Sensor Networks for Indoor Sensor Data Fusion

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Presentation at Chemical Biological Information Systems Conference, January 2007, Austin, TX

This work was supported in part by the Office of Chemical Biological Countermeasures, of the Science and Technology Directorate of the Department of Homeland Security and performed under U.S. Department of Energy Contract No. DE-AC03-76SF00098.

Why is Sensor Data Fusion in Buildings Important?

- People spend 90% of their time indoors
- Buildings are both direct and indirect targets
- Long residence time may result in many people exposed to agent
- Buildings can protect people
  - — active protection (filters, zoning for isolation, ventilation)
  - — passive protection (settling, sorption)

Operational Objectives of an Indoor SDF System

- Detect:
  - — confirm an attack has occurred
- Characterize event:
  - — locate and characterize sources
  - — identify contaminated areas in building
  - — predict future migration of agent through building
  - — identify safe zones, evacuation routes

- Assess hazards:
  - — predict exposures and casualties
- Respond:
  - — is information "actionable"?
  - — what is the response sequence?

Factors Complicating SDF and Decision Analysis

- Problem is inherently probabilistic and uncertain
  - — release conditions are unknown
  - — models are imperfect and potentially error-prone
  - — data may contain false positives/negatives

- Decisions are time-critical. Consequences exist for:
  - — responding too quickly to uncertain information
  - — delaying response until more information is available

- Monitoring is costly
  - — limited supply of hardware
  - — sensor hardware must be operated and maintained

Steps toward SDF and Sampler Siting

- Develop algorithm that accounts for uncertainties in:
  - release conditions (e.g, locations, amounts, durations)
  - dispersion drivers (e.g, HVAC operation, meteorology)
  - model parameters
  - sensor performance characteristics (e.g, effects of fouling on filters)

- Code software package that integrates:
  - fate and transport modeling
  - statistical inference techniques, and
  - optimization algorithms

- Test algorithm against data from real and synthetic experiments

- Refine algorithm and develop user-friendly software

Bayes Monte Carlo Formulation for Real-Time SDF

$$p(Y_k|O) = \frac{L(O|Y_k)p(Y_k)}{\sum_{i=1}^{K} L(O|Y_i)p(Y_i)} \tag{1}$$

- $p(Y_k|O)$ is the posterior probability of the k^{th} Monte Carlo simulation for prediction Y_k given the sensor measurements O;

- $L(O|Y_k)$ is the likelihood of observing measurements O given model prediction Y_k;

- $p(Y_k)$ is the prior probability of the k^{th} Monte Carlo simulation;

- N is the number of Monte Carlo simulations.

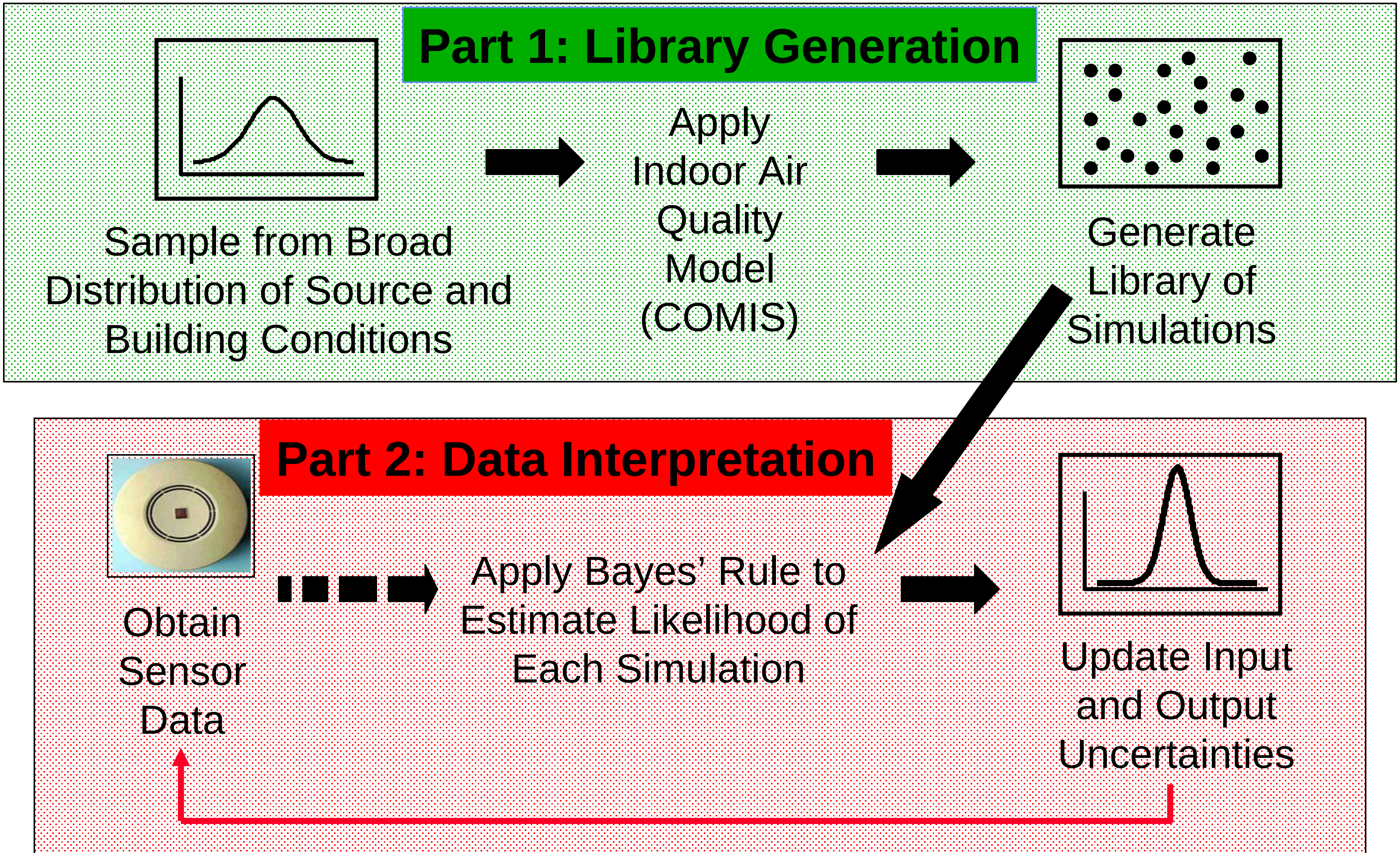
$$\mu'_V = \sum_{i=1}^{K} V_i \cdot p(Y_i|O) \tag{2}$$

$$\sigma'^2_V = \sum_{i=1}^{K} (V_i - \mu'_V)^2 \cdot p(Y_i|O) \tag{3}$$

- V and W represent any model input or output.

BASSET

(Berkeley Algorithm for Sensor System Engineering and Testing)



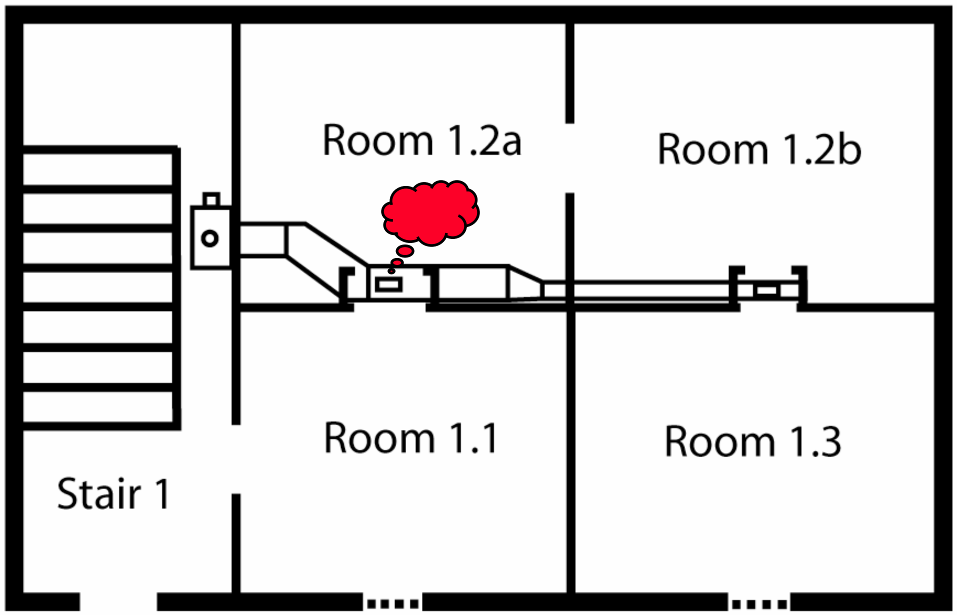
Illustrative Example:
Application to Real Building and Dataset

Test Facility at Dugway Proving Grounds, Utah

- A propylene tracer experiment represented a CB release event
- A tracer released at real possible source location: the intake of the HVAC in one of the rooms

Floor Plan of First Floor

- 3 floors
- 10 possible source locations
- Operational HVAC system
- Real-time sensors in each room
- Unknowns:
  - — source location
  - — source duration
  - — source magnitude
  - — door positions



Challenges to Test BASSET

1. Can we locate an unknown source by interpreting sensor data in real time?

   Sohn, M.D., Reynolds, P., Singh, N., Gadgil, A.J. (2002). Rapidly locating and characterizing pollutant releases in buildings: An application of Bayesian data analysis. *J. Air and Waste Management Association*, 52:1422-1432.

2. Can we locate an unknown source by interpreting trigger-type sensor data in real time?

   Sreedharan, P., Sohn, M.D., Gadgil, A.J., and Nazaroff, W.W. (2006). Evaluating sensor characteristics for real-time monitoring of high-risk indoor contaminant release. *Atmospheric Environment,* 40:3490-3503 2006.

3. Can we chose sensor performance characteristics when optimizing a network?

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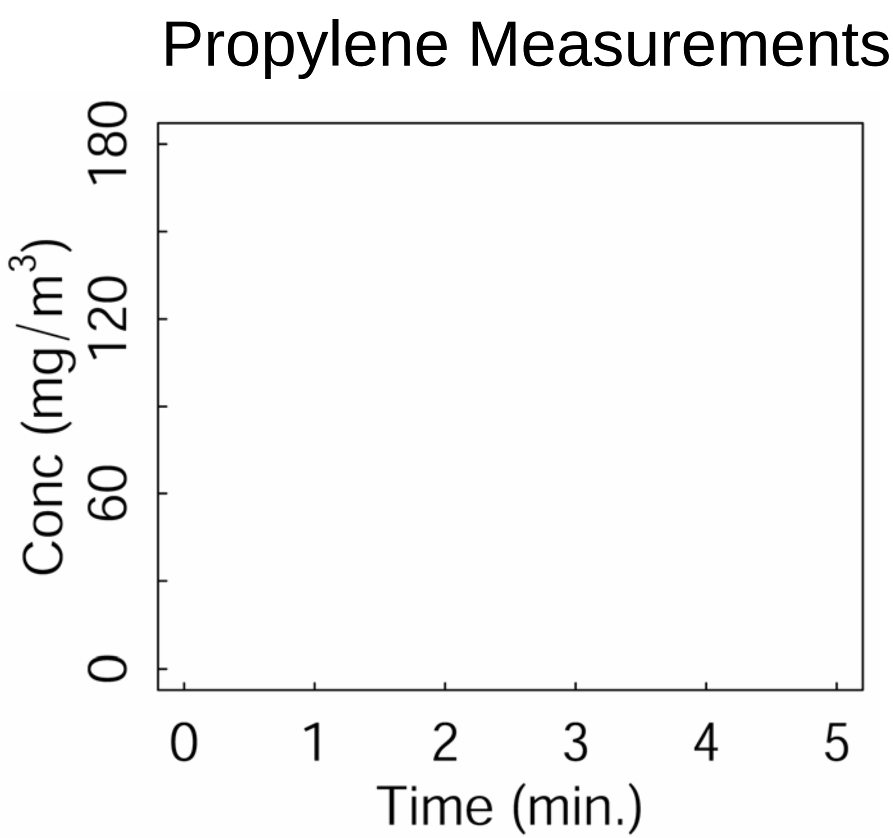
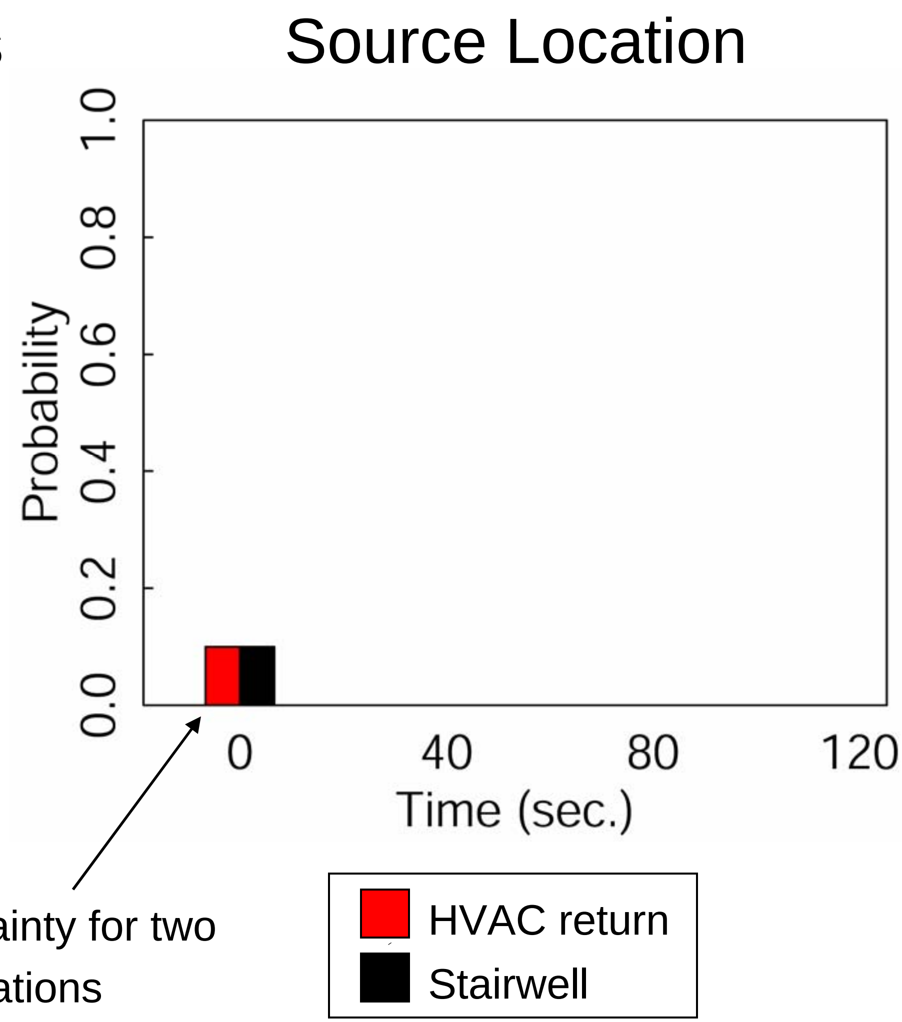
Estimating Source Location in Real Time

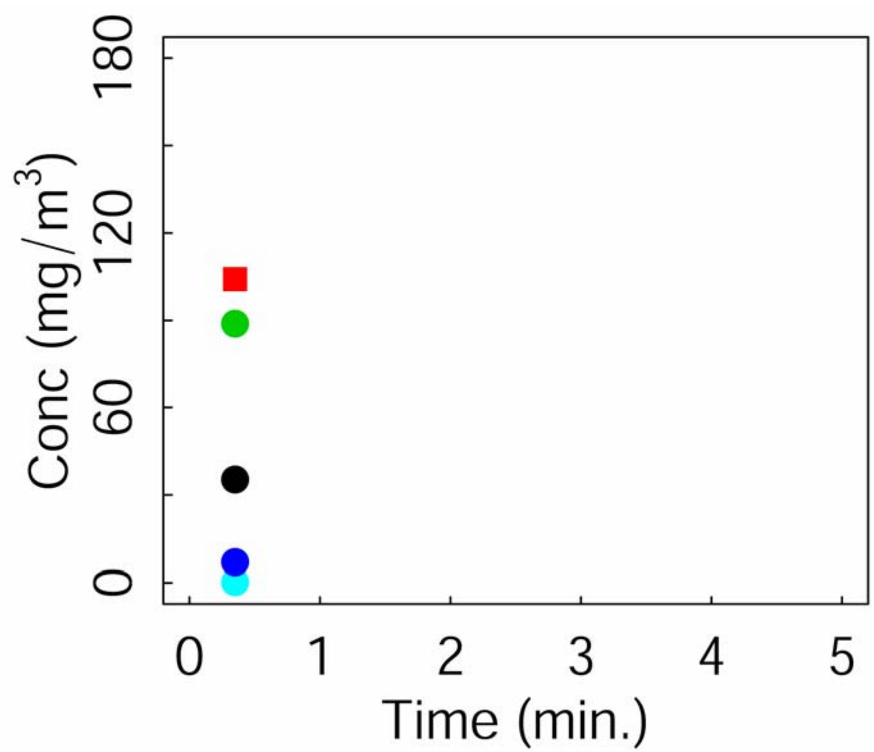




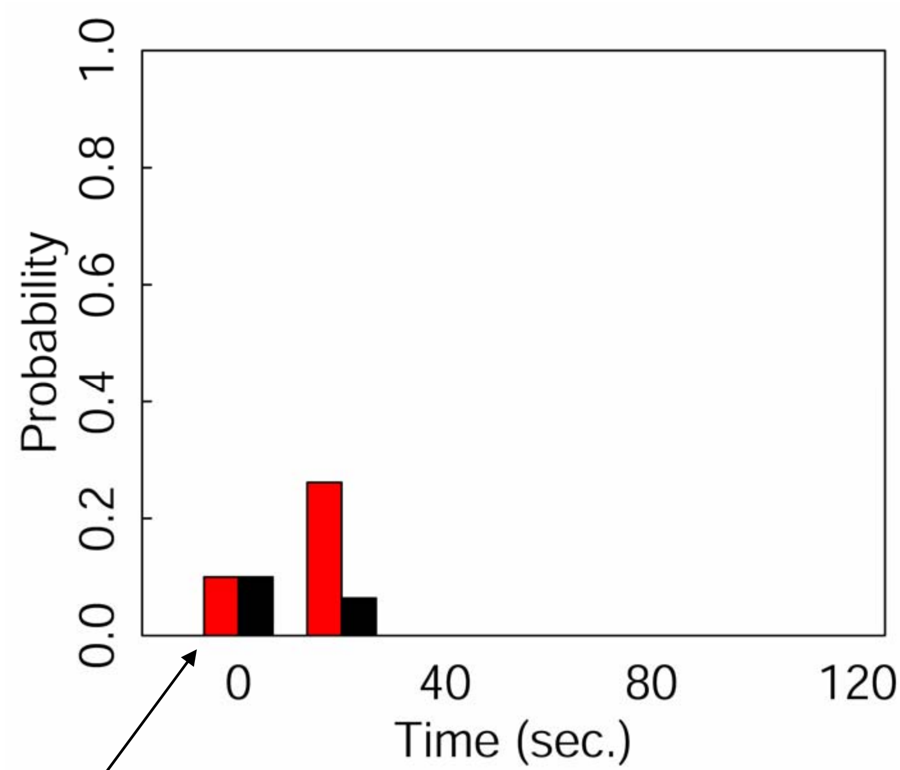
Initial uncertainty for two
of the 10 locations

Estimating Source Location in Real Time

Propylene Measurements



Source Location



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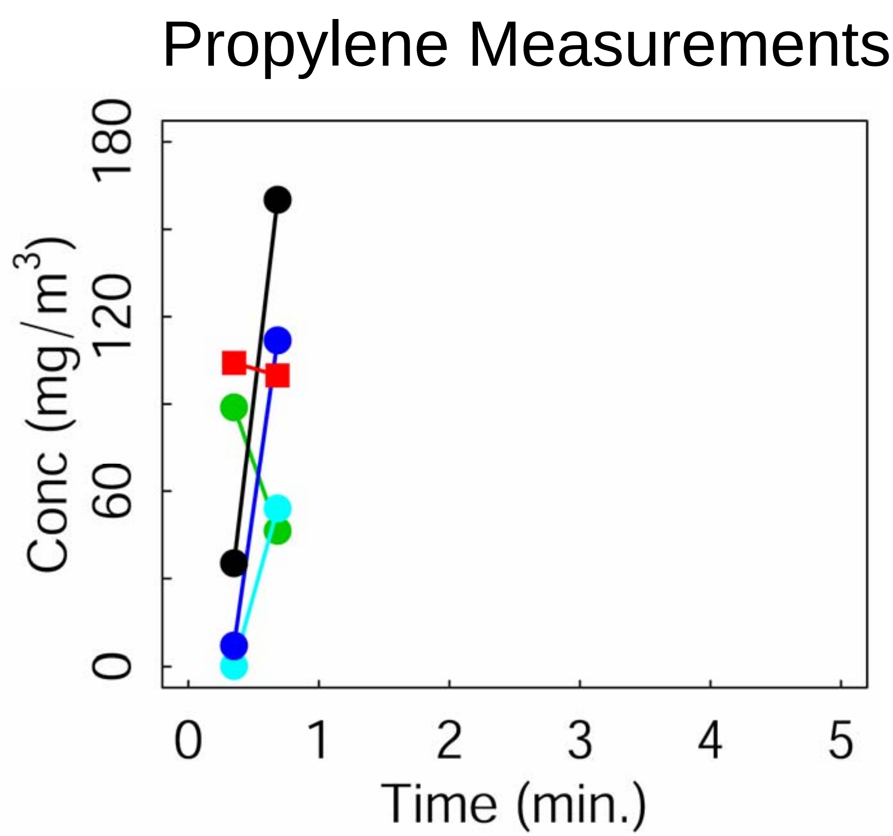
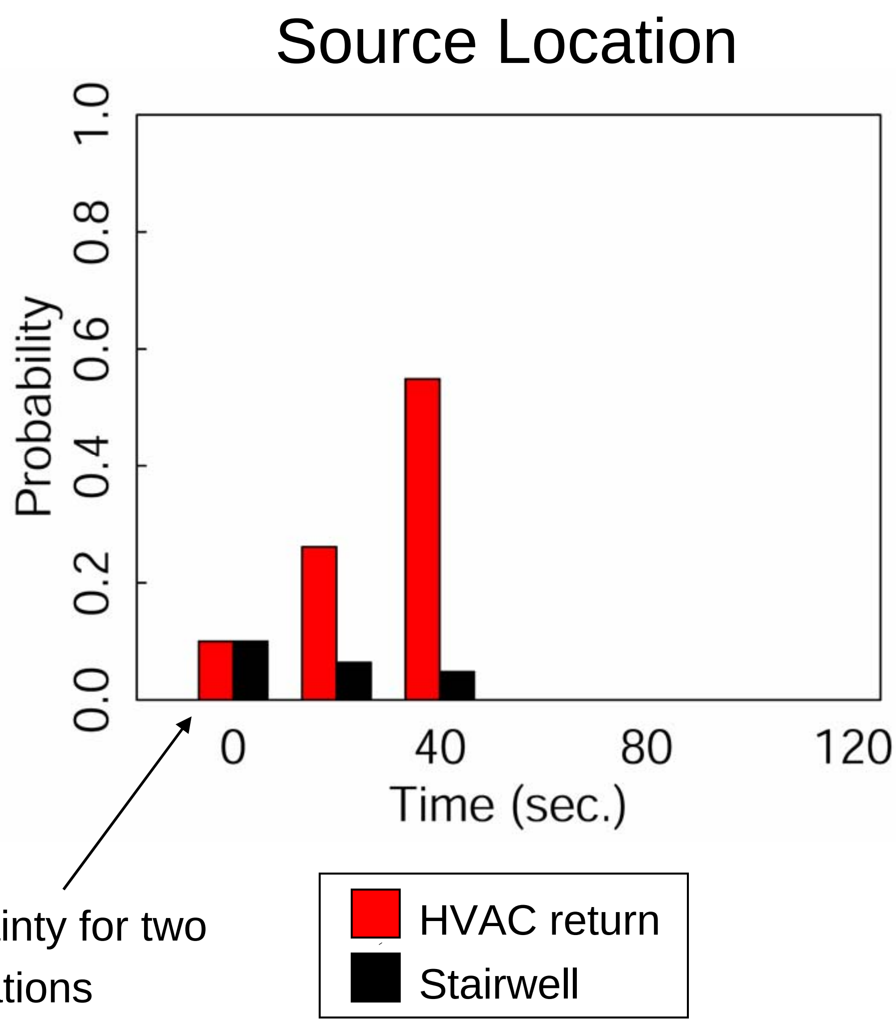
HVAC return

Stairwell

Estimating Source Location in Real Time





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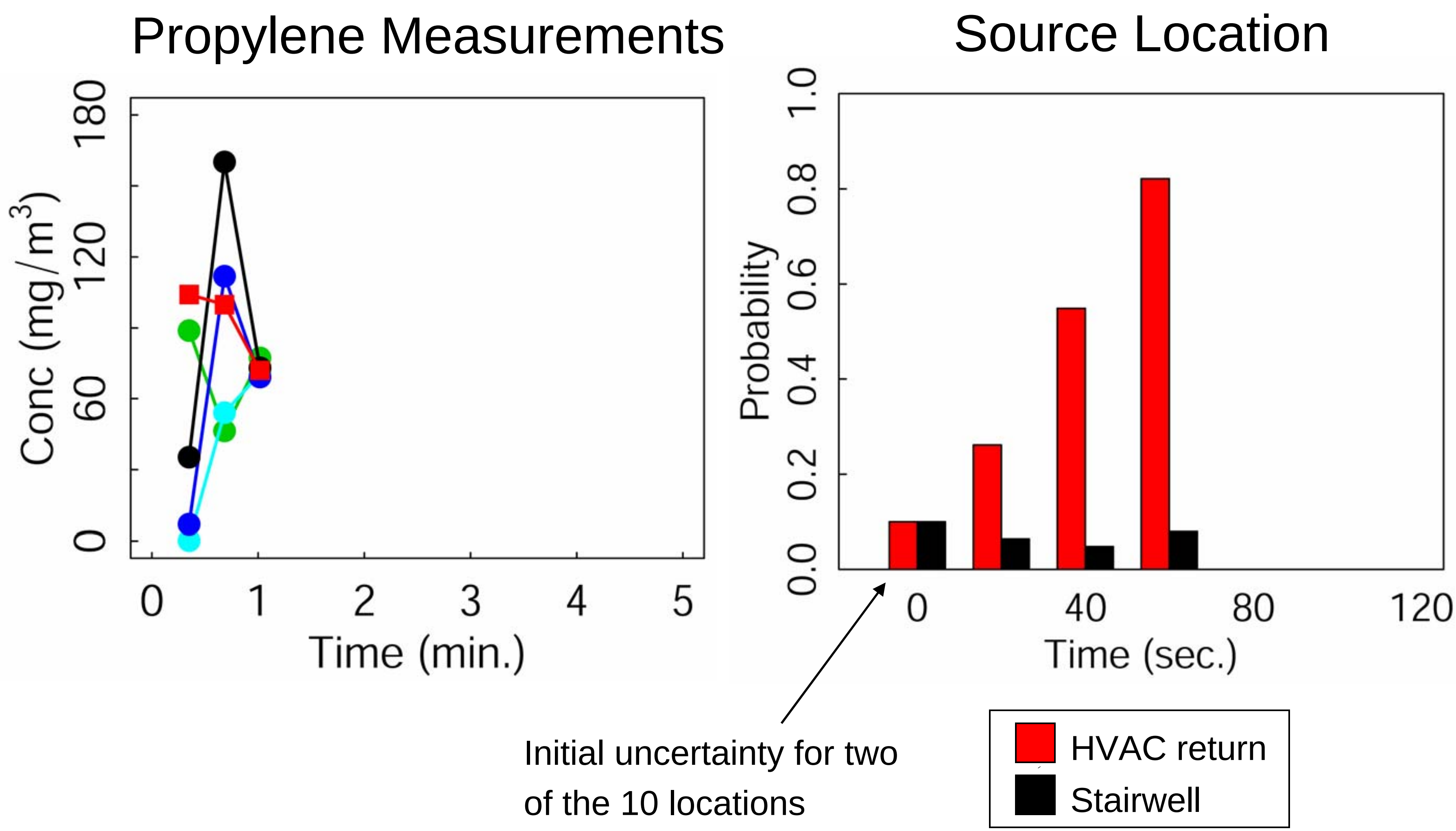

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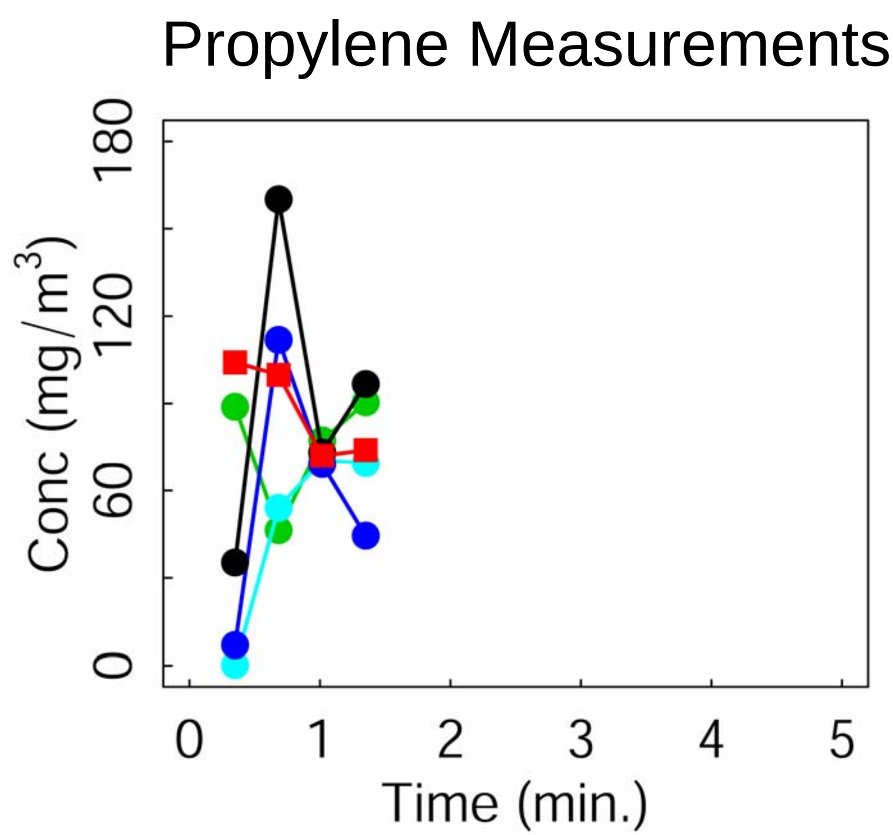

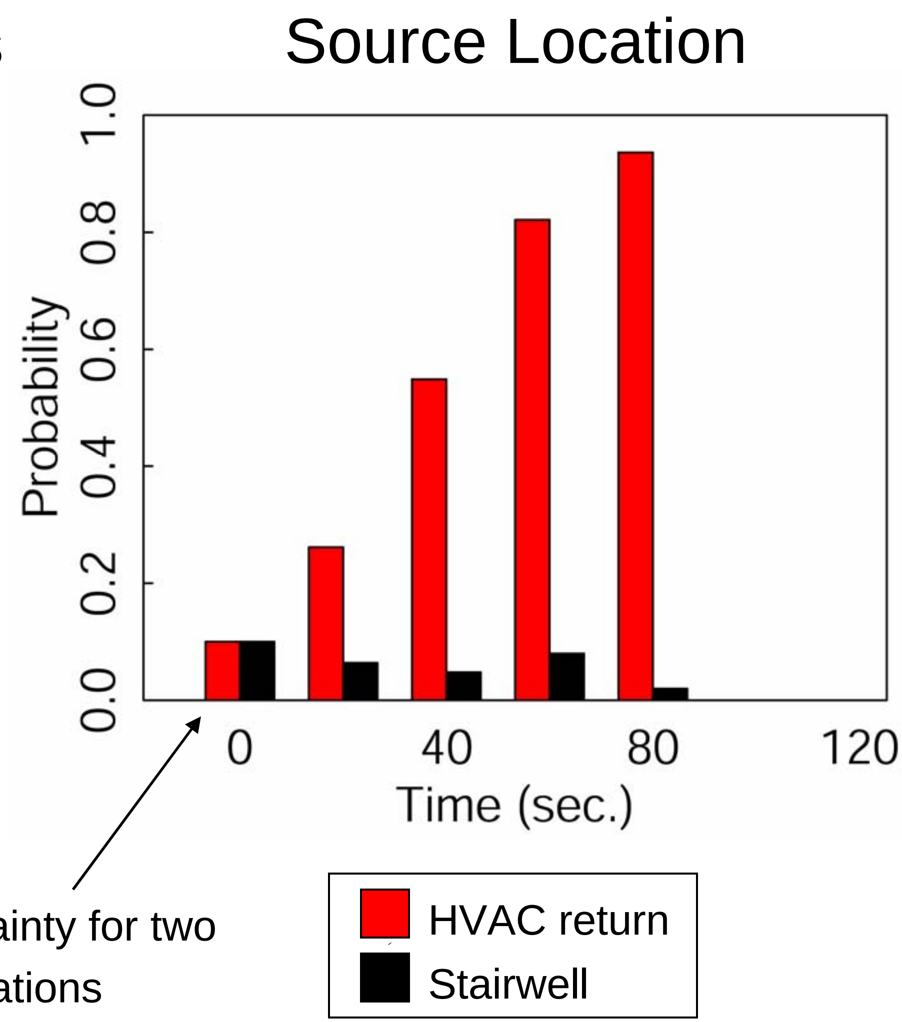

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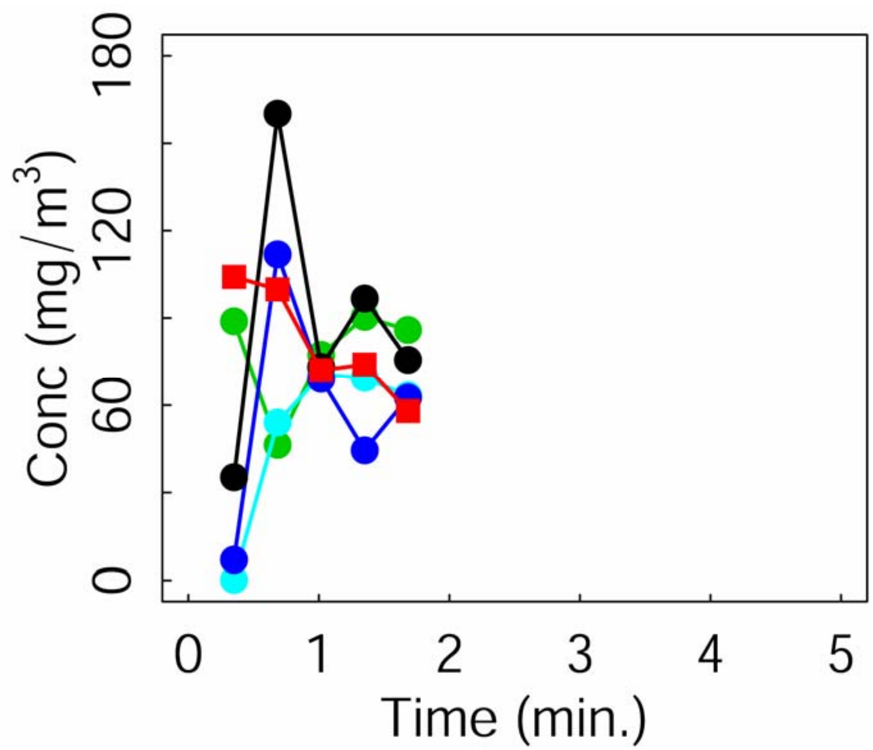
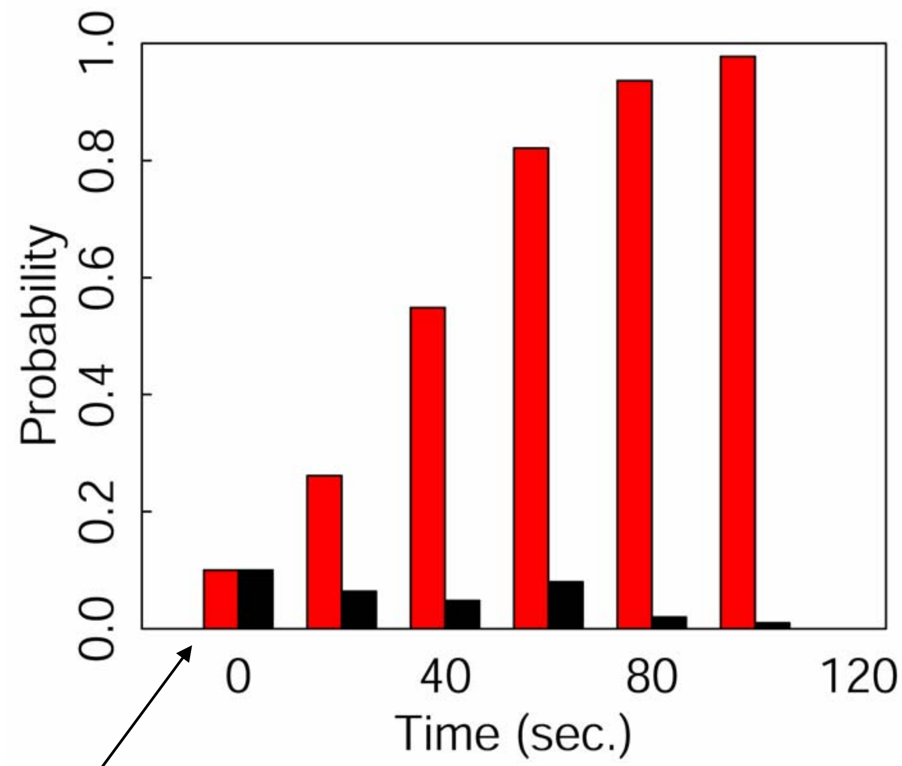


Source Location



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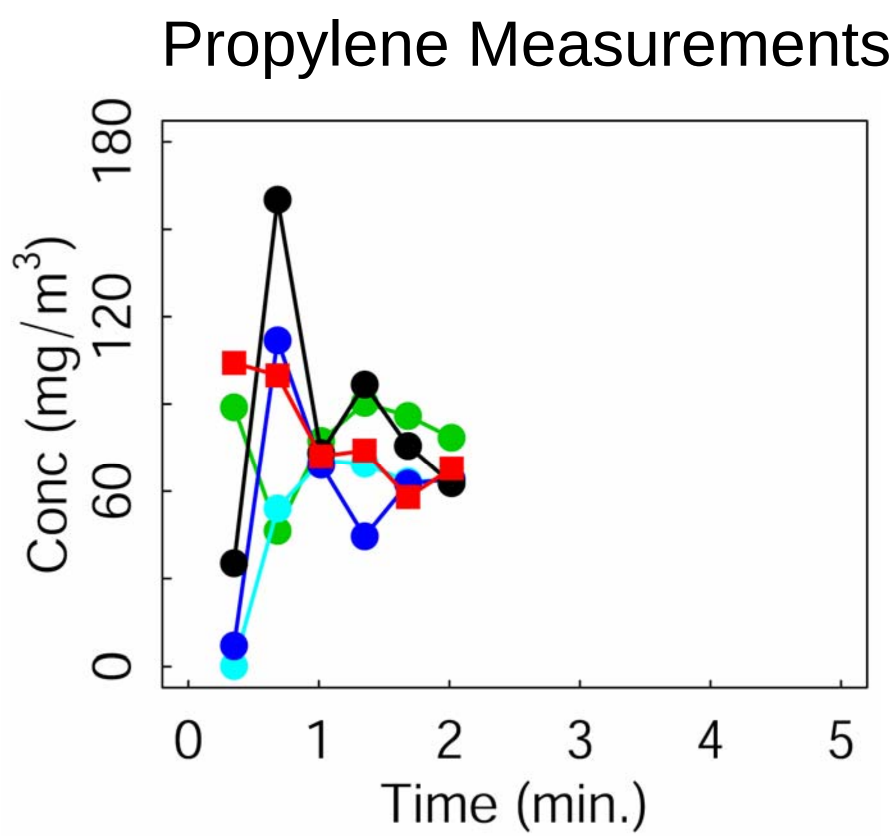

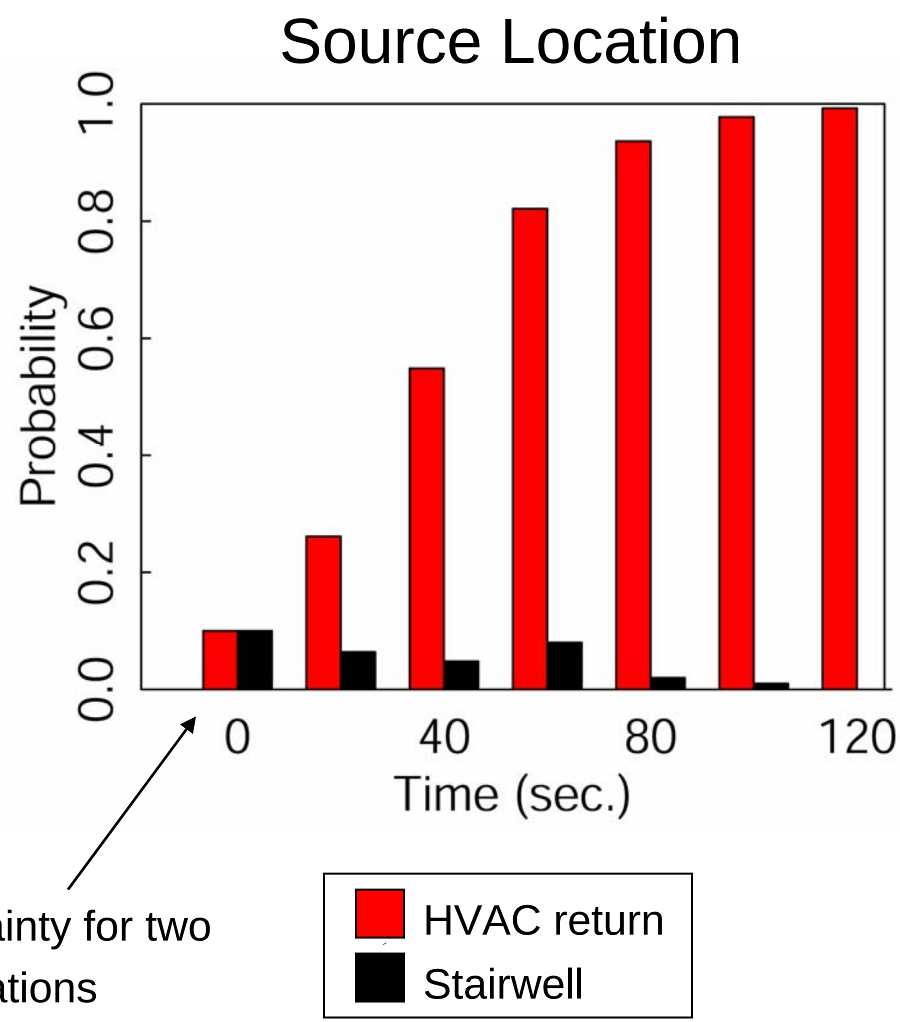

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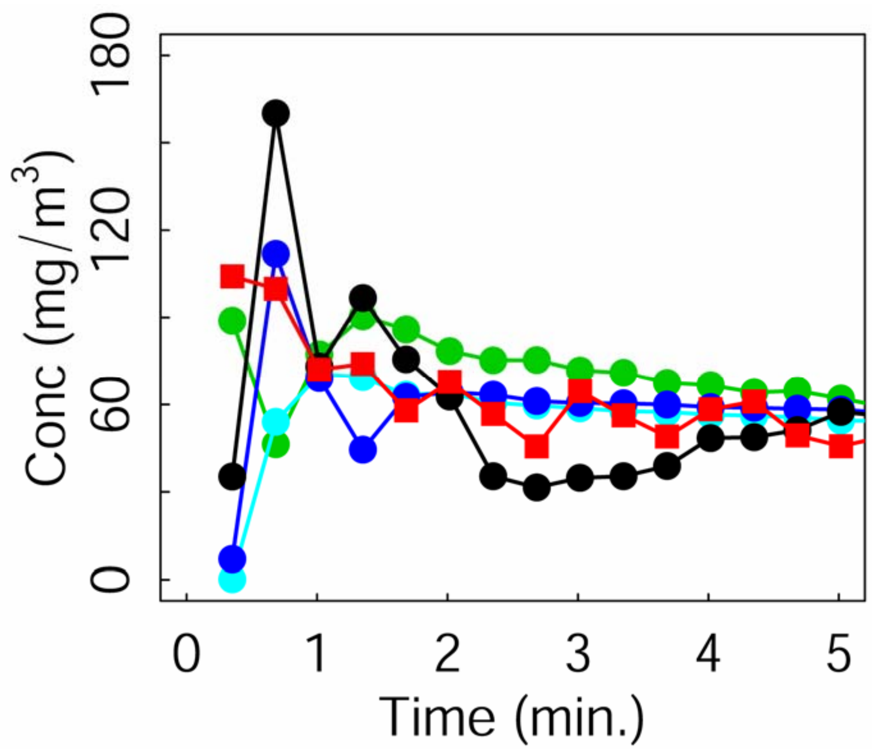

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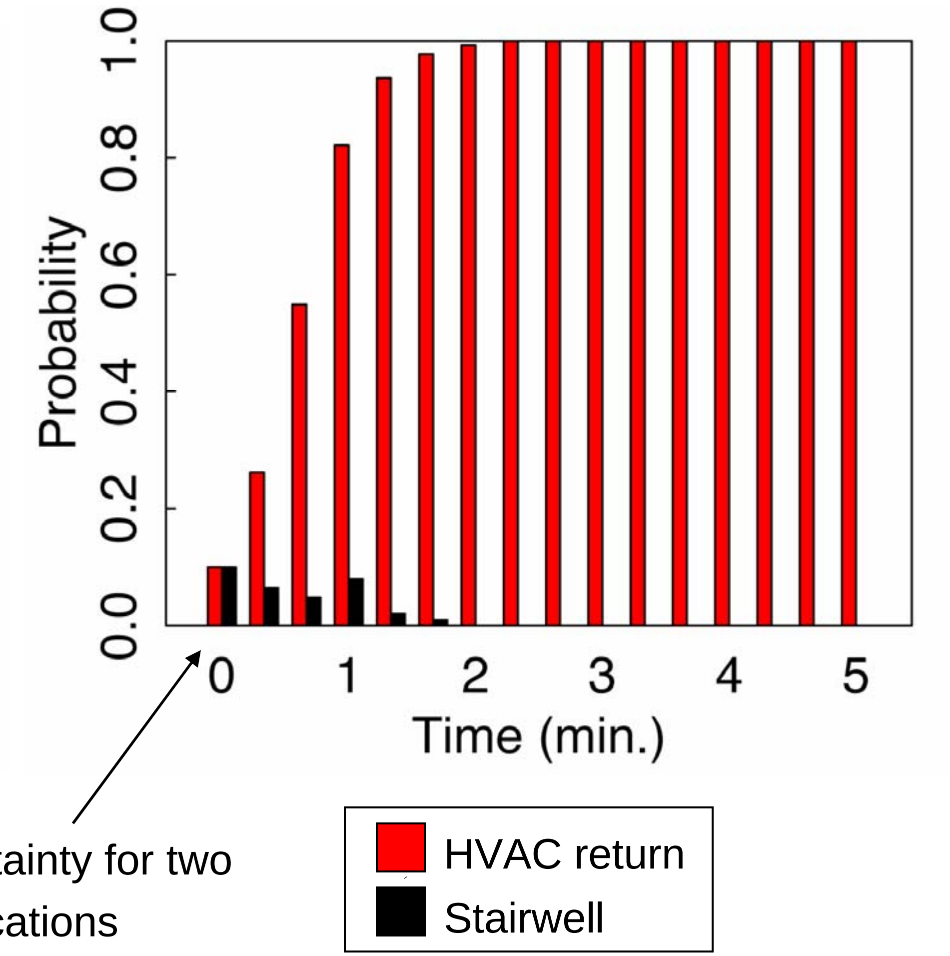
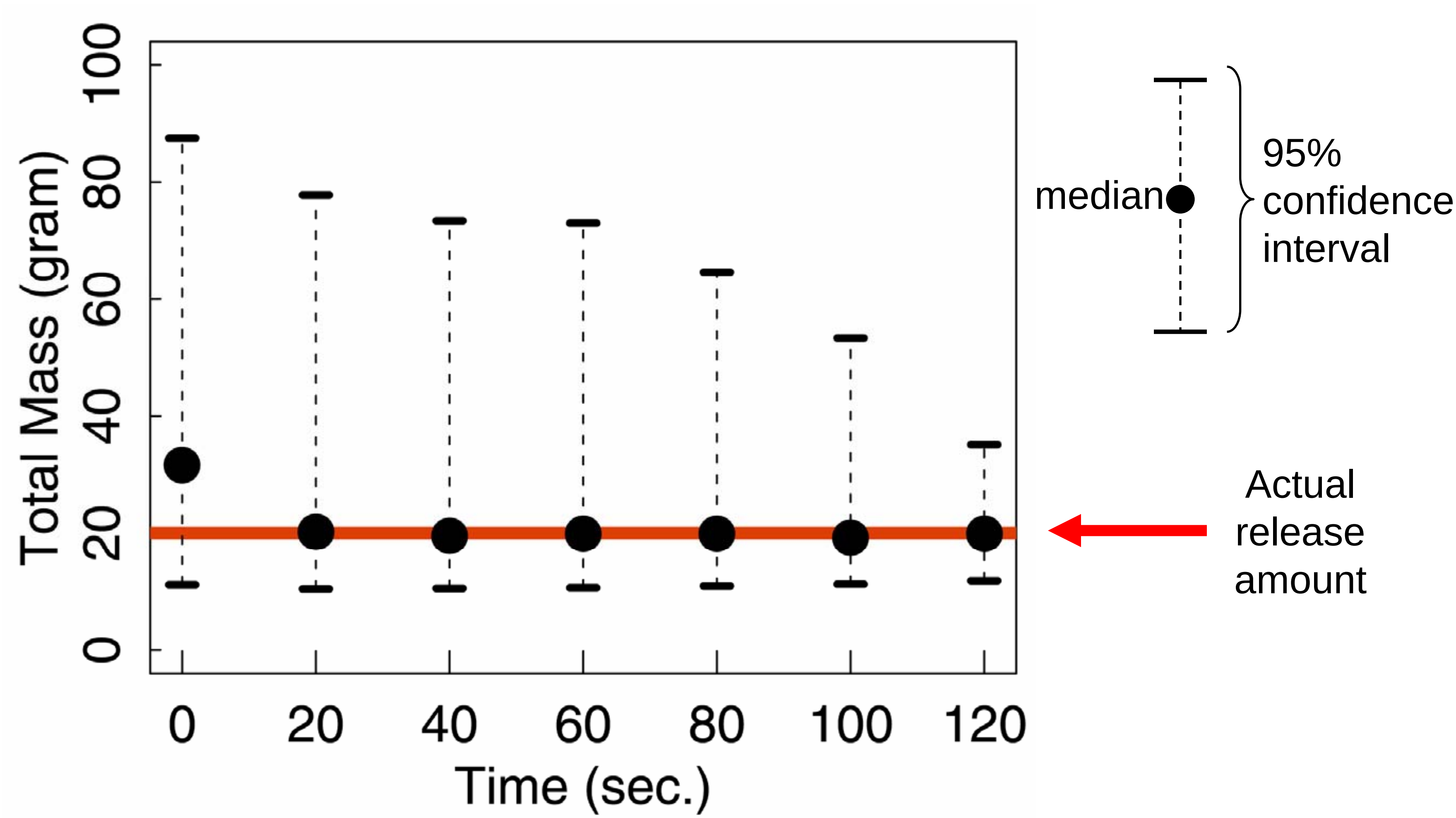


Estimating Amount Released in Real Time



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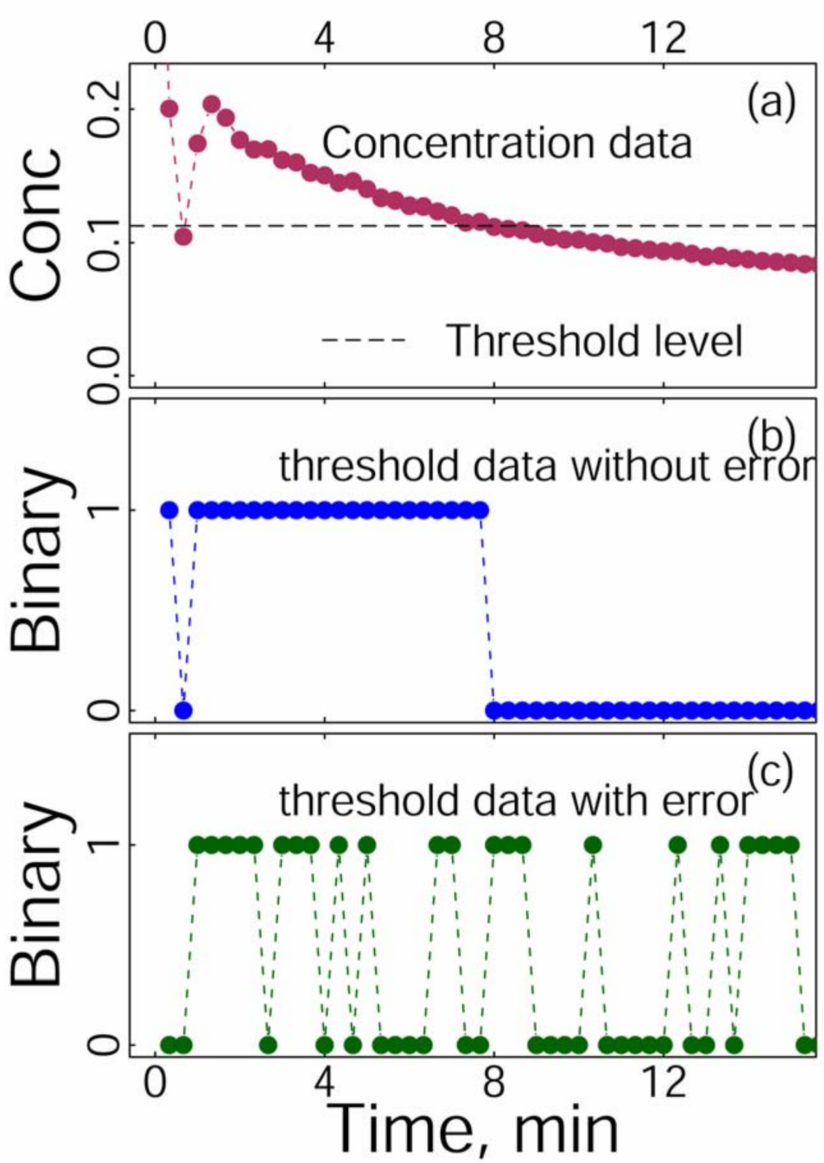
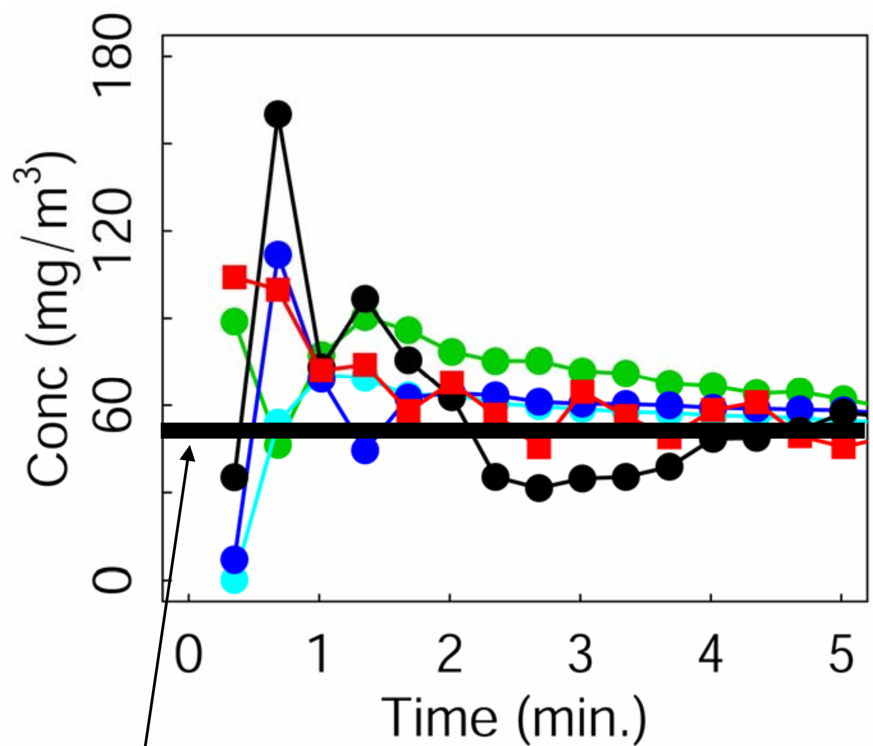
Can We Interpret Data Received as “Trigger” Alarms?



- Measurements above the line are flagged as a “1”, and those below as a “0.” BASSET only receives the flags.
- Flags are randomly corrupted with false positive and false negative rates. Tested rates of 10% and 30%.

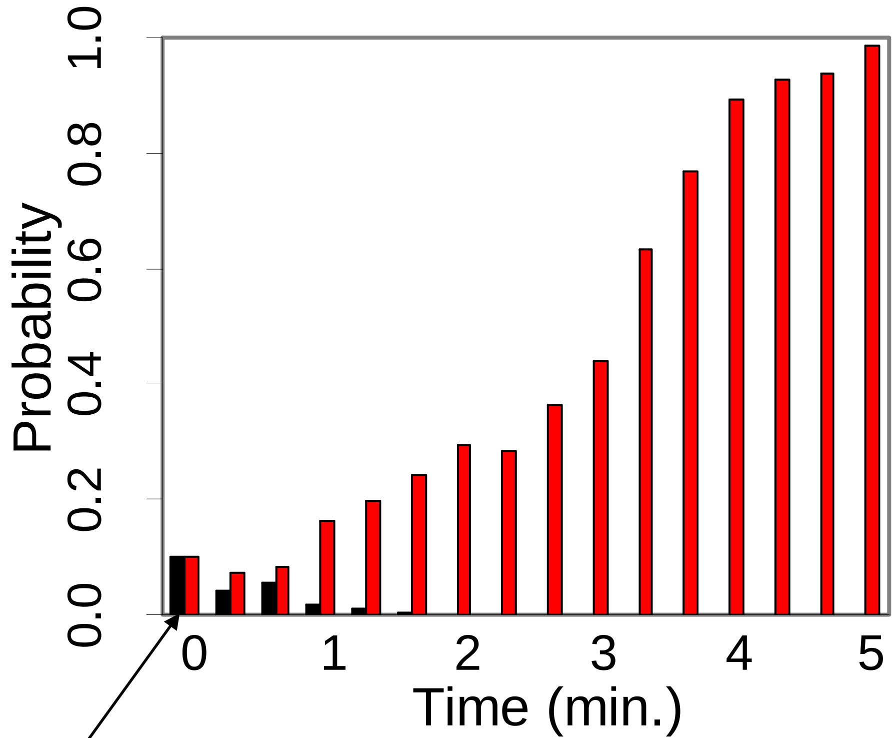
Locating Source using Trigger Alarms

Propylene Measurements



threshold = 55 mg/m^3
integration time = 20 sec

Source Location



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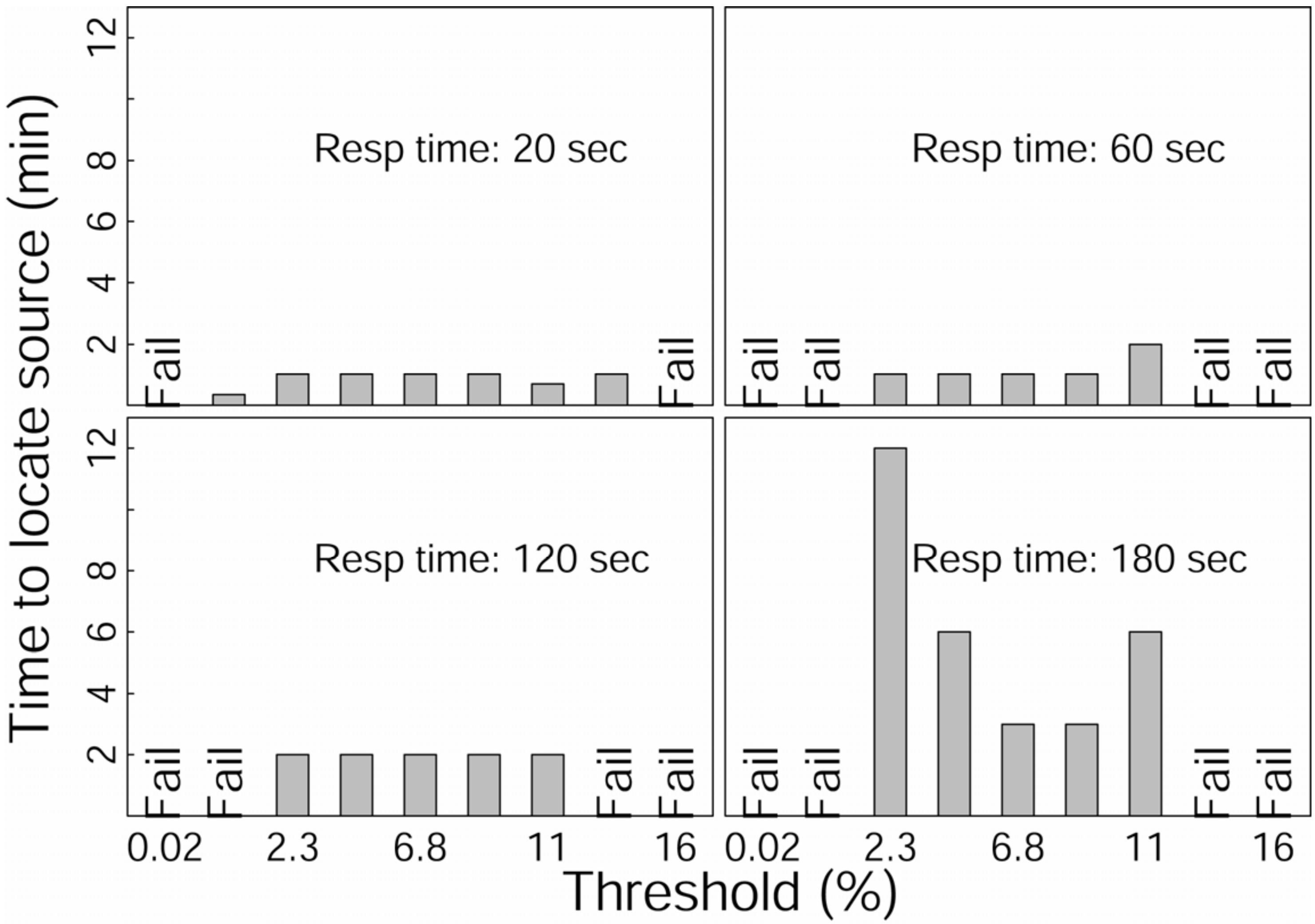
Trade-off Between Sensor Integration Time and Sensor Trigger Level



Summary and Concluding Remarks

- We have developed and demonstrated a successful framework for indoor detect-to-protect applications.

- The resulting software packages will be
  — linkable to any suitable airflow and transport model
  — capable of reading simple ASCII data feeds from various data sources (e.g., weather stations, pressure sensors, and sensor hardware)