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Analyzing the response to traffic accidents in Medellín, Colombia, with facility location models

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ABSTRACT

In this paper we analyze the emergency medical service (EMS) devoted to attend the victims of traffic accidents in Medellín (Colombia). This work was motivated by the steep increase in injuries derived from these events over the last years. This project has been developed in a partnership with the local authorities of Medellín. In our analysis we used several facility location models to evaluate different courses of improvement. The impact of the proposed measures (a larger fleet of ambulances and different alternatives for their location) is evaluated in terms of the reduction in the number of uncovered districts, the decrease in the busyness of the system, and the resulting improvement in the quality of service. The results of the analysis suggest that to improve the service of the EMS, it is more important to increase the size of the fleet of ambulances than to change their locations at the fire stations.

1. Introduction

One of the world's leading causes of death and disability is road traffic injuries. According to the World Health Organization (WHO), nowadays this is the ninth major cause of death globally and the main cause of death for young people aged 15–29. Current trends suggest that injuries derived from traffic accidents will be the seventh main cause of death in 2030 unless urgent action is taken [1]. In addition, more than a million people die each year on the world's roads, and 90% of those deaths occur in low- and middle-income countries that represent 82% of the world's population [1,2].

Because of the severity of this problem, the United Nations declared 2011–2020 as a decade of action for road safety [3], aiming to stabilize and reduce the number of victims of traffic accidents around the world through national and citywide plans. This campaign has five pillars of action [4]: road safety management, safer roads and mobility, safer vehicles, safer road users, and post-crash response. These pillars concentrate on prevention and security, corresponding to strategies in the medium and long term, where the commitment of nations is a key success factor to achieve the goal of the decade, through the design of management plans including investment, transfer and creation of knowledge, and also international cooperation to face the current problem and to implement sustainable actions in the future [5]. Preventative actions are fundamental because they have a great impact over time. However, they may be complemented by short term actions. Thus, the last pillar, post-crash response, focuses on the attention to the injured people.

This problematic situation is also visible at regional levels. Colombia is a middle-income country with 13.4 deaths in traffic accidents per 100,000 inhabitants in 2014, whereas the rate for high-income countries is less than 9. Besides, between 2010 and 2014 the second largest cause of violent death in Colombia has been traffic accidents, with approximately 22% of the total number of deaths [6]. Likewise in Medellín, which is one of the largest cities in Colombia, with 2,368,282 inhabitants, there has been an increasing trend in the number of traffic accidents. According to 2014 statistics by the Municipality [7], from 2008 to 2014, the number of traffic accidents grew by 20.13%. One of the main causes of this problem is the growing number of vehicles, from 2008 to 2014 this figure increased from 767,548 to 1,234,946 (i.e., by 60.9%).

The aforementioned circumstances and the increase in the number of traffic accidents reported to the emergency telephone number of the city (hereafter referred to as NUSE), motivated the local authorities of Medellín to search for alternatives to address this problem from the point of view of expedient emergency care to the victims of traffic crashes. NUSE is responsible for allocating the

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available resources to serve different types of emergencies in the city; one of those resources is the ambulance fleet of the EMS.

Medellín's local government is searching for alternatives to improve the emergency medical process, not only in an operational way but also at a strategic level. In a joint partnership with a research center of the city, they have run a project composed of: the design of an electronic medical record, the simulation and redesign of the call center process, the training of the staff that answer the emergency calls at NUSE, and an analysis of the location of the ambulance fleet. Hence, in this paper we describe the application of facility location models for the last stage of the project. The aim was to determine the number of ambulances required to serve the people involved in traffic accidents reported to NUSE, and to determine their appropriate location (according to the temporal and geographic distribution of the estimated demand obtained from historical information) in order to maximize the events covered by this service.

The main contribution of this paper is to highlight how (classical) facility location models can support the government authorities in a city from a middle-income country that is facing the challenge of improving the attention to injured people in traffic accidents. Likewise, this paper also shows how Operations Research can be a way to respond to the call for improvement measures promoted by the United Nations in their decade of action on road safety.

The remainder of this paper is structured as follows. Initially, we outline the background of facility location models applied to emergency medical services (EMS), then we present the mathematical formulation of the models used in this paper. In the next section we present the details of the case study, emphasizing the information analyzed and the results obtained by the solution of the mathematical models. The last section presents our conclusions and proposes future research directions.

2. Literature review

The methodologies used to locate ambulances in emergency systems can be classified into two main categories: probabilistic models that use simulation [8,9] or spatial queuing theory [10] and facility location models [11]. Only recently have authors begun to hybridize these two methodologies, see for instance [12]. For a detailed review of ambulance location and relocation models, the interested reader can refer to [8,11,13].

Facility location models are widely used in the design and optimization of health care systems. In particular, the location of ambulances for emergency service is one of the most studied decisions. In general, integer programming models for locating ambulances have a relatively similar structure [14]. In order to maximize the response capacity of the system, these models assume a maximum response time to measure the quality of attention of the events reported. This maximum response time produces a coverage distance (and a coverage area) where an ambulance is located in a certain place. Events within the coverage area of an ambulance are considered well served. On the other hand, events attended by ambulances outside the coverage distance are not well served. Early models, like the Set Covering Location Problem (SCLP), are based on this principle. In this model, the objective is to minimize the number of ambulances needed to cover all demand points spread over a region [15]. When the available budget is not enough to guarantee total coverage, the Maximal Covering Location Problem (MCLP) [16] appears as an alternative. The MCLP aims to select the locations of a given number of servers that maximize the demand within the target service time (i.e., the covered demand).

Although SCLP and MCLP have been applied successfully to locate ambulances, these early models ignore the unavailability of the ambulances while they are attending an emergency. Recognizing the limitations of disregarding the times when ambulances are in use, there are probabilistic facility location models that explicitly consider in their formulation the level of busyness of the ambulances. Daskin [17] introduces the Maximum Expected Coverage Location Problem (MEXCLP) that maximizes the demand covered but weighted by the service availability that each demand zone observes. Service availability is calculated through the global estimation of the average busyness of the system and considers the number of ambulances located within the maximum response time for each demand zone.

Ambulance location models have been applied using real data from their beginnings. For instance, in Austin (Texas), Eaton et al. [18] describe the application of an MCLP-like model for the location of ambulances, and Daskin and Stern [19] introduce a hierarchical set covering model that first minimizes the number of ambulances required to cover all the zones in a given time and then maximizes the number of zones covered by more than one ambulance. Also, in Ref. [20] the authors use the MCLP to model the location of ambulances in rural areas in Spain. Likewise, Rajagopalan and Saydam [21] apply two minimum expected response models to the EMS from Mecklenburg County (USA): the first one uses the expected coverage and the second one uses the available coverage. Recently, Moeini et al. [22] present a dynamic redeployment problem where location and relocation decisions are made in order to maximize the covered demand and to minimize the cost of relocating the vehicles. They consider the fluctuation patterns of the demand that can occur during certain periods and different kinds of coverage. They use data from the county of Val-de-Marne (France) to validate and compare different models. Lastly, Céspedes et al. [23] analyze the improvement of the response time to incidents reported to the emergency number of Bogotá (Colombia) through the location and relocation of a limited fleet of ambulances.

Some studies, like [24], address the EMS response to mass casualty incidents derived from rapid-onset disasters like earthquakes. We, on the contrary, focus on the EMS response to traffic accidents that are everyday small scale events. Usually, an EMS performs medical assistance for any kind of incident reported to the emergency number (e.g., SAMU, the French EMS [25]). In Medellín, the EMS is mainly dedicated to attending the victims of traffic accidents, since other pathologies (e.g., cardiac arrest or home healthcare) are served by resources from other public agencies or private organizations (NGOs or private health-insurance companies).

Most facility location models applied to traffic accidents study highway crashes, using exact or heuristic methods [26–28]. By contrast, in this paper we consider the application of location models for the response to traffic accidents occurring in an urban area. Kepaptsoglou et al. [29] also use a location model to deploy emergency vehicles to respond to traffic accidents in the city of Thessaloniki (Greece). However, they use a genetic algorithm to solve their optimization model. In this paper, we rely on a commercial optimizer (CPLEX) to solve the resulting mathematical programming models.

3. Facility location models for EMS location

The main mathematical model used to deploy the ambulances in Medellín is based on the MEXCLP formulation presented in Ref. [30]. We added to their model some SCLP elements to analyze the number and location of dispatching stations. The resulting model, (hereinafter referred to as SCLP+MEXCLP), uses as parameters the results obtained from two other models: first, the number of dispatching stations from a standard SCLP, and second, the number of ambulances from a parametric implementation of MEXCLP. The elements to build these models follow.

The set $J = \{1, \ldots, m\}$ represents the possible locations in which to place the ambulances (i.e., dispatching stations), and p is the number of available ambulances. Likewise, $I = \{1, \ldots, n\}$ is the set of demand zones for the ambulance service (i.e., districts of the city). Each district $i \in I$ has a demand d_i (the number of calls) that represents the number of traffic accidents reported in that zone of the city (calculated using historical records). The distance between a dispatching base $j \in J$ and a district $i \in I$ is denoted by h_{ij}. The quantity h_{max} represents the maximum coverage distance (according to the maximum response time established for the design of the system). The parameters h_{ij} and h_{max} allow us to find the set of stations N_i that are able to serve district $i \in I$ within the maximum response time: $N_i = \{j \in J : h_{ij} \leq h_{max}\}$. Based on the shift length l (given in minutes), the standard service attention time t (also in minutes) for each incident, and the aggregate demand, we follow the approach of Refs. [17] and [30] to estimate the busyness of the system b, using Eq. (1):

$$b = \frac{t\sum_{i\in I}d_i}{l \times p} \tag{1}$$

When b is calculated, it is possible to measure a quality index q_k that indicates the availability of the service in a district when there are k ambulances located in the set of covering stations N_i. The value of q_k is calculated for each possible value of k $(k = 1, \ldots, p)$ with Eq. (2).

$$q_k = 1 - b^k \quad \text{for} \quad (k = 1, \ldots, p) \tag{2}$$

The integer decision variables x_j represent the number of ambulances located in station $j \in J$. The binary variables y_{ik} indicate the coverage offered to each district $(\forall i \in I, k = 1, \ldots, p)$; $y_{ik} = 1$ if district i is covered by k ambulances, $y_{ik} = 0$ otherwise; and the binary variables w_j indicate the location of the stations; $w_j = 1$ when site $j \in J$ is selected to locate a station and $w_j = 0$ otherwise. Using the aforementioned notation, the facility location model formulated as an integer program follows:

$$max \sum_{i\in I}\sum_{k=1}^{p} d_i q_k y_{ik} \tag{3}$$

Subject to:

$$\sum_{j\in N_i} x_j \geq \sum_{k=1}^{p} k y_{ik} \quad \forall i \in I \tag{4}$$

$$\sum_{k=1}^{p} y_{ik} \leq 1 \quad \forall i \in I \tag{5}$$

$$\sum_{j\in J} w_j = r \tag{6}$$

$$\sum_{j\in J} x_j = p \tag{7}$$

$$x_j \leq p w_j \quad \forall j \in J \tag{8}$$

$$w_j \in \{0, 1\} \quad \forall j \in J \tag{9}$$

$$x_j \in Z^+ \quad \forall j \in J \tag{10}$$

$$y_{ik} \in \{0, 1\} \quad \forall i \in I, k = 1, \ldots, p \tag{11}$$

The objective function (3) maximizes the total weighted expected coverage of the districts. Constraints (4) and (5) allow the calculation of the coverage of each district. Constraints (4) state that y_{ik} can take the value of 1 when district i has at least k ambulances located in the set of its covering stations N_i. Constraints (5) guarantee that only one value of q_k is considered for each district. Eqs. (6) and (7) establish that r dispatching stations and p ambulances will be deployed in the city, respectively. Constraints (8) ensure that ambulances are located only in opened stations. Finally, constraints (9), (10) and (11) define the domain of the decision variables.

To obtain the parameter r that represents the number of dispatching stations to operate the system, we use an SCLP formulated as follows:

$$min \quad r = \sum_{j\in J} w_j \tag{12}$$

Subject to:

$$\sum_{j\in N_i} w_j \geq 1 \quad \forall i \in I \tag{13}$$

$$w_j \in \{0, 1\} \quad \forall j \in J \tag{14}$$

The objective function (12) minimizes the number of dispatching stations needed to operate the system. Constraints (13) guarantee that every district will have at least one open station in N_i. Constraints (14) represent the domain of the decision variables.

Note that the first step (model (12) thru (14)) ignores the busyness of the system, which depends mostly on the number of ambulances deployed in the stations. Then, we use an MEXCLP to obtain the parameter p that represents the number of ambulances to deploy in the city; this model is formulated as follows:

$$max \;\; z(p) = \sum_{i\in I}\sum_{k=1}^{p} d_i q_k y_{ik} \tag{15}$$

Subject to:

$$\sum_{j\in N_i} x_j \geq \sum_{k=1}^{p} k y_{ik} \quad \forall i \in I \tag{16}$$

$$\sum_{k=1}^{p} y_{ik} \leq 1 \quad \forall i \in I \tag{17}$$

$$\sum_{j\in J} x_j = p \tag{18}$$

$$x_j \in Z^+ \quad \forall j \in J \tag{19}$$

$$y_{ik} \in \{0, 1\} \quad \forall i \in I, k = 1, \ldots, p \tag{20}$$

The objective function (15) represents the total weighted expected coverage of the districts obtained with p ambulances. Constraints (16) thru (20) define the structure of a classical MEXCLP as stated before.

We use the SCLP formulated in Eqs. (12) thru (14) to select the minimum number of stations r needed to deploy the ambulances of the system. Simultaneously, with the MEXCLP described in Eqs. (15) to (20), we find the size of the ambulance fleet p, through an iterative increment in the number of ambulances, beginning from the minimum value $\underline{p} = \left\lceil \frac{t\sum_{i\in I}d_i}{l} \right\rceil$, until the weighted average availability $Q = \frac{z(p)}{\sum_{i\in I}d_i}$ reaches a given target value Q_{min}. Then, r and p are parameters of the integrated model SCLP+MEXCLP expressed in Eqs. (3) to (11) that determines the location of the stations and the deployment of ambulances maximizing the expected coverage.

4. Case study

This section describes the application of the SCLP+MEXCLP to analyze Medellín's EMS for traffic accidents. Initially, we describe the EMS of the city, then we present the data processing and analysis of the

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information provided by NUSE, and finally we summarize the results obtained when we solved the SCLP+MEXCLP using these data.

4.1. Medellin EMS for traffic accidents

The emergency system that assists injured people in Medellín has a similar structure to that of other systems in the world [31,32], and its service process can be described as follows. First, requests from emergency calls arrive at NUSE's call center. There, dispatchers evaluate the priority and type of call and assign it to the appropriate agency for attending to the request, depending on the type of event reported. In case of traffic accidents, two different agencies are involved: the Medellín Department of Transportation sends their personnel to register the accident, and if there are injured people, the Fire Department sends ambulances with paramedical personnel to provide emergency medical care.

After the triage and dispatching phase at the call center, the emergency medical service can be described by four stages: (i) ambulances go from their base location to the place of the accident; next, (ii) emergency medical care is provided to the injured people in place; if necessary, (iii) the ambulance moves the injured people to a nearby hospital where medical care continues; and finally, (iv) after leaving the hospital the ambulance goes back to its base where it is set up (cleaned, disinfected, replenished with materials, etc.) to continue with its duty period. In these cases, ambulances are unavailable from when they are assigned by the dispatcher until they return to the base after leaving the patients at the hospital.

4.2. Data analysis

NUSE provided the records of traffic accidents requiring ambulances reported between June 2010 and May 2011. The emergencies considered in this article are those served by basic life support ambulances. We assumed homogeneity of the fleet (i.e., all the ambulances are equipped with the same resources and personnel so that anyone can respond to any emergency, which is consistent with the operating fleet). We obtained 14,103 records after the data cleansing phase, where we eliminated duplicate records, the data that could not be geocoded due to an inaccurate address, and some incidents outside the urban area of the city.

As can be seen in Fig. 1, the distribution of the events during the week differs, depending on the day of the week, in terms of the median, the skewness of the data, and the dispersion of the distribution of the number of events. This suggests that the pattern of the occurrences depends on the day of the week, something consistent with a priori knowledge of the behavior of the system. Following the data analysis presented in Ref. [33], we clustered the seven days of the week using the number of events per hour (for the 24 h) as multivariate observations. According to the results of the clustering, the best grouping of the days is $G1 = \{\text{Sunday}\}$, $G2 = \{\text{Thursday, Saturday}\}$ and $G3 = \{\text{Monday, Tuesday, Wednesday, Friday}\}$. Then, we analyzed the system's performance dividing the data into these three groups.

The analysis of the occurrence of events during the day (depicted in Fig. 2) shows that the distributions of the events in all groups are alike. There is a greater frequency of incidents in the afternoon (between 11 h and 19 h), which is typically the busiest period of the city. The number of reported events decreases during the evening until the early morning hours, when a progressive increase in the frequency of events occurs between 5 h and 11 h to reach again the pattern in the following hours, and the cycle repeats. Based on this pattern and according to the shifts used in the system, we split our analysis into two shifts of 12 h each: the day shift (with higher demand) beginning at 7 h and ending at 19 h, and the night shift (with smaller demand) beginning at 19 h and ending at 7 h.

NUSE provided us the aggregated number of accidents reported in the 271 districts of the city. To calculate the service load generated by the events reported in each district (d_i), we analyzed the service time records. We considered the elapsed time between the dispatch of an ambulance and the completion of the service cycle after its cleaning and setup to be available again. Using these time records for each shift (see Fig. 3), we decided to use the upper quartile as the standard service time for each shift because the central measures do not seem representative of the service time. We found that the data in the day shift present more dispersion than in the night shift. In both shifts, the distribution of data is skewed to the right, and the average is far from the median because of some high values of the service time. Although 25% of the observations are above the third quartile and some of them represent outliers, their occurrence is due to the structure of the Colombian health system, and its reduction is out of the scope of this paper (however, its causes were tackled through other complementary projects like the electronic record and other interoperation measures). From this information, we allocated a standard service time for each event per shift, corresponding to $t = 113.34$ min in the day, and $t = 98.83$ min in the night. With these values we use Eqs. (1)–(2) to calculate the busyness of the system (b) and $q_k (k = 1, \ldots, p)$ for different values of p.

To determine the set N_i for each district, we estimated the distances $h_{ij} \forall i \in I, j \in J$ through the shortest path between all pairs of districts in the road network of the city calculated with

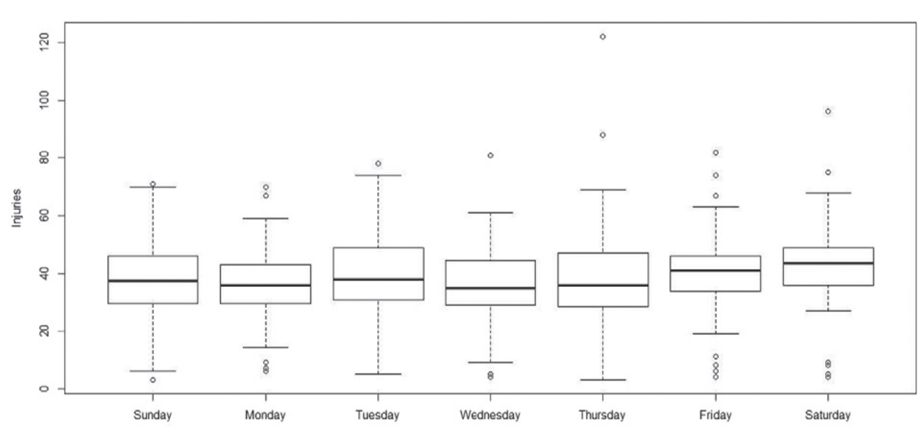
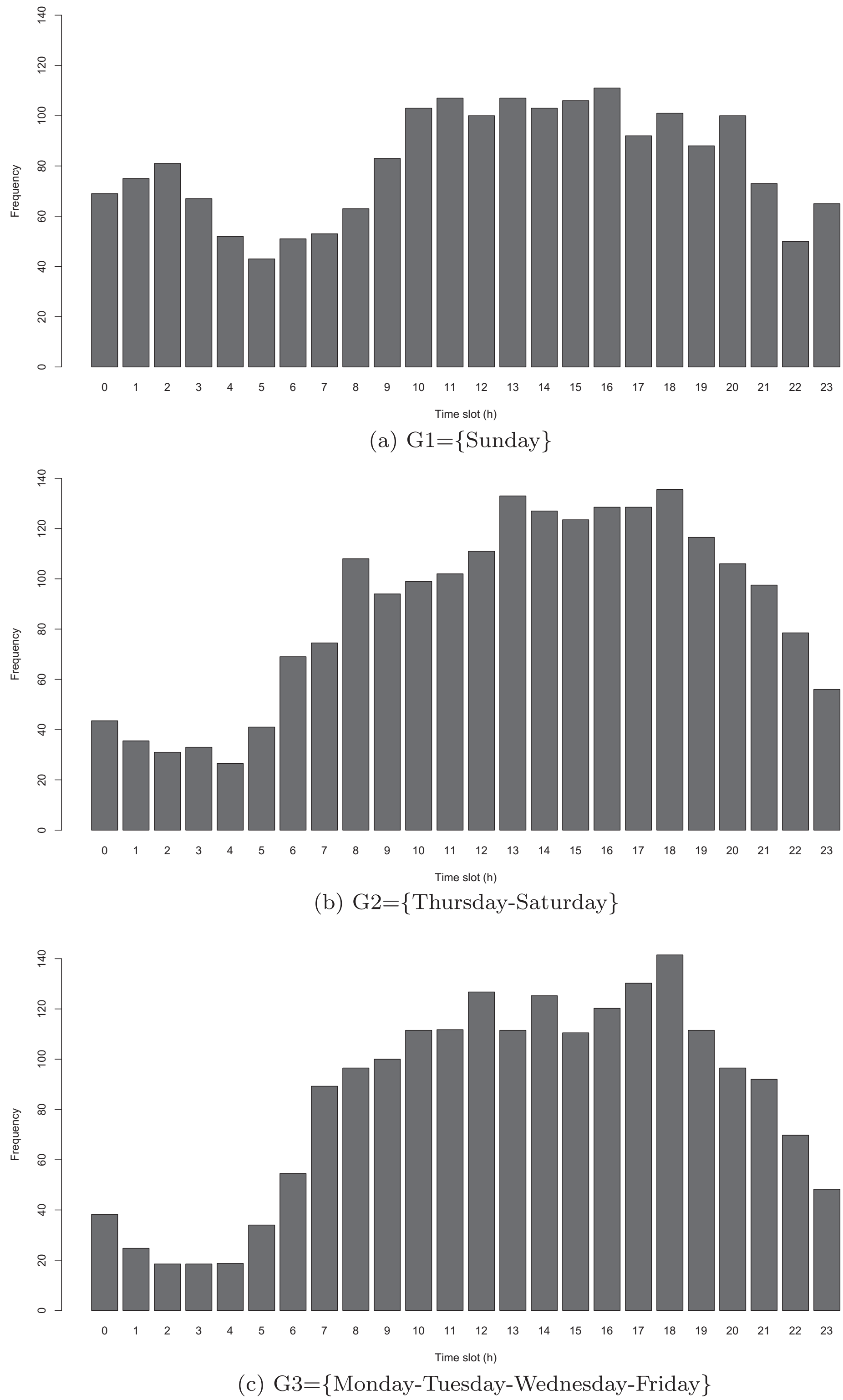


Fig. 1. Distribution of events in the week.



(a) G1={Sunday}

(b) G2={Thursday-Saturday}

(c) G3={Monday-Tuesday-Wednesday-Friday}

Fig. 2. Distribution of events during the day for each group of days.

GoogleMaps™. As a result, we obtained an asymmetrical distance matrix h_{ij}. Finally, to find the maximum distance h_{max} that defines the coverage area of each located ambulance, we used NUSE's desired response time of 10 min. Using the average speed of 34 km/h reported by the Municipality [34], the value for h_{max} was 5.67 km.

4.3. *Selection of the number of bases r and the number of ambulances p*

We used IBM ILOG CPLEX Optimization Studio Version 12.6 to implement the optimization models, using the data described previously. The solution to all optimization problems took less than 5

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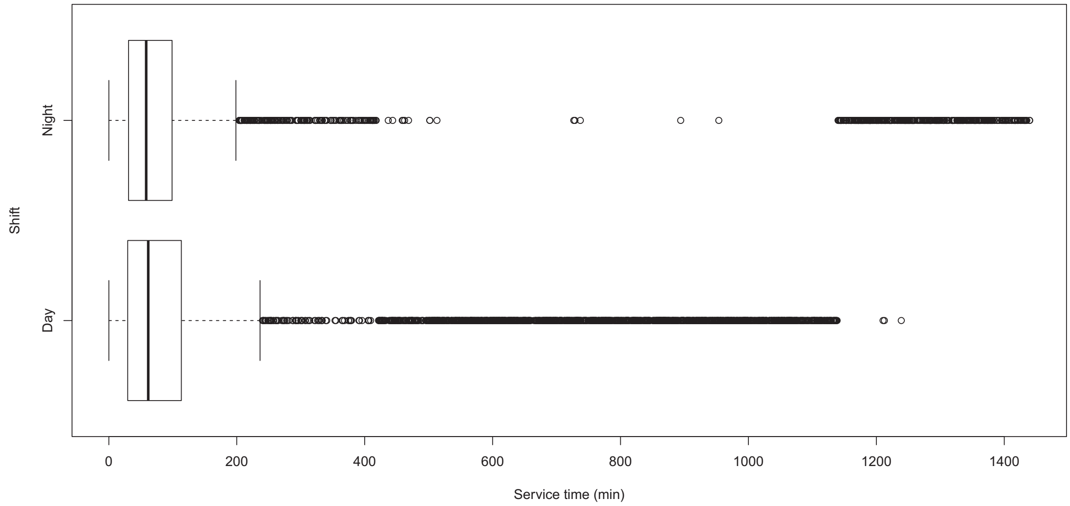

Fig. 3. Distribution of service time per shift.

min for each shift on a computer with an Intel Core 2 Quad processor at 2.67 GHz with 4 GB of RAM running under Windows 7 (64 bits).

As described in Section 3, with the SCLP we found the minimum number of stations that should be opened to operate the system. This analysis depends on the average speed used to calculate the coverage distance h_{max}. Speed records for the road network of Medellín were only available for some road segments and the speed estimates from GoogleMaps™ depend on the path selected to travel between points, something that is only decided upon dispatching of the ambulance. Then, to evaluate the appropriateness of the number and location of the dispatching bases, we solved the SCLP with several values of h_{max} calculated with a range of average speeds between 18 km/h and 50 km/h. Fig. 4 summarizes the results of the analysis.

As can be seen in Fig. 4, for values of h_{max} greater than 4.5 km, the changes in the number of stations are less frequent, and from seven to four bases seem good to cover all districts in different speed intervals. Based on the results of Fig. 4, we selected $r = 6$ as the ideal number of bases to dispatch Medellín's EMS ambulances. This quantity covers the distance calculated with the average speed of Medellín ($h_{max} = 5.67$ km, corresponding to 34 km/h), and allows responding to possible reductions of the average speed as recent reports indicate [34]. The ambulances that belong to Medellín's EMS operate from the seven fire stations of the city. Selecting six bases does not make the system more expensive. However, it could decrease the quality of the service provided. The difference between these two values will be analyzed further in the next section.

Besides, the EMS of Medellín had six ambulances to serve the incidents reported in the urban area of the city. To find the ideal number of ambulances p required in each shift and group of days, we solved iteratively the MEXCLP by increasing the value of p one ambulance at a time, beginning with a minimum number of vehicles $\underline{p}$, until Q reaches the target value $Q_{min} = 0.999$ (a value where one more ambulance produces negligible improvements in Q). Since only the average speed in the city is available, we made a parametric analysis in a speed interval between 22 km/h and 34 km/h in steps of 4 km/h to select the size of the fleet per shift for each group. Fig. 5 shows the analysis for $G2$. The results indicate that notwithstanding the value of the speed, high service levels (greater than 95%) were reached with similar numbers of ambulances per shift. Based on this analysis, the number of ambulances in each group per shift are those reported in Table 1. For the night shift in all groups the number of ambulances is 12. On the other hand, in the day shift we decided to use the maximum size of the fleet between the groups (16 ambulances), corresponding to $G3$.

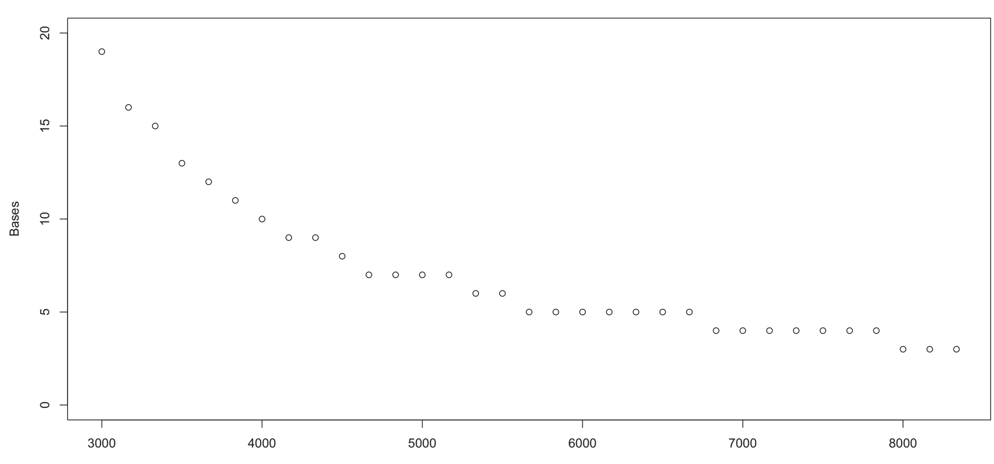

Fig. 4. Analysis of the number of bases according to the h_{max} value.

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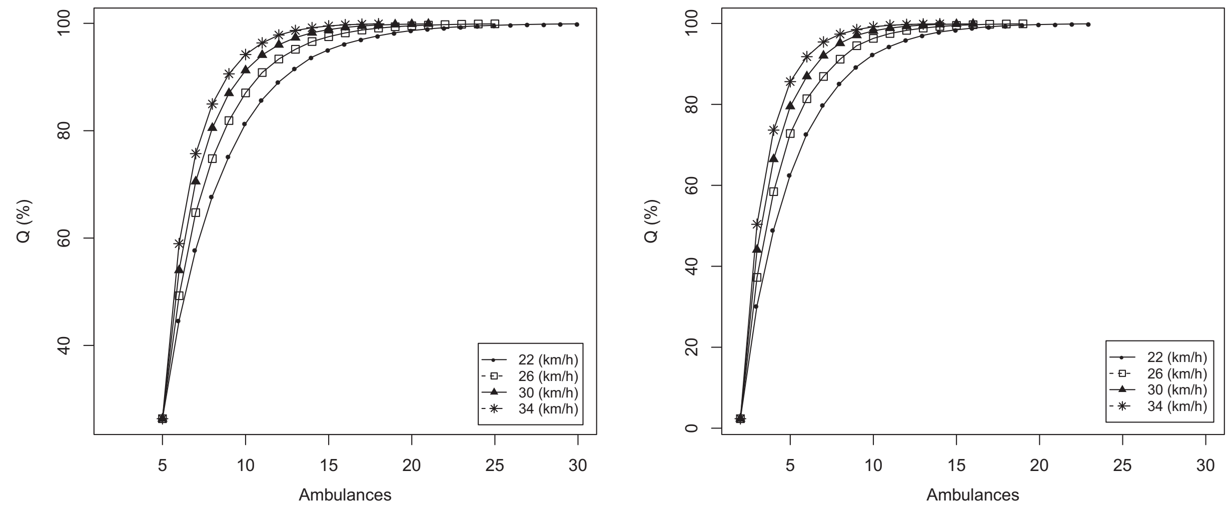

(a) Day shift (b) Night shift

Fig. 5. Analysis of the number of ambulances per shift in G2 considering changes in the speed.

Table 1
Number of ambulances per shift for each group.

	Group		
Shift	1	2	3
Day	14	15	16
Night	12	12	12

Table 2
Summary of explored scenarios.

Scenario	p (day, night)	J	r
1	(6,6)	Fire stations	7
2	(16,12)	Free location (any district in the city)	6
3	(16,12)	Fire stations	7
4	(16,12)	Fire stations	6

This value does not worsen the service level of the other groups, and the difference is only one and two ambulances, with respect to $G2$ and $G1$.

After the analysis described above, we found that the system should operate from six or seven bases with 16 ambulances in the day shift and 12 ambulances in the night shift.

4.4. Scenarios

We used the SCLP+MEXCLP in four different scenarios to find the best location for the dispatching bases and the deployment of ambulances. Scenario 1 uses fire stations as possible locations for the ambulances and only considers six ambulances (a number provided by NUSE according to their resource availability). In the other scenarios, we used the SCLP+MEXCLP to deploy the number of ambulances found with MEXCLP(p). Scenario 2 considers all districts of the city as possible locations of the r stations obtained with SCLP to dispatch the ambulances. As benchmarks, scenario 3 uses fire stations as fixed locations for the ambulances, and scenario 4 takes the fire stations as possible locations of the r dispatching bases obtained with SCLP. Table 2 summarizes the configuration of the scenarios.

For each scenario, we calculated three metrics to measure the performance of the solutions: (i) the weighted average availability Q; we decided to use Q rather than $z(p)$ because Q can be seen as the weighted average probability that a district finds an available ambulance when needed; (ii) the busyness rate of the system (b); and (iii) the number of uncovered districts, we measured coverage based on ambulance availability instead of station location (i.e., a district without enough ambulances in N_i to meet its demand is considered as uncovered). Tables 3 and 4 summarize the results of these key metrics for all scenarios in the day and night shifts, respectively.

Scenario 1 represents the configuration of Medellín's EMS (six ambulances, and seven fire stations as dispatching bases). For both shifts, this scenario presents the worst performance of the system with the lowest Q in all scenarios and the highest number of uncovered districts. This poor service estimate can be explained mainly by the expected unavailability of ambulances revealed by the high busyness of the system, which is on average 65% in the day shift. By contrast, scenario 2 has the best performance of the system, with a minimum weighted covered demand of 99.7% in the day shift and

Table 3
Results for the day shift.

	Scenario 1			Scenario 2			Scenario 3			Scenario 4		
Group	1	2	3	1	2	3	1	2	3	1	2	3
Q (%)	70.83	63.55	61.46	99.83	99.72	99.72	98.69	98.51	98.31	98.67	98.47	98.28
b (%)	56.66	68.54	68.87	21.25	25.70	25.83	21.25	25.70	25.83	21.25	25.70	25.83
Uncovered districts	37	58	62	0	0	1	5	7	7	5	7	7
(p,r)	(6,7)			(16,6)			(16,7)			(16,6)		

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Table 4
Results for the night shift.

	Scenario 1			Scenario 2			Scenario 3			Scenario 4		
Group	1	2	3	1	2	3	1	2	3	1	2	3
Q (%)	84.16	87.70	89.06	99.58	99.73	99.78	97.70	98.65	98.34	97.64	98.65	98.32
bs (%)	35.77	32.29	27.32	17.88	16.15	13.66	17.88	16.15	13.66	17.88	16.15	13.66
Uncovered districts	10	10	8	0	0	0	5	7	7	5	7	7
(p,r)	(6,7)			(12,6)			(12,7)			(12,6)		

99.6% in the night shift. This scenario uses as parameters all the recommended values for the system found with the models described in previous sections (six bases, 16 ambulances for the day shift and 12 ambulances for the night shift) with free location of the bases in the city.

The results for scenario 3 show that the location of the bases in any district of the city improves on average the expected coverage just by 1.3% for the day shift, and by 1.5% for the night shift. These results support the use of fire stations as fixed dispatching bases for the service. In scenario 4, we selected from among the seven fire stations the best six (the number obtained with the SCLP) with the size of the fleet found with MEXCLP. With this configuration, the system has a very similar performance to scenario 3. These results indicate that even a reduction of the number of dispatching bases could be considered, provided the system has a larger fleet.

To evaluate the impact of a larger fleet in more detail, we analyzed scenarios 3 and 4 with discrete increments in the number of ambulances from six to *p*. Fig. 6 presents the results for scenario 3 (the results for scenario 4 are very similar). This figure indicates that, as expected, the performance of the system improves with a progressive increase of the ambulances. For the day shift, beyond 12 ambulances, all groups have a weighted expected coverage greater than 95%. On the other hand, for the night shift with six ambulances, the system has a better initial performance, and requires at least nine ambulances to reach a weighted expected coverage of 95%. Moreover, if it enjoys the same fleet size as that for the day shift, the maximum service level for the night shift reaches 99%.

Fig. 7 shows the geographical distribution of the fire stations and the demand for EMS of the districts of Medellín. Darker districts have larger demands. This figure depicts the system configuration for scenario 3 where all fire stations are used as dispatching bases. This figure shows how the demand pattern changes with the shift. As can be seen, the ambulance deployment changes accordingly for each day of the week.

5. Conclusions

This paper presents the use of facility location models to support Medellín's local authorities in the improvement of the EMS provided to people injured in traffic accidents. The resulting model (SCLP+MEXCLP) combines the elements of the Set Covering Location Problem and the Maximum Expected Coverage Location Problem. The use of historical data in this model demonstrates that the system can provide much better service by increasing the size of the ambulance fleet. However, the alternative of moving the ambulances from fire stations to other places in the city does not seem to produce a great improvement in the service. Also, reducing the number of fire stations used as dispatching bases but increasing the size of the fleet could provide an acceptable service level for this system.

The use of these models sheds some light on the discussion of this problem and helped Medellín's local authorities to objectively evaluate the impact of different courses of improvement. This paper also shows how simple classical Operations Research tools can be used to support the evaluation of improvement measures comprised in the UN decade of action on road safety.

Future research possibilities include the use of optimization/simulation models to evaluate the proposed scenarios and the use of spatial queuing models to refine the estimates provided by simple location models.

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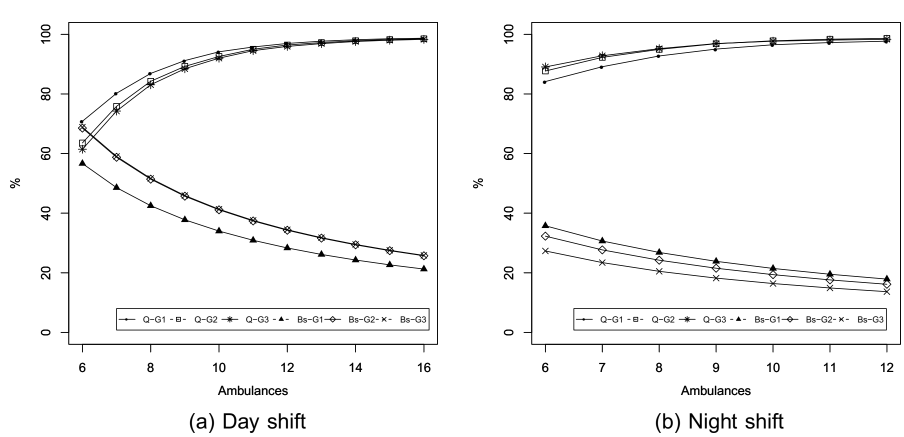

Fig. 6. Results for scenario 3 with discrete increments of *p*.

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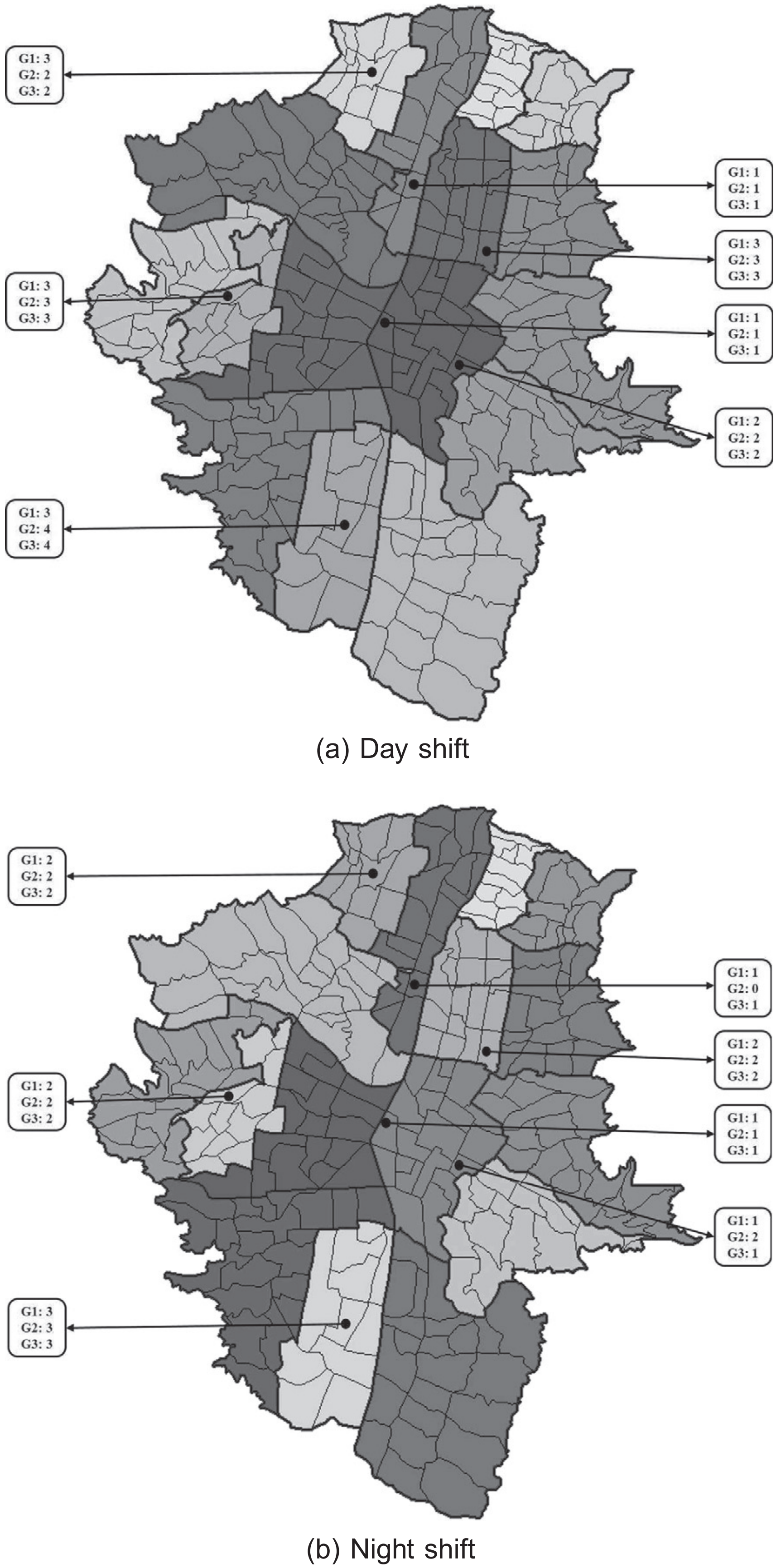

Fig. 7. Geographical location of bases.

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