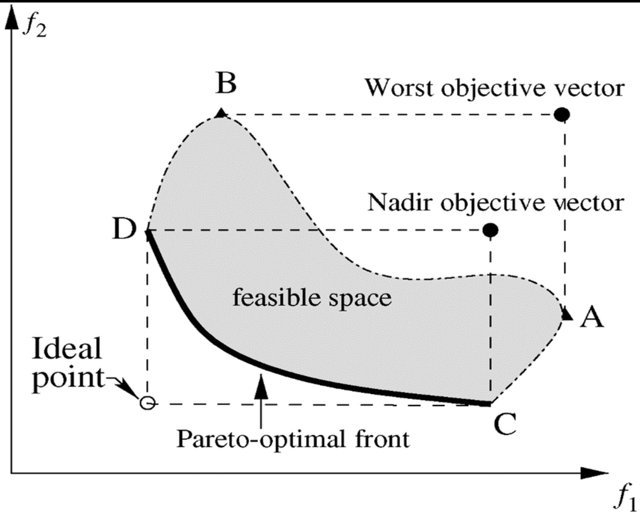


Fig. 2 An example of feasible space and Pareto optimal front

4. Computational Analyses

This section is divided into three sub-sections. Since the proposed problem has not been investigated before, there are no test instances of the problem available in the literature; in the first sub-section, it is described how new test instances are generated. Then, in the second sub-section, these generated instances are used to verify the proposed solution method and, then, the results are discussed. The last sub-section contains sensitivity analysis on various parameters and parts of the model.

4-1. Data instances

In general, two test instances are explained and discussed in the rest of the paper. These instances are generated based on the Solomon instance sets from the literature (Solomon, 1987). In these instances, the distance between every two nodes is computed as $d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$, where (x_i, y_i) are the coordinates of vertex i. The lower and upper bounds of the speed for each type of vehicle are set as 20 km/h and 70 km/h, respectively. In total, 5 speed levels are defined, meaning that the speed value may be among one of the 5 intervals (i.e., [20, 30], [30, 40], [40, 50], [50, 60], [60, 70]). Vehicles may also have different capacities: 20, 30, and 40 for light duty, medium duty, and heavy duty, respectively. Data related to Instance 1 with 10 customers are shown in Table 3. Moreover, the related data of a larger example with 15 customers (Instance 2) are presented in Table 4.

Tab. 3. Data instance for 10 customers

i	XCoord	YCoord	Demand	LBTW	UBTW	Service Time
0	35	35	0	0	230	0
1	41	49	10	0	204	10
2	35	17	7	0	202	10
3	55	45	13	0	197	10
4	55	20	19	139	169	10
5	15	30	26	0	199	10
6	25	30	3	89	119	10
7	20	50	5	0	198	10
8	10	43	9	85	115	10
9	55	60	16	87	117	10
10	30	60	16	114	144	10

Tab. 4. Data instance for 15 customers

i	XCoord	YCoord	Demand	LBTW	UBTW	Service Time
0	35	35	0	0	230	0
1	41	49	10	0	204	10
2	35	17	7	0	202	10
3	55	45	13	0	197	10
4	55	20	19	139	169	10
5	15	30	26	0	199	10
6	25	30	3	89	119	10
7	20	50	5	0	198	10
8	10	43	9	85	115	10
9	55	60	16	87	117	10
10	30	60	16	114	144	10
11	20	65	12	57	87	10
12	50	35	19	0	205	10
13	30	25	23	149	179	10
14	15	10	20	32	62	10
15	30	5	8	51	81	10

4-2. Implementation

The proposed method is programmed in CPLEX 12.6 with a PC equipped with dual core 2GHz CPU and 4 GB RAM. Results of applying the solution method to the first example (Tables 3) are presented and discussed in Tables 5 and 6 as well as Figs. 3-7. To implement the ε - constraint approach, the first objective function of the model remained as the objective function, and the second function was used as an additional constraint in the form of $f_2 \leq \varepsilon$. The obtained best and worst values of each objective function are shown in Table 5. Then, based on the achieved intervals, various ε values have been tested to create a Pareto set. These ε values are shown in Table 6. Fig. 3 shows how the change in ε value has an impact on the running time. For this example, the maximum running time occurring for epsilon equals 388. Furthermore, the Pareto solutions for this example are shown in Fig. 4.

Tab. 5. The best and worst values of functions for Example 1

best f1	236.056	best f2	386.049
nadir f1	434.722	nadir f2	442.139
Interval 1	198.666	Interval 2	56.09

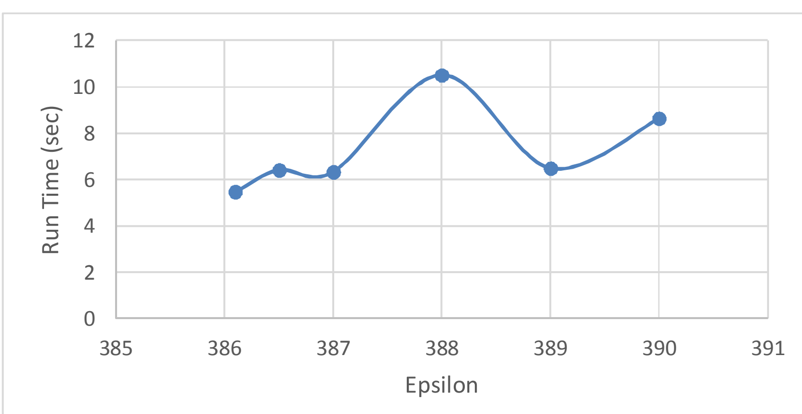


Fig. 3. Chart of run time change versus Epsilon for Example 1

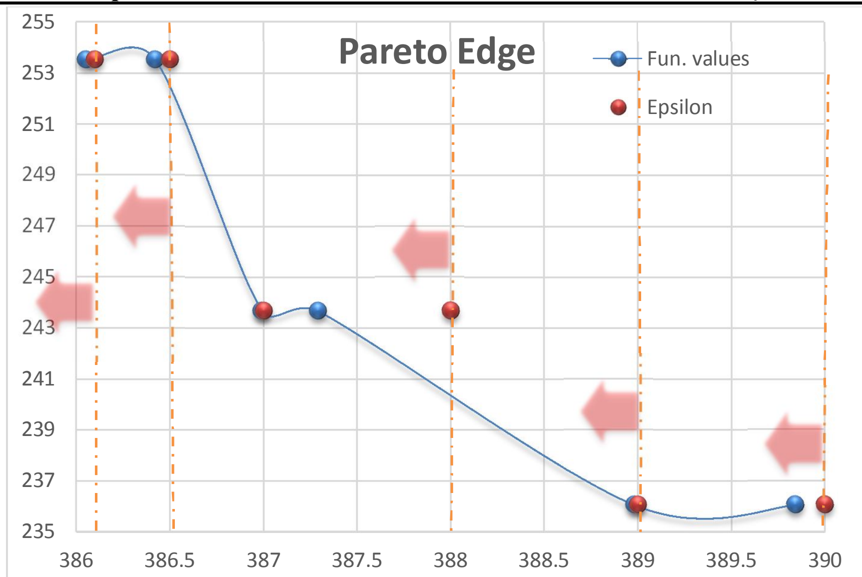


Fig. 4. **Pareto edge for example 1**

Tab. 6. Various epsilons and value functions for Example 1

epsilon	z2	z1	Run Time (sec)
386.1	386.05	253.509	5.47
386.5	386.42	253.509	6.42
387	386.99	243.667	6.33
388	387.29	243.667	10.51
389	388.98	236.056	6.49
390	389.84	236.056	8.64

The type of vehicles is assigned to each route when only the first function considered is shown in Fig. 5, indicating that vehicle type 2 is selected and 3 routes are considered, too. Therefore, only Function 1 is considered, and the mathematical model seeks the best route and, also, responds to demands, thus making this solution rational. Furthermore, as shown in Fig. 6, when only the second objective function is considered, the mathematical model seeks the minimum of CO2 emission; thus, the vehicle with lower emission is selected. Finally, as shown in Fig. 7, when two-objective models are considered and epsilon is 387, both route and CO2 emission are optimized, and the vehicle with low emission is selected and route distance is minimized.

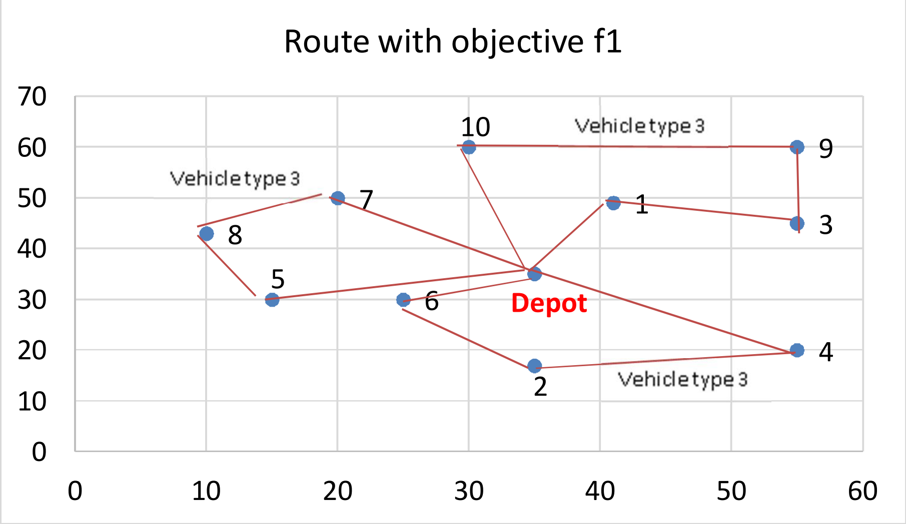


Fig. 5. **Vehicle route with objective f1 for Example 1**

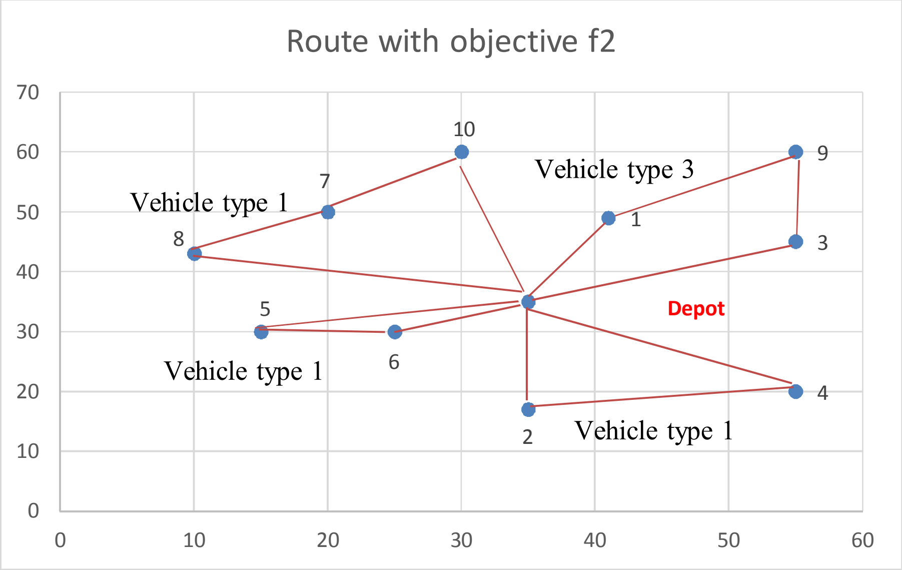


Fig. 6. **Vehicle route with objective f2 for Example 1**

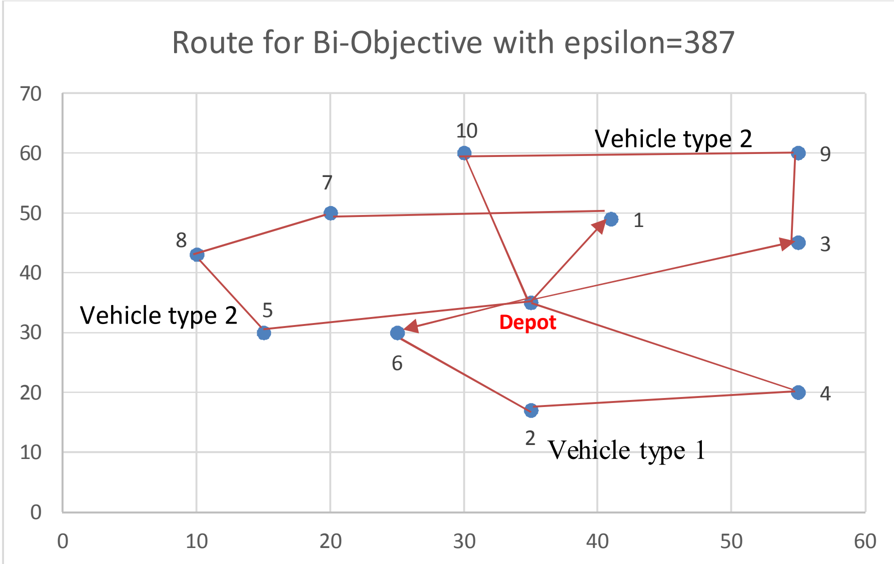


Fig. 7. Vehicle route with Bi-objective for example 1

To clarify the impact of modeling the problem as a bi-objective model rather than a single-objective version, a larger instance is used in this section for sensitivity analyses. The number of nodes in this example is 15, and other parameters are constructed in the same way as explained for Example 1 and are presented in Table 4. The experiments performed for Example 1 were executed similar to Example 2, and the best and worst values of objective functions, various epsilons, and value functions are shown in Tables 7 and 8, respectively. The results of the comparison of run time change versus Epsilon, Pareto Edge, vehicle route with objective f1, vehicle route with objective f2 and vehicle route with Bi-objective are shown in Figs. 8 to 12, respectively.

Tab. 7. The best and the worst values of functions for Example 2

best f1	343.381	best f2	892.662
runtime	41 min	runtime	23 min
nadir f1	428.324	nadir f2	1139.102
runtime	38 min	runtime	21 min
Interval 1	84.943	Interval 2	246.44

Tab. 8. Various epsilons and value functions for Example 2

epsilon	z2	z1	Run Time (sec)
344	895.22	343.38	3822
346	894.47	345.78	2883
350	893.94	346.49	1995
360	893.81	358.08	2861
370	893.02	368.15	1833
380	892.66	374.74	1296

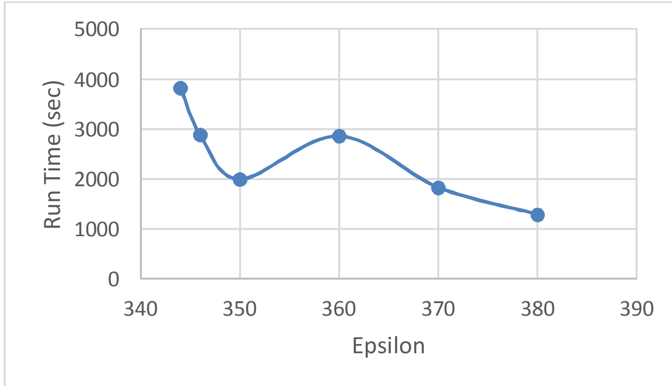
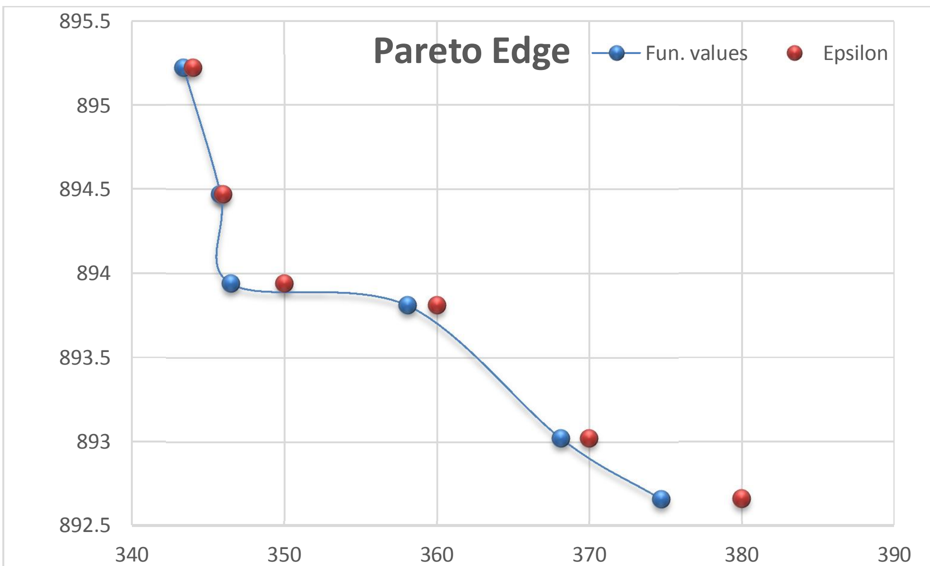


Fig. 8. Chart of run time change versus Epsilon for Example 2



Tab. 9. Various epsilons and value functions for Example 2

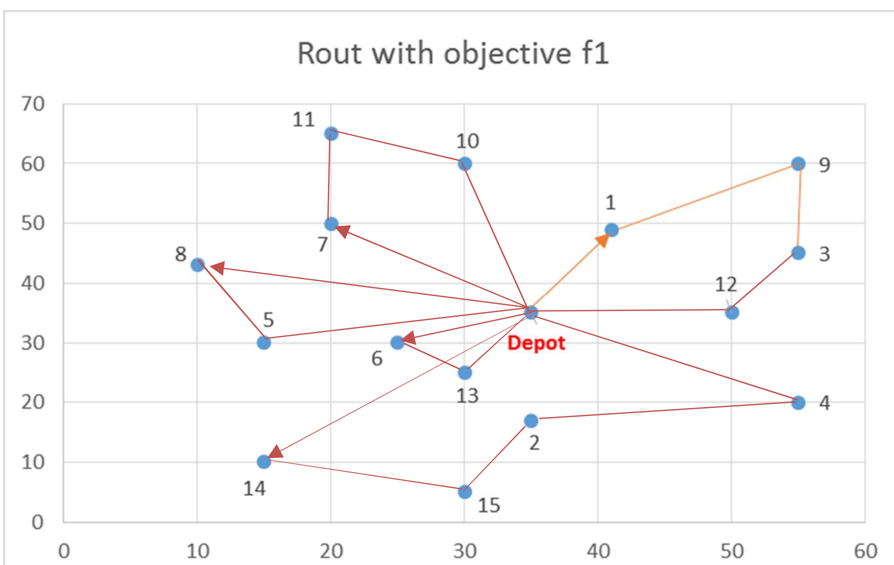


Fig. 10. Vehicle route with objective f1 for Example 2

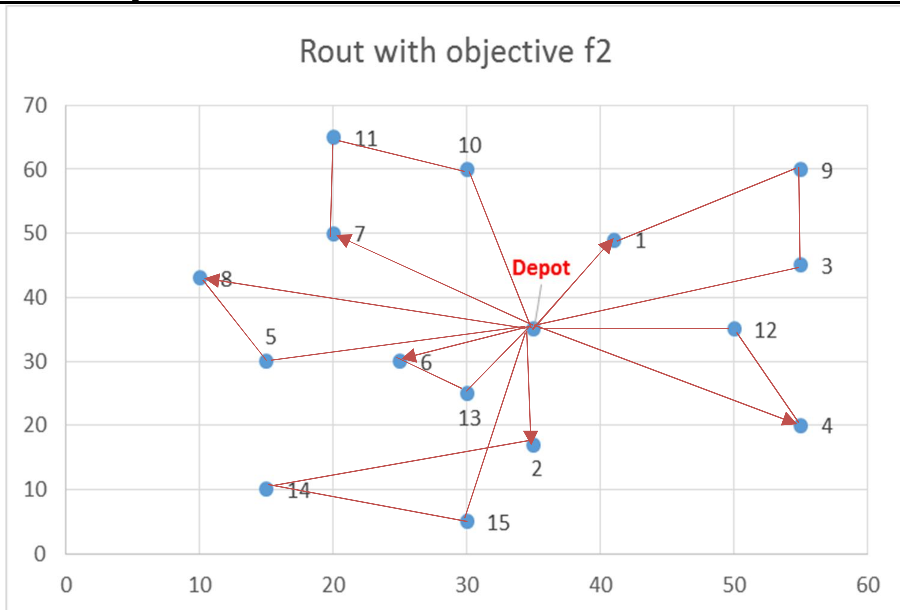


Fig. 11. Vehicle route with objective f2 for Example 2

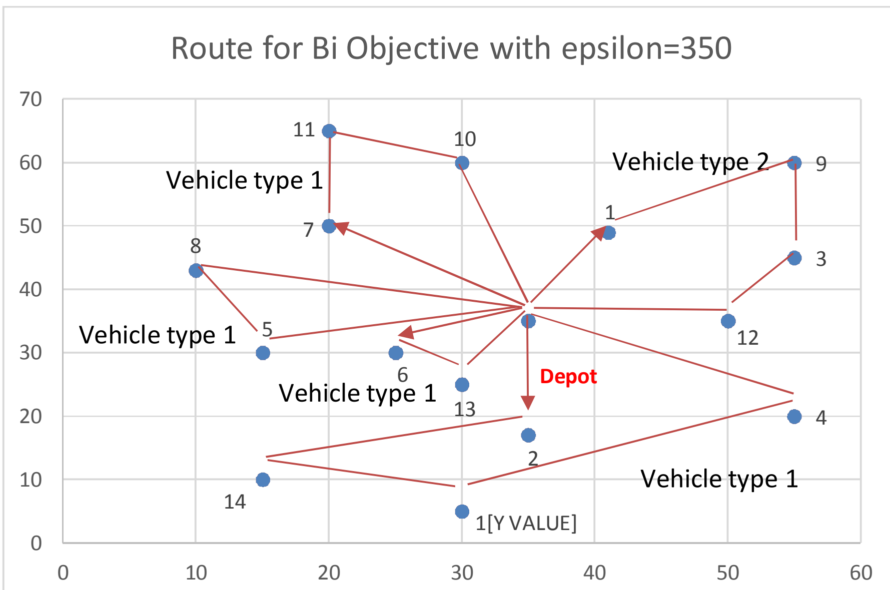


Fig. 12. Vehicle route for bi-objective for Example 2

4-3. Sensitivity analyses

In this section, some sensitivity analyses on key parameters of the model, including speed level, vehicle capacity, and curb weight, are performed. Then, the effects of changing each parameter on the objective values as well as the computational time are investigated.

As indicated in Section 4.1, the speed levels of each vehicle are considered among one of the intervals: [20, 30], [30, 40], [40, 50], [50, 60], [60, 70]. Furthermore, 3 other speed levels with different speed intervals are tested as follows:

[50, 55], [55, 60], [60, 65 [65, 70 [70, 75] and speed interval= 5

[40, 50], [50, 60], [60, 70], [70, 80], [80, 90] and speed interval= 10

[20, 35], [35, 50], [50, 65], [65, 80], [80, 95] and speed interval= 15

Results of the speed level sensitivity analyses are shown in Table 9. In this table, an interval represents the difference between each speed level (for example, the interval for speed level 2= 55-50=65-55=…=75-70=5). Furthermore, lower-upper column shows the minimum and maximum speeds at each speed level.

Tab. 9. Result of speed level sensitivity analyses

No.	interval	Lower-upper	objective value	runtime (ms)
1	10	20 - 70	386.9	550.33
2	5	50 - 75	395.2	500.45
3	10	40 - 90	390.9	400.57
4	15	20 - 95	384.86	360.16

Fig. 13 shows the change of each objective value and runtime for different values of the speed levels. At a speed level of 4 and an interval of 15 as well as the minimum and maximum speeds of 20 and 95, the best objective value is achieved.

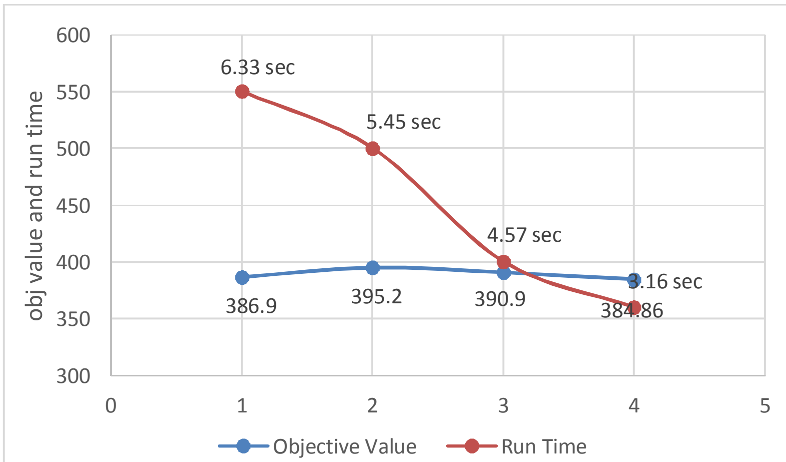


Fig. 13. changes of objective value and runtime for different values of speed level

Furthermore, another sensitivity analysis is performed on the impact of the vehicle capacity on the solution quality. For the above-mentioned example, vehicle capacity was considered 20, 30, and 40 for light duty, medium duty, and heavy duty, respectively. In this section, other vehicle capacities are also tested: (30, 40, 50), (20, 40, 60), and (25, 50, 75). The result of this analysis is shown in Table 10. In this table, the column interval is the difference between load duties in a row (light duty, medium duty, and heavy duty).

Tab. 10. Sensitivity analysis results of vehicle capacity

No.	light duty	medium duty	heavy duty	interval	Objective value	runtime
1	5	8	11	3	387.6	1.98
2	5	10	15	5	386.8	1.88
3	20	30	40	10	386.9	6.33
4	20	35	50	15	384.8	4.24
5	20	40	60	20	384.8	3.94

In Fig. 14, objective value and run time for each capacity interval are shown. The maximum run time is 6.33 sec and is related to vehicle capacity 10. This chart shows that, for vehicle capacity 10, run time is the highest, while this value of vehicle capacity is sensitive to run time. Furthermore, the objective value in this figure shows the best value for vehicle capacity with respect to the objective value, and it can be obtained with vehicle capacity between 15 and 20.

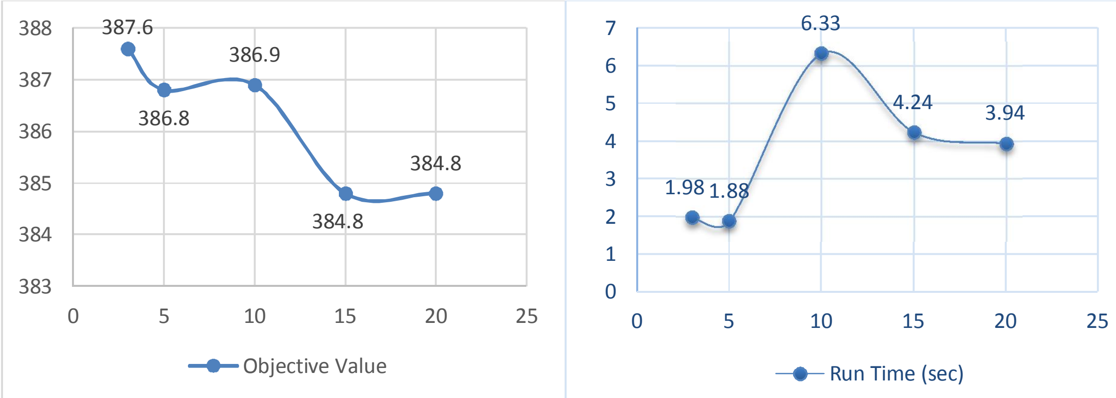


Fig. 14. Changes of objective value and runtime with respect to different vehicle capacities

Another sensitivity analysis is performed on the impact of curb weight (kg) on the solution quality. Two changes in the curb weight are tested. In the first case, the curb weight – 30% decreases. In the second case, the curb weight 30% increases. The reason behind this analysis is that the curb weight may affect fuel consumption and CO2 emission. In general, as the curb weight decreases, emissions also decrease. The result of this analysis is shown in Table 11. Columns' light duty, medium duty, and heavy duty are the curb weights in each case. The column% change is the difference between each curb weight with respect to Row 2 of the table. Furthermore, %gap is calculated using Equation (18).

$$\%gap = \frac{|\text{ obj value row 2 (base)-}obj\text{ value(with \%change)}|}{\text{obj value row 2 (base)}} \quad (18)$$

For example, $\%gap = \frac{386.9 - 384.4}{386.9} = -0.65\%$.

Tab. 11 Result of curb weight sensitivity analyses

No.	% change	light duty	medium duty	heavy duty	objective value	runtime	gap %
1	-30	3270	4430	9207	384.4	20.99	-0.65
2	0	4672	6328	13154	386.9	60.33	0
3	30	6074	8226	17100	391.4	10.93	1.17

The curb weight analysis is also presented in Fig. 15. In this chart, the minimum objective value is 384.4 and occurs for -30% change in curb weight. Of note, by decreasing the curb weight by 30%, the objective value gap is 0.065%; however, by increasing the curb weight by 30%, the objective value gap is 1.17%, which means that the objective values are more sensitive to increasing the curb weight than decreasing it.

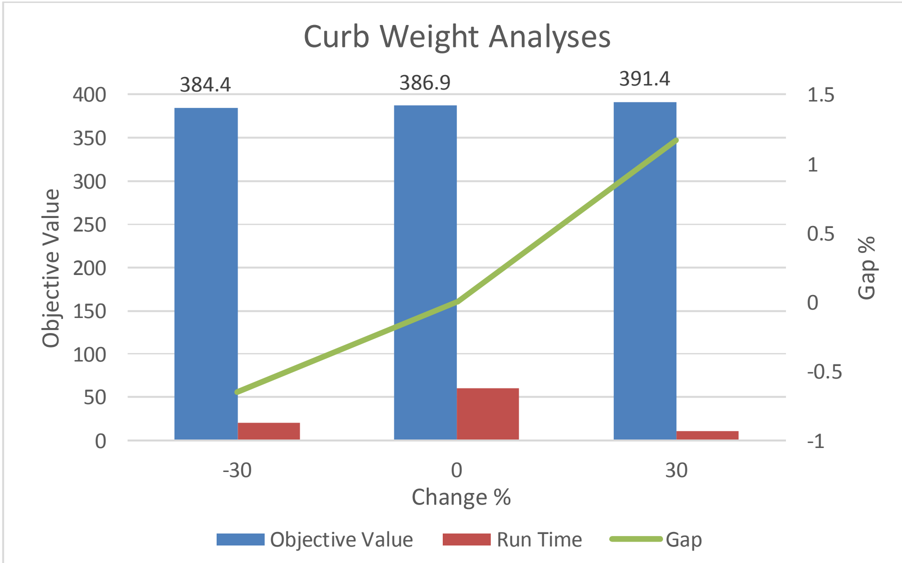


Fig. 14. Curb weight sensitivity analyses

5. Conclusion

One of the most important issues in the transportation industry is the vehicle routing and scheduling while satisfying time availability of customers. Moreover, with respect to global warming and increasing fuel consumption next to the environmental organization's pressure on transportation industries, it is inevitable to consider the environmental aspects in any quality planning. For this reason, in this research, a mathematical model was developed that considered both of the mentioned aspects, simultaneously. In Fact, green aspects were added to the conventional vehicle routing problem with time windows (VRPTW). Two objective functions presented in this article were incompatible, meaning that decreasing one objective caused an increase in another objective. Therefore, the problem was modeled as a bi-objective VRPTW. Two instances of the problem were constructed and used to verify both the model and solution strategy. The Pareto set was found for each instance and was shown how each objective function might affect the other objective function. Vehicle routs were shown for different situations in terms of objective functions. It is illustrated how vehicle routes change in the case of considering each objective function individually as well as considering the bi-objective model. If a company intends to consider environmental aspects, what type of vehicle to use in a vehicle route should be decided. Furthermore, many sensitivity analyses were performed, and management insights were discussed. Changes of objective value and runtime for different values of speed level were analyzed, and it was shown what speed level would give us the best objective value. Vehicle capacity was also used in the sensitivity analysis of the model, and the best capacity that caused the best objective value was tested. Another analysis was performed on the curb weight and its effect on the objective values. Because of the complexity, future research may develop a metaheuristic solution approach to tackle larger instances of the problem. Furthermore, the proposed green objective function in this research can be used in other variants of vehicle routing problems.

References

[1] Abad, H. K. E., Vahdani, B., Sharifi, M., & Etebari, F., "A bi-objective model for pickup and delivery pollution-routing problem with integration and consolidation shipments in cross-docking system. *Journal of Cleaner Production,* Vol. 193, (2018), pp. 784-801.

[2] Affi, M., Derbel, H., & Jarboui, B., "Variable neighborhood search algorithm for the green vehicle routing problem". *International Journal of Industrial Engineering Computations*, Vol. 9, No. 2, (2018), pp. 195–204.

[3] Alinaghian, M., Ghazanfari, M., & Hamedani, S. G., "A new bi-objective periodic vehicle routing problem with

maximization market share in an uncertain competitive". *Computational and Applied Mathematics*, Vol. 17, (2017), pp. 1-23.

[4] Barth, M., & Boriboonsomsin, K. "Energy and Emissions Impacts of a Freeway-Based Dynamic Eco-Driving System". *Transportation Research Part D: Transport and Environment,* Vol. 14, No. 6, (2009), pp. 400-410.

[5] Beheshti, A. K., & Hejazi, S. R., "A Quantum Evolutionary Algorithm for the Vehicle Routing Problem with Delivery Time Cost We consider the Vehicle Routing Problem with Delivery Time Cost", International Journal of Industrial Engineering and Production Research Vol. 25, No. 4, (2014), pp. 287-295.

[6] Behnke, M., Kirschstein, T., & Bierwirth, C., "An Emission-Minimizing Vehicle Routing Problem with Heterogeneous Vehicles and Pathway Selection", Operations Research Proceedings, (2018), pp. 285–291.

[7] Belgin, O., Karaoglan, I., & Altiparmak, F., "Two-echelon vehicle routing problem with simultaneous pickup and delivery: Mathematical model and heuristic approach". Computers & Industrial Engineering, Computers & Industrial Engineering, Vol. 115, (2018), pp. 1-16.

[8] Cheng, C., Yang, P., Qi, M., & Rousseau, L. M., "Modeling a green inventory routing problem with a heterogeneous fleet". *Transportation Research Part E: Logistics and Transportation Review*, Vol. 97, (2017), pp. 97–112.

[9] Dabiri, N., J. Tarokh, M., & Alinaghian, M., "New mathematical model for the bi-objective inventory routing problem with a step cost function: A multi-objective particle swarm optimization solution approach", *Applied Mathematical Modelling,* Vol. 49, (2017), pp. 302-318.

[10] De Bruecker, P., Beliën, J., De Boeck, L., De Jaeger, S., & Demeulemeester, E., "A model enhancement approach for optimizing the integrated shift scheduling and vehicle routing problem in waste collection". *European Journal of Operational Research*, Vol. 266, No. 1, (2018), pp. 278–290.

[11] Demir, E., Bektaş, T., & Laporte, G., "An Adaptive Large Neighborhood Search Heuristic for the Pollution-Routing Problem". *European Journal Of Operational Research,* Vol. 223, No. 2, (2012), pp. 346-359 .

[12] Hojabri, H., Gendreau, M., Potvin, J. Y., & Rousseau, L. M., "Large Neighborhood Search with Constraint Programming for a Vehicle Routing Problem with Synchronization Constraints". *Computers and Operations Research,* Vol. 92, (2018), pp. 87-97.

[13] Hooshmand, F., & MirHassani, S. A., "Time dependent green VRP with alternative fuel powered vehicles". *Energy Systems journal*, (2018), pp. 1–36.

[14] Karimi, H., & Seifi, A., "Acceleration of Lagrangian Method for the Vehicle Routing Problem with Time Windows". *International Journal of Industrial Engineering & Production Research*, Vol. 23, No. 4, (2012), pp. 309-315.

[15] Lin, C., Choy, K. L., Ho, G. T. S., Chung, S. H., & Lam, H. Y., "Survey of Green Vehicle Routing Problem: Past and future trends". *Expert Systems with Applications,* Vol. 41, No. 4, (2014), pp. 1118-1138 .

[16] Liu, X., Qi, M., & Cheng, C., "Green Vehicle Routing Problem with Path Flexibility". In *IEEE International Conference on Industrial Engineering and Engineering Management*. (2017), pp. 1037-1041.

[17] Marler, R. T., & Arora, J. S., "Survey of multi-objective optimization methods for

engineering". *Structural and Multidisciplinary Optimization*, Vol. 26, No. 6, (2004), pp. 369–395.

[18] Mehrjerdi, Y. Z. Y., "Stochastic Approach to Vehicle Routing Problem: Development and Theories". *International Journal of Industrial Engineering*, Vol. 24, No. 4, (2013), pp. 285-295.

[19] Salimifard, K., & Raeesi, R., "A green routing problem: Optimising CO2 emissions and costs from a bi-fuel vehicle fleet". *International Journal of Advanced Operations Management,* Vol. 6, No. 1, (2015), pp. 27-57.

[20] Salimifard, K., & Shahbandarzadeh, H & Raeesi, R., "Green Transportation and the Role of Operation Research". In *Proceedings of 2012 International Conference on Traffic and Transportation Engineering*. Vol. 26, (2012), pp. 74-79.

[21] Sbihi, A., & Eglese, R. W., "Combinatorial optimization and Green Logistics". *4OR Journal*, Vol. 5, No. 2, (2007), pp 99–116.

[22] Solomon, M. M., "Algorithms for the Vehicle Routing and Scheduling Problems with Time Window Constraints". *Operations Research*, Vol. 35, (1987), pp. 254–265.

[23] Wang, N., Zhang, M., Che, A., & Jiang, B., "Bi-Objective Vehicle Routing for Hazardous Materials Transportation With No Vehicles Travelling in Echelon". *IEEE Transactions on Intelligent Transportation Systems,* Vol. 19, No. 6, (2018), pp. 1867-1879.

[24] Yang, W.-T., & Chu, L.-C., "A heuristic algorithm for the multi-depot periodic vehicle routing problem". *Journal of Information and Optimization Sciences*, Vol. 21, No. 3, (2013), pp. 359–367.

[25] Yi, J., & Bortfeldt, A., "The Capacitated Vehicle Routing Problem with Three-Dimensional Loading Constraints and Split Delivery—A Case Study". *Operations Research Proceedings (GOR (Gesellschaft Für Operations Research e.V.)), Cham*, (2018), pp. 351-356.

Follow This Article at The Following Site:

Jandaghi H, Divsalar A., Paydar M. M., A Bi-Objective Vehicle Routing Problem with Time Windows Considering Fuel Consumption and Co2 Emission. IJIEPR. 2019; 30 (1) :117-134
URL: http://ijiepr.iust.ac.ir/article-1-878-en.html