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Towards Smarter Metropolitan Urgent Situation Response

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ABSTRACT— ***A core ingredient of Smart Cities is the use of emergency services both as a lens through which to monitor their ever-changing state and as a rapid response mechanism to the needs of their population. We supply proof that our combined proactive transfer and dispatch model produces significant improvements in measured performance in terms of meeting citizen needs.***

KEYWORDS— routing, emergency services, computer simulation, medical information systems

1. INTRODUCTION

Smart Cities are one of the most active areas of application of ubiquitous computing technologies. Notably, the information gathered and processed by emergency services in a metropolitan setting can be used as a lens for observing and reacting to human dynamics as well as the needs of individuals in the city. In this way emergency service systems and related infrastructure act as both a contributor and beneficiary to smartness and dynamic adaptation. In this paper we consider in detail the case of the ambulatory service in London to identify the costs and benefits afforded by the integration of diverse metropolitan socio-technical systems and services within a unified approach and the potential cause on the welfare of its citizens.

A well-established clinical outcome is that shorter ambulance arrival times play a critical role [1] in the case of emergency patients involved in incidents of high severity. The mobility characteristics of ambulances in their various forms, however, differ from normal civilian traffic. This is partly because ambulance crew travelling with flashing lights are exempt from traffic regulations that would otherwise impede progress to a patient. For example, ambulances are permitted to treat red traffic lights as a give way sign, are able to pass the wrong side of a keep left bollard and disobey the speed limit. Urgent situation response units in particular employ diverse ubiquitous computing technologies for sensing, flexible communication, and dispatch and depend on extensive command and control infrastructure that links into the healthcare and transportation scheme. Taking the London Ambulance Service (LAS) as our case study we develop a simulation framework and introduce an enhanced routing and dispatch method that combines concurrent assignment and redeployment of units in a particular algorithm.

Moreover, the collection of data on the human condition by ambulatory services reveals many specific attributes that can be used to enhance social governance. For example, the temporal and spatial characteristics of acute cardiac events follow specific pattern. Driving conditions in urban road networks also have well-defined patterns that affect ambulance arrival times .In this paper search how data captured from a variety of ubiquitous computing technologies deployed as part of emergency response systems can be utilized to create a realistic predictive model of their performance in dense urban environments. This model reveals facts about life in the city from a healthcare perspective that has remained unobserved until now. A core ingredient of our approach is the development of an accurate and precise simulator that can be used to evaluate new ambulance dispatch algorithms. Indeed, we introduce such a novel algorithm that combines both strategic and tactical elements into a unified model and test its viability through the simulator. In this part, first we provide some background on how a typical ambulance service handles emergency medical calls. It's followed by analysis of real data streams obtained from the London Ambulance Service. We then proceed to discuss the simulator we developed, introduce our dispatch algorithm and assess its performance.

2.BACKGROUND

Incoming emergency medical calls in London are processed in one of two call centres operated by the LAS, each covering a different area of London. In the vast majority of cases the caller confirms the location of the patient either by passing an address or other land feature such as road junction to the call- taker. The caller is then asked a series of questions that quickly determine the type and severity of the emergency. The Command and Control system uses this information to dispatch one or more responders as and if appropriate. For life-threatening cases such as Cardiac/Respiratory Arrest also known as Category A incidents, at least two units (vehicles with crew) are dispatched. When responders arrive at the scene they assess and provide any treatment necessary.

London's ambulances carry extensive instrumentation that monitors their location as well as vehicle state including temperature, handbrake, door open, blue lights, siren, battery level and so forth. Approximately 95% of all data traffic is received within 1 second of transmission. Retransmissions generally account for less than 1% of the total data traffic.

Ambulances also carry a Siemens GPS/Navigation unit with embedded gyros and accelerometers, augmented with wheel sensors that measure speed. Information sent from headquarters over the data network is used in conjunction with GPS data by the on-board computer to provide the crew with map-based navigation, search facilities and details about the patient and the incident. Of course, similar to all UK emergency services, ambulances also carry TETRA two-way transceivers which allow encrypted voice communication with the LAS Command and Control centre. The transceivers also contain GPS receivers and also transmit location data back to headquarters.

One obligation placed upon the LAS is to reach at least 75% of all Category A incidents within 8 minutes. Failure to achieve this target is met with heavy penalties. The LAS use several vehicle types to accomplish this target. The entire operational fleet consists of nearly 400 ambulance thing, over 200 fast response units (FRU) and a smaller collection of Improvement on linear regression methods that preceded it. Potvin [iv] used long term non-stochastic and short-term stochastic elements to produce efficient routing, thereby reducing overall travel time. As travel time is a key factor in survival, novel methods of traffic avoidance are investigated for example the use of crowd-sourced data has attracted considerable interest recently [v].

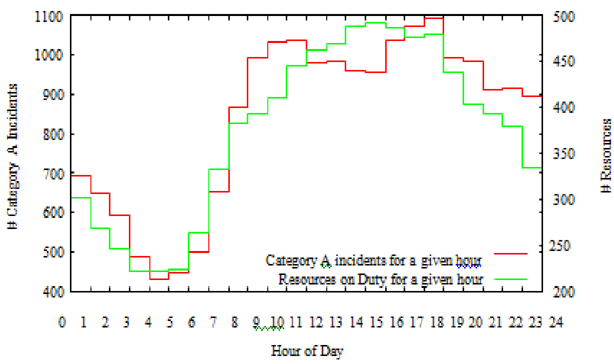
3. DATA AND ANALYSIS

Here, we describe some of the key characteristic of the core data set used in this research. In particular, we discuss the temporal and spatial characteristics of emergency events in London and patterns derived from the telemetry obtained from ambulances. The data used in this research originated from the London Ambulance data warehouse. Most of the data originates from vehicle telemetry as previously described. Emergency incident data from London Ambulance was also analysed from the year 2012.

A. **Emergency event:**

Fig.1 shows how the number of life-threatening medical emergencies is distributed around London, revealing that a large proportion of these incidents occur in the centre of the city. The shape of this distribution changes throughout the day as the population swells during working hours.

Fig. 2 shows the total number of critical incidents and the average number of units on duty in London, per hour, during 2012. This is at a minimum at around 4am with just over 400 critical incidents being reported during 2012. The busiest period appears to be around 6pm when just less than 1,100 events were statement.



It can be obviously seen that the provide of units on bicycles and motorcycles. In London there are some 77 'standby points' or locations where vehicles and their crew will wait for work. These locations have been selected because they provide good coverage of London but also for practical reasons such as crew safety and the ability for crew to obtain refreshments. Under certain conditions considerable friction is observed between the need to meet strategic targets and positioning tactics.Previous models that attempted to work out the coverage location problem [ii] ignored road networks completely, relying instead on a set of so-called geographical atoms. Goldberg [iii] used mean and variance to determine estimated travel times, an Closely matches the demand. This spatial and temporal dynamic behavior of emergency incidents adds to the complexity of where and how many units to site at standby points.

B. Road Network Spatial Analysis

Our preliminary analysis aimed to determine by how much the road speeds were slower in the centre of London compared to the suburbs. The distribution shown in Fig. 3 illustrates averages vehicle road speeds from 9:00-9:59 for the year 2012. When superimposed on a map of London it clearly, and obviously, shows that vehicles travelling in surrounding urban areas average higher speed than those in central London regardless of the time of day.

C. Road Network Temporal Analysis

Whilst recognizing that there are spatial differences in road speeds Fig. 4 also shows the temporal speed difference by vehicle style. Particularly it explain vehicle style, speed and time of day data collected for the year 2012 across the whole of London. Fig. 4 implies that FRUs are, as expected, faster than ambulances due to their smaller physical size and handling characteristics. Whilst this might sound obvious, there was no pre-existing data to quantify this difference in speed.

Our analysis shows that on average the FRU is about 5 mph faster than ambulances in an urban environment, with the greatest variation in the morning rush hour of around 6 mph. Note that we do not take into consideration spatial variation so the difference in road speeds could vary further depending on whether vehicles are travelling in central London or in outer urban areas. Clearly, any road speed model used for simulation would need to take into account vehicle type, spatial and temporal distribution.

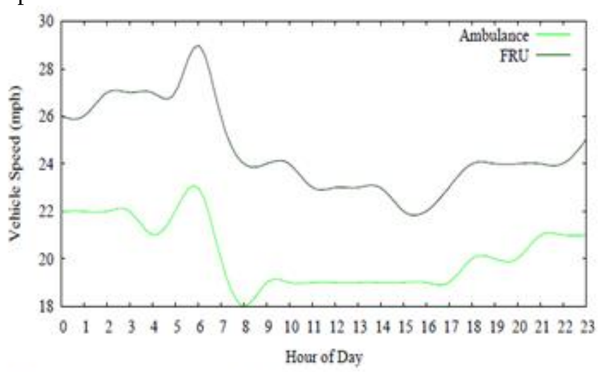


Fig. 4. Vehicle speeds by hour of day.

4. SIMULATOR

We developed a discrete event simulator to model ambulance workflow so that novel dispatch algorithms could be tested. The workflow involves dispatching a units to incidents and standby points, waiting on scene whilst dealing with the patient, optionally transporting the patient to hospital and then becoming available again for further work. Our ultimate aim was to measure the performance of the simulator in terms currently used by the LAS, i.e. the percentage of category A calls where an ambulance arrived with 8 minutes. By improving on the dispatch model we aimed to improve the performance metric.

At the heart of the simulator is the discrete event priority queue. The queue facilitates inter-module communication. Emergency events are replayed by passing message to the command and control module. This module tracks emergency events and asks the dispatch module to recommend units for assignment.

A. Routing Engine

The routing engine is used both to determine the quickest vehicles to a patient and calculate the route to be taken by an ambulance. Accurate routing estimates were the key factor in producing an accurate simulator.
Analysis of the road speeds was carried out using 204million telemetry records data captured by LAS during 2012 from the on-based GPS units travelling to an emergency. Each of the position reports were snapped to the nearest road and the road type identified. London was spatially divided up into 100*100 square cells, every 300mts in width and height. Speeds were average for each position report that occurred in each cell for every hour of the day, each vehicle type and road type. This produced a 5-dimensional table containing average road speeds.
We built a routing engine that could calculate the quickest route between two locations using the actual road network using Dijkstra's shortest path algorithm on London's 19134 links and 15986 road nodes. The algorithm used the 5-dimensional speed data to calculate route speed and total duration.

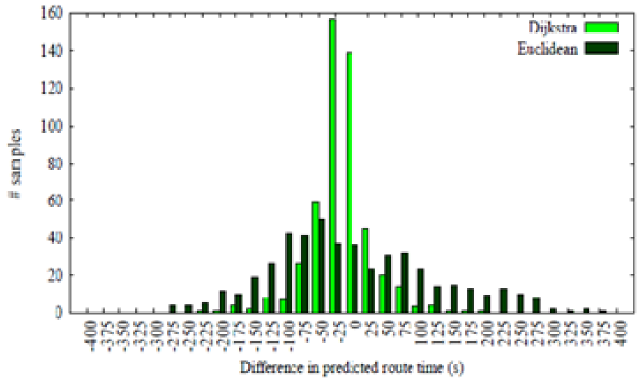


Fig. 5. Accuracy of different routing engines.

To validate the accuracy of the routing engine we compared its performance with 500 actual journeys carried out by ambulances en-route to emergency incidents. Fig. 5 shows a comparison of straight-line (Euclidean) and Dijkstra's routing arrival times with actual arrival times. The Dijkstra's routing engine had an accuracy of -3.085 seconds per trip, a standard deviation of 46.21 seconds with a high precision of 80% of estimated journey times within 1 minute of the actual drive time.

B. Turning and Validation

The simulator was tuned and validated by running the simulator with historic incident data. We then compared the simulated arrival time performance with actual performance. We configured the simulator to use a dispatch model that closely resembles the existing dispatch policy at LAS. This policy dispatches units that will arrive in the shortest time but does not attempt to dispatch units to standby points.

5. COMBIND AUTOMATIVE DISPATCH MODEL

We developed the Combined Automatic Dispatch Model (CARD) to deploy units to incidents and standby points using a static evaluation function to measure the value of the current state of deployment of ambulances around London. At any points in time there will be a number of incidents in progress, either awaiting units to be assigned or in some other state, such as en-route, on scene or at hospital. A state with a low number of waiting incidents is preferable than a state with a larger number of waiting incidents. Units are also better placed in locations where incidents are likely to occur. These requirements for positioning vehicles were combined using a static evaluation function (SEF) consisting of a set of five weighted basis functions. The basis functions are summed (1) to provide a single value that provides a ranking value of the current state of deployment.

$$f(x) = \sum_{i=1}^{5} b_i(x) \times w_i \qquad (1)$$

The basis functions selected are directly related to the need to judge the importance of un-dispatched incidents for category A and C incidents, the total drive time to category A and C incidents and the overall coverage at that point in time.

TABLE I
BASIS FUNCTIONS FOR THE STATIC EVALUATION FUNCTION

Basis function	Description
$\sum waiting_A$	The number of category A calls that are awaiting an ambulance to be dispatched. Higher values represent a *worse* position.
$\sum waiting_C$	The number of category C calls that are awaiting an ambulance to be dispatched.
Weighted Coverage	The % of the London area that available units can reach in 8 minutes multiplied by the expected incident density in that area. Higher values represent a *better* position.
$\sum Travel\ Time_A$	The current total travel time for units en-route to category A calls. Higher values represent a worse position.
$\sum Travel\ Time_C$	The current total travel time for units en-route to category C calls.

Table 1 lists the five basis functions that we used in the static evaluation function.

A. Weighted Coverage

To locate units at appropriate standby points we use strategy of attempting to ensure that units cover the London area whilst simultaneously taking into account the number of incidents that will occur at any one location. The weighted coverage takes into consideration incident density and unit coverage at grid location within London. To calculate the weighted coverage we created two equally sized grids of 300m x 300m tiles that cover London. The first grid contains a static pre-computed incident density map where each tile contains the number of incidents that occurred during the September 2011 period. The second grid contains the number of available units that can reach a given tile within 8 minutes at the time that the SEF is calculated. The basis function for weighted coverage multiplies corresponding incident density and unit coverage tiles and sums the resultant values. This cumulative sum is then normalized by divided the result by the total number of incidents in the incident density grid. Therefore, the weighted coverage value increases when units cover high incident-rate areas.

B.Using the SEF within the simulator

At any moment in time, the dispatch module can evaluate, using the SEF, the current state. As the SEF contains a weighted coverage element, the dispatch engine will favour deployment of vehicles that do not leave areas of London with poor coverage. The basis function weights, w_i, were adjusted randomly using small perturbations over several hundred simulations in order to find suitable values. The final weights used are listed in Table II. Future work will focus on other optimisation techniques, such as Nelder-Mead, to avoid the possibility of a Local Minima problem and locate better performance.

TABLE II
BASIS FUNCTIONS FOR THE STATIC EVALUATION FUNCTION

Basis function	Weight
$\sum waiting_A$	201
$\sum waiting_C$	210
Weighted Coverage	-3
$\sum Travel\ Time_A$	0.194
$\sum Travel\ Time_C$	0.138

We used actual emergency incident data and actual performance figures from September 2011 as, during this period there were no outages or major events that would skew the results. The simulator was eventually able to improve performance, measured as arrival times within 8 minutes, from 74.19% to a simulated 76.84% for category A and from 57.82% to a simulated 80.28% for all other incidents. Fig. 6 shows the predicted improvement in arrival times compared with actual times during that period. The histogram shows that the majority of category A incidents wee reached in 254 seconds(4 minutes 14s) compared to 360 seconds (6 minutes) historically. These figures provide promising evidence that a combined incident and standby dispatch model can significantly improve arrival times, and therefore, the outcome of critically ill patients.

6. CONCLUSIONS

Emergency service fleets provide a unique perspective on the dynamics of densely populated metropolitan areas. They carry a variety of wireless communication and sensing devices that link into the complex city transportation and healthcare socio-technical systems thus revealing human and urban dynamic. Information streams generated through the active deployment of emergency service units can also be used to improve their performance for example by better utilizing standby points to reduce arrival times and improve the prognosis especially in the case of severe incidents. Our proposals for CARD and the use of enhanced routing illustrate

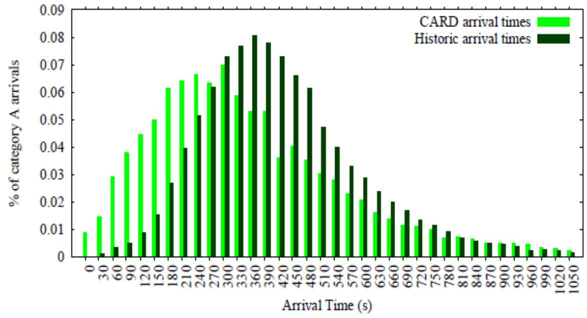


Fig. 6. Historic and predicted arrival times using CARD. There is a marked improvement, i.e. faster, in arrival time using the CARD dispatch algorithm compared to actual performance during September 2011.

how such data-driven models can adapt to the changing conditions encountered in the field balancing strategic and tactical objectives. We anticipate that such benefits can be further extended to address healthcare governance concerns hence further extending the smartness of emergency response.

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