Optimizing the Coordination of Ambulances and Drone-delivered Equipment Operated by Bystanders

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Motivation. According to the American Heart Association, more than 350,000 people experience out-of-hospital cardiac arrest (OHCA) each year in the US. Survival from OHCA is only 10%, as compared to 26% for in-hospital cardiac arrest. This difference is primarily due to the timeliness of treatment initiation such as cardiopulmonary resuscitation (CPR) and defibrillation. Research has estimated that each minute delay in treatment leads to a 10% decrease in the odds of survival.

Defibrillation by nearby *bystanders* has been shown to improve survival rates (Weisfeldt et al. 2010), but there are large regional variations in bystander participation. A key factor improving bystander defibrillation is the ready availability of an automated external defibrillator (AED). However, only 1.7% of OHCAs involve a bystander-applied AED (Benjamin et al. 2018).

Noting the improvement in survival due to bystander-assisted defibrillation, many regions have implemented Public Access Defibrillation (PAD) programs to improve AED accessibility. However, more than 70% of OHCAs occur in private homes where AEDs are inaccessible (Winkle 2010). Hence, to complement PAD programs, *drone-delivered AEDs* have received significant attention and may serve as a transformative innovation for private location OHCAs.

Claesson et al. (2017) report drone-delivered AED can reduce time to defibrillation. Boutilier et al. (2017) study the location of drones to complement ambulances with the objective of drones delivering AEDs within pre-specified time while minimizing implementation costs. Both studies compare drone response time with EMS response time to measure improved survival; however, these studies do not explicitly capture bystander availability. Because of the uncertainty in bystander availability discussed above, results from these studies might overestimate the true improvement in response time because a drone-delivered AED is ineffective until a bystander arrives.

In this work, we study the design of a drone network to deliver AEDs, which explicitly captures drone response time, bystander response, and EMS response in conjunction, to capture the true service level experienced by a user served by this coordinated system. In this abstract, we restrict our model discussion to the novel coordinated system constraints, due to limited space.

Problem. We consider the practical case where an ambulance-based EMS system wants to adopt drones to deliver AEDs and optimize the combined network of ambulances and drones;

while explicitly capturing bystander availability. Our objective is to determine the number and location of drone bases, and the number of drones at each base required to improve response time by a pre-determined amount, compared to the baseline EMS. We propose a integrated queuing model of drone-bystander-ambulance coordinated service, which involves the joint distribution of ambulance, drones and bystander's availability, where each ambulance and drone base is an $M/G/k/k$ queue; and bystanders from each demand node have $M/M/\infty$ (with different regional service rates depending on demand location to capture regional variation in bystander response).

We quantify the service level θ as the fraction of incidents receiving first response within the benchmark response time T. In traditional EMS, a call is assigned to the nearest idle ambulance and it is solely responsible to serve the incident. In the drone-bystander-ambulance coordinated EMS system, a call can be assigned to a traditional ambulance EMS service or to both ambulance and drone EMS service. In the latter case, the first responder can be either a paramedic reaching by an ambulance or a qualified bystander operating a drone-delivered medical device. We formulate the service level in the drone-bystander-ambulance coordinated EMS.

Approach.

A location-allocation model for drones with pre-specified ambulance locations. We aim to optimally locate drones at bases, with the current ambulance allocation and current dispatch policy. That is, the fraction of users at demand node j assigned to an ambulance at base i, x_{ij} is given. Drones are added to the system when the current ambulance EMS system cannot achieve the target service level. The service level of ambulance is determined by its availability and the travel time to the call. The ambulance availability at base i is provided by Erlang-B formula, $B(\rho_i, n_i)$, where $\rho_i = \sum_j x_{ij}\lambda_j/\mu^a$ is the ambulance offered load at i, with arrival rate from j λ_j and the ambulance service rate μ^a and n_i is the number of ambulances at i. Suppose we know the distribution of ambulance travel time from i to j, τ^a_{ij}, then the following equation implies that an arrival from j assigned to an ambulance at i can be reached within T with the probability of θ^a_{ij}:

$$(1 - B(\rho_i, n_i))P(\tau^a_{ij} \leq T) = \theta^a_{ij}, \forall i, j \tag{1}$$

If $\theta^a_{ij} < \theta$ for any i, j, then ambulance EMS system is not enough to meet the target service level and our model finds the minimum number of drones to meet the target service. We define variable x_{ikj}, which represents a fraction of demand from j assigned to an ambulance at base i and a drone at base k. We add a new service level constraint to capture the possibility that a bystander starts service with drone-delivered equipment before an ambulance arrives on scene. Then, the service level constraint for the coordinated service is: P(EMS is available) x P(EMS *or* Drone delivered AED and bystander arrive within T) $\geq \theta$. For constant drone travel time τ^d and the exponential bystander travel time with rate τ^b, the constraint becomes:

$$(1-B(\rho_i,n_i))(P(\tau^a_{ij}\le T)+(1-B(\delta_k,m_k))P(\tau^a_{ij}>T)P(\tau^d_{kj}\le T)(1-e^{\tau^b_j T}))\ge\theta,\forall i,j,k, \quad (2)$$

where $\delta_k=\sum_{i,j}\lambda_j x_{ikj}/\mu^d$ is an offered load for drone with exponential service rate μ^d and m_k is the number of drones at k. (2) has nonlinear terms in ρ_i and δ_k from Erlang loss formua. Adapting a result from Marianov and Serra (1998), if the left-hand side of (2) is strictly decreasing in δ_k, we can use a linear equivalent constraint $\delta_k\le\delta_{k(\theta,i,j,m)}$ where $\delta_{k(\theta,i,j,m)}$ is the value of δ_k which makes (2) hold as an equality for given θ,i,j and m. Defining $\delta_k=\sum_{i,j}\lambda_j x_{ikj}/\mu^d$, and a new variable z_{km} which is 1 if at least m drones are located at base k and 0 otherwise, (2) becomes:

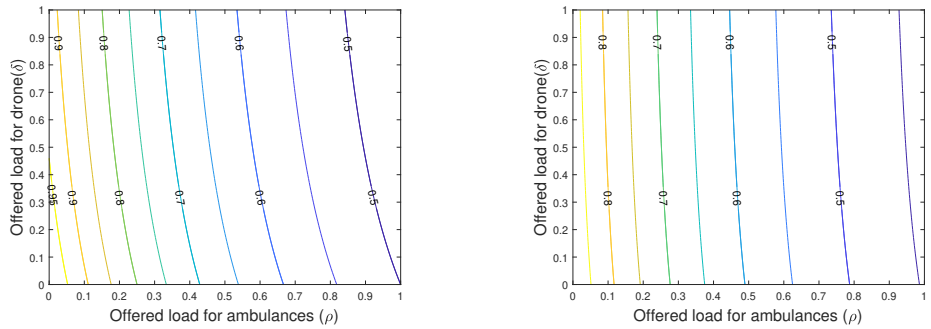
$$z_{km}\le z_{k(m-1)},\qquad m=\{2,...\} \quad (3) \qquad\qquad x_{ikj}\le I_{ikj},\qquad \forall i,k,j \quad (4)$$

$$\sum_{i,j}\lambda_j x_{ikj}\le\mu^d(\delta_{k(\theta,i,j,1)}z_{k1}+\sum_{m=2}(\delta_{k(\theta,i,j,m)}-\delta_{k(\theta,i,j,m-1)})z_{km}+M(1-I_{ikj})),\forall i,k,j \quad (5)$$

(4) ensures I_{ikj} to be 1 if any positive flow between i,k and j exists ($x_{ikj}>0$) and 0 otherwise, so that (5) doesn't unnecessarily tighten bound on the assignment variable if the network is unused.

A joint location-allocation model for drones and ambulances. This model minimizes the number of drones required to complement an ambulance fleet of size N_a, to achieve the desired service level; allowing the ambulance fleet to be re-allocated on the network. We define a new variable $y_{i,n}$ to each base i, which is one if at least n number of ambulances are located at base i and zero otherwise. Then, the constraints to ensure the service level of ambulance service system at i can be obtained simply by replacing x_{ikj},I_{ikj},z_{km} and $\delta_{k(\theta,i,j,m)}$ in (3),(4),(5) with x_{ij},I_{ij},y_{in} and $\rho_{i(\theta,j,n)}$ respectively. $\rho_{i(\theta,j,n)}$ is the value of ρ_i which makes the left-hand side of equation (1) equal to θ. Since the ambulance network is no longer given, the service level constraint of the ambulance-drone coordinated service system (2) becomes a formula with four variables, ρ_i,n_i,δ_k,m_k. We used binary variables for the number of vehicles to linearize the nonlinear formula in the previous model, but with two continuous variable (ρ_i,δ_k), the trick doesn't apply. Therefore, we approximate ρ_i by letting model choose one value from a set of discrete values, $p\in P=\{1,2,...\}$ and use a new indicator variable $I_{(i,k,n,m,p)}$, which is one if and only if base i has ρ offered load and n ambulances and base k has at least m drones. With additional constraints ensuring that $I_{(i,k,n,m,p)}$ has a proper value according to the other binary variables for the number of vehicles at each base and the approximated level of ρ_i, the constraints to ensure the service level of drone-ambulance coordinated service system can be obtained by replacing z_{km} and $\delta_{k(\theta,i,j,m)}$ in (5) with $I_{(i,k,n,m,p)}$ and $\delta_{k(\theta,i,j,n,m,p)}$ respectively, where $\delta_{k(\theta,i,j,n,m,p)}$ is the value of δ_k which makes (2) hold as an equality given that base i has n ambulances with the approximate utilization αp and base k has m drones.

Results. This is research in progress and we are in the process of obtaining real-world data from a major city. We expect to present our real-world results at the conference. Current experiments are on simulated data, for cities on a grid. Figure 1 shows how the service level θ changes as the



(a) Bystander's mean response t = 1min (b) Bystander's mean response t = 20min

Figure 1 The service level θ changes in bystanders participation as well as the capacities of ambulances, drones

offered load for ambulance (ρ) and drone (δ) changes with bystander's response time. Bystanders' response rates, ignored in earlier works, clearly affects the efficiency of the joint drone-bystander system. Analyzing the constraint (2) for collaborative service, we expect the optimal solution is less likely to assign a demand node with larger expected bystander response time for drone-assisted service; and may instead assign more ambulances to bases closer to such demand nodes. Because bystander response is slower in rural than urban areas, we expect the model to allocate more drones and place ambulances less densely in urban areas; and rely more on drone delivered AED and bystanders for quick first response compared to rural areas. However, the exact spatial distribution will depend on the relative population density, and response times.

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