Advances in Probabilistic Physics-of-Failure

Keynote Talk
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by

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Outline of this Talk

- Overview
- Reliability engineering timeline
- Frontiers in reliability engineering research
- Probabilistic physics of failure
- Confluence of recent data analytics and reliability
- Entropy as the fundamental science of reliability
- Entropy-based physics of failure
- Conclusions

Timeline of Reliability Engineering

- Post WWII Initiatives in 1950's
  - Weakest link
  - Exponential life model
  - Reliability Block Diagrams (RBDs)
- Exponential Distribution Retreat in 1960's
  - Birth of Physics of Failure (POF)
  - Uses of other distributions
  - Reliability growth
  - Life testing
  - Failure Mode and Effect Analysis (FMEA)
- Deductive Models: Fault Tree Analysis in 1970'S
  - Probabilistic Risk Assessment (PRA)
  - Common Cause Failures (CCFs)
  - Uncertainty analysis

Timeline (Cont.)

– Accelerated Life and Degradation Testing in1980's
  - Environmental screening tests
– Revival of Physics-of-Failure in 1990's
  - Probabilistic Physics-of-Failure (PPoF)
  - Time varying accelerated tests (e.g., Step-Stress Test)
  - Highly Accelerated Life Testing (HALT)
– Hybrid Reliability and Prognosis Models in 2000's
  - Powerful simulation tools (MCMC, Recursive Bayes and Particle Filtering)
  - Integrated PoF and probabilistic models (e.g., BBN)
  - Machine learning tools for Prognosis and Health Management (PHM)
– Exploring Fundamental Sciences of Reliability in 2010 and Beyond 2020
  - Entropy as damage and entropic-based reliability science
  - Supervised, semi-supervised and unsupervised reliability predictive analytics
  - Reliability of intelligent, autonomous and cyber-physical systems
  - PoF-informed deep learning

Frontier Research Areas in Reliability Engineering

- Probabilistic Physics-of-Failure (PPoF)
  - Empirical models for Unit-Specific reliability assessment
  - Simulation-based reliability
- Hybrid System Reliability
  - Combined Techniques: NN, CNN, RNN, GAN, BBN, DBN, DFT, DET, FEM and FDM.
- Deep Learning, Data-driven Sensor-based Reliability Analysis
  - Diagnostic and prognostic reliability: Data Fusion, Predictive Analytics, Deep Learning
- Fundamental Sciences of Reliability Engineering
  - 2nd Law of thermodynamics and entropy
  - Statistical mechanics
  - Information entropy and Kullback–Leibler Divergence (KLD)

What is a Physics-of-Failure (PoF) Model?

- *PoF is a regression-based mathematical model of failure, developed based on the empirical science of failure mechanisms such as fatigue, fracture, wear, and corrosion.*

- *PoF is of the form:* $Damage\ (of\ life) = f\ (stress\ \&\ envirnmental\ variables, geometry, material\ properties, model\ parameters)$

- *When model error, parameter uncertainties in the mathematical PoF model are also estimated, the model is called Probabilistic PoF (PPoF)*

Why PoF-Based Modeling in Reliability?

- To avoid repeating long and costly tests
  - Reduce the development time
  - Cost reduction toward cheaper products
- When impractical to build many identical units for testing
  - Large systems like off-shore platforms, space vehicles
  - One-of-a-kind or highly expensive systems
  - The products that must work properly at the first time
- When there is no prototype to test during the design
- When highly reliable products and systems that don't fail
  - The life time is long and possibly nonrepairable
  - Internal control or safety related devices limit the stress
- Design for reliability optimization a dynamic prediction
- Predicting the occurrence of rare or extreme events

Strengths and Weaknesses of PoF

- *Strengths:*
    - *Based on sound science and experimental data*
    - *Offers a well-define path to modeling aging and degradation*
    - *Integrates well with modern machine learning*
    - *Provides unit-specific reliability predictions*
- *Weaknesses:*
    - *More expensive to build*
    - *Hard to specialize applications involving multiple, interactive failure mechanisms*
    - *Extension of lab test data to field applications involving complex stresses is difficult*

PoF Development Steps

1. Specify component's operating limits, pertinent characteristics and operating requirements.
2. Define operating environment and profile.
3. Use the profile to assess the applied static and dynamic mechanical, thermal, electrical and chemical stresses.
4. Identify hot spots exposed to the highest stress.
5. Identify failure mechanisms that become activated and their interactions.
6. Determine materials characteristics and their vulnerabilities to the applicable failure mechanisms.

PoF Steps (Cont.)

7. Propose a mathematical model that correlates loads (stresses) applied to amount or rate of degradation.
8. Use generic data or accelerated reliability test data to estimate the PoF model parameters, uncertainties and model error.
9. Validate and revise the model considering adequacy of the PoF mathematical model fit to the data.
10. Determine a level of degradation beyond which the component fails to operate or endure more damage.
11. Using the PoF model and the endurance limit, estimate the time- or cycle-to-failure, including uncertainties associated with such estimation.
12. Perform computer-based simulation to estimate expected life or remaining life of an item.

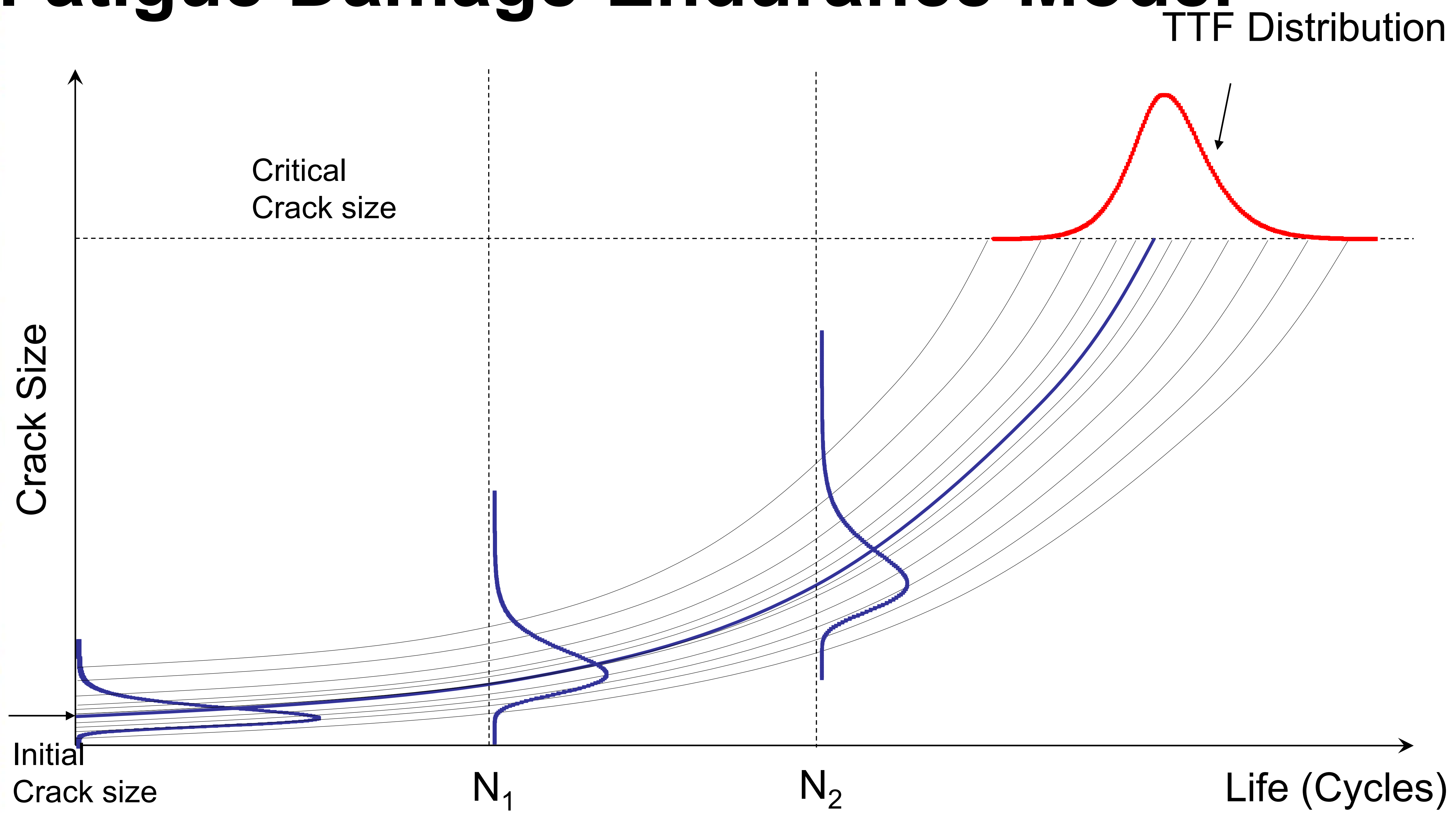
Data-Driven Failure Models vs. PoF Models

- Data-driven failure (DDF) reliability models explore relationships between the failure time or degraded state of a component without knowledge of the underlying physical behaviors, such as applied failure mechanisms
- Strengths
  - Relies on data specific to a system
  - Could Rely on strong learning algorithms
- Weakness
  - Needs significant amount of data to predict (i.e., path to failure is unknow, a priori)

Data-Driven Failure Models vs. PoF-Informed Hybrid Models

- PoF-Informed hybrid models consider both the information and data from the components and the anticipated path to failure governed by the PoF
- Strengths
    - Reduces the need for voluminous field and test data
    - Substantially reduces reliability prediction error
- Weakness
    - Analytically involved and more expensive

A Conceptual PPOF Fatigue Damage-Endurance Model



Entropic-Based PPoF in Reliability

- Describes damage resulted from failure mechanisms and time-to-failure within the confines of the laws of thermodynamics and information theory
- Sources of irreversible energy dissipation in failure mechanisms in terms of mechanical, thermal, chemical and acoustic are defined
- Entropy generation for each dissipation represent the aging and accumulation of damage
- Measures of entropy based on thermodynamic, information, and statistical mechanics theorems are used

Why Entropy as a measure of damage in PoF?

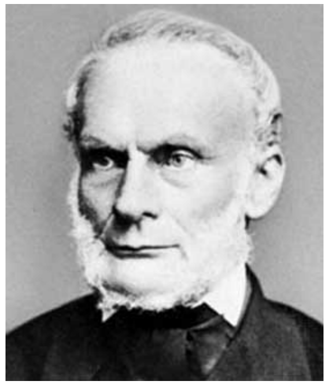
Common definitions of damage are based on observable markers of damage which vary at different geometries and scales

- Macroscopic Markers of Damage (e.g. changes in elastic modulus, pit densities, weight loss)
- Macroscopic Fatigues Markers include: crack length, reduction of modulus, . . .
- Issue: When markers of damage observed 80%-90% of life has been expended

An Entropic Theory of Damage: A Fundamental Science of Reliability

- Failure mechanisms leading to degradation share a common feature at a deeper level: ***Dissipation of Energy***
- Dissipation (or equivalently entropy generation)≅Damage

[redacted] → Dissipation energies → Entropy generation

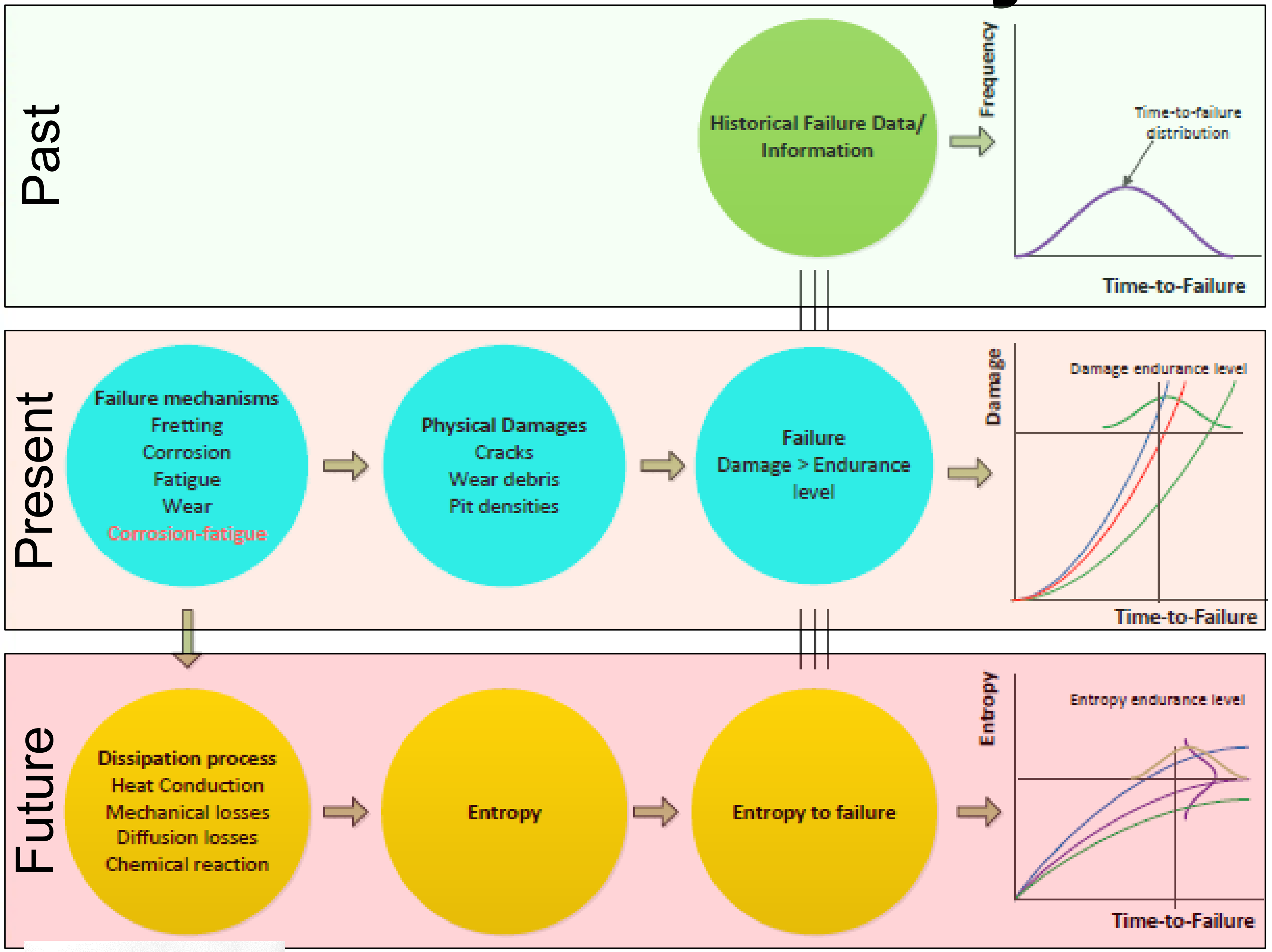


Rudolf Clausius
1822 –1888

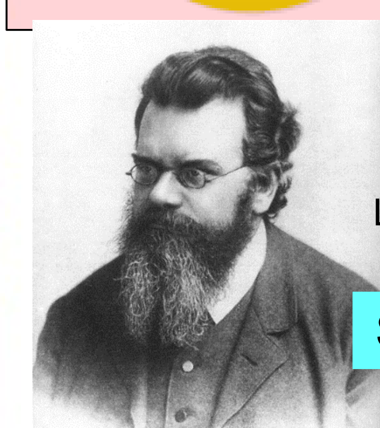
Failure occurs when the accumulated total entropy generated exceeds the entropic-endurance of the unit

- Entropic-endurance describes the capacity of the unit to withstand entropy
- Entropic-endurance of identical units is equal
- Entropic-endurance of different units is different
- Entropic-endurance to failure can be measured (experimentally) and involves stochastic variability

Thermodynamics as a Science of Reliability



- ✓ Entropy can model multiple competing degradation processes leading to damage
- ✓ Entropy is independent of the path to failure ending at similar total entropy at failure
- ✓ Entropy accounts for complex synergistic effects of interacting degradation processes
- ✓ Entropy is scale independent



Ludwig Boltzmann
1844-1906

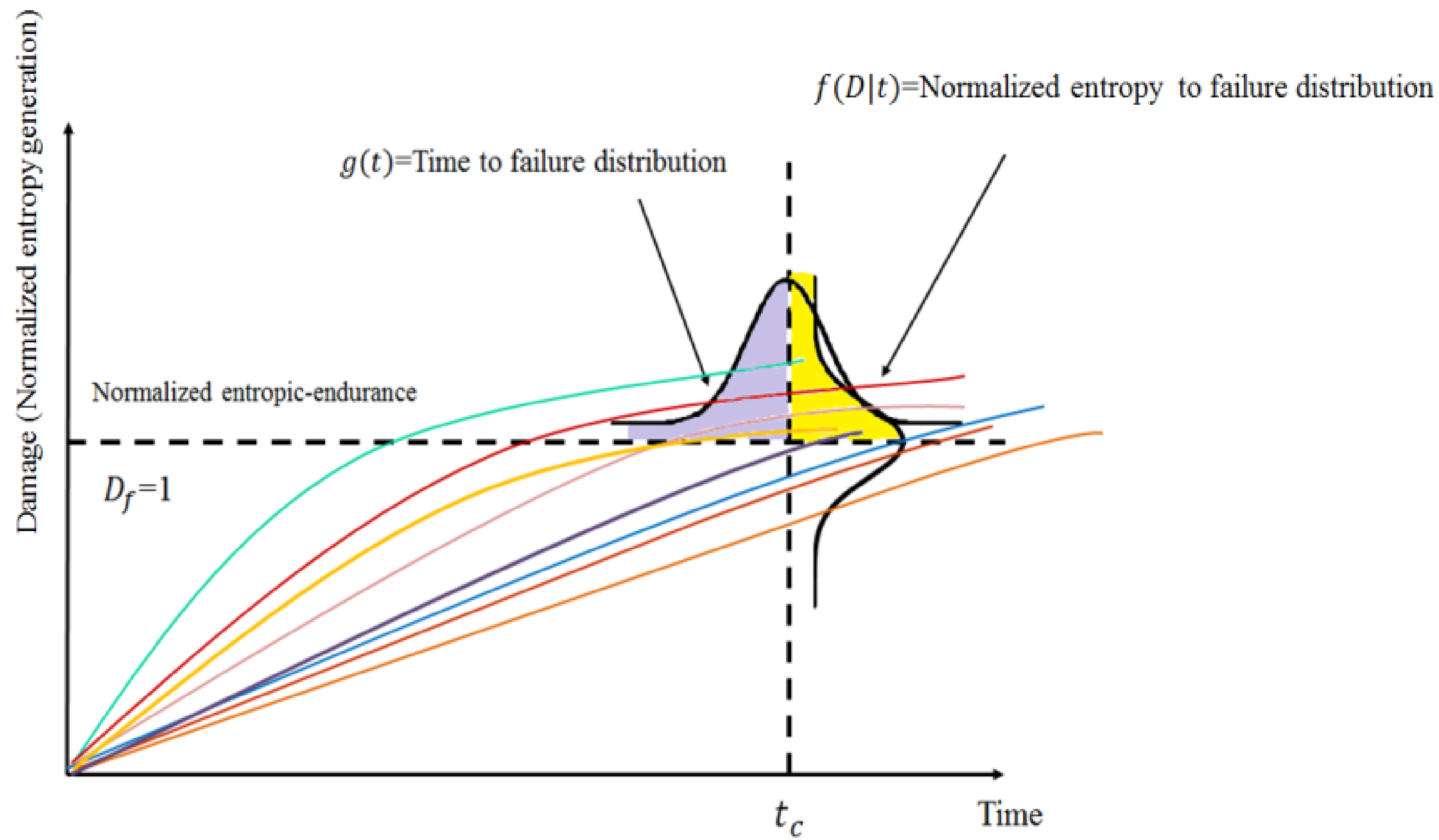
Statistical Mechanics Entropy

An Entropic PPOF Perspective

- Assuming a constant *entropic-endurance*, D_f
- The reliability function can be expressed as

$$P_r(T \leq t_c) = \int_0^{t_c} g(t)dt$$

$$R(t_c) = 1 - P_r(T \leq t_c) = \int_0^{D_f=1} f(D)d$$



T_c =Current operating time; $g(t)$=distribution of time-to-failure, $f(D|t)$= distribution of damage at t

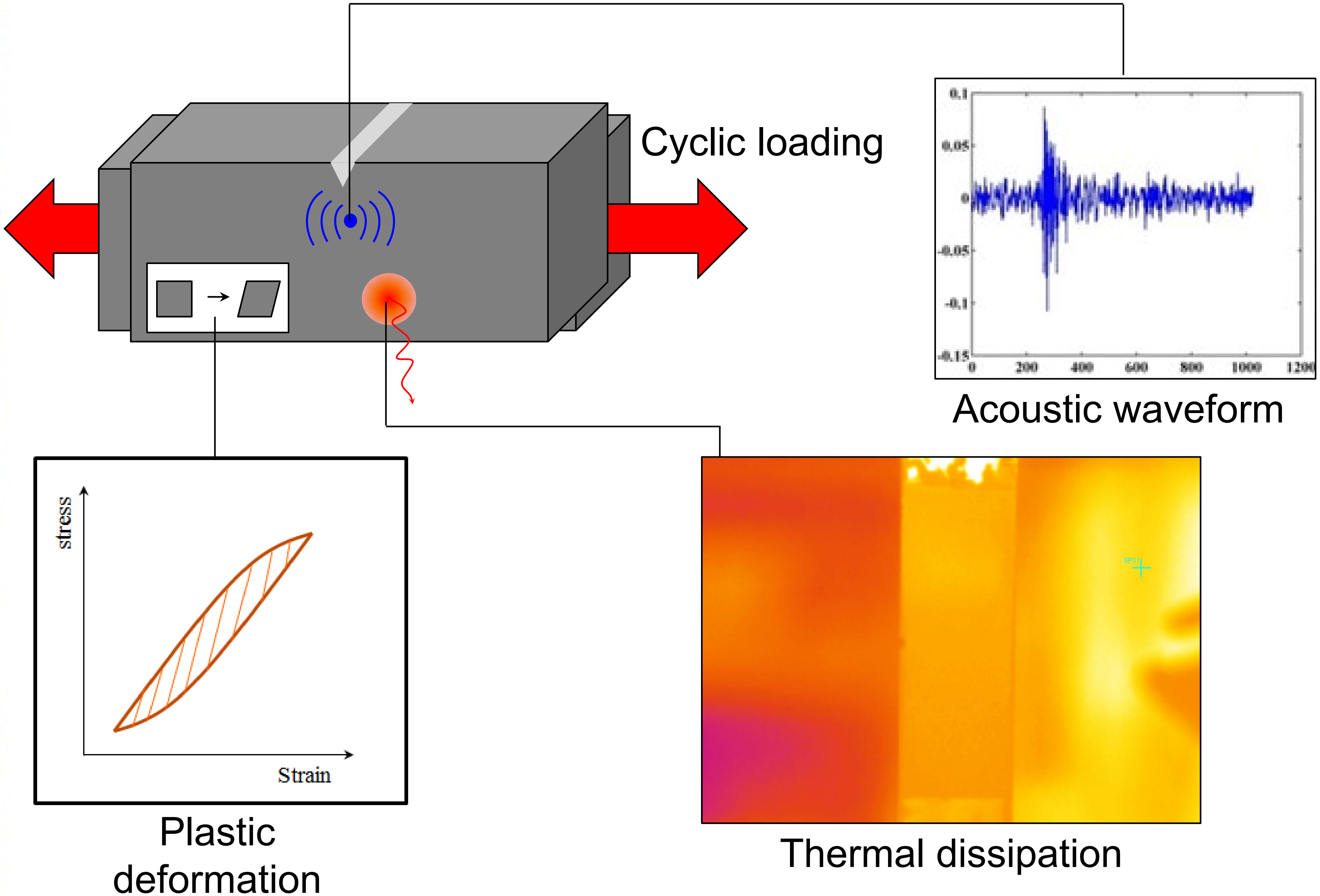
[1] Thermodynamics as a Fundamental Science of Reliability, A. Imanian, M. Modarres, Int. J. of Risk and Reliability, Vol.230(6), pp.598-608. DOI: 10.1177/1748006X16679578.(2016).

Entropic Approaches to Represent Damage

Dissipation Source
Plastic Deformation
Thermal
Acoustic Emission

Entropic Approach	Related Equation
Second Law of Thermodynamics	$\sigma = \frac{1}{T^2} \boldsymbol{J}_q . \nabla T - \Sigma_{k=1}^{n} \boldsymbol{J}_k \left(\nabla \frac{\mu_k}{T} \right) + \frac{1}{T} \boldsymbol{\tau} : \dot{\boldsymbol{\epsilon}}_p + \frac{1}{T} \Sigma_{j=1}^{r} v_j A_j + \frac{1}{T} \Sigma_{m=1}^{h} c_m \boldsymbol{J}_m (-\nabla \psi)$
Information Theory (Shannon)	$S = -\sum p_i \log p_i$
Statistical Mechanics (Crooks)	$D(P_F \vert\vert P_R) = \sum P_{F,i} \ln \frac{P_{F,i}}{P_{R,i}}$

Sources of Dissipation in Fatigue Process



Ali Kahirdeh and M.M. Khonsari, Energy dissipation in the course of the fatigue degradation: Mathematical derivation and experimental quantification, International Journal of Solids and Structures 77 (2015): 74-85

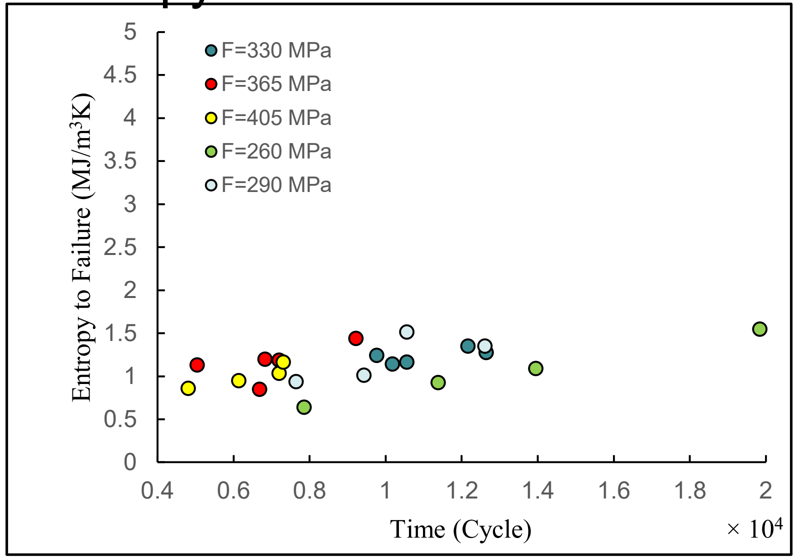
Thermodynamics Entropy in Fatigue Damage (Cont.)

$$\sigma = \frac{1}{T^2} J_q \cdot \nabla T + \frac{1}{T} \tau : \dot{\epsilon}_p$$

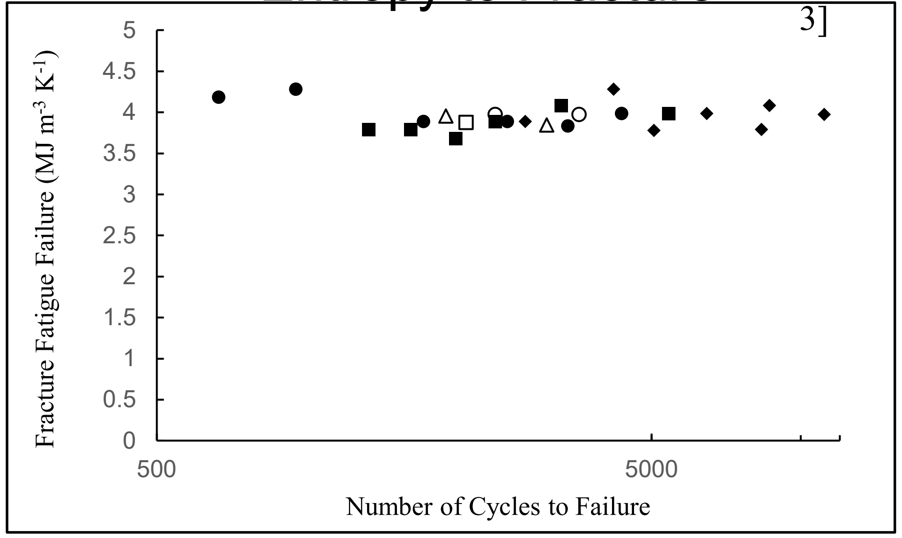
$$\sigma = \sum_{i=1}^{m} X_i J_i$$

Product of thermodynamic forces and fluxes

Entropy to crack initiation [1]

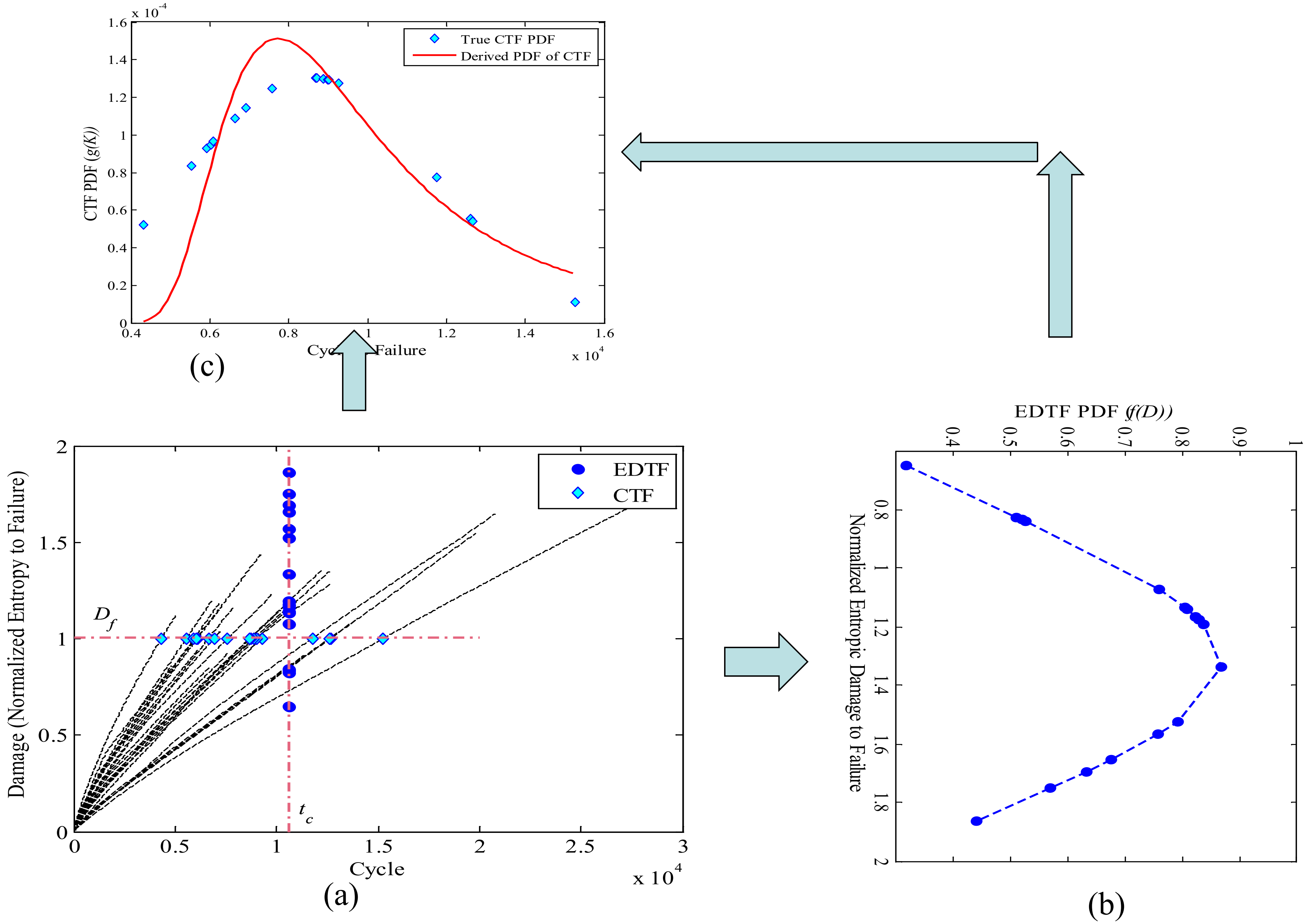


Entropy to Fracture [2, 3]



[1] Anahita Imanian and Mohammad Modarres, A Thermodynamic Entropy Approach to Reliability Assessment with Application to Corrosion Fatigue, Entropy 17.10 (2015): 6995-7020
[2] M. Naderi et al., On the Thermodynamic Entropy of Fatigue Fracture, Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences, 466.2114 (2009): 1-16
[3] M. Naderi et al., Thermodynamic Analysis of Fatigue Failure in a Composite Laminate, Mechanics of Material 46 (2012): 113-122

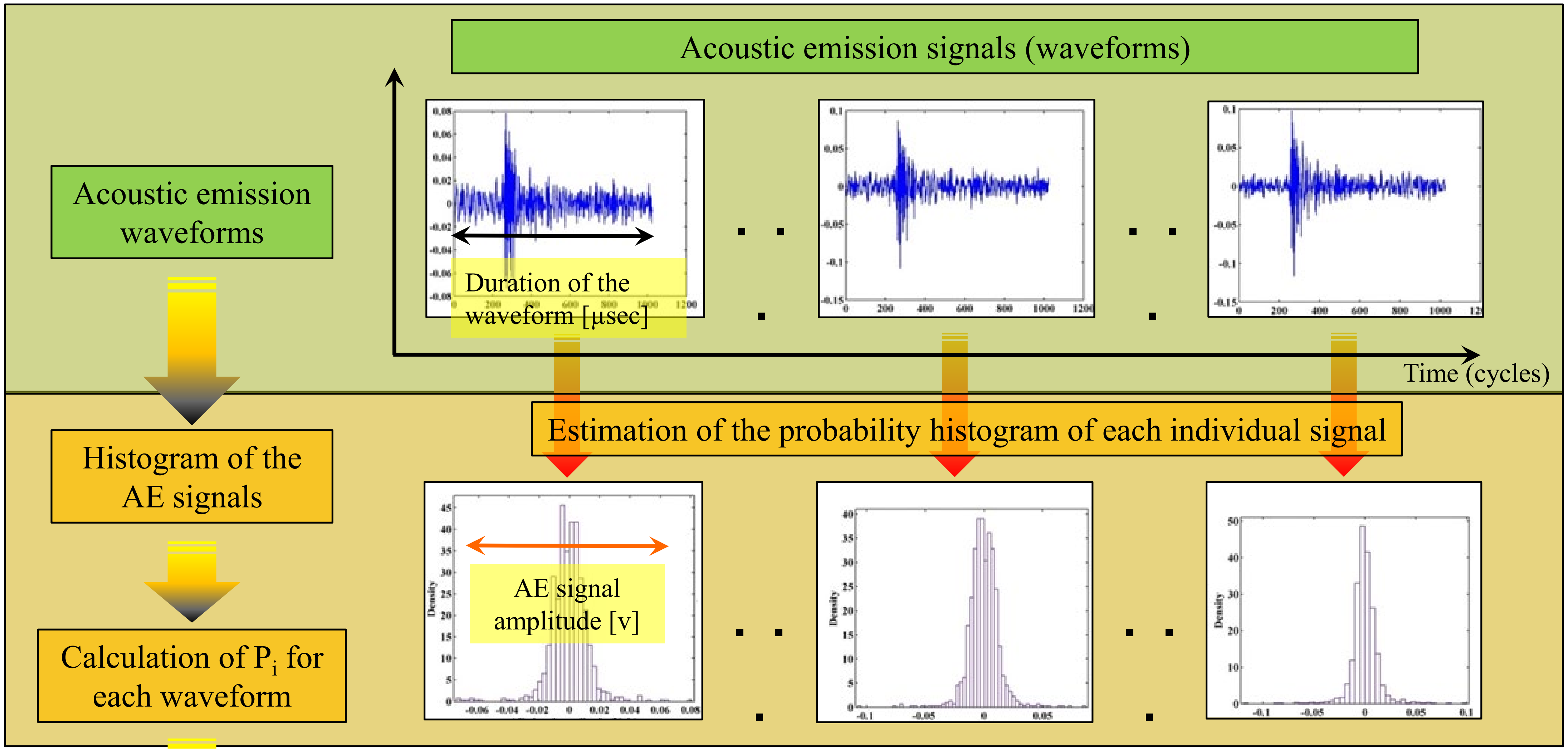
Thermodynamic Entropy in Corrosion-Fatigue Modeling



Thermodynamics as a Fundamental Science of Reliability, A. Imanian, M. Modarres, Int. J. of Risk and Reliability, Vol.230(6), pp.598-608. DOI: 10.1177/1748006X16679578.(2016).

Anahita Imanian and Mohammad Modarres, A Thermodynamic Entropy Approach to Reliability Assessment with Application to Corrosion Fatigue, Entropy 17.10 (2015): 6995-7020

Entropy of AE Information



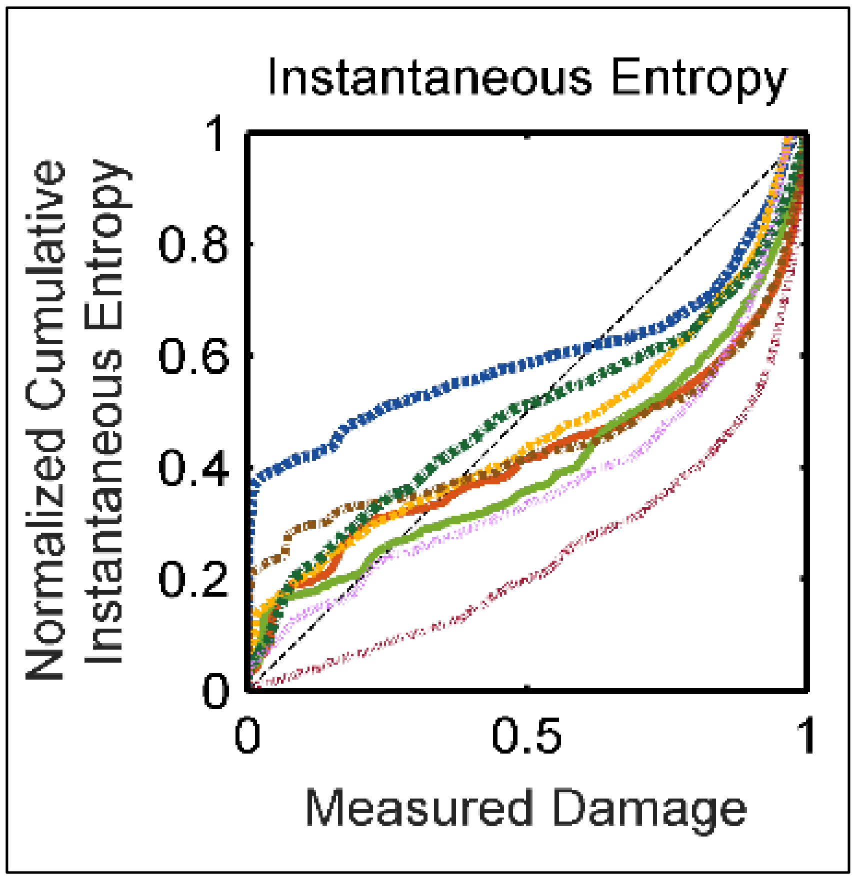
Probability distribution (P_i) → Entropy

$$S_I = \sum_{i=1}^{n} p_i \log_2\left(\frac{1}{p_i}\right) = -\sum_{i=1}^{n} p_i \log_2(p_i)$$

$$S_R = \sum_{i=1}^{n} p_i \log \frac{p_i}{p_{R,i}}$$

Entropy of AE Information

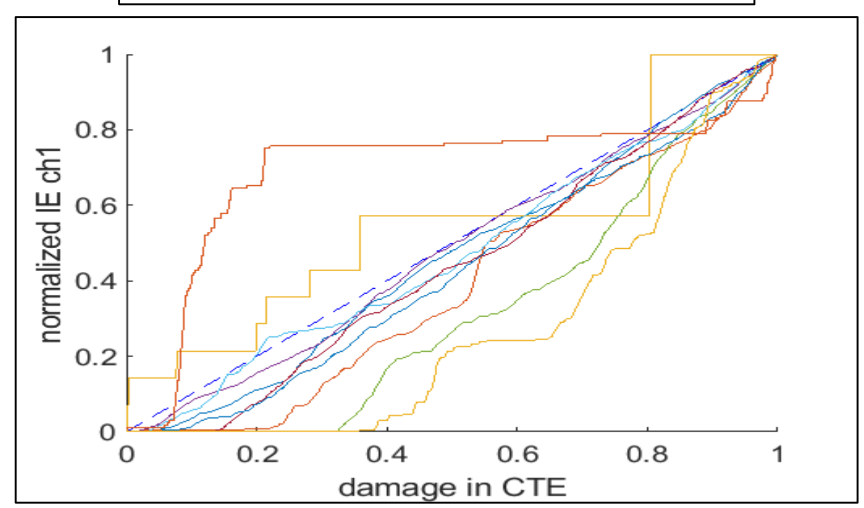
- Cumulative AE information entropy better correlates with the measured damage in terms of changes in the elastic modulus



Aluminum

Normalized damage

$$D = \frac{M_i - M_o}{M_f - M_o}$$



AE information entropy

High Carbone SS

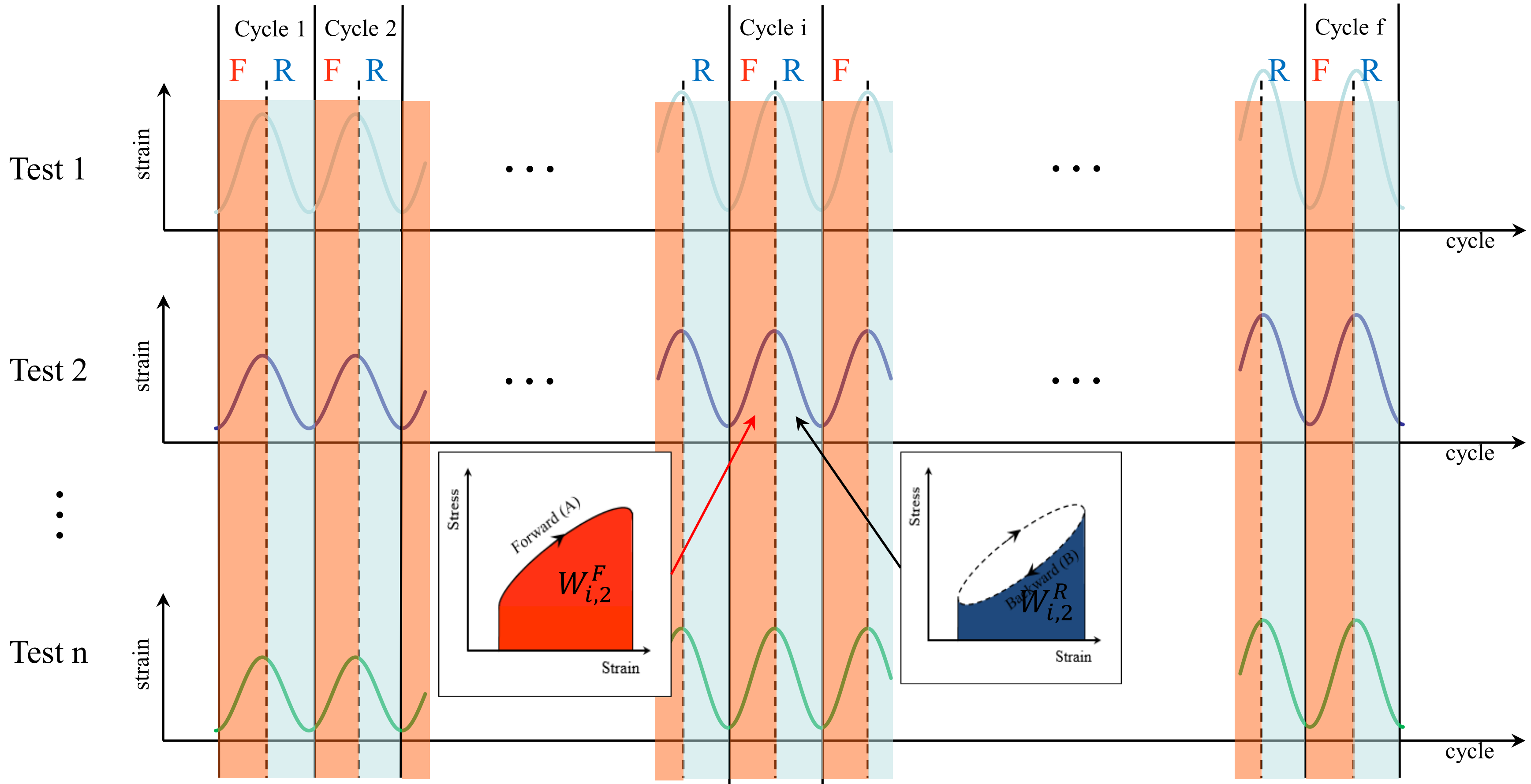
[6] Sauerbrunn, C. M., et al. "Damage Assessment Using Information Entropy of Individual Acoustic Emission Waveforms during Cyclic Fatigue Loading." *Applied Sciences* 7.6 (2017): 562

Entropy in Statistical Mechanics

- Relative entropy (Kullback-Leibler Divergence)

$$D(P_F||P_R) = \sum P_{F,i} \ln \frac{P_{F,i}}{P_{R,i}} = \Delta S_F^{Total} \quad [1]$$

- KLD equals the total entropy in a forward process or a reverse process.
- KLD is computed by repeating many similarly conditioned fatigue tests to measure forward / reverse work distributions

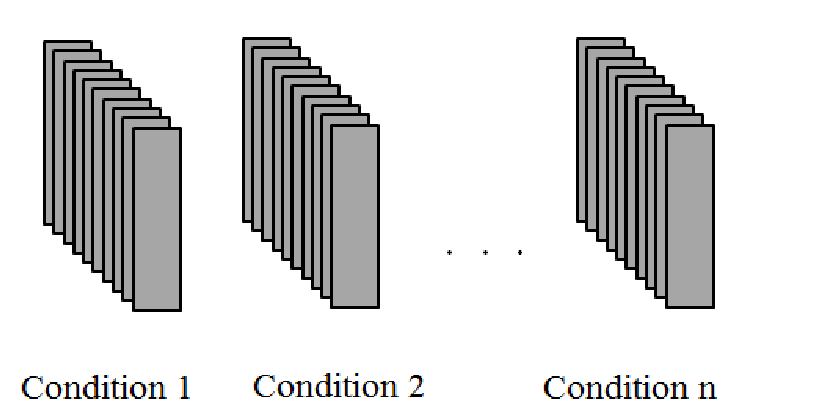


[1] Gavin E Crooks and David A Sivak, Measures of trajectory ensemble disparity in nonequilibrium statistical dynamics, Journal of Statistical Mechanics: Theory and Experiment, doi: 10.1088/1742-5468/2011/06/P06003

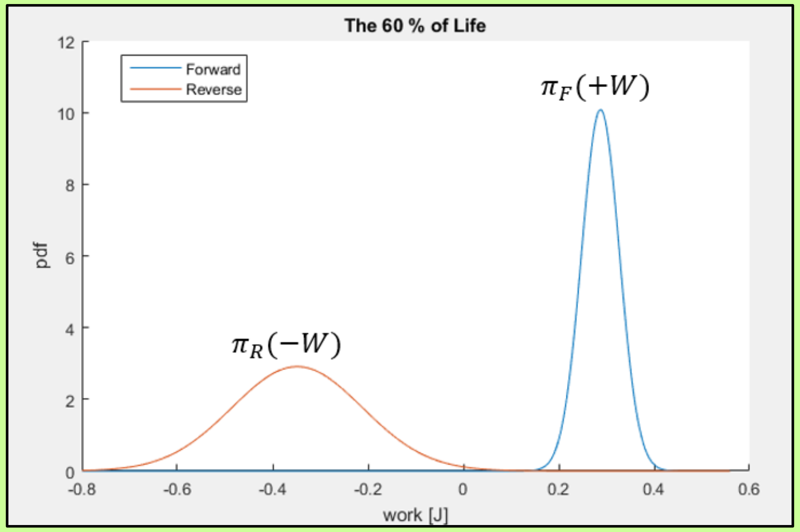
Entropy in Statistical Mechanics (Cont.)

- Analysis Procedure

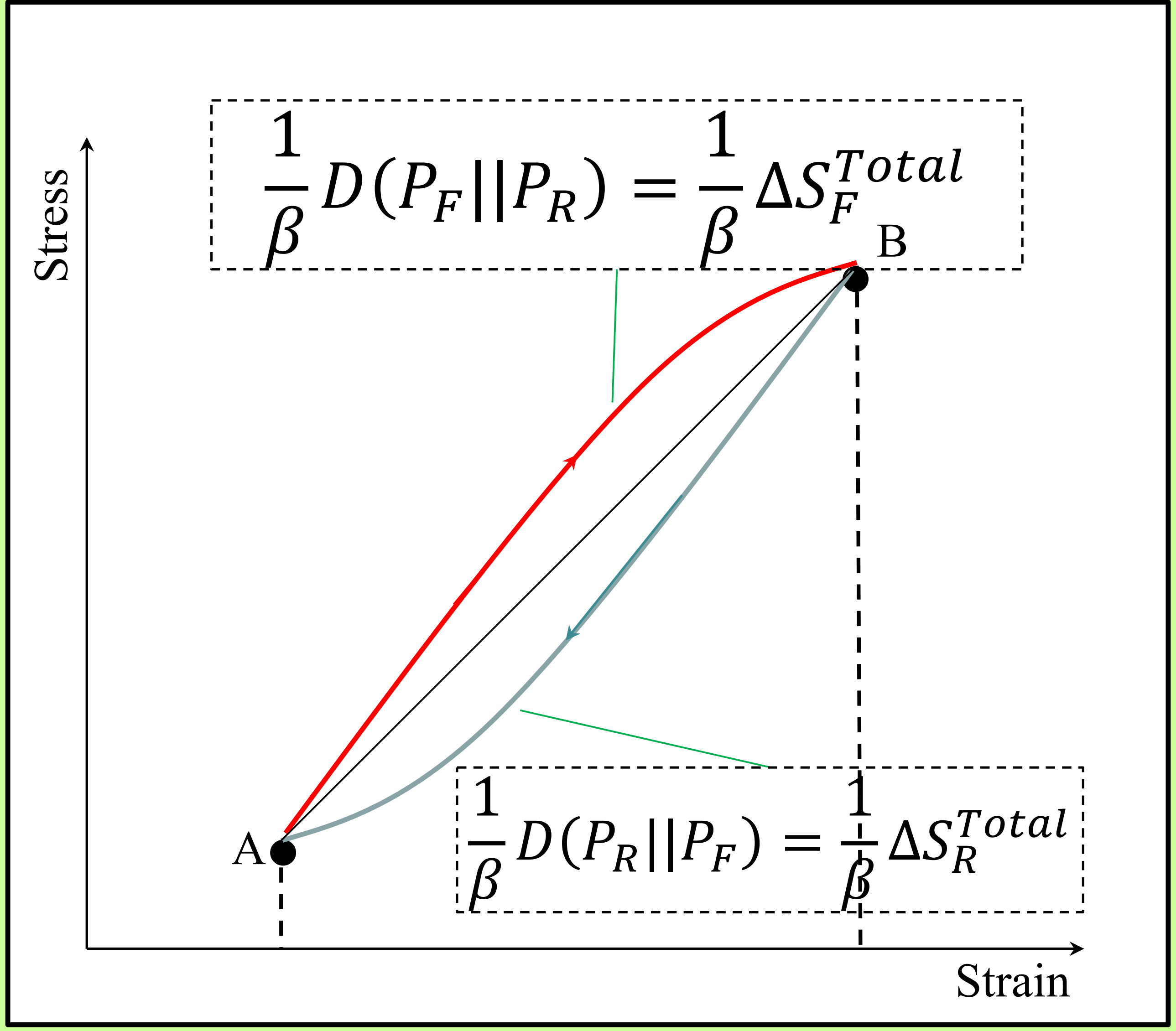
Multiple tests



Distributions of Forward and Backward



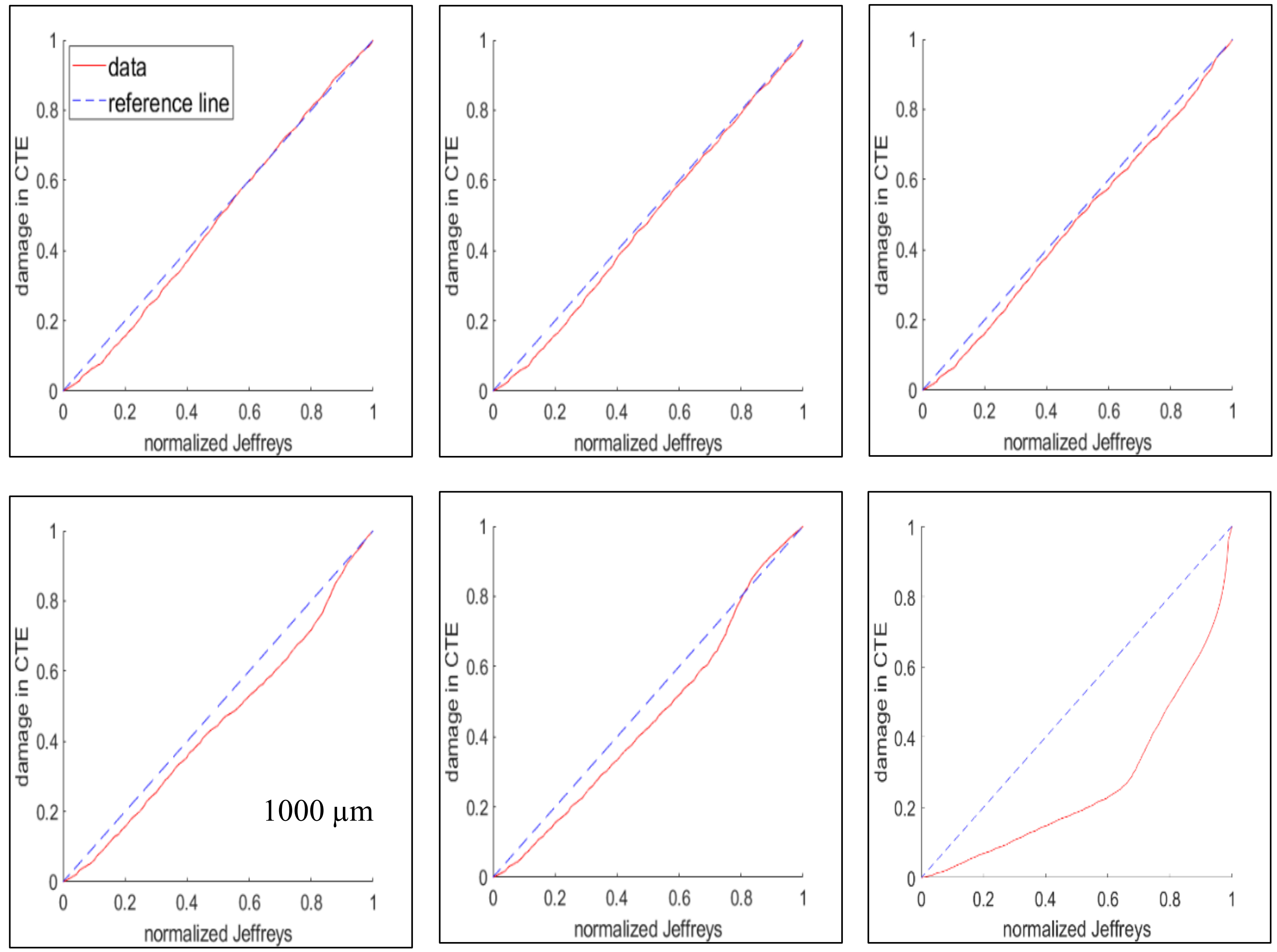
Relative entropy



Statistical Mechanics PoF

Normalized damage

$$D = \frac{M_i - M_o}{M_f - M_o}$$

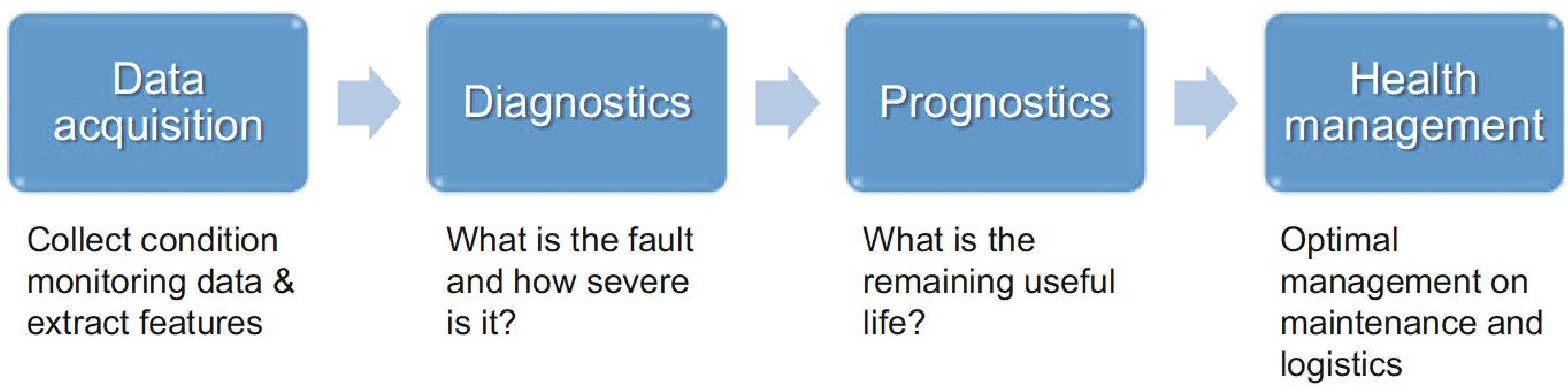


M_o: the measured damage at time zero or the pristine state, M_f: the damage at the failure, M_i: the damage at a given instance

Data Analytics and Machine Learning in Pipeline Integrity Management

- Prognosis and health management (PHM) is the field where data analytics is applied
  - Cost effective and conditioned based pipeline integrity management

- What is PHM?



[From:DOI 10.1007/978-3-319-44742-1

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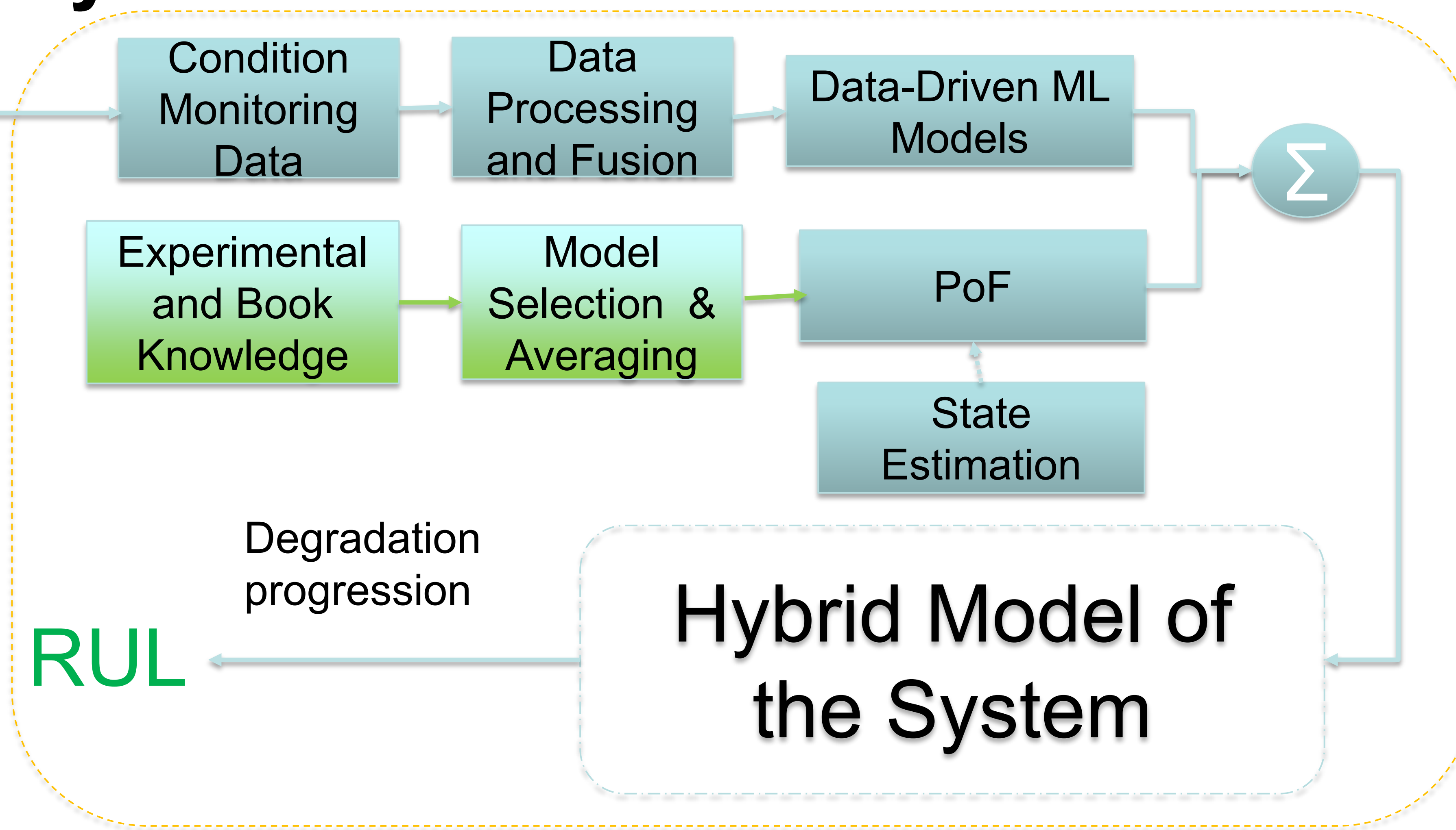
Data Analytics and Machine Learning in Pipeline Integrity Management

- PHM categories
  - Data-driven models
  - Physics of Failure-based models (PoF)
  - **Hybrid models**



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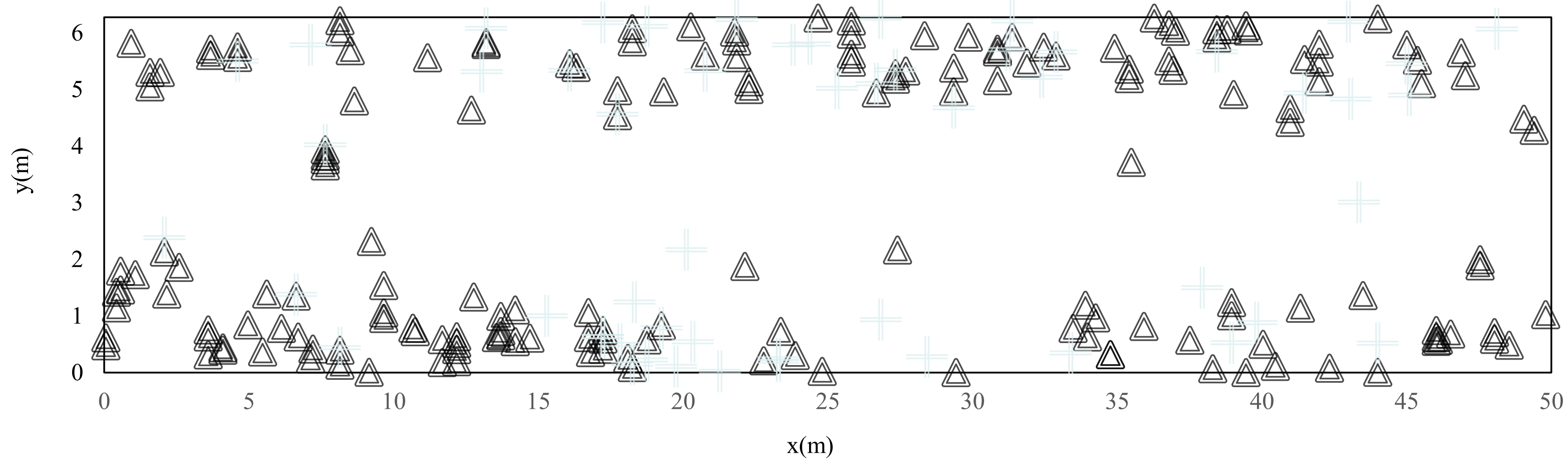
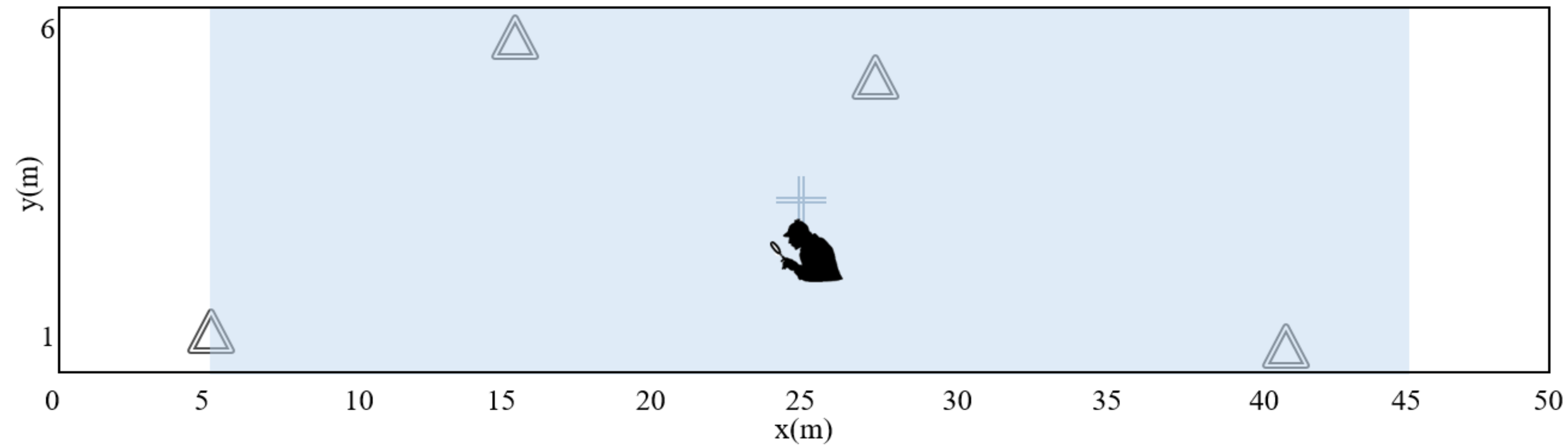
Sensor Placement for PHM

- Example:
- 46 random realizations are aggregated to find the final sensor layout
  - Triangles: 176 Acoustic emission sensor
  - Pluses: 54 human Inspection Nodes
- On average , each aggregate layout has:
  - 4 acoustic emission sensors
  - 1 human inspection
- Final layout is obtained using K-means clustering



Scatter plot corresponding to all 46 HM layouts



Final Aggregate Layout

Conclusions

- PoF and PPoF are the critical to assess long-life units
- Entropy as damage and aging provides a sound reliability science
- The entropic theory offers a more fundamental non-empirical PPoF model of damage and better accounts for interacting failure modes and mechanisms
- Physics-Informed deep-learning methods are critical to integrity management of aging structures
- Exciting developments in computational speed, AI, IoT and cheap sensors will revolutionize the reliability engineering as a discipline

For more details visit my website for more detail and publicly available information http://modarres.umd.edu

Thank you for your attention!