© International Journal of Combinatorial Optimization Problems and Informatics, Vol. 8, No. 3, Sep-Dec 2017, pp. 64-70. ISSN: 2007-1558.

Optimization Model for the Location of Prehospital Care Ambulances in the city of Cali Colombia

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Abstract. In 2015, authorities in Cali, Colombia, reported more than 309 deaths in traffic accidents, where 70% of the cases involved motorcycles. These figures generate concern in the city authorities, which leads to the study of alternatives for improving prehospital emergency care. The localization of ambulances is currently based on the experience of staff in Medical Emergencies. Thus, the distance between the location of the ambulances and the point of care is considered minimal. This paper presents a localization model to determine the number of ambulances needed to deal with emergencies reported by the city traffic bureau and its geographical location; different alternatives for improvement are evaluated. The proposed model is based on the expected maximum coverage location problem (MEXCLP), whose objective is to maximize the satisfied demand weighted by the availability of the service, which is calculated through the global estimate of the average occupancy level for each ambulance, based on the geographical and temporal distribution of historical demand. This means that research contributes to maximize coverage of reported emergencies by determining the number of ambulances needed for such care in the City under study. Finally, for its solution, a mathematical programming language and the platform NEOS Server for Optimization (https://neos-server.org/) are used.

Keywords: Prehospital care, Ambulance location, Model of maximum coverage expected.

1. Introduction

The emergency medical response service is responsible for providing timely care to the user or patient who is a victim of an illness or accident. In this case, the ambulance is required for the transfer of the patient to the hospital with medical assistance or to provide care in the same place where he has had the accident. The response time is considered as the time from the end of the emergency call to the time the ambulance arrives at the place; while the level of preparedness calculates the ability of the ambulance to provide medical service within the response time [1]. Medical Emergency Services (EMS) are systems that are responsible for the stabilization and pre-hospital transportation of patients with medical emergency. One of the constant concerns of the SEM is to improve the response time to the occurrence of an event, since this is a very important performance measure to determine the quality of prehospital care of the SEM and for the health of patients [1]. In addition, some studies have shown that there is a direct relationship between decreased response time and decreased mortality [2]. Generally, the response time is defined as the time interval between the time the service request is received and the time the SEM vehicle arrives at the scene of the incident [3]. Many variables in the operation of the SEM that affect the response time have been identified, and some of them are the location of ambulances.

The Traffic Operations Center in Cali and the Controlling and Emergency Center are responsible for receiving emergency calls. By simply dialing 1-2-3, the emergency call will be received by one of the reception operators in any center. The system identifies the telephone number and displays information on a city digital map. The operator asks basic questions contained in the system about the emergency, to get the necessary information to address the emergency. Once all the information is gathered, the system automatically identifies and sends dispatchers of the center that should address this incident, taking into account the type of emergency and its location. Subsequently the prehospital care is done at the place of occurrence and the patient is moved to the most appropriate care center. Once the emergency has been resolved, the operator is responsible for closing it and storing the information on a database of reported incidents (see Figure 1).

Received Jan 19, 2017 / Accepted Jun 10, 2017

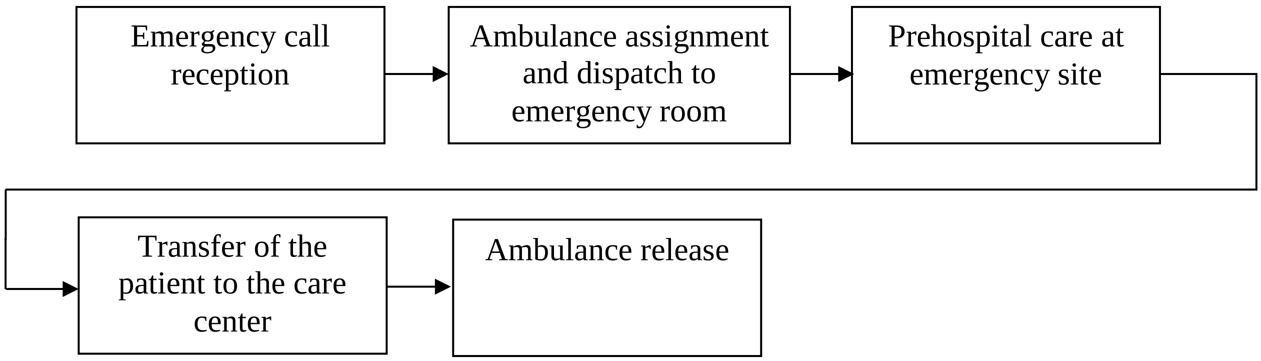

Fig. 1. Emergency care process in the city of Cali, Colombia.

2. Literature Review

The location of vehicles that are used for the provision of emergency services is important to ensure that the highest number of incidents is dealt with within a set time. There are several models, which are used to solve the problem of ambulance localization. The Location Set Covering Model (LSCM) is one of the first models of graphs proposed for the location of this type of vehicle, which aims to minimize the number of vehicles being required to cover all points of demand [4]. On the other hand, such authors as [5], [6] and [7] address the Maximal Covering Location Problem (MCLP), which considers the available number of vehicles to be assigned. In addition, this model improves the formulation of the problem by assigning a relative weight or demand to each demand point, aspect that in the present investigation is considered unlike the other works. The MCLP seeks to maximize covered demand within the maximum service time by a predetermined number of ambulances.

Also, such authors as [8] use the model MEXCLP (Maximal Expected Covering Location Problem) which includes the calculation of the probability that a vehicle is occupied, using an assumption of independence in the operation of vehicles in the system. Additionally, a heuristic for the location of vehicles is proposed, and the effect of the change in the number of available vehicles, on the coverage of demand, is analyzed. In addition [9] used genetic algorithms for vehicle location in an EMS, together with a forecast of future demand growth to evaluate the potential location of emergency vehicles under a projected scenario. However, unlike the present work, the availability of the service of a neighborhood or locality is not included when a certain number of ambulances are possessed within a coverage radius. Finally, [10] proposes a mathematical model based on the guidelines of the MEXCLP to find the number of ambulances that are needed to meet the demand of victims of traffic accidents. A second model is used, which combines the elements of the Set Covering Location Problem (SCLP) and the MEXCLP to minimize the number of stations where the ambulances, determined in the previous model, will be located.

There are variations of this model such as the TIMEXCLP, which includes the effect of the variation of the speed of movement throughout the day, and this is evaluated under a simulation environment [11], as well as the adjusted AMEXCLP or MEXCLP [12] in which an adjustment factor is applied to the objective function to take into account the fact that emergency vehicles do not operate independently, but unlike the present work, it does not involve the assignment of a relative weight or demand to each locality or place of attention. Another variation proposed for the SCLM and MCLP models takes into account that more than one vehicle is often required to assist an emergency report at a point of demand [13]. This variation is known as MLLSCP or Multi Level Location Set Covering, and this is also discussed in [14].

On the other hand, in [15] and [16] a programming model by objectives to determine the minimum number of vehicles required for emergency care in Riyadh City, Saudi Arabia, as well as their location, with a probabilistic component in the coverage of demand point is proposed. Also, [17] employs genetic algorithms for the current vehicle location in an EMS, together with a forecast of future demand growth to assess the potential location of emergency vehicles under the projected scenario in Niigata prefecture, Japan. However, the latter authors do not consider the calculation of the occupancy of the system, which is one of the most relevant elements of the model in this research.

Authors such as [18] addresses the problems of ambulance dispatching and ambulance redeployment, that is, deciding on which ambulance to send to an accident and choosing a base for the ambulance to return to after it finishes service. The goal in these problems is to minimize the fraction of late arrivals. As an alternative to the well-known closest-idle policy, they propose a dispatching policy that makes a weighted choice between distance to the accident and the coverage an idle ambulance currently provides. However, dynamic models are more recent. They consider the possibility to relocate the ambulances during the day. One of these models is presented by [19].

Finally, [21] present a problem regarding the response time, before the planned requirements and unforeseen situations, in which emergency vehicles or ambulances are requested. This article seeks to propose a dynamic routing model of vehicles with time windows DVRPTW, considering that the majority of ambulance transport operations, involve factors to the random requirements of emergencies and accidents, with the purpose of establishing an oriented structure the location, relocation and allocation of ambulances.

In general, the mathematical programming models used for the location of ambulances have a similar structure in which it is sought to maximize the responsiveness of the system [4]. To measure it is considered a maximum response time that determines the success of care, which in turn induces an area of coverage when it is decided to locate an ambulance in a certain place. So that it contributes to maximize the population coverage of the service.

However, the models applied to the location of ambulances did not consider the occupation of the system, implicitly assuming unlimited capacity [10]; which makes it impractical for the actual behavior of medical emergency systems. Therefore, the present investigation considers the occupation of the system, besides contributing to maximize ambulance service coverage to the target population.

3. Methodology

The methodology to be developed is part of the identification of basic information related to the Emergency Medical System connected to the number of traffic accidents that occur in a neighborhood or municipality, maximum coverage distance and the required time of ambulance care, as well as the results of such parameters of interest as the index of quality and occupation of the system. Subsequently a whole linear programming model is formulated from the given information, and by using a mathematical programming language, the respective model files, data and commands are designed. Finally, an analysis of the results is performed from the NEOS Server for Optimization platform (see Figure 2).

In other words, in the first instance, based on a mathematical programming model, the number of ambulances needed will be determined in order to maximize coverage for reported emergencies. For this purpose, it is considered relevant information such as number of accidents by communes or neighborhoods of the city, maximum distance of coverage, time required for care, Quality score and System Occupation.

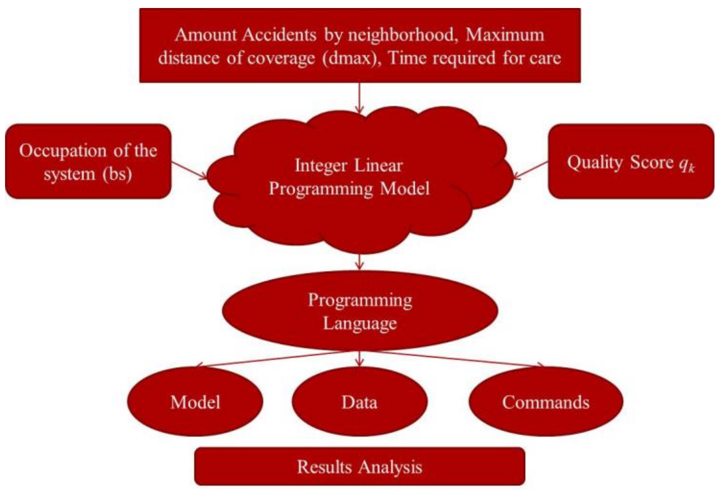

Fig. 2. Application Methodology

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4. Mathematical model

For the development of this research, a linear optimization model is used, whose structure is explained below.

4.1 Model Assumptions

The assumptions defined for the construction of the mathematical model were as follows:

(a) The dispatch bases are known;
(b) The neighborhoods or areas of attention are known and only those of the city urban perimeter are considered;
(c) A homogeneous fleet of ambulances is considered, that is to say, that they are equipped with the same resources and that they can address the same types of emergency,
(c) Relocation of ambulances is not considered and
(d) The demand of each neighborhood in Cali is given in minutes and is known.

4.2 Main Sets

BAR: Set of Neighborhoods in Cali indexed by i
AMB: Set of Potential Ambulance indexed by k
BAS: Set of Dispatch Bases indexed by j
$BMAX\{BAR\} \subseteq BAS$: Set of Dispatch Bases that are able to assist the neighborhood within the maximum response time indexed by j

4.3 Parameters

dem_i: Demand from each neighborhood i and Cali (minutes).
q_k: Index of quality that determines the availability of the service in a neighborhood when it has k ambulances within the coverage radius.
K: Number k of ambulances.
p: Number of potential ambulances to locate (Servers).

4.4 Decision Variables

Y_i: 1, if the neighborhood $i \in BAR$ is covered by the ambulance $k \in AMB$; 0 otherwise.
X_j: Number of ambulances located in the dispatch base $j \in BAS$

4.5 Model

$$Z_{max} = \sum_{i \in BAR} \sum_{k \in AMB} dem_i * q_k * Y_{ik} \quad (1)$$

Subject to:

$$\sum_{j \in BMAX} X_j \geq \sum_{k \in AMB} K * Y_{ik} \ ; \quad \forall\, i \in BAR \ \ (2)$$

$$\sum_{k \in AMB} Y_{ik} \leq 1; \quad \forall\, i \in BAR \ \ (3)$$

$$\sum_{j \in BAS} X_j <= p \quad (4)$$

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$$X_j \in \mathbb{Z}^+; \quad \forall\, j \in BAS \quad (5)$$

$$Y_{ik} \in \{0,1\};\ \forall\, i \in BAR, k \in AMB \quad (6)$$

Equation (1) is the performance function whose purpose is to maximize the expected total coverage weighted by the demand of each neighborhood, that is, it contributes to minimizing the expected weighted total demand of attention to the population of the districts or communes of the city under study (see Figure 3). The constraints (2) and (3) determine the level of availability offered to each neighborhood, where (2) ensures that the binary variable equals 1 when a neighborhood has k ambulances within a coverage radius and (5) ensures that only one quality index is considered for each neighborhood. Restriction (4) establishes the number of ambulances to be located. Finally restrictions (5) and (6) represent the logical or non-negativity constraints.

From the duration of the shift t and the total aggregate demand, the occupation of the system is estimated, which is one of the most relevant elements of the model, which is given by the following equation:

$$bs = \frac{Total\ Demand\ (time)}{\#servers * shift\ duration\ (time)} \quad (7)$$

Finally, based on obtaining this value, the quality index q_k is calculated from the following expression:

$$q_k = 1 - bs^k \quad (8)$$

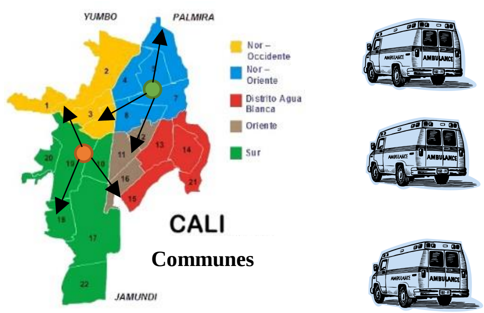

Fig. 3. Emergency Care Coverage.

5. Case study

In order to conduct this research, information provided by the city's traffic center in 2015 was taken as a basis. A statistical analysis of the information provided was performed, determining the number of incidents per neighborhood. An important factor to be considered within the model is the time required for addressing events. It was found that more than 75% of the events reported, in which there was record of attention, time is approximately 60 minutes. Based on this information, it was decided to use a time period of 60 minutes per event when determining the care load generated by each neighborhood; there were only available records for 25 of them. Another important factor of the model is the maximum coverage distance (d_{max}). In this case, the desired maximum response time was 15 minutes, which implies a maximum distance of 7.50 km when using an average speed of 30 km / h and shift t, which is equal, in this case, to 8 hours (6:00 a.m. - 2:00 p.m.).

6. Analysis of Results

The computational results obtained by the mathematical model, using the computer language AMPL (A Mathematical Programming Language), and using the CPLEX solver of the platform NEOS SERVER for OPTIMIZATION, will be presented and the mathematical model will be forced to decide the number of ambulances that are going to be located in

Cali; this issue will allow validation of the results obtained in the optimization instance. A total of 252 variables were generated, of which 250 of these are binary and 2 of integer type; likewise, a total of 51 restrictions. Table 1 shows the result achieved for the model, whose optimum result corresponds to the opening of ten ambulances, generating a total coverage of the ambulance network of 1392 units of time (minutes); where the first column of table 1 denotes the total aggregate demand in hours; column 2 is the number of servers or ambulances in the system and the calculation of the occupation and availability of the system in columns 3 and 4 respectively. The model also suggests a uniform distribution of ten ambulances in two dispatch bases.

Table 1. Model ambulance localization results in Cali, Colombia.

Demand (hours)	Number of serves (p)	Occupation (bs)	Availability (qk)
25	4	78,13%	62,75%
25	5	62,50%	90,46%
25	6	52,08%	98,00%
25	7	44,64%	99,65%
25	8	39,06%	99,95%
25	9	34,72%	99,99%
25	10	31,25%	100,00%

Based on the results of the table, it is possible to identify that the optimal number of ambulances necessary to meet the emergency demand of the population under study are 10 (ten), in this way it contributes to maximize the coverage of the demand Expected. The ambulances are uniformly distributed in two bases of dispatch of the city.

Comparing the results of the model of the present research against some formulated by authors cited in the literature as (5-7) and (15-21), present good results; Because in addition to maximizing the coverage of emergency demand from the population under study, it considers the occupation of the system; Which makes from the practical point of view, a viable alternative for the city. On the other hand, other authors assume that this is unlimited, which in real cases of hospital logistics or emergency medical services are not real.

7. Conclusions and Future Research

In the configuration of the ambulance network, an important result that contributes to the decision-making process is related to the location of ambulances to cover the total demand of each neighborhood or area of attention; thus, generating an optimal decision-making at a strategic level. It can be seen from the results that the location of ambulances plays an important role in the logistic decision-making in the city under study; however, it should be taken into account that this selection is based on the total coverage of the population,

Therefore, for future research, different criteria that support the location of ambulances should be included. Otherwise, it would be important to include restrictions of capacity and availability of vehicle resources and consider different types of ambulances or vehicles to be used in the network. Although it is true that the development of a network of ambulances generates positive impacts, both in the attention of the accident rate, reduction of the mortality rate, among others, these are issues that were not taken into account; if they were to be considered, that could imply a multiobjective problem. Finally, the best configuration of the ambulance network is obtained with the location of ten vehicles in the city; however, it would be interesting to extend this case study to other neighborhoods in the city and include operational decisions regarding routing of the vehicle care units. Based on the size of the example used in this research, the results were obtained in an efficient computational time. Finally, ambulance relocation and its impact on patient care are suggested for future research. Likewise, the diffuse coverage to determine the quantity and location of dispatch bases in the city under study should be considered as well and an analysis of computational complexity from this variant.

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