Journal of Transport & Health 12 (2019) 60–74

Contents lists available at ScienceDirect

Journal of Transport & Health

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

How do traffic and demand daily changes define urban emergency medical service (uEMS) strategic decisions?: A robust survival model

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ARTICLE INFO

Keywords:
emergency medical service
robust optimization
simulation
city dynamics
survival functions

ABSTRACT

This paper presents a methodology to locate vehicle base stations using robust optimization to address daily traffic and demand changes, which are due to what we define as city dynamics. The model allows us to better understand how these daily changes affect an urban emergency medical service (uEMS) response system.

The methodology incorporates two steps. The first step uses scenario-based optimization and survival function theory to locate vehicle base stations, whereas the second step uses agent-based simulation to assess the solution performance and compare it with less robust and non-survival prone solutions. The proposed models are tested for different situations using real data from the city of Porto.

The results of the sensitivity analysis of the model show the relevance of understanding the dynamics of cities and how they impact uEMS response systems. Useful insights regarding the number of stations and the average response time are addressed together with the minimum number of stations required for different maximum response time limits and different survival coefficients.

Finally, we conclude on how a robust solution improves response time by accounting for city dynamics, and how a heterogeneous survival based approach benefits victims' by properly measuring the system response in terms of the victim' outcomes.

1. Introduction

1.1. Motivation and contribution

The post-crash response is pillar 5 of the WHO (2011) global plan for the decade of action for road safety 2011–2020. It is divided into several activities; the last one, Activity 7, explicitly encourages research and development into improving post-crash response, pointing to the improvement of the response of emergency medical services.

Some researchers have worked to create models for planning emergency medical services, EMS, solely to assist road crashes in a city (Kepaptsoglou et al., 2012) or in specific road networks (Zhu et al., 2012). However, emergency medical services usually respond to all types of medical emergencies, and no separate service may exist to assist just one type of medical emergency. Clearly, one can

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https://doi.org/10.1016/j.jth.2018.12.001
Received 20 October 2017; Received in revised form 13 September 2018; Accepted 4 December 2018
Available online 11 December 2018

argue that there are moral issues regarding having emergency resources that cannot be used in a certain emergency because these resources are strictly allocated to other types of emergencies. Thus, to tackle post-crash response one must tackle the whole emergency medical service expecting that the outcome benefits the EMS response to road crashes (Couto et al., 2015).

In recent works, the focus of EMS response research has been on dynamic EMS where vehicles are dynamically allocated, dispatched or routed to better prepare for the upcoming hours (Vasić et al., 2014, Zhang, 2012, Panahi and Delavar, 2009), and on the fact that emergency medical calls are heterogeneous, thus response time affects victims' survival differently (Mccormack and Coates (2015), Erkut et al., 2008, Blackwell and Kaufman, 2002, Amorim et al., 2017b).

The aim of this work is to study the importance of city dynamics when planning an urban emergency medical service (uEMS) response system. We describe dynamic as a force that stimulates changes in short periods of time, such as hours or days. City dynamics can then be defined as the urban behaviour that results from citizens' routines, and their movement patterns (Silva et al., 2014).

More specifically, the present work argues that the location of people and traffic, through the day, is not static in an urban environment (Lam et al., 2015, Vasić et al., 2014), and these two variables (people and traffic) are the most relevant ones when designing an urban EMS strategic plan. Whereas people in constant movement represent a possible dynamic demand (Krishnan et al., 2016, Wang et al., 2015), traffic represents the network load, which on one hand constrains how quickly an emergency vehicle can reach a medical emergency (Erkut et al., 2009, Kim, 2016, Ingolfsson et al., 2008, Budge et al., 2010, Westgate et al., 2013) and on the other hand correlates with road crashes and injuries (Ferreira and Couto, 2013, Amorim et al., 2017a).

To assess how the urban behaviour interferes with uEMS, we propose a scenario-based optimization model to locate uEMS vehicle stations according to victims' heterogeneity and city dynamics, and compare it with less robust solutions using a numerical simulation and different performance metrics. In sum, this framework analyses the performance of the uEMS response under different station configurations and contributes to the literature in the following ways:

- Formalizing a methodology to plan a strategic EMS response solution prepared for a dynamic environment;
- Accounting for urban dynamics and objectively maximizing survival, thereby implementing a scenario-based optimization model;
- Use of a numerical application of the proposed methodology and models;
- Assessing the impact of city dynamics using several performance metrics calculated through simulation.
- Compare the proposed robust survival solution with less robust or non-survival ones, showing the importance of these two concepts and its applicability.

1.2. EMS response models

The foundational stream of research for emergency response traces back to the year 1955 with the fire station location planning studies of Valinsky (1955). Additionally, Hogg (1968) together with Savas (1969) filled the base archetypes for this theme. However, the two most relevant works, which actually fermented the OR community interest in EMR, were those of Toregas et al. (1971) and Church and Velle (1974). Toregas et al. (1971) present a solution to solve the location set covering problem (LSCP), making sure all demand is covered within a maximum time or distance radius. Church and Velle (1974) note a solution for a maximal coverage location problem (MCLP) that attempts to overcome the resource limitations of the problem of Toregas et al. (1971).

The classical interpretation of the facility location problem was soon surpassed by models that implement uncertainty such as the double coverage, robust and dynamic location models.

Daskin and Stern (1981, 1983) and Hogan and Revelle (1986, 1989) account for the business probability and reliability of facilities to solve the fact that once a facility is called for service the demand under its coverage is no longer covered. The former solves the maximum expected covering location problem (MEXCLP), and the latter moves forward to a maximum availability location problem (MALP).

Maxwell et al. (2009) classified research on dynamic allocation problems into three categories depending on the following: the model is solved in real time each time a redeployment decision is to be made (Brotcorne et al., 2003; Kolesar and Walker, 1974; Gendreau et al., 2001; Nair and Miller-Hooks, 2006), solving the model involves computing optimal vehicle positions for every number of available vehicles via an integer programming formulation in an offline preparatory phase (Ingolfsson, 2006; Gendreau et al., 2005); or if one intends to incorporate system randomness into the model by using Markov decision processes (Berman, 1981c, 1981b, 1981a; Zhang et al., 2008; Alanis et al., 2013; Berman and Odoni; 1982, Jarvis, 1981) or make decisions under particular system configurations (Andersson and Varbrand, 2006; Andersson, 2005).

In fact, when addressing dynamic location models, the bibliography tends to show its relation with multi-period location models, where time is discrete, which are much more useful than single period models, where time is continuous. This is proven by Miller et al. (2007) and supported by Boloori Arabani and Farahani (2012).

The concept of scenario-based approaches is also used when uncertainty is present. Serra and Marianov (1998) solved the p-median problem (PMP) under scenario-based demand uncertainty. When the number of facilities, or vehicles, is uncertain, Current et al. (1998) propose a scenario-based approach and solve the problem with a general-purpose mixed integer programming (MIP) solver.

Moreover, with the advance of computer power and the availability of powerful personal computers, simulations have become a useful tool for researchers wanting to formulate more realistic and complex models, be it to assess solutions or to support optimization models (Restrepo et al., 2008; Maxwell et al., 2010; Yue et al., 2012; Mccormack and Coates (2015), Iannoni et al., 2009; Su and Shih, 2003).

Nevertheless, in urban Emergency Medical Services (uEMS), contrary to non-emergency facility location problems, underestimated or overestimated solutions not only have a monetary impact but also carry a social impact. A wrong decision can lead to, e.g., higher response times to severe medical emergencies, which may seriously reduce the survivability of the victims to be rescued. For instance, Sánchez-Mangas et al. (2010) indicate that a reduction of 10 minutes in the emergency response time could result in a 30% reduction of traffic accident fatalities. Although this number can vary depending on many factors, it is obvious that a quicker medical response will result in an improved medical assistance (Blackwell and Kaufman, 2002; Pons et al., 2005). In conformity, Erkut et al. (2008) note that the EMS response research direction is to substitute the covering concept with concepts that account for survival probabilities and for the heterogeneity of the victims. This type of concept has already been used in recent works (Knight et al., 2012; Mccormack and Coates (2015)).

Mccormack and Coates (2015) prove the possibility of increasing cardiac arrest victims' survival without the need of additional resources; however, the proposed model only divides medical emergencies in two types: cardiac arrests and non-cardiac arrests. In contrast, Kepaptsoglou et al. (2012) focused their work on a uEMS model for the special case of road crashes disregarding other types of medical emergencies. Knight et al. (2012) address the heterogeneity of medical emergencies in a more direct way. They propose a Maximal Expected Survival Location Model for Heterogeneous Patients, where a decaying survival function is used for cardiac arrests and step functions for other types of medical emergencies. Furthermore, a weight parcel is added to capture emergency type priority.

Amorim et al. (2017b) investigate uEMS station location for long term planning periods and identify differences in the station configurations depending on how they assess victims' heterogeneity. However, by using a concept of long term planning, they are unable to detect the influence of city dynamics in the system response, and the solution might fail for specific periods of time according to the different traffic and demand characteristics. In the other hand, Dibene et al. (2017) implement robust scenario based solutions for the classic Location Set Covering Model (LSCM), the Maximal Covering Location Problem (MCLP) and the Double Standard Model (DSM), considering such factors as the time of day, work and off-days, geographical organization and call priority, but not directly applying survival functions when measuring system performance. They prove that the current solution in Tijuana, Mexico, could be improved in terms of response time and demand coverage but could not show evidences regarding victims' survival. Moreover, they only account for dynamics related to demand, thus not accounting for traffic changes. Krishnan et al. (2016) apply risk-based metrics to vehicle location problem using Conditional-Value-at-Risk (CVaR). However, the problem is tackled under the view of system failure which assesses the number of calls not served, thus the authors do not consider victims' heterogeneity or victims' survival.

A recent work by Zaffar et al. (2016) compares performance statistics used in emergency vehicle location models. The authors focus on coverage, response time and survivability, and conclude that survivability models perform better in both survivability and coverage metrics. The conclusions are made based on the application of a simulation-optimization model, which although not being a robust model, allows vehicles to be reallocated to different stations giving flexibility to the solution so it can adapt to city dynamics. The authors also show that demand varies in time and space along the day and week. Nevertheless, the model disregards traffic changes and even simplifies the travel component by assuming Manhattan distances and using an average speed for the emergency vehicles. Moreover, the authors' work does not account for victims' heterogeneity, and victims' survivability is assessed by a linear function simplified from a work by Mclay and Mayorga (2010) that focuses on cardiac arrest.

There is clearly a gap in the study and performance assessment of EMS strategic decisions such as vehicle or station locations. The literature review shows an important progress in performance metrics and robust solutions, but there is yet no significant scientific input in using robust survival based solutions to assess the impact of urban dynamic factors such as traffic and demand. Our work tries to fill this gap by providing a data-driven robust optimization solution that accounts for demand and traffic fluctuations, and presents a performance comparison between robust and non-robust solutions by analysing different performance metrics, using real data, through simulation.

2. Methodology

The present methodology intends to provide insight for a vehicle station location plan and a vehicle dispatching service simulation that serves as a tool to assess uEMS system performance in a dynamic environment. For the dynamic environment we assume cyclical fluctuations of demand and traffic both in intensity and location. The methodology is structured with the intention of offering an assessment in the impact of city dynamics - people movement and traffic changes - by providing a robust uEMS response system.

To capture the cyclic dynamics of a city (traffic changes and people location), we define a cycle as a pattern of traffic and demand changes. The cycle captures the city's routine in terms of people movement and traffic changes, whereas a single period captures a static moment of a cycle.

We developed a two-step methodology to achieve the previously mentioned objectives. The first step of the proposed methodology entails a robust vehicle station location optimization model, whereas a second step provides a framework to analyse station location solutions and assess the impact of a robust approach and the use of survival functions.

2.1. Optimization model

A system optimization requires a performance measure. In a uEMS response network, the literature shows that some of the most common measures of performance are coverage and system reliability. However, different types of emergencies have different requirements and priorities. Thus, the concept of maximum survival, first presented by Erkut et al. (2008), can measure the system's performance in the perspective of the victim.

The performance P_i of a uEMS response to an event i of type k can be defined by a survival function that depends on the time between the event start and the arrival of the assistance team, r_i, as per Eq. (1). Therefore, a simple performance metric for an emergency system is the sum of all response performances. The average, minimum and mode could also be defined as an overall performance metric. Nevertheless, for simplicity and for this work, the sum of all uEMS response performances is the chosen metric to assess the system's overall performance.

$$P_i = f^k(r_i) \tag{1}$$

we discussed that a city behaves as a dynamic entity where traffic load and people location vary with time but repeats in cycles (e.g. daily, weekly, monthly). To meet our beliefs, a robust optimization model is essential to produce a solution that performs and adapts as best as possible through the system's life time. As mentioned in the literature review, a possible way to respond with robustness to a dynamic behaviour is to use a scenario-based approach. Scenario-based optimization is typically used to produce a robust solution that is prepared for different possible situations. This is usually the case when part of the model's inputs is unknown; thus the system designer predicts possible scenarios where a positive performance of the system is mandatory.

For us, the goal is slightly different. We are able to compute the model inputs by using real data, and each of our scenarios is a representation of a period from a defined cycle; thus our model aims to provide a solution that will perform as well as possible throughout the defined cycle using static instances as scenarios.

This method allows us to create a station locations solution for a cycle, C, of length $T = t_p - t_0$. C is an infinite set of instants t_i, with inputs $f(t_i)$, where $t_0 \le t_i \le t_p$.

However, for short periods we assume a static behaviour. Thus, C has a finite number of periods ($\#S_i = S$) so that $C = [S_0, S_1, \ldots, S_s]$ is a cycle C with periods $S_0, S_1, \ldots,$ and S_s, where S_0 is the period between 0 and n, S_1 is the period between n and m, and S_s is the period between l and p with $l > m$, thus the model inputs become:

$f(t_0) = f(t_1) = f(t_2) = \ldots = f(t_n) \neq f(t_{n+1}) = f(t_{n+2}) = \ldots = f(t_m) \neq \ldots \neq f(t_{l+1}) = f(t_{l+2}) = \ldots = f(t_p)$, and $f(t_{p+a}) = f(t_0)$ with a as an infinitesimal.

The proposed model maximizes, in a cycle, victims' survival by deciding where to locate vehicle stations, e, and allocating them to demand cluster nodes, p, in a nodal network:

$$\text{maximize} \sum_k \sum_s \sum_l \sum_p y_{l,p} \times e_{s,p} \times f^k(r_{s,l,p}), \tag{2}$$

subjected to

$$\sum_l y_{l,p} \times r_{s,l,p} \le M_r \quad \forall\ p \text{ in } P, \forall\ s \text{ in } S \tag{3}$$

$$\sum_l y_{l,p} = 1\ \forall\ p \text{ in } P \tag{4}$$

$$y_{l,p} \le x_l\ \forall\ l \text{ in } L, \forall\ p \text{ in } P \tag{5}$$

$$\sum_l x_l \le M_l, \tag{6}$$

where

S is the set of periods s\{period 1, period 2, …, period s\} and $S = C$,
L is the set of possible vehicle stations location l\{station 1, station 2, …, station l\},
P is the set of demand cluster nodes p \{node 1, node 2, …, node p\},
$e_{s,p}$ is the number of events in demand cluster node p for period s,
$x_l = 1$ if a vehicle station is located at l and 0 otherwise,
$y_{lp} = 1$ if vehicle station l serves events at location p and 0 otherwise,
r_{slp} is the travel time required for a vehicle located at l to arrive at p during s,
M_r is the maximum allowed response time, and.
M_l is the maximum number of stations.

Eq. (2) maximizes the sum of the survival function for each event type occurring at each period of the defined cycle.

Eqs. (3), (4), (5) and (6) control the model properties. Eq. (3) defines an upper bound for the response time. Decision variable y_{lp} and Eq. (4) are added to ensure that for every node, only one station is allocated. Finally, Eq. (5) ensures that if node p is served by a station at l, then a station must be located at l.

Furthermore, there is the problem in deciding how many stations should be deployed. This can be addressed if one can assess the worth of the performance gain by adding a new station. Because this relation is not yet defined, Eq. (6) limits the number of stations (which can be assessed by the total available funding), allowing the model to run for different upper bounds.

To reduce the model size, there is a preparation step that merges sets L and P into an availability tuple $a = \{\text{pair } l\text{-}p \mid \textit{if } l \text{ can assist } p\ \forall\ s \text{ in } S\}$ from set $A = [a_1, a_2, \ldots, a_w]$. This transforms Eqs. (3) and (4), respectively, into Eqs. (7) and (8):

$$\sum_s \sum_l y_{l,p} \times r_{s,l,p} \le M_r\ \forall\ a \text{ in } A \tag{7}$$

$$\sum_l y_{l,p} = 1\ \forall\ p \text{ in } A. \tag{8}$$

The preview modification implies a reduction in the number of decision variables as well as the number of constraints and sum parts of the objective function.

So far, for different periods, each station is forced to serve the same nodes. To make the model more flexible and to allow a station to serve different nodes at different periods, decision variable $y_{l,p}$ should be transformed into $y_{s,l,p}$, which takes a value of 1 if during period s node p is served by a station located at l. Thus, the final model is represented by Eq. (9):

$$\text{maximize} \sum_k \sum_s \sum_l \sum_p y_{s,l,p} \times e_{s,p} \times f^k(r_{s,l,p}) \tag{9}$$

subjected to

$$\sum_l y_{s,l,p} \times r_{s,l,p} \leq M_r \ \forall \ p \text{ in } A, \forall \ s \text{ in } A \tag{10}$$

$$\sum_l y_{s,l,p} = 1 \ \forall \ p \text{ in } A, \forall \ s \text{ in } A \tag{11}$$

$$y_{s,l,p} \leq x_l \ \forall \ p \text{ in } A, \forall \ s \text{ in } A, \forall \ l \text{ in } L \tag{12}$$

$$\sum_l x_l \leq M_l. \tag{13}$$

2.2. Second step – assessment

To calculate the significance of city dynamics on uEMS systems and their impact on strategic station locations, we first test our scenario based optimization model for different maximum number of stations. This will give a first impression on how the number of stations might affect the maximum response time we can theoretically offer. Further, we assess how different response time thresholds lead to resource requirements in terms of stations. Finally we assess the sensitivity of the survival coefficients used in the different survival functions and assess the dynamics of victims' heterogeneity, i.e. cardiac arrest versus road crashes.

After this first analysis we proceed with a base case study where a robust survival solution and less robust and non-survival prone solutions are computed. This will give us different station configurations, with different levels of robustness and survivability.

To assess the performance of these configurations and predict the impact of city dynamics we run several numerical simulations using real data and calculating different performance indicators, i.e. average response time, maximum response time, victims' survival.

A simulation algorithm, based on Amorim et al. (2018), to numerically compute solutions performance is constructed using an agent based model built on several models found on the literature (Haghani and Yang, 2007, Mccormack and Coates (2015), Su and Shih, 2003) and is resumed in Algorithm 1.

Algorithm 1. Simulation algorithm.

<u>Definitions:</u>
$\boldsymbol{N}$ = set of nodes n
$\boldsymbol{n}$ = node, where s = node of type station and h = node of type hospital
$\boldsymbol{V}$ = set of vehicles v_s
$\boldsymbol{v_s}$ = vehicle in station s
$\boldsymbol{S}$ = set of stations s
$\boldsymbol{H}$ = set of hospitals h
$\boldsymbol{E}$ = set of events e_n^t
$\boldsymbol{e_n^t}$ = emergency event occurring at node n during t
$\boldsymbol{M}$ = set of matrices M^t
$\boldsymbol{M^p}$ = matrix of real travel times for period p
$\boldsymbol{T}$ = total simulation time
$\boldsymbol{t}$ = time
step = temporal resolution
f( ) = programming function
While $t < T$:
1. **Update city( )** "set $\boldsymbol{t}$ and activate $\boldsymbol{e_n^t}$."
2. **Update network( )** "interact through every $\boldsymbol{v_s}$ to travel one ***step*** and transfers it to destination nodes"
3. **Update events( )** "activates $\boldsymbol{e_n^t}$ and the vehicle dispatching algorithm"
   -Network calculates time travel from all stations
   -Network returns the shortest one
   -Vehicle dispatching algorithm runs
4. **Update vehicles job( )** "updates v_s status"
   -If v_s arrived to $\boldsymbol{e_n^t}$, activate assisting timer
   -If assisting timer ends, request network to be processed to $\boldsymbol{h}$
   -If v_s arrived to $\boldsymbol{h}$, transfers $\boldsymbol{v_s}$ to $\boldsymbol{s}$.
5. **Update results( )** "calculates the EMS performance at the current ***step***"
6. $\boldsymbol{t = t +}$ ***step***

This model is controlled by a city agent that takes the role of the emergency medical service by allocating and dispatching vehicles using the closest dispatching rule (Haghani and Yang, 2007; Jagtenberg et al., 2017; Yang et al., 2005). A network agent simulates traffic conditions and EMS vehicle movements by using nodes and arcs as an abstraction of the reality, and pre-computed travel times for different daily conditions using Google's Directions API. Events are agents that request assistance when they occur and the city allocates to them a vehicle agent. The network controls the vehicle agent's movement from node to node and the vehicle agent is responsible for transporting the occurrence from its initial location to a hospital. In between, the vehicle agent is also responsible for in site assistance. The required assistance is generated by the event agent using a function to randomly attribute an assistance time. A data agent keeps track of the individual performance of each EMS response for final calculations.

3. Model application

The proposed methodology was tested with real data from Porto during the period between May 2012 and May 2013. According to the available EMS calls and travel times data, the daily uEMS response network operation was divided into three periods of equal length: The morning period (6:00 am to 2:00 pm), the afternoon period (2:00 pm to 10:00 pm), and the night period (10:00 pm to 6:00 am). These periods are eight hours long, which is the usual daily working time across many countries. The network operation also differentiates weekdays (Monday through Friday) from weekend days (Saturday and Sunday). Accordingly, a total of 5 periods are formed: Period 1 Weekday 6 am to 2 pm, Period 2 Weekday 2 pm to 10 pm, Period 3 Weekday 10 pm to 6 am, Period 4 Weekend 6 am to 10 pm and Period 5 Weekend 10 pm to 6 am. The weekend morning and afternoon periods were joined together due to their similarities in terms of traffic conditions.

For the maximum response time, it is known within reasonable simplifications, that without any sort of intervention, the survival rate of a cardiac arrest victim drops, linearly, to zero after 10 minutes (Eisenberg et al., 1990). Moreover, Valenzuela et al. (1997) indicate that the time interval needed for EMTs or paramedics to attach a defibrillator and clear the patient for defibrillation is estimated to be 2 minutes past EMT arrival or 1 minute past the time of initiation of CPR by EMTs. This leads to a threshold of 8 minutes for the medical team to arrive at the event scene if we consider a 1 minute average for the dispatching time.

Whereas the influence of the response time to cardiac arrests is very well defined in the literature, other types of medical emergencies do not have such survival function studies. To overcome this issue, we assumed that every type of emergency survival function follows an exponential law represented by a survival coefficient m^k and constant C^k, similar to the survival functions found on Mccormack and Coates (2015), Erkut et al. (2008) and Knight et al. (2012). This transforms Eq. (9) into Eq. (14):

$$\text{maximize} \sum_k \sum_s \sum_l \sum_p y_{l,p} \times e_{s,p} \times [1 + \exp(C^k + m^k \times r_{s,l,p})]^{-1} \tag{14}$$

where K is the set of type of events k {cardiac arrest, car crash, others}

The Porto's EMS data was collected from the INEM (National Institute of Medical Emergency of Portugal) database containing information on the type of emergency, timestamp and address of the crash spot. There are a total of 33 736 events in a one-year period. The addresses were geolocated using a python script that connects with the Google Maps API for geocoding. The care-assisting time on the crash scene of each event is unknown, so a uniform distribution between 1 and 30 min was assumed and picked at random for each event during the simulation.

For the optimization model, the city network was converted into a nodal network where each node is the centroid of the city census sub zones, for a total of 87 nodes. Using a radial-distanced based cluster algorithm, each event was allocated to the closest node.

The vehicle station location was assumed possible in any of the 87 nodes. Afterward, a python script was created to use the Google Directions API and calculate the OD matrix of time travels for the different periods. This script asks Google Directions API for the fastest travel time, by car, between two coordinates for the morning peak hour (8 am), the afternoon peak hour (6 pm), the weekend peak hour (3 pm), and the uncongested travel time. The latter was allocated to the night periods.

All the data was processed and stored in an SQL Database using Python, SQLite3 and DB Browser for SQL. Later, the data was prepared to be used by the optimization and the simulation models. To reduce the number of calls to the SQL database, the time travel matrix and the availability set were compiled into python raw files, which reduce the data processing time when running the models. The two models were also programmed in Python. For the optimization model, the Gurobi Optimizer python library, a state-of-the-art math programming solver, was used.

The optimization model was run for this study case, followed by the simulation model. Sensitivity analysis was processed by changing the relevant optimization model parameters to understand their implications on the scope of this work.

4. Results and discussion

4.1. Model preparation and computing resources

To support our claims, we propose a thorough sensitive analysis regarding the spatial and temporal dynamics that may influence how the EMS system is planned.

With the optimization model, we tested the impact of the maximum number of stations, M_l, the maximum response time, M_r, and the victims' heterogeneity with an emergency type weight, α^k. With the simulation model, we tested the impact of different uEMS network configurations from the optimization model.

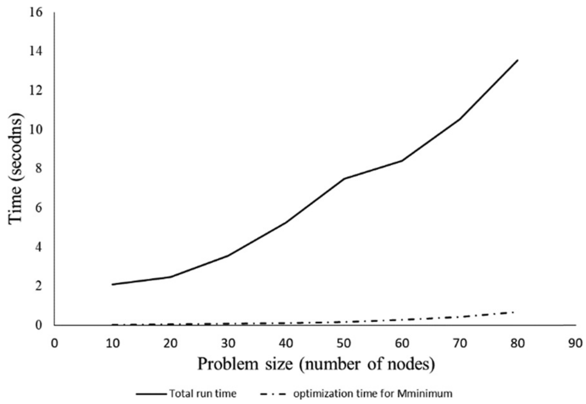

Fig. 1. Optimization model performance.

Each model's run was computed on a machine with an Intel quad core processor at 1.73 GHz and 8GB of memory RAM in a WIN10 64bits operative system. The models were implemented using Python v.2.7.8 and Gurobi v.6.5.2, both in 64 bits.

We assessed the computing time of the optimization model for different problem sizes. The optimization model was run for crescent integer values of M_l (from 1 till $M_{minimum}$) until the model returned a solution (thus identifying the minimum number of stations $M_{minimum}$), and then we recorded the total running time and the optimization time for the identified $M_{minimum}$. The results are presented in Fig. 1. It is obvious that as the problem size grows, the total run time grows exponentially due to the growth of the minimum number of required stations. However, when the model runs for one single M_l the exponential growth is much slower and reaches a maximum of 0.7 seconds for a problem size of 80 nodes.

4.2. Station locations

In this analysis we test different values of M_l and M_r and from the produced results we assess the impact of the number of stations on the average response time and the station network requirements for different thresholds of the maximum response time. Furthermore, we propose a base case that will serve as an overall solution for the presented optimization problem. We also assess solutions regarding and not regarding the explained concepts of dynamism (robust solution), and victims' heterogeneity and survival (survival functions). This will indicate the impact of city dynamics on a uEMS response system. We also test the sensibility of the victims' heterogeneity by weighting cardiac arrest and road crashes victims differently, thus assessing the importance of considering the heterogeneity of medical emergencies and its spatial impact on the optimization solution.

4.2.1. Number of stations versus average response time

The optimization model was run for different threshold of uEMS vehicle stations, M_l. Fig. 2 shows these results, where the objective function result was converted into the average travel time.

As the number of stations increases, the average response time quickly drops in the first few additional stations and then slows down as the number of stations approaches the number of nodes. It is important to remember that events were clustered into nodes; thus a station implemented in a certain node will respond to the events of that node instantly. It is also important to understand that the response time is only the driving time; it does not account for the time the emergency call is being processed and the time for the paramedic team to prepare the victim for any necessary intervention.

Moreover, Fig. 2 shows an apparent correlation between the average response time and the number of stations implemented. To the naked eye, there seems to be a hyperbolic or exponential relationship between both variables. Nevertheless, it is important to note that as the number of stations increases, theoretically, the average response time will never reach zero. In addition, when the average time grows, towards infinite, the number of stations required will lower but will never be null.

In a further analysis, we tested several types of fitting curves and several variable transformations to assess a possible law between the number of stations and the average travel time. Fig. 3 groups the best-found relations.

The analysis assessment leads to the identification of two different correlations. One occurs in the first 7 observations, sample 1, and the other occurs in the remaining observations, sample 2. Undoubtedly, a power law explains the sample 1 correlation, whereas the sample 2 correlation is better described by an exponential law, or, if we transform $x \rightarrow 1/(x + 10)$ by a linear law.

Clearly, there is a disruption at the 7th observation, corresponding to 7 stations implanted in the network. When adhering to the x transformation, the samples behave differently. The sample 1 average time drops more than 30% faster than sample 2 when $1/(n + 10)$ decreases (number of stations increase), pointing to differences in the network behaviour at the macro scale (few stations try to support the whole network) and micro scale (many stations in the network, allowing each of them to focus in specific city areas) due to possible dynamic effects.

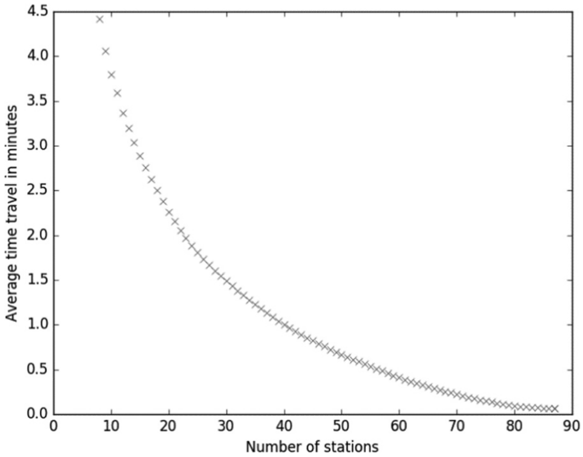

Fig. 2. Average time travel for different number of implemented stations.

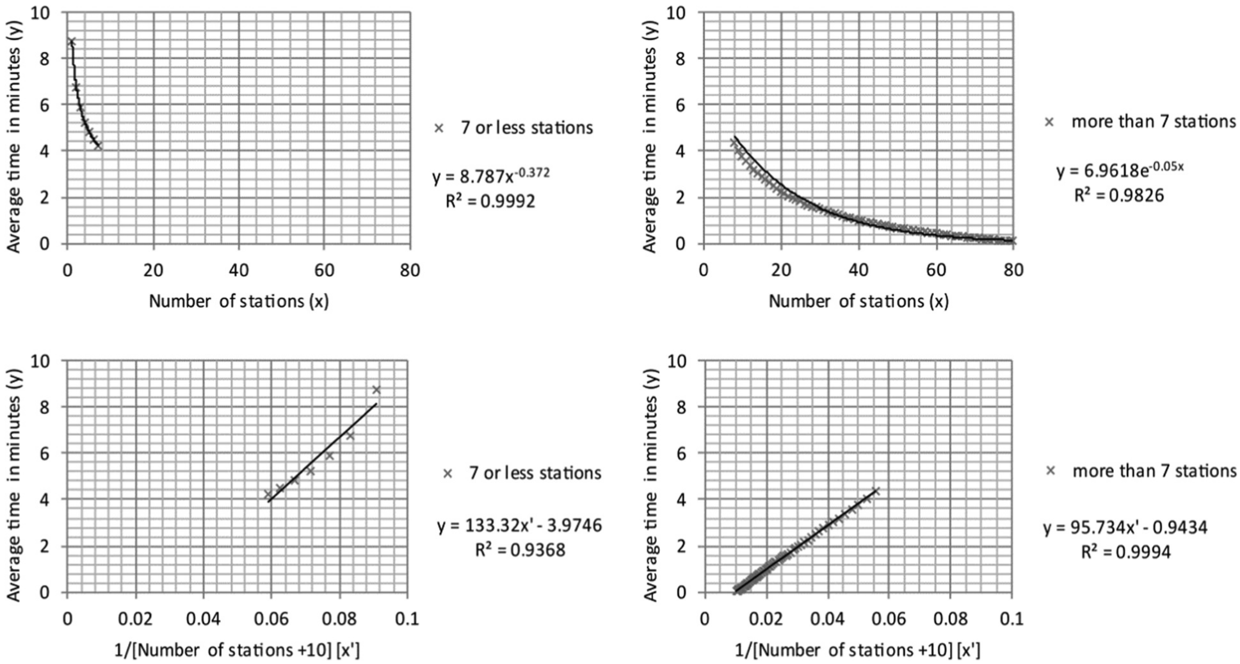

Fig. 3. Correlation analysis between average time and number of stations.

4.2.2. Maximum response time

The maximum response time is one of the key parameters in an EMS optimization system. The response time defines the quality of an EMS system; nevertheless, a shorter response time requires more stations.

Fig. 4 shows the decrease in required stations when the maximum response time is increased. For 5 minutes of the maximum response time, 24 stations are required, but as soon as this limit is extended by a half minute, the requirements drop to 18 stations. When increasing the time by one-third (from 5 minutes to approximately 8 minutes), the required stations drop to one-third (from 24 to approximately 8). After the 8^{th} min, the number of required stations drops with a lower rate. With an increase of 5 minutes (total of 13 min), the number of required stations drops from 8 to 3 stations. The critical maximum times are 6.5 minutes and 9 min. These seem to be the boundaries of a quick but costly response system ($<$ 6.5 min response time and $>$ 13 stations required), a standard response system (between 6.5 minutes and 9 min, and between 13 stations and 6 stations), and a slow but cheap response system ($>$ 9 min response time and $<$ 6 stations required).

These results show that a maximum response time of approximately 7 to 8 min can better equilibrate both the number of stations (10 to 8 stations) and the quality of the uEMS service. In fact, from 10 to 11 min, the number of required stations is the same as when the limit is set to 9.5 min.

Nevertheless, this value is tightly connected with the road network configuration and land use.

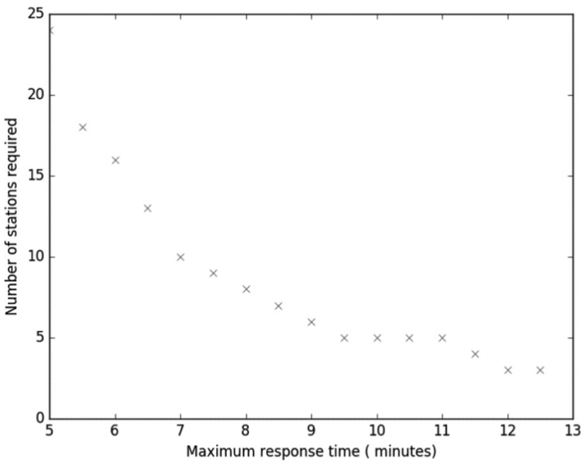

Fig. 4. Number of minimum stations required for different maximum response times.

4.2.3. Alpha sensitivity test for cardiac arrests and road crash events

To analyse the influence of victims' heterogeneity we focus on cardiac arrests and road crashes. This choice is twofold. First, cardiac arrests are considered the event which survival is most influenced by the response time. Second, road crash victims, although not always in a life-threatening situation, impose a road network impact. This means that while a road crash event is active it is locally impacting the traffic which may cause traffic jams that can easily propagate through the city. These traffic jams or delays will influence the uEMS response to other events.

A batch of test cases were computed varying the weight, α^k, of each victims' emergency type by 2^n with $n = \{0, 1, 2, 3, 4, 5, 6\}$, Eq. (15).

$$\sum_k \sum_s \sum_l \sum_p y_{s,l,p} \times e_{s,p} \times \alpha^k \times r_{s,l,p} \tag{15}$$

The idea underneath is to understand how victims' heterogeneity behaves in terms of spatial occupation. For each test case, a centroid is calculated by averaging the position of the optimal station location. In Fig. 5, the centroids for each tested case are presented.

The coordinate (0, 0) shows the centroid when both emergency types have the same weight. We increase the cardiac arrest weight and observe that the solution centroid moves towards the city centre - from northwest to southeast. In the opposite situation (the road crash weight is increased relatively to the cardiac arrest weight), we observe an opposite movement of the solution centroid - from southeast to northwest, and towards the outer bound of the city.

4.2.4. Solutions for comparison

We define our solutions for comparison by setting the number of stations to 7, the survival parameters to $m^k = 0.262$ and $C^k = 0.679$ for cardiac arrests and, $m^k = 0$ and $C^k = 0.100$ for other life-threatening emergencies. We assume a maximum response of 15 minutes to all emergencies to give more flexibility to the robust and survival models' component. Five solutions are computed for

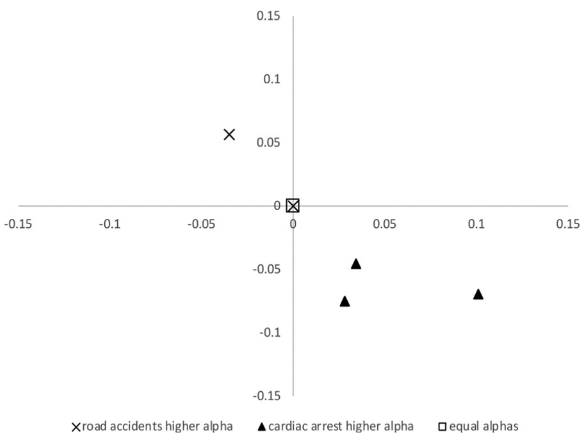

Fig. 5. Percentage towards the city limit of the displacement of each test case solution centroid (for different combinations of alpha) with respect to the robust solution centroid.

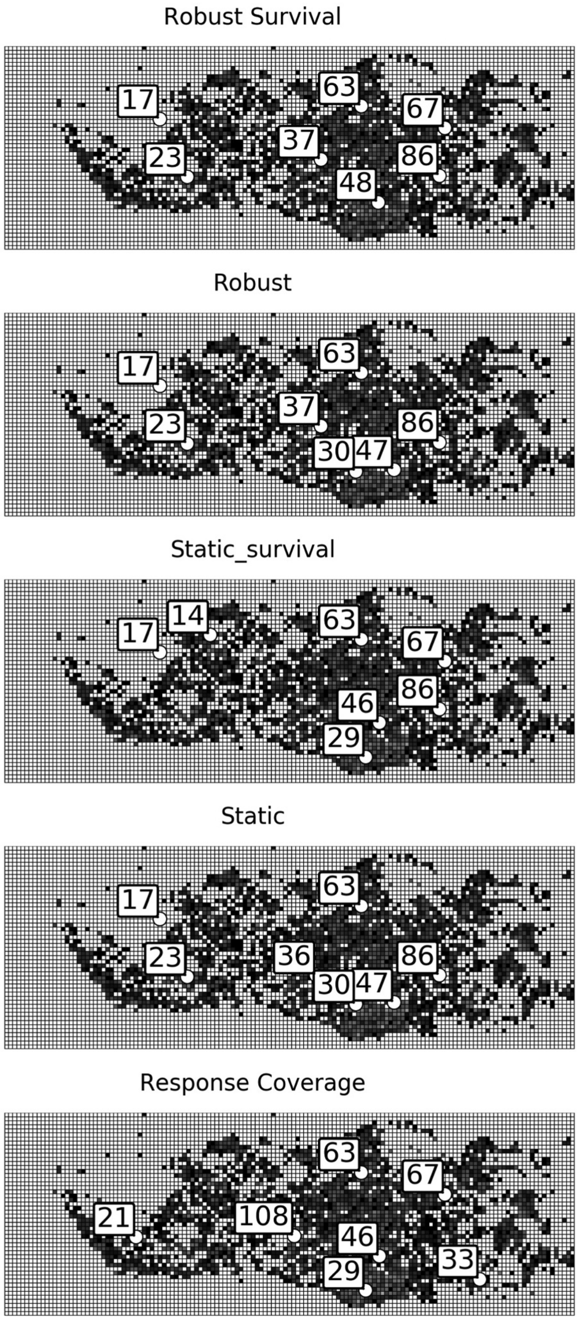

Fig. 6. Station locations for the different solutions.

analysis. The "Robust Survival" solution, when we use our proposed robust model with maximum survival, the "Robust" solution where robust optimization is used but without maximum survival; a "Static Survival" solution where no robust optimization is used but survival is accounted; and a "Static" solution which does not use robust optimization and does not use survival functions. A "Response Coverage" solution is also identified by minimizing the response time to each network node.

The station locations for each solution are presented in Fig. 6. We notice that the robust solutions and the Response Coverage solution have the stations more dispersed across the urban area, while it seems that the static solutions concentrate stations in the areas with higher number of yearly EMS calls. Noticeably, for this urban area, when we account for demand and traffic dynamism during the day and week, the location of the stations adapts from a position centred in the higher demand nodes slightly towards nodes with lower yearly demand. This means that the model is trying to compensate for the demand movements, weighting each period and node accordingly. It is a clear evidence of the importance of considering city dynamics when planning for strategic decisions.

Table 1
Simulation results summary for the unrestricted resources test of each solution.

Unrestricted resources	Time in minutes					
	Robust survival	Robust	Static survival	Static	Response coverage	
Response time	Average	4.24	4.22	4.41	4.23	4.40
	Max	12.50	13.68	12.50	13.68	12.50
	Std	2.20	2.42	2.51	2.42	2.05
	> 8 min	0.024	0.042	0.068	0.039	0.035
	> 12 min	0.001	0.001	0.001	0.001	0.001
	> 15 min	0.000	0.000	0.000	0.000	0.000
	> 20 min	0.000	0.000	0.000	0.000	0.000
Delay	Total	0	0	0	0	0
	Average	0.00	0.00	0.00	0.00	0.00
	Max	0.00	0.00	0.00	0.00	0.00

4.3. Solutions performance

To assess how the different proposed solutions perform in a realistic environment we use the simulation model presented in the methodology chapter. Contrary to the optimization model that computes over static scenarios (or a single scenario in the Static solutions), simulation runs through a whole year, minute by minute and events occur according to a real-life case. The simulation model allows for a continuous evaluation of each solution using different indicators and tries to make the link between theory and practice.

As mentioned in the subchapter “solutions for comparison” our solutions are based on a 7-station network solution. We now compare the performance of the proposed solutions under different resource restrictions. First we assume that resources are unlimited by having an emergency vehicle always available. On a second run we assume that each station has two vehicles available at the start of the simulation.

A summary of the simulation results for each run are presented on Table 1 and Table 2. The classic metrics, average response time and percentage of emergencies covered by time thresholds of 8, 12, 15 and 20 minutes give a first assessment of each solution. Clearly, the solutions that account for city dynamics have better performance due to a better positioning of the stations that account for demand and traffic changes, while static solutions focus on quickly responding to the nodes with higher demand and calculating travel times using daily average values. When resources are scarce, the service performance degrades, as expected, mostly due to the existence of delays. These delays seem to be more frequent when the solutions are computed using survival functions. Nevertheless, the use of survival functions does not affect response time average significantly although in terms of time thresholds the impact is noticeable.

When focusing in the victims’ survival, the analysis must be made with regards to life-threatening emergencies. In the introduction we emphasize that accounting for victims’ heterogeneity is important, thus we measured our survival performance indicators with this in account. For cardiac arrest victims we assumed an exponential survival function with parameters $m^k = 0.262$ and $C^k = 0.679$, and for other life-threatening emergencies the parameters are $m^k = 0$ and $C^k = 0.100$ (the same parameters used during the optimization). Non-life-threatening emergencies have a survival rate of 1, thus were neglected in this analysis. We also considered a threshold performance metric, where a binary evaluation assesses if a cardiac arrest is responded within 8 minutes and other life-threatening emergencies within 12 min. These results were plotted in Fig. 7 and Fig. 8 for the unrestricted resources run, and Fig. 9 and Fig. 10 for the two vehicles per station run. Fig. 7 and Fig. 9 show the survival gain of each solution when compared to the simplest solution - the Response Coverage. Fig. 8 and Fig. 10 show how many life-threatening emergencies took longer to be

Table 2
Simulation results summary for the 2 vehicles per station test of each solution.

2 vehicles per station	Time in minutes					
	Robust survival	Robust	Static survival	Static	Response coverage	
Response time	Average	4.77	4.77	4.88	4.83	4.90
	Max	24.07	23.53	25.67	23.87	24.02
	Std	2.66	2.84	2.80	2.89	2.52
	> 8 min	0.088	0.098	0.110	0.104	0.087
	> 12 min	0.010	0.013	0.011	0.015	0.014
	> 15 min	0.003	0.004	0.003	0.005	0.002
	> 20 min	0.000	0.001	0.000	0.000	0.000
Delay	Total	139	130	140	130	119
	Average	28.32	18.51	27.31	23.52	23.32
	Max	66.00	43.00	71.00	52.00	51.00

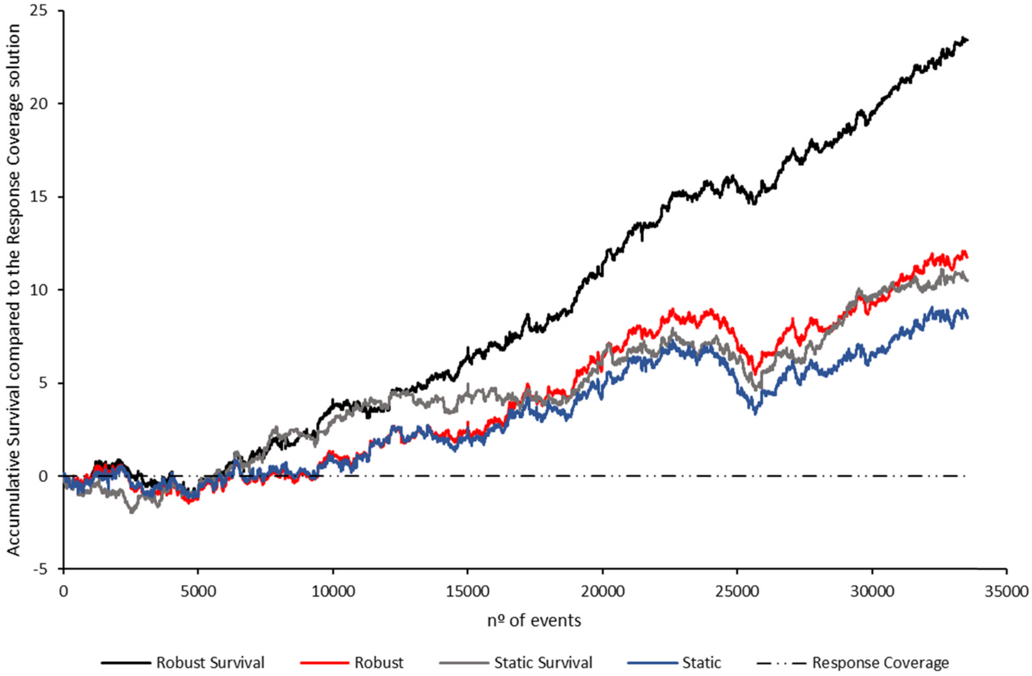

Fig. 7. Accumulated survival gain of each solution compared with the response coverage solution when resources are unlimited and a total of 7 stations exist.

responded than the defined thresholds.

The results are clear to which solution provides a better service to the EMS victims. As expected, when we account for victims' heterogeneity and survival, and use a robust solution that considers city dynamics we can provide a solution that is much more adequate. For the tested cases, The Robust Survival solution reached almost a double gain than the other solutions (Robust, Static Survival and Static solutions) for unrestricted resources. When resources are restricted, the robust solutions gain is not so notorious, but the use of survival functions clearly outperforms their counterparts. It is obvious that using survival as a metric will benefit the solutions that had survival in account. Nevertheless, these solutions although slightly underperform when assessed by the classic metrics in an unrestricted resources scenario, when resources are scarce the difference in the classic performance metrics is negligible. When assessed by survival thresholds, Fig. 8 and Fig. 10, the survival based solutions outperforms the other solutions in both resource scenarios.

It is also interesting to notice how the Robust and Static Survival solutions perform pair to pair when resources are unrestricted, but the performance of the Robust solution relatively drops when resources are limited.

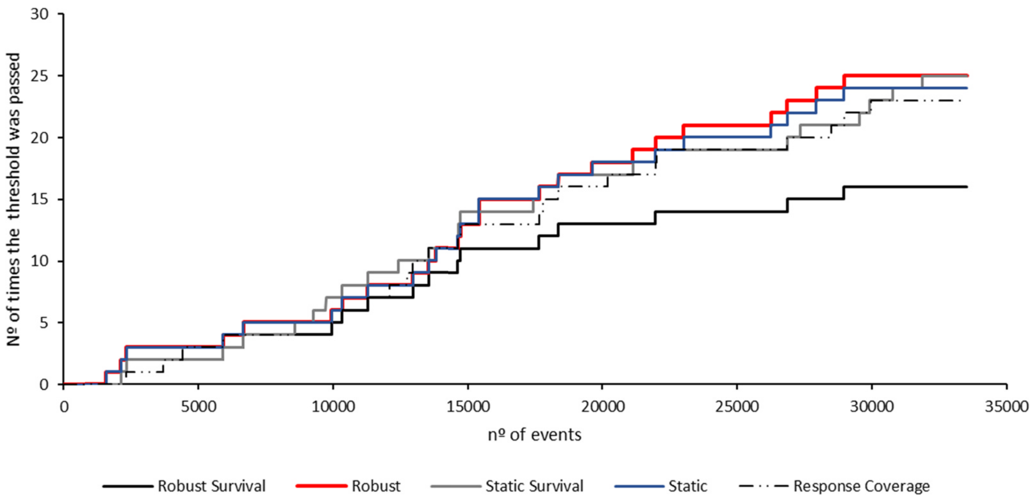

Fig. 8. Number of times the EMS response crossed a fixed threshold when resources are unlimited and a total of 7 stations exist. The threshold is 8 min for cardiac arrest emergencies and 12 min for other life-threatening emergencies.

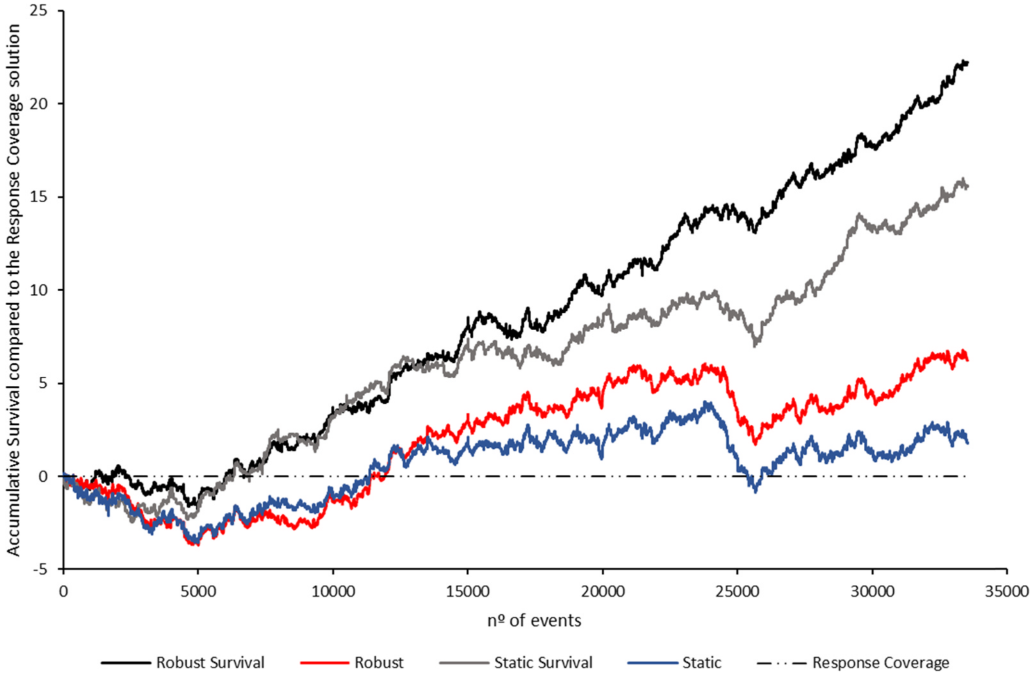

Fig. 9. Accumulated survival gain of each solution compared with the response coverage solution when resources are limited to 2 vehicles per station and a total of 7 stations exist.

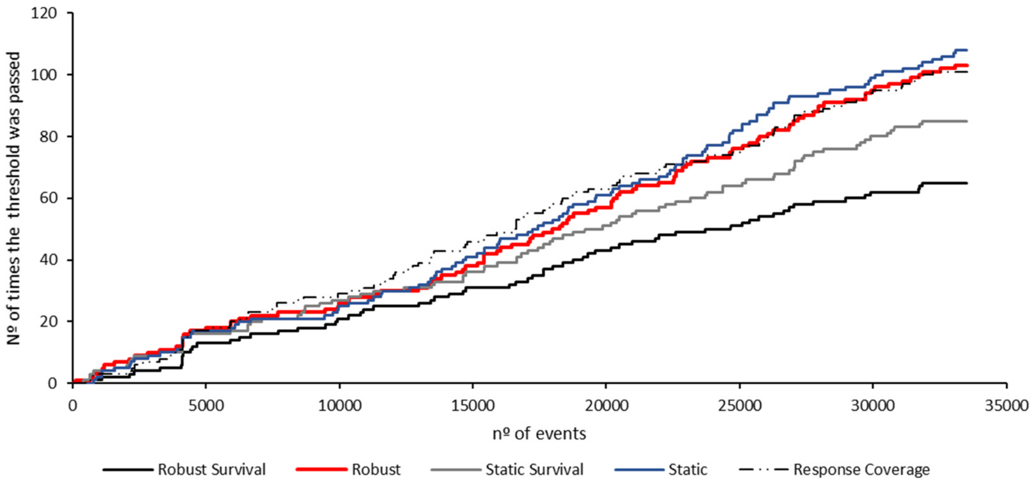

Fig. 10. Number of times the EMS response crossed a fixed threshold when resources are limited to 2 vehicles per station and a total of 7 stations exist. The threshold is 8 minutes for cardiac arrest emergencies and 12 minutes for other life-threatening emergencies.

One final remark worth mention is the fact that during the analysed year there seems to exist two timeframes where the solutions performance degrade. First, at the start of the simulation, during May 2012, and second a more abrupt performance fall happens around the 25 000th event, during February. Although the Robust Survival solution is relatively less affected, it is worth note that even on a month basis, there might exist dynamism that clearly influences the uEMS response and probably would influence a robust solution.

5. Conclusions

This work opens doors to the study of city dynamics and its influences in the strategic planning of an uEMS response system.

We defined a performance metric for the uEMS response by summing the survival score of each rescued victim. Afterwards, we proposed a scenario-based optimization model where the scenarios capture day periods to infer city dynamics.

An agent-based model simulation is offered to assess uEMS performance and stress the importance of a dynamic system.

The optimization model was validated and, after minor simplifications, performed quickly, allowing for several cases to be tested within a reasonable time. The validation and sensitive tests were performed using real data from Porto city, collected during one year with a total of 33 736 events from 10 May 2012 to 9 May 2013. The validation confirms the model importance in informing the decision makers on how to better rationalize station locations and the average response time of the system.

The division of the timeline in periods is a simple and efficient way to deal with city dynamics and is proven to be relevant in the positioning of the stations. The city has its own dynamics concentrating people and traffic in distinct parts of its network throughout the day as proven by the dynamic versus non-dynamic solutions analysis. Moreover, road accidents and cardiac arrests were proven to have different time and space behaviours, supporting our assumptions and showing the relevance of victims' heterogeneity.

In terms of available vehicles, it was shown that a good management of resources is fundamental to avoid response delays which easily propagate to future calls. This is a clear point for future investigation, by defining the number and location of vehicles using the same concepts that we applied for the station locations.

It was revealed that the location of stations is impacted by the city dynamics and the survival functions, stressing the need for further developments in the study of these functions for road accidents and other types of meaningful (survival or system related) emergency events. In addition, the use of realistic survival functions would allow a better assessment of the sensitive analyses provided here and possibly achieve clearer and more eloquent proofs.

Different period sizes should be tested as exposed in the results discussion when it was found that different months might have different dynamic behaviours. Moreover, the simulation model should be relaxed to allow vehicles to be reallocated to different stations, and allow vehicles returning from a hospital to be allocated to an active event without the need of return to their base first and be allocated after.

Additionally, we propose a study of the impact of road crashes in the uEMS response time for other occurrences so that, first, a better performance function can be added to the optimization model, and, second, the simulation model is improved accordingly. Adding double coverage to the optimization is also worth investigating to indirectly input stations' reliability.

Acknowledgements

We acknowledge the support of FCT (Portuguese national funding agency for science, research and technology) under the grant PD/BD/52355/2013 during the development of this work. We also express gratitude to INEM (Portuguese Institute of Medical Emergency) for the information and data that they provided us.

Financial disclosure

This work was developed under the Ph.D. Grant PD/BD/52355/2013 from FCT (Portuguese national funding agency for science, research and technology).

Conflict of interest

None.

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