Presenting a Location-Routing Problem for Multi-vehicle Hazardous Materials Transport, Considering the Cost Dependent to the Amount of Materials Loaded

Mohammad Jamali
Industrial Engineering, Engineering Major Logistics and Supply Chain Management
Faculty of Industrial and Mechanical Engineering
Islamic Azad University, Qazvin Branch

Abstract-Regarding the significance and role of fuel materials in growth of industries, and considering the point that the transportation of these products is always encountered with risk and has its own dangers, and also given the increasing importance and applicability of combined transport (multimodal) in various industries and the prominent role of this type of transportation in the supply chain, in this research, first a bi-objective mathematical model is presented for location-routing the hazardous materials transport considering the weight of materials loaded. In this model, the objective cost function including transportation costs, construction of multimodal transportation terminal (for movement of the type of transport vehicle), and also the risk of transportation of hazardous materials, are minimized. Then, using precise solving methods and using the NSGA II algorithm, the proposed model is solved. After assessment of solving methods, the best solving method is chosen and the model is solved based on the real information received from the Iran Road Maintenance & Transportation Organization, the Islamic Republic of Iran Railways, the National Iranian Oil Refining and Distribution Company. In this research, the problems were divided into three small, medium and large groups, and for each of the solving methods the evaluation criteria was calculated. The results of this comparison indicated that non-dominated optimization algorithm outperforms the exact solving method. Therefore, it was concluded that this algorithm should be used to solve the model of real data. Likewise, to ensure the performance of this algorithm, the sensitivity analysis of the model was conducted and it was indicated that by changing the parameters of the model, this algorithm gives the expected results and thus its structural performance is confirmed. Finally, the proposed model indicated how the amount of carried load of hazardous materials is related to a location-routing problem.

***Keywords**: Location-Routing, Hazardous Materials, Combined Transport, Cost Function, Dependent on Weight.*

1. Introduction

One of the important issues that had high applicability in the past few decades and has been raised to increase the efficiency of transportation systems was the issue of vehicle routing problem (VRP). Vehicle routing problem refers to a set of issues in which a number of vehicles focused on one or more locations should refer to a set of customers and provide services that each have a specific demand. This problem intends to minimize the traversed distance, total travel time, the number of transportation vehicles, delayed payment penalties with mathematical models and optimization and ultimately maximize the customer satisfaction. Various constraints on these problems, consists different types of classical problems. Location-routing problem is the integration result of the location and routing decisions. The aim of this problem is to find the appropriate location and the number of facilities, as well as distribution routes and timetable of transportation vehicles. In routing, problems are divided into two groups of nodes and strains. The nature of the strain problems is in a way that requests (demands) are arranged on network arcs, but on nodal problems, these requests are placed on the network nodes. Using this distribution system, that are applied in variety of industrial and service problems, the transportation costs can be considerably reduced. The

International Journal of Supply Chain Management
IJSCM, ISSN: 2050-7399 (Online), 2051-3771 (Print)

location-routing problem consists of 3 parts: 1- The location problem 2- The allocation problem 3- The routing problem. In classical facility location models, when calculating distribution costs, assume that each customer is in a direct round trip route. This situation is only true when the demand of each customer fully completes the capacity of the carrying truck. However, in many applications in practice, the demand of each customer may be less than the load capacity of the truck carrying it. Therefore, several customers are arranged on a single route and served. In this case, the distribution costs depend on a sequence of customers that are arranged on a route. In this case, in order to accurately reflect the distribution costs of routes in a location model, the routing and location problem must be solved simultaneously. Clearly, location-routing problems are related to the classical location problem and vehicle routing. Both of these recent problems are expressed as specific cases of location-routing problem, and if it is necessary for all customers to be directly connected to a warehouse, then the location-routing problem becomes a standard location problem, and on the other hand, if the location of the warehouses are maintained fixed, our location-routing problem converts to a simple vehicle routing problem [9].

In today's world, by the expansion and intensification of the competitive environment, supply chain management has become one of the fundamental issues facing enterprises. Investigation of various routing methods of fast public transportation systems indicates that designing route for these systems is a very complicated problem that, while influencing operational function and construction and utilization cost, will have a significant role in performance indicators such as the amount of carried load, travel speed, decrease of travel time, land use modifications and environmental impacts. In this regard, the two travel time and coverage factors are considered as the most important factors in locating an extension. The locating cost includes fixed acquisition costs, construction of centers, equipment purchases and variable costs, including salaries, etc. Travel costs include travel distance or travel time. In this research, in addition to the cost of travel distance, other types of costs, including the cost of route type, the fixed cost of the number of vehicles, the cost of non-observance of the soft time window,the cost of fuel, and the cost of depreciation due to the amount of load on the vehicle, are also considered. In previous studies, the weight of load on a vehicle had no effect on costs, but it is clear that the weight of load amount carried by vehicle has effect on the cost of fuel and vehicle depreciation [10].

• Routing problem

The vehicle routing problem or VRP is a combined optimization and discontinuousscheduling problem that aims to serve customers with a fleet of vehicles. The VPR is an important issue in the field of transportation, distribution and logistics. VPR often involves the transfer of goods located at a central station toward the customers who ordered these goods. The aim of VRP is to minimize the total cost of transferring goods from the central station to customers.

Determining the optimal solution is considered as a complete NP-problem in combined optimization and many definitive and heuristic practical methods are developed to find acceptable solutions for VRP. There are various types of vehicle routing problems including:

- Vehicle Routing Problem with Pickup and Delivery (VRPPD)
- Vehicle Routing Problem with Time Windows (VRPTW)
- Capacitated Vehicle Routing Problemor Capacitated Vehicle Routing Problem with Time Window (CVRP or CVRPTW)
- Vehicle Routing Problem with Multiple Trips (VRPMT)
- Open Vehicle Routing Problem (OVRP)

• Location Problem

The facilities location problem generally includes a set of distributed demands in the problem area and a set of facilities to meet those demands.

In location problem, two basic questions must be answered. These questions include:

1. Which facilities should be used? (This question itself is the answer to two other questions that are understandable with little thought: “How many facilities should be deployed,” and “where should be these facilities deployed”)?

2. Which demands should be met by which facilities?

The facility location problem in the supply chain management area is of particular importance in both the facility location and supply chain management.

• Location-Routing Problem

Over the past three decades, the integrated optimization approach to logistics systems has become one of the most important aspects of supply chain optimization. This approach examines simultaneously the dependencies between the facilities location, the allocation of suppliers/customers to facilities, the structure of transportation routes, and inventory planning and control. One of the most important locationproblemsto consider this approach is the location-routing problem. In this problem, the number and location of facilities, the size of transportation fleet, and the structure of routes are determined considering the location and characteristics of the suppliers and customers.

Among the usedreviewedliterature the following can be referred:

- ✓ Ref [1] Considering that one of the permanent competitive advantages for countries and companies is to make the transportation network more efficient, in this paper, a new formulation for locating axes and forming local tours to visit customersis presented. The number of axes and the maximum number of vehicles are assumed according to the number of fixed customers, and each customer can receive more than one service vehicle. In this case, no customer is served by the pre-stored load, but the load is transported between customers, that is, the load is received from one or more customers and is delivered to one or more other customers. Vehicle capacity limitations have been ignored, but the number of visits of each vehicle is considered. The model of this problem is formulated using GAMP and regarding its NP-hardness, it is precisely solved for a sample with 10 points of demand. The computational results are also indicated for this generated numerical example.
- ✓ Ref 2 in their research, investigated the location-routing problem. In the investigated problem, there are a number of demand points as a customer, each of which has a specific handing over and delivery demand or return of each kind of product, and each customer determines a delivery deadline for each product. In order to send products from warehouse to demanded points by customers, transportation vehicles are used that each of them has the ability to carry a group of products, and fixed usage costs, variable costs of transporting between points and its volumetric capacity is determined. To solve problems in larger dimensions regarding the time, genetic algorithm was used.
- ✓ Ref [3] in their research, created a mathematical model for garbage collection in Hanoi, Vietnam. Considering the fact that the main problem in routing this type of problems is related to picking up and delivery, they created time windows to solve this problem, then solved the model using integer programming.
- ✓ Ref [4] in their research, created a new location-routing model with several warehouse, several vehicles with potential demand. In that model, they paid special attention to reloading of warehouses and then solved the problem with the help of robust optimization.
- ✓ Ref [5] in their research investigated choosing of public transportation vehicles in the UK. They proved that an integrated and dynamic transportation system is one of the key social and political factors, and only improving the performance of the public transportation system can prevent people from using personal transportation vehicles. Then, they studied the transportation industry in the UK.
- ✓ Ref [6] in their research presented a new method of new goods transportation between cities. They presented a formula based onthe supply-demand balance, in which demand represents the behavior of the load owners and the supply side, indicates the behavior of the load carrier. Then, they indicated this equilibrium using a mathematical model and solved it using a general solving approach.

2. Methodology

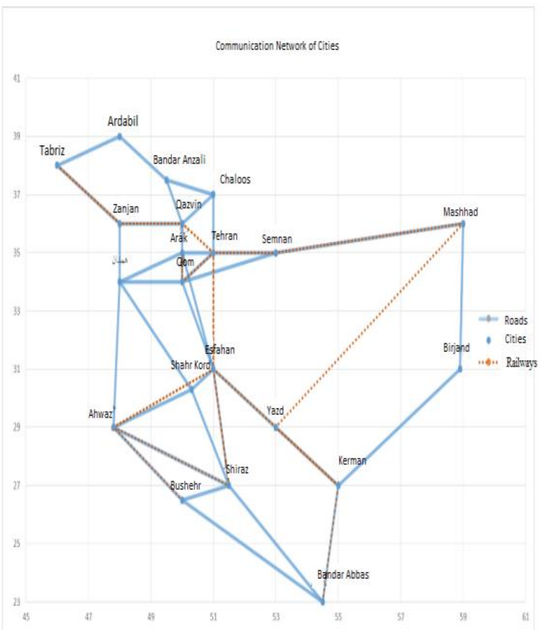
2.1 Collecting the Required Information

The information used in this research was obtained through searching on the Internet and through Iran Road Maintenance & Transportation Organization and the Islamic Republic of Iran Railwaysas follows:

• The distance between cities of the country through roads and railways
• Risk ratiofor country roads
• Freight rates based on different types of vehicles with different capacities
• The fixed cost of constructing multipurpose terminals and the transportation cost
• Geographic coordinates of cities
• The fixed cost of using the vehicle
• The supply and demand rate of different cities

After conducting the required surveys, the communication between the surveyed cities in this study was presented as Figure 1.

Figure 1 - The Communication between the Surveyed Cities in This Study



2.2 Mathematical Model

2.2.1 Introducing Decision Variables

✓ Sets

S: Set of Supply Centers

D: Set of demand points

E: Set of transportation methods

G: Set of valid routes

K: Set of Containers (Rail and Road)

The used parameters are presented in Table 1.

Table 1. Parameters Used in the Model

Variable	Description	Range
d_i	demand rate of i^{th}city	$\forall$ i∈ D
S_i	supply rate by the i^{th} supplier	$\forall$ i∈ S
f_i	The cost of constructing a multimodal transportation terminal in the i^{th} city	$\forall$ i∈ (S ∪ D)
fc_i	The cost of changing the transportation method in thei^{th} city	$\forall$ i∈ (S ∪ D)
r_i	The risk rate of changing the transportation method in thei^{th} city	$\forall$ i∈ (S ∪ D)
Q_k	The portable capacity of k^{th} container	$\forall$ k∈ K
ft_k	Transportation cost coefficient for k^{th} container	$\forall$ k∈ K
c_{ij}^{e}	The transporting cost from i^{th} city to j^{th} city via e^{th} transportation method	$\forall$ i،j∈ (S ∪ D)، $\forall$ e∈ E
r_{ij}^{e}	The transporting risk from i^{th} city to j^{th} city via e^{th} transportation method	$\forall$ i،j∈ (S ∪ D)، $\forall$ e∈ E

✓ Decision variables

The used decision variables in the model are presented in Table 2.

Table 2. Decision Variables

Variables	Description	Range
X_{ijk}^{e}	Will be equal to 1 if the k^{th} container is transferred from i^{th} city to j^{th} city via e^{th} transportation method, otherwise it will be 0	$\forall$ i،j∈ {R ∪ D}، $\forall$ k∈K ، $\forall$ e∈E
W_{ijk}^{e}	The amount of goods transported by k^{th} container from i^{th} city to j^{th} city via e^{th} transportation method	$\forall$ i،j∈ {R ∪ D}، $\forall$ k∈K ، $\forall$ e∈E
Y_{ik}	Will be equal to 1 if the demand of i^{th} city is provided by the k^{th} container, otherwise it will be 0.	$\forall$ i∈ D ، $\forall$ k∈K
U_{ik}	The rank of i^{th} city in the direction of the k^{th} container	$\forall$ i∈ D ، $\forall$ k∈K
Z_i	Will be equal to 1 if a multimodal terminal is constructed in the i^{th} city, otherwise it will be 0.	$\forall$ i∈ {R ∪ D}
T_{ik}^{e}	is equal to the number of transporting method changes of k^{th} container that occurs in the i^{th} city from e^{th} carrier to other carriers.	$\forall$ i∈ {R ∪ D}، $\forall$ k∈K ، $\forall$ e∈E

3.2.2. Objective Function and Constraints

$$\text{Min Cost} = \sum_{i\in S\cup D}\sum_{j\in S\cup D}\sum_{k\in K}\sum_{e\in E} c_{ij}^{e}\left(ft_k X_{ijk}^{e} + W_{ijk}^{e}\right) + \sum_{i\in S\cup D}\sum_{k\in K}\sum_{e\in E} fc_i T_{ik}^{e} + \sum_{i\in S\cup D} f_i Z_i \quad (1)$$

$$\text{Min Risk} = \sum_{i\in S\cup D}\sum_{j\in S\cup D}\sum_{k\in K}\sum_{e\in E} r_{ij}^{e} W_{ijk}^{e} + \sum_{i\in S\cup D}\sum_{k\in K}\sum_{e\in E} r_i T_{ik}^{e} \quad (2)$$

St

$$\sum_{i\in S\cup D}\sum_{e\in E} W_{pik}^{e} - \sum_{i\in S\cup D}\sum_{e\in E} W_{ipk}^{e} \le S_p \quad \forall\, p \in S \quad (3)$$

$$\sum_{i\in S}\sum_{j\in D}\sum_{e\in E} W_{ijk}^{e} \le Q_k \forall\, k \in K \quad (4)$$

$$\sum_{j\in S\cup D}\sum_{e\in E} X_{ijk}^{e} \le 1 \quad \forall\, i \in S \cup D ، k \in K \quad (5)$$

$$\sum_{k\in K} Y_{ik} = 1 \quad \forall\, i \in D ، d_i > 0 \quad (6)$$

$$\sum_{e\in E} X_{ijk}^{e} \le \sum_{p\in S}\sum_{e\in E} X_{pik}^{e} + M(U_{ik} - 1) \quad \forall\, i ، j \in D \quad k \in K \quad (7)$$

$$U_{ik} - U_{jk} + (N-1)\sum_{e\in E} X_{ijk}^{e} \le (N-1) - 1 \quad \forall\, i ، j \in D \quad k \in K \quad (8)$$

$$\sum_{i\in S\cup D}\sum_{e\in E} X_{pik}^{e} = \sum_{i\in S\cup D}\sum_{e\in E} X_{ipk}^{e} \quad \forall\, p \in S \cup D \quad k \in K \quad (9)$$

$$W_{ijk}^{e} \le M X_{ijk}^{e} \quad \forall\, i ، j \in S \cup D ، k \in K ، e \in E \quad (10)$$

$$\sum_{i\in S\cup D}\sum_{\substack{e\in E \\ Arc_{eip}\in G}} W_{ipk}^{e} - \sum_{i\in S\cup D}\sum_{e\in E} W_{pik}^{e} \ge d_i Y_{ik} \quad \forall\, p \in D ، k \in K \quad (11)$$

$$T_{ik}^{e} \ge \sum_{i\in S\cup D} X_{ipk}^{e} - \sum_{i\in S\cup D} X_{pik}^{e} \quad \forall\, p \in S \cup D ، k \in K ، e \in E \quad (12)$$

$$U_{ik} \in \text{Integer} \;\; 1 \le U_{ik} \le N - 1 \quad \forall\, i \in D ، k \in K \quad (13)$$

$$X_{ijk}^{e} \in \{0 ، 1\} W_{ijk}^{e} \ge 0 \forall\, i ، j \in S \cup D ، k \in K ، e \in E \quad (14)$$

$$Y_{ik} \in \{0 ، 1\} ، T_{ik} \ge 0 \quad \forall\, i \in D ، k \in K \quad (15)$$

$$Z_i \in \{0 ، 1\} \forall\, i \in S \cup D \quad (16)$$

Equation (1) includes the cost objective function that consists of four main components. The cost of transportation variable is calculated per unit of goods in the unit of distance. The fixed transportation cost is calculated considering the type being selected. The cost of changing the transportation method is calculated proportional to the city and each change of method. And ultimately, the cost of constructing a multimodal transportation terminal in cities that the change of transportation method occurs.

Equation (2) contains risk objective function that consists of two general components. The transportation risk proportional to the amount of goods and the route risk, and the second part includes the risk of changing the transportation method appropriate to each city.

Equation (3) ensures that the total amount of goods extracted from the supplier is not greater than the supply capacity.

Equation (4) ensures that the total amount of goods transported by the container is less than its capacity.

Equation (5) ensures that a container does not cross a single city more than once.

Equation (6) ensures that one container is allocated to the cities having demand.

Equations (7 and 8) are written to eliminate the sub-tour and ensure that the closed tours are not formed in the container loop.

Equation (9) is a conventional flow continuity equation that ensures the number of inputs is equal with the number of outputs.

Equation (10) limits the amount of transported goods to the decision variable of allocated route.

Equation (11) ensures that the demands of cities having demand is covered.

Equations (12 and 13) are written to determine the number of changes in the transportation method and the requirement for constructing a multimodal transportation terminal.

Equations (14, 15, 16, and 17) determine the range of decision variables.

3. Data Analysis

3.1. Solving the Mathematical Model

3.1.1. Solving Methods

- ✓ ε Constraint Method

The Epsilon constraint method is one of the known approaches to encounter with multi-objective problems, which solves this type of problems by conveying all of the objective functions, except one of them at each stage to the constraint. The steps of this approach are as follows:

i. Select one of the objective functions as the main objective function.
ii. Each time, solve the problem considering one of the objective functions, and obtain the optimal values of each objective function.
iii. Divide the interval between the two values of the sub-objective function into the predefined number and obtain a table of values for ε_1 ... ε_n.
iv. Each time obtain the problem with the main objective function, with each of the ε_1 ... ε_n values.
v. Report the obtained Pareto answers.

Research consists of four main decisions:

- Allocation of supply and demand points to the route
- Possible and optimized routing for each created path (container)
- Determining mode changing points of the transportation
- Determining the equipment points to change the mode of transportation

Since each of the research decisions alone are considered a hard problem, the research is also a hard problem, so in order to solve the problem in industrial and real dimensions, an algorithm must be proposed that can provide answer to the problem, at logical and low time. Therefore in the following, a solving algorithm based on the non-dominated Sorting Genetic Algorithm (NSGA II) is presented. In this method, in addition to using the structure of the NSGAII algorithm for the superior chromosomes, the neighborhood search algorithm, based on the optimizations obtained from the research literature, is presented. The proposed neighborhood search increased the algorithm convergence.

- ✓ The method of the NSGA II algorithm

The meta-heuristic NSGAII algorithm is one of the most applied and powerful algorithms available to solve multi-objective optimization problems and its efficiency in solving various problems is proved. In 1995, the NSGA optimization method was introduced to solve multi-objective optimization problems. Considering the relatively high sensitivity of the performance and the quality of the NSGA algorithm answers to the fitness sharing parameters and other parameters, the second version of the NSGA algorithm, called the meta-heuristic NSGAII algorithm, was introduced by Deb et al. (2000). Along the all features that meta-heuristic NSGAII algorithm has, it can be considered as a model for the formation of many multi-objective optimization algorithms. This algorithm and its unique approach to deal with multi-objective optimization problems have been used many times by different individuals to create newer multi-objective optimization algorithms. Undoubtedly, this algorithm is one of the most fundamental members of the evolutionary multi-objective optimization algorithm that can be called the second generation of these methods.

The method of the NSGAII algorithm is shown in Figure 2.

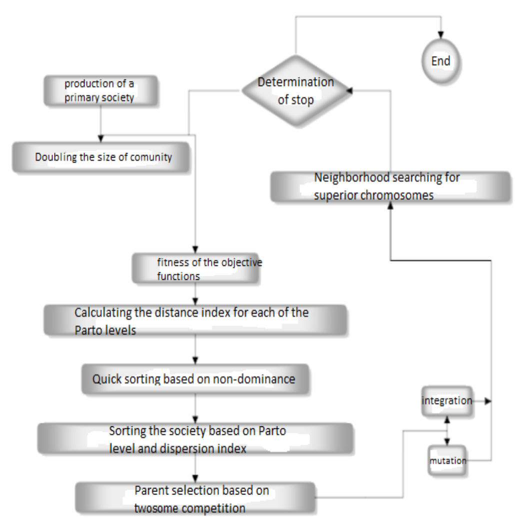


Figure 2. The Process of the Suggested Solving Method\

Title	Chromosome strand							
X				D1	D2	D3	D4	D5
				1	1	2	1	2
R		R1	R2					
		2	1					
Y		S1	S2	D1	D2	D3	D4	D5
	R1	0	1	1	0	1	1	1
	R2	1	0	0	0	1	1	1
RT		S1	S2	D1	D2	D3	D4	D5
	R1	1	2	1	2	1	1	1
	R2	1	1	1	1	1	1	1
Seq		S1	S2	D1	D2	D3	D4	D5
	R1	7	6	4	5	1	3	2
	R2	6	3	7	4	1	2	5

The chromosome structure of the problem consists of four major strands.

X Strand: This strand determines that the demand for each of the demand points should be provided by which (route) container. In other words, a route will only have delivery at the points that is determined by this strand. Likewise, the loading amount of container at the supply station will be as much as the total demand of determined points for the container.

R Strand: This strand specifies each of the containers will be loaded from which supply source. In other words, all of the demands of all of the points that will be supplied by this container will be loaded from the specified source determined for this route.

Y Strand: This strand determines the points that the container will pass. In other words, the container will pass through the points that their value is 1 and will not pass the rest of the points.

RT Strand: This strand determines which transporting mode will be used to carry the container to its next destination.

Seq Strand: Indicates the sequence of points on the route of each container. In other words, this sequence indicates that the container with what sequence will pass through the points (based on the Y strand, the points whose Y value is equal to 1, and the points that their X value are equal to the current container number, and the points that based on the R strand are source and ultimate destination of the container). Table 3 shows the chromosome structure of this problem. Genetic operators

For the above presented genetic structures, classical genetic operators are perfectly appropriate, but in order to increase the searching speed, appropriate preparations should be considered according to the objective functions and problem constraints. One of the five strands is selected randomly and the following operators are applied on it. It's worth noting that for the Y, Seq, and RT strands, in addition to selecting the strand, one of the routes (containers) is randomly selected and the genetic operators are performed on it.

- Mutation operator

Common operators to solve similar problems, especially operators that are more suitable for inventory problem solving, are listed below:

Displacement of genes: Two different genes are randomly selected and their values are changed with each other.

Reinitializing: Reinitializing a gene according to the method of producing the initial answer. Optimal Search for the cost objective function: Using the SA algorithm, the selected chromosome is optimized and replaced the current answer.

Optimal Search for the risk objective function: Using the SA algorithm, the selected chromosome is optimized and replaced the current answer.

- Integration operator

In general, classical operators have been used to integrate this type of problems.

4.2 Algorithm Comparison Indicators

In order to evaluate the performance of multi-objective meta-heuristic algorithms, there are two main categories of convergence indicators and dispersion indicators. The indicators of the first category include the number of Pareto answers indicator, mean ideal distance indicator, and the sets coverage indicator. The indicators of the second category include the space metric, diversity and the most expansion indicator. Now, we look at the indicators used in this research to compare the algorithm:

- Mean Ideal Distance (MID) Indicator

This indicator is used to calculate the mean distance of the Pareto answers from the origin of the coordinates.

In relation 1, c_i is the distance between the Pareto answer and the ideal point. Considering this relation, it is clear that as much as this indicator is lower, the efficiency of this algorithm will be more.

$$MID = \sum_{i=1}^{n} \frac{Ci}{n}$$

(1)

Since in multi-objective discussions based on Pareto approach, one of the goals is the boundaries closest to the origin of the coordinates, therefor this indicator calculates the distance of the fronts from the best value. In this research, considering the point that both target functions are of minimization type, then the ideal point is considered equal to the minimum of each objective function in all algorithms. Relation 2 is used to calculate the MID indicator.

$$MID = \sum_{i=1}^{n} \frac{\sqrt{\left(\frac{f_{1\,i}-f_1^{best}}{f_{1.total}^{max}-f_{1.total}^{min}}\right)^2+\left(\frac{f_{2\,i}-f_2^{best}}{f_{2.total}^{max}-f_{2.total}^{min}}\right)^2}}{n}$$

(2)

In this equation, n is equal to Pareto points, $f_{i.total}^{max}$, $f_{i.total}^{min}$ are respectively equal to the maximum and minimum value of the objective functions among all the performances of the algorithm. Likewise, f_1^{best}, f_2^{best} are the coordinates of ideal point.

- CPU Time Indicator (CPU T):

In major problems, one of the important indicators is the implementation time of solving, and therefore the implementation time of the algorithm is considered as a quality assessment indicator.

- Space Metric (SM):

This indicator shows the uniform distribution of Pareto answers in the solution space. The calculating method of this indicator is according to Equation 3.

$$SM = \frac{\sum_{i=1}^{n-1}|\bar{d}-d_i|}{(n-1)\bar{d}}$$

(3)

Where d_i is equal to the Euclidean distance between the two side Pareto answers in the solution space and $\bar{d}$ is equal to the mean distances of d_i. As much as this indicator is low, the better is the performance of algorithm.

- Quality Metric (QM)

The quality metric is such that all of the obtained Pareto answers by each of the algorithms are considered together, and then the negligence operation is performed for all the solutions. Ultimately, the quality of each algorithm is equal to the share of new Pareto answers specific to that algorithm. The higher quality means the better performance of the algorithm.

- ✓ Diversification Metric (DM)

This parameter indicates the extent of Pareto answers of an algorithms and can be calculated by equation 4. As much as this indicator is higher, the performance of the algorithm is better.

$$DM = \sqrt{\left(\frac{maxf_{1\,i}-minf_{1\,i}}{f_{1.total}^{max}-f_{1.total}^{min}}\right)^2+\left(\frac{maxf_{2\,i}-minf_{2\,i}}{f_{2.total}^{max}-f_{2.total}^{min}}\right)^2}$$

(4)

3.3. Solving the numerical example

To confirm the validity of the presented mathematical model, first the model was created by a small sample and according to the information received from National Iranian Oil Refining and Distribution Company, and the five cities indicated in Table 4 were selected as the supply location, then the model was solved in GAMS and these outputs were the proof for correct performance of the model.

Table 4. Supply Cities along with answerable demands

Name of the city	Answerable demands
Tehran	1000
Bandar Abbas	1000
Mashhad	500
Tabriz	500
Ahwaz	500

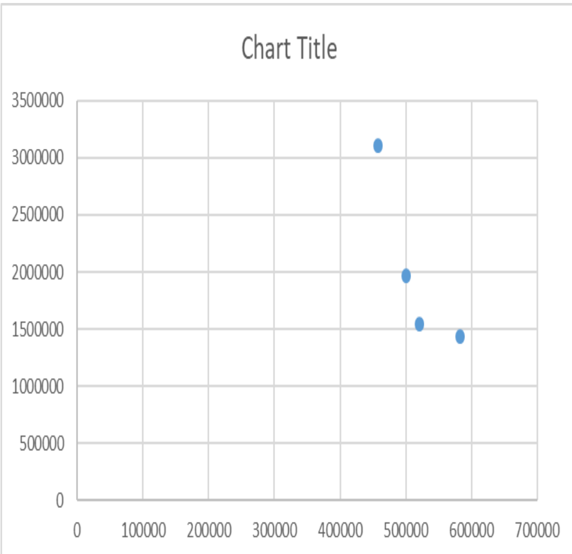
Now, we consider the Epsilon constraint solving method. To solve this problem, it was implemented 10 times in GAMS, and the answer of this implementation is represented in Table 5.

Table 5 – The Results of Implementing the Model in GAMS

Implementation number	Cost	Risk
Implementation 1	458,072	310,713
Implementation 2	500,263	196,196
Implementation 3	520,295	154,077
Implementation 4	582,222	143,751

In Figure 3, the Pareto chart of the answers is drawn based on risk and cost.

Figure 3. Pareto Chart of Answers



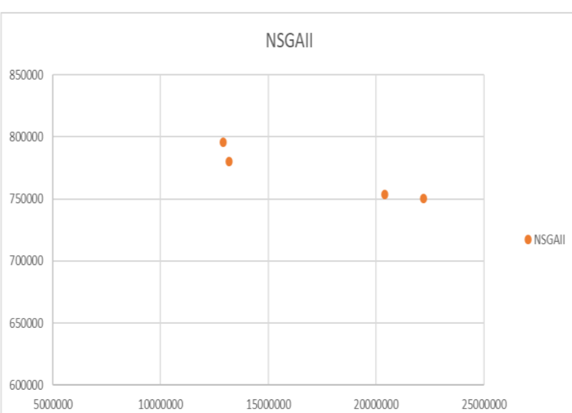
Now, the above example is solved according to the proposed algorithm and the results are described in Table 6.

Table 6. The Results of Solving the Sample with Algorithm

Implementation number	Cost	Risk
1	1026790	93770
2	1051210	92080
3	1056530	90480
4	1080950	88790

Likewise, its Pareto chart is represented in Figure 4.

Figure 4. Pareto chart of NSGA II Algorithm



✓ Determining the parameters of the solution method

Heuristic and meta-heuristic methods for searching the answer space usually take into account the parameters that affect the route of optimal answer. In each presented algorithm, finding the best mode for these parameters, as they are expected to achieve better result in a short time, is one of the problems that researchers must address. In the following, to determine the optimal values, parameters of the proposed solving method, a set of experiments are presented based on the Pareto method and the results are analyzed to determine the best value for each parameter.

3.4. Designing Experiments

Since the complexity of hard problems is very sensitive to their size, and also the effective parameters in heuristic solving method are a function of complexity, in this research, to determine the appropriate parameters of the solution, samples with different complexity levels are used.

In this research, the size of problem is mainly influenced by several main parameters that include the number of cities, the number of routes, the number of axes and the percentage of edges that have both rails and the road. The experiments are designed at three levels of small, medium and large size. The size of each problem parameter is randomly selected from the intervals that are presented in Table 7. For each level 10 problems and finally 30 problems are used to determine the parameters of the solving method. In each level, the mean efficiency indicator of the solving method was used with various parameters as a comparison indicator to determine the parameters. The four main parameters of the solving method, were investigated and their optimal levels were determined. In order to minimize the number of tests, the Taguchi method and the Minitab 16 were used. Table 7 represents the parameters of the problem and different complexity levels. Likewise, the parameters of the solving method and its levels are indicated in Table 8.

Table 7. Determining the Parameters of Level Determination

Parameters	Small	Medium	Large
Number of cities	5-29	30-69	70-100
Number of containers	1-5	6-10	11-15
Number of axes	10-30	31-69	70-100
percentage of edges that have both rails and the road	10-40	41-69	70-100

Table 8. The Level of Solving Method Factors

	Level 1	Level 2	Level 3
The size of community	30	45	60
Mutation rate-Integration rate	0.3-0.7	0.5-0.5	0.3-0.7
Repetition	500	2000	4000
Optimization rate	0.2	0.5	-

✓ Determining the optimal parameters of solving method

After determining the factors of solving method and the levels of each one, the experiments were designed by Taguchi method and the results of each experiment were determined for ten problems at each level. Using Taguchi method the number of tests were reduced from 54 to 18.

The mean of these results for different settings is given in tables 9, 10 and 11, respectively, for small, medium and large problems.

Table 9. The Mean of Indicators for Problems with Small Size

Number	community size	Mutation rate	Integration rate	Optimization rate	Repetition	Quality indicator	Size indicator	Distance indicator	Time	Combined indicator
1	60	0.3	0.7	0.2	1000	0.042379	1.131406	1399.531	5396.875	0.646588
2	60	0.5	0.5	0.2	2000	0.049555	1.141008	1153.727	10818.75	0.634342
3	60	0.7	0.3	0.2	3000	0.046615	1.025223	1648.549	16129.69	0.637267
4	100	0.3	0.7	0.2	1000	0.060636	1.040924	1252.52	16748.44	0.657911
5	100	0.5	0.5	0.2	2000	0.063019	1.53298	5385.074	32206.25	1.264962
6	100	0.7	0.3	0.2	3000	0.057185	1.141958	2322.619	49573.44	0.689811
7	150	0.3	0.7	0.2	2000	0.060547	1.320625	3110.294	95745.31	0.691968
8	150	0.5	0.5	0.2	3000	0.060606	1.194299	3188.914	141229.7	0.514964
9	150	0.7	0.3	0.2	1000	0.060386	1.141055	2449.751	46545.31	0.732458
10	60	0.3	0.7	0.5	3000	0.049547	1.07358	941.1578	19612.5	0.560266
11	60	0.5	0.5	0.5	1000	0.04489	0.983174	805.8686	6515.625	0.54293
12	60	0.7	0.3	0.5	2000	0.047033	1.086936	2729.705	13134.38	0.804103
13	100	0.3	0.7	0.5	2000	0.057292	1.208067	2206.452	37315.63	0.733599
14	100	0.5	0.5	0.5	3000	0.057203	0.882033	266.8373	56139.06	0.33927
15	100	0.7	0.3	0.5	1000	0.060628	1.22073	2090.987	18881.25	0.802056
16	150	0.3	0.7	0.5	3000	0.06083	1.243187	2423.693	151178.1	0.394772
17	150	0.5	0.5	0.5	1000	0.057784	1.048636	1269.486	50751.56	0.530329
18	150	0.7	0.3	0.5	2000	0.063865	1.328934	4096.386	100215.6	0.822398

Table 10. The Mean of Indicators for Problems with Medium Size

Number	community size	Mutation rate	Integration rate	Optimization rate	Repetition	Quality indicator	Size indicator	Distance indicator	Time	Combined indicator
1	60	0.3	0.7	0.2	1000	0.000617	0.844059	1830.031	9620.313	0.351598
2	60	0.5	0.5	0.2	2000	0.00667	1.055907	4193.458	18946.88	0.579387
3	60	0.7	0.3	0.2	3000	0.013323	0.939633	3892.431	27851.56	0.53936
4	100	0.3	0.7	0.2	1000	0.01859	0.973685	3366.153	22810.94	0.557222
5	100	0.5	0.5	0.2	2000	0.026254	0.953741	5119.947	45610.94	0.650701
6	100	0.7	0.3	0.2	3000	0.082995	0.808854	1758.82	68725	0.645081
7	150	0.3	0.7	0.2	2000	0.070421	0.823479	3074.309	107985.9	0.566425
8	150	0.5	0.5	0.2	3000	0.183274	0.892298	4061.21	162959.4	1.139812
9	150	0.7	0.3	0.2	1000	0.054215	1.031013	6821.575	56704.69	0.912189
10	60	0.3	0.7	0.5	3000	0.0251	1.162321	5127.611	42312.5	0.715648
11	60	0.5	0.5	0.5	1000	0.000364	0.83249	2373.717	14100	0.370877
12	60	0.7	0.3	0.5	2000	0.01527	0.758842	1081.943	27359.38	0.313964
13	100	0.3	0.7	0.5	2000	0.038146	0.779905	3033.904	61676.56	0.488141
14	100	0.5	0.5	0.5	3000	0.022924	0.869294	3366.768	92939.06	0.373282
15	100	0.7	0.3	0.5	1000	0.028492	1.021011	6237.886	31314.06	0.792228
16	150	0.3	0.7	0.5	3000	0.16113	0.727637	841.7634	199050	0.666543
17	150	0.5	0.5	0.5	1000	0.02498	1.088313	9820.312	66356.25	0.937844
18	150	0.7	0.3	0.5	2000	0.127227	1.112877	10686.96	133945.3	1.399698

Table 11. The Mean of Indicators for Problems with Large Size

Number	Community size	Mutation rate	Integration rate	Optimization rate	Repetition	Quality indicator	Size indicator	Distance indicator	Time	Combined indicator
1	60	0.3	0.7	0.2	1000	0	0.910602	2302.417	38660.94	0.399903
2	60	0.5	0.5	0.2	2000	0.022746	0.684018	805.1866	74028.13	0.320204
3	60	0.7	0.3	0.2	3000	0.031894	0.883963	3643.658	110171.9	0.574334
4	100	0.3	0.7	0.2	1000	0	1.053303	6295.329	69851.56	0.665088
5	100	0.5	0.5	0.2	2000	0.003946	0.915514	5608.515	134045.3	0.545725

6	100	0.7	0.3	0.2	3000	0.056634	0.876018	4932.414	197890.6	0.702354
7	150	0.3	0.7	0.2	2000	0.017279	0.739198	1232.944	250989.1	0.190774
8	150	0.5	0.5	0.2	3000	0.313921	1.009918	13420.39	371398.4	2.410063
9	150	0.7	0.3	0.2	1000	0	0.925199	5728.748	126779.7	0.542467
10	60	0.3	0.7	0.5	3000	0	0.776265	1482.34	183928.1	0.186782
11	60	0.5	0.5	0.5	1000	0	0.897684	2834.938	63007.81	0.408433
12	60	0.7	0.3	0.5	2000	0	0.97889	7314.895	123514.1	0.65977
13	100	0.3	0.7	0.5	2000	0.00102	0.790791	2648.767	240017.2	0.222003
14	100	0.5	0.5	0.5	3000	0.243428	0.780257	2596.357	364956.3	1.3244
15	100	0.7	0.3	0.5	1000	0	0.925687	6386.185	120996.9	0.587803
16	150	0.3	0.7	0.5	3000	0.123013	0.810954	6040.386	584293.8	0.762867
17	150	0.5	0.5	0.5	1000	0	0.80575	1062.315	198689.1	0.158249
18	150	0.7	0.3	0.5	2000	0.186118	0.921126	7011.944	383598.4	1.338782

The results of Table 11 are analyzed by Taguchi method and Minitab 16, and the following results are separately presented for optimal levels of factors in different problem sizes.

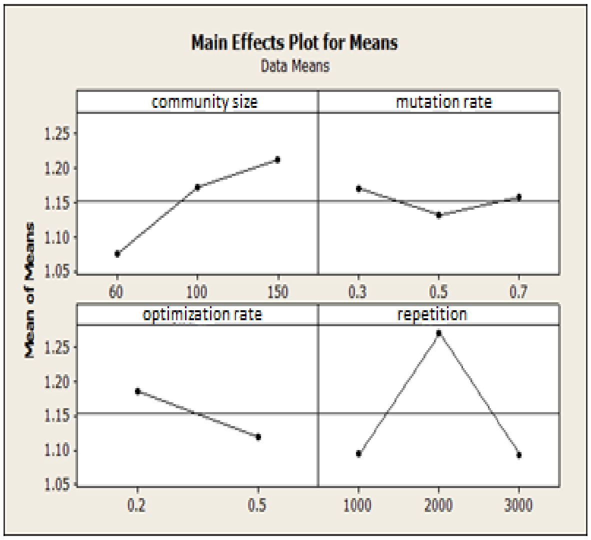
The results for the small size of problem has estimated the level of community size factors 150, the mutation rate of 0.3, the optimization rate of 0.2 and the number of 2000 repetitions. Likewise, the combined indicator has the most sensitivity to changes in factors like the number of repetitions, the mutation rate, community size and optimization rate.

The results for the small size of the problem has estimated level of community size factors 150, the mutation rate of 0.3, the optimization rate of 0.2 and the number of 2000 repetitions. Likewise, the combined indicator has the most sensitivity to changes in factors like the number of repetitions, the mutation rate, community size and optimization rate, respectively. The obtained results are represented in Table 12 and Figure 5.

Table 12. The Results of Taguchi Analysis for Small Problems

Level	Community size	Mutation rate	Optimization rate	Repetition
1	0.6376	0.6142	0.7189	0.652
2	0.7479	0.6378	0.6144	0.8252
3	0.6145	0.748		0.5227
Delta	0.1335	0.1338	0.1045	0.3025
Rank	3	2	4	1

Figure 5. The Results of Taguchi Analysis for Small Problems

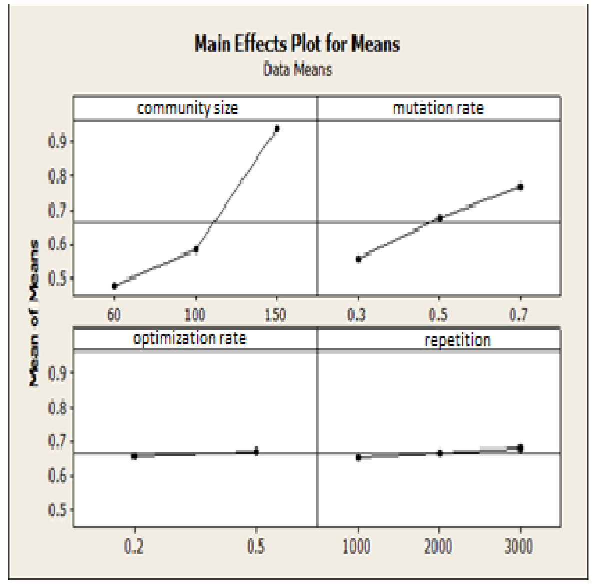


Likewise, the results for the medium size of the problem has estimated the level of community size factors to be 150, the mutation rate of 0.7, the optimization rate of 0.5 and the number of 3000 repetitions. And, the combined indicator has the most sensitivity to changes in factors like the community size, the mutation rate, the number of repetitions, and optimization rate, respectively. The obtained results are represented in Table 13 and Figure 6.

Table 13. The Results of Taguchi Analysis for Medium Problems

Level	**Community size**	**Mutation rate**	**Optimization rate**	**Repetition**
1	0.4785	0.5576	0.6602	0.6537
2	0.5844	0.6753	0.6731	0.6664
3	0.9371	0.7671		0.68
Delta	0.4586	0.2095	0.0129	0.0263
Rank	1	2	4	3

Figure 6. The Results of Taguchi Analysis for Medium Problems

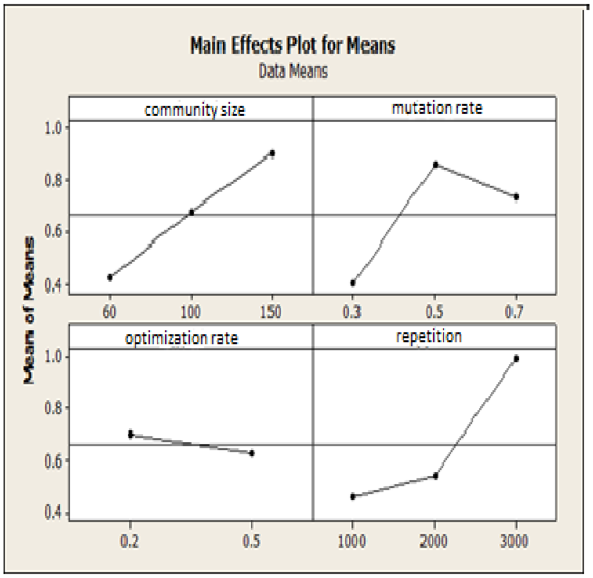


The results for the large size of the problem has also estimated the level of community size factors to be 150, the mutation rate of 0.5, the optimization rate of 0.2 and the number of 3000 repetitions. And, the combined indicator has the most sensitivity to changes in factors like the number of repetitions, the community size, the mutation rate, and optimization rate, respectively. The obtained results are represented in Table 14 and Figure 7.

Table 14. The Results of Taguchi Analysis for Large Problems

Level	**Community size**	**Mutation rate**	**Optimization rate**	**Repetition**
1	0.4249	0.4046	0.7057	0.4603
2	0.6746	0.8612	0.6277	0.5462
3	0.9005	0.7343		0.9935
Delta	0.4756	0.4566	0.078	0.5331
Rank	2	3	4	1

Figure 7. The Results of Taguchi Analysis for Large Problems



The results of Figure 7 clearly indicate that the optimal levels of parameters are very sensitive to the size of the problem, and also in large problems, the results are more sensitive to the number of repetitions, and the size of community.

3.5. The Comparison of Two Solving Methods in Different Dimensions

After setting the parameter, we investigated the efficiency of solving methods based on the mentioned criteria, and the results of these investigations are presented in Table 15.

Table 15. The Comparison of Two Solving Methods in Different Dimensions

Number	community size	Mutation rate	Integration rate	Optimization rate	Repetition	Quality indicator	Size indicator	Distance indicator	Time	Combined indicator
1	60	0.3	0.7	0.2	1000	0.000617	0.844059	1830.031	9620.313	0.351598
2	60	0.5	0.5	0.2	2000	0.00667	1.055907	4193.458	18946.88	0.579387
3	60	0.7	0.3	0.2	3000	0.013323	0.939633	3892.431	27851.56	0.53936
4	100	0.3	0.7	0.2	1000	0.01859	0.973685	3366.153	22810.94	0.557222
5	100	0.5	0.5	0.2	2000	0.026254	0.953741	5119.947	45610.94	0.650701
6	100	0.7	0.3	0.2	3000	0.082995	0.808854	1758.82	68725	0.645081
7	150	0.3	0.7	0.2	2000	0.070421	0.823479	3074.309	107985.9	0.566425
8	150	0.5	0.5	0.2	3000	0.183274	0.892298	4061.21	162959.4	1.139812
9	150	0.7	0.3	0.2	1000	0.054215	1.031013	6821.575	56704.69	0.912189
10	60	0.3	0.7	0.5	3000	0.0251	1.162321	5127.611	42312.5	0.715648
11	60	0.5	0.5	0.5	1000	0.000364	0.83249	2373.717	14100	0.370877
12	60	0.7	0.3	0.5	2000	0.01527	0.758842	1081.943	27359.38	0.313964
13	100	0.3	0.7	0.5	2000	0.038146	0.779905	3033.904	61676.56	0.488141
14	100	0.5	0.5	0.5	3000	0.022924	0.869294	3366.768	92939.06	0.373282
15	100	0.7	0.3	0.5	1000	0.028492	1.021011	6237.886	31314.06	0.792228
16	150	0.3	0.7	0.5	3000	0.16113	0.727637	841.7634	199050	0.666543
17	150	0.5	0.5	0.5	1000	0.02498	1.088313	9820.312	66356.25	0.937844
18	150	0.7	0.3	0.5	2000	0.127227	1.112877	10686.96	133945.3	1.399698

Problem number	Problem type	MID		SM		DM		QM	
	Small size	ε-Constraint	NSGA II	ε-Constraint	NSGA II	ε-Constraint	NSGA II	ε-Constraint	NSGA II
1		0.0452	0.0562	0.565	0.645	750	632	0.159	0.89
2		0.0523	0.0657	0.452	0.532	695	645	0.125	0.115
3		0.0365	0.0559	0.345	0.518	859	762	0.168	0.137
4		0.0458	0.0641	0.436	0.512	723	658	0.147	0.179
5	Medium size	0.457	0.369	0.369	0.425	865	968	0.238	0.361
6		0.592	0.458	0.459	0.562	956	1035	0.365	0.459
7		0.459	0.395	0.347	0.482	814	896	0.247	0.381
8		0.523	0.468	0.467	0.568	964	1036	0.251	0.362
9	Large size	0.857	0.715	0.236	0.359	1657	1869	0.419	0.523
10		0.759	0.0635	0.348	0.419	1457	1657	0.394	0.462
11		0.729	0.569	0.198	0.235	1369	1457	0.317	0.425
12		0.732	0.732	0.143	0.239	1.294	1.414	0.316	0.684
Mean		0.440	0.299	0.363	0.419	925	1085	10	15

As it is observed in Table 15, the Epsilon method for small problems and the algorithm for medium and large problems have better efficiency.

3.6. Solving the Model Using Real Data

Using the above issues and comparing the solving method, the model was solved considering the mentioned information, and the results are represented in table 16. Likewise, the performance comparison of the two solving methods is represented in Table 17.

Table 16. The Obtained Results from Model Solving with Real Information

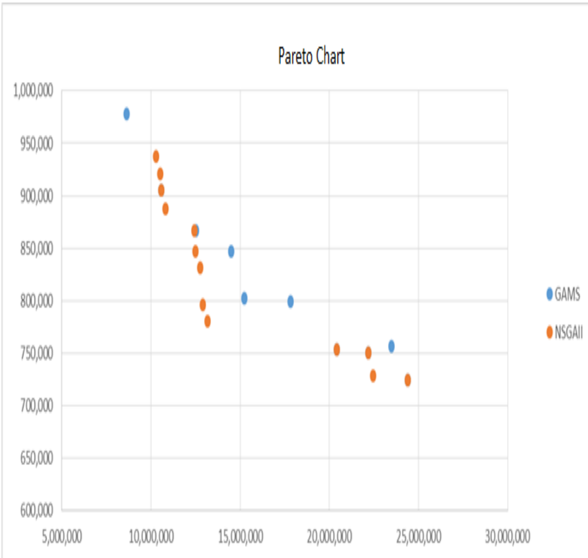
Implementation number	Total Cost	Total Risk	Total Cost	Total Risk
	NSGA II		Epsilon Method	
1	10,267,896	937,700	24,390,592	724,550
2	10,512,096	920,800	8,618,699	977,700
3	10,565,298	904,800	10,565,298	904,800
4	10,809,498	887,900	12,519,898	867,250
5	12,419,898	867,250	14,481,418	847,300
6	12,488,915	847,300	15,236,815	802,700
7	12,753,615	831,750	17,808,787	799,150
8	12,905,305	795,750	20,407,216	753,700
9	13,170,005	780,200	22,188,928	750,150
10	20,407,216	753,700	23,484,229	756,150

Table 17. Comparing the Performance of NSGA II with Epsilon Method

Solving method	**MID**	**SM**	**DM**	**QM**
NSGAII	0.732	0.239	1.414	0.684
Epsilon Method	0.732	0.143	1.294	0.316

Likewise, the Pareto chart of the answers of both problems is represented in Figure 8.

Figure 8. Investigating the Pareto Chart of Both Solving Methods

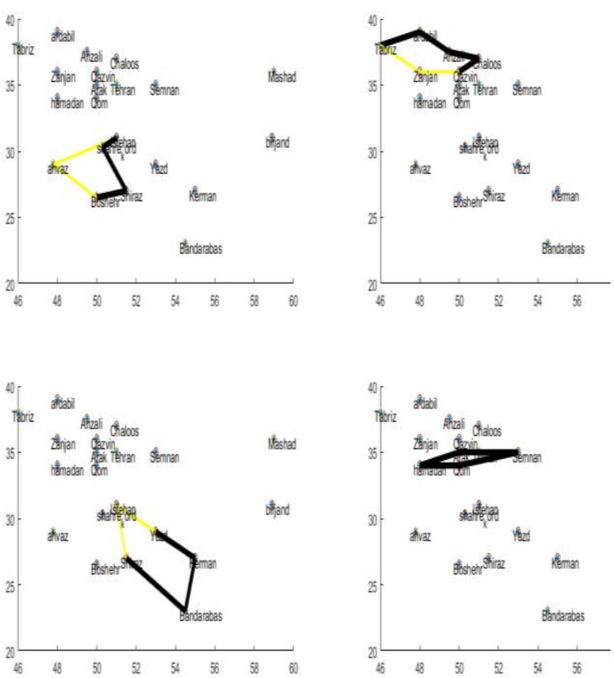


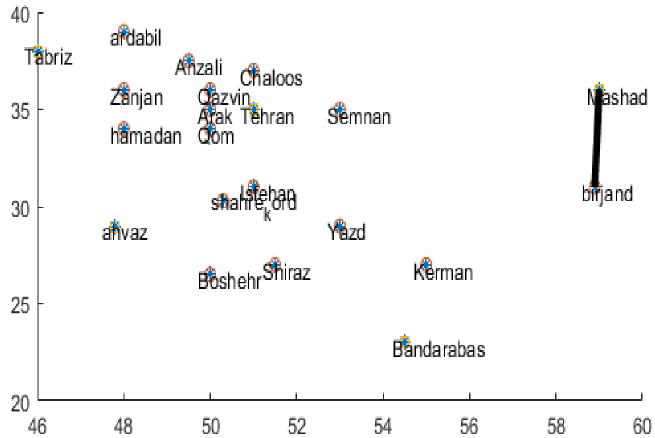
3.7. Selected Routes by Two Methods

- ✓ Selected routes by NSGAII for the lowest cost

These routes are represented in Figure 9.

Figure 9. Selected Routes by NSGAII for the Lowest Cost

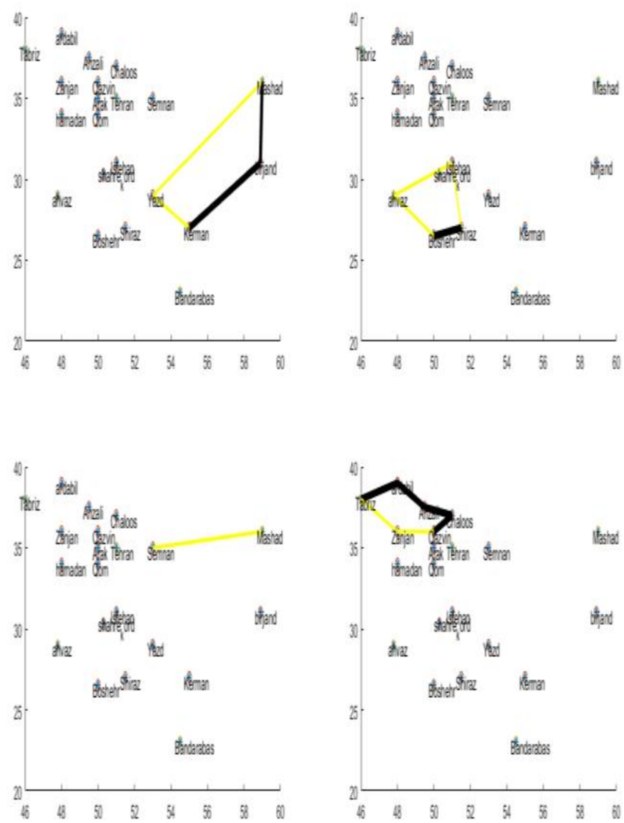


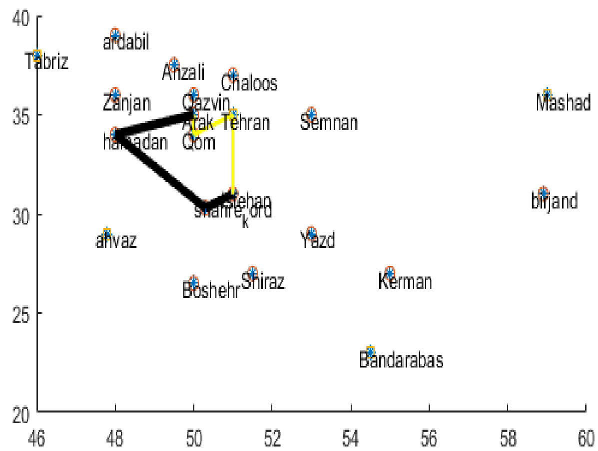


- ✓ Selected Routes by NSGAII for the Lowest Risk

These routes are represented in Figure 10.

Figure 10. Selected Routes by NSGAII for the Lowest Risk

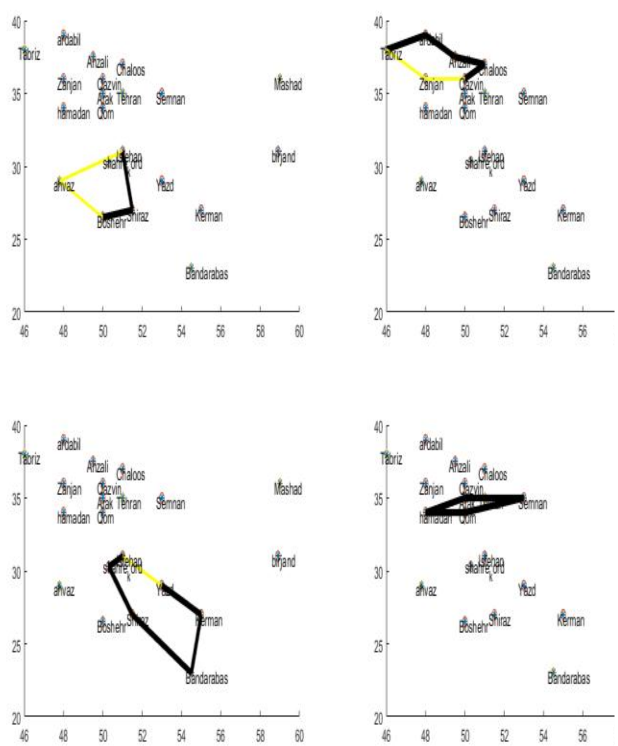


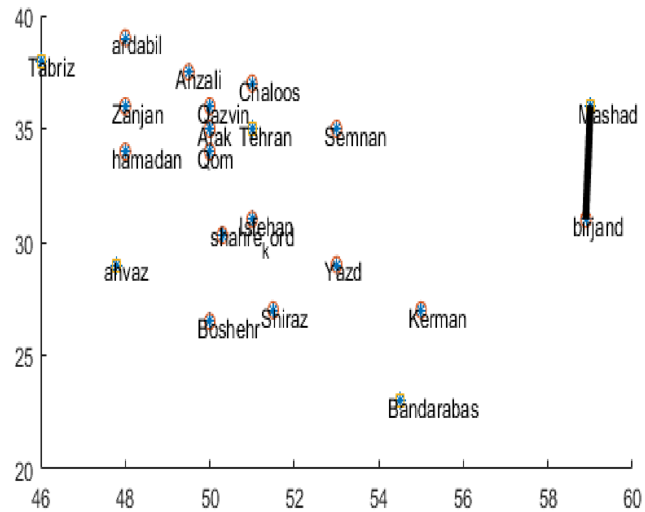


- ✓ Selected Routes by Epsilon method for the Lowest Cost

These routes are represented in Figure 11.

Figure 11. Selected Routes by NSGAII for the Lowest Cost

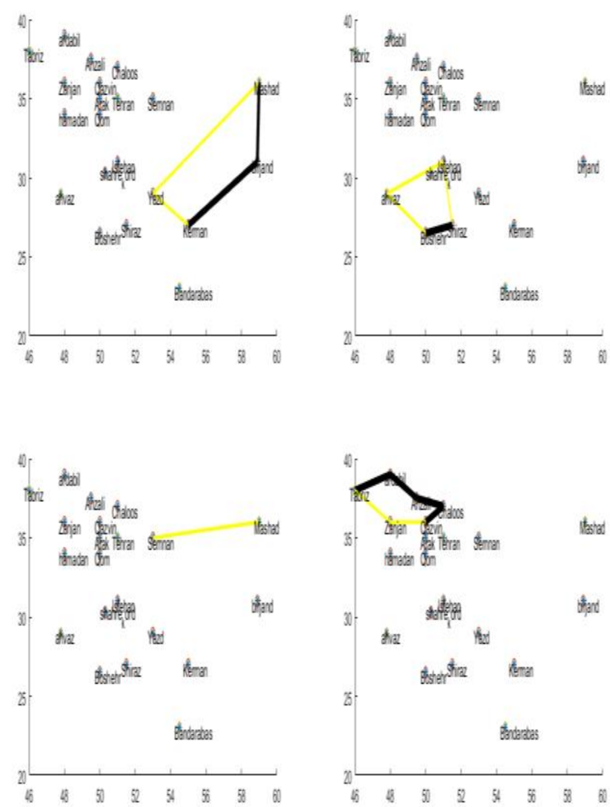


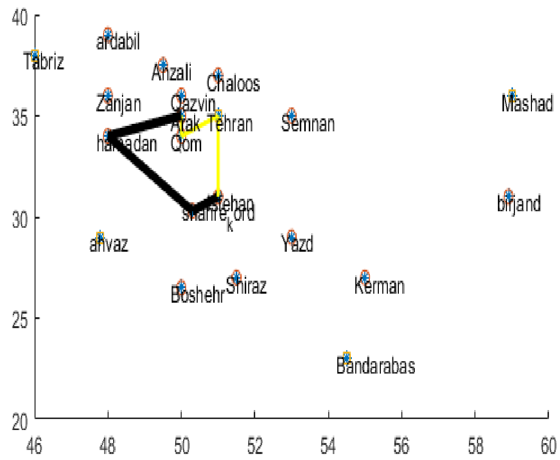


- ✓ Selected Routes by Epsilon method for the Lowest Risk

These routes are represented in Figure 12.

Figure 12. Selected Routes by Epsilon method for the Lowest Risk





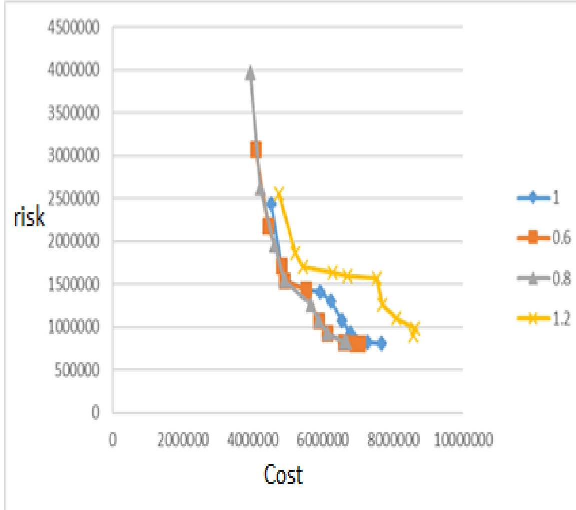
3.8. Sensitivity Analysis

In this section, by changing the effective parameters on the model, it is observed that how the results will be changed. For this purpose, the parameters that are considered critical for sensitivity analysis including demand of cities, fixed construction cost, variable transportation cost, transportation risk factor and change of vehicle type and capacity of containers were investigated. In the sensitivity analysis, parameters are considered constant except the studied parameters.

- ✓ Demand of cities

In order to study this parameter, the demand value was considered 0.6, 0.8 and 1.2 times of the initial value, and the results are indicated in Figure 13.

Figure 13. Studying the Effect of Demand on the Objective Function

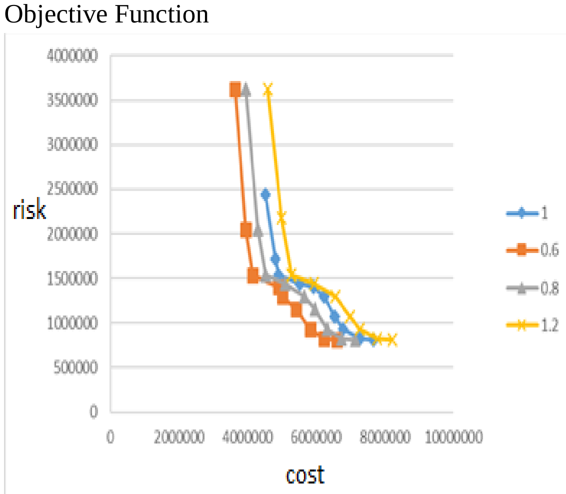


As it can be observed in Figure 13, risks and costs are increased by the increase of demand, which can be attributed to increase of transportation costs, increased costs of movement, and increased terminal construction cost as well as increased transportation and movement risks.

- ✓ The fixed construction cost and transportation costs

In order to study this parameter, the demand value was considered 0.6, 0.8 and 1.2 times of the initial value, and the results are indicated in Figure 14.

Figure 14. Studying the Effect of Cost Change on the Objective Function



As it is observed in Figure 14, by the increase of fixed costs of the terminal construction and transporting costs, risks and costs increase, which can be due to increased transportation costs, increased cost of terminal construction, and there is no considerable change in the amount of risk.

- ✓ Risk coefficient of transportation and changing the vehicle type

In order to study this parameter, transportation risk and changing the vehicle type coefficients were considered 0.6, 0.8 and 1.2 times of the initial value, and the results are indicated in Figure 15.

Figure 15. Studying the Effect of Changes in the Risk Coefficients

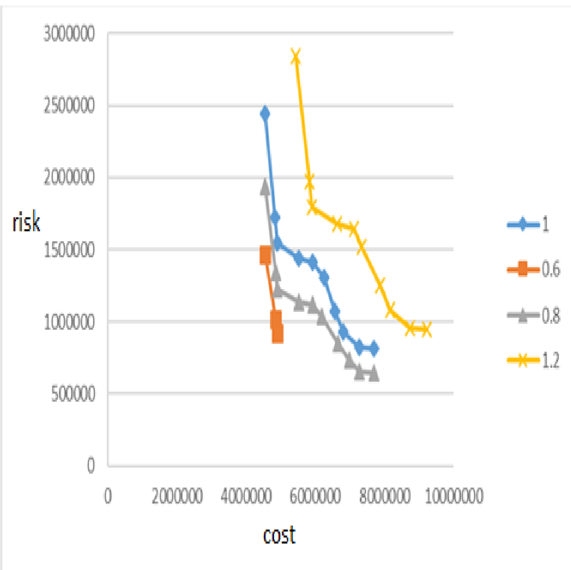
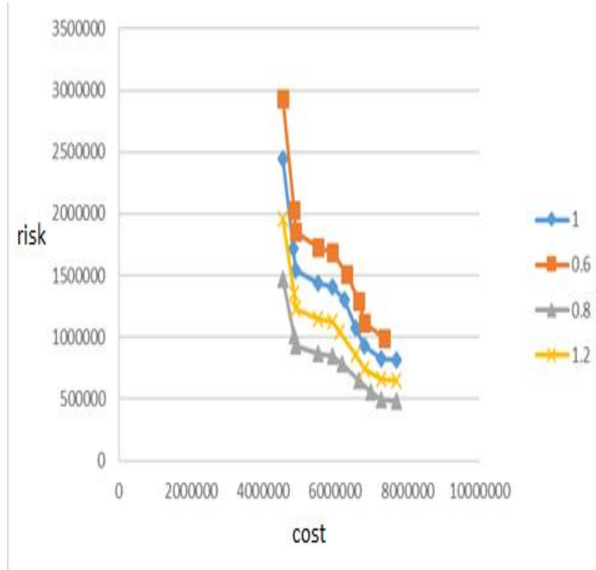


Figure 15 indicates that the 0.6 and 0.8 of changes had not a different effect on the objective function, and also it shows that risk reduction encounters with a high increase of cost.

- ✓ Capacity of containers

In order to study this parameter, the capacity of containers were assumed 0.6, 0.8 and 1.2 times the initial value, and the obtained results are represented in Figure 16.

Figure 16. Studying the Effect of Changes in the Capacity of Containers on the Objective Function



As it is observed in Figure 16, the changes in the capacity of containers encounters with the increase of cost and reduction of risk, that by the increase of the cost, the capacity of the container increases so the amount of transporting load will increase.

4. Conclusion

In this study, after reviewing a comprehensive literature on the location-routing problem of hazardous materials transportation, a research gap was found. After studying the modeling of similar cases with modeling assumptions, a new model with a two-objective function was expressed.

In this research, the location-routing problem of hazardous materials transportation by multiple vehicle was studied, considering the weight of transported materials. At first, from the supply points the hazardous materials including petrol, oil, and gas, were sent to demand points by a mode of transportation, then the type of vehicle was changed in cities that there were the possibility of changing the transportation mode. Since the nature of hazardous materials transportation is risky, these issues are also examined in the mathematical model.

After modeling, in order to validate the model, first by solving the problem in small dimensions and using the exact solving method, it was shown that the model provides consistent answers, and also indicated that the proposed model reaches the answer and the answer satisfies all the considered constraints. Then, regarding the complexity of the solving algorithm, the non-dominated meta-heuristic optimization method was used to solve the problem.

By solving numerical examples, it was indicated that the used algorithm also gives consistent answers that meets all the constraints of the problem. Then the parameters of the algorithm were set and using the Taguchi method, the most suitable parameters were selected for the algorithm. After adjusting the parameters of the algorithm, the problems were divided into three small, medium and large groups, and for each of the solving methods the evaluation criteria were calculated. The results of this comparison indicated that the non-dominated optimization algorithm has a better performance compared to the exact solution method. Therefore, it was concluded that this algorithm should be used to solve the model of real data. Likewise, in order to ensure the performance of this algorithm, the sensitivity analysis of the model was performed and it was indicated that by modifying the parameters of the model, this algorithm generates the expected results and thus its structural performance is confirmed. Finally, the proposed model indicated the relation of the transported load amount of the hazardous materials in a location-routing problem.

Suggestions

Some suggestions that are relevant to this research and have the capability of expansion are as listed below:

- ✓ The use of other precise solving methods, heuristic and meta-heuristic methods to solve the proposed model and comparing their performance with the presented methods in this research.
- ✓ Considering new risk factors in the risk objective function.
- ✓ The amount of demand is assumed indefinite.
- ✓ Considering the time constraints, the hard and soft time windows, and creation of new cost function in the objective function
- ✓ Adding a new level to the supply chain

Reference

[1] Sovizi, Mohammad and Emad Roghaniyan. 2016. The Problem of Locating the Axis-Routing of Vehicle with Transportation of Goods between Customers, The First International Comprehensive Competition Conference on Engineering Sciences in Iran, Anzali, Conference Secretariat, Gilan University - Tabriz University

[2] Ali Nasab, Maedeh; Peyman Ghasemi and Mahdi Alipour. 2016 Presenting of a Location-Routing Model and Solving It with Genetic Algorithm, International Conference on Management and Accounting, Tehran, Nikan Institute of Higher Education

[7] Ebrahimi Majid, Farid Khoshalhan, Meysam Barajea, Omid Tehraniyan. 2014. Multi-Objective Routing Problem with Pickup and Delivery Cost and Solving It Using a Meta-Heuristic Distributed Search Algorithm, Operational Research in Its Applications, No. 3, Volume 11, Pages 35-57.

[8] Rajabi Mohammad Reza, Ali Mansourian, Mohammad Talie, Abbas Ali Mohammadi Sarab. 2012. Presenting a Heuristic Method to Solve the Travelling Salesman Routing Problem, Remote Sensing & GIS Iran, No. 4, Volume 4, Page 1-20.

[9] Nowroozi Narges, Reza Tavakoli Moghadam, Mohsen Sadegh Amalnik, Sadegh Khaefi. 2015. New Mathematical Modeling for Facilities Location and Vehicle Routing Problem Solving by a Hybrid Imperialist Competitive Algorithm, Journal of Industrial Engineering, Issue 1, Spring and Summer, p. 129-137.

[10] Sargardani Fard Aranni Vahid, Kia Reza, Ghaffari Mahdi. 2015. Modeling Vehicle Routing Problem Considering Multiple Warehouses, Simultaneous Load Pickup and Delivery, Soft and Hard Time Window, Cost and Depreciation Dependent to the Existing Amount of Load in the Vehicle and Route Type, International Conference on Modern Research in Management and Industrial Engineering, Oct. 20, Tehran, Iran.

[11] Amorim, P. and Almada-Lobo, B. 2014. The impact of food perishability issues in the vehicle routing problem, Computers & Industrial Engineering, 67, pp.223-233.

[12]Androutsopoulos, K.N. and Zografos, K.G. 2010 Solving the bicriterion routing and scheduling problem for hazardous materials

distribution.Transportation Research Part C: Emerging Technologies, 18(5), pp.713-726.

[13] Camm, J.D., Magazine, M.J., Kuppusamy, S. and Martin, K. 2017. The demand weighted vehicle routing problem. European Journal of Operational Research, 262(1), pp.151-162.

[14] Deb, K., Agrawal, S., Pratap, A. and Meyarivan, T. 2000. September. A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II. In International Conference on Parallel Problem Solving From Nature (pp. 849-858). Springer, Berlin, Heidelberg.