ORIGINAL PAPER

Minimizing response time to accidents in big cities: a two ranked level model for allocating fire stations

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Abstract

In crowded cities, like Tehran, when a major accident occurs, such as a fire, the response from more than one fire station is usually needed at the scene. The present study focuses on demand allocation to fire stations at two ranked levels to determine the priorities of fire stations to service relevant demands. To solve this problem, this paper uses the Vector Assignment Ordered Median Problem (VAOMP), a new location–allocation model that can allocate demands to facilities at several ranked levels, based on the particular objective function. Thus, this paper uses the meta-heuristic methods of Tabu and genetic algorithms to minimize the arrival time from fire stations to demands, at two levels, at up to 5 min in the GIS environment of the 21st and 22nd districts of Tehran. The optimum parameters for each algorithm were obtained through sensitivity analysis. The results of applying the model with two algorithms in these districts with 10 existing fire stations and 336,600 inhabitants showed that the current stations are insufficient for two levels of service and that 52,840 people at level 1 and 81,320 people at level 2 have no access to services. As such, the results of two algorithms for relocation–reallocation analysis at two levels with different weightings for 13 potential and existing fire stations showed that at least 3 new stations need to be created. Furthermore, the genetic algorithm produced qualitatively superior results, in optimal values, the accuracy of allocation and timeframe, compared with the Tabu algorithm.

Keywords Two ranked level allocation · Vector Assignment Ordered Median Problem · Tabu search and genetic algorithm · GIS

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Introduction

Planning theory and practice focus mainly on urban areas (Beyazli et al. 2017). Human activities have caused great changes on the environment, and the excellent location of service providers can avoid further environmental damages (Akbary et al. 2018). At the same time, the probability of accidents occurring is higher in large cities with large populations. If the relief forces and service providers are not located in the right place or if the priority of their arrival at the accident site is not evaluated, there will be considerable financial and human losses. Tehran is a city populated with high-rise buildings that expose it to significant fires and incidents, such as the fire in the Plasco building. Districts 21 and 22 of Tehran city are vast new areas, with a population of 336,600 and an area of 11,500 hectares, which are currently facing a shortage of urban facilities.

One of these service providers is the fire service, for which the optimal location of fire stations and the optimal allocation of the population to those stations are extremely important. Especially when an incident occurs on a large scale, one fire

station will not be enough to service the people affected. More stations are required in the incident area to deal with emergencies, and among the existing stations, one has greater priority than the others in reaching the affected area. Hence, this paper investigates the relative priority, at two levels, of the 10 existing fire stations in districts 21 and 22 to reach the incident site. According to international standards, firefighters must be able to reach an incident within approximately 5 min (Yang et al. 2007). If they reach an incident scene within this timeframe, the financial and human costs will be lowered.

Thus, the problem of allocating population to existing fire stations is very important, and it must be determined which stations prioritize in providing service to the population. Given that districts 21 and 22 are large and there are only 10 fire stations in the area, it should be examined whether the existing stations can meet all the necessary demands, at two levels, within 5 min and whether there is a need to create new stations. Evidently, the intended problem is a combinatorial location–allocation problem, and therefore, the new unified VAOMP approach (Lei et al. 2016) is used to solve it. This model is a completely new approach that is used in this research to solve multi-ranked and multi-level allocation problems. This model has not yet been used to solve any problems. The current study uses the capability of this unified model for the first time to solve the problem of fire station allocation at two ranked levels.

This approach involves a very difficult and NP-Hard model, which cannot be solved by exact methods. To solve the problem, meta-heuristic algorithms must be used. Considering that genetic and Tabu search algorithms have succeeded in solving location and allocation problems, these two algorithms will be used to solve this problem (Bolouri et al. 2018; Aghamohammadi et al. 2013). Hence, the purpose of present study is to investigate the demand allocation for 10 existing fire stations at two ranked levels, with the objective of minimizing the arrival time of firefighters to an incident scene in Tehran's 21st and 22nd districts. For this, the study uses the VAOMP model to prioritize existing stations in providing services to the population in the districts. If the number of stations is insufficient to satisfy demand at two ranked levels, a relocation and reallocation analysis will be undertaken to find the minimum optimal number of stations to satisfy all relevant demands. The quality of the solutions generated by two algorithms and the time required to solve the problem are also compared.

The questions that this research will answer are as follows:

1. Is the number of existing fire stations enough to serve all demands in these districts at two levels? How many demands are without access to the service?

2. How many new stations will need to be created to allocate all relevant demands to the fire stations at two levels?

3. Which algorithm is more effective in solving this problem?

The remainder of this paper is organized as follows. The next section reviews the literature to identify which similar studies have already been undertaken, before the following section presents the VAOMP model and its formulation. The subsequent section identifies the Tabu search and genetic algorithms, and the next section then presents the methodology or workflow of the VAOMP model. After that, the next section presents the implementation of the model in a case study, before the required data are presented, and the sensitivity analysis for the genetic and Tabu search algorithms is undertaken in two following sections. After the relocation–reallocation analysis is presented, we then conclude with a summary of findings and a discussion of necessary future work.

Literature review

Given that the problem concerning fire stations addressed in this paper is a location–allocation problem, it is necessary first to describe the nature of location–allocation problems. The location–allocation problem aims to select the appropriate locations from a number of possible supply centers to provide the appropriate services for customers and decision makers in relation to the customer allocation (demand centers), based on given criteria for the facilities. There are different models for location and allocation problems. Hitherto, many investigations have been undertaken with these models. Furthermore, these models have been classified in different ways (Brandeau and Chiu 1989; Murray 2010). Nevertheless, there are several main models for location–allocation problems, including the P-Median, P-Center, and covering models. The problem of minimizing the arrival time from fire stations to demand site at two levels is a P-Median problem. As always, location and allocation problems are complex, NP-Hard problems, and unified models make the problem more complicated, despite the fact that these make the problem more realistic.

The OMP[1] (Nickel and Puerto 1999) problem is one of the unified approaches, which provide a general structure for combining median and center problems. Church and ReVelle (1976) argued that MCLP[2] problem can be converted into a median problem by converting the distance or cost matrix. Furthermore, Hillsman (1984) showed that if input data are properly edited, many location-based problems, including a variety of coverage problems and the similar, can be structured by median problems. To solve these models, meta-heuristic methods have mostly been used. For example, meta-heuristic methods such as the genetic algorithm and variable neighborhood have been developed by Domìnguez-Marìn et al. (2005) and Stanimirovìc et al. (2007) to solve the OMP problem. Boland et al. (2006) developed an exact

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[1] Ordered median problem
[2] Maximal covering location problem

method for solving discrete OMP problems. They proposed ILP[3] formulae to solve OMPs. So far, various meta-heuristic methods have been used to solve location–allocation problem for fire stations. Yang et al. (2007) used the min–max location–allocation model for solving the optimal location of fire stations using the genetic algorithms. Habibi et al. (2008) provided a model for fire station locations in district 6 of Tehran using the Geographic Information System (GIS). For the optimal location of fire stations in Kuwait city, Algharib (2011) used the location–allocation analysis in a GIS environment. Meanwhile, Bolouri et al. used both genetic and simulated annealing algorithms to solve a variety of location and allocation problems for fire stations in district 11 of Tehran as multi-objective problems; comparison results for the algorithms showed the superiority of the genetic algorithm (Bolouri et al. 2018). Bolouri et al. (2019) investigated the effect of capacity criterion on the optimal allocation of fire stations. None of these studies used the new VAOMP model, and none has investigated the priority of demand allocation to fire stations at two ranked levels. The current paper determines the allocation status of fire stations and their service priority at two levels, using the new unified VAOMP model in the 21st and 22nd districts of Tehran.

VAOMP model

The most recent development in location–allocation problems is the VAOMP model. This model can solve a large number of classical location–allocation problems. In addition, this new model can determine the priority of facilities for service to demands with different weights. In this section, the VAOMP formula is presented. The VAOMP involves allocating demand to its first closest facility and then to its second closest facility, and so on. In this paper, considering two ranked levels, the model first allocates a demand to the first closest fire station (in terms of time) and then the second closest fire station. In this way, the model minimizes the arrival time of fire stations to demands at two ranked levels. To formulate the model, the relevant parameters must be defined (Lei and Church 2014):

$$\text{Minimize } Z = \sum_{k=1}^{n} \lambda_k w_k \tag{1}$$

$$\sum_{k=1}^{n} w_k = \sum_{i \in I} \sum_{j \in J} \sum_{l=1}^{L} a_i \theta_{il} d_{ij} x_{ij}^l \quad \text{for every } i \in I \tag{2}$$

a_i Demand (population) at the point i

d_{ij} Time between i (demand) ε I and j (fire station) ε J that extracted from OD cost matrix

L The maximum number of closeness levels being considered in this paper is equal to 2 levels.

θ_{il}

The weight in each ranked level

The proposed model, along with its constraints, helps to allocate any demand to its closest facility at several ranked levels. Given that the problem of minimizing time is a problem of median type, with two ranked access levels, it would be enough to transform the VAOMP model into a median problem at two ranked level by considering the λ vector as $\lambda_1 = \lambda_2 = \ldots = \lambda_n = 1$.

Genetic and Tabu search algorithms

The problem of allocating demand to fire stations is one of the spatial optimization. There are various meta-heuristic methods to solve these problems, which are integrated with GIS, such as genetic, simulated annealing, and Tabu. In the 1960s, John Holland worked on the genetic algorithm, inventing it as a meta-heuristic method and introducing a not only mutation into this algorithm, but also copying natural behavior and biology in artificial systems (Holland 1975). In fact, the genetic algorithm attempts to mimic the process of natural transformation using genetic operators (selection, crossover, and mutation) (Didier Lins and López Droguett 2011). The most important parameters that should be set for this algorithm are mutation, crossover, the number of generations, and population size. The Tabu search algorithm is also a high-consumption and cost-effective meta-heuristic for combined optimization problems (Habet 2009). The Tabu search algorithm explicitly uses the search history to implement a search strategy and escape from the local minimum. The list length in the Tabu controls the search process memory, because it is forbidden to re-visit more solutions. The most important parameters that should be set for this algorithm are Tabu tenure, the number of generations, and the number of search neighbors.

Methodology

First, in accordance with Lei and Church (2014), VAOMP will be used in Tehran's 21st and 22nd districts to solve the relevant location–allocation problem, with the aim of minimizing arrival time from two fire stations to an incident site to less than 5 min (in accordance with international standards). Two Tabu search and genetic algorithms will be applied separately to find optimal solutions. As it is necessary to reach appropriate solutions in a short time, sensitivity analysis is undertaken for both algorithms and their parameters to determine which changes in parameters will have the greatest effect on the solutions for any algorithm. Then, if the number of existing fire stations is not sufficient to serve the area, relocation–reallocation will be performed to select an appropriate number of stations to fully serve all demands. Finally,

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[3] Integer linear programming

Fig. 1 Main steps of the methodology
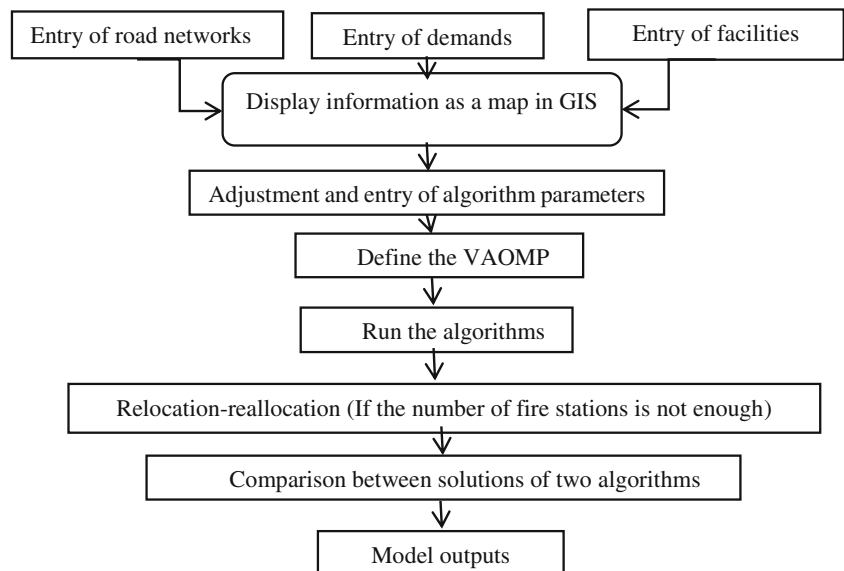
the results of both algorithms in solving location–allocation problem for existing fire stations at two ranked levels are compared. Figure 1 shows the steps in the methodology. The system used for all processes is an Intel® i7 4.2 GHz CPU and 16 GB of memory. The model programming is done in MATLAB environment.

To solve the model in the study area, all the effective parameters in the problem must be considered in the model programming. These parameters include minimizing the arrival time of fire trucks to the incident sites, population density in the area, average traffic on the road network, and speed of road network. Each section of the road has a specific speed

and average traffic rate (in seconds that are added to the road travel time), which are stored as road descriptive information in GIS. To speed up the processes, the OD cost matrix is produced using the OD cost analysis of time in GIS (the distance of each road section/speed of each road section), based on the objective to minimize the arrival time of fire trucks to their demands (this matrix calculates the minimum time between each demand and each fire station). In this way, the first and second closest fire stations in terms of time are determined for each demand. Then, the parameters of each algorithm are refined with optimal values for achieving the best solutions. Each of the algorithms solves the location–allocation problem

Fig. 2 Location of the existing fire stations and main road network in Tehran's 21st and 22nd districts
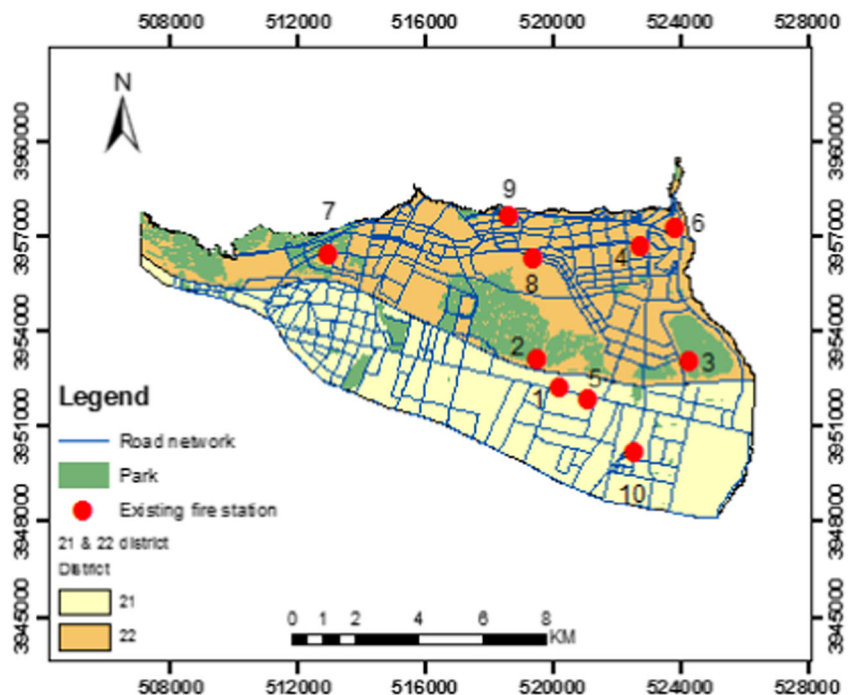
Fig. 3 Population demand in the 21st and 22nd districts of Tehran and population distribution in statistical zones
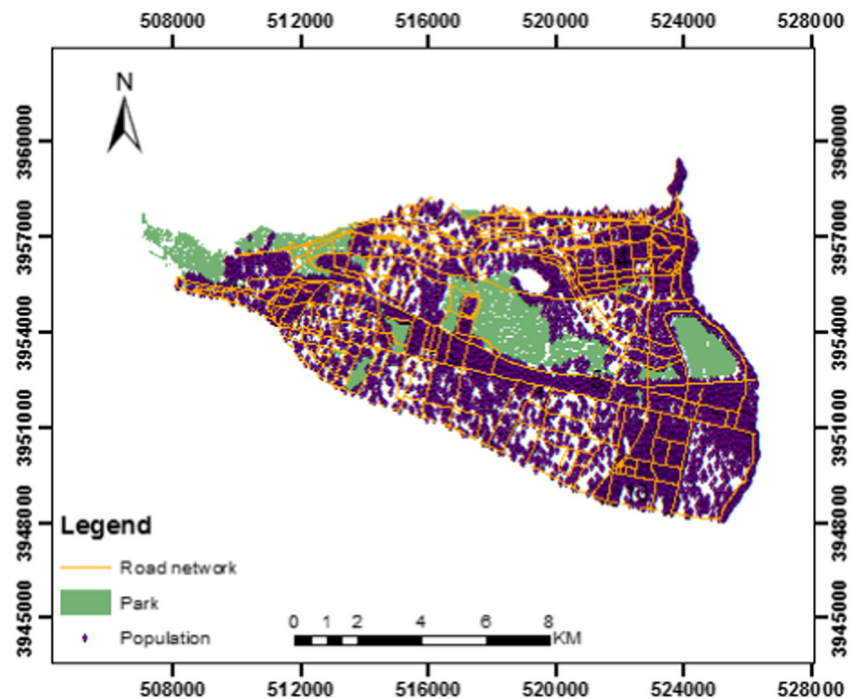
of fire stations at two ranked levels in districts 21 and 22 of Tehran using Eq. (1). The details of the research methodology in the case study are explained as follows.

First, for existing fire stations in districts 21 and 22, Eq. (2) is calculated for each demand point. The population density at each point forms a_i. Then, a_i is multiplied by the time parameter between that demand and fire station j. This result is multiplied by 1 (if the requested demand, based on the time in the OD cost matrix and two ranked levels, can be allocated to that station (i.e., the fire station is the first or second closest facility in terms of time to demand)) or otherwise by 0. The result of this step creates a partial sum. All of these partial sums (for all demands) are ranked from the smallest to the largest. Then, these partial sums based on Eq. (1) are multiplied by $(\lambda_1 = \lambda_2 = \ldots = \lambda_n = 1$, transformation the VAOMP to P-Median problem), and their results are summed to form the final result. Thus, each algorithm shows which existing fire stations have the first and second priority in servicing demands.

After calculating the allocation of each existing fire station, the number of unallocated demands is determined based on time up to 5 min. If the number of existing fire stations in districts is insufficient to service all the demands, the relocation–reallocation is implemented in the regions. To implement this analysis, candidate stations need to be created. Suitable locations for building candidate fire stations are determined through site generation, taking into account parameters such as faults, slope of the land, soil type, elevation, land use, and vegetation. Then, the best locations are selected as candidate stations using the opinion of experts in this field,

considering the standard distance between the stations, and a point is located for each new candidate station. The appropriate number of stations is randomly selected by each algorithm from the candidate stations introduced in the previous step. For existing and candidate fire stations, Eqs. (2) and (1) are calculated by each algorithm to achieve the minimum results and meet all the demands to the fire station services. Each time, the algorithms select a number of stations (from existing and candidate fire stations), and this process is repeated to meet the optimal values.

Practical implementation of the model in the study area

The metropolis of Tehran has witnessed disastrous incidents in recent years, such as the fire at the Plasco building. The 22nd district is located in the northwest of Tehran with many tall buildings. The area of this district is about 6200 ha. District 22 is geographically the largest part of the capital. Due to its size and increasing population, this district requires greater attention. According to the latest census, the population of this district is over 150,000, and it will reach 450,000 persons by the year 1404 based on the Detailed Plan. District 21 measures about 5,156 hectares. This is 7.8% of the total area of Tehran and, in comparison with other areas, it is one of the largest areas of the Tehran municipality. The population of this district is 186,600, according to the latest census, which is more than 8% of the Tehran's population.

Fig. 4 Sensitivity analysis for the Tabu search algorithm: **a** number of generation, **b** Tabu tenure, and **c** number of search neighbor
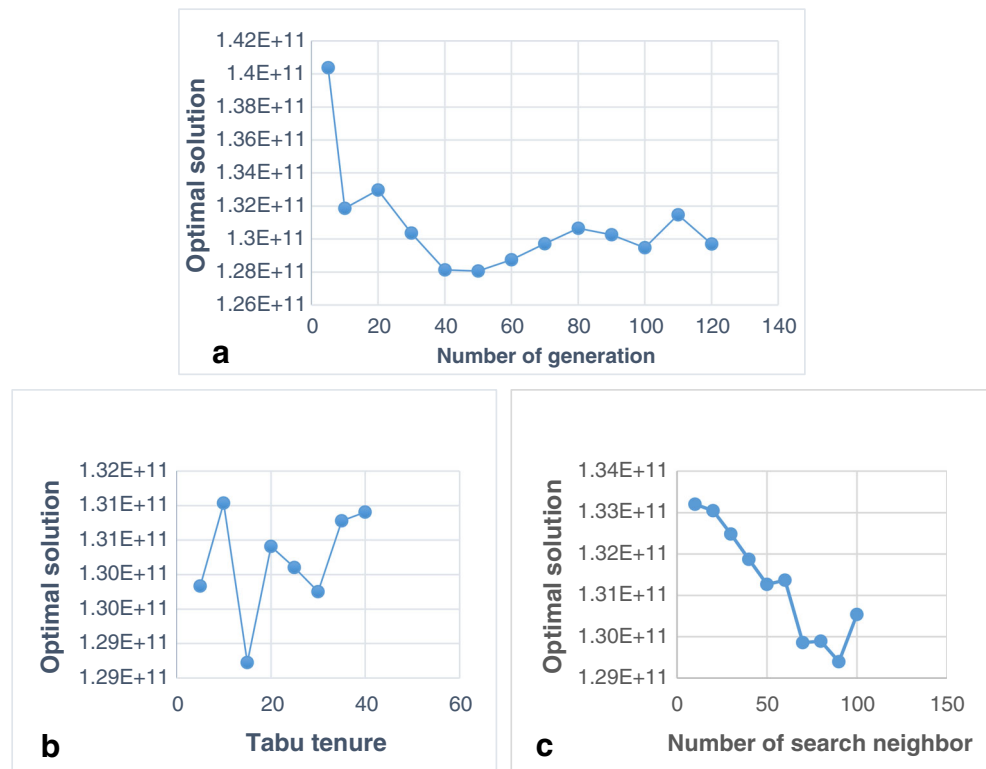

Data

In this research, the main road networks and fire stations in the 21st and 22nd districts of Tehran and their populations (as demands) are required data. Area, statistical zones, and demand data are derived from the latest census websites for the 21st and 22nd district municipalities in 2018 and prepared in GIS. Nowadays, GIS technology is accepted worldwide and used in various applications (Vafaeinejad 2017; Radwan et al. 2018; Zolekar 2018; Abd-El Monsef and E. Smith 2019). GIS is a powerful tool with great promise for use in environmental problem-solving (Saidi et al. 2017). Figure 2 shows the location of 10 existing fire stations and the main roads network in Tehran's 21st and 22nd districts. Figure 3 shows the population demands and distribution in statistical zones, located in Tehran's 21st and 22nd districts. In this research, the model

Fig. 5 Sensitivity analysis for the genetic algorithm: **a** number of generation, **b** crossover, **c** mutation, and **d** population size
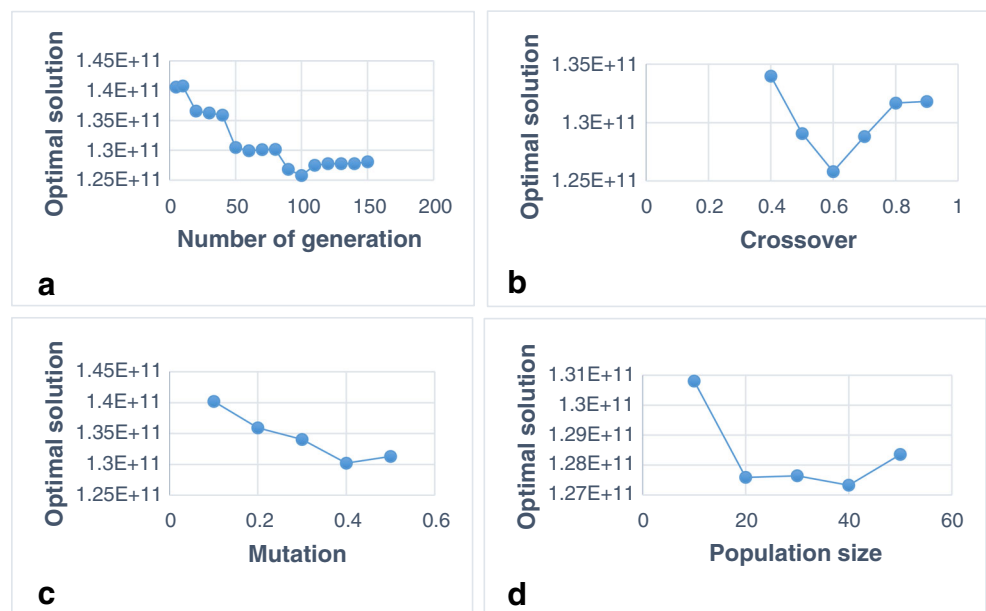
will be implemented in the studied area by assuming that the population remains constant. Beforehand, the model needs to be tested and the parameters set for each algorithm.

Sensitivity analysis and validation of the VAOMP model accuracy

To determine the best parameters for each algorithm, sensitivity analysis is performed in the next section. After this analysis, the algorithms are implemented in the study area to examine the allocation of existing stations and evaluate the performance and accuracy of the models by comparing the results of two algorithms and the convergence diagram for each algorithm. For both algorithms, the parameters will be adjusted to achieve the best results. The efficient and effective implementation of each algorithm depends on the parameters set for it. Although these parameters can accept different values, the values are considered for each parameter for the simplicity of processing.

Sensitivity analysis for the Tabu search algorithm

In performing sensitivity analysis, the algorithm parameters to be adjusted include the number of generations, Tabu tenures, and the number of neighbors. In the following, we discuss how to set these parameters.

Effect of generations

The number of generations means the repetition of all process steps for the algorithm. This value can range from 1 to infinite positive. In a previous study, the effect of this parameter was examined from 5 to 100 (Fan and Machemehl 2008). In this research, the range from 5 to 120 is examined, and the results are shown in Fig. 4a. As the figure shows, increasing the number of generations up to 50 reduces the value of objective function. As the number of generations increases, the processing time will also increase. The minimum value of objective function occurs at 50 generations. Thus, it is suggested that this number of generations be selected as optimal.
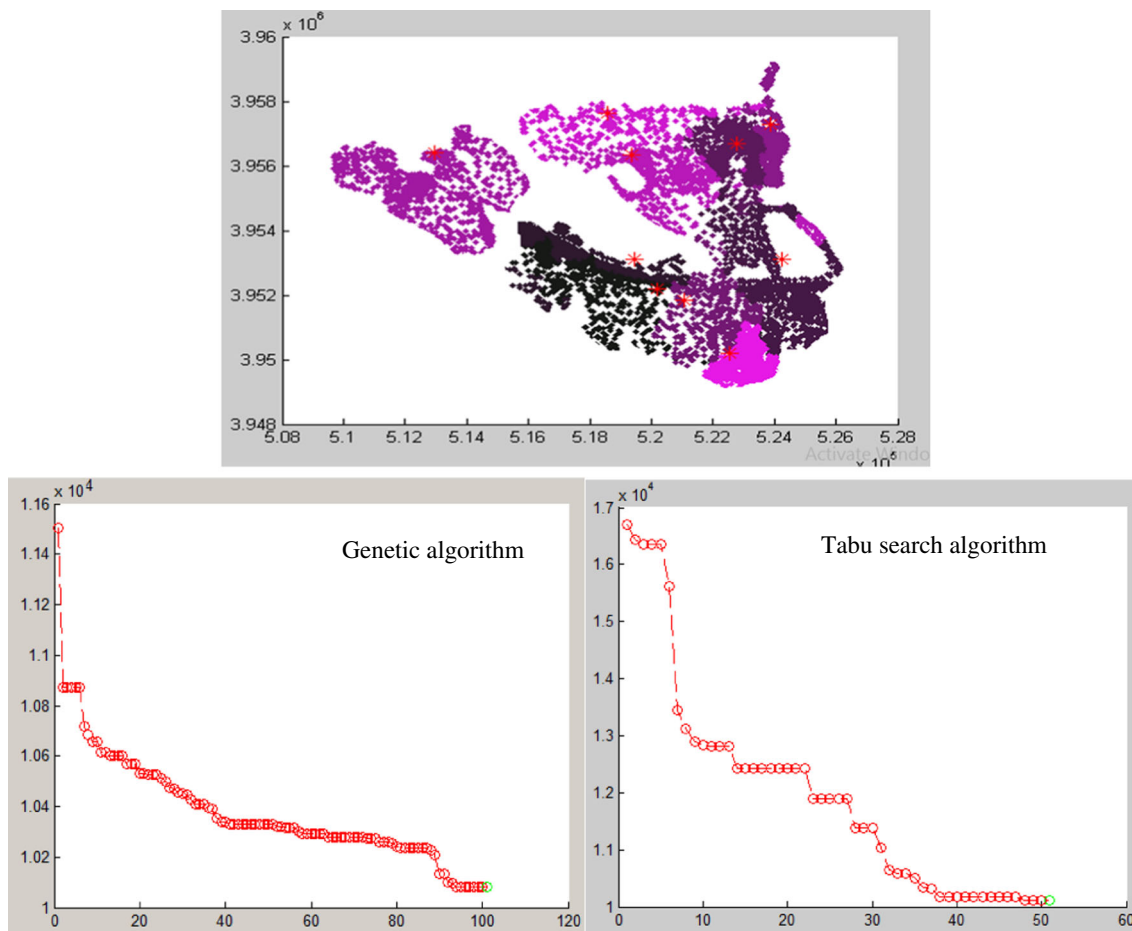

Fig. 6 Allocation at the first ranked level and convergence graph for the genetic and Tabu search algorithms

Table 2 Number of demands for each station

Station number	1	2	3	4	5	6	7	8	9	10	Number of unallocated demands
Number of allocation at level 1	25760	18200	35840	33240	21960	17520	51240	17760	8880	52360	52840
Number of allocation at level 2	25240	17160	40960	30720	20160	18480	32440	17320	10640	42160	81320

Effect of Tabu tenures

The effect of Tabu tenures is investigated in the range from 5 to 40 (Fan and Machemehl 2008), and the results are shown in Fig. 4b. The minimum value of objective function occurs at 15 Tabu tenures. Therefore, this value is chosen as the optimal number of Tabu tenures.

Effect of search neighbors

The neighborhood effect is examined in the range from 10 to 100 (Fan and Machemehl 2008). The results are shown in Fig. 4c. This shows that 90 neighborhoods should be the optimal value, and the same number of neighbors is recommended in the implementation of the algorithm. Therefore, as can be seen, 50 generations, 15 Tabu tenures, and 90 neighborhoods are suggested in all these cases to achieve the minimum objective function, and these should be the values constituting the optimal set of parameters for solving this type of location and allocation problem.

Sensitivity analysis for the genetic algorithm

In performing the sensitivity analysis, the parameters for this algorithm that should be adjusted include the number of generations, population size, crossover, and mutation. Details are discussed below.

Effect of generations

Neema and Ohgai (2010) used 100 generations for this algorithm. In this research, the number of generations is considered up to a value of 150. The results are presented in Fig. 5a. As the figure shows, increasing the number of generations up to 100 generations reduces the value of objective function. As the number of generations increases, the processing time is also increased. The minimum value of objective function occurs when the number of generations is equal to 100. Therefore, it is suggested to select this number of generations as optimal.

Effect of crossover

Liao et al. (2011) used a crossover 0.8, while Zhou et al. (2003) used a crossover within 0.2–0.4. Wang et al. (2011) applied a crossover 0.8, and Kratica et al. (2007) also used a crossover 8.5. Geroliminis et al. (2011) obtained the best results from a crossover 0.4. In this study, a crossover within 0.4–0.9 is used. The results are shown in Fig. 5b. The best results were obtained within a crossover 0.6.

Effect of mutation

Jaramillo et al. (2002) states that the mutation level used should be at a smaller value. Liao et al. (2011) used a mutation 5 to 10%, while Zhou et al. (2003) used a mutation 0.2–0.4. Wang et al. (2011) used a mutation 10%, and Geroliminis et al. (2011) obtained their best results within a mutation 0.1. They tested the mutation rate 0.05–0.1 and 0.2. In this research, a mutation 0.1–0.5 is used. The results are presented in Fig. 5c. As the figure shows, the best mutation is 0.4.
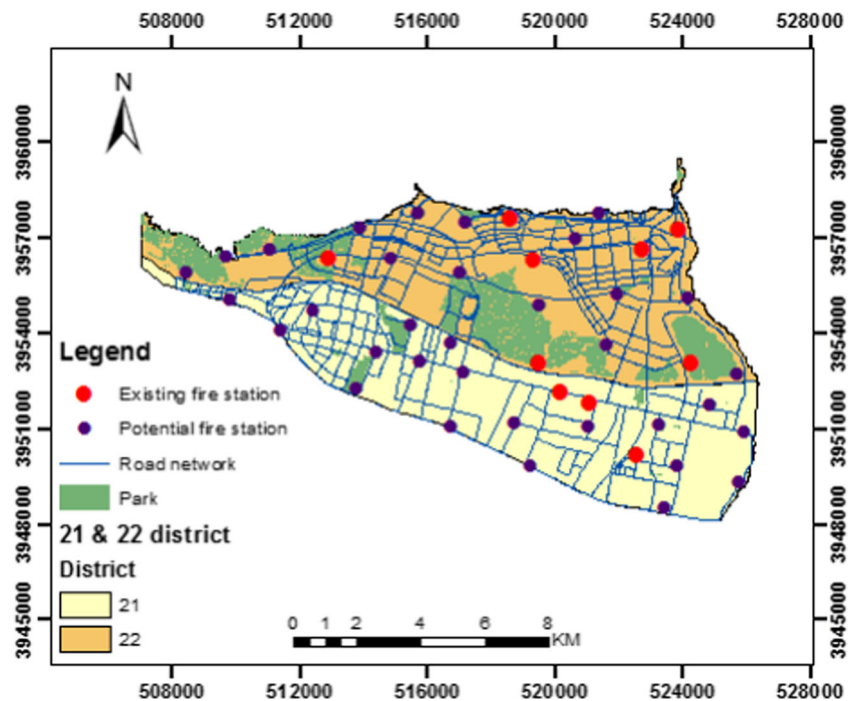
Effect of population size

To reach the desired result, Li and Yeh (2005) suggested a population size 10. Gong et al. also proposed a population size 10, while Shamsul Arifin (2011) used a population size 10, 30, and 50 in his research. In this research, the population size is 10–50. The results are shown in Fig. 5d, which indicates that the best results occur in a population size 40.

Results and discussion

After adjusting the relevant parameters for two algorithms, the population or demand allocation in the case study should be checked at two ranked levels, to minimize the arrival time of firefighters at the demand site to less than five minutes. To facilitate the implementation of the model, one point is placed for every 40 people in each building block. Hence, for 336,600 people in the 21st and 22nd districts, 8,415 points

Table 1 Runtime and optimal value for both algorithms

Tabu algorithm run time (s)	Genetic algorithm run time (s)	Optimal value of both algorithms (min)
522.921	455.945	10080.3283

Fig. 7 Candidate or potential fire stations

were placed on the map of these districts. Each algorithm is implemented separately and calculates the allocation of each existing station and their optimal value by Eq. (1). We then compare the results of both algorithms to determine their efficiency and validity.

It should be noted that since the desired problem in this study is of the median type, the vector λ will be defined by arrays 1. Figure 6 shows the allocation results at level 1 for both algorithms. Displaying the second level is impossible due to the vagueness of the shape and the dislocation of lines. Instead, the information for that level can be extracted from Table 2. Table 1 shows the runtime and optimal value of both algorithms. As expected from the

ranked model, all demands are ranked according to the minimum time to the existing stations and are allocated to their closest stations; thus, both algorithms produce similar results for the allocation of the existing stations. Table 2 shows the number of demands for each station at two ranked levels. Both algorithms show extremely similar results in runtime differentiation, and as Table 1 shows, the genetic algorithm has less runtime.

As Table 2 shows, some stations have allocated a large number of people, but some other stations only have small allocations, because of their proximity to nearby stations or due to an arrival time of more than 5 min to their population demands. In addition, 52,840 people at level 1 and 81,320

Table 3   The best optimum value, the runtime of the genetic algorithm and the non-allocation results at two ranked levels, for 10 independent implementations of the model

		11 stations	12 stations	13 stations
$\theta_1 = 0.7$, $\theta_2 = 0.3$	Optimal value	15,613.7008	13,580.0677	11,776.2478
	Runtime	519.401	524.972	542.146
	Number of unallocated demands at level 1	28,400	7960	0
	Number of unallocated demands at level 2	47,560	19,240	160
$\theta_1 = 0.8$, $\theta_2 = 0.2$	Optimal value	14,512.6955	13,224.7708	11,042.2475
	Runtime	522.718	593.876	597.390
	Number of unallocated demands at level 1	27,360	7240	0
	Number of unallocated demands at level 2	46,440	18320	360
$\theta_1 = 0.9$, $\theta_2 = 0.1$	Optimal value	14,112.9768	13,091.8656	10,990.8754
	Runtime	542.324	597.880	644.230
	Number of unallocated demands at level 1	22,360	8760	0
	Number of unallocated demands at level 2	46,440	18,200	400
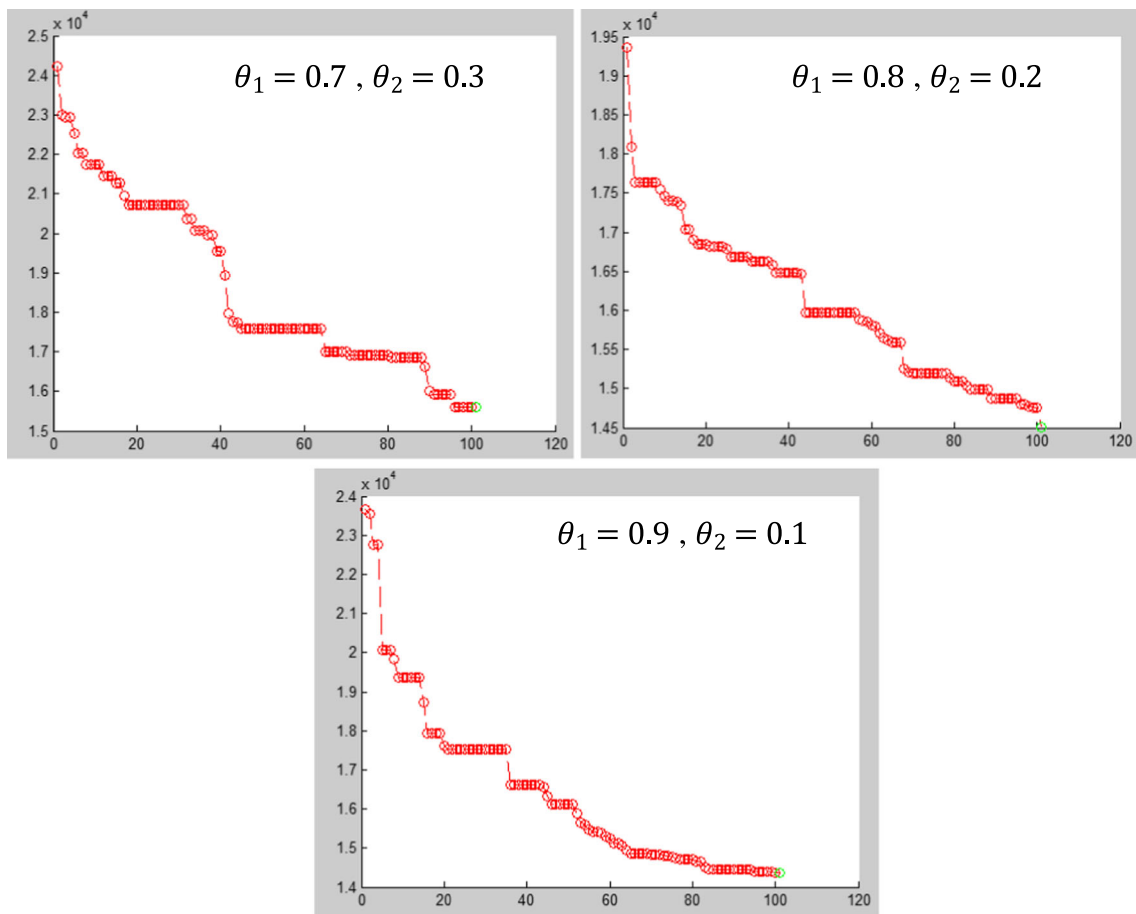
Fig. 8 The best convergence graph of the genetic algorithm, with 11 stations, for 10 independent implementations of the model and different values of θ_1 and θ_2

people at level 2 remained without access to fire services. This indicates that the existing stations are not properly distributed in relation to the existing population, and road networks. Thus, the number of stations should be increased to achieve an optimal service.

Relocation and reallocation

A total of 52,840 demands are not allocated to any stations at level 1; this indicates that the arrival time of firefighters to the place of demand is more than 5 min. It is necessary to reduce

Table 4 The best optimum value, the runtime of the Tabu search algorithm, and the non-allocation results at two ranked levels, for 10 independent implementations of the model

		11 stations	12 stations	13 stations
$\theta_1 = 0.7$, $\theta_2 = 0.3$	Optimal value	16,129.3610	13,591.4627	11,777.2461
	Runtime	568.453	644.827	681.781
	Number of unallocated demands at level 1	31,160	9880	0
	Number of unallocated demands at level 2	50,320	22,360	560
$\theta_1 = 0.8$, $\theta_2 = 0.2$	Optimal value	15,012.5815	13,342.0447	11,512.3697
	Runtime	576.593	651.575	687.048
	Number of unallocated demands at level 1	29980	9000	0
	Number of unallocated demands at level 2	51,400	25,560	920
$\theta_1 = 0.9$, $\theta_2 = 0.1$	Optimal value	14,252.1165	13,118.3119	11,291.4636
	Runtime	594.551	677.776	699.573
	Number of unallocated demands at level 1	28,760	8760	0
	Number of unallocated demands at level 2	51,440	23,440	920
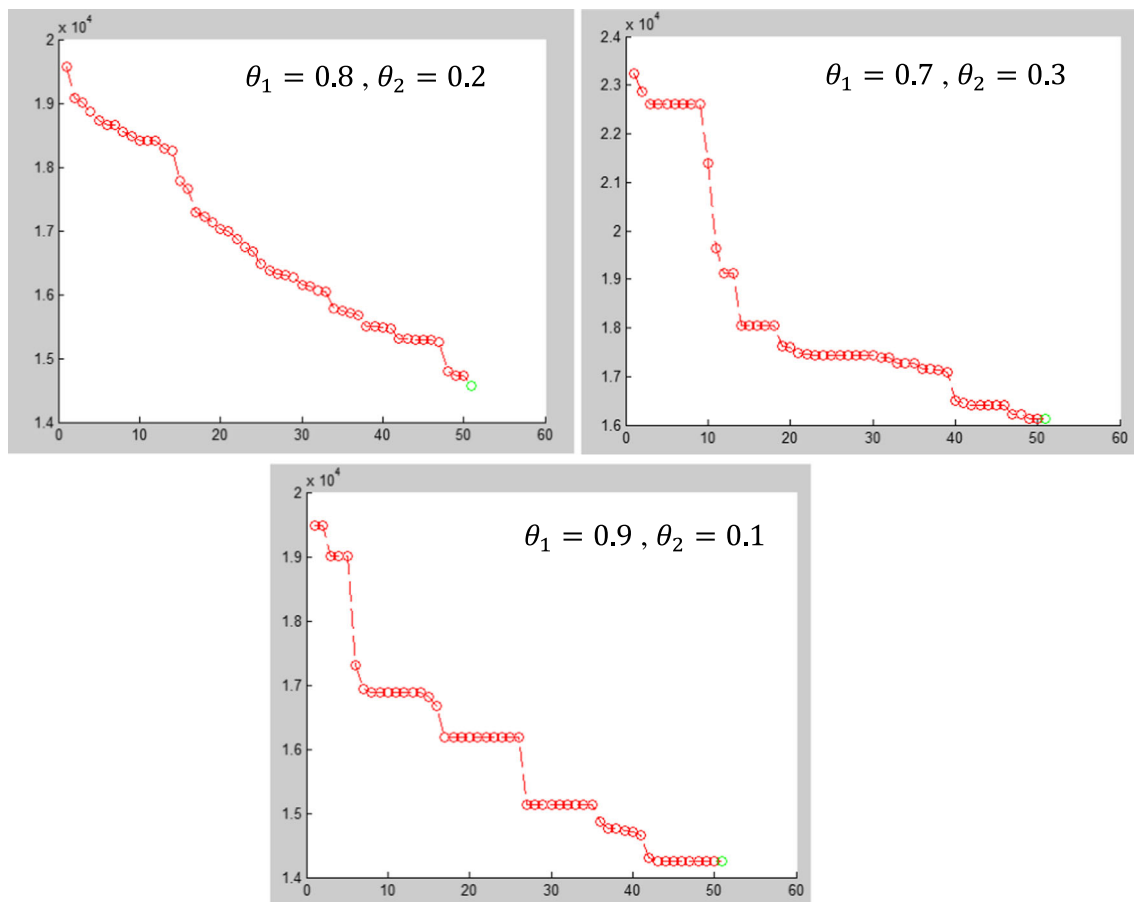
Fig. 9 The best convergence graph of the Tabu search algorithm, with 11 stations, for 10 independent implementations of the model and different values of θ_1 and θ_2

this time. To serve the demands in an optimal manner, it is necessary to add a number of stations to the existing ones and to re-run the location and allocation analysis. To implement a relocation and reallocation analysis, 35 candidate stations are added to the location processing. The aim is to relocate and reallocate 11, 12, and 13 stations (10 existing stations and 1, 2, and 3 candidate stations) among 45 stations, in order to minimize the arrival time of firefighters to the place of demand at less than 5 min. Figure 7 shows the candidate fire stations. Now, for the first ranked level or priority for allocating demand to the closest stations, the value of θ_1 is 0.7, and for the second ranked level, the value of θ_2 is considered at 0.3, then θ_1 and θ_2 are set at 0.8 and 0.2 and then at 0.9 and 0.1. Then, the results of both algorithms are compared with each other, in order to evaluate the effectiveness of two algorithms. Table 3 shows the optimal value, the runtime of the genetic algorithm,

and the non-allocation results at two ranked levels, for 10 independent implementations of the model.

Figure 8 shows the best convergence graph of the genetic algorithm for 10 independent implementations of the model with 11 stations and different values of θ_1 and θ_2. Table 4 shows the best optimal value, the runtime of the Tabu search algorithm, and the non-allocation results at two ranked levels, for 10 independent implementations of the model. Figure 9 shows the best convergence graph of the Tabu search algorithm for 10 independent implementations of the model with 11 stations and different values of θ_1 and θ_2.

Table 5 shows the average percentage of similar allocations in 10 runs for 13 stations using the genetic and Tabu search algorithms. As Tables 3 and 4 show, when the number of stations increases from 11 to 13, the value of the objective function decreases, because the time or cost in the OD Cost

Table 5 The average percentage of similar allocations in 10 runs with 13 stations using the genetic and Tabu search algorithms

$\theta_1 = 0.7$, $\theta_2 = 0.3$	$\theta_1 = 0.8$, $\theta_2 = 0.2$	$\theta_1 = 0.9$, $\theta_2 = 0.1$	
83	84	88	Genetic algorithm
78.5	80	81	Tabu search algorithm

Matrix decreases with the increasing number of stations, and each demand can be allocated to its optimal stations. Some demands that were not allocated to any station—which means the average of arrival time is more than five minutes between the fire stations and the demand location—were not part of the calculation of the objective function, but are now included in it. However, the value of the objective function decreases, due to a decrease in the average of arrival time of each firefighting vehicle to each demand. However, by decreasing the weight of the first level from 0.9 to 0.7, the value of the objective function increases, as the processing time decreases. In addition, as the number of stations increases, more demands will be serviced at both levels. Comparing the results of the genetic algorithm and Tabu search, the genetic algorithm provides better results in terms of runtime, quality of solutions and, number of allocations. Furthermore, at least 13 stations are necessary to service existing demands.

As the results show, the new VAOMP model is a qualitatively unified model that can solve the location–allocation problems for fire stations at ranked levels. One of the benefits of using this model is that it can prioritize the arrival of fire trucks to demand sites. Given that the number of demands in the study area is equal to 336,600 people and the number of road sections equals 1,560, it was very difficult to solve the problem and create the OD cost matrix of time for all demands; modeling and programming to create the ranked levels were also very difficult. As a result, it will be very time consuming and difficult to solve the problem by increasing the size of the problem.

Conclusions

In the event of a major incident, one single station will not be sufficient; rather, several stations are required to provide fire services for this kind of incident. Therefore, the present study has evaluated the allocation of fire stations at two ranked levels for the 21st and 22nd districts of Tehran, which are large areas with very high population levels. The genetic and Tabu search algorithms with the VAOMP model were used to minimize the arrival time of fire trucks to demand sites. It was found that the number of existing fire stations in districts 21 and 22 is insufficient to serve all the relevant demands. A total of 52,840 people at level 1 and 81,320 at level 2 remained without access to fire services, and this indicates that the existing stations are not distributed well in relation to the existing population and road networks.

Therefore, after implementing the relocation–reallocation at two ranked levels, it was found that at least three candidate stations, which had obtained by locating the fire stations, should be established in these districts. It was also found that the genetic algorithm had a shorter processing time and can provide better and more accurate results in terms of optimal

allocation at two levels. It also creates a lower optimal value for the objective function relative to the Tabu search algorithm. A total of 13 stations are considered necessary for the optimal allocation of citizens at two levels for optimal services. With an increase of θ equals to 0.9 and a higher priority for stations at level 1, the number of unallocated demands decreased at level 1.

This study showed that the VAOMP model can yield good results in solving the median problem of fire station allocation at two levels and can even be used in solving the other problems, as this unified model is completely new and has not yet been used to solve any other problems. For further research, the authors propose that other researchers consider the capacity of all fire stations in the VAOMP model, because each fire station can serve a specific number of demands based on its capacity. It can make the problem space more realistic. If solving the problem with adding the capacity criterion was difficult and very time consuming, the others can use parallel processing cores.

Compliance with ethical standards

Conflict of nterest The authors declare that they have no conflict of interest.

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