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A robust linear model for the maximum expected coverage location problem considering the relative coverage

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A B S T R A C T

Emergency medical services (EMS) stations reduce mortality and irreparable damage from injuries through the timely treatment of patients. After performing the initial measures at the scene of the accident, if necessary, they transfer the patient to the hospital. In such cases, the goal is to save human lives. Thus, suggestions and solutions that can improve the performance of these centers are very welcome. One of the most important parameters in providing high-quality EMS is the timing of these services. Therefore, the location of these centers plays a key role in diminishing the response time to demand. In that regard, the location of these centers in cities, especially large and densely populated cities, is very important. In this study, in order to answer the mentioned questions, a linear mathematical model based on the maximum expected coverage model is presented. In this model, by considering the relative coverage conditions, the best locations in the city, as well as the coverage of demand points and distance traveled by the vehicles will be obtained. Furthermore, robust optimization (RO) is used to provide better situations for the operation of the model. Finally, according to the results, it is found that the proposed model has a better resolution time than nonlinear models and is also able to solve cases with high input data. The proposed model is implemented in District 10 of Tehran, Iran.

1. Introduction

Every day, many people are exposed to accidents or diseases such as heart attacks and poisonings that require immediate rescue treatments. The first option in such cases to save the patients' lives is to send the first medical aid usually provided by EMS centers. They are a part of medical aids that start at the patient's bedside and end in the hospital. The chain of events that take place in an EMS process consists of four stages:

1- Report the accident, 2- Check the accident severity, 3- Send a vehicle, and 4- Do the medical operation.

In the fourth stage of the process, after the medical examination at the scene of the accident, if the medical team determines that the patient needs further care, in cases such as severe car accidents or heart attacks, the ambulance should transport the patient to the nearest hospital where he can be treated. Typically, people contact the regional command center by telephone to get help from EMS centers. Then the command center announces the mission via radio to the nearest EMS center to the applicant's location. These EMS centers are equipped with several ambulances. The main purpose of these centers is to reduce mortality, disability, and human suffering. Since the goal is to save human lives in such matters, suggestions and solutions that can improve the performance of these centers are very considerable. One of the most important parameters in

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providing high-quality EMS is the timing of these services. As well as this, the location of these centers plays a key role to reduce the service time. Therefore, determining this location in cities, especially in large cities, is very vital. Determining the location of the centers from several potential locations as well as the number of ambulances in each of these centers is done using location models. The purpose of these models is mainly to obtain maximum demand coverage in the city due to time and budget constraints.

Over the past thirty years, extensive research and studies have been conducted in this field and several models have been presented. But, before modeling and locating these centers, two very substantial points that have not been considered so far should be addressed. First, in many studies, the assumption of demand coverage by a service is assumed to be 0 and 1, which causes a significant deviation in the model outputs. As a result, relative coverage is provided to make the results realistic. Second, due to the limited admission capacity of EMS centers and hospitals, the existing demand for EMS should be allocated to these centers and hospitals based on this limitation.

2. Literature Review

In the past, EMS facilities' location was based on two perspectives: Firstly, which places should be selected for locating, and secondly, how many vehicles (ambulances) should be allocated. There are so many models for solving these issues in which the distribution of calls has been assumed discretely so as to simplify the problems.

According to studies, Toregas et al. (1971) conducted the first study on EMS centers' location based on Location Set Covering Problem (LSCP). In the following years, Church and Roll (1974) introduced the first certain maximization coverage model based on the Maximum Coverage Location Problem (MCLP). Both LSCP and MCLP models have a particular drawback, which is that when a facility is called, other demand points within its coverage radius do not receive any service. Gendreau et al. (1997) proposed the Dual Standard Model (DSM) which pursued the goal of allocating facilities to locations that have the potential for full coverage in a larger standard radius while maximizing coverage in a lower standard radius. Daskin (1983) and ReVelle and Hogan (1989) presented a new category of studies that sought to explicitly consider the probability of the service being busy and its reliability on the basis of Maximum Expected Coverage Location Problem (MEXCLP) and Maximum Availability Location Problem (MALP) respectively.

The assumptions such as independent facilities and the probability of equal avocation for all facilities which were used in the MEXCLP model are discarded in the cube queue models. These models offer more accurate conditions than real systems. With the development of information technology, dynamic allocation models have been recommended for real-world allocation and location issues. These models were presented based on the Dual Dynamic Standard Model (DDSM[t]) and the Dynamic Available Covering Location (DACL) by Gendreau et al. (2001) and Rajagopalan et al. (2008), respectively. Fig 1 shows the classification of location models for emergency medical systems.

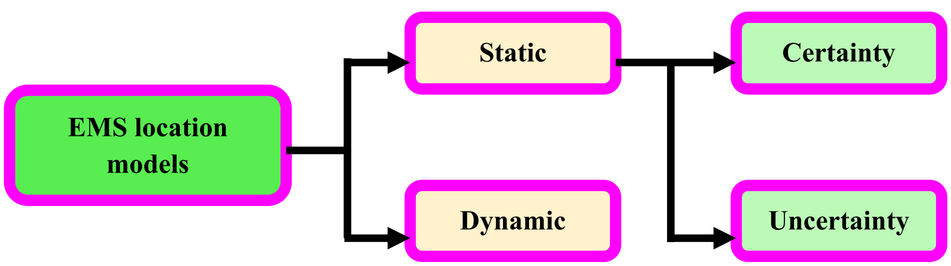

Fig. 1. Classification of location models of EMS

Considering the MEXCLP model as the basic model in this study, the articles based on this model will be described. Saydam and McKnew (1985) proposed a separable programming method for rewriting the MEXCLP model into a nonlinear mode. Fujiwara et al. (1987, 1988) utilized the MEXCLP model to locate the EMS system in Bangkok and obtained relatively optimal results using simulated models. Rajagopalan et al. (2007) proposed several meta-innovative methods including Evolutionary Algorithm (EA), Tabu Search (TS), Simulated Annealing (SA), and Hybridized Hill-Climbing (HC) to optimize the MEXCLP model. Sorensen and Church (2010) suggested a model with local reliability based on the MEXCLP model (LR-MEXCLP) with the same objective function as well as a combination of local reliability prediction. Maleki et al. (2014) calculated the parameters of EMS using the MEXCLP model in four areas of Isfahan, Iran. They demonstrated the inefficiency of the basic model of MEXCLP in the current conditions of densely populated cities by presenting a general model to minimize the maximum travel time of ambulances. Zhang and Jiang (2014) offered a two-objective model with a RO approach for the problem of EMS management planning, under uncertainty, which simultaneously performed optimal location and optimal allocation of facilities. Van den Berg and Aardal (2015) developed a new model for time-dependent MEXCLP. The purpose was to maximize the expected coverage during the day and to minimize the number of busy services and the number of redeployments, simultaneously in Amsterdam, Netherlands. Ansari et al. (2015) presented a hybrid linear-integer model for location and allocating ambulances to demand points simultaneously. Their model took into account the possible conditions during the travel time and the availability of ambulances and maximizes the amount of coverage. Van den Berg et al. (2016) proposed a linear-integer model for the MEXCLP model. They considered the relative coverage conditions, thus showing that due to the linearity of the model, the computation time was reduced, and the number of inputs could be greatly increased. Lam et al. (2016) introduced a robust model in Singapore based on the MEXCLP model under uncertainty of the demand parameter. Rojas-Trejos et al. (2017) presented an optimal model for reducing urban accident injuries using local information from existing stations, the establishment of a new station, and possible consideration of demand, based on the MEXCLP model in Cali, Colombia. Zhang and Zeng (2019) developed two-stage RO models to plan a reliable ambulance system subject to the unavailability of ambulances, with and without ambulance relocation. For the RO problem with mixed-integer recourse for relocation, they customized the column and constraint generation method with an approximation strategy so as to manage the computational challenge. Adarang et al. (2020) addressed a location-routing problem (LRP) using a RO approach. The objectives contained minimizing relief time and the total cost including location costs and the cost of route coverage by ambulances and helicopters. A shuffled frog leaping algorithm (SFLA) was developed to solve the problem and the performance was assessed using both the ε constraint method and NSGA-II algorithm.

Jenkins et al. (2020) programmed an integer mathematical formulation to determine the location and allocation of the medical evacuation assets over the phases of a military deployment to support large-scale emergency medical response. Their model sought to address the multi-objective problem of maximizing the expected demand coverage as a measure of solution effectiveness, minimizing the maximum number of located mobile aeromedical staging facilities (MASFs) in any deployment phase as a measure of solution efficiency, and minimizing the total number of MASF relocations throughout the deployment as a measure of solution robustness.

Trujillo et al. (2020) evaluated various solution strategies based on the Double Standard Model (DSM) for ambulance locations for the Red Cross of Tijuana in Mexico. The first approach was to apply a robust version of the DSM that found the best trade-off solutions across all possible periods, or scenarios, throughout the day. The second approach was to apply the DSM to each scenario independently and then performed relocations based on the different types of ambulances in different scenarios. The final approach was to utilize a precise relocation model, the multi-period DSM. All approaches were evaluated based on the percentage of double coverage, total number of relocations, relocation travel time, relocation travel distance, and the financial cost of performing relocations. Boutilier and Chen (2020) presented a RO approach to optimize both the location and routing of emergency response vehicles, accounting for uncertainty in travel times and spatial demand characteristics of low- and middle-income countries. The case study in this research was Dhaka, Bangladesh. They incorporated their prediction-optimization framework with a simulation model and real data. Sun et al. (2021a) proposed a RO model for strategic and operational response to determining the emergency resource allocation, facility location, and casualty transportation plans in a three-level rescue chain composed of casualty clusters, hospitals, and temporary facilities based on the Yushu Earthquake. The model considered various uncertainties in demand including the number of casualties and the number of rescue supplies and transportation time. Also, this model was solved with the ε-constraint method. Sun et al. (2021b) developed a RO model for combined facility location and casualty transportation under uncertainty in the number of casualties in order to improve the performance of medical service in the case study of the Yushu Earthquake. Casualties were divided into two categories: serious casualties who were carried with helicopters to general hospitals and mild casualties who were transported with rescue vehicles to on-site clinics. A summary of studies on the MEXCLP model is depicted in Table 1.

Table 1
A summary of literature review

Reference	Year	Model						Solution Method	
		Linear	Nonlinear	Certainty	Uncertainty	Single objective	Multi objective	Exact	Meta-Heuristic
Daskin	1983	✓		✓		✓			✓
Saydam and McKnew	1985	✓		✓		✓		✓	
Fujiwara et al.	1987		✓	✓		✓			✓
Fujiwara et al.	1988		✓	✓		✓			✓
Rajagopalan et al.	2007		✓		✓	✓			✓
Rajagopalan et al.	2008		✓		✓	✓		✓	
Sorensen and Church	2010	✓			✓	✓		✓	
Maleki et al.	2014	✓			✓	✓		✓	
Zhang and Jiang	2014		✓		✓		✓	✓	
Van den Berg et al.	2015	✓			✓	✓		✓	
Ansari et al.	2015	✓			✓	✓			✓
Van den Berg et al.	2016	✓			✓	✓		✓	
Lam et al.	2016	✓			✓	✓		✓	
Rojas-Trejos et al.	2017	✓		✓		✓		✓	
Zhang and Zeng	2019		✓		✓		✓	✓	
Adarang et al.	2020	✓			✓		✓		✓
Jenkins et al.	2020	✓			✓		✓	✓	
Trujillo et al.	2020	✓			✓	✓		✓	
Boutilier and Chen	2020	✓			✓		✓	✓	
Sun et al.	2021	✓			✓		✓	✓	
Sun et al.	2021	✓			✓	✓		✓	
This Study	2022	✓			✓		✓	✓	

In this paper, coverage is considered relative, which increases the coverage of demand points. Capacity is also considered for emergency management systems and hospitals. In the proposed model, two objectives are introduced. Also, the model is linear, which simplifies the implementation, even for a large amount of data. To eliminate the uncertainty of the model, RO is used. In the next section, the location model is presented and then, the model is examined in a case study, and finally, the results of the model are evaluated.

3. Description of the MEXCLP location problem

In this section, firstly, the availability of each facility and the difference between 0 and 1 coverage and relative coverage will be described briefly. Secondly, a dual-objective model will be presented. In the third part, RO in the model will be performed due to uncertainty in some parameters.

3.1 Availability and difference between relative coverage and 0 and 1 coverage

As mentioned previously, both LSCP and MCLP models are among the most rudimentary models in EMS centers' location problems. There are two basic assumptions in these two models that have led to more complete models in subsequent studies.

The first assumption is that access to all facilities is considered infinite, while in real conditions, some or all facilities may not be available because of serving another applicant or the ambulance preparation process. To solve this problem, more complete models such as DSM and MALP models were presented. According to the former model, two ambulances are needed to cover the demand point and in the latter model, the concept of the average ratio of ambulance unavailability time has been applied to calculate the required number of an ambulance in order to cover the demand. Another method that provides better real-world conditions to solve this problem is to use the concept of expected coverage. In this model, the avocation ratio factor is utilized to calculate the probability of having at least one ambulance during the desired response time to cover the demand. The second assumption used in both the LSCP and MCLP models is the allocation of the ambulance to the point of demand in full or none, or in other words 0 or 1.

As the same with the original MEXCLP model, it is assumed that each ambulance will not be available in some percentage of its operating time which is denoted by q. It is also assumed that the lack of access to each ambulance is independent of the others. According to the examples provided in (Fujiwara et al., 1988), it is clear that by considering different values for q, with increasing q, we see an acceptable coverage level of the facilities at the time of relative coverage, compared to certain coverage.

3.2 The two-objective linear model of MEXCLP

This model has two objective functions. One is to maximize the coverage of demand points and the other is to minimize the distance traveled by facilities. In this model, for each facility, the ratio of working time is considered independent of others. The number of stations to be activated as well as the number of facilities allocated to each station is limited and predetermined. In the following, sets, parameters and variables are introduced.

N: Set of demand points

M: Set of locations suitable for emergency station location

i: Demand point indicator

j: Emergency station indicator

R_i: Demand value of point *i*

D_{ij}: The distance between point *i* and station *j*

B_i: The capacity of station *j* to allocate an ambulance

β: Maximum number of activated stations

b: Total number of ambulances available

q: Possibility of occupying any ambulance

α: Upper limit of operation time

μ_i: The weight ratio of demand point *i* to the total amount of demand

w_{ij}: Possibility of covering an ambulance from station *j* for demand point *i*, which is within acceptable time.

x_j: Number of ambulances assigned to station *j*

t_{ij}: Travel time between point *i* and station *j*

h_x: Preparation time of ambulance for travel to the point of demand (independent of *i* and *j*).

y_j: A decision variable of 0 and 1, it is equal to 1 when it is located in station *j* (this variable limits the number of stations used).

z_{ijk}: The decision variable of 0 and 1, it is equal to 1 when the ambulance *k* is available for demand point *i* in station j.

The two-objective model of MEXCLP with relative coverage is formulated as follows:

$$\max r(z) = \sum_{i \in N} \sum_{k=1}^{b} \sum_{j \in M} (1-q) q^{k-1} \mu_i R_i z_{ijk} w_{ij} \tag{1}$$

$$\min d(z) = \sum_{i \in N} \sum_{j \in M} \sum_{k=1}^{b} D_{ij} z_{ijk} \tag{2}$$

subject to

$$\sum_{k=1}^{b} z_{ijk} \leq x_j \quad \forall j \in M, i \in N \tag{3}$$

$$\sum_{j \in M} z_{ijk} = 1 \quad \forall j \in M, k \leq b \tag{4}$$

$$\sum_{j \in M} y_j \leq \beta \tag{5}$$

$$x_j \leq b_j y_j \quad \forall j \in M \tag{6}$$

$$\sum_{j \in M} x_j = b \tag{7}$$

$$y_j . z_{ijk} \in \{0.1\} \quad \forall j \in M, i \in N, k \leq b \tag{8}$$

$$x_j \in N \quad \forall j \in M \tag{9}$$

In this model, the objective function (1) seeks to maximize the coverage of demand points and the objective function (2) seeks to minimize the distance traveled between the demand points and EMS stations. Constraint (3) ensures compliance with the maximum number of ambulances assigned to each station. Constraint (4) ensures that the ambulance *k* designed to respond to demand point *i* is located at only one station. The maximum number of established stations is limited in constraint (5) to create real conditions in the model. Constraint (6) considers the condition of maintaining the capacity of each station to absorb a certain number of ambulances. Constraint (7) also limits the total number of ambulances utilized in the model.

In this model, to calculate the value of w_{ij}, it is necessary to estimate the possible distribution of the two parameters h_x and t_{ij} and use them in the following formula,

$$w_{ij} = \mathrm{P}(Q_{ij} \leq \alpha) = \int_{\cdot}^{\alpha} h(x) t_{ij} (\alpha - x) dx \tag{10}$$

where Q_{ij} is a random variable that indicates the response time of demand point *i* from station *j*.

3.3 Robust Optimization

In the presented model in the previous section, we are faced with several parameters that have uncertainties. Therefore, parameters (D_{ij}, R_i, t_{ij}, and h_x) have been identified with this property. Due to access to the urban emergency database, information about the three parameters R_i, t_{ij} and h_x is available, so we will be able to estimate the possible distribution of these three parameters using Easyfit software.

Regarding the parameter D_{ij}, due to the fact that the occurrence location of demands at the district level is not precisely known, to eliminate these conditions, a RO approach is performed. As a result, the RO method will be implemented with the Bertsimas & Sim (B&S) (2003, 2004) approach regarding the parameter distance traveled between the EMS station and the point of demand. The most important reason for choosing the B&S approach is to maintain the linearity of the model.

Since the distribution of demands in the zoning of the applicant sections is unclear, the nearest and farthest points to the EMS station are considered as the minimum and maximum distance range for the parameter D_{ij} in RO with the B&S approach. Fig 2 shows the station position and the distance between the nearest and the farthest demand points.

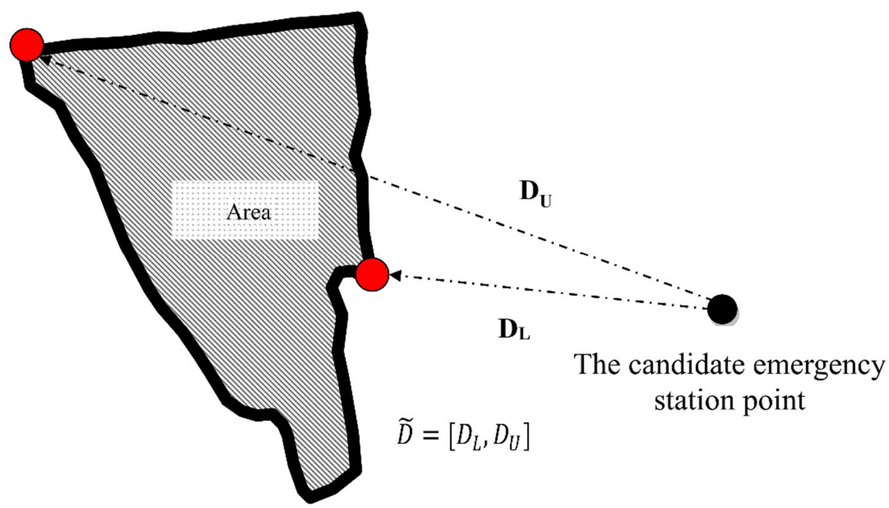

Fig. 2. The minimum and maximum distance between the demand area and the candidate emergency station point

3.4 Model Robustness

According to the fact that the parameter with uncertainty to perform robustness is only in the objective function (2), the following constraints are added to the model:

$$\min d(z) \tag{11}$$

subject to

$$\mathrm{d}(z) - \sum_{i\in N}\sum_{j\in M}\sum_{k=1}^{b} D_{ij} z_{ijk} - \lambda\Gamma - \sum_{i\in N}\sum_{j\in M} p_{ij} \geq 0 \tag{12}$$

$$\lambda + p_{ij} \geq D_{ij}\mu \sum_{k=1}^{b} z_{ijk} \quad \forall i.j \tag{13}$$

$$\lambda \geq 0. p_{ij} \geq 0 \tag{14}$$

In this section, p_{ij} is an auxiliary variable that indicates the number of parameters that have uncertainty. Γ is also a parameter that controls the stability of the model, which takes values from 0 to the number of uncertain parameters. Thus, the larger this value, the greater the robustness of the model, consequently, the much worse answer than the optimal certain condition. λ is an auxiliary variable related to model robustness. $\widehat{D}_{ij}$ indicates the change interval of the D_{ij} parameter.

As mentioned in the previous section, this robustness approach does not change the linear nature of the model and, as a result, the model can be coded with the help of conventional software and the final result can be achieved. In the next section, the model will be run and the necessary analysis will be performed using GAMS software, which is practical to solve mathematical optimization problems.

4. Case Study

In this section, applying the data obtained from the Medical Emergency Organization of Iran, the model presented in the previous chapter will be implemented. The case study is District 10 of Tehran, Iran. District 10 is about 100 years old and is one of the oldest residential areas in Tehran. Due to the population and area, this area is one of the most densely populated residential areas in Tehran. The following table provides general information about this area:

Table 2
District 10 specifications

Area	**817 Hectares**
Population	**420000 People**
The number of neighborhoods	**10**
The number of hospital emergencies	**4**
The number of urban EMS stations	**7**

According to the specifications and features of District 10, the number of neighborhoods is considered as a set of demand points and urban EMS stations as a set of potential points for locating EMS stations. In this section, we intend to locate 4 EMS stations out of these 7 candidate points.

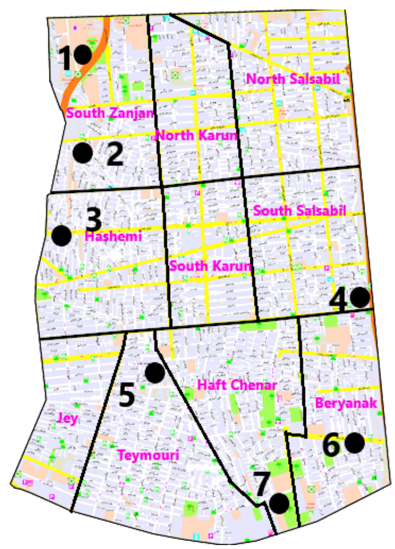

Fig. 3. The geographical location of current neighborhoods and urban EMS stations

According to the previous sections, using urban emergency medical data, the possible distributions of the desired parameters are determined. It is also necessary to point out that in this case study, the distance between two points on the map of Tehran Municipality has been employed. Therefore, due to the difference between the direct distance and the distance of the traffic route in the city, direct distance has been used to simplify the distance between points.

The following tables depict the distances between the demand areas and the candidate points for the EMS station location. Assuming the certainty of the parameter D_{ij}, the center of each area is considered to estimate the distance to the stations, and assuming the uncertainty of this parameter, the minimum and maximum distances of the regions to the stations are noted to determine the interval for the robustness of the model. The unit of numbers in the tables is based on kilometers.

Table 3
Minimum and maximum distances between demand areas and candidate points in case of uncertainty

j	i									
	1	2	3	4	5	6	7	8	9	10
1	0.01-1.03	0.51-1.38	0.79-2.05	0.88-1.91	1.08-2.12	1.44-2.58	1.90-3.04	1.93-3.48	1.96-3.52	2.34-3.58
2	0.01-0.94	0.57-1.22	1.10-2.00	0.37-1.38	0.67-1.67	1.19-2.23	1.37-2.51	1.39-2.98	1.42-3.00	1.95-3.12
3	0.30-1.53	0.78-1.65	1.32-2.38	0.01-0.95	0.71-1.41	1.28-2.15	0.80-1.91	0.90-2.50	0.96-2.58	1.76-2.82
4	1.93-2.83	1.32-2.49	1.07-2.38	1.37-2.27	0.79-1.58	0.01-1.22	1.68-2.66	1.38-2.38	0.50-1.56	0.01-1.47
5	1.50-2.66	1.46-2.59	1.62-2.85	0.49-1.58	0.49-1.52	0.81-1.95	0.51-1.26	0.01-1.14	0.01-1.20	0.84-1.58
6	2.23-3.41	2.02-3.15	1.96-3.05	1.47-2.51	1.10-2.10	0.95-1.83	1.70-2.20	0.80-1.84	0.38-1.45	0.01-0.89
7	2.35-3.58	2.30-3.40	2.26-3.36	1.45-2.57	1.28-2.24	1.30-2.30	1.36-1.83	0.17-1.50	0.01-1.44	0.01-1.42

Other explanations for solving the proposed model are as follows:

- ❖ The two-objective model with the Global Criterion method with grade 1 has become a single-objective (the reason for choosing this method is the lack of access to the policymaker to create interaction regarding the ideal results considered by the decision-maker).
- ❖ In the above table, the robust model with $\Gamma = 1$ is implemented.
- ❖ Parameter q in this model is equal to 0.3 according to Tehran emergency medical information.

Now, according to the information obtained, first, the model is coded in GAMS software in a certain condition, and then the robust model is implemented, which is presented in the following table of software output in both modes:

Table 4
Software output

Title	Demand number	The number of ambulances	The number of stations	Coverage	Traveled distance (Km)
Certain model	10	10	4	0.50	142.3
Robust model	10	10	4	0.50	145.2

After solving the model, it was found that stations 2, 3, 4, and 5 were activated, as shown in Fig 4. To evaluate the accuracy of the model and its outputs, we analyze the sensitivity of the model to changes in some important and effective parameters. Therefore, purposeful changes to the two parameters β and Γ are made and their effect on the model output is examined. With the increase in the number of EMS stations (β), it can be observed an increase in demand coverage as well as, an increase in the distance traveled by the facilities. But it is noteworthy that there is no noticeable change in distance traveled by the service, which does not change very much with increasing the number of stations from 4 to 7, which in turn shows the less effect of changing the number of stations on the second objective function in the presented model. The results of changes in β are shown in Table 5.

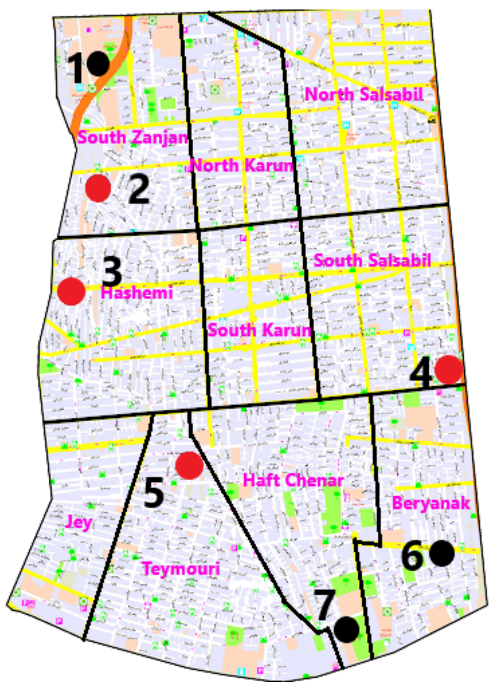

Fig. 4. The geographical location of neighborhoods and urban EMS stations

Table 5
The changes in the values of the objective functions by increasing the number of stations

Number of stations	Coverage	Traveled distance (Km)
4	0.50	145.2
5	0.54	146.7
6	0.65	148
7	0.70	151

Previously, it was mentioned that the parameter Γ illustrates the number of uncertainty parameters. It takes the maximum value in the model. Additionally, it is expected that by increasing the value of this parameter, the outputs of the functions that depend on this parameter will deviate from the optimal result in a certain model. In this model, Γ can be 1, 2, 3, …, and 70.

Table 6
The changes the values of the objective functions by increasing the parameter Γ

Γ	Coverage	Traveled distances (Km)
0	0.50	142.3
1	0.50	145.2
5	0.50	154.7
10	0.50	163.9
15	0.50	171.5
20	0.50	177.4
25	0.52	183
30	0.52	188.2
35	0.54	192.8
40	0.54	196.5
45	0.55	196.5
50	0.55	196.5
55	0.56	196.5
60	0.57	196.5
65	0.61	196.5
70	0.61	196.5

The results of changes in objective functions in exchange for changes in the parameter Γ are displayed in Table 6. As expected, by increasing the value of the parameter Γ, the outputs of both functions that depend on this parameter deviate from the optimal result in the certain model. As a result, the proposed model has sufficient validity.

5. Conclusion

In this study, to locate 4 EMS centers among 7 candidate points in District 10 of Tehran, Iran, a two-objective developed model is utilized. Moreover, the goals are maximizing the expected coverage and minimizing the distances between the demand areas and the emergency station by considering the relative coverage of demand areas, the uncertainty of the exact location of demand, the probability of demand and travel time, and preparation time. Due to the uncertainty of the exact location of the demand, as a result, the distance traveled by ambulance to provide the service is unknown. To solve this problem, the RO approach using the B&S method is applied. After the implementation of the model, suitable locations for the establishment of the EMS centers are identified. Then sensitivity analysis is performed on two parameters the number of stations and Γ. With the increase in the number of stations, an increase in the expected coverage and an increase in the distance traveled are observed. Besides, due to the nature of the robustness of the model, an increase in the values of the second objective function was expected.

The possibility of time-dependent avocation according to the high demand period during 24 hours and days of the week, and classification of applications according to the type of service would be noted in future studies. In addition to that, considering the leveling of vehicles (ambulance, helicopter, ambulance engine) to send each by considering the applicant's needs and choosing other methods to calculate the coverage probability (w_{ij}), such as considering the reducing function according to the distance between the demand point and the station, is suggested for future research.

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