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A Bi-objective Model of Many-To-Many Hub Vehicle Location-Routing Problem by Considering Hard Time Window and Vehicle-Cost Balancing

Amir-Mohammad Golmohammadi[1,*], Hamidreza Abedsoltan[2]

Enhancing the efficacy and productivity of transportation system has been on the most common issues in recent decades, noteworthy to the industrial managers and expert so that the products are delivered to the clients at right time and the least costs. Therefore, there are two important issues; one is to create hub as the as intermediaries for streaming from multiple origins to multiple destinations and also responding to the tours of every hub at the proper time. The other is a route where the vehicles should pay at time window of each destination node. On the other hand, these problems may cause cost differences between hub and interruption of their balance. Accordingly, this paper presents a model dealing with cost balancing among the vehicles as well as reducing the total cost of the system. Given the multi-objective and NP-Hard nature of the issue, a multi-objective imperialist competitive algorithm (MOICA) is suggested to provide Pareto solutions. The provided solutions are at small, average and large scales are compared with the solutions provided by Non-Dominated Sorting Genetic Algorithm (NSGA-II) algorithm. Then, its performance is determined using the index for evaluating the algorithm performance efficacy to solve the problem at large dimensions.

***Keywords**: Location-Routing Problem; Multiple Allocation; Hard Time Window; MOICA Algorithm*

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1. Introduction and Literature Review

The Hub Location Problem (HLP) has gained substantial prominence in recent decades owing to its extensive applications in modern transportation and communication networks. The HLP seeks to optimize the location of hubs, which serve as intermediary distribution nodes between origin-destination pairs, to efficiently manage the movement of individuals, goods, and information [1]. The flow of demands through hubs can be either two-way or one-way, depending on the demand patterns. Some the applications for hub problems are: Telecommunication industries [1], air freight [2], land [3], postal services [4], and public transportation, urban transportation, telecommunications systems and emergency services. Hub Location-Routing Problems (HLRPs) encompass the optimization of hub locations and non-hub node allocations within a distribution network to minimize overall transportation costs, including collection, distribution, and communication expenses. While some studies have focused solely on hub location optimization [5], others have addressed both location and allocation decisions [6]. Given the inherent interdependence of these two aspects [7], simultaneous

*Corresponding Author
1 Department of Industrial Engineering, Arak University, Arak, Iran. E-mail:a-golmohammadi@araku.ac.ir
2 School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran. E-mail: abedsoltan@ut.ac.ir

consideration is crucial, as adopted in this study. Hubs facilitate efficient network operation by reducing the number of direct connections between origin-destination pairs, leading to cost savings compared to fully connected networks [8]. Classic Hub Location-Routing Problems (HLRPs) adhere to three fundamental assumptions: (1) a complete graph representation of the network, (2) communication among hubs governed by alpha coefficients ranging from 0 to 1, and (3) a prohibition on direct communication between non-hub nodes [9]. Hamacher and Nickel [10] proposed a comprehensive categorization of location-routing problems, examining them from seven distinct perspectives. Passenger transportation routing, particularly urban and public transportation, presents an application of the location-routing problem framework that is often overlooked in the literature. Routing problems encompass five distinct categories, each a combination of various routing problem types. The Vehicle Routing Problem (VRP) encompasses a set of optimization problems involving a fleet of vehicles tasked with providing services to clients at geographically dispersed locations, returning to the depot or a predetermined station to minimize overall transportation costs. Baños et al. [11] proposed a bi-objective model for a VRP with hard time windows, aiming to minimize total transportation costs and balance vehicle travel distances. They employed metaheuristic solution methods and Pareto's approach to evaluate the effectiveness of their model. Cetiner et al. [6] developed an iterative two-stage VRP with multiple hub allocations, considering simultaneous pickup and delivery within maximum tour length constraints. The proposed methodology employs a two-stage approach to address the hub location-routing problem. In the first stage, hub locations are determined, and non-hub nodes are assigned to multiple hubs. This is followed by the second stage, where the traveling salesman problem (TSP) is solved for each established hub, considering the updated distance ratios among the nodes. Since the TSP for each hub is solved independently, it is possible for a non-hub node to appear in multiple routes. This two-stage procedure was applied to seven instances. Notably, the problem formulation does not impose any capacity constraints on hubs or vehicles, and only tour routing is restricted. Additionally, each vehicle departs from a hub, visits all assigned non-hub nodes, and returns to the hub. The Benders decomposition algorithm was employed to solve the problem due to its effectiveness in handling mixed-integer programming (MIP) problems with a two-stage structure. The objective of the problem was to minimize the associated costs. The algorithm was implemented with a focus on precision and was primarily applied to small-scale instances. Golmohammadi et al. [12] presented a multi-objective dragonfly algorithm for a production, inventory, location, and routing problem by considering shared logistics resources. They made a comparison between their algorithm results with Non-Dominated Sorting Genetic Algorithm (NSGA-II) and epsilon constraint method. De Camargo et al. [13] investigated a variant of the many-to-many location-routing problem, incorporating multiple commodities and inter-hub transport processes. A mixed-integer linear programming (MILP) model was developed for the problem, and CPLEX 12.4 was employed to solve small-scale instances. Additionally, a multi-start procedure based on a fix-and-optimize scheme and a genetic algorithm was introduced to efficiently construct promising solutions for medium- and large-scale instances. Computational performance analysis demonstrated the suitability of the proposed methods for practical applications. Also, Mokhtari and Abbasi [14] solve the many-to-many location-routing problem by VNPSO algorithm. Zarandi et al. [15] developed a location-routing problem with time windows (LRPTW) under uncertainty. A fuzzy chance-constrained programming (CCP) model was formulated using credibility theory, and a simulation-embedded simulated annealing (SA) algorithm was presented to solve the problem. To initialize the SA solutions, a heuristic method based on fuzzy c-means (FCM) clustering with Mahalanobis distance and sweep method was employed. Moshrefi [16] conducted a study to optimize a multi-objective location-routing problem (MOLRP). The study aimed to integrate routing and location decisions to determine the optimal placement of warehouses, satisfy customer demands from these warehouses, and design efficient vehicle routes to minimize overall transportation costs. Factors such as customer satisfaction, vehicle fuel constraints, and adherence to hard time windows, which are often neglected in MOLRP studies, were explicitly considered in this research. The study's objectives included achieving the best priority by identifying the shortest route and minimizing deviations from time windows. A MILP model was developed, followed by a metaheuristic method based on the NSGA-II to determine the optimal solution. The proposed approach demonstrated its effectiveness in balancing multiple objectives and addressing practical constraints in the MOLRP context. Tadaros and Migdalas [17] conducted a comprehensive review of 80 journal articles published in the field of MOLRP from 2014 to 2020. The reviewed papers were systematically categorized based on various factors encompassing model assumptions and characteristics, objectives, solution approaches, and application areas. Within each application area, individual papers were presented and subjected to in-depth analysis. The review concluded with insightful remarks and suggestions for future research directions in the MOLRP domain. Fallah-Tafti et al. [18] proposed a novel mathematical model for designing hub-and-spoke rapid transit networks that deviates from conventional hub location models due to the unique characteristics of rapid transit systems. The proposed model encompasses both hub-level and spoke-level sub-networks, enabling the transshipment of flows among spoke nodes and considering the setup costs and capacity constraints of both hub and spoke nodes and edges. Additionally, the model determines the hub-and-spoke rapid transit lines along with the routes of demands within these lines, incorporating profit and service time objectives. An efficient adaptive large neighborhood search algorithm is developed to solve the proposed model, demonstrating its effectiveness through computational results. Pourmohammadi et al. [19] proposed a novel multi-objective optimization framework for the hub location and routing problem (HLRP) under various uncertainties. The proposed model aims to minimize the total transportation cost, including routing and fixed costs, while simultaneously maximizing employment opportunities and regional development, reflecting social responsibility considerations. Mahmoudi et al. [20] presented a study which focused on the integrated routing and scheduling problem in a home delivery network characterized by distinct pickup and delivery operations. A fleet of capacitated vehicles stationed at the network's central hub is employed to transport goods between network nodes. The proposed MIP model aims to minimize total transportation costs while considering demand splitting flexibility. This model is applicable to both general hub networks and many-to-many networks. Due to the problem's inherent complexity, valid inequalities are introduced to strengthen the model's formulations. Subsequently, a genetic algorithm is employed to solve problems of varying sizes. The performance of the reinforced model, augmented with valid inequalities and the genetic algorithm, is evaluated using a case study of a same-day postal delivery company. Moreover, An M/M/c/K queueing system is employed by Amiari Fourk [21] to estimate waiting times at hub nodes and enhance responsiveness. Additionally, a fuzzy queuing approach is implemented to model the inherent uncertainties in the network. To address the complex multi-objective nature of the problem, a powerful evolutionary meta-heuristic algorithm is developed, combining fuzzy invasive weed optimization (FIWO), variable neighborhood search (VNS), and game theory. This hybrid algorithm effectively generates near-optimal Pareto solutions, providing valuable insights for decision-makers.

In this study, a mathematical planning model is proposed considering the transportation cost balancing for each vehicle, and then the proposed meta-heuristic multi-objective imperialist solution is developed for the problem. The suggested algorithm is performed on various scales. The performance of the proposed solution is approved compared with NSGA-II given to various metrics.

2. Suggested Model

The proposed model incorporates several optimization objectives to enhance the efficiency of the transportation network. Each vehicle, equipped with a specified capacity, can pick up and deliver goods from multiple origins to multiple destinations. Vehicles must pass through at least one hub, adhering to the hard time windows of each hub and maximum traveling time and distance constraints.

The model simultaneously minimizes the total transportation cost, the maximum and minimum differences in distance and travel time among vehicles, and the overall service level at each node. This comprehensive approach aims to improve labour, equipment, and energy utilization while reducing environmental impacts and driver fatigue.

2.1. Mathematical Model

2.1.1. Assumption

- There is a certain demand among tow nodes and problem parameters all are certain.
- All the nodes can be change into the hub and discount factor exists to interconnect the hubs.
- Simultaneous pickup and delivery operations are performed, with hubs serving as the vehicle departure points.
- Vehicles must return to their assigned hub upon completing their route, adhering to maximum time and distance constraints.
- Each node can be serviced by multiple hubs (multi-allocation) and is subject to a hard time window for service completion.
- The vehicle fleet is homogeneous, with each vehicle having the same capacity. Both the single-product and single-period models employ bi-objective functions.
- Hubs with capacity constraints and their connections are complete graph and their numbers varies.

2.1.2. Notations

Indices and Sets:

N : Set of nodes;
K : Set of potential nodes for hub;
A : Set of arcs;
V : Set of vehicles;

Parameters:

w_{ij} : flow demand from client *i* to customer *j*;
$D_j = \sum_i w_{ij}$: the total of demand destined to customer *j*;
$O_i = \sum_j w_{ij}$: the total of demand originated from *i*;
t : the traveling time of arc (u, v);
st : Time to service node v including loading and unloading time;
T : the maximum time allowed for the tours;
a_k : the fixed cost of installing a hub;
$\hat{c}_{ik}$: the cost of handling the incoming and outgoing demands of client i by hub k;
$\ddot{c}_{uv}$: the cost of traveling arc (u, v);
$\dot{c}_l$: the cost of assigning a vehicle l to a hub;
km : the transportation cost of demands w_{ij} and w_{ij} with economic coefficient of α which is $\check{c}_{ij}^{km} = \alpha(w_{ij} * c_{km} + w_{ji} * c_{mk})$;
c : the transportation cost of demands w_{ij} and w_{ji} for the inter-hub connection (k,m);

V	:	Capacity of hub k;
Cap	:	Maximum capacity of vehicle l;
E	:	Maximum length of vehicle tour ;
r	:	Distance between nodes u ,v;
M	:	Very big number;

Decision Variables:

$\boldsymbol{z_{kk}}$	:	If node k is selected as hub it is *1* and otherwise it is zero.
$\boldsymbol{z_{ik}}$	:	If the node i is assigned to the hub k ,it is one and otherwise it is zero.
$\boldsymbol{x_{ijkm}}$	:	A percentage of w_{ij} and w_{ij} passing hubs k and m.
$\boldsymbol{q_{kl}}$	:	If the vehicle l is assigned to the hub k , it is one and otherwise it is zero.
$\boldsymbol{Y_{uv}^{kl}}$	:	If the vehicle l assigned to the hub k uses arc u ,v in its path it is one and otherwise it is zero.
$\boldsymbol{P_u^{kl}}$	:	If the vehicle l assigned to the hub provide service to node u ,it is one and otherwise it is zero.
$\boldsymbol{S_j^l}$	:	The time of beginning to service each j node by the vehicle l

2.1.3. The Mathematical Model

Accordingly ,the MMHLRP model can be stated as follows:

$$Min\ f_1 = \sum_k z_{kk} a_k + \sum_i \sum_k z_{ik} \hat{c}_{ik} + \sum_k \sum_l \sum_{u,v} Y_{uv}^{kl}\ \ddot{c}_{uv} + \sum_k \sum_l \dot{c}_l\, q_{kl} + \sum_i \sum_j \sum_k \sum_m x_{ijkm}\, \breve{c}_{ij}^{km} \tag{1}$$

$$Min\ f_2 = Max_{l\in V} \left\{ \sum_k \sum_{(u,v)\in A} Y_{uv}^{kl}\, \ddot{c}_{uv} \right\} - Min_{l\in V} \left\{ \sum_k \sum_{(u,v)\in A} Y_{uv}^{kl}\, \ddot{c}_{uv} \right\} \tag{2}$$

Subject to:

$$\sum_k z_{ik} \ge 1 \qquad \forall\, i\ \in N \tag{3}$$

$$z_{ik} \le z_{kk} \qquad \forall\, i,k\ \in N: i \ne k \tag{4}$$

$$\sum_{m\in N} x_{ijkm} = z_{ik} \qquad \forall\, i,j,k \in N; i < j \tag{5}$$

$$\sum_{k\in N} x_{ijkm} = z_{jm} \qquad \forall\, i,j,m \in N; i < j \tag{6}$$

$$\sum_{(u,v)} y_{uv}^{kl} = p_u^{kl} \qquad \forall\, u,k \in N, l \in V \tag{7}$$

$$\sum_{(u,v)} y_{uv}^{kl} = p_v^{kl} \qquad \forall\, v,k \in N, l \in V \tag{8}$$

$$y_{uv}^{kl} \le q_{kl} \qquad \forall\, (u,v) \in A, l \in V, k \in N \tag{9}$$

$$q_{kl}\ \le q_{k(l-1)} \qquad \forall\, l \in V, k \in N: l > 1 \tag{10}$$

$$\sum_{l} p_t^{kl} = z_{tk} \qquad \forall\, t,k \in N: k \neq t \qquad (11)$$

$$\sum_{(u,v)} y_{uv}^{kl} t_{uv} + \sum_{(u,v)} y_{uv}^{kl} st_v \leq T \qquad \forall\, l \in V, k \in V \qquad (12)$$

$$\sum_{i} \sum_{m} O_i \times x_{ijkm} \leq V_k \times z_{kk} \qquad \forall k,j \in N \qquad (13)$$

$$\sum_{i} \sum_{k} D_i \times x_{ijkm} \leq V_k \times z_{mm} \qquad \forall\, m,j \in N \qquad (14)$$

$$\sum_{(u,v)} r_{uv} \times Y_{uv}^{kl} \leq E \qquad \forall\, k \in N, l \in V \qquad (15)$$

$$\sum_{k} \sum_{(u,v)} O_i \times Y_{uv}^{kl} \leq Cap_l \qquad \forall l \in V \qquad (16)$$

$$\sum_{m} \sum_{(u,v)} D_i \times Y_{uv}^{ml} \leq Cap_l \qquad \forall l \in V \qquad (17)$$

$$S_i^l + t_{uv} + st_v - M(1 - Y_{uv}^{kl}) \leq S_j^l \qquad \forall\, u,v,k \in N, l \in V \qquad (18)$$

$$a_j \times z_{kk} \leq S_j^l \leq b_j \times z_{kk} \qquad \forall\, j,k \in N, l \in V \qquad (19)$$

$$z_{kk}, z_{ik},, P_u^{kl}, q_{kl} \in \{0,1\} \qquad \forall\, u,v,k,l,i \qquad (20)$$

$$0 \leq x_{ijkm} \leq 1 \qquad \forall\; i,j,k,m \qquad (21)$$

$$S_j^l \geq 0 \qquad \forall\; l,j \qquad (22)$$

The objective functions aim to minimize the total transportation costs, encompassing installation costs, handling costs, local tour execution costs, vehicle-hub allocation costs, and inter-hub transportation costs. Objective function (2) specifically addresses the balance of vehicle loading, ensuring efficient route planning. Constraint (3) stipulates that every non-hub node must be assigned to at least one hub node. Constraint (4) ensures that a non-hub node is assigned to a node only if that node is designated as a hub. Constraints (5) and (6) establish that if a node is not assigned to a hub, then the hub and the node must lie on the same path. Constraints (7), (8), and (9) define the connections between vehicles, nodes, and arcs. Constraint (10) limits the maximum number of hubs to which a vehicle can be assigned. Constraint (11) ensures that if a vehicle from a hub is assigned to a node, the node must first be assigned to that hub. Constraint (12) imposes a maximum time constraint on each tour. Constraints (13) and (14) address hub capacity restrictions. Constraints (15) and (16) indicate path constraints for ach tour. Constraints (17) and (18) are vehicle capacity. Constraints (19) and (20) are related to hard time window. Finally, constraints (21) and (22) are related to variation ranges.

3. Problem Solution Approaches

First of all, the one-objective problem at small scale was solved. Then the ε- constraint method is provided for the multi-objective model and hybrid imperialist competitive algorithm, NSGA-II and PEAS is explained to answer the problem at large scale.

3.1. Model Validation

GAMS software was used to solve the instances of small-scale problems to approve the correct performance of the model. The instances used the data of urban transportation in Iran [16] and the conclusions are provided below:

Table 1. GAMS output

Number of nodes	Number of hubs	Optimized solutions of GAMS
6	3	۵۷۱۸۹۰۱/۴
7	3	۸۰۱۵۲۷۵/۰۸۳
9	4	۱۷۷۰۲۸۰۲/۵۲
10	4	۲۷۰۰۳۲۰۹/۲۴

Given the findings, it can be concluded that the model has had a good performance and large-scale problems can also be solved using this model. Following, ε-constraint is used to solve the model as multi-objective problem. Table 2 demonstrates the problem output with 10 nodes and 4 vehicles using GAMS. Table 3 presents the minimum transportation cost based on ε values in cost balance constraint.

Table 2. Total costs based on various ε values

Row	ε	Min f_1	Min f_2
1	81	37002210	79
2	72.9	37178630	71,6
3	64.8	38000380	60.9
4	56.7	38052950	56.7
5	48.6	40065830	45.5
6	40.5	40060990	40.3
7	32.4	40868790	30.4
8	24.3	41071500	22.1
9	16.2	42142000	10.7
10	8.1	43211320	8.1

Table 3. Objective function values based on ε values

	$\mathbf{f_1}$	$\mathbf{f_2}$
Min $\mathbf{f_1}$	37000102	89.1
Min $\mathbf{f_2}$	43211320	8.1

3.2. Imperialist Competitive Algorithm

In optimization problem of Imperialist Competitive Algorithm (ICA), the optimized values are defined as an array of country= [p_1, p_2, p_3, ..., p_N]. The total process of ICA is shown in figure 1.

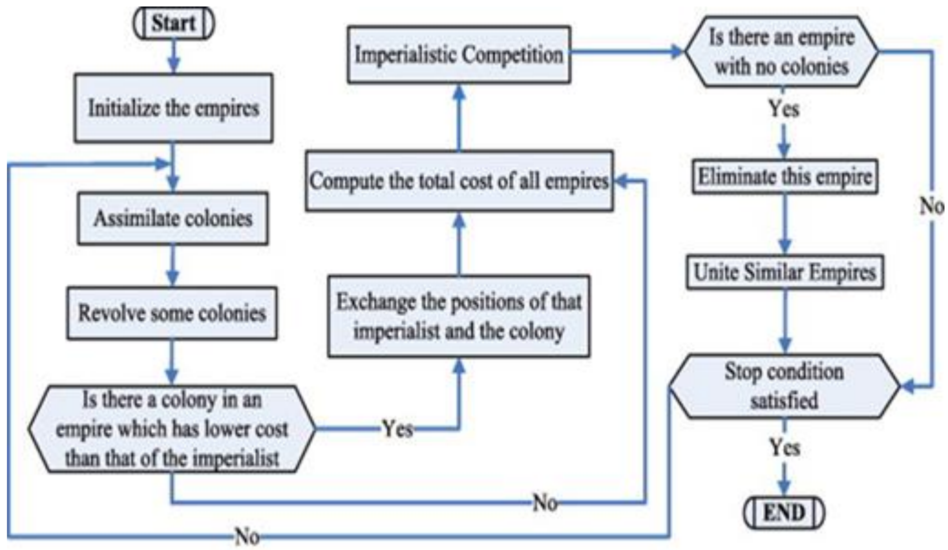

Figure 1. Flowchart of imperialist competitive algorithm

3.3. Solution

Consider a scenario with *n* customers, *m* available vehicles, and *d* potential hub locations. The blue cell (*n*) represents the sequence of nodes in each route, the green cell (*m*) indicates the number of nodes assigned to each vehicle, and the red cell (*d*) denotes the positions of the hubs and the starting hub for each vehicle.

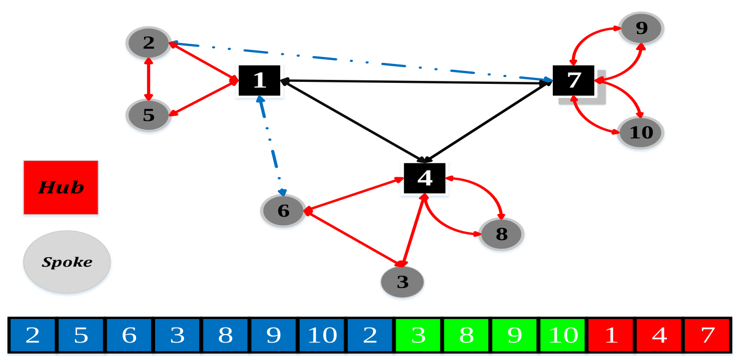

Figure 2. Solution representation

4. Numerical Results

Two indices of QM = quality metric and DM = diversity metrics proposed by Schaffer et al (16) were used in order to compare the proposed algorithm with the NSGA-II algorithm. The values given the values of table 4 for small, average and large-scale instances are obtained as shown in table 5 and charts 1 and 2.

Table 4. Parameters of the Algorithm

Factors	**Optimal real value**		**Optimal real value**	
	S	L	S	L
n-Pop	0.85	1	193	300
N-imp	-0.20	-1	5	8
P_A	0.18	0.20	0.54	0.64
P_C	1	0.50	0.60	0.60
P_R	-0.80	0.19	0.12	0.32
ξ	0.90	0.50	0.19	0.12
β	-0.20	0.15	1.80	2.15

Diversity metrics shows the uniform distribution of Pareto solutions. The metric was calculated based on equation (22) and the quality metric of all the solutions for each algorithm are totally considered and non-domination operations were done for all the solutions. The quality of each algorithm equals the share of Pareto solutions for that algorithm and higher quality indicated the more optimized algorithm.

$$DM = \frac{\sum_{i=1}^{n-1}\left|\bar{d} - d_i\right|}{(n-1)\bar{d}} \tag{23}$$

Table 5. Comparison of quality and diversity metrics for scale 100

	NSGAII	**MOICA**	**NSGAII**	MOICA
Problem No.	**QM**		**DM**	
100#3	0	1	0.957	1.136
100#4	0	1	0.788	1.016
100#5	0	1	1.035	1.147
100#6	0	1	1.089	0.928
100#7	0	1	1.039	0.804
100#8	0.05	0.950	0.902	1.066
100#9	0	1	0.811	0.939
100#10	0	1	0.999	1.274
100#11	0	1	0.795	1.254
100#12	0.5	0.950	1.083	0.996

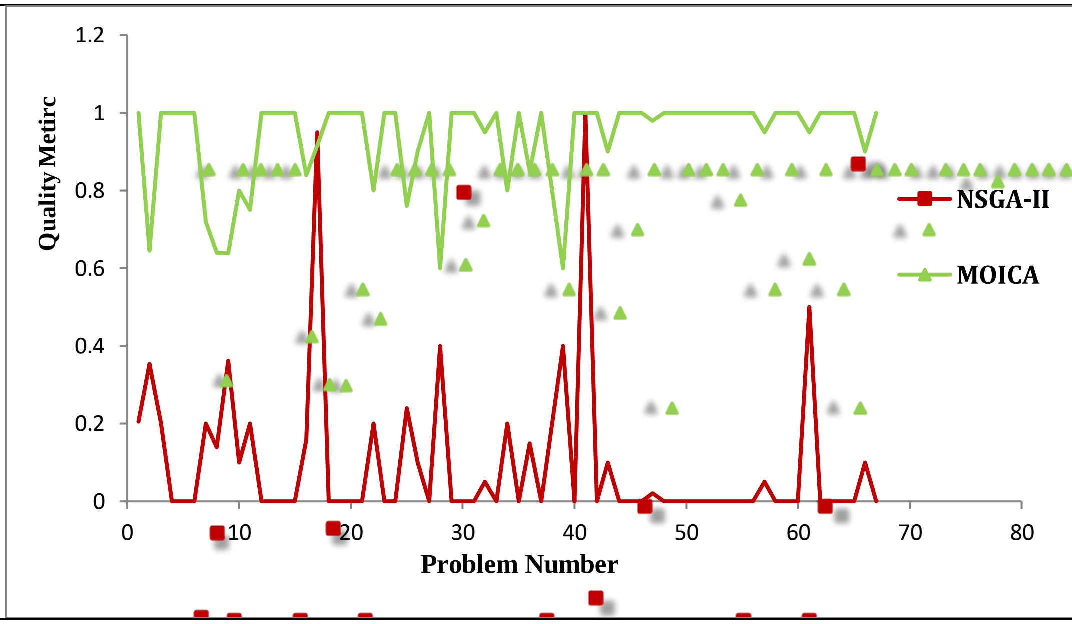

Figure 3. Comparison of quality metrics

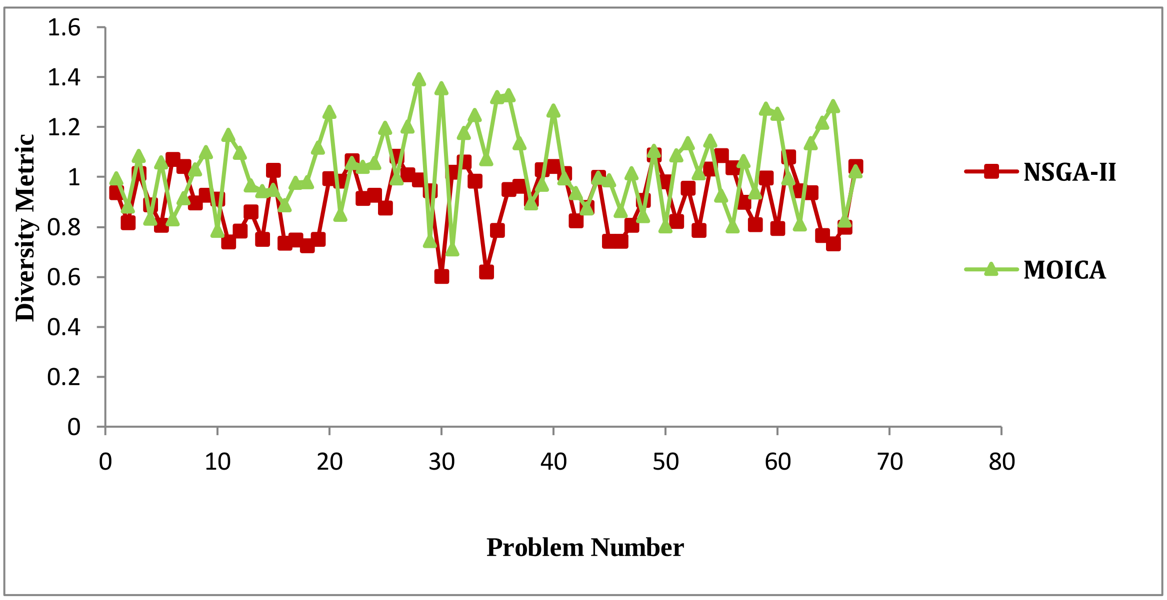

Figure 4. Comparison of diversity metrics

5. Conclusion

As shown in table 5, the quality metrics and diversity metrics of the ICA at large scale have better performance in comparison with NSGA-II. Given the fact that scales higher than 20 in hub location-routing problems indicate the hard phase problems which cannot be solved by the mathematical optimization algorithms, high-efficiency meta-heuristic algorithms should be used. It is noteworthy that the proposed algorithm can be one of the efficient meta-heuristic algorithms to solve the hub location and many-to-many routing problems based on hard time windows. In this study, a mathematical planning model was proposed considering the transportation cost balancing for each vehicle, and then the proposed meta-heuristic multi-objective imperialist solution was developed for the problem. The suggested algorithm was performed on various scales. The performance of the proposed solution was approved compared with NSGA-II given to various metrics.

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