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UAVs Provide Life-Saving Medical Care

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Abstract

Unmanned Aerial Vehicles (UAVs, UAS, or Drones) are expanding from their military provenance to provide unique utility to the private and public sector. UAVs outfitted with automated external defibrillators (AEDs) recently emerged as a practical, humanitarian purpose for the aircraft. The UAV-AED combination has the potential to deliver life-saving defibrillation to a patient experiencing an out of hospital cardiac arrest faster than a traditional ambulance. This paper works to establish criteria for locating and dispatching the UAVs with the goal of reducing response time and hence increasing the likelihood of surviving a cardiac episode. Simulation is used to evaluate the effectiveness of a specific set of parameters governing the location and dispatching of the UAVs as well as what potential vehicle parameters are of importance to the overall results.

Keywords
Simulation, emergency medicine, UAV

1. Introduction

1.1 Background

Heart disease was the leading cause of death in the U.S. in 2010 [1]. As such, out of hospital cardiac arrests (*OCHA*) are of great concern to emergency service providers. The acute nature of OCHAs positions the condition as a barometer for the overall measurement of an emergency medical service (*EMS*) system's effectiveness [2]. Outside the context of emergency medicine, a great deal of research has been conducted to evaluate the effectiveness of Automated External Defibrillators (*AEDs*) in the acute treatment of ventricular fibrillation and ventricular tachycardia -the two types of cardiac arrhythmia commonly treated by defibrillaton[3]. AEDs are well documented in their ability to increase the likelihood a patient survives an OCHA through to hospital discharge [4].

With this in mind, this paper presents a hypothetical new transportation mode to increase the availability of AEDs to the public in conjunction with a pre-existing EMS system. In 2014, researches at the Delft University of Technology have successfully created an unmanned, autonomously navigating, mini airplane with an AED on board. The explicit goals is to reduce response times for cardiac arrests [5]. While they have created a working prototype, we must emphasize this a hypothetical technology.

In this paper, we aim to find an optimal location and dispatching policy for one UAV when added to a previously-existing EMS system. Additionally, we evaluate the effect one UAV can have on system-wide response times and system-wide survivability. The remainder of this paper presents our framework for using simulation to evaluate location and policy decisions as well as evaluate and compare the simulation results.

1.2 Literature Review

There is a substantial body of research into facility location problems with a large recent push to apply these techniques to the public sector [2, 6, 7]. Much of this work is related to modeling location decisions as linear, integer, and mixed-integer programs; all aimed at establishing optimal criteria for facility location given a set of assumptions [6–9]. McLay extends these models to cover multiple vehicle types [9], however both are considered land-based.

As the transportation technology presented here is hypothetical, we turned to simulation for evaluation. Simulation is used extensively in the literature to evaluate model effectiveness. [9–11]. Additionally, simulation is used to make recommendations in the absence of, or prior to an analytical model being created [12].

1.3 UAV Framework

While the use of UAVs in conjunction with EMS has been proposed by a handful of cities across the country [13], as of today UAVs with AEDs are not operated municipally. In line with the goal of finding an optimal dispatching and locating policy, our simulation must make assumptions about the potential use of the UAVs in the future. First we assume that a UAV could be located anywhere within the EMS system. When a 911 call arrives, the UAV is dispatched should the call meet the dispatching criteria. Once the UAV arrives at the patient, bystanders can administer the AED treatment to the patient before the advanced life support (*ALS*) unit arrives. The explicit advantage is this reduction in time to defibrillation which has been shown to significantly increase OCHA survival [14, 15]. Figure 1 provides a visual overview. The other key assumption about how UAVs operate is there is a given amount of time for which the drone is inoperable after treating a patient. Civilian AEDs are generally equipped with one-time use defibriliation pads. As such, we incorporate a cool-down time after the drone is used in which the vehicle is rendered inoperable. This represents the time associated with the UAV's resetting. As a part of the development of the simulation, we perform a sensitivity analysis of this cool-down time in Section 4.

2. Simulation Model Description

The simulation is a trace-driven model of a major metropolitan EMS system. The discrete event simulation follows the arrival and processing of incoming 911 calls. 911 calls are traditionally classified by the emergency operator into Priority 1, Priority 2 and priority 3 [9]. Priority 1 corresponds to a life threatening condition and is the only type considered in this simulation as response to acute calls is an indicator of the system's overall performance [15]. The EMS system's coverage area is divided up into 2x2 mile districts, with all demand occurring in the zone aggregated to the center. The districts can be seen in Figure 2. These center points also serve as the potential ALS or UAV locations. Average response times across the system, as well as estimated survival probabilities are collected with and without the addition of a UAV. To evaluate the effectiveness of a UAV-AED, we first locate the ALS units to maximize their expected coverage through the system. Holding those locations constant, we then run the simulation while testing the UAV in all possible locations.

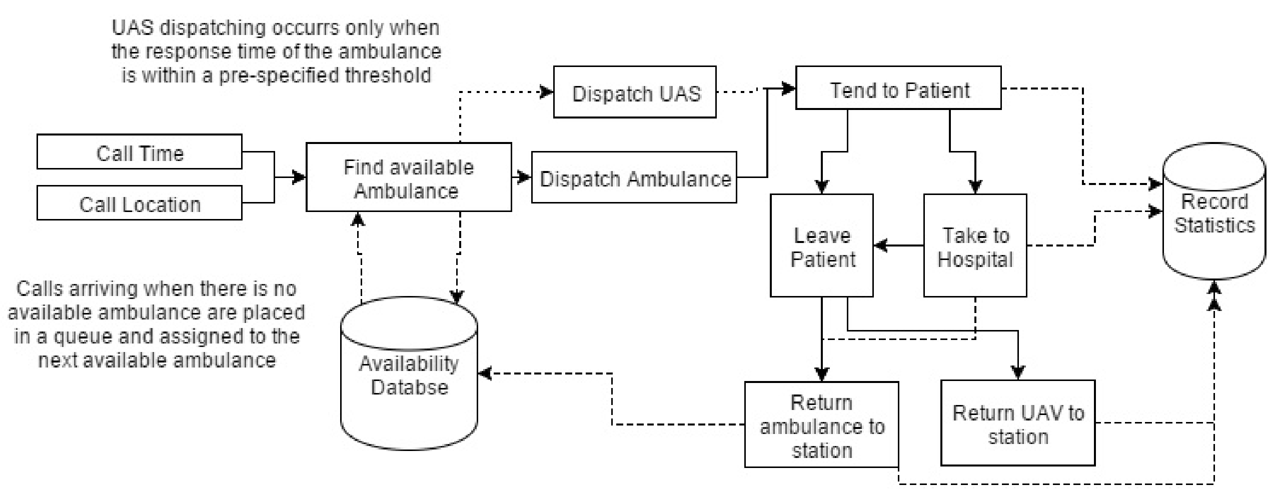


Figure 1: Simulation Structure overview

2.1 Model Outline

The simulation is implemented in Java. The incoming 911 calls are read from a trace of call arrival times from Mecklenberg County, NC in 2004. The call's priority, location, and arrival time are used to dispatch the nearest ALS unit. Should *all* ALS units be actively helping patients, incoming calls are queued. In accordance with standard EMS dispatching policies, the next available ALS is dispatched to the first call in the queue. Once dispatched, the ALS either remains on the scene and treats the patient or transports the patient to the nearest hospital for further care. After the transport or treatment is complete, the ALS returns to its pre-determined base station and once again becomes available.

To examine the efficacy of the UAV, we have established a set of dispatching criteria. For any incoming 911 call, the UAV will be dispatched if the criteria are met. As the UAV is modeled as traveling faster than an ALS unit, we believe the UAV to be most beneficial to calls with a non-extreme response time. In other words nearby calls will be tended to by an ALS quickly regardless of the drone, while more distant calls face comparatively long response times either way. These far-off calls have a small likelihood of survival regardless of any improvement in response time. As such, we established dispatching thresholds based on the estimated arrival time of the ALS. The lower and upper dispatching criteria are k_{thL} and k_{thH} respectively. Assume t_n^{ALS} is the ALS response time for the nth call. If $k_{thH} \geq t_n^{ALS} \geq k_{thL}$ then the UAV is sent in conjunction with the ALS unit. This process is outlined in Figure 1 below.

To evaluate effectiveness, we calculated response times (1) and average survival probability (2) for each incoming 911 call in accordance with typical EMS analysis [2]. For a given replication, average response time $\bar{t}$ is calculated as seen in Equation (1). N is the total number of calls and t_n^{ALS} is the ALS response time of the nth call, while t_n^{UAV} is the UAV response time of the nth call. Note that if a UAV is not dispatched t_n^{UAV} is arbitrarily large compared to t_n^{ALS}.

$$\bar{t} = \frac{1}{N}\sum_{i=1}^{N} \min(t_i^{ALS}, t_i^{UAV}) \tag{1}$$

The response time is defined as the time between when an ALS unit or UAV is dispatched to the system and when it arrives at the patient's location as seen in Equation (1). For this paper, we modified a survival probability model developed by Larsen et. al. [14] and extended by McLay & Mayorga [2]. As seen in Equation (2), the probability of survival of the nth call, S_n, is a function of t_n^{UAV} and t_n^{ALS}.

$$S_n = \left\{ \begin{matrix} \max\,(0.67 - 0.441 t_n^{ALS} - .011 t_n^{UAV}) & \text{if } k_{thL} \leq t_n^{ALS} \leq k_{thH} \\ \max\,(0.594 - 0.55 t_n^{ALS}) & \text{otherwise} \end{matrix} \right\} \quad \forall n \in N \tag{2}$$

This survival model was chosen as it considers the time interval from OCHA collapse to cardiopulmonary resuscitation (*CPR*), collapse to defibrilation, and collapse to advance care [14]. As seen in Equation (2), we consider CPR, defibrillation, and advanced care to all occur when the ALS arrives. Additionally, if the UAV is dispatched, it can preempt the time to defibrillation, potentially raising the patient's likelihood of survival.

3. Results

With data from Mecklenberg County North Carolina for the year 2004, 45 replications were taken and confidence intervals constructed for both average response time and average survival probability. Each replication corresponds to 24 hours of incoming calls. As there are significant discrepancies between traffic intensities for individual days of the week, one weekday was chosen and the replications were sampled from random instances of that day. Call volumes ranged between 133 and 161 calls per day. 17 ALS units were considered to be in service along with the UAV. Our estimated parameters -UAV cool-down time and UAV speed- were estimated at 60 minutes and 50% of ALS response time respectively. Survival probability and response time averages were determined *without* the addition of a UAV to establish a baseline. This can be seen in Table 1. One UAV was then added. k_{thL} values between 0 and 7 minutes, and k_{thH} values between 3 and 14 minutes, as well as all 168 potential sites in Mecklenberg county were tested in all possible combinations. A partial list of results is seen in Table 1. The locations correspond to the indices of the district and those chosen were those which showed statistical significance. Bold values within the table represent statistically significant differences from the baseline.

Table 1: Results of 45 replications

UAV Location	Dispatch Range	Response Time	Survival Probability
Baseline	—	8.753	0.182
68	[0,5]	8.725	0.183
	[5,10]	8.279	0.186
	[7,14]	**8.105**	0.186
78	[0,5]	8.711	0.183
	[5,10]	**8.234**	0.186
	[7,14]	**8.055**	0.187
91	[0,5]	8.681	0.183
	[5,10]	8.280	0.186
	[7,14]	**8.084**	0.187
92	[0,5]	8.639	0.183
	[5,10]	8.244	0.186
	[7,14]	**8.075**	0.187

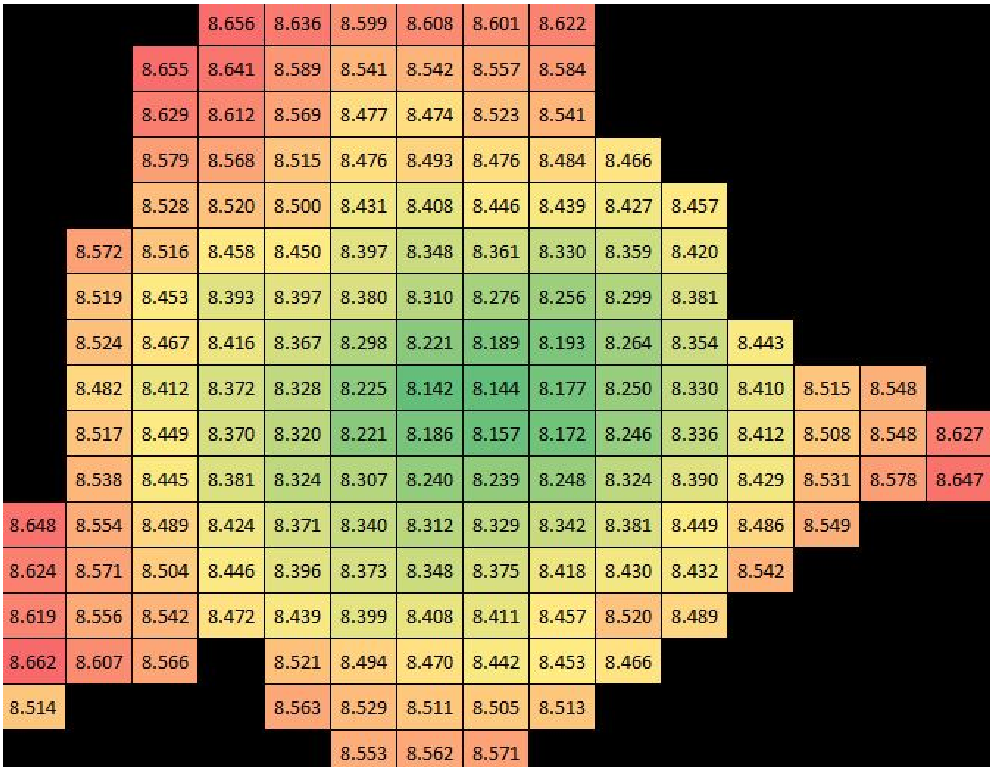
4. Sensitivity Analysis

As mentioned in Section 1.3 two parameters of the system- UAV speed and UAV cool-down- were estimated based on commercial UAV specifications. Our simulation calculates UAV speed as a fraction of the ALS travel time from location to location. There are, areas in which this will over and underestimate the *true* travel time for a UAV. However for approximation purposes, we believe it to be accurate enough to allow the simulation to provide insight. In Table 2, the UAV Speed column is the coefficient which is multiplied by the ALS response time to determine the UAV response time. Additionally, the time to reset the UAV after flight could vary greatly depending on the implementation of the UAV within the existing EMS system. We let this parameter vary as well. To examine the potential impact of these two estimates, we took the location and dispatching policy which provided the lowest mean response time and varied the two parameters combinatorially. The results are shown below in Table 2.

Table 2: Sensitivity Analysis of UAV cool-down and UAV speed

UAV speed	UAV cool-down	Mean response time
0.25	15	7.4799
	30	7.6106
	45	7.7546
	60	7.8690
	90	8.5876
	120	8.6690
0.5	15	7.8920
	30	7.9955
	45	7.9894
	60	8.0551
	90	8.2012
	120	8.3746
0.75	15	8.4068
	30	8.5502
	45	8.5147
	60	8.5876
	90	8.6420
	120	8.6429

Figure 2: Estimates of the average response time of the system when a UAV was placed at that location



5. Discussion

Dispatching windows of 7 to 14 minutes (the highest lower and upper limit tested) consistently showed statistically significant decreases in response time. This appears to be due -in part- to the quantity of time saved. That is, the longer the ALS will take to arrive on the scene, the larger the potential gap between ALS and UAV. As is the case when locating traditional ambulances, location plays a key role. Figure 2 shows the discrete grid and the average response time across all dispatching thresholds given the UAV is located in that specific district with a dispatching window of [4,10] minutes. It should be noted the population of Mecklenberg County is roughly centered. It then follows that placing the UAV in areas of higher population density appears to have a greater positive effect than placing it toward the outskirts of the county. Additionally, no statistically significant increase in survival likelihood was recorded under any circumstance. This is most likely the result of the chosen survival probability model. The model weights improvement in ALS arrival time to be four times as beneficial as an equal improvement in UAV arrival time. The sensitivity analysis shows logical improvements when increasing the speed of the UAV and improvements when the cool-down time is reduced. These results all combine to show UAVs can be a simple and effective emergency medical tool when used correctly. From the perspective of municipalities, properly locating and dispatching these vehicles has the potential to increase the system's quality of service. The sensitivity analysis makes it abundantly clear the effect UAV speed can have on their overall effectiveness. As the UAV technology continues to advance, a vehicle's potential speed will be critical in evaluating its potential effectiveness when located in a city. Increases in vehicle speed provide generally positive benefits to the system.

6. Conclusions

As policy and technology allow new innovations to form, successful implementation requires analysis. Novel technological ideas have the potential to make substantial impacts to our quality of life, however their use and implementation must be measured and considered to fully maximize their benefit. UAVs outfitted with AEDs can aid EMS systems in treating patients experiencing out of hospital cardiac arrests. We have shown locating drones in centers of high population, as well as dispatching them in conjunction with traditional ALS units can reduce average response times across the system. We hope this work functions as not only a framework for analyzing this particular technology but also as an example of how simple analysis can help to maximize the potential of new innovations. Adding multiple UAVs to a system, optimizing the UAV locations in tandem with the locations of ALS units, or using UAVs to aid police or fire departments are all areas of future work and analysis. However, even with only one vehicle, our results strongly suggest unmanned aerial vehicles have the possibility to be of great service to the public sector.

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