Where to place emergency ambulance vehicles: use of a capacitated maximum covering location model with real call data

Soheil Hashtarkhani,[1] Stephen A. Matthews,[2] Ping Yin,[3] Alireza Mohammadi,[4] Shahab MohammadEbrahimi,[5] Mahmood Tara,[6] Behzad Kiani[7]

[1]Center for Biomedical Informatics, Department of Pediatrics, College of Medicine, University of Tennessee Health Science Center, Memphis, TN, USA; [2]Department of Sociology and Criminology, and Department of Anthropology, The Pennsylvania State University, University Park, PA, USA; [3]Department of Geography, University of Mary Washington, Fredericksburg, Virginia, USA; [4]Department of Geography and Urban Planning, Faculty of Social Sciences, University of MohaghegArdabili, Ardabil, Iran; [5]Department of Medical Informatics, School of Medicine, Mashhad University of Medical Sciences, Mashhad, Iran; [6]Rajaei Heart Institute, Tehran, Iran; [7]School of Public Health, University of Montreal, Montreal, Canada

Abstract

This study integrates geographical information systems (GIS) with a mathematical optimization technique to enhance emergency medical services (EMS) coverage in a county in the northeast of Iran. EMS demand locations were determined through one-year EMS call data analysis. We formulated a maximal covering location problem (MCLP) as a mixed-integer linear programming model with a capacity threshold for vehicles using the CPLEX optimizer, an optimization software package from IBM. To ensure applicability to the EMS setting, we incorporated a constraint that maintains an acceptable level of service for all EMS calls. Specifically, we implemented two scenarios: a relocation model for existing ambulances and an allocation model for new ambulances, both using a list of candidate locations. The relocation model increased the proportion of calls within the 5-minute coverage standard from 69% to 75%. With the allocation model, we found that the coverage proportion could rise to 84% of total calls by adding ten vehicles and eight new stations. The incorporation of GIS techniques into optimization modelling holds promise for the efficient management of scarce healthcare resources, particularly in situations where time is of the essence.

Introduction

A foundational goal of emergency medical services (EMS) is to provide timely and life-saving care to individuals who are experiencing a medical emergency (Aringhieri *et al.*, 2017, Martinez, 1998).The patients' survival rate in pre-hospital care is mainly associated with response time, which refers to the time from call for service received to arrival at the scene of a medical emergency (Ong *et al.*, 2009). According to Haddadi *et al.* (2017) over 50% of individuals who lost their lives in emergency events died at the scene and about 16% died on their way to the hospital. In EMS, an 8-minute response time is widely regarded as a generally accepted standard in many regions (Pons *et al.*, 2002, Rhodes *et al.,* 2023).

Thus, the distribution of EMS plays an influential role in timely pre-hospital service delivery (Sasaki *et al.*, 2010).

Geographical information systems (GIS) are used in the public health domain in a variety of applications. GIS and related spatial techniques have been used for a variety of investigations, including analysis of the spatial patterns of diseases resource allocations

Correspondence: Soheil Hashtarkhani, Center for Biomedical Informatics, Department of Pediatrics, College of Medicine, University of Tennessee Health Science Center, Memphis, TN, USA.
Tel.: +1.901.287-5841. E-mail: s.hashtarkhani@gmail.com

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Contributions: SAM and MT designed the study and revised the text critically. SM geocoded and pre-processed the data. BK and AM conducted the spatial analysis. PY and SH conducted and interpreted the mathematical modelling. SH drafted the manuscript. All authors read and approved the final manuscript.

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Consent for publication: no consent to publish was needed for this study as we did not use any details, images or videos related to individual participants.

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and planning (Hashtarkhani *et al.*, 2020; Kiani *et al.*, 2018; Nykiforuk & Flaman, 2011; Tabari *et al.*, 2020). For EMS, GIS provides a powerful tool to capture and analyze call for service data, call location, and responding vehicle locations (Azimi *et al.*, 2021). The call for service data contains timestamps such as the time when the call was received, the time when the call was assigned to an ambulance, the time when the ambulance departed, etc. (Thi Nguyen, 2015). With network analysis functionalities and online navigation tools, GIS assists in decision-making, e.g., through optimization modelling that can be used by EMS planners to explore resource allocation (Chuvieco, 1993).

Location-allocation problems deal with identifying optimal facility locations for addressing specific demands on service use (Vafaeinejad *et al.,* 2020). Due to the importance and sensitivity of the EMS settings, a large portion of the location-allocation literature is devoted to this domain (Sher *et al.*, 2008). These models are typically adopted from three types of classic models, p-median models, p-centre models and the location-covering models, which optimally locate facilities in order to minimize the total or average travel time from the demand location to their nearest facility (Daskin & Maass, 2015). The p-centre problem minimizes the maximum service distance from all facilities location covering operation by considering a demand point covered when receiving service from a facility within the specified threshold of travel time or distance (Daskin & Maass, 2015; Farahani *et al.,* 2012). The location set cover problem (LSCP), introduced by Toregas *et al.* (1971) and the maximum cover location problem (MCLP) introduced by Church and ReVelle (1974), have received considerable attention in the literature on location covering (Farahani *et al.*, 2012). The objective of the LSCP is to find the minimum number of facilities and their locations to cover all of the demand points in a pre-defined standard (Toregas *et al.*, 1971). The MCLP, on the other hand, aims to locate a fixed number of facilities in order to maximize the total demand covered by at least one facility (Church & ReVelle, 1974). The first is a planning tool to determine the appropriate number of facilities needed to cover all service demands, while the second attempts to make the best possible use of all available resources (Brotcorne *et al.*, 2003).

A basic underlying assumption of the different versions of the MCLP model is that a facility can deliver service to unlimited service demands inside the coverage area. In reality, however, many service facilities cannot ensure an acceptable level of service due to limited capacity. For example, an ambulance station can only respond to all emergency calls within a given time frame. Therefore, the capacity limit is a crucial consideration in location problems, especially in the placement of EMS facilities. Efforts have been made to solve this constraint through probabilistic modelling approaches (Daskin, 1983; de Assis Corrêa *et al.*, 2009; Marianov & Serra, 1998). These models assign a probability of unavailability to facilities that reduce or prevent unlimited service delivery (Galvão *et al.*, 2005). Another approach, introduced by Current and Storbeck (1988) and applied by researchers in various fields (Gazani & Niaki, 2021; Liao & Guo, 2008; Vafaeinejad *et al.*, 2020 Yin & Mu, 2012), is to develop the capacitated version of the MCLP. This model adds a maximum capacity constraint into the mathematical formulations of the MCLP to ensure that the demands allocated to a facility should not exceed the maximum capacity of that facility (Gazani & Niaki, 2021). However, the classic capacitated MCLP only considers the demands within the service coverage standard and ignores remote uncovered demands. This issue may be acceptable in many contexts, such as allocating retail stores, where the aim is to cover the maximum customers in a short time even by losing a portion of them due to long distance (Cazabat *et al.*, 2017). However, in settings that deal with emergency response and saving lives, every demand must receive a minimum of acceptable care in a reasonable time, even in remote and low-population areas. Accordingly, some researchers have applied multi-objective models that target more than one aim including, such as minimizing response times, reducing vehicle operating costs and improving overall system performance. However, the complexity of these models and the practical constraints on the resources available for allocation is challenging (Yin & Mu, 2012; Haghani, 1996). *Supplementary Materials, file no. 1* summarizes some of the famous location-allocation models and outlines their limitations in relation to the present study.

This study aimed to find the best locations for existing and new ambulance vehicles using a modified version of the capacitated MCLP that maintains an acceptable level of service for all EMS calls. The objectives of the study were to i) relocate existing vehicles optimally within the existing facilities in a way that all of the demand points have acceptable access; and ii) allocate new vehicles in optimum locations, including existing facilities and new candidate facility sites. These objectives were tested in two different scenarios by using them as baseline compared to the current situation.

Materials and Methods

Study area

This study was conducted in county of Mashhad, including Mashhad City, the capital of Razavi Khorasan Province, located in the north-eastern region of Iran. In 2016, Mashhad had an estimated population of almost 3.8 million, with over 3 million in the urban areas (www.amar.org.ir/english). This is the second most populous city in Iran, and also the number-one tourist destination in the country, with over 20 million visitors per annum (Kafashpor *et al.*, 2018). Mashhad county has one EMS call centre, which dispatches ambulances.

Data and design

To perform a location-allocation model, three input datasets are necessary. To that end a set of potential service facilities; a set of demand points; and a cost matrix that shows the travel cost (e.g., drive time) between any pair of EMS stations and demand point (Schietzelt & Densham, 2003) were used. Using GIS, these components were prepared as follows.

i) Potential EMS stations

Mashhad County has 94 ambulance vehicles distributed across 74 stations. Most of these resources are allocated to the urban area of Mashhad (79 ambulances in 59 stations). Figure 1 shows the study area and the current EMS station locations. Each station includes one, two or three ambulances. Moreover, our assessment has identified 233 potential new candidate locations, including existing hospitals and other public health-related facilities, where new EMS stations could be established. Figure 2A provides an overview of the distribution of these candidate locations within Mashhad County.

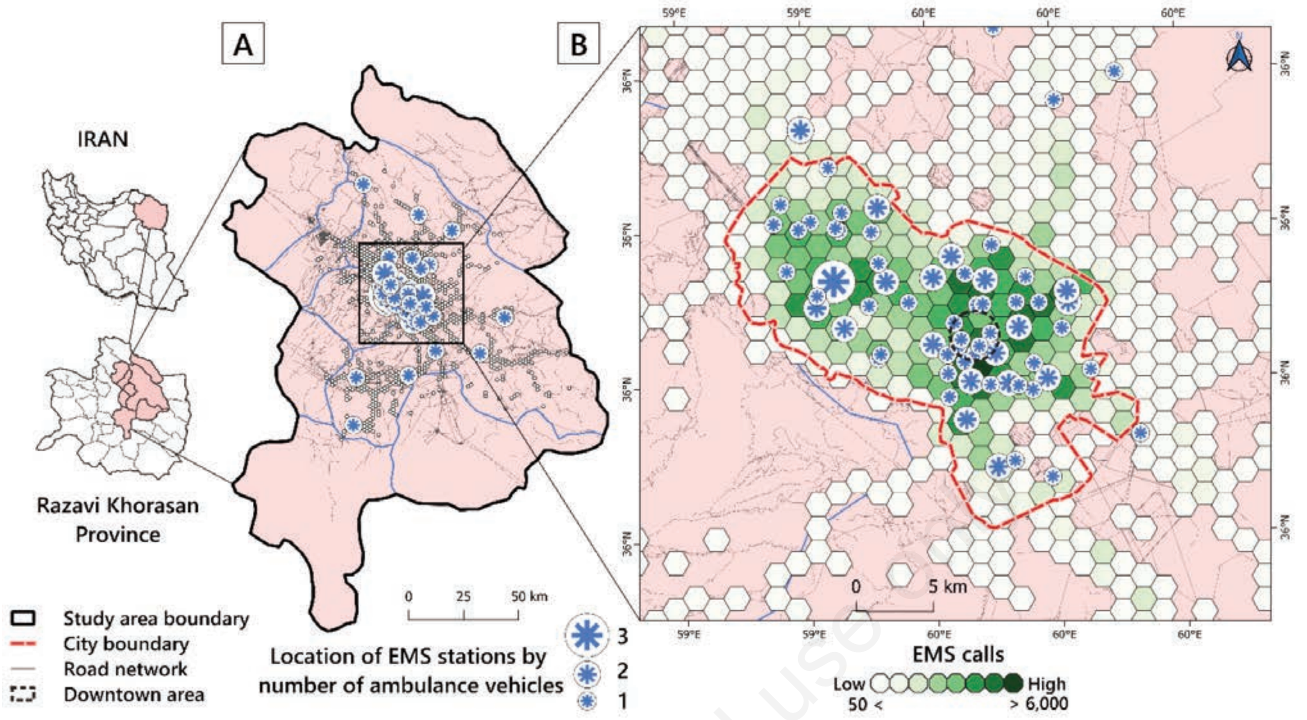

Figure 1. Distribution of existing stations and demand polygons. A) whole study area; B) urban area.

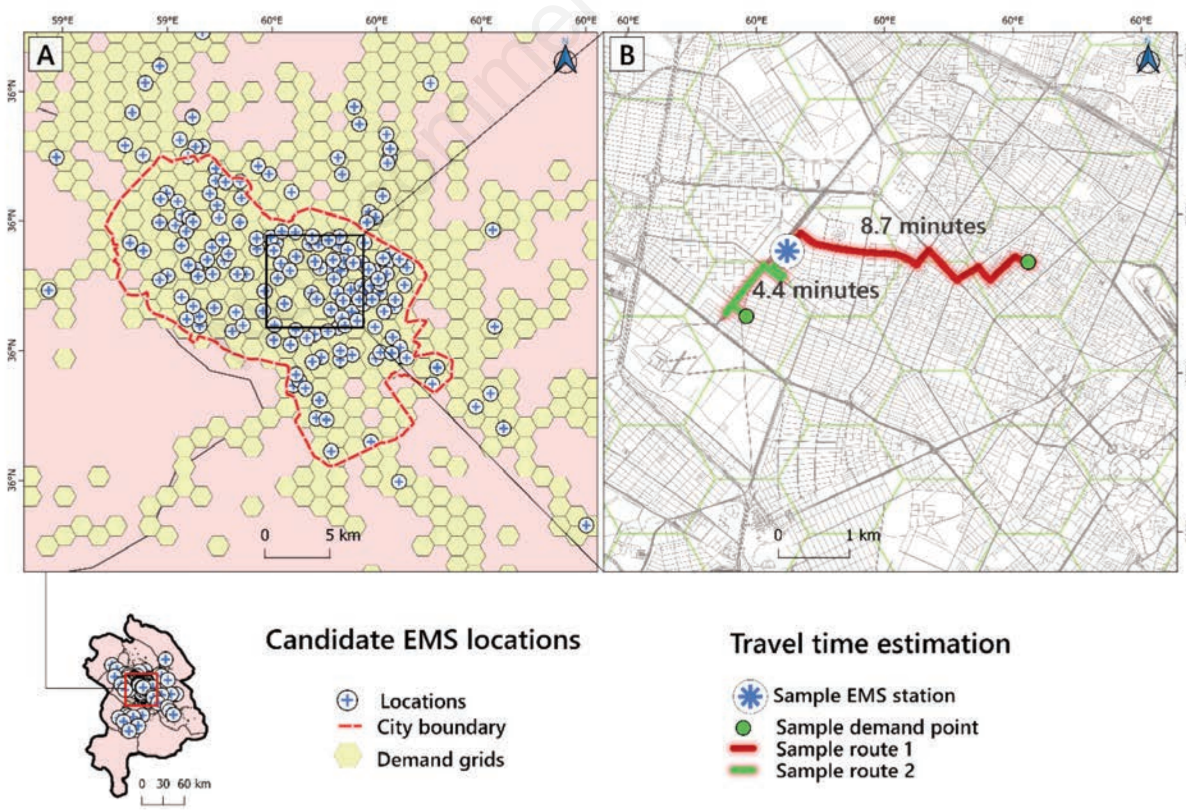

Figure 2. Required datasets for EMS location-allocation. A) 233 candidate locations for new EMS stations; B) road network dataset with two example routes.

ii) Demand points

This study used historical EMS calls to represent the spatial distribution of the demand in the study area. We extracted 224,355 anonymized EMS request data from 1 June 2019 to 31 May 2020 from the EMS call centre of Mashhad. All of the records contained the geographical location of the emergency event expressed in decimal degrees. To reduce the computational intensity while keeping high locational accuracy of demand in the location-allocation modelling, we created a hexagonal tessellation network covering the emergency call points in the study area (Figure 1B). To this end, hexagonal polygons equivalent to the two km^2 average area of neighbourhoods in Mashhad (Hashtarkhani *et al.*, 2020) were used. After removing polygons with zero calls for service 990 polygons remained out of 7,200, with a minimum of one call and a maximum of 6,144 calls for service over the year (Figure 1B). Out of 990 demand polygons, 231 were urban and 759 rural. Centroids of these 990 polygons were used as the location of demand points, while the number of calls within each polygon represented the demand weight. The spatio-temporal characteristics of the EMS callers have been described in a recent research article (Hashtarkhani *et al*., 2021). This study revealed that the Holy Shrine in the downtown area of Mashhad is an influencing factor with regard to EMS requests.

iii) Cost matrix

Network distance was used to estimate the travel times of facility-to-demand routes. To this end, the digital road network of the study area was downloaded from the OpenStreetMap (OSM) database, a free and editable geographical database covering the whole world. The OSM speed limit for Iran were used for different types of road types, including motorway (120 km/h), trunk (100 km/h), primary (80 km/h), secondary (60 km/h), tertiary (40 km/h), unclassified (30 km/h), and residential roads (20 km/h) (OpenStreetMap, 2021. We performed pre-processing on the digital road network of the study area to correct digitizing errors. We manually corrected errors where possible and used automated algorithms to remove any remaining errors. Then the Origin-Destination cost matrix tool of ArcGIS™, v.10.5 (ESRI, Redlands Ca, USA) was used to create the cost matrix of travel times measured in minutes. Figure 2B shows two examples of routing in the road network dataset as well as the estimated travel times.

The ocation-allocation model

The basic model of capacitated MCLP was adopted from Haghani (1996) and implemented with IBM ILOG CPLEX Optimization Studio v. 20.1 with the Python3 interface. CPLEX is a prescriptive analytics solution that enables rapid development and deployment of decision optimization models using mathematical and constraint programming (Nickel *et al.*, 2022). The capacitated MCLP is a mathematical optimization problem that aims to determine the best locations to place facilities or vehicles to cover a set of demand points while considering constraints on facility capacity and travel time. In the context of EMS, it refers to the problem of locating ambulance vehicles or stations to ensure that all demand points are covered within a certain travel distance, while considering the capacity of the ambulance vehicles and the number of vehicles that can be stationed at each facility. The objective is to maximize the number of covered demand points while considering the capacity constraints. To address the drawback of ignoring demands that cannot be reached within the service standard, we modified the formulation by adding a constraint ensuring that all demand points must have at least one ambulance vehicle within a given travel time threshold. We defined this threshold as the target travel time. As urban and rural areas naturally have different spatial configurations of demands and EMS stations, we applied two target time thresholds, with the shorter one used for the urban demand points and the longer one for the rural demand points.

Sets/parameters

I_u = the set of urban demand points;
I_r = the set of rural demand points;
I = the set of all demand points {1, …,i, …, m}; I = {I_uUI_r};
J = the set of potential facility sites {1, …, j, …, n};
s = the service coverage standard for optimisation (minute);
d_{ij}= the travel time from potential facility site i to demand point j;

$$z_{ij} = \begin{cases} 1\ if\ d_{ij} \le s \\ 0\ otherwise \end{cases}$$

a_i = the amount of service demands at demand point i;
p = the total number of ambulance vehicles to be located;
c = the capacity of one ambulance vehicle (i.e., the maximum number of demands that a vehicle can cover);
k = the maximum number of ambulance vehicles that can be stationed on each potential facility site
q_u = the maximum service distance within which each urban demand point has at least one ambulance;

$$u_{ij} = \begin{cases} 1\ if\ d_{ij} \le q_u \\ 0\ otherwise \end{cases}$$

q_r = the maximum service distance within which each rural demand point has at least one ambulance;

$$r_{ij} = \begin{cases} 1\ if\ d_{ij} \le q_r \\ 0\ otherwise \end{cases}$$

b_j = the number of existing ambulance vehicles stationed at potential facility site j;
x_j = the number of ambulance vehicles newly added to potential facility site j; an EMS station is located on potential site j when $b_j + x_j > 0$;
y_{ij}= the percentage of demands at demand point i that is allocated to the facility on site j.

Model formulation

$$\text{Maximize} \quad \sum_{i\in I}\sum_{j\in J} z_{ij} a_i y_{ij} \tag{1}$$

Subject to

$$\sum_{i\in I} a_i y_{ij} \leq c(b_j + x_j) \quad \forall j \in J \quad (2)$$

$$\sum_{j\in J} x_j = p \quad (3)$$

$$\sum_{j\in J} y_{ij} = 1 \quad \forall i \in I \quad (4)$$

$$x_j = 0,1,..,k \quad \forall j \in J \quad (5)$$

$$0 \leq y_{ij} \leq 1 \quad \forall i \in I, j \in J \quad (6)$$

$$\sum_{j\in J} u_{ij}(b_j + x_j) \geq 1 \quad \forall i \in I_u \quad (7)$$

$$\sum_{j\in J} r_{ij}(b_j + x_j) \geq 1 \quad \forall i \in I_r \quad (8)$$

where (1) is the objective function, which seeks to maximize the number of covered demands; (2) the constraint ensuring that the total allocated demands to any facility cannot exceed the total capacity of ambulance vehicles stationed there; (3) the constraint specifying the total number of ambulance vehicles to be located; (4) the constraint ensuring that the summation of demand ratios allocated to facilities should be one for any demand point; (5) the constraint restricting the discrete decision variable x_j, which ranges from 0 to k; (6) the constraint restricting the continuous decision variable y_{ij}, which ranges from 0 to 1; and (7) and (8) two constraints added in this study to ensure that all of the demand points would have at least one ambulance vehicle within the travel time of q_u and q_r for urban and rural locations, respectively. It should be noted that the model in the current format was designed to optimally locate newly added vehicles, while keeping the current distribution of the existing vehicles. However, when the existing vehicles at all stations were set to 0 (i.e., b_j=0, $\forall$ j ∊ J), the model converted to a model capable of optimally locating all vehicles without any existing vehicles already located. The Python script related to this model is available in *Supplementary Materials, file no. 2*.

Scenarios

The location-allocation problem was studied within the context of different scenarios: the current situation, named scenario 0, and the two main ones under study: 1 and 2. The results of these scenarios were visualized in GIS maps.

Scenario 0: the current situation

This scenario aims to calculate the covered demand in the current situation without modifying the location of stations or ambulances. In fact, this scenario does not include any optimization techniques and serves only as a baseline for our study providing reference for comparisons. The parameters were set to calculate the coverage of 990 call-for-service demand locations (m) based on 94 existing ambulances (p) in 74 existing stations (n) using a 5-minute coverage standard. The recommended ideal response time, which refers to the duration from the moment of an emergency call to the arrival of EMS personnel at the scene, is typically set at less than eight minutes in various EMS systems (Cabral *et al.*, 2018; Pons & Markovchick, 2002; Thi Nguyen, 2015). According to calculations from our recent study (Hashtarkhani *et al.*, 2021), the average preparation time (from call to starting the mission/journey) is almost 2.3 minutes; thus, we adjusted the specified coverage standard to a 5-minute travel time. The capacity of each ambulance vehicle (c) was set to 2,387, which represents the average number of emergency missions per year and vehicle.

Scenario 1: relocation of existing vehicles

This scenario aims to maximize the covered demand by relocating the current ambulances with the existing stations (without adding any new facilities). It inherits all parameters from scenario 0 plus *k*=3, q_u=18min, and q_r=48min. These values were set according to our current practice data according to which there is no station with more than three ambulances present, and all of the demand points are serviceable either at ≤18 minutes within the urban area or <48 minutes within the rural areas of Mashhad County. We forced the suggested model to preserve thresholds while maximizing the 5-minute coverage standard.

Scenario 2: allocation of new vehicles and stations

Scenario 2 aims at adding new ambulances to existing or newly proposed locations to maximize coverage of demand. To do so, we added one to ten new ambulance vehicles, iteratively, in two ways: i) by keeping the current distribution of 94 existing vehicles from scenario 0 and optimally locating new vehicles (p=1 to 10) to the current stations (n=74) (scenario 2.1); or ii) by keeping the optimal distribution of 94 existing vehicles from scenario 1 and optimally locating the new vehicles (p=1 to 10) to the expanded list of facilities (m=307) that included the 74 existing stations and 233 candidate sites (scenario 2.2).

Results

Scenario 1: relocation of existing vehicles

Figure 3 shows the distribution of ambulance vehicles in Scenario 1 (the relocation model) comparing it with Scenario 0 (the current situation). The relocation model removed 12 existing stations and relocated their vehicles to the remaining 62 stations, resulting in 37 stations with one vehicle, 18 stations with two vehicles and seven stations with three vehicles. It is notable that using the relocation model increased the proportion of covered demands (from 69.4% to 75.2%) in comparison to the current distribution. The nearly 6% increase in the coverage without adding any vehicles or stations is significant, as it can potentially save more lives. It is worth noting that all of the stations with more than one vehicle were located in the urban area in both scenarios. This could be result of the high number of demands from urban population in our dataset. The changes in the number of ambulances within each station ranged from -2 to 2 vehicles. The strongest variation was seen in the eastern part of the city, including the downtown area. *Supplementary Materials, file no. 3* includes a detailed comparison between scenario 1 and scenario 0.

Scenario 2: allocation of new vehicles

Table 1 shows the optimum locations of new ambulances according to Scenarios 2.1 and 2.2. Most of the selected locations in Scenario 2.2 were among new candidate locations (Station IDs of 75 and higher are new stations). Indeed, only stations 5 and 65 received new ambulance vehicles among the existing stations. The difference in the amount of in the amount of demand covered by the two versions of the scenario is noticeable. This is even more obvious in Figure 4, which visualizes the trend of demand coverage for scenario 2. The proportion of covered demand for Scenario 2.1 was about 69% in the initial specification (equal to Scenario 0). The increasing trend remained almost steady at 75% after adding six vehicles. In contrast, Scenario 2.2 showed a steady increase from the initial point of 75% (equal to Scenario 1) rising to almost 85% after adding ten new vehicles.

The proposed spatial locations of the new ambulance vehicles added by Scenarios 2.1 and 2.2 are shown in Figures 5 and 6, respectively. All of the allocated, additional ambulances by

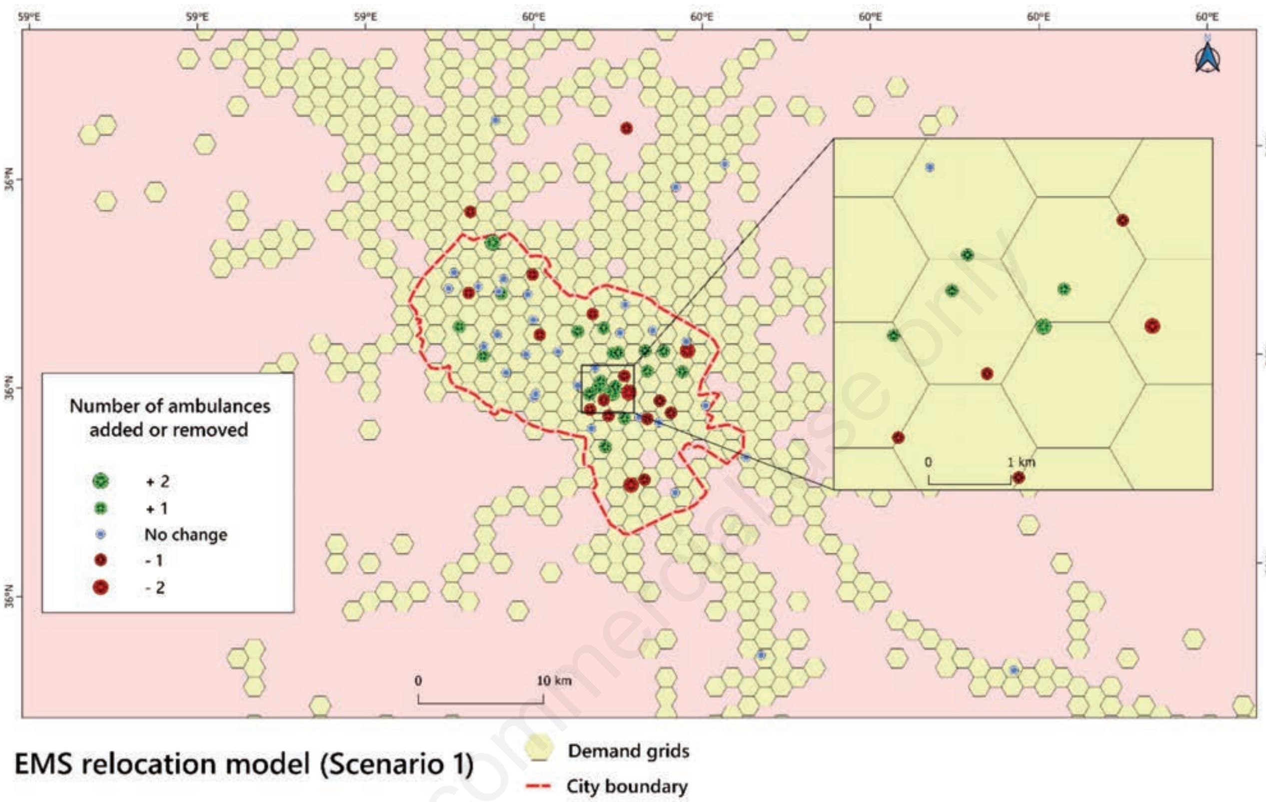

Figure 3. Proposed relocation of ambulance vehicles based on Scenario 1.

Table 1. Locations with total covered demand for 1 to 10 new ambulances.

No. of new vehicles	Scenario 2.1 Added vehicles (Station ID)	Scenario 2.1 Total covered demands (%)	Scenario 2.2 Added vehicles (station ID)	Scenario 2.2 Total covered demands (%)
0	-	155,617 (69.3)	-	168,700 (75.1)
1	11	158,004 (70.4)	75	171,087 (76.2)
2	11, 65	160,391 (71.4)	153,195	173,474 (77.3)
3	10, 11, 65	162,355 (72.3)	65,182,283	175,861 (78.3)
4	10, 11, 24, 65	164,055 (73.1)	75,80,93,93	178,248 (79.4)
5	10,11, 16, 21, 65	165,694 (73.8)	75, 80, 91, 91, 91	180,635 (80.5)
6	10, 11, 24, 31, 52, 65	167,249 (74.5)	75, 80, 91, 91, 91, 102	182,974 (81.5)
7	10, 11, 24, 31, 48, 52, 65	168,270 (75.0)	5, 65, 75, 80, 92, 181, 283	184,960 (82.4)
8	3, 10, 11, 24, 31, 48, 52, 65	168,492 (75.0)	5, 65, 75, 80, 91, 92, 181, 283	186,884 (83.3)
9	3, 10, 11,16, 19, 31, 48, 52, 65	168,606 (75.1)	5, 65, 75, 80, 91, 92, 178, 181, 283	188,591 (84.0)
10	3, 10, 11, 16, 19, 31, 34, 48, 52, 65	168,700 (75.1)	5, 65, 75, 80, 91, 92, 94, 178, 181, 283	190,257 (84.8)

Scenario 2.1, existing facility distribution without adding a new station; Scenario 2.2, relocated facility distribution with the addition of new stations; ID, identification.

Scenario 2.1 were connected with the urban stations, which could be due to the higher number of emergency requests from urban population in the dataset. The first five vehicles were added to the eastern part of the city, but additional vehicles were added to cover the western part of the city as well. No station received more than one vehicle in this scenario.

In scenario 2.2, once again, most of the vehicles were assigned to the stations in urban areas (Figure 6) leading to more of a balance between East and West of the city with respect to the allocation of vehicles compared to Scenario 2.1. After adding seven vehicles, one location outside the city (a north-eastern suburb) received one ambulance (Figure 6G to H). This station was added in the third (Figure 6C) but did not reappear as a permanent new site until a seventh vehicle was added. In Scenario 2.2, up to three vehicles were added to a single facility location. The station changes in each step shows how the number of available vehicles changes the location of stations. For instance, the addition of four ambulance vehicles resulted in a completely different situation compared to adding three vehicles as the model recalculates the covered demands and redistribute the new vehicles for optimum coverage.

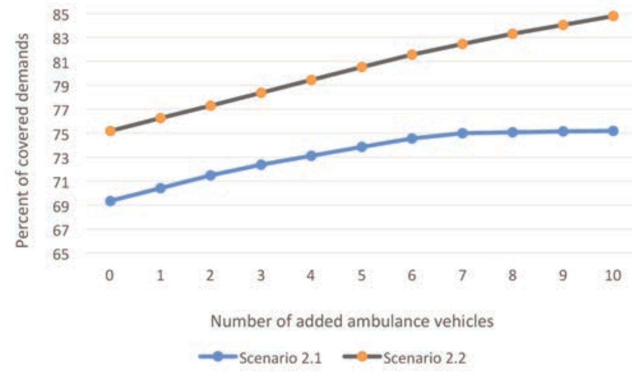

Figure 4. Percent of covered demands in scenario 2.1 *v.* scenario 2.2 for each added ambulance vehicle.

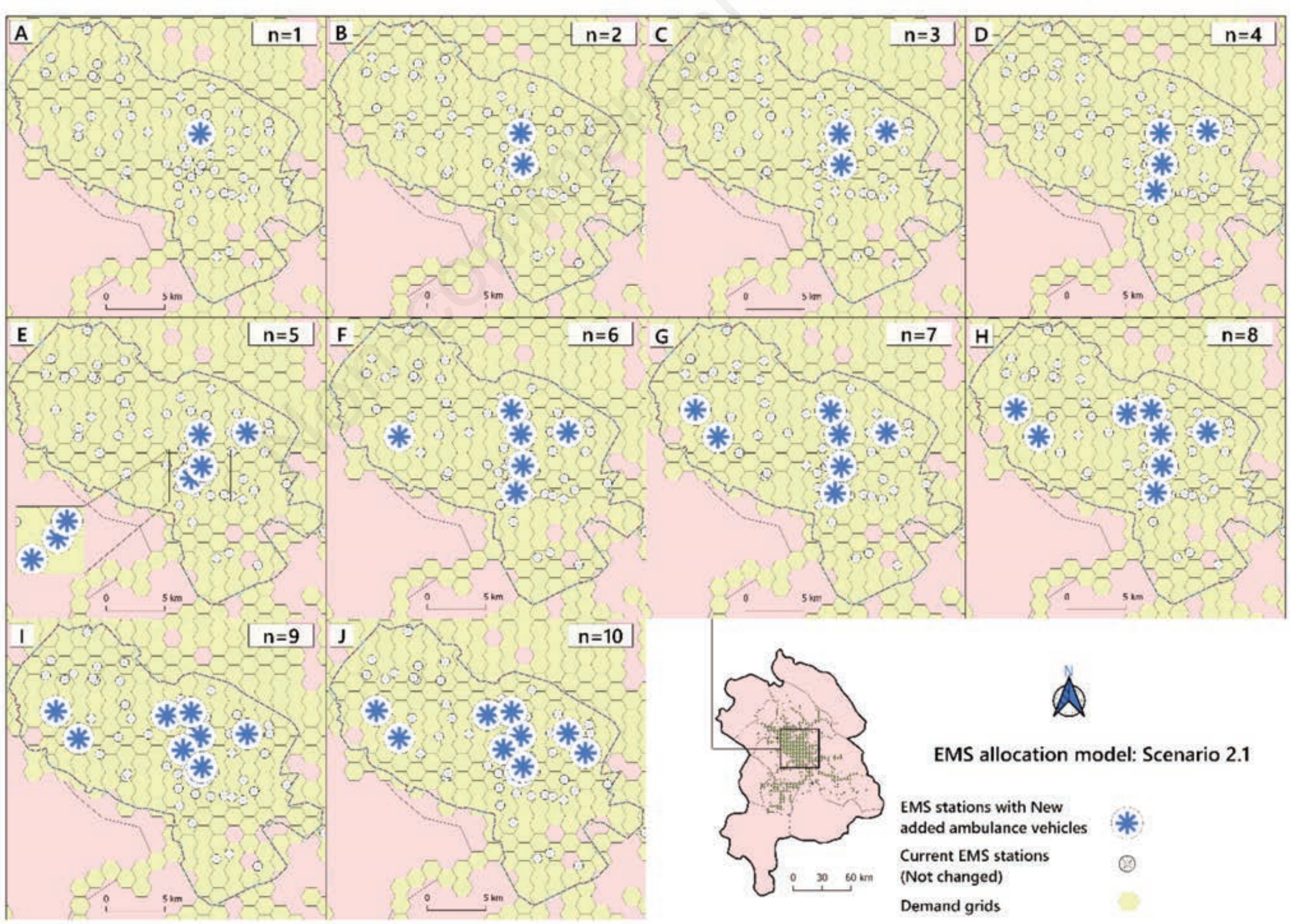

Figure 5. Visualized depiction of scenario 2.1 results.

Discussion

Optimizing the location of ambulance vehicles has the potential to improve EMS service delivery. Response time is a crucial determinant of patients' survival in emergency events. Our previous study (Hashtarkhani *et al.*, 2021) showed that the average response time is 10.1 and 12.2 minutes for urban and rural events, respectively, in Mashhad County, which exceed the 8-minute universal standard (Pons & Markovchick, 2002). Part of this total response time is related to preparations in the dispatch centre and the EMS station facility. Therefore, the allocation of ambulances vehicles capable of reaching potential emergency cases within a 5-minutes catchment area is of great importance for the final care outcome. In our study, the proportion of demands within the 5-minute coverage standard increased from 69% in the current situation to 75% using the proposed relocation model based on existing vehicles. Our suggested allocation models also revealed that this figure could rise to almost 84% by adding up to ten vehicles in different scenarios.

At the first stage, we used GIS tools to extract data on facilities, demands and cost matrix. In addition to the existing stations, we used 233 candidate locations for establishing potentially new stations. Most of the studies in the location-allocation context used residential population and administrative divisions to obtain demand points. However, the residential population does not include visitors/tourists, while resident characteristics, such as age distribution and comorbidities needed for weighting the demand points. Moreover, for studies at a bigger scale than the city level, there are no population data for roads and remote areas, which are potential areas for road traffic emergencies (Tabari *et al.*, 2020). To address these limitations, we utilized EMS call data (and a tessellation network covering the study area) as representative for all year-around fluctuation of population-based demands. Although the overall pattern of calls may change every year, the geographical distribution is likely to be mostly stable, and as such the year of call data leveraged in this study is a useful proxy for the actual demand. Online web mapping databases, such as OpenStreetMap enabled us to calculate network distances from facilities to demands which would be the better proxy for real travel time data compared to the Euclidean distance (Buczkowska *et al.*, 2019).

Although the development of location-allocation theories was independent of GIS development, commercial GIS software (*e.g.*, ArcGIS) have started to provide functionalities to solve location

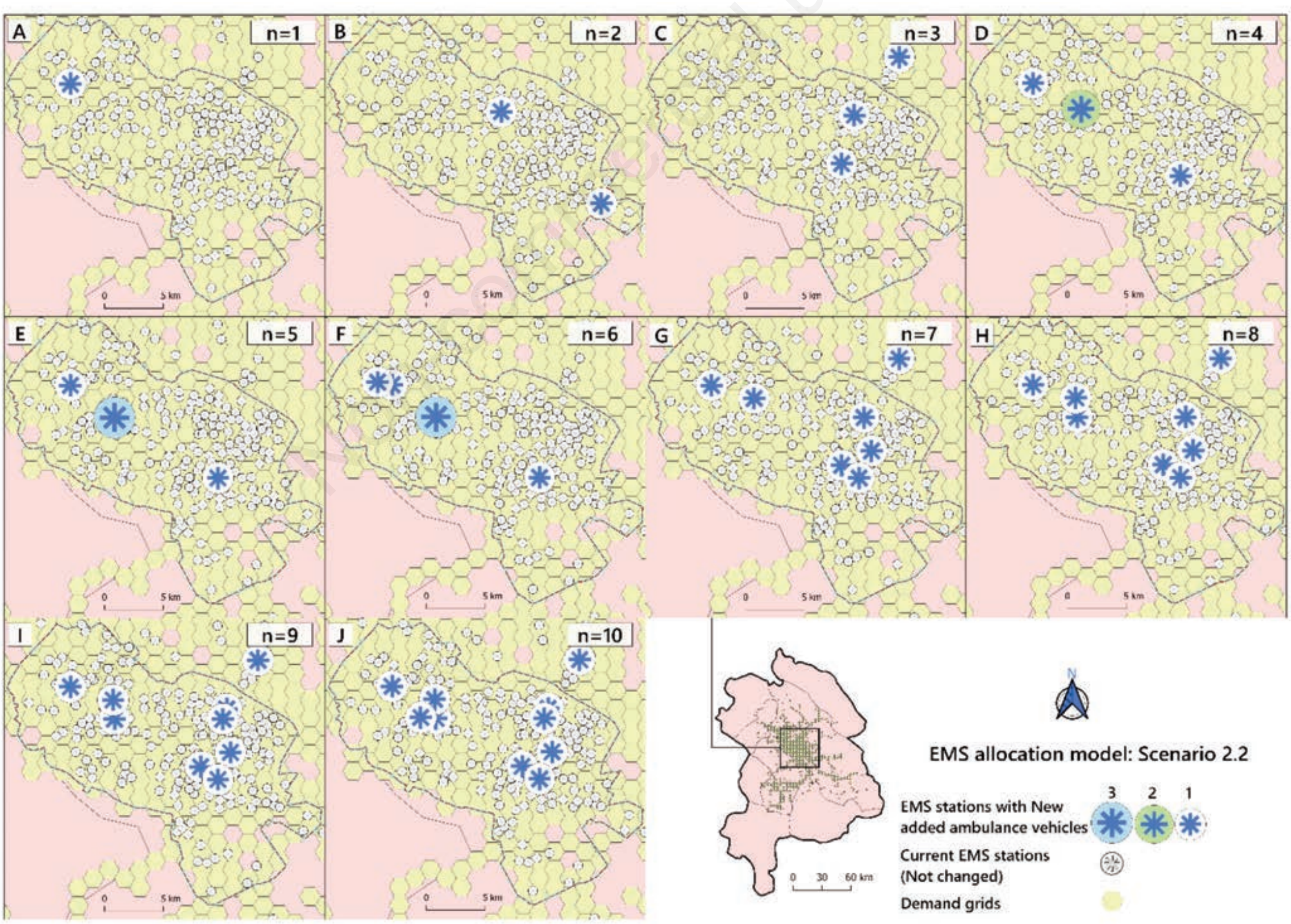

Figure 6. Visualized depiction of scenario 2.2 results.

problems. For example, ArcGIS provides a toolbox capable of solving six different types of location-allocation problems by minimising impedance; maximising coverage; minimising facilities; maximising attendance; maximising market share; and targeting market share (Tomintz *et al.,* 2015). However, these tools provide mostly basic functions and are not flexible enough to catch the characteristics of various real-world problems. For example, in the maximized capacity coverage problem type, which is almost similar to the model we used in this study, a demand node can only receive service from one facility. If the demand weight exceeds the service capacity of facilities, the demand point would not be covered (Tomintz *et al.,* 2015). In 2002, Church published (2002) a review study on GIS applications in the location-allocation domain where he mentioned the capabilities of GIS such as storage, retrieval, analysis, visualization and mapping geospatial data and stated that it is hard to believe that GIS in the future would just play a supporting role in location science. However, after almost two decades, GIS still plays a supporting role in location-allocation literature and only few studies have employed tools embedded within a GIS to solve location-allocation optimization models (Alifi *et al.*, 2017; Ferguson *et al.*, 2016; Mindahun & Asefa, 2019). Using mathematical modelling, we were able to modify the capacitated MCLP in a way to fit our study context. The modifications involved adding new constraints to the model to prevent the removal of stations in rural areas that provide service to a lower number of calls for service. Without these modifications, the relocation model would have resulted in the closure of some stations, which would have negatively impacted the delivery of emergency services in these areas.

Scenario 1 revealed how much a proper relocation plan could potentially improve the final outcome of an EMS system. Such an improvement was equal to adding ten vehicles to the existing stations. Furthermore, the relocation model allowed the evacuation of 12 out of 74 stations and proposed a new efficient distribution resulting in better service accessibility. Most of the proposed changes in the station capacities by Scenario 1 were related to the eastern part of the city, near downtown and the Holy Shrine area (Figure 3). This area, with a large number of proposed changes, overlaps with the hotspot cluster of EMS requests we identified earlier using the spatio-temporal scan statistics method (Hashtarkhani *et al.*, 2021). Downtown Mashhad is an area with a high concentration of hotels, residential complexes, and shopping malls. Changes in ambulance deployment in this area show greater effects in the coverage performance measure. Meanwhile, Scenario 2.2 highlights the importance of incorporating new locations into the EMS resource management plan. Our analysis revealed that establishing new stations at optimal locations can significantly improve demand coverage efficiency. Specifically, we found that while the performance measure becomes saturated after adding six vehicles in Scenario 2.1, the addition of new stations in strategic locations expands opportunities for better demand coverage.

The limitations in this study concern the fact that we used one-year call data as a proxy of demand points. The analysis would have been more accurate or realistic if we have had data for multiple years. For instance, with the emergence of COVID-19, the pattern of EMS requests were probably different compared to our study period. In addition, the severity of reported medical emergencies in EMS calls was not recorded in the database. It is evident that most severe cases have priority for EMS service delivery, and if available, we would be able to weigh our demand points according to the level of severity. Finally, the issue of modifiable areal unit problem (Openshaw, 1981) remains inherent to all studies that focus on aggregated spatial data. Changing the demand polygons, making them bigger or smaller, could affect the results of the location-allocation analysis.

Conclusions

Integrating GIS and optimization modelling has a great potential to improve the accessibility and equity in the distribution of EMS resources. The modified version of the capacitated MCLP model proposed and evaluated in this study is generalizable to any resource management problem where the aim is to maintain an acceptable service coverage level for all demands while maximizing the coverage as much as possible. We strongly believe that our model also has the potential to be used in prospective health service planning according to current and future patterns of service demands, especially when the equity of service delivered is essential.

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Online supplementary material:
File 1. Main location-allocation models used in the literature and their implications for use in this study.
File 2. Location allocation model script.
File 3. Comparison of current distribution (scenario 0) vs. relocated distribution (scenario 1) of ambulance vehicles in Mashhad, Iran.