Multimodal Transportation p-hub Location Routing Problem with Simultaneous Pick-ups and Deliveries

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Abstract

Centralizing and using proper transportation facilities cut down costs and traffic. Hub facilities concentrate on flows to cause economic advantage of scale and multimodal transportation helps use the advantage of another transporter. A distinctive feature of this paper is proposing a new mathematical formulation for a three-stage p-hub location routing problem with simultaneous pick-ups and deliveries on time. A few studies have been devoted to this problem; however, many people are still suffering from the problems of commuting in crowded cities. The proposed formulation controlled the tumult of each node by indirect fixed cost. Node-to-node traveling cost was followed by a vehicle routing problem between nodes of each hub. A couple of datasets were solved for small and medium scales by GAMS software. But, for large-scale instances, a meta-heuristic algorithm was proposed. To validate the model, datasets were used and the results demonstrated the performance suitability of the proposed algorithm.
Keywords: Hub location routing problem, Multimodal transportation, Economic optimal design, Traffic optimal design, Genetic algorithm.

1. Introduction

Location is a strategic decision in supply chain management and hub location problem refers to locating some nodes as hub and allocating non-hub nodes to them. Hubs are some facilities that commonly assist transportation, telecommunication, and logistic networks such as airline passengers, data transmissions, and express packages for organizing network routes to decrease cost. Hubs try to aggregate some allocated non-hub nodes with indirect routes to decrease cost (Alumur & Kara 2008). But, the important point is which nodes are chosen as hubs and which non-hub nodes are allocated to each hub. However, determining the location of hub nodes and allocating non-hub nodes to them are challenging. In such a situation, the hub location problem emerges, which involves economic aspects. Then, the formulation would reduce total cost by considering flow and distance between the nodes. The issues that are important include the allocation manner of non-hub nodes to hubs and selection of proper transportation routes between the nodes of a hub. Moreover, their hub-to-hub vehicle transporter costs are chosen by considering cost in a new network design. Clients are allocated to their hub using a loop considering the lead time that consists of traveling time and setup time. The unique feature of this study was in using multimodal transportation for finding a good relationship between time and cost in transportation planning of Post Company.

Recently, many studies have been done on hub location problems with different assumptions, including Zhi-Hua (2011) who proposed a new model for scheduling a container multimodal transportation based on immune affinity model for emergency relief. They tried to minimize the total cost of transportation by considering a setup cost for changing transportation type by simulating the structure of the immune system. They also studied it in terms of container multimodal transport emergency relief. Moreover, path optimization was modeled as a multi-objective integer linear programming model and the optimal path was found by Lingo 8.0 software. Rabbani et al. (2013) formulated the p-hub center problem by considering the relationship of flow and overhead cost and tried to control the flow of overhead cost related to hubs.

Van Schijndel and Dinwoodie (2000) investigated cargo transport operators in the Netherlands because of the rising traffic jams to find solutions such as multimodal transport that involves the movement of cargo from shipper to consignee using two or more different modes through billing and through liability under one rate (Hayuth 1987). In addressing the question of whether congestion in the Netherlands provides enough reason for

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companies to switch from road transport to multimodal transport, they established twelve working hypotheses.
Tancrez et al. (2012) proposed a nonlinear continuous formulation including transportation, fixed, handling, and holding costs, distribution centers, and safety stocks all in the same model, which was decomposed into a closed-form equation and a linear program when distribution center (DC) flows were fixed. The model integrated three decisions: distribution center location, flow allocation, and shipment sizes. So, they developed an iterative heuristic that deductively estimated DC flows, solved the linear program, and then improved the DC flow estimations. Presenting and developing a mathematical model to design hybrid fiber co-axial (HFC) networks were performed by Pirkul and Gupta (1997) and Gupta and Pirkul (2000) to locate optical network units (ONUs) considering their different capacities. Breakdown of the model showed that it belonged to the NP-complete class of problems. So, they proposed a heuristic solution procedure for the designed task. Computational testing of their procedure showed that it was applicable to the design of fairly large networks and provided better solutions. Razmi and Rahmanniya (2013) introduced a new mixed-integer programming for p-hub median location problem by considering customer satisfaction level and capacitated hub candidates. A new formulation introduced by Camargo et al. (2013) considered arc routes for allocating nodes of the hub. Their model had some shortcomings, including the involvement of many parameters, which made the model difficult to solve. In order to simplify the model, they considered all parameters in constant values, which made the model impractical and inefficient. A new formulation for vehicle routing problem was developed by Norouzi et al. (2012) to decrease transportation cost, raise customer satisfaction, and decrease environmental pollution. They concentrated on reducing vehicles in their supply chain and used a metaheuristic algorithm to solve their NP-hard problem.
Gelareh et al. (2013) introduced a new formulation for a hub and spoke network planning of liner shipping with p nodes in the main string which were allocated to other nodes with some secondary strings. They described maritime transportation to be safe and low-cost; so, they assumed that air transport was not competing for liner shipping. However, it seems that this assumption is a constraint for allocating this model just for maritime transportation and another transporter should be sometimes used to keep lead time and prevent shortage cost. Julai et al. (2011) considered a distribution planning problem. They developed a multi-objective linear programming model and used goal programming.
Alumur et al. (2012a) studied a hierarchical multimodal hub network. They wanted to find the location of grounds and airport hubs, allocations of demand nodes to these hubs, and allocations of ground hubs to airport hubs, and route the flow and reduce total transportation and operational costs within a predetermined time bound. They proposed a mixed-integer programming formulation and performed a comprehensive sensitivity analysis on the Turkish network. Finally, they concluded first that the locations of the ground hubs were more sensitive to the total hubs to be located, compared with the airport hubs. Second, it was possible to find better service levels at little more costs. Third, transportation and operational cost were reduced by investment in establishing new hubs. Another similar research was done by Alumur et al. (2012b), who introduced the multimodal hub location and hub network design problem and assumed transportation costs and travel times simultaneously. Thus, they presented one allocation multimodal hub location and hub network design problem on a couple of grounds and airways by considering long-time transportation for the ground way and more cost transportation for the airway. They also provided a linear mixed-integer programming formulation for the most general case of the multimodal hub location and hub network design problem and presented computational analysis of the Turkish network datasets.

This literature review demonstrates a research gap in the modeling of multimodal hub location routing problem, as described in Table 1.

Table 1
Literature review

Authors	Model				Costs	
	Hub location	Allocated nodes VRP	Multi-modal transportation	Hub's capacity	Fixed cost	Distance traveling cost
Authors approach	*	*	*		*	*
(Gelareh et al. 2013)	*	*		*		*
(Camargo et al. 2013)	*	*	*		*	
(Razmi and Rahmanniya 2013)	*				*	*
(Norouzi et al. 2012)		*				*
(Alumur et al. 2012a)	*		*	*	*	*
(Alumur et al. 2012b)	*		*	*	*	*
(Tancrez et al. 2012)					*	*
(Zhi-Hua 2011)			*			*
(Zhang et al. 2011)		*	*			
(Eskigun et al. 2005)			*		*	*
(Van Schijndel and Dinwoodie 2000)			*			
(Pirkul and Gupta 1997)	*		*		*	*

According to the literature review, none of the studies have simultaneously worked on a hub location network design without the shortcomings of indirect distances and locating hubs. Another important research gap refers to the lack of attention to fixed establishment cost, transportation cost, and allocation of non-hub nodes along a route simultaneously.

In this paper, multimodal transportation was considered by a strategic decision for locating p hubs in a network and assigning demands to their hubs by single allocation with routes through solving vehicle routing problem. The goal was to minimize total cost by choosing the right transportation mode, which consists of transportation time and setup time, to meet customers' demand at the right time. Another feature was considering the ability of each hub to use transportation modes with a variety of fixed costs for establishing hub terminals. The rest of this report is as follows: Section 2 presents the proposed model and a new mixed-integer programming model of this problem and linearization by solving an illustrative case in small and medium sizes. Section 3 presents a genetic algorithm (GA) for solving the problem in a reasonable time. Section 4 provides computational results and, at the end, Section 5 presents the conclusions.

2. The Proposed Model

In this section, a mixed-integer formulation will be introduced to design a multimodal p-hub location routing problem. The design included simultaneous pick-ups and deliveries by p-hub median with the single allocation problem. Let p denote the number of hubs that is going to be established. The existing facilities and crowd have a direct relationship with the fixed cost of establishing value. In this problem, a route is assumed between allocated nodes for each hub sets. Each client has an input and an output for the route. The travel time and cost of the hub-to-hub connection are reduced to θv (teta of vehicle v) and αv (alpha of vehicle v) factors by considering the selected facility. The model assumes that the flow of each origin-destination must be routed via at least one hub. If the origin or destination is a hub, then the collection or distribution component may be at the origin or destination nodes. This problem is a three-stage one, so that a vehicle picks up the materials and continues to render them to the hub. Materials are sent to their destination hub and a vehicle crossing its path delivers them to the destination (the vehicle on the path for each node simultaneously picks up and deliveries the materials). Materials should be delivered at a specific time that is lead time. Thus, there would be p. (p-1) vehicles between hubs and a vehicle for each hub to turn between its allocated nodes.

2.1. Sets

i, j : Sets of nodes $\{i, j = 1, 2, \dots, n\}$

k, m: Sets of hubs $\{k, m = 1, 2, \dots, p\}$

v: Sets of vehicles $\{v = 1, 2, \dots, V\}$

2.2. Parameters

p: number of hubs.

W_{ij}: flow between nodes i and j.

d_{ij} : distance between nodes i and j.

A_k: Initial cost of establishing for hub k.

$\propto_v$: cost discount factor for using vehicle v.

t_{ij}: travel time between nodes i and j .

Ti: travel time to node i from its hub.

Sk: setup time for hubs.

hd: maximum time of stages one and two.

Ld: lead time.

P_k^v: $\begin{cases} 1 & \text{if vehicle } v \text{ is acceptable for hub } k \\ 0 & \text{O.W.} \end{cases}$

2.3. Variables

Z_{ik} : $\begin{cases} 1 & \text{spoke } i \text{ is servicing by } k^{th} \text{ hub} \\ 0 & \text{O.W.} \end{cases}$

r_{ijk}: $\begin{cases} 1 & \text{if there is a way from } i \text{ to } j \text{ in hub } k \\ 0 & \text{O.W.} \end{cases}$

$\boldsymbol{y_{km}^v}$ $\begin{cases} 1 & \text{if vehicle } v \text{ links hub } k \text{ and } m \\ 0 & \text{O.W.} \end{cases}$

2.4. Model formulation

$$Min\, Z = \sum_k A_k . z_{kk} + \sum_i \sum_j \sum_k \sum_m \sum_v w_{ij} \left(z_{ik} . z_{jm} . d_{km} . y_{km}^v . \propto_v . \beta \right) + \sum_i \sum_j \sum_k r_{ijk} . d_{ij} \qquad (1)$$

s.t.

$$\sum_k z_{ik} = 1 \qquad \forall i \qquad (2)$$

$$\sum_k z_{kk} = p \qquad (3)$$

$$z_{ik} \leq z_{kk} \qquad \forall i, k \qquad (4)$$

$$r_{ijk} \leq z_{ik} \qquad \forall i, jk \qquad (5)$$

$$r_{ijk} \le z_{jk} \quad \forall i,j,k \quad (6)$$
$$r_{ijk} + r_{jik} \le 1 \quad \forall i,j,k \quad (7)$$
$$\sum_i \sum_k r_{ijk} = 1 \quad \forall j \quad (8)$$
$$\sum_j \sum_k r_{ijk} = 1 \quad \forall i \quad (9)$$
$$y_{km}^v \le x_{kk} \quad \forall k,m,v \quad (10)$$
$$y_{km}^v \le x_{mm} \quad \forall k,m,v \quad (11)$$
$$\sum_v \sum_{m \ne k} \sum_k y_{km}^v = p.(p-1) \quad \forall k \quad (12)$$
$$\sum_v y_{km}^v \le 1 \quad \forall k,m \quad (13)$$
$$T_j \ge \sum_j \sum_{k \ne j} (T_i + t_{ij}).r_{ijk} \quad \forall j \quad (14)$$
$$\max\{(T_i + t_{ij}).r_{ijk}\} + \max\left\{\sum_v z_{ik}.z_{jm}.t_{km}.y_{km}^v.\theta_v + 2.sk\right\} \ge hd \quad \forall i,j,k,m \quad (15)$$
$$hd + T_j \le ld \quad \forall j \quad (16)$$
$$y_{km}^v \le (p_k^v + p_m^v)/2 \quad \forall k,m,v \quad (17)$$
$$y_{km}^v, z_{ik}, r_{ijk} \in \{0,1\} \quad \forall i,j,k,m,v \quad (18)$$

Equation (1) is total cost that consists of the hub network by considering the fixed cost to establish a node as a hub and the transportation cost between nodes. Hub allocation process was considered by Constraints (2-4); (2) is single allocation constraint and (3) helps choose p nodes as a hub, allocating nodes to its hub (4). A loop was needed for allocating nodes (5- 6). Equation (5) shows the origin and equation (6) shows the destination is allocated to a hub. Direction of each loop is demonstrated in Constraint (7). Constraint (8) shows that each node has at least one input. Constraint (9) demonstrates that each input requires an output. Vehicles between hubs should be assigned to hubs demonstrated by constraints (10-11). All of vehicles should be equal p.(p-1) that was demonstrated by Constraint (12). Constraint (13) allocates just a mode of transportation between hubs. Constraint (14) calculates the time from hub to allocated node j, except hub-nodes. Constraint (15) is the time for maximum turning in loops and the maximum time of traveling between hubs. Constraint (16) consists of pick-up time and transportation time that should be less than lead time. To prevent the unavailable vehicles of a hub node, Constraint (17) helps in selection. Equation (18) shows that z, r, and y are binary variables.

2.5. Linearization techniques

Because of the complexity in this model, a new variable with Equations (19, 20, 21, 22) is presented below:

$$x_{ijkm} \le z_{jm} \quad \forall i,j,k,m \quad (19)$$
$$x_{ijkm} \le z_{ik} \quad \forall i,j,k,m \quad (20)$$
$$x_{ijkm} \le \frac{z_{ik} + z_{jm} - 1}{2} \quad \forall i,j,k,m \quad (21)$$
$$x_{ijkm} = \{0,1\} \quad \forall i,j,k,m \quad (22)$$

Hub-to-hub connections would become linear and objective function (1) would change to (23):

$$Min\ Z = \sum_k A_k.z_{kk} + \sum_i \sum_j \sum_k \sum_m \sum_v w_{ij}(x_{ijkm}.d_{km}.y_{km}^v.\propto_v.\beta) + \sum_i \sum_j \sum_k r_{ijk}.d_{ij} \quad (23)$$

The second stage of Equation (15) shifts to the new Equation (24):

$$\max\{(T_i + t_{ij}).r_{ijk}\} + \max\left\{\sum_v x_{ijkm}.t_{km}.(y_{km}^v.\theta_v + 2.sk\right\} \ge hd \quad \forall i,j,k,m \quad (24)$$

GAMS 23.5/BARON software cannot handle Equation (24) because of the maximization type. However, DICOPT solver could solve the model. So, linearization techniques were applied to utilize the benefits of BARON solver. Equation (24) was replaced with Equations (25, 26, 27):

$$(T_j + t_{jk}).r_{ijk} \le q_{ijk} \quad \forall i,j,k \quad (25)$$

$$\sum_{v} x_{ijkm}.t_{km}.(y_{km}^{v}.\theta_v + 2.sk \leq b_{ijkm} \qquad \forall i,j,k,m \qquad (26)$$

$$q_{ijk} + b_{ijkm} \geq hd \qquad \forall i,j,k,m \qquad (27)$$

2.6. Illustrative example

To acquire the profound apprehension of this new formulation, the model was solved for the sample data taken from AP (Australian Post) and dataset. Datasets were accessed through the website: http://people.brunel.ac.uk. In this case, the required information for a simple problem with the total of 14 nodes were pressed out where hubs (p) were set to two from AP dataset. When distance data (dij in Table 2) and flow data (wij in Table 3) were taken from AP, other data (used for the fixed cost of establishment, facility of each node) were randomly generated by the authors, as in Table 4.

Table 2
Distance of AP (14 nodes)

d_{ij}	i=1	i=2	i=3	i=4	i=5	i=6	i=7	i=8	i=9	i=10	i=11	i=12	i=13	i=14
j=1	0	10	17352.52	1448	17829.29	33426.47	5792	18746.49	10426.17	10136	33282.96	16479.7	13346.87	31629.5
j=2	10	0	17351.69	1438	17826.86	33425.17	5782	18742.63	10417.84	10126	33279.91	16471.8	13337.11	31625.38
j=3	17352.52	17351.69	0	17292	2896	50518.08	17829.29	5792	24166.02	19351.86	49758.35	13641.89	18488.84	47544.77
j=4	1448	1438	17292	0	17532.83	33269.28	4344	18236.24	9254.258	8688	32870.93	15360.23	11937.13	31060.93
j=5	17829.29	17826.86	2896	17532.83	0	50435	17352.52	2896	23461.66	18236.24	49335.17	11286.87	16826.45	46923.32
j=6	33426.47	33425.17	50518.08	33269.28	50435	0	33174.62	50518.08	27721.47	33645.29	5968.563	44094.38	37057.82	9704.106
j=7	5792	5782	17829.29	4344	17352.52	33174.62	0	17352.52	6450.621	4344	31998.24	12416.33	7792.53	29715.48
j=8	18746.49	18742.63	5792	18236.24	2896	50518.08	17352.52	0	23101.43	17532.83	49079.52	9244.419	15530.47	46474.33
j=9	10426.17	10417.84	24166.02	9254.258	23461.66	27721.47	6450.621	23101.43	0	5943.097	25978.39	16435.47	9675.932	23461.66
j=10	10136	10126	19351.86	8688	18236.24	33645.29	4344	17532.83	5943.097	0	31702	10494.49	4085.675	28965.14
j=11	33282.96	33279.91	49758.35	32870.93	49335.17	5968.563	31998.24	49079.52	25978.39	31702	0	41889.23	34705.04	4085.675
j=12	16479.7	16471.8	13641.89	15360.23	11286.87	44094.38	12416.33	9244.419	16435.47	10494.49	41889.23	0	7205	38907
j=13	13346.87	13337.11	18488.84	11937.13	16826.45	37057.82	7792.53	15530.47	9675.932	4085.675	34705.04	7205	0	31702
j=14	31629.5	31625.38	47544.77	31060.93	46923.32	9704.106	29715.48	46474.33	23461.66	28965.14	4085.675	38907	31702	0

Table 3
Flow of AP (14 nodes)

w_{ij}	i=1	i=2	i=3	i=4	i=5	i=6	i=7	i=8	i=9	i=10	i=11	i=12	i=13	i=14
j=1	0	0.01	0.18523	0.39476	0.01	0.09534	0.51509	0.32455	0.01	0.75632	0.01	0.19896	0.01	0.01
j=2	0.01	0	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
j=3	0.19363	0.01	0	0.19769	0.01	0.04775	0.25796	0.16253	0.01	0.37877	0.01	0.09963	0.01	0.01
j=4	0.19271	0.01	0.09232	0	0.01	0.04752	0.25674	0.16176	0.01	0.37697	0.01	0.09916	0.01	0.01
j=5	0.01261	0.01	0.01	0.01288	0	0.01	0.0168	0.01059	0.01	0.02468	0.01	0.01	0.01	0.01
j=6	0.07185	0.01	0.03442	0.07336	0.01	0	0.09573	0.06031	0.01	0.14056	0.01	0.03697	0.01	0.01
j=7	0.30252	0.01	0.14492	0.30887	0.01	0.0746	0	0.25394	0.01	0.59177	0.01	0.15567	0.01	0.01
j=8	0.11461	0.01	0.0549	0.11701	0.01	0.02826	0.15268	0	0.01	0.22419	0.01	0.05897	0.01	0.01
j=9	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0	0.01	0.01	0.01	0.01	0.01
j=10	0.15759	0.01	0.07549	0.1609	0.01	0.03886	0.20994	0.13228	0.01	0	0.01	0.08109	0.01	0.01
j=11	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0	0.01	0.01	0.01
j=12	0.06344	0.01	0.03039	0.06477	0.01	0.01564	0.08451	0.05325	0.01	0.1241	0.01	0	0.01	0.01
j=13	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0	0.01
j=14	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0

Table 4
Property of nodes

Node	Truck (v_1)	Ship (v_2)	Air (v_3)	Lead time	Fixed cost
i=1	✓	✓	×	500	5000
i=2	✓	✓	✓	500	6600
i=3	×	✓	✓	500	6500
i=4	✓	✓	✓	500	4540
i=5	✓	×	✓	500	8258
i=6	×	✓	✓	500	4365
i=7	✓	×	✓	500	5485
i=8	✓	✓	✓	500	6545
i=9	✓	✓	×	500	6525
i=10	✓	✓	✓	500	4655
i=11	×	✓	✓	500	5698
i=12	×	✓	✓	500	6458
i=13	✓	✓	✓	500	5125
i=14	✓	✓	×	114	6000

This small scale test problem was coded in GAMS 23.5/BARON solver on a PC with 2.2 GHz CPU and 4 MB RAM. The following global optimum solution was found at iteration 1297 in 3233 sec. Nodes 8 and 10 were chosen as hubs and Fig. 1 shows the hub and its node connections.

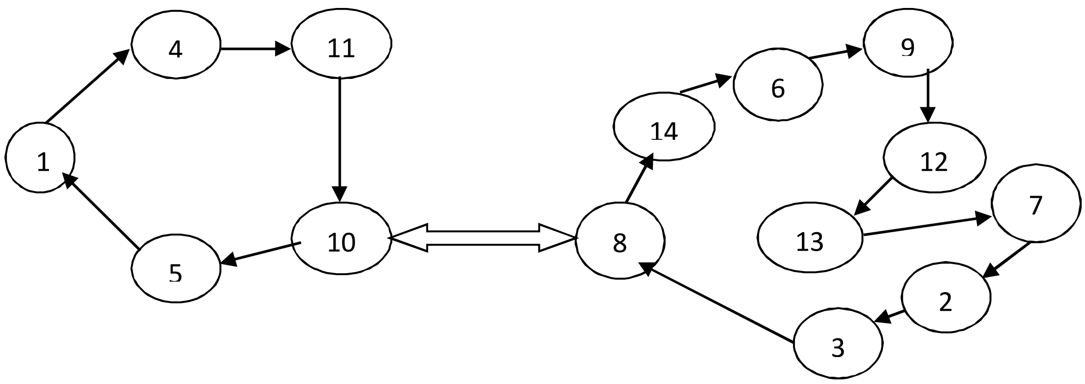

Fig. 1. AP with 14 node optimized network

In this network, a ship was chosen to move between the hubs (nodes 8 and 10) by considering the traffic. The optimum objective function value of the problem was equal to 18861.714, which was the minimum cost of this network. Result of GAMS 23.5/DICOPT solver was equal to 19659.251, which was not a good result at the level of GAMS 23.5/BARON solver. As mentioned before, it took about an hour to solve the medium scale problem. To handle large scale problems, GA approach was proposed, because the CPU time would be rapidly increased with the increase of problem size.

3. The Proposed Algorithm

A large network could not be solved by GAMS software. The network with 14 nodes solved it for about an hour. In reality, it is not reasonable to wait for a long time to solve such a problem. Therefore, metaheuristic was proposed and, due to successful experience, GA was suggested for problem solving.

3.1. Solution representation

The genetic solution started with some examples and tried to find better hub locations and their node allocation in order to obtain locally optimum answers through the relatively good answers of this algorithm. So, a chromosome that could distinguish hubs and their allocated nodes was required. A sample chromosome had 10 genes; their values would be equal to their numbers if they were hubs; otherwise, the value would be their allocated hub plus the decimal order.

Figure 2 shows an illustration of a chromosome. 4, 5, and 9 were located as hubs and their value was equal to their numbers. 1 and 2 that were allocated to hub 4 had the value of 4 plus the decimal order. Nodes 3 and 6 allocated to hub 5 had value of 5 plus their order value. According to the recent description, 7, 8, and 10 allocated to hub 9 had the value of 9 plus their order as well. The connection between hubs 4 and 5, 4 and 9, 5 and 4, 5 and 9, 9 and 4, and also 9 and 5 is ship, ship, truck, truck, truck, and truck, respectively. The second part of chromosome was designed in an ascending hub order. Therefore, a chromosome with 4, 5, and 9 values would be available, the connection of which are presented in Figure2.

1	2	3	4	5	6	7	8	9	10
4.121	4.856	5.325	4	5	5.254	9.365	9.569	9	9.321
Ship	Ship	Truck	Truck	Truck	Truck				

Fig. 2. Example of chromosome

To develop a population, first, some chromosomes were needed according to the following chart:

Step 1:

Select p nodes randomly as hubs and give them their order number. Choose 2p vehicles randomly as well.

Step 2:

If i≤0 (*i*=value of a gene),

Randomly choose a hub value.

Step 3:

After that, some new chromosomes would be added to the population by crossover and mutation processes on parents.

Step 4:

If the offspring gain more hubs as its parents and if there are some nodes that are allocated to non-hub nodes, they should be changed to correct chromosomes as a child using the chart below:

Step 1:

Set all node-allocated hubs as hubs.

Step 2:

Randomly choose p hubs as the offspring hubs and randomly certify the offspring hubs that are not selected hubs as the offspring hubs. The second part of chromosome should be synchronized with the existing facilities of each hub.

Step 3:
Randomly choose the offspring hubs for incorrectly allocated nodes.
Step 4:
Set the correct offspring as child.

3.2. Crossover

Crossover operator in the GA is of single-point crossover type of selection. In this method, an integer value was randomly selected as a crossover point. Afterward, two selected parents swapped their gens. Consider that two chromosomes are selected and crossover point of 7 and multimode of 3 are randomly selected. So, 8 to 10 genes and 4 to 6 multimode parents are changed between them and a couple of new chromosomes are developed as the offspring, as shown in figure 3.

3.3. Mutation

Mutation operator tries to produce irregular chromosomes to help in exiting from locally optimum answers. New chromosomes consist of a selected parent by selection operation with changes between random integer value gene and its next genes until another random integer value like 3 and 6. Multimode 2 and 4 genes are shown in figure 4.

3.4. Fitness function

In the proposed GA, the fitness function is computed using the objective function value of the related solution.

3.5. Selection

Sample choosing operation for selecting solutions (chromosomes) for the existing population was Roulette Wheel selection method, which is a stochastic sampling operator. So, for each chromosome, a selection probability is adapted considering its fitness function value.

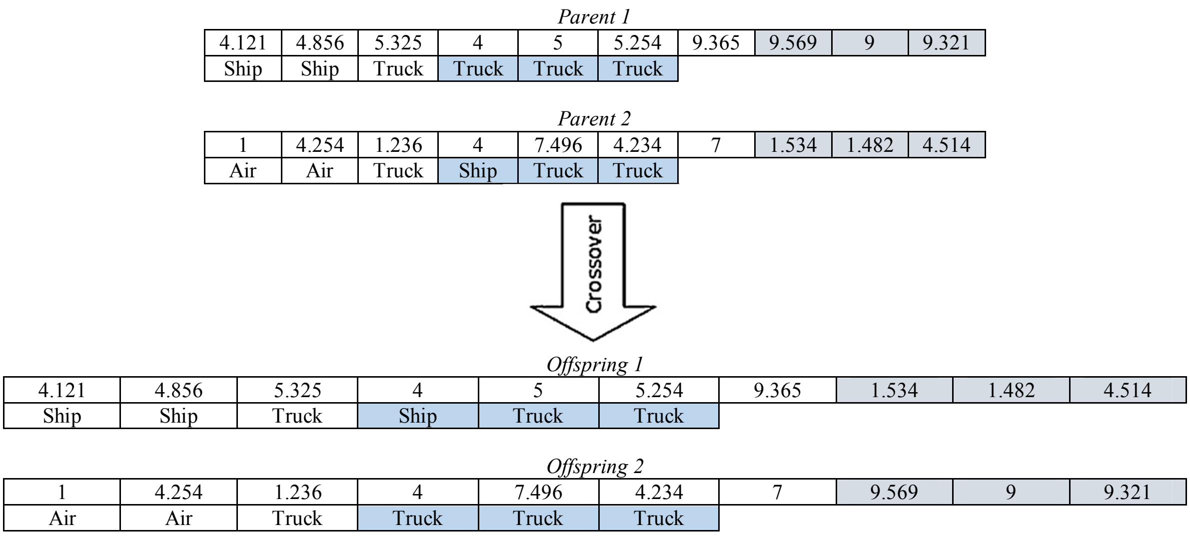

Fig. 3. Example of crossover operator

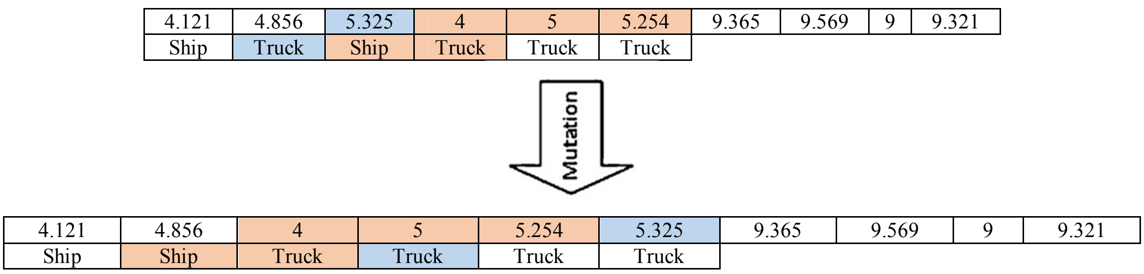

Fig. 4. Example of mutation operator

4. Computational Results

In this section, AP and CAB datasets and their reduced examples with different number of hubs (p) are solved by the proposed GA programmed in MATLAB 7.14.0.739 (R2012a) software. Datasets were accessed through the following website: http://people.brunel.ac.uk. When distance data (d_{ij}) and flow data (W_{ij}) were taken from AP

and CAB, the other data were randomly generated by the authors.
The number of initial population for solution in CAB and AP was equal to 15 and 6, respectively.
The number of solutions in each iteration and number of best chromosomes chosen for the next generation in CAB and AP were equal to 15 and 3, respectively.
Crossover rate (or probability): 1.2
Mutation rate (or probability): 0.2
Number of iterations: 100
In order to validate the proposed algorithm, AP instances in small and medium scales are evaluated in Table 5. The gap between the optimal solution and the one obtained by the proposed algorithm was defined as: $(best\ cost_{genetic} - best\ cost^{*})/best\ cost^{*} \times 100$, where $best\ cost_{genetic}$ is the objective function value obtained by the proposed algorithm and $best\ cost^{*}$ is the optimal objective function.
Average gap was calculated as 0.044%. The CPU time between small and medium scales increased rapidly. Time* shows the CPU time of the optimal solution and $time_{genetic}$ is the CPU time obtained by the proposed algorithm. The 14 node AP instances of the time ratio ($time^{*}/time_{genetic}$) was equal to 32.76.

The computed result, which tried to reduce maximum route cost and total cost of networks, was solved as mentioned in Table 5 and the cost value for AP (n=14, p=2) had a value with 0.035% gap of illustrative example solved using exact methods in 986.3 sec.

Table 5
Results of the AP instances

n	P	Lead time(h)	Best cost$_{genetic}$	Time$_{genetic}$(sec)	Best cost*	Time*(sec)	gap
50	2	1000	19946.17	1139.70	19935.798	24622	0.052
50	4	1000	92843.14	971.0366	92794.861	24501	0.052
50	8	1000	229567.40	970.575	229452.616	24412	0.050
25	2	1000	18568.02	1154.90	18560.592	6591	0.040
25	4	1000	61192.52	1161.20	61166.819	6584	0.042
25	8	1000	133782.30	1188.23	133727.449	6586	0.041
25	2	500	Infeasible	--------	---------	--------	--------
25	4	500	84510.80	1188.50	4477.840	6571	0.039
25	8	500	26589.11	1274.90	26577.942	6589	0.042
14	2	500	18863.32	98.630	18856.717	3233	0.035

Table 6
Alpha effect

N	P	alpha	Teta	Lead time (h)	Best cost	Mean cost	Time(sec)
20	4	0.3, 1, 3	2, 1, 0.1	500	65042.58	99334.18	77.1132
20	3	0.3, 1, 3	2, 1, 0.1	500	29569.17	85463.5	75.6633
20	2	0.3, 1, 3	2, 1, 0.1	500	20135.6	75244.38	67.5698
20	4	0.15, 1, 3	2, 1, 0.1	500	48135.6	93765.73	69.8412
20	3	0.15, 1, 3	2, 1, 0.1	500	23868.71	84245.24	61.8352
20	2	0.15, 1, 3	2, 1, 0.1	500	19577.58	79334.04	64.4614

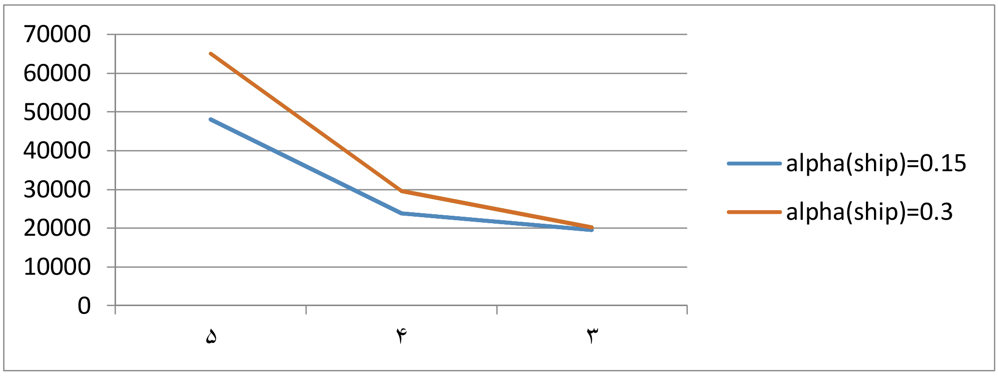

Fig. 5. Effect of changing ship discount factor on AP (n=20) with different numbers of hubs

Figure 5 shows the effect of ship discount factor as an example. When the number of hubs was equal to 2, the cost function value would be 20135.6; however, if the ship alpha was reduced to α_{ship}=0.15, cost would be equal to 19577.58 as expected. This value raised to 29569.17 when there were 3 hubs in the network. If the ship alpha was reduced to α_{ship}= 0.15, cost would reduce to 23868.71. Thus, cost variation depended on the number of hubs.

Table 7
CAB dataset

p	Lead time(h)	Best cost	Mean cost	Time(sec)
2	200	298409324.2	7229990635	98.1919
4	200	208651202.6	6433359384	98.9872
6	200	278535096.9	6444816578	105.9188
10	200	656459346.8	9290471570	108.6852

The best answer's first chromosome in CAB with *p*=4: 25.78816397, 6.791620845, 9.737773019, 25.02564962, 9.068453091, 6, 9.42380001, 16.44021602,9, 6.583107173, 25.53115566, 16.00264178, 9.665678903, 9.19367807, 6.701297533, 16, 25.86500648, 16.23905978, 25.87692062, 16.28314588, 9.931246838, 16.22058506, 25.34860236, 16.1402597, 25.

Table 8
Australia post dataset

P	Lead times(hour)	Best cost	Mean cost	Time(sec)
20	2000	3082095	11496616	450236.8

This network was designed with 162 ships, 34 planes, and 184 trucks for hub-to-hub routes.

Table 9
Comparing multimodal and truck vehicle type

Compare	Multimodal transport	Truck mode transportation
Total cost	83661.714	8500.365
Maximum periods time	70 hours	67 hours
Maximum number of trucks using in nodes	1	2

Table 9 shows that, as a result of using multimodal transportation and three-hour increased time in the network, 1300 units of cost was reduced and crowding was decreased by half.

5. Conclusion

Using the new mathematical formulating of a multimodal transportation, we solved hub location routing problem with simultaneous pick-ups and deliveries. This paper presented an idea along with some references for being used in hub networks considering the crowding rate of nodes.

A mixed-integer nonlinear programming formulation was provided for this specific multimodal hub location routing problem. Locations are the most important issue in p-hub location problem, as illustrated by CAB dataset with 4 hubs as the optimal network shown in Table 7. Increasing the cost function and variable values showed cost reduction by multimodal. A comparison between using multimodal transportation and truck vehicle is given in Table 9. Multimodal transportation helped to have an economically optimal design and less crowd in the network. Another important issue was the effect of lead time, as demonstrated in Table 56, which made the application of faster and much more expensive facilities necessary. Another one was that the tumult was scattered in other ways (roads, sea lanes, and airlines). The gaps in Table 5 have an average of about 0.044%, representing the good validation of the proposed algorithm. The value of the time ratio ($\text{time}^{*}/\text{time}_{\text{genetic}}$) was equal to 32.76. Considering the CPU time that would rapidly increase with the increase in the problem size, the benefits of the proposed algorithm are clearly evident.

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