#### **EMERGENCY MEDICAL SERVICE RESPONSE: ANALYZING VEHICLE DISPATCHING RULES**

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# 1 ABSTRACT

2 In an era of information and advanced computing power, emergency medical services (EMS),

3 still rely on rudimentary vehicles dispatching and reallocation rules. In many countries, road

- 4 conditions such as traffic or road blocks, vehicles exact position, and demand prediction are
- 5 valuable information which is not considered when locating and dispatching emergency vehicles.
- 6 Within this context, this paper presents an investigation of different EMS vehicle
- dispatching rules by comparing them using different metrics and frameworks. An intelligent
   dispatching algorithm is proposed and survival metrics introduced to compare the new concepts
- 9 with the classical ones.
- 10 This work shows that the closest idle vehicle rule (classic dispatching rule) is far from 11 optimal and even a random dispatching of vehicles can outperform it. The proposed intelligent 12 algorithm has the best performance in all the tested situations where resources are adequate. If 13 resources are scarce, especially during peaks in demand, dispatching delays will occur degrading 14 the system's performance. In this case, no conclusion could be made to which rule might be the
- 15 best option. Yet, it draws attention to the need for research focused in managing dispatch delays,
- 16 by prioritizing the waiting calls that inflict the higher penalty to the system performance.
- Finally, the authors conclude that the use of real traffic information introduces huge gain tothe EMS response performance.
- 19
- 20

21 Keywords: Vehicle dispatching, Emergency Medical Service, Intelligent algorithm, Victims

- 22 survival, Simulation
- 23

## INTRODUCTION

1

2

## 3 Motivation and contribution

4 The emergency medical service (EMS) is a vital part of today's modern cities. This is the service 5 that must respond promptly to medical emergencies that can occur at any time and any place.

6 Depending on the country, the EMS "modus operandi" may vary, but in general it relies on 7 an emergency phone line (e.g. 911 in the USA, 112 in the EU) that directs all the medical 8 emergencies to an EMS call receiver. There, an operator acquires the relevant information from 9 the caller and makes a pre-assessment of the medical emergency needs. Usually, the EMS call 10 center has an implemented algorithm that manually or automatically defines the priority of the 11 emergency and triggers a request for a vehicle dispatching. The most used EMS dispatching rule

12 is to send the closest idle vehicle.

Nevertheless, it is important to investigate why and if the closest vehicle is really the best
practice. One can conclude that, individually, the faster the victim is rescued the better.
However, sending that vehicle might debilitate the system's response for the next emergencies
compared to sending a different one. This is particularly true if we take in account the type and

17 severity of the case, where the response time may impact the victims' outcome.

Moreover, the urban environment where the system is implemented also influences the quality of the response it can provide. In fact, time-dependent information within this urban environment plays an important role in the system's response, has shown by Schmid [1]. With recent technological improvements, practitioners and researchers are in the position to collect and integrate, in real-time, large amounts of diversified data, such as traffic congestion, and real-

23 time emergency calls [2].

One can claim that dispatching an emergency vehicle is a complex decision that goes beyond the request for the closest unit available. It requires the management of a vital network of vehicles, the assessment of the victims' severity and heterogeneity, and an understanding of the urban environment where the system is integrated. Thus, this paper investigates this claim by assessing several dispatching rules in different temporal contexts. This is achieved by using various performance metrics to evaluate the versatility of the closest vehicle dispatching rule and

30 its possible substitutes.

## 31

# 32 Literature review

33 The classic emergency service problems tracks back to the year of 1955, with the fire station

34 location planning study by Valinsky [3]. Additionally, Hogg [4] together with Savas [5] fill the

35 base archetypes for this field of investigation, where the latter gives special focus to the

36 emergency medical service. EMS station and vehicle locations, allocation and dispatching have

37 since been widely studied however there has been always a gap between theory and practice due

38 to the lack of possibilities to test these models in a real environment.

With computers becoming ever more powerful and accessible to everyone, simulation also becomes an interesting tool when researchers want to formulate more realistic and complex

- 41 models, be it to assess solutions or to support optimization models [6-11]. Haghani and Yang
- 42 [12] proposed a simulation model to assess EMS performance. To abstract from the complexity
- 43 of the road system, they adopt a nodal network and assume that real-time traffic information is
- 44 known. McCormack and Coates [9] also use simulation to assess vehicle allocation performance

45 with focus on increasing victims' survival. The use of simulation has proven to be valuable due

to the ability of directly using real EMS call data, compared with other methods where demandmust be modeled, thus simplified.

3 When assessing EMS performance, researchers fall back on metrics from the two most 4 relevant works on EMS - those of Toregas, et al. [13] and Church and Velle [14]. The former, 5 presents a solution to the location set covering problem (LSCP), guaranteeing that all demand is 6 covered within a maximum time or distance radius. Church and Velle [14] approach the problem 7 with a solution for the maximal coverage location problem (MCLP) that intends to overcome the resource limitations neglected by Toregas, et al. [13]. Nevertheless, once a facility is called to 8 9 service, its allocated demand points are no longer covered. Daskin and Stern [15], [16] and 10 Hogan and ReVelle [17], [18] tackle this problem by adding facility busy probability and 11 reliability.

12 In these models, the metric used to evaluate the system performance and/or optimize it, is 13 the response time, which is usually simplified by a maximum response time threshold, e.g.

14 percentage of population covered within a response radius of 8 minutes [19]. Although it is

15 obvious that a quicker medical response will always result in an improved medical assistance

16 [20, 21], response time affects different types of medical emergencies in different ways. For

- 17 instance, Sánchez-Mangas, et al. [22] indicated that a response time reduction of 10 minutes
- 18 could result in a 30% reduction of fatalities in traffic crashes. While Valenzuela, et al. [23]

19 showed that cardiac arrest fatalities could be reduced by 50% if the victims were assisted no later

20 than three minutes after a collapse. Thus, by relying on homogenous performance metrics that

21 are time or distance based, no consideration to the victims' survival and heterogeneity is made.

22 Erkut, et al. [24] point out that the trend in EMS response research is to substitute time and

distance covering concepts with concepts that account for survival probabilities. This type of
 metric is used in recent works [9, 19, 25] and shown to be more suitable when assessing

emergency medical services from the user perspective, plus it allows benchmarking comparisons
 [24, 25].

27 Yet, as of today, vehicle dispatching rules for medical emergency requests follow distance or time-based metrics such as the classic closest idle vehicle dispatching rule [12, 26, 27], which 28 29 consist of allocating the vehicle that is closest to the emergency occurrence site. This rule is tied on the earlier mentioned classic performance metrics that focus on the overall system response 30 31 time, thus there is no account for the victims' heterogeneity or survivability. Several studies have started to investigate the fact that the closest idle vehicle is not always the optimal solution. The 32 33 subsequent closest vehicles could still provide an acceptable service while the closest vehicle 34 provides a better coverage of the network if it is available in the following hours [28, 29].

In many countries, the emergency response service does not even consider real-time information when assessing the closest idle vehicle. Mostly, it relies on spatial distances or on the operator skills and experience. Moreover, time-dependent information has been shown to be one of the keys for better vehicle dispatching rules [1].

39 Clearly, real time information and different vehicle dispatching rules are the most recent 40 topics in EMS optimization. Travel times and changes with respect to EMS call volumes are

40 topics in EMS optimization. Travel times and changes with respect to EMS call volumes are 41 used by Schmid [1] to achieve a decrease in the average response time of emergency services.

41 used by Schind [1] to achieve a decrease in the average response time of emergency services.
 42 Haghani, et al. [30] propose an optimization model for real-time emergency vehicle dispatching

43 and routing, using real-time traffic information to better support dispatching decisions.

44 Nevertheless, the proposed model presents major issues when applied in real-time situations due

45 to its computation time burden. Thus, Haghani and Yang [12] upgrade this model by drastically

1 reducing the computational burden by using the rolling-horizon approach, and adding coverage

- 2 concerns for future demand. Undoubtedly, demand prediction presents an interesting challenge
- for researchers [19], as is the use of real-time information to better model dispatching rules. Li,
- 4 et al. [31] uses the uncertainty theory to deal with uncertain factors, such as demand, when
  5 dispatching medical emergency resources. Still, they do not consider environment randomness
- 6 which can be captured using simulation. On the other side, Knopps and Lundgren [32] compiles
- 7 the most common dispatching rules the classic closest rule, and the preference rule, which tries
- 8 to minimize the response time for high priority calls [33] and proposes new ones. These are the
- 9 modified preference rule which adds to the original a maximum response time threshold for
- 10 lower priority calls, and the preparedness rule which employs a function that measures the
- preparedness of the system for future calls and tries to maximize it when dispatching vehicles to lower priority emergencies. In the work of Jagtenberg, et al. [26] a benchmark model is proposed
- 13 and when applied in a case study, the authors were able to show that the closest idle vehicle is a 14 factor of 2.7 away from the optimum.
- These state of the art research topics (real-time information, EMS heterogeneity, survival indicators) are scattered and analyzed individually, thus no relevant research combines them with emergency vehicle dispatching rules performance and assess their consequences. In this work a simulation model is used, different performance metrics applied and vehicles dispatching rules performance are assessed in different contexts, with the objective of providing practitioners with
- 20 proof of concept, applicability and empirical results in different emergency contexts.

# 2122 METHODOLOGICAL APPROACH

The literature review clarified that simulation is a superior tool to assess EMS dispatching rules performance with realism and accuracy. Furthermore, it was pointed that although the preferred EMS performance metrics is the system response time, survival functions are more suitable for measuring the victims' outcome.

Consequently, to investigate this work claim, a simulation is proposed using an agentbased model. The authors suggest performance metrics related to response time and survival, and
dispatching rules based on the classic closest idle vehicle rule and survival functions.

The method consists in building a simulation of a real city with real emergency call data to test different scenarios where the different dispatching rules are applied in different conditions such as the existence or not of real-time information and various periods of the year. The simulation results are calculated based on the chosen performance metrics and a comparison is made.

34 I 35

# 36 Simulation Model

To test the EMS vehicle dispatching rules and simulate urban environment conditions, an agent
based model is used, where a city agent controls a group of lower level agents: events, road
network, vehicles, and nodes, Algorithm 1.

40 The city agent is the main model agent and is responsible for storing and controlling all 41 other agents, by giving them update requests. The EMS calls are simulated by an event agent

- 41 which is responsible to activate events and keep track of their status. When an event is activated,
- 43 this agent sends an assistance request to the city. When assisted by a vehicle agent, the event
- 44 agent is also responsible for requesting directions from the city to the nearest hospital.
- 45

Definitions:

N = set of nodes n

n =node, where s =node of type station and h =node of type hospital

 $V = \text{set of vehicles } v_s$ 

 $v_s$  = vehicle in station s

S = set of stations sH = set of hospitals h

E = set of nospitals I $E = \text{set of events } e_n^t$ 

 $e_n^t$  = emergency event occurring at node *n* during *t* 

 $M = \text{set of matrices } M^t$ 

 $M^p$  = matrix of real travel times for period p

T =total simulation time

t = time

*step* = temporal resolution *f*() = programming function

While *t* < *T*:

- 1. Update city() "set t and activate  $e_n^t$ ."
- 2. Update network() "interact through every  $v_s$  to travel one *step* and transfers it to destination nodes"
- 3. Update events() "activates  $e_n^t$  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  $e^t_n$  , activate assisting timer

-If assisting timer ends, request network to be processed to **h** 

-If  $v_s$  arrived to h, transfers  $v_s$  to s.

- 5. Update results() "calculates the EMS performance at the current *step*"
- 6. t = t + step

2 To simulate the transport network, a network agent is created with the responsibility of 3 routing all vehicles and assisting in vehicle dispatching and transport. It is also responsible for 4 calculating the fastest origin-destination routes for different temporal scenarios or network status. 5 A vehicle agent is added to simulate each individual EMS transport/assistance unit. Each vehicle agent keeps track of its position and informs the network agent when it arrives at any 6 7 destination. It is simulated in a micro scale by tracking the distance when traveling between 8 nodes, the delays and assisting times that are randomly generated by the event agent. The vehicle 9 agent transports victims (event agents) from the occurrence node to the hospital node. It is also 10 responsible to keep track of the station where it must return after a job is completed. 11 The node agent can be of three types: network node, hospital node or station node. This

12 agent assists the network and city agent by storing vehicles and events, and constitutes the 13 origins and destinations of the network agent. Routing is abstracted by a previous calculation of 14 travel times between origins and destinations for different conditions, which then are stored in 15 the network agent. This simplification doesn't bring any set back to the methodology because 16 this research does not focus on vehicle rerouting. And, by simplifying, the simulation model 17 becomes faster, allowing for more complex dispatching algorithms and longer analyzed periods.

18

1

1 **Performance metrics** 

2 The performance  $P_i$  of an EMS response to an event *i* of type *t* can be defined by a function that 3 may depend on the time between the event start and the arrival of assistance vehicle,  $r_i$ , equation 4 (1).

5

$$P_i = f^t \left( r_i \right) \tag{1}$$

The classic response time metric,  $P_i^c$  can then be described as equation (2): 8

$$P_i^c = r_i \tag{2}$$

10 Which is then generalized for the overall service either by its summing parts, equation (3) or its average, equation (4): 11

12

9

$$P^{c} = \sum_{i=1}^{n} r_{i}$$
(3)

13

This metric is sometimes simplified into a binary evaluation,  $P_{i}^{T}$ , equation (5), where T is a time 14 15 threshold:

 $\overline{P^c} = \frac{\sum_{i=1}^n r_i}{\sum_{i=1}^n r_i}$ 

16 
$$\begin{cases} P_i^T = 0 \text{ if } r_i > T \\ P_i^T = 1 \text{ if } r_i \le T \end{cases}$$
 (5)

17 Recently, as pointed out in the literature review, these solely time-based metrics (or  
18 distance based metrics if 
$$r_i$$
 is substituted by the distance between  $i$  and the station that responds  
19 to it) can be replaced by a survival function that measures the likelihood of a victim to survive a  
20 medical emergency of type  $e$  when assisted within  $r_i$  in line with Erkut, et al. [24] work, equation  
21 (6):

22

25

$$P_i^s = \left(e^{c^{e^s \times r_i}}\right)^{-1} \tag{6}$$

23 Where  $c^{e}$  is a survival coefficient for an event of type e. This metric can also be generalized to 24 the system by taking the form of a sum or average, equation (7):

$$P^{s} = \sum_{i=1}^{n} \left( e^{c^{e} \times r_{i}} \right)^{-1} \text{ or } \overline{P^{s}} = \frac{\sum_{i=1}^{n} \left( e^{c^{e} \times r_{i}} \right)^{-1}}{n}$$
(7)

#### 26 **Dispatching rules**

27 Three dispatching rules are proposed for this investigation, algorithm 2. The classic rule where the closest vehicle is dispatched - ClosestDR. When this rule uses real-time information of 28

traffic it becomes RT-ClosestDR. A random vehicle dispatching rule, RT-RandomDR is

29 30 considered to infer how choosing the closest vehicle might compare with choosing any other

- 31 vehicle, proving the inadequacy of the classical rule.
- A final intelligent survival dispatching rule, RT-InteligentSurvivalDR, is proposed by the 32 authors. The survival performance metric is used to calculate the system status after dispatching 33
- 34 a certain vehicle, and the intelligent algorithm maximizes the system status,  $S^{p}$ , at period s by
- 35 dispatching to non-life-threatening emergencies the vehicle that penalizes  $S^{p}$  the less. This is

(4)

1 calculated using the busy fraction  $q_s$  [16] and the expected response time by Berg, et al. [34],

- 2 according to Snyder and Daskin [35]:
- 3

$$S^{p} = \sum_{i} \sum_{s} \sum_{k} \sum_{s} d_{i}^{es} \left( e^{c^{e} \times r_{is}^{p}} \right)^{-1} \times (1 - q_{s}) \times q^{k-1} \times z_{kis}$$

$$\tag{8}$$

4 where:

$$q = \frac{\sum_{e} d_i^{ep}}{a_s} \tag{9}$$

8

5 6

$$q^{k-1} = \prod_{j=1}^{k-1} q_j \tag{10}$$

7  $d_{i}^{es}$  is the predicted number of events of type *e* during the period *s* at demand point *i*,

8  $a_j$  is the number of idle vehicles allocated at station s, and

9  $z_{kis}$  is 1 if s is the  $k^{th}$  nearest station of *i*, zero otherwise.

10 Thus, the decision of dispatching a vehicle from a station *s* to a certain event can be scored 11 as  $Q_s$ :

 $Q_{s} = \left(e^{c^{e} \times r_{is}^{p}}\right)^{-1} + S^{p'}$ (11)

13 Where  $S^{p'}$  is the system survival status when an ambulance from *s* was dispatched to *i* making  $a_s$ 14 =  $a_s - 1$ .

15

### Algorithm 2 Dispatching rules

While no  $v_s$  is dispatched:

If ClosestDR or RT-ClosestDR is active:

1. Sort *S* by ascending  $r_i$ 

2. From index 0 to size of S, dispatch  $v_s$  if idle

If RT-RandomDR is active:

- 3. Select all s within  $r_i$  < maximum response limit which have at least one idle  $v_s$ . If none go step 5.
- 4. Dispatch a random  $v_s$  from step 3.
- **5.** Go step 1

If RT-InteligentSurvivalDR:

- 6. Select all s within  $r_i$  < maximum response limit which have at least one idle  $v_s$ . If none go step 10.
- 7. For every s in step 6, calculate system status using equation (11)
- 8. Sort solution from step 7 by descending  $Q_s$
- **9.** From index 0 to size of solution from step 7, dispatch  $v_s$  if idle
- **10.** Go step 1

Both the RT-RandomDR and RT-InteligentSurvivalDR algorithms can be controlled by a
threshold time to ensure that any emergency is assisted within a maximum response time limit. If
no vehicle within this maximum response time limit is available, then, the closest vehicle is

- 20 dispatched. Also, they are only activated for non-life-threatening emergencies.
- 21
- 22
- 23 24

## 1 APPLICATION OF THE MODEL

2 To assess the validity of this work's arguments and the performance of the different dispatching

- rules the methodology is applied to a simulation created with real data from San Francisco,
   FIGURE 1.
- 5 The data was collected from the U.S. Government's open data strategic American
- 6 resources and consists of a collection of Calls-For-Service database which includes all the fire
- 7 units' responses to calls in a total of 4.4 million vehicles dispatched between 2000 and 2017. The
- 8 fire department is responsible for managing the EMS calls and response, requesting a private unit
- 9 when required. Thus, the dispatch of private units (to 911 calls) is also recorded in the database.
- 10 The data was processed and filtered into a SQL database for easy access and data
- manipulation. From the same open data source, fire station locations were acquired and added tothe SQL database.
- 13



14

FIGURE 1 San Francisco experiment area with available stations at the left and total
 number of calls (2000-2017) at the right. Each circle in the left map represents a station,
 and each square on the right map represents one grid cell.

18

The city was divided in a grid of 500 meters by 500 meters (right map in FIGURE 1) and each unit is represented by a node corresponding to its center in a total of 518 nodes. The fire stations, a total of 45, were then assigned to the closest node as well as three fictional hospitals representing the major San Francisco hospitals. The lack of information on the destination hospital for each call forced a random allocation of calls to hospitals based on their proximity. It would be possible to identify the most likely hospital to receive the victims using the San Francisco EMS assignment algorithm. However, the required information for this allocation is
 also not present in the database.

- To implement the system performance metrics and the simulation model, travel time matrices were built using real travel times collected from Google through its Directions API. This specific API allows the calculation of travel times for different days and hours. Because of the burden of this process and the API limitations a resolution of week vs weekend and 3 hour intervals was used when building the OD matrices.
- 8 The intelligent vehicle dispatching algorithm coefficients were trained with the calls from 9 2010 to 2015 and the priority calls were defined as the ones tagged as "Potentially Life-10 Threatening" in the original data.
- Finally, several runs of the simulation model were computed for different months of the year of 2016, different number of vehicles and for the different dispatching rules.
- All the scripts for collecting the data and for the simulation model were programmed in Python 2.7 and were run on a machine with an Intel core i7 quad core processor at 1.73GHz and 8GB of memory RAM in a WIN10 64bits operative system. The running time for each experiment depends on the dispatching algorithm used and the number of simulated days, but
- 17 each experiment took between 20 seconds to 4 hours.
- 18 The relevant results were processed and compiled in comparative graphs which are 19 analyzed in the next chapter.

# 2021 **RESULTS**

22 To analyze the performance of each dispatching rule to "Potentially Life-Threatening"

- 23 emergency events, the ClosestDR algorithm is set as the base rule for comparison. Then each
- rule is tested for different scenarios and different metrics are calculated: the survival rate,
- average response time, and the number of assisted victims within 8 minutes. The use of the 8
- 26 minutes threshold is considered because this is a common threshold used in several works [9,
- 27 19]. For a better understanding of the results, several graphs were compiled where the
- accumulative performance of each dispatching rule is calculated as a gain over the base rule.
   The methodology was firstly applied to the month of February and tested for each
- Ine methodology was firstly applied to the month of February and tested for each
   dispatching rule in configurations of one vehicle per station and two vehicles per station. This
   allows an understanding of how the number of available vehicles might influence EMS response
   and how each dispatching rule performs in each condition.
- TABLE 1 presents a resume of the different performance metrics for the different configurations and dispatching rules, and FIGURE 2 shows the gain of each dispatching rule when compared with the base rule. There is an obvious increase in performance when the number of vehicles doubles. One of the reasons why, is the fact that with the existence of two vehicles per station there are no delays in responding to emergency calls. This means that at least one vehicle is always idle and available to be dispatched.
- 39 Interestingly, the random dispatching rule, RT-RandomDR, outperforms all other rules 40 when resources are scarce (one vehicle per station). Nevertheless, when measuring the
- 41 performance by the number of assisted victims within 8 minutes, the RT-InteligentSurvivalDR 42 shows to be the optimal one, and as expected the RT-ClosestDR algorithm provides the overall
- 43 lower average response time when all calls are accounted.
- 44 From FIGURE 2 a break is visible in the tendency of each rule's performance around the 45 4000<sup>th</sup> event. Further research concludes that this disruption corresponds with the period when

the "Superbowl 50" event was held near the San Francisco area, which leads to the occurrence of several smaller events across the city, and probably an increase in the number of tourists/visitors. This also shows that in that unpredictable situation, the ClosestDR algorithm performs better than the non-random rules as it minimizes the delays felt at the demand peaks. This can be owed to the fact that this algorithm acts as a restricted random dispatching rule due to the fact that it not uses real-time information.

To further investigate on the problem of sporadic events that may overload the EMS
response and produce system delays, a simulation was placed for the period around the New
Year's Eve (from 30 December of 2016 to the 3<sup>rd</sup> January 2017), which is believed to be the
event that might create the higher demand peak and every reader might relate to.

The results, FIGURE 3, show that when the EMS resources (number of vehicles) are low, the system performance degrades independently of the rule applied, which is explained by the existence of delays. In a situation where resources are not scarce, each dispatching rule seems to perform alike, recovering its usual performance when the demand peak vanishes. Moreover, it is important to note that the time response metric is the most sensitive one in encumbered periods and low resources; because it is the only metric that captures delays.

Finally, the seasonal adaptability of each dispatching rule performance is analyzed in FIGURE 4 by running simulations of different months. For the simulations where the number of vehicles is scarce, the intelligent survival algorithm underperforms in all of the analyzed months due to delay propagation. The exception is February where the closest dispatching rule is the weaker rule. In the rest of the months the best performance is achieved either by the closest rule or the random rule. When the number of vehicles per station is doubled, the intelligent survival

- dispatching rule becomes again the best practice although the random dispatching rule performs
   in a similar fashion.
- 25 Apparently, the existence of insufficient resources to timely respond to every life-

26 threatening emergency significantly affects the system's response by creating delays. This

- becomes more obvious in the RT-InteligentSurvivalDR algorithm and when the performance is
- measured by the accumulated response time. This gap is less noticeable in the other performancemetrics.
- 30

# 31 **TABLE 1 Resume of the results for the month of February with two different**

# 32 configurations: one vehicle per station and two vehicles per station. Different performance 33 indicators are presented.

	All calls				Possible life-threatening					
Dispatching rule	average response (sec)		average delay (sec)		average response (sec)		total events assisted in less than 8 min		average survival rate per event	
Nº vehicles/station	1	2	1	2	1	2	1	2	1	2
ClosestDR	585	337	24	0	634	348	5116	9463	42%	59%
RT-ClosestDR	520	287	64	0	601	295	6086	10397	45%	64%
RT-RandomDR	563	396	26	0	536	290	6617	10526	48%	64%
RT-InteligentSurvivalDR	609	329	36	0	558	288	6447	10571	47%	64%



FIGURE 2 Gain of each dispatching rule when compared to the base rule - ClosestDR. The
 left side presents the dispatching rules performance for a configuration of one vehicle per

station while the right side for a configuration of two vehicles per station.



FIGURE 3 Micro analysis of the gain in performance of each dispatching rules for the New Year's Eve event.



### 1 2

FIGURE 4 Comparison of the response time performance gain when compared with the
 base rule for different months of the year and different vehicle configurations.

4

## 5 CONCLUSIONS

- 6 This paper presents a methodology to assess EMS dispatching rules performance, providing
- 7 several performance metrics and dispatching rules, including a dispatching rule proposed by the
- 8 authors that aims to increase victims' survival, without excessively penalizing non-life-
- 9 threatening emergencies. Furthermore, the method is experimented with real data from San
- 10 Francisco city.
- 11 The presented results open doors to the study of EMS vehicle dispatching; to their
- 12 consequences; and to the characteristics that influence their performance. It gives an important
- 13 remark to the state of the art by providing proof of concept and empirical results that illustrate
- 14 that the optimal dispatching rule is not the obvious one sending the closest vehicle. They also
- 15 show that having one single rule is neither the optimal in the long term.

- In an EMS system where resources are not scarce, the proposed intelligent survival
   dispatching rule is the obvious choice in every scenario. Moreover, a random dispatch of
   vehicles (without penalizing non-life-threatening events more than 15 minutes) can outperform
   the classical rule in almost every tested case.
- 5 This work proves that the use of real-time traffic information is essential in every situation, 6 and improves significantly the system's performance in terms of response time, survival rate and 7 total number of emergencies assisted within 8 minutes.
- 8 It was found that demand peaks, due to special occasions where the number of people in 9 the same area increase or when people take more risky behaviors presents an interesting 10 challenge, and the optimal solution in this case is hard to assess with the presented dispatching 11 rules. It came to the authors' attention that the lower performance of the dispatching rules in this 12 situation is due to the poor handling of delays. It is also possible that different dispatching rules 13 fit better to different configurations of demand: local demand peaks, or dispersed demand peaks. 14 This is a topic worth investigating.
- 15 It is important to note that the victims in waiting list for a vehicle were processed using a 16 greedy algorithm that tries to minimize the total number of delays by avoiding delays
- propagation. This is clearly not the optimal approach, thus the authors propose the creation of
   delay handling algorithms that can consider the same EMS performance principles that were
- 19 discussed through this paper.
- This work concludes that sending the closest vehicle (for non-life-threatening emergencies) to a certain demand point is debilitating that same demand point and its surroundings. This is because, statistically speaking, that same demand point just proves to have higher chances of having more emergencies. The last sentence questions the use of a Markov process in EMS demand prediction.

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