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Presenting the Mathematical Model of Vehicle Routing Considering the Time Window and Customer Clustering using a Meta-Heuristic Algorithm

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Abstract

This research discusses the multi-objective modeling of vehicle routing by considering time windows, traffic conditions and customer clustering in mbazar online stores. Considering the traffic situation of Tehran city and the necessity of timely delivery of goods to customers, especially customers, it is necessary to consider the amount of traffic in the route of store vehicles. This research presents a two-objective model for the vehicle routing problem by considering priority time windows, traffic conditions, and customer clustering. The first objective is minimizing the transportation fleet costs and the second is maximizing customer satisfaction. The relevant indices have been calculated, and acceptable results have been obtained to compare the weed algorithm with the exact solution method of the mathematical model. Finally, a sensitivity analysis shows changes in the objective functions. According to the obtained results, with the increase in average dissatisfaction, the value of the first objective function is constant, but the value of the second objective function has increased. There has really been a lot of dissatisfaction.

Keywords: Routing, Time Window, Clustering, Invasive Weed, Customer Satisfaction.

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1. Introduction

The vehicle routing problem (VRP) is one of the most critical problems in goods distribution. Optimizing vehicle routing will reduce costs and improve the quality of service to customers. The problem of vehicle routing was raised by Danzig and Ramser in 1959 (Rezaei et al., 2021). Among the applications of the vehicle routing problem, we can mention the collection of domestic and industrial waste, service routing for schools, employees, and academics, bank, and postal transfers, transfer of blood samples from medical institutions to laboratories, newspaper distribution, restaurant services, the movement of robots and cranes, and the distribution of factory products between wholesalers and retailers. In practice, various side limitations and assumptions have led to the development of the vehicle routing problem and the formation of new models (Najati et al., 2017; Asgharizadeh et al. 2022). In today's competitive world, the routing of vehicles and the proper timing of delivering orders to customers are very important. The vehicle routing problem tries to work with mathematical models and optimization so that the distance traveled, the total travel time, the number of vehicles, late fines, and finally, the transportation cost function are minimized. Ultimately, customer satisfaction should be maximized (Hosseinzadeh lotfi et al., 2016; Ashoka and Keihani, 2020). A fundamental step in formulating and implementing the strategy of commercial enterprises has been customer segmentation for a long time because it provides the possibility of gaining more and better knowledge of customers. Based on customer segmentation (clustering), suitable strategies for keeping current customers and attracting new customers can be formulated to prevent the loss of customers, which is one of the major concerns of companies, and to gain more market share, which itself is an essential indicator of competitive advantage (Nozari et al., 2016; Mehrani et al. 2019, Bathaee et al., 2023, Aliahmadi et al., 2013, Nozari & Ghahremani-Nahr, 2023).

Based on the cases mentioned above, this research presents a dual-objective model for the vehicle routing problem by considering priority time windows, traffic conditions, and customer clustering. The goal is to minimize the costs of the transportation fleet and maximize customer satisfaction. Because the problem is NP-hard, and since the research model includes two objectives, multi-objective meta-innovative algorithms are used to solve it, which will be briefly explained in the following. When an optimization problem includes more than one objective function, the search operation to find optimal solutions is called multi-objective optimization. Such search and optimization problems in management science are known as multi-criteria decision-making. Most search and optimization problems in the real world usually include several objectives. In such problems, one cannot only look for the optimal solution of one of the objective functions, but all the objective functions are important. Therefore, this research to realize its main innovations is as follows:

- Multipurpose routing of vehicles to minimize freight costs and maximize customer satisfaction by considering the assumption of no return to the warehouse.

- Considering the delivery time window, traffic conditions, and customer clustering simultaneously.

The remainder of the article is organized as follows. In the second part, a literature review is presented. The third part presents the proposed research method, which includes the introduction of mathematical modeling. The research results are presented in the fourth section, and finally, in the fifth section, a general conclusion is presented, along with suggestions for future research.

2. Literature review

In this research, we classify the literature on the vehicle routing problem into two internal and external dimensions. In this matter, the vehicles do not need to return to the warehouse. This article is a kind of meta-heuristic method, which in the first phase uses the correction method of the ant sample to find sub-optimal answers. In the second phase, insertion and displacement algorithms are used to find better answers. This algorithm was tested on a set of 15 examples with 400-50 customers, and it turned out that this algorithm can achieve the best solution found so far in 10 examples. In addition, in terms of the quality of the obtained answers, it was proved that the proposed algorithm is very competitive, and the standard deviation is around 1% in all examples. In general, it can be said that the proposed algorithm has obtained better results regarding the quality of the answers compared to other existing methods for solving the problem. Koch et al. (2018) investigated the problem of vehicle routing with simultaneous delivery and reception, time windows, and three-dimensional capacity constraints. They used a neighborhood search algorithm to solve the problem. Vinai et al. (2018) presented a two-level model for routing and locating distribution centers under conditions of uncertainty. Replenishment at intermediate depots (CLRPR) is one of the innovations of this research. Considering the time window for transporting the goods and the loading and docking time for the goods are also among the things that have been paid attention to in this research. Finally, due to the NP-hard nature of the model, the Ant algorithm has been used to solve it. Noham et al. (2018) presented a mathematical model to manage the supply chain network before and after the crisis. In the pre-crisis phase, distribution centers will be located; in the post-crisis phase, inventory will be allocated to demand points. The proposed model is of the mixed integer type, and its goal is to maximize the number of goods allocated per unit of time. Also, the p-median approach has been used to minimize the coverage radius. The considered case study was 49 possible scenarios for an earthquake in Israel. Maharajan et al. (2018) presented a multi-objective mathematical model for locating temporary hubs in earthquake conditions. This research aims to minimize costs and unsatisfied demand for injured people. A fuzzy weighting strategy is used to solve this two-objective model. The considered case study was the Nepal earthquake in 2015. The results show the accuracy of the presented model. Yu et al. (2018) investigated a multi-period and multi-product supply chain. Considering the limitation of facility capacity and resilience in the supply chain is one of the strengths of this research. A two-level approach has been used to model this issue, in which strategic decisions, including capacity allocation, are made at the first level, and operational decisions are made at the second level, including reducing supply chain costs. Hamdem et al. (2019) presented a multi-level and multi-objective mathematical blood supply chain management model. Decisions related to the number of distribution centers at the first level, the amount of blood stored, and inventory control have been made at the second level. Minimizing costs, delivery time and the number of spoiled products, are among the goals of this research. The results of the case study in Jordan indicate the proper performance of the model after implementation. Babaei and Rajabi (2019) presented a mixed model with integers to investigate the school service routing problem. Their studies analyzed the bus station with 86 students and 56 bus stations. The further explanation is that this model is in urban and single-school mode and is only focused on bus routing. Also, the timing of school bells is one of the goals of this research. Banerjee et al. (2019) investigated school service routing with 2000 students in a simulated environment. Their basic innovations consider variables such as car capacity, maximum driving time, maximum distance, and time traveled by students. The most important goal of their research is to consider justice for students in transportation. Bertsimas et al. (2020) assumed three schools as a warehouse (depot) of goods and routes started from and ended at the school. They also considered the bus fleet similar and assumed that students have the right to choose a station and it is unnecessary to board at the desired station. Considering these assumptions, they designed an integer programming model and used it for an example with 10 stations and 50 students. Although their model was very simple, they did not consider practical limitations such as maximum riding time. Hu et al. (2020) solved the routing problem by considering the urban bus station and the variables of vehicle capacity and maximum driving time. They considered the problem a single school and modeled it as zero-one programming. Considering mixed loading is one of the considered innovations. Finally, the proposed model has been solved using a meta-heuristic algorithm. The results show that the costs increase sharply with the increased number of students. Ghasemi and Abolghasemian (2023) have presented a mathematical model for a sustainable supply chain. Their innovations include consideration of resilience and product pricing. Also, the government affects the environment by imposing taxes. This is done by a Stackelberg game where the government is the base, and the producers are the followers. Tirkalai et al. (2022) presented a transportation model for managing perishable products. The uncertainty considered is fuzzy. Considering sustainability is one of their research innovations. The lp-metric approach is used to solve the model. Liu et al. (2022) presented a centralized and decentralized mathematical model for green supply chain management in scenario mode. According to game theory, product pricing and a cooperation mechanism are considered innovations. The results of the designed mechanism indicate that retailers' income is a function of the market share. Kumari et al. (2023) presented an integrated sustainable supply chain network for one seller and multiple buyers with a trade credit policy. In this study, the seller offers a trade credit policy to its buyers. Emissions from production, vehicle routing, and storage are considered. A cap and trade policy has been implemented to minimize carbon emissions. All assumptions of the model are formulated in the form of a mathematical formula to minimize the total cost under a set of constraints. The mathematical formulation focuses on minimizing the total cost, thereby determining an optimal production-transportation policy and an appropriate routing plan for the existing fleet of vehicles. In addition, a unique meta-heuristic technique is also proposed to solve the proposed problem.

Based on the research conducted in the research literature, in this study, for the first time, the following issues are investigated simultaneously in the vehicle routing problem:

-Failure to pay attention to multi-purpose routing (to minimize freight costs and maximize customer satisfaction).

-Not paying attention to open routing (without returning to the warehouse).

-Failure to consider the delivery time window, traffic conditions, and clustering of customers at the same time.

- According to the conducted studies, the problem of routing considering these conditions and limitations has not been raised in any research so far.

3. Methodology

In today's competitive world, the routing of vehicles and the proper timing of delivering orders to customers are very important. The correct routing of vehicles can be significantly effective in reducing costs, and customer satisfaction plays a key and important role in the survival and promotion of organizations. This research aims to model the vehicle routing problem of the mbazar online store. The vehicle routing problem in this research includes n customers with specific demand and c types of vehicles. The distribution company does not own vehicles, and fixed and variable costs are defined for them. The company offers customers a set of non-overlapping time windows, and customers prioritize these time frames. In other words, deviation from the time windows does not directly cost the customer but causes a change in customer satisfaction. Therefore, maximizing customer satisfaction is also important for the company in addition to minimizing vehicle costs.

3.1. Mathematical modeling

This section describes all the items required for the development of the mathematical model, including assumptions, notations of parameters and variables, constraints and objective functions.

Model assumptions

1. Each customer is met exactly once by one vehicle, and each vehicle is assigned to only one route.
2. All customer information, such as geographical location and demand, is clear.
3. Each vehicle starts moving from the depot and ends its movement at the depot.
4. There are different types of vehicles, each with different capacities.
5. All routes start and end at the depot.
6. Vehicles have two types of fixed and variable costs.
7. The fixed cost of renting vehicles.
8. A strict time window is considered for each client
9. A customer's request must be satisfied in one visit

Indices and parameters

In Table 1, all the symbols used in the development of the model are shown.

Table (1) Notation

The symbol of indices	Description
$l \in \{1, \dots, L\}$	A set of scenarios
$a, b \in \{1, \dots, M\}$	Collection of customers and depots

$v \in \{1, \dots, V\}$	vehicles
o	The length of the interval of each scenario
c	The cluster considered for customers (1=vip, 2-loyal customers, 3-regular customers)
The symbol of indices	Description
p_{abl}	The time between two points a and b in scenario l
h'_{bc}	The earliest service time of customer b in cluster c
I_{bc}	The latest service time of client b in cluster c
jc_v	Fixed cost of vehicle v
ic_v	The variable cost of vehicle v
r_b	total customer demand b
g_l	Scenario start time
h_l	The end time of the scenario
dis_{ab}	The distance between points a and b
sv_{bc}	
$n \in \{1, \dots, N\}$	Service time to customer b in cluster c
BM	The maximum number of scenarios available on the route
ε	A big number
rb_{abn}	A value close to zero
Q	Vehicle speed between two points a and b in scenario n
adm_{b1}	Vehicle capacity
adm'_{b2}	Dissatisfaction level in case of non-service to customer b in cluster 1
adm''_{b3}	Dissatisfaction level in case of lack of service to customer b in cluster 2
α_1	Dissatisfaction rate in case of lack of service to customer b in cluster 3
α'_2	Allowed period for servicing customers of cluster 1
α''_3	Allowed time for servicing cluster 2 customers
W	Allowed time for serving customers of cluster 3
W'	Weight of customers in Cluster 1
W''	Weight of customers in Cluster 2
	Weight of customers in Cluster 3
Variables	Description
m_{bln}	The auxiliary variable of the scenario calculator
u_{aln}	The auxiliary variable of the scenario calculator
k_{bc}	Cumulative service demand from visiting customer b in cluster c
p'_{abn}	Auxiliary variable to update the time between nodes a and b in scenario n
t_{ab}	The updated time between two points a and b
z^{v}_{abl}	Calculator of the number of scenarios between two points a and b in scenario l by vehicle v

w_{ab}	The number of scenarios between two points a and b
y_v	Equal to 1 if customer b is visited by vehicle v after customer a in scenario l, otherwise equal to zero
e_{bc}	Time to reach customer b in cluster c
dt_{bc}	Departure time from customer b in cluster c
dt'_{1bc}	Travel time from depot to customer b in cluster c

Two auxiliary variables have been defined to specify the scenario of onset and end of periods according to the next nodes. These variables are to determine in which scenario the vehicle starts to move and what is the speed of the vehicle. In this research, the longest route in terms of time is considered for the problem and the total number of possible scenarios is equal to n.
Objective functions and constraints:

$$min\ z1 = \sum_{a=1}^{M}\sum_{b=1}^{M}\sum_{l=1}^{L}\sum_{v=1}^{V} ic_v\ t_{ab}\ s_{abl}^{v} + \sum_{v=1}^{V} jc_v\ y_v \tag{1}$$

$$min\ z2 = \sum_{b=1}^{M}(e_{b1} - \alpha_1)W.adm_{b1} + (e_{b2} - \alpha_2)W'.adm'_{b2} + (e_{b3} - \alpha_3)W''.adm''_{b3}$$

$s.t.$

$$\sum_{a=1}^{M}\sum_{l=1}^{L}\sum_{v=1}^{V} s_{abl}^{v} = 1, \qquad \forall\ b = 2, \dots, M, a \neq b \tag{2}$$

$$\sum_{a=1}^{M}\sum_{l=1}^{L} s_{abl}^{v} = \sum_{a=1}^{M}\sum_{l=1}^{L} s_{bal}^{v}, \qquad \forall\ b, \forall\ v,\ a \neq b \tag{3}$$

$$\sum_{v=1}^{V}\sum_{l=1}^{L} s_{abl}^{v} \leq 1, \qquad \forall\ b, \forall\ a,\ a \neq b \tag{4}$$

$$\sum_{b=2}^{M}\sum_{l=1}^{L} s_{1bl}^{v} \leq 1, \qquad \forall\ v \tag{5}$$

$$\sum_{a=1}^{M}\sum_{b=1}^{M}\sum_{l=1}^{L} s_{abl}^{v} \leq BMy_v, \qquad \forall\ v \tag{6}$$

$$k_a - k_b + Q\sum_{v=1}^{V}\sum_{l=1}^{L} s_{abl}^{v} \leq Q - r_b, \quad \forall\, b = 2, \dots, M, \forall\, a,\ a \neq b \tag{7}$$

$$r_b \leq k_b \leq Q, \quad \forall\, b = 2, \dots, M, \tag{8}$$

$$h'_{bc} \leq e_{bc} \leq I_{bc} - sv_{bc}, \quad \forall\, b = 2, \dots, M, \forall c \tag{9}$$

$$e_{ac} - e_{bc} \leq BM\left(1 - \sum_{v=1}^{V}\sum_{l=1}^{L} s_{abl}^{v}\right) - \sum_{v=1}^{V}\sum_{l=1}^{L}(t_{ab} + sv_{ac})s_{abl}^{v}, \quad \forall\, b = 2, \dots, M, \forall\, a,\ a \neq b, \forall c \tag{10}$$

$$e_{ac} - e_{bc} \geq -BM\left(1 - \sum_{v=1}^{V}\sum_{l=1}^{L} s_{abl}^{v}\right) - \sum_{v=1}^{V}\sum_{l=1}^{L}(t_{ab} + sv_{ac})s_{abl}^{v}, \quad \forall\, b = 2, \dots, M, \forall\, a,\ a \neq b, \forall c \tag{11}$$

$$p'_{ab1} = min\{\sum_{l=1}^{L}\sum_{v=1}^{V}(\sum_{n=1}^{N}\left[\big((n-1)Lf + h_l\big)(1 - u_{aln})\right] - dt_{ac})s_{abl}^{v}, \sum_{v=1}^{V}\sum_{l=1}^{L} t_{ab}s_{abl}^{v}\} \quad \forall\, a = 2, \dots, M, \forall\, b,\ a \neq b, \forall c \tag{12}$$

$$p'_{1b1} = min\{\sum_{l=1}^{L}\sum_{v=1}^{V}(\sum_{n=1}^{N}\left[\big((n-1)Lf + h_l\big)(1 - m_{bln})\right] - dt'_{1bc})s_{1bl}^{v}, \sum_{v=1}^{V}\sum_{l=1}^{L} t_{1b}s_{1bl}^{v}\} \quad \forall\, b = 2, \dots, M, \forall c \tag{13}$$

$$p'_{abn} = min\left\{f, dis_{ab} - \sum_{p=1}^{n-1} d_{abp} \Big/ rb_{abn}\right\}, \quad \forall\, a = 2, \dots, M, \forall\, b,\ a \neq b, \forall\, n \tag{14}$$

$$t_{ab} = \sum_{n=1}^{ab} p'_{abn}, \quad \forall\, a, \forall\, b, a \neq b, \forall\, n \tag{15}$$

$$I_{bc} = e_{bc} + sv_{bc}, \quad \forall\, b = 2, \dots, M, \forall c \tag{16}$$

$$-BMy_{aln} + \big((n-1)Lf + g_l\big)\sum_{v=1}^{V}\sum_{b=1}^{M} s_{abl}^{v} \leq dt_{ac}\sum_{v=1}^{V}\sum_{b=1}^{M} s_{abl}^{v}, \quad \forall\, a = 2, \dots, M, \forall\, l, \forall\, n, c \tag{17}$$

$$dt_{ac}\sum_{v=1}^{V}\sum_{b=1}^{M} s_{abl}^{v} \leq BMu_{aln} + \left((n-1)Lf + h_l\right)\sum_{v=1}^{V}\sum_{b=1}^{M} s_{abl}^{v} - \varepsilon, \qquad \forall\, a = 2, \dots, M, \forall\, l, \forall\, n, c \tag{18}$$

$$\sum_{n=1}^{N} u_{aln} = N - 1, \qquad \forall\, a = 2, \dots, M, \forall\, l \tag{19}$$

$$z_{abl}^{v} = max\left\{0, \left(p_{abl} - \left(\sum_{n=1}^{N}\left[\left((n-1)Lf + h_l\right)(1 - u_{aln})\right] - dt_{bc}\right.\right.\right. \qquad \forall\, a = 2, \dots, M, \forall\, b,\ a \neq b, \forall\, v, \forall\, l, c \tag{20}$$

$$z_{1jl}^{v} = max\left\{0, \left(p_{1bl} - \left(\sum_{n=1}^{N}\left[\left((n-1)Lf + h_l\right)(1 - m_{bln})\right] - dt'_{1b}\right.\right.\right. \qquad \forall\, b = 2, \dots, M, a \neq b, \forall\, v, \forall\, l, c \tag{21}$$

$$w_{ab} = \begin{cases} [\sum_{v=1}^{V}\sum_{l=1}^{L} z_{abl}^{v}] + 1, & if\ \sum_{v=1}^{V}\sum_{l=1}^{L} z_{abl}^{v} \quad is\ integer \\ [\sum_{v=1}^{V}\sum_{l=1}^{L} z_{1bl}^{v}] + 2\,, & otherwise \end{cases} \qquad \forall\, a, \forall\, b,\ a \neq b \tag{22}$$

$$dt'_{1bc} \leq e_{bc} - \sum_{v=1}^{V}\sum_{l=1}^{L} t_{1b} s_{1bl}^{v} + BM(1 - \sum_{v=1}^{V}\sum_{l=1}^{L} s_{1bl}^{v}) \qquad \forall\, b = 2, \dots, M, \forall c \tag{23}$$

$$dt'_{1bc} \geq e_{bc} - \sum_{v=1}^{V}\sum_{l=1}^{L} t_{1b} s_{1bl}^{v} - BM(1 - \sum_{v=1}^{V}\sum_{l=1}^{L} s_{1bl}^{v}) \qquad \forall\, b = 2, \dots, M, \forall \mathrm{c} \tag{24}$$

$$-BMm_{bln} + \left((n-1)Lf + g_l\right)\sum_{v=1}^{V} s_{1bl}^{v} \leq dt'_{1bc}\sum_{v=1}^{V} s_{1bl}^{v}, \qquad \forall\, b = 2, \dots, M, \forall\, l, \forall\, n, c \tag{25}$$

$$dt'_{1bc}\sum_{v=1}^{V} s_{1bl}^{v} \leq BMm_{bln} + \left((n-1)Lf + h_l\right)\sum_{v=1}^{V} s_{1bl}^{v} - \varepsilon, \qquad \forall\, b = 2, \dots, M, \forall\, l, \forall\, n, c \tag{26}$$

$$\sum_{n=1}^{N} m_{bln} = N - 1, \qquad \forall\, b = 2, \dots, M, \forall\, l, \forall\, n \qquad (27)$$

$$s_{abl}^{v}, y_v \in \{0,1\}, \qquad \forall\, a,\ b,\ l,\ v. \qquad (28)$$

The objective function (1) minimizes fixed and variable costs. The objective function (2) minimizes the level of customer dissatisfaction. Limitations (2) to (5) are inherent limitations of routing. For example, limitation 3 indicates that the outgoing route and the return route are equivalent to each other. Limitation (6) indicates that a vehicle is used if an equivalent fee has been paid. Limitation (7) shows the capacity of the transport equipment. Limitation (8) states that the amount of satisfied demand must be greater than the amount of demand and less than the capacity of the vehicle. Limitation (9) shows the time window between periods. Limitation (10) shows the time window at the beginning of periods. Limitation (11) shows the time window at the end of periods. Limitations 12 to 15 indicate that the time window limitation will not be violated if the service time expires. Limitations 16 to 19 are limitations related to traffic. For example, limitation 16 shows the last customer service time in the time window. Limitations (20) to (22) are related to scenarios between routes. In the limitations, the scenarios are defined using the m_{bln} , u_{aln} and s_{1bl}^{v} variables of the scenarios. Therefore, the number of scenarios in the routes changes based on the start time. Suppose in scenario 1, from time 0 to 30, the start time and the length of the route are equal to 10, and we reach the destination in time 20; in this case, there is only one scenario. But if we move at time 25, we will arrive at time 35, related to the second scenario. Limitations 23 and 24 determine the time of movement of vehicles from the depot. These limitations determine the relationship between the times of movement of vehicles from the warehouse to the customer based on the time window determined. Limitations 25 to 27 are for calculating the variablem_{bln}, which specifies the scenario of movement from the depot. Limitation 28 also shows the research decision variables.

3.2. linearization of mathematical modeling

Limitations 1, 10, 11, 23 and 24 are underlined.

$$p_{abl}^{v} \le BMs_{abl}^{v}, \qquad \forall\, a,\ b,\ l,\ v \qquad (29)$$
$$p_{abl}^{v} \ge t_{ab} - BM(1 - s_{abl}^{v}), \qquad \forall\, a,\ b,\ l,\ v \qquad (30)$$
$$p_{abl}^{v} \le t_{ab}, \qquad \forall\, a,\ b,\ l,\ v \qquad (31)$$
$$p_{abl}^{v} \ge 0, \qquad \forall\, a,\ b,\ l,\ v. \qquad (32)$$

Therefore, the objective function 1 and limitations 10, 11, 23 and 24 are written as equations 33 to 37:

$$min\ z = \sum_{a=1}^{M}\sum_{b=1}^{M}\sum_{l=1}^{L}\sum_{v=1}^{V} ic_v\ p_{abl}^{v} + \sum_{v=1}^{V} jc_v\, y_v + \sum_{b=1}^{M}(e_{b1}-\alpha_1)W.cost_{b1} + (e_{b2} - \alpha_2)W'.cost'_{b2} + (e_{b3} - \alpha_3)W''.cost''_{b3} \quad (33)$$

$$e_{ac} - e_{bc} \le BM\left(1 - \sum_{v=1}^{V}\sum_{l=1}^{L} s_{abl}^{v}\right) - \sum_{v=1}^{V}\sum_{l=1}^{L} p_{abl}^{v} + sv_{ac}s_{abl}^{v}, \quad \forall\, b = 2,\dots,M, \forall\, a,\ a \ne b, \forall c \quad (34)$$

$$e_{ac} - e_{bc} \ge -BM\left(1 - \sum_{v=1}^{V}\sum_{l=1}^{L} s_{abl}^{v}\right) - \sum_{v=1}^{V}\sum_{l=1}^{L} p_{abl}^{v} + sv_{ac}s_{abl}^{v}, \quad \forall\, b = 2,\dots,M, \forall\, a,\ a \ne b, \forall c \quad (35)$$

$$dt'_{1bc} \le e_{bc} - \sum_{v=1}^{V}\sum_{l=1}^{L} p_{1bl}^{v} + BM(1 - \sum_{v=1}^{V}\sum_{l=1}^{L} s_{1bl}^{v}) \quad \forall\, b = 2,\dots,M, \forall c \quad (36)$$

$$dt'_{1b} \ge e_{bc} - \sum_{v=1}^{V}\sum_{l=1}^{L} p_{1bl}^{v} - BM(1 - \sum_{v=1}^{V}\sum_{l=1}^{L} s_{1bl}^{v}) \quad \forall\, b = 2,\dots,M, \forall c \quad (37)$$

$$p2_{abl}^{v} \le BMs_{abl}^{v}, \quad \forall\, a,\ b,\ l,\ v \quad (38)$$
$$p2_{abl}^{v} \ge dt_{ac} - BM(1 - s_{abl}^{v}), \quad \forall\, a,\ b,\ l,\ v \quad (39)$$
$$p2_{abl}^{v} \le dt_{ac}, \quad \forall\, a,\ b,\ l,\ v, c \quad (40)$$
$$p1_{abl}^{v} \ge 0, \quad \forall\, a,\ b,\ l,\ v, c \quad (41)$$

$$p3_{abl}^{v} - s_{abl}^{v} - u_{aln} + 1.5 \ge 0, \quad \forall\, a,\ b,\ l,\ n \quad (42)$$
$$1.5p3_{abl}^{v} - s_{abl}^{v} - u_{aln} \le 0, \quad \forall\, a,\ b,\ l,\ n \quad (43)$$

$$-BMy_{aln} + \big((n-1)Lf + g_l\big)\sum_{v=1}^{V}\sum_{b=1}^{M} s_{abl}^{v} \le \sum_{v=1}^{V}\sum_{b=1}^{M} p2_{abl}^{v}, \quad \forall\, a = 2,\dots,M, \forall\, l, \forall\, n \quad (44)$$

$$\sum_{v=1}^{V}\sum_{b=1}^{M} p2_{abl}^{v} \le BMy_{aln} + \big((n-1)Lf + h_l\big)\sum_{v=1}^{V}\sum_{b=1}^{M} s_{abl}^{v} - \varepsilon, \quad \forall\, a = 2,\dots,M, \forall\, l, \forall\, n \quad (45)$$

$$z_{abl}^{v} = max\{0\,, (t_{abl}s_{abl}^{v} + \sum_{n=1}^{N}\left[\left((n-1)Lf + h_l\right)p3_{abl}^{v}\right] - \sum_{n=1}^{N}\left[\left((n-1)Lf + h_l\right)s_{abl}^{v}\right] + p2_{abl}^{v}) \Big/ o \qquad \forall\, a = 2, \dots, M, \forall\, l, v, b \quad (46)$$

Therefore, limitations 21, 25 and 26 are linearized as equations 47 to 55.

$$p4_{bl}^{v} \le BMs_{1bl}^{v}, \qquad \forall\, b = 2, \dots, M, \forall\, l \quad (47)$$

$$p4_{abl}^{v} \ge dt'_{1bc} - BM(1 - s_{abl}^{v}), \qquad \forall\, b = 2, \dots, M, \forall\, l, c \quad (48)$$

$$p4_{abl}^{v} \le dt'_{1bc}, \qquad \forall\, b = 2, \dots, M, \forall\, l, c \quad (49)$$

$$p4_{abl}^{v} \ge 0, \qquad \forall\, b = 2, \dots, M, \forall\, l \quad (50)$$

$$p5_{aln}^{v} - s_{1bl}^{v} - m_{bln} + 1.5 \ge 0, \qquad \forall\, b = 2, \dots, M, \forall\, l, \forall\, n \quad (51)$$

$$1.5p5_{aln}^{v} - s_{1bl}^{v} - m_{bln} \le 0, \qquad \forall\, b = 2, \dots, M, \forall\, l, \forall\, n \quad (52)$$

$$z_{1bl}^{v} = max\{0\,, (t_{1bl}s_{1bl}^{v} + \sum_{n=1}^{N}\left[\left((n-1)Lf + h_l\right)p5_{abl}^{v}\right] - \sum_{n=1}^{N}\left[\left((n-1)Lf + h_l\right)s_{1bl}^{v}\right] + p4_{abl}^{v}) \Big/ f \qquad \forall\, b = 2, \dots, M, \forall\, l, \forall\, v \quad (53)$$

$$-BMm_{bln} + \left((n-1)Lf + g_l\right)\sum_{v=1}^{V} s_{1bl}^{v} \le \sum_{v=1}^{V} p4_{1bl}^{v}, \qquad \forall\, b = 2, \dots, M, \forall\, l, \forall\, n \quad (54)$$

$$\sum_{v=1}^{V} p4_{1bl}^{v} \le BMm_{bln} + \left((n-1)Lf + h_l\right)\sum_{v=1}^{V} s_{1bl}^{v} - \varepsilon, \qquad \forall\, b = 2, \dots, M, \forall\, l, \forall\, n \quad (55)$$

3.3. Mathematical problem-solving approach: invasive weed algorithm

The invasive weed algorithm is inspired by the growth of weeds in an agricultural field. In general, any plant and creature that does not need to exist on agricultural land is called a weed. One of the distinguishing features of weeds is that they are versatile, strong, and aggressive, and they are a serious threat to the plants growing around them, which is why we call them invasive; One of their other characteristics is that the more we cut them and remove them from the roots, the speed and process of grass growth in the next series will increase more and more. There is a saying that grass always wins; The more farmers work, the more they will grow. The algorithm for optimizing the growth of invasive weeds is a simple and effective solution to solve such problems, which optimizes the problem and brings it to the point of convergence by using simple and practical concepts and solutions such as creating competition and seeding. The solution algorithm of the optimization method is as follows, which are:

Generation of initial population: a set of initial solutions are randomly distributed in the problem space.
Reproduction: Each seed reproduces according to its merit. Since the invasive weed algorithm is one of the evolutionary algorithms, they help us get closer to solving the problem by distributing more seeds in a space closer to the final solution. The closer the seeds are to the final answer, the more merit they have and the more valuable they are to us. The seeds, or more generally, the more competent species, are selected for reproduction. Reproduction for each grass is obtained from formula 56:

$$S = [S_{min} + (S_{max} + (S_{max} - S_{min}) \times \frac{f - f_{worst}}{f_{best} - f_{wrost}}] \quad (56)$$

In relation (3-16), S_{min} is the minimum seed production, S_{max} is the maximum seed production, f_{min} is the minimum merit, f_{max} is the maximum amount of merit, and f is the merit of the desired grass.
Regional dispersion: The seeds are distributed with a normal distribution with a mean of zero and a standard deviation of $\Delta x_i \sim N(0, \sigma^2)$ for σ, we consider an initial value and a final value. In the beginning, the dispersion has a higher value, which goes towards a lower dispersion with the formula of relation (57).

$$\sigma_{iter} = \frac{(iter_{max} - iter)^n}{(iter_{max})^n} . (\sigma_{initial} - \sigma_{final}) + \sigma_{final} \quad (57)$$

Equation (57) shows the amount of scattering in each step. Here we see the continuous change of the survival policy from choosing r to choosing k.
Competitive exclusion: if a grass remains childless, it will become extinct; otherwise, it will have a representative in the next generations and can take resources from it; Therefore, we need some competition for the population and having children. That our population does not exceed a certain limit, in the early stages of the algorithm implementation, grasses reproduce quickly and spread in the problem space until we reach the maximum population limitation. From here on, each grass produces seeds according to the mentioned procedure and spreads them in the surrounding space. Then all the seeds and grasses are evaluated together, and the amount added to the maximum population should be subtracted from the population; Therefore, grasses and seeds with the least merit will be removed to reach the maximum population. Grasses with more fitness are allowed to survive and reproduce. Also, this algorithm allows grasses with low fitness to reproduce to survive in the colony if their children have more fitness. This algorithm creates a kind of competition for survival and reproduction between grasses so that finally, the most competent grasses, or the closest options to the final solution, remain in the colony.
The flowchart related to the invasive weed meta-heuristic algorithm is shown in Figure 1.

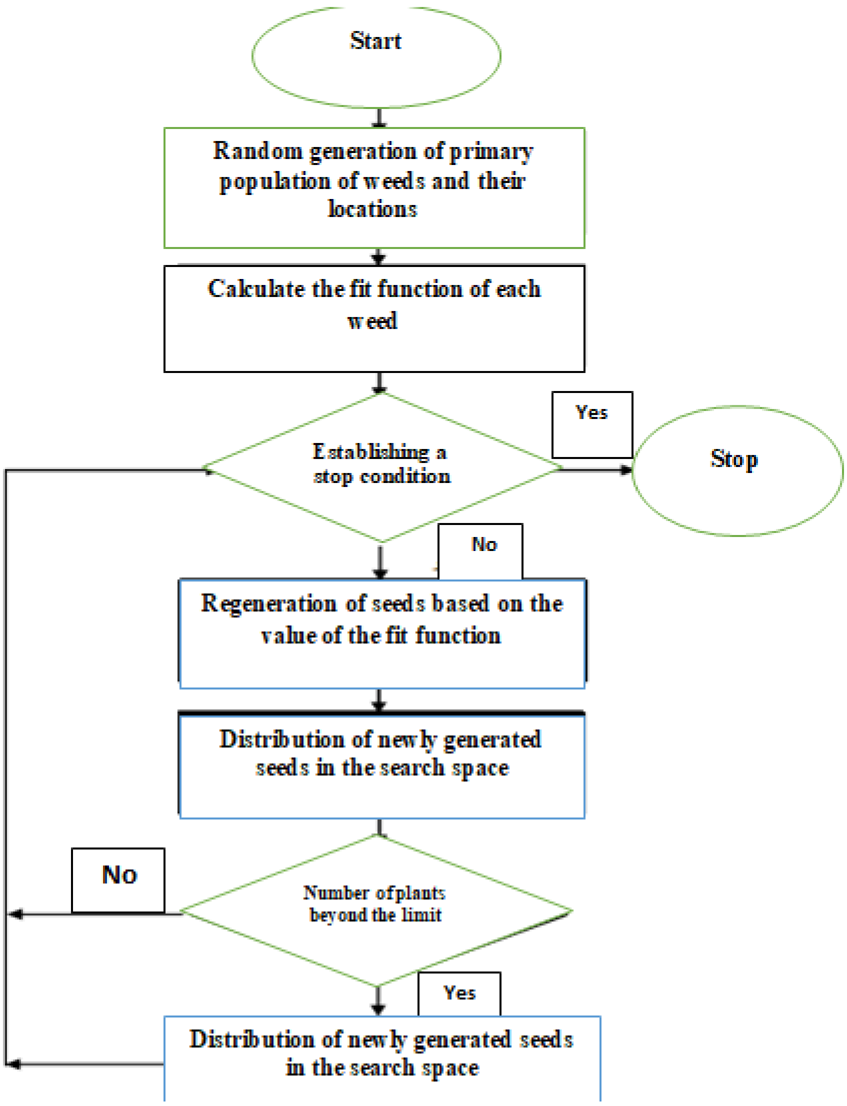

Figure 1- Flowchart of invasive weed meta-heuristic algorithm

4. Numerical results of research

A sample example is designed to validate the model so that the optimal solution can be calculated approximately manually and by trial and error. For example, the parameters are embedded so that the optimal solution can be easily calculated in all cases. In the example with small dimensions, the results obtained from the exact solution with the help of GAMS software are almost identical to those obtained from the trial and error method. Since imprecise and meta-heuristic algorithms do not guarantee finding the optimal global solution, we may reach different solutions and observe the different performances of the algorithm every time these algorithms are used. Therefore, a meta-heuristic algorithm works well when it reaches almost the same answers every time. The most influential parameters in the weed algorithm are the number of initial population (N_i), the number of repetitions (I_{max}), the maximum number of grasses (P_{max}) and the number of seeds (S_{max}). We will adjust some parameters of these algorithms using the Taguchi method. For this purpose, we first consider three levels of low (1), medium (2), and high (3) for each parameter, which are given in Table (2). Then, the set of experiments proposed by the Taguchi method for 4 factors in 3 levels has been calculated, which are 9 different modes, shown in Table (3).

Table (2) quantification of weed factors/parameters at three levels

Weed parameter/factor	low level(1)	Intermediate level (2)	high level(3)
N_i	60	80	100
I_{max}	100	300	500
P_{max}	10	20	30
S_{max}	5	7	10

Table (3) experiments designed by Taguchi method to adjust the parameters of the weed algorithm

Test .No	$level\ N_i$	$level\ I_{max}$	$level\ P_{max}$	$level\ S_{max}$
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

Tables (2) show the levels of weed parameters, and it can be seen that three different levels have been considered for each parameter. Table (3) shows the tests determined to adjust the parameters of the weed algorithm. Table (4) shows the result of running the weed algorithm for a problem.

Table (4) the results of the weed algorithm tests

No.	MID	Spacing	Diversity	Nos	Time(s)
1	76.3	2.34	18.9	5	27.4
2	77.25	1.9	23.29	6	48.4
3	76.77	2.24	24.53	10	30.4

4	77.45	7.08	26.77	9	42.7
5	76.15	5.8	30.41	9	69.5
6	78.01	9.1	30.19	7	25.9
7	76.04	3.21	19.24	8	48.7
8	76.7	3.92	28.56	7	50.5
9	76.7	3.06	25.98	9	52.9

Finally, in the last step, based on the response variable calculated in the previous step, the S/N rate is calculated, and the optimal levels of the Rordi parameters are determined.

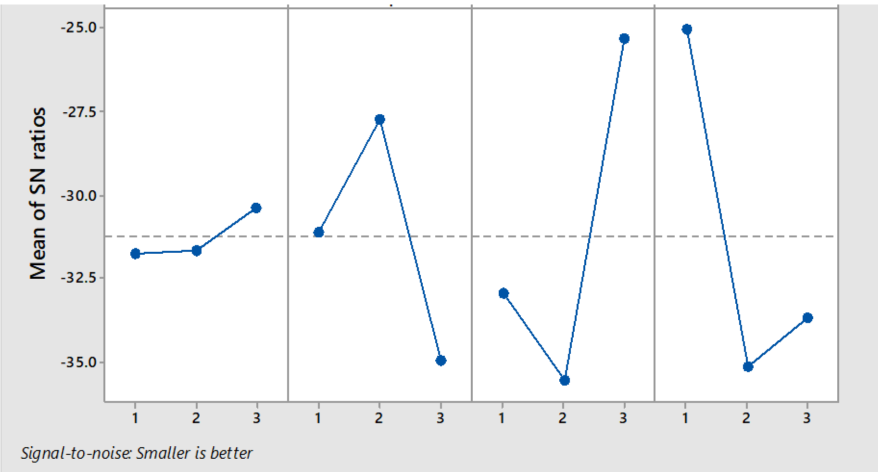

Figure 2- Minitab output for weeding algorithm parameter setting

According to Figure (2) and the above tables, the optimal levels for the parameters of the investigated algorithm are summarized in Table (4):

Table (4) the optimal levels determined for the weed algorithm

	N_i	I_{max}	P_{max}	S_{max}
Weeds	Level 3	Level 2	Level 3	Level 1
	100	300	30	5

4.1.Solving the proposed mathematical model

To validate the presented model and ensure the correctness of the solutions obtained with the help of GAMS software, a small example was produced. With its mathematical calculation, the possible states of the answer were checked and compared with the answer obtained from GAMS software. Then, to solve the problem in large dimensions, we do this by using the weed meta-heuristic algorithm. Table (5) to (17) show example specifications in small dimensions.

Table (5) specifications and main parameters of an example in small dimensions

2	Number of customers	**2**	Number of scenarios
3	Number of clusters	**2**	Number of vehicles

The values of other (sub) parameters of this example in small dimensions, such as costs, capacity, etc., are shown in table (6) to (17).

Table (6) specifications and parameters of an example in small dimensions

p_{abl}		L1	L2
A1	A1	0	0
A1	A2	1.550375	1.301138
A2	A1	1.292212	1.224053
A2	A2	0	0

Table (7) specifications and parameters of an example in small dimensions

h'_{bc}	C1	C2	C3
A1	5.335569	7.501053	9.990588
A2	7.893667	9.955665	8.811252

Table (8) specifications and parameters of an example in small dimensions

I_{bc}	C1	C2	C3
A1	15.65346	18.19859	15.79759
A2	16.2504	18.34464	17.17678

Table (9) specifications and parameters of an example in small dimensions jc_v

V1	6.798501
V2	6.757207

Table (10) specifications and parameters of an example in small dimensions ic_v

V1	5.657458
V2	5.750509

Table (11) specifications and parameters of an example in small dimensions r_b

A1	1.589114
A2	1.830893

Table (12) specifications and parameters of an example in small dimensions

dis_{ab}	A1	A2
A1	0	8.328672
A2	8.879288	0

In this example, the large M value is considered equal to 100,000.

Table (13) specifications and parameters of an example in small dimensions

sv_{bc}	C1	C2	C3
A1	0.555246	0.751192	0.580086
A2	0.936231	0.632557	0.642907

Table (14) specifications and parameters of an example in small dimensions

rb_{abn}		N1	N2	N3	N4	N5	N6
A1	A1	0	0	0	0	0	0
A1	A2	59.71318	55.69827	60.07825	57.73149	64.68591	63.41118
A2	A1	66.54943	59.46709	64.91659	66.33733	64.41171	59.25796
A2	A2	0	0	0	0	0	0

Table (15) specifications and parameters of an example in small dimensions adm_{b1}

A1	5.363835
A2	5.878305

Table (16) specifications and parameters of an example in small dimensions adm'_{b2}

A1	7.628163
A2	8.751038

Table (17) specifications and parameters of an example in small dimensions adm''_{b3}

A1	5.890619
A2	5.170705

After solving the model using the epsilon limitation method in Games, the Poff table and the corresponding Pareto points are shown in Tables (18) and (19).

Table (18) PF table, for example, in small dimensions

Pay off	f_1	f_2
f_1	6.75	573.29
f_2	16.3	294.60

Table (19) set of Pareto points by Gams, for example, in small dimensions

The value of the first objective function	The value of the second objective function	Answer. No
6.75	573.29	1
7.6	570.3	2
9.1	562.1	3
9.8	502.6	4
11.23	480.9	5
11.86	432	6
16.3	294.6	7

After solving using GEMS, the desired model was implemented using the weed algorithm, and the results were obtained according to table (20).

Table (20) set of Pareto points by weeding algorithm, for example, in small dimensions

Answer. No	The value of the second objective function	The value of the first objective function
1	573.29	6.75
2	563.3	8.1
3	504.6	8.9
4	423.69	9.1
5	418.6	13.6
6	365.98	14.3
8	329	14.9
9	325.9	15.63
10	318.4	15.9
11	310	16.01
12	300.5	16.13
13	294.6	16.3

It can be seen in figure (3) and (4) that as the value of the first objective function deteriorates, the values of the objective function no longer deteriorate; In other words, either these values remain constant, or they approach their optimal value, which is the trend expected from multi-objective models.

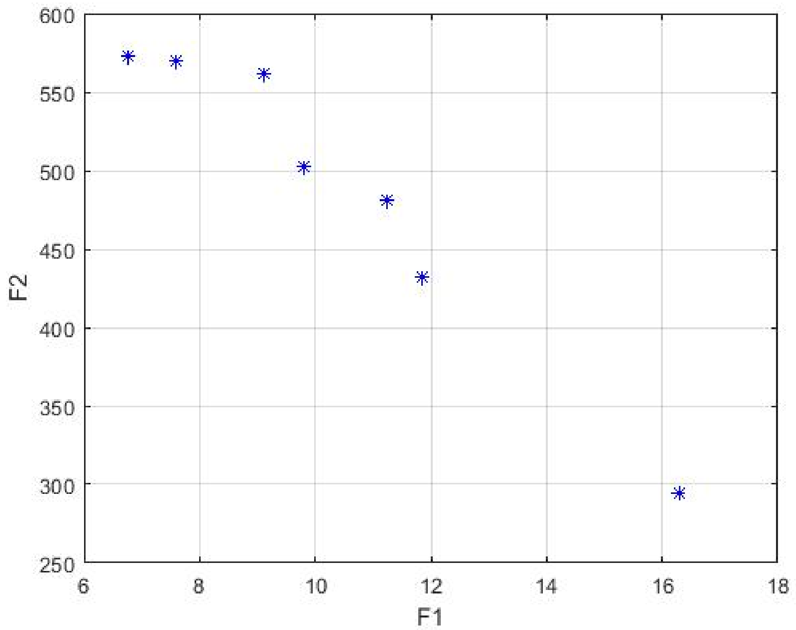

Figure 3- The set of Pareto points resulting from Gams solution

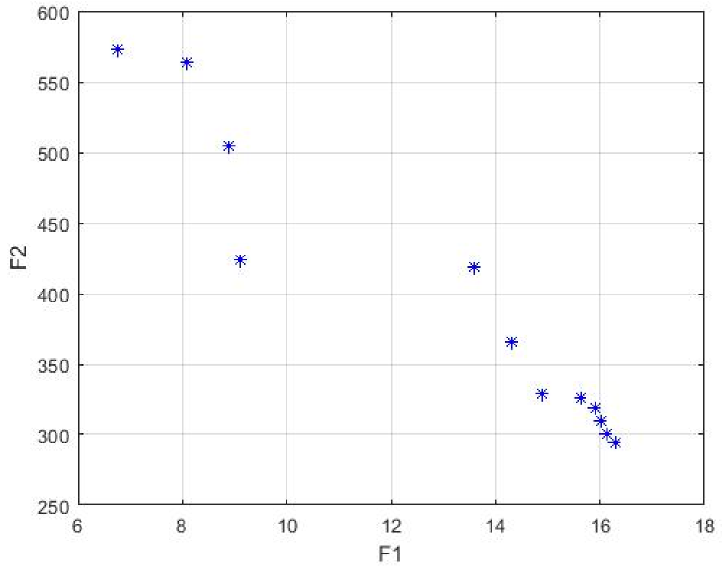

Figure 4- The set of Pareto points resulting from the weeds algorithm

To compare the weed algorithm with the Gems' exact solution method and calculate the relevant indices, we randomly formed 5 examples with different dimensions; after calculating the indices, the results are given in Table (21).

Table (21) calculation results for 5 sample problems by weed algorithms and epsilon limitation method

Row	**Epsilon Constraint**					**Weeds**				
	MID	Spacing	Diversity	Nos	Time(s)	MID	Spacing	Diversity	Nos	Time(s)
1	85.56	5.17	25.2	5	4	72.8	1.3	28. 5	7	26
2	75.7	7.3	38.2	8	7.5	77.4	7.9	22.4	9	32.1
3	53.8	18.01	67.09	7	23	67.2	3.08	36.16	7	26.3
4	63.17	18.14	52.09	9	45	71.5	2.8	24.23	14	27
5	71.09	24.2	52.19	12	200	79.03	1.38	16.5	13	28.1

4.2.Sensitivity analysis

A sensitivity analysis should be done concerning some parameters to check how the values of the objective functions change. Considering the multi-objective nature of the model, we perform two types of analysis. The first type is that the change of Pareto values is checked to the change of a parameter. This type of analysis is performed to change the dissatisfaction value parameter. The example solved in small dimensions was used in the model validation section, and the results of this sensitivity analysis are shown in table (22) and (23). This analysis is done for the dissatisfaction value parameter, which has increased by 10%, whose results are also shown in Figure (5). Another type is to perform this analysis for one of the Pareto points. This work has been done to analyze the sensitivity to the service time parameter for one of the Pareto solutions. The variability of the value of the second objective function to the level of dissatisfaction is shown in Table (23) and the graph in Figure (5).

Table (22) PF table, for example, in small dimensions by changing the dissatisfaction parameter

Pay off	f_1	f_2
f_1	6.75	603.56
f_2	16.3	309.04

Table (23) changes in the set of Pareto points, for example, in small dimensions with changes in demand

Answer. No	Before changing the demand parameter		After changing the demand parameter	
	The value of the second objective function	The value of the first objective function	The value of the second objective function	The value of the first objective function
1	573.29	6.75	603.56	6.75

2	570.3	7.6	580.6	7.6
3	562.1	9.1	523.6	9.1
4	502.6	9.8	489	9.8
5	480.9	11.23	477	11.23
6	432	11.86	326.01	11.86
7	294.6	16.3	309.04	16.3

According to Table (23), with the increase in average dissatisfaction, the value of the first objective function is constant, but the value of the second objective function has increased. There has really been a lot of dissatisfaction

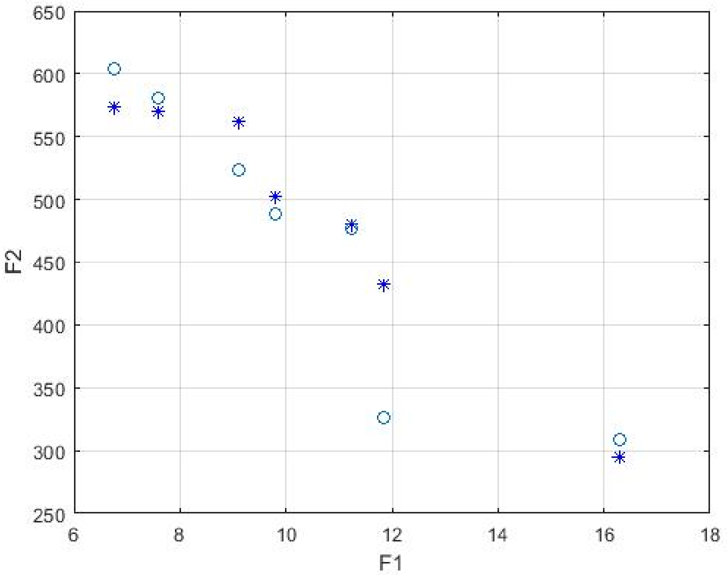

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Figure 5- The set of Pareto points, for example, in small dimensions with a change in the amount of dissatisfaction

In Figure 5, the stars represent the Paretos before the change, and the circles represent the Paretos after the change.

Table (24) the changes in the second objective function, for example, in small dimensions, by changing the amount of service time

Row	Average value of service time	The value of the second objective function
1	0.75	569.27
2	0.78	567.27
3	0.82	565.26

4	0.88	561.25
5	0.95	557.24

In Table (24), the first objective functions are assumed to be constant, and only the changes of the first objective function have been examined. It can be seen that with the increase in the average service time of the second objective function, it decreases.

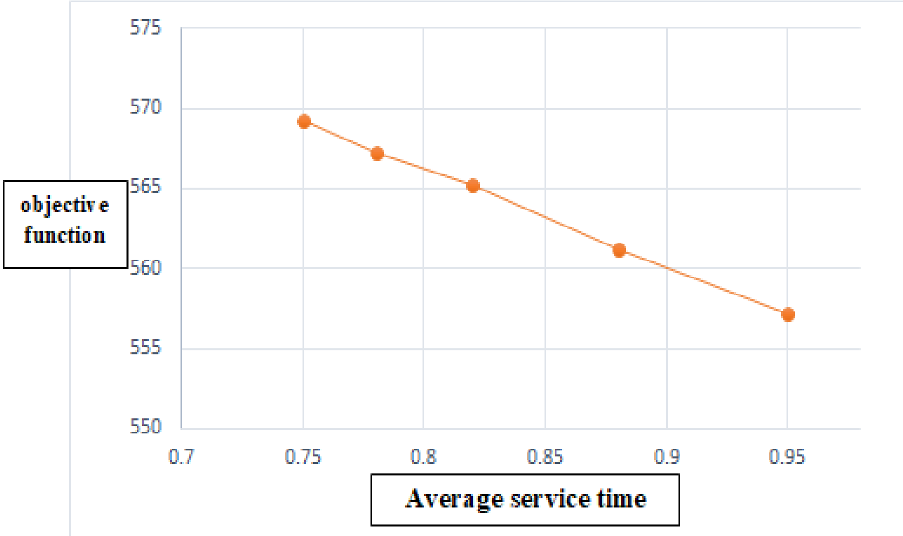

Figure 6- Sensitivity analysis of the first objective function in terms of average service time

5. Conclusion

In this research, for the first time, the problem of vehicle routing has been considered for several goals. This routing aims to reduce freight costs and increase customer satisfaction. In addition, open routing without returning to the warehouse and simultaneously considering the delivery time window, traffic conditions, and customer clustering is considered. According to the conducted studies, this issue has not been investigated in any research by applying the mentioned conditions and limitations. The results of this research are used in many fields and industries. For example, in collecting domestic and industrial waste, the routing of vehicles to transport the waste to the dumping site must be optimized. Also, in routing the service for schools, employees, and students, it should be noted that each user's exact delivery time and specific needs are different. The routing issue in the bank and postal delivery is also very important. In addition, in the transfer of blood samples from medical institutions to laboratories, the routing of vehicles should be such that the quality of the samples is guaranteed from the place of sample delivery to the laboratory. In restaurant services, vehicle routing is also important for timely and good-quality food delivery. In routing cranes and robots, optimal routing is done to transfer loads to the final destination. This research discusses the multi-objective modeling of vehicle routing by considering time windows, traffic conditions and customer clustering in mbazar online stores. Considering the traffic situation of Tehran city and the necessity of timely delivery of goods to customers, especially customers, it is necessary to consider the amount of traffic in the route of store vehicles. This research presents a dual-objective model for the vehicle routing problem by considering priority time windows, traffic conditions, and customer clustering. The goal is to minimize the costs of the transportation fleet and maximize customer satisfaction. Since the problem is NP-hard and the research model includes two objectives, meta-initiative multi-objective algorithms have been used to solve it. Algorithm coding is done in MATLAB software, and as mentioned before, to increase the algorithm's efficiency, the parameters are adjusted using the Taguchi method. To evaluate the correctness of the model's performance and the algorithm's efficiency in solving the problem, first, some examples of simple, medium, and complex problems were designed and solved. For further research, the information related to the customers of this model can be directed to artificial intelligence. Also, a distribution center (depot) is considered in this research, while it can be upgraded to a multi-depot model.

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