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Realistic strategies for dynamic ambulance relocation

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ABSTRACT

The location of vehicles is a decision of significant importance for Emergency Medical Services. However, the delivery of emergency care is dynamic in nature and the initial locations of ambulances may quickly prove inadequate for maintaining coverage as they are dispatched to attend to patients. Rather than increasing the size of the fleet of vehicles, research has focused on the dynamic relocation of ambulances. This approach allows available vehicles to move to sites beyond their usual bases, maintaining an appropriate level of service. The scientific community has proposed a wide variety of ambulance relocation strategies using different methodological approaches. However, most of the strategies have not been implemented by real life Emergency Medical Services. This study proposes a scenario-based dynamic relocation algorithm that incorporates the following realistic aspects: it allows ambulances to start and end their work shift at their usual base, regardless of the number of relocations performed; a methodology based on Geographic Information Systems is developed to determine the positions of ambulances en route in order to be able to assign these ambulances to emergencies. In addition, the importance of relocating ambulances at different times of the day is studied. The proposed algorithm is validated by applying it to a real life case, in the city of Valencia, Spain, where the importance of considering these realistic aspects is shown.

1. Introduction

Ambulance relocation is a branch of study that considers the dynamic nature of the process of responding to health emergencies and consists of assigning ambulances to waiting areas other than their usual bases. Unlike the static location of ambulances, which determines the positions of vehicles at strategic and tactical levels, the relocation of ambulances corresponds to the operational level [1]. Relocation can be *multi-period* or *dynamic*. Multi-period relocation is determined by population movements from one area to another during the day or week. In this case, different distributions of the fleet of medical vehicles are proposed in a territory over different periods of time. On the other hand, dynamic relocation is determined by the variation in the number of available ambulances, which decreases when vehicles are assigned to emergencies and increases when ambulances end their services.

The scientific community has proposed a large number of relocation strategies of the two types mentioned above over the last thirty years. However, the vast majority remain at an academic or theoretical level and are not applied to real Emergency Medical Services (EMS). More than ten years ago, the authors of [2] indicated that more than 40% of the papers presented at meetings of The European Working Group on Operational Research Applied to Health Services (ORAHS) between 1975 and 2009 were developed in collaboration with health care organizations. However, the implementation level of the proposed models or tools was only 6%. Today, the problem of a lack of implementation still exists [3,4]. Moreover, as the authors of [5] indicate, it is difficult to know whether implementation has actually taken place. In the ambulance relocation field of study, there is no clear understanding of the implementation of the proposed strategies. Many authors thank real EMS in their articles, but in most cases, it is for the data provided and not for the validation of the strategies in a real service setting.

There are many reasons for a lack of implementation of relocation strategies in real EMS, but we would highlight the following two identified in discussions with EMS personnel:

1. EMS organization is typically structured around shifts, where a crew is assigned to a base. This base is where they begin their working day and where they return after completing each service. Ambulance personnel are generally resistant to changing their base assignments, and it is important to consider labor legislation regarding workplace location. The assignment of a crew to a base is a tactical decision, according to [1], meaning

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it does not usually change on a daily or weekly basis. Consequently, implementing a fully dynamic relocation strategy, where crews start and end their shifts at different bases every day, would be challenging. This approach would require a drastic change in current practices and would incur not only economic costs, but also intangible costs (annoyances suffered by the staff with the continuous movements) in an already stressful work environment.
2. The process of responding to medical emergencies is quite complex, and modeling it in a virtual environment can be challenging. Simulation is one of the most commonly used methods to evaluate relocation strategies. However, simulation models are not used in all academic works; some authors create their own dynamic environments to recreate the emergency health care process and evaluate representative instances [6–8]. Despite efforts to reproduce the emergency response process as realistically as possible, both simulation and dynamic environments often include simplifications, such as aggregated demand, linear distances and the absence of call queues, etc. These simplifications reduce the credibility of the relocation strategies proposed by academics, as they do not realistically quantify their impact. Consequently, EMS managers may not trust the validity of results obtained through the application of these relocation strategies.

This paper aims to address the two previously mentioned problems. The objectives of this paper are as follows:

- Propose a relocation algorithm that minimally disrupts existing work habits within a real EMS. Given that health care systems are generally resistant to change, the algorithm focuses on strategies that require minor adjustments, making implementation more feasible. The algorithm restricts the number of ambulances relocated, allowing all ambulances in the system to begin and end their shifts at their designated base. To our knowledge, this consideration has not been addressed in previous research, despite the organizational structure of most real EMS being shift-based. In addition, the explicit inclusion of the *demand period* concept in the dynamic relocation algorithm is proposed. This involves coupling multi-period relocation with dynamic relocation, an innovation not previously explored.
- Evaluate relocation strategies within an environment that closely mirrors the actual process of emergency health care. To achieve this, various tools from Geographic Information Systems (GIS) are utilized. One such tool is the *isochron*, which defines the area accessible within a set time frame from a specific point using a particular mode of transport (such as on foot, by bicycle, or by car). Using isochrons, a methodology is developed to determine the positions of ambulances en route, aiming to incorporate them into the emergency assignment process. An evaluation of the relocation strategies is conducted using instances proposed in [9] for the city of Valencia, Spain. This methodology can be adapted to other health areas, both nationally and internationally.

The sections of this paper are distributed as follows: Section 2 reviews academic literature concerning dynamic ambulance relocation. Section 3 describes the ambulance relocation problem, while Section 4 details the algorithmic part of the problem. Section 5 shows the results of a real case study and we end with the conclusion section.

2. Literature review

Over the past thirty years, the scientific community has proposed a wide range of relocation strategies for medical vehicles. These strategies can be classified in various ways. One of the most general classifications divides them into multi-period relocation and dynamic relocation problems. Since this paper proposes an algorithm for dynamic relocation, the literature review focuses on papers that adopt this approach. For studies on multi-period relocation, please refer to [10].

Dynamic relocation strategies can be categorized according to the moment of resolution into two groups: offline and online. Offline strategies precalculate optimal ambulance positions for each number of available vehicles [11–13]. In contrast, online strategies solve the problem in real time, often utilizing heuristic methods to find solutions [14–16].

There is a wide range of approaches which can be used to formulate the ambulance relocation problem, from linear programming [17], dynamic programming [18,19] and heuristics [14], to geometric optimization [20] and Geographic Information Systems (GIS) [8]. This last approach is quite recent, as although GIS originated in the 1960s, the application of GIS tools to medical vehicle relocation problems did not begin until the early years of the 21st century. The authors of [21] use isochrons to determine the locations of ambulances during different time periods. Another similar work is [22]. However, both works deal with multi-period relocation. The only work that utilizes isochrons for dynamic relocation is [8], where an isochron overlap analysis is conducted to identify scenarios suitable for applying a relocation strategy. Although isochrons have been widely used as a reachability tool [23,24] and also in static ambulance location problems [25,26], their use in medical vehicle relocation problems is uncommon.

Since the first relocation models [14,17,27], it has become evident that continuous ambulance movement generates stress in the system and has to be restricted. There are different ways to do this: with a maximum allowed relocation time [13,14,28], with a minimum time between two consecutive relocations [7,29,30], or with consideration of the cumulative workload of each ambulance [17,31]. Another way to restrict movement, which is also used in this article, is through the number of vehicles to be relocated. Instead of considering the entire available fleet, the authors of [8,32,33] only relocate ambulances that have recently completed a service. The strategy of relocating only newly-available ambulances is quite balanced, as it achieves good results without placing excessive strain on the system [30].

The evaluation of relocation strategies is typically conducted within an environment that simulates the real process of responding to health emergencies. When modeling this environment, numerous aspects must be determined, such as the emergency call rate, the spatial distribution of calls, the type of distance and speed used to calculate routes, among others. The authors strive to incorporate realistic elements into the modeling of the emergency response process. However, the complexity of the process often necessitates simplifications, which can widen the gap between academic models and real-world applications. Notable among these simplifications are the following:

- The concept of aggregate demand is used [13,16,28], where calls are generated at a limited number of points that represent demand zones, instead of working with a continuous space.
- Distances such as Euclidean, Haversine, or Manhattan are often used, though they fail to accurately represent the real structure of road networks with traffic restrictions [19,29,34].
- It operates with a zero-queue system, meaning if an emergency cannot be attended to at the time of the call, the emergency is not queued but instead discarded [13,33,35,36].
- Ambulances en rote are not assigned to emergencies due to the difficulty in determining their positions [31,33,37].

Contribution of this work

The algorithm proposed in this paper follows an online strategy, resolving ambulance relocation problem in real time. We adopt an approach that combines heuristics with GIS tools. Heuristics, due to their flexibility, allow for the inclusion of realistic problem aspects, enable real-time solutions and are often intuitive and easy to understand. Many authors, even those who formulate the ambulance relocation problem with mathematical models, use heuristics to solve it [13,17,32].

Furthermore, GIS tools assist in obtaining inputs, building relocation strategies and visualizing results. In 2005, the authors of [38] noted the enthusiasm of EMS managers when viewing simulated results via GIS. Based on our experience, this enthusiasm remains evident today when showing actual area coverage.

This paper places special emphasis on the two aspects mentioned above: proposing simple strategies, which do not alter the dynamics of the system too much, and performing the validation of the strategies in an environment which resembles the real one as much as possible. The main contribution of this paper in these two areas is the following:

- Regarding relocation strategy
  - Ambulance relocation may solve coverage problems, but it also introduces other challenges that cannot be overlooked. In nearly every work involving ambulance relocation, vehicles are assigned to a base at the beginning of their shift. However, in most of these papers no mention is made about the positions of the ambulances at the end of their shift. Given that most of EMS operate around shifts, each ambulance must conclude its work shift at the starting base, which is not a straightforward task. This paper develops an algorithm that ensures all ambulances return to their usual base at the end of their workday, regardless of the number of relocations performed.
  - The authors of [39] found that the demand for emergency services fluctuates both throughout the week and over the course of each day. Similar behavior is shown in [40,41]. The results of [8] show that for instances with low workloads, relocation does not bring benefits. Although some authors consider the non-homogeneous call rate when proposing dynamic relocation strategies [17,19,37], they do not explicitly include the concept of a demand period. In this paper, different dynamic relocation strategies are proposed based on the demand patterns and the effect of employing relocation during different time periods is studied, i.e., the dynamic relocation approach is combined with the multi-period relocation approach.
- Regarding the environment for the evaluation of the strategies
  - The use of GIS has made it possible to include many realistic aspects when modeling the emergency health care process. Thanks to GIS tools, the real distance with traffic restrictions has been used for the calculation of travel times. Continuous land space has been considered and demand aggregation has been avoided. The distribution of the population in a territory and, especially, of the elderly population, who are, according to [42], those who make the greatest use of health emergency services, has been obtained. The inclusion of the age characteristic of the population is a novel aspect in this area of study, since it has only been used in article of [7].
  - Using isochrons, we developed a methodology to determine the positions of ambulances en route. This enables these ambulances to participate in the assignment of vehicles to emergencies, thereby making the modeling of the emergency care process more realistic.

3. Problem description

The process of responding to a medical emergency can be represented as a series of steps in an iterative algorithm named *Operating*, shown in Fig. 1. The algorithm starts at moment $m = 0$, operates over a time period N and a new iteration is done every n time units. The process begins with the arrival of an emergency call, which is managed in a call queue (Step 1). Once the call's severity is determined, a medical vehicle is assigned (Step 2). It is important to note that, in many European countries, all emergency calls (medical and non-medical) are initially received by a call center and then redirected to a specialized one, depending on their nature. Not all calls necessitate dispatching emergency vehicles; some involve consultations where assistance is provided over the phone. In this article, however, we focus on medical emergencies that are life-threatening and demand an urgent response. When the ambulance arrives at the emergency site, the patient receives medical attention and is taken to the hospital (Step 3). In some cases, if the patient does not need to be transported to the hospital, the ambulance becomes available to attend to other emergencies or return to its base. When the ambulance arrives at the hospital, the patient is admitted. If at this moment there are no emergencies to attend to, the vehicle returns to its base (Step 4). This is a typical sequence of steps in many real EMS systems when ambulance relocation is not involved.

3.1. Ambulance relocation

When ambulances are assigned to emergencies, they become unavailable to serve other people. In such cases, some zones may experience a decline in service levels, and it may be beneficial to cover these zones with other ambulances. Since the fleet of medical vehicles is limited and their number remains constant over a given period, sending an ambulance to one area to improve coverage means leaving another area uncovered. Therefore, ambulance relocation is not a simple task and should not merely involve exchanging bases. It is important to avoid strategies that require excessive vehicle movement to prevent an increase in stress levels in the system. In some countries [37], ambulances waiting at a base cannot be relocated to another standby location. Consequently, in studies such as [32,33], only ambulances that have recently completed a service can be relocated. When an ambulance becomes available again, moving it to a different base, instead of its usual one, is considered.

The authors of [8,43], which also only relocate ambulances that have finished a service, determine specific relocation conditions, which depend on several factors, including the status of other ambulances. While in [43] an urgency index is defined for each ambulance base, [8] outlines scenarios using isochrons, which represent combinations of bases left without ambulances. An example of a scenario is illustrated in Fig. 2, where bases $b2$ and $b6$ are left without ambulances. This figure shows how the coverage of those areas changes as the isochrons associated with each vehicle at its corresponding base disappear.

This article uses the same methodology proposed by [8] for scenario construction. However, instead of using the distribution of the total population in an area to determine coverage, the population of people over 60 years of age is used. The use of population as a demand indicator is quite common, given the significant correlation between these two measures [32,44]. This study, however, includes an important characteristic of the population: age, as older adults are the primary users of emergency services [44].

To explain the construction of the scenarios, we use the notation in Table 1.

An EMS area is equipped with a number of vehicles, denoted as A, each having the same characteristics and dedicated to attending health emergencies. Each vehicle a is assigned a usual base b_a^u in set B, where the ambulance starts its work shift and returns after concluding each service, unless it is relocated to another base. Notably, each base can accommodate only one vehicle.

The construction of a set of possible scenarios (E) in an EMS area is performed with the following steps[2]:

1. Calculate the isochrons from each of the bases of set B, i.e. determine the areas of coverage from each base within a given time t_{max}.

[2] Note that when we talk about the population, we are referring to the population over 60 years of age.

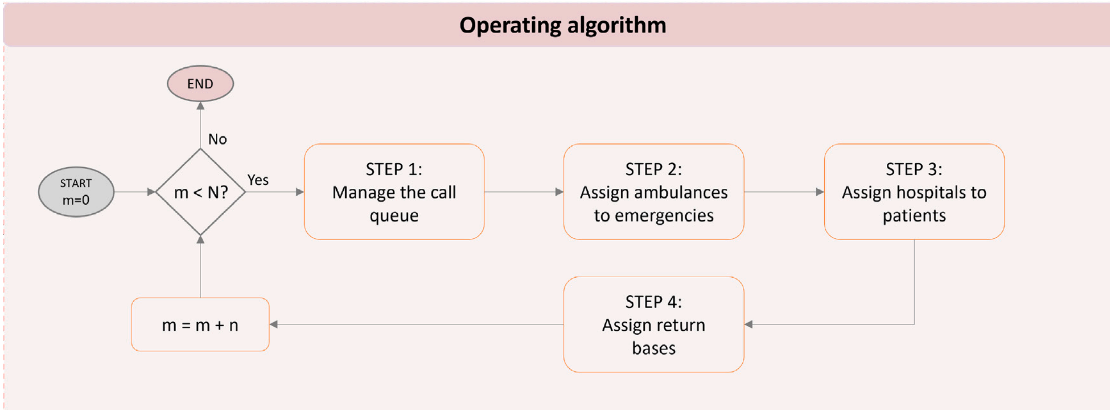


Fig. 1. Diagram of Operating algorithm without relocation.

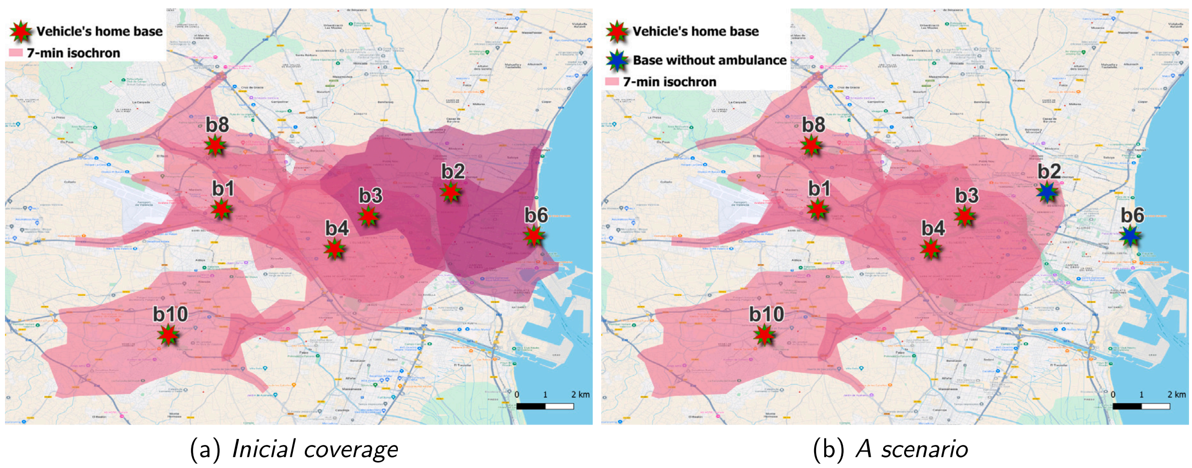


Fig. 2. Example of a scenario.

Table 1
Notation.

A	Set of ambulances
A^f_m	Set of available ambulances at time m
A^w_m	Set of ambulances waiting to be sent to a base at time m
B	Set of location bases
b^u_a	Usual base (home base) of ambulance a, $b^u_a \in B$
a^u_b	Usual ambulance of base b, $a^u_b \in A$
N	Work shift period
n	Time between two iterations
T	Maximum response time
t_{max}	Maximum driving time for isochron calculation
t_R	Maximum relocation time
c_{b_j}	Population of people over 60 covered by an ambulance from b_j in t_{max}
E	Set of possible relocation scenarios
E_m	Set of relocation scenarios at time m

2. Sort the set of bases B in non-increasing order based on the population each base covers. The population covered, denoted as (c_{b_j}), is determined by the isochron area around base b_j. The relative importance of each base is then calculated as follows:

$$C_{b_j} = \frac{c_{b_j}}{\sum_{b_i \in B} c_{b_i}} 100\% \tag{1}$$

3. Identify the so-called *similar* bases for each base in set B. For example, base b_2 (see Fig. 2(a)) is considered similar to another base, b_6, if a significant portion of the same population covered by base b_6 is also covered by base b_2, i.e. when there is a significant overlap of the isochrons (% overlap > OV_{min}). Such multiple coverage of the same population is typical in densely populated areas, where the likelihood of receiving a call, and therefore having an ambulance occupied, is very high. The fact that base b_2 is similar to base b_6 does not imply an inverse relationship.
4. For a base with a relative importance C_{b_j} exceeding a certain threshold C_{min}, a scenario arises when all its similar bases are left without ambulances. These empty bases collectively form a scenario. The objective here is to prevent a future critical situation where the entire area, comprising the base and its similar bases, lacks coverage. For less important bases, where the relative covered population is below C_{min}, a scenario occurs when both the base and its similar bases are devoid of ambulances, indicating a complete lack of coverage in the area. Bases without similar bases do not generate a scenario.
5. The importance of the scenarios is determined by the order of the bases defined in point 2.

For each possible scenario $e \in E$ the destination base (b_d) is determined, which is the base where the ambulance is dispatched to address the scenario. This base is selected because it covers the largest population among the bases within the same scenario. The set E_m represents a subset of E at time m.

Once the set of scenarios is obtained, the *Relocation conditions* are defined:

1. Set A^w_m is not empty, that is, when there are ambulances that have just finished a service and have to be sent to a return base, since there are no calls to attend to.

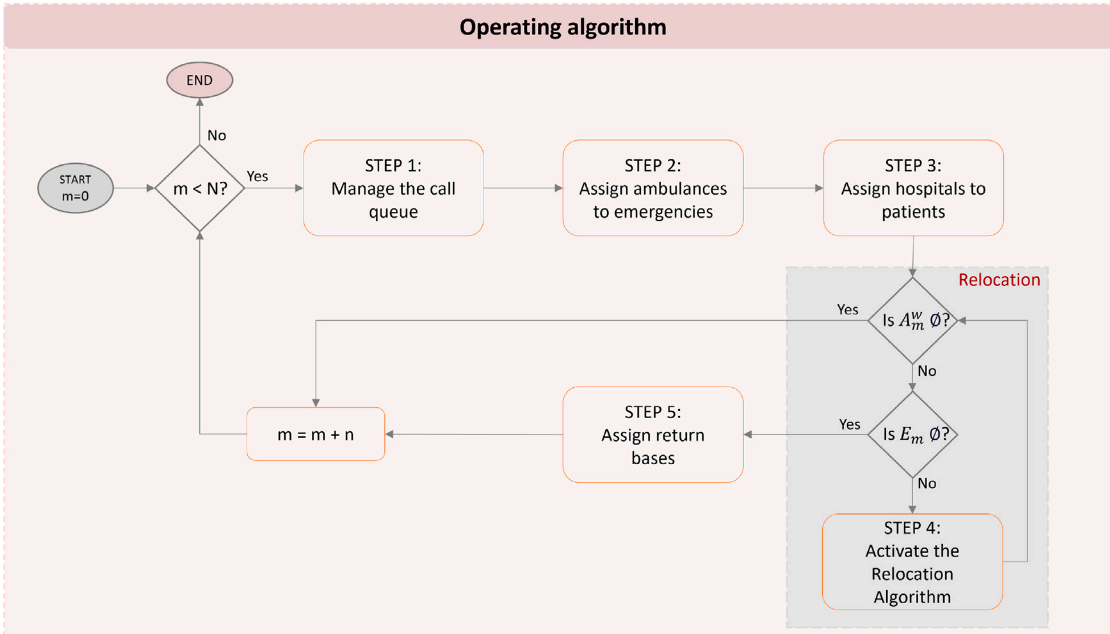


Fig. 3. Diagram of Operating algorithm with relocation.

2. Set E_m is not empty, i.e. there is a relocation scenario.

Fig. 3 shows how the relocation algorithm is included within the operating algorithm. The relocation algorithm (Step 4) is activated when both of the above conditions are met. If the first condition is not met, i.e. there are no ambulances to send to a base, the next iteration ($m = m + n$) is continued. If the first condition is met but there is no scenario, Step 5 in Fig. 3 is activated, meaning the ambulance must return to its base. However, there may be cases where the ambulance's usual base is occupied due to a previous relocation. In such cases, the ambulance is directed to the base of the ambulance that is occupying its usual location. If this base is also occupied, the ambulance is sent to an available base nearest to its usual location.

The process depicted in Fig. 3 has a significant limitation compared to a real-world process: it lacks the incorporation of the concept of a *work shift*, where ambulances not only begin but also conclude their workday at their usual base. It is true that parameter N indicates the time horizon of the process. However, there is a wide range of possible system configurations at the end of a shift, especially after ambulances have been involved in relocations. It is not straightforward to ensure they all return to their usual bases. Simply ceasing the relocation at a certain time and redirecting ambulances finishing services to their usual bases is not always possible, as some bases might be occupied. Therefore, a solution to this limitation will be proposed in the following section.

3.2. Relocation of ambulances considering work shift and demand periods

Dynamic ambulance relocation is a process of organizing the fleet of vehicles with the objective of maintaining/improving the level of service when the number of available ambulances changes. Ambulance relocation involves movements of ambulances to waiting locations that are not their usual bases. Each base change poses a challenge for ambulance personnel, as organizational habits and, even legal requirements designate a specific workstation for each shift. If crews are asked to begin their shift in one location and end it in another, it complicates matters for both the staff and the emergency services managers, making such conditions hard to accept. Despite recognizing these challenges, many proposed relocation strategies do not address the shift aspect.

In this article we present a novel strategy that allows each ambulance to start and end its work shift at its usual base, regardless of the number of relocations performed. Fig. 4 illustrates the emergency care process in our case. The following sections describe the modified aspects related to Fig. 3, encompassing both the relocation component (shaded in gray) and the operating algorithm itself, highlighting its altered steps with pink shading.

3.2.1. Relocation strategy

According to the statistical analyses of [31,40,41], the demand for pre-hospital health care services varies during the day and the week. These changes in demand at different periods are the reason for multi-period relocation, however, so far they have not been explicitly accounted for in dynamic relocation. In this paper, we propose integrating the multi-period relocation approach with the dynamic relocation approach by adapting the relocation strategies to the workload. As can be observed in Fig. 4, a new condition (the right red diamond) is added to activate the Relocation algorithm (Step 4). This condition specifies a period, defined by moments R and L, during which relocation is permitted. This approach examines whether dynamic relocation is necessary across all time periods.

To ensure all ambulances complete their work shift at their usual base, a new algorithm is developed, named as the Usual base assignment algorithm (Step 5 of Fig. 4). This algorithm is activated within a specified period $[L; K]$ (left red diamond). Section 4 provides detailed explanations of both the relocation algorithm and the usual base assignment algorithm.

3.2.2. Assignment of ambulances en route

In a real EMS system, it is possible to track an ambulance's position en route and determine if it is the closest to the scene of an emergency. However, this is not as straightforward in a virtual environment. According to [45], simulating travel times is quite challenging and requires sophisticated GIS-related methods. The authors propose an approximate method based on real travel times between M known points (600 in this case). The travel time t_{ab} between two points a and b, which are not included in the matrix M, is calculated using the travel times of the closest known points a' y b'. These points are identified by

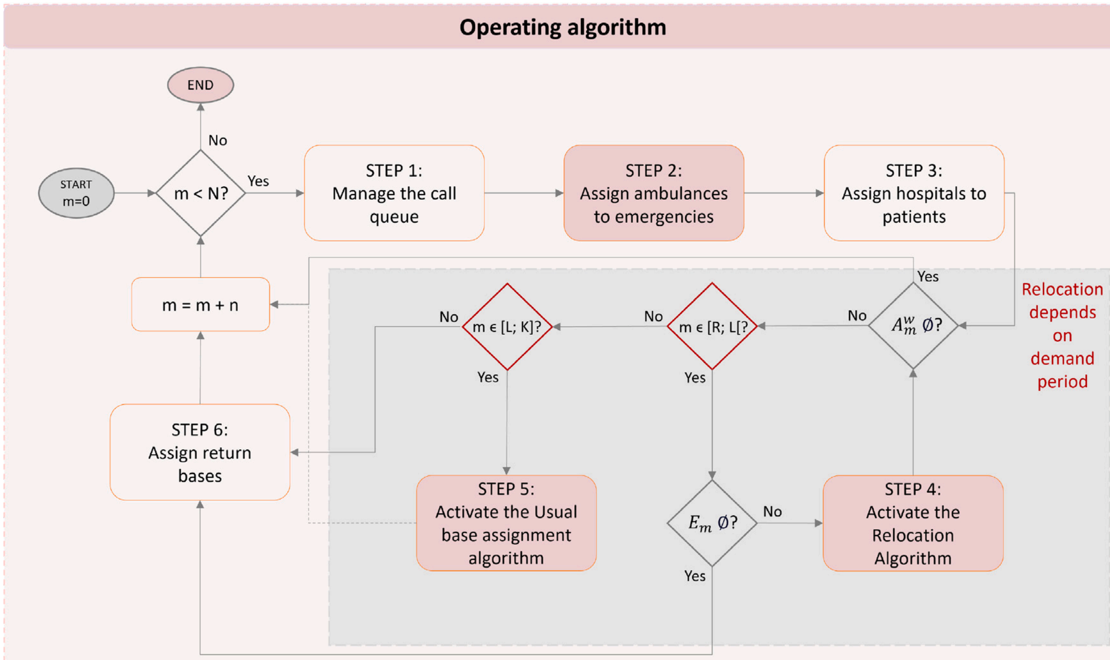


Fig. 4. Diagram of current operating algorithm.

their proximity to a y b, respectively, based on Euclidean distances d_{ab} and $d_{a'b'}$. The calculation proceeds as follows:

$$t_{ab} = \frac{d_{ab} \times t_{a'b'}}{d_{a'b'}}, \tag{2}$$

In many other studies, ambulances en route cannot be assigned to new emergencies until they arrive at a base.

This paper develops a methodology based on the use of GIS to calculate the positions of ambulances en route. It should be noted that it is not a sophisticated methodology, but one that is quite intuitive and easy to implement. The steps of the procedure are detailed below.

For each pair of origin–destination points, where the origin is, for example, a hospital h and the destination is a base b:

1. The fastest path (direction) from h to b is determined.
2. The arrival time is obtained (t_{hb}).
3. Since in the operating algorithm the time is discretized (an iteration is done every n time units), the isochrons for n, $2n$, …, $t_{hb} - n$ time units from h are calculated.
4. The intersections of the isochrons with the fastest path are performed, obtaining the paths traveled in n, $2n$, …, $t_{hb} - n$ time units.
5. The last vertexes of each path are extracted, which are the arrival points from the hospital h in the direction of the base b at time n, $2n$, …, $t_{hb} - n$.

Fig. 5 shows two examples of obtaining the positions of an ambulance en route. Suppose an ambulance has completed a service at the hospital, marked with a blue diamond, and must proceed to the base, marked with a red star. The fastest route to this base has a travel time of 5 min. Considering that n is equal to 1 min, we obtain the isochrons from the hospital for 1 min (Fig. 5(a)), 2 min (Fig. 5(b)), and so forth, up to 4 min (5 − 1). The points where the path intersects with the edge of each isochron represent the positions of the ambulances en route at each iteration of the operating algorithm. Once the positions of the ambulances en route are obtained, we can calculate the travel times to emergency locations. This methodology is integrated into the Ambulance Assignment Algorithm (Step 2 in Fig. 4), enabling ambulances en route to be involved in the emergency assignment process, thereby making the emergency care process more realistic.

4. Algorithms

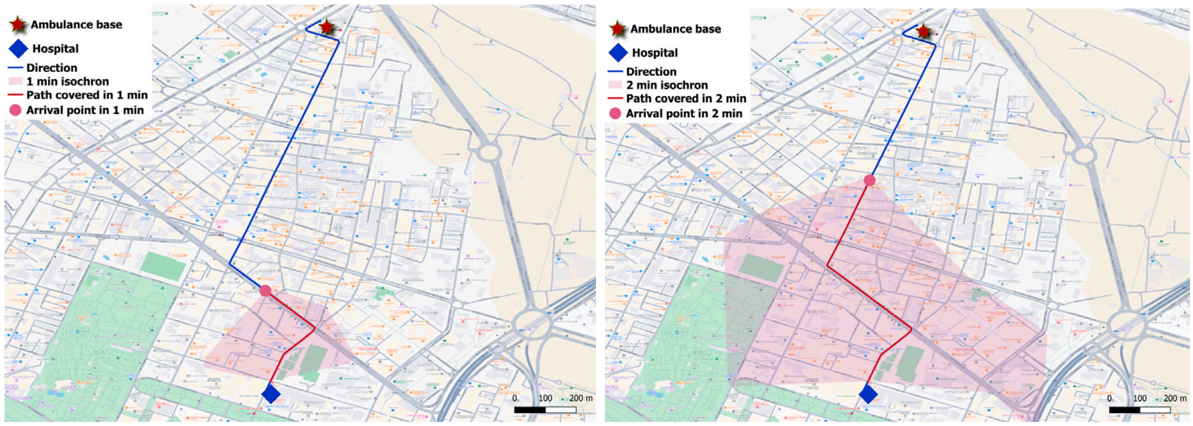
This section of the article details both the relocation algorithm and the usual base assignment algorithm.

4.1. Relocation algorithm

Response time, defined as the interval between receiving a call and the ambulance arriving at the emergency scene, is often regarded as a key indicator of an EMS's service quality. The goal of relocating medical vehicles is to decrease this response time not only for current calls, but also for future ones. As mentioned in Section 2, only ambulances that have recently completed a service can be relocated in this paper. The algorithm has two features to highlight:

- It is able to look into the near future. Some authors, such as [15, 43] suggest considering vehicles with only a few minutes remaining to complete a service as available ambulances. It makes sense to identify ambulances that are in an area and will be able to provide coverage in this area in a short space of time, before sending an ambulance from another area there. In this work, we propose considering ambulances that will be available soon only for relocation purposes, not for assigning to patients, to avoid increasing the risk of them not turning out to be available at the expected time.
- Priority is given to locating each ambulance at its usual base. The location of vehicles provides initial coverage of the population in a service area. Ideally, ambulances should always be at their assigned bases. Since this is unrealistic because vehicles have to move to serve patients, relocation strategies that affect this initial configuration as little as possible could be more acceptable to health service managers. Therefore, it is always better for a base to be occupied by its usual ambulance and not by another. The relocation algorithm proposed in this work prioritizes returning the base's usual ambulance, even if it is still occupied, but will be available soon.

The pseudocode Relocation algorithm shows the steps to perform ambulance relocation. The algorithm can be activated within the time



(a) *Arrival point in 1 min* (b) *Arrival point in 2 min*

Fig. 5. Obtaining the positions of an ambulance en route.

interval $[R;L[$ while there are ambulances to send to bases (set A_m^w is not empty), and while there are relocation scenarios (set E_m is not empty). The first, most important scenario is selected (line 3 of Algorithm 1) and the destination base b_d is determined to cover this scenario. A check is carried out to see if the destination base is the usual base of any of the ambulances that are in set A_m^w (line 7). If this is the case, this ambulance is dispatched to the destination base, giving priority to the usual ambulance, regardless of its proximity. If the destination base's usual ambulance is not in set A_m^w (line 11), a subset A_m^* of A_m^w is created to identify ambulances eligible for relocation (line 14). The *Conditions for eligibility* are as follows:

- The travel time between the point where the ambulance is located and the destination base does not exceed t_R.
- The ambulance covers more of the population at the destination base than at the alternative return base.

The alternative return base for an ambulance a is its usual base. If this base is occupied by another ambulance (q) in a previous relocation, then the alternative return base for a is the usual base of q. If this base also is occupied, then the alternative return base for a is the free base closest to its usual base.

When subset A_m^* is not empty (there are ambulances eligible for relocation) (line 16 of Relocation algorithm), at this point we look into the near future. The status of the usual ambulance of the destination base (a_d^u) is checked. If the ambulance is already at the hospital with the patient (line 18), regardless of whether the patient has been transferred or not, this ambulance is also considered as a candidate to be sent to the destination base. Then, the closest ambulance of A_m^* is dispatched to the destination base. When we talk about the closest ambulance, we are referring to the vehicle that will reach the base in the shortest time. Note that for ambulances still completing transfer of patient, the time to reach the base includes both transfer time and travel time. If the destination base's usual ambulance is not at the hospital (line 21), the closest ambulance among the previously selected candidates is sent to the destination base. If the conditions to be eligible to relocate are not met by any of the ambulances from A_m^w, then this scenario cannot be satisfied and is removed from the list (line 24) to make way for the following scenario. At the end of each iteration, both sets A_m^w and E_m are updated.

Thus, the algorithm only considers relocating ambulances that have completed a service and whose travel time to the destination base does not exceed t_R. Priority is given to locating each ambulance at its usual base. In addition, the status of the destination base's usual ambulance is considered when covering the corresponding scenario.

Algorithm 1: Pseudocode of Relocation algorithm

1 **if** $m \geq R$ *and* $m < L$ **then**
2   **while** A_m^w*!= null and* E_m*!= null* **do**
3     $e = E_m[0]$;
4   Determine b_d;
5   **for** $i = 1, \ldots, |A_m^w|$ **do**
6   Determine b_i^u;
7   **if** $b_i^u == b_d$ **then**
8   Send a_i to b_d;
9   AmbulUsual = True;
10   Break
11   **if** *AmbulUsual == False* **then**
12       $A_m^* =$ null;
13   **for** $i = 1, \ldots, |A_m^w|$ **do**
14   **if** a_i *meets the conditions to be a relocation candidate* **then**
15   Update A_m^* (a_i)
16   **if** A_m^**!= null* **then**
17   Determine a_d^u;
18   **if** a_d^u *is at hospital* **then**
19   Update A_m^* (a_d^u);
20   Send the closest ambulance to b_d
21   **else**
22   Send the closest ambulance to b_d
23   **else**
24   Update E_m (remove e)
25   Update A_m^w and E_m

4.2. Usual base assignment algorithm

The usual base assignment algorithm (Step 5 of Fig. 4) ensures that each ambulance completes its work shift at the base where it began. It is not possible to simply deactivate the relocation algorithm and start sending ambulances to their usual bases, since some of them may be occupied. Consequently, to ensure all ambulances complete their shifts at their usual bases, any idle ambulances at other bases will eventually need to return to their own starting locations. The pseudocode Usual base assignment algorithm shows the details of this process.

The algorithm has two criteria for assigning ambulances depending on time instant m: a soft part, called "Relax movement", which is activated for a period $[L;K[$, and an abrupt part, called "Shock

Algorithm 2: Pseudocode of Usual base assignment algorithm

```
1  if m ≥ L and m < K then
2      "Relax movement"
3      for i = 1, ..., |A_m^w| do
4          Determine b_i^u;
5          if b_i^u is free then
6              Send a_i to b_i^u;
7          else
8              Do not move a_i
9  else
10     m == K;
11     "Shock movement"
12     for i = 1, ..., |A_m^{f*}| do
13         Determine b_i';
14         if b_i' != b_i^u then
15             Update A_m^w (a_i)
16     if A_m^w != null then
17         for i = 1, ..., |A_m^w| do
18             Determine b_i^u;
19             Send a_i to b_i^u;
```

movement", which is performed at time K. In "Relax movement" for each ambulance waiting to be sent to a base (set A_m^w) a check is carried out to see whether its usual base is free. If it is (line 5), the ambulance is sent there. If it is not, no movement is made, i.e. the ambulance will have to wait at the hospital until the "Shock movement". In "Shock movement" (line 10) all ambulances from set $A_m^{f^*}$ (available at time m and idle at a base) are selected if they occupy a base (b_i') that is not their usual one (line 14). All these ambulances are added to set A_m^w and the bases they occupied (b_i') are considered free to receive their usual ambulances. Thus, set A_m^w can have both ambulances that were at hospitals pending dispatch to a base after a service, and ambulances that are already at a base, but not their usual one. If set A_m^w is not empty (line 16), each of its ambulances are sent to their usual bases (lines 17–19). Therefore, "Relax movement" corresponds to the preparatory part of "Shock movement". It is relatively short and is done to avoid back-and-forth movements, when an ambulance is relocated to a base, but within a few minutes will need to be sent back to its usual base. In this way, Algorithm 2 ensures that each medical crew finish their workday at their usual base, where they had started, regardless of the number of relocations performed by the ambulance.

5. Computational results

In order to carry out an accurate evaluation of ambulance relocation strategies, access to real data (population density, real distance matrices, etc.) is essential. Geographic Information Systems (GIS) can help with this task. In this paper we have used QGIS 3.22 [46], which is a free GIS software that not only allows us to make maps, but also has many plugins to download spatial objects, calculate isochrons and population within polygons, calculate distance matrices and determine emergency sites. To calculate isochrons, population within its area, real distances and shortest paths, the QGIS plugin Openrouteservice [47] has been used. To calculate the population over 60 years old within the polygons, the raster layer *esp_elderly_60_plus* [48] has been utilized. To determine the possible areas of demand, the areas of continuous urban network, discontinuous urban network, industrial and commercial areas, sports and recreational facilities and urban green areas were selected from the land use layer of the Institut Cartogràfic Valencià [49]. The road map has been obtained with the QGIS Download OSM plugin. All algorithms have been programmed in Python 3.7. The experiments have been performed with Intel Core i7, 3.2 GHz and 8 GB RAM.

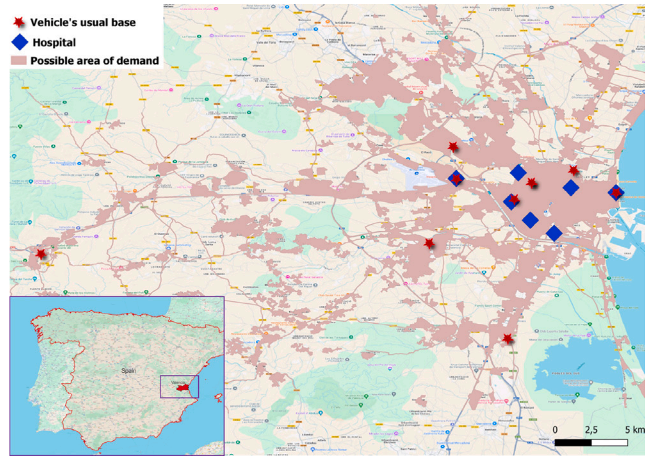


Fig. 6. Valencia service area.

5.1. A realistic case study

Similar to many studies on ambulance relocation [7,15,32], the evaluation of strategies is often conducted using a real case study. In this case, it involves the city of Valencia, Spain.

Valencia is a city located on the east coast of Spain, in the Province of Valencia (see Fig. 6). With a population of 807,693 inhabitants (Source: [50]) it is the third most populated city in Spain, behind Madrid and Barcelona. Valencia's health emergency system is part of the regional public health system.

The study area in this paper is a mixed one, encompassing both urban and rural regions. It includes 19 neighborhoods within the city of Valencia, where the majority of the population resides, as well as 58 nearby municipalities, totaling 77 zones with an approximate population of 1.7 million. Fig. 6 also shows the location of the 7 hospitals and the 10 bases of the 10 Advanced Life Assistance (AVA) vehicles, which are those that respond to health emergencies.

Fig. 7 outlines the analysis of the historical date for emergencies that occurred in 2019, sourced from the Servicio de Atención Sanitaria a Urgencias y Emergencias (SASUE).

The initial dataset comprised emergencies from the Province of Valencia. A selection was made of cases attended by an AVA vehicle within the specified study area. Statistical analysis revealed that the daily average of emergencies on working days differed from that on non-working days. However, there was no significant difference in the daily average among the five working days of the week. Thus, the final dataset consists of emergencies which occurred on working days. This dataset is divided according to the time of the occurrence of the emergency, resulting in 24 subsets, each with its call rate, as shown in Table 2. Finally, some of these periods are grouped into: high demand, medium demand and low demand periods, which are used for the construction of relocation strategies.

5.1.1. Parameters for the operating algorithm

For the configuration of the operating algorithm, the following parameters have been established: the work shift (N) is 1440 min (24 h) and the system update is done every minute (n = 1 min). The triage time is 3 min and the chute time is not considered. The duration of on-site assistance is randomly generated between 15 and 30 min and the transfer time at the hospital is random, between 15 and 20 min. Given that these are health emergencies, all patients require transfer to the hospital, as in [6,51].

The 600 instances generated by [9] have been used. The instances are 40, 60, 80 and 100 emergencies per day. The calls come in according to the Poisson distribution with the call rates indicated in

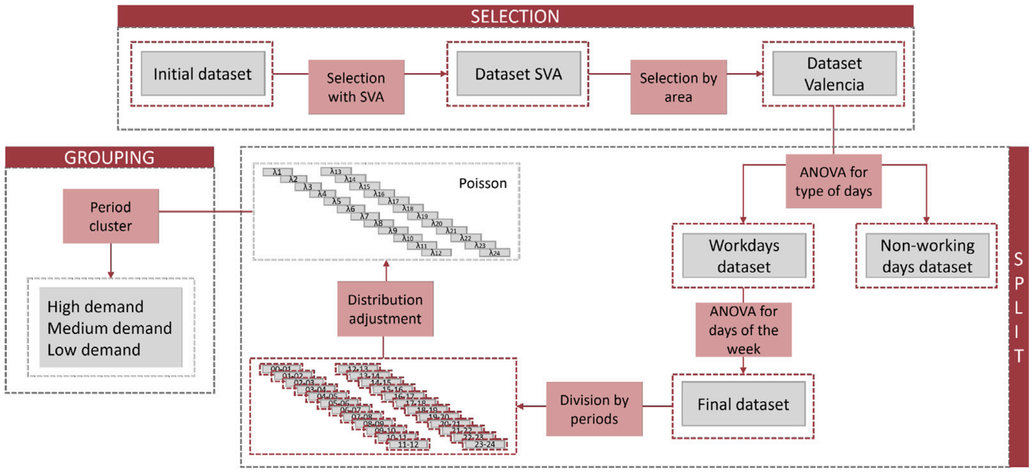


Fig. 7. Data analysis diagram.

Table 2
Hourly call rates.

00–01	01–02	02–03	03–04	04–05	05–06	06–07	07–08	08–09	09–10	10–11	11–12
0.88	0.78	0.62	0.59	0.54	0.43	0.56	0.84	1.22	1.82	2.23	2.39
12–13	13–14	14–15	15–16	16–17	17–18	18–19	19–20	20–21	21–22	22–23	23–24
2.54	2.24	1.92	1.51	1.50	1.30	1.64	1.52	1.50	1.53	1.28	1.02

Table 2. Emergencies are generated in the 77 areas of potential demand based on the population of people over 60 years of age. Although the distribution of the total population across the country is similar to that of the population over 60 years of age [9], they are not identical. The real distance and maximum speed allowed on each section of road are used for the trips. The duration of the trips is increased by 10% when the ambulance is without a patient. In order to consider ambulances en route, more than 44 million routes have been generated, as explained in Section 3.2.2.

5.1.2. Construction of relocation scenarios

Taking each of the 10 bases in set B as a starting point, isochrons have been calculated with a maximum travel time (t_{max}) of 7 min. The areas of the isochrons indicate the population of people over 60 years of age covered (c_{b_j}) by ambulances from each of these bases. Table 3 illustrates the ranking of the 10 bases based on c_{b_j}. To determine the similar bases for each of the 10 bases, an isochron overlap analysis is performed. A base is similar to another base when it covers at least 50% of the same population, that is, when there is an overlap of their isochrons (OV_{min} = 50%). Similar bases for each of the bases in set B have been marked with a red circle in Table 3.

Once the similar bases are known, the possible scenarios (E) are searched for in each of the rows of Table 3. For bases whose relative importance (C_{b_j}) is greater than 10% (C_{min} = 10%), a scenario arises when their similar bases become free. These are the first four rows of the table. Thus, four scenarios are obtained: (1) when bases $b7$ and $b4$ are left without ambulances, (2) when bases $b3$ and $b4$ are left without ambulances, (3) when bases $b3$ and $b7$ are left without ambulances and (4) when bases $b3$ and $b7$ are left without ambulances. Given that scenarios 3 and 4 are the same, we consider them as one. For bases whose relative importance is less than 10% ($b6$ and $b1$), scenarios arise when both the base itself and its similar bases are left free. In this case, scenarios are obtained: (4) when bases $b6$ and $b2$ are left without ambulances and (5) when bases $b1$ and $b4$ are left without ambulances. Bases $b10$, $b8$, $b5$ and $b9$ do not generate scenarios because they do not have similar bases. Table 4 indicates the destination base (b_d) for each of the scenarios obtained. The maximum relocation time (t_R) is 10 min. The maximum response time (T) is 10 min.

5.1.3. Relocation strategies

Fig. 8 shows the annual averages of emergency calls per hour in the Valencia area on weekdays in 2019. Some periods have similar averages, allowing them to be grouped together (this is the Grouping section in Fig. 7), obtaining: a high demand period marked with squares, a period of medium demand marked with triangles and a low demand period marked with circles.

Since the workload is different in each period, five strategies are proposed with the aim of studying the importance of relocation in different periods:

- Strategy_a. Relocation is done only for the period of high demand.
- Strategy_b. The relocation is done for the period of high demand, but with a small margin, taking into account the two previous hours that correspond to the period of medium demand (see Fig. 8).
- Strategy_c. Relocation is performed during the high demand period and during the subsequent medium demand period hours.
- Strategy_d. Relocation is done during periods of high and medium demand.
- Strategy_e. Relocation is done in all periods.

Considering that the work shift starts at 8 am and lasts 1440 min, Table 5 summarizes the details of the proposed strategies. The Relocation algorithm can be activated at time R, marking the minute when ambulances may begin to be relocated. At time L, the preparatory phase of Usual base assignment algorithm begins, lasting 44 min (which is the travel time between the two most distant bases). At time K, the "Shock movement" of Usual base assignment algorithm occurs. The duration (in minutes) of the relocation period is displayed in the final column in Table 5.

The results of each of the proposed strategies are compared with the results of the algorithm without relocation (Str_0), as in [18,20,31,37]. Finally, we examine the impact of assigning ambulances while en route on the outcomes.

5.2. Numerical results

Three measures are used to evaluate the performance of relocation strategies: the number of emergencies attended within 10 min, the

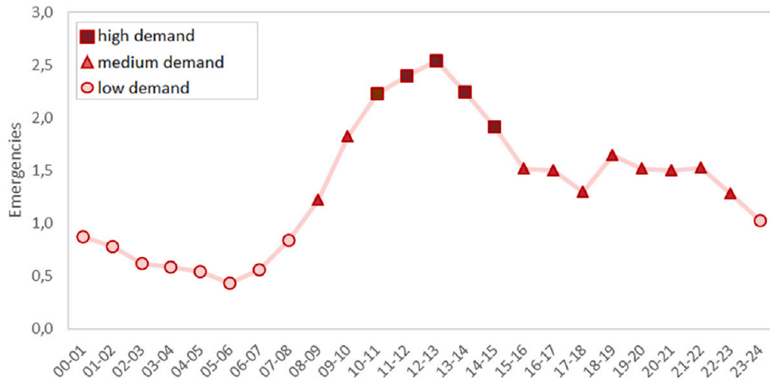


Fig. 8. Annual average of emergencies.

Table 3
Similar bases.

Bases	c_{b_j}	C_{b_j}	Similar bases *b3*	*b7*	*b4*	*b2*	*b6*	*b10*	*b1*	*b8*	*b5*	*b9*
b3	105,312	22.3%		•	•							
b7	105,312	22.3%	•		•							
b4	99,889	21.2%	•	•								
b2	79,308	16.8%	•	•								
b6	41,769	8.8%				•						
b10	15,175	3.2%										
b1	13,779	2.9%			•							
b8	5,103	1.1%										
b5	4,546	1.0%										
b9	2,034	0.4%										
Total	472,226	100%										

Table 4
Set E.

Scenario	Free bases	b_d
1	*b7b4*	*b7*
2	*b3b4*	*b3*
3	*b3b7*	*b3*
4	*b6b2*	*b2*
5	*b1b4*	*b4*

Table 5
Relocation strategies.

Strategies	*R*	*L*	*K*	*Duration*
Str_a	120	316	360	196
Str_b	0	316	360	316
Str_c	120	796	840	676
Str_d	0	796	840	786
Str_e	0	1396	1440	1396

average lateness and the average number of relocations per instance. Table 6 summarizes the numerical results. The left side of the table shows the data for the case when ambulances en route cannot be assigned to emergencies, while the right side of the table shows the results with the assignment of ambulances en route.

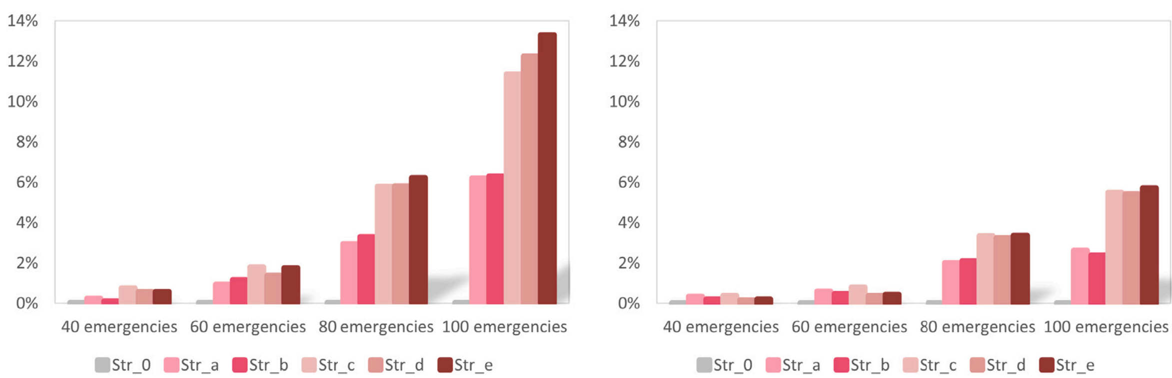
According to Table 6, when ambulances are assigned while en route, more calls are answered within 10 min. This result is fairly predictable, as returning ambulances are available and do not need to reach a base before being dispatched to emergencies. In order to better appreciate the effect of relocation, Fig. 9 shows the percentage difference in the number of calls answered within 10 min for each strategy compared to the strategy without relocation. This is shown both for scenarios without en route ambulance assignment (Fig. 9(a)) and with en route assignment (Fig. 9(b)). Both figures share the same y-axis, illustrating that the relocation effect is smaller when ambulances are assigned en route. This can be explained by the context of relocation scenarios, which often occur in densely populated areas, mostly in the center of Valencia, where hospitals are situated. During relocation, vehicles move from hospitals to these central areas rather than traveling to distant bases, resulting in shorter hospital-to-base trips. Consequently, when vehicles cannot be assigned en route, relocation enables ambulances to become available sooner than if they returned to their usual bases. In contrast, when ambulances can be assigned en route, the relocation effect is clearer and more realistic. This result is important because it shows that when ambulances are not assigned en route, the capacity of relocation algorithms can be significantly overestimated (6% in Fig. 9(b) versus 13% in Fig. 9(a) for Strategy *e*).

Focusing on the most realistic case (Fig. 9(b)), it can be observed that relocation increases the number of emergencies attended within 10 min. In instances of 40 and 60 daily emergencies, this increase is between 5 and 32 emergencies (0.18 and 0.80%), while in the larger instances the improvement is between 97 and 306 emergencies (2 and almost 6%) with respect to the algorithm without relocation. While five emergencies may seem few, it is important to remember that each represents a potential life saved. There is not much difference between Str_a (relocate only in the period of high demand) and Str_b (relocate in the period of high demand and in the previous two hours). We observe a rise in the number of calls attended within 10 min when relocation is applied during the medium demand period. In the largest instances, with 100 emergencies per day, this strategy yields an improvement of nearly 4%. Thus, relocating only in the high demand period is not the best option. The difference between Str_c, Str_d and Str_e is not very large, suggesting that implementing relocation during low demand periods does not yield significant improvements.

Fig. 10 shows the average lateness for each type of instance. On the left side, we have the results without the assignment of ambulances en route and on the right side, with it. The effect of relocation is smaller for the more realistic case, when returning ambulances participate in the assignment to emergencies. In other words, if ambulances are not assigned en route, the capacity of relocation algorithms may be significantly overestimated. For instances of 100 emergencies per day without the assignment of ambulances en route, the average lateness drops from 6.15 min (without relocation) to 5.29 min (with relocation) for Str_e, while with the assignment of returning ambulances the average drops

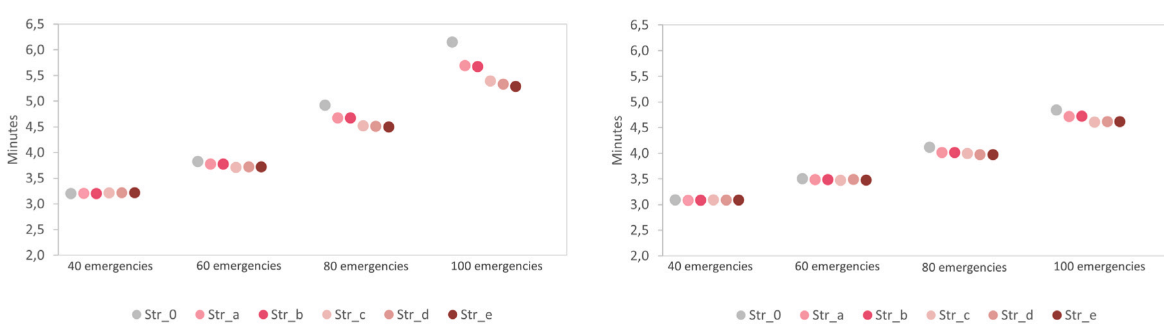
Table 6
Numerical results.

Daily call number	Without ambulances en route						With ambulances en route					
	Str_0	Str_a	Str_b	Str_c	Str_d	Str_e	Str_0	Str_a	Str_b	Str_c	Str_d	Str_e
Number of calls with response time ≤ 10 min												
40	2786	2793	2789	2807	2802	2802	2854	2864	2860	2865	2859	2860
60	3746	3781	3790	3813	3798	3812	3988	4012	4007	4020	4003	4006
80	4301	4428	4443	4550	4551	4569	4809	4906	4910	4970	4965	4971
100	4460	4737	4741	4967	5006	5053	5350	5490	5478	5644	5640	5656
Average lateness (min)												
40	3.20	3.20	3.20	3.21	3.21	3.21	3.09	3.08	3.08	3.09	3.09	3.09
60	3.82	3.77	3.77	3.71	3.72	3.72	3.50	3.48	3.48	3.47	3.48	3.47
80	4.92	4.67	4.67	4.52	4.51	4.50	4.12	4.01	4.01	3.99	3.97	3.97
100	6.15	5.69	5.67	5.39	5.33	5.29	4.84	4.71	4.72	4.61	4.62	4.62
Average number of relocations												
40		3	3	10	10	14		3	3	9	10	14
60		5	6	16	17	23		5	6	16	17	24
80		8	9	23	24	34		8	9	24	25	34
100		10	11	30	31	43		10	12	30	31	43



(a) *Without vehicles en route* (b) *With vehicles en route*

Fig. 9. % difference in number of calls compared to the algorithm without relocation.



(a) *Without vehicles en route* (b) *With vehicles en route*

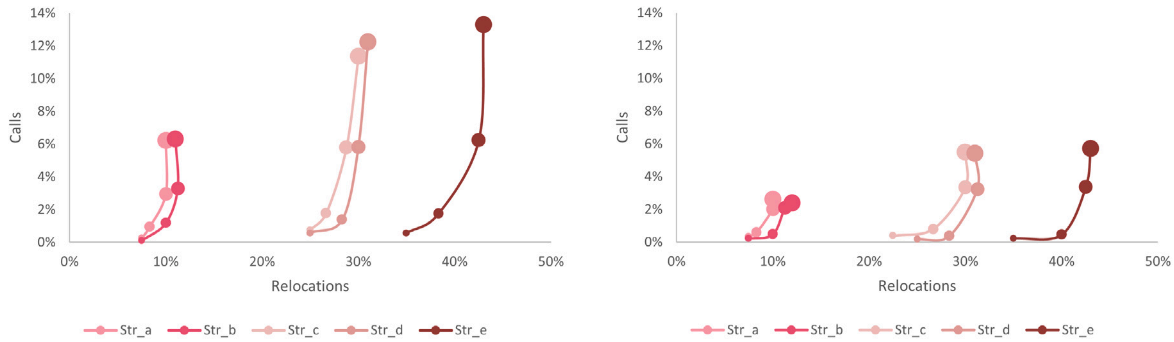
Fig. 10. Average lateness.

from 4.84 min (without relocation) to 4.62 min (with relocation) for the same strategy.

Analyzing Fig. 10(b), for smaller instances, relocation has minimal impact on the average lateness. However, for larger instances, relocation effectively reduces this lateness. Comparing the strategies, we observe that Str_c, Str_d, and Str_e result in slightly lower average lateness compared to Str_a and Str_b, demonstrating the benefits of relocating during both high and medium demand periods. Nevertheless, there is no notable difference between Str_c, Str_d, and Str_e, indicating that relocating during low demand periods offers limited improvement.

Fig. 11 shows the correlation between relocations and emergencies attended within 10 min. The x-axis represents the percentage of relocations out of the total number of trips, while the y-axis shows the percentage of improvement in the number of calls answered within 10 min for each of the relocation strategies compared to the algorithm without relocation. The size of the dots indicates the size of the instances. The smallest ones represent instances of 40 emergencies per day and the largest ones correspond to instances of 100 emergencies per day.

The relocation effect is more pronounced when ambulances en route are excluded, as indicated by the longer curves in Fig. 11(a). Notably,



(a) *Without vehicles en route*

(b) *With vehicles en route*

Fig. 11. Relocations & Calls within 10 min.

Daily call number	With ambulances en route				
	Str_a	Str_b	Str_c	Str_d	Str_e
Average number of times an ambulance stays in a hospital					
40	0.4	0.5	0.5	0.5	0.2
60	0.6	0.6	0.6	0.6	0.3
80	0.5	0.5	0.7	0.7	0.3
100	0.4	0.4	0.6	0.6	0.3
Average number of base-to-base movements					
40	1.4	1.4	2.3	2.3	3.3
60	1.0	1.1	2.1	2.1	3.2
80	0.5	0.5	1.5	1.6	3.1
100	0.3	0.3	1.0	1.0	2.7

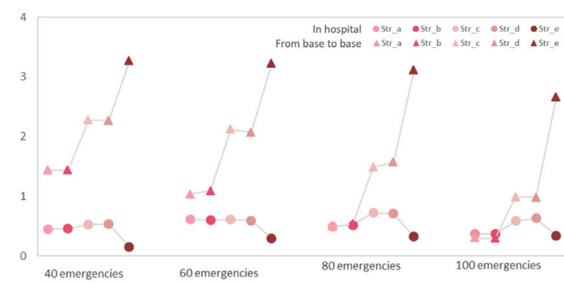


Fig. 12. Number of times an ambulance stays at a hospital and number of base-to-base movements.

in all cases, the percentage of relocations relative to total trips does not exceed 45%. It can also be observed that there is no linear relationship between relocations and calls attended within 10 min. As the workload increases, indicated by the larger size of the points, a moment is reached when the number of relocations does not grow (in fact, it decreases), as ambulances must address queued calls immediately after completing a service. This effect is evident in the convex shapes of the curves, particularly in Fig. 11(b). The same figure shows that with Str_e there are more relocations, but the improvement provided by them is not reflected in the number of calls answered within 10 min (the curves of Str_c, Str_d and Str_e are practically parallel). This confirms the idea already mentioned above that relocation in the period of low demand does not generate great improvements.

Finally, we collected the average number of times an ambulance stays at the hospital in the preparatory period of the Usual base assignment algorithm and the average number of base-to-base movements in an instance when the “Shock movement” is made. Both the table and the graph in Fig. 12 show the data for the case when ambulances en route are taken into account when answering calls (there are no significant differences for the case when returning ambulances are not assigned to emergencies). It is noted that when considering the number of times an ambulance remains at the hospital, the figures are quite small (with the mean not reaching 1), suggesting minimal disruption to the system configuration. Across all types of instances, Str_e yields the smallest mean. This can be explained by the fact that the algorithm Usual base assignment algorithm is activated in the period of low demand, when there are few ambulances in circulation. Regarding the number of base-to-base movements, the average fluctuates between 0.3 and 3.3 depending on the chosen strategy. The longer the relocation algorithm has worked, the more ambulances can occupy bases that are not theirs. Even so, these numbers of base-to-base movements would not generate much inconvenience for the ambulance crews.

6. Conclusions

In this paper, a scenario-based dynamic ambulance relocation algorithm has been presented. A scenario is a combination of bases that have been left without ambulances. Scenarios are built based on the analysis of isochron overlaps. Only ambulances that have recently finished a service can be sent to a base other than their usual base to cover a scenario.

Unlike in previous work, the presented relocation algorithm takes into account several aspects of a real EMS. Including realistic aspects in the evaluation process enhances the credibility of the proposed tools. Given that many pre-hospital health services still operate in shifts, an algorithm has been developed to ensure each ambulance starts and ends its workday at its usual base. Additionally, the possibility of assigning ambulances en route to emergencies is considered. A methodology based on the concept of isochron is presented to determine the positions of moving ambulances.

Five relocation strategies are evaluated, taking into account the variation in demand throughout the day. The results show that vehicle relocation can provide improvements to the number of calls attended within 10 min and a reduction in average delays, especially when dealing with large instances. It is not enough to relocate solely during high demand period. The best results are achieved by relocating during both high and medium demand periods. On the other hand, relocating during low demand period primarily creates noise; it incurs costs without substantial benefits.

Assigning ambulances en route increases the number of calls attended within 10 min and reduces the average delay across all algorithms. However, it diminishes the relative advantage of relocation compared to non-relocation, particularly in larger instances. Failing to consider ambulances en route can significantly overestimate the capacity of relocation algorithms.

In future research, we aim to leverage the methodology to determine the positions of moving ambulances to propose additional dynamic relocation strategies. This includes expanding the potential bases to incorporate health centers not currently designated as such. We also plan to apply the proposed strategies in different service areas with characteristics unlike those of Valencia. Additionally, we aim to exploit our proposed strategy by relaxing certain assumptions, such as sending all patients to hospitals. In reality, some patients do not require hospitalization. However, it is not a simple task to consider locations other than hospitals as origin points for routes, since obtaining the positions of vehicles en route in these cases would require significant computational overhead.

CRediT authorship contribution statement

Yulia Karpova: Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Fulgencia Villa:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Eva Vallada:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The authors do not have permission to share data.

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