Computers in Biology and Medicine 80 (2017) 107–113

Contents lists available at ScienceDirect

Computers in Biology and Medicine

journal homepage: www.elsevier.com/locate/compbiomed

Optimizing the location of ambulances in Tijuana, Mexico

Juan Carlos Dibene[a], Yazmin Maldonado[a,*], Carlos Vera[b], Mauricio de Oliveira[c,*], Leonardo Trujillo[a,*], Oliver Schütze[d]

[a] Posgrado en Ciencias de la Ingeniería, Instituto Tecnológico de Tijuana, Tijuana, BC, Mexico
[b] Universidad Autónoma de Baja California, Tijuana, BC, Mexico
[c] MAE, University of California San Diego, La Jolla, CA, USA
[d] CINVESTAV-IPN, Mexico, DF, Mexico

ARTICLE INFO

Keywords:
Emergency Medical Services
Ambulance Location Problem
Optimization
Double Coverage Models
Integer Programming

ABSTRACT

In this work we report on modeling the demand for Emergency Medical Services (EMS) in Tijuana, Baja California, Mexico, followed by the optimization of the location of the ambulances for the Red Cross of Tijuana (RCT), which is by far the largest provider of EMS services in the region. We used data from more than 10,000 emergency calls surveyed during the year 2013 to model and classify the demand for EMS in different scenarios that provide different perspectives on the demand throughout the city, considering such factors as the time of day, work and off-days. A modification of the Double Standard Model (DSM) is proposed and solved to determine a common robust solution to the ambulance location problem that simultaneously satisfies all specified constraints in all demand scenarios selecting from a set of almost 1000 possible base locations. The resulting optimization problems are solved using integer linear programming and the solutions are compared with the locations currently used by the Red Cross. Results show that demand coverage and response times can be substantially improved by relocating the current bases without the need for additional resources.

1. Introduction and related work

The population in Tijuana is approximately 1.6 million inhabitants [13]. Currently, the Red Cross of Tijuana (RCT) has 11 ambulances in service and 8 ambulance bases, this means that there is one ambulance for every 145,000 inhabitants, while smaller cities in the USA by the 1990's already had around one ambulance per 51,000 inhabitants [3]. Nevertheless, the RCT covers about 98% of the requests for emergency medical services (EMS) received by the city [6], providing medical attention to 37,000 people in 2013. The lack of resources, and their sub-optimal use, is evident when we consider that the average response time of RCT ambulances was approximately 14 min with a standard deviation of 7 min. These performance measures are discouraging. For instance, the National Fire Protection Association of USA recommends that basic life support services should arrive to the scene of an emergency within 4 min, while advanced life support providers should arrive within eight minutes for all EMS calls [21,29]. Another example is the *United States EMS Act* [2], which states that 95% of EMS calls should be served within 10 min. The US EMS is the standard that we will adopt in the present work.

One of the core problems for EMS is to determine the optimal location of available resources, particularly ambulances [10]. The ability of EMS to save lives greatly depends on the time it takes for an ambulance to arrive on the scene of an emergency after an emergency call is received. A useful summary on how EMS operate is provided in Brotcorne et al. [4], who state that *time is vital in emergency situations*, and it is therefore *critical that vehicles be at all time located so as to ensure and adequate coverage and quick response time* of EMS units or ambulances. EMS planners must determine the best locations for the ambulances at their disposal such that EMS can be delivered in a timely and efficient manner, what is known as the ambulance location problem [4]. Despite the fact that some works suggest that meeting these response times may not improve the patients probability of survival [21], it has been found that large deviations from these standards can greatly degrade the condition of the patients [29].

1.1. Previous work

The ambulance location problem has been studied for several years now, with a variety of solution methods and approaches proposed over the years [4]. Ranging from very simple approaches, such as the set

* Corresponding authors.
E-mail addresses: juan.carlos.dibene.simental@gmail.com (J.C. Dibene), yaz.maldonado@tectijuana.edu.mx (Y. Maldonado), cvera@eng.ucsd.edu (C. Vera), mauricio@ucsd.edu (M. de Oliveira), leonardo.trujillo@tectijuana.edu.mx (L. Trujillo), schuetze@cs.cinvestav.mx (O. Schütze).

http://dx.doi.org/10.1016/j.compbiomed.2016.11.016
Received 17 June 2016; Received in revised form 28 November 2016; Accepted 28 November 2016

covering model [27], or more complex probabilistic models like the maximum expected covering location problem [7]. Moreover, solution strategies to these problems have varied from mathematical programming techniques, such as Integer Linear Programming, to meta-heuristic approaches like genetic algorithms, recently reviewed in [15]. In particular, one of the most successful approaches has been the *Double Standard Model* (DSM) of [9]. This model has been used to optimize the location of ambulance services in Belgium [26], Canada [9] and Austria [8], proving to be one of the most widely accepted and used models of the ambulance location problem [14]. One recent example is the work by Schmid and Doerner [24], that apply the DSM over successive time periods to account for varying travel times across the day. For these reasons, this work proposes an extension of the DSM, considering multiple scenarios concurrently to obtain robust solutions over all scenarios. However, we first provide a brief overview of other recent approaches to the ambulance location problem.

The reference [23] concurrently solves the dynamic ambulance relocation problem along with the ambulance dispatching problem. The model proposed by Schmid is a Markovian state-based representation, where states are defined by the location and status of each ambulance and the status of all emergency calls received up to time t. The model is posed as a reinforcement learning problem using Bellmann's equation and solved using Approximate Dynamic Programming. The case study is for the city of Vienna, with a substantial improvement based on average response time. This work confirms the need to consider how the problem changes relative to the time of day, as is done in the present paper.

Another recent approach is presented by Hoon Kim [22], they propose a hypercube method to minimize the number of ambulances at each candidate base i, using a confidence level $\epsilon[0, 1]$ [5], that should be less than the probability that one or more ambulances are available within a time to get a reliable coverage S. Their approach is based on the probabilistic location set cover problem (PLSCP) [1] and implement a simulation based method based on [25] to replace the hypercube method and evaluate their approach. The proposed algorithm initializes the interaction parameters and the optimization model generates the number and location of ambulances according to the initialization. The hypercube model validate the optimization solution, if the solution is viable the algorithm is finished, if not, it iterates to generate new values. The authors conclude that both approaches are equivalent in terms of solution quality, but the hypercube method is more efficient and requires less computation time.

Similarly, Geroliminis [20] also employ a hypercube model for the optima deployment of emergency response units, focusing on the city of Athens, Greece, and transit mobile repair units. They solve the problem using a meta-heuristic search (genetic algorithm), using a two step approach considering both the partitioning of the service area and the number of units per partition concurrently, based on the queuing model. Their results show adequate performance for the studied problem. The authors show that it is important to consider a proper partitioning of the service area, which in the present work is done through hierarchical clustering.

1.2. Summary of proposal

In this work we propose solutions to the ambulance location problem in Tijuana using a robust version of the well known and widely adopted *Double Standard Model* (DSM) [9]. Historical data from the RCT is used to build realistic scenarios, each with distinct characteristics and requirements. In particular, our results show that the current deployment and usage of the limited resources by the RCT leads to a sub-optimal coverage of the city. We show that by expanding the number and location of possible bases the coverage can greatly improve and meet stringent performance criteria, such as those used in USA [2]. Moreover, by posing a robust version of the DSM, we are able to find a solution that covers different demand scenarios quite well without the need to use possibly costly or logistically complex relocations, as is done, for instance, by Schmid and Doerner [24].

The remainder of this paper is organized as follows. The current ambulance location problem in Tijuana is described in Section 2. A detailed analysis of the considered EM demand is presented in Section 3. The proposed model for the ambulance location problem is presented in Section 4, which is based on the DSM. A discussion of the obtained results is given in Section 5. Finally, Section 6 contains our main conclusions and outlines future work.

2. Ambulance location problem in Tijuana

In order to optimize the location of the ambulances in the city of Tijuana, Mexico, a model was built that includes the following information:

1. *Potential Base Locations*, which consists of public and private spots in Tijuana identified as potential locations for the ambulances to be placed while waiting for calls.
2. *Call Demand and Priority*, in the form of a history of EMS calls and the geographic location of their origination; calls where classified using a color scale representing the priority level of each call.
3. *Demand Scenarios*, representing demand variations due to the time of the day (mornings, afternoons, evenings or night) and type of day (workdays or off-days).
4. *Demand Points*, representing meaningful partitions of the city in discrete regions for the purpose of concentrating EMS calls;
5. *Average Travel Time*, between the potential base locations and the demand points.

The methods and procedures used to gather the above information will be described in the next paragraphs.

2.1. Potential base locations

We selected a total of 961 potential location sites in the city of Tijuana among shopping malls, schools, government offices and fire stations. Potential bases should provide some basic features, such as a proper parking space for the ambulance, access to electrical sockets to recharge equipment, shade, WC, and general security for the personnel and equipment. To these locations we added the 8 locations currently used as bases by the RCT, totaling 969 potential base locations. The geographic coordinates of these potential bases were obtained from the *Google Places API* [12]. All potential base locations are shown in the map of Fig. 1.

2.2. Call demand and priority

A total of 10,512 calls requesting EMS provided by RCT were collected from January, 1st to August, 31st of 2014. Of these, 7746 contained information that could be used to locate the site where the medical service was required. Those calls were the ones used to generate our demand models. Note that getting access to this data requires special permissions from the RCT. Furthermore, the database requires extensive processing before performing the optimization process since data collection is currently not done with this task in mind.

These records contain the GPS location of the call originator as well as a color representing the *priority* of the call. Four priority levels were used: priority *Red* being the highest of all, then *Yellow*, then *Green* and finally *Black*, which is the lowest priority. The location of all EMS calls used in our demand model are shown in Fig. 2. A summary regarding call priority is given on Table 1, which is discussed in the next subsection.