Fleet tracking through Model-Adaptive Event Triggering

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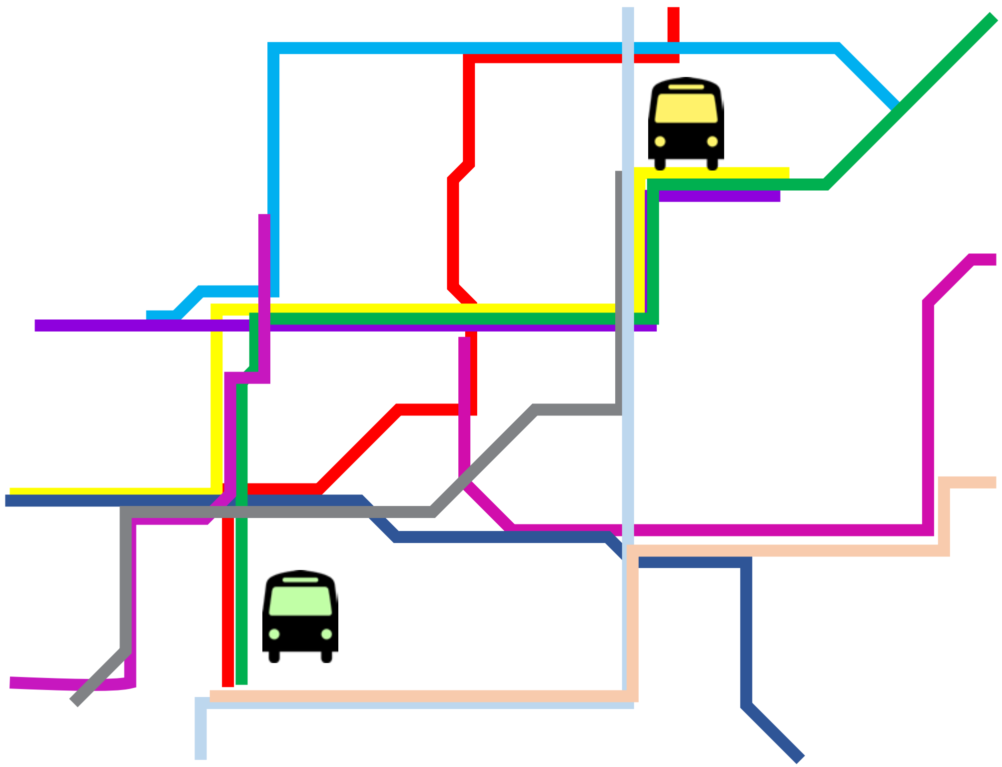
Background

- KIOS Research Center
  - Established in 2008 as part of the University of Cyprus
  - Upgraded to **KIOS Centre of Excellence** in 2017 through H2020 TEAMING
  - Strategic collaboration with Imperial College London
- Dedicated to the study of intelligent systems and networks applied to Critical Infrastructures.
- Collaborations with national and international industrial and governmental organizations.

Transport Research @ KIOS

- Monitoring, Control, Management and Security of Intelligent Transportation Systems (ITS)
  - Fault-tolerant traffic management
  - Intelligent Bus Fleet Monitoring
  - UAV-based Traffic Monitoring
- New architectures for congestion-free routing (applied to autonomous vehicles)
- V2X communication for innovative services

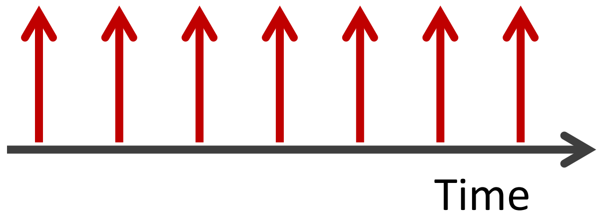
Intelligent Bus Fleet Monitoring

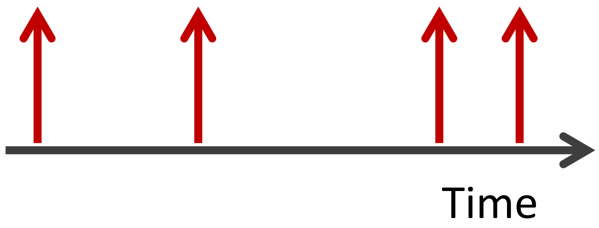


Event Triggering

- **Paradigm shift**

  Continues triggering → Periodic triggering → Aperiodic triggering



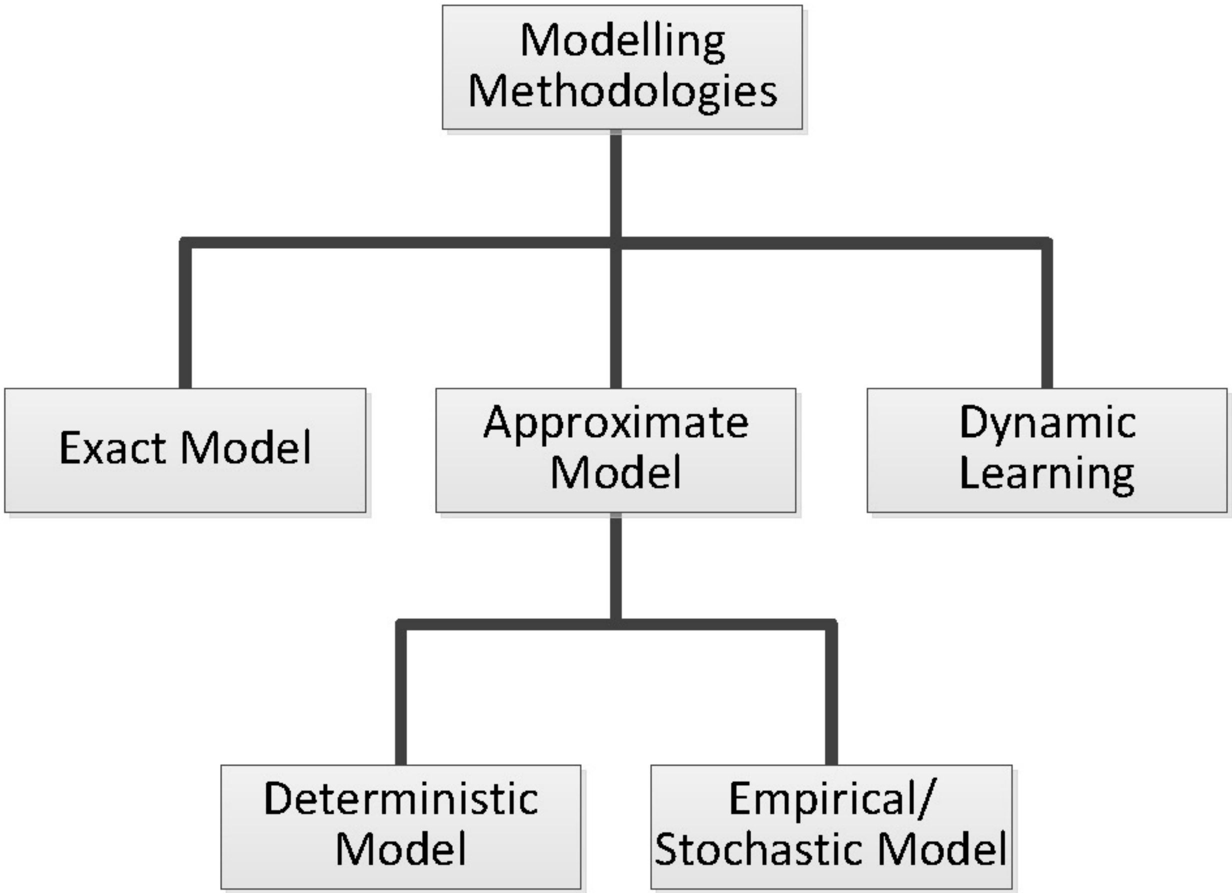


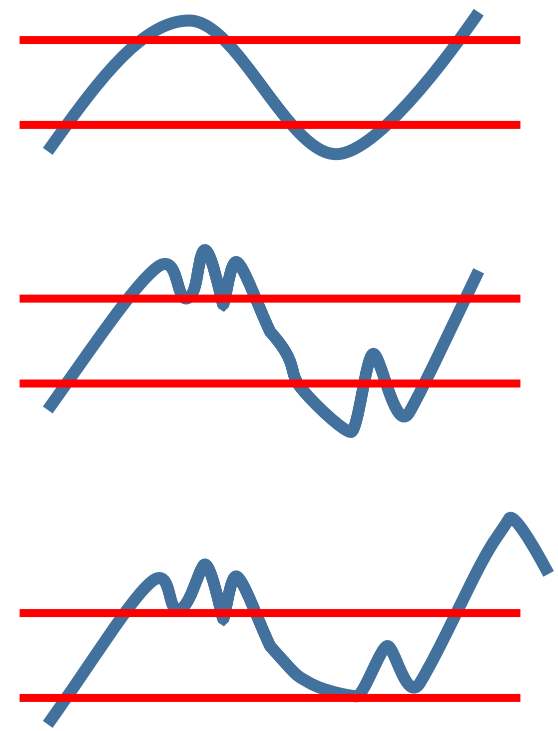
- Events triggered using for example:

  thresholds, **state observers**, **residuals**, **etc**

- Wakeup occurs only when an **event** is triggered
  - Resource-utilization centric approach
  - Shown to benefit control stability due to reduced computational load
  - Achieve data minimization due to thrifty data exchange

Model-based triggering





Stochastic Event Triggering

- Stochastic

  having a random probability distribution or pattern that may be analyzed statistically but may not be predicted precisely

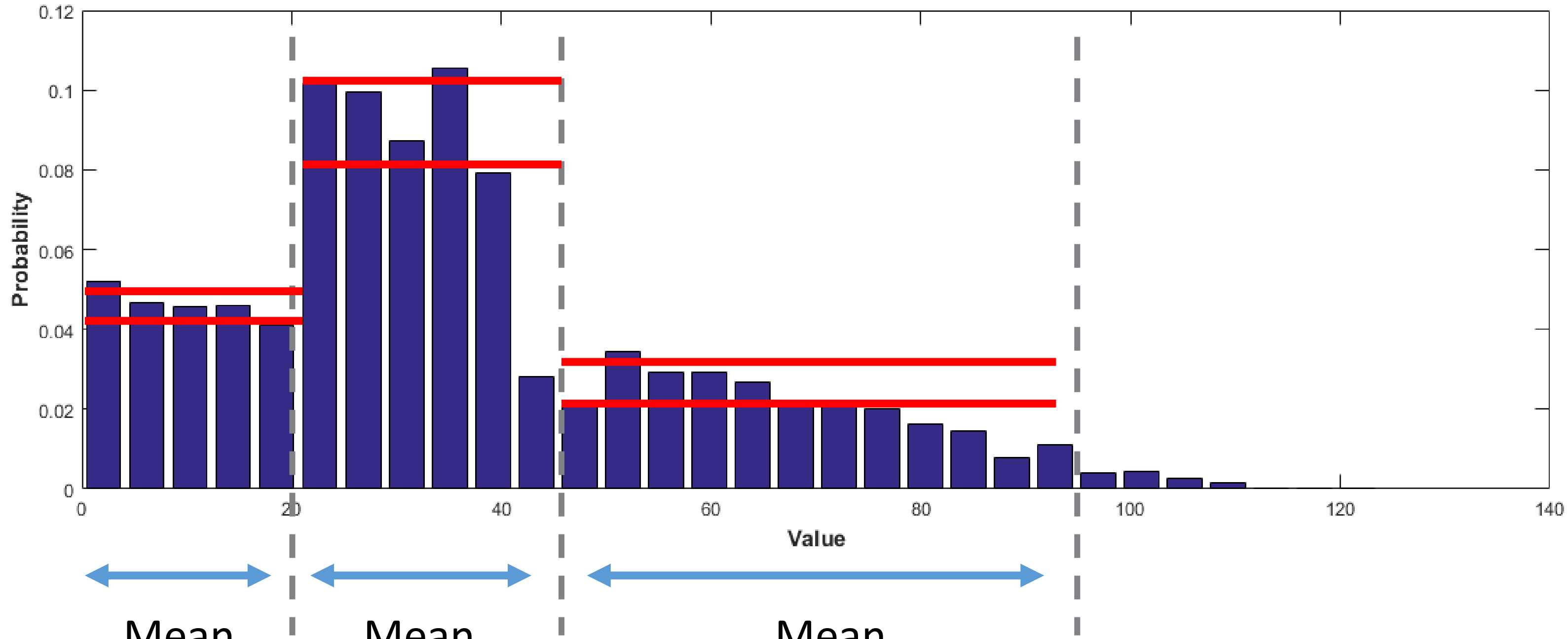
$$\theta_{lN}^{k} = \frac{1}{N}\sum_{n=1}^{N}[t_{ln}]^{k} \qquad \theta_{l(N+1)}^{k} = \frac{1}{N+1}\sum_{n=1}^{N+1}[t_{l(n+1)}]^{k}$$

$$= \frac{N\theta_{lN}^{k} + [t_{l(N+1)}]^{k}}{N+1}$$

- Binomial transform to compute central moments

$$\theta_{lN}^{k} = \sum_{i=0}^{k}\binom{k}{i}(-1)^{k-i}\theta_{lN}^{k}(\theta_{lN}^{1})^{\,k-i}$$

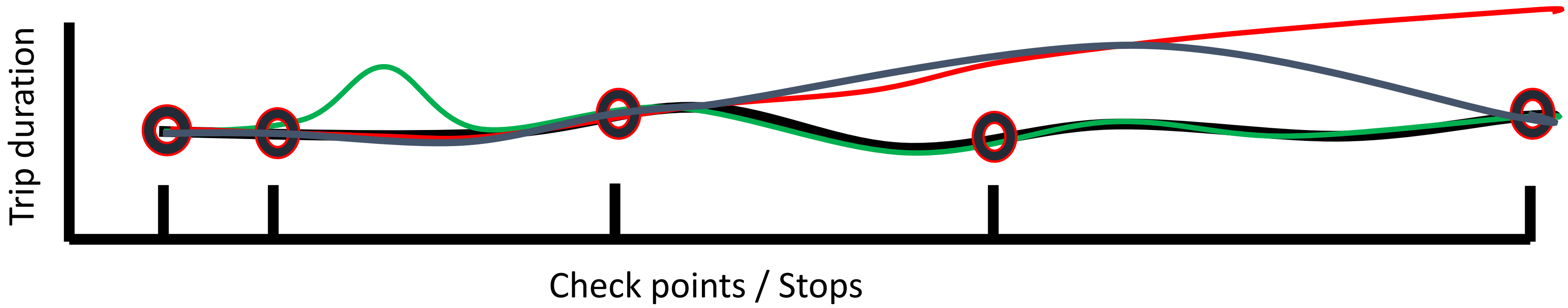
Kernel density estimates



Mean	Mean	Mean
Std	Std	Std
Skewness	Skewness	Skewness
Kurtosis	Kurtosis	Kurtosis

- Event triggering times are probabilistically bounded depending on the threshold sensitivity

Setting the thresholds



- Consider each segment between consecutive check points (i,j)
  - Let t_{ij}^{n} be the travel tip between (i,j) for successive iterations (n)
  - Different statistics can be computed for each (i,j)
    - τ_{ij} mean travel time
- Then τ_{ij}– a provides a probabilistic bound on the expected trip duration for each (i,j)

Formulation and Solution

- Probability of consecutive events:

$$P(i,j) = \bar{P}(i,i+1) \times (i,i+2) \times \cdots \times \bar{P}(i,j-1) \times (1-\bar{P}(i,j))$$

- Probability of no event

$$\bar{P}(i,j) = P(\tau_{ij} - a \leq S_{ij} \leq \tau_{ij} + a)$$

- Border conditions should also be considered

$$\bar{P}(1,i) \; \& \; \bar{P}(j,B)$$

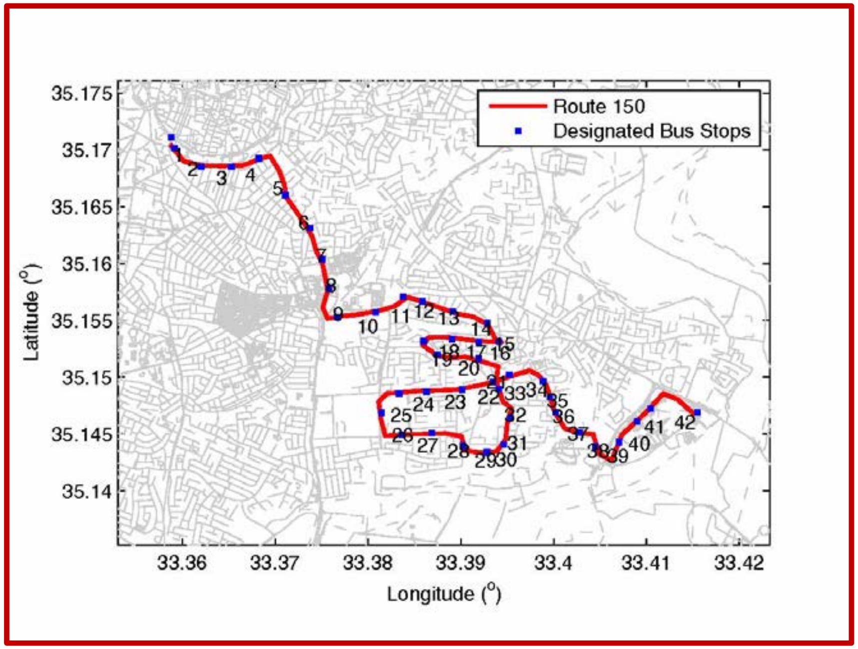
- Probability of all possible combination of events

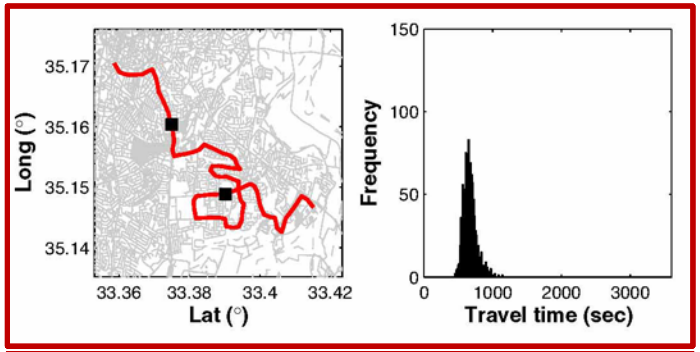
$$P_T = \sum_{c=1}^{C} \prod_{k=1}^{K} [P(\boldsymbol{C}_{ck}, \boldsymbol{C}_{ck+1})] \times P(1, \boldsymbol{C}_{c1}) \times P(\boldsymbol{C}_{cK}, B)$$

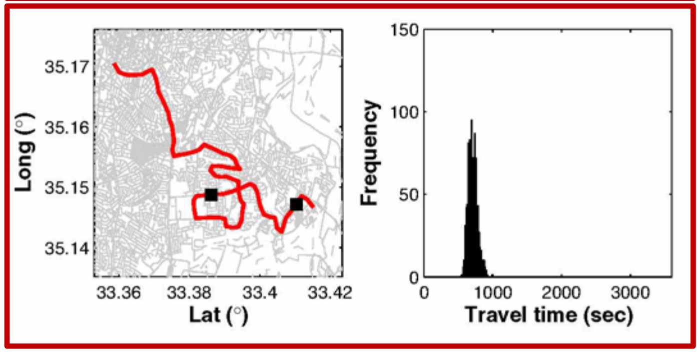
- Solved using the Bisection method

Fleet monitoring

- GPS traces collected from buses serving route 150 of the Transport Organization of Nicosia District (OSEL)
  - Every 15 seconds, from 3 buses
  - 500,000 traces considered

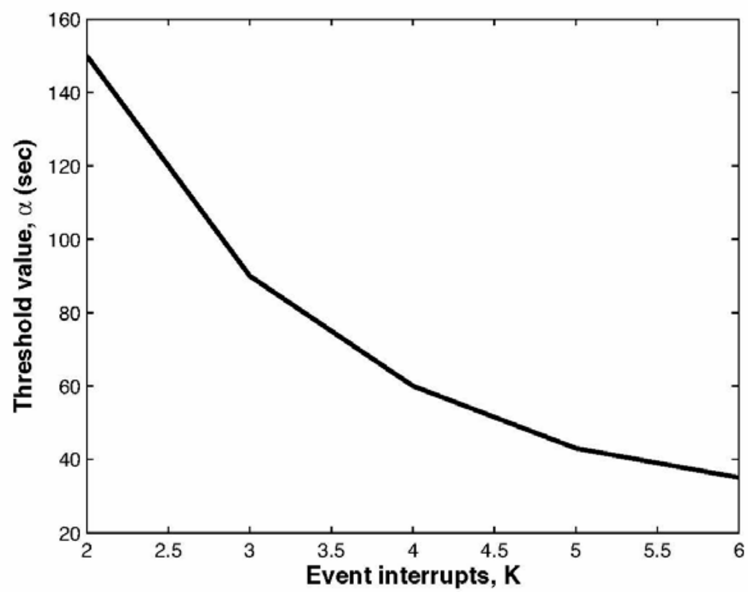


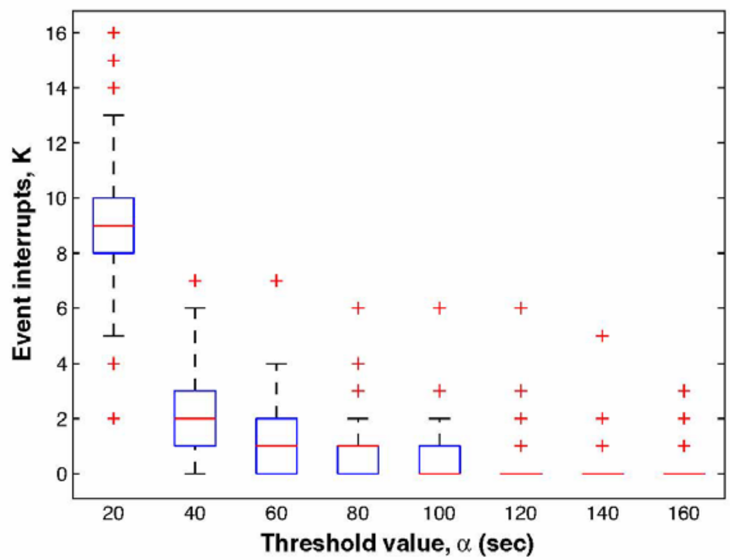




Fleet monitoring

- Threshold tightens dramatically with increasing volume in K
  - 80% of samples used to compute bounds, 20% for testing
  - Threshold vs Events





Thank you for your attention!!!