A Comparison of Ambulance Location Models in Two Mexican Cases

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Abstract

The development of several ambulance location models have been discussed in the academic literature. Most of these models have been further extended to consider more realistic situations into account and the use of different assessment criteria. However, there is not an exhaustive literature that takes the existing standard models to compare them according to the criteria used in practice. In this work, we undertake the task of comparing the performance of several ambulance location models on coverage and response time criteria. The results of this work are important to help emergency medical organizations to define their most adequate model for defining their ambulance base structure. The comparison of the models is carried out in two Mexican emergency operations of the Red Cross located in the cities of Monterrey and Tijuana.

Keywords
Ambulance location; response time; demand covering; ambulance availability

1 Introduction

The emergency medical services (EMS) providers are responsible of the pre-hospital care and transportation of the patients to a medical center. They are in charge of the first medical contact with the patient since an emergency call enters to a call center. The quality of these services, offered either by public or private companies, has a potential direct impact on the patient survival, especially when the cause of the call is a life-threatening disease (Rodriguez et al, 2016), and it has been of interest for OR researchers in the last four decades.

There is a vast literature in OR approaches to solve the problems arisen in both strategic and tactical levels of the EMS planning process. There are several recent reviews that address them as well as identify new challenges (Hadiyul et al, 2018, Rodriguez et al, 2017, Reuter-Oppermann, 2017, Aringhieri et al, 2017 Ahmadi-Javid et al, 2016, Li et al., 2011). The location of bases for ambulances is one of the strategic decisions of this EMS planning process. Only Reuter-Oppermann et al. (2017) refer more than 33 papers dealing with ambulance location problems especially in European countries such as UK, Germany and the Netherlands. However, very few studies have been found in LA countries (Dibene, 2017 in Mexico; Andrade et al, 2015 in Brazil; Cespedes et al, 2008 in Colombia, and Rodriguez et al, 2016, a review).

One of the most common process' performance indicator of the ambulance location problem is the response time (RT), which is measured since a call enters until the ambulance arrives at the patient's location. It includes a pre-trip delay for triage and dispatch, and the ambulance travel time. RT is one of the five key indicators defined to monitor and evaluate the pre-hospital emergency care by the European Emergency Data Project (Reuter-Oppermann, 2017). In Tijuana, Mexico, for example, the average response time was reported to be 14 min with a standard deviation of 7 min (Dibene et al., 2017); nevertheless the National Fire Protection Association's recommendation is to attend a call within 8 minutes, so that there is still room for researchers to improve this situation. The Average Response Time model (ARTM), which is equivalent to a p-median model, has shown to outperform others in terms of response time (van den Berg, 2016).

There are other process indicators that are used in the objective function such as preparedness level, vehicle utilization, staff utilization or balance, late response, lost calls, etc. (Rodríguez et al, 2016). Among the outcome quality indicators used in OR approaches is the survival rate, however a general patient's health status to include all patients and not only the critical ones should be preferred.

Another way to evaluate the performance of EMS services is from the covering perspective. In this case, a standard or goal is defined in terms of the amount of demand that should be covered in a given period. (i.e. the EMS Act of 1973 says that in urban areas 95% of requests should be reached within 10 min (Li et al, 2011)). Covering location problems have been addressed since the 70's, either guaranteeing a total covering or maximizing it. However, while a call is being attended, other demand points in the same call's area are left unattended. This has motivated additional coverage approaches. The double standard model (DSM), proposed by Gendreau et al (1997) has been the pioneer approach in the strand of models providing additional covering.

When uncertainty is taken into account, it is considered in three types of factors: demand, availability of EMS vehicles, and response times. Those models that include uncertainty have shown to give better coverage estimates (Erkut et al., 2008). In the strand that considers the probability that an ambulance is busy, the Maximum Expected Covering Location Problem (MEXCLP) has proven to outperform other related models (van den Berg, 2016). This model has also been the basis for multiple extensions, including stochastic programming techniques (Reuter-Opermann et al, 2017).

In this work, we undertake the task of comparing the performance of three static location models that have shown to perform well in European scenarios: the DSM, the ARTM, and the MEXCLP. Unlike the literature found, the models compared include some extensions, such as service differentiation and multi-period decisions. In addition, the comparison of the models is carried out in two Mexican emergency operations of the Red Cross located in the cities of Monterrey and Tijuana, in Mexico. The rest of the paper is structured as follows: Section 2 describes the three models to be compared, using common notation. Section 3 describes the data structure and collection for the two cases. Section 4 presents the most interesting results that emerged from the comparison. Finally, some summary conclusions are remarked.

2 Ambulance Location Models

In this section we describe the three models to be compared. These versions extend the originals in the sense that they (a) consider different type of services and (b) are multi-period.

2.1 Double Standard Model (DSM)

The DSM focuses on covering each demand zone twice (e.g. by two ambulances). To do this, it considers two target response times r_1 and r_2, $r_1 < r_2$. While the r_2 target must be covered for all demand zones, the r_1 target must be covered by a fraction α of the weighted demand.

Sets:

$i \in I$: demand zones $\{1,2,3,\cdots,D\}$
$j \in J$: potential bases $\{1,2,3,\cdots,B\}$, so p is the maximum number of locations to open.
$k \in K$: ambulances $\{1,2,3,\cdots,A\}$, so A is the maximum number of ambulances to be assigned
$s \in S$: service types $\{1,2,3\}$, so each service type has its own priority.
$t \in T$: time slots $\{1,2,3,\cdots T\}$

Parameters:

α: Minimal coverage in r_1 (%)
W_{its}: Weighted demand in point i, for service type s, at time t.
q_j: Maximum number of ambulances at location i (e.g. 1 $\forall j$)

$a_{ij}^1 = \begin{cases} 1 \text{ if location } j \text{ covers demand point } i \text{ within } r_1 \\ 0 \text{ otherwise} \end{cases}$

$a_{ij}^2 = \begin{cases} 1 \text{ if location } j \text{ covers demand point } i \text{ within } r_2 \\ 0 \text{ otherwise} \end{cases}$

Variables:

$y_{ikt} = \begin{cases} 1 \text{ if demand point } i \text{ is covered } k \text{ times at time interval } t, \text{within } r_1 \\ 0 \text{ otherwise} \end{cases}$

$x_j = \begin{cases} 1 \text{ if a base is open at location } j \\ 0 \text{ otherwise} \end{cases}$

u_{jt} = Number of identical ambulances assigned at base *j* at time *t*.

Z_{DC}= Weighted double coverage

DSM

$$\max Z_{DC} = \sum_i \sum_s \sum_t (w_{its}\, y_{i2t}) \quad (1)$$

Subject to:

$$\sum_j a_{ij}^2\, u_{jt} \geq 1 \quad \forall\, i, t \quad (2)$$

$$\sum_s \sum_j w_{its} y_{i1t} \geq \alpha \sum_s \sum_j w_{its} \quad \forall t \quad (3)$$

$$y_{i,k+1,t} \geq y_{2ikt} \quad \forall i, t \quad (4)$$

$$\sum_j a_{ij}^1\, u_{jt} \geq y_{i1t} + y_{i2t} \;\forall i, t \quad (5)$$

$$u_{jt} \leq q_j\, x_j \quad \forall j, t \quad (6)$$

$$\sum_j u_{jt} = A \quad \forall t \quad (7)$$

$$\sum_j x_j \leq p \quad (8)$$

$$x_j \in \{0,1\} \quad \forall j; \qquad y_{ikt} \in \{0,1\} \quad \forall i, t \qquad u_{jt} \geq 0, integer \quad \forall j, t \quad (9)$$

The objective function (1) maximizes the weighted demand double coverage. Total coverage by at least one vehicle in response time r_2 is given by equation (2). Equation (3) set the partial coverage by at least one vehicle in r_1. Equation (4) guarantees the order of ambulances covering a given base every time, while equation (5) establishes the double coverage. Equation (6) determines the number of ambulances located at each base, and equations (7) and (8) limit the number of ambulances to be located and the number of bases to be opened. Equation (9) establishes the domain of the variables.

2.2 Average Response Time Model (ARTM)

The ARTM looks to minimize the average response time from the nearest base. Although placing more than one ambulance does not improve the objective function, the same decision variables and nomenclature are maintained for comparison purposes. An additional variable y_{ij} is used to identify the nearest base.

Sets: Same sets as DSM.

Additional Parameters:

tp_{ij}: Response time from location *j* to point *i*.

Additional Variables:

$y_{ijt} = \begin{cases} 1 \text{ if the open base } j \text{ is the nearest opened base to demand point } i \text{ at time } t \\ 0 \text{ otherwise} \end{cases}$

tm_{it}: Minimum response time to get location *j* from the nearest base opened at time t

Z_{RT}: Average response time

y_t^2: Total weighted demand covered within r_1

α_t: % weighted covered demand at time *t*

ARTM

$$\min Z_{RT} = \sum_i \sum_s \sum_t \sum_j w_{its}\, tp_{ij}\, y_{ijt} \quad (10)$$

Subject to:

$$\sum_j y_{ijt} = 1 \quad \forall i, t \quad (11)$$

$$y_{ijt} \leq x_j \quad \forall\, i, j, t \quad (12)$$

$y_{ijt} \in \{0,1\} \quad \forall\, i, j, t$ (13)
+ equations (6) to (9)

In addition, the following constraints were used to correlate the other models:

Equations (1), (4) and (20)
$\sum_j a_{ij}^2\, u_{jt}/BD = y_t^2 \quad \forall\, i, t$ (14)
$\sum_s \sum_j \, w_{its} y_{i1t} = \alpha_t \quad \forall t$ (15)
$tp_{ij}x_j \;\geq\; tp_{ij}y_{ijt} \quad \forall i, j, t$ (16)
$tm_{it} = \sum_j tp_{ij}y_{ijt} \quad \forall i, t$ (17)
$tm_{it} \geq 0 \quad \forall i, t; \qquad y_t^2 \geq 0 \quad \forall t$ (18)

The objective function (10) minimizes the average response time. Equations (11) and (12) guarantees that every demand zone has a nearest opened base covering it. Equations (6) to (9) set the available resources as mentioned before. In this model, there is no a total coverage by at least one vehicle in response time r_2, so the coverage is computed in (14). Equation (15) computes the partial coverage by at least one vehicle in r_1 at each time. Equations (16) and (17) identify the nearest opened base to demand zone *i* and keeps the corresponding minimum response time to that zone in tm_{it}. Equations (13) and (18) establish the domain of the variables. Equation (20) is part of the MEXCLP model which will be explained next.

2.3 Maximum Expended Covering Location Problem (MEXCLP)

This model considers the concept of marginal coverage. Proposed by Daskin (1983), it uses the expected coverage where each additional ambulance can offer some coverage to a given region. To do this, it considers a fixed long-term probability, $\rho < 1$, that an ambulance is busy within the target response r_1 (Kerkkamp. 2014).

Sets: Same sets as above.

Additional Parameters:
ρ: Probability that an ambulance is busy (or not available/ not working) within r_1.

Additional Variables:
Z_{XC}: Expected coverage

MEXCLP

$\max Z_{XC} = \sum_i \sum_s \sum_t w_{its} \sum_k \rho^{k-1}\,(1-\rho)\, y_{ikt}$ (19)

Subject to:

equations (6) to (9)
$\sum_k \, y_{ikt} = \sum_j a_{ij}^1\, u_{jt} \quad \forall i, t$ (20)

In addition, the following constraints were used to correlate the other models:

Equations (1), (4) , (10), (14), (15), and (19)

The objective function (19) maximizes the expected coverage within r_1. Equations (6) to (9) set the available resources, as expressed before. Equation (20) counts the number of covering locations within r_1, guaranteeing that all ambulances covering demand zone *i* within r_1 are identified.

3 The Two Mexican Cases

3.1 Mexican Red Cross in Monterrey

Monterrey is the capital of the northeastern state of Nuevo Leon, in Mexico. Its metropolitan area is the third-largest in Mexico with more than 5,300 km^2 of area and 4.7 million inhabitants (INEGI, 2015). To optimize the location of ambulances in this city, the model considered the following:

Demand zones: Demand zones were constructed such that they represent significant partitions of the city in discrete regions in order to concentrate the EMS calls. The city of Monterrey and its metropolitan area was divided into quadrants of approximately 23km^2, dividing it into 42 equal parts, allowing each incident to be cataloged within a quadrant. Each demand zone corresponds to a quadrant. Figure 1 shows the area under study and identifies the centroids of each quadrant, which will be referred as demand points.

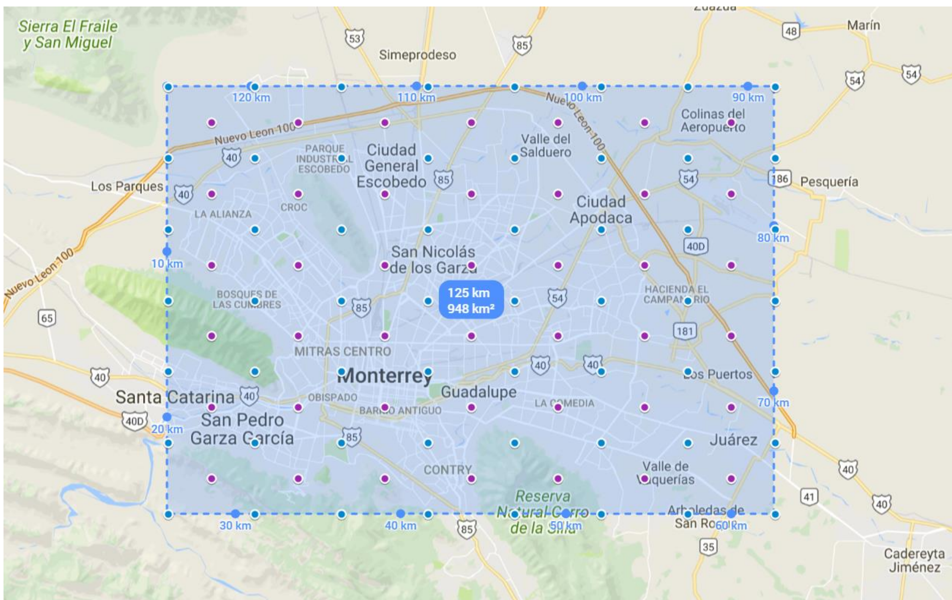


Figure 1. Monterrey area under study with demand points.

Potential base locations: Potential bases should provide some basic features, such as an adequate parking space for the ambulance, access to electrical outlets for recharging equipment, shade, WC and general security for personnel and equipment. The potential base locations considered in this work consist of convenience stores in Monterrey identified as potential locations to place ambulances while waiting for calls. We selected a total of 884 possible sites of location in the city of Monterrey. The geographic coordinates of these potential bases were obtained from INEGI. All possible base locations are shown in Figure 2.

Demand call and priority: To represent the demand, we use from an EMS provider the call history and the geographical location of the calls origin. In this case, a total of 14,368 calls that requested EMS provided by Red Cross of Monterrey were collected from November 2016 to April 2017. These records contain the GPS location of the originator of the call, as well as three priority levels of each call (Siren, Silent Urgency, Make the service brief). Figure 3 shows the location of all EMS calls used in our demand model.

Demand scenarios: After analyzing the demand behavior, we selected four scenarios which represent variations in demand due to the time of day: morning, afternoon, night, and an overall case.

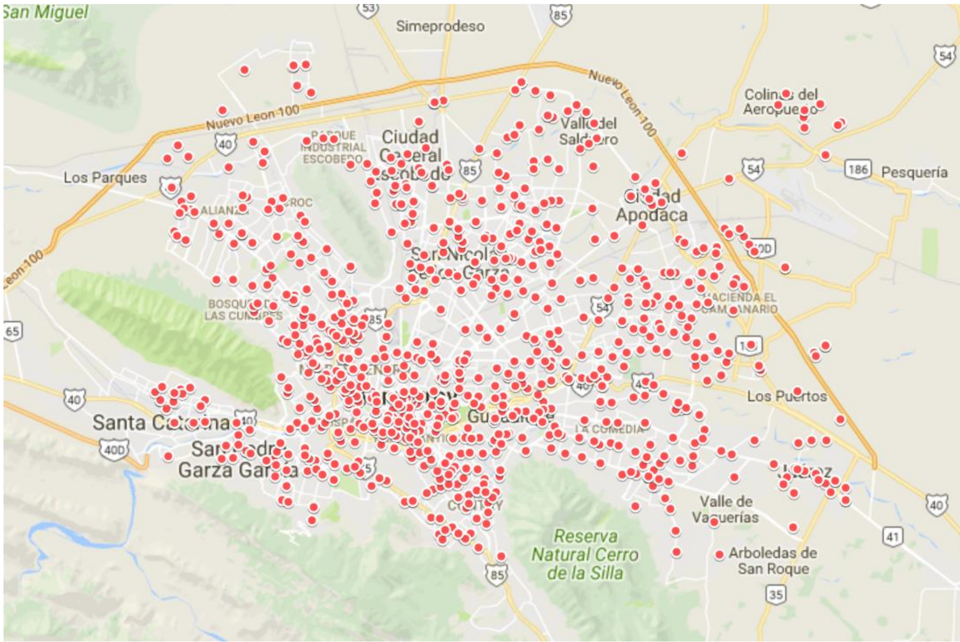


Figure 2. Potential base locations in Monterrey

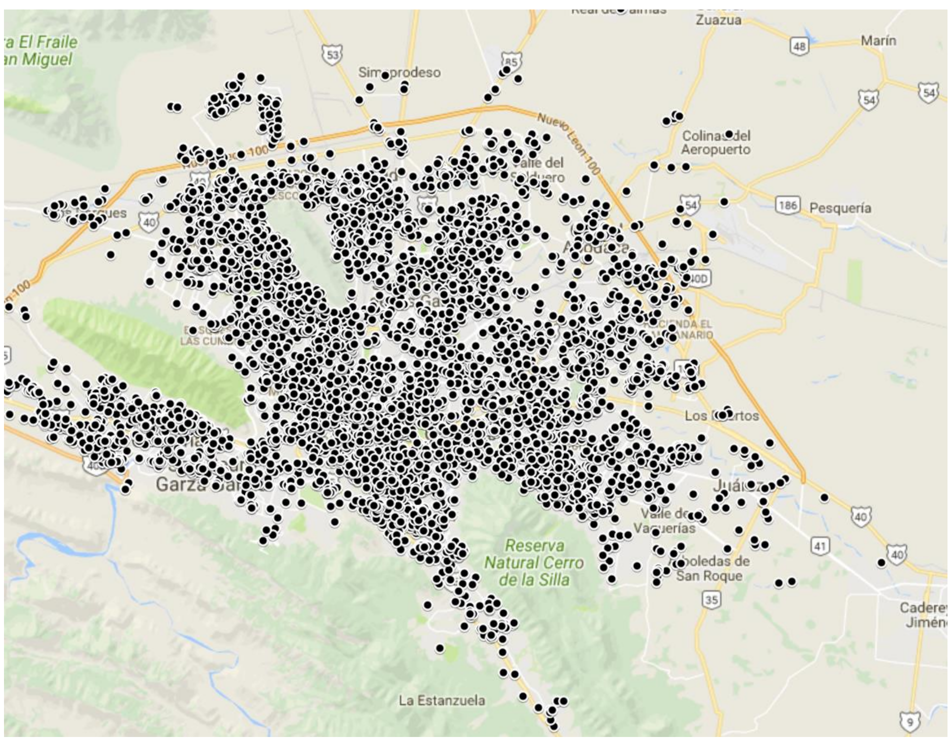


Figure 3. Location of calls during the period of study in Monterrey

Average travel time: The travel times used in the models are the average travel time between the potential base locations and the demand points, calculated by an average speed using Google Maps and its forecast of average transfer times between strategic points in the city.

3.2 Tijuana

Tijuana is the largest city on the Baja California Peninsula, located at the northwestern of Mexico, next to the US border. Its metropolitan area has more than 1,390 km^2 of area and 1.8 million inhabitants (INEGI, 2015). To optimize the location of ambulances in this city, the model considered the following:

Demand zones: The city of Tijuana and its metropolitan area was divided into quadrants of approximately 25km^2, dividing it into 15 equal parts, allowing each incident to be cataloged within a quadrant. Figure 4 shows the area under study and identifies the demand points.

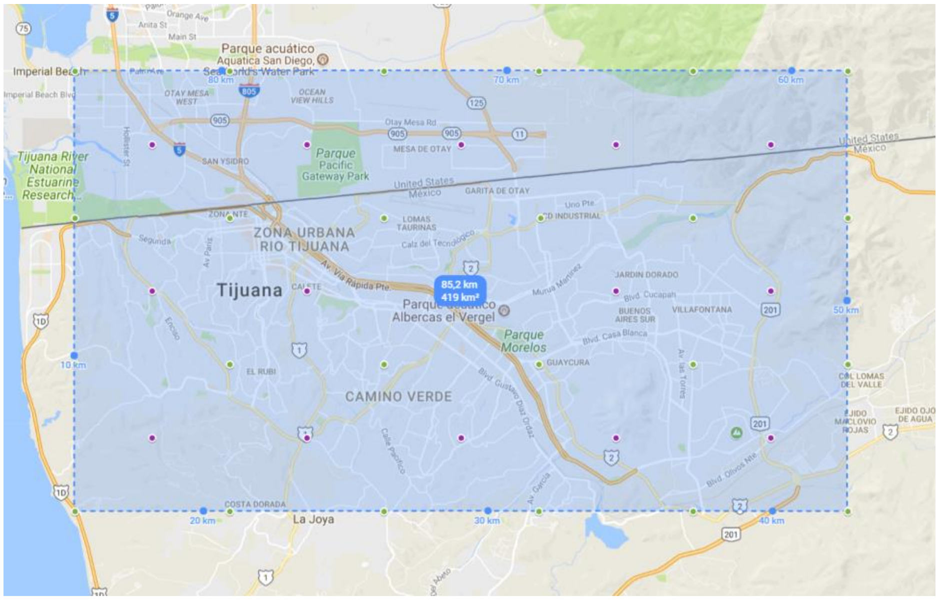


Figure 4. Tijuana area under study with demand points.

Potential base locations: With the same considerations as for Monterrey, we selected a total of 434 possible location sites in the city of Tijuana. The geographic coordinates of these potential bases were also obtained from INEGI. All possible base locations are shown in Figure 5.

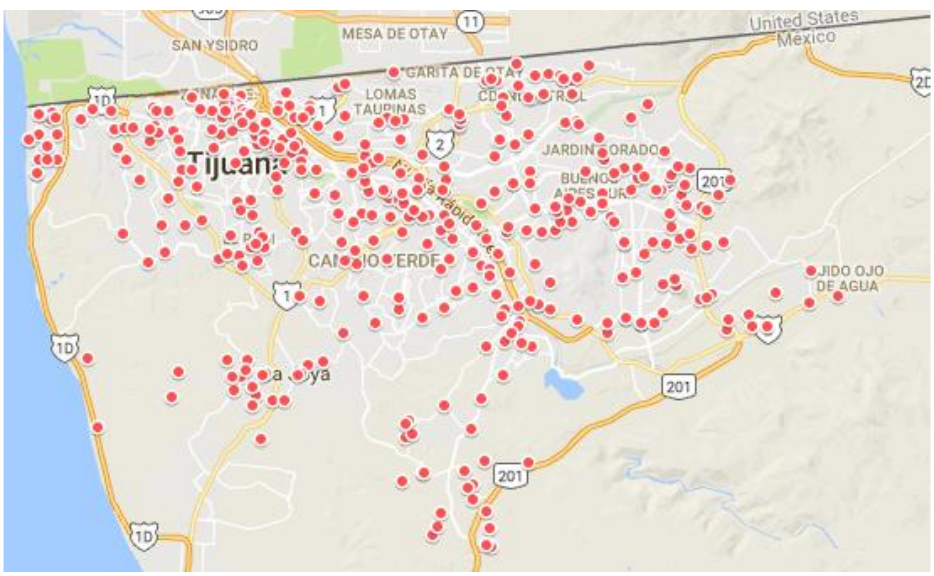


Figure 5. Potential base locations in Tijuana

Demand call and priority: As for Monterrey, we use from an EMS provider the call history and the geographical location of the calls origin. In this case, a total of 10,176 calls that requested EMS provided by the Red Cross of Tijuana were collected from January 1 to August 31, 2014. These records contain the GPS location of the originator of the call, as well as the same priority levels of each call. The location of all EMS calls used in our demand model is shown in Figure 6.

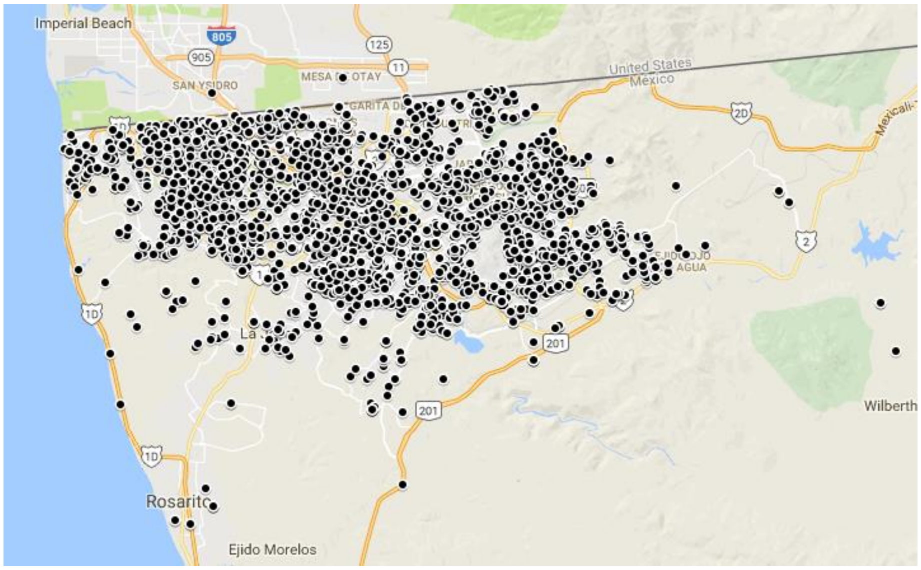


Figure 6. Location of calls during the period of study in Tijuana

Demand scenarios and average time travel were constructed in the same way as for Monterrey.

4 Numerical Experimentation and Results

In this section we describe the experimentation settings, the performance measures used to compare the three models under study, and finally the results obtained from the numerical experimentation.

4.1 Experimentation settings

The three models were implemented in GAMS 23.5 and solved with CPLEX in a standard laptop (i.e. Intel® Core™ i7-4600M CPU @ 2.90 GHz 2.90 GHz with 8GB RAM). They were run for the both cases: Tijuana and Monterrey. After solving each model, the additional variables needed to evaluate the other two models were computed either in GAMS or post-processed in Matlab. The same values were used in the three models for the following parameters: r_1= 15 minutes, $r_2 = 30$ minutes, $\alpha = 0.7,\ \rho = 0.7.$ p was set to 20 for Tijuana and 40 for Monterrey. The number of ambulances A were varied one by one from 6 to p, since below 6 at least one model was infeasible in both cases. Though the models consider multi-period data and decisions, available demand data were split in three scenarios, depending the time of the day (i.e. am, pm, and night), and a fourth scenario was also considered, which includes the entire day. The scenarios were run independently, to be able to distinguish the behavior in each scenario.

4.2 Performance indicators

The indicators chosen to compare the three models are based on their objective functions; and are the most common criteria considered in the literature (van den Berg et al, 2016, Rodriguez et al, 2016, Hadiyul et al, 2018). Computation times turned out to be irrelevant to the discussion because their values were small and very similar (i.e. just a few seconds), especially considering that these models are used for strategic decisions.

The comparison criteria used are grouped in coverage related and response time related indicators:

Coverage related criteria: the first three criteria represent the % of locations covered once, twice, and three times within r_1. This criteria has into account an equity principle which is not affected by the demand weight. The fourth criterion corresponds to the objective function of the DSM, this is, the double weighted demand coverage.

Response time related criteria: we compared the maximum response time, the average response time which is the objective function of the ARTM, and the first location coverage in two time thresholds: 10 minutes and 30 minutes.

4.3 Experimentation results and discussion

Table 1 presents the results for the 8 performance indicators. They consist on the average of the runs varying the number of ambulances from 6 to p for the four scenarios.

Table 1. Average results of the three models for the two cases

Criterion	Description	TIJUANA			MONTERREY		
		DSM	ARTM	MEXCLP	DSM	ARTM	MEXCLP
1	Single zone coverage	91.6%	80.4%	85.8%	86.3%	73.6%	66.5%
2	Double zone coverage	87.1%	26.2%	69.3%	74.8%	38.8%	50.5%
3	Triple zone coverage	12.0%	9.8%	52.9%	4.6%	8.5%	38.3%
4	Double coverage	98.6%	46.0%	92.1%	88.4%	63.6%	81.8%
5	Max. response time (min)	27.94	30.81	39.95	29.72	44.69	68.44
6	Avg. response time (min)	11.84	5.74	14.24	11.60	8.33	17.45
7	10 min threshold	30%	77%	18%	36%	56%	18%
8	30 min threshold	100%	100%	96%	100%	96%	87%

The first thing to note from table 1 is that, in general, the behavior patterns that will be discussed shortly apply for both cases. Related with single coverage the DSM outperforms the other two models. As expected, this is also true in double zone coverage and double weighted demand coverage, with MEXCLP values closely behind them. The ARTM shows acceptable single coverage but very bad performance in backup coverage. However, in the Monterrey case, DSM behaves even worst for the triple zone coverage. It also worth noting that when coverage that the three models behave better for weighted demand coverage than for zone coverage.

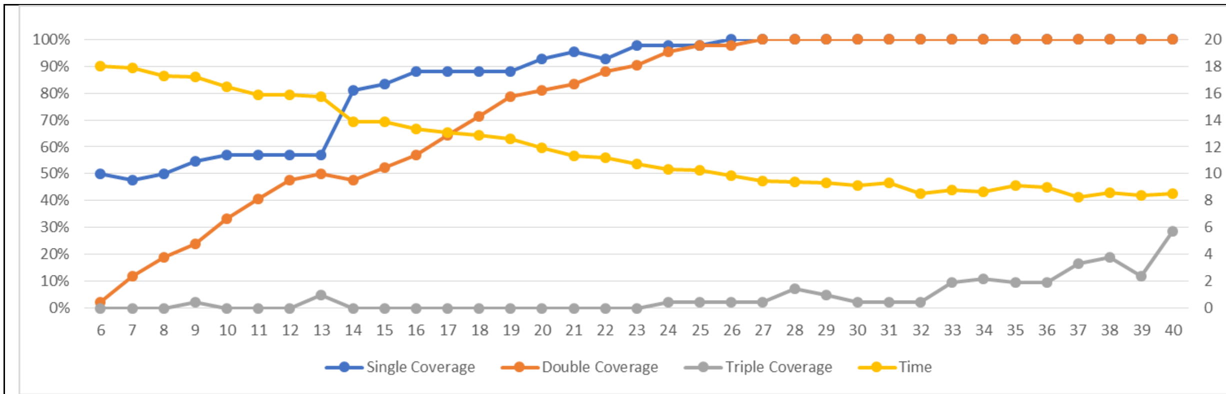
For the average response time criteria, the ARTM performs much better than the other models, as it was expected since this is its objective function. The interesting thing is that the DSM shows very similar results on maximum RT and average RT for both cases, while the MEXCLP behaves worst for the largest city (i.e. Monterrey) with extremely high values of maximum RT.

Regarding the last two criteria, when a threshold is set a low value (i.e. 10 minutes) the ARTM outperforms by far the other models and behaves very well for a loose threshold. Remember that the DSM guarantees the 100% coverage for thresholds greater or equal r_2 = 30 minutes. The MEXCLP performs badly for low thresholds.

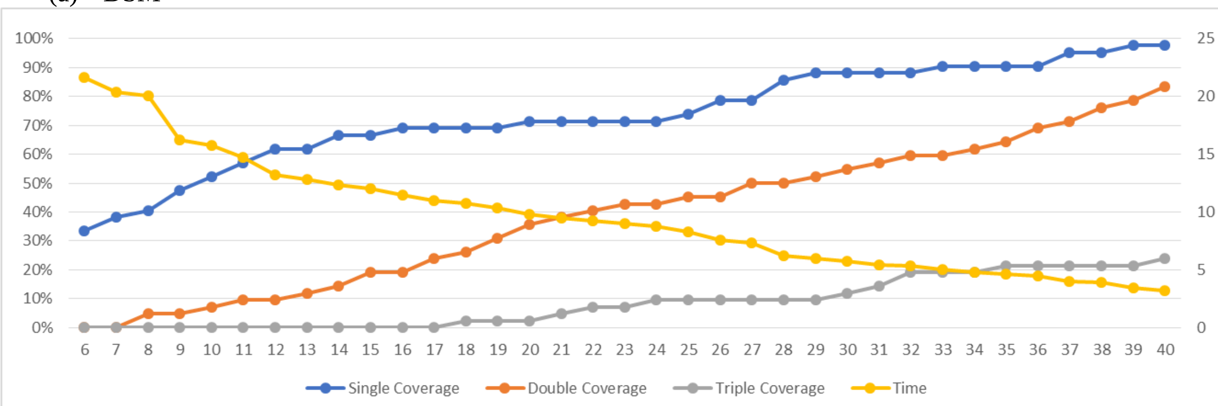
By other hand, figures 7 and 8 shows the results of running the models for different values of A, so the behavior improvement as A increases can be observed.The graphs show the coverage percentage in the principal y-axis and the average response time in the secondary y-axis of each model for each case, respectively. This information allows decision makers to act in accordance to their own performance goals, and gives insights of the marginal contribution of having one more ambulance in operation. For example, Figure 7 shows that for Monterrey, perfect double coverage is achieved from 27 ambulances and that the average RT does not improve from 24 while the expected coverage increases. In addition, the expected RT steadily decreases in about a half minute for each additional ambulance from the 12th.

Figure 8 shows for the Tijuana case that the best double coverage is attained with 9 ambulances but only after 15 ambulances the RT stabilizes at its best value. The expected coverage is also constantly increasing when increasing the number of ambulances for single and both backup coverage.

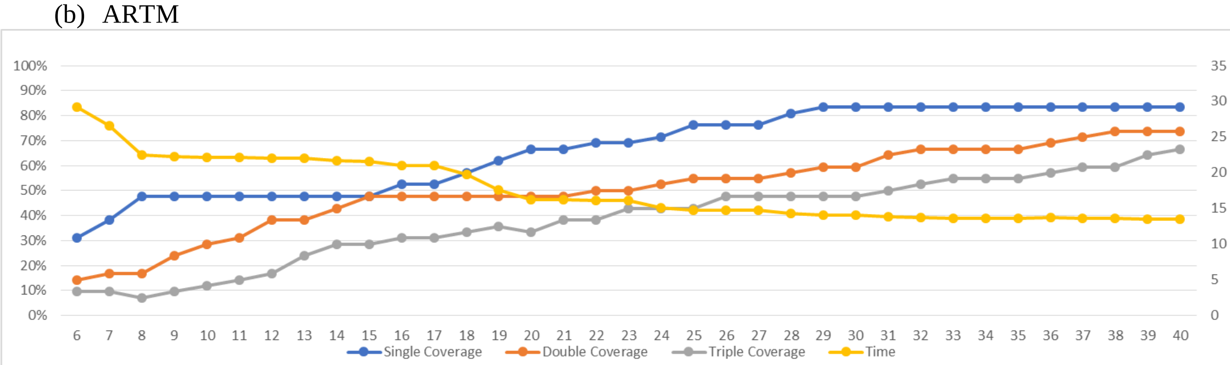
Finally, it must be mentioned that the different scenarios showed similar behaviors in terms of marginal improvements as the number of ambulances increase, so no more discussion is presented here.



(a) DSM



(b) ARTM



(c) MEXCLP

Figure 7. Coverage versus response time for different number of ambulances: Monterrey case

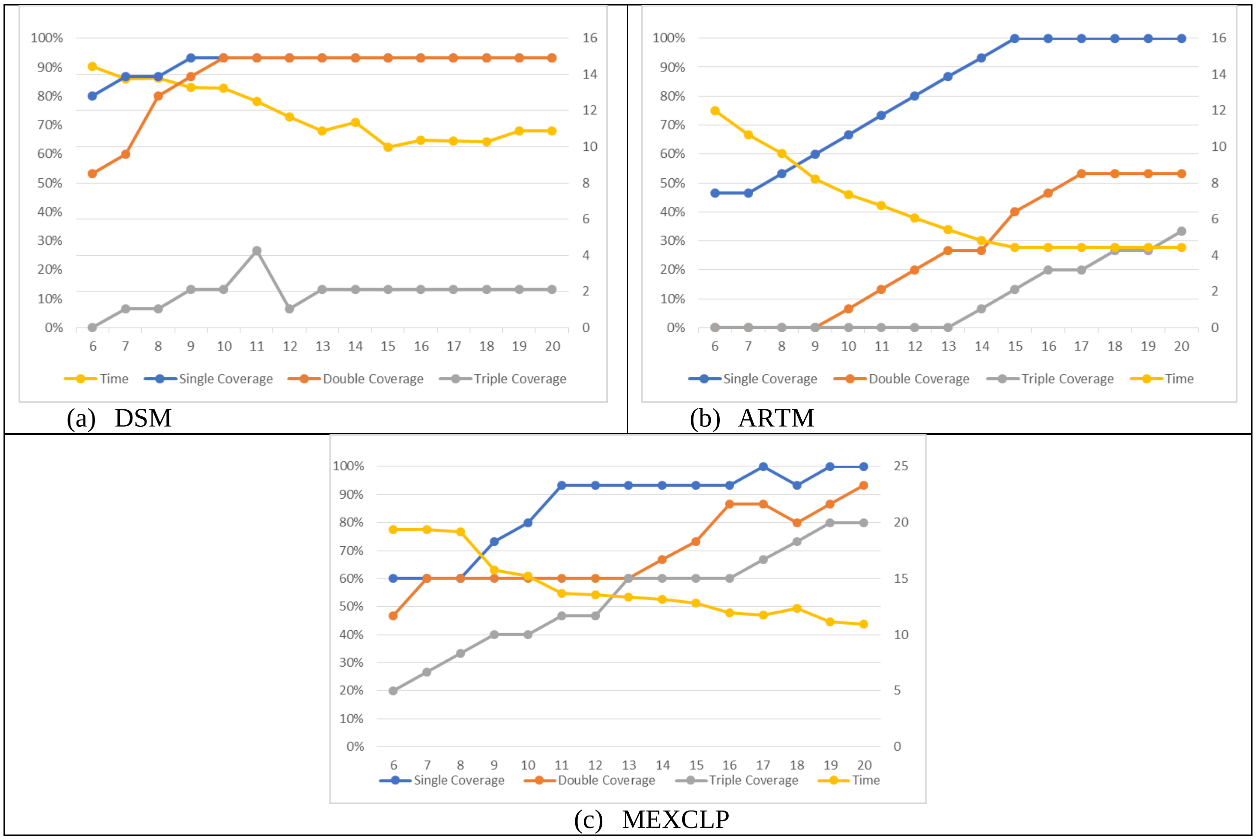


Figure 8. Coverage versus response time for different number of ambulances: Tijuana case

5 Conclusions

Similar performance behavior of the three models compared in this study, the DSM, the ARTM, and the MEXCLP, were observed for the two Mexican cases studied: Monterrey and Tijuana. These cities are different in size, demand behavior and density. It was observed that when the DSM reaches its performance limits (i.e. 100% or almost), the increase of ambulances does not contribute to an improvement in RT. However, this is not true the other way around, since the RT is always susceptible to improvement. For the ARTM, an increase in the number of ambulances contributes steadily to improvements in both the objective function and the coverage.

It should be addressed a multi-objective approach with objective functions that promote at the same time to maximize coverage and minimize response times; since each model pulls the solution towards its objective function but does not necessarily promote an improvement in the other criteria. The MEXCLP is the model that shows a constant improvement with the increase of ambulances in both types of criteria (coverage and RT), but the RTs obtained are well above the optimal ones, which is not good. It is suggested to complement the ARTM, in a way that involves the backup coverage. On the other hand, the MEXCLP has a great potential for improvement if it is considered dynamically, so that the probability parameter that an ambulance is occupied *pr* is observed and taken as a changing value according to the time interval and the actual number of ambulances in operation.

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