

# Long-Term Monitoring Strategy using Nonlinear Kalman Filtering

K.A. Snyder<sup>1</sup> Z.Q. Lu<sup>2</sup>

<sup>1</sup> Building and Fire Laboratory, NIST

<sup>2</sup> Information Technology Laboratory, NIST

Work sponsored by the U.S. Nuclear Regulatory Commission

# Present State

- Existing computer models are limited
- Monitoring provides assurance
- Model revision rationale is needed

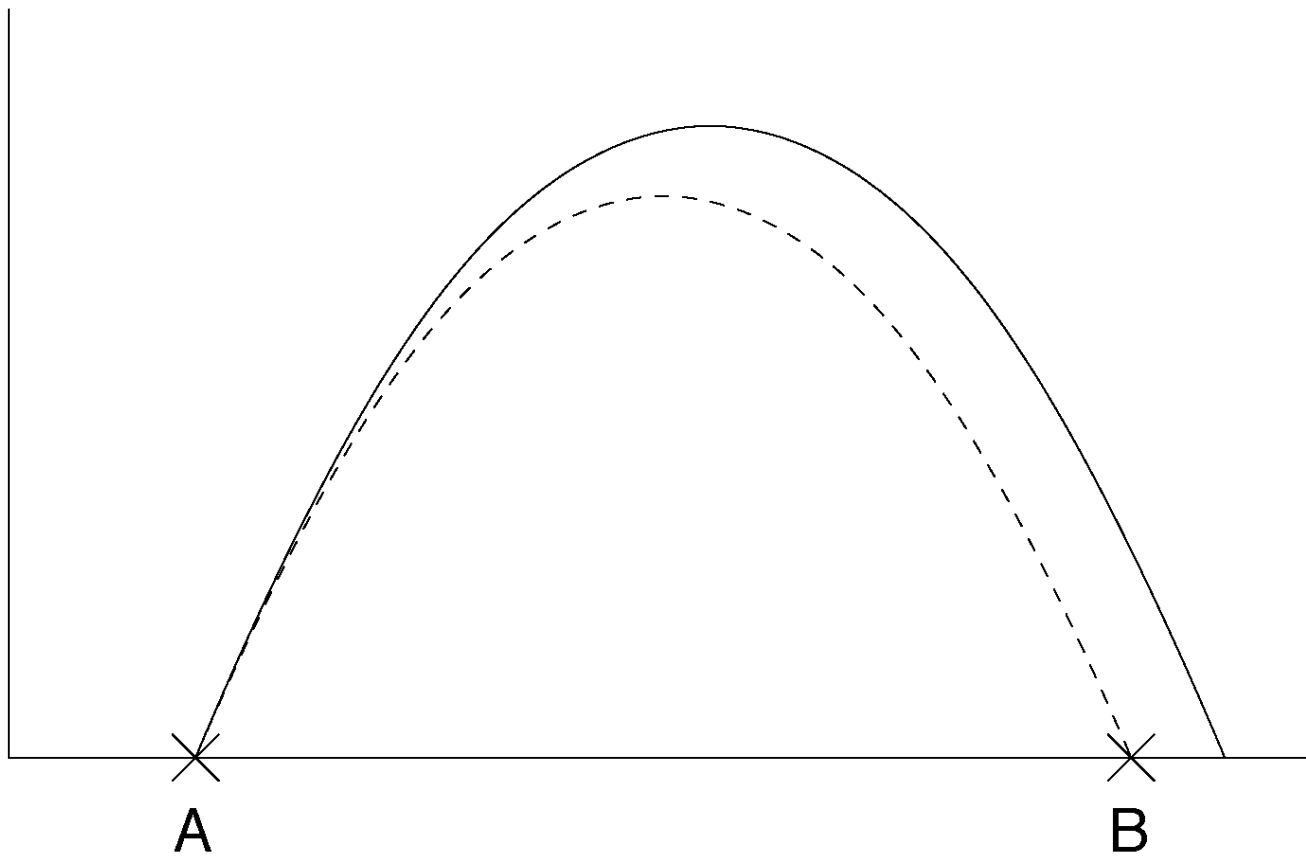
# Objectives

- Long-Term Monitoring
- Rational Monitoring Strategy
- Combine Models and Measurements

# Classical Example

Rocket from A to B

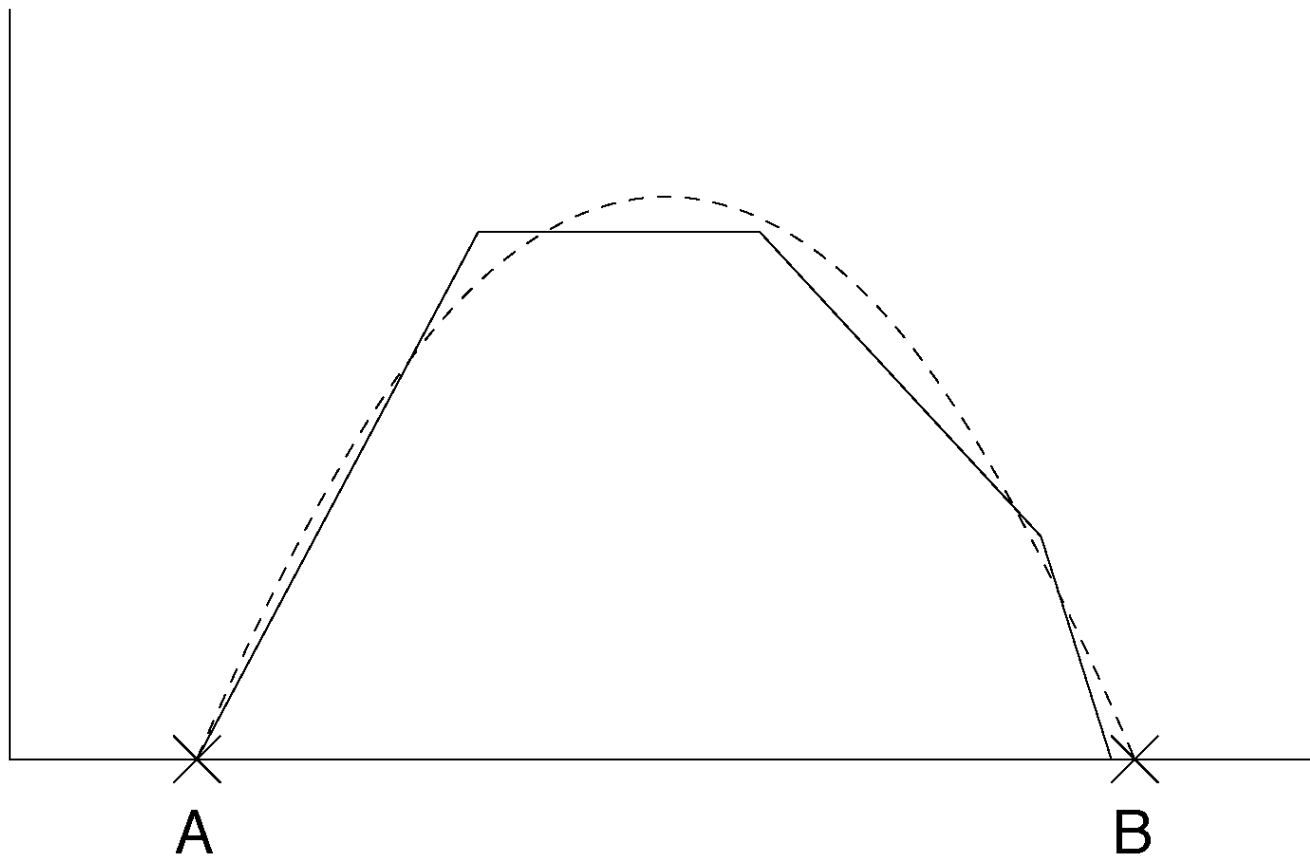
Accelerometer



# Classical Example

Rocket from A to B

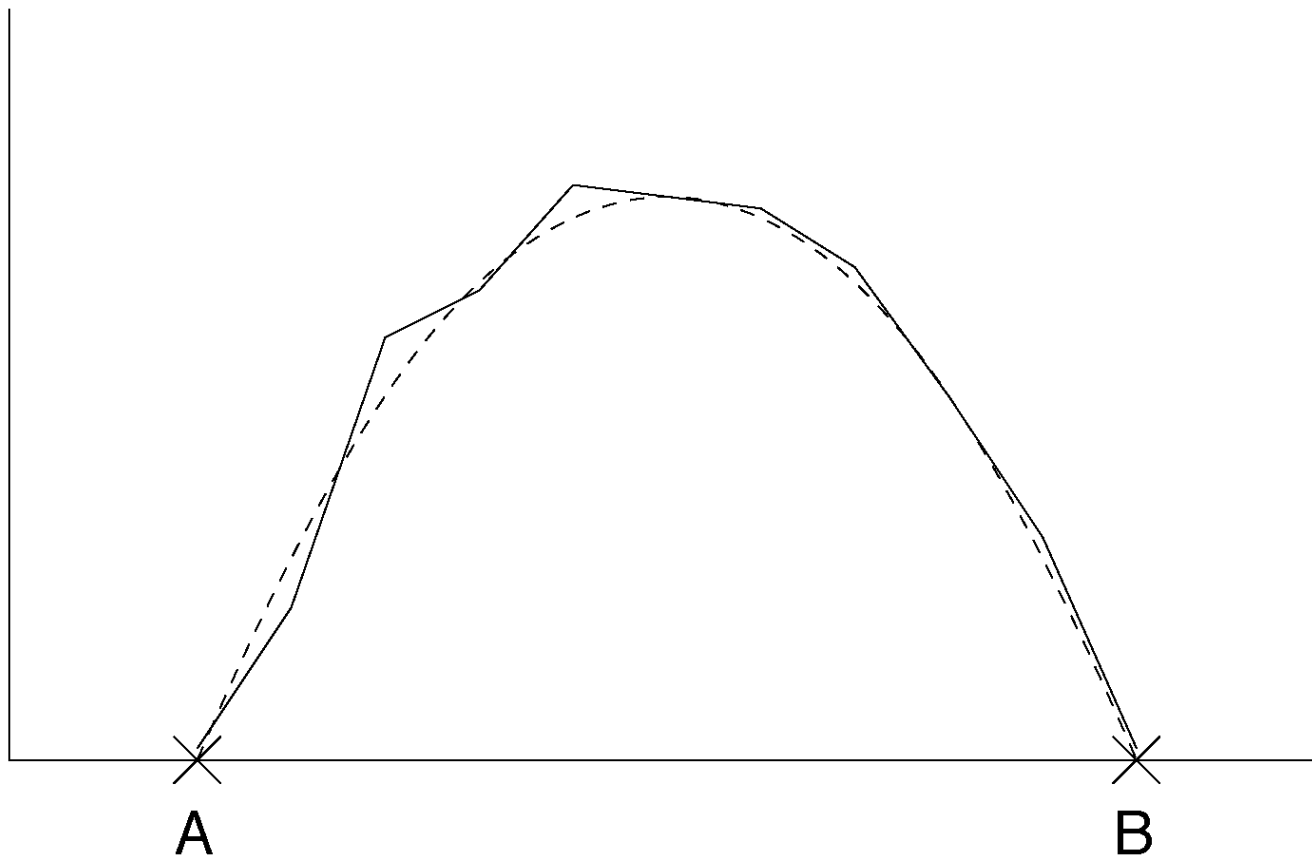
GPS positioning



# Classical Example

Rocket from A to B

Accelerometer + GPS + Filtering



# Kalman Filtering

- Process model:  $F = ma$
- State vector:  $x, v, a$
- Measurements: GPS
- Minimum state vector uncertainty

# Kalman Filtering

## General Description

State Vector:  $\mathbf{x} = \{x_0, x_1, \dots, x_N\}$

Propagation Model:  $\mathbf{x}(t + \Delta t) = \mathbf{f}[\mathbf{x}(t)]$

Measurements:  $\mathbf{y} = \{y_0, y_1, \dots, y_M\}$

Predictions:  $\hat{\mathbf{y}}(t + \Delta t) = \mathbf{g}[\mathbf{x}(t + \Delta t)]$

# Kalman Filtering

## Linear Filtering

Propagation Model:

$$\hat{\mathbf{x}}^{k-} = \mathbf{A}_k \hat{\mathbf{x}}^{k-1} + \mathbf{B}_k \mathbf{u}^{k-1}$$

Measurement Prediction:

$$\hat{\mathbf{y}}^k = \mathbf{C}_k \hat{\mathbf{x}}^{k-}$$

# Kalman Filtering

## Linear Filtering

Error Covariance Matrix:

$$P_{k-} = A_k P_{k-1} A_k^T + Q_k$$

Kalman Gain Matrix:

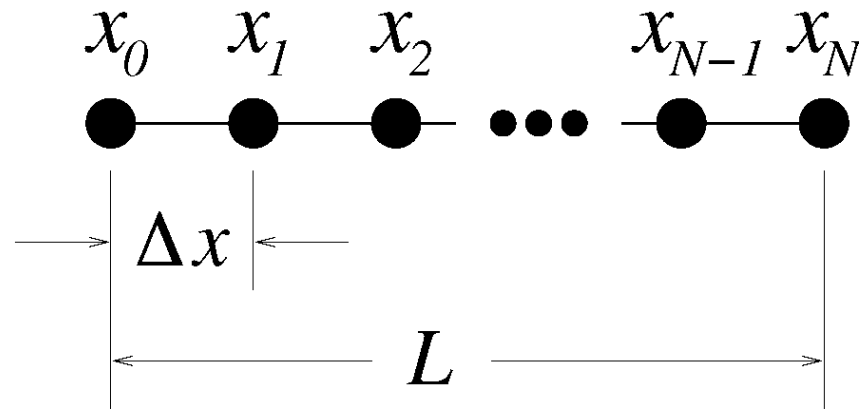
$$K_k = P_{k-} C^T (C_k P_{k-} C^T + R_k)^{-1}$$

Filtered State Vector:

$$\hat{\mathbf{x}}^k = \hat{\mathbf{x}}^{k-} + K_k \left[ \mathbf{y}^k - C_k \hat{\mathbf{x}}^{k-} \right]$$

# Fickian Diffusion

$$\frac{\partial c}{\partial t} = D \nabla^2 c$$



$$\hat{\mathbf{x}}^k = A(\eta) \hat{\mathbf{x}}^{k-1}$$

$$\eta = \frac{D \Delta t}{(\Delta x)^2}$$

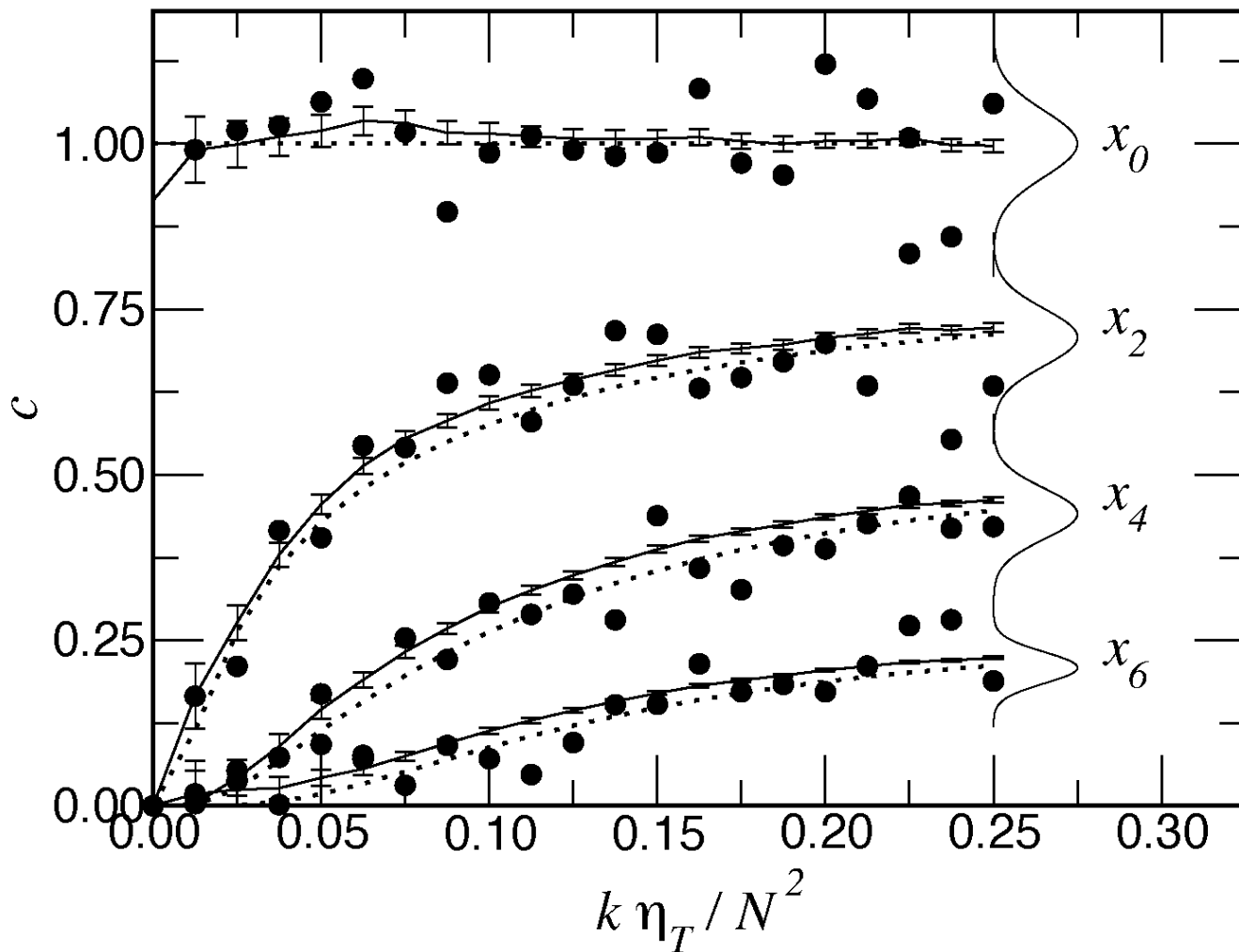
$$c(0, t) = 1.00 \pm 0.05$$

$$\eta = 0.80 \pm 0.16$$

# Fickian Diffusion

$$\eta = 0.9867$$

$$x_0 = 0.9140$$



# Kalman Filtering

## Extended Kalman Filtering (EKF)

Process Model:

$$\mathbf{x} = [x_0, x_1, \dots, x_N, \eta]^T \qquad \hat{\mathbf{x}}^{k-} = \mathbf{f} \left[ \hat{\mathbf{x}}^{k-1} \right]$$

Jacobian Matrix:

$$\mathbb{F} = \frac{\partial \mathbf{f}}{\partial \mathbf{x}} = \begin{bmatrix} \mathbf{A} & \mathbf{a}_\eta \\ \mathbf{0}^T & 1 \end{bmatrix} \qquad (\mathbf{a}_\eta)_i = \frac{\partial f_i}{\partial \eta}$$

# Kalman Filtering

## Extended Kalman Filtering (EKF)

Error Covariance Matrix:

$$\mathbf{P}_{k-} = \mathbb{F}_k \mathbf{P}_{k-1} \mathbb{F}_k^T + \mathbf{Q}_k$$

Kalman Gain Matrix:

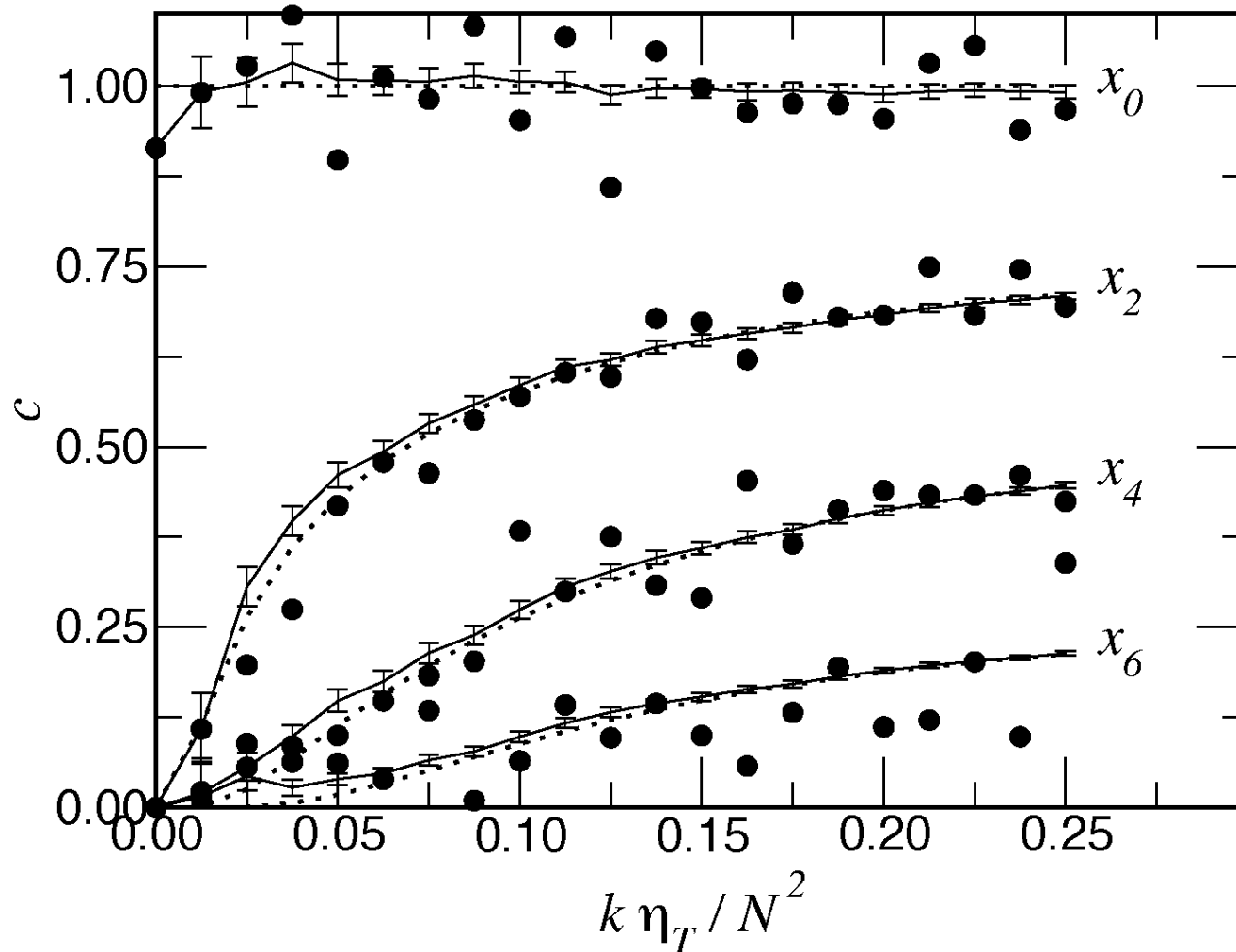
$$\mathbf{K}_k = \mathbf{P}_{k-} \mathbf{C}^T (\mathbf{C}_k \mathbf{P}_{k-} \mathbf{C}^T + \mathbf{R}_k)^{-1}$$

Filtered State Vector:

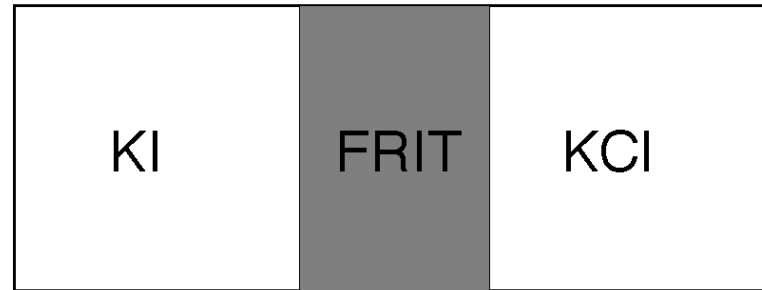
$$\hat{\mathbf{x}}^k = \hat{\mathbf{x}}^{k-} + \mathbf{K}_k \left[ \mathbf{y}^k - \mathbf{C}_k \hat{\mathbf{x}}^{k-} \right]$$

# Fickian Diffusion

## Extended Kalman Filtering (EKF)



# Diffusion Example



$$\mathbf{j}_i^e = -D_i \left( 1 + \frac{\partial \ln y_i}{\partial \ln c_i} \right) \nabla c_i - z_i c_i u_i \nabla \psi$$

$$\frac{\partial \theta c_i}{\partial t} = -\nabla \cdot \left( \frac{\mathbf{j}_i^e}{Y} \right) \quad F \sum_i z_i \mathbf{j}_i = 0$$

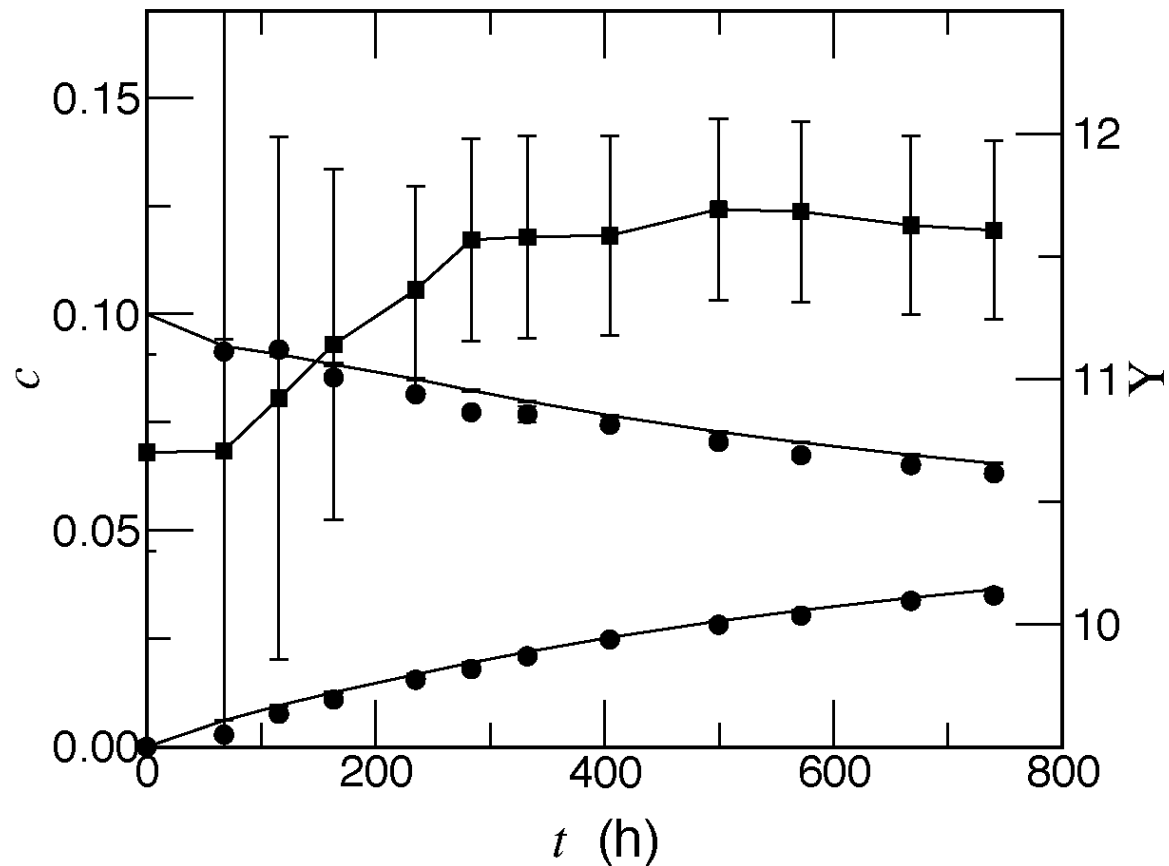
# Diffusion Example

State Vector:

$$\mathbf{x} = \begin{bmatrix} \mathbf{I} \\ \mathbf{CI} \\ \theta \\ \gamma \end{bmatrix}$$

# Diffusion Data

KI/KCl



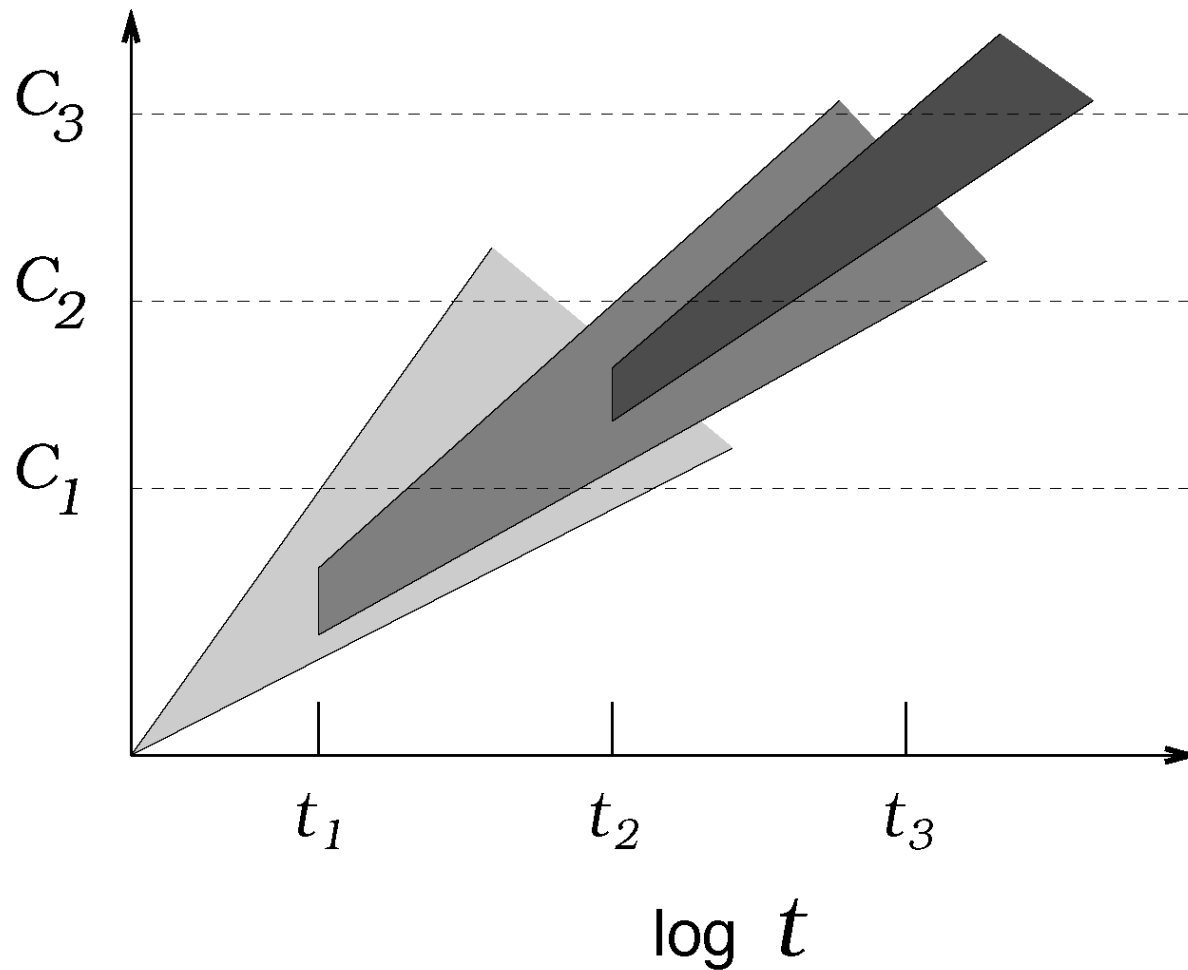
Snyder, Lu, and Philip, *Eur. J. Phys.*, (to be published) 2007.

# Future Directions

- Other nonlinear Kalman filters
- Optimum state vector basis set
- State vector constraints

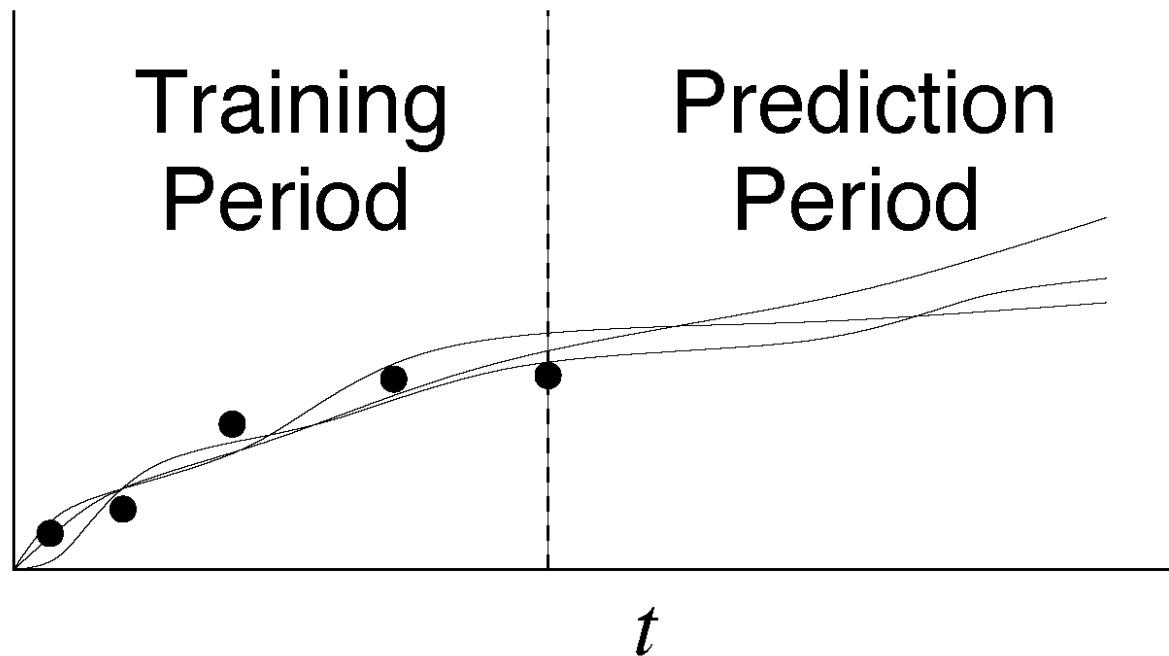
# Monitoring Analogy

## Measurement Thresholds



# ML-BMA

Maximum Likelihood - Bayesian Model Averaging



NUREG/CR-6843 PNNL-14534 March 2004

# Summary

- Rational basis for long-term monitoring
- Initial measurements “prime” the filter
- Utility of surrogate samples
- Analysis of laboratory data