Optimization for AED placement and emergency response

Timothy C. Y. Chan       K.H. Benjamin Leung
University of Toronto

International Seminar on Geospatial Analytics and Operations Research in Emergencies
Singapore General Hospital
February 18, 2019
What We Do – Centre for Healthcare Engineering

• Data-driven research to improve system efficiency and enhance patient care

• Research Areas:
  – Policy and Strategy
  – Healthcare Operations
  – Medical Technologies
  – Information Engineering
  – Human Factors
What We Do – Applied Optimization Laboratory

• Quantitative methods for decision making
  – Optimization
  – Machine Learning
  – Simulation

• Applications
  – Healthcare
  – Energy
  – Sports
Acknowledgments

• Toronto
  – Laurie Morrison
  – Steve Brooks
  – Sheldon Cheskes
  – Michael Feldman
  – Damon Scales

• Copenhagen
  – Fredrik Folke
  – Lena Karlsson
  – Christian Torp-Pedersen

• Students
  – Christopher Sun
  – Justin Boutilier
  – Benjamin Leung
  – Clara Stoesser
  – Minha Lee
  – Derya Demirtas
  – Auyon Siddiq
  – Heyse Li
  – Alyf Janmohamed
Today’s topics

• Understand where (and when) OHCA risk is...
  – Data analytics
  – Simulation
  – Stochastic modeling

• ...and then optimize AED placements accordingly
  – Integer optimization (robust, stochastic)
  – Queuing
  – Routing
Risk

- Spatial risk by location type (*Ann Emerg Med* 2013)
- Spatial risk in enclosed pedestrian walkways (*Resuscitation* 2017)
- Spatiotemporal risk by location type (*Circulation* 2017)
Risk

- Spatial risk by location type (*Ann Emerg Med* 2013)
- Spatial risk in enclosed pedestrian walkways (*Resuscitation* 2017)
- Spatiotemporal risk by location type (*Circulation* 2017)
Toronto’s PATH System
## Results: Spatial Risk and OHCA Characteristics

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>PATH-accessible (n = 49)</th>
<th>Downtown (n = 371)</th>
<th>p-values</th>
<th>Toronto (n = 1752)</th>
<th>p-values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age, mean±SD, yrs</td>
<td>60.4 ± 18.0</td>
<td>55.2 ± 16.9</td>
<td>0.047</td>
<td>61.5 ± 17.4</td>
<td>0.662</td>
</tr>
<tr>
<td>Male proportion, %</td>
<td>89.8</td>
<td>83.6</td>
<td>0.259</td>
<td>80.6</td>
<td>0.106</td>
</tr>
<tr>
<td><strong>Bystander Witness, n (%)</strong></td>
<td>41 (83.7)</td>
<td>214 (58.5)</td>
<td>0.001</td>
<td>1091 (62.6)</td>
<td>0.003</td>
</tr>
<tr>
<td><strong>Bystander CFR, n (%)</strong></td>
<td>36 (73.5)</td>
<td>196 (53.0)</td>
<td>0.007</td>
<td>991 (56.6)</td>
<td>0.019</td>
</tr>
<tr>
<td><strong>Bystander AED use, n (%)</strong></td>
<td>20 (42.6)</td>
<td>51 (14.1)</td>
<td>&lt;0.001</td>
<td>189 (11.0)</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>911 Call-to-arrival, mean±SD, min</td>
<td>5.34 ± 1.44</td>
<td>5.45 ± 2.15</td>
<td>0.736</td>
<td>6.30 ± 2.30</td>
<td>0.004</td>
</tr>
<tr>
<td>911 Call-to-first rhythm analysis, mean±SD, min</td>
<td>9.43 ± 3.71</td>
<td>10.65 ± 10.88</td>
<td>0.486</td>
<td>10.61 ± 4.29</td>
<td>0.089</td>
</tr>
<tr>
<td>911 Call-to-first shock, mean±SD, min</td>
<td>10.76 ± 4.82</td>
<td>12.61 ± 6.59</td>
<td>0.178</td>
<td>12.93 ± 6.72</td>
<td>0.109</td>
</tr>
<tr>
<td><strong>Shockable, n (%)</strong></td>
<td>35 (72.9)</td>
<td>147 (40.3)</td>
<td>&lt;0.001</td>
<td>786 (45.5)</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td><strong>Survival, n (%)</strong></td>
<td>16 (33.3)</td>
<td>66 (18.2)</td>
<td>0.014</td>
<td>319 (18.5)</td>
<td>0.009</td>
</tr>
<tr>
<td>Survival among shockable, n (%)</td>
<td>14 (41.2)</td>
<td>52 (36.1)</td>
<td>0.582</td>
<td>264 (34.2)</td>
<td>0.402</td>
</tr>
<tr>
<td>Survival among non-shockable, n (%)</td>
<td>1 (7.7)</td>
<td>11 (5.2)</td>
<td>0.693</td>
<td>43 (4.6)</td>
<td>0.603</td>
</tr>
<tr>
<td><strong>Bys. CPR among bystander-witnessed, n (%)</strong></td>
<td>32 (78.0)</td>
<td>138 (64.5)</td>
<td>0.091</td>
<td>683 (62.7)</td>
<td>0.045</td>
</tr>
<tr>
<td><strong>Bys. AED use among bystander-witnessed, n (%)</strong></td>
<td>19 (47.5)</td>
<td>36 (17.4)</td>
<td>&lt;0.001</td>
<td>134 (12.6)</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

---

![Map of Toronto showing high-traffic public spaces: Yonge-Dundas Square, Roy-Thomson Hall (orchestra hall), Union Station (transportation hub).]
• Spatial risk by location type (*Ann Emerg Med* 2013)
• Spatial risk in enclosed pedestrian walkways (*Resuscitation* 2017)

• Spatiotemporal risk by location type (*Circulation* 2017)
Coffee, Tea or an AED?

• How many cardiac arrests occurred **within 100 m** of certain businesses and public points of interest **when those locations were actually open?**
### Results: Top 10 List

<table>
<thead>
<tr>
<th>Rank</th>
<th>Location Type‡</th>
<th>Location Category</th>
<th>Actual Coverage</th>
<th>Assumed 24/7 Coverage (Rank)</th>
<th>No. of Facilities (Rank)</th>
<th>Coverage Efficiency (Rank)</th>
<th>Coverage Loss, % (Rank)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Tim Hortons</td>
<td>Coffee shop</td>
<td>200</td>
<td>234 (1)</td>
<td>312 (2)</td>
<td>0.64 (18)</td>
<td>14.5 (16)</td>
</tr>
<tr>
<td>2</td>
<td>RBC ATM</td>
<td>Bank ATM</td>
<td>172</td>
<td>193 (2)</td>
<td>264 (4)</td>
<td>0.65 (16)</td>
<td>10.9 (12)</td>
</tr>
<tr>
<td>3</td>
<td>Subway</td>
<td>Restaurant chain</td>
<td>162</td>
<td>190 (3)</td>
<td>281 (3)</td>
<td>0.58 (21)</td>
<td>14.7 (17)</td>
</tr>
<tr>
<td>4</td>
<td>Scotiabank ATM</td>
<td>Bank ATM</td>
<td>136</td>
<td>148 (5)</td>
<td>181 (9)</td>
<td>0.75 (7)</td>
<td>8.1 (9)</td>
</tr>
<tr>
<td>5</td>
<td>CIBC ATM</td>
<td>Bank ATM</td>
<td>134</td>
<td>152 (4)</td>
<td>187 (8)</td>
<td>0.72 (8)</td>
<td>11.8 (13)</td>
</tr>
<tr>
<td>6</td>
<td>Green P Parking</td>
<td>Parking lot</td>
<td>127</td>
<td>135 (7)</td>
<td>229 (5)</td>
<td>0.55 (23)</td>
<td>5.9 (7)</td>
</tr>
<tr>
<td>7</td>
<td>TD ATM</td>
<td>Bank ATM</td>
<td>121</td>
<td>146 (6)</td>
<td>178 (10)</td>
<td>0.68 (14)</td>
<td>17.1 (19)</td>
</tr>
<tr>
<td>8</td>
<td>Starbucks</td>
<td>Coffee shop</td>
<td>104</td>
<td>125 (8)</td>
<td>166 (11)</td>
<td>0.63 (19)</td>
<td>16.8 (18)</td>
</tr>
<tr>
<td>9</td>
<td>BMO ATM</td>
<td>Bank ATM</td>
<td>101</td>
<td>104 (10)</td>
<td>142 (13)</td>
<td>0.71 (9)</td>
<td>2.9 (6)</td>
</tr>
<tr>
<td>10</td>
<td>Pizza Pizza</td>
<td>Restaurant chain</td>
<td>69</td>
<td>90 (12)</td>
<td>100 (19)</td>
<td>0.69 (12)</td>
<td>23.3 (23)</td>
</tr>
</tbody>
</table>
Optimization

- First optimization model (Circulation 2013)
- Effect of varying coverage radius (Resuscitation 2013)
- Optimization with coverage decay (Manag Sci 2016)
- Spatiotemporal optimization (JACC 2016)
- Optimization with uncertain OHCA locations (Oper Res 2017)
- AED optimization in high-rises (Prehosp Emerg Care 2017)
- Drone-delivered AEDs (Circulation 2017)
- Generalizability of spatiotemporal optimization (Resuscitation 2018)
Optimization

- First optimization model (*Circulation* 2013)
- Effect of varying coverage radius (*Resuscitation* 2013)
- Optimization with coverage decay (*Manag Sci* 2016)
- Spatiotemporal optimization (*JACC* 2016)
- Optimization with uncertain OHCA locations (*Oper Res* 2017)
- AED optimization in high-rises (*Prehosp Emerg Care* 2017)
- Drone-delivered AEDs (*Circulation* 2017)
- Generalizability of spatiotemporal optimization (*Resuscitation* 2018)
A First Optimization Model

• Data
  – Five years of OHCAs
  – Locations of existing, registered AEDs
  – Large database of public buildings

• Optimization model to place AEDs to maximize cardiac arrest coverage

• Compared with population-guided approach to AED placement based on estimated daytime population spread across buildings in a census tract
10-Fold Cross Validation

10 folds

1  2  3  4  5  6  7  8  9  10

Whole OHCA dataset
10-Fold Cross Validation

10 folds

1 2 3 4 5 6 7 8 9 10

Whole OHCA dataset

Training Set
Test Set

10 folds
10-Fold Cross Validation

10 folds

10 runs

Whole OHCA dataset

Training Set

Test Set
Performance (coverage) based of the OHCAs in the test sets, summed over the 10 folds.
Results

- Optimization approach consistently outperforms population-guided approach
Registered AEDs in Toronto
Where Do You Place the Next 30 AEDs?
Optimization

- First optimization model (*Circulation* 2013)
- Effect of varying coverage radius (*Resuscitation* 2013)
- Optimization with coverage decay (*Manag Sci* 2016)
- **Spatiotemporal optimization** (*JACC* 2016)
- Optimization with uncertain OHCA locations (*Oper Res* 2017)
- AED optimization in high-rises (*Prehosp Emerg Care* 2017)
- Drone-delivered AEDs (*Circulation* 2017)
- **Generalizability of spatiotemporal optimization** (*Resuscitation* 2018)
Spatiotemporal Optimization Model

• Most studies focus on spatial factors; limited study of temporal factors
  – American Heart Association guidelines: place AEDs “in public locations where there is a relatively high likelihood of witnessed cardiac arrest”

• Two related questions:
  – How much is AED availability overestimated when we do not consider building hours of operation?
  – How much better can we do if we optimize AED locations considering temporal information?
Methods

• Data
  – Eight years of historical cardiac arrest data
  – Location and hours of operation for registered AEDs

• Analysis
  – *Assumed 24/7 coverage*: number of cardiac arrests that occur within 100 m of AED
  – *Actual coverage*: number of cardiac arrests that occur within 100 m of AED and when the AED is available
  – Coverage loss = \( \frac{\text{assumed 24/7} - \text{actual}}{\text{assumed 24/7}} \)
# Results: Characteristics of Cardiac Arrests

<table>
<thead>
<tr>
<th>Characteristic*</th>
<th>Total (n=2440)</th>
<th>Cardiac Arrests</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Daytime (n=1252)</td>
<td>Evening (n=840)</td>
<td>Night (n=348)</td>
<td></td>
</tr>
<tr>
<td>Average age ±SD</td>
<td>59.0±17.5</td>
<td>60.3±17.9</td>
<td>58.9±16.8</td>
<td>54.6±16.9</td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>58.9±16.7</td>
<td>60.1±17.2</td>
<td>58.7±16.1</td>
<td>55.1±15.7</td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>59.4±20.6</td>
<td>61.1±21.0</td>
<td>60.3±19.5</td>
<td>52.6±20.7</td>
<td></td>
</tr>
<tr>
<td>Male sex, n (%)</td>
<td>1979 (81.1)</td>
<td>1021 (81.5)</td>
<td>686 (81.7)</td>
<td>272 (78.2)</td>
<td></td>
</tr>
<tr>
<td>Witnessed by bystander, n (%)</td>
<td>1142 (46.8)</td>
<td>590 (47.1)</td>
<td>446 (53.1)</td>
<td>106 (30.5)</td>
<td></td>
</tr>
<tr>
<td>Received bystander CPR, n (%)</td>
<td>1019 (41.8)</td>
<td>533 (42.6)</td>
<td>371 (44.2)</td>
<td>115 (33.0)</td>
<td></td>
</tr>
<tr>
<td>Bystander applied AED, n (%)</td>
<td>191 (7.8)</td>
<td>96 (7.7)</td>
<td>75 (8.9)</td>
<td>20 (5.8)</td>
<td></td>
</tr>
<tr>
<td>Ambulance response interval, median (IQR), minutes</td>
<td>5.88 (2.68)</td>
<td>5.75 (2.60)</td>
<td>5.82 (2.62)</td>
<td>6.45 (2.58)</td>
<td></td>
</tr>
<tr>
<td>Initial cardiac rhythm, n (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shockable</td>
<td>868 (35.6)</td>
<td>465 (37.1)</td>
<td>327 (38.9)</td>
<td>76 (21.8)</td>
<td></td>
</tr>
<tr>
<td>Not Shockable</td>
<td>1504 (61.6)</td>
<td>747 (59.7)</td>
<td>494 (58.8)</td>
<td>263 (75.6)</td>
<td></td>
</tr>
<tr>
<td>Survival to discharge, n (%)</td>
<td>361 (14.8)</td>
<td>196 (15.7)</td>
<td>129 (15.4)</td>
<td>36 (10.3)</td>
<td></td>
</tr>
</tbody>
</table>
Results: AED Availability in Toronto

- **Daytime** (8:00AM – 3:59PM)
- **Evening** (4:00PM – 11:59PM)
- **Night** (12:00AM – 7:59AM)

The chart shows the proportion of time AEDs are available across different time periods and days of the week.
Results: Coverage Loss by Time of Day

- Overall: 21.5% loss
- Daytime: 8.6% loss
- Evening: 28.6% loss
- Night: 48.4% loss

Time of day:
- 8:00am – 3:59pm
- 4:00pm – 11:59pm
- 12:00am – 7:59am
### Results: Coverage Loss by Location Type

<table>
<thead>
<tr>
<th>Location Type</th>
<th>Number of locations with an AED, n (%)</th>
<th>OHCAs covered</th>
<th></th>
<th>Coverage loss (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Assumed 24/7</td>
<td>Actual</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>coverage, n</td>
<td>coverage, n</td>
<td></td>
</tr>
<tr>
<td>School</td>
<td>190 (25.8)</td>
<td>68</td>
<td>41</td>
<td>39.7</td>
</tr>
<tr>
<td>Recreation/sports facility</td>
<td>165 (22.4)</td>
<td>89</td>
<td>56</td>
<td>37.1</td>
</tr>
<tr>
<td>Transportation facility</td>
<td>93 (12.6)</td>
<td>144</td>
<td>144</td>
<td>0.0</td>
</tr>
<tr>
<td>Industrial facility</td>
<td>62 (8.4)</td>
<td>28</td>
<td>17</td>
<td>39.3</td>
</tr>
<tr>
<td>Office</td>
<td>54 (7.3)</td>
<td>56</td>
<td>36</td>
<td>35.7</td>
</tr>
</tbody>
</table>
## Discussion: Toronto vs. Copenhagen

<table>
<thead>
<tr>
<th>Location Type Coverage Loss</th>
<th>Toronto</th>
<th>Copenhagen (Hansen et al*)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall coverage loss</td>
<td>21.5%</td>
<td>33.5%</td>
</tr>
<tr>
<td>Percent of AEDs available 24/7</td>
<td>26.5%</td>
<td>9.1%</td>
</tr>
<tr>
<td>Daytime coverage loss</td>
<td>5.7%</td>
<td>4.1%</td>
</tr>
<tr>
<td>Evening, night, and weekends coverage loss</td>
<td>31.6%</td>
<td>53.4%</td>
</tr>
</tbody>
</table>

Spatiotemporal Optimization Model

• What is the improvement potential if we deploy “prospective” AEDs with knowledge of building hours?

• Compare an optimization model that combines both spatial and temporal information with one that uses spatial information only
Methods

• Data
  – Eight years of historical cardiac arrest data
  – Location and hours of operation for registered AEDs
  – Location and hours of operation for candidate AED sites

• Model
  – Spatial (basic) model: Place AEDs in $N$ locations to maximize *assumed 24/7 coverage* of cardiac arrests
  – Spatiotemporal model: Place AEDs in $N$ locations to maximize *actual coverage* of cardiac arrests
  – 10-fold cross validation (90/10 training/testing)
Model Comparison

**Model Inputs**

- Candidate AED locations
  - Address / Location
  - Hours of operations
- Historical OHCAs
  - Address / Location
  - Time of arrest

**Model Outputs**

- Selected candidate AED locations
- Covered OHCAs

**Compare in terms of actual coverage**

**Model Inputs**

- Candidate AED locations
  - Address / Location
- Historical OHCAs
  - Address / Location

**Model Outputs**

- Selected candidate AED locations
- Covered OHCAs
Results: Spatiotemporal Optimization

P<0.002 for all N

+25.3%
Results: Coverage Gain Due to Spatiotemporal Opt.

- Relative coverage gain = \( \frac{\text{spatiotemporal} - \text{spatial}}{\text{spatial}} \)
- Overall coverage gain: weighted average over \( N \)
Generalizing the Spatiotemporal Approach

Coverage loss when measuring actual coverage versus assumed 24/7 coverage

<table>
<thead>
<tr>
<th>Time of day</th>
<th>Overall</th>
<th>Daytime</th>
<th>Evening</th>
<th>Night</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of OHCAs covered</td>
<td>0</td>
<td>200</td>
<td>400</td>
<td>600</td>
</tr>
</tbody>
</table>

Toronto, Canada

- Assumed 24/7 Coverage
- Actual Coverage

- Overall: 21.5% loss
- Daytime: 8.6% loss
- Evening: 28.6% loss
- Night: 48.4% loss

Copenhagen, Denmark

- Assumed 24/7 Coverage
- Actual Coverage

- Overall: 24.4% loss
- Daytime: 11.3% loss
- Evening: 35.8% loss
- Night: 45.4% loss

Toronto, Canada

8:00am – 3:59pm
4:00pm – 11:59pm
12:00am – 7:59am

Copenhagen, Denmark

8:00am – 3:59pm
4:00pm – 11:59pm
12:00am – 7:59am
## Generalizing the Spatiotemporal Approach

![Graph showing overall coverage gain (%)]

<table>
<thead>
<tr>
<th>OHCA Category</th>
<th>Toronto (Public OHCAs)</th>
<th>Copenhagen (Public OHCAs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total</td>
<td>25.3 ± 15.3</td>
<td>122.5 ± 37</td>
</tr>
<tr>
<td>Daytime</td>
<td>10.9 ± 5.9</td>
<td>13.9 ± 2.6</td>
</tr>
<tr>
<td>Evening</td>
<td>38.0 ± 2.4</td>
<td>53.8 ± 5.8</td>
</tr>
<tr>
<td>Night</td>
<td>21.0 ± 2.1</td>
<td>42.6 ± 7.4</td>
</tr>
<tr>
<td>Weekday</td>
<td>21.1 ± 3.1</td>
<td>21.1 ± 3.1</td>
</tr>
<tr>
<td>Weekend</td>
<td>20.9 ± 5.2</td>
<td>27.7 ± 5.9</td>
</tr>
<tr>
<td>City Center</td>
<td>9.5 ± 1.5</td>
<td>15.9 ± 2.7</td>
</tr>
<tr>
<td>Downtown</td>
<td>20.9 ± 5.2</td>
<td>27.7 ± 5.9</td>
</tr>
</tbody>
</table>

(8:00AM – 3:59PM) (4:00PM – 11:59PM) (12:00AM – 7:59AM)
Optimization

- First optimization model (*Circulation* 2013)
- Effect of varying coverage radius (*Resuscitation* 2013)
- Optimization with coverage decay (*Manag Sci* 2016)
- Spatiotemporal optimization (*JACC* 2016)
- Optimization with uncertain OHCA locations (*Oper Res* 2017)
- **AED optimization in high-rises** (*Prehosp Emerg Care* 2017)
- Drone-delivered AEDs (*Circulation* 2017)
- Generalizability of spatiotemporal optimization (*Resuscitation* 2018)
Vertical AED Placement

- Almost all studies have focused on “2D” problem
- Response delays and lower survival in high-rises
- No guidelines on vertical AED placement

Out-of-hospital cardiac arrest in high-rise buildings: delays to patient care and effect on survival

Ian R. Drennan ACP, Ryan P. Strum PCP BSc, Adam Byers BSc, Jason E. Buick PCP MSc, Steve Lin MDCM MSc, Sheldon Cheskes MD, Samantha Hu, Laurie J. Morrison MD MSc; for the Rescu Investigators
Elevator vs. Lobby?

Elevator-based AED has shorter average response distance in this region.

Lobby-based AED has shorter average response distance in this region.
Optimization

- First optimization model (*Circulation* 2013)
- Effect of varying coverage radius (*Resuscitation* 2013)
- Optimization with coverage decay (*Manag Sci* 2016)
- Spatiotemporal optimization (*JACC* 2016)
- Optimization with uncertain OHCA locations (*Oper Res* 2017)
- AED optimization in high-rises (*Prehosp Emerg Care* 2017)
- **Drone-delivered AEDs** (*Circulation* 2017)
- Generalizability of spatiotemporal optimization (*Resuscitation* 2018)
Drone-Delivered AEDs

- Most OHCAs occur in private locations
- Drones are being tested to deliver everything from pizza to medicine
- Specialized AED-drones exist

- Where would you put drone bases?
- How many drones would you need?
- How do drones compare to existing EMS response?
Defibrillator Drone
Objective

The goal of this study is to develop a mathematical approach that determines:

1. the number and location of drone bases, and
2. the number of the drones required at each base,

to meet any AED arrival time goal in any geographical area.
Data

- 8 regions
  - 7.5 million people
  - 10,000 sq. miles

- 53,702 OHCAs from 2006 to 2014
  - 86% private location
  - 7.8% survival

- 538 paramedic, fire, and police stations
Mathematical Model

• Two-stage mathematical model:

1. Optimization model to determine base locations to cover \( f \% \) of historical OHCAs in under \( t \) minutes
2. Queuing model to determine number of drones at each base so there is 99\% chance drone is free when a OHCA occurs inside that base’s catchment area
Analysis

- Determine the number and location of drones to improve the historical median 911 response by 1, 2, and 3 minutes.

- Compare region-specific drone networks with coordinated drone-network integrating all eight regions.
Results: An Example Drone Network

- 23 bases, 37 drones:
  - Reduce median response time by 1 minute
  - Reduce 90th percentile response time by over 6 min in some regions
  - Drone arrives ahead of EMS 2/3 of the time
### Drone Network Performance

<table>
<thead>
<tr>
<th>Goal</th>
<th>Region</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Toronto</td>
<td>Durham</td>
<td>Simcoe</td>
<td>Muskoka</td>
<td>Peel</td>
<td>Hamilton</td>
<td>Halton</td>
<td>York</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of bases</td>
<td>3 (6)</td>
<td>3 (6)</td>
<td>5 (6)</td>
<td>3 (3)</td>
<td>2 (4)</td>
<td>1 (2)</td>
<td>3 (4)</td>
<td>3 (6)</td>
<td>23 (37)</td>
<td></td>
</tr>
<tr>
<td>(number of total</td>
<td>6 (12)</td>
<td>5 (7)</td>
<td>11 (12)</td>
<td>5 (5)</td>
<td>4 (8)</td>
<td>1 (2)</td>
<td>3 (4)</td>
<td>5 (7)</td>
<td>40 (57)</td>
<td></td>
</tr>
<tr>
<td>drones)</td>
<td>13 (26)</td>
<td>14 (16)</td>
<td>20 (20)</td>
<td>6 (6)</td>
<td>10 (11)</td>
<td>5 (7)</td>
<td>5 (5)</td>
<td>8 (9)</td>
<td>81 (100)</td>
<td></td>
</tr>
<tr>
<td>Proportion of</td>
<td>69.0</td>
<td>64.2</td>
<td>65.0</td>
<td>76.3</td>
<td>71.7</td>
<td>54.1</td>
<td>64.4</td>
<td>63.9</td>
<td>67.9</td>
<td></td>
</tr>
<tr>
<td>cases where drone</td>
<td>87.6</td>
<td>82.1</td>
<td>78.6</td>
<td>79.7</td>
<td>84.7</td>
<td>75.3</td>
<td>73.9</td>
<td>79.5</td>
<td>84.6</td>
<td></td>
</tr>
<tr>
<td>AED arrives prior to</td>
<td>96.1</td>
<td>94.6</td>
<td>89.6</td>
<td>84.2</td>
<td>94.6</td>
<td>92.2</td>
<td>92.7</td>
<td>89.2</td>
<td>94.6</td>
<td></td>
</tr>
<tr>
<td>911 (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Impact on Response Time Distribution

**Toronto (Urban)**

1. **Historical**
   - 50th percentile
   - 90th percentile

2. **1 min**
   - Number of cardiac arrests

3. **2 min**

4. **3 min**
   - Time to AED arrival at the scene (minutes)
   - 6 min 43s

**Muskoka (Rural)**

1. **Historical**

2. **1 min**
   - Number of cardiac arrests

3. **2 min**

4. **3 min**
   - Time to AED arrival at the scene (minutes)
   - 10 min 34s
Results: Equity vs. Efficiency

Region-specific
1 min. faster

Integrated
1 min. faster

40% fewer drones
Summary of Past/Current Work

• Data-driven mathematical models for AED placement or delivery
  – Models that improve accessibility or consider bystander response
  – Utilizing drones to deliver AEDs, other medicines
  – Application to new contexts (LMICs, indoor networks)
Going Forward

• Continue to be interested in innovative applications of optimization in emergency response
  – New problem contexts
    • Integrating static and moving AEDs
    • Simulated clinical trials
    • High-rise response
    • Traffic accidents
    • Centralized decision-making systems
  – New technologies
    • Optimal notification radius for mobile app-based responders
    • Analysis of wearables data
    • OHCA recognition via security systems
Thank You!