Pc=0.8 and Pm=0.2 are considered. At first, for $\alpha = 0.5$ we solve the instance with $0.5 < \gamma \text{ and } \aleph < 1$, with increasing in $\gamma \text{ and } \aleph$, the cost is worse, so we assume $\gamma = \aleph = 0.5$ and solve the instance with $0 < \alpha < 1$, with the reduction of α , the cost becomes better. Hence, we assumed $\alpha = 0.1$, and solve the problem with $0.1 < \gamma \text{ and } \aleph < 0.5$, in that case, the best cost is obtained with $\gamma \,\&\aleph = 0.4$, basis of this analysis the discount factors were assumed $\alpha = 0.1$, $\gamma = 0.4$, $\aleph = 0.4$.

For each instance, O-D matrix, establishment costs, economic coefficients, vector of parameters of the hinterland of the origin hub, distance matrix and consequently the cost matrix had been generated once for GA1 and then they are used in related GA2. The results of small instances are condensed in Table 10 and for large instances they are shown in Table 11.

Table 10 presents the results for GA based on the small problems and table 11 presents the result of executing the large size problems. For each problem instance, n denotes the number of nodes, pre-hub denote the initial state of network, $\text{Opt}_{\text{cost}}1$, the optimal values of the objective function (initiate cost of the network before assuming the time as a fuzzy parameter), the numbers in the column labelled "$\text{Opt}_{\text{cost}}2$" , the final cost of the objective function after applying the proposed model. "Num of new hubs" shows the number of established hubs in the network after applying the fuzzy method via our proposed model, while NO_p, denotes the new-hub numbers. Total running time is shown in the last column. As we can see from the Table 10, the network with n=10 nodes and $\text{H}^* = 1$and $\text{NO}_\text{p} = 0$ show the minimum network cost.

Table10. The results of small instances

n	**case**	**Primary network**			**Final network**			
		Pre-Hub	$Opt_{cost}1$		**Num of new hubs**	NO_p	$Opt_{cost}2$	**t**
	10H1	3	6578.14		0	0	4223.66	32.4
10	10H2	3,6	7640.16		0	0	6017.29	45.6
	10H3	2,3,6	7737.06		1	5	7507.22	45.0
	10H4	2,3,6,7	7905.52		1	4	7528.98	50.9
	10H5	3,4,5,6,7	8755.83		0	0	7536.68	56.4
	20H1	12	11184.58		0	0	9986.24	130.4
	20H2	2,12	10772.30		1	7	9577.21	165.5
20	20H3	2,7,8	11246.05		2	3,5	11253.12	179.7
	20H4	2,5,7,12	10036.71		1	8	10025.98	190.3
	20H5	2,5,8,12,13	12544.03		0	0	12143.32	200.8
	30H3	3,12,22	13834.01		3	13,18,22	10142.26	299.2
	30H4	12,17,18,22	11222.32		1	3	99787.93	286.1
30	30H5	3,12,17,18,22	11387.80		0	0	11325.22	280.2
	30H6	2,3,17,18,22,25	10279.41		0	0	10022.44	273.3
	30H7	3,15,17,18,20,22,25	16998.92		1	5	162529.12	272.1

By increasing the number of hub, the network cost is increased too. The results for the network with n=20 can be analyzed in the same way. For the networks with n=30 the minimum cost is obtained with $\text{H}^* = 4$ and $\text{NO}_\text{p} = 1$. Note that for each problem size, $\text{H}^* \in$ {1,2,3,….,n/2} was assumed. But we show 5 solutions around the optimum one. As an example, for n=20, the problem was solved by 1to10 pre-established hubs.

As it is clear in table 11, the optimal costs for network with n=50, $\text{H}^* = 7$and $\text{NO}_\text{p} = 3$ and for network with n=100, $\text{H}^* = 11$and $\text{NO}_\text{p} = 2$ are obtained.

4.3. Comparison of Computational results

In order to measure the effectiveness of our method, we solved an instance with n=10, 20 node with deterministic and fuzzy time parameter and then compare the solution quality and running times in the both models.

Table11. The results of large instances

	case	Primary network				Final network	
		Pre-Hub	Opt_{cost}	New hubs	NO_P	Opt_{cost}	t
50	50H5	3,4,7,8,13	81332.8	0	0	74915.30	1208.7
	50H6	3,4,7,8,41,45	76694.3	0	0	72515.23	1001.3
	50H7	4,7,8,9,26,37,45	69931.8	5	2,3,6	61122.65	985.2
	50H8	8,13,25,28,32,37,39,45	65334.1	2	12,17	61741.78	979.4
	50H9	13,18,23,26,28,32,37,45,48	61225.4	2	10,15	86959.11	944.6
	50H10	5,8,13,18,32,35,39,41,45,48	95132.5	4	1,27,38,42	102888.00	900.2
100	100H10	12,18,32,45,52,68,70,75,82,95	157222.8	5	4,5,10,14	198478.88	3241.5
	100H11	12, 15, 17, 19, 26, 32, 45,52, 67, 75,82	175325.7	2	5,8	151784.24	2999.4
	100H12	3,5,8,12,18,32,43,55,62,70,82,95	195342.0	0	0	162214.33	2514.6
	100H13	1,5,8,12,14,18,32,45,52,67,70,82,95	152340.3	3	22,40,58	201782.14	2387.8
	100H14	8,12,15,18,26,32,39,43,52,55,62,67,82,92	200142.3	1	35	199852.92	1978.2

We also compared the solution results with those had obtained by LINGO solver 15. Both GA and LING were run on the same system with the same parameters.

To perform the comparison of experiments, the population size P=20 and the number of generation for GA are set to 30 and $P_c = 0.8$, and $P_m = 0.2$ and the discount factors are assumed as $\alpha = 0.1$, $\gamma = \aleph = 0.4$. Tables 12 gives the results of comparison experiment for two kinds of networks (n=10, 20) with various hubs ($P = 1,2,3,4,5$).

The third, fifth and seventh columns of the table 12 present set of hubs. The fourth and sixth columns of the table5 shows the corresponding costs from the results generated by our GA-based framework assuming the time as a deterministic and as a fuzzy parameter respectively. The eighth columns show the corresponding costs generated by LINGO. The running time of the three methods are given in the CPU (Time) columns which are measured in CPU seconds.

As we can see from table 12, the results demonstrate that the solutions of the fuzzy model because of more accurate seeking the solution space would be better than the model with deterministic parameters.

Table12. Effectiveness of the proposed algorithm

n	case	GA (Deterministic)		GA (Fuzzy)		LINGO (Fuzzy)		CPU(Time)		
		Hubs	Cost	Hubs	Cost	Hubs	Cost	GA_{Dtr}	GA_{Fuzzy}	LINGO
	10H1	3	6578.14	3	4223.66	3	4223.66	35.2	32.4	1300
10	10H2	3,6	7640.16	3,6	6017.29	3,6	6017.29	50.4	45.6	2070
	10H3	2,3,6	7737.06	2,3,5,6	7507.22	2,3,5,6	7507.22	52.9	45.0	2550
	10H4	2,3,6,7	7905.52	2,3,4,6,7	7528.98	2,3,4,6,7	7528.98	57.8	50.9	2490
	10H5	3,4,5,6,7	8755.83	3,4,5,6,7	7536.68	3,4,5,6,7	7536.68	60.2	56.4	2360
	20H1	12	11184.58	12	9986.24	12	9986.24	133.4	130.4	7821
	20H2	2,12	10772.30	2,7,12	9577.21	2,7,12	9577.21	184.6	165.5	10245
20	20H3	2,7,8	11246.05	2,3,5,7,8	11253.12	2,3,5,7,8	11253.12	194.8	179.7	9482
	20H4	2,5,7,12	10036.71	2,5,7,8,12	10025.98	2,5,7,8,12	10025.98	203.9	190.3	11254
	20H5	2,5,8,12,13	12544.03	2,5,8,12,13	12143.32	2,5,8,12,13	12143.32	213.0	200.8	8759

Moreover, comparison between the sixth and eighth columns of Table 7 illustrates that GA concept reaches optimal solution in significantly shorter CPU time compared to LINGO. Specifically, when the problem size is 20, the average running time of GA method is 173s. LINGO solver achieves the same optimum values by an average running time of 9512 s. In addition, LINGO solver fails to efficiently solve large and complicated instances. It is due to the fact that LINGO solver achieves its optimal solution using the branch and bound procedure by examining nodes, where number of nodes becomes very large when the test problem size increases. Due to the memory requirements, LINGO solver is unavailable for large problem size.

5. Conclusions and future research

Among all of network parameters, travel time is one of the most important factors that cannot be considered deterministic since its values may vary because of traffic conditions, speed, and time of day, climate conditions, and land and road types. Due to the uncertainty of relevant data, the estimated travel time by automobile between two points has fuzzy features due to the measurement imprecision and perception (Yang et al. 2013).

In this paper we extended the model of the incapacitated hub location problem with fixed costs on networks under decentralized management (UHLP-DM) which was created by Vasconcelos et al. (2011). In our proposed extension, the time had been supposed as a fuzzy parameter and then the model was solved by genetic algorithm.

The results revealed that, because of exploring the more pieces of the solution space, using the fuzzy parameters contributed to more accurate system analysis. Using non-deterministic parameters has large practical real-world application in network design. Since, in the model, we sought to solve the large-sized UHLP-DM problem, it was solved using two genetic algorithms; the first one, GA1, was applied to create the initial network in which there were some pre-established hubs and the second one, GA2, was applied to find new hubs in such a network with regarding to the objective function. The proposed model was implemented for small-sized and large-sized problems using Matlab optimization software (R2013b v8.2) and it was run on the Windows 7 operating system with an Intel ® Core™ i3-4030 processor and 4.00 GB of RAM. The described GA method used a binary encoding of the individuals and an appropriate objective function. However, the proposed GA algorithm surpasses the LINGO solver with respect to efficiency. It obtains optimal values in significantly less time than the LINGO solver for the same test problems. The proposed GA was also able to solve practical size problems that were out of reach for exact methods.

The presented solution is applicable to analyse the transport networks in free markets. Additionally, there are many other points for future research. Some of the points are:

- Consideration of demand in P_{ijkm} calculation.
- Consideration of the transferring cost in network cost calculation.
- Consideration the demand as a fuzzy parameter
- Creation of a new constraint to cover the demand in any hinterland.

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