Heuristic algorithms based on the isochron analysis for dynamic relocation of medical emergency vehicles

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Abstract

Among the wide range of medical services, prehospital health care is one of the most relevant, as it usually involves an emergency situation. The qualified medical team is dispatched to the scene of the incident as soon as possible. One of the most influential factors in response time depends on where the ambulances are stationed, however, when a medical vehicle is attending an emergency, it becomes unavailable for other calls. Increasing the ambulance fleet is a costly option that does not guarantee efficiency. An alternative solution is the relocation of available ambulances to increase the population covered by them. Obtaining the optimal solution in real time is not feasible for this problem. Therefore, this work addresses the problem of dynamic relocation of ambulances through the design and development of heuristic tools. The isochron overlap analysis defines possible scenarios that may occur when ambulances become unavailable for emergencies and determines the appropriate conditions to carry out the relocation of ambulances. Computational experiments are run using a benchmark of instances based on the characteristics of a real Emergency Medical Service. Based on the results of the study, we can conclude that the designed relocation algorithms perform better than if there was no relocation strategy.

Keywords: Ambulances, Relocation, Heuristics, Isochron, Emergency.

1 Introduction

Providing qualified medical care to avoid death would be the main objective of the prehospital Emergency Medical Services (EMS). The time that elapses from when an emergency call is made until it is answered at the scene of the event is known as response time. This period of time is extremely important and some countries have defined the performance standards of an ambulance explicitly in their national regulations (United States (Gendreau et al., 2001), Canada (Cabral et al., 2018), United Kingdom (UK, visited October 6, 2021), Slovakia (Jánošíková et al., 2019)). The World Health Organization and the European Union recommend that the response time for an emergency should not exceed 480 seconds (Reuter-Oppermann et al. (2017), Cabral et al. (2018)).

There are many factors that influence response time: quantity and quality of resources, dispatch policies, population density, frequency of calls, socio-economic factors and, obviously, location of ambulance bases. Even with the optimal location of the bases, as soon as the ambulances begin to attend the calls, some areas could be left without coverage and it would be difficult to maintain the adequate level of assistance. In this context, the coverage is the amount of people who are in an area that can be reached by an ambulance in a given time. Once an ambulance is moved from the base due to an emergency, all the people in this area are without coverage. To solve this problem, the amount of resources could be increased, but this solution would be expensive, somewhat inefficient and a lengthy process to carry out. An alternative solution would be to relocate the vehicles that are still available to achieve the highest possible coverage.

There are two types of relocations: *multi-period relocation*, due to changes in demand caused by population movements, for example, at different times of the day, and *dynamic relocation*, due to variations in the state of the system when the number of available ambulances changes (this number decreases when a vehicle moves to attend an emergency and increases when an ambulance completes a service). In this work, a set of heuristic algorithms for the dynamic relocation of ambulances in real time is developed, using a tool called isochron. An isochron is the area that covers all the points that can be reached within a given time from a specific location and with a specific mode of transport: on foot, by bicycle, by car. Figure 1 shows different examples of isochrons. Each colored area is covered by an isochron from the same starting point, using different means of transport and in a given travel time. In this work, the mean of transport will be an ambulance, then the isochron is obtained according to a driving time.

The isochron concept has been used in some studies related to health emergencies (Peleg and Pliskin (2004), Lam et al. (2015), Otamendi and

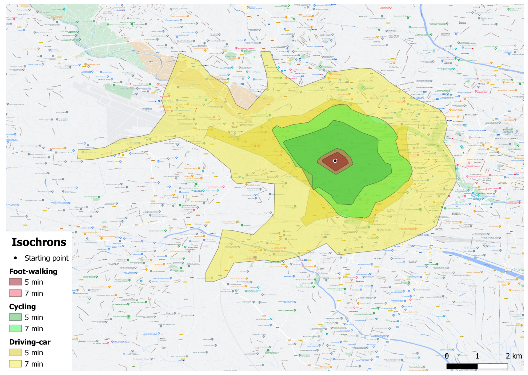

Figure 1: *Isochron example*

García-Heredia (2015)). The main contribution of this work, which combines geographic optimization and heuristic techniques, is to tackle the dynamic relocation problem applying a new approach to the concept of isochron. The isochron overlap analysis defines possible scenarios that may occur when ambulances become unavailable for emergencies and determines the suitable conditions to carry out the relocation of ambulances. The objective of the algorithms is to maximize coverage. In addition, the heuristic technique not only provides the location of the ambulances to maximize coverage, but also determines which ambulances are candidates for relocation and, therefore, the dispatchers do not have to deal with these issues. On the other hand, it is shown that the proposed technique favors the balance in the workload of different emergency vehicles. With a suitable study of any emergency service, the proposed heuristic algorithms could be easily adapted and applied to the dynamic relocation of ambulances in different health areas, both national and international.

The use of geographic information systems (GIS) is very important in solving the problem of relocation of ambulances, since it allows obtaining reliable information in real time. While many studies validate the proposed methodologies using the discrete event simulation, for this work we rely on the GIS for this purpose. Additionally, the possibility of visualizing the coverage status on a map can help managing EMS. In this study we use the free georeferencing software QGIS Desktop 3.12.2 and the Openrouteservice plugin.[1]

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Finally, note that the designed algorithm in this work can help to achieve sustainable human development. The 2030 Agenda for Sustainable Development adopted by all the Member States of the United Nations in 2015 determines 17 objectives, which not only focus on the problems of the environment, underwater or terrestrial ecosystems, but also cover problems of inequality, unemployment problems or health among others (UN, visited May 24, 2022). This work contributes to the accomplishment of the following Sustainable Development Goals (SDG):

- Goal 3: Ensure healthy lives and promote well-being for citizens of any age.

- Goal 9: Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation.

The remainder of this paper is organized as follows. In Section 2 related studies are reviewed and in Section 3 the problem is described. The designed heuristic algorithm is described in Section 4. The computational results are presented and discussed in Section 5, where the proposed approach is applied to a real case as well. Finally, Section 6 presents the conclusions of the study and outlines future work.

2 Literature review

In the last two decades there have been many advances in solving the problem of relocation of medical emergency vehicles. The first static models have evolved into dynamic models, which have incorporated both the complexity and the realism of the ambulance management process. There is currently a wide range of relocation models, but one of the more generic classifications separates them into multi-period relocation models and dynamic relocation models. Multi-period models capture the changes that occur in demand at different periods of the day (or week) and relocate ambulances based on these changes to provide better service in each period. As an example of multi-period models we can cite Rajagopalan et al. (2008), Schmid and Doerner (2010), Andrade and Cunha (2015), van den Berg and Aardal (2015), Boujemaa et al. (2020). On the other hand, dynamic relocation models capture the changes that occur in the state of the system due to the variation in the number of ambulances available.

There are many approaches to solving the problem of dynamic relocation. There are models that recalculate the new positions in real time for the entire fleet (although with some restrictions) as soon as there is a change in the number of available vehicles (Gendreau et al. (2001), Moeini et al. (2015), Enayati et al. (2018)). There are models that pre-calculate the positions for each number of available vehicles generating compliance tables (Gendreau et al. (2006), Alanis et al. (2013), Sudtachat et al. (2016), van Barneveld (2016), Sudtachat et al. (2020)). There are models that use dynamic programming (Maxwell et al. (2010), van Barneveld et al. (2017), Nasrollahzadeh et al. (2018)). Reviews for the dynamic relocation problem can be found in Bélanger et al. (2015), Bélanger et al. (2019).

Although many authors formulate the ambulance relocation problem with mathematical models, one of the most common techniques to solve this problem in real time is the heuristic technique (Gendreau et al. (2001), Rajagopalan et al. (2008), Schmid and Doerner (2010), Jagtenberg et al. (2015)). The application of heuristic algorithms has experienced exponential growth in the last 30 years due to its ability to provide quality solutions in real time. Among other advantages of heuristic techniques, we can mention the possibility of easily incorporating realistic aspects and the ease of explaining them to users, since these techniques can be a very intuitive tool. In health emergency problems, heuristics have been used for the allocation of resources (Fogue et al., 2013) and for the location of health centers (Landa-Torres et al., 2013), among others.

One of the first models of dynamic ambulance relocation to use a heuristic was the Gendreau et al. (2001), in which the relocation problem is solved as a location problem every time the number of available vehicles changes. The authors add a penalty coefficient in the objective function to control the number of relocations. The heuristic used in this case is the Tabu Search.

Another work in which the authors try to optimize at all times the positions of all the ambulances still available is the Billhardt et al. (2014), but in this case using a completely different method, the geometric optimization approach. The authors minimize the expected time to reach potential new patients by using Voronoi tessellations.

Among the first studies to use an indicator to relocate ambulances is the Andersson and Värbrand (2007). The system automatically detects the area in which the level of the indicator, "Preparedness", is below a critical level and an algorithm is implemented to relocate the ambulances to this area.

The "Preparedness" in a zone i can be calculated as:

$$p_i = \frac{1}{d_i} \sum_{l=1}^{L_i} \frac{\gamma^l}{t_{il}}, \tag{1}$$

where L_i is the number of ambulances that contribute to "Preparedness" in zone i, t_{il} is the travel time of ambulance l to zone i and γ^l is the contribution factor for the ambulance l such that:

$$\begin{aligned} & t_{i1} \leq t_{i2} \leq \ldots \leq t_{iL_i} \\ & \gamma^1 > \gamma^2 > \ldots > \gamma_i^{L_i} \end{aligned} \tag{2}$$

The objective is to minimize the maximum travel time necessary to relocate the ambulances until the level of "Preparedness" in each zone is at an acceptable level.

The technique proposed by Andersson and Värbrand (2007) has been the basis of development for many other works. Lee (2011) incorporates different social welfare functions to obtain the critical level of "Preparedness". Liu et al. (2013) introduces the term of probability of availability of a vehicle to cover an area. Paz Roa et al. (2020) modifies the index introducing the probability of a vehicle being available based on the multi-server queue model.

The most recent work related to the concept of "Preparedness" is Carvalho et al. (2020). The index is determined not for each zone, but for the set of available ambulances A in the period τ:

$$p_A^\tau = \frac{1}{\sum_{i \in V} d_i^\tau (1 + min_{k \in A}\{t_{ki}^\tau\})}, \tag{3}$$

where d_i^τ represents the demand for ambulances in area i in the period τ and t_{ki}^τ represents the travel time between the ambulance location k and the location of the zone i in the period τ. The authors propose a mathematical model and a heuristic algorithm to solve the relocation problem, trying to maximize the preparation of the system at each moment.

In the works cited above, the relocation algorithm takes into account the entire fleet available for relocation, although there are always restrictions that reduce the number of movements. The study proposed by Jagtenberg et al. (2015) only considers relocating the vehicle that has just completed a service. The destination base for each ambulance that has become available is determined based on the marginal coverage, defined by Daskin (1983).

Authors such as van Barneveld et al. (2016) use the concept of "unpreparedness" to relocate ambulances. This indicator is the sum of the travel times of the inactive ambulances closest to each demand area, weighted by the probability of an incident occurring in each zone. Relocation is done from an origin base to a destination base, but only if the indicator falls below a specific level, and chain relocations are also allowed.

The work of van Barneveld et al. (2018) considers the two previous heuristics, that of Jagtenberg et al. (2015) and that of van Barneveld et al. (2016). The first is taken as a basis, where only the vehicles are relocated at the end of a service, but some concepts from the second are added.

In this article we use a heuristic approach to solve the problem of dynamic relocation of ambulances. This choice is due to the fact that the main objective of our work is to develop relocation algorithms applicable to real services (there are many theoretical models of relocation, but few of them have actually been implemented). Furthermore, heuristic algorithms allow many realistic aspects of the problem to be incorporated. Heuristics can be very intuitive and more effective than mathematical programming (see Carvalho et al. (2020)).

Most of the works that solve the problem of dynamic relocation in real time consider the entire fleet to be relocated, that is, both the ambulances that finish a service and those that are inactive in their bases. According to Bélanger et al. (2016), better results are obtained when the system is absolutely dynamic. But the same authors indicate that relocation costs, especially intangible costs, must be controlled. The managers of the EMS are very reluctant to send the ambulances to bases other than the usual ones and they are even more opposed to relocating the ambulances that are inactive in the bases. For these reasons, we have decided to only relocate the ambulances that finish a service, such as in Maxwell et al. (2010), Schmid (2012) and Jagtenberg et al. (2015).

Both Maxwell et al. (2010) and Schmid (2012) use dynamic programming. To find the parameters of the models, iterative simulation based on historical data is used. These parameters cannot be applied to all models, that is, they have to be adjusted to each particular case and that can take, as Jagtenberg et al. (2015) says, up to a year. On the other hand, the authors of Jagtenberg et al. (2015) propose a heuristic, which is used in urban areas, that is, where the occupancy fraction is the same for all ambulances. However, in our case there are mixed (urban and rural) areas, where ambulances do not have the same workload. We explicitly study the balance in the workload of the crews of different ambulances. Furthermore, the authors of Jagtenberg et al. (2015) indicate that using a strategy (their strategy) where the concept of "usual base" does not exist can be difficult. Taking this into account, we propose a heuristic, where each crew has its usual base, where the turn starts, where it returns if the conditions for relocation are not met, and even where the crew could return at the end of their turn (the algorithm can be easily adapted under instructions from EMS managers).

Like in other works that automatically evaluate the state of coverage (Andersson and Värbrand (2007), Paz Roa et al. (2020), Carvalho et al. (2020)), our algorithm is activated when some areas have been left without sufficient coverage. However, unlike these works, which use an indicator to calculate the readiness of the system (see Equation 1 or 3), our algorithm is based on the use of Geographic Information Systems tools, which is very widespread, but, in our opinion, its full potential in modeling the relocation problems of health emergency vehicles and in the real management of these services has not yet been exploited. The definition of the scenarios based on the analysis of the isochrons is a technique that until now had not been used for the problem in question. Another point to highlight is the possibility of showing the real coverage in different scenarios provided by these tools, which can be very important in managing the service.

3 Problem Description

Emergency Medical Services (EMS) have a fleet of ambulances (A) to carry out their activity. Each ambulance a is located at a base denominated usual base (b_a^u). The set B is integrated by all the bases. Ambulances leave its usual base to assist an emergency and come back when the service has finished. The assignment of bases to ambulances is carried out by EMS and aims to cover the maximum population. This problem is known as *static ambulance location problem.* The authors also have worked with the static problem and a mathematical model has been proposed and is accepted for publication in Vecina García et al. (2022). However, the configuration of this initial coverage changes as emergencies arise and ambulances leave their bases. Note that we should cover the demand for emergency services, that is, it is necessary to model the demand. Developing a demand model requires a lot of data and information and it is not always easy to collect. Several analysis show that there is a high and direct correlation between population and demand for emergency services. Therefore, there are many authors who use the population as a good indicator of the demand, since the population covered by an ambulance from a base at a given time is known in advance (Andersson and Värbrand (2007), Gendreau et al. (2001), van Barneveld et al. (2016)). Then, after a statistical analysis using data related to population and the demand for emergency services, we consider that the covered demand is maximized when we maximize the covered population.

There are several steps involved in managing an emergency. A call activates a series of actions where a brief recognition of the event is made (triage) and the need for a specific resource sent to the emergency site is evaluated. Once the ambulance has arrived, healthcare is carried out on the scene. When the patient is stabilized, the need to transfer to the assigned hospital center is considered. In the event that the patient does not require hospitalization, the ambulance can be assigned to another emergency or return to its usual base. Otherwise, the vehicle goes to the assigned hospital. The ambulance crew remains with the patient until they are treated by the hospital's medical team. When the service has been completed, the ambulance can be assigned to another call or return to its usual base. When the ambulances move and are not at their usual bases, the initial coverage changes. This fact can affect the quality of services and EMS management is needed. The *relocation problem* appears in this context. This problem is dynamic and its objective is to assign each free ambulance at a base in order to maximize the coverage. The relocation occurs when the assigned base is different from the usual one.

According to several studies, there are two ways of dynamic ambulance relocation: relocating vehicles that have just completed a service and relocating any available vehicle, even if it is idle at the base. The relocation of any ambulance usually gives better results, but at the same time generates higher costs. Relocation costs are understood as the number of trips, the kilometers traveled, the operating costs (fuel and vehicle maintenance) and the intangible costs (annoyances suffered by the staff with the continuous movements). In this paper, we propose relocating only ambulances that have just completed a service. In this way, good results can be obtained while keeping costs down (Bélanger et al., 2016).

Table 1 shows some notation needed for the different methods proposed that will be introduced in the following subsections.

In our problem and in general, each base has its usual ambulance (a_b^u). Each ambulance is associated with a base, known as usual base (b_a^u), where the vehicle returns after a service if relocation is not carried out. Note that

A	Set of ambulances
A^*	Set of ambulances waiting to be sent to a base
B	Set of location bases
b_a^u	Usual base (home base) of the ambulance a, $b_a^u \in B$
a_b^u	Usual ambulance of the base b, $a_b^u \in A$
N	Work shift period
t_{max}	Maximum driving time for isochron calculation
c_{b_j}	Population covered by an ambulance from b_j in t_{max}
E	Set of possible relocation scenarios
e	Scenario of relocation $e \in E$

Table 1: *Notation*

we suppose one ambulance per base. Then, one base is free when its usual ambulance is absent and part of the population is not covered.

4 Heuristic algorithm

Figure 2 shows the general steps of the process (operating algorithm) used to manage a medical emergency call. This algorithm is linked to a period of time of N units, for example a shift. It starts at $m = 0$ and finishes when $m = N$. The operating algorithm manages the call queue, ambulances assigned to emergencies, hospitals to patients and, when the conditions for relocation are met, the relocation algorithm is activated. The following subsections introduce the concepts needed to understand how the relocation algorithm works.

4.1 Conditions to relocate

Relocation algorithm will be activated when the following two conditions are satisfied simultaneously:

- *Condition 1. An ambulance could be relocated to a different base from its usual if the vehicle belongs to the set of ambulances waiting to be sent to a base (A^*).*
- *Condition 2. An ambulance that meets the condition 1 could be relocated if there is at least one relocation scenario.*

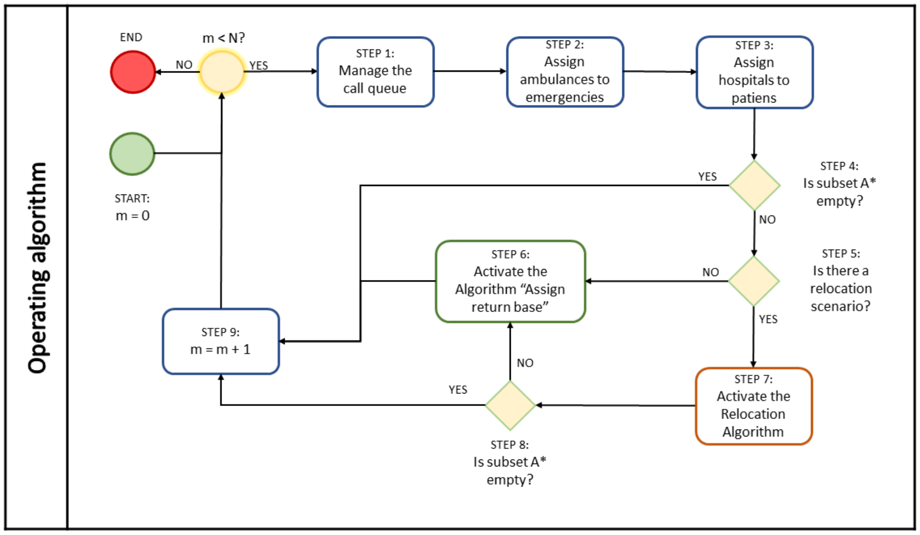


Figure 2: *General diagram of the operating algorithm*

The first condition indicates which ambulances can be relocated at a different base from its usual. The set A^* consists of those that meet the following conditions:

1. The ambulance has completed a service at a hospital. According to various studies, around 75-80% of patients need to be transferred to a hospital (75% Maxwell et al. (2010), 77% Enayati et al. (2018)). Since this work only deals with medical emergencies (known as maximum severity), the cases in which a patient is stabilized after an on-site intervention and does not need to be transferred to the hospital are not included in this study. Therefore, any medical vehicle that has just completed a service will be in a hospital center.

2. The hospital where the ambulance has finished service is not the usual base of this ambulance. If the ambulance terminates in a hospital that is its usual base, the ambulance will not move from there.

3. The ambulance is not assigned to another emergency.

If A^* subset is not empty, the first condition is met (step 4 in Figure 2).

4.2 Relocation scenarios

According to condition 2, an ambulance can be relocated if a relocation scenario is given (step 5 in Figure 2).

A relocation scenario (e) can occur when a geographic area and, consequently, its population are uncovered. A zone must be covered from one or more bases depending on its density of population. Zones with a big concentration of people have more probability to generate emergencies in a more continuous way and they need to be covered by more than one ambulance (from more than one base). We identify a relocation scenario when a zone covered by more than one base (zone with multiple coverage) is total or partially uncovered. Our procedure is focused on this kind of zones because we do not carry out the simple exchange of ambulances between two bases.

Each relevant zone is covered by a base referred to as the *pivot base* and one or more *similar bases* which generate additional coverage for that same zone. Note that a zone with simple coverage (just from one base) is not a possible scenario in our case.

All the elements that are essential to design our strategy of relocation (*procedure to build the relocations scenarios, relocation algorithm...*) have been designed considering the following reflections. Relocation involves changes on the usual configuration of the emergency service. Depending on the amount and frequency of these changes, the emergency system can undergo stress. Therefore, relocation should be carried out when the advantages of relocation could be greater than the costs associated with this relocation. Our strategy is used when a zone with multiple coverage is uncovered, since it is highly likely an emergency may occur and, as a consequence, no nearby ambulance is available to answer the call.

Procedure to identify scenarios

The algorithm 1 shows the steps to build each scenario e that makes up the set of possible relocation scenarios E. The set E is a catalog of scenarios that an EMS identifies as relevant and if one occurs it must be covered. In the following, a description of algorithm 1 is given:

- Each base $b_j \in B$ is considered as pivot base (b_p). An isochron for a maximum driving time t_{max} is calculated (IS_{b_p}) and the population covered from this base (c_{b_p}), that is, population inside of the area represented by an isochron, is stored. Figure 3 shows four examples of an isochron (colored area) for each base. To identify if a base b_i is *similar* to the pivot base b_p, the level of overlap of the isochron from b_i on the isochron from b_p ($OV_{(b_i,b_p)}$) is calculated. This parameter shows the percentage of the population covered by isochron from b_p that is also covered by the isochron from b_i. If this level is higher than a minimum value (OV_{min}) then, b_i will be *similar* to b_p and it will be included in its set of similar bases ($Similar_p$). Determining the value of OV_{min} is relevant because it relates to the size of the relocation scenario. OV_{min} is an indicator of prudence. A very high value, for example, 90%, would result in a few similar bases considered. It would imply that a base only would be considered as similar to a pivot base if 90% of the population of the pivot base is also covered. Otherwise if OV_{min} is small, the size of $Similar_p$ set is increased. In the most extreme case when $OV_{min} \approx 0\%$ for each pivot base the rest of the bases would be similar bases.

Therefore, a value between 50-60% can be a good decision. Figure 3 shows two examples of overlap. If we suppose $OV_{min} = 60\%$, we can note b_2 would not be similar base of the pivot base b_1 (Figure 3a) because the level of overlap is less than 60%. If the base b_4 were the pivot base then, b_3 will not be its similar base (see Figure 3b) because the violet isochron covers 56.45% of the population covered by the brown one. However, if the pivot base were b_3, the b_4 would be its similar because the brown isochron covers the 71.29% of the population covered by the violet one.

- If the $Similar_p$ set is not empty, we define two cases to identify scenarios. These cases depend on the relative importance, that is, the percentage of covered population from each pivot base in t_{max} units of time (C_{b_p}) according to the expression 4.

$$C_{b_p} = \frac{c_{b_p}}{\sum_{b_j \in B} c_{b_j}} \tag{4}$$

  - $Case_1$: If $C_{b_p} \geq C_{min}$ and all bases from set $Similar_p$ are free (without ambulances) then a scenario appears. That is, if a pivot base covers more percentage of population than a minimum given (C_{min}), it means this zone is important, therefore we have to anticipate the situation when the entire zone is left without coverage.

Then we should relocate an available ambulance to a base from set $Similar_p$, even when the pivot base is not empty.

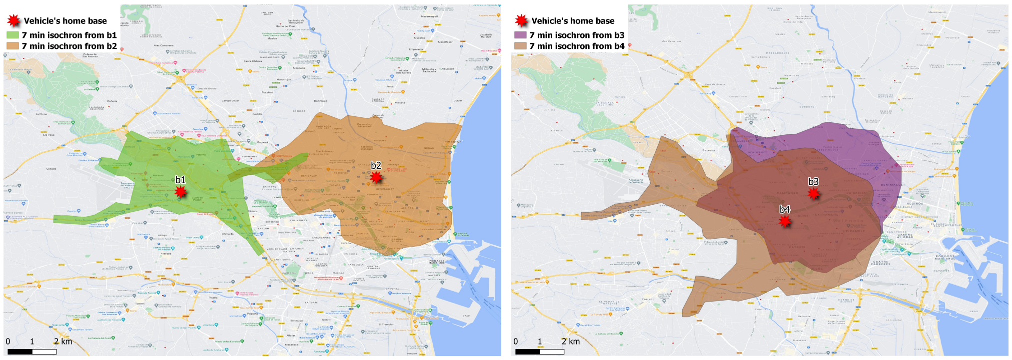
- $Case_2$: If $C_{b_p} < C_{min}$, a scenario will appear if both the pivot base and all bases from set $Similar_p$ are free. In this case, the pivot base covers less percentage of population than the minimum given and the scenario occurs when the pivot base is also free (without an ambulance).

The set E will be updated with each new scenario. Section 5.1 shows an example about building the set E for a real Spanish emergency medical service. Table 4 shows different scenarios for this real case. Note that, all the scenarios are composed by a pivot base b_p and its set $Similar_p$. For example, scenario e_1 is composed by $\{b_3, (b_7, b_4)\}$ that is, b_3 is pivot base and (b_7, b_4) is the set $Similar_3$ of this pivot base.

- After building the set E, it is ordered in non increasing order of C_{b_p} from each pivot base that belongs to each scenario in E. The aim is to give more priority to the scenarios such that the probability of emergency is greater, since there are more population to cover.

Algorithm 1: Pseudocode of build relocation set()

for $j = 1, ..., |B|$ **do**
  b_p=b_j
  Calculate IS_{b_p}
  $Similar_p$ = null
  for $i = 1, ..., |B|$ **do**
    if $i! = j$ **then**
      Calculate IS_{b_i}
      $OV_{(b_i,b_p)}$=:Calculate Overlap (IS_{b_i}, IS_{b_p})
      if $OV_{(b_i,b_p)} \geq OV_{min}$ **then**
        Update $Similar_p(b_i)$
  if $Similar_p$!= null and $Case_1$ or $Case_2$ is found **then**
    e=:Generate relocation scenario
  Update E(e)



(a) *Base b_1 and Base b_2* ***(b)*** *Base b_3 and Base b_4*

Figure 3: *Isochron overlap*

4.3 Relocation algorithm

This algorithm is activated inside the operating algorithm (Figure 2) when the conditions 1 and 2 are satisfied, that is, sets A^* and E^* are not empty at time m. E^* is composed by the scenarios of E that exist at time m. The algorithm 2 shows the steps of this procedure.

The process starts from the most important scenario, the first one in the set E^*. Note that, E^* is ordered with the same criterion as E. Each scenario involves more than one free base. Therefore it is necessary to select among these bases one where a free ambulance of A^* has to be sent. This base is identified as destination base, b_d. We select as b_d the base from where more population is covered.

After choosing b_d the procedure assigns an ambulance from A^* to base b_d. All bases have a usual ambulance, so we can find two cases:

- Case 1: b_d is the usual base of one ambulance a of A^*. Then this ambulance a will be send to b_d and the set A^* and E^* will be updated.

- Case 2: b_d is not the usual base of any ambulance from A^*. Then, a set named *candidate ambulances of base* d, A^*_d is created. This set is composed by the ambulances of A^* which meet the following two conditions:

  2a. The ambulance $a \in A^*$ will be part of A^*_d if its driving time to arrive at b_d from its current location is less than a maximum relocation time (t_R). This time parameter has to be a small value, since our algorithm does not consider an ambulance available while it is "en route".

2*b*. The ambulance $a \in A^*$ will be part of A^*_d if from the destination base b_d covers more population than from the base where it would return to provided that no relocation was required. However, this usual base could be occupied by a different ambulance because of a previous relocation movement. In that case, it would be necessary to identify another base to return to, referred to as *alternative base* (b^*_d). Finally, the ambulance $a \in A^*$ will be part of A^*_d if from the destination base covers more population than from the alternative base, that is if $C_{b_d} > C_{b^*_d}$. The algorithm identify alternative base() shows the process to find the b^*_d. If the usual base of the ambulance a is free, this base is the alternative base. If the usual base of the ambulance a is not free, it is necessary to identify the ambulance (n) that is at the usual base of a. If the usual base of ambulance n is free, it is the alternative base, otherwise the closest free base of usual base of a is considered the alternative base.

If the set A^*_d is not empty, the ambulance closer to b_d will be sent to this base. Otherwise the selected relocation scenario can not be covered and the process starts again for the next relocation scenario. The set E^* is updated in both cases.

Note that more than one scenario can have the same destination base (b_d), then, when one scenario is covered the remaining scenarios with the same b_d are covered as well.

The algorithm of relocation finishes when the sets E^* or A^* are empty. Then, if there are ambulances that need assigning to bases but no relocation scenarios, the algorithm assign return base() starts to work.

4.4 Assignment of return base algorithm

An ambulance is always assigned to a base when it finishes a service at the hospital unless it has been to another emergency. If the ambulance is not relocated, it should go to the usual base. However, this base could be

Algorithm 2: Pseudocode of relocation()

while $A^{*}!=$ null and $E^{*}!=$ null **do**
    $e = E^{*}[0]$
    Determine b_d
    for $i = 1, ..., |A^{*}|$ **do**
        Determine b_i^u
        if $b_i^u == b_d$ **then**
            Send a_i to b_d
            AmbulUsual = True
            Break
    if AmbulUsual == False **then**
        $A_d^{*} =$ null
        for $i = 1, ..., |A^{*}|$ **do**
            if a_i meets conditions $2a$ and $2b$ **then**
                Update A_d^{*} (a_i)
        if $A_d^{*}!=$ null **then**
            Send the closest ambulance to b_d
    Update A^{*} and E^{*}
if $A^{*}!=$ null and $E^{*}==$ null **then**
    assign return base()

Algorithm 3: Pseudocode of identify alternative base()

if b_a^u is free **then**
    $b_d^{*}=b_a^u$
else
    Identify ambulance n in b_a^u
    if b_n^u is free **then**
        $b_d^{*}=b_n^u$
    else
        b_d^{*} is the closest unoccupied base to b_a^u

occupied by another ambulance as a result of a previous relocation movement, in which case, it is necessary to find a return base for this ambulance.

Algorithm 4 is applied when any of the following situations occurs. Both cases are very common in dynamic environments.

1. It is not possible to carry out the relocation because both conditions are not met. As a result, the ambulance has to return to its usual base and it is occupied by another ambulance. In this case we have to assign a new base to the ambulance.

2. The relocation algorithm stops because there are not pending scenarios of relocation but there are pending ambulances to assigned (line 18 of pseudocode 2). In this case, we also have to decide on a base where the ambulances will be sent.

The algorithm is active as long as there are pending ambulances to be assigned to a base, that is the set A^* is not empty. The algorithm 4 shows the pseudocode of this procedure. Each ambulance a is assigned to its usual base (b_a^u) if it is free. Otherwise, the process identifies the usual base of the ambulance n which occupies b_a^u. If b_n^u is free, the ambulance a is sent to b_n^u, if not a will be sent to the closest free base to b_a^u.

Algorithm 4: Pseudocode of assign return base()

while $A^*!=$ null **do**
    $a = A^*[0]$
    Determine b_a^u
    if b_a^u is free **then**
        Send a to b_a^u
    else
        Identify ambulance n in b_a^u
        Determine b_n^u
        if b_n^u is free **then**
            Send a to b_n^u
        else
            Send a to the closest unoccupied base to b_a^u
    Update A^*

5 Computational Results

Several studies of the dynamic ambulance relocation problem show that there is not a unique solution for all EMS. The legislation, the structure and the quantity of the resources of each health area and the geographical elements have an important influence on the solutions obtained. For these reasons, a proposed model is usually accompanied by the resolution of a particular case (Schmid (2012), Jagtenberg et al. (2015), Carvalho et al. (2020)) to analyze its effectiveness. Therefore, to check the performance of the designed algorithm, it is necessary to generate different instances related to a specific EMS.

To analyze the performance of the designed heuristic, it is applied to a real case of the EMS in the region of Valencia (Spain). Then, we use relevant information and data related to this EMS to build the necessary framework and generate instances.

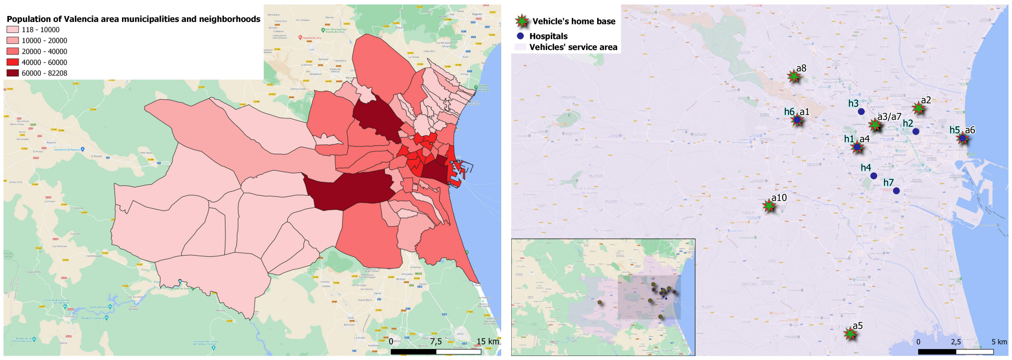
All the experiments have been run on a Intel Core i7, 3.2 GHz and 8 GB RAM. Python 3.7. has been used to code the different methods. QGIS Desktop 3.12.2 and the Openrouteservice plugin have been used to draw isochrons, calculate travel times and covered population.

5.1 A realistic case study

This section shows the information used to identify the set of possible relocation scenarios and the characteristics that describe the emergency management environment. All this information is necessary to specify how the operating algorithm works and, consequently, to check the performance of the proposed relocation algorithm using the instance benchmark (section 5.3).

The EMS in Valencia area is part of the regional public health system. Access to emergency services is guaranteed 24 hours a day by calling 112. The calls are classified into different groups: medical *emergencies* (Priority 1 or Priority 2 calls, if it is a process with imminent or non-imminent vital risk, respectively), medical *urgencies* (Priority 3, Priority 4 or Priority 5 calls, depending on whether or not care can be delayed) and, finally, *other calls* (medical consultation or request for information).

This work is focused on medical emergencies (Priority 1 and 2). This type of calls is handled by the Advanced Life Assistance (AVA) medical vehicles, whose crew consists of medical, nursing, health technician and / or driver personnel.



(a) *Valencia area population* ***(b)*** *Location of vehicles and hospitals*

Figure 4: *Vehicles' service area*

The region of Valencia is a mixed area, with urban and rural zones and with more than 1.5 million population. Figure 4a shows the 58 municipalities near Valencia and 19 neighborhoods of the city of Valencia.

Ten AVA vehicles operate in the Valencia area (five ambulances in the city of Valencia, called a_2, a_3, a_4, a_6, a_7, and another five, a_1, a_5, a_8, a_9 and a_{10}, in nearby municipalities).[2] The usual bases of the vehicles have the same numbering, that is, b_1 is the usual base of ambulance a_1, b_2 is the usual base of ambulance a_2 and so on. Bases b_3 and b_7 have the same location. In most cases, bases are located in health centers or hospitals, where the necessary material can be replaced after assisting an emergency and where the staff can rest until the next service. The location of the ambulances can be seen in Figure 4b. The same Figure shows the 7 hospitals in Valencia area.

Table 2 shows values for the parameters used in this study. In most countries there are recommendations about a maximum response time (T) to an emergency (urban areas between 8 and 10 minutes, rural areas between 12 and 15 minutes). Since in our case urban and rural areas are served by the same EMS, a maximum limit of 10 minutes has been established for the response time.

Since the historical data obtained has not allowed for the modeling of demand for emergency services and given that the correlation coefficient between the number of calls answered and the population in each municipality is more than 95%, the population will be considered as an indicator of demand.

[2]Data from Valencia EMS

T	10 min
t_{max}	7 min
t_{triage}	3 min
$t_{on-site}$	random between 15 and 30 min
$t_{transfer}$	0 min
N	720 min
C_{min}	10%
OV_{min}	50%

Table 2: *Parameters*

When isochrons are performed, the Openrouteservice plug-in estimates the population c_{b_j} that is within the area of the isochron. The Global Human Settlement raster layer (UE, visited July 2, 2021) has been used to estimate the population in any polygon that is not an isochron.

Both, idle ambulances on their bases and those that have finished a service, could be assigned to attend an emergency. The closest ambulance is always assigned (based on travel time). When there is no ambulance available to answer a call, a queue is generated, which is served by the FIFO method (first in, first out). Ambulances heading to a base cannot be assigned to calls until they get there. Only one patient is considered in each emergency and the closest hospital is always assigned. Once the ambulance arrives at the hospital, the patient is transferred to the hospital's medical team. There are quite a few differences with respect to the transfer time of the patient to the hospital. In the American continent this period can last up to an hour (Paz Roa et al. (2020)), while in Europe it is much shorter (10-30 minutes). In this work we are going to consider that hospitals have unlimited capacity and the transfer time ($t_{transfer}$) of the patient is equal to zero.

We determine C_{min} as the half of the maximum value of the relative importance (C_{b_p}). Table 3 shows that in our case the maximum value of the relative importance is equal to 20%, therefore C_{min} is 10%.

We define the maximum relocation time (t_R) as the average travel time between each hospital and each destination base. To calculate the response time is necessary to set the triage time. We suppose that this time is equal to 3 minutes. The maximum driving time for isochron calculation is equal to 7 minutes.

We consider that emergencies can occur during a shift (N) of 720 minutes. The time an ambulance can spend attending the patient at the site of the emergency ($t_{on-site}$) is randomly generated between 15 and 30 minutes.

Pivot Bases (b_p)	Covered Population (c_{b_p})	Relative Importance (C_{b_p})	Similar bases									
			b_3	b_7	b_4	b_2	b_6	b_8	b_{10}	b_1	b_5	b_9
b_3	454341	20%	■	●	●							
b_7	454341	20%	●	■	●							
b_4	445122	19%	●	●	■							
b_2	361106	16%	●	●		■						
b_6	208231	9%				●	■					
b_8	124808	5%						■		●		
b_{10}	103288	5%							■			
b_1	92864	4%	●	●	●			●		■		
b_5	36735	2%									■	
b_9	9708	0%										■
TOTAL	2290544											

Table 3: *Pivot and Similar bases*

5.1.1 Determination of relocation scenarios

The steps of algorithm 1 are followed to build the set of possible relocation scenarios (E). The determination of the scenarios begins with the determination of the pivot bases and their similar bases (see Table 3).

We obtain the scenarios comparing C_{b_p} with C_{min}. For the cases where $C_{b_p} \geq 10\%$, the scenario arises when similar bases are left free. In these cases we want to anticipate the situation when the entire zone (pivot and similar bases) is left without coverage. While for the cases with $C_{b_p} \leq 10\%$, the scenario arises when both the pivot base and the similar bases are left free. Table 4 shows, in the first column, the seven scenarios that make up the set of possible relocation scenarios (E). The importance of the scenarios is determined by the order of C_{b_p} in Table 3 (non-increasing order). The second column shows the bases that must be free to activate the relocation algorithm and, the last column shows the destination base where an ambulance must be sent to cover that scenario.

5.2 Different relocation algorithms

One of the most common procedures to evaluate the proposed strategies is to compare them with the current strategy used in EMS, without relocation (Maxwell et al. (2010), Schmid (2012), Billhardt et al. (2014), Enayati et al. (2018)). In addition to analyzing the performance of the relocation versus non-relocation strategy (in the section 5.3), we aim to examine the effect on performance of the relocation algorithm if some elements are changed.

Scenario $\{b_p, (Similar_p)\}$	**Free bases**	**Destination base** (b_d)
$e_1 : \{b_3, (b_7, b_4)\}$	b_7 , b_4	b_7
$e_2 : \{b_7, (b_3, b_4)\}$	b_3 , b_4	b_3
$e_3 : \{b_4, (b_3, b_7)\}$	b_3 , b_7	b_3
$e_4 : \{b_2, (b_3, b_7)\}$	b_3 , b_7	b_3
$e_5 : \{b_6, (b_2)\}$	b_6 , b_2	b_2
$e_6 : \{b_8, (b_1)\}$	b_8 , b_1	b_8
$e_7 : \{b_1, (b_3, b_7, b_4, b_8)\}$	b_1, b_3, b_7, b_4 , b_8	b_3

Table 4: *Scenarios and Destination bases*

Four versions of the relocation algorithm (see Table 5) have been proposed. Depending on the maximum value for t_R we have two pairs of algorithms: Alg_1 and Alg_3 with 12 minutes and Alg_2 and Alg_4 with 10 minutes. The aim is to study how affects the increase in the maximum relocation time to the relocation strategy. The relocation algorithm according to pseudocode 2 sends to b_d, if it is possible, the ambulances of A^* whose usual base was b_d (lines 4-9 of the pseudocode). This strategy is followed by Alg_1 and Alg_2. Alg_3 and Alg_4 changes the criterion and they always send the ambulance closest to b_d.

Algorithms	t_R **(min)**	**Ambulance to be send**
Alg_1	12	Usual
Alg_2	10	Usual
Alg_3	12	Nearest
Alg_4	10	Nearest

Table 5: *Relocation algorithms*

5.3 Benchmark of instances

The validation of the proposed heuristic technique is not trivial. To test the performance of the four relocation algorithms, their results will be compared with those of the static model, when there is no relocation (Alg_0). As performance measures we propose to use:

- The number of calls with response time T $\leq$ 10 minutes. T is the result of adding the triage time, the time it takes for the ambulance to arrive at the scene of the emergency and the waiting time. The latter appears when there are no ambulances available to assist the emergency.
- Average lateness in minutes. To calculate this measure we select the calls with T$>$ 10 minutes.
- % of relocations of total displacements.
- Standard deviation of displacements of each ambulance.

Based on historical data, 5 types of instances are generated (30, 40, 50, 60 and 80 emergencies for a period of 12 hours). For each type of instance, 5 replicas are obtained with the location of each of the 30, 40, 50, 60 and 80 emergencies. To obtain the location, the tool for generating random points within the polygons of the QGIS software is used. The usual service area in this case is a mixed (urban and rural) area. Instead of considering the entire municipalities (Figure 4a), areas of possible demand for emergency services are generated considering continuous urban network, discontinuous urban network, industrial and / or commercial areas, sports and recreational facilities, urban green areas and roads. Random points are generated based on the population of the municipalities / neighborhoods. For example, Figure 5 shows the locations of the fifty emergencies for instance named 50_1.

The Openrouteservice plugin provides the distance matrix calculation service. Travel time is calculated taking into account speed limits and different road surfaces. The fastest route is selected. Since the traffic lights are not taken into account (only the maximum speed allowed), we consider that these times would be quite similar to those of an ambulance, when it is on the way to an emergency or a hospital, with sirens and lights on. When an ambulance travels without a patient back to a base, the times obtained with the Openrouteservice are increased by 10% because the ambulances will travel under the same conditions as the rest of the vehicles (see Jagtenberg et al. (2015)).

For each of the five instances of each type, another 5 replicas are generated in turn, preserving the same location of the emergencies, but modifying the moment in which the call occurs and the time of on-site assistance. This results in a total of 125 instances ($5 \times 5 \times 5$). The arrival time of the calls (between 1 and 720, a period of 12 hours) and the duration of on-site assistance (between 15 and 30 min) are randomly generated.

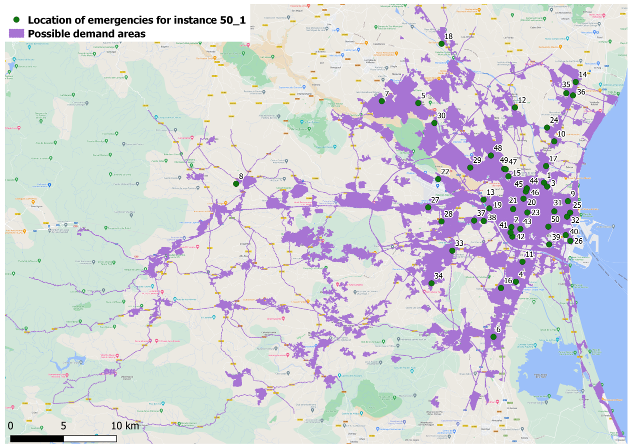


Figure 5: *Example of location of emergency calls for an instance*

Instances of 80 emergencies represent a saturated system, which is unlikely, but not impossible (we have seen this in the current pandemic). Note that this saturation level depends on the characteristics, number of ambulances and size of the emergency system used to generate instances.

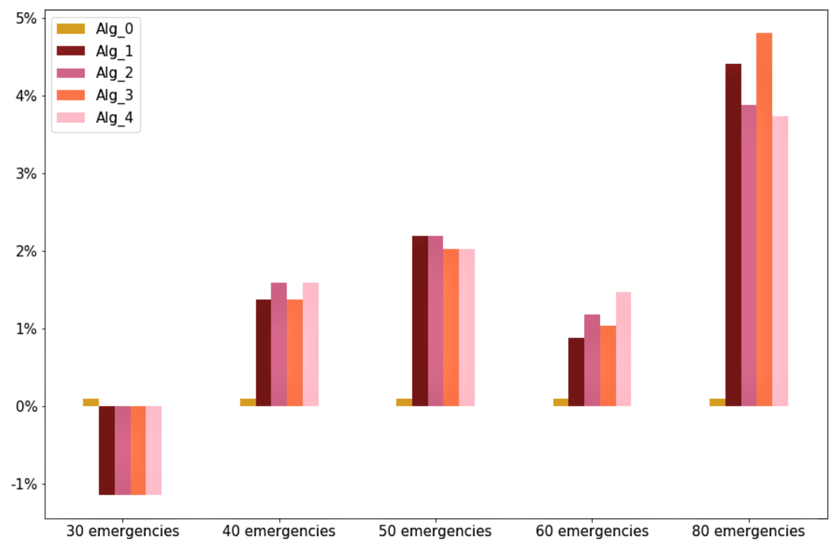
Table 6 shows the results for the five types of instances obtained with each algorithm.

The algorithm without relocation (Alg_0) shows better behavior with respect to the number of calls answered within the time limit of 10 minutes in the instances of 30 emergencies, while, in the instances of 40, 50, 60 and, especially, 80 emergencies the four algorithms with relocation outperform the algorithm without relocation. It can be observed that relocation is more effective with a greater workload. For a better visualization, Figure 6a shows the percentage of calls with response time within 10 minutes for each algorithm with respect to the algorithm without relocation. In the case of instances of 80 emergencies, the improvement can be greater than 4%.

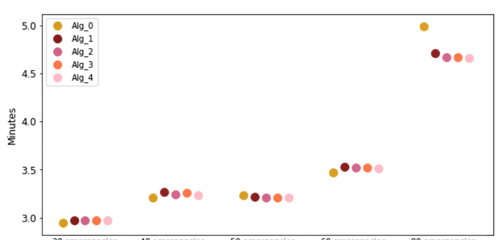
Relocation algorithms do not provide a substantial improvement in the average lateness in the instances of 30, 40, 50 and 60 emergencies (see Figure 6b). In a saturated system (80 emergencies) the delay average increases sharply, which is a fairly obvious result. However, it is important that, in the case of the algorithm without relocation, this increase is larger than in the algorithms with relocation. In this case, when relocation is carried out, not only does the number of calls answered within the 10-minute limit increase, but also the average lateness decreases.

		Alg_0	Alg_1	Alg_2	Alg_3	Alg_4
		Number of calls with response time $\leq$ 10 min				
Instances	**30 emergencies**	349	345	345	345	345
	40 emergencies	439	445	446	445	446
	50 emergencies	592	605	605	604	604
	60 emergencies	679	685	687	686	689
	80 emergencies	749	782	778	785	777
		Average lateness (min)				
	30 emergencies	2.94	2.97	2.97	2.97	2.97
	40 emergencies	3.21	3.26	3.24	3.26	3.24
	50 emergencies	3.23	3.21	3.21	3.21	3.21
	60 emergencies	3.47	3.53	3.52	3.52	3.51
	80 emergencies	5.00	4.71	4.67	4.67	4.66
		% of relocations of total displacements				
	30 emergencies	0.0	32.3	31.3	32.7	32.0
	40 emergencies	0.0	37.0	36.8	35.5	35.3
	50 emergencies	0.0	39.4	39.0	40.5	40.0
	60 emergencies	0.0	41.9	39.7	43.7	41.5
	80 emergencies	0.0	45.9	43.6	46.9	44.2
		Standard deviation of displacements of each ambulance				
	30 emergencies	37	29	29	29	28
	40 emergencies	47	37	37	40	39
	50 emergencies	56	46	46	46	45
	60 emergencies	57	39	41	38	39
	80 emergencies	58	44	45	41	41
		For instances of 80 emergencies				
Number of calls in queue		84	43	43	49	47
% of calls in queue		4.2	2.2	2.2	2.5	2.4
Average (SD) of km traveled per vehicle in the 25 instances		172 (49,0)	170 (43,5)	170 (44,5)	171 (44,4)	171 (45,5)
Total km traveled in the 25 instances		38618	38180	38217	38368	38494

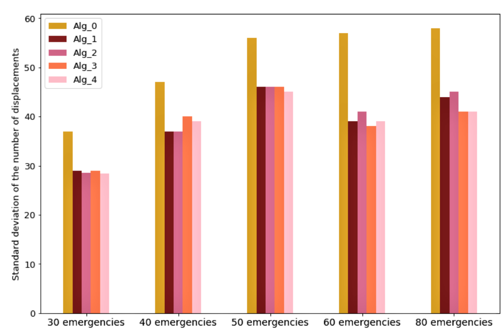
Table 6: *Numerical results*



(a) *Percentage variation of the number of calls with respect to Alg_0*



(b) *Average lateness*



(c) *Imbalance in the workload*

Figure 6: *Numerical results*

Since relocations are only performed at the end of a service, the number of movements in each instance is the same as in a static model. The difference is that instead of going to usual base, the ambulances travel to other bases. Table 6 shows the percentage of trips (out of the total number) made by ambulances to another base, different from their usual base. The number of relocations is not very high (the percentage of relocations of the total displacements does not reach 50% in any case).

Table 6 shows the standard deviation of the number of trips for each type of instance in each of the algorithms. Small deviation means less difference in workload of different ambulances. In Figure 6c it is observed that in the four algorithms with relocation in all types of instances the deviation is smaller than in the algorithm without relocation.

If we compare the relocation algorithms between them, we observe that the variation of the maximum relocation time influences the % of relocations of total displacements. As expected, in all types of instances with Alg_1 and Alg_3 (with t_R = 12 min) the number of relocations is higher than with Alg_2 and Alg_4 respectively, but this increase in relocations does not provide a clear improvement in the number of calls answered within the time limit. While in the instances of 40 and 60 emergencies the algorithms with lower t_R are better, in the instances of 80 emergencies the algorithms with higher t_R show better behavior. With respect to the average of lateness, the algorithms with higher t_R show somewhat worse performance than ones with lower t_R. This could be due to the ambulances moving towards a base do not participate in the assignment to emergencies. In general terms, we can conclude that there is no difference in the behavior of algorithms with $t_R =$ 12 min and $t_R = 10$ min for our case study.

If we compare the algorithms regarding the preferences for sending the ambulances to the destination bases (usual or closest), we cannot conclude that some are better than others.

With respect to the difference in workload, although there are not many differences between the four relocation algorithms, in the instances of 60 and 80 emergencies the strategy of sending the closest ambulance provide the best balance of the workload of different medical vehicles.

We end the presentation of the results with a data, which has emerged in the instances of 80 emergencies (saturated system). It is the number of calls that have not been answered immediately due to a lack of available ambulances and, therefore, have had to be put in the queue. Out of a total of 2000 calls answered in the instances of 80 emergencies, 84 were queued in the algorithm without relocation (see Table 6), while in the four algorithms with relocation this value is low (almost halfway). Furthermore, these results are obtained without increasing the kilometers traveled. Note, in Table 6, the values of the average and of the standard deviation of the kilometers traveled by vehicle and the values of the total of kilometers traveled in the 25 instances are smaller if the ambulance relocation is carried out.

6 Conclusions and future research

In this work, motivated by the need to reduce the response time to emergencies and by the unavailability of vehicles to assist emergencies while answering other calls, heuristic algorithms are developed to help prehospital care services in dynamic ambulance relocation decision making. Based on the analysis of isochron overlaps, Scenarios are generated, which are suitable conditions for the relocation of medical vehicles.

The results obtained in this study show that the advantages of carrying out the relocation of ambulances are obtained thanks to the better allocation of vehicles to the bases and not due to the increase in additional costs. The dynamic relocation of medical emergency vehicles increases the number of calls with response time within 10 minutes. This increase is especially notable in instances with a high workload, where there is also an important advantage over the static model (without relocation) in the average of lateness. The proposed model provides balance in the workload of the different ambulances. This fact is seen not only in the number of services attended, but also in the number of kilometers traveled by each ambulance. There are no obvious disadvantages of saturation of the system: the number of trips made by ambulances is the same as in a static model, there is no increase in the total number of kilometers traveled, same as in the study by Billhardt et al. (2014). The unique disadvantage is that ambulances do not always return to their usual base, but the occurrence of this fact does not exceed 50% in any case.

It has also been observed that it is not always necessary to relocate vehicles, but only when an emergency threshold is exceeded in a certain time. In the analyzed case, this threshold is approximately 30 emergencies in a 12-hour shift.

The prognosis of pathologies that are classified as emergencies (cardiac arrest, severe respiratory failure, severe trauma, cerebrovascular accident, etc.) is related to the time elapsed since they occur until they are treated.

The greater number of emergencies attended within a certain time can have a direct impact on the survival of patients. This fact is an example of a way to meet the Goal 3 of the SDG (Ensure healthy lives and promote well-being for citizens of any age). The proposed tools can help in the management of the EMS avoiding many inconveniences in a work environment that is already stressful. The relocation of medical emergency vehicles promotes a more efficient use of resources to build resilient infrastructure and promote sustainable industrialization (the Goal 9 of the SDG).

In the future research we intend to corroborate the results obtained in this paper with the most exhaustive analysis of historical data and the simulation of discrete events with the incorporation of different emergency generation distributions. The possibility of modifying or developing other relocation algorithms is contemplated based on the results of future analyzes.

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References

Alanis, R., Ingolfsson, A., Kolfal, B., 2013. A Markov Chain Model for an EMS System with Repositioning. Production and Operations Management 22, 216–231.

Andersson, T., Värbrand, P., 2007. Decision support tools for ambulance dispatch and relocation. Journal of the Operational Research Society 58, 195–201.

Andrade, L.A.C.G., Cunha, C.B., 2015. An ABC heuristic for optimizing moveable ambulance station location and vehicle repositioning for the city of Sao Paulo. International Transactions in Operational Research 22, 473–501.

van Barneveld, T., 2016. The Minimum Expected Penalty Relocation Problem for the Computation of Compliance Tables for Ambulance Vehicles. INFORMS Journal on Computing 28, 370–384.

van Barneveld, T., Jagtenberg, C., Bhulai, S., van der Mei, R.D., 2018. Real-time ambulance relocation: Assessing real-time redeployment strategies for ambulance relocation. Socio-Economic Planning Sciences 62, 129–142.

van Barneveld, T.C., Bhulai, S., van der Mei, R.D., 2016. The effect of ambulance relocations on the performance of ambulance service providers. European Journal of Operational Research 252, 257–269.

van Barneveld, T.C., Bhulai, S., van der Mei, R.D., 2017. A dynamic ambulance management model for rural areas. Health Care Management Science 20, 165–186.

Billhardt, H., Lujak, M., Sánchez-Brunete, V., Fernández, A., Ossowski, S., 2014. Dynamic coordination of ambulances for emergency medical assistance services. Knowledge-Based Systems 70, 268–280.

Bélanger, V., Kergosien, Y., Ruiz, A., Soriano, P., 2016. An empirical comparison of relocation strategies in real-time ambulance fleet management. Computers & Industrial Engineering 94, 216–229.

Bélanger, V., Ruiz, A., Soriano, P., 2015. Recent Advances in Emergency Medical Services Management. CIRRELT 28.

Bélanger, V., Ruiz, A., Soriano, P., 2019. Recent optimization models and trends in location, relocation, and dispatching of emergency medical vehicles. European Journal of Operational Research 272, 1–23.

Boujemaa, R., Jebali, A., Hammami, S., Ruiz, A., 2020. Multi-period stochastic programming models for two-tiered emergency medical service system. Computers & Operations Research 123, 104974.

Cabral, E.L.S., Castro, W.R.S., Florentino, D.R.M., Viana, D.A., Costa Junior, J.F., Souza, R.P., Rêgo, A.C.M., Araújo-Filho, I., Medeiros, A.C., 2018. Response time in the emergency services. Systematic review. Acta Cirúrgica Brasileira 33, 1110–1121.

Carvalho, A., Captivo, M., Marques, I., 2020. Integrating the ambulance dispatching and relocation problems to maximize system's preparedness. European Journal of Operational Research 283, 1064–1080.

Daskin, M.S., 1983. A Maximum Expected Covering Location Model: Formulation, Properties and Heuristic Solution. Transportation Science 17, 48–70.

Enayati, S., Mayorga, M.E., Rajagopalan, H.K., Saydam, C., 2018. Real-time ambulance redeployment approach to improve service coverage with fair and restricted workload for EMS providers. Omega 79, 67–80.

Fogue, M., Garrido, P., Martinez, F.J., Cano, J. C. Calafate, C.T., Manzoni, P., 2013. A novel approach for traffic accidents sanitary resource allocation based on multi-objective genetic algorithms. Expert Systems with Applications 40, 323–336.

Gendreau, M., Laporte, G., Semet, F., 2001. A dynamic model and parallel tabu search heuristic for real-time ambulance relocation. Parallel computing 27, 1641–1653.

Gendreau, M., Laporte, G., Semet, F., 2006. The maximal expected coverage relocation problem for emergency vehicles. Journal of the Operational Research Society 57, 22–28.

Jagtenberg, C.J., Bhulai, S., van der Mei, R.D., 2015. An efficient heuristic for realtime ambulance redeployment. Operations Research for Health Care 4, 27–35.

Jánošíková, L., Kvet, M., Jankovič, P., Gábrišová, L., 2019. An optimization and simulation approach to emergency stations relocation. Central European Journal of Operations Research 27, 737–758.

Lam, S.S.W., Zhang, J., Zhang, Z.C., Oh, H.C., Overton, J., Ng, Y.Y., Ong, M.E.H., 2015. Dynamic ambulance reallocation for the reduction of ambulance response times using system status management. American Journal of Emergency Medicine 33, 159–166.

Landa-Torres, I., Manjarres, D., Salcedo-Sanz, S., Del Ser, J., Gil-Lopez, S., 2013. A multi-objective grouping Harmony Search algorithm for the optimal distribution of 24-hour medical emergency units. Expert Systems with Applications 40, 2343–2349.

Lee, S., 2011. The role of preparedness in ambulance dispatching. Journal of the Operational Research Society 62, 1888–1897.

Liu, Y., Yuan, Y., Li, Y., Pang, H., 2013. A Chance Constrained Programming Model for Reliable Emergency Vehicles Relocation Problem. Procedia - Social and Behavioral Sciences 96, 671–682.

Maxwell, M., Restrepo, M., Henderson, S., Topaloglu, H., 2010. Approximate Dynamic Programming for Ambulance Redeployment. INFORMS Journal on Computing 22, 266–281.

Moeini, M., Jemai, Z., Sahin, E., 2015. Location and relocation problems in the context of the emergency medical service systems: a case study. Central European Journal of Operations Research 23, 641–658.

Nasrollahzadeh, A.A., Khademi, A., Mayorga, M.E., 2018. Real-Time Ambulance Dispatching and Relocation. Manufacturing & Service Operations Management 20, 467–480.

Otamendi, F.J., García-Heredia, D., 2015. Isochrones as Indicators of the Influence of Traffic in Public Health: A Visual Simulation Application in Ávila, Spain. International Journal of Environmental Research and Public Health 12, 12556–12576.

Paz Roa, J.C., Escobar, J.W., Marín Moreno, C.A., 2020. An online real-time matheuristic algorithm for dispatch and relocation of ambulances. International Journal of Industrial Engineering Computations 11, 443–468.

Peleg, K., Pliskin, J.S., 2004. A Geographic Information System Simulation Model of EMS: Reducing Ambulance Response Time. American Journal of Emergency Medicine 22, 164–170.

Rajagopalan, H.K., Saydam, C., Xiao, J., 2008. A multiperiod set covering location model for dynamic redeployment of ambulances. Computers & Operations Research 35, 814–826.

Reuter-Oppermann, M., van den Berg, P.L., Vile, J.L., 2017. Logistics for Emergency Medical Service systems. Health Systems 6, 187–208.

Schmid, V., 2012. Solving the dynamic ambulance relocation and dispatching problem using approximate dynamic programming. European Journal of Operational Research 219, 611–621.

Schmid, V., Doerner, K.F., 2010. Ambulance location and relocation problems with time-dependent travel times. European Journal of Operational Research 207, 1293–1303.

Sudtachat, K., Mayorga, M., Chanta, S., Albert, L., 2020. Joint relocation and districting using a nested compliance model for ems systems. Computers & Industrial Engineering 142, 106327.

Sudtachat, K., Mayorga, M.E., Mclay, L.A., 2016. A nested-compliance table policy for emergency medical service systems under relocation. Omega 58, 154–168.

UE, visited July 2, 2021. URL: https://ghsl.jrc.ec.europa.eu/download.php?ds=pop.

UK, visited October 6, 2021. URL: https://www.gov.uk/government/publications/supplements-to-the-nhs-constitution-for-england/the-handbook-to-the-nhs-constitution-for-england.

UN, visited May 24, 2022. URL: https://sdgs.un.org/goals.

van den Berg, P.L., Aardal, K., 2015. Time-dependent MEXCLP with start-up and relocation cost. European Journal of Operational Research 242, 383–389.

Vecina García, M.Á., Villa Juliá, M.F., Vallada Regalado, E., Karpova Krylova, Y., 2022. A mixed integer linear program for a real relocation problem of emergency medical vehicles in the province of valencia. Journal of Applied Research in Technology & Engineering 3, 85–92.