Forecasting EMS demand, response times, and workload
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Change the Defaults:

☐ Travel time = distance / speed
☑ Travel time = f(distance)

☐ $a_{ij} = 1$ if $i$ is covered by $j$, 0 otherwise
☑ $p_{ij} =$ probability that $i$ covers $i$

Longer trips have faster average speeds
Travel times are stochastic
It’s not hard to incorporate these features in most EMS planning models
Longer trips have faster average speeds.

Travel times are stochastic.

7,457 high priority calls, from 2003, Calgary EMS.
Outline

• Scope and Scale
• Predicting Demand, Response Times, and Workload
• Policy Implications
• Performance Measures
Reference

EMS Scope and Scale
## EMS Statistics

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<tbody>
<tr>
<td>Population (000)</td>
<td>5,104</td>
<td>7,754</td>
<td>313,625</td>
<td>586</td>
</tr>
<tr>
<td>Annual calls per capita</td>
<td>1/8.8</td>
<td>1/5.24</td>
<td>1/8.54</td>
<td>1/12.1</td>
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<tr>
<td>Ambulances per capita</td>
<td>1/8,954</td>
<td>1/8,615</td>
<td>1/3,858</td>
<td>1/5,581</td>
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<tr>
<td>EMS professionals per capita</td>
<td>Not available</td>
<td>1/1,551</td>
<td>1/380</td>
<td>1/750</td>
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<tr>
<td>Annual operating expenses per capita</td>
<td>US$92 (Alberta)</td>
<td>US$55</td>
<td>Not available</td>
<td>US$41</td>
</tr>
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</table>
EMS Call Components

- Call
- Pre-travel delay: 0.93 (0.64)
- Travel time: 4.02 (0.55)
- On-scene time: 20.1 (0.40)
- Transport time: 12.2 (0.53)
- Hospital time: 44.0 (0.45)

- Unit begins travel
- Unit arrives at scene
- Unit departs scene
- Unit arrives at hospital
- Unit departs hospital

- 34.5% not transported
- Response time
- Unit service time
EMS Planning and Management is Challenging Because …

• … call volume, location, and severity are highly variable

• Planning is facilitated by ever increasing data collected by EMS agencies
  – Event time stamps
  – Geographical coordinates
Decomposing Performance

- Performance estimates:
  - $p_{ij}$ = estimated performance for calls from $j$ if station $i$ responds
  - “performance:” could be coverage probability / survival probability / average response time / …

- Dispatch probabilities:
  - $f_{ij} = \Pr\{\text{station } i \text{ responds} \mid \text{call from } j\}$
  - This is where queueing / service system models are needed

- Call arrival rates:
  - Neighborhood $j$: $\lambda_j$, system: $\lambda$

- System performance: $\sum_j \frac{\lambda_j}{\lambda} \sum_i f_{ij} p_{ij}$
Predicting Demand, Response Times, and Workload
Call Volumes: Weekly Cycle

Percent of weekly call volume

Hour (24 x 7 days)


0.2%     0.3%     0.4%     0.5%     0.6%     0.7%     0.8%     0.9%     1.0%
0 24 48 72 96 120 144 168
A Theory about EMS Demand

- Theory: Demand follows a Poisson arrival process
  \[
  \text{Pr}\{n \text{ arrivals in } (t_1, t_2)\} = \frac{(\lambda(t_2 - t_1))^n \exp(-\lambda(t_2 - t_1))}{n!}
  \]
  \[
  \text{E[number of arrivals in } (t_1, t_2)] = \lambda(t_2 - t_1)
  \]
  \[
  \text{var[number of arrivals in } (t_1, t_2)] = \lambda(t_2 - t_1)
  \]
Why Poisson? Theoretical Reason

• Cox and Smith (1954): The superposition of a large number of independent renewal processes, each with a small renewal rate, approaches a Poisson process.

• Interpretation: If …
  – … the number of potential patients is large
  – … patients act independently
  – … the probability of arrival for each patient in each infinitesimal interval is small

• Then the patient arrival process will be approximately Poisson.

• **Exercise**: Think of reasons why an EMS arrival process might **not** be Poisson.
Are M&Ms good?
Or: If Not Poisson then What?

• If the first M in M/M/s is unrealistic, then how can we make it more realistic?
• M means interarrival times are:
  – Independent
  – Identically distributed
  – Exponentially distributed
• G/M/s?
• M(t)/M/s?
• M(t)/M/s with random arrival rate? (Cox process)
Poisson with Random Arrival Rate

Arrival rate for tomorrow

Arrival rate for two weeks from today
Forecasting EMS Calls: Are they Poisson?

Daily average = 174
If arrivals are Poisson, then the standard deviation (\(\approx \text{RMSE}\)) should be \(\sqrt{174} \approx 13\)

RMSE(1 day ahead) \(\approx 14\)
RMSE(2 weeks ahead) \(\approx 18\)

Simulating tomorrow’s arrivals: Almost Poisson

Simulating arrivals two weeks from now: Poisson with random rate

Channouf et al. (2007), Calgary data

(Much more sophisticated analysis in recent papers by Kim and Whitt)
Within-Day Forecasting

• Forecasting arrivals from 4 to 5 pm:
  – Using calls up to midnight the day before: RMSE = 3.5 calls
  – Using calls up to 11 am today: RMSE = 2.3 calls

Channouf et al. (2007), Calgary data
EMS Arrivals: Opportunities for Further Research

• Forecasting of arrivals over time and space (Setzler et al. 2009 provides one example)


  – What level of spatial resolution is needed / possible? (finer resolution dilutes sample sizes)

  – What level of accuracy is needed / possible? (Poisson process with known rate gives upper bound on accuracy?)
The Data

7,457 high priority calls, from 2003, Calgary EMS

Conditional Travel Time Distributions

Distance: 0-1 km
Median: 2.0 min.
CV: 0.41
Df: 4
Conditional Travel Time Distributions

Distance: 4-5 km
Median: 5.2 min.
CV: 0.24
Df: 5
A “Physics 101” Model for Median Travel Time

A long trip:
- Speed
- Acceleration = \(a\)
- Deceleration = \(a\)
- Cruising speed - \(v_c\)

A short trip:
- Speed
- \(\text{median}[\text{Travel time}|d] = \begin{cases} 
  \frac{2\sqrt{d/a}}{} & d \leq 2d_c \\
  \frac{v_c}{a + d/v_c} & d > 2d_c 
\end{cases}\)
Model

Travel time = $m(\text{distance}) \times \exp(c(\text{distance}) \times \varepsilon)$

or:

$log(\text{travel time}) = \log(m(\text{distance})) + c(\text{distance}) \times \varepsilon$

- Log transformation to symmetry
- Median curve: $m(\text{distance})$
- CV curve: $c(\text{distance})$
- “Error term:” $\varepsilon \sim \text{Student } t \text{ distribution}$
  - Better fit than normal distribution
  - Less sensitive to outliers than normal distribution
Model Estimation

• Non-parametric: Median and CV can be any smooth functions of distance

• Parametric
  – Median: RAND fire engine first-principles model
  – CV: New first-principles model
Non-parametric Functions

![Graphs showing the relationship between median travel time and distance, as well as the coefficient of variation with distance.](#)
Parametric Functions

![Graphs showing parametric functions for median travel time and coefficient of variation vs. distance.]

- Median travel time (min.) vs. Distance (km)
- Coefficient of variation vs. Distance (km)
Travel Times: Median and Coefficient of Variation

\[ p_{ij} = \Pr\{\text{Traveltime} \leq 9 \text{ min.}\} \]
Pre-travel Delays

\[ p_{ij} = \Pr\{\text{Pre-travel delay} + \text{Travel time} \leq 9 \text{ min.}\} \]
Scene and Hospital Times

On-scene time for $T$ and $T^c$ (min.)

Number of busy ambulances

Workload – needed to predict dispatch probabilities ($f_{ij}$)
Overall Service Time

![Graph showing the relationship between percent busy servers and average service time, with a peak at around 40% busy servers and a coefficient of variation (CV) indicating variability.](image)
Probability-of-Coverage Maps

(a): Closest Available Ambulance Responds

(b): Closest Station Responds
Why Study EMS Data?

- **Fundamental knowledge**: Does average service time vary with system load? Why? Variation between regions and with system organization?
- **Modeling**: How can load-dependent service times be incorporated in EMS models? Validity, tractability, scalability.
- **Implications for planning**: How do load-dependent service times impact estimated performance and recommended number of ambulances?
Why EMS Data is Important: Another Perspective

Dear Dr. Tyrrell:

Further to our recent discussion, concerns have been raised over the quality of emergency medical services (EMS) response times.

Pursuant to Section 15(1) of the Health Quality Council of Alberta (the Council) to review the transfer of medical services in Alberta.

The Review shall include but is not limited to:

- transition issues related to the transfer of municipalities to the former regional health
dispatch consolidation;

Timeline:

2009: Responsibility for EMS service in Alberta transferred from municipalities to Alberta Health Services

Feb 2012: Health Minister asks Health Quality Council to review transfer of EMS, including dispatch consolidation

(Consolidation put on hold)

Jan 2013: Review completed
Because of the significant limitations in provincial EMS data some of the important questions that this review was asked to address could not be answered. For example, the time-stamp data within AAIMS are not considered sufficiently valid and there are insufficient historical data from across the province. Consequently the central question for the review concerning the impact of the transition on the provision of EMS could not be quantitatively answered.

What’s needed to collect better data?

Dispatch consolidation!
Performance Measures
Performance Measures: Issues

• Report response time statistics or outcome statistics?
• Report averages, quantiles (90\textsuperscript{th} percentile), or fractiles (proportion within a standard)?
• Different standards for different call types?
• Different standards for urban vs. rural?
• Report system-wide statistics or by region?

Equity
Equity: Equal Access vs. Optimize System-Wide Performance?

• In practice, rural and urban standards are different
• Equal access implies lives are valued more highly in sparsely populated areas
Access to Medical Care vs. Urban Sprawl
Can Medical Outcomes by Incorporated in Planning Models?

• Example of a survival probability equation for cardiac arrest patients:

\[ s(I_{CPR}, I_{Defib}) = \frac{1}{1 + \exp(-0.260 + 0.106I_{CPR} + 0.139I_{Defib})} \]
Coverage vs. Survival Probabilities

\[ p_{ij} = \Pr\{\text{Response time} \leq 9 \text{ min.}\} \quad \text{vs.} \quad p_{ij} = \Pr\{\text{survival}\} \]
Policy Implications
More data …

• Computer Aided Dispatch and GPS systems collect more and more EMS data
• Makes it possible to:
  – Better understand EMS operations
  – Use more detailed models for planning
• But: Parsimony and tractability still matter
… but is it the right data?

- EMS is neither the beginning nor the end of a patient’s journey through a healthcare system
- Outcomes are tracked after EMS
- Information about what happens before EMS typically not tracked (e.g., when did the accident occur)
- Linking EMS data to hospital data might enable EMS to be more outcome-driven