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AMBULANCE REDEPLOYMENT USING DYNAMIC DATA PROGRAMMING

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Abstract— *Emergency medical service (EMS)are of great importance to saving people's lives from emergent accidents and diseases by efficiently picking up patients using ambulances. We propose a data driven real-time ambulance redeployment approach that redeploys an ambulance to a proper station it becomes available, so as to optimize the transporting capability of an EMS system. Many possibility that EMS cannot be accessible by the patients because it went for another destination and not making the closest EMS to dispatch. The crucial moments in dispatching an ambulance correctly with the least response time in case of trains or other threatening situations will contribute and determine patient survival. The performance of our real time approach is evaluated by a discrete event simulation developed for a large real dataset and compared with two approaches. EMS are concerned with providing maximum possible coverage in the service area.*

Key Words: Emergency medical services, ambulance redeployment, data and knowledge management

1. INTRODUCTION

Crisis Medical Services assume fundamental parts in saving individuals' lives in urban communities from rising mishaps and illnesses, through proficiently getting patients, leading in-site medicines for patients and moving patients to clinics Once an EMS framework has been laid out, its moving ability altogether depends on the dispatching and redeployment system of ambulances [2]. Nonetheless, as concentrated in past writings, For example, when an EMS demand comes, whether there are accessible ambulances in stations close by the solicitation altogether relies upon the redeployment consequences of past ambulances. we propose to consider essentially the accompanying information. D1: the quantity of accessible ambulances at each station. For an emergency vehicle station, the less accessible ambulances it contains, the more essential for the EMS focus to redeploy the ongoing accessible emergency vehicle a1 to this station. D2: the quantity of EMS demands close by each station in the future. D3: the topographical area of every emergency vehicle statioD4: the movement time for the ongoing accessible emergency vehicle to arrive at every emergency vehicle station. D5: the situation with other involved ambulances. To manage this issue, in this paper, we propose an information driven constant rescue vehicle redeployment approach [4] which can naturally consider the previously mentioned D1-D10. In particular, we have commitments as follows. For example, when an EMS demand comes, whether there are accessible ambulances in stations close by the solicitation fundamentally relies upon the redeployment consequences of past ambulances.

The proposed rescue vehicle redeployment approach can well integrate all connected information previously mentioned D1-D5 into the continuous redeployment of ambulances. Exhaustively, to manage the different information, our proposed approach comprises of two phases, a wellbeing time sensitive desperation file and an idea matching calculation. After an emergency vehicle become accessible, the initial step is to get all connected information, for example the D1-D5. Then, at that point, to redeploy the rescue vehicle and to well think about D1-D10, our move toward comprises of two phases: the Safety Time Based Urgency Index what's more, the Optimal Matching Algorithm.

Safety Time-Based Urgency Index: we propose a method (i.e. a safety time-based urgency index) to organically incorporate D1-D5 into the urgency degree of each station gent the station. For each station, we apply a gradient descend algorithm to learn its threshold μj such that the geographical location of each station can be well considered for calculating the D*. Under the already devised urgency index h and optimal matching algorithm O (see below), the transporting capability g of an EMS system can be seen as a function of each station threshold μj i.e. g $(\mu 1, \cdots, \mu J)$. Then, we can use a gradient descend algorithm to learn station discriminative thresholds for stations in order to optimize the transporting capability. Note that n j is knowable to an EMS center and that λ j is an estimated value.

Optimal Matching Algorithm: After obtaining D* (using the devised safety time-based urgency) D4, and D5, we propose an optimal matching algorithm O to find a proper station for the ambulance which has just become available. Our optimal matching algorithm further contains two stages: the station selection and the travel time minimization. The second stage is to match the ambulances in A with the selected |A r | stations, aiming to minimize the overall travel time needed for each ambulance to reach the station matched. From the matching result, we can get the station (i.e. the redeployment result) for the current available ambulance.

D1: the number of available ambulances at each station.

D2: the number of EMS requests.

D3: the number of EMS requests nearby each station in the future

D4: the travel the current available ambulance

D5: the travel the current available ambulance to reach each ambulance station

D6: the travel to the current location can be displayed to the ambulance

D7: the status of occupied ambulances

D8: the status of other occupied ambulances

D9: the dispatching time for ambulances

D10: the status to be completed deployment of ambulance

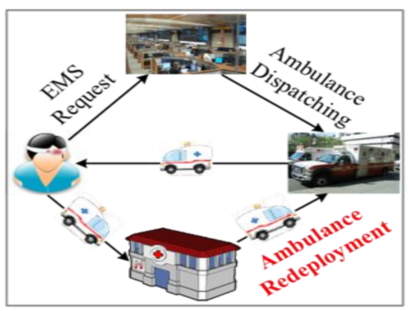


Fig-1: Emergency event

1.1 Overview

EMS Request: An EMS request r_q from a patient is a tuple, if the station s_j is the nearest station to the request, in terms of *the travel time* of ambulances on *road networks*. Emergency Medical Service (EMS) is a branch of emergency services dedicated to providing out-of-hospital acute medical care and/or transport to definitive care, to patients with illnesses and injuries which the patient, or the medical practitioner, believes constitutes a medical emergency.

Ambulance Station: We denote the total number of ambulance stations in an EMS system by *J*.

Emergency Medical Service (EMS) is provided by a variety of individuals, using a variety of methods. To some extent, these are determined by country and locale, with each individual country having its own 'approach' to how EMS should be provided, and by whom. In some parts of Europe, for example, legislation insists that efforts at providing Advanced Life Support (ALS) services must be physician-led, while others permit some elements of that skill set to specially trained nurses, but have no paramedics. Elsewhere, as in North This is most likely a Casualty at a hospital or another place where physicians are available. The term Emergency Medical Service (EMS) evolved to reflect a change from a simple transportation system (ambulance service) to a system in which actual medical care occurred in addition to transportation. In some developing regions, the term is not used, or may be used inaccurately, since the service in question does not provide treatment to the patients, but only the provision of transport to the point of care.

In this paper, hereinafter, we utilize addendum q for an EMS demand, addendum j for an emergency vehicle station, and membership for a rescue vehicle

1.2Problem Definition

The moving ability of an EMS framework can be characterized in numerous ways, for example the typical pickup season of EMS demands [2], [7], the proportion of EMS demands with pickup times inside a given time edge (for example 10 minutes) [16], and so forth [17]. In this work, we utilize the typical pickup season of patients to mean the shipping capacity of an EMS framework, leaving others as the measurements in our assessment (see Section 5.3). Officially, the shipping capacity is signified by g and is figured out as

$$g = \frac{1}{Q}\sum_{q=1}^{Q} t_q^p \qquad (1)$$

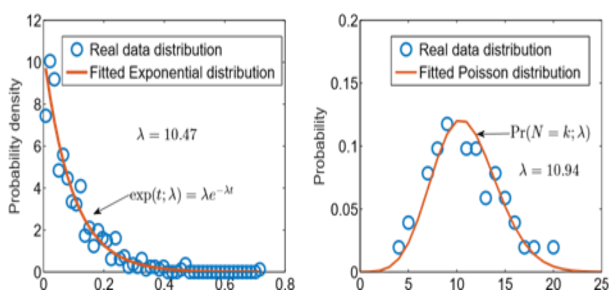
where Q is the quantity of EMS demands showing up in quite a while period (for example one month).

2. Methodology

our methodology comprises of two phases: the Safety Time Based Urgency Index and the Optimal Matching Algorithm. Beneath, we detail the fundamental thought of the wellbeing time sensitive direness file and the ideal matching calculation.

2.1 Safety Time-Based Urgency Index: as shown in Figure 2, after obtaining the current status (n_j, λ_j, μ_j) of each station s_j (I .e. D1, D2,D3,D4 and D5), we propose a method (i.e. a safety time-based urgency index) to organically incorporate D1-D5 into the urgency degree of each station s_j (D*). Specifically, given n_j and λ_j, we first define the *safety time* of station s_j as the length of time after which station s_j will

For each station s_j, we apply a gradient descend algorithm to learn its threshold μ_j such that the geographical location of each station can be well considered for calculating the D*.



2.2 Optimal Matching Algorithm: as illustrated in Figure 2, after obtaining D* (using the devised safety time-based urgency index), D4, and D5, we propose an optimal matching algorithm O to find a proper station for the ambulance which has just become available. A set of ambulances containing the MS ambulances and the current available ambulance. Our optimal matching algorithm further contains two stages: the *station selection* and the *travel time minimization*.

(Safety time urgency index) we propose an optimal matching algorithm O to find a proper station for the ambulance which has just become available. Let's denote A^r as a set of ambulances containing the MS ambulances and the current available ambulance. Our optimal matching algorithm further contains two stages: the *station selection* and the *travel time minimization*.

Time interval of two consecutive requests Number of requests this segment is to integrate the acquired D*, D4, and D5 into the redeployment of the ongoing accessible rescue vehicle. Towards this end, we propose an ideal matching calculation.

3. EXISTING SYSTEM

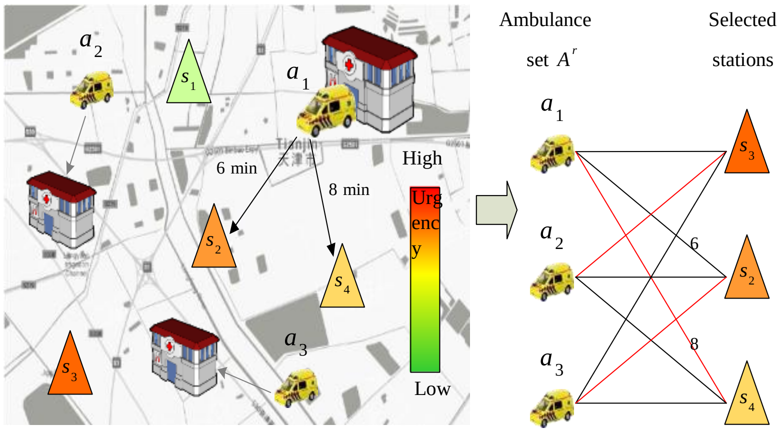


Fig 2: The optimal matching algorithm to incorporate D*The optimal matching algorithm to incorporate D*, D4, and D5.

3.1 EMS request records; EMS request records are obtained from October 1 to November 21, 2014, i.e. totally 51 days. Each EMS request contains a time stamp and a geographical location (i.e. a latitude and a longitude). In total, there are 23,549 EMS requests appeared in the 51 days. That is, on average, in Coimbatore city there are around 462 EMS requests every day, and around 20 EMS requests every hour.

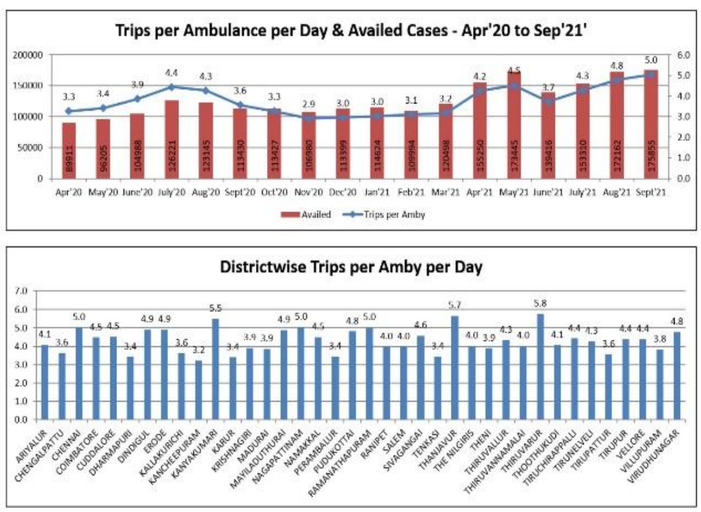


Fig 3 : EMS Request per day & Availed cases

3.2 Road networks

According to vehicles accidents by the Government and private buses have been reduced by (-) 63.88% and (-) 66.92 % respectively comparing the previous year up to Nov 2020.. Accordingly, Death by Government /Private buses have been reduced by (-) 64.81% and (-) 65.19% respectively when comparing to previous year up to Nov 2021. The death by two wheelers was dropped by (-) 18.12 percent when compared to previous year Nov 2021. From the above table it reveals that during Nov 2020 the most number of accidents occurs in State Highways (33.91%) followed by National Highways (32.21%), other district roads 21.31% and other village roads 12.57%. According to Death, Death occurs in National Highways (39.27%) and State Highways (29.34%) in TamilNadu.

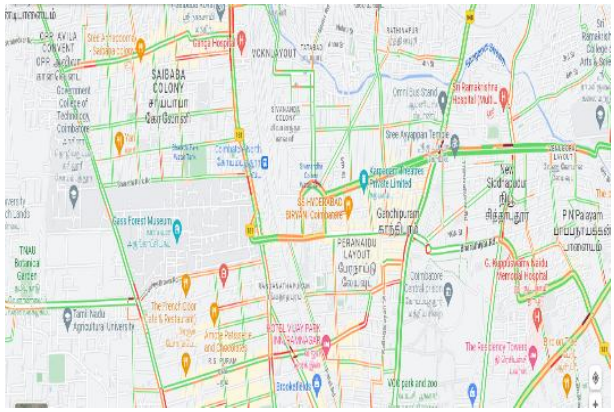


Fig 4: GPS trajectories of ambulances

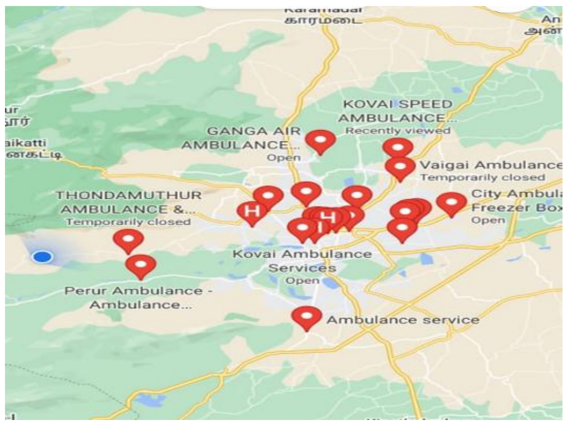


Fig 5: Ambulance stations and hospitals

In coimbatore city, there exist 538 ambulance stations[3] and 750 hospitals, to which ambulances will transport patients. We also collect 51 days of the GPS trajectories of ambulances in coimbatore city. According to this data and EMS request record data, we can obtain the length of time that ambulances spend at scene and at hospital the length of time that ambulances spend at scene and at hospital can be fitted as Exponential distributions, being exp(0.0834) and exp(0.2260), respectively.

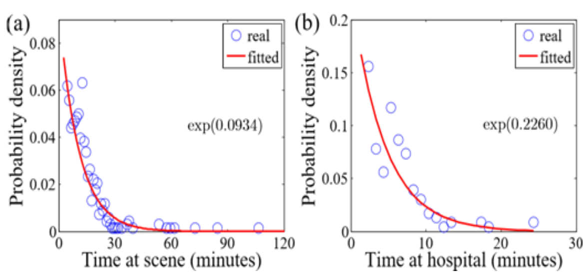


Chart-1: The length of time that ambulances spend at scene and at a hospital in real

3.3 Baselines

To better evaluate the effectiveness of our real-time ambulance redeployment method, we compare our redeployment method with many state-of-the-art baseline methods.

- **B1: RS.** RS method randomly selects a station, after an ambulance becomes available.
- **B2: NS.** NS method redeploys the current available ambulance to the nearest station in terms of travel time.
- **B3: LS.** LS method redeploys the current available ambulance to the station with the least available ambulances.
- **B4: ERTM** [7]. ERTM method is a static ambulance redeployment method.
- **B5: MEXCLP** [3]. MEXCLP method is a static method, too. MEXCLP method aims at maximizing the expected coverage of stations.

Characteristics (%)	Jan–May 2018 (*n* = 1213)	Jan–May 2019 (*n* = 1280)	Jan–May 2020 (*n* = 1400)
Age in years, median (Q1–Q3)	71 (59–82)	71 (60–83)	73 (60–84)
Gender, male	779 (64.2)	818 (63.9)	882 (63.0)
Race			
Chinese	804 (66.3)	905 (70.7)	992 (70.9)
Malay	201 (16.6)	192 (15.0)	199 (14.2)
Indian	142 (11.7)	135 (10.6)	171 (12.2)
Others	66 (5.4)	48 (3.8)	38 (2.7)
Location Type			
Home residence	866 (71.4)	943 (73.7)	1081 (77.2)
Healthcare facilities	90 (7.4)	108 (8.4)	137 (9.8)
Public areas	229 (18.9)	196 (15.3)	161 (11.5)
In EMS/Private ambulance	25 (2.1)	25 (2.0)	17 (1.2)
Others	3 (0.3)	8 (0.6)	4 (0.3)
Arrest Witnessed By			
Not witnessed	563 (46.4)	690 (53.9)	533 (38.1)
EMS/Private ambulance	129 (10.6)	130 (10.2)	157 (11.2)
Bystander	521 (43.0)	460 (35.9)	710 (50.7)
Family member	295 (56.6)	241 (52.4)	464 (65.4)
Lay person	184 (35.3)	170 (37.0)	145 (20.4)
Healthcare provider	42 (8.1)	49 (10.7)	101 (14.2)
Bystander Interventions			
Bystander CPR performed			
No CPR	466 (38.4)	508 (39.7)	671 (47.9)
Unassisted CPR	227 (18.7)	238 (18.6)	272 (19.4)
DA-CPR	520 (42.9)	534 (41.7)	457 (32.6)
First CPR initiated by			
Family	475 (39.2)	432 (33.8)	438 (31.3)
Non-related layperson	272 (22.4)	340 (26.6)	291 (20.8)
Bystander AED applied	66 (5.4)	142 (11.1)	131 (9.4)
First arrest rhythm			
Shockable rhythm	191 (15.7)	198 (15.5)	206 (14.7)
Non-shockable rhythm	1014 (83.6)	1060 (82.8)	1178 (84.1)
Pre-hospital Defibrillation	313 (25.8)	296 (23.1)	298 (21.3)
Total response time in minute, median (Q1–Q3)	11.9 (9.8–14.9)	11.3 (9.4–13.5)	12.6 (10.5–15.1)
-Call received to dispatch	2.4 (1.8–3.2)	2.1 (1.6–2.9)	2.0 (1.5–2.8)
-Dispatch to scene arrival	6.1 (4.5–8.4)	6.0 (4.6–8.0)	6.3 (4.9–8.2)
-Scene arrival to first patient contact	3.2 (2.2–4.7)	3.0 (1.9–4.2)	3.8 (2.5–5.4)
* Scene time in minute, median (Q1–Q3)	22.4 (19.0–25.9)	22.7 (19.5–26.3)	24.3 (20.8–28.1)
EMS Outcome			
Resuscitation at scene	1213 (100.0)	1260 (98.4)	1365 (97.5)
Transported to acute hospital	1195 (98.5)	1190 (93.0)	1238 (88.4)
Pre-hospital ROSC	164 (13.5)	160 (12.5)	131 (9.4)

4. EMS Models

Some countries closely regulate the industry (and may require anyone working on an ambulance to be qualified to a set level), whereas others allow quite wide differences between types of operator.

a) Government Ambulance Service – Operating separately from (although alongside) the fire and police service of the area, these ambulances are funded by local, provincial or national government. In some countries, these only tend to be found in big cities, whereas in countries such as U.K., almost all emergency ambulances are part of a national health system.

b) Fire or Police Linked Service – In countries such as the U.S.A., Japan, and France; ambulances can be operated by the local fire or police service.

c) Volunteer Ambulance Service – Charities or non-profit and patient transport function. They may be linked to a voluntary fire service, with volunteers providing both services.

d) Private Ambulance Service – Normal commercial companies with paid employees, but often on contract to the local or national government. Private companies may provide only the patient transport elements of ambulance care

e) Combined Emergency Service – these are full service emergency service agencies, which may be found in places such as airports. Their key feature is that all personnel are trained not only in ambulance (EMT) care, but as a firefighter and a peace officer (police function).

e) Hospital Based Service – Hospitals may provide their own ambulance service as a service to the community, or where ambulance care is unreliable or chargeable. Their use would be dependent on using the services of the providing hospital.

f) Company Ambulance - Many large factories and other industrial centers such as chemical plants, oil refineries, breweries and distilleries have ambulance services provided by employers as a means of protecting their interests and the welfare of their staff.

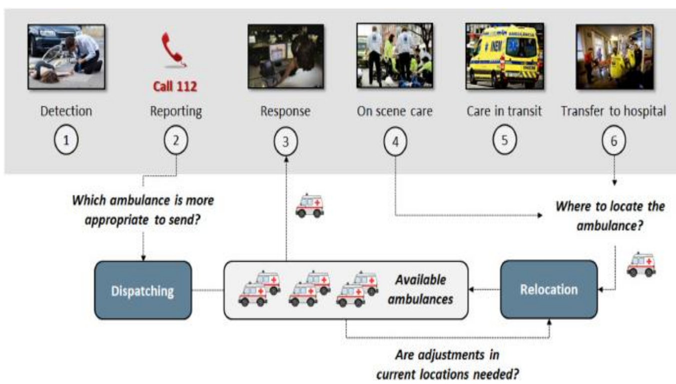
5. Proposed system

In our work, we propose a wellbeing time sensitive earnestness record for each station. In past written works, writers normally utilize the negligible inclusion [5] the peripheral expected inclusion [3], [4], the activity esteem [2], or the minimal expected pickup time to measure each station's criticalness. Consequently relegating the emergency vehicle to the solicitation client.

Number of adjacent EMS demand from now on and geological area into the earnestness level of this station. Which can integrate each stations with the movement season of the current ambulance to arrive at each station and the situation with other station

6. RELATED WORK

Ambulance Location and Ambulance Dispatching The rescue vehicle dispatching issue is to dispatch a rescue vehicle to get a patient, after the patient sends an EMS solicitation to the EMS community. The dispatching technique proposed in work [1] decreases the proportion of EMS demands with pickup times throughout a given time edge, but the strategy likewise to a great extent expands the typical pickup season of patients. Along these lines, the emergency vehicle redeployment issue turns out to be significantly more significant. In the event that ambulances can be very much redeployed, for every EMS demand, the closest station can be with accessible ambulances, the base pickup time.



6.1 Ambulance Redeployment

The rescue vehicle redeployment issue is to redeploy an emergency vehicle to a station after it opens up. For the emergency vehicle redeployment issue, related works can be partitioned into three classes. The first is the static emergency vehicle redeployment strategy [3], [7], [17]. The static techniques initially select a base (home) station for every emergency vehicle, and afterward when an emergency vehicle opens up, it is straightforwardly redeployed to its base station. Obviously, static strategies can't catch the time-differing status of an EMS framework, including the spatial and transient appearance example of EMS demands, the progressively evolving status (for example direness) of stations, and the dynamical status of ambulances (counting the ongoing accessible emergency vehicle and other involved ambulances).

In our work, we propose a wellbeing time sensitive earnestness record for each station. In which can measure stations' desperation degrees all the more precisely and is gainful to further developing the shipping capacity of an EMS framework.

7. CONCLUSION

In this paper, we fostered a constant rescue vehicle redeployment approach which redeploys a rescue vehicle to a legitimate emergency vehicle station after it opens up. Utilizing our redeployment approach, the moving capacity of an EMS framework in a city can be essentially gotten to the next level. In particular, as indicated by our trial results, when the quantity of absolute ambulances is 50, contrasting and many cutting edge rescue vehicle redeployment draws near, our redeployment approach can save ~4 minutes EMS frameworks can more readily save individuals' lives from rising mishaps and infections.

8. FUTURE WORK

Dependent upon an extra imperative to hold the most extreme conceivable inclusion result from the primary model. While the ROA makes a choice about the following area of recently inactive rescue vehicle at each assistance culmination occasion redeployment choices in regards to sit emergency vehicle should be settled on at every decision appearance occasion.

The ongoing inclusion According to the framework state is processed in time intricacy preceding running the advancement models.

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