Forecasting EMS demand, response times, and workload

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Change the Defaults:

☐ Travel time = distance / speed

☑ Travel time = f(distance)

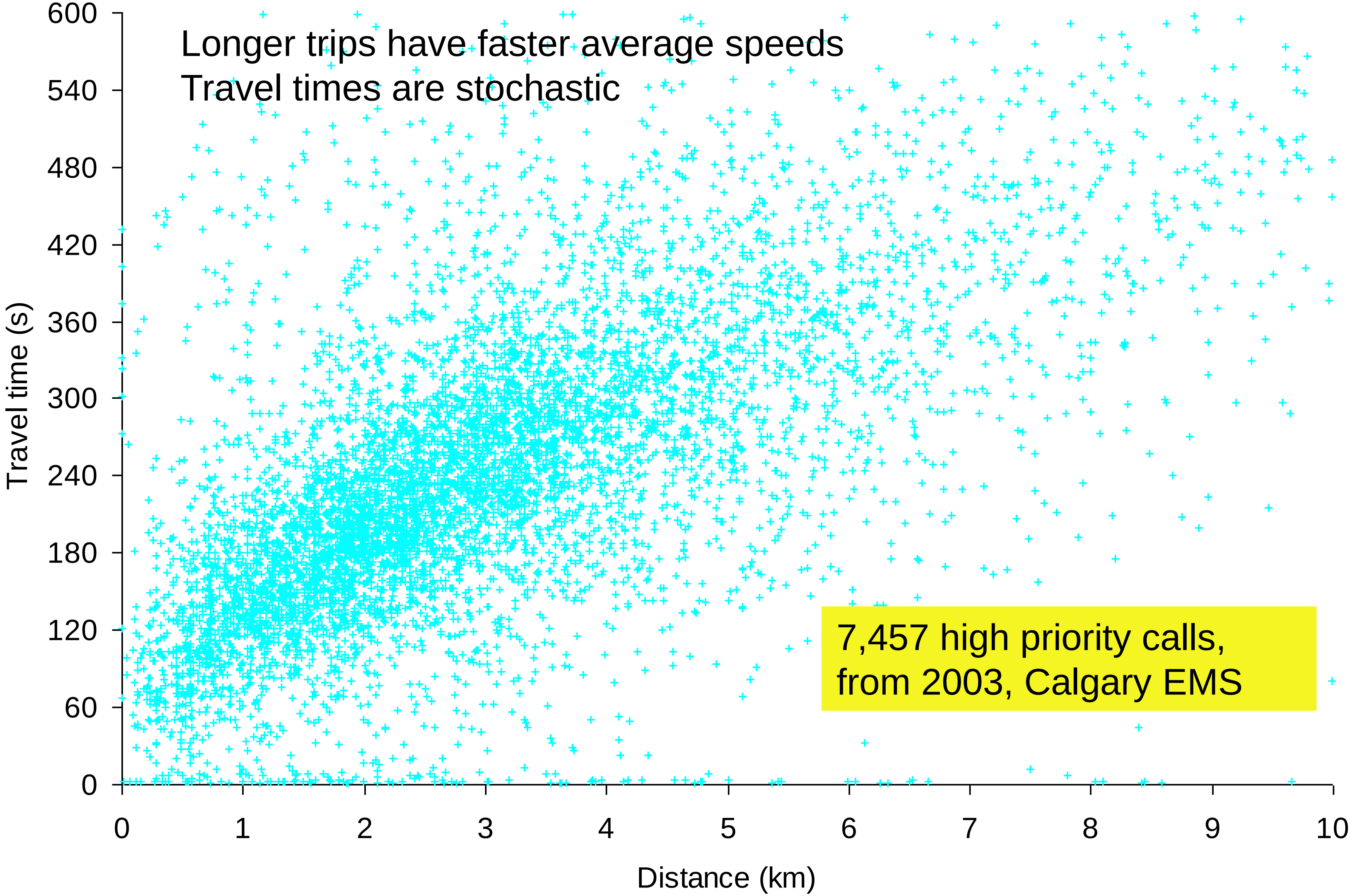
☐ a_{ij} = 1 i is covered by j, 0 otherwise

☑ 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
Travel time (s)
0
60
120
180
240
300
360
420
480
540
600
Distance (km)
0
1
2
3
4
5
6
7
8
9
10

Outline

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

Reference

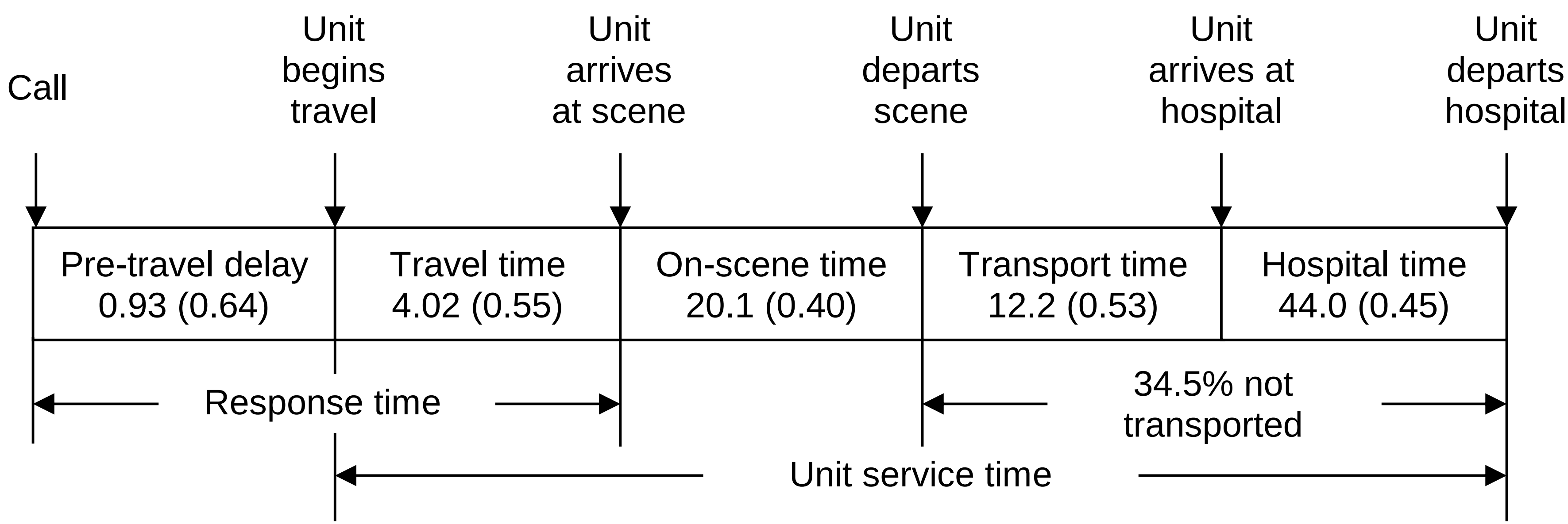
Ingolfsson, A. (2013). EMS Planning and Management. In *Operations Research and Health Care Policy* (pp. 105-128). Springer New York.

EMS Scope and Scale

EMS Statistics

Region (Year)	Canada (2012)	London, England (2009	United States (2011)	Rural Iceland, Scotland, Sweden (2007)
Population (000)	5,104	7,754	313,625	586
Annual calls per capita	1/8.8	1/5.24	1/8.54	1/12.1
Ambulances per capita	1/8,954	1/8,615	1/3,858	1/5,581
EMS professionals per capita	Not available	1/1,551	1/380	1/750
Annual operating expenses per capita	US$92 (Alberta) US$64 (Toronto)	US$55	Not available	US$41

EMS Call Components

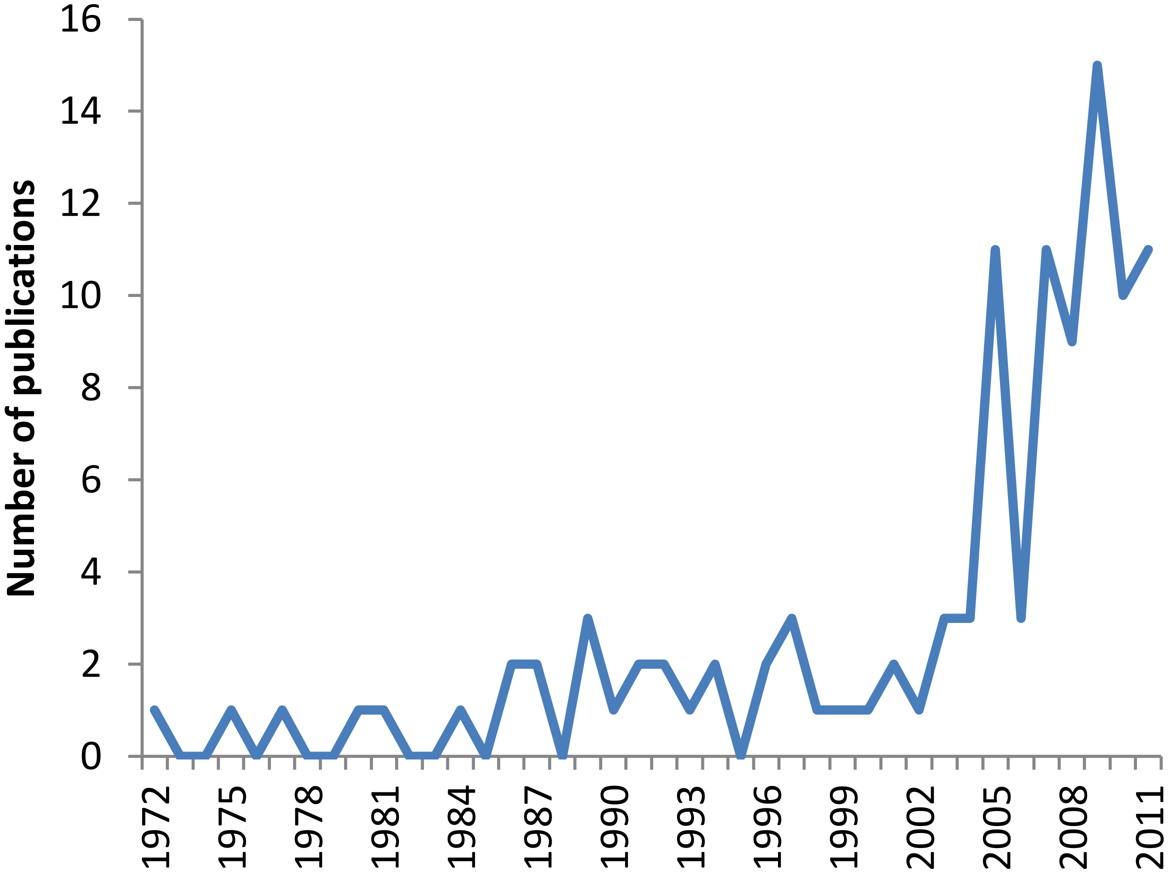


EMS Planning and Management is Challenging Because …

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

- Planning is facilitated by ever increasing data collected by EMS agencies
  - Event time stamps
  - Geographical coordinates

OR/MS EMS Publications



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{station i responds | call from j}
  - This is where queueing / service system models are needed
- Call arrival rates:
  - Neighborhood j: λ_j, system: λ
- System performance: $\sum_j \frac{\lambda_j}{\lambda} \sum_i f_{ij} p_{ij}$

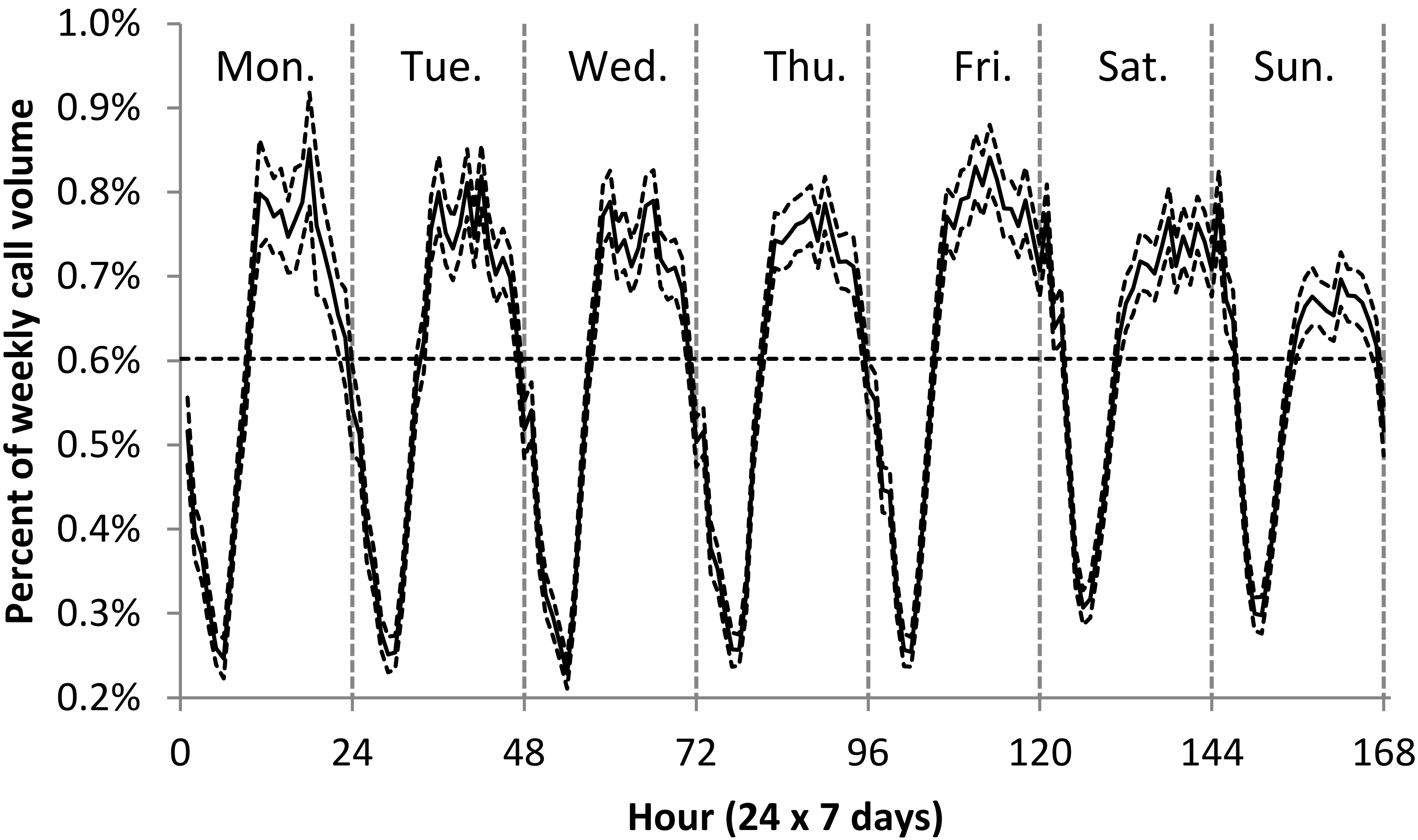
λ

Predicting Demand, Response Times, and Workload

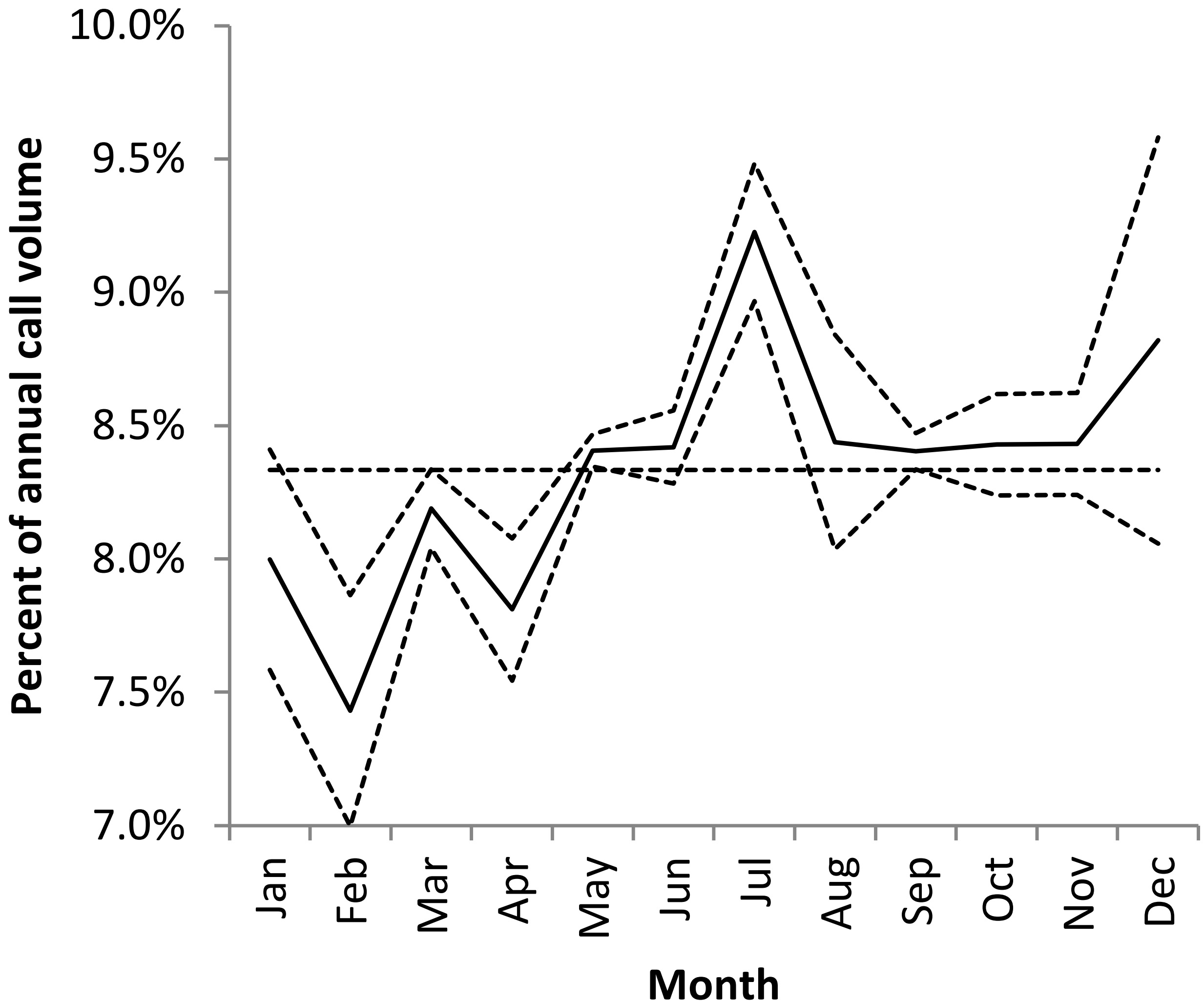
p_{ij}

f_{ij}

Call Volumes: Weekly Cycle



Call Volumes: Annual Cycle



A Theory about EMS Demand

- Theory: Demand follows a Poisson arrival process

$$\Pr\{n \text{ arrivals in } (t_1, t_2)\} = \frac{(\lambda(t_2 - t_1))^n \exp(-\lambda(t_2 - t_1))}{n!}$$

$$\text{E}[\text{number of arrivals in } (t_1, t_2)] = \lambda(t_2 - t_1)$$

$$\text{var}[\text{number of arrivals in } (t_1, t_2)] = \lambda(t_2 - t_1)$$

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 <u>not</u> be Poisson

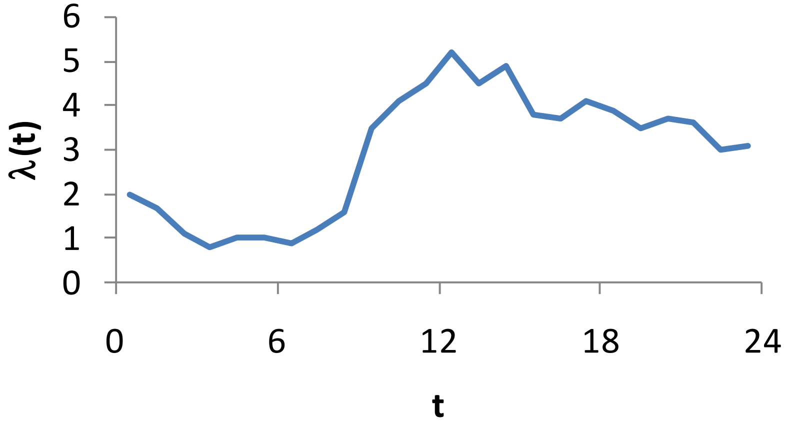
Are M&Ms good?

Or: If Not Poisson then What?

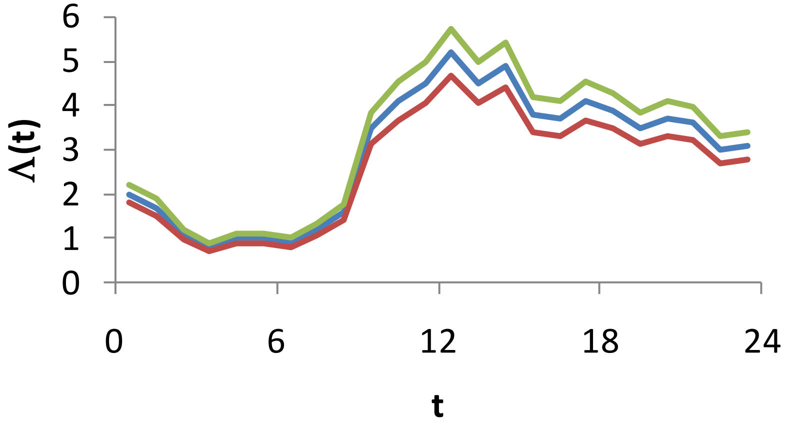
- If the first M in M/M/s is unrealistic, then how can we make it more realistic?
- M means interarrival times are:
  - Independent
  - Identically distributed
  - Exponentially distributed
- G/M/s?
- M(t)/M/s?
- M(t)/M/s with random arrival rate? (Cox process)

Poisson with Random Arrival Rate

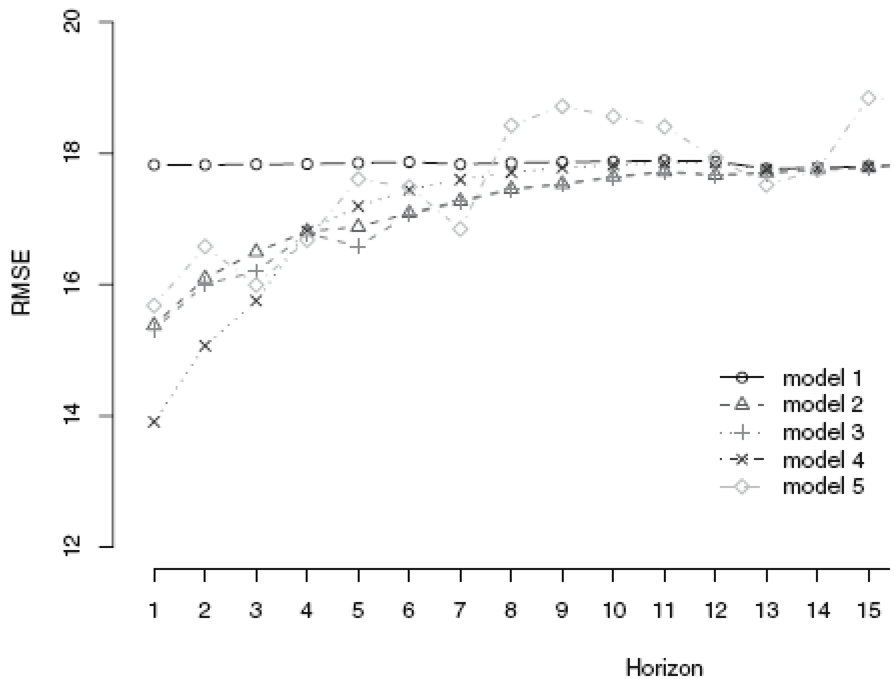
Arrival rate for tomorrow



Arrival rate for two weeks from today



Forecasting EMS Calls: Are they Poisson?



Channouf et al. (2007), Calgary data

Channouf, N., L'Ecuyer, P., Ingolfsson, A., & Avramidis, A. N. (2007). The application of forecasting techniques to modeling emergency medical system calls in Calgary, Alberta. Health Care Management Science, 10(1), 25-45.

(Much more sophisticated analysis in recent papers by Kim and Whitt)

Such as Kim, S. H., & Whitt, W. (2014). Are Call Center and Hospital Arrivals Well Modeled by Nonhomogeneous Poisson Processes?. Manufacturing & Service Operations Management.

Daily average = 174
If arrivals are Poisson, then the standard deviation (= 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

Within-Day Forecasting

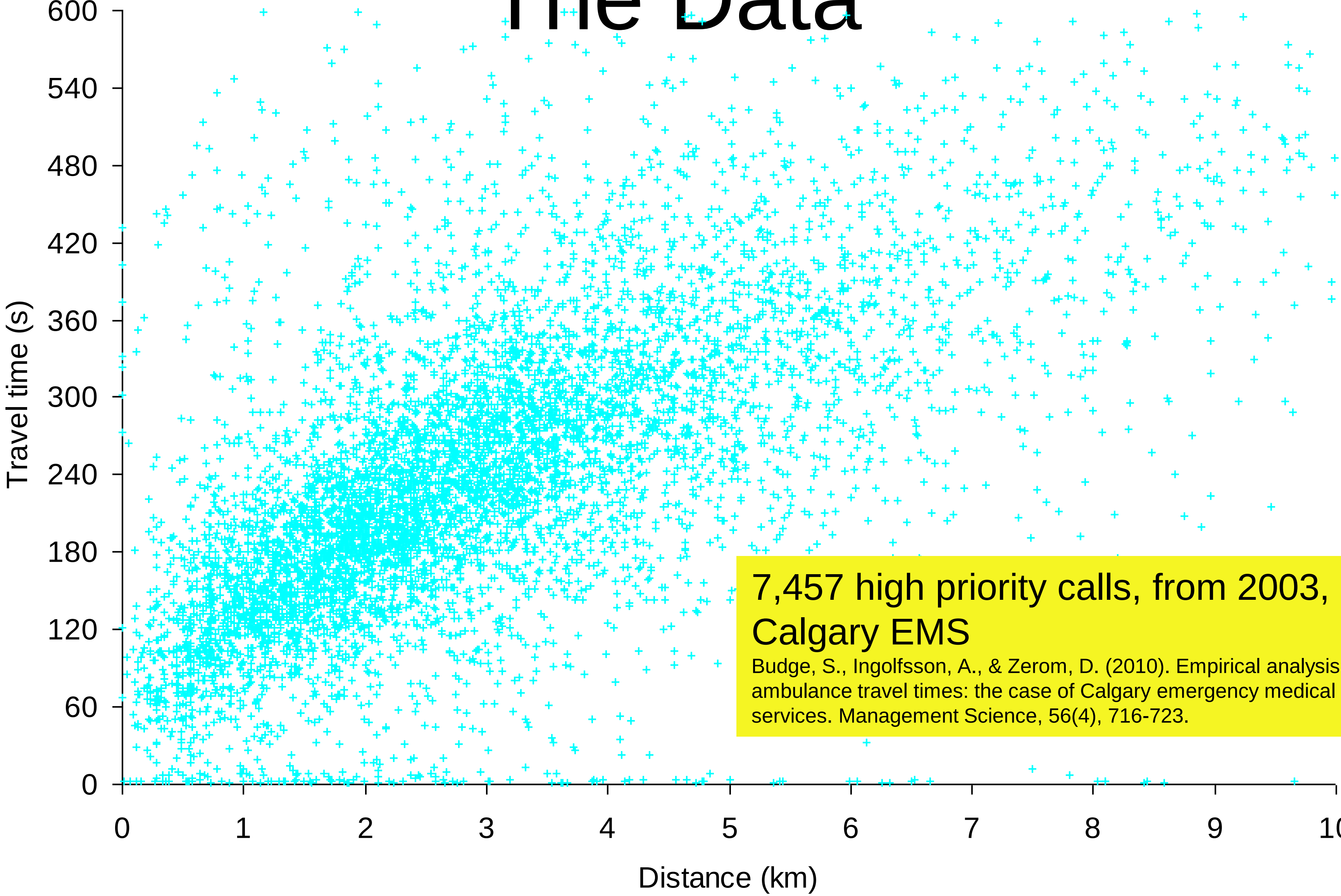
- Forecasting arrivals from 4 to 5 pm:
  - Using calls up to midnight the day before: RMSE = 3.5 calls
  - Using calls up to 11 am today: RMSE = 2.3 calls

Channouf et al. (2007),
Calgary data

EMS Arrivals: Opportunities for Further Research

- Forecasting of arrivals over time <u>and space</u> (Setzler et al. 2009 provides one example)
  Setzler, H., Saydam, C., & Park, S. (2009). EMS call volume predictions: A comparative study. Computers & Operations Research, 36(6), 1843-1851.
  - 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?)

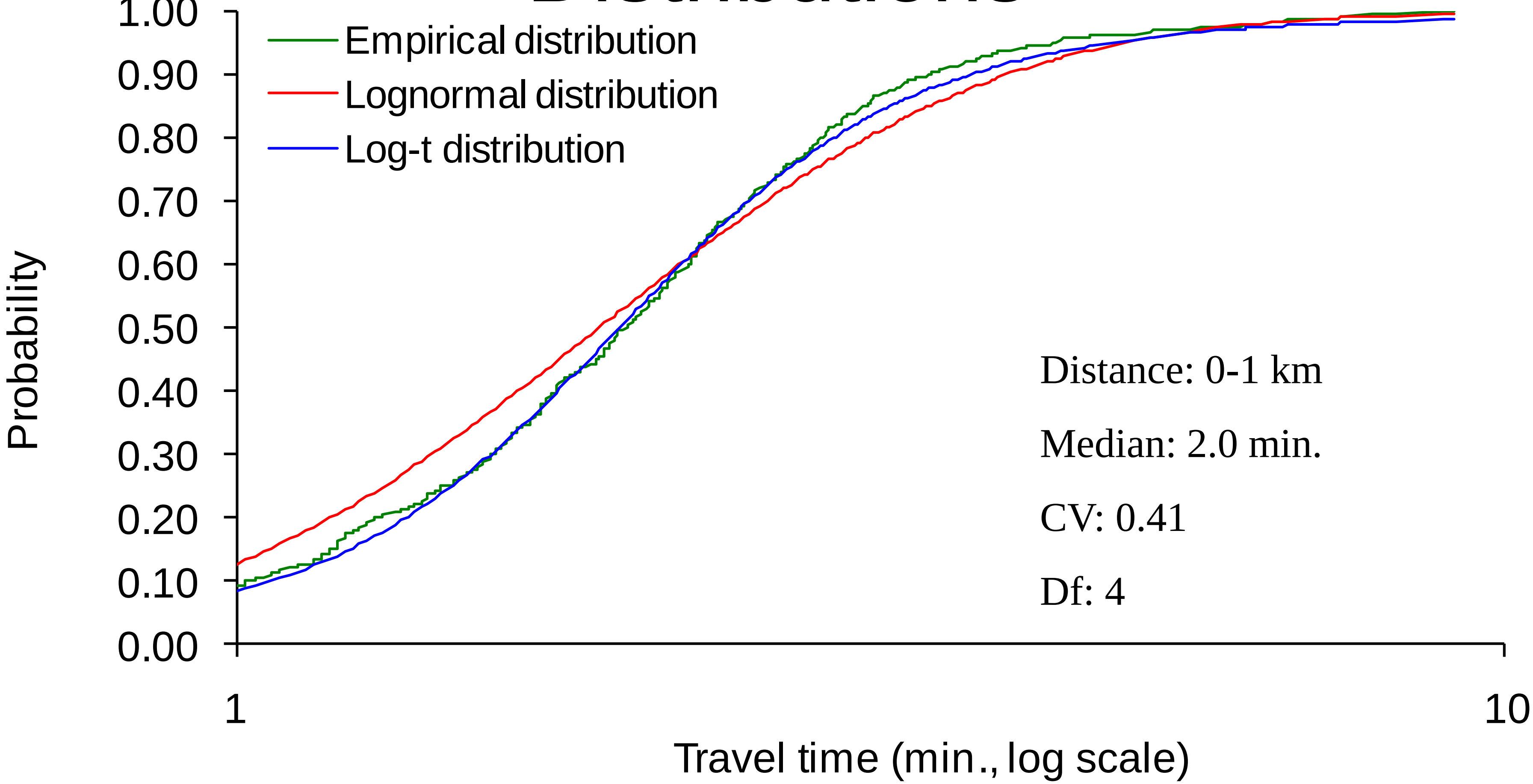
The Data



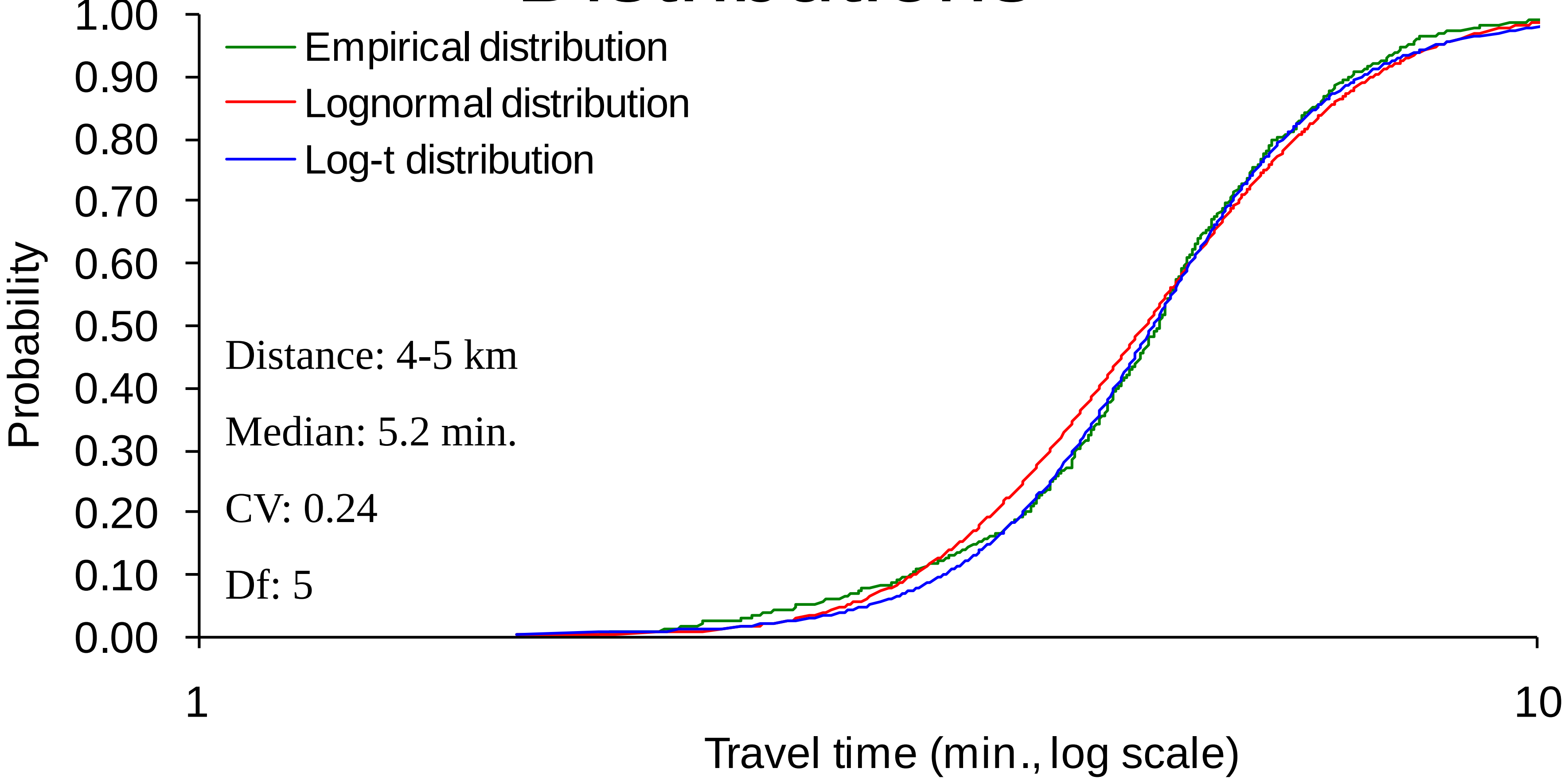
7,457 high priority calls, from 2003, Calgary EMS

Budge, S., Ingolfsson, A., & Zerom, D. (2010). Empirical analysis of ambulance travel times: the case of Calgary emergency medical services. Management Science, 56(4), 716-723.

Conditional Travel Time Distributions

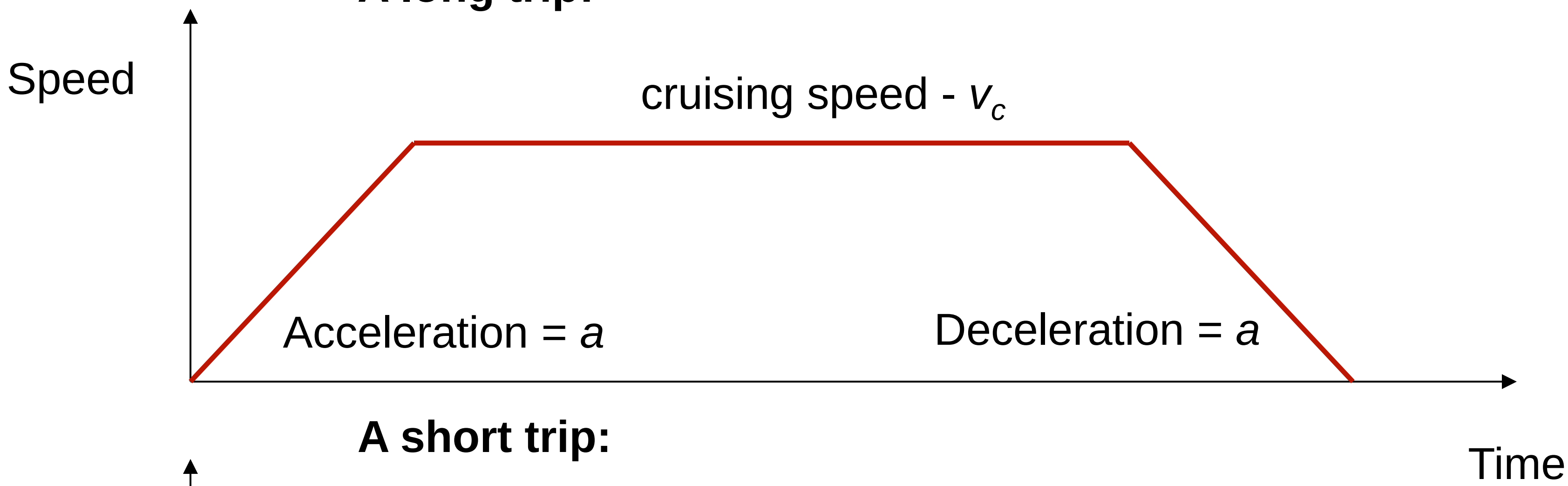


Conditional Travel Time Distributions

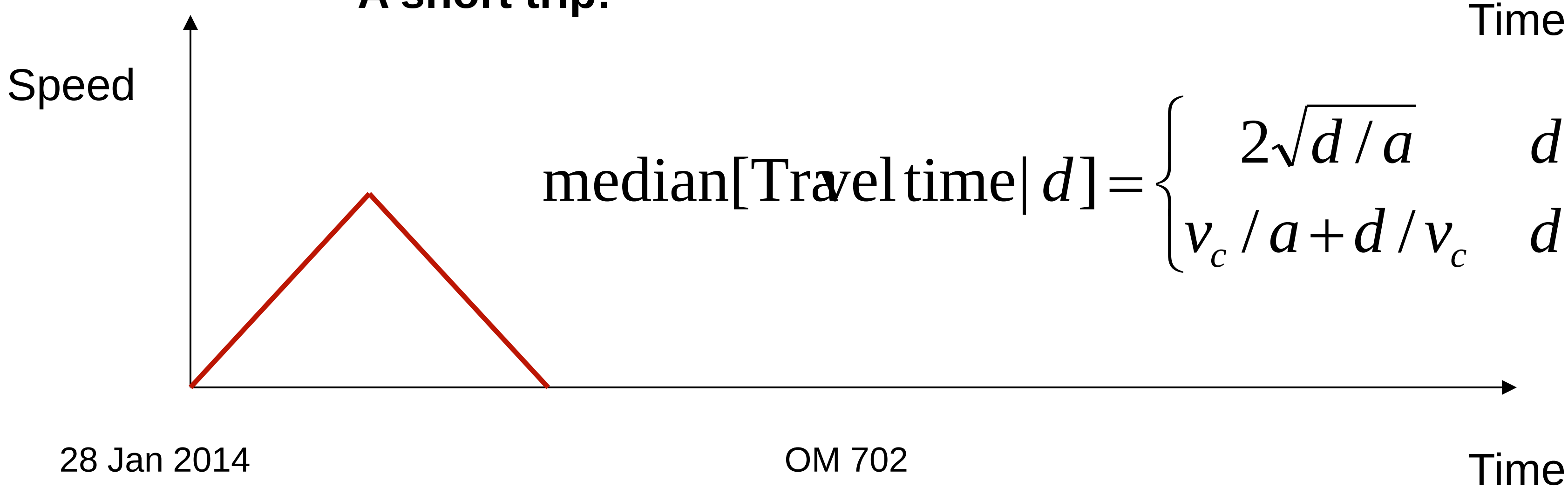


A "Physics 101" Model for Median Travel Time

A long trip:



A short trip:



$$\text{median}[\text{Travel time} \mid d] = \begin{cases} 2\sqrt{d/a} & d \le 2d_c \\ v_c/a + d/v_c & d > 2d_c \end{cases}$$

Model

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

or:

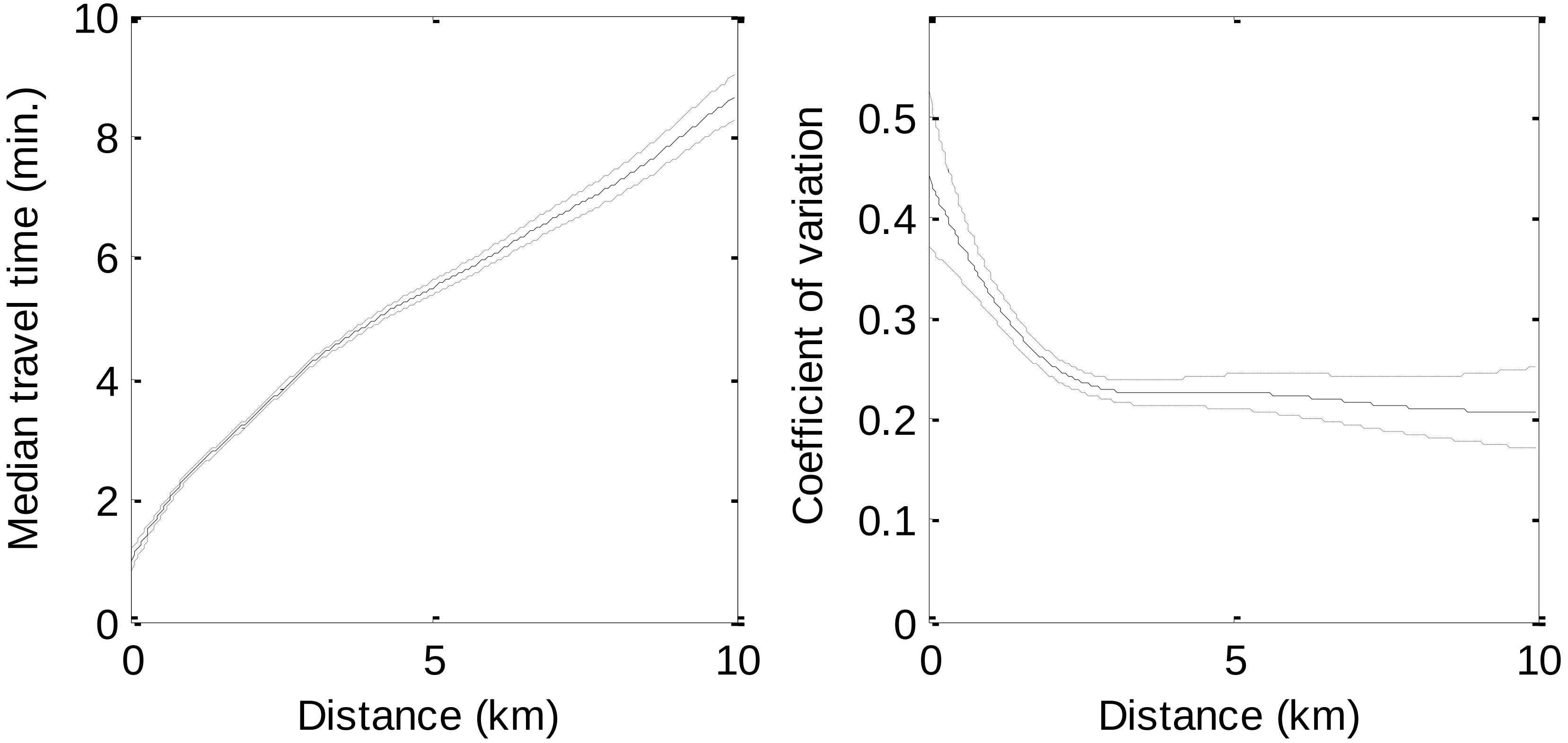
$$\log(\text{travel time}) = \log(m(\text{distance})) + c(\text{distance}) \times \varepsilon$$

- Log transformation to symmetry
- Median curve: m(distance)
- CV curve: c(distance)
- “Error term:” ε ~ Student t distribution
  - Better fit than normal distribution
  - Less sensitive to outliers than normal distribution

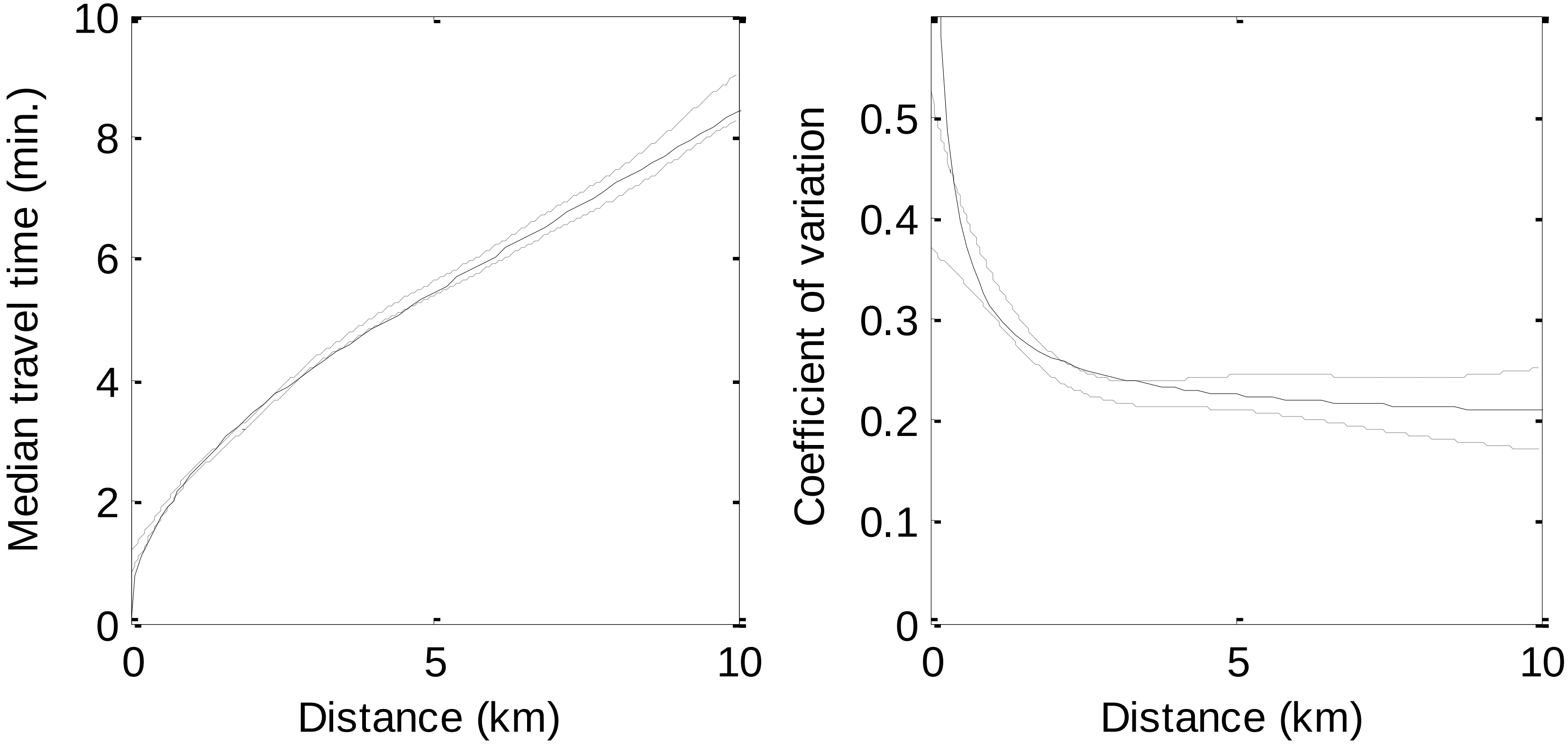
Model Estimation

- 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

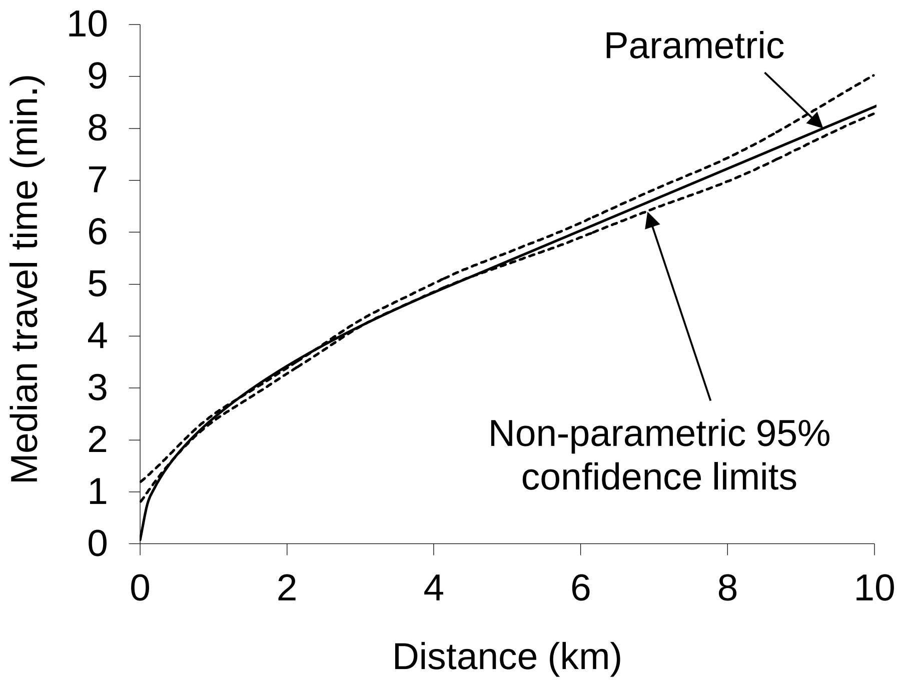
Non-parametric Functions

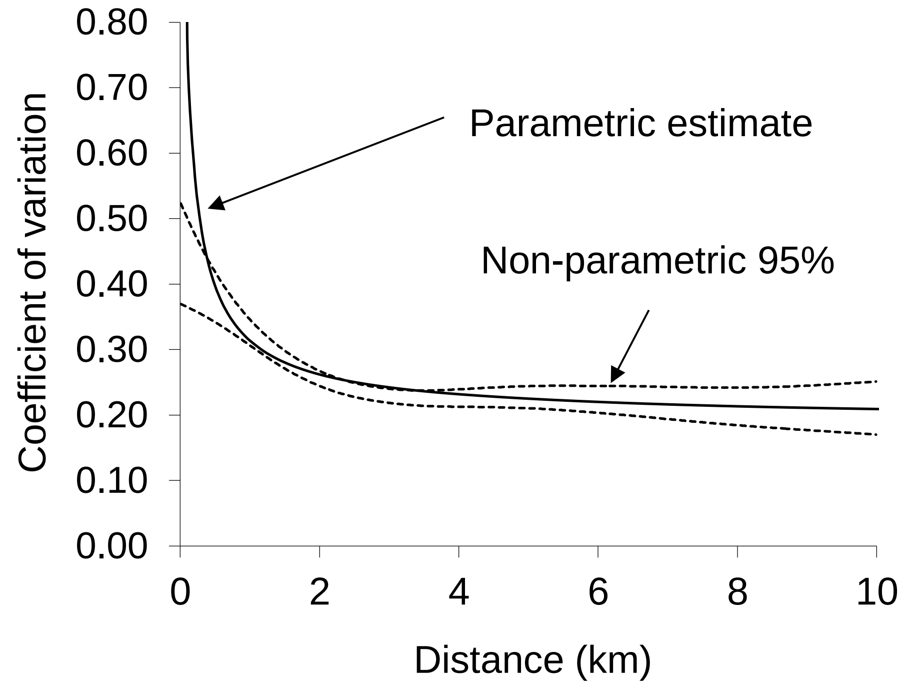


Parametric Functions



Travel Times: Median and Coefficient of Variation

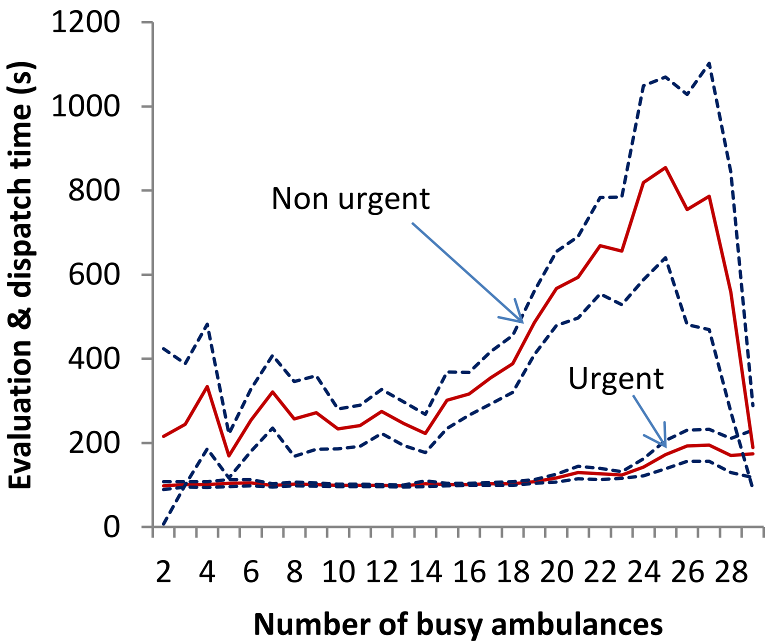


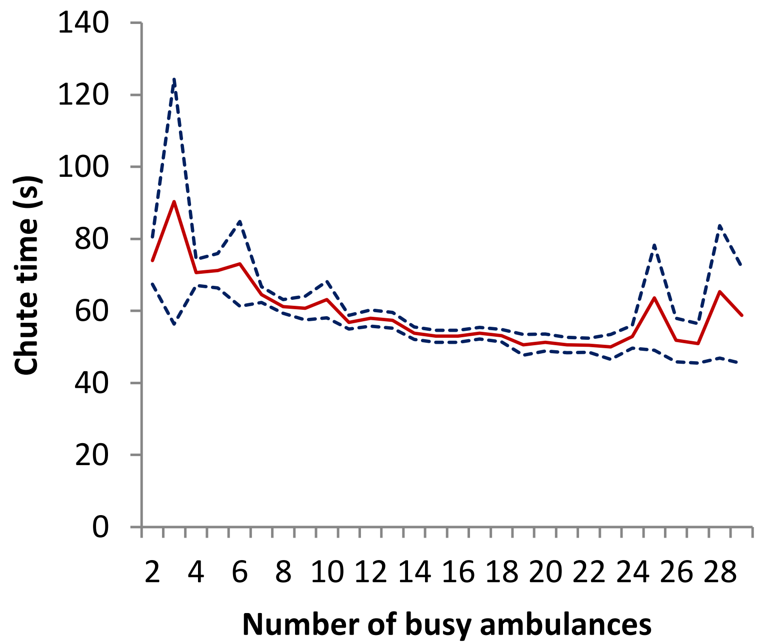


$$p_{ij} = \Pr\{\text{Travel time} \leq 9 \text{ min.}\}$$

Alanis, R., Ingolfsson, A., & Kolfal, B. (2013). A Markov chain model for an EMS system with repositioning. Production and Operations Management, 22(1), 216-231.

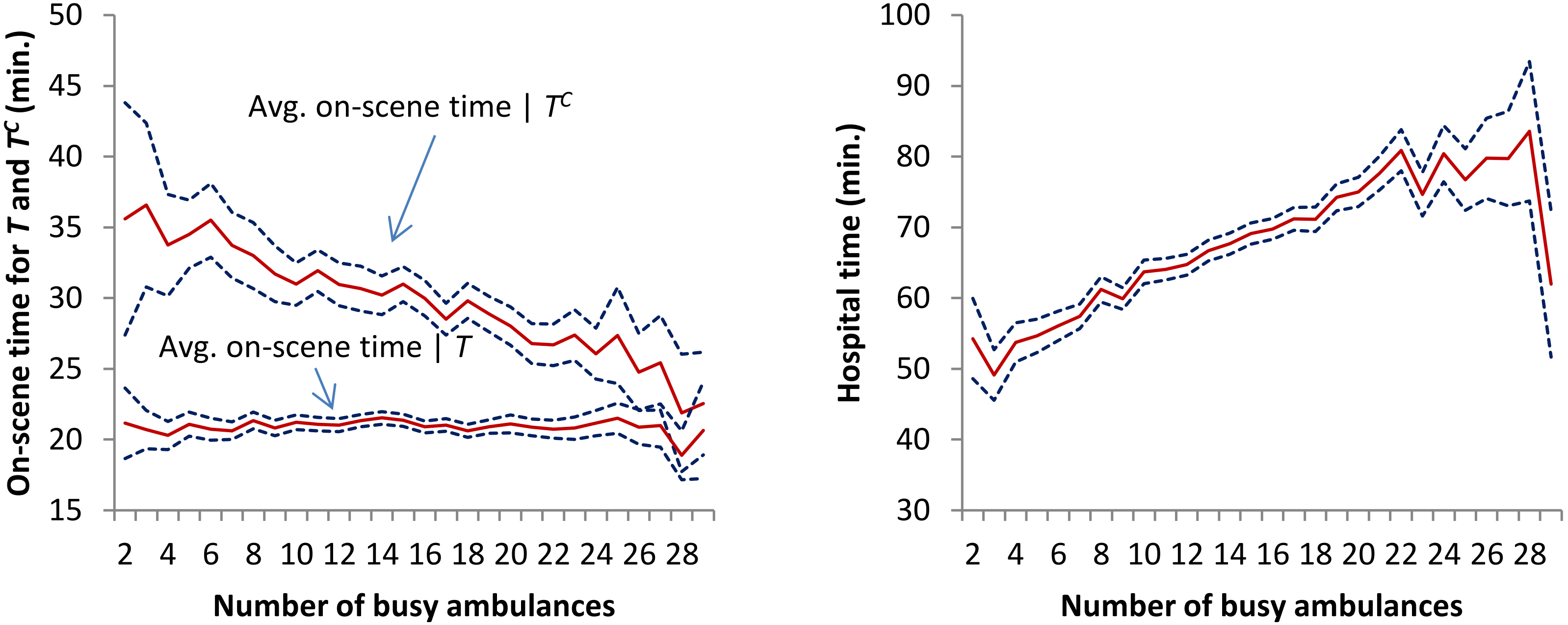
Pre-travel Delays





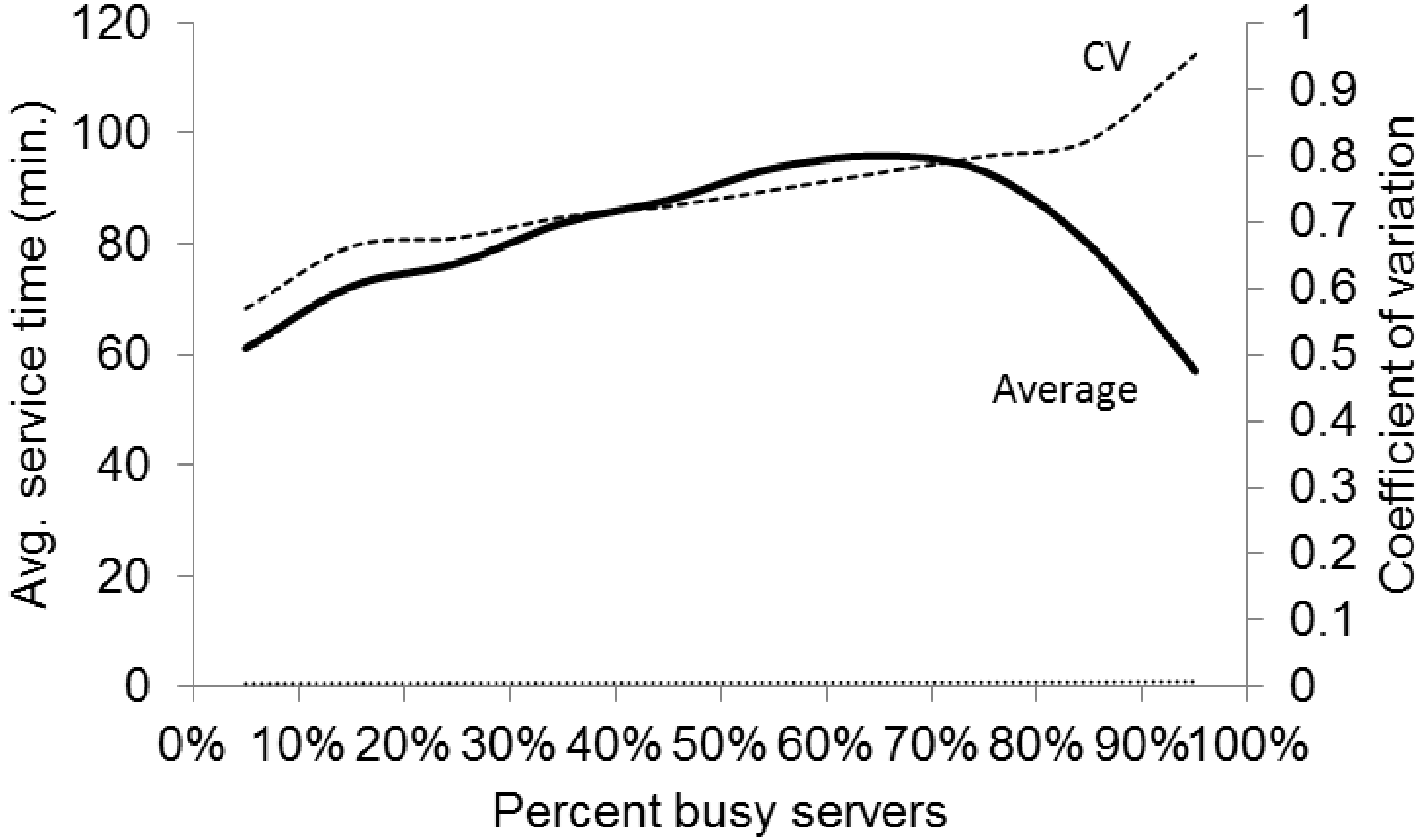
$$p_{ij} = \Pr\{\text{Pre-travel delay} + \text{Travel time} \leq 9\ \text{min.}\}$$

Scene and Hospital Times



Workload – needed to predict dispatch probabilities (f_{ij})

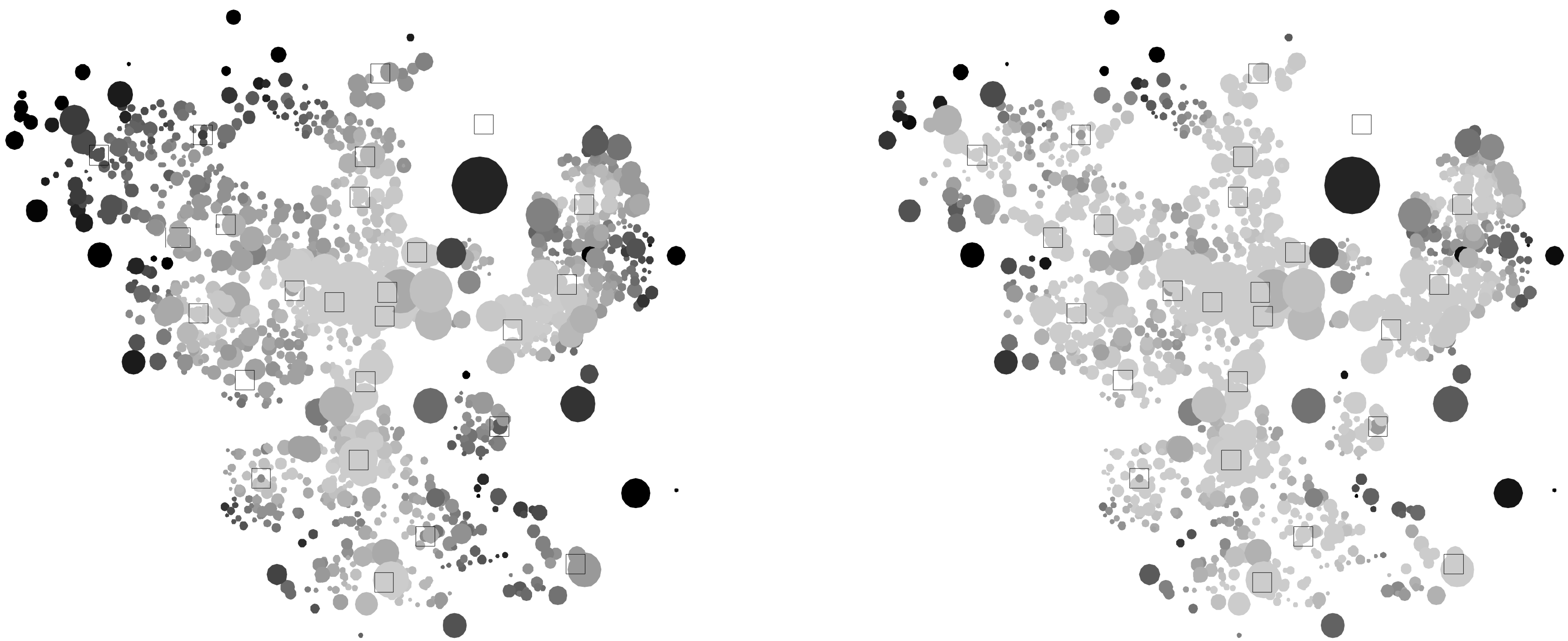
Overall Service Time



Probability-of-Coverage Maps

(a): Closest Available Ambulance Responds

(b): Closest Station Responds



Why Study EMS Data?

- <u>Fundamental knowledge</u>: Does average service time vary with system load? Why? Variation between regions and with system organization?
- <u>Modeling</u>: How can load-dependent service times be incorporated in EMS models? Validity, tractability, scalability.
- <u>Implications for planning</u>: 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 ha ... ect to emergency medical services (EMS) respo ... times.

Pursuant to Section 15(1) of the *Health Qua* ... lth Quality Council of Alberta (the Council) to ... medical services in Alberta.

The Review shall include but is not limited t ... respect to:

- transition issues related to the transfer of ... municipalities to the former regional hea ...
- 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

Review of Operations of Ground Emergency Medical Services in Alberta

In Accordance with Section 15 (1) of the *Health Quality Council of Alberta Act*

January 2013

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 (90th 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

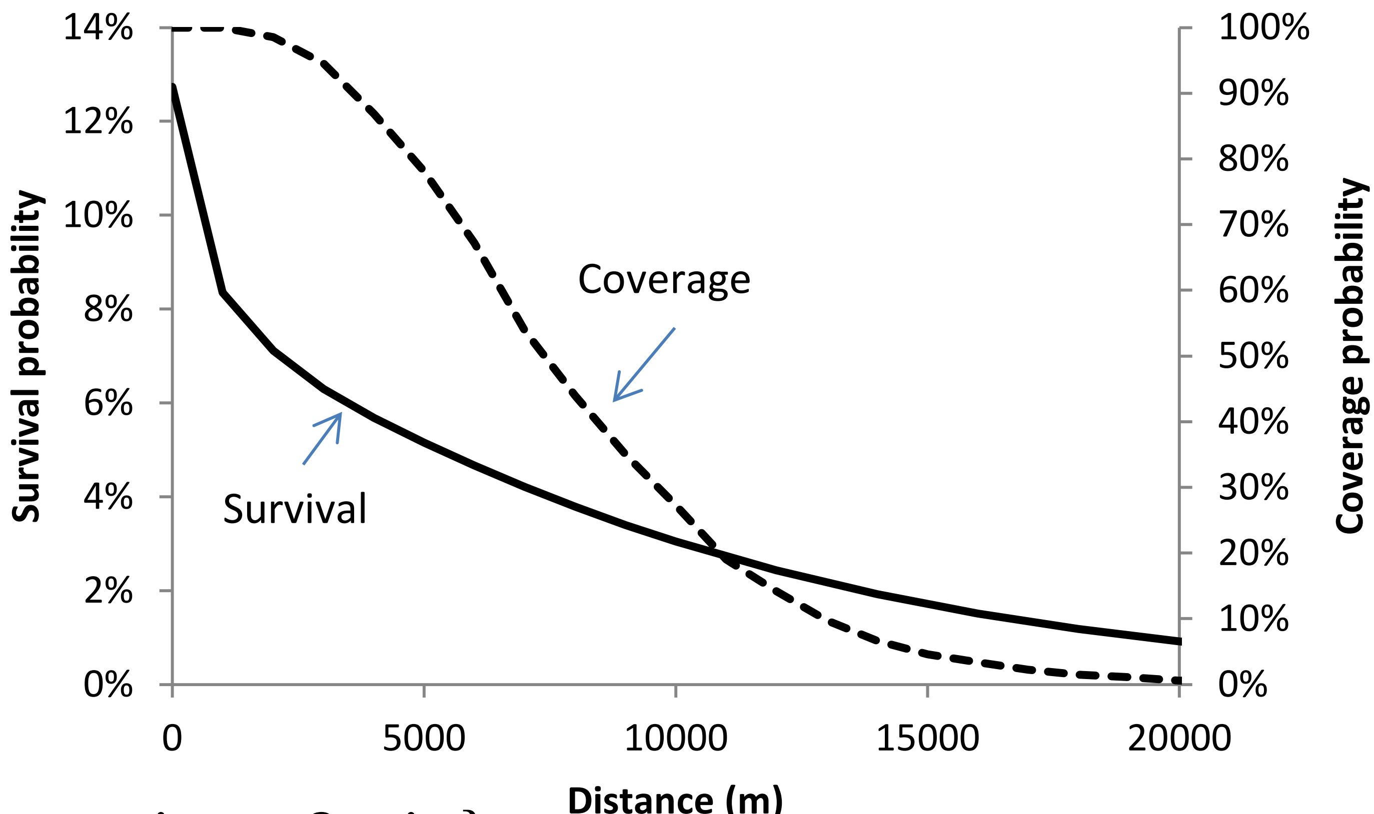
Access to Medical Care vs. Urban Sprawl

Can Medical Outcomes by Incorporated in Planning Models?

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

$$s(I_{\text{CPR}}, I_{\text{Defib}}) = \frac{1}{1 + \exp(-0.260 + 0.106 I_{\text{CPR}} + 0.139 I_{\text{Defib}}}$$

Coverage vs. Survival Probabilities



$$p_{ij} = \Pr\{\text{Response time} \le 9\ \text{min.}\}\ \text{vs.}$$

$$p_{ij} = \Pr\{\text{survival}\}$$

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