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A MIXED INTEGER LINEAR PROGRAM FOR A REAL RELOCATION PROBLEM OF EMERGENCY MEDICAL VEHICLES IN THE PROVINCE OF VALENCIA

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Abstract:

The rapid intervention of Advanced Life Support (ALS) and Basic Life Support (BLS) when an emergency arises is of vital importance for the welfare of citizens. Currently, these Emergency Medical Vehicles (EMV) are located, in the province of Valencia, in certain logistical bases according to the criteria of those responsible for the Emergency Medical Services (EMS). However, it is not possible to cover the entire population of the province within the stipulated maximum times of 12 and 15 minutes (depending on whether it is an ALS or BLS, respectively). For this reason, a maximum coverage model is used to relocate the EMV bases in order to minimize the amount of uncovered population in the province. Thanks to the proposed model, the total coverage defect of the province's population is reduced by more than half compared to the current distribution.

Keywords: location; isochrone; optimization; emergencies; mathematical model.

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1. Introduction

The Emergency Medical Services (EMS) of any country is responsible for the stabilization and pre-hospital transport of patients with medical urgency and emergency. This service aims to perform this task with the shortest possible response time. This time is essential to measure the effectiveness of the service, evaluate its quality and, consequently, preserve the life and health of patients. Any EMS has a fleet of Emergency Medical Vehicles (EMV) to carry out pre-hospital care. Specifically, to deal with emergencies, there are two types of EMV: Basic Life Support (BLS) and Advanced Life Support (ALS). The former attend to less severe emergencies, while the latter deal with more life-threatening situations. The more serious the emergency, the shorter the response time should be. In this context, response time is defined as the time interval between the moment the emergency call is received and the moment the EMV arrives at the scene of the incident. Each of these vehicles is assigned a base from which it departs to attend a service and to which it returns when the service is completed. Response times depend on several factors, including the location of these bases. This article presents a mathematical model that assigns a base to each of the EMV, with the aim of covering the maximum possible number of emergencies within maximum response times, depending on their severity. In order for the proposed model to include aspects that may appear in real problems and, in addition, to analyze its effectiveness, the characteristics of the EMS in the province of Valencia have been analyzed and incorporated.

The development of this model constitutes an effective tool to help the EMS to identify the best location for the EMV fleet. Thanks to this, a more efficient use of resources is achieved, which will result in an improvement of the service offered to citizens. The decision to assign a base to each EMV is strategic and, as long as circumstances do not change, is maintained over time. However, sometimes changes occur, such as: incorporation of new vehicles, occasional vehicle unavailability, changes in emergency demand due to changes in the population, etc. which imply rethinking this initial location. These changes imply modifications of the model's input data, but not of its mathematical structure. Therefore, the model is able to respond to these changes quickly and easily.

In addition, the mathematical model implemented will contribute to achieving the Sustainable Development Goals (SDGs). Specifically, goal 3 to ensure a healthy life and promote well-being at all ages.

This article presents the following structure: section 2 presents the literature review, section 3 describes the problem in detail, section 4 shows the mathematical model designed, section 5 shows the results and, finally, section 6 presents the conclusions of the study and future lines of research, respectively.

2. Literature review

The study into problems stemming from the location of Emergency medical vehicles location has been

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on-going and using different approaches. These models have evolved over the years to integrate more realistic aspects of the problem, such as demand uncertainty, vehicle availability, traffic congestion, etc. Authors such as ReVelle (1989) and Brotcorne, Laporte, & Semet (2003) conducted a review of different mathematical models applied to the location of emergency medical vehicles. The models presented could be divided into two categories: deterministic coverage models (which ignored stochastic considerations regarding the availability of ambulances) and probabilistic models (which allowed for randomness in the availability of resources).

Marianov & ReVelle (1996) proposed a probabilistic maximum coverage model based on queuing theory, considering randomness in the availability of medical services. In the same line, Geroliminis, Karlaftis, & Skabardonis (2009) contemplated minimizing the average response times in patient care by considering the probability that a resource is unavailable both temporally and spatially. Ingolfsson, Budge, & Erkut (2008) also took into account randomness in ambulance availability but added randomness in delays and response times. By using an optimization model, the authors attempted to minimize the number of ambulances needed to provide a specific level of service.

Gendreau, Laporte, & Semet (1997) employed the "tabu search" heuristic to solve the ambulance location problem and they propose a double standard model. As opposed to maximum coverage models, Erkut, Ingolfsson, & Erdogan (2008) opted for mathematical models incorporating survival functions, so that such models would return the probability of patient survival as a function of the response time to treat him. The objective in this case was to maximize survival and not the coverage, as they considered that coverage models did not adequately differentiate the consequences of different response times.

Cheu, Huang, & Huang (2008) using an integer programming model, wanted to maximize coverage of critical hard-to-reach areas. This model optimized the placement of multiple EMV among a set of candidate stations. The area was only considered covered when all EMV types were able to reach within the specified distance and reliability level.

Shariat-Mohaymany, Babaei, Moadi, & Mahdi Amiripour (2012) presented a linear programming model with two objectives: to minimize the number of ambulances needed and to minimize the total response time. To this end, they developed two integral submodels. The first minimized the number of ambulances to achieve the minimum level of coverage reliability. The second located the ambulances to minimize the arrival time at the point of demand. Both models calculated the unavailability of ambulances simultaneously to ensure that the unavailability did not exceed the preset limit.

Su, Luo, & Huang (2015) refined the dual coverage model with a new objective function that minimized the expected cost of delayed emergencies plus the operating cost of EMS. This model was based on the ant colony optimization algorithm (Dorigo, Birattari, & Stutzle, 2006).

Bélanger, Ruiz, & Soriano (2015) conducted a comprehensive compilation of mathematical models for solving static ambulance location problems. In their article they detailed from simple deterministic models with simple coverage to more sophisticated stochastic models, many of them based on queuing theory, with different objective functions and different characteristics. In addition, they mentioned that it might be beneficial to change the location of ambulances during a day (i.e., relocate them) based on the evolution of the situation faced by the EMS. They thus introduced the dynamic ambulances relocation problems, the aim of which was to improve the evolution of the system over time.

In this case, the location problem will be solved by means of a maximum coverage model, as will be justified in subsection 3.2.

3. Problem description

The EMS of any country has a fleet of ALS and BLS identified as F_A and F_B respectively, and a set N of possible bases where the vehicles can be parked to start their shift and return to after attending the call. The problem consists of assigning each vehicle a base in such a way as to cover or satisfy the largest number of emergencies demanded. However, the demand for emergencies is a random variable that needs to be modeled. In this case, there was not enough information to be able to model this demand adequately; It was only able to ascertain the how much of the population could be reached in a given time from a base. However, It was verified that there is a strong correlation between the demand for emergencies and the population. That is, the greatest demand for emergencies arises when there is a greater concentration of population. Consequently, meeting the maximum emergency demand is equivalent to minimizing the total amount of population left uncovered in a given time. To calculate the population covered from a base, the concept of isochrone must be introduced.

3.1. Isochrone

The EMS has used a concept to classify whether or not an ambulance can reach a point in a given time: the isochrone.

The isochrone is defined as the area or polygon bounded by a set of points that take the same time to reach from a common origin via a means of transport. It is represented by a line on a map that connects places from which it takes the same time to reach a given point. Figure 1 shows an example of an isochrone for a time of 5 minutes and for three different means of transport (walking, cycling and car) from the same start point.

You can see how the isochrone for the car is the largest, followed by the isochrone for the bicycle and ending with the isochrone for a pedestrian. This makes sense since the car generally covers greater distance in the same amount of time. You can also determinate the number of people falls within that area.

The isochrone is what will graphically measure how much area is covered and, consequently, how much of the

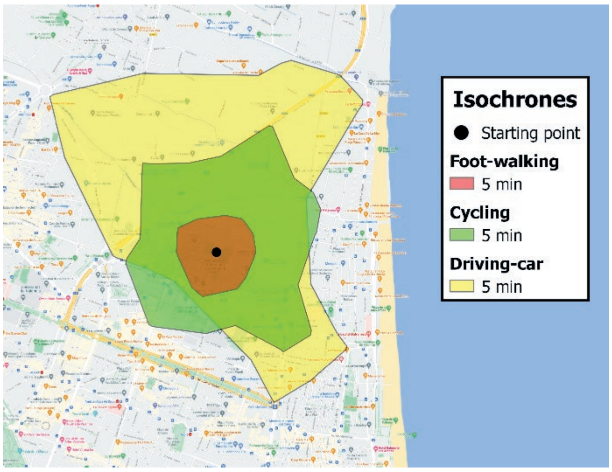


Figure 1: Example of isochrones calculated for different means of transport and a time of 5 minutes.

population linked to that area is covered, so that it can be treated visually on the map. The isochron time to be used as a reference for ALS and BLS will be identified as and, respectively. This time is defined as the time it takes for the EMV to be activated (since it starts up) until it arrives at the emergency site.

3.2. Coverage assuming unlimited resources

Usually, any area in which one wants to work to solve this type of problem will consist of a determined set N of possible bases where to locate the EMV. In the case of the province of Valencia, there are 158 possible bases, whose location can be seen in Figure 2. The red dots correspond to each possible base and the blue line to the territorial delimitation of the province.

To solve any location problem, it is necessary to define the reference unit to work with. In this case, the province of Valencia is organised by departments of health, so this concept will be used as the reference unit, dividing the province into the 11 departments it consists of. As a next step, it would be necessary to see if it would be possible to cover the whole province of Valencia with the defined and times (being these times the maximum minutes that the ALS or BLS should take to arrive at the place of the incident, respectively).

Figure 3 shows that, although an EMV is placed in each of the N possible bases in the province of Valencia and with an isochron time (as it is the least restrictive), it is not possible to cover the entire population of the province, so the problem to be solved will be addressed by a maximum coverage model.

Generally, these types of problems are approached using maximum coverage models. Total coverage does not make sense because there is usually not enough road infrastructure to reach all points in a reasonable amount of time. Also, there is not an unlimited number of EMV available.

Figure 3 shows that there are areas that are impossible to reach in the stipulated isochron time with the available

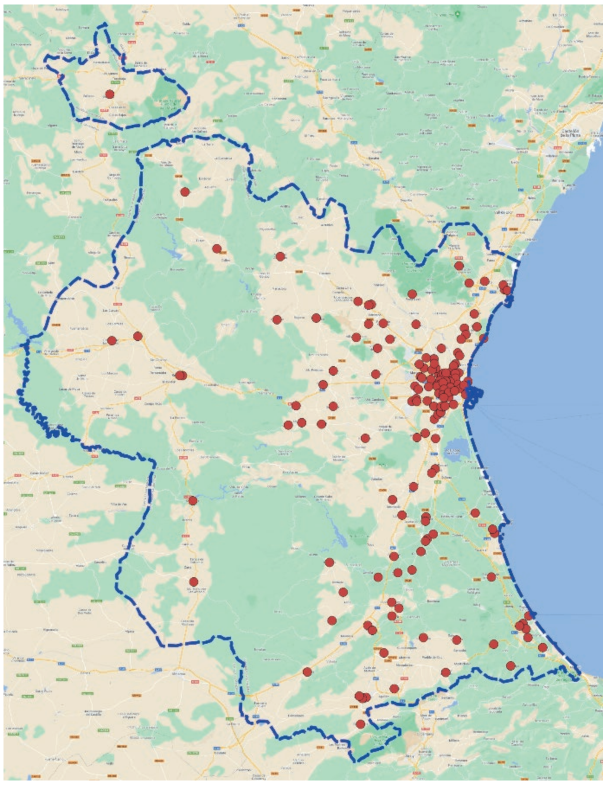


Figure 2: Map of possible bases in the province of Valencia where the VES can be located.

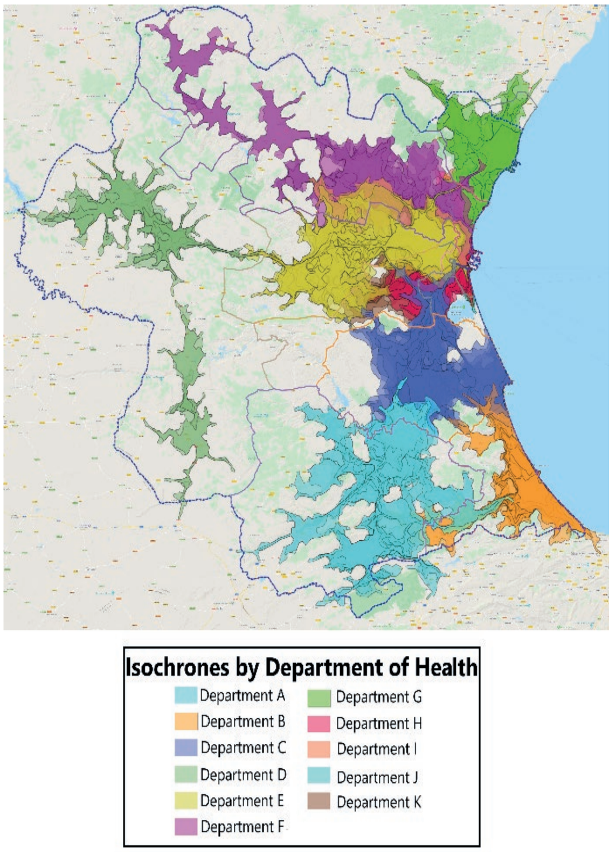


Figure 3: Visualization through isochrones of the maximum possible coverage by placing a VES in each possible base in the province of Valencia.

bases. Consequently, an attempt will be made to place the available EMV in such a way that the largest possible population can be covered for the stipulated times.

4. Mathematical modeling

In order to set up the Mixed Integer Linear Program (MIP) necessary to model the maximum coverage problem, it is necessary to calculate the covered population matrices for each type of vehicle and each possible base. There will be a covered population matrix for the maximum isochron time (for ALS),, and another for the maximum isochron time (for BLS),. To construct these two matrices, first the isochrones for the times and must be obtained for each of the N possible bases available to locate the EMV. The matrices will show the population covered in each department of health if the EMV is placed in the corresponding base.

4.1. Parameters and decision variables

In order to express the proposed model, the parameters and nomenclature shown in Table 1 must be introduced.

Table 2 shows the decision variables that will appear in the implemented mathematical model.

Table 1: Main parameters in the MIP.

Parameter	Meaning
M={A,B,…,m}	Set of departments of health into which the province is divided.
N={1,2,…,n}	Set of possible bases for locating the EMV.
i ∈ M	Index of the departments of health.
j ∈ N	Index of possible bases
h_i	Total population to be covered in each department.
N_i	Set of bases at department i
h_{ij}^A	Population covered in department if an ALS in base is placed.
h_{ij}^B	Population covered in department if a BLS in base is placed.
F_A	Available fleet of ALS.
F_B	Available fleet of BLS.
f_A	Minimum number of ALS to be placed in each department of health.
f_B	Maximum number of BLS to be placed in each department of health.
$K=\{k_1,k_2,\dots,k_v\}$	Set of the set of bases whose isochrones overlap and whose covered population is small.
$L=\{l_1,l_2,\dots,l_w\}$	Set of the set of bases whose isochrones overlap and whose covered population is large.

Table 2: Decision variables in the MIP.

Decision variable	Meaning
$x_j^A \in \{0,1\}$	It will take the value 1 if the ALS is located in base j and 0 otherwise.
$x_j^B \in \{0,1\}$	It will take the value 1 if the BLS is located in base j and 0 otherwise.
D_i	Denotes the amount of population left uncovered in department i.
E_i	Shows the amount of population covered more than once in department i.

The last two variables are added because, otherwise, the problem could be infeasible, so they must be used to force the model to provide a consistent solution.

4.2. MIP

The proposed model would be:

$$\sum_{i=A}^{m} D_i \qquad (1)$$

s.t.

$$\sum_{j=1}^{n} (x_j^a \cdot h_{ij}^A + x_j^b \cdot h_{ij}^B) + D_i - E_i = h_i \ ; \ \forall \ i \in M \qquad (2)$$

$$\sum_{j=1}^{n} x_j^A = F_A \qquad (3)$$

$$\sum_{j=1}^{n} x_j^B = F_B \qquad (4)$$

$$x_j^A + x_j^B \leq 1 \ ; \ \forall \ j \in N \qquad (5)$$

$$\sum_{j=1}^{N_i} x_j^A \geq f_A \ ; \ \forall \ i \in \mathrm{M} \qquad (6)$$

$$\sum_{j=1}^{N_i} x_j^B \leq f_B \ ; \ \forall \ i \in \mathrm{M} \qquad (7)$$

$$\sum_{j \in k_s} (x_j^A + x_j^B) \leq 1 \ ; \ \forall \ k_s \in K, \quad s=\{1,2,\dots v\} \qquad (8)$$

$$\sum_{j \in l_s} (x_j^A + x_j^B) \leq 2 \ ; \ \forall \ l_s \in L, \quad s=\{1,2,\dots,w\} \qquad (9)$$

$$x_j^A \in \{0,1\}; \quad \forall \ j \in N \qquad (10)$$

$$x_j^B \in \{0,1\}; \quad \forall \ j \in N \qquad (11)$$

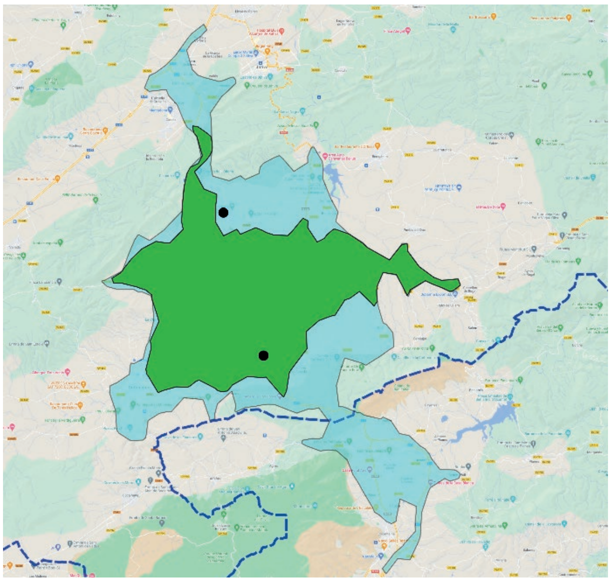
$$D_i, E_i \geq 0 \qquad (12)$$

The objective function (1) minimizes the set of the population that remains uncovered in the whole province. Constraint (2) establishes that, for each department, the whole of its population must be covered by ALS and BLS. Constraints (3) and (4) set out that the entire fleet of ALS and BLS, respectively, must be located. Constraint (5) establishes that an ALS and a BLS cannot be present at the same base at the same time. Constraints (6) and (7) require that in each department there must be at least one number f_A of ALS and at most one number f_B of BLS, respectively. This last restriction is added because there are departments whose population is widely distributed throughout the territory, so the model tries to cover most of them using a large number of BLS, which would limit the availability of these ambulances in other departments. For this case, the values chosen for the parameters f_A and f_B have been 1 and 10, respectively.

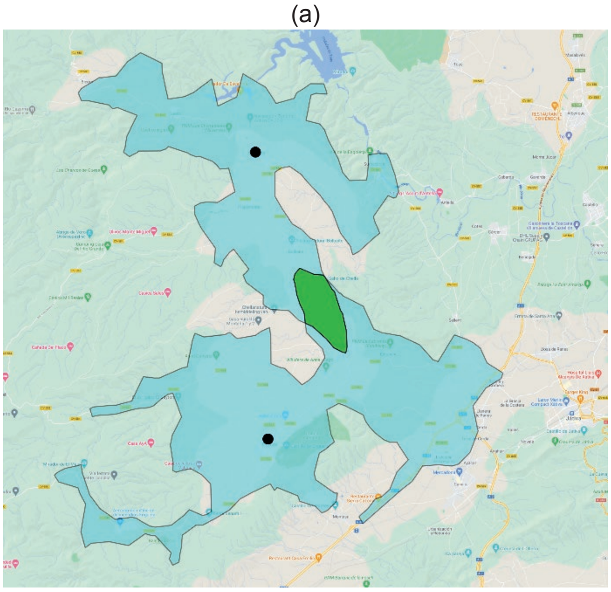
Before explaining constraints (8) and (9), one of the problems that arise when performing the model must be pointed out: overlaps between isochrones. This implies that the same population will be overcovered and the model will not be able to discern between the population that is being covered more than once, so it may provide a false result of the total population that is actually covered, since it is counting the same population more than once (depending on the number of isochrones that overlap in the same place).

To avoid this, it will be necessary to see which isochrones are overlapping (visually on the map you will see the isochrones that have a high percentage of overlapping) to avoid placing a EMV in each of these bases. That is, if a EMV is placed in one of these bases it will not be placed in the other and vice versa. In this way, overlapping isochrones and, consequently, overcoverage will be avoided. To better understand what these overlaps are, an example is shown in Figure 4.

The green coloured section is the overlap that occurs between the isochrones of two different bases (represented by the black dots). In Figure 4a the overlap produced is quite extensive, so the population covered from these two bases will be almost identical. If, in addition, the number of inhabitants in that area is low, locating an EMV in these areas may not be necessary. If the amount of population that falls below these isochrones is high, it may be of interest to locate a EMV at each base to cover that area, since the probability of an emergency arising would be greater. Figure 4b) shows the overlap produced between two other different bases. This time the amount of overlap is very small, so that populations covered from these two bases will be different. In these cases, restrictions (8) and (9) would not apply.



(a)



(b)

Figure 4: Overlapping produced between isochrones of two different bases: a) large overlapping; b) small overlapping.

However, there will be times when overcoverage may be of interest, due to the high population of the area, which consequently translates into a higher probability of emergencies. This will be the case, for example, in the city of Valencia, where overlaps will be allowed to occur in order to deal with emergency calls when another EMV covering the area is busy or out of service.

In conclusion, in the mathematical model, overlapping restrictions will be written for areas where such overlapping does not imply a high population, since, otherwise, overcoverage will be of interest.

Therefore, constraint (8) indicates that there cannot be more than one EMV in overlapping bases with a small population, since, as there is less population, the probability of an emergency will be lower. Constraint (9) implies that in the set of overlapping isochrones in high population areas, at most 2 EMV can be placed, because overcoverage in this case will be beneficial. Constraints (10) and (11) impose that these decision variables be binary. Finally, constraint (12) implies that both variables are non-negative.

It should be noted that the model has been solved in two iterations: in the first iteration the ALS are located and in the second iteration the BLS are located. This is done in this way because, otherwise, the model would first locate the BLS in the bases where the largest population is covered (since, $t_B > t_A$ so its isochrones will group a larger amount of population) and would locate the ALS in bases where a smaller amount of population is covered. This is not wanted, since ALS are responsible for more serious emergencies than BLS, so it is in their interest to be strategically located in areas with a higher risk of several emergencies.

5. Computational results

In order to check the validity of the implemented model and to be able to obtain quantitative results, It will be applied to a real case: the province of Valencia.

It is worth mentioning that all the tasks of vehicle location, calculation of isochrones, calculation of the covered population matrix, creation of the maps, visualization of the solution, etc. have been carried out with QGIS 3.10.5 software. This software is totally free and free of charge, as well as very powerful and ideal for the problem to be addressed.

The implemented model has been solved using the Microsoft Excel OpenSolver 2.9.0 tool on a computer with Windows 10 operating system, with 6GB RAM and an Intel® Core™ i5-4200U 1.60GHz processor. This model takes an average of approximately 3 seconds to solve, which is ideal for this type of problem where speed is of the essence.

5.1. Ideal coverage for the province of Valencia

As seen in subsection 3.2, there are areas in the province of Valencia that will not be covered even assuming an ideal case, where there is no resource limit and the isochron time is the least restrictive. In the case applied to Valencia, t_B is equal to 15 minutes.

Table 3 shows quantitatively the exact amount of the population that cannot be covered in the province with the defined characteristics (D_i^{min}), both in absolute and relative terms.

Table 3: Minimum coverage defect in the province of Valencia by departments of health for an isochrone time of 15 minutes.

Department of Health	Total population (inhabitants)	D_i^{min} (inhabitants)	D_i^{min} (%)
A	194397	5203	2.7
B	176288	1329	0.8
C	245855	0	0.0
D	66000	4195	6.4
E	195000	0	0.0
F	316919	2578	0.8
G	118832	0	0.0
H	284060	0	0.0
I	344019	0	0.0
J	277280	0	0.0
K	364017	701	0.2
TOTAL	2582667	14006	0.5

Table 3 shows that the population that cannot be covered with the resources available for an isochrone time of 15 minutes is 0.5% of the total population, i.e., 14006 people. If the uncovered population is analyzed by department, there are six departments that have the capacity to cover their entire population while there are five that do not. The five departments that have a population that is impossible to cover and, therefore, will always have a minimum default are departments that have municipalities or areas that are difficult to access easily, especially because they are located in the mountains or have infrastructure that is not suitable for access.

5.2. Current coverage of the province of Valencia

The resources available to the EMS to deal with emergencies are limited. Specifically, the EMS in the province of Valencia has at its disposal, as of today, 67 EMV to use, of which 20 correspond to advanced life support and 47 to basic life support. Not all these vehicles are available 24 hours a day, but, depending on the availability of the health center or hospital where they are located, or even on the decisions of the SES, they can be available for as little as 12 hours (either during the day or at night).

Currently, in the province of Valencia the logistic bases of the emergency medical vehicles are located according to the criteria of the *Conselleria de Sanitat Universal i Salut Pública* through the *Subdirección General de Actividad Asistencial* in the EMS, but it cannot be assured that these are the optimal locations due to the possibility of coverage problems.

Figure 5 shows the current coverage of the province of Valencia with the maximum isochron times of 12 and 15 minutes defined, depending on whether the ambulance is an ALS or a BLS, respectively.

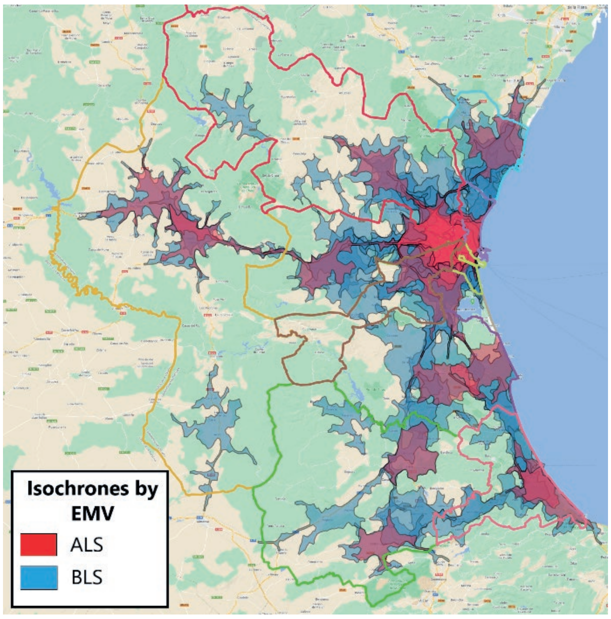


Figure 5: Visualization through isochrone of the current coverage of the province of Valencia by type of ambulance.

It can be seen how there is a very high density in the city of Valencia, so there is an overcoverage, while in the inland area of the province vehicles are not able to arrive in the maximum isochrone time. These areas would be unprotected with this distribution of ambulances, as they would not be able to respond to emergencies in the stipulated time. For this reason, an attempt will be made to propose a model that, according to the restrictions imposed, locates the EMV in the available bases in such a way as to cover as much of the population as possible.

5.3. Coverage obtained by the model and comparison of results

Table 4 shows the numerical results of the final model obtained in comparison with the current distribution proposed by the EMS.

The first column represents the eleven health departments that exist in the province of Valencia. The second column represents the percentage of the population that cannot be covered in the supposed ideal case explained in subsection 5.1. The third and fourth columns express the percentage of population that remains uncovered with the solution offered by the EMS and with the solution proposed in this work, respectively.

Table 4 shows how, thanks to the proposed mathematical model, it is possible to reduce the total coverage defect of the province by more than half compared to the current distribution.

Figure 6 graphically compares the solution provided for the case of unlimited resources (Figure 6a), for the current distribution of EMV proposed by the EMS (Figure 6b) and for the distribution proposed by the mathematical model implemented (Figure 6c). It can be seen that the solution provided by the model is the closest to the ideal.

Table 4: Comparison of the results obtained.

Department of Health	D_i^{min} (%)	D_i (%)	
		Current sol.	MIP sol.
A	2.7	8.8	2.7
B	0.8	0.8	0.8
C	0.0	0.5	0.0
D	6.4	12.1	10.0
E	0.0	0.0	0.0
F	0.8	3.3	1.4
G	0.0	0.0	0.0
H	0.0	0.0	0.0
I	0.0	0.0	0.0
J	0.0	0.0	0.0
K	0.2	0.2	0.2
TOTAL	0.5	1.5	0.7

6. Conclusions and future research

In this article, a mathematical model has been developed with the aim of improving the solution currently offered by the service, minimizing the population that remains uncovered throughout the province. It has been proved how an adequate introduction of the restrictions leads to a better performance of these models. With the model implemented, it has been possible to improve the defect or uncovered population by almost 50% with respect to the current one. In other words, the desired objective has been achieved, so the model has been satisfactory. In addition, this model is capable of offering solutions in a very short time, which is very important to help EMS decision-makers and thus help to better respond to the needs of the service and its reality.

In addition, it has been possible to clearly observe the limitations that arise in the province of Valencia in terms of population coverage, and it has been possible to verify that it is not possible to achieve total coverage of the province for the stipulated times of 12 and 15 minutes with the availability of resources and possible bases.

In order to improve the results obtained and get even closer to reality, one of the lines of research to be carried out is to be able to model the demand. The objective is to obtain historical data on demand in the province and readjust the model with the new input data.

Another line of research is to detail more exhaustively the area of the city of Valencia, since it is here where a greater number of people is concentrated and, therefore, where a greater number of emergencies arise. In addition, it is also intended to look for other alternatives to model the problem and contrast the results obtained through each scenario.

7. Acknowledgements

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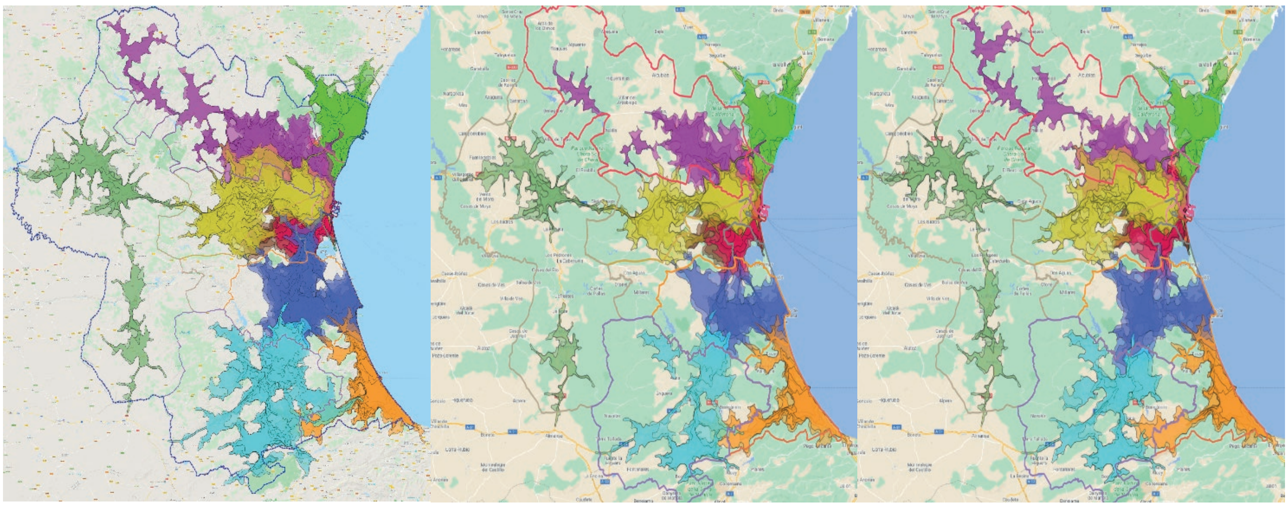

(a) (b) (c)

Figure 6: Coverage of the province of Valencia according to the distribution of the EMV: a) Ideal coverage; b) Current coverage; c) Coverage proposed by the model.

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