Robust Data-Driven Design of a Smart Cardiac Arrest Response System

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Out-of-Hospital Cardiac Arrest (OHCA)

- sudden and unexpected loss of heart function
- survival rate drops by 7-15%/minute (Larsen et al. 1993)
- 400,000 deaths/year in North America (Coute et al. 2021)
- ≈ productivity loss of 10.2 billions dollars
Out-of-Hospital Cardiac Arrest (OHCA)

- three critical interventions:
  1. CPR
  2. Defibrillation
  3. ACLS

- survival rate = $67\% - 2.3\%t_{\text{CPR}} - 1.1\%t_{\text{AED}} - 2.1\%t_{\text{ACLS}}$

status quo:
- low bystander CPR rate: 20-40% (Virani et al. 2021)
- low AED utilization rate: <5% (Delhomme et al. 2019)
- heavily rely on ambulance paramedics
-⇒ low OHCA survival rate: 3-12%
Smart Initiative I: AED-Loaded Drone

• flying height $\sim 60\text{m}$, maximum velocity $\sim 28\text{m/s}$

• widespread exploration of clinical trials (Schierbeck et al. 2022)
Smart Initiative II: Responder Crowdsourcing App

(a) app dashboard  
(b) alert prompting  
(c) post-acceptance
The Proposed Smart OHCA Response System

- alert nearby community responders via crowsourcing Apps
- send an AED-loaded drone from the nearest base
- dispatch an ambulance from the nearest station
Characteristics of the Smart Response System - I

- Ambulance/Drone Dispatch: Controllable & Predictable
- Responder Crowdsourcing: Exogenous & Uncertain

V.S.
Characteristics of the Smart Response System - II

- rescue forces interact by competition
- first come first intervene
Our Interest: Optimal Resource Deployment

How to optimally deploy drones and ambulances in the system?

  - describe and quantify responder’s behavior
  - capture rescue forces’ interactions

- alleviate data uncertainty in model primitive estimation (Atamturk and Zhang 2007, Baron et al. 2011, Chan et al. 2018)
  - OHCA demand
  - responder’s acceptance probability
  - responder’s response time (right-censored)
Research Framework

Google Map API
1. Ambulance travel time
2. Drone travel time

Discrete Facility Location Model

Interaction Model

Historical Demand
1. Report time
2. Incidence location

Intervention Times
1. CPR
2. Defibrillation
3. Advanced care

Survival Rate Prediction

Overall Expected Survival

Robust Optimization Module (MILP)

Optimal Deployment

Data Input

Mathematical Model

Intermediate Output

Final Output

myResponder App
1. # of alerts sent
2. # of responders accepted
3. Responder arrival times

Hedging Against Data Uncertainty
The Robust Deployment Model

- **\( d = (d_1, \ldots, d_I) \):** OHCA demand rate
- **\( p = (p_1, \ldots, p_I) \):** responder’s acceptance probability
- **\( \tilde{u} = (\tilde{u}_1, \ldots, \tilde{u}_I) \):** responder’s random response time
- **\( \tilde{u} \sim Q \):** responder’s response time distribution
Contributions

• the first joint deployment model of ambulance and drone incorporating responders’ behavior

• ambiguity set tailored to the right-censoring feature

• reformulation technique that exploits program constraint

• a customized row-and-column generation algorithm with convergence speed analysis
Contributions

**Proposition 1.** Let the ambiguity set $\mathcal{Q}$ be defined as in (11), where the parameters satisfy $0 \leq \theta_i \leq \bar{\theta}_i \leq 1$, $0 \leq \delta_i \leq \bar{\delta}_i$, and $\epsilon_i \geq 0$, $i \in [I]$. Suppose that $\sum_{i \in [I]} \theta_i \leq \bar{\theta}$ for $i \in [I]$. Then the maximization problem over $\mathcal{Q} \in \mathcal{Q}$ in (R-JD), i.e.,

$$\max_{x \in \mathcal{X}} \mathbb{E}_{\theta} \left( \sum_{i \in [I]} d_i \min \left( \epsilon_i, \sum_{a \in \mathcal{A}} x_{i,a} \right) \right)$$

is independent of the dispersion upper bounds $\{\epsilon_i\}_{i \in [I]}$ and evaluates to

$$\sum_{i \in [I]} d_i \left( 1 - \bar{\delta}_i \right) \min \left( \epsilon_i, \sum_{a \in \mathcal{A}} x_{i,a} \right) + \bar{\delta}_i \sum_{a \in \mathcal{A}} x_{i,a}.$$ 

**Theorem 1.** The robust joint deployment problem (R-JD) with ambiguity set $\mathcal{Q}$ defined by (11), uncertainty set $\mathcal{D}$ defined by (12), and uncertainty set $\mathcal{P}(\mathbf{d})$ defined by (13) is equivalent to the following MILP, where $M \triangleq \max \{\max_{i \in [I], j \in [J]} \mu_i^{(j)}, \max_{i \in [I], j \in [J]} \chi_i^{(j)}\}$ is a large enough positive constant:

$$\min_{\mathbf{y}, \mathbf{z}, \mathbf{x}, \mathbf{\lambda}, \mathbf{\mu}, \zeta} \zeta$$

s.t.

$$\zeta \geq \sum_{i \in [I]} d_i \left( \phi_i + (1 + p_2) \sum_{a \in \mathcal{A}} x_{i,a} + \sum_{i \in [I]} \sum_{i \in [I]} d_i \left( \bar{p}_i \chi_i^{(i)} - \bar{p}_j \chi_j^{(j)} \right) + \sum_{i \in [I]} \mu_i^{(j)}, b \in [B] \right)$$

$$d_i \sum_{i \in [I]} \chi_i^{(j)} \lambda_i^{(j)} + \mu_i^{(j)} \geq d_i \left( 1 - \bar{\delta}_i \right) \psi_i \sum_{a \in \mathcal{A}} x_{i,a}, i \in [I], v \in [V], b \in [B],$$

$$\mathbf{\lambda} \in \mathbb{R}_+^I, \chi_i^{(j)} \in \mathbb{R}_+^I, \mu_i^{(j)} \in \mathbb{R}_+^I, b \in [B]$$

$$\phi_i \geq \sum_{j \in [J]} \psi_{i,j}^{(j)} - M\lambda_i^{(j)}, \psi_i \geq \sum_{j \in [J]} \lambda_i^{(j)} \psi_{i,j}^{(j)} - M\lambda_i^{(j)}, i \in [I],$$

$$v_1 + v_2 = 1, v_3 + v_4 = 1, i \in [I],$$

$$\psi_{i,j}^{(j)} \in \{0, 1\}^I, i \in [I],$$

$$\psi_{i,j}^{(j)} \in \psi_{i,j}^{(j)}, \psi_{i,j}^{(j)} \in \psi_{i,j}^{(j)}.$$ 

**Proposition 5.** The scenario generation algorithm terminates in not greater than $S + 1$ iterations, where $S$ is the cardinality of $\mathcal{D}^*$. 
Case Study on Singapore

- ambulance bases: public hospitals and fire stations
- drone bases: plus police centers
Deployment Results and Benchmarks

- benchmark I: a *sample average approximation (SAA)*
- benchmark II: an *ex post model* having perfect foresight
- evaluate models on multiple sets of *test data*

Figure 5  Deployment solutions of 15 ambulances/drones on the main island of Singapore produced by the proposed robust model (left) and the SAA model (right) based on the October 2017 data (cf. Section 7.1). The grid map in the background is adopted from Figure 1.
Values of Accounting for Data Uncertainty

Figure 6  The survival rates (left), means (middle) and standard deviations (right) of the survival rates under each test data setting for the robust, SAA and ex post deployments. The bw-1 setting mimics the October 2017 data, while the other settings simulate deviations from the October 2017 data.

- bw1 → bw3: high similarity → low similarity
Impacts of Resource Level

Figure 8  Mean survival rates for the robust and SAA deployments of different numbers of ambulances/drones under the test data settings bw-1 (a), bw-2 (b) and bw-3 (c). The number of ambulances (resp. drones) is fixed at 15 when varying the number of drones (resp. ambulances).
Impacts of Responders’ Behavior

- almost triples the largest possible improvement obtained by simply adding drones/ambulances

Figure 9  Mean survival rates for the robust deployment of 15 ambulances/drones derived in Section 8.2 under the test data indexed by \((h, p, u)\): When generating the test data, each OHCA incident is responded with probability \(p\) by a responder whose response time is exactly \(u\). Larger \(h\) indicates higher dissimilarity between the test data and the October 2017 data in terms of OHCA spatial distribution.
Summary

• a robust data-driven joint deployment model of ambulance and drone incorporating responders’ behavior

• robust deployment leads to higher survival rate

• adding drones/ambulances exhibits diminishing return

• a few drones can dramatically increase the survival rate

• the benefit of improved responder response is significant
Q&A

Thank You!

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