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EMERGENCY VEHICLES ALLOCATION MODEL FOR URBAN CITY

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Abstract

The Emergency Medical Service (EMS) plays a vital role in any community. The accessibility, distribution, and utilization of the emergency health care services have a great impact on the effectiveness and the efficiency of the EMS. In this study, an algorithm has been devised to optimize choosing the appropriate station location, allocating the right number of emergency vehicles to a station, and directing the critical and non-critical patients to the most suitable hospitals. XPRESS-MP solver engine was used in this study to derive a deterministic mathematical model using mixed integer linear programming. This model is customized for Beirut city. The aim of the study is to design a system that ensures that an emergency vehicle should be available at the time of the incident and the travelling time required must be less than the standard travelling time. The outcome of the study optimizes the number and the location of the EMS stations as well as the number of emergency vehicles allocated to each station. In addition, it optimizes addressing and readdressing the patients to the most suitable hospitals taking into consideration deterioration of the patients' health conditions while being driven to the hospital. Furthermore, the travel time presented in this study shows the shortest travel distance between any two zones.

Keywords

Linear Programming, Emergency Medical Service.

1. INTRODUCTION

The aim of the Emergency Medical Service (EMS) is to react quickly to an incident. However, emergency vehicles resources are often insufficient, resulting in slower response to emergency calls. This slow response is often due to the fact that emergency vehicles might not be available at the station nearby the source where the call for emergency service was generated. Furthermore, one of the primary objectives of the provision of EMS is to deploy and to optimize the number of emergency vehicles allocated to a station, which would maximize the capacity to service an increase in the demand for the EMS. However, the response time of EMS becomes a random phenomenon as emergency vehicles are responding to calls from various locations often while driving back to the station.

This research study presents a deterministic mathematical model (mixed integer linear programming model) that seeks to maximize the probability of arriving at the sites of incidents within a target time in Beirut city. The mathematical model described in this paper considers the demand for the emergency vehicles as well as the time needed to travel from one zone to another, with the objective to minimize the cost of the emergency network compromising fixed stations costs and operating cost. Moreover, alternative dynamic scenarios have been tested considering limited and non-limited number of available beds at the hospital emergency ward, as well as the possibility that a patient's condition might deteriorate during the trip to the hospital and, as a result, that patient must be redirected to another hospital.

2. LITERATURE REVIEW

In the past years, significant efforts have been invested in the modelling of EMS. Toregas et al. considered the first EMS covering a model known as the Location Set Covering Model (LSCM) (Toregas et al, 1971)]. This model assigns at least one emergency service station for every patient demand point located within a standard time or distance. The objective of the model is to minimize the number of service stations. The LSCM model has a drawback, which is providing service stations to all the patient points regardless if the demand for the emergency service is low or isolated from other demand points. Church and Revelle proposed the Maximal Covering Location Problem (MCLP) (Church and Revelle, 1974). Their model maximizes the coverage of the whole geographical area with possibilities of not covering all demand points. Neither LSCM nor MCLP recognize the fact that emergency vehicles of several types may be dispatched to the scene of incident. Consequently, Schilling and co-workers developed the first TEAM (Tandem Equipment Allocation Model) model to handle several vehicle types (Schilling, 1979). This model is an extension of the MCLP, except for a constraint that imposes a hierarchy between the two vehicle types. Furthermore, the LSCM and MCLP don't take into account the issue of system congestion; this implies that both types of covering models tend to overestimate the possibility of a demand point finding a server busy in order to calculate the probability that at least one server will be available on demand in congestion time.

Daskin and Stern formulated a Hierarchical Objective Set Covering (HOSC) model that takes into account the possibility that a server covers more than one zone (Daskin and Stern 1981). However, one of the weaknesses of the HOSC model is that it multi-covers zones without distinguishing among them since it equally weighs each zone. The weakness related to the HOSC model is that it could redundantly cover some demand nodes while leaving others to be covered just once. Later on, Dasking introduced the first probabilistic model for emergency vehicles location Maximum Expected Covering Location(MEXCLP) Model (Daskin, 1983). The model assumed that the probability of a facility being busy is identical and unrelated to other facilities providing medical services with the constraint limiting the number of servers serving demands. Eaton et al. used MCLP to reorganize the emergency medical service in Austin Texas (Eaton, 1986). In 1985, this plan saved the city $3.4 million in construction and $1.2 million in operations costs. Instead, ReVelle and Hogan formulated the Maximum Availability Location Problem (MALP) (ReVelle and Hogan, 1989), which seeks the deployment of servers to maximize the population which has the service available within a desired travel time with a given reliability. Later on, ReVelle and Hogan introduced the Maximal Backup Coverage Problem (BACOP), requiring coverage of all demand nodes, which may not be feasible given a limited budget (ReVelle and Hogan, 1989).

Bernardo and Repede developed TIMEXCLP, an extension of MEXCLP, where variations in travel speed throughout the day are explicitly considered (Bernardo and Repede, 1994). The model demonstrated an increase in the proportions of calls covered in less than 10 minutes, from 84% to 95%.Musolino et al. dealt with forecasting the travelling time, and considered a dynamic routing model that designs optimal routes of emergency vehicles (Musolino et al, 2013). However, it failed to take into consideration the variation of population density between zones and hence the demand for the emergency services.

Wang et al. developed a model to estimate the travelling time for emergency vehicles under pre-emption control conditions, such as path, intersection and section preventions (Wang et al, 2013). However, they failed to consider the population density and the number of emergency vehicles available at various emergency centers. Zhang et al. considered the comparison between the travelling times of emergency vehicles and those of ordinary vehicles, applying dynamic modelling (Sang et al, 2016).

Krasko et al, considered two stages stochastic mixed integer nonlinear programming model for post-wildfire debris flow hazard management of emergency evacuation (Krasko et al, 2017). Francello et al. developed a mixed integer programming (MIP) model to maximize the number of answered called in relief operations, by focusing on industrial disasters where a huge number of rescue operations must be carried out immediately(Francello et al, 2017). Seguin et al, worked on improving patient transportation in hospital using mixed integer programming model while avoiding major changes in the staff schedules (Seguin et al, 2019). Bastos et al, applied mixed integer programming approach to solve the issue related to schedule the admission of patients. By assigning patients to beds to maximize the treatment efficiency and the comfort of patient and the utilization of hospital (Bastos et al, 2019).

Younespour et al, merged both mixed integer programming and constraint programming for operating rooms scheduling with modified block strategy. The study aims to find the optimal sequence and schedule of patients by minimizing the cost of overtime, makespan and completion time of surgeons' operations by considering the resource constraints. However, they failed to consider the priority to medicate a patient as low or high risk cases (Younespour et al, 2019). Huizing et al, applied the median routing problem for simultaneous planning of emergency response and non-emergency jobs by optimizing timetabling jobs and moving responders over a discrete network while keeping response time to minimal (Huizing et al, 2020).

As a summary of the literature review, models did not consider variable population density within a city, nor optimizing the number of emergency vehicles assigned to various stations. Furthermore, these models didn't address the zones with low population demand. In this study, a new model was developed to optimize the number of emergency vehicles assigned to emergency stations and their locations. This model took under consideration fluctuation in the number of received emergency calls from various zones, as well as the deterioration in the patient's health condition while being transported to the hospital.

3. METHODOLOGY

The adapted methodology was divided into two parts. Part A dealt with choosing the appropriate emergency station location, while Part B dealt with addressing critical patients to the most suitable hospital within the appropriate time.

3.1 Part A

The allocation of emergency vehicles is not a simple task, as it contains a large amount of data related to patients (injuries' severity, number of patients), hospital (location, number of beds and specializations) and emergency vehicles (types and locations). Therefore, a mixed integer programming model was considered in this study due to the complexity and the challenging constraints related to the EMS (Francello et al, 2017). The model parameters, sets and variables are as follows:

3.1.1 Indices and input data

- I – the set of demand nodes representing zones where emergency services are needed.
- J – the set of area zones where emergency stations may be potentially located
- T_{IJ} – the shortest travelling time from station located in zone J to zone I
- $T_{MAX\ IJ}$ –standard maximum time needed to travel from station J to cover zone I. According to the EMS Service Act of 1973 (Ball and Lin, 1993), the maximum time allowed is 10 minutes in urban zones and 30 mins in rural zones.
- O_{IJ} – the running cost of an emergency vehicle per trip including fuel and maintenance cost. The cost is a function of the distance separating zone I from zone J
- D_I – the demand for the emergency service generated by zone I
- λ_J – the annual fixed cost of a station located in zone J
- C – the maximum number of emergency vehicles assigned to a station located in zone J
- A_J – corresponding to the number of emergency vehicles to be assigned to a station located in Zone J.
- α – annual depreciation cost of an ambulance

3.1.2 Decision variables

This model seeks to optimize two types of decision variables. The first type is binary discreet variables, defined as:

- Y_J – denotes the opening of a station in a certain zone J (1 if yes, 0 if No).
- X_{IJ} – indicates if a zone I is covered by a station located in zone J (1 if yes, 0 if No).

3.1.3 Constraint 1: coverage of all zones

All zones considered in this study area should be covered, regardless of generating a demand for the emergency service or not. The demand should be served by at least one station:

Eq. (1) $\sum_{k=1}^{J} X_{IK} \geq 1,$ *Zone I covered by at least one station*

Demand for the emergency services generated from zones I served by one or more station J

Eq. (2) $\sum_{K=1}^{J} X_{IK} \leq \sum_{K=1}^{J} Y_{K}$

3.1.4 Constraint 2: travelling time

A zone I is considered to be covered by a station J, if the time needed to travel to zone I from station J defined by TIJ is less than the maximum defined standard travelling time, known as TMAXI

Eq. (3) $X_{IJ}.T_{IJ} \leq T_{MAXIJ} \quad if\ X_{IJ} = 1,\ \forall\ I, J$

3.1.5 Constraint 3: limits on the number of emergency vehicles assigned to a station

The first constraint states that every emergency station must have at least 2 emergency vehicles allocated to it. Otherwise, the number of emergency vehicles is 0.

Eq. (4) $a_J \geq 2.Y_J,\ if\ Y_J = 1,\ \forall\ J$

The second constraint ensures that the number of emergency vehicles should be sufficient to serve all emergency incoming calls during peak hours, generated from zones served by the station.

Eq. (5) $a_J \geq \sum_{k=1}^{I} D_k . X_{IJ} \quad if\ X_{IJ} = 1,\ \forall\ I, J$

The third constraint guarantees that the number of emergency vehicles must not exceed maximum station capacity.

Eq. (6) $a_J \leq C.Y_J$; the number of emergency vehicles should be less than station capacity.

3.1.6 Objective function

The proposed model will optimize the system with the objective to minimize the total cost. The cost is broken down into three components: the annual capital cost of stations, the annual capital cost emergency vehicles (these two costs include depreciation and overhead costs) and the operating costs of emergency vehicles, Bearing in mind that the number of emergency vehicles at any service station J is a function of the demand for the emergency services during peak hours.

Eq. (7) $TotalCost = \sum_{k=1}^{J} \lambda_k Y_k + \sum_{k=1}^{J} \alpha . a_k + \left(\sum_{l=1}^{I} \sum_{k=1}^{J} O_{lk} . X_{lk} . D_l\right) . \frac{TotalAnnualDemand}{\sum_{l=1}^{I} D_k}$

3.1.7 Model solving statement

Since some of the decision variables are discrete and all the equations are linear, the model falls in the mixed integer linear programming with the objective to minimize the total cost. The model would be solved applying Xpress-MP which uses branch and bound for executing the model. Branch and bound combines relaxation and partial or subset enumeration strategy. The solver finds the minimal value of a function f(x) over a set of admissible values; x known as feasible region. Both f and x may be a variable of arbitrary nature which can presume any value abiding by the constraints. A branch-and-bound procedure requires two methods, branching and bounding.

3.2 Part B

Part A of the model dealt with the emergency stations and emergency vehicles allocations. Part B of the model will consider a set of hospitals, in terms of location, specialization and number of beds available in the emergency ward. Each emergency vehicle can carry one patient at a time; the patients are categorized as high-risk cases, which necessitates having high priority to medical assistance, or low risk patients, for which treatment can be slightly delayed. For both cases there is a time penalty for the delay in getting a patient to the hospital. The aim of this study is to minimize the objective function of the rescue times added to the penalty. The parameters and variables of Part B of the model are as follows:

3.2.1 Indices and input data

- CPH_{PH} – equals to 1 if patients P can be treated by hospital H.
- CPV_{PV} – equals to 1 if patients P can be carried by vehicle V.
- T_{SP} – travel time between the emergency stations S and the patient location P
- T_{PH} – travel time between the patient location P and the hospital H
- TH_{SP} – Time Threshold for Pickup patient P, if so, Penalty will be imposed.
- TH_{PH} – Time Threshold for Dropping off patient P at the Hospital H,
- $PRIO_P$– priority level of patient P
- CONG – traffic Congestion penalty, if exceed TH_{SP} and TH_{PH}
- PIN_P – Penalty time to transfer Patient P to Hospital H
- WP_P – additional Penalty if pick up time is higher than TH_{SP}
- WPP_P – additional Penalty if drop off time is higher than TH_{PH}
- $Load_P$ – Loading/unloading patient P into vehicles
- P– Patients

- V – Vehicles
- H – Hospitals
- Y_P– equals to 1, if transfer time is higher than threshold TH_{SP}, and 0 otherwise
- YY_P – equals to 1, if transfer time is higher than Threshold TH_{PH}, and 0 otherwise
- $CARR_{IJV}$ – equals to 1, if patient J is carried by ambulance after patient I, and 0 otherwise.
- $CARR_{0jv}$ – equals to 1, patient J is first addressed by ambulance

3.2.2 Objective function

The proposed objective function is as follow:

Eq. (8) $\min\left(\sum_{i\in P}(T_{Si}+T_{iH})\times PIN_i+\sum_{i\in P}(Y_iWP_i+YY_iWPP_i)+\sum_{i\in P}CONG_i\times(PIN_i+PRIO_i)\right);\quad \forall H,S$

This function is subjected to the following constraints:

3.2.3 Constraints 1

In this study patients were serviced by the emergency vehicles. The first and second constraints depicted in equations (9) and (10) state that patients must be addressed by emergency vehicles only.

Eq. (9) $\sum_{v\in V}\sum_{i\in P}CARR_{ijv}=1\ for\ any\ j\ \in P$

Eq. (10) $\sum_{v\in V}\sum_{j\in P}CARR_{ijv}\leq 1\ for\ any\ i\ \in P$

3.2.4 Constraints 2

If a considered patient to be serviced by a specific emergency vehicle that has a capacity of one patient and would be carried as first patient by that ambulance.

Eq. (11) $\sum_{j\in P}CARR_{0jv}\geq\sum_{j\in P}\sum_{i\in P}CARR_{ijv}\ for\ any\ v\ \in V$

Eq. (12) $\sum_{j\in P}CARR_{ojv}\ \leq 1\ for\ any\ v\ \in V$

3.2.5 Constraints 3

Compute the rescue time for a patient to be picked up by an emergency vehicle and dropped off at the hospital. Eq (13): if patient j to be picked up first ahead of i.Eq (14) if patient i has been given the first priority to be serviced.

Eq. (13) $T_j\geq T_i+\sum_{s\in S}T_{sP}+LOAD_P+\sum_{i\in P}T_{iH}+CARR_{ijv}\ for\ any\ i\in P,j\in P,v\in V$

Eq. (14) $T_i\geq CARR_{oiv}+\sum_{h\in H}T_{PH}\ +\sum_{s\in S}T_{SP}+\ LOAD_j\ \ for\ any\ i\in P\ and\ v\in V$

3.2.6 Constraints 4

Eq (15): if the rescue time is bigger than the threshold, a penalty would be paid.

Eq. (15) $\sum_{i\in P}Y_i\ \geq CONG(T_i-PIN_i)\ for\ any\ i\ \in P$

3.2.7 Constraints 5

Eq (16):A patient is assigned to a hospital depending on whether the hospital addresses this type of injury.

Eq. (16) $\sum_{i\in P}CARR_{ijv}\leq CPV_{iv}\ \ for\ any\ j\ \in P\ and\ v\ \in V$

3.2.8 Constraints 6

Eq (17): constraints specify variable domain.

Eq. (17) $CARR_{ijv}\&T_i\&Y_i\ \in\ \{0,1\}\ for\ any\ i,j\ \in\ P,v\ \in V,and\ h\ \in H$

4. DATA COLLECTION

The suggested model has been tested by considering the demand for the emergency services in Beirutcity. Beirut city is divided into 12 zones. There are 16 hospitals (H) operating within Beirutcity, located in six zones (Z) only (see table 1). Eight of the listed hospitals are equipped to medicate all types of incidents. The remaining hospitals handled the light cases.

Table 1: List of zones and hospitals in Beirut city

Zone	Hospitals
a	H1-Za, H2-Za
b	
c	
d	H1-Zd
e	
f	
g	H1-Zg, H2-Zg, H3-Zg
h	H1-Zh
i	H1-Zi, H2-Zi, H3-Zi, H4-Zi, H5-Zi, H6-Zi
j	H1-Zj, H2-Zj, H3-Zj
k	
l	

The following information was obtained from the emergency service provider in Beirut city, yet it is considered as only a good approximation of the accurate figures, due to the confidentiality agreement imposed on this study. Two emergency stations (ES) with a total of 12 emergency vehicles distributed equally were considered. Table 2 shows the location zone (Z) of the two stations and the hospitals (H) they serve.

Table 2: List of zones and hospitals in Beirut city

Zone	Emergency Station	Hospitals
i	ES-Zi	H1-Zi, H2-Zi, H3-Zi, H4-Zi, H5-Zi, H6-Zi, H1-Zd, H1-Zg, H2-Zg, H3-Zg
k	ES-Zk	H1-Za, H2-Za, H1-Zh, H1-Zj, H2-Zj, H3-Zj

This paper considers the demands for emergency vehicles during New Year'sEve, which is the peak day of the year. 87 different types of incidents were recorded on that day. The patient case severity is used to determine the patient's priority for treatment. Two types of patients were considered in this study:

- High Risk: 26 cases have high and immediate priority to be transported to hospitals
- Low risk: 61 cases have low priority, and their treatment can be slightly delayed.

5. MODEL INPUT PARAMETERS

Table 3 summarizes the demand for the service required by each zone and type of case. It shows that the total demand for the emergency services has reached a peak value of 87 emergency calls in one night with a ratio of 30% classified as high-risk calls, demanding immediate treatment. The objective of this report is to allocate emergency stations and the number of emergency vehicles in order to assist all patients (high and low risks) in the most efficient way.

Table 3: Emergency Demands during New Year's Eve.

Zones	High risk	Low risk	Zones	High risk	Low risk
a	1	7	g	1	8
b	1	4	h	4	5
c	2	3	i	4	10
d	4	8	j	2	5
e	1	2	k	2	2
f	2	4	l	2	3

The current number of available emergency vehicles is 12. The time needed to place the patients into the emergency vehicles quantified as 7 and 3 minutes, for high and low risk patients, respectively. These values are a good approximation of the accurate figures, which obey the same confidentiality agreement mentioned above. A time penalty was imposed for emergency vehicles with rescue time more than 20 minutes for high risk patients, and 60 minutes for low risk patients.. The input parameters of the mixed integer model implemented in this model are listed in Table 4.

Table 4: Mixed Integer Model Input Parameters

Input Parameters	Value
Maximum capacity per station	5
T_{IJ}max for urban zones (mins)	10
Operating cost of ambulance per km	$0.8
Annual depreciation cost per station	$24,000
Annual depreciation cost per ambulance	$7,500

6. RESULTS AND DISCUSSIONS

The XPRESS-MP solver engine was used, as it provides adequate representations of large complex mathematical models and interface large and complex solution algorithms. Using the input parameters mentioned in Table 4, the model optimized the locations of the emergency stations.

6.1 First Scenario

Scenario 1 will implement the first part of the model that will suggest a new emergency station to be considered in order to optimize the speed of transporting the patients to the hospital. The output is incorporated into scenario2 and 3 with respect to the limitations on the hospital number of beds in the emergency ward (Scenario 2), and the deterioration of the patient health condition while being transferred to the hospital (Scenario 3). Table 3 shows that the total number of emergency demands for zone d and its neighboring zones (a and g) is 29, which is equivalent to 33% of the emergency cases. Therefore, zone d has been chosen as the new location.

The estimated building and operating cost of a new emergency service station is around $150,000, regardless of the area and the size of the station. This cost was obtained from the Emergency Services Head Office in Beirut. yet it is considered as only a good approximation of the accurate figures, due to the confidentiality agreement imposed on this study. The life span of a station is considered to be 10 years, resulting in an annual depreciation cost of $15,000.Furthermore, the cost of an emergency vehicle is $45,000, therefore, with a life span of 8 years. Hence, the annual depreciation cost of an emergency vehicle was estimated to be $5,625. This data obeys the same confidentiality agreement mentioned above. Google Pro provides users with the shortest travelling route between the zone where the call is generated and the emergency station that serviced the call. Table 5 lists the time and the distance among the considered 12 zones and the 3 emergency stations. On the other hand, table 5lists the travelling distance and time from the emergency location to the hospital.

Table 5: Travelling Distance and Time between Emergency Location and Emergency Stations.

Zones	Distance in Km/Travelling Time in minutes		
	Existing Emergency Stations (ES)		Proposed ES
	ES-Zi	ES-Zk	ES-Zd
a	3.3km/19mins	2/15	2/12
b	1.2/11	2.7/12	4.5/18
c	2.3/12	1.7/12	2.3/17
d	2.5/11	3/13	1.1/5
e	5.3/19	1.7/16	4.6/24
f	1.2/11	2.8/16	4.6/19
g	1.4/12	2.3/11	1.1/7
h	4.3/16	3.1/13	5.6/22
i	2.6/17	5.7/19	4.1/17
j	4.1/17	1.8/13	5.4/22
k	2.4/13	0.5/8	3.2/19
l	2/13	2.4/15	2.5/13

Table 5 shows clearly that the proposed emergency station would reduce the time needed to reach the emergency cases for zones a, d, and g. Also it would have a similar travelling time to zone i which experiences the highest number of demands. As a result of that, the model managed to optimize the number of emergency vehicles assigned to the three stations, as shown in table 6. It is clear that the suggested optimized model was able to manage a reduction of one emergency vehicle while maintaining the fact that all emergency trips would be achieved within the standard travelling time (TMAX I). Furthermore, in order to cover the whole study area and provide services for the 87 emergency cases, the opening of a third station was required with a total of 11 emergency vehicles assigned to the three stations. This reduction in the number of emergency vehicles would lead to cost reduction while providing the same service and better treatment for the patients.

Table 6 shows clearly that the suggested optimized model was able to manage a reduction of one emergency vehicle. A total of 11 emergency vehicles were assigned to the three stations. The newly suggested emergency station located in zone d has a capacity of 3 cars. This station would impose an extra cost of building the station and running cost of $175,000. Bearing in mind, the acquired land is donated by Charities. Although, this cost seems extremely high, it is will be incorporated within the total cost of scenario 2 and 3 in order to assess the feasibility of scenario 1.

Table 6: Optimized Emergency Station Locations and the Number of Assigned vehicles

Location	Number of Emergency vehicles cars
ES-Zi	5
ES-Zk	3
ES-Zd	3

6.2 Second Scenario

In a realistic situation, there would be limitations on the number of beds available in the hospital emergency ward. These limitations result in diverting the patient to another hospital. In the second scenario, the emergency vehicles re-allocation strategy has been studied.

Starting without considering limitations on the hospital beds in the emergency ward, Table 7 shows the optimal solution that consists into carry patients to the most suitable and nearest hospital. Table 7 shows the demand on H1-Zd hospital is 6 high risk cases and 11 low risks, which required 17 beds. The ER available beds at H1-Zd hospital could not accommodate that number of patients.

The exact number of available beds obeys the same confidentiality agreement mentioned above. Furthermore, the demand on the H2-Za hospital is 2 high risk cases and 5 low risks, which required 7 beds. The demand on the H1-Zh hospital is 5 low risk cases, which required 5 beds. Similarly, The ER available beds at both H2-Za and H1-Zh hospitals could not accommodate that number of patients.

Clearly, there is a problem in hospitalizing the patients. Yet, the model used in this study was able to re-allocate the patients in a way that the number of patients does not exceed the number of available beds in the emergency wards. The model considered a traffic congestion penalty for the trip time that spans more than a time limit. The model managed to address 87 cases into the nearest hospital within the time standard Tmax. Table 7 shows the suggested new patient's allocation plan.

Table 7: Total Number of Cases Admitted to Hospital Before and After Considering Limitations on Hospital Beds

Hospitals	Before Considering Limitations on Hospital Beds		After Considering Limitations on Hospital Beds	
	Number of Patients with High Risk	Number of Patients with Low Risk	Number of Patients with High Risk	Number of Patients with Low Risk
H1-Zi	1b+2i+1l	2i+2f	1b+2i+1l+1h	2i+2f
H2-Zi		1b+1i		1b+1i
H3-Zi		1b+1i+1l		1b+1i+1l
H4-Zi		1b+2i		1b+2i
H5-Zi	2i+2f	2i+2f	2i+2f+1c	2i+2f
H6-Zi		1b+2i		1b+2i
H1-Zd	2c+4d	3c+8d	4d	8d
H1-Zg		3g+1l		3g+1l
H2-Zg		3g+1l		3g+1l
H3-Zg	1g+1l	2g	1g+1l	3c+2g
H1-Za	1a+1k	3a+1k	1a+1k+1c	3a+1k+1h
H2-Za	1k+1h	4a+1k	1k	4a
H1-Zh		5h		3h
H1-Zj	1e+1j+1h	3j	1e+1j+1h	3j
H2-Zj	1j+2k	2j	1j+2k	2j+1k
H3-Zj		2e		2e+1h

Scenario 2 was carried out for the current number of stations and compared to the new suggested number of emergency stations obtained in Model 1 (Scenario 1). Table 8, compares the output of reallocating patients to other hospitals before and after considering limitations on the number of beds at the emergency ward. It is clearly that, introducing a third emergency station has managed to reduce the total rescue cost per night and to reduce the average time per rescue.

Table 8: Total Rescue Cost/Night and Average Time Per Rescue Before and After Limitation on the Number of Beds

	Total Rescue Cost Per Night		Average Travelling Time per Rescue	
	Bed Limitations		Bed Limitations	
Number of Stations	With	Without	With	Without
2 Emergency Stations	$1537/night	$1085/night	29 mins/rescue	22 mins/rescue
3 Emergency Stations	$871/night	$557/night	21 mins/rescue	18 mins/rescue

Table 8 shows clearly that, the patient reallocation plan due to bed limitation slightly affects the average travelling time per rescue. In both cases, considering 3 emergency stations has proven to be efficient as it would drive down both the total rescue cost as well as the average travelling time per rescue. Table 8 shows that the daily saving rescue cost ranges between $500 and $700 depends on the limitations on the number of beds.

This figure represents the worst case of the year (New Year Eve's). The annual cost of considering and running the new emergency station is $15,000 which is equivalent to $41 daily. In this study, it is well recommended to introduce new station due to the fact that the total saving resulting will overweight the total expenses.

However, due to the limitations on the number of beds available in the hospitals' emergency wards, it is well recommended to get confirmation from the hospital to avoid wasting crucial time. This limitation will not affect the priority of hospitalizing the patients.

6.3 Third Scenario

In the third scenario patient's condition was evolved and deteriorate on the way to the hospital, while being assigned to the hospital that deals with low risk cases. Therefore, from a medical point of view, the assignment has to be altered to another hospital that deals with all cases in order to maximize the number of successfully treated patients. The following two cases were considered in this study:

- For a patient from zone h who was supposed to be taken to H1-Zh, the medical condition has deteriorated, thus moving from a low to a high risk. Similarly,
- Another patient from zone l who was supposed to be taken to H1-Zg, suffered a medical condition change from a low to a high risk.

Table 9: Total Rescue Cost/night and Average rescue time if Patients condition deteriorates on the way to the hospital

	Total Rescue Cost Per Night		**Average Travelling Time per Rescue**	
	Bed Limitations		**Bed Limitations**	
Number of Stations	**With**	**Without**	**With**	**Without**
2 Emergency Stations	$1642/night	$1114/night	34 mins/rescue	27 mins/rescue
3 Emergency Stations	$995/night	$615/night	24 mins/rescue	21 mins/rescue

Table 9 shows clearly that the proposed emergency station would reduce the time needed to reach the emergency cases for all residential zones. Also it would have a great effect on the total rescue cost per night. As mentioned above, implementing 3 emergency stations would achieve a saving that ranges between $500 and $700 which would overweight the total expenses induced by considering a third station. As a result, the model has managed to optimize the number of emergency vehicles assigned to the three stations, this reduction in the number of emergency vehicles would lead to cost reduction while providing the same service and better treatment for the patients.

In this case, both patients must be assigned to other hospitals. Considering the large number of parameters and conditions, the re-allocation problem is not a minor issue that can be solved by simple calculations. To successfully run the model, patient condition, hospital location, available beds, and traffic congestion were taken into consideration. From both the medical and transport points of view, the model was able to re-allocate both patients considering that their health condition evolved while being transferred to the hospital. Furthermore, the model was able to optimize travelling time based on real time information on the patient's health condition.

7. CONCLUSIONS

The crucial decision that must be considered by the Emergency Vehicles System managers is the assignment and the allocation of emergency vehicles for the purpose of aiding all patients. The allocation of emergency vehicles is not a simple task, it is complicated because it contains a large amount of data to be measured. Therefore, a mixed integer programming model was considered. The outcome of the model addressed the optimum number of emergency vehicles and their allocation to the available stations while taking into account a possible re-evaluation of the patients' conditions during the transport time to the hospital.

The outcome of this study provides an approach that would ensure a fast response of the rescue operations by an efficient emergency vehicles management. It is an effective synchronized system integrating emergency staffs, equipment, and facilities to deliver fast services to patient of sudden illness or unexpected injury.

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