Thermodynamic Assessment of Fatigue Crack Initiation

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Presentation at the Army/Navy TIM

July 26, 2012

Irvine, CA

Outline

- Objective and Reserach Thrusts
- Thermodynamics of Fatigue Crack Initiation
  - Energy Approach
    - Experiments, Material, Results
  - Entropy Approach
    - Experiments, Material, Results
- Conclusions and Future Steps

Objectives

- Goal: Prediction of fatigue crack initiation based on Strain Energy Expended and Thermodynamic Entropy Generation
- Thermodynamic assessment of fatigue of specimens with stress concentration (center and edge hole specimens)
- Develop a probabilistic model of the Life Expended of Al 7075-T561

Energy Approach

Total strain energy is the summation of plastic and elastic energy

$$\Delta W = \Delta W_p + \Delta W_{e+}$$

Total strain energy is correlated to life with constants *A* and *B*

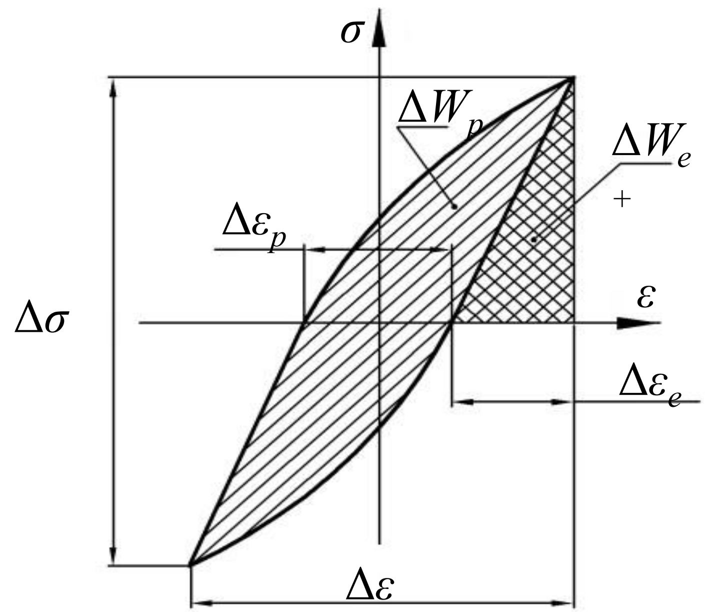
$$\Delta W = A\, N_f^B$$

ΔW_p: plastic strain energy per cycle

ΔW_{e+}: elastic strain energy per cycle in tension

$\Delta \varepsilon_e$: elastic strain range

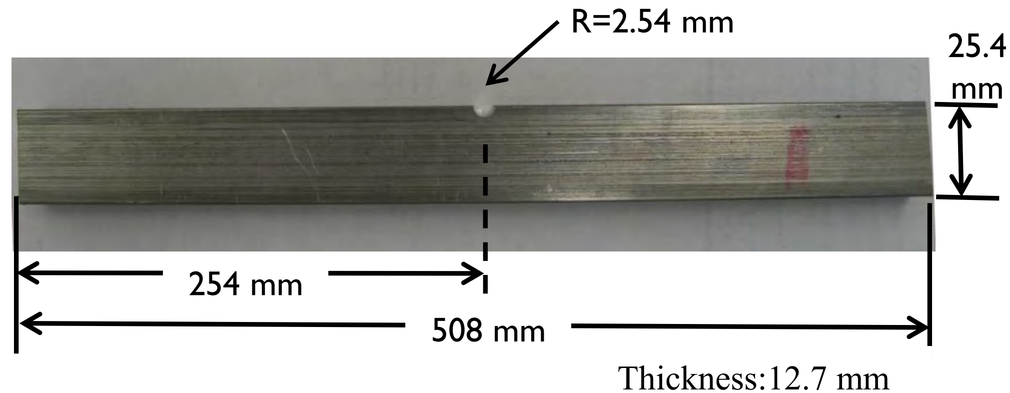
$\Delta \varepsilon_p$: plastic strain range



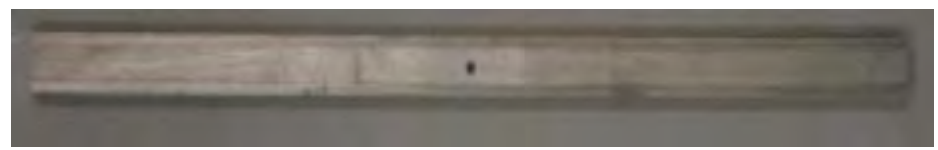
Experimental Overview
Experimental Apparatus and Sample Geometry

Heavy-duty uniaxial fatigue testing machines
Rated 100 kN capacity; 30 Hz frequency

Edge Notch Sample



Single Hole Sample



Material:

Aluminum 7075-T6, T651

Strain Energy Model

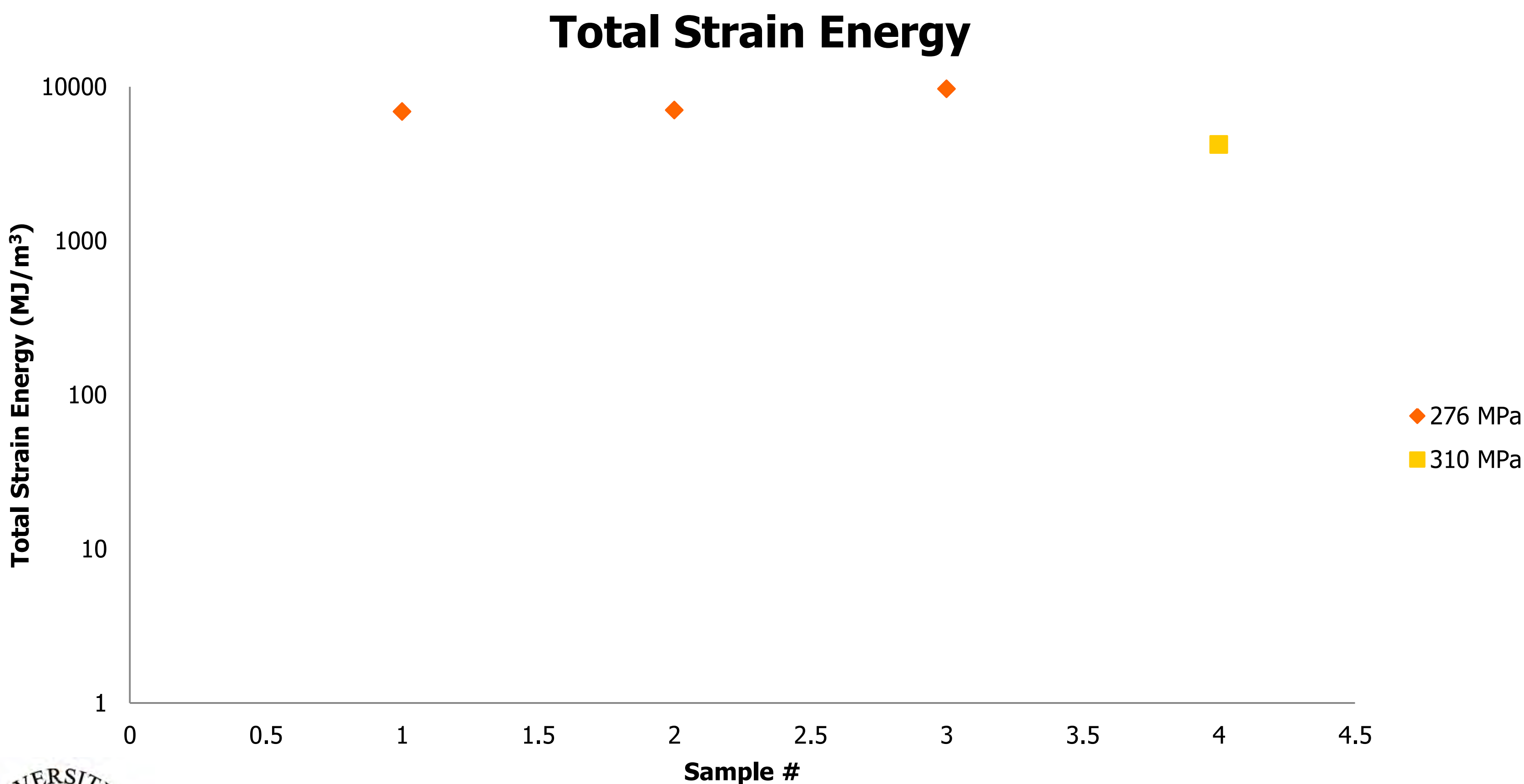
➢ Cumulative Strain Energy Model

- Transformed to Bayesian Regression Form

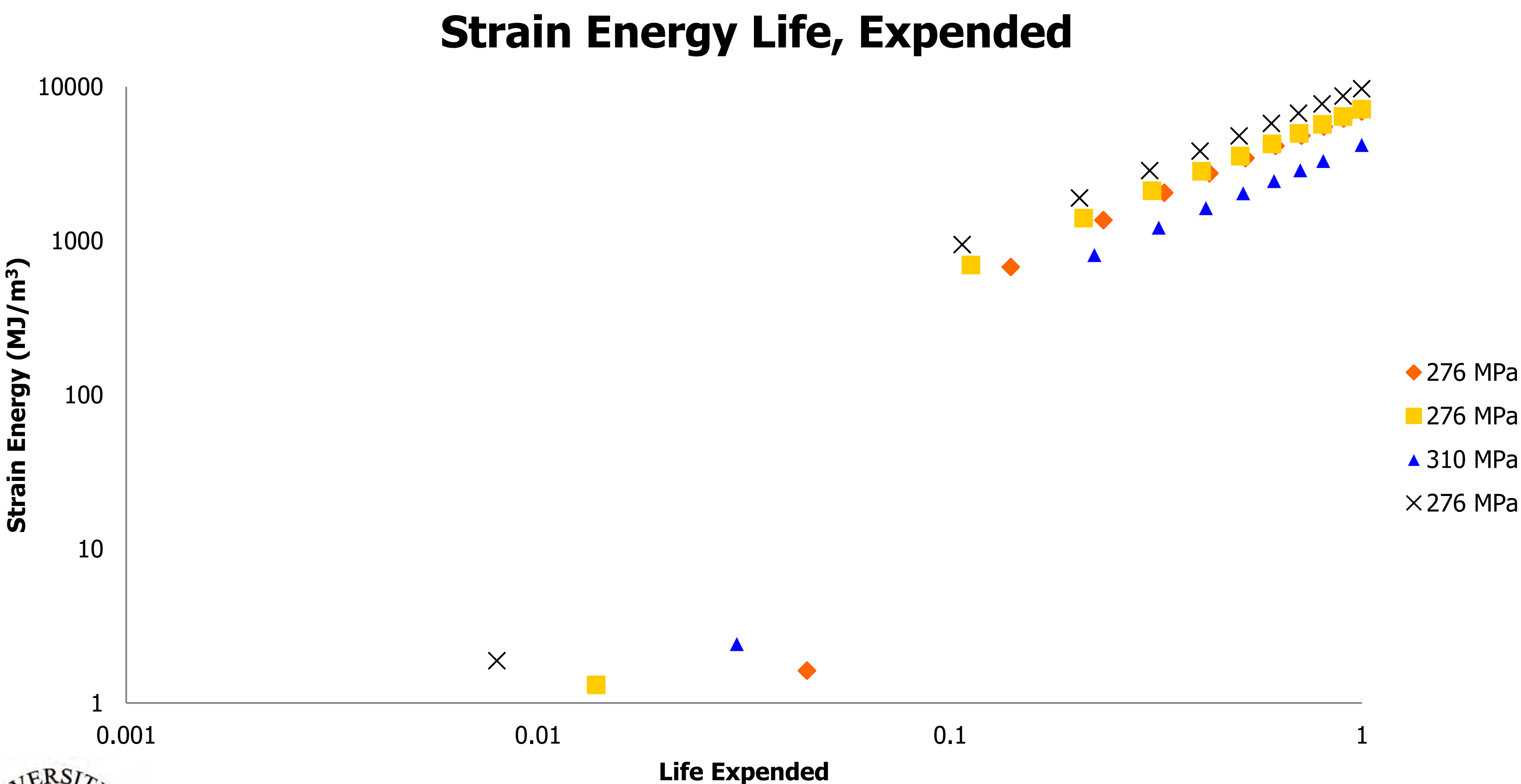
$$\log W_{tot} = \log C - m \log L_e + \varepsilon$$

  - Error modeled as $\varepsilon = NOR(0, \sigma)$
  - C and m – Parameters
  - W_{tot} – Cumulative Total Strain Energy
  - L_e – Life Expended (0 – 100%) $L_e = \frac{N}{N_i}; N < N_i$
  - N_i is the crack initiation, N is the cycle number

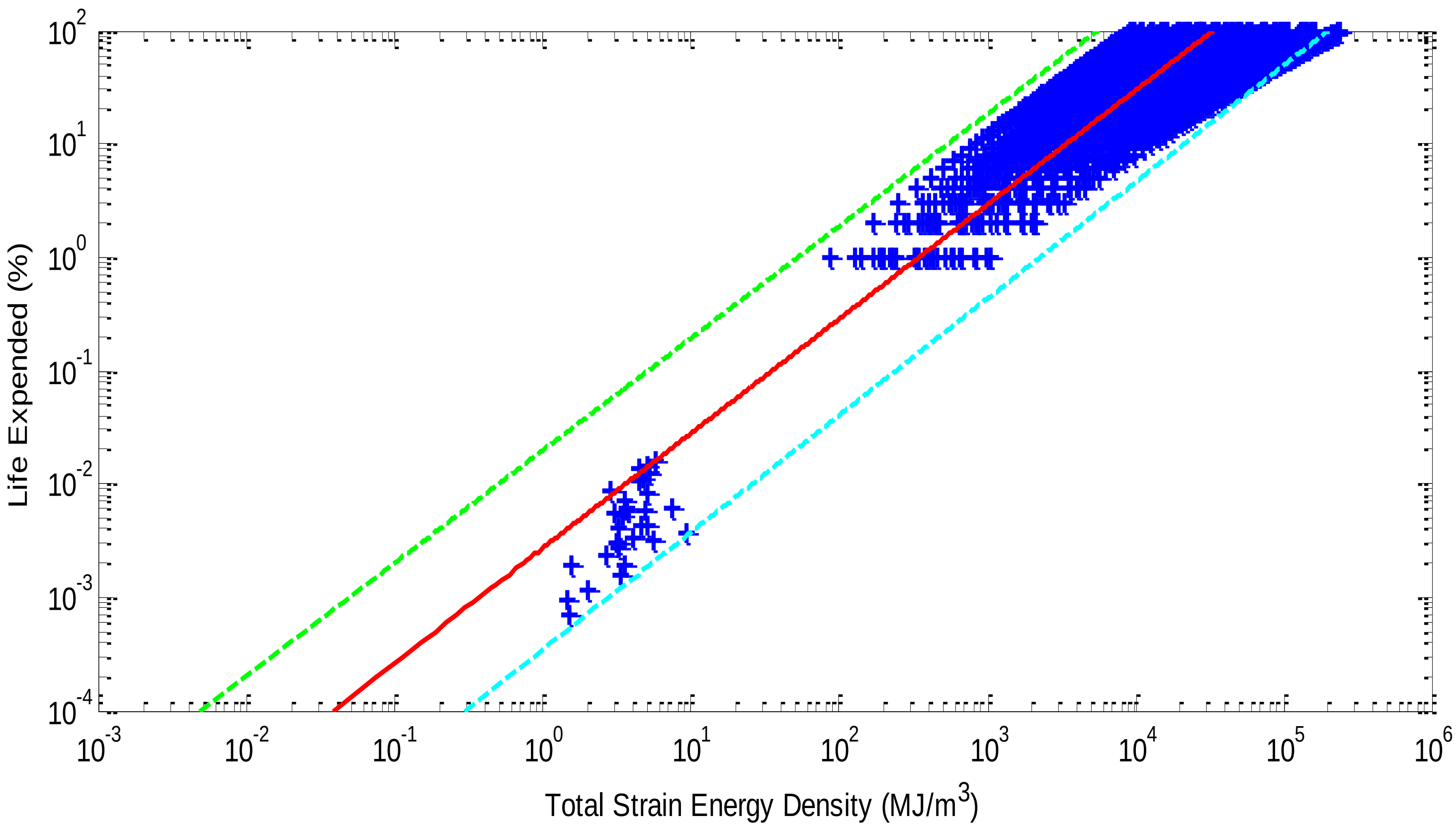
Strain Energy Approach to Crack Initiation



Total Strain Energy
Crack Initiation



Strain Energy Results

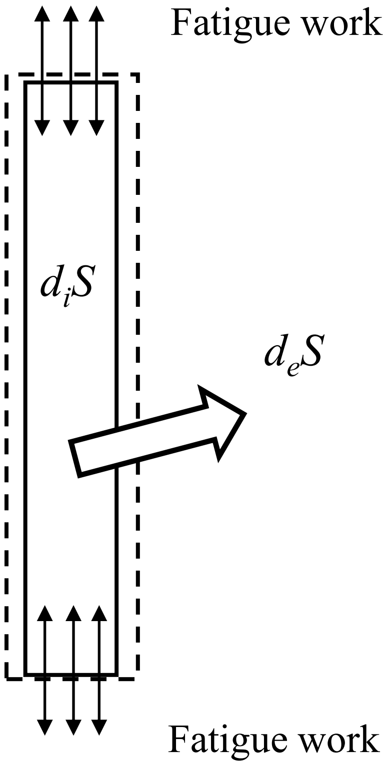


Note:

Some samples are from different batches with different microstructures

Resutls of both edge notch and single hole samples are included

Entropy Approach to Crack Initiation



Specimen as a thermodynamic system

Total Entropy = Entropy Exchange + Entropy Generation

$$dS = d_eS + d_iS$$

Entropy exchange with the surroundings

Entropy generation due to fatigue

Indication of fatigue degradation; related to plastic deformation

Entropy Generation in Fatigue

- All the deformations cause positive entropy generation rate

$$\dot{s}_I = \frac{1}{T}\sigma : \dot{\varepsilon}_p - \frac{1}{T}A_k\dot{V}_k - \frac{1}{T}Y\,\dot{D} - \frac{1}{T^2}\mathrm{q.grad}T$$

- $\frac{1}{T}\sigma : \dot{\varepsilon}_p$ Entropy generation due to plastic deformation
- $\frac{1}{T}A_k\dot{V}_k$ Entropy generation due to internal variables

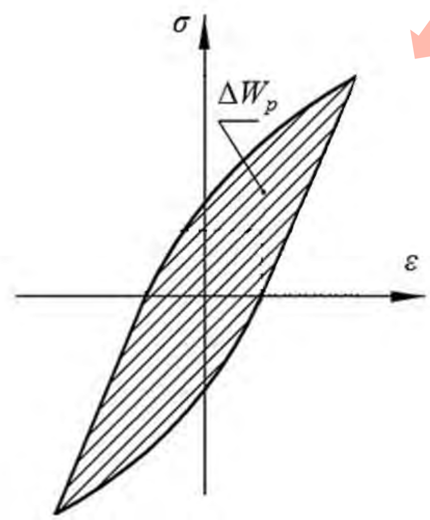
  This term is generally associated with the work hardening effect and is almost 5-10% of the plastic strain energy. This is often neglected.
- $\frac{1}{T}Y\dot{D}$ Entropy generation due to damage
- $\frac{1}{T^2}\boldsymbol{q.grad}T$ Entropy generation due to heat conduction in the material

$\dot{s}_i$ – entropy generation rate; $\boldsymbol{\sigma}$ – stress tensor; $\dot{e}_p$ – plastic strain rate; Y – elastic energy release rate
T – absolute temperature; V_k – internal variable; A_k – associated thermodynamic forces; **D** – damage variable
q – heat flux; Wp – cyclic plastic strain energy;

Assessment of Entropy Generation in Fatigue Experiment

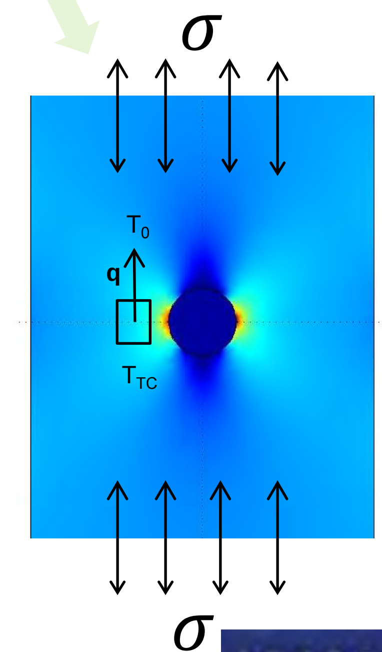
Accumulated entropy generation, s_i up to crack initiation time, t_i :

$$s_i = \int \left(\frac{1}{T} \sigma : \dot{\varepsilon}_p - \frac{1}{T} A_k \dot{V}_k - \frac{1}{T} Y \dot{D} - \frac{1}{T^2} \mathrm{q.grad} T \right) dt$$



Hysteresis Loop

σ: stress
q: heat flux
T_0: Ambient Temperature
T_{TC}: thermocouple temperature



Fatigue Life Estimation based on Entropy Generation

- Thermodynamic Entropy and Life Expended are Correlated:

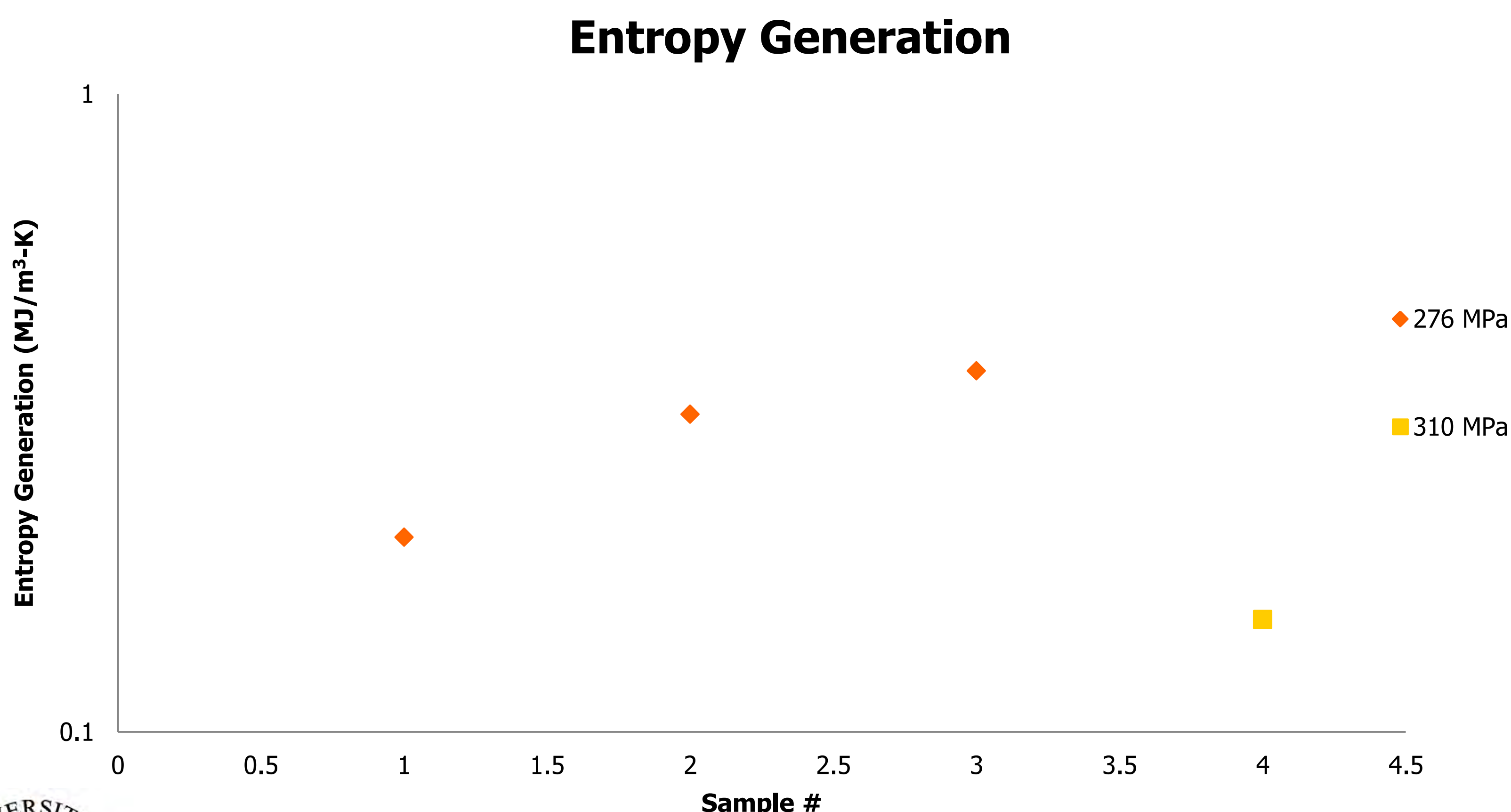
$$L_e = f(s_i)$$

- Experimental results show a good correlation between entropy generated and life expended

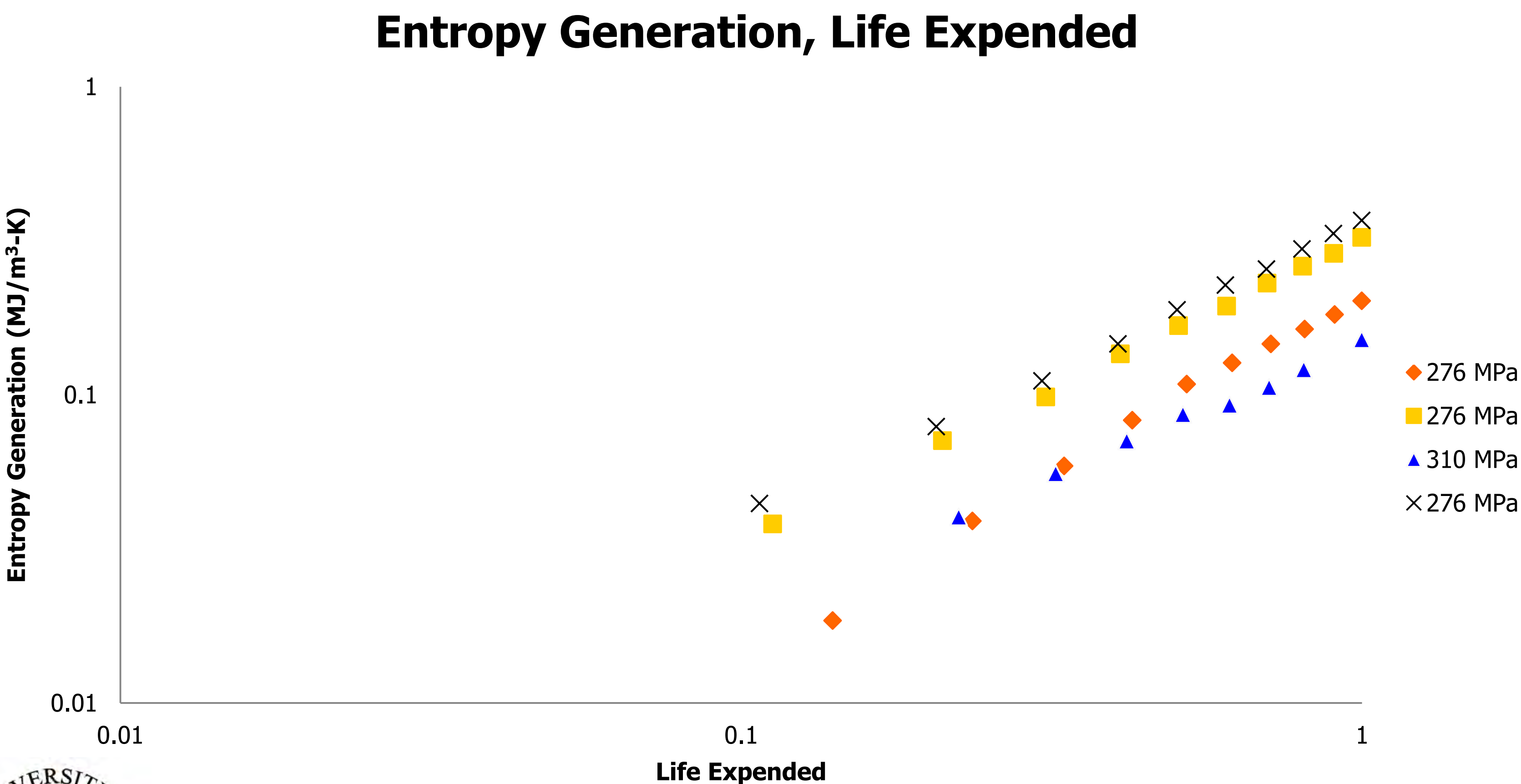
$$\frac{S}{S_i} \mu \frac{N}{N_i}$$

S= Cumulative entropy generation at a given cycle
S_i=Cumulative entropy at entropy generation
N= Given Cycle
N_i=Cycle to crack initiation

Entropy Generation at Crack Initiation



Entropy Generation
Crack Initiation



Conclusions

- Fatigue life assessment based on strain energy expended and thermodynamic entropy generation can provide a physical explanation without a large number of model parameters
- Test results and data are generic and applicable to a variety of structural geometries and components
- The accumulated entropy for crack initiation for Aluminum 7075-T6 was found to range between 0.15 to 0.36 MJ/(M^3K) with an average of 0.26 MJ/(M^3K).
- Further experimental work is required to prove the existance of the entropy limit for crack initation at variable stress amplitude and variable frequency
- The entropy accumulation shows a linear correlation with the life expended, providing a reliable tool for fatigue life assessment

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- Bayels, R., Moore, D., Dowling, N., "Detecting Cracks with Differential Thermographic Imaging," Presentation Slides, June 2011

Acoustic Emission Based Model Development for Fatigue Crack Growth Prediction

UMD-NAWCAD Research

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GLOBAL CAPABILITY

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

- Current periodic fleet inspection practices:
  - ✓ Labor-intensive, time consuming and expensive
  - ✓ Subject to human error
  - ✓ Inspection itself may cause damage

- Inspection intervals selected such that an undetected crack will not grow to critical size before the next inspection

- High levels of uncertainty regarding current & future damage state of structure drive recurring manual inspection requirements:
  - ✓ In-situ NDI (Acoustic Emission, Lamb Waves, etc.) can reduce manual inspection requirements by reducing underlying uncertainty.

CONTRIBUTION

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

- Current Acoustic Emission systems can detect the presence of growing cracks, but cannot determine the sizes of such cracks:
  - ✓ Acoustic Signal must be correlated to crack lengths and growth rates
  - ✓ Must be discriminated above background noise level
  - ✓ Must be able to account for variable amplitude loading environment

- Measurement of small and large cracks allows an AE system to be used to determine future inspection and repair requirements based on true current damage state

- UMD has Demonstrated Correlation of AE signal to crack size and growth rate for constant-amplitude loading

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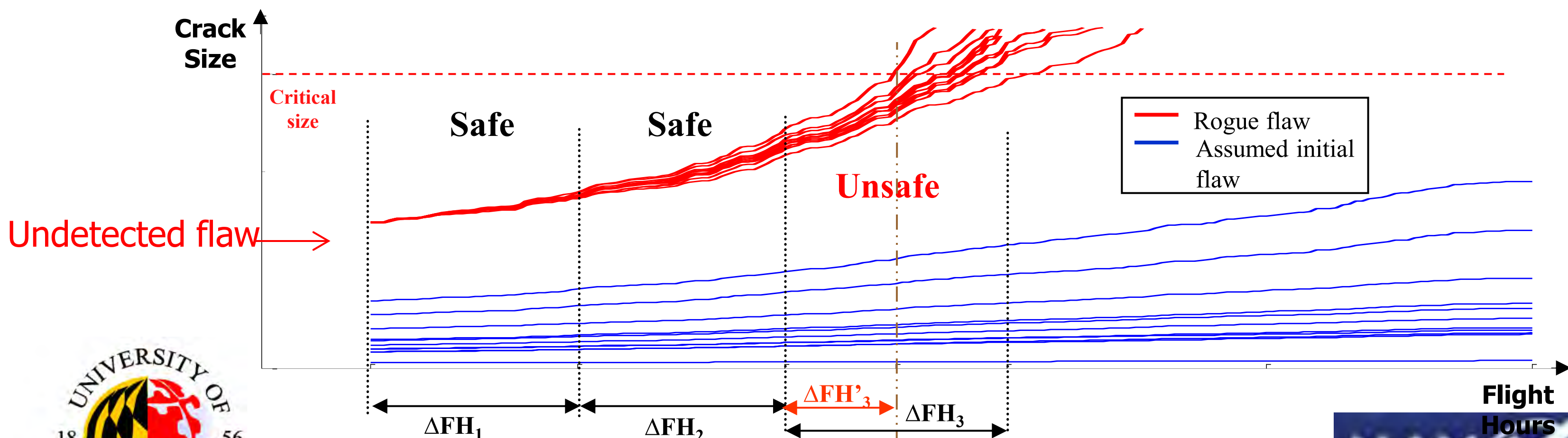
OBJECTIVES

- **Model development and validation of crack growth rates correlation with AE signals**
- **Probabilistic AE-model development of in-situ monitoring of small crack growth**
- **Investigating the sensitivity of AE signal features to crack initiation**

Structural Health Management (SHM)

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



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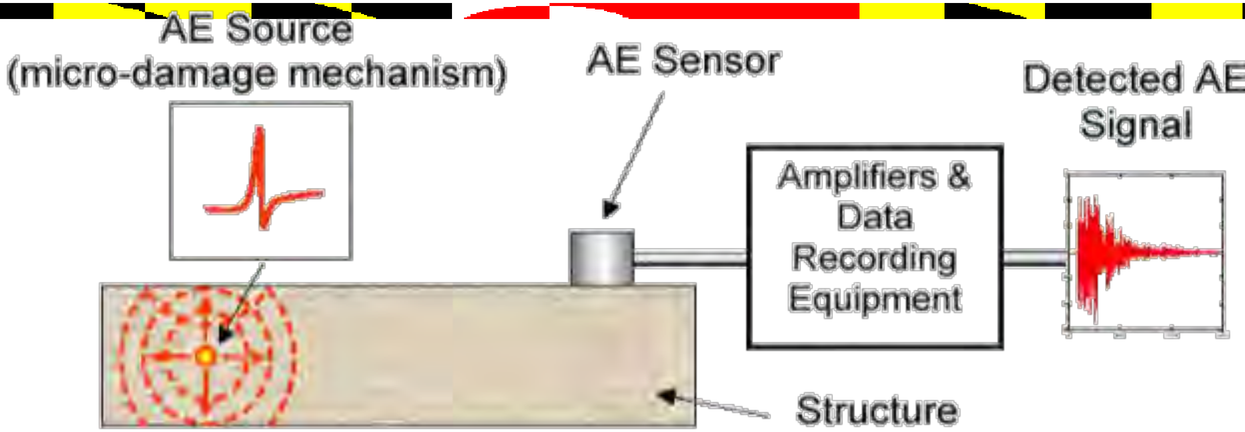
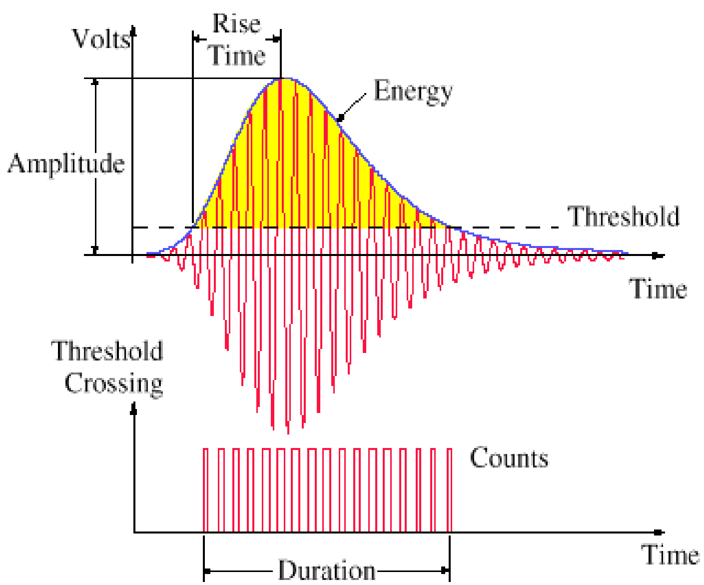
AE monitoring: Theory & Background





AE Features

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

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Correlation between AE features & Fracture parameters

AE Features

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

Fracture Parameters

da/dN
ΔK

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

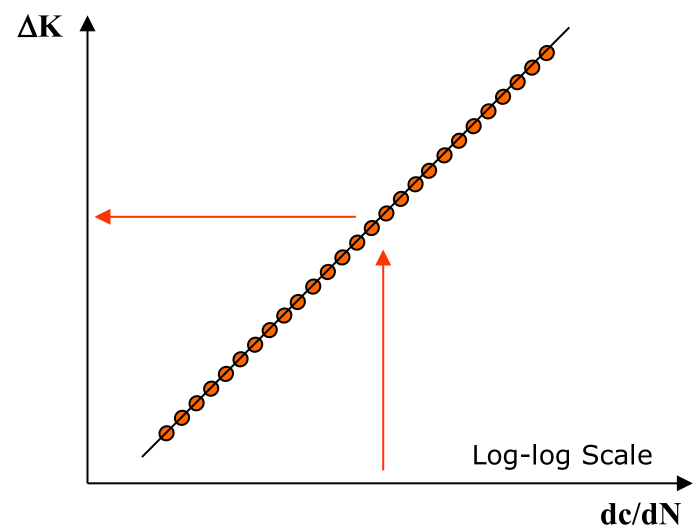
$$\Downarrow$$

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

$$\Downarrow$$

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

[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.



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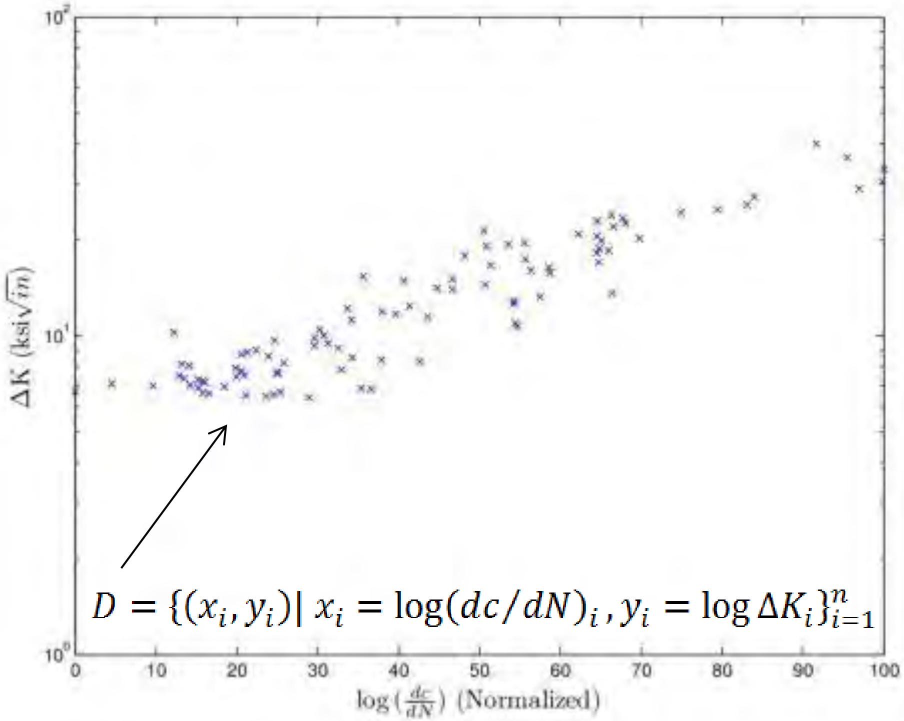
Statistical model development



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

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

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

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

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

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

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

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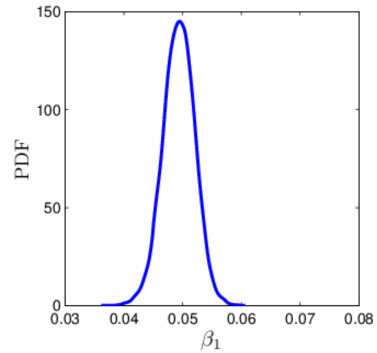
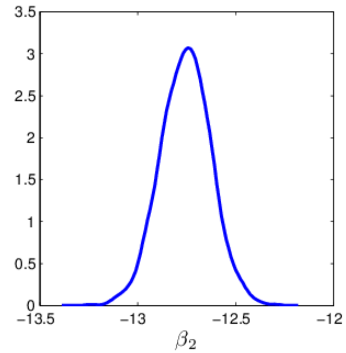
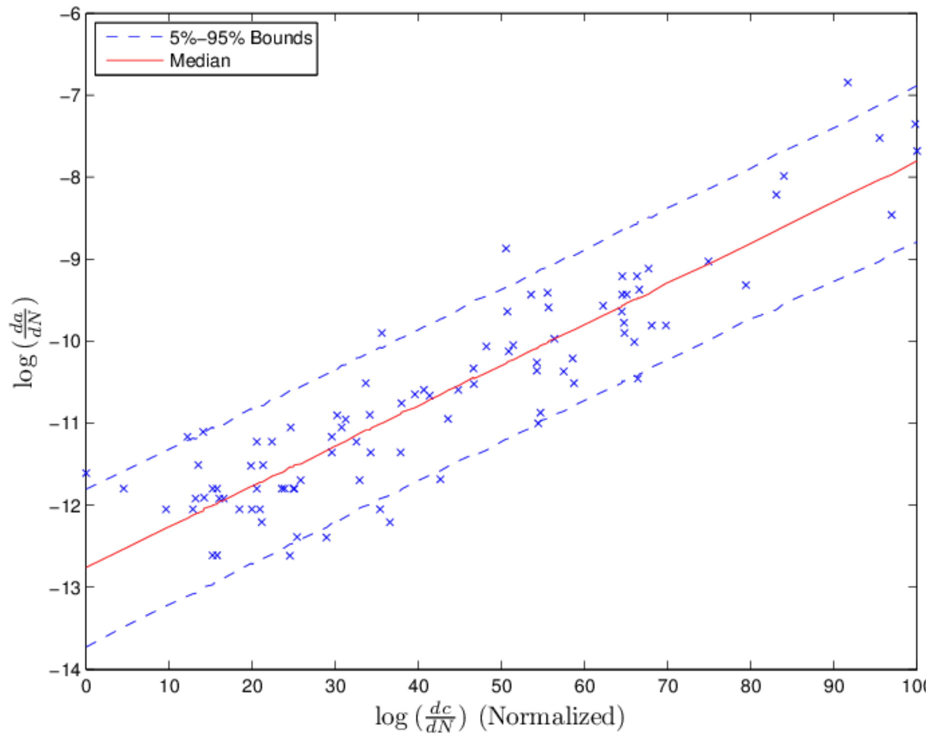
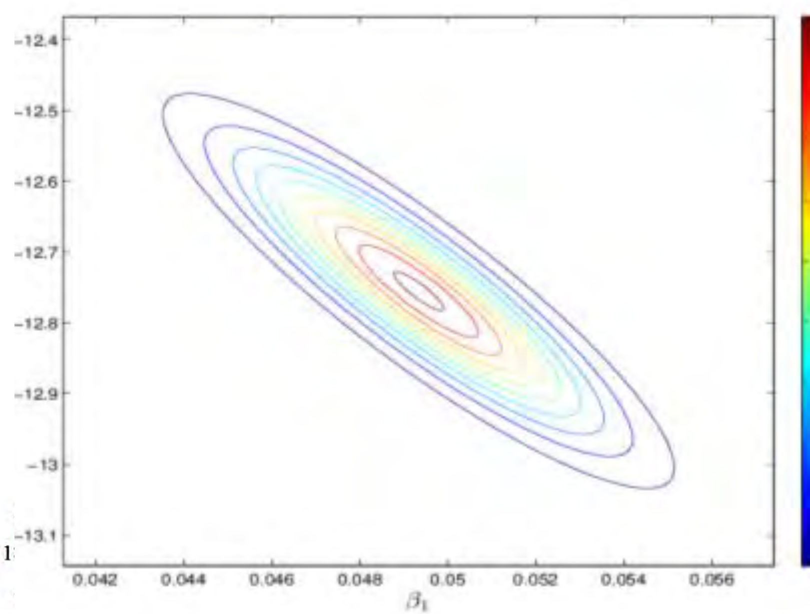
AE-based Crack Size Estimation

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









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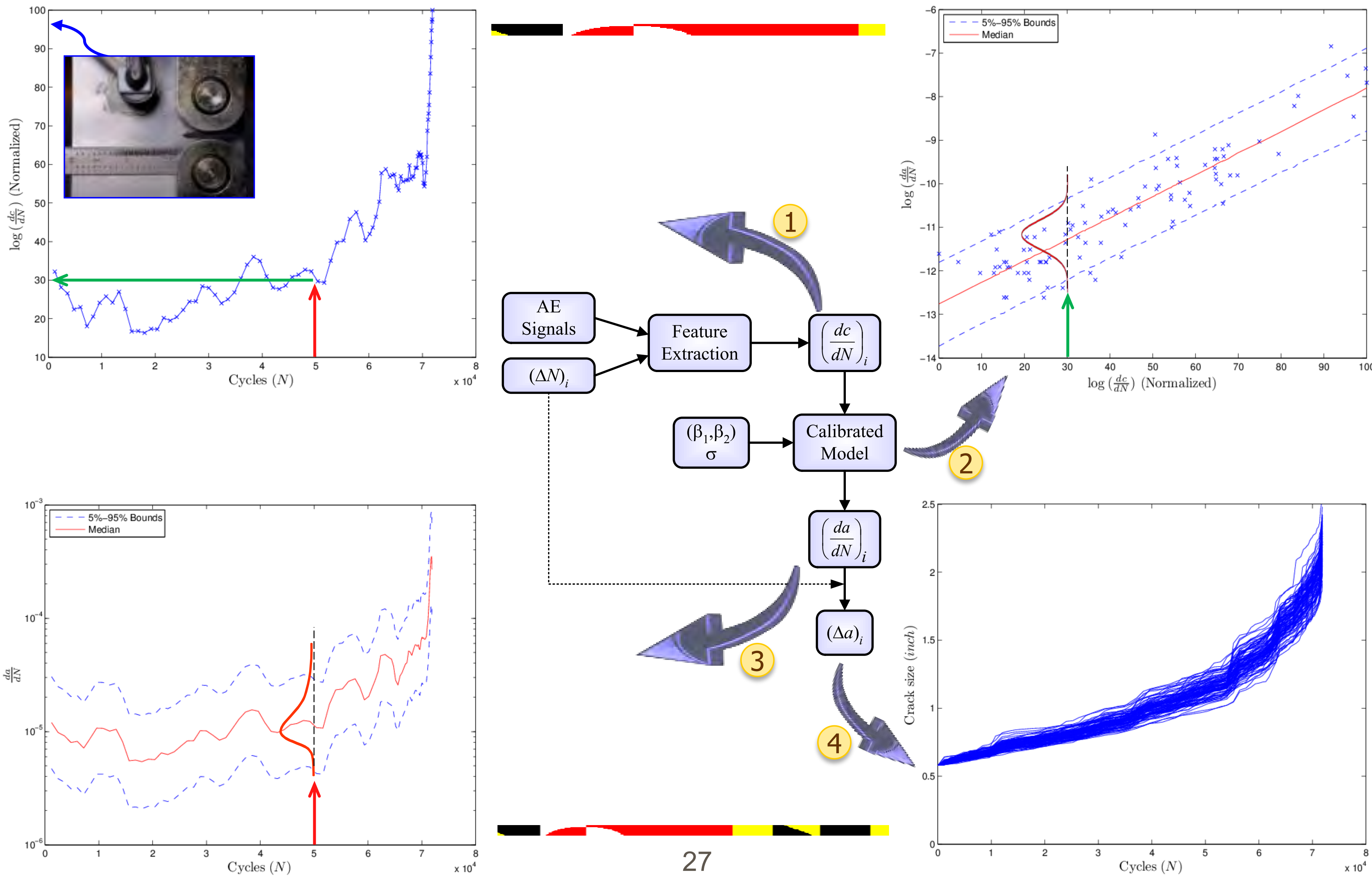
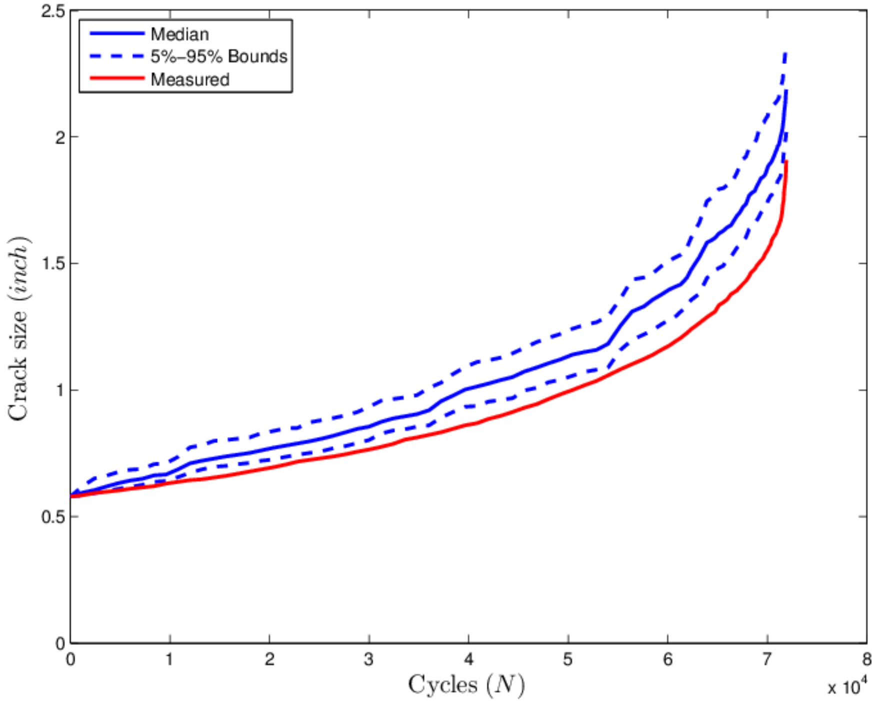
AE-Based Crack Size Estimation

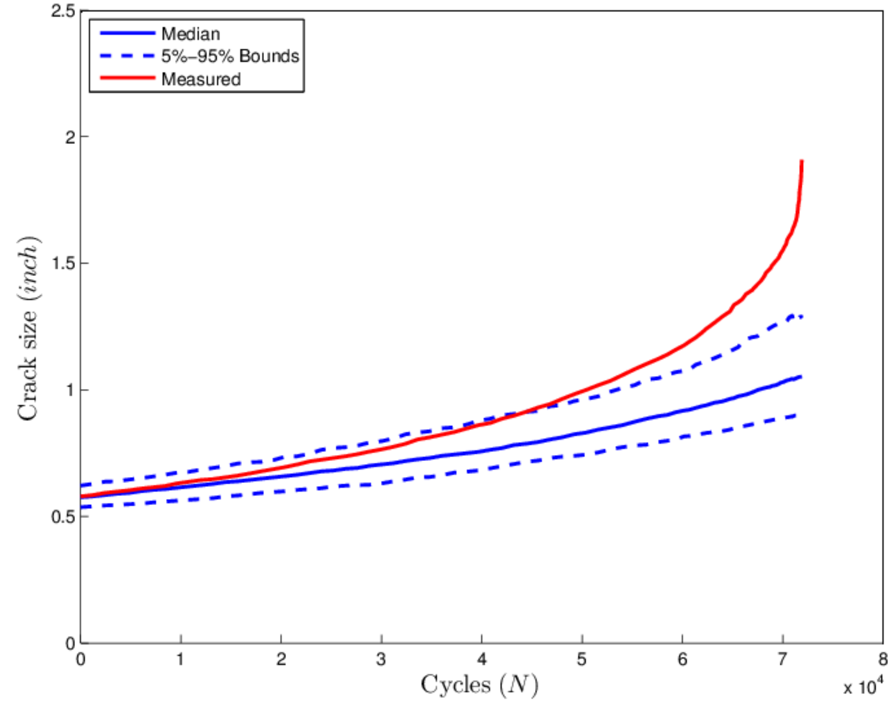


AE-Based vs. Empirical Crack Growth Model

AE-Based Crack Growth Model



Empirical Crack Growth Model



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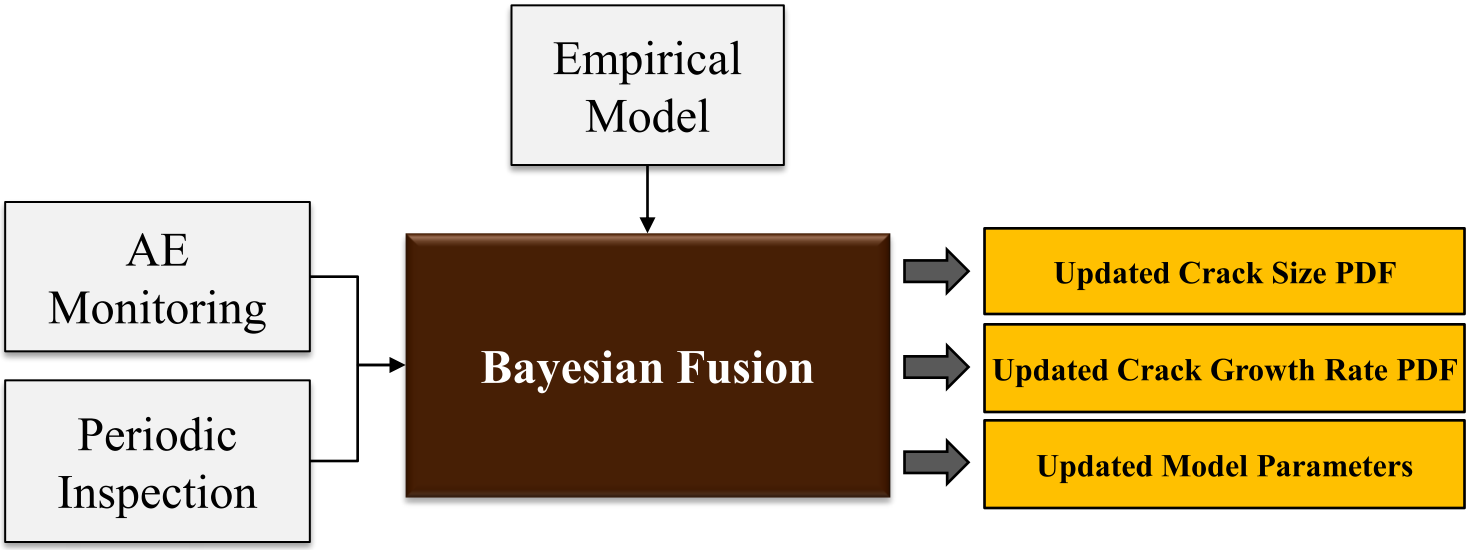
Bayesian Fusion

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



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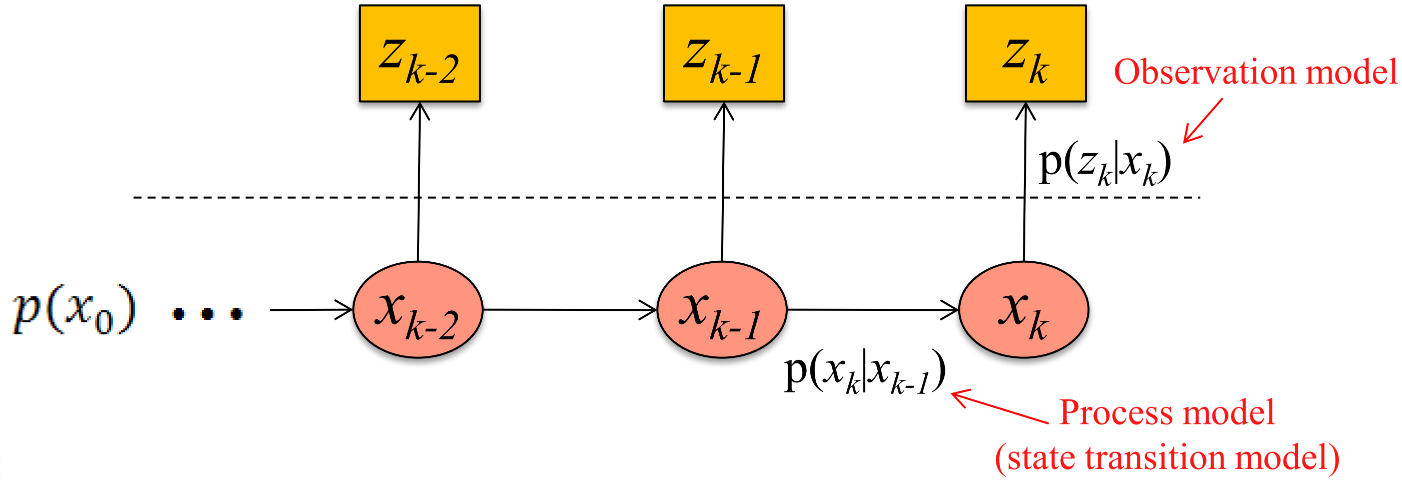
Dynamic State-Space Model

⌘ *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:

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

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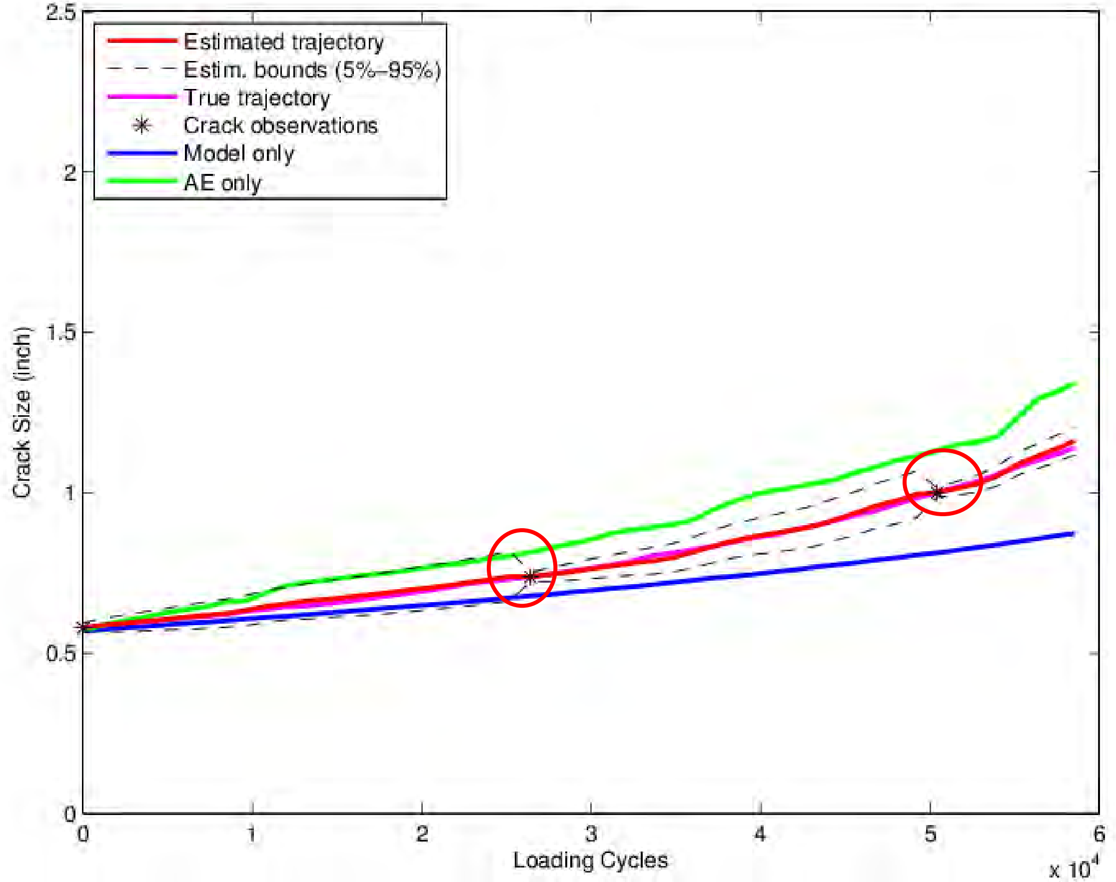
Results: Effect of Frequency of Inspections



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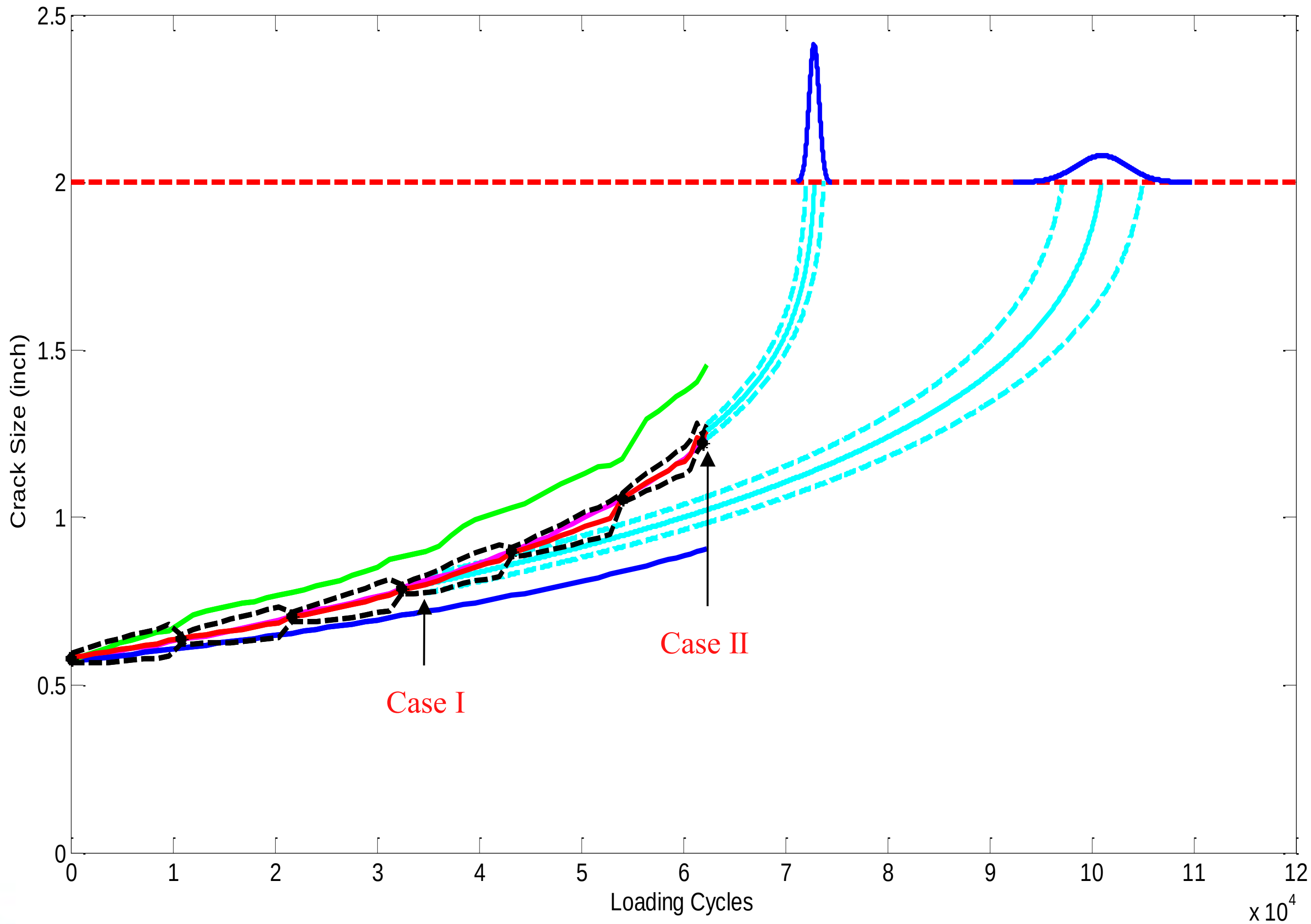
Prognosis Results



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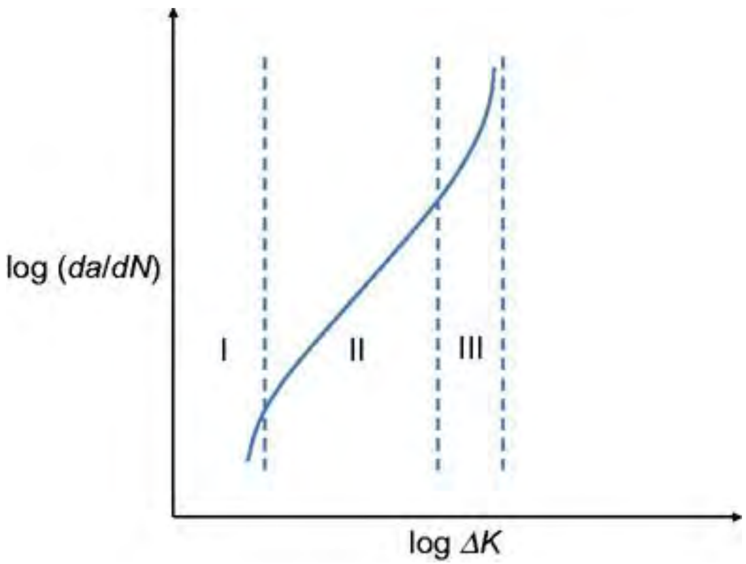
Crack Initiation and Small Crack Growth

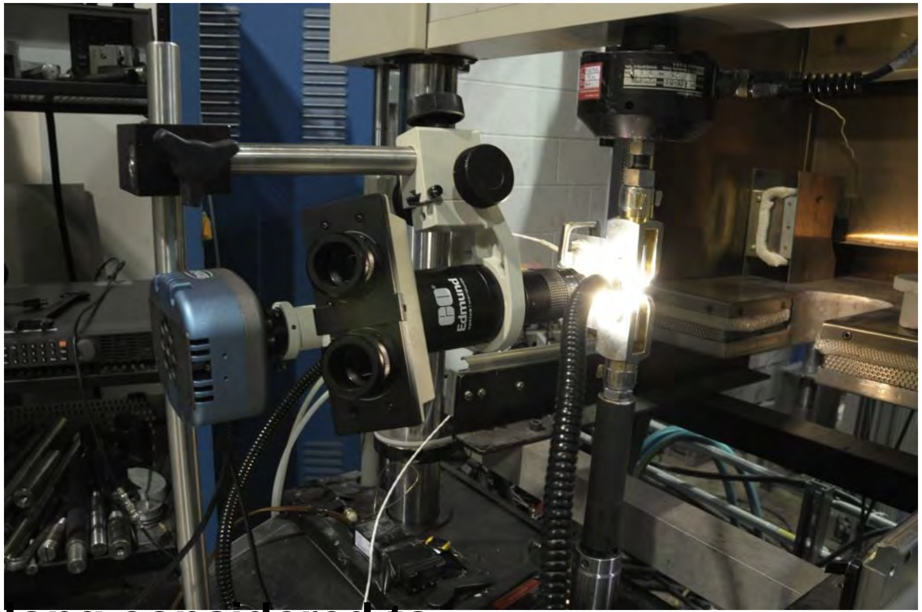
Probabilistic model development for steady state crack growth:

Started development of a probabilistic model for small crack growth:

- **Small crack length measurement**
  - **Close-up camera for large cracks**
  - **Optical microscopy for small cracks**
- **Correlation between Small crack growth rates and AE signals**

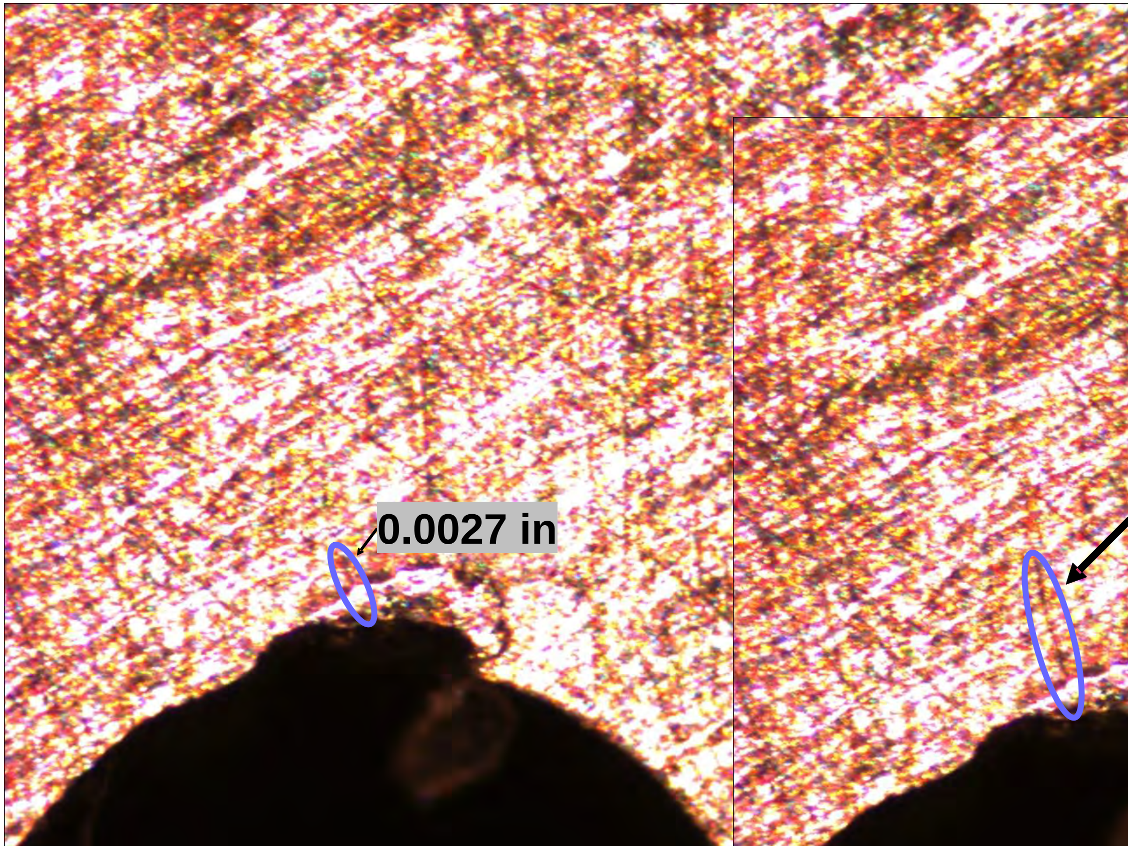
Crack Initiation and Small crack measurement

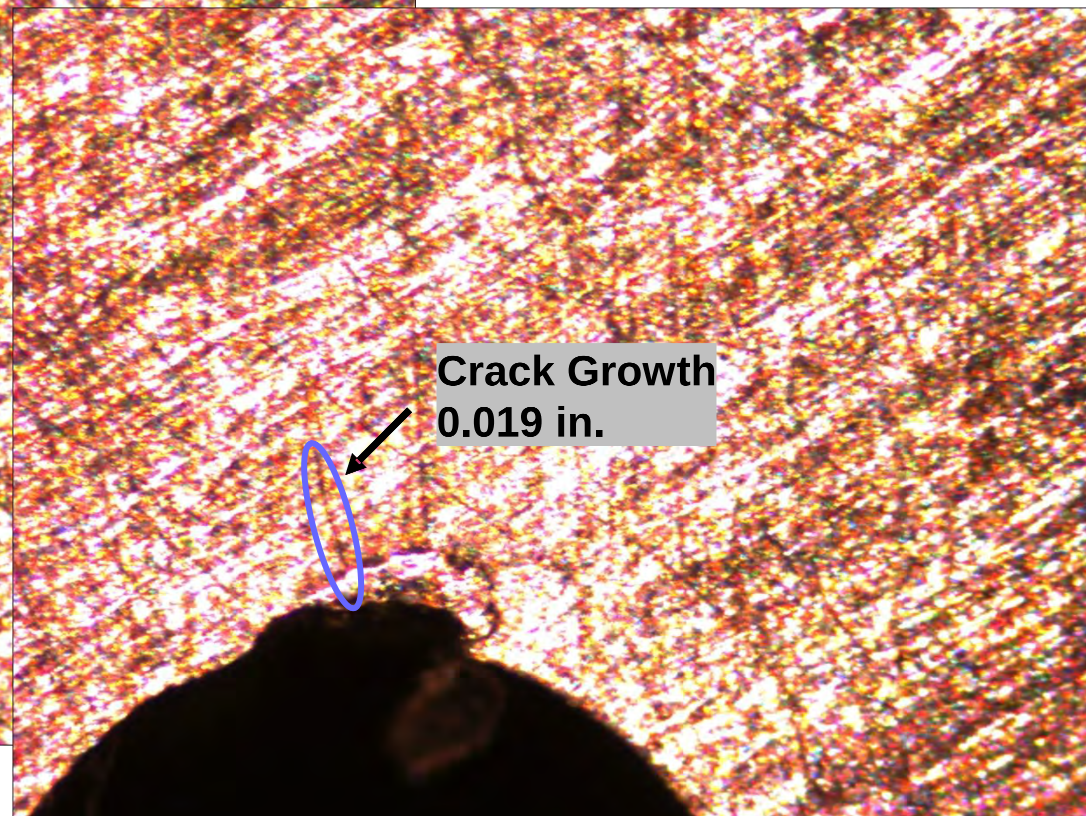




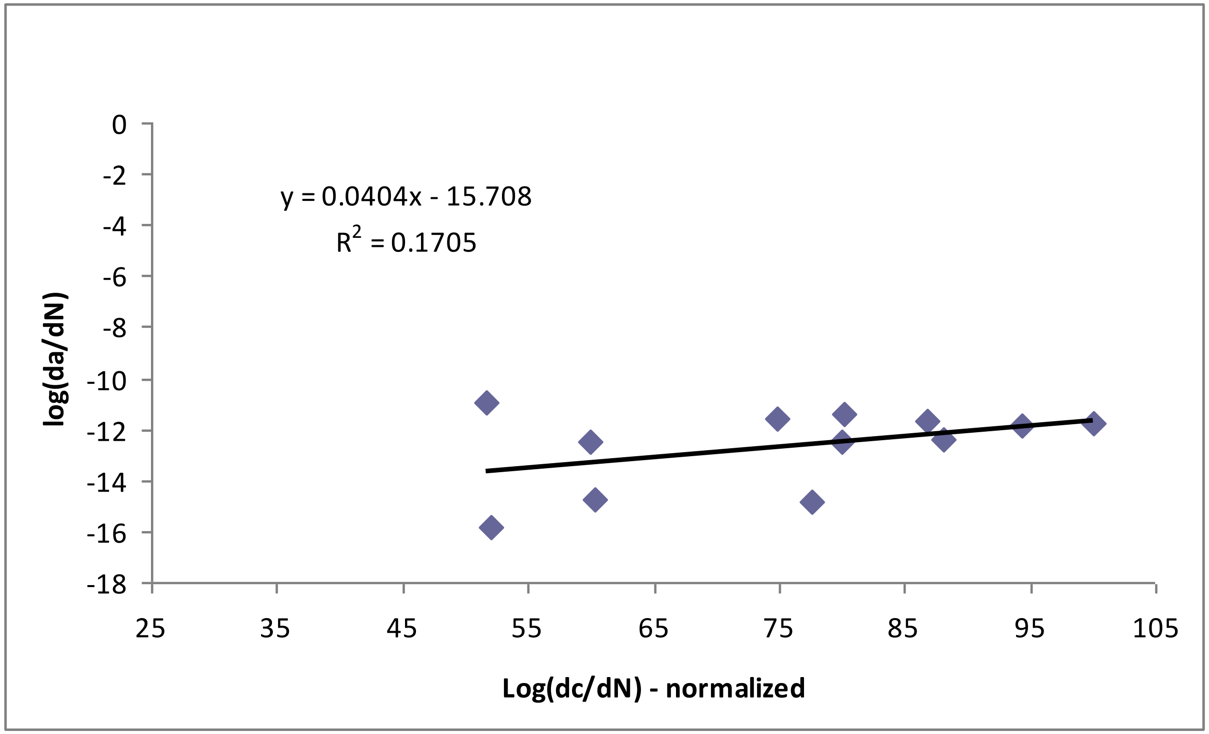
- Cracks less than 1mm long considered to be small
(<0.04 in. or <0.001 m)
- Time-lapse photography
  - 50X magnification microscope for small cracks
- Image processing toolbox for crack size measurement

Optical microscopy for small cracks



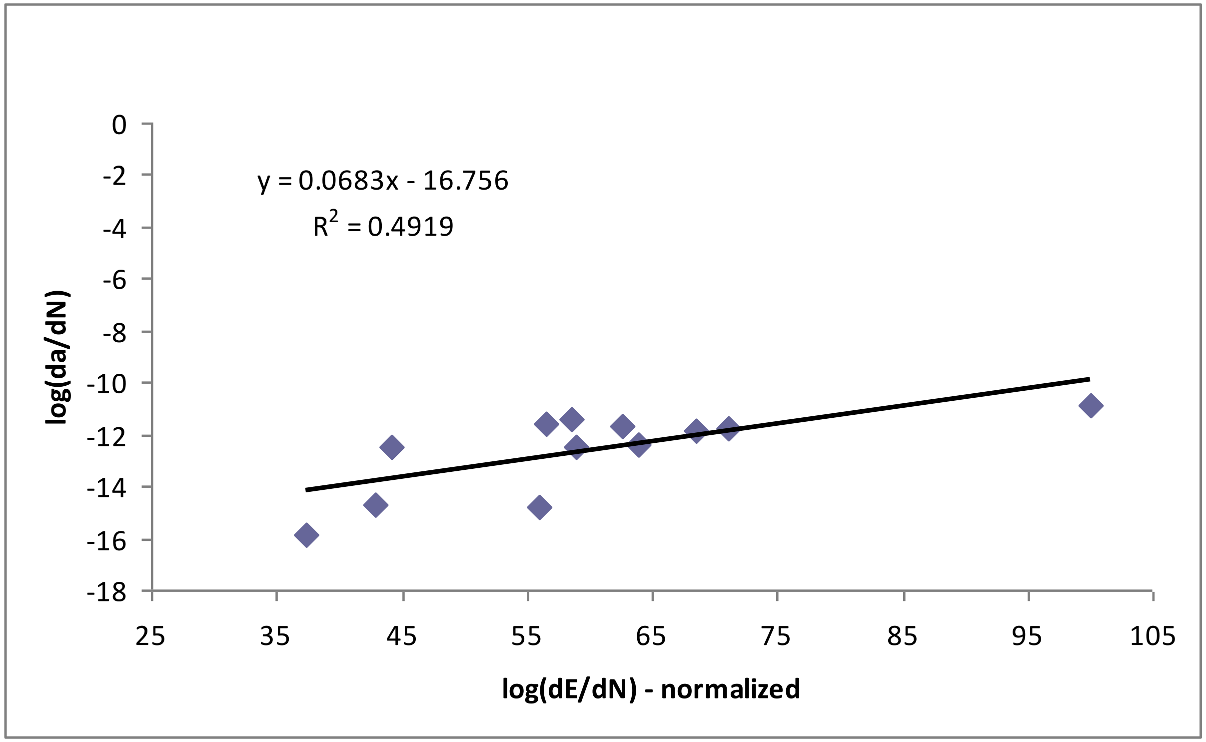


Small crack growth rate versus AE count rate



- Linear correlation observed
- Probabilistic prediction model can be achieved with more data

Small crack growth rate versus AE energy rate



- Linear correlation observed
- Higher R^2 and larger slope than count rate
- Energy showed more sensitivity to crack growth

Conclusions and Future Steps

- The AE count rates showed a linear correlation with crack growth rate for large cracks
- The probabilistic model was successfully applied for large crack estimation
- For small cracks the AE energy rates showed more sensitivity to crack growth
- Ongoing AE-based experiments to account for different loading conditions
- Ongoing experiments to investigate the sensitivity of AE signal features to crack initiation
- Probabilistic model development for small crack length

Backup Slides

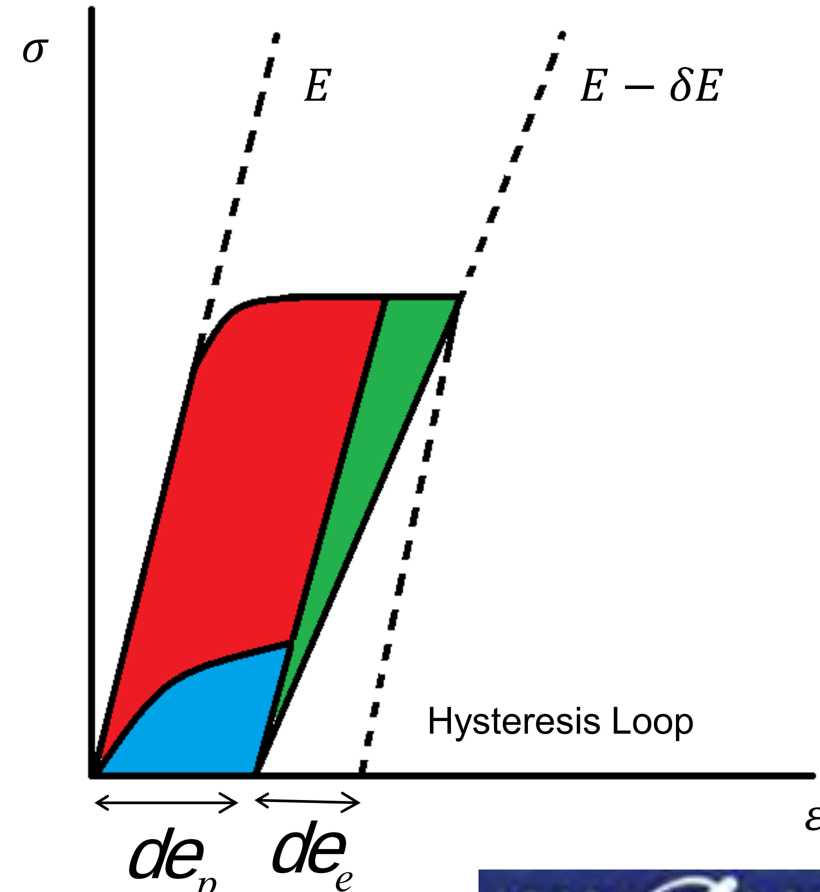
Thermodynamic Entropy as Defined in Fatigue

- Hysteresis Dissipation: $s : e_p - A_k V_k - YD$

-Energy dissipated due to internal variables

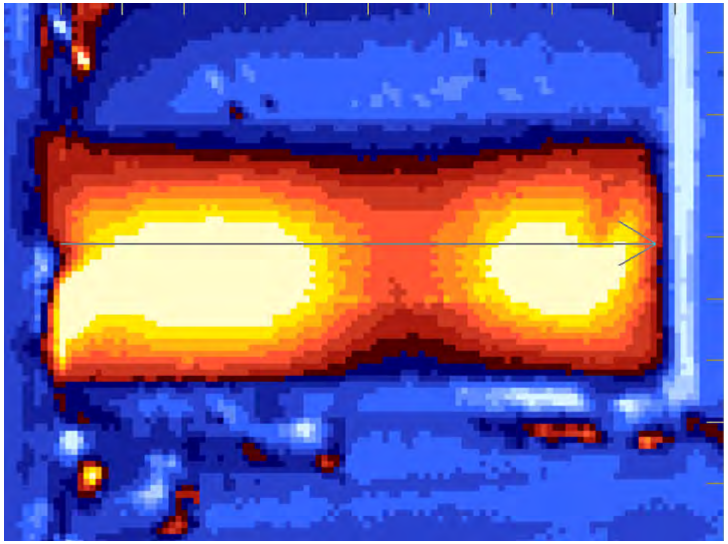
-Energy dissipated due to elastic damage

- Energy dissipated due to plastic deformation (minus the energy dissipated resulting from internal variables)



Accomplishments for past year

- Experimental
  - Implement use of
    - Strain gauges and thermocouples
    - Force and displacement control tests
  - Multiple stress ratios:
    - R = 0, 0.1, 0.4
  - Finite element modeling
  - Implementing Infra Red technique for T



Preliminary IR camera results showing temperature change at edge notch

- Model development
  - Developed a Bayesian regression framework in MATLAB
    - Move away from WinBUGS
    - Investigating conversion to C

Expected accomplishments for current year Ending Sept. 31, 2012

- Experimental
  - Continued optical and electron microscope inspection
  - IR Camera
  - Finite Element Modeling (Temperature)
- Model development
  - User’s guide
  - Conversion to C
  - Fine tuning / updating with additional experimental results

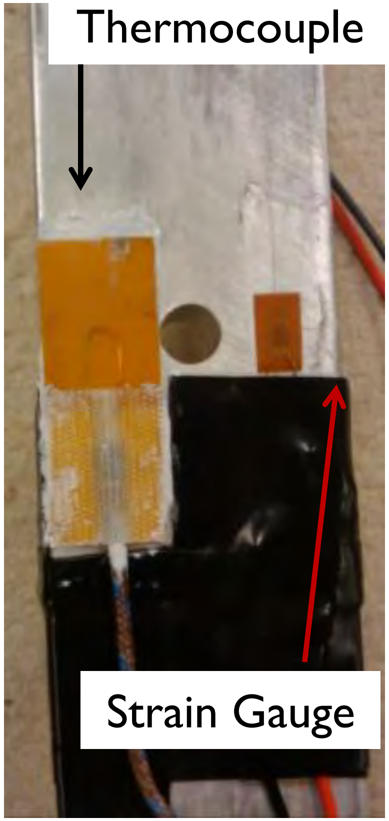
Fracture Mechanics and Probabilistic Physics of Failure Laboratory

Two heavy-duty uniaxial fatigue testing machines
Rated 22000 lb (100kN) force capacity; 30 Hz frequency
Air cooled hydraulic power pack

Fracture Mechanics and Probabilistic Physics of Failure Laboratory

Heating Chamber

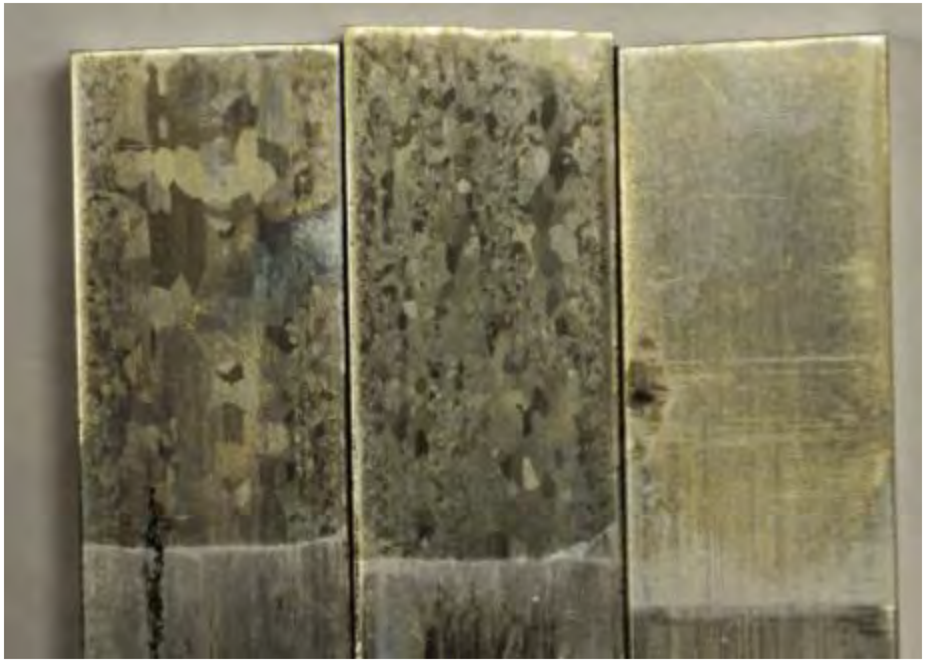
Corrosive Medium Chamber



Strain gauges and Thermocouples

Scatter Reduction

- Different batches
  - Sample etching
  - Single Batch
- Inclusion vs. flaw
  - SEM
- Temperature
  - IR camera
  - Sample alignment



Samples from different batches showing different microstructures

Information ‘Entropy’

- Statistical Entropy
  - Entropy of a macroscopic system consisting of a large number of microscopic identical particles

$$S = k_B \ln \Omega$$

$$S \equiv -k_B \sum_{i=1}^{m} P_i \ln(P_i)$$

k_B: Boltzmann’s constant
Ω : thermodynamic probability
P: probability of finding a particle in a microstate i

- Information Entropy

$$S = -K \sum_{i=1}^{m} P_i \ln(P_i)$$

K: Constant

- Maximum (information) entropy:
  - “maximally noncommittal with regard to missing information”
  - Lagrangian multipliers

Janes, E.T., “ Information Theory and Statistical Mechanics,” *The Physical Review*, 1957 **106**