Bayesian Knowledge Fusion in Prognostics and Health Management of Structures

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Presentation

At the

2011 Pressure Vessels & Piping Conference

July 20, 2011 Baltimore, MD

Motivation: Structural Integrity of Aging Structures

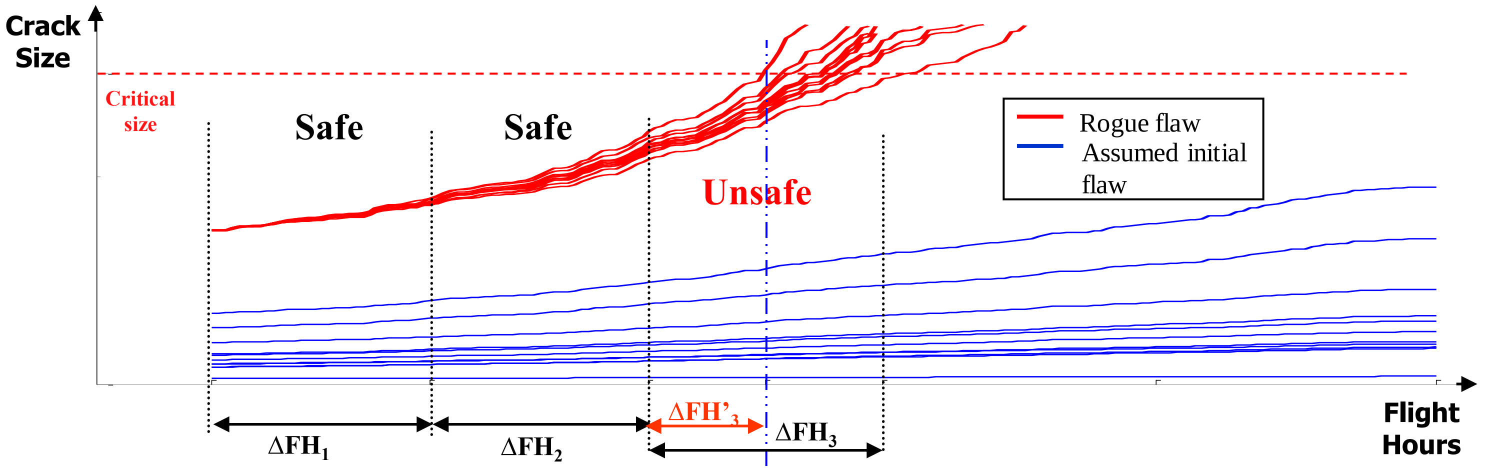
Structures weakened by cracks → Many structures currently past their fatigue life → Structures routinely inspected to stay in service

- **Current periodic inspection** practices:
  - ✓ Labor-intensive, time consuming and expensive
  - ✓ Subject to human error
  - ✓ Inspection itself may cause damage
- **Inspection intervals** selected such that an undetected flaw will not grow to critical size before the next inspection
- **Empirical crack growth** models used to determine the inspection intervals suffer from **uncertainty**:
  - ✓ Idealized theories and simplistic assumptions may **fail to capture the underlying mechanistic failure**

Structural Health Management (SHM)

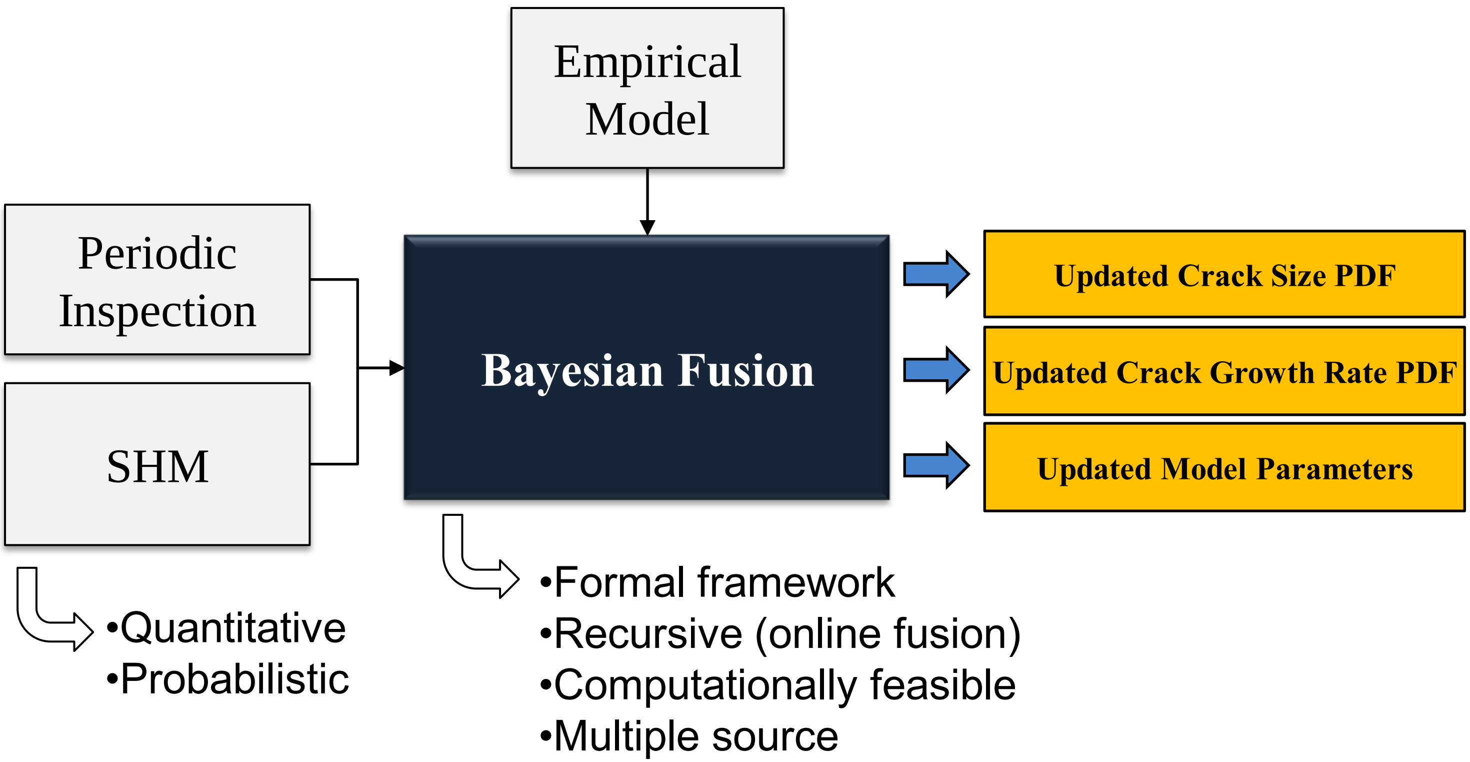
- **Paradigm shift: offline periodic inspections + online SHM**
- Structural health management (SHM) is the online assessment of structural integrity using appropriate NDE technology

- SHM used for:
  - ✓ Direct assessment of the state of structural health in real-time
  - ✓ Provide feedback from the structure to improve the prediction of the empirical models

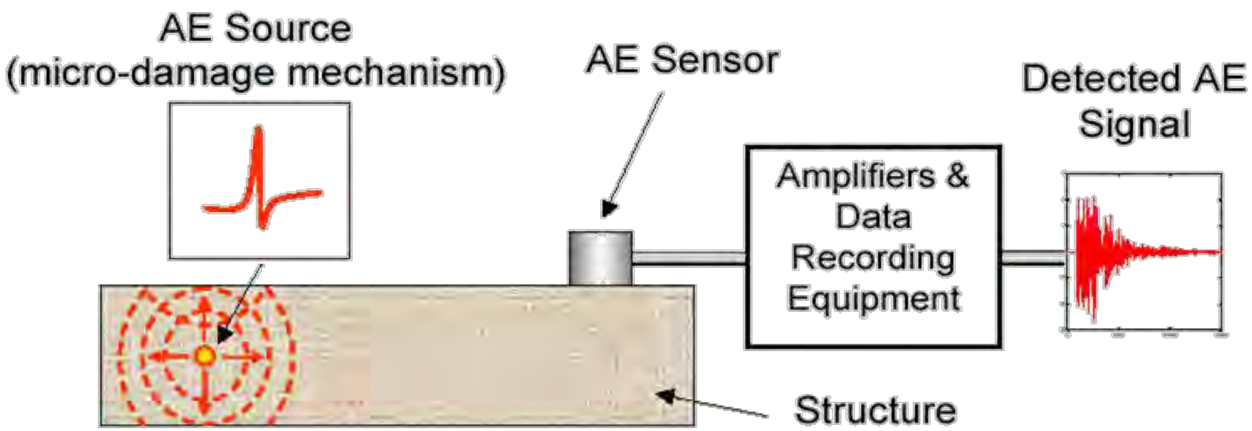


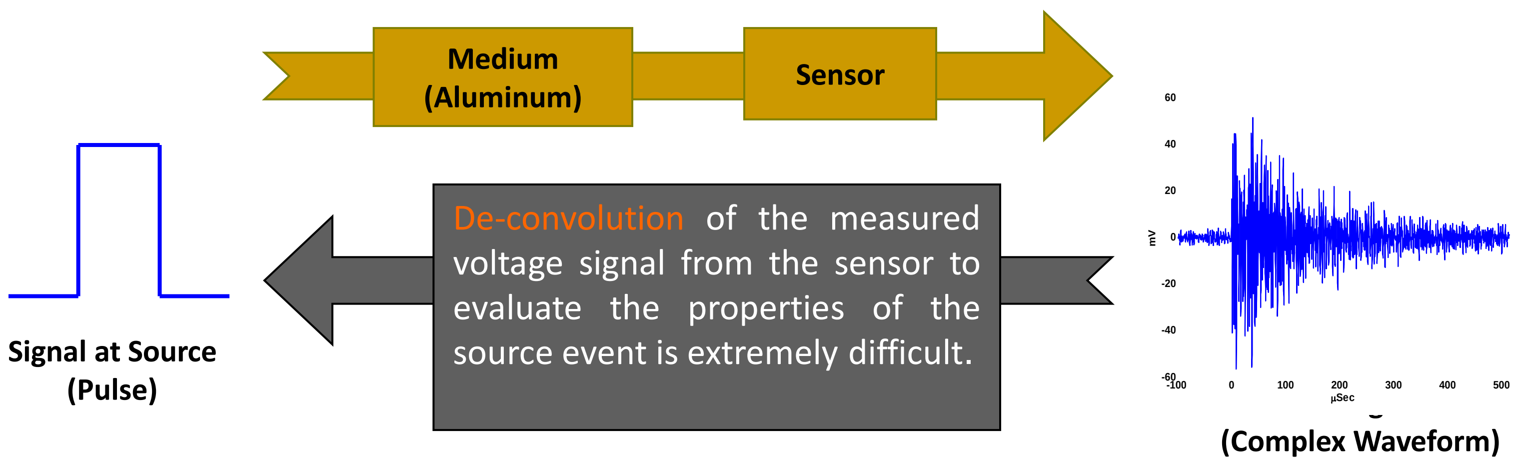
Research Objectives and Methodology

- Research Objective: Provide a hybrid framework for SHM that use sensor and visual inspection data

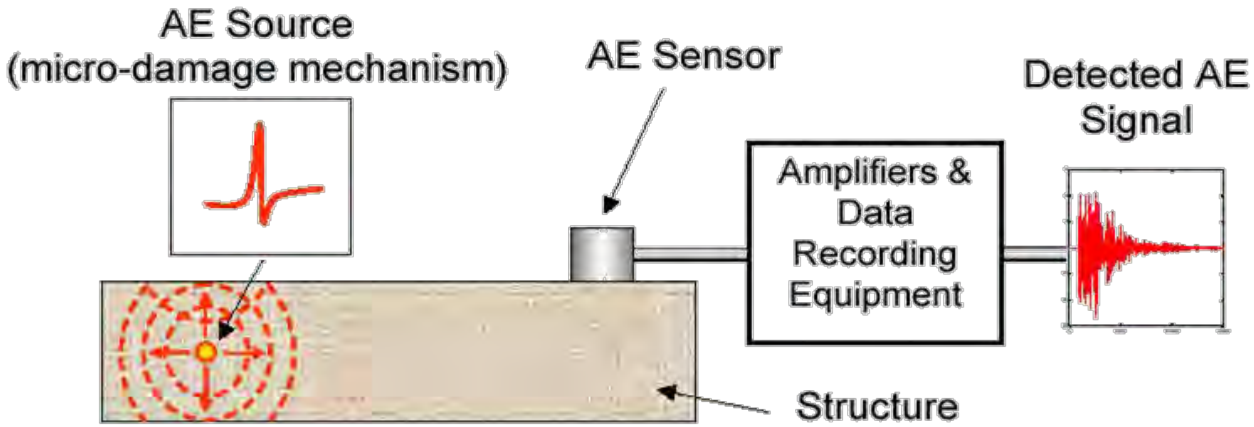


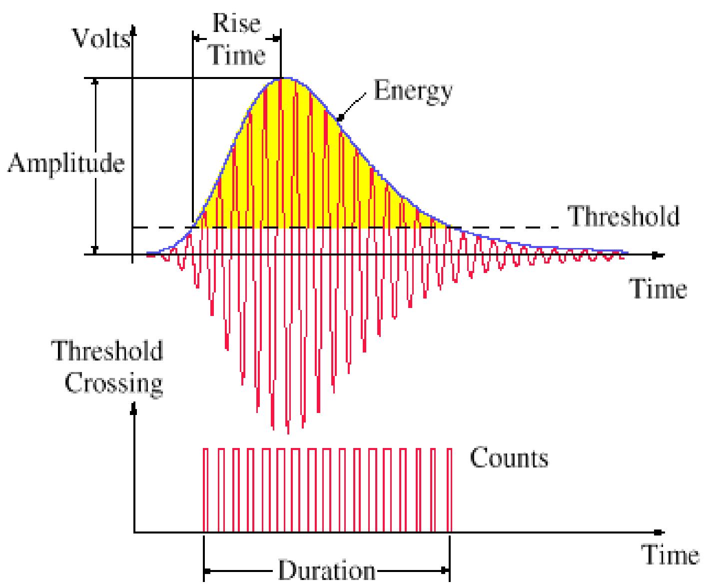
AE monitoring: Theory & Background





AE monitoring: Theory & Background (Cont.)





AE Features

- Amplitude
- Energy
- Rise time
- **Counts (Threshold crossing)**
- Frequency content
- Waveform shape

Correlation between AE features & Fracture parameters

AE Features

Amplitude
Energy
Rise time
Count rate (dc/dN)
Frequency Waveform shape

Fracture Parameters

da/dN
ΔK

$$\frac{dc}{dN} = A_1(\Delta K)^{A_2}$$

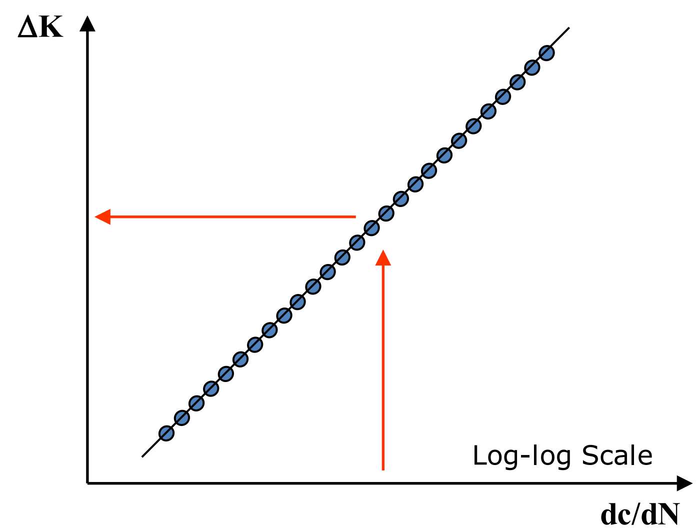
$$\Downarrow$$

$$\Delta K = A_1^{-1/A_2}\left(\frac{dc}{dN}\right)^{1/A_2}$$

$$\Downarrow$$

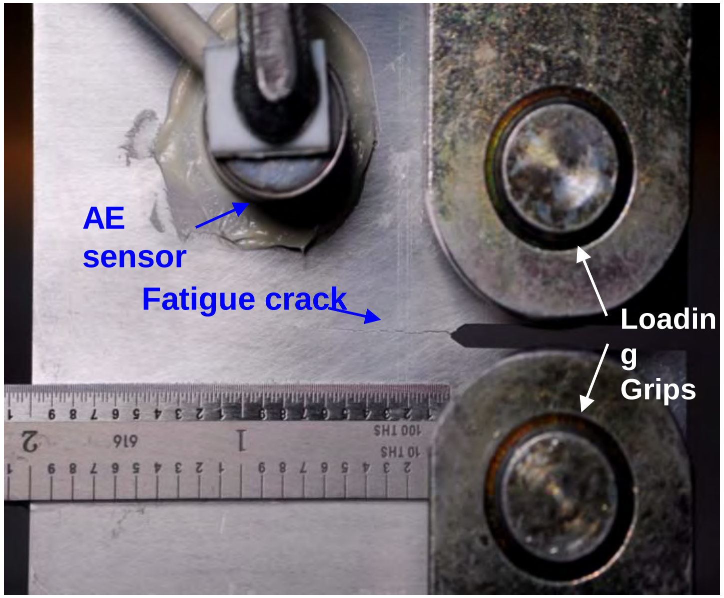
$$\boxed{\log \Delta K = \alpha_1 \log\left(\frac{dc}{dN}\right) + \alpha_2}$$

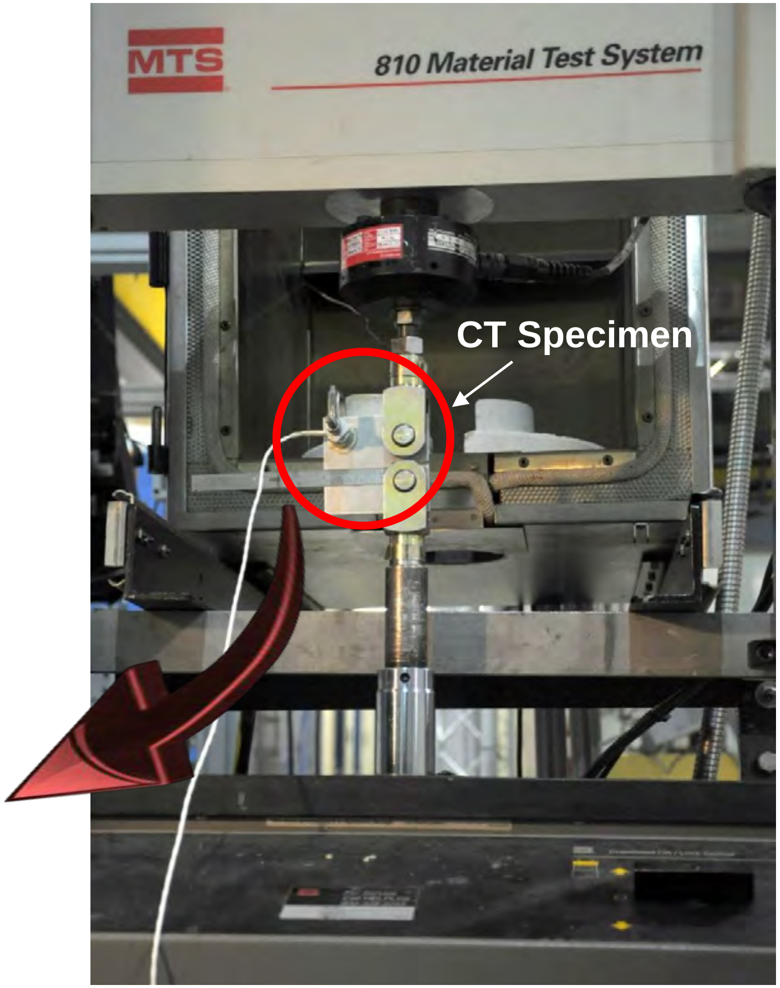
[Bassim, M.N., St Lawrence, S. & Liu, C.D., 1994. Detection of the onset of fatigue crack growth in rail steels using acoustic emission. *ENG FRACT MECH*, 47(2), 207-214.



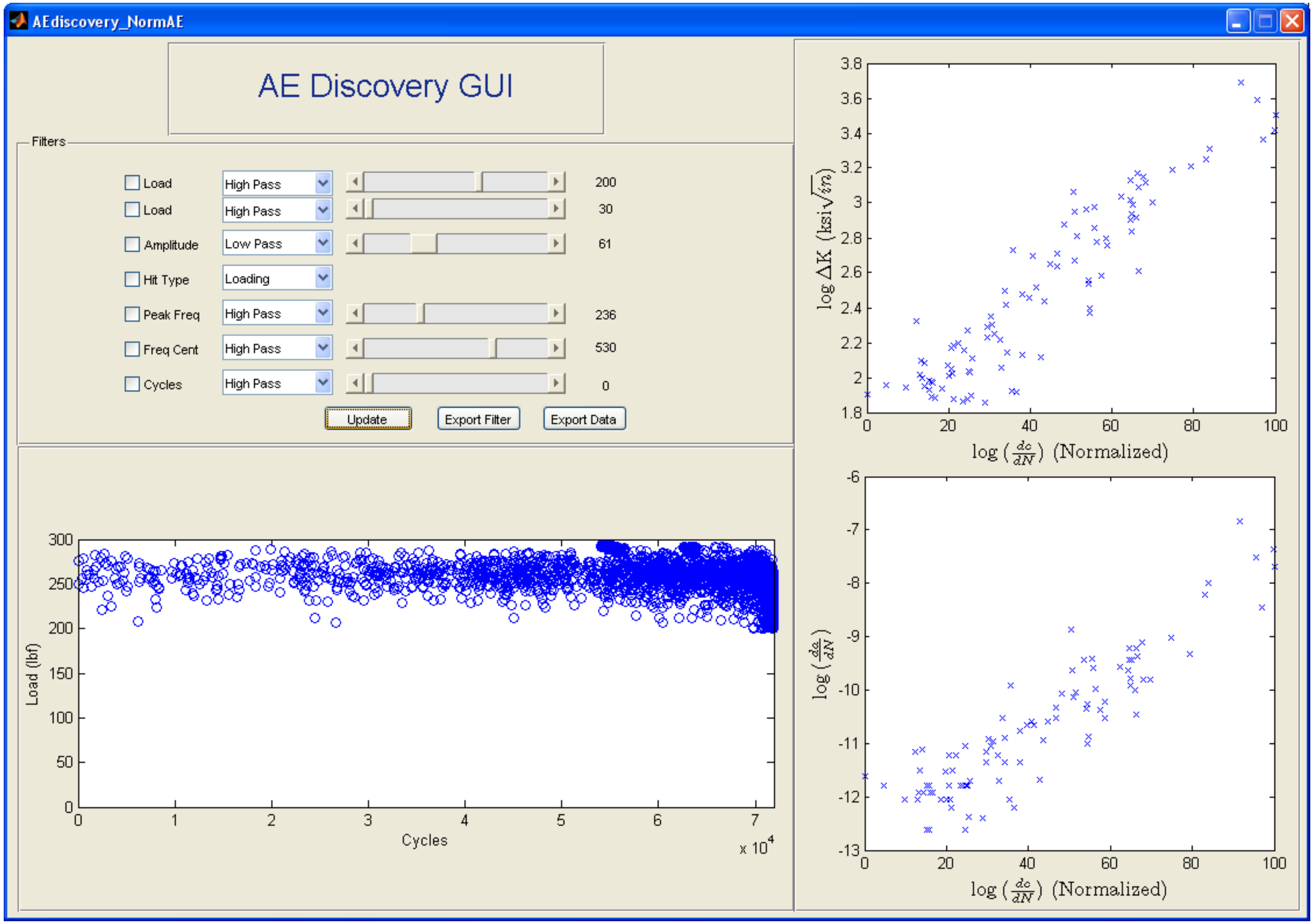
Crack Growth Monitoring Using AE

- **Test objectives:**
  1. Investigate/verify the correlation between AE and fracture parameters.
  2. Obtain experimental data needed for model development.



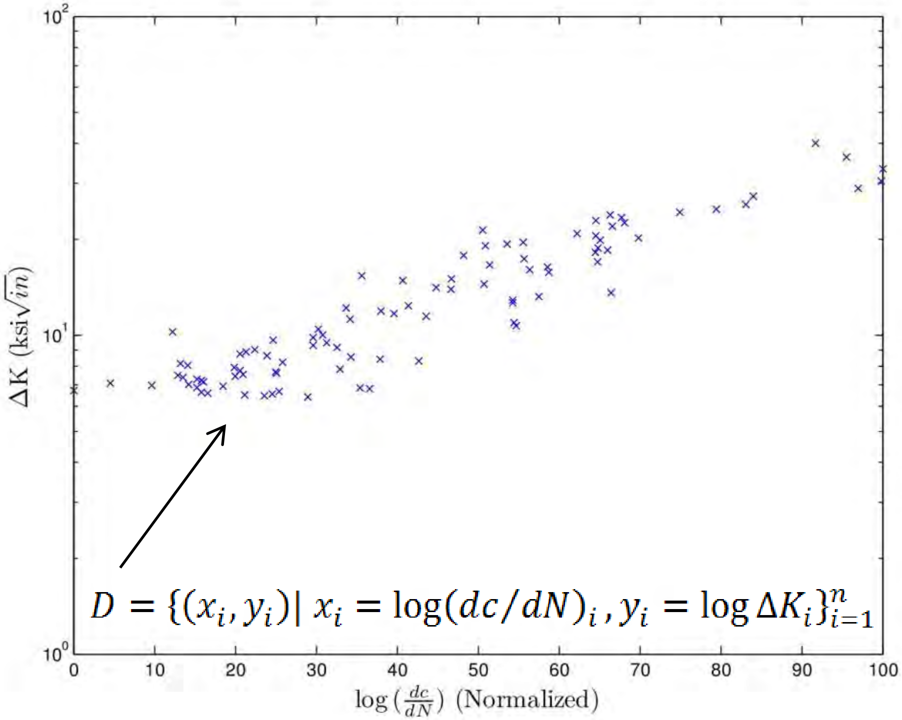


AE Discovery MATLAB GUI



Probabilistic Model development

$$\log \Delta K = \alpha_1 \log\left(\frac{dc}{dN}\right) + \alpha_2$$



$$D = \{(x_i, y_i) \mid x_i = \log(dc/dN)_i, y_i = \log \Delta K_i\}_{i=1}^{n}$$

$$y_i \sim \mathrm{N}(\mu_i, \sigma_i)$$

$$\mu_i = \alpha_1 x_i + \alpha_2$$

$$\sigma_i = \gamma_1 \exp(\gamma_2 x_i)$$

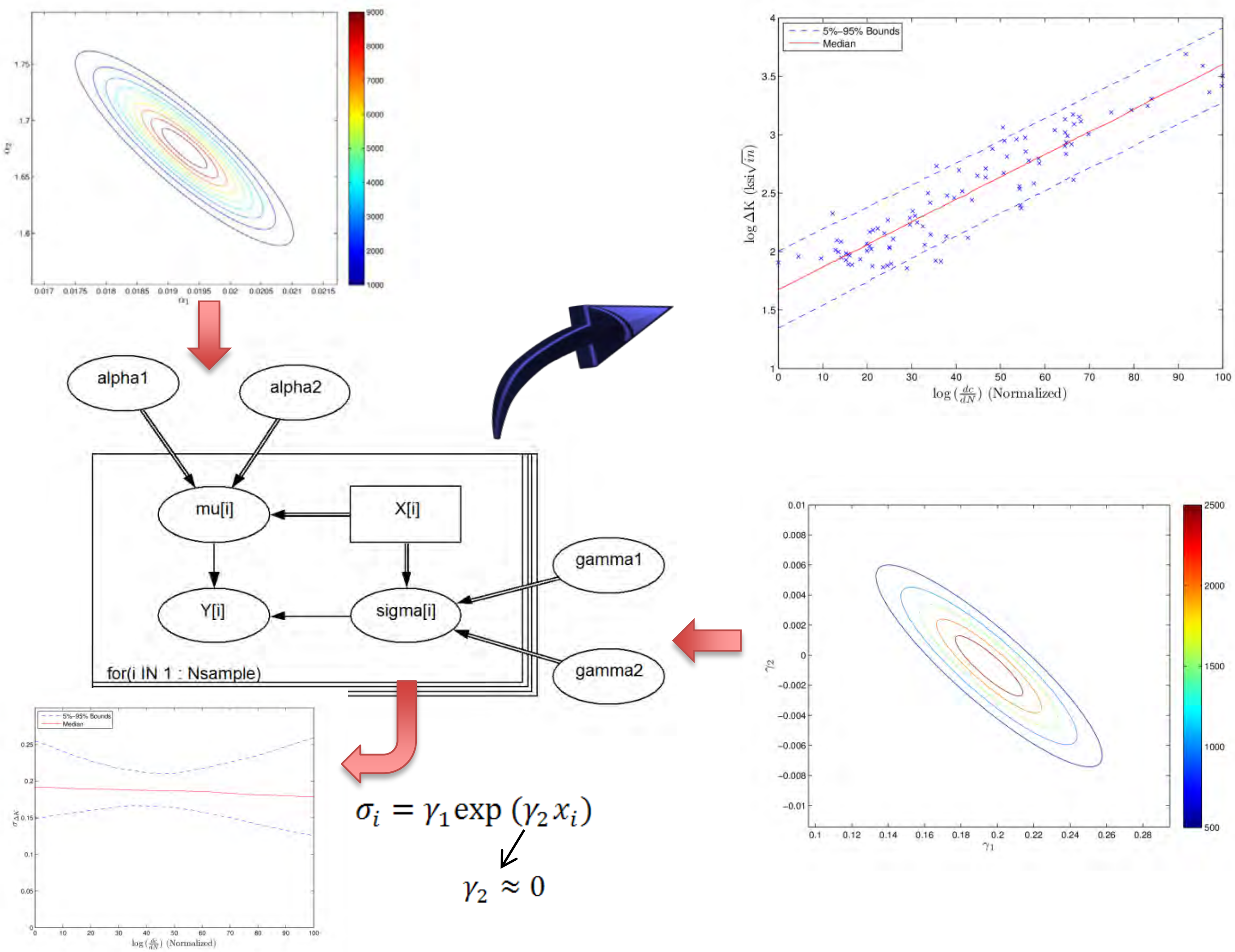
$$p(D|\alpha_1,\alpha_2,\gamma_1,\gamma_2) = \prod_{i=1}^{n} \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{1}{2}\left(\frac{y_i - (\alpha_1 x_i + \alpha_2)}{\gamma_1 \exp(\gamma_2 x_i)}\right)\right)$$

$$p(\Theta|D) = \frac{p(D|\Theta)p(\Theta)}{p(D)}$$

$$\Theta = \{\alpha_1, \alpha_2, \gamma_1, \gamma_2\}$$

$$p(D) = \int p(D|\Theta)p(\Theta)d\Theta$$

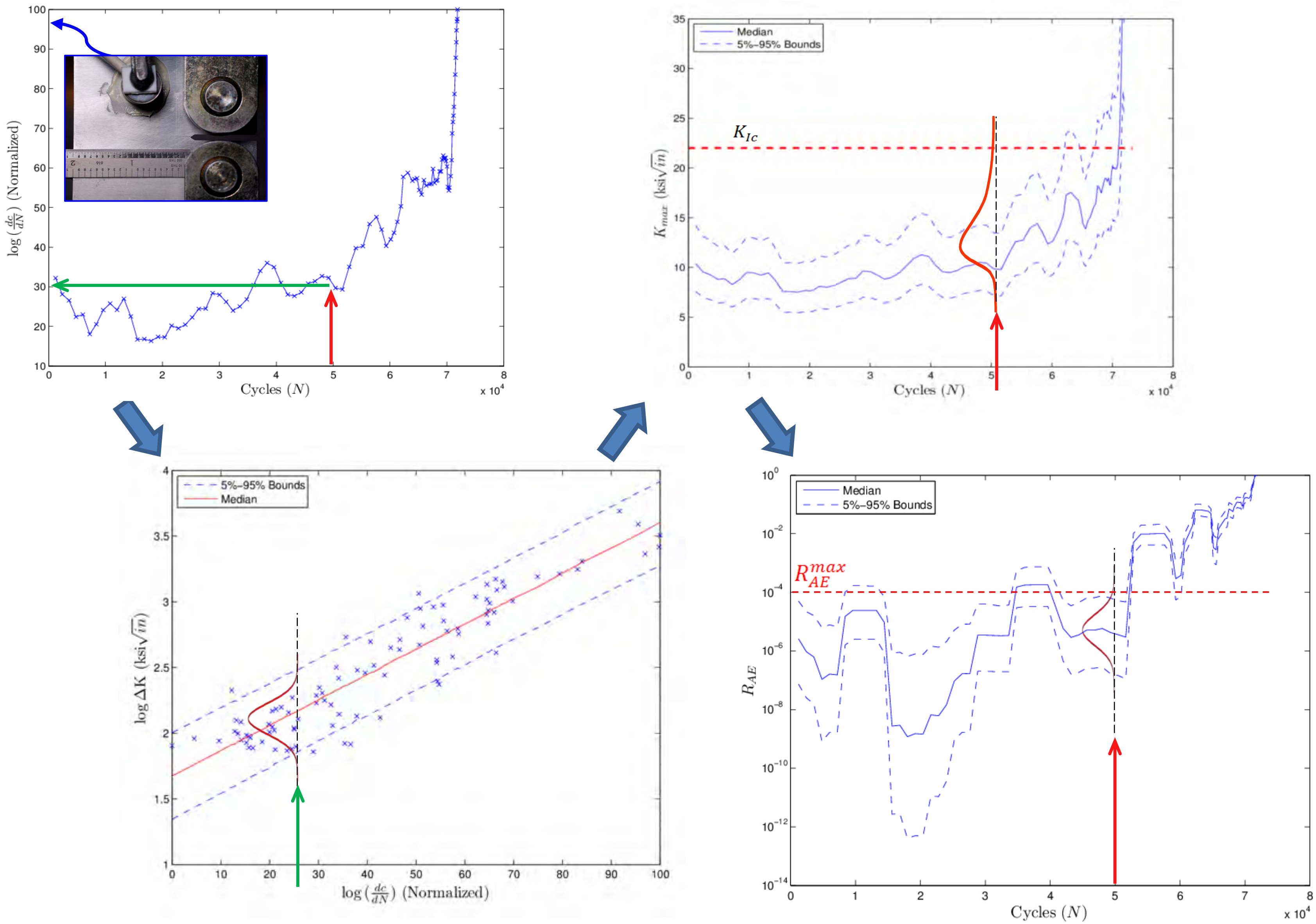
Bayesian Regression



$$\sigma_i = \gamma_1 \exp\left(\gamma_2 x_i\right)$$

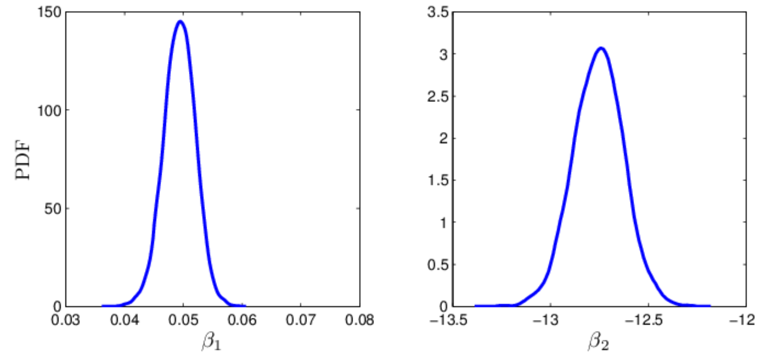
$$\gamma_2 \approx 0$$

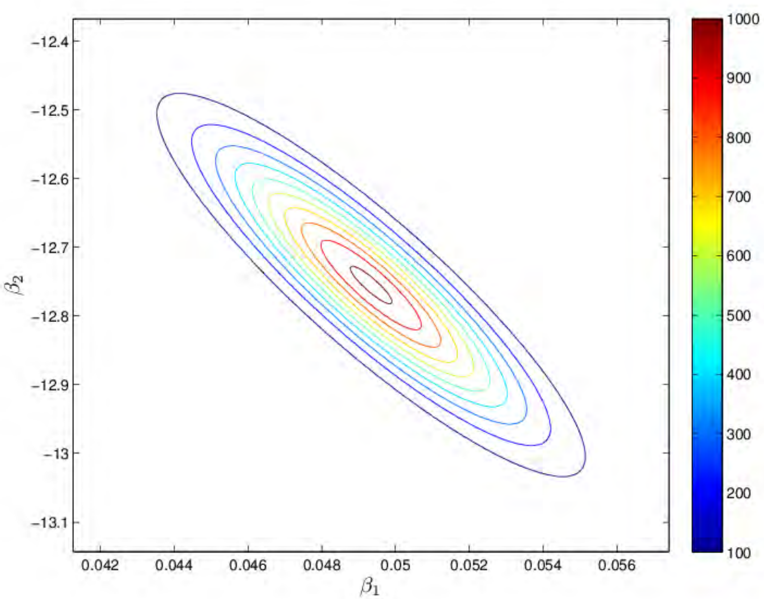
AE-Based Risk Factor

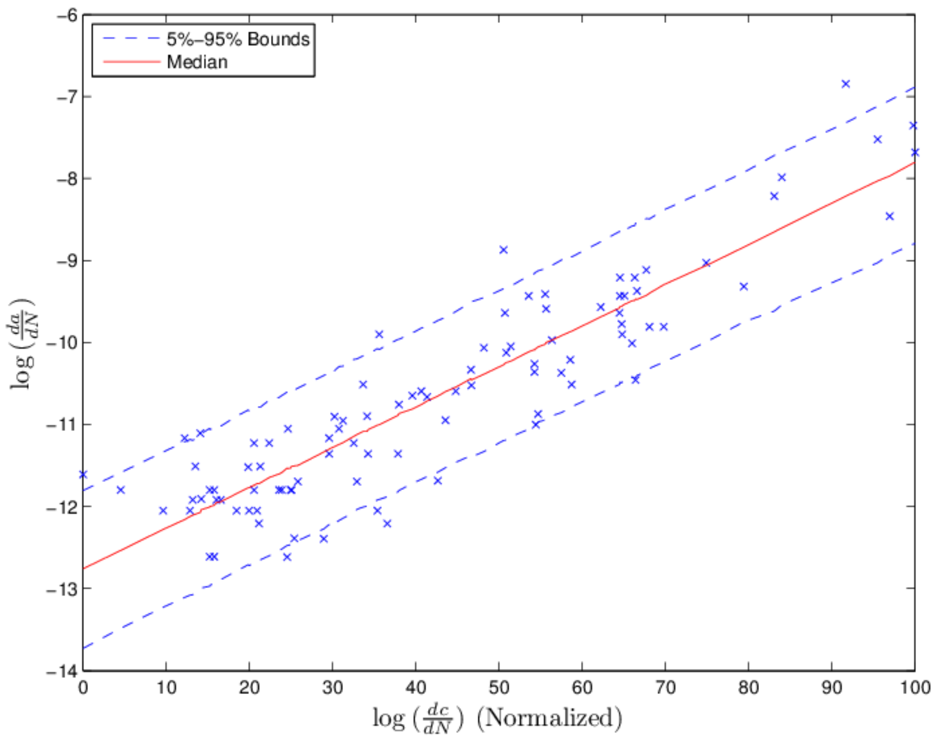


AE-based Crack Size Estimation

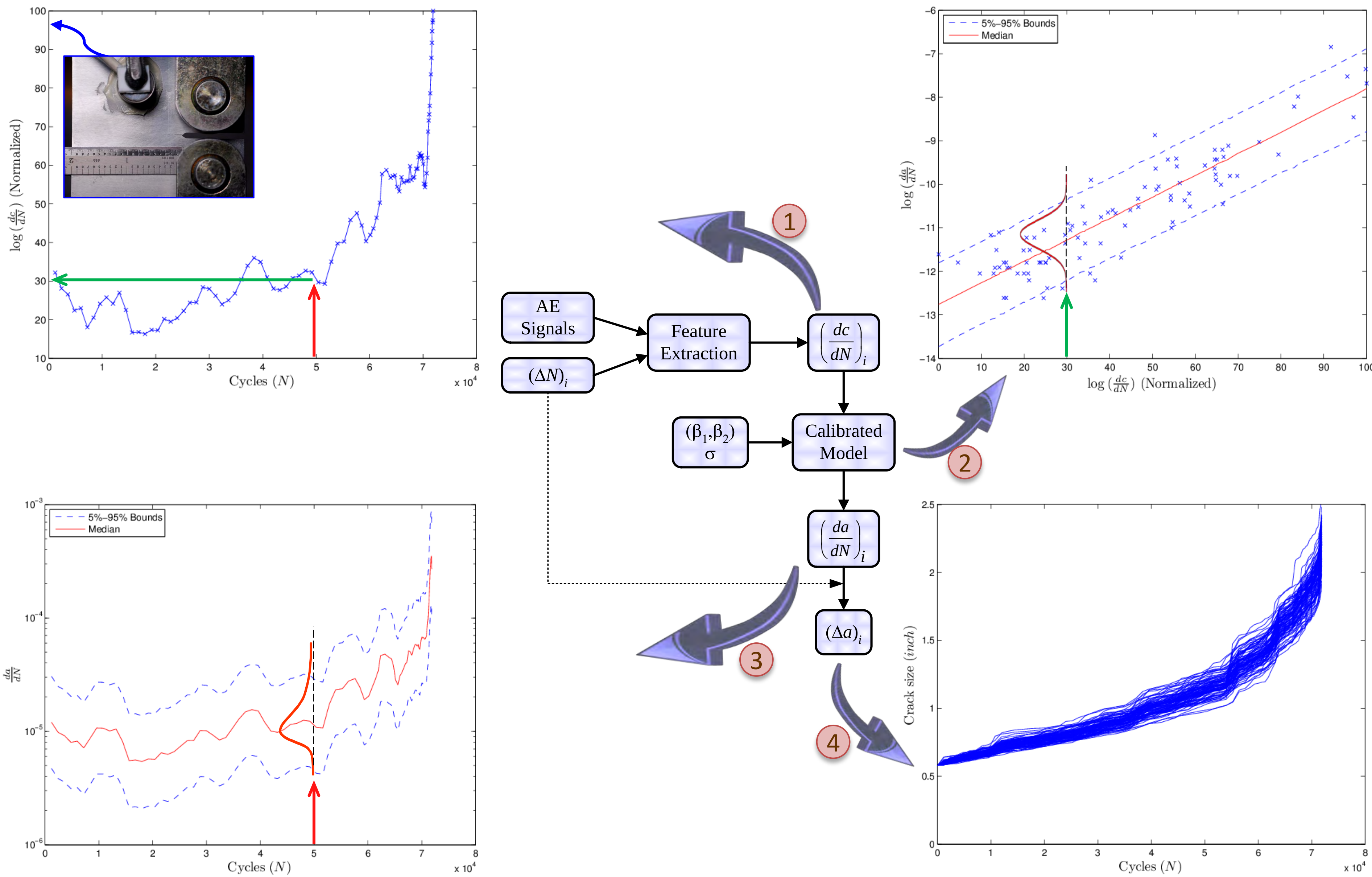
$$\log\left(\frac{da}{dN}\right) = \beta_1 \log\left(\frac{dc}{dN}\right) + \beta_2$$





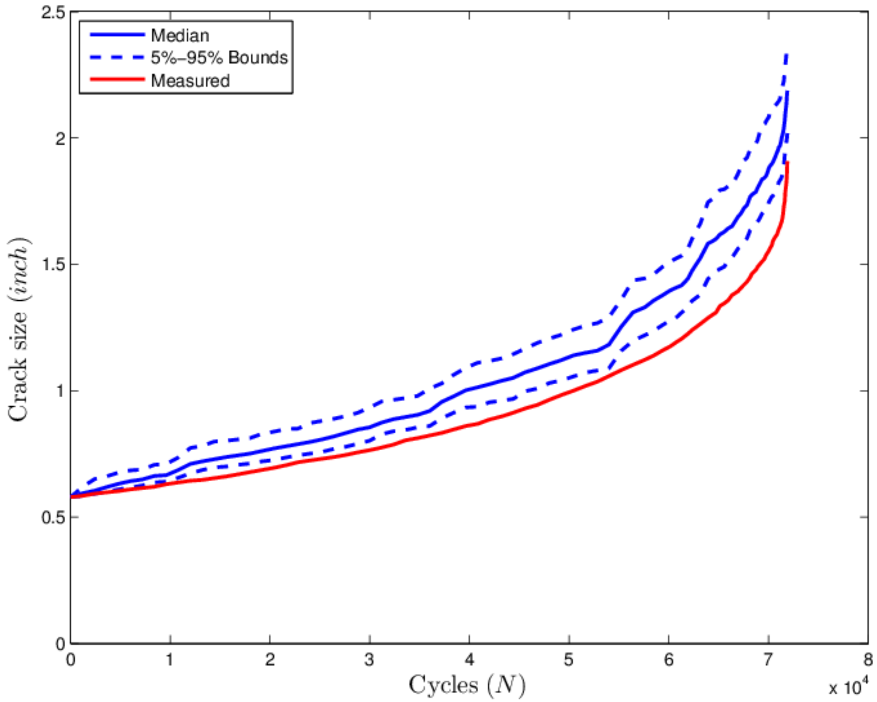


AE-Based Crack Size Estimation

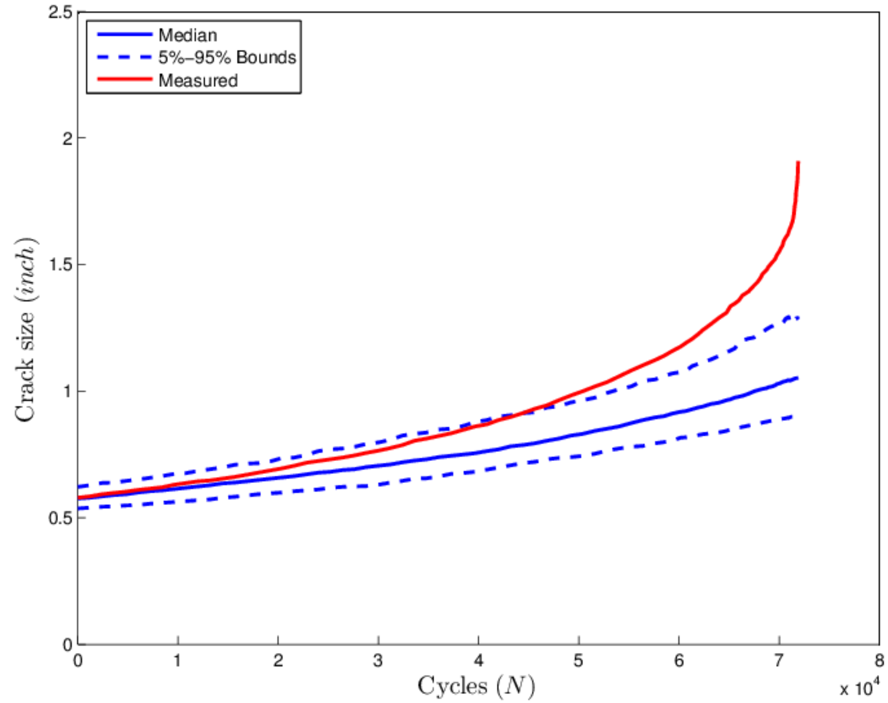


AE-Based vs. Empirical Crack Growth Model

AE-Based Crack Growth Model

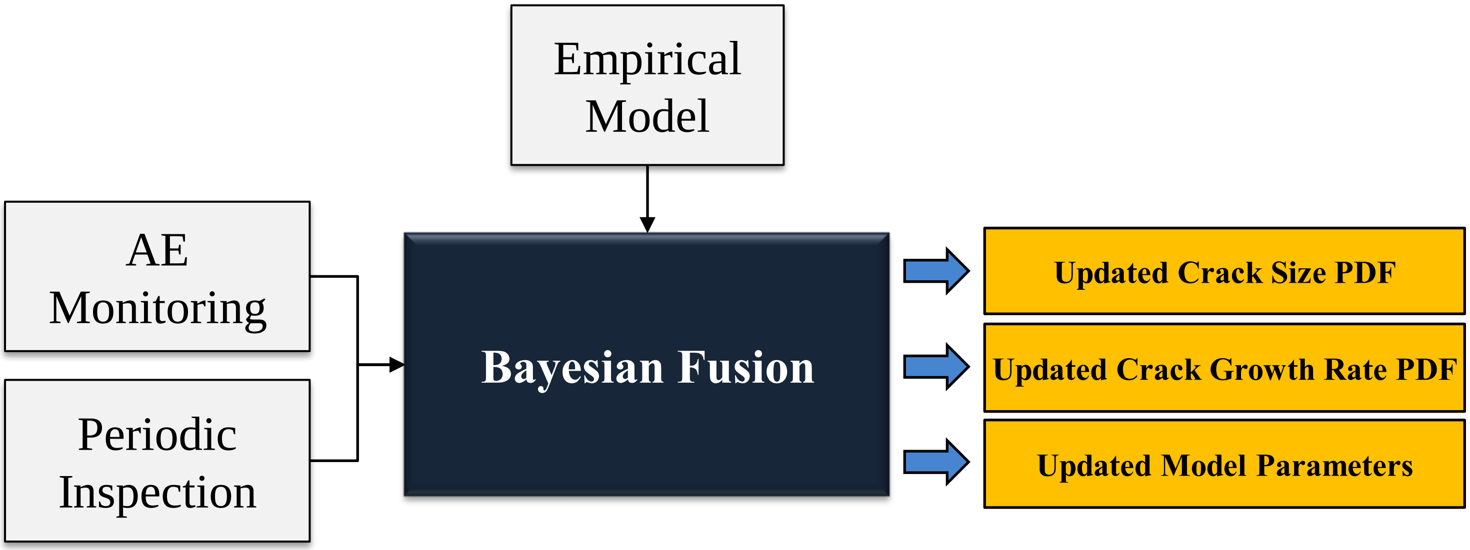


Empirical Crack Growth Model



Bayesian Fusion

- The necessary information for developing a structural health diagnostic and prognostic (i.e., SHM) solution is often obtained from various sources.

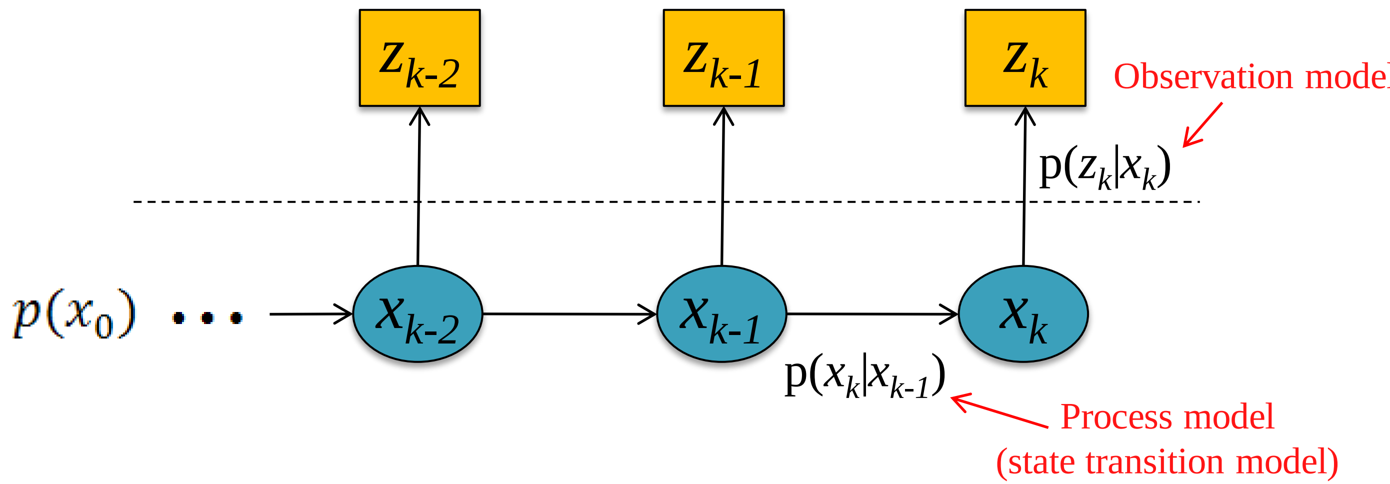


Dynamic State-Space Model

- *Recursive Bayesian estimation* is a probabilistic approach for estimating an unknown probability density function recursively over time using incoming uncertain observation (noisy measurements) and a mathematical process model that describes the evolution of the state variables over time.

Observations at time step *k*:
$z_k \in \mathbb{R}^m$

State variable at time step *k*:
$x_k \in \mathbb{R}^n$



Key assumptions:

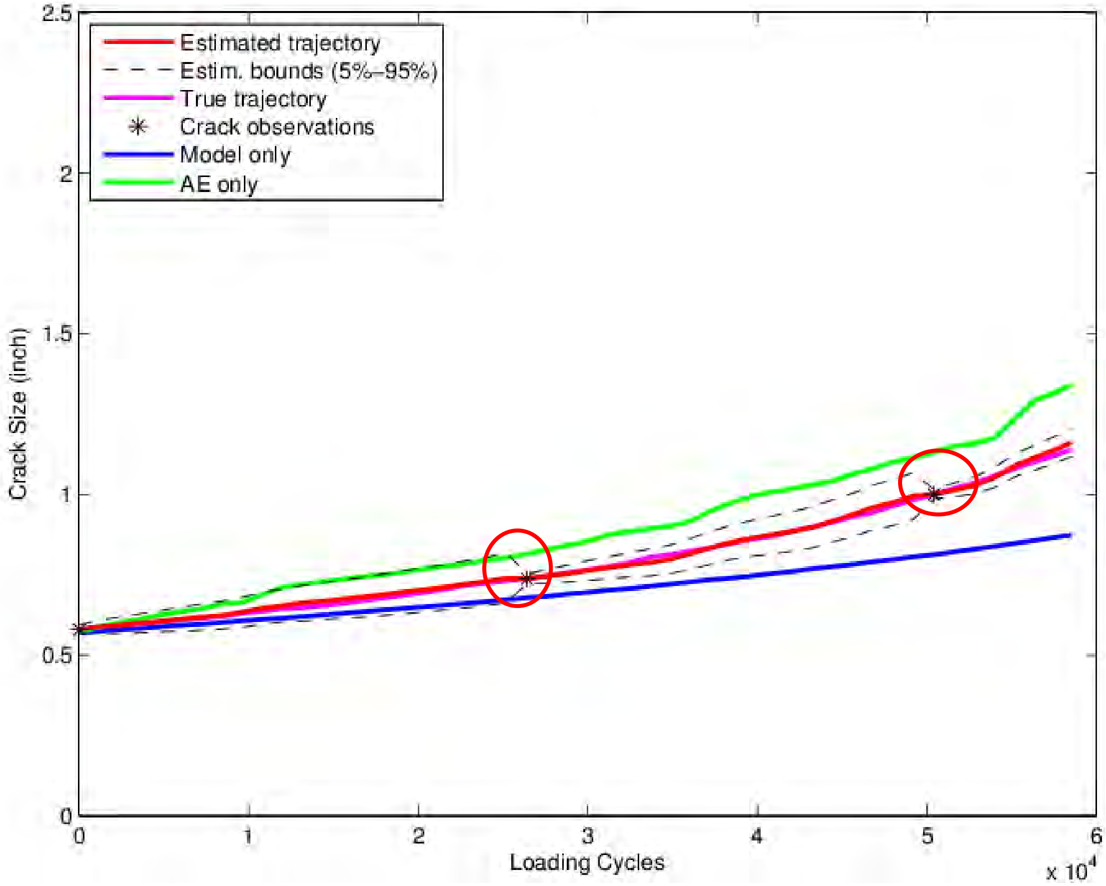
1. States follow a first order Markov process. $p(x_k|x_{k-1}, x_{k-2}, \ldots, x_1) = p(x_k|x_{k-1})$

2. Observations independent given the states. $p(z_k|x_k, z_{k-1}, \ldots, z_1) = p(z_k|x_k)$

We are interested in posterior distribution of state x_k, given the time series of past observations:

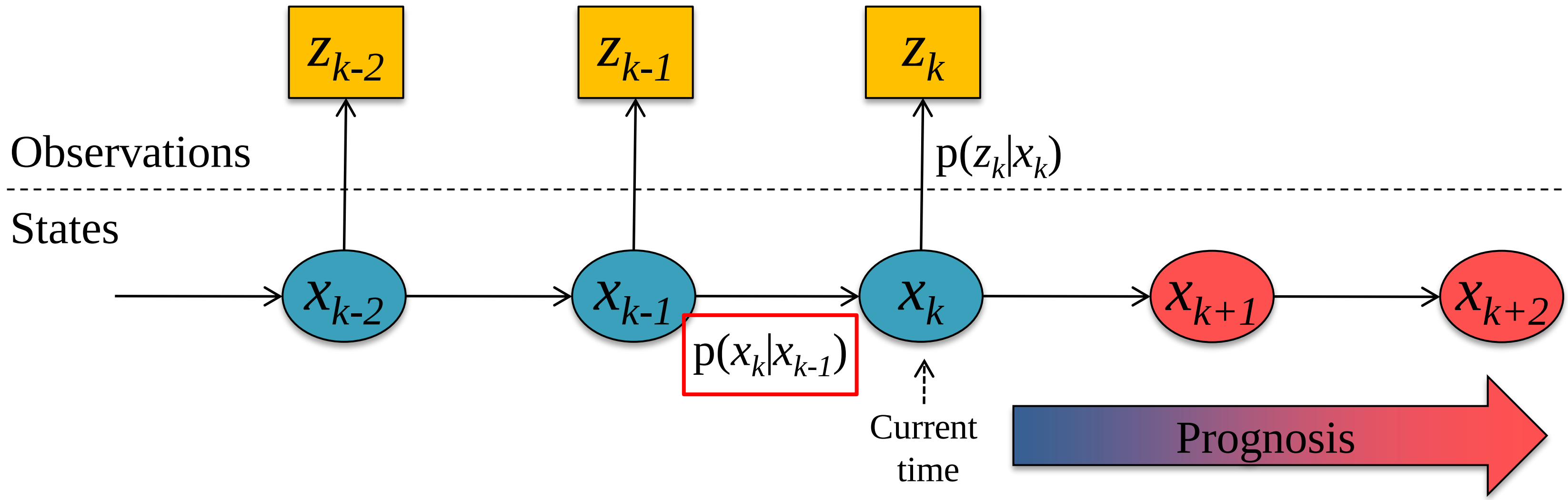
$$\boxed{p(x_k|z_k, z_{k-1}, \ldots, z_1) = ?}$$

Results: Effect of Frequency of Inspections



Prognosis: Predicting Future Crack Size

- Step1: Update the empirical model parameters (process model) given the crack size and rate observations.
- Step2: Predict future crack size given assume usage profile.
  - ✓ Estimate remaining useful life (RUL)
  - ✓ Estimate probability of exceeding critical crack size



Prognosis Results