Optimising emergency medical centres location with a response-time-decreasing approach using hybrid methods of optimisation and simulation

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Abstract: Decision making about the emergency medical centres location is a complicated problem which managers of healthcare systems are confronted to. In order to respond to requests as fast as possible, the emergency medical centres should be placed in the best condition. There are some cases that affect on emergency medical service operation, like calls distribution, traffic condition and operative costs. The paper combines the optimisation techniques with simulation in locating the emergency medical centres in order to decrease the operative costs and also increase the quality of medical emergency services. The method first locates the centres using optimisation techniques, and then having assigned the ambulances to the centres, it analyses different scenarios of locating the centres and assigning the ambulances to them in a dynamic method using computer simulation. The proposed method of emergency centres location and ambulance-assignments was implemented in Isfahan (Iran) as a case study and resulted in lower response time. The comparison of results with real situations shows the efficiency of this method.
1 Introduction

Nowadays in all countries, public properties of healthcare may be insufficient to meet healthcare demands. Hence, the policy makers and providers of healthcare should provide citizens with most effective methods when available resources are limited. During the past decades, a large number of research efforts in the healthcare issue and its applicable models have been considered by researchers and practitioners. One of the most important subjects of healthcare is emergency medical services (EMSs).

The aim of EMS is to decrease the number of deaths and injuries resulting from crashes; and consequently increase the health level of the society. EMS requisition has developed much more than before, because of longer lifetimes, more street struggles, more crashes due to more cars in more urban areas, harder crashes due to more speeds in highways, and older societies. This issue has led to growth of healthcare costs. In most countries there are not enough resources to satisfy the whole demand in healthcare systems; that is why the managers should update the emergency service facilities to decrease the risks of such defects. The initial mission of emergency centres is to give instant vital services and transfer the patient to a medical centre/hospital. The locations, on which the ambulances are assigned, are of special importance in order to cover the most possible areas of a city. Many studies on ambulance fleet management, at least for their specific context, show the adoption of a relocation strategy can help the system performance improve (Bélanger et al., 2014).
There is major group of works on the operative locating of EMS facilities and an extensive range of models have been created to resolve the problem (Brotcorne et al., 2003). Despite of diverse models, the main aim of these models is to define the sharing of emergency facilities to offer the best services for a specific demand. Almost all studies on this issue have used operation research models (Gendreau et al., 2006). First models did not consider the probabilistic modality of EMS structures and used certain methods (Li et al., 2011; Goldberg, 2004). Some researchers developed stochastic models by using queuing theory. These models consider the ambulances as servers in a queuing system (Galvao and Morabito, 2008). Ingolfsson et al. (2008) developed a model to maximise expected demand coverage by minimising the number of allocated ambulances to each EMS station. This model applies the uncertainty due to delays and travel times.

New research in relation with EMS system uses some methods like simulation as EMS models have been complicated. Simulation uses a computerised model of a system to start its processes or properties in order to figure out the performance of that system for a specific collection of states (Kelton et al., 2008). McCormack and Coates (2015) developed a simulation model to enable the optimisation of EMS ambulance fleet allocation and base station location. They use an integrated genetic algorithm with an integrated EMS simulation model. In comparison with other techniques, simulation can increase realism and accuracy of EMS model (Yue et al., 2012). Simulation has been also applied through a large number of researches in relation with supply chain management (Carvalho et al., 2012), production optimisation (Malekpour et al., 2016), scheduling (Dorfman and Medanic, 2004), inventory systems (Kapoor and Shah, 2016), manufacturing systems (Renna and Mancusi, 2017), disaster management (Zavvar Sabegh et al., 2017) and healthcare. In addition to EMS, simulation has been used in an extensive range of healthcare problems. Jittamai and Kangwansura (2016) proposed a method for hospital admission planning. Salam and Khan (2016) proposed an integrated model for healthcare service facilities analysis. Their model can improve patient satisfaction. Sah et al. (2017) used goal programming and simulation for overall process improvement in an Indian hospital. They identified various key factors for process improvement.

This paper proposes a hybrid model of emergency centres location using simulation and optimisation methods. This model can compare different combinations of emergency centres and their numbers of ambulances and also analyse them in a simulated atmosphere. The model parameters are tuned based on real data from Isfahan, a metropolitan in Iran.

The rest of this paper first reviews the literature of both facility locating and discrete event simulation then describes the modelling methodology before discussing on the real data in a case study.

2 Facility location

The aim of locating problems is to find the optimum location of a facility subjected to the distribution (supply) constraints. EMS centres locating problems attempt not only to guarantee the minimum readiness of the ambulances in all the regions, but also to cover as more areas of a city as possible. As the demands for urgent medical services differ on different days of a week and at different hours of a day, it is possible to improve the
performing the system by relocating the centres and resetting the number of
ambulances in a centre. Two questions are asked in the context about the minimum
resources to cover the demands and the maximum centres sizes to minimise the
responding time (Drenzer, 1995).

The deterministic and indeterministic models of emergency centres location
problems of three decades are reviewed in a study by Brotcorne et al. (2003). Attractive topics
of health management issues include emergency centres static and dynamic location
problems, equipment distribution, objective correction problems and resource
management problems (Goldberg, 2004). Sahin and Sural (2007) have reviewed the most
important facility location problems such as health systems, recycling management,
manufacturing-distribution systems, educational systems, communicational systems, and
emergency management systems in a hierarchy structure. Facility location problems
models can be categorised into three following sets:

<table>
<thead>
<tr>
<th>Solution models of facility locating problems</th>
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</thead>
<tbody>
<tr>
<td>Stochastic problems</td>
</tr>
<tr>
<td>Stochastic models</td>
</tr>
<tr>
<td>Scenario planning models</td>
</tr>
<tr>
<td>Dynamic periodical models</td>
</tr>
</tbody>
</table>

The first categories of these models are deterministic ones which have launched by a
simple linear integer programming. These models are considered to be deterministic due
to their ignorance of the probability of the busy status of an ambulance in a certain time.
They are also considered to be static because of impossibility of ambulance transfer
between the centres. The LSCM ambulance location problems are the first models
proposed by Toregas et al. (1971) with the objective of minimum number of ambulances
to cover all the demand points with the same costs. The main mistake of such models was
the assumption of ever-accessibility of all the ambulances which were followed by some
models to diminish the gap. The MCLP model, for instance, proposed by Church and
Revelle (1974) assumed the limitation of p ambulances in a station in order to cover as
many demands as possible within a certain time interval. Zarandi et al. (2013) developed
MCLP in order to figure out the way of assigning p ambulance to m bases. They consider
dynamic conditions in new model. In this model, the locations of ambulances could
change in every period. A hierarchial objective function model (HOSC), presented by
Daskin and Stern (1981) both maximised the number of at least one-time being-met
demand points and minimised the number of ambulances. DADP, an extended
two-objective version of both LSCM and MCLP models, was formulated by Eaton and
Morgan (1986) to locate the ambulances stations in Santo Domingo in Dominican
Republic. Hogan and Revelle (1986) developed two models, BACOP1 and BACOP2, in
which two integer (0–1) variables were used to cover all the points once or twice. DSM
model by Gendreau et al. (1997) used two standards of r1 and r2 time units, where r1 ≤ r2.
The model covered all the points in r2 time units and α percent of them in r1 time units
and maximised the demands which were covered twice in r1 time units.

Deterministic static models were mostly resulted in fewer number of ambulances or
more coverable areas in comparison to what was in reality, because they did not
considered the probability of a busy status for the ambulances in the time a demand
arrives. This led to the second category, stochastic models, which can be modelled in a queue framework. One of initial probabilistic models was the maximum expected coverage locating problem (MEXCLP) designed by Daskin (1983) which tried to cover as many demands as possible while an ambulance is not available with the constant probability of $q$, independently. Revelle and Hogan (1989) developed PLSCP out of LSCP to minimise the number of ambulances in order to cover the minimum required demands by the help of a certain reliability. They developed two other models, MALPI and MALPII to maximise the covered demands with the certain probability of $\alpha$ and independent ambulances. The probability an ambulance is busy (business ratio) at the moment of a call is assumed to be the constant value of $q$ in MALPI. Betta et al. (1989) developed a model, named AMEXCLP, in which the objective function was multiplied by a corrective coefficient due to the fact of impossibility of independency of ambulances in reality. Their business ratio was calculated by the hypercube method which had been proposed by Larson (1974). Ball and Lin (1993) proposed the Rel-P model, as a development of LSCM, which used a linear constraint on the number of required ambulances in order to reach at a certain value of coverage reliability. Marianov and Revelle (1994) developed the PLSCP to QPLSCP in which a certain business ratio was calculated for every ambulance station and assured a maximum probability up to which all the ambulances were busy together. They also developed the MALP to Q-MALP two years later; the new model with a different calculation method for the minimum number of ambulances to give service to a certain point. Galvão et al. (2005) relaxed the MEXCLP and MALPI models from the assumptions of the independency of ambulances and the constancy of business ratio and proposed two other models, called EMEXCLP and EMALP, in which the business ratio of any ambulance was calculated by the hypercube model. Rajagopalan and Saydam (2009) designed two models, MERLP 1 and MERLP 2, in which a constant number of ambulances were located in a way to minimise the responding time while the coverage constraints were satisfied. The coverage constraints in MERLP 1 were similar to those in MEXCLP, while the ones in MERLP 2 were assumed considering the coverage concept in MEXCLP.

Dynamic models are presented to allow the ambulances transport between the stations during day and night in order to give better services to the customers. Kolesar and Walker (1974), first, considered the assumption in a relocation problem of fire-machines. Repede and Bernardo (1994) developed the MEXCLP to TIMEXCLP with the objective of maximising the expected coverage in different moments during day and night. One of the privileges the model presented was the fact that the velocity of ambulances differed during day and night. The transfer of ambulances amongst the stations was also allowed. Gendreau et al. (2001) developed DSM model to DDSM which was solved in the moment of $t$ in which a demand occurred. The objective function of this model maximised the difference between the sum of penalty values of ambulances transfers on the time $t$ and the demands which are covered twice in a certain period of time. Gendreau et al. (2006) developed MCLP to MECP model considering the probability of being occupied at the time the demand was received. The aim of their model was to determine new locations for the ambulances stations in a way to maximise the expected covered demands while control the number of transfers. Andersson et al. (2004) proposed a parameter for the readiness of a region which was dependent on the number of ambulances which covered that region, each of ambulances’ travelling time to the destinations, and the partnership of each ambulance in covering a region. Andersson and
Värbrand (2007) designed an OR model of optimum relocations for ambulances. Rajagopalan et al. (2008) proposed a model, called DACL, to determine the minimum number of ambulances with optimum locations in a highly changing demand patterns context, using a pre-determined reliability to cover the expected demands. Schmid and Doerner (2010) developed DDSM to MDSM, considering time-dependent coverage distances with the permission of transferring the ambulances between the stations.

It is inferred that the possibility of sending more than one ambulance to a mission and the location problem with the permission of ambulances transfers is sort of a literature gap; thus, the contributions of this paper are focused on these attributes.

3 Discrete event simulation

Discrete-event simulation is an effective instrument to evaluate and analyse new and existing systems, which got even much more popular after computer revolution (Robinson, 2005; Morohosi and Furuta, 2013). An emergency station system starts when an accident or a natural catastrophe and finishes when the patient is transported to a medical centre (Fitzsimmons, 1971). Therefore, these systems are complicated and dynamic. Emergency management systems include many processes and stochastic events; the fact makes it easier to be analysed by a discrete-event simulation method than an analytic model. One of the most important performance evaluation criteria of EMS is the solution time, which means the duration it takes for an ambulance to get to the calling location from the moment it is called (Takeda, 2000). WHO suggests a less-than-8-minute solution time as an ideal value (Pons and Markovichka, 2002). However, the average solution time is different from a city to another. It is an essential prerequisite to have the demand for highly efficient and effective services and consumer goods for modern organisations. Efficiency and effectiveness in healthcare mean reducing disabilities and maintaining human life; a main challenge is to guarantee rapid EMS response – a study analysed the EMS of Belo Horizonte, Brazil, using two modelling techniques: optimisation and simulation, the optimisation model located the ambulance bases and allocates ambulances to those bases, the simulation was run to analyse the dynamic behaviour of the system, the main assumption was that optimising the ambulance base locations could improve the system response time; Feasible solutions were found and the current system may be improved while considering economic and operational changes (Nogueira, 2014). Nguyen (2015) has proposed an idea of novelty on relocating the ambulance bases just within the time that one of them is sent for a mission. Their methodology predicts the future status of the system, each time an ambulance is gone to a position, to make a decision for the best location of all through a period of time. A three steps approach has also been presented to deal with the problem of ambulance bases relocating. The first step is the real life data analysis of the considered system behaviour, the second step is the consideration of integer linear programming models with the aim of finding new post locations. The third step is to represent a simplification and an abstraction with respect to the real life situation, testing the behaviour of the proposed solutions with a simulation framework, tailored on the considered problem features. The approach as a whole has also been tested over the Milano city area case, with the aim of pointing out the criticality of the system and providing suggestions for the emergency service management (Aringhieri et al., 2007). Simulation has been used in
other issues of healthcare. The emergency department of a governmental hospital is simulated by arena and simulated annealing algorithm is applied to find the appropriate schedule for nurses (Sajadi et al., 2016). Simulation model is designed to decrease the waiting time and patient stay by using Arena software (Sepehri et al., 2015). A model is simulated to reduce the waiting times of the trucks that enter to factory to load the final products (Sajadi et al., 2015). A discrete-event simulation with the help of ARENA software is used for estimating healthcare system costs (Malekpour et al., 2016). Jittamai and Kangwansura (2016) proposed a model for hospital admission planning. They used the model for operating room allocation under uncertain demand requirements.

**Figure 1** The response process of an ambulance station

The ambulance is waiting for a new call in the base location

A: A new call enters the ambulance base call center

B: The call is categorized and then an ambulance is assigned to it

C: The ambulance moves toward the demand point

D: The ambulance arrives at the demand point

E: The ambulance moves toward the hospital

F: The ambulance arrives at the hospital

G: The ambulance moves back toward the base

H: The ambulance is sent to a new demand point before arriving at the base

I: The ambulance arrives at the base

The ambulance will be waiting for a new call in the base location
4 Methodology

4.1 Contributions

Because of stochastic property of variables and conditions like travel and service times, traffic and weather conditions, Ems has a stochastic and uncertain nature. So location and allocation planning is a dynamic problem in EMS system. Using discrete-event simulation to locate the stations of an emergency system in a dynamic environment, and analysing the different combinations of stations locations and the numbers of their ambulances are some of the innovations this paper contributes. The paper, first, uses an existing dynamic method from the literature to locate the stations, and then proposes a simulation model to relocate the stations in order to make it possible to analyse the different combinations of stations locations and ambulances quantities to make the best decision. The rest of the paper is devoted to evaluate the model efficiency, using real data gathered from the city of Isfahan, Iran to make a final conclusion. General steps of proposed method in this paper are:

1. Making the mathematical model of problem. Making this model does not need to consider stochastic and uncertain variables and conditions.
2. Solving the mathematical model of problem to define the location of EMS bases and needed number of ambulances for each base.
3. Making the simulation model. This model considers the stochastic variables and conditions.
4. Defining various scenarios for simulation model.
5. Gathering the stochastic variables and conditions data.
6. Running simulation model for each scenario several times.
7. Analysing results of step 6 to choose the best answer.

The next diagram shows the flowchart of the process of responding to a call, by an ambulance in the station.

As shown in Figure 1, once a call is received, the operator determines its degree of necessity. Emergency organisations use different methods for calls categorisation, one of most important of which is ProQA. The pattern hold 100 different types of calls, just to one of which a call belong. The next stages can classify the calls in smaller categories. The logic of distribution determines which ambulances should be sent to the calling position; for instance, a less important event requires a near general ambulance while a more important one needs a professional more-equipped ambulance regardless of the distance. This logic helps routine actions be executed better by the medics on the emergency calling position. A short delay is occurred while the emergency management centre is broadcasting the details of the new call to the ambulance which is called the shooting time \( T_{sh} \). When the ambulance is coming back from the previous call, the shooting time is zero, but at nights, for example, it may takes even several minutes. Then the ambulance moves to the location in an urgent status (alarm bell and rotating lights) or in a normal status. There are some cases in which the call is cancelled while the ambulance is still on the way; the mission is finished at these occasions and the ambulance goes back to the station. An appropriate statistic which describes the response
process in short is the response time ($T_R$) which is the period starting from the moment of receiving the call by the centre to the time the ambulance arrives at the calling position. The time is consisted of three main parts: the duration of receiving the call, the shooting time, and the time it takes for the ambulance to get to the place (travel time). When the ambulance arrives at the position, the medics examine the patient to assign it to a category of diseases (which can be different from the one it belonged to at the time the call was received by the centre). The new classification may lead to send more equipment to the location. If there is no need to take the patient to a hospital, the ambulance will get free from the position itself and it will return to the station. But if the patient needs more treatments in a medical care centre, (s)he will be carried into the ambulance and then brought to a hospital in an urgent/normal status (regarding to the compulsion of the situation). It should be intensified, here, that the ambulance can be missioned again while it is going back to the station. The service time ($T_S$) is referred to duration from the moment an ambulance arrives at the calling position till the time the next mission is assigned to it. Response time is one the most important criteria in EMS system. Some healthcare managers use response time to evaluate the performance of EMS operation. They try to improve quality level of EMS operation by reducing this time. This paper proposed a model to plan ambulances location and allocation. This planning would lead to response time reduction.

4.2 Modelling

The mathematical model of locating the emergency stations requires defining the sets, parameters, and the variables of the problem, first.

**Sets**

The sets in the problem are as follows:

- $I$: demand points
- $J$: emergency stations
- $H$: hospitals
- $W$: variety of ambulances.

**Parameters**

The problem parameters are as below:

- $TT$: the total time in terms of minutes
- $TS_{ji}$: the minimum time (minutes) between the emergency station $j$ and the demand (calling) position $i$
- $TH_{ih}$: the minimum time (minutes) between the demand (calling) position $i$ and the hospital $h$
Optimising emergency medical centres location

\( TB_{hj} \) the minimum time (minutes) between the hospital \( h \) and the emergency station \( j \)

\( d_{iw} \) the necessity of ambulance type \( w \) in the demand (calling) position \( i \)

\( CI \) the cost of activating the station

\( CW \) the cost of purchasing an ambulance

\( CT \) the transportation cost

\( Q_{jw} \) the maximum necessary number of ambulance type \( w \) in the demand (calling) position \( i \)

\( DF \) the availability of the ambulances

\( N_{Aw} \) the total number of ambulance type \( w \) in busy mode

\( TR \) response time (min)

\( n \) the number of demand (calling) points

\( P \) the number of emergency stations to be selected

\( K \) the maximum number of emergency stations which can be activated

\( u \) the number of hospitals.

Variables

The problem variables come in the following:

\( x_{jihw} \) the sum of travels of an ambulance type \( w \) in the emergency station \( j \) to the demand (calling) point \( i \) and hospital \( h \)

\( y_j \) a zero-one variable which shows whether an emergency station in the location \( j \) is (not) activated

\( A_{jw} \) the number of ambulances type \( w \) which are assigned to the emergency station \( j \).

Model

\[
\text{Min} \sum_{j=1}^{P} (CI \cdot y_j) + \sum_{j=1}^{K} \sum_{w=1}^{2} (CW \cdot A_{jw}) \\
+ \sum_{i=1}^{n} \sum_{j=1}^{K} \sum_{h=1}^{u} \sum_{w=1}^{2} (CT \cdot (TS_{ji} + TH_{ih} + YB_{hi})) \cdot x_{jihw}
\]

(1)

St:

\[
\sum_{j=1}^{K} \sum_{h=1}^{u} x_{jihw} \geq d_{iw} \quad \forall i, w
\]

(2)

\[
A_{jw} \leq Q_{jw} \cdot y_j \quad \forall j, w
\]

(3)
This model is not a dynamic model as it does not consider the stochastic and uncertain variables and conditions. As mathematical model is not complicated so it can be solved to get a primary answer. To make a dynamic model and find an appropriate solution, next phases should be followed.

### 4.3 Proposed model for emergency stations location

The proposed method for the problem of locating the emergency stations is consisted of the following steps:

1. **Determining the current positions of the stations**
   - First of all, the current position of each station should be determined via the databases and info banks.

2. **Determining the locations of the hospitals**
   - The type and the location of the hospitals in the under-studying city should be determined. The study considers two types of hospitals: the general ones which can give all kinds of services and those which are smaller and are not able of giving some special kinds of services.

3. **Determining the demand positions**
   - Demand points are randomly scattered throughout the case-studied city. To simplify the model, we gather all of the demands of a region in a representative point: a point per region.

4. **Determining the distances between the positions**
   - The model measures the distances between every two point through the Euclidian distance equation. Moreover, to see how much the ambulances really go through,
corrective coefficient should be used which in this paper Drenzer (1997) coefficient is selected.

5 Determining the costs

- The cost of activation operation ($C_I$): the fund needed to start a station up which has different averages in different cities.
- The cost of purchasing ambulances ($C_W$): different kinds of ambulances cost different. In this study, two types (normal and advanced) are considered which can be bought in fixed prices.
- Costs of transportations ($C_T$): all the costs which are necessary in ambulances transportations including: the medics salaries, and ambulances fuel, amortisation, and preventive maintenance. These costs are also supposed to be constant as an average amount.

6 Emergency stations location using mathematical modelling

The model, presented above, outputs the position of the stations.

7 Problem simulation model

The discrete-event simulation model of this case study is of Silvia and Pinto type in the Arena software package. The model is used to compare the durations resulted from optimisation simulations. To consider different scenarios, the following tunings are set:

a. increasing the number of ambulances
b. creating new emergency stations
c. relocating the stations
d. creating new hospitals
e. increasing the accessibility of the ambulances through PM activities.

The rescue process starts by an entering call to the emergency station, determining some features of the call including: the geographical position, type of disease (clinical, injury, or psychological), the type of physician guide (e.g., just a phone call help or the necessity of dispatching an ambulance), and also the calling place coordinates.

Once a call enters, the operator will do an initial analysis over it in order to determine the call type. These types are wrong calls, phone guide calls, and urgent calls which consequently requires more information such as the place and the severity of the disease. Then the responsible physician analyse the call again to make a decision on the type of ambulance to be dispatched.

The model considers two basic fundamental items to determine what kind of ambulances should be dispatched: the distance between the demand place and the required ambulance and the time it takes for the ambulance to travel to the demand position. Considering these two items simultaneously helps the decision maker select that ambulance which will be backed to its station soonest, instead of selecting the nearest one. As soon as the ambulance gets to the demand position, the medics operate the initial cares. On intensive cases, the patient is carried to the nearest hospital. In such cases, the ambulance is on-call again when all the above-mentioned stages passed. If the ambulance is needed for a new demand position it directly gets there; otherwise it returns to the
station to wait for the next call. Figure 2 illustrates the stages of responding to a phone call demanding an emergency help.

**Figure 2** The flowchart of answering to the calls

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5 Model implementation in a real case (Isfahan – Iran)

To test the verification/validation of the model, a real case is used in this study: Isfahan: the third biggest city of Iran based on population. Four regions (1, 3, 5, and 6) of the city are the most population-dense among all with 41% of the emergency calls of all in the city: showing the high level of importance considering these regions has. Thus the geographical scope of the study is limited to these regions (highlighted in blue in Figure 3).

There are 255 urban points, four hospitals, and eight one-ambulanced stations in these four regions. The populations of all 255 urban demand points \(d_1\) to \(d_{255}\) were prepared based on the Atlas and the gravity centres were concentrated using GIS application: each one as a representative for its region (Figure 4).

Forty-four potential ambulance stations (red triangles) other than the current eight ambulance stations (yellow triangles) were recognised using the demands distribution map of Isfahan emergency centres in two months (Figure 5) and also the population...
distribution of Isfahan. The potential points (Figure 6) were selected in a way that they are simultaneously close to more-populated places, more demanding points, and the main streets.

**Figure 3**  The selected zone in Isfahan (see online version for colours)

![Map of Isfahan showing the selected zone](image1)

**Figure 4**  The population distribution map of Isfahan (see online version for colours)

![Population distribution map of Isfahan](image2)

**Figure 5**  The two-month demands distribution in Isfahan (see online version for colours)

![Two-month demands distribution map of Isfahan](image3)
The ambulances of advanced type are only dispatched to those missions which require more complicated services, because both the costs of purchasing and operative costs of them are higher than their counterparts of the normal type.

Figure 6 The population – potential stations distribution map of Isfahan (see online version for colours)

The executive steps of implementing the model in the case study are as what follows below.

The gravity centres of 255 urban locations are those points which the method is implemented on them. The distance matrices were established using Google Maps; one $52 \times 255$ and one $4 \times 255$, for the distances from the 255 demand points to the 52 stations and four hospitals, respectively. A corrective coefficient was used to prevent from impreciseness of the objective function and consequently of the optimum solution resulting from considering the 255 discrete dense demand points.

It was necessary to split a day into some intervals due to different traffic heaviness and different rates of demands in different moments of days. The intervals were supposed to be as dawn (12–6 a.m.), morning (6 a.m.–12 p.m.), afternoon (12–6 p.m.), and evening (6 p.m.–12 a.m.). The ambulances travel paces in those intervals were calculated at all the intervals. The demand rates of the intervals were also recorded within a two-month observation. Table 2 shows these two items for each of the intervals, based on real amounts.

Table 2 The incoming calls distributions in different time intervals

<table>
<thead>
<tr>
<th>Time intervals</th>
<th>Total number of calls within 2 months</th>
<th>Percentage of calls</th>
<th>Average pace (km/h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Morning</td>
<td>4,510</td>
<td>30%</td>
<td>60</td>
</tr>
<tr>
<td>Afternoon</td>
<td>4,509</td>
<td>30%</td>
<td>50</td>
</tr>
<tr>
<td>Evening</td>
<td>3,758</td>
<td>25%</td>
<td>50</td>
</tr>
<tr>
<td>Dawn</td>
<td>2,255</td>
<td>15%</td>
<td>60</td>
</tr>
<tr>
<td>TOTAL</td>
<td>15,032</td>
<td>100%</td>
<td>-</td>
</tr>
</tbody>
</table>
Five scenarios are suggested to optimise the locations of stations. The best solutions of
the optimisation models of each scenario play the role of that scenario simulation model,
in order to have a dynamic environment. The suggested scenarios are as follows:

1 The current combination in Isfahan including eight stations and 13 ambulances (eight
normal and five advanced ones) in order to find the best response time of Isfahan
Emergency Center.

2 The current combination with two defected normal ambulances due to maintenance
activities: eight stations with six normal-type ambulances and five advanced-type
ones.

3 The locations of eight stations are selected based on potential demands: the more the
demands of a location are the more probable a station may be allocated there.

4 Up to eight stations are selected in this scenario among 52 possible locations (eight
current positions plus 44 other potential places).

5 Exactly eight stations are selected in this scenario among 52 possible locations (eight
current positions plus 44 other potential places).

The simulations for these scenarios are run for the above-mentioned time intervals. It is
expected to find a solution between eight to 16 minutes due to standard duration of WHO
regulations and the current response time of the system. Thus, any scenario with a
more-than-16-minute average response time is eliminated. To analyse the results from
running the scenarios, Tables 3 to 6 summarise the results. The results of the second
scenario are not expressed in the following tables due to its more-than-16-minute
response time.

Table 3 The results of running the scenarios in the interval between 12 am and 6 am

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Max # of ambulances in the stations (Q)</th>
<th>Best response time (TR)</th>
<th>Constructed stations</th>
<th># of normal ambulances</th>
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</table>

Table 3 show when no maximum number of ambulances is in hand, the fifth scenario
gives the best result in dawn (12–6 a.m.).
Table 4  The results of running the scenarios in the interval between 6 am and 12 pm

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Max # of ambulances in the stations (Q)</th>
<th>Best response time (TR)</th>
<th>Constructed stations</th>
<th># of normal ambulances</th>
<th># of advanced ambulances</th>
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</table>

Table 4 shows the response time of scenarios 4 and 5 in the morning have significant decreases in comparison to scenario 1 (the current status).

Table 5  The results of running the scenarios in the interval between 12 pm and 6 pm

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Max # of ambulances in the stations (Q)</th>
<th>Best response time (TR)</th>
<th>Constructed stations</th>
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</table>

Table 5 shows the response time of scenarios 4 and 5 in the afternoon have significant decreases in comparison to scenario 1 (the current status) just like the results for the morning time period.
Table 6 The results of running the scenarios in the interval between 6 pm and 12 am

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Max # of ambulances in the stations (Q)</th>
<th>Best response time (TR)</th>
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</table>

Table 6 also shows the response time of scenarios 4 and 5 in the evening are the best of all.

To choose the best scenario through the given scenarios, the response time should be checked. As the response time is the most important criterion in this model, so the scenario should be chosen that has the least repose time. The results show scenarios 4 and 5 have best results of all in all the time intervals. Of course any of these scenarios implementations require acceptable funds for establishing new stations. The costs of constructing new stations to implement the scenarios 4 or 5 are ignorable due to the importance of human beings rescue in such significant shorter response durations. Scenarios 4 and 5 need more ambulances and EMS stations in comparison with other scenarios but their response time is nine minutes. The response time of other scenarios is 14 minutes. As the time is they key performance indicator in EMS system so the nine is accepted. Scenario 4 is even more preferable to the fifth one due to little difference of response time and also requiring less new stations.

6 Conclusions

A hybrid approach of simulation – optimisation is used in this study for locating the emergency stations in a healthcare system. The outputs of the optimisation model were used as the inputs of the simulation model. Having defined four different time intervals during a whole day-night and also defined five different scenarios, we evaluated the performance of Isfahan Emergency Center in all the possible states and ran the selected scenarios many times, two of which gave better solutions than the current status.
Regarding the importance of short response time in the health systems, it was inferred from the results that without the need for adding any more stations or ambulances, it is possible to reach a much more better response time.

Stochastic and uncertain variables and conditions have considered in proposed model, so the model is dynamic. As accurate methods do not have ability to solve big dynamic problems in a logical time, so simulation method was used to solve the problem in a logical time with the least cost. Simulation can run various scenarios without any executive cost. Data gathering for stochastic variables and conditions is the most limitation of this research. Data collecting is time consuming because of databases shortages.

The performance of the case studied system was evaluated in a dynamic environment and with an open approach assignable to any other emergency systems such as fire stations (the establishing costs of fire stations are of more importance than ambulance stations). Although the efficiency of the suggested model is acceptable enough, but it is recommended to add some other assumptions such as the effect of seasonal climate changes on the travel pace of the ambulances. It is also recommended to do a detailed cost-benefit analysis besides this study in order to verify how much it costs to decrease one minute of response time in terms of changing the status tunings (number/places of the stations/ambulances). Proposed method can be used for similar problems in future research. For example it can be applied for fire fighting station location.

Acknowledgements

The authors would like to acknowledge the reviewers for their constructive and helpful comments.

References


Optimising emergency medical centres location


