Emergency Medical Service Station Location-Allocation and Sizing Problem for Istanbul

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Abstract

Emergency Medical Services (EMSs) provide necessary urgent medical care and transport patients to the nearest medical center for treatment. Due the to nature of the service, response time is of utmost importance for reducing mortality and alleviating human suffering. Moreover, the availability of service at the time of the call is another planning factor that should be considered. In fatal traffic accidents, for instance, the probability of death increases dramatically as a function of response time. Therefore, locating EMS stations and allocating ambulances to emergency calls requires careful and analytical planning. In this study, we aim to determine the locations and sizes of EMS stations in Istanbul. We formulate a multi-objective integer programming model that finds optimal locations of service stations and the number of ambulances to be stationed while satisfying response time and availability constraints. Our model also addresses allocation decisions where each demand point (subdistrict) is allocated to an EMS station that will ensure predetermined service levels in terms of response time and availability. In order to determine the number of ambulances to be located at a station, historical EMS calls are analyzed. To ensure a particular level of availability, the problem is formulated as a *Q*-coverage problem where the total number of ambulances to be stationed at an EMS station is driven by the demand (EMS calls) of subdistricts that are covered. The objectives of the model are to minimize the total cost of opening EMS stations and to minimize the total demand weighted distance of subdistricts to EMS stations. We solve the problem for the Anatolian side of Istanbul.

Keywords
Facility location, set coverage location problem, emergency medical services, integer programming.

1. Introduction
Being a critical part of the modern health system, the Emergency Medical Service (EMS) aims at providing urgent medical care and transporting patients to the nearest medical center for treatment. An efficient EMS system is expected to respond to emergency calls rapidly and provide timely treatment because response time is of utmost importance for reducing mortality and alleviating human suffering. Considered as an essential performance measure for the EMS, the response time is the time between an emergency call and arrival of the ambulance to the scene (Olivos and Caceres 2022). In fatal traffic accidents, for instance, the probability of death increases dramatically as a function of response time. Therefore, locating EMS stations and allocating ambulances to emergency calls require careful and analytical planning.

The trade-offs between efficiency vs. equity and service quality vs. cost pose additional challenges for decisions pertaining to EMS planning. The conventional emergency vehicle location problem deals with locating the vehicles to proper stations so as to provide adequate coverage to the demand. Along with the coverage, the number of vehicles to be located at a particular station is another decision to be made. Due to high costs of emergency vehicles, i.e., ambulances, allocating a large number of vehicles to stations is not a viable option. Therefore, optimally locating a limited (or minimum) number of ambulances to improve the responsiveness of the EMS system is an important problem faced by the healthcare authorities (Moeini et al. 2015).

Based on the decision-making levels, decisions pertaining to EMS management can be classified into (*i*) strategic, (*ii*) tactical, and (*iii*) operational decisions (Belanger et al. 2019). Strategic level decisions involve determining the locations of EMS stations and the number of ambulances to allocate these stations (sizing). Along with strategic decisions, tactical-level decisions consist of locating stand-by or backup EMS stations and crew pairing/scheduling. Strategic and tactical decisions are static in nature because once implemented, the relevant decisions remain unchanged. Conversely, researchers considered that real-time data might be beneficial for tailoring strategic and tactical decisions. Due to the inherent temporal fluctuations in demand for EMS, relocating ambulances during the day based on real-time data or short-term forecasts might improve the efficiency of the system. These dynamic decisions such as relocating ambulances and dispatching them correspond to operational level decisions. Nowadays researchers focus on developing new methodologies that consider real-time data to address operational level decisions.

The response time is a function of the availability of ambulances and the distance of the EMS station to the demand point. In this respect, these two factors should be considered when making decisions regarding EMS location and sizing. Countries enforce different standards for ambulance response time while some do not enforce any standard at all. For instance, National Health Service (NHS) England implements response time standards based on triage categories. According to these standards, response time to 90% of all Category 1 incidents, which corresponds to life-threatening conditions such as cardiac or respiratory arrest, should be less than 15 minutes. Similar standards for Category 2 (a serious condition, such as stroke or chest pain, which may require rapid assessment and/or urgent transport), Category 3 (an urgent problem, such as an uncomplicated diabetic issue, which requires treatment and transport to an acute setting), and Category 4 (a non-urgent problem, such as stable clinical cases, which requires transportation to a hospital ward or clinic) incidents are 40 minutes, 2 hours, and 3 hours, respectively (NHS North East Ambulance Service 2022). In other countries such as USA and Canada, the responsibility for determining response time standards belongs to municipalities. As an example, according to San Francisco's Emergency Medical Services Agency, ambulances should arrive at the scene of a life-threatening emergency medical incident within 10 minutes at least 90% of the time (City and Country of San Francisco 2022). Consequently, a common standard for ambulance response time is assumed to be between 10-15 minutes for 90% of life-threatening emergency calls.

EMS location-allocation and sizing problem is an inherently multi-objective problem. While availability and response time requirements enforce opening as many EMS stations with numerous ambulances as possible, budget limitations impose vice versa. Hence, trade-offs between these two objectives should be considered when making pertaining decisions. As we will discuss in section 2, most of the studies addressing EMS location and sizing problems consider only one objective, in particular, the response time. However, as the economic depression continues to strike many countries after the COVID-19 outbreak, cost turns out to be an important planning factor that cannot be neglected. In this respect, in order to find locations and sizes of EMS stations in the Anatolian side of Istanbul, we formulate a multi-objective integer programming model that finds optimal locations of service stations and the number of ambulances to be stationed while satisfying response time and availability constraints. Our model also addresses allocation decisions where each demand point (subdistrict) is allocated to an EMS station that will ensure predetermined service levels in terms of response time and availability. The EMS call demand for each subdistrict is estimated based on historical data. To ensure a particular level of availability, the problem is formulated as a *Q*-coverage problem where total number of ambulances to be stationed at an EMS station is driven by the demand (EMS calls) of subdistricts that are covered. Having two conflicting objectives, we also implement *a posteriori* approach and generate a representative set of non-dominated solutions to provide decision support to healthcare planners. This approach helps healthcare planners understand the problem structure and compare results yielded by different objective weights as in the sensitivity analysis. To that end, our model addresses strategic and tactical-level decisions for EMS planning.

The paper is organized as follows: in section 2 we provide a review of the relevant literature. In section 3 we make a formal problem definition and present a model formulation. Section 4 of the paper presents and discusses computational results. Finally, in section 5, we conclude.

2. Literature Review

EMS location-allocation problem has been well studied in the literature. In general, this problem has been addressed in the context of the facility location problem. Early versions approached the EMS location-allocation problem either as a set covering problem where the aim is to find the minimum number of facilities to serve demand points or maximal coverage problems where covered demands are maximized by the limited number of EMS facilities. These early versions are single coverage models, in other words, the model assumes that a vehicle is always available once an emergency call arrives. Considering the unrealistic nature of this assumption, multiple coverage or back-up coverage models have been developed. The study of Daskin and Stern (1981) was the first one to apply the multiple coverage concept to EMS location problems. This idea has paved the way for *Q*-coverage models where a demand is covered by at least *Q* facilities. Essentially, *Q*-coverage models in the context of EMS location-allocation and sizing problem aim to provide ambulance availability by increasing the robustness of the solution.

The demand for EMS is inherently involves uncertainty. In order to hedge against uncertainty, robust and stochastic programming models have been proposed in the literature. Among those, Beraldi and Bruni (2009) focused on determining the optimal location and sizing of emergency stations so as to assure a given quality of service. In their study, they proposed a two-stage stochastic model for solving the problem. They presented a heuristic solution method to solve the problem in reasonable times. Boujemaa et al. (2013) developed a two-stage stochastic optimization model to determine the locations of ambulance stations and allocations to demand points. Their model aims to minimize overall costs of operation while providing a predetermined response time. Their first stage decisions involve location and number of ambulances to station decisions while second stage decisions address allocations. They applied their model to locate EMSs in the northern region of Tunisia. Zhang and Li (2015) proposed a probabilistic model utilizing chance constraints for locating and sizing EMSs. In an effort to solve the model efficiently, they transformed the model into a conic quadratic mixed-integer program and solved it with commercial solvers. They also add valid inequalities to improve the model. They showed the applicability of their model with a case study in Beijing, China. Adapting a robust probabilistic approach, Navazi et al. (2018) formulated a bi-objective model to address several decisions regarding EMS location and allocation problem, namely, (*i*) locating EMS stations, (*ii*) allocating the accident-prone points to EMS stations, (*iii*) determining hospital bed capacities for critical patients, and (*iv*) deciding inventory levels at opened stations. Their bi-objective model minimizes total setup costs while minimizing the time average of receiving medical service for all points. They utilize the ϵ-constraint method to solve the problem. Focusing on the availability of ambulances and long-term operational costs, Liu et al. (2019) proposed a distributionally robust model for determining the location, number of ambulances, and demand assignment in for EMSs by minimizing the expected cost. They developed a second-order conic representable program to approximate their model. They utilized an outer approximation algorithm for solving the model efficiently.

To hedge against temporal fluctuations in demand for EMS, some researchers have focused on operational level decisions such as relocating and dispatching ambulances. Considering the variations in travel times of ambulances, Shmid and Doerner (2010) proposed a multi-period covering model for locating and relocating ambulances to respond emergency calls. Their model takes into account coverage of EMSs with respect to the time of the day. They presented a mixed-integer program that aims at optimizing coverage at various points in time simultaneously. They utilized a variable neighborhood search heuristic for solving the problem. Referring it *dynamic redeployment problem*, Moeini et al. (2015) proposed a mathematical model that can control the movements and locations of ambulances in order to provide a better coverage of demand points by accounting for the demand fluctuation patterns during a given period of time. The objective of the model is to maximize the coverage of demand points and to minimize the relocation costs of vehicles. They applied their approach to French EMS. Amorim et al. (2019) proposed an integrated strategic and tactical planning decision methodology for locating and allocating ambulances to EMSs. Their approach consists of two stages: in the first stage a scenario-based optimization model determines locations of EMSs and allocates ambulances to these EMSs. Then, in the second stage, the neighborhood of the optimal solution found in the firsts stage is explored to find better solution based on empirical data. Solution methodology is applied to case of Porto. In their study, Belander et al. (2020) considered determining the location of available ambulances and their dispatching policy. Their model addresses both static decisions (location) and dynamic decisions (dispatching). The availability of ambulances is estimated with a simulation framework. Hence, they propose a recursive simulation-optimization approach that consists a mathematical model and discrete event simulation.

Compared to single objective models proposed for EMS location and sizing problems, relatively few studies considered multiple objectives simultaneously. However, EMS location and sizing problem inherently involves multiple objectives that should be accounted for. Among existing studies, Navazi et al. (2018) formulated a bi-objective model to address several decisions regarding EMS location and allocation problem by adapting a robust probabilistic approach. In a recent study, Janosikova et al. (2021) discussed the objectives of the mathematical models proposed in the literature for locating EMSs and allocating ambulances to these locations. They stated that simplifying assumptions may have adverse effects on the real life circumstances. Later, they propose a bi-objective mathematical model where objectives aim at providing accessibility for high-priority patients within a short time limit and minimize average response time to all patients, respectively. They compared results of their model with those of the *p*-median model having a single response time objective. Olivos and Caceres (2022) formulated a multi-objective optimization model to locate ambulances to improve EMS in Antofagasta, Chile. They considered mean response time, maximum response time, and uncovered demand as the objectives. They solved the model with the ϵ-constraint method and generated a Pareto set of efficient solutions. They utilized historical data from the years 2015 and 2016 to estimate demand.

We also refer the interested reader to the study of Belanger et al. (2019) for a detailed review of the topic. In this study, the authors presented an excellent review summarizing and discussing modeling approaches that address problems regarding ambulance location and relocation, and dispatching decisions. They concentrate on recent approaches that consider tactical and operational decisions and their interactions. The authors provide mathematical models and solution approaches proposed in the literature by discussing their evolution through time.

3. Problem Definition and Formulation

Istanbul, the largest city in Turkey, occupies two different continents. One part of Istanbul lies in Europe and the other part lies in Asia. Lying in the Asia continent, the Anatolian side of Istanbul has 270 subdistricts. The healthcare authority in Istanbul desires to determine the locations of EMS stations and the number of ambulances to allocate to these EMSs on the Anatolian side of Istanbul. A total of 230 candidate locations are determined. Even though there is a current location layout of existing EMS stations, healthcare authority would like to ignore it and make a location plan from scratch in order to improve the responsiveness of the EMS system. The response time is a function of the availability of ambulances and the distance of the EMS station to the demand point. Hence, established EMS stations should have an adequate number of ambulances to meet emergency demands and a demand point should be within a predefined distance (or coverage) of an EMS station. To increase the availability of ambulances, a backup coverage is also stipulated. Therefore, a demand point would be covered by two EMS stations. This requirement also yields allocation decisions where each demand point would be allocated to two EMS stations.

Locations and number of emergency calls are important for EMS location planning. Sarıyer et al. (2017) analyzed all calls reaching EMS system during the first six months of 2013 in İzmir, the third largest city of Turkey. Their analyses revealed that the number of calls from a demand point, i.e., a district, is highly correlated with population. The correlation coefficient between the number of calls and the population of a district is calculated as 0.924. Based on the historical data obtained by Sarıyer et al. (2017), the number of daily emergency calls from a district is 0.012% of the population. In this respect, we calculated the daily demand for EMS of each subdistrict based on its population. Moreover, locations of demands for emergency calls are assumed to be centroids of these subdistricts.

Availability of service is closely related to the number of ambulances allocated to an EMS station and the time of the call. Consecutive emergency calls may saturate available ambulances at an EMS station, however, we expect the emergency calls to be scattered during the time of the day. Even though at some time periods the frequency of calls is expected to be higher than the rest of the day (such as daytime vs. night), the probability that all emergency calls occur at the same time or in a short time period is low. To that end, when determining the number of ambulances to allocate to an EMS station, we impose that the total number of ambulances allocated to EMS stations that cover a demand point should meet one-fourth of the total demand.

To ensure an admissible response time, we enforce a predefined distance between an EMS station and allocated demand point. As we discuss in Section 1, a common standard for ambulance response time is considered to be between 10-15 minutes for 90% of life-threatening emergency calls. Assuming that the average travel speed of an ambulance is 75 km/h, a maximum distance of 17 km. ensures that any emergency will be responded in less than 14.5 min., provided that an ambulance is available at the EMS station. Hence, we ensure that allocated EMSs are within 17 km. of the centroid of the district.

We consider two conflicting objectives for the optimization model. The first objective is the total cost of establishing EMS stations. The total cost consists of the cost of opening (installing) EMS stations and the acquisition cost of ambulances. Even though existing ambulances can be redeployed for the new EMS setup, the idea is to deploy the existing ones to other cities, hence, we assume that all ambulances will be acquired. Installing a new EMS station is $50.000 and the acquisition cost of an ambulance is $200.000. To clarify, EMS stations do not provide healthcare to patients requiring immediate medical care, rather, they provide utilities for the ambulances and allocated healthcare personnel. The second objective minimizes the total demand weighted distance of subdistricts to the EMS stations. To that end, the integer programming model for the EMS location-allocation and sizing problem is given below.

Indices and Sets

$i \in I$: indice and set of candidate locations for EMS stations
$j \in J$: indice and set of demand points (subdistricts)
$g \in G$: indice and set of objectives

Parameters

$cost_{fixed}$: fixed cost of opening and EMS station
$cost_{amb}$: cost of acquisition of an ambulance
$dist_{max}$: maximum coverage distance for admissible response time
$dist_{ij}$: distance from demand point *j* to candidate location *i*
d_j: daily ambulance demand of demand point *j*
Q: minimum # of allocations required
w_g: weight of objective *g*
θ_g: normalization factor for objective g

Decision Parameters

$$y_i = \begin{cases} 1, if\ candidate\ location\ i\ is\ opened \\ 0, otherwise \end{cases}$$

$$x_{ij} = \begin{cases} 1, if\ demand\ center\ j\ is\ covered\ by\ location\ i \\ 0, otherwise \end{cases}$$

z_i: # of ambulances to be located at location *I*

The Model

$$\Phi_1 = \sum_{i \in I} cost_{fixed} y_i + \sum_{i \in I} cost_{amb} z_i \tag{1}$$

$$\Phi_2 = \sum_{j \in J} \sum_{i \in I} d_j dist_{ij} x_{ij} \tag{2}$$

$$min \sum_{g \in G} w_g \theta_g \, \Phi_g \tag{3}$$

Subject to

$$dist_{ij} x_{ij} \leq dist_{max}, \qquad \forall i \in I, \forall j \in J \tag{4}$$

$$\sum_{j \in J} x_{ij} \leq M y_i, \qquad \forall i \in I \tag{5}$$

$$\sum_{j \in J} x_{ij} \geq y_i, \qquad \forall i \in I \tag{6}$$

$$z_i \geq \sum_{j \in J} x_{ij} \left(\frac{d_j}{4Q} \right), \qquad \forall i \in I \tag{7}$$

$$\sum_{i \in I} x_{ij} = Q, \qquad \forall j \in J \tag{8}$$

$$z_i \geq 0, \qquad \forall i \in I \tag{9}$$

$$y_i \in \{0,1\}, \qquad \forall i \in I \tag{10}$$

$$x_{ij} \in \{0,1\}, \qquad \forall i \in I, \forall j \in J \tag{11}$$

$$z_i \in \mathbb{Z}, \qquad \forall i \in I \tag{12}$$

Equations (1)-(2) represent two objective functions. We utilize the linear scalarizing approach to aggregate the objective functions, therefore, the aggregated objective function that is formulated as the weighted sum of these objectives is given in equation (3). Objective terms are multiplied by normalization factors θ_g to remove the scaling effect caused by the incommensurability of the objectives (Eriskin et al. 2022). Normalization factors are calculated as $\theta_g = 1/(z_g^N - z_g^U)$ where z_g^N and z_g^U represent the Nadir and Utopia points of objective g. These points correspond to the maximum and minimum attainable values by these two objective terms, respectively.

Equation (4) imposes the maximum distance of a district to allocated EMSs. Constraints (5)-(6) ensure that a district is allocated to an EMS provided that it is located. Equation (7) provides that the total number of ambulances allocated to EMS stations that cover a demand point should meet one-fourth of the total demand. Equation (8) requires that a district is covered by Q EMS stations simultaneously. Equations (9)-(12) define variable domains.

4. Computational Results

In this section, we present the computational results of the EMS station location-allocation and sizing model. Our model involves two conflicting objectives and the relative importance of these objectives are defined with weights. These weights are determined by the Decision Maker (DM) and are inherently subjective. In order to elicit DM preferences that are quantified with these weights, three approaches are used in the literature: (*i*) *a priori* approach: in this approach DM determines his/her preferences before the model is solved, (*ii*) *interactive* approach: DM preferences are elicited progressively during the problem-solving process, (*iii*) *a posteriori* approach: a representative set of non-dominated or Pareto optimal solutions are presented to the DM (Eriskin and Koksal 2016). Non-dominated solutions are candidate solutions to be the best choice for the DM. In this study, we follow *a posteriori* approach and firstly generate a set of non-dominated solutions with respect to different objective weights. To that end, we solved the optimization model for a set of weights where $\boldsymbol{w_1}, \boldsymbol{w_2} \in \{\mathbf{0.0}, \mathbf{0.01}, \dots, \mathbf{0.99}, \mathbf{1.0}\}$ and $\boldsymbol{w_1} + \boldsymbol{w_2} = \mathbf{1}$. The model is implemented with General Algebraic Modeling System (GAMS) and R, and solved with CPLEX 12.5.

Computational runs yielded a total of 101 solutions. Among these solutions, some of them are dominated by other solutions. A solution is said to be Pareto-optimal or non-dominated if none of its objectives can be improved without deterioration to at least one of the other objectives. Two types of non-domination can be mentioned for solutions. To define it formally, let $\mathbf{z} = \mathbf{f}(\mathbf{x}) = \{f_1(x), \dots, f_n(x)\}$ be the objective vector of the problem. Then;

Definition 1: A solution $x' \in S$ is called a *strongly non-dominated solution* if there exists no $x'' \in S, x' \neq x''$ such that $f_i(x'') \leq f_i(x')$ for all $i = 1, \dots, n$ and $f_i(x'') < f_i(x')$ for at least one index j.
Definition 2: A solution $x' \in S$ is called a *weakly non-dominated solution* if there exists no $x'' \in S, x' \neq x''$ such that $f_i(x'') < f_i(x')$ for all $i = 1, \dots, n$.

To that end, all generated non-dominated solutions and strongly non-dominated solutions are shown in Figure 1 (a) and (b). Among all solutions, five of them are strongly non-dominated. These five solutions are candidates to be the most preferred solution with respect to DM preferences.

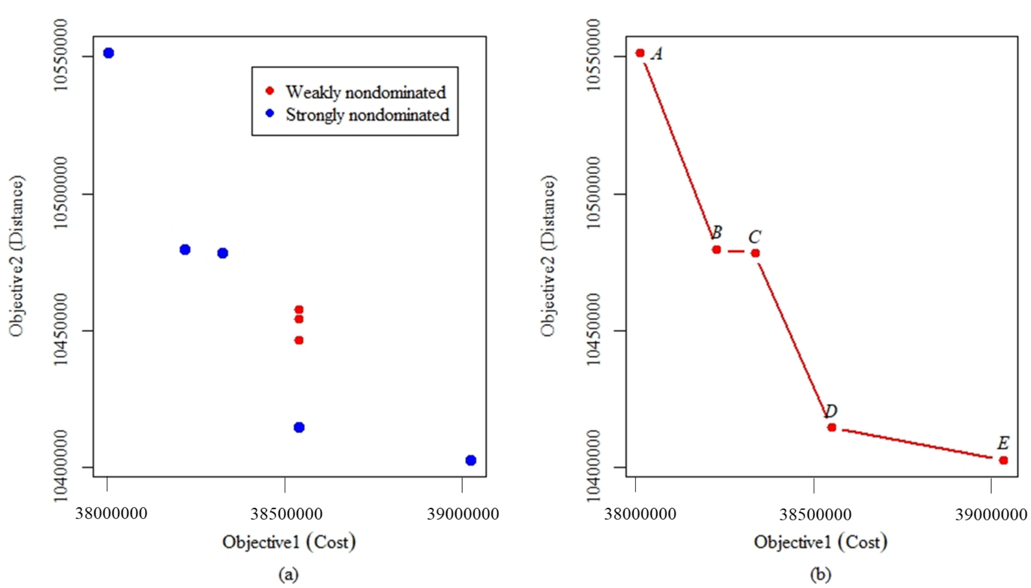

Figure 1. (a) Weakly and strongly nondominated solutions (b) Strongly nondominated solutions (Pareto-frontier).

Solution characteristics of five strongly non-dominated solutions are presented in Table 1. In this table, the second and third columns represent the objective weights that generate the solution. The fourth column provides aggregated objective function value while the subsequent two columns show the individual values of two objectives. The seventh column indicates the mean demand weighted distance of subdistricts to allocated EMS stations. The eighth and ninth columns present the total number of opened EMS stations and the total number of ambulances to be acquired for that solution. Finally, the last column provides the opened locations and the number of ambulances allocated to these locations in parenthesis.

Table 1. Solution characteristics

Sol. ID	w_1	w_2	**Obj. Fun. Val.**	**Obj-1 Value**	**Obj-2 Value**	**Mean Dist. to EMSs (km)**	**# Op. EMSs**	**# of Amb. Acq.**	**Opened Location IDs and Allocated Ambulances**	**Mean # of Locs Opened**	**Max # of Locs Opened**
A	0.90	0.10	0.005	38,350,000	10,551,431	15.07	27	185	2(20)-7(1)-32(21)-34(3)-37(4)-42(1)-49(1)-54(1)-61(1)-65(1)-68(1)-92(22)-93(16)-102(16)-103(20)-136(1)-168(1)-170(8)-184(1)-187(16)-190(3)-193(3)-195(1)-196(17)-216(1)-219(3)-225(1)	6.4	21
B	0.40	0.60	0.008	38,550,000	10,479,753	14.97	27	186	2(20)-7(1)-32(22)-34(3)-37(4)-42(1)-49(1)-54(1)-61(1)-65(1)-68(1)-92(23)-93(15)-102(18)-103(20)-136(1)-168(1)-170(8)-184(1)-187(16)-190(2)-193(3)-195(1)-196(16)-216(1)-219(3)-225(1)	6.9	22
C	0.38	0.62	0.001	38,650,000	10,478,251	14.97	29	186	2(21)-7(1)-32(21)-34(3)-36(1)-37(4)-42(1)-49(1)-51(1)-54(1)-61(2)-65(1)-68(1)-92(21)-93(12)-102(19)-103(20)-136(2)-168(1)-170(8)-184(2)-187(17)-190(2)-193(3)-195(1)-196(15)-216(1)-219(2)-225(1)	6.3	21
D	0.05	0.95	0.008	38,850,000	10,414,515	14.88	29	187	2(20)-7(1)-32(22)-34(3)-36(1)-37(4)-42(1)-49(1)-51(1)-54(1)-61(2)-65(1)-68(1)-92(21)-93(13)-102(20)-103(19)-136(2)-168(1)-170(8)-184(2)-187(17)-190(2)-193(3)-195(1)-196(15)-216(1)-219(2)-225(1)	6.9	23
E	0.01	0.99	0.005	39,300,000	10,402,793	14.86	30	189	2(20)-7(1)-32(21)-34(3)-36(1)-37(4)-42(1)-49(1)-51(1)-54(1)-61(2)-65(1)-68(1)-92(21)-93(14)-102(20)-103(20)-136(2)-168(1)-170(8)-184(2)-185(1)-187(17)-190(2)-193(3)-195(1)-196(15)-216(1)-219(2)-225(1)	6.4	22

As expected, when the second objective is favored more, i.e., more weight is attained, the model tends to open more locations and allocates more ambulances. This is why the first objective function value (total installation cost) deteriorates as the weight of the second objective function increases. Recall that the second objective aims at minimizing the total demand weighted distance of subdistricts to the EMS stations. In this respect, it represents the social acceptability of a solution. When all solutions are considered, the number of opened locations varies between 27-30 while solutions propose allocating 185-189 ambulances to these locations. Conversely, the mean number of ambulances allocated to opened locations varies between 6.3-6.9. The maximum number of ambulance allocations observed is 23, which is yielded by $(0.05,0.95)$ weight pair. When we look at the demand weighted mean distances of subdistricts to opened EMS stations, we observe that all of the solutions provide mean distances less than 15.07 km while solution E yields the least mean distance, i.e., 14.86 km. Note that solution E is yielded by a weight pair $(0.01,0.99)$, hence favors the social acceptability of a solution.

Numerical results and the corresponding analysis are explained to the DM in detail. This process is particularly beneficial for the DM to understand the nature of the problem and the impact of the weights assigned to each objective. In the light of these findings, the DM can make the trade-offs between these two objectives and determine his/her most preferred solution.

5. Conclusion

In this paper, we aim to solve the EMS station location-allocation and sizing problem for the Anatolian side of Istanbul. Establishing an efficient EMS system is of utmost importance for saving lives and alleviating human suffering. The time between an emergency call being received and an ambulance arriving at the location of the incident is critical because the probability of death increases dramatically as a function of response time. Therefore, locating EMS stations and allocating ambulances to emergency calls requires careful and analytical planning.

To that end, we formulate a multi-objective integer programming model that finds the optimal locations of EMS stations and the number of ambulances to be stationed while satisfying response time and availability constraints. EMS location-allocation and sizing problem inherently involves multiple objectives to consider. Hence, we seek to minimize the total cost of establishing ESM stations which comprises the cost of opening (installing) EMS stations and the acquisition cost of ambulances while minimizing the total demand weighted distance of subdistricts to EMS stations. Having two conflicting objectives to optimize, we adopted *a posteriori* approach and generated a representative set of non-dominated solutions which constitute the Pareto frontier. In this regard, we presented comprehensive solution information to the DM to provide adequate decision support for selecting the most preferred solution among the five Pareto-optimal solutions.

There are two research directions for future work. Firstly, our model does not consider uncertainty within emergency call demand. However, the demand for EMS is inherently uncertain and varies with respect to the time of the day. Therefore, a stochastic or robust modeling framework that also addresses operational decisions such as relocation and dispatching can be utilized to hedge against uncertainty. For this purpose, historical data should be obtained and analyzed thoroughly. Secondly, other preference elicitation approaches such as *a priori* and *interactive* methods can be used to elicit DM preference structure

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