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# Prognostics

The Science of Prediction


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Prognostics CoE

Stinger Ghaffarian Technologies

# Prognostics Center of Excellence

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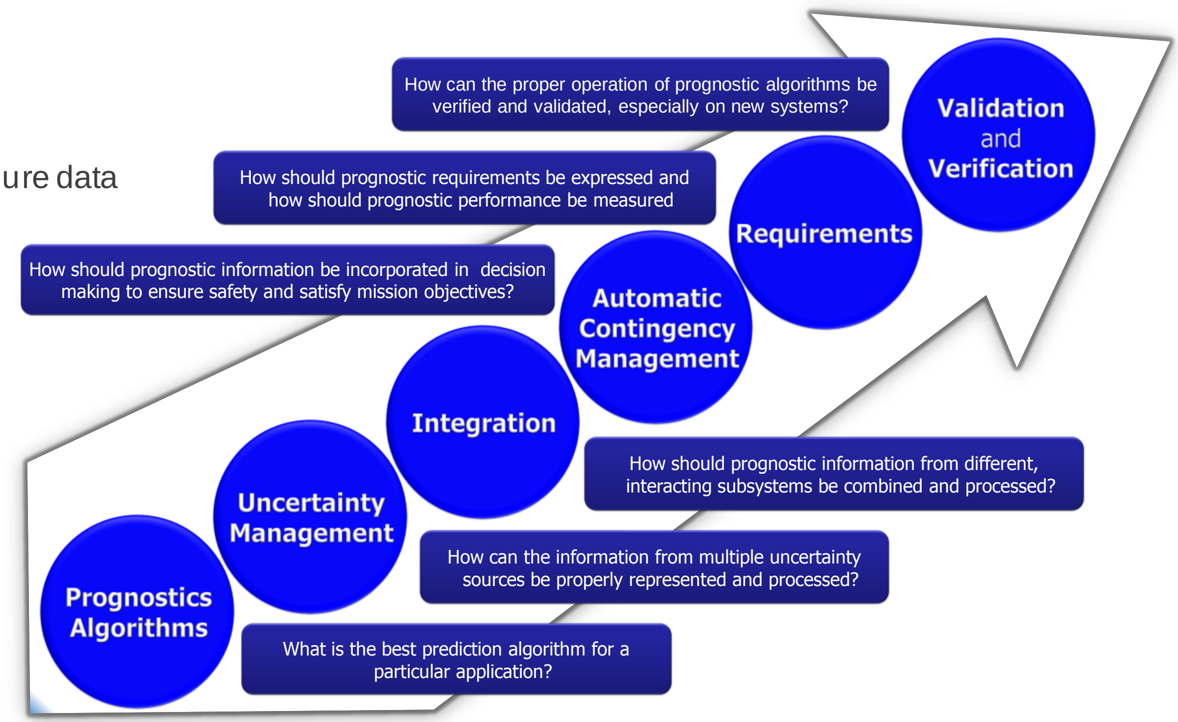
## NASA Ames Research Center, CA

### Mission: Advance state-of-the-art in prognostics technology development

- Investigate algorithms for estimation of remaining life
  - Investigate physics-of-failure
  - Model damage initiation and propagation
  - Investigate uncertainty management
- Validate research findings in hardware testbeds
  - Hardware-in-the-loop experiments
  - Accelerated aging testbeds
  - HIL demonstration platforms
- Disseminate research findings
  - Public data repository for run-to-failure data
  - Actively publish research results
- Engage research community

Prognostics CoE




- Prognostics Center of Excellence, NASA Ames Research Center, CA [http://www.prognostics.nasa.gov]

Introduction to Prognostics

# Outline

# Today we will discuss…

- What is prognostics?
  - It's relation to health management
  - Significance to the decision making process
- How is prognostics used?
  - Reliability
  - Scheduled maintenance – based on reliability
  - Kinds of prognostics – interpretation & applications
    - Type I, Type II, and Type III prognostics
    - Various application domains
- Condition based view of Prognostics
- Prognostic Framework

# Also…



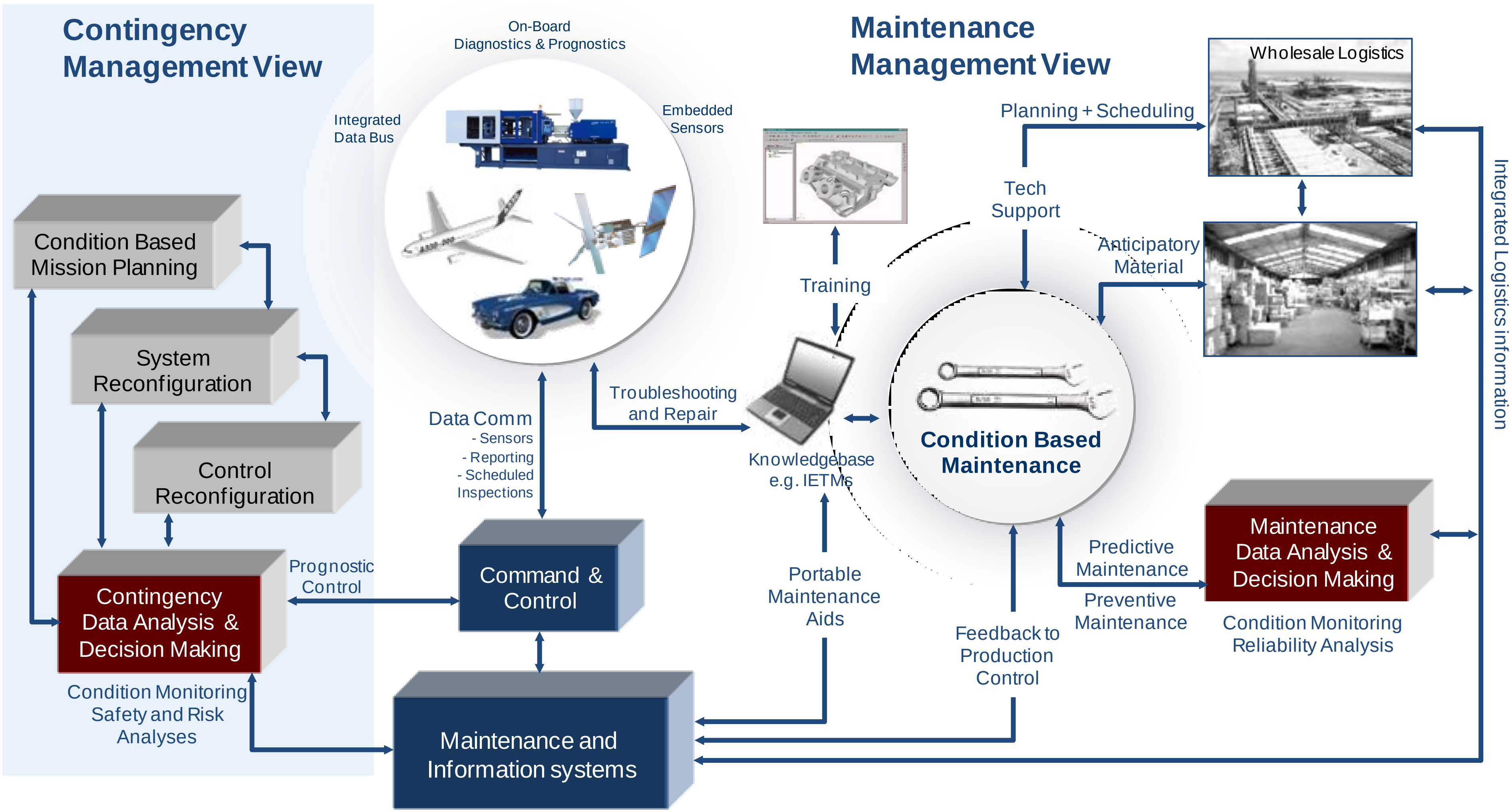
- What are the key ingredients for prognostics
  - Requirements specifications – Purpose
    - Cost-benefit-risk
  - Condition Monitoring Data – sensor measurements
    - Collect relevant data
  - Prognostic algorithm
    - Tons of them - examples
  - Fault growth model (physics based or model based)
  - Run-to-failure data
- Challenges in Validation & Verification
  - Performance evaluation
  - Uncertainty
    - representation, quantification, propagation, and management

Prognostics and Health Management

# The Perspective

# Health Management

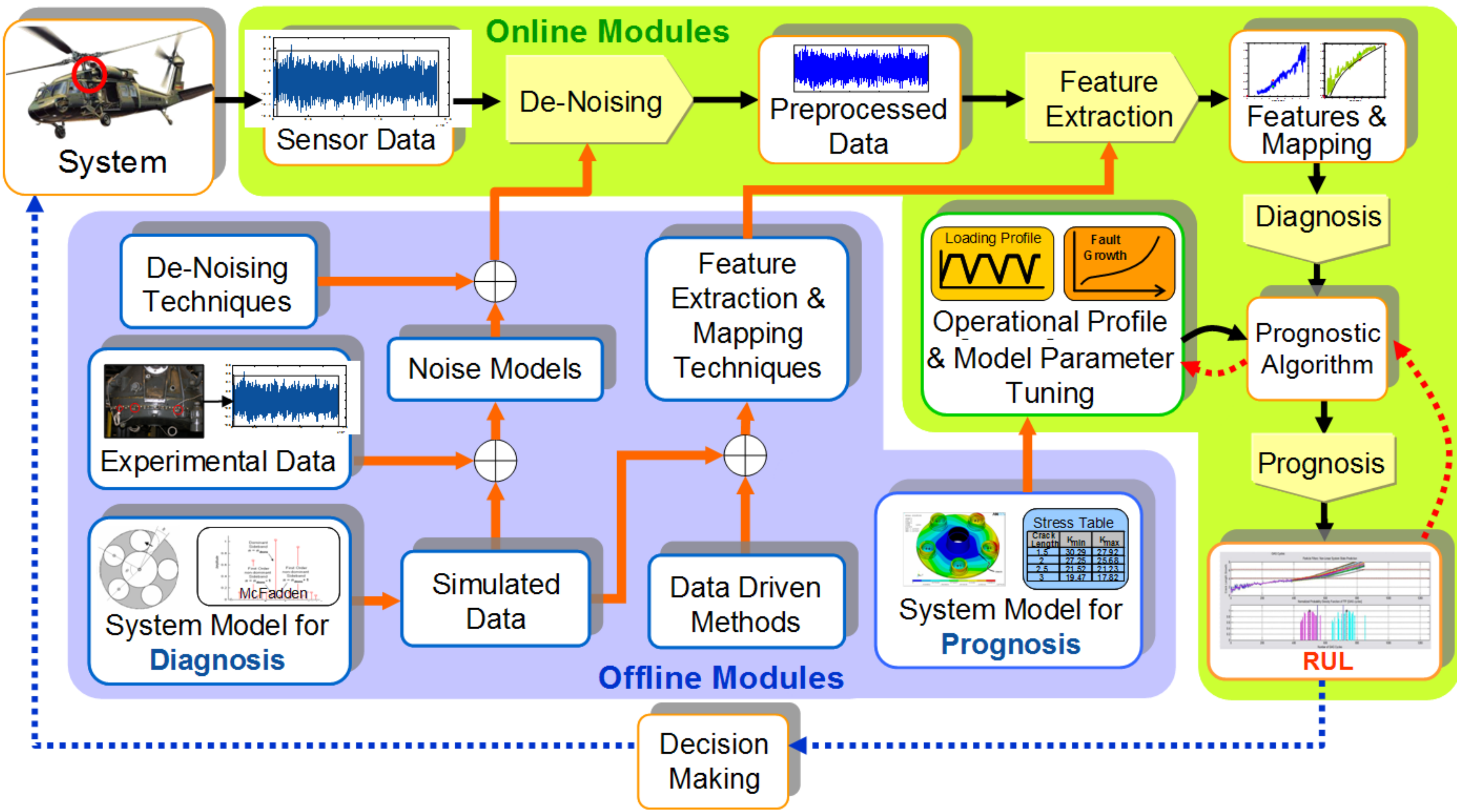





- Schematic adapted from: A. Saxena, *Knowledge-Based Architecture for Integrated Condition Based Maintenance of Engineering Systems*, PhD Thesis, Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta May 2007.
- Liang Tang, Gregory J. Kacprzynski, Kai Goebel, Johan Reimann, Marcos E. Orchard, Abhinav Saxena, and Bhaskar Saha, *Prognostics in the Control Loop*, Proceedings of the 2007 AAAI Fall Symposium on Artificial Intelligence for Prognostics, November 9-11, 2007, Arlington, VA.

# Data Analysis & Decision Making






- Adapted from presentations and publications from Intelligent Control Systems Lab, Georgia Institute of Technology, Atlanta [http://icsl.gatech.edu/]

# Prognostics



- Dictionary definition – "foretelling" or "prophecy"

- PHM definition –
  "***Estimation of remaining life of a component or subsystem***"

- Prognostics evaluates the *current health* of a component and, conditional on *future load* and *environmental exposure*, estimates at what time the component (or subsystem) will no longer operate within its *stated specifications*.

- These predictions are based on
  - Analysis of failure modes (FMECA, FMEA, etc.)
  - Detection of early signs of wear, aging, and fault conditions and an assessment of current damage state
  - Correlation of aging symptoms with a description of how the damage is expected to increase ("damage propagation model")
  - Effects of operating conditions and loads on the system

- Prognostics Center of Excellence, NASA Ames Research Center, CA [http://www.prognostics.nasa.gov]
- Prognostics [http://en.wikipedia.org/wiki/Prognostics]

# Goals for Prognostics

What does prognostics aim to achieve?

## Contingency Management View

- **Increase Safety and Mission Reliability**
  - Improved mission planning
  - Ability to reassess mission feasibility
- **Decrease Collateral Damage**
  - Avoid cascading effects onto healthy subsystems
  - Maintain consumer confidence, product reputation

## Maintenance Management View

- **Decrease Logistics Costs**
  - More efficient maintenance planning
  - Reduced spares
- **Decrease Unnecessary Servicing**
  - Service only specific aircraft which need servicing
  - Service only when it is needed

- Prognostics goals should be defined from users' perspectives
- Different solutions and approaches apply for different users

# User Centric View on Prognostics Goals

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| Category | End User | Goals | Metrics |
|---|---|---|---|
| Operations | Program Manager | Assess the economic viability of prognosis technology for specific applications before it can be approved and funded | Cost-benefit type metrics that translate prognostics performance in terms of tangible and intangible cost savings |
| | Plant Manager | Resource allocation and mission planning based on available prognostic information | Accuracy and precision based metrics that compute RUL estimates for specific UUTs. Such predictions are based on degradation or damage accumulation models |
| | Operator | Take appropriate action and carry out re-planning in the event of contingency during mission | Accuracy and precision based metrics that compute RUL estimates for specific UUTs. These predictions are based on fault growth models for critical failures |
| | Maintainer | Plan maintenance in advance to reduce UUT downtime and maximize availability | Accuracy and precision based metrics that compute RUL estimates based on damage accumulation models |
| Engineering | Designer | Implement the prognostic system within the constraints of user specifications. Improve performance by modifying design | Reliability based metrics to evaluate a design and identify performance bottlenecks. Computational performance metrics to meet resource constraints |
| | Researcher | Develop and implement robust performance assessment algorithms with desired confidence levels | Accuracy and precision based metrics that employ uncertainty management and output probabilistic predictions in presence of uncertain conditions |
| Regulatory | Policy Makers | To assess potential hazards (safety, economic, and social) and establish policies to minimize their effects | Cost-benefit-risk measures, accuracy and precision based measures to establish guidelines & timelines for phasing out of aging fleet and/or resource allocation for future projects |


- *Saxena, A., Celaya, J., Saha, B., Saha, S., Goebel, K., "Metrics for Offline Evaluation of Prognostics Performance", International Journal of Prognostics and Health Management (IJPHM), vol.1(1) 2010*
- Wheeler, K. R., Kurtoglu, T., & Poll, S. (2009). A Survey of Health Management User Objectives Related to Diagnostic and Prognostic Metrics. ASME 2009 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (IDETC/CIE), San Diego, CA

# Prognostics Categories

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- Type I: Reliability Data-based
  - Use population based statistical model
  - These methods consider historical time to failure data which are used to model the failure distribution. They estimate the life of a typical component under nominal usage conditions
  - Example: Weibull Analysis
- Type II: Stress-based
  - Use population based fault growth model – learnt from accumulated knowledge
  - These methods also consider the environmental stresses (temperature, load, vibration, etc.) on the component. They estimate the life of an average component under specific usage conditions
  - Example: Proportional Hazards Model
- Type III: Condition-based
  - Individual component based data-driven model
  - These methods also consider the measured or inferred component degradation. They estimate the life of a specific component under specific usage and degradation conditions
  - Example: Cumulative Damage Model, Filtering and State Estimation

- *For more details please refer to last year's PHM09 tutorial on Prognostics by Dr. J. W. Hines*: [http://www.phmsociety.org/events/conference/phm/09/tutorials]

# Forecasting Applications

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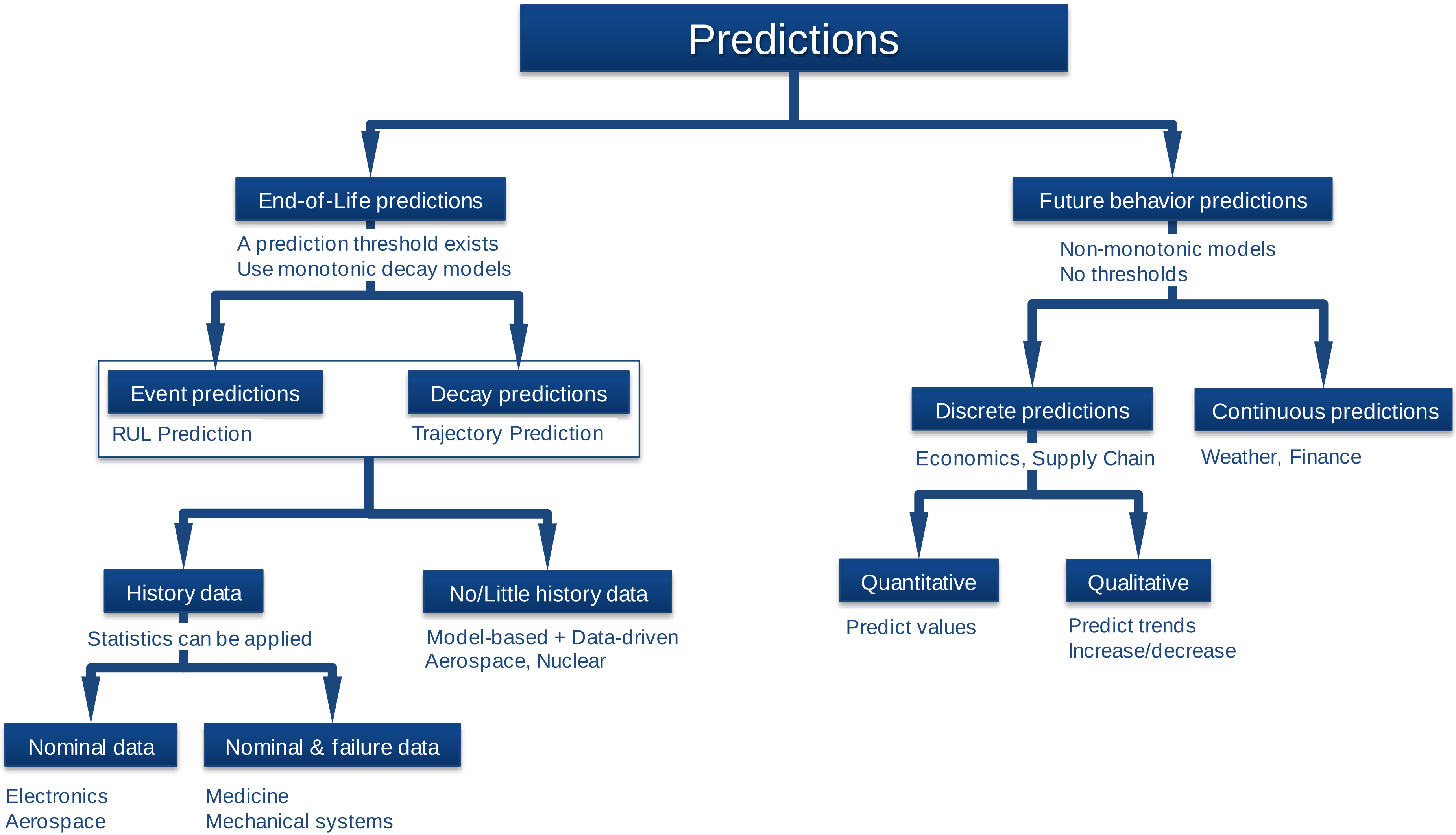




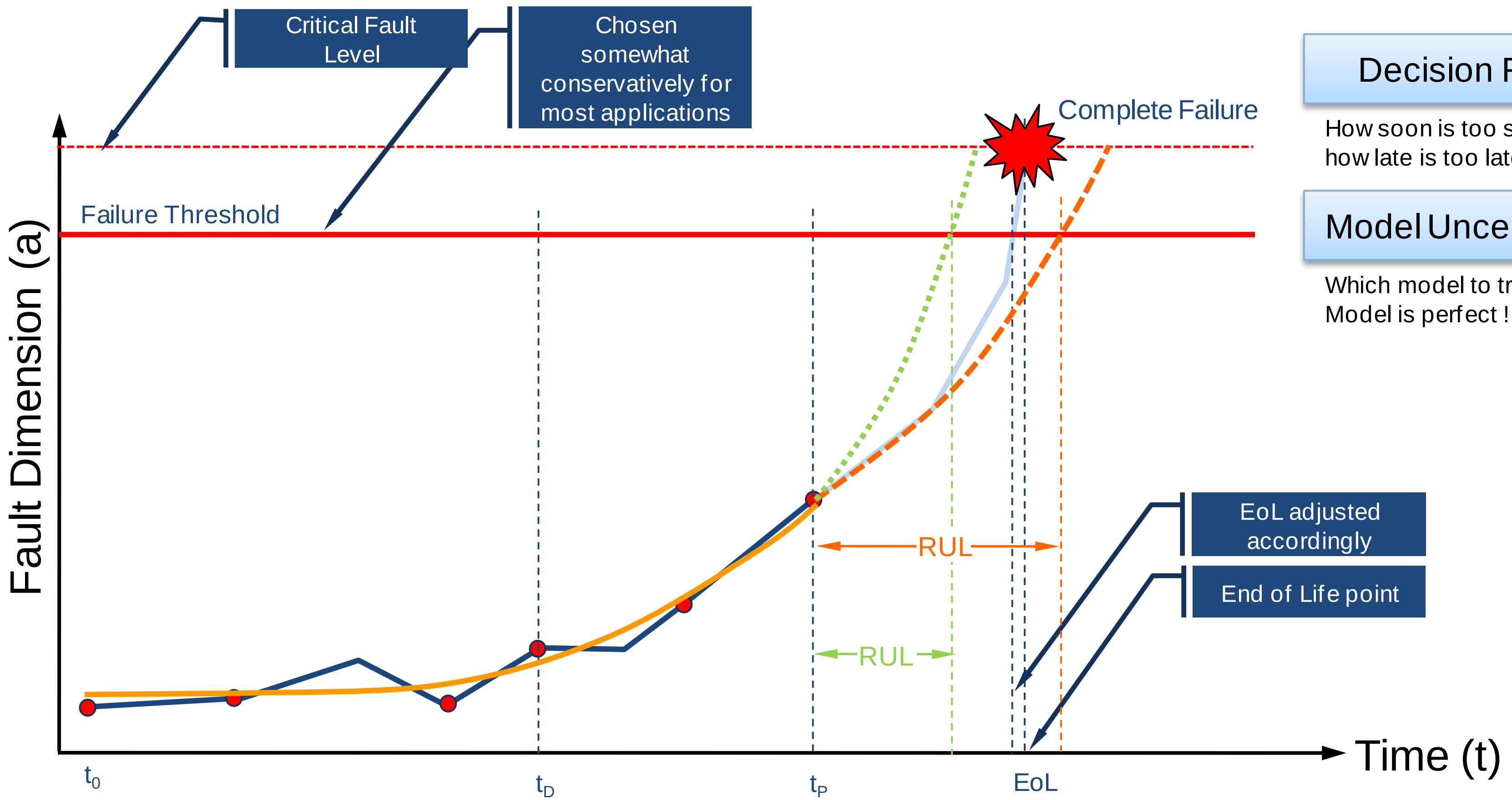
- Saxena, A., Celaya, J., Saha, B., Saha, S., Goebel, K., "Metrics for Offline Evaluation of Prognostics Performance", International Journal of Prognostics and Health Management (IJPHM), vol.1(1) 2010.
- Saxena, A., Celaya, J., Balaban, E., Goebel, K., Saha, B., Saha, S., and Schwabacher, M., "Metrics for Evaluating Performance of Prognostics Techniques", 1st International Conference on Prognostics and Health Management (PHM08), Denver CO, pp. 1-17, Oct 2008.

Predicting Remaining Useful Life

# Understanding the Prognostic Process

# Prognostics Framework






**Decision Risk**

How soon is too soon and how late is too late?

**Model Uncertainty**

Which model to trust? No Model is perfect !

# Prognostics Framework

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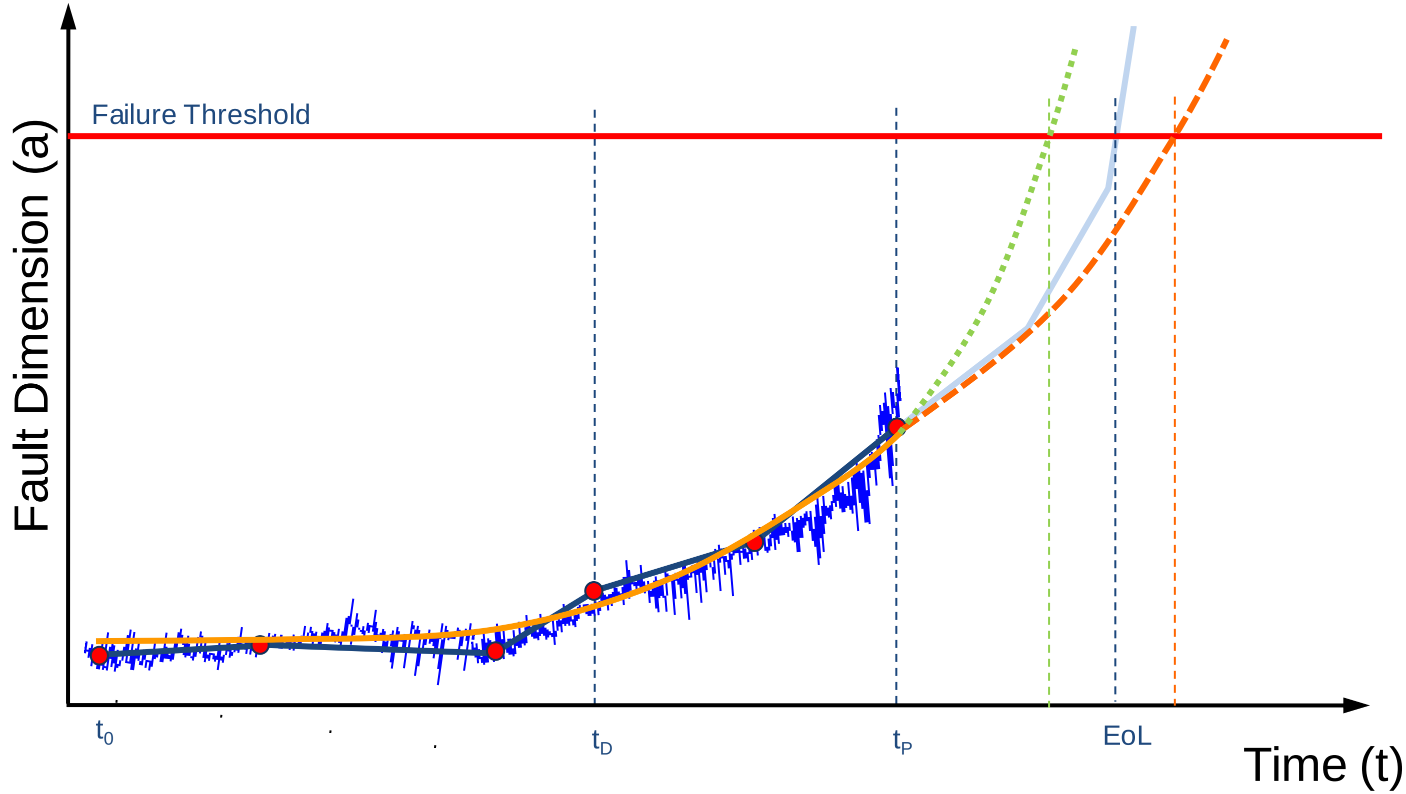
We hardly have access to ground truth

Instead we have measurements, appropriate features of which may correlate to damage. such data are usually noisy!

We use these data to learn the model, which may be noisy

Noise may have a significant effect on the learnt model…




**Decision Risk**

How soon is too soon and how late is too late?

**Model Uncertainty**

Which model to trust? No Model is perfect !

**No Ground Truth**

Ground truth measurements are hard to come by

**Noisy Data**

Measurement noise leads to more uncertainty!

# Uncertainties in Prognostics



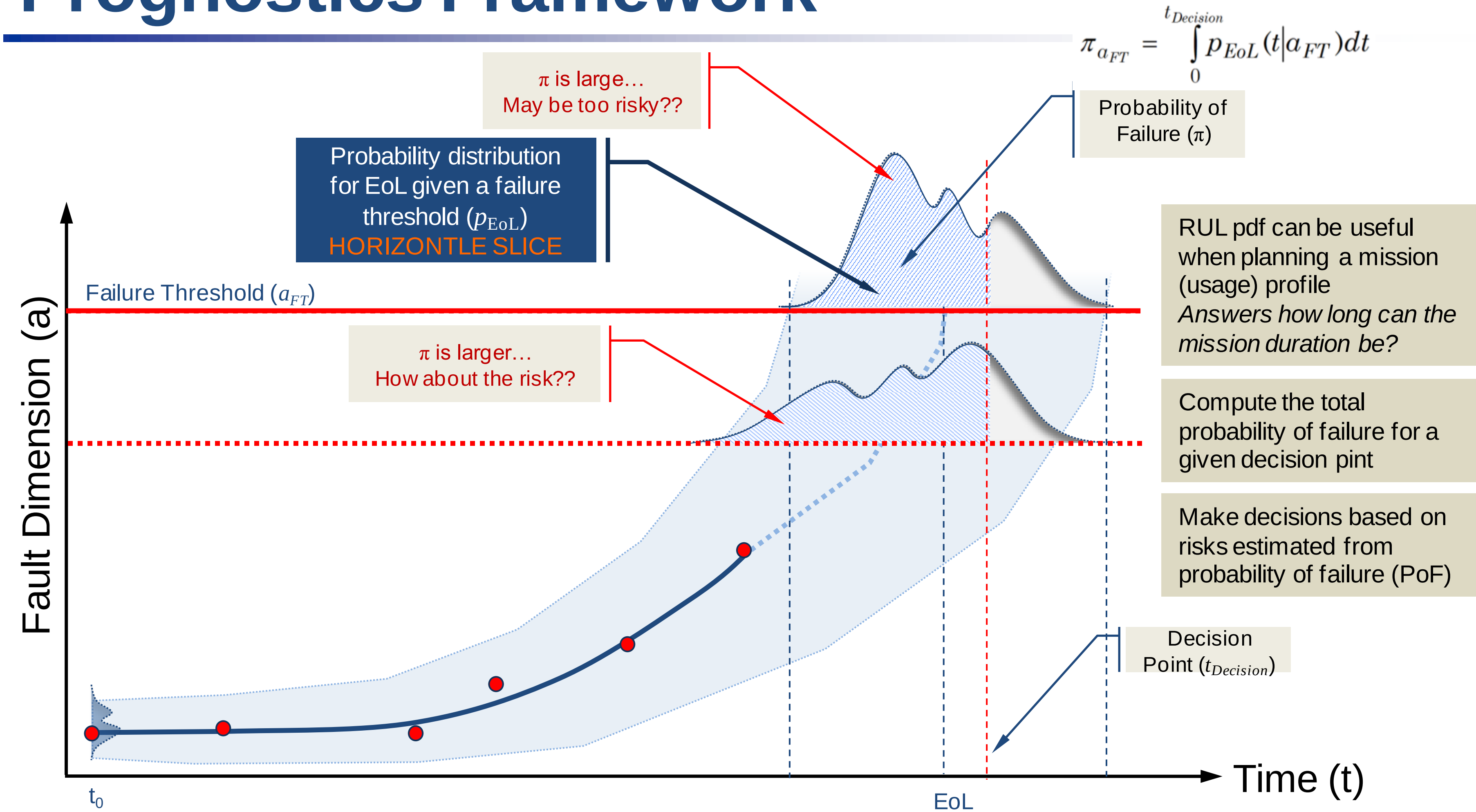
- Uncertainties arise from a variety of sources
  - Modeling uncertainties – **Epistemic**
    - Numerical errors
    - Unmodeled phenomenon
    - System model & Fault propagation model
  - Input data uncertainties – ***Aleatoric***
    - Initial state (damage) estimate
    - Variability in the material
    - Manufacturing variability
  - Measurement uncertainties – **Prejudicial**
    - Sensor noise
    - Sensor coverage
    - Loss of information during preprocessing
    - Approximations and simplifications
  - Operating environment uncertainties – *Combination*
    - Unforeseen future loads
    - Unforeseen future environments
    - Variability in the usage history data

Unknown level of uncertainties arising due lack of knowledge or information

Inherent statistical variability in the process that may be characterized by experiments

Unknown level of uncertainties arising due to the way data are collected or processed

# Prognostics Framework



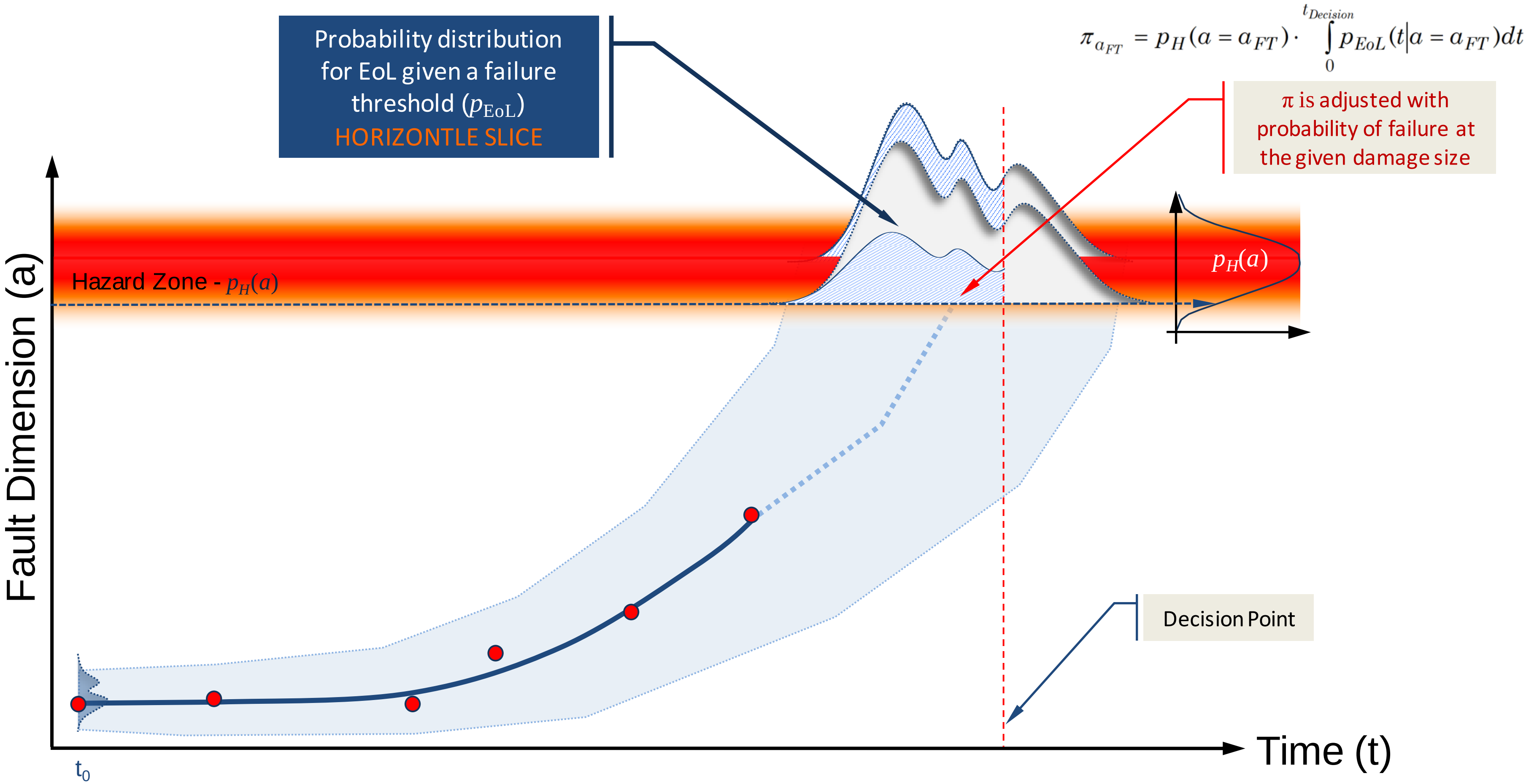

These uncertainties can be represented as a probability distribution on the initial state.
Probability distribution need not be Normal “always”.

we can propagate the learnt model along with a confidence bound until the Failure Threshold is reached

The Horizontal slice tells us when the system can be expected to reach a specified failure threshold given “all” uncertainties considered

# Prognostics Framework



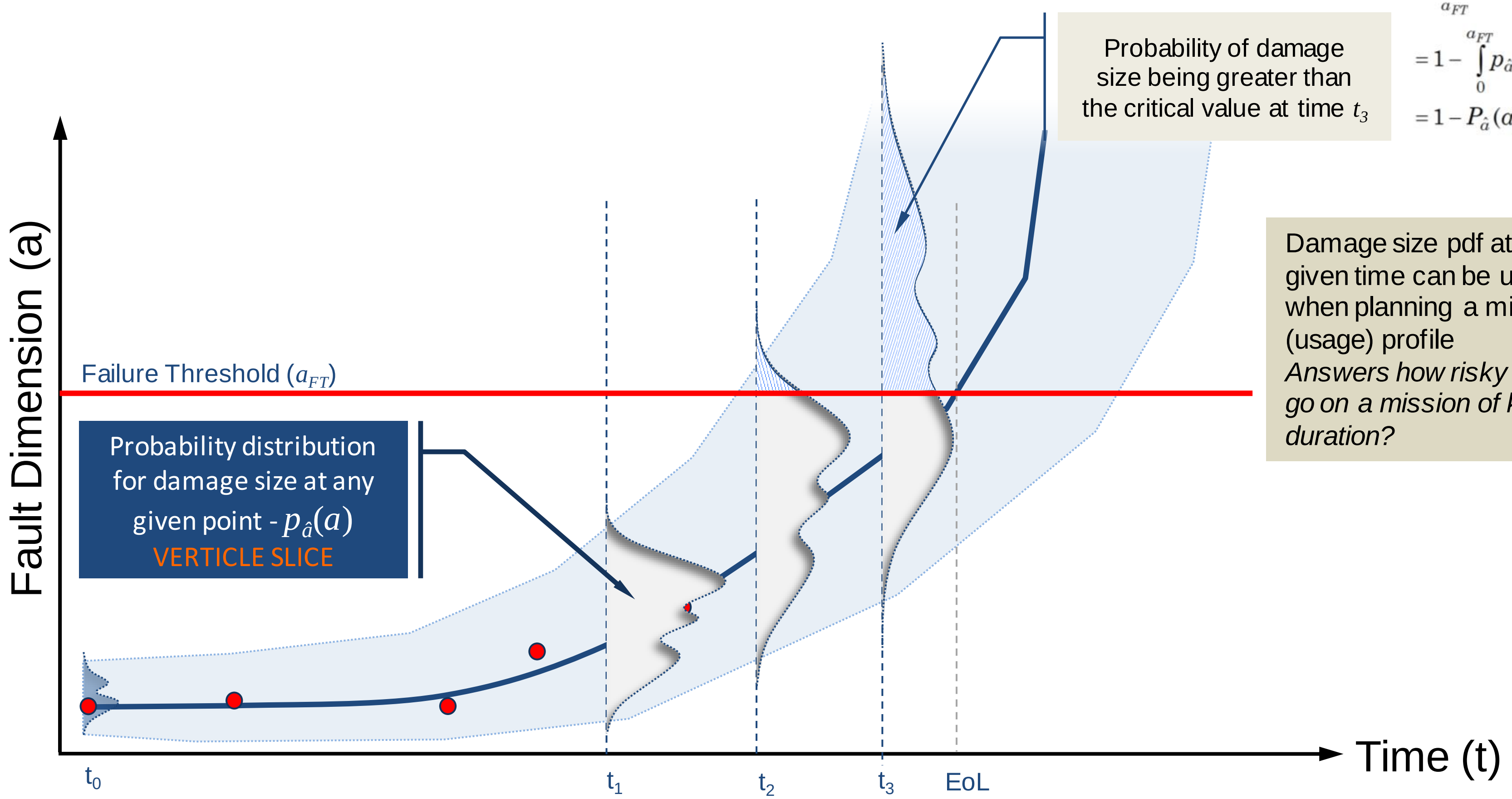



Risk is now a compound function of chosen failure threshold and the decision point

# Prognostics Framework

$$\pi_{t_3} = \int_{a_{FT}}^{\infty} p_{\hat{a}}(a|t=t_3)da$$
$$= 1 - \int_{0}^{a_{FT}} p_{\hat{a}}(a|t=t_3)da$$
$$= 1 - P_{\hat{a}}(a_{FT}|t=t_3)$$

Probability of damage size being greater than the critical value at time $t_3$




Damage size pdf at a given time can be useful when planning a mission (usage) profile
*Answers how risky it is to go on a mission of known duration?*

We can figure out if the system would withstand by the time mission is completed

# Prognostics Framework

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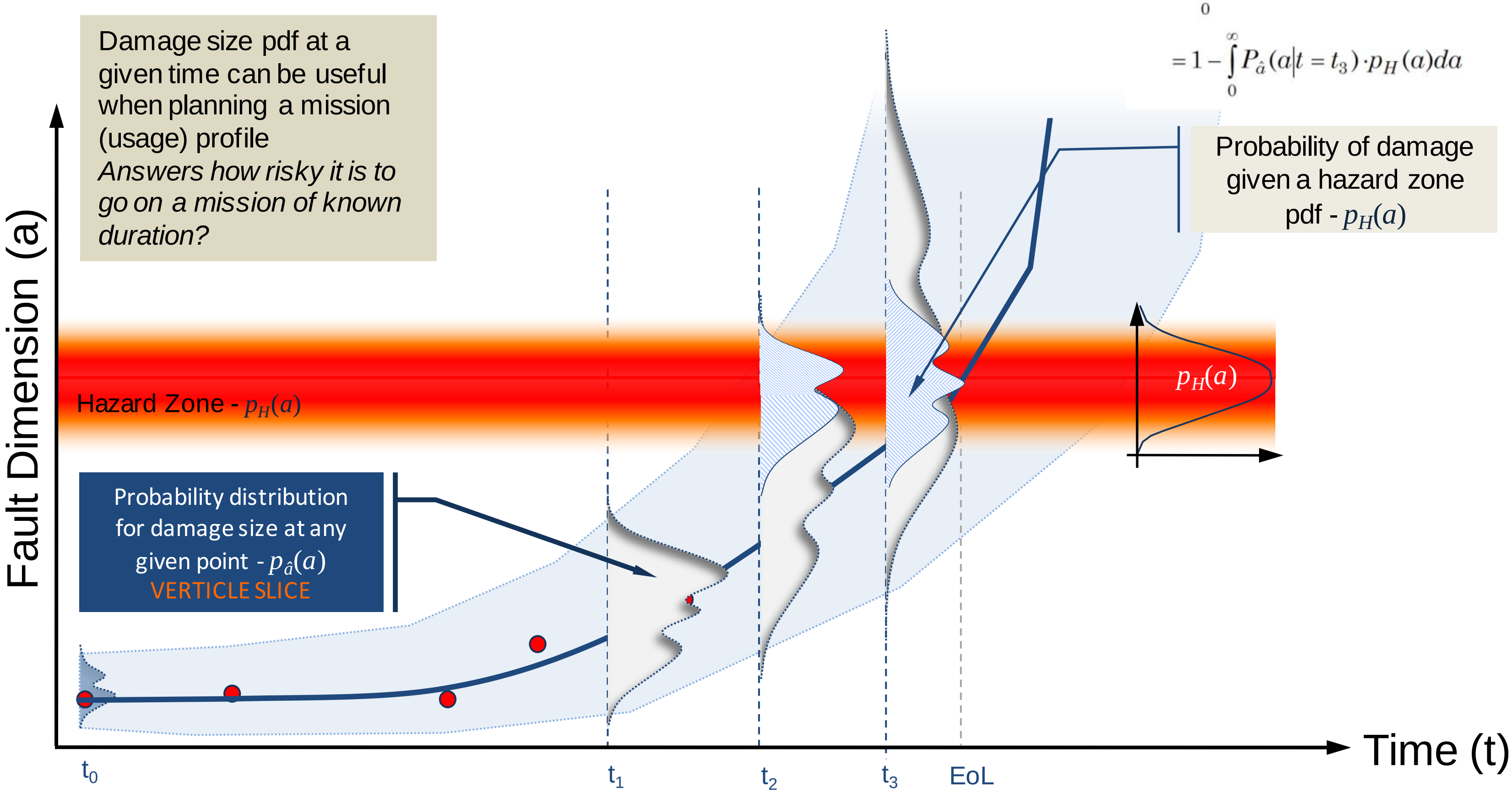
$$\pi_{t_3} = \int_0^{\infty} \left(1 - P_{\hat{a}}(a|t = t_3)\right) p_H(a)da$$
$$= 1 - \int_0^{\infty} P_{\hat{a}}(a|t = t_3) \cdot p_H(a)da$$




We can figure out if the system would withstand by the time mission is completed

Examples

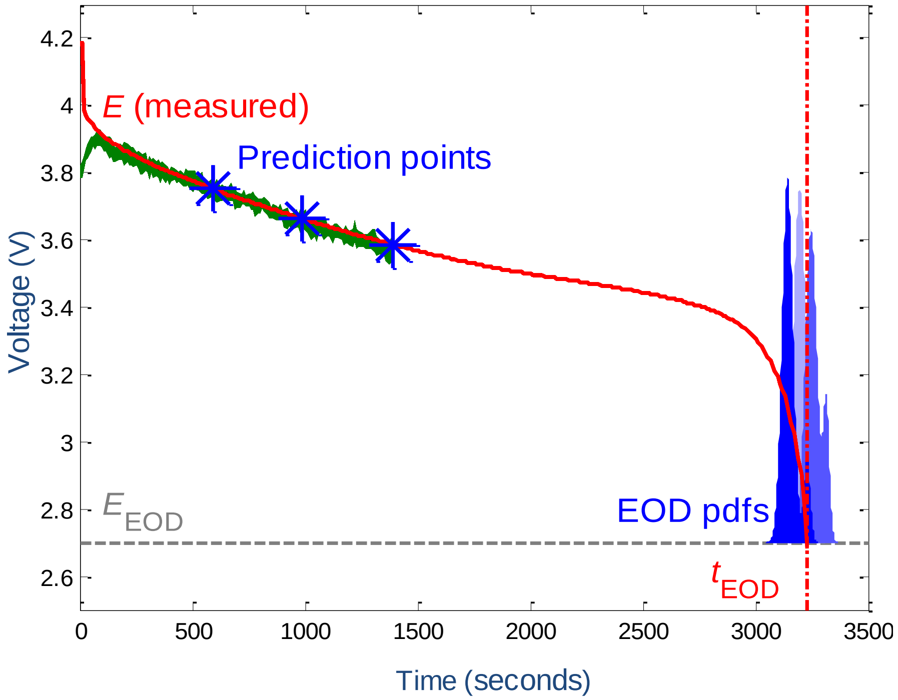
# Prognostics Applications

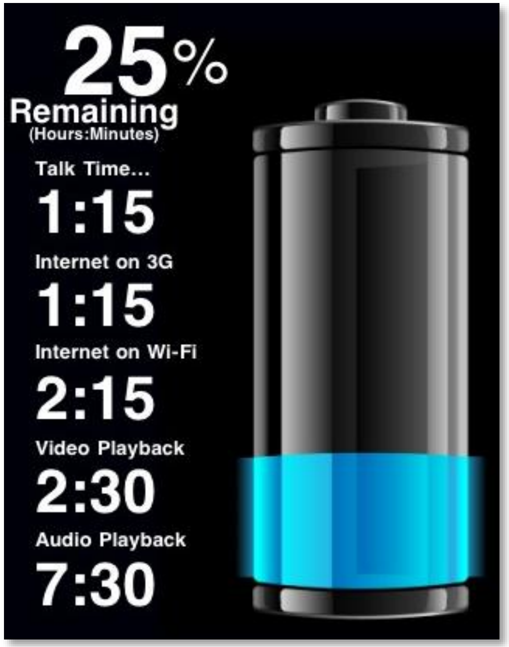
# Power Storage Systems



## Predicting Battery Discharge

- Objective: Predict when the battery voltage will dip below 2.7 volts
- Example: when to recharge laptop or cell phone batteries




- Complexity: Non-linear failure growth characteristics

- *Data Source:* NASA PCoE Data Repository [http://ti.arc.nasa.gov/tech/dash/pcoe/prognostic-data-repository/]
- B. Saha, K. Goebel, *Modeling Li-ion Battery Capacity Depletion in a Particle Filtering Framework*, Proceedings of Annual Conference of the PHM Society 2009

# Power Storage Systems

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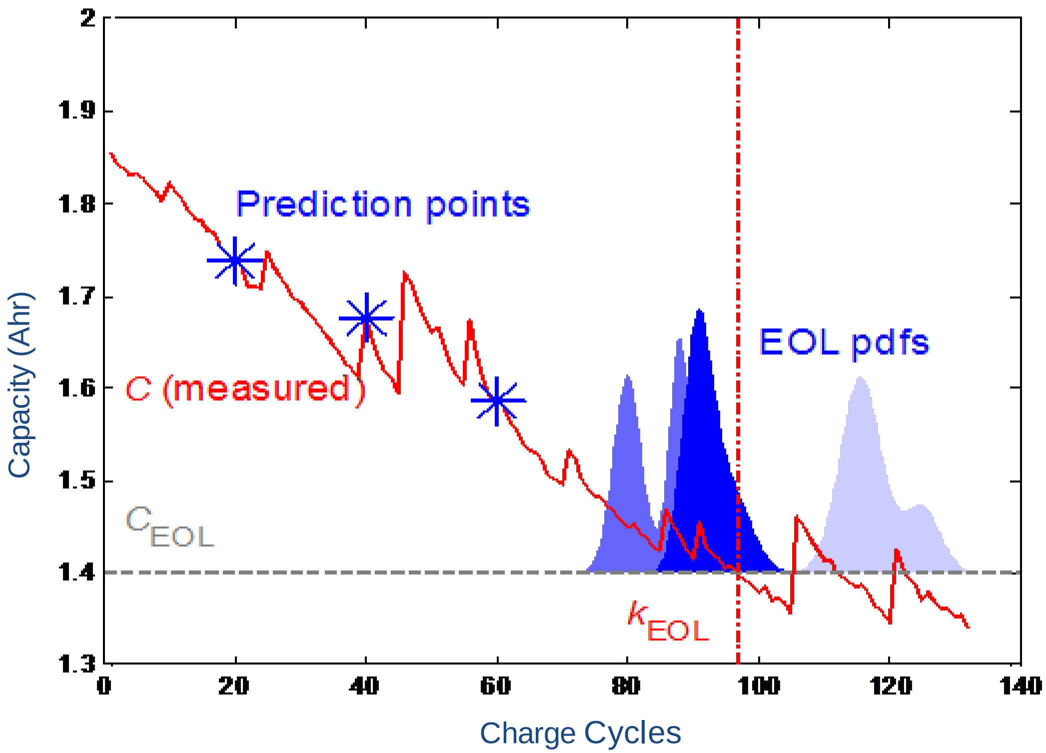
## Predicting Battery Capacity – Long Term

- Objective: Predict when Li-ion battery capacity will fade by 30% indicating life (EOL)
- Example: when to replace batteries



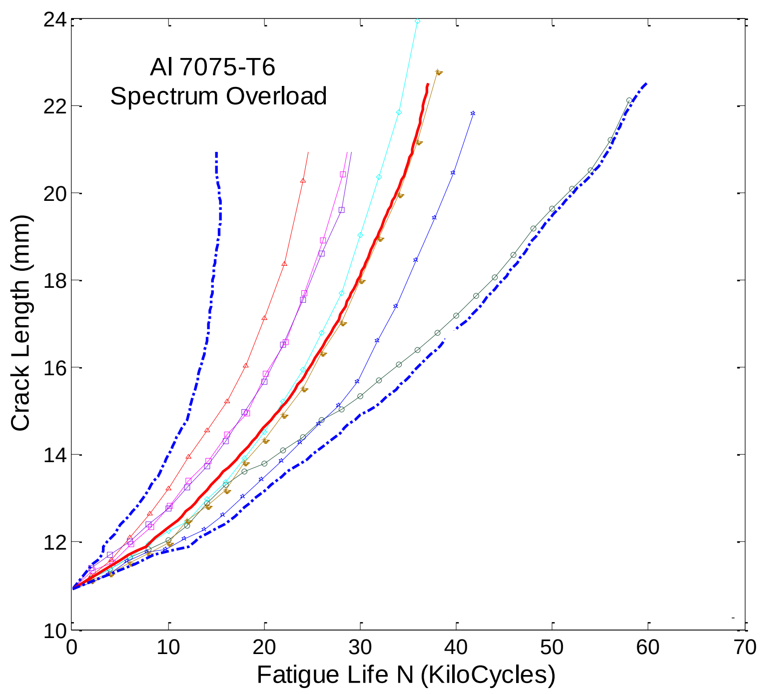

- Complexity: Self-healing characteristics make them highly non-linear

- *Data Source:* NASA PCoE Data Repository [http://ti.arc.nasa.gov/tech/dash/pcoe/prognostic-data-repository/]
- B. Saha, K. Goebel, *Modeling Li-ion Battery Capacity Depletion in a Particle Filtering Framework*, Proceedings of Annual Conference of the PHM Society 2009

# Structural Integrity

## Predicting crack size in metallic structures

- Objective: Predict when the crack size will exceed a critical length
- Example: aircraft structures, bridges, buildings, etc.





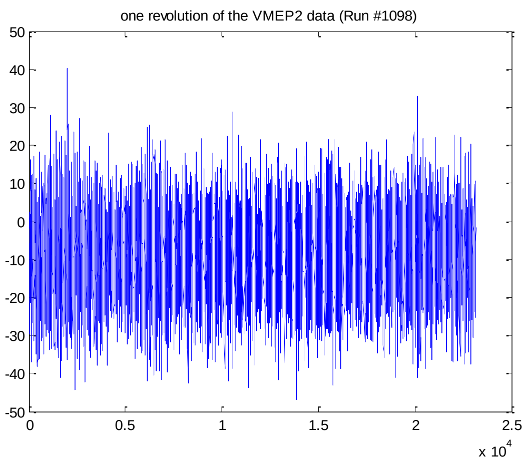
- Complexity: Effects of load spectrum, uncertain future loads

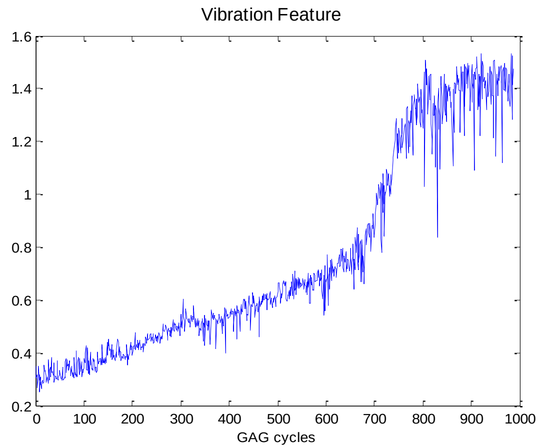
• Zhang, W. and Liu, Y., *In-Situ Optical Microscopy/SEM Fatigue Crack Growth Testing of Al7075-T6"* Aircraft Airworthiness & Sustainment 2010. 11 May-14 May. Austin, TX.

# Structural Integrity

## Predicting crack size in a gearbox

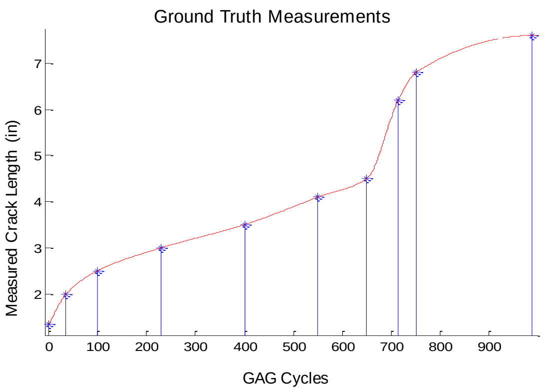
- Objective: Predict when the crack size will exceed a critical length
- Example: planetary gearbox for UH-60A

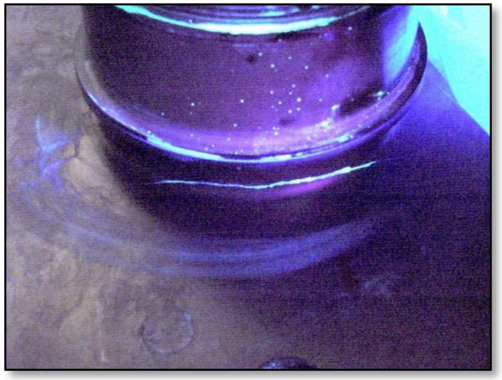




- Complexity:
  - Lack of run-to-failure data
  - Expensive and risky tests
  - Varying load levels



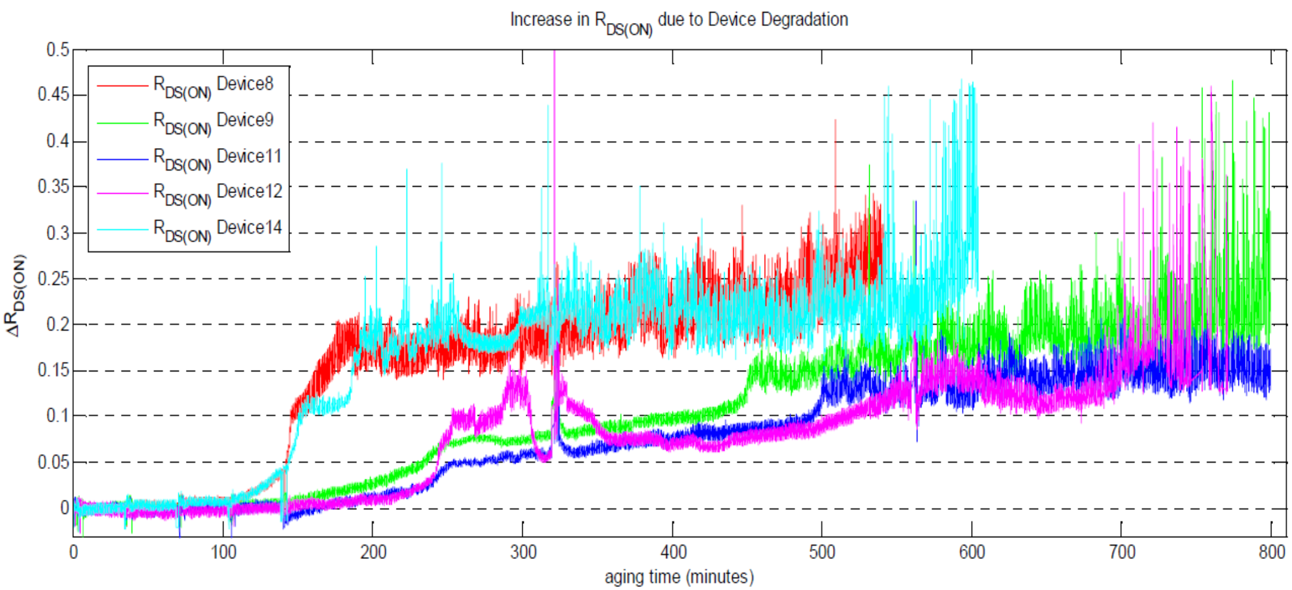



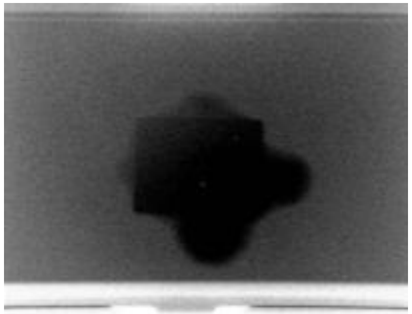

- Keller, J., Grabill, P., *Vibration Monitoring of a UH-60A Main Transmission Planetary Carrier Fault*, the American Helicopter Society 59thAnnual Forum, Phoenix, Arizona, May 6 –8, 2003
- Sahrmann, G. J., *Determination of the crack propagation life of a planetary gear carrier,* 60th Annual Forum Proceedings, Baltimore, MD, Jun. 7-10 2004, American Helicopter Society
- Intelligent Control Systems Group at Georgia Tech [http://icsl.gatech.edu/icsl/Research_Groups#Fault_Diagnosis_and_Failure_Prognosis_for_Engineering_Systems]

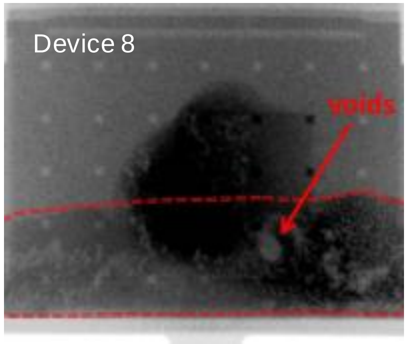
# Electronics Failure



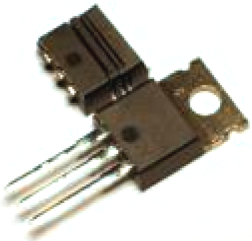
- Objective: predict abnormal functioning of electronic devices
- Example: thermal degradation of die attach in power MOSFETS






- Complexity:
  - Manufacturing variability
  - Competing degradation mechanisms
  - Environmental conditions



- Celaya, J., Saxena, A., Wysocki, P., Saha, S., Goebel, K., "*Towards Prognostics of Power MOSFETs: Accelerated Aging and Precursors of Failure*" Annual conference of the PHM Society, Portland OR, October 2010.

# NASA Repository

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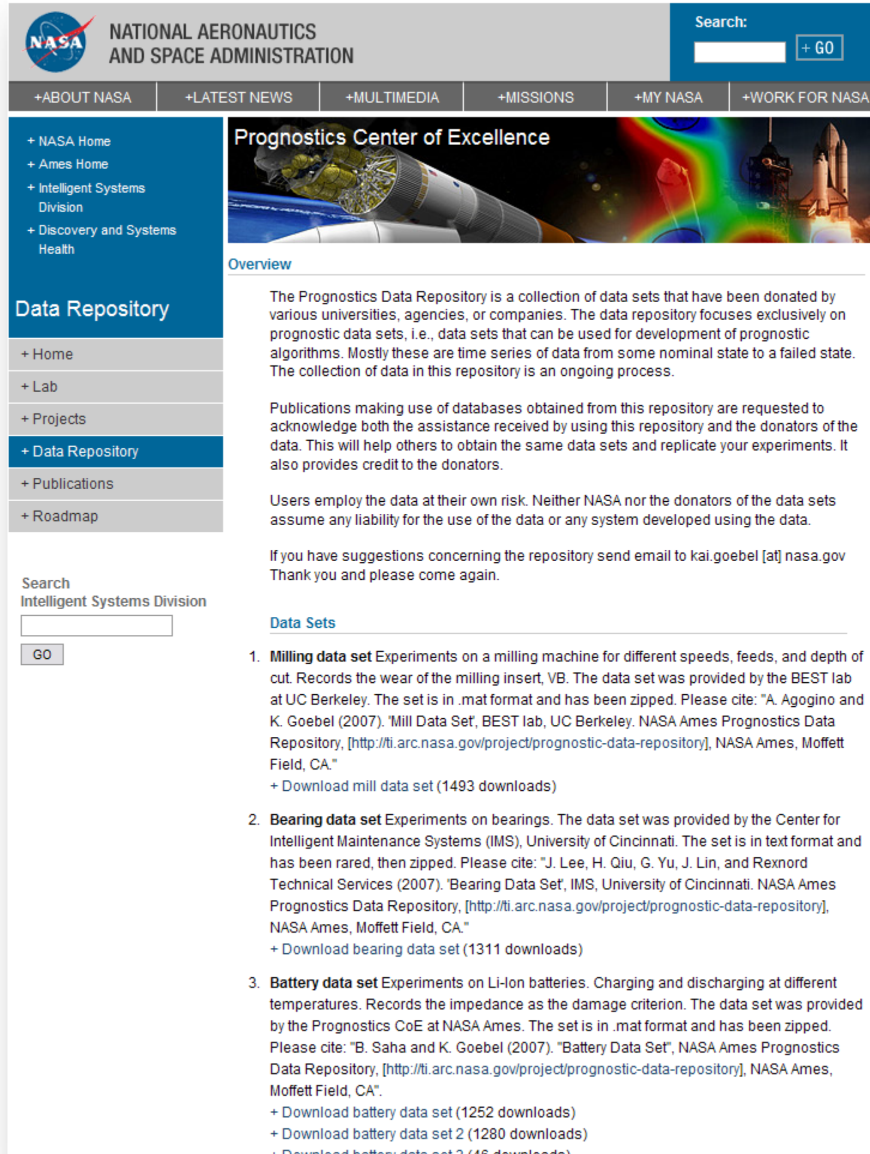
- Collection of run-to-failure data from a variety of domains
  - Rotating mechanical systems
  - Power storage systems – batteries
  - Electronics
  - EMAs
  - Turbofan engine simulation dataset
    - PHM08 challenge data
- Allows benchmarking the algorithms
- Explore challenges associated with different application domains
- Make hard to come by run-to-failure data to the research community



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Overview

The Prognostics Data Repository is a collection of data sets that have been donated by various universities, agencies, or companies. The data repository focuses exclusively on prognostic data sets, i.e., data sets that can be used for development of prognostic algorithms. Mostly these are time series of data from some nominal state to a failed state. The collection of data in this repository is an ongoing process.

Publications making use of databases obtained from this repository are requested to acknowledge both the assistance received by using this repository and the donators of the data. This will help others to obtain the same data sets and replicate your experiments. It also provides credit to the donators.

Users employ the data at their own risk. Neither NASA nor the donators of the data sets assume any liability for the use of the data or any system developed using the data.

If you have suggestions concerning the repository send email to kai.goebel [at] nasa.gov Thank you and please come again.

Data Sets

1. **Milling data set** Experiments on a milling machine for different speeds, feeds, and depth of cut. Records the wear of the milling insert, VB. The data set was provided by the BEST lab at UC Berkeley. The set is in .mat format and has been zipped. Please cite: "A. Agogino and K. Goebel (2007). 'Mill Data Set', BEST lab, UC Berkeley. NASA Ames Prognostics Data Repository, [http://ti.arc.nasa.gov/project/prognostic-data-repository], NASA Ames, Moffett Field, CA."
   + Download mill data set (1493 downloads)
2. **Bearing data set** Experiments on bearings. The data set was provided by the Center for Intelligent Maintenance Systems (IMS), University of Cincinnati. The set is in text format and has been rared, then zipped. Please cite: "J. Lee, H. Qiu, G. Yu, J. Lin, and Rexnord Technical Services (2007). 'Bearing Data Set', IMS, University of Cincinnati. NASA Ames Prognostics Data Repository, [http://ti.arc.nasa.gov/project/prognostic-data-repository], NASA Ames, Moffett Field, CA."
   + Download bearing data set (1311 downloads)
3. **Battery data set** Experiments on Li-Ion batteries. Charging and discharging at different temperatures. Records the impedance as the damage criterion. The data set was provided by the Prognostics CoE at NASA Ames. The set is in .mat format and has been zipped. Please cite: "B. Saha and K. Goebel (2007). "Battery Data Set", NASA Ames Prognostics Data Repository, [http://ti.arc.nasa.gov/project/prognostic-data-repository], NASA Ames, Moffett Field, CA".
   + Download battery data set (1252 downloads)
   + Download battery data set 2 (1280 downloads)
   + Download battery data set 3 (46 downloads)

- *NASA* PCoE Data Repository [http://ti.arc.nasa.gov/tech/dash/pcoe/prognostic-data-repository/]

Setting up the Problem

# Prognostics Modeling

# Data-Driven Prognostic Methods

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## Primarily use data obtained from the system for predicting failures

- What kind of data?
  - Something that indicates a fault and fault growth or is expected to influence fault growth
    - Sensor measurement to assess system state
    - Sensor measurements and communication logs to identify operational modes and operational environment
  - Process data to extract features that “clearly” indicate fault growth
    - Preferably monotonically changing since faults are expected to grow monotonically
  - Predictions can be made in many ways
    - Use raw measurement data to map onto RULs
    - Use processed data to trend in feature domain, health index domain, or fault dimension domain against a set threshold
- How?
  - Learn a mathematical model to fit changing observations
    - Regression or trending
    - Learnt model may not be transparent to our understanding but explains observed data
  - Use statistics if volumes of run-to-failure data is available
    - Map remaining useful life to various faulty states of the system
    - Reliability type RUL estimates

# Example - Data-Driven Prognostics Model

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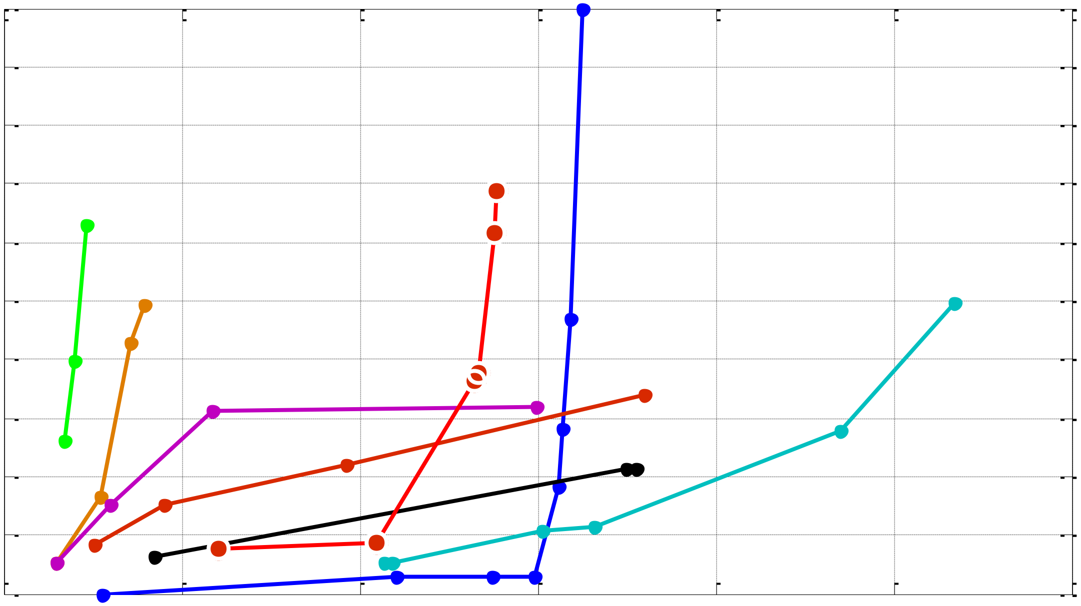
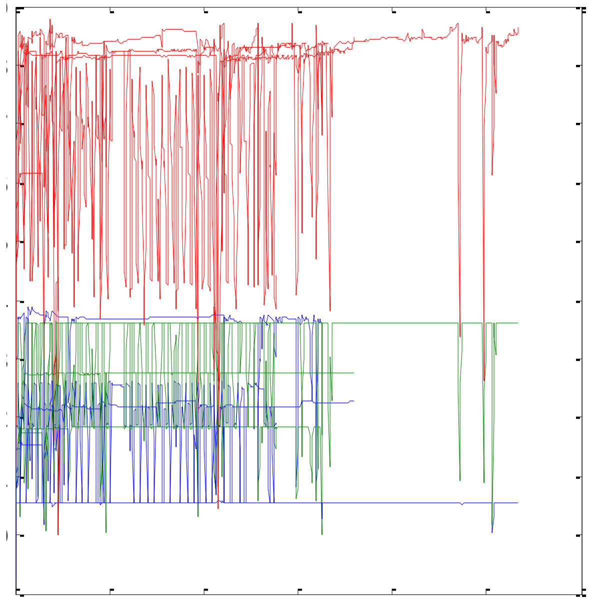
- Operational conditions
  - Indicate level of stress on the system
- Ground truth measurements
  - Ground truth measurements are less frequent

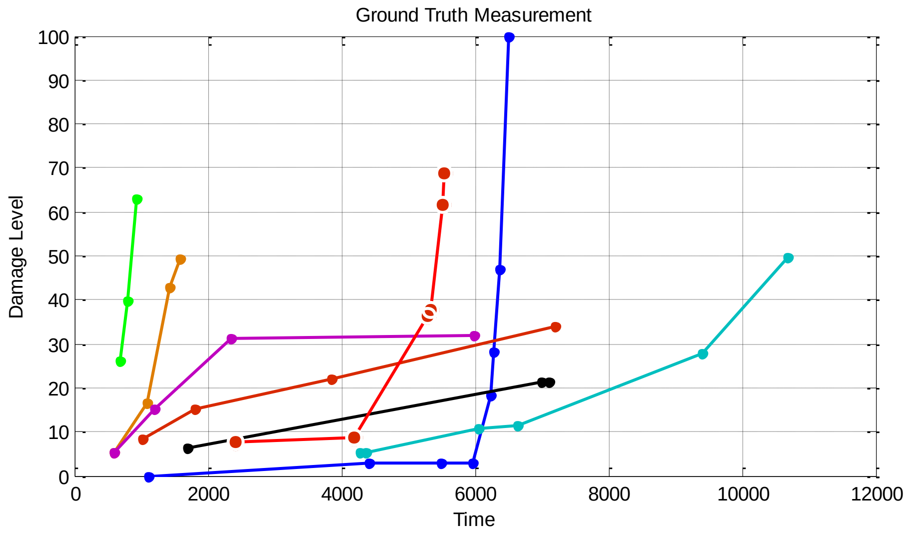


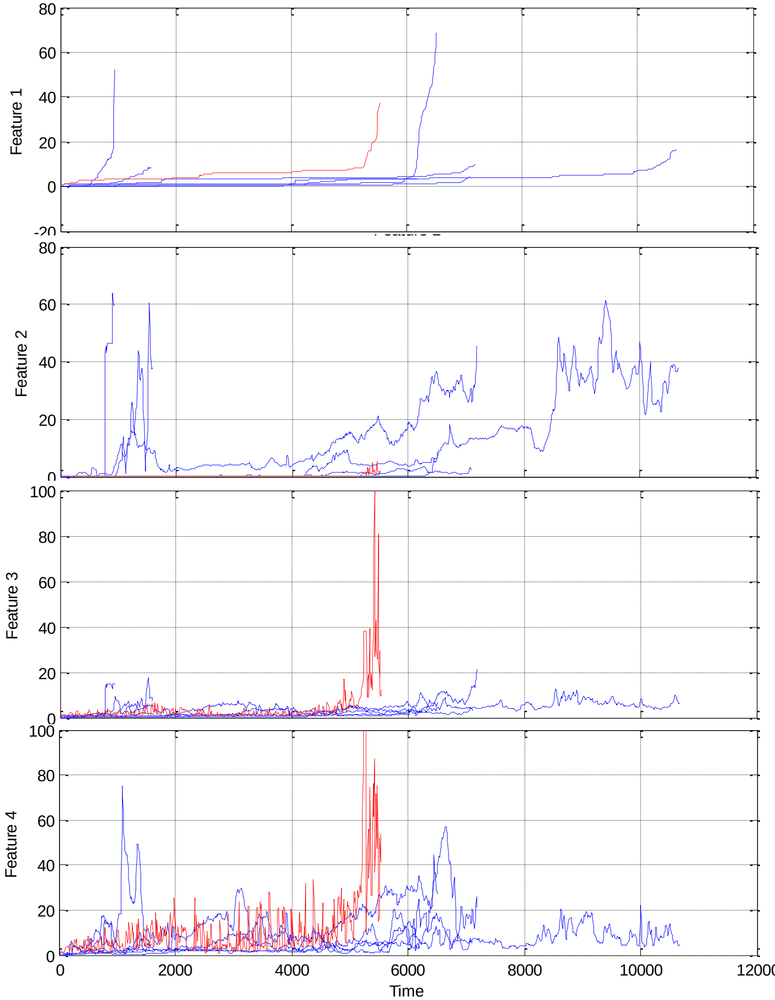


**Operational conditions seem to make an impact on how fast the damage grows !**

# Example - Data-Driven Prognostics Model

- Sensor Measurements
  - Features are extracted form sensor data
  - Depending on what is measured features will have noise w.r.t. damage growth
  - All run-to-failure units follow their own track



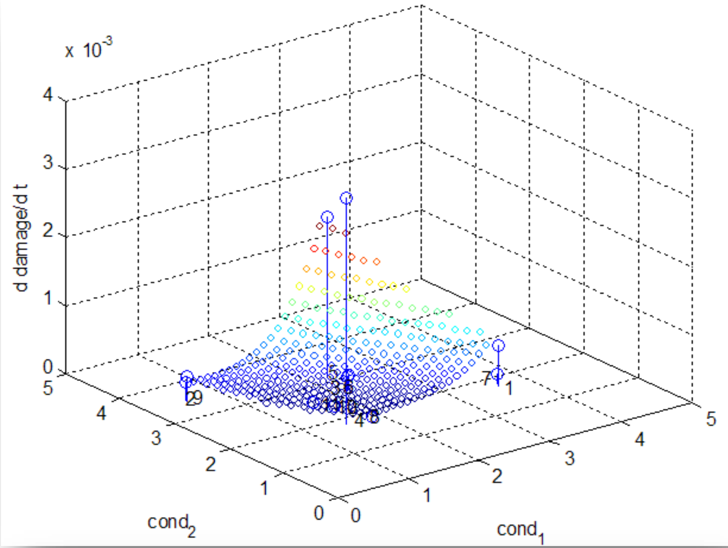



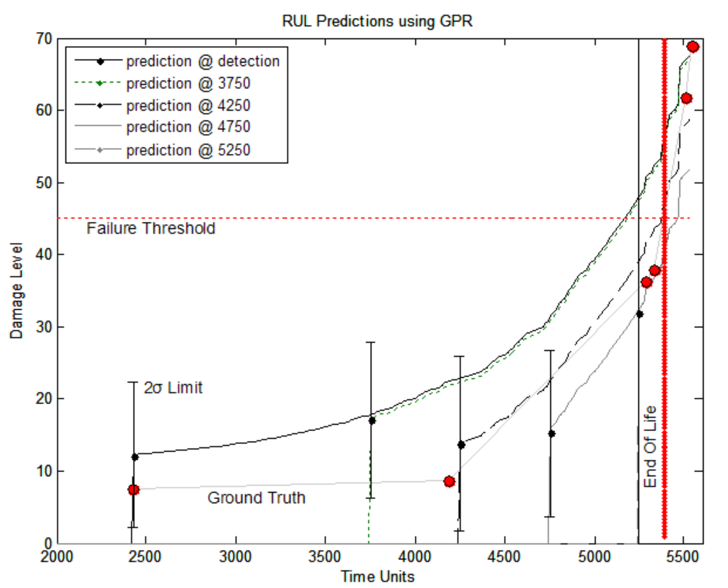

Generally speaking features indicate the level of damage at any given time

# Approach



- Learning/training
  - Learn a mapping (M1) between features and the damage state
  - Learn a mapping (M2) between operational conditions and damage growth rate
- Prediction
  - At any given time use M1 & latest measurements to estimate damage state
  - Assuming a future load profile (if unknown) estimate damage accumulation for all future instants using M2




• Goebel, K., Saha, B., and Saxena, A., "A Comparison of Three Data-Driven Techniques for Prognostics", Proceedings of the 62nd Meeting of the Society For Machinery Failure Prevention Technology (MFPT), pp. 119-131, Virginia Beach VA, May 2008

# Data-Driven Prognostic Methods

- Advantages
  - Relatively Simple to implement and faster
    - Variety of generic data-mining and machine learning techniques are available
  - Helps gain understanding of physical behaviors from large amounts of data
    - These represent facts about what actually happened all of which may not be apparent from theory
- Disadvantages
  - Physical cause-effect relationships are not utilized
    - E.g. different fault growth regimes, effects of overloads or changing environmental conditions
  - Difficult to balance between generalization and learning specific trends in data
    - Learning what happened to several units on average may not be good enough to predict for a specific unit under test
  - Requires large amounts of data
    - We never know if we have enough data or even how much is enough
- Examples
  - Regression
  - Neural Networks (NN)
    - RNN, ARNN, RNF
  - Gaussian process regression (GPR)
  - Bayesian updates
  - Relevance vector machines (RVM)

# Physics-Based Models for Prognostics

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## Use fault propagation models to estimate time of failure

- What kind of models?
  - A model that explains the failure mode of interest
  - A model that maps the effects of stressors onto accumulation of damage – Physics of failure driven
    - e.g. fatigue cycling increases the crack length, or continuous usage reduces the battery capacity over a long term can be modeled in a variety of ways
      - Finite Element Models
      - Empirical models
      - High fidelity simulation models, etc.
  - Modeled cause-effect phenomenon may be directly observable as a fault or not
    - Structural cracks are observable faults
    - Internal resistance changes in a battery causing capacity decay are not directly observable
- How?
  - Given the current state of the system simulate future states using the model
    - Recursive one step ahead prediction to obtain k-steps ahead prediction
  - Propagate fault until a predefined threshold is met to declare failure and compute RUL

# Physics-Based Models for Prognostics

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- Advantages
  - Prediction results are intuitive based on modeled case-effect relationships
    - Any deviations may indicate the need to add more fidelity for unmodeled effects or methods to handle noise
  - Once a model is established, only calibration may be needed for different cases
  - Clearly drives sensing requirements
    - Based on model inputs, its easy to determine what needs to be monitored
- Disadvantages
  - Developing models is not trivial
    - Requires assumptions regarding complete knowledge of the physical processes
    - Parameter tuning may still require expert knowledge or learning from field data
  - High fidelity models may be computationally expensive to run, i.e. impractical for real-time applications
- Examples
  - Population growth models like Arrhenius, Paris, Eyring, etc.
  - Coffin-Manson Mechanical crack growth model

- Engineering Statistics Handbook [http://www.itl.nist.gov/div898/handbook/apr/section1/apr15.htm]

# Hybrid Approaches

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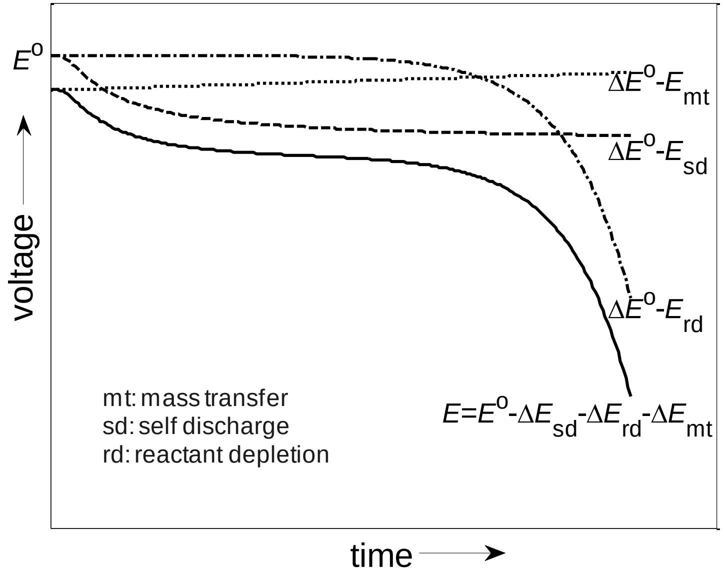
**Use knowledge about the physical process and information from observed data together**

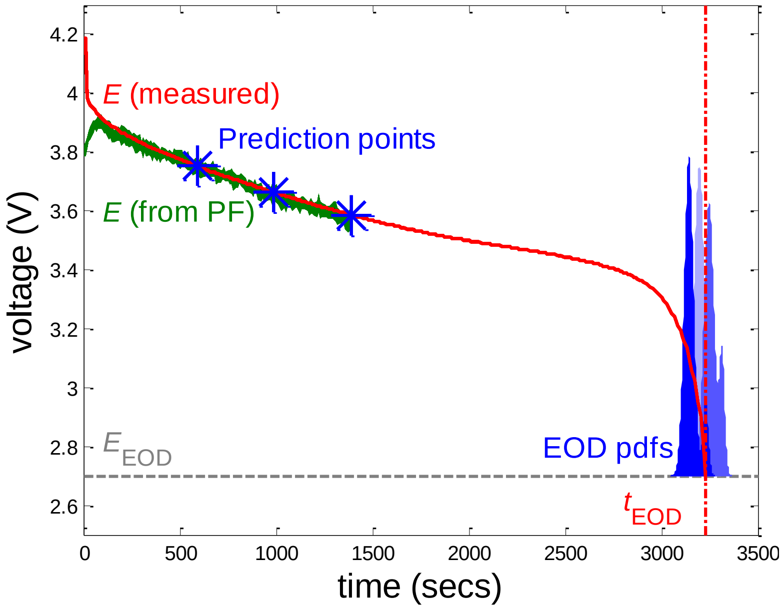
- How?
  - Learn/fine-tune parameters in the model to fit data
  - Use model to make prediction and make adjustment based on observed data
  - Learn current damage state from data and propagate using model
  - Use knowledge about the physical behavior to guide learning process from the data
    - Improve initialization parameters for learning
    - Decide on the form for a regression model
  - Use understanding from data analysis to develop models
    - Discover the form of the fault growth model
  - Fuse estimates from two different approaches
  - *or any other creative way you can think of…*

# Example1 – Physics Model Tuned with Data

## Predicting Battery Discharge – Short Term

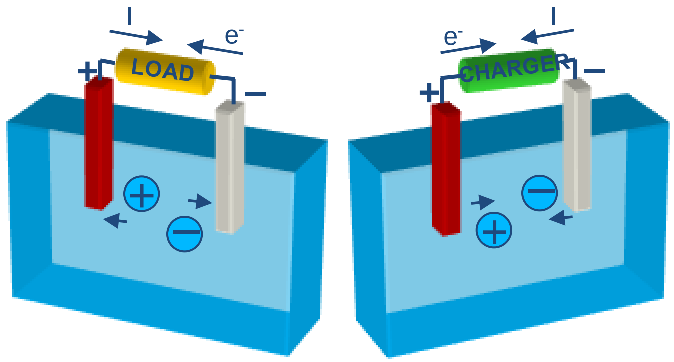
- Objective: Predict when Li-ion battery voltage will dip below 2.7 volts
- Hybrid approach using Particle Filter
  - Model non-linear electro-chemical phenomena that explain the discharge process
  - Learn model parameters from training data
  - Let the PF framework fine tune the model during the tracking phase
  - Use the tuned model to predict EOD



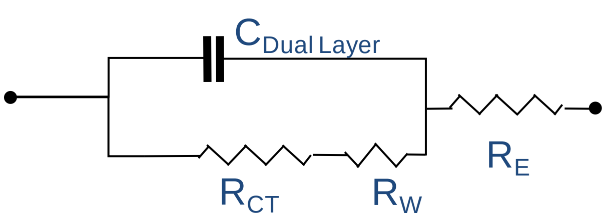

- *Data Source:* NASA PCoE Data Repository [http://ti.arc.nasa.gov/tech/dash/pcoe/prognostic-data-repository/]
- B. Saha, K. Goebel, *Modeling Li-ion Battery Capacity Depletion in a Particle Filtering Framework*, Proceedings of Annual Conference of the PHM Society 2009

# Example2 – Develop Empirical Model from Data




DISCHARGE CHARGE

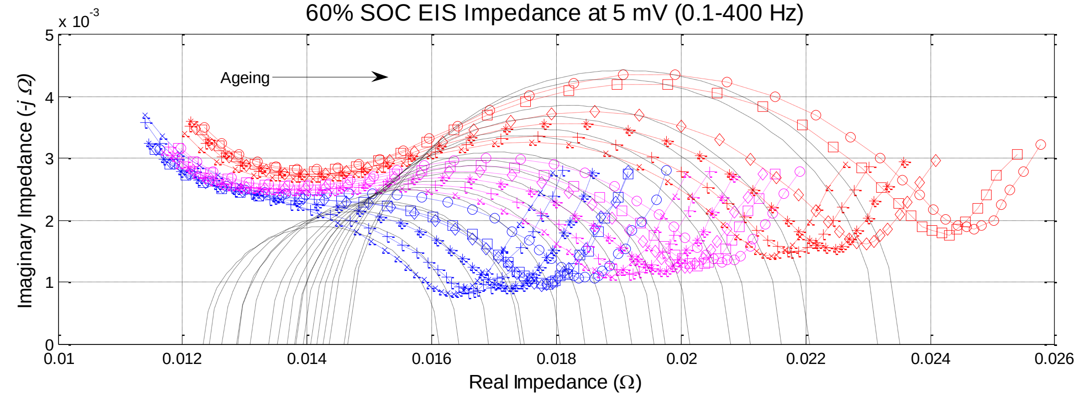
Battery Schematic

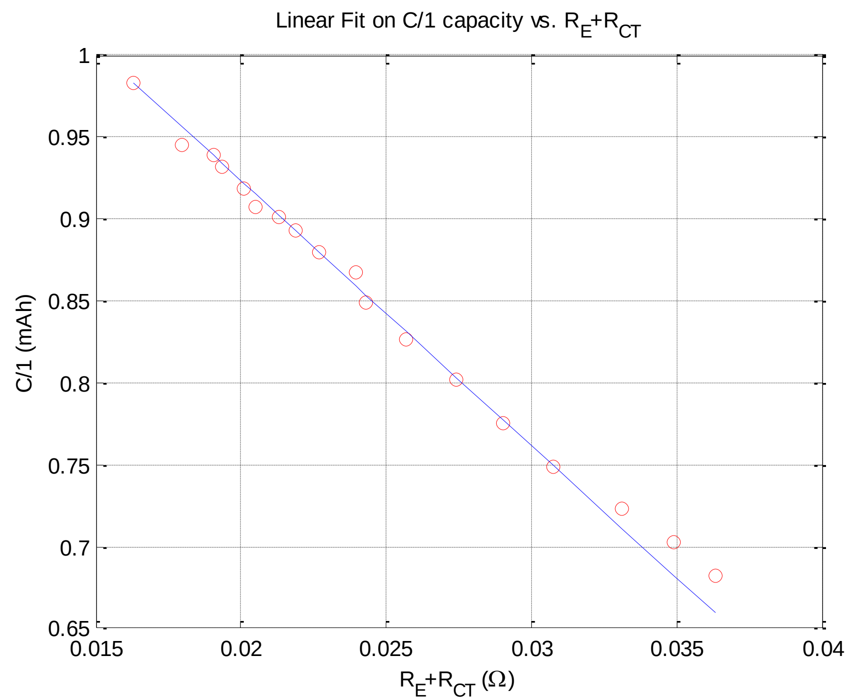



Charge Transfer

$Z=R+jX$

Lumped Parameter Model




***Source:*** Goebel, K., Saha,B., Saxena, A., Celaya, J. R. , Christopherson, J. P., "Prognostics in Battery Health Management", IEEE Instrumentation and Measurement Magazine, Vol. 11(4), pp. 33-40, August 2008

# Example2 – Data-driven Regression

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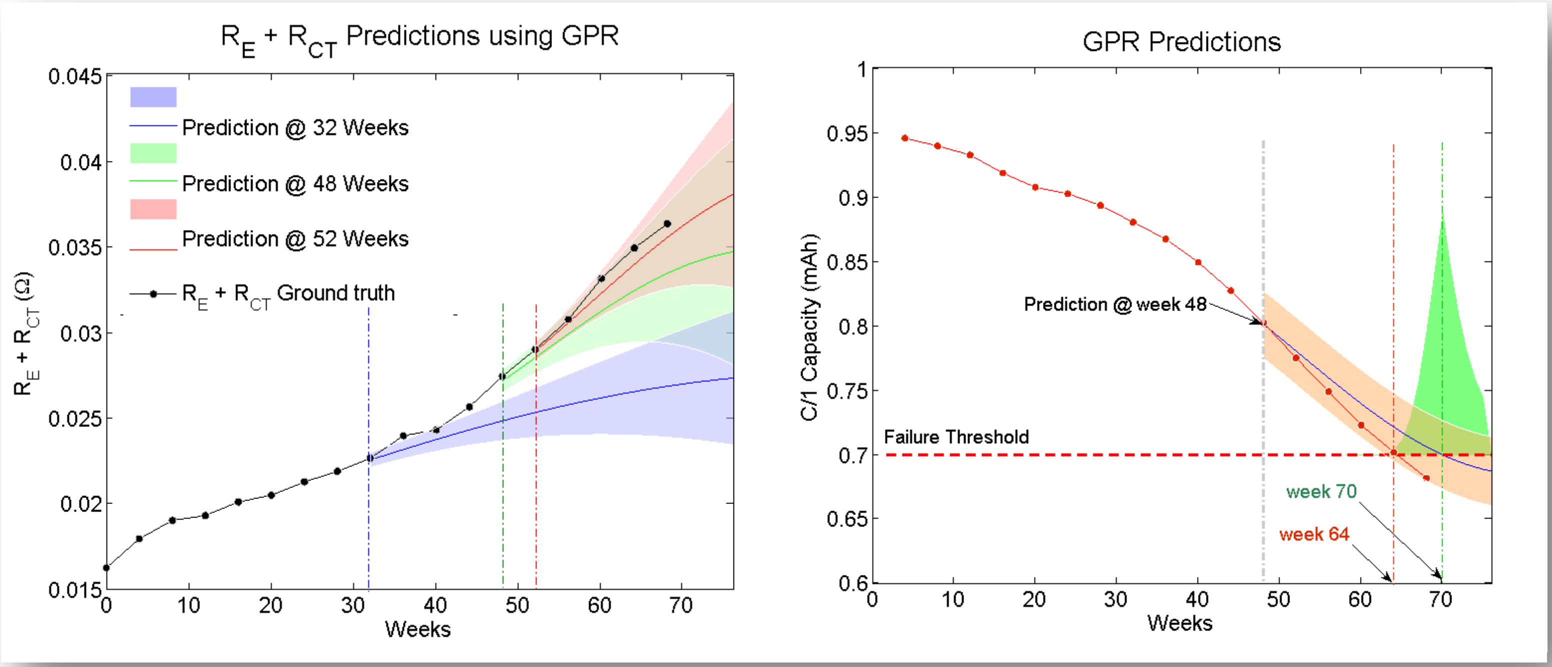
- Use a regression algorithm to make predictions
  - Gaussian Process Regression



# Hybrid Approaches

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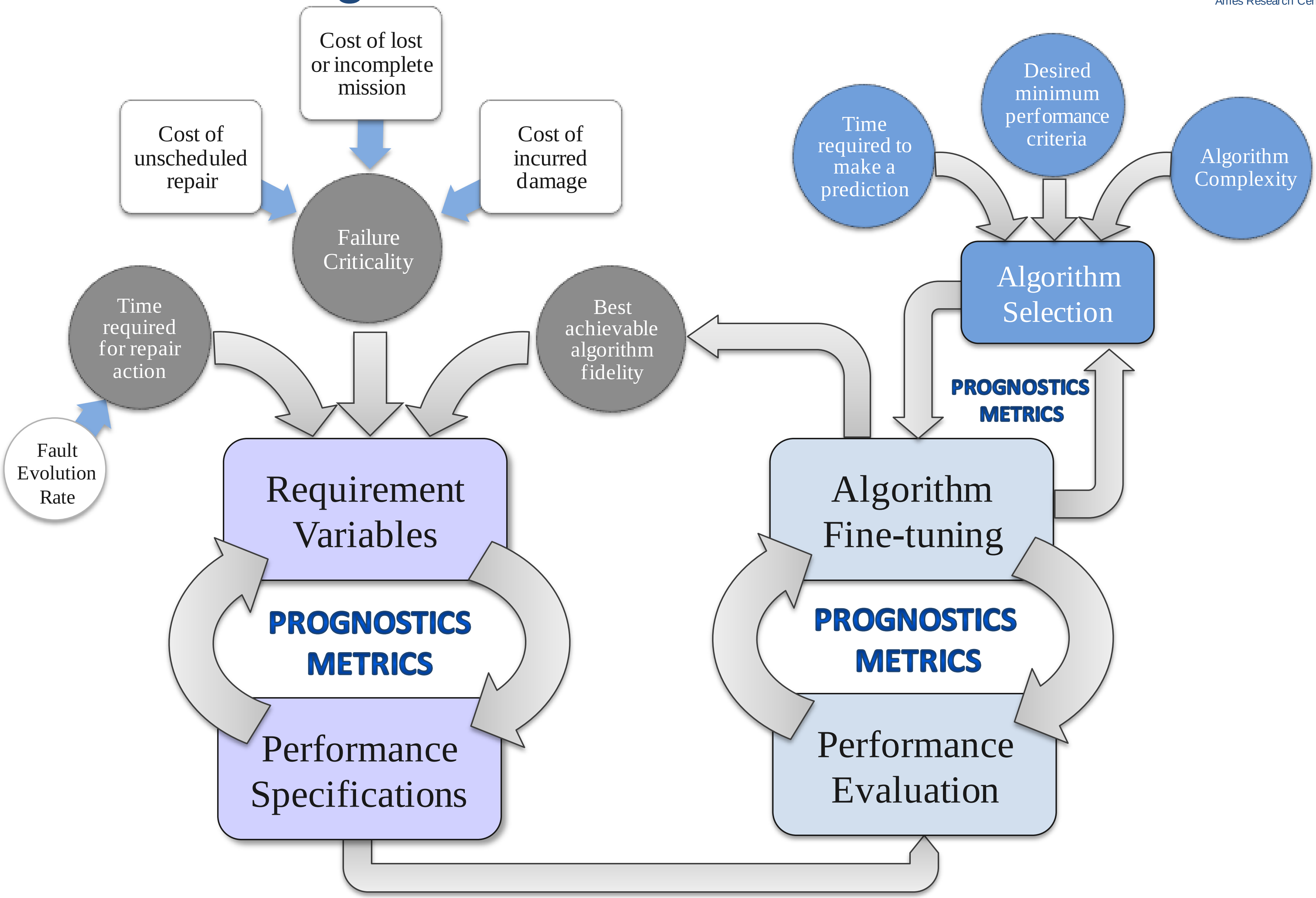
- Advantages
  - Does not necessarily require high fidelity models or large volumes of data – works in a complementary fashion
  - Retains intuitiveness of a model but explains observed data
  - Helps in uncertainty management
  - Flexibility
- Disadvantages
  - Needs both data and the models
  - An incorrect model or noisy data may bias each other's approach

  *Otherwise, it's a compromise to get the best out of both so any disadvantage may be alleviated*
- Examples
  - Particle Filters, Kalman Filters, etc.
  - or any clever combination of different approaches…

Prognostic Performance Evaluation

# Prognostics Metrics

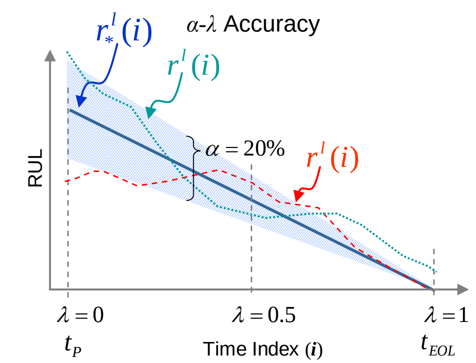
# Role of Prognostics Metrics

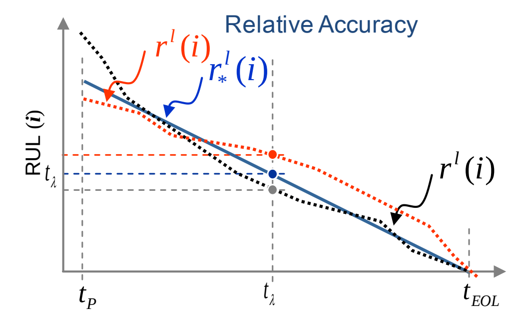


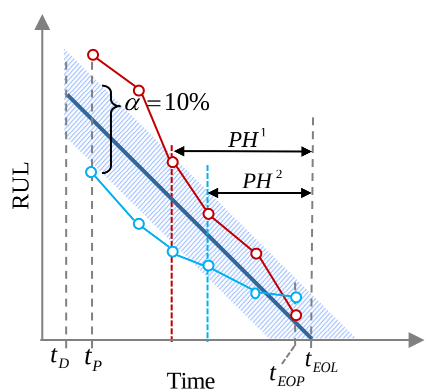
# Prognostic Performance Metrics

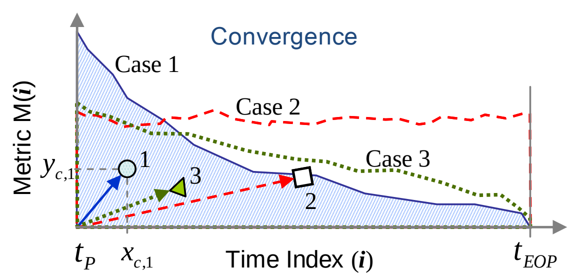
- New metrics were proposed specific to prognostics for PHM
- These metrics were applied to
  - A combination of different algorithms and different datasets
- Metrics were evaluated and refined

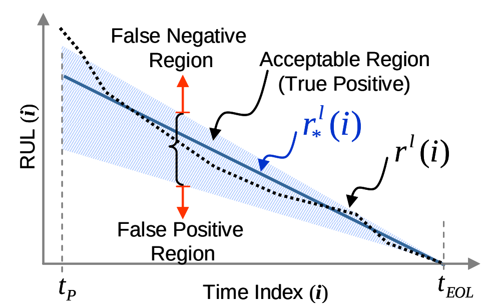
- Prognostics horizon
- *α-λ* performance
- Relative accuracy
- Cumulative relative accuracy
- Convergence




*Source:* A. Saxena, J. Celaya, E. Balaban, K. Goebel, B. Saha, S. Saha, and M. Schwabacher (2008). *Metrics for evaluating performance of prognostic techniques. International Conference on Prognostics and Health Management*, PHM 2008. 6-9 Oct. 2008 Page(s): 1-17.

# Prognostic Performance Metrics

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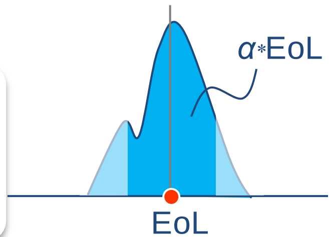
- Metrics Hierarchy

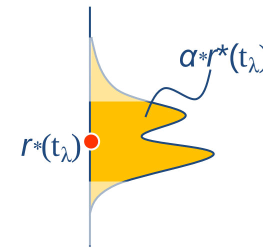
## I. Prognostic Horizon

- Does the algorithm predict within desired accuracy around EoL and sufficiently in advance?




## II. *α-λ* Performance

- Further does the algorithm stay within desired performance levels relative to RUL at a given time?




## III. Relative Accuracy

- Quantify how well an algorithm does at a given time relative to RUL

## IV. Convergence Rate

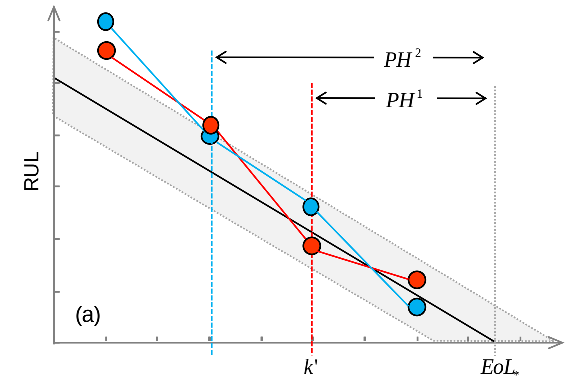
- If the performance converges (i.e. satisfies above metrics) quantify how fast does it converge

# Prognostic Horizon (PH)



- **Prognostic Horizon** is defined as the difference between the time index $i$ when the predictions first meet the specified performance criteria (based on data accumulated until time index $i$) and the time index for End-of-Life (EoL). The performance specification may be specified in terms of allowable error bound ($\alpha$) around true EoL.

$$PH = t_{EoL} - t_{i_{\alpha\beta}}$$




$i_{\alpha\beta}$ is the first time index when predictions satisfy $\beta$-criterion for a given $\alpha$

$$\min\left\{k \mid (k \in p) \wedge \left(\pi[r(k)]_{-\alpha}^{+\alpha}\right) \geq \beta\right\}$$

$p$ is the set of all time indexes when predictions are made

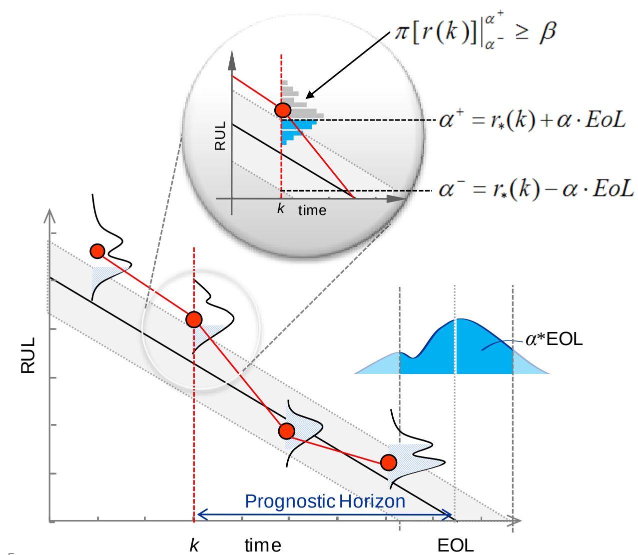
$l$ is the index for $l^{th}$ unit under test (UUT)

$\beta$ is the minimum acceptable probability mass

$\pi[r(k)]_{\alpha^-}^{\alpha^+}$ is the probability mass of the prediction between $\alpha$-bounds given by $\alpha^+ = r_* + \alpha \cdot t_{EoL}$ and $\alpha^- = r_* - \alpha \cdot t_{EoL}$

$r(k)$ is the predicted RUL distribution at time $t_j$

$t_{\text{EoL}}$ is the predicted End-of-Life

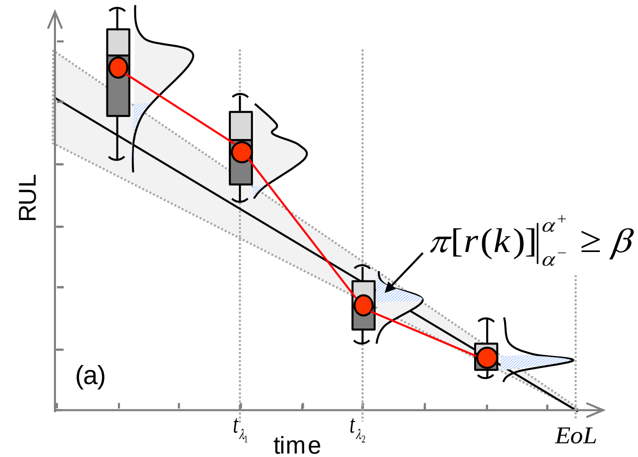


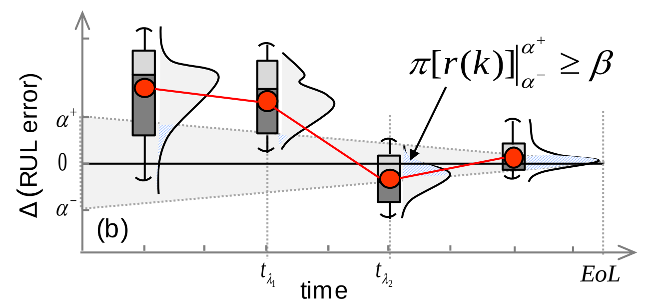

The range of PH is between ($t_{EoL}$-$t_P$) and $max[0, t_{EoL}$-$t_{EoP}]$

# α-λ Accuracy

- ***α-λ Accuracy*** determines whether at given point in time (specified by $\lambda$) prediction accuracy is within desired accuracy levels (specified by $\alpha$). Desired accuracy levels for ant time $t$ are expressed a percentage of true RUL at time $t$.

$$\alpha - \lambda\ Accuracy = \begin{cases} 1 & \text{if} \quad \pi\left[r(i_\lambda)\right]_{-\alpha}^{+\alpha} \geq \beta \\ 0 & \text{otherwise} \end{cases}$$




$\lambda$ is the time window modifier such that $t_\lambda = t_P + \lambda(t_{EoL} - t_P)$

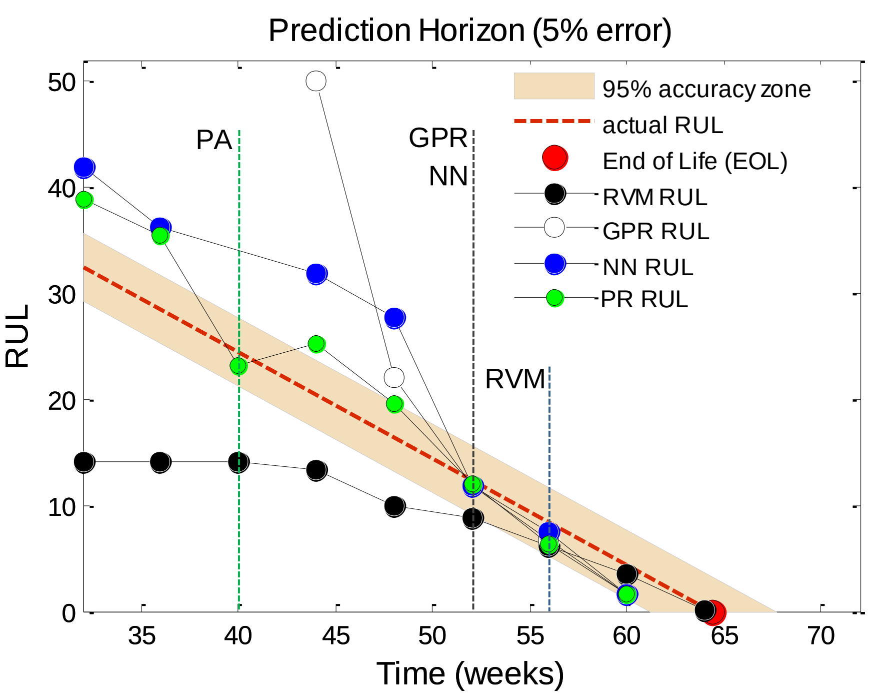
$\beta$ is the minimum acceptable probability mass

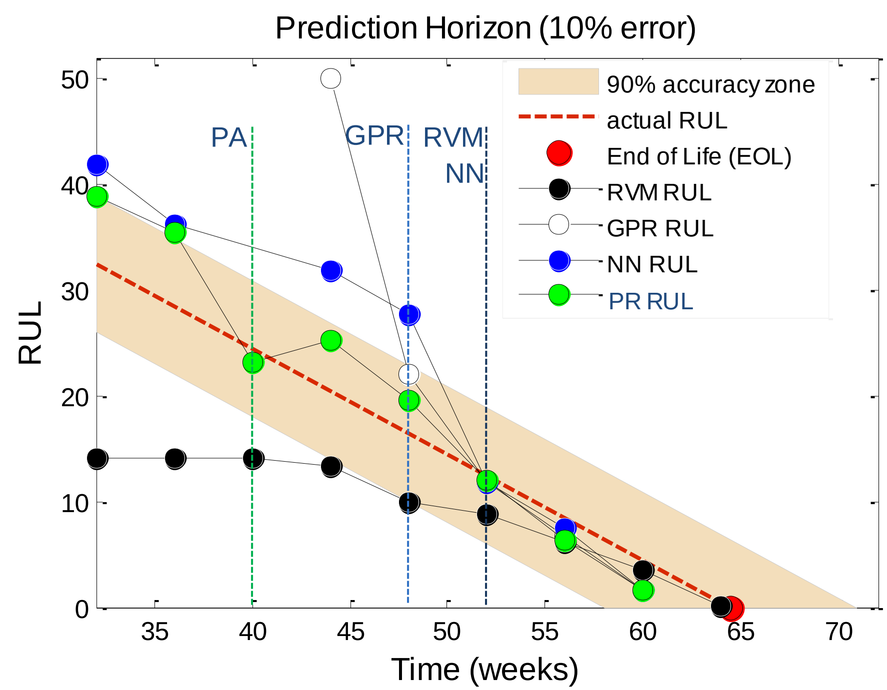
$r(i_\lambda)$ is the predicted RUL at time $t_\lambda$

$\pi\left[r(i_\lambda)\right]_{\alpha^-}^{\alpha^+}$ is the probability mass of the prediction between $\alpha$-bounds given by $\alpha^+ = r_*(i_\lambda) + \alpha \cdot r(i_\lambda)$ and $\alpha^- = r_*(i_\lambda) - \alpha \cdot r(i_\lambda)$

# Comparing Various Algorithms






| | RVM | GPR | ANN | PR |
|---|---|---|---|---|
| PH (weeks) | 8.46 | 12.46 | 12.46 | 24.46 |

| | RVM | GPR | ANN | PR |
|---|---|---|---|---|
| PH (weeks) | 12.46 | 16.46 | 12.46 | 24.46 |

PR > GPR = ANN > RVM

PR > GPR > ANN = RVM

Improving State-of-the-Art

# Prognostics Challenges

# Challenge Areas in Prognostics



- Requirements Specification
  - How can a requirement be framed for prognostics considering uncertainty?
  - How to define and achieve desired prognostics fidelity
- Uncertainty in prognostics
  - Quantification, representation, propagation and management
  - To what extent the probability distribution of a prediction represent reality
- Validation and Verification
  - How can a system be tested to determine if it satisfies specified requirements?
  - If a prediction is acted upon and an operational component is removed from service, how can its failure prediction be validated since the failure didn’t happen?
  - Prognostics performance evaluation – offline and online?
  - Verifiability of prognostics algorithms

# Prognostic Fidelity – What does it mean?

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- Definition of fidelity not clearly identified
  - Baseline assessment for prognostics techniques (NASA IVHM 3.3.1)
  - Baseline assessment for uncertainty management (NASA IVHM 1.2.3.7)
- What is “good” is defined by
  - Time-scales involved in the system under consideration
    - Time needed for problem mitigation
  - Criticality of the system
    - Can afford run-to-failure but cannot accept false positives
    - Cannot afford run-to-failure or accept false negatives
  - What is done post prognosis
  - Costs and risks involved with action/inaction
  - Confidence in the prognostics system itself
    - Uncertainty management still an issue
    - V&V methods not well developed for prognosis yet

# Cost-Benefit Analysis

*Imposing Requirements on Prognostics Algorithms*

# Prognostic Fidelity: One Interpretation

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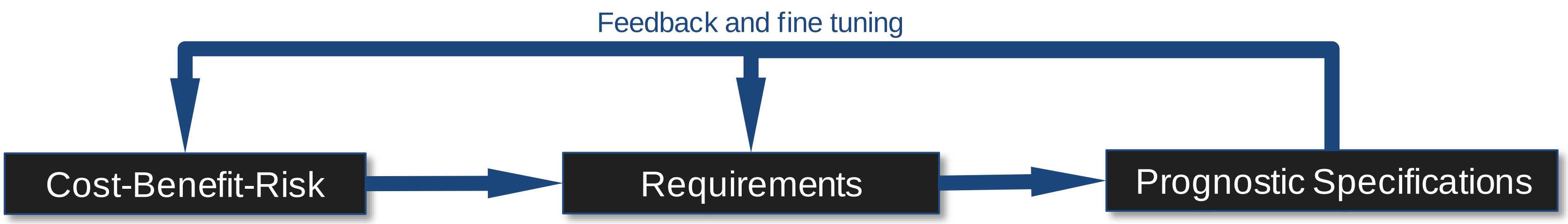


**Objectives**

- Cost-value proposition of PHM
- PHM Design
- Optimal maintenance policy
- Comparison of PHM approaches
- Determine tolerance limits on input uncertainty for desired performance
- Optimal life cycle cost

**Inputs**

- Mission goals and objectives
- Constraints on resources and time
- Cost function

**Integrate from various levels**

- Mission planning level
- Maintenance level
- Operation (runtime) level
- Fleet vs. system levels
- …

**Process**

- Requirement gathering
- Requirement analysis & conflict resolution
- Requirement prioritization
- Requirement flow down

**Methods**

- Simulation techniques
- Cost-value optimization
- Sensitivity & Pareto frontiers
- Use of prognostics metrics
- Requirements flow down methodology suitably adapted for PHM
- Techniques for uncertainty
  - representation
  - management
  - quantification

***Source:*** Saxena, A., Celaya, J., Saha, B., Saha, H., Roychoudhury, I., Goebel, K., "Requirements Specification for Prognostics Perform ance – An Overview", AIAA Infotech @ Aerospace, Atlanta GA, Apr. 2010

# Cost Benefit Analysis (CBA)

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- Various CBA approaches in literature differ in
  - cost function definition
  - identifying different pros and cons of PHM
  - assigning different cost metrics to these pros and cons
- Main goals for conducting CBA

**1) Optimize planning, scheduling and decision making for maintenance**

- For maintenance scheduling by operators of the PHM enabled system
- For a contract based service provider that relies on PHM to guarantee uptime

*Note:* mostly from aircraft (military and commercial) domain.

**2) Generate a set of alternative solutions given user's flexibility in relaxing various constraints**

- Sensitivity analysis to figure out most critical components
- Break even curves w.r.t. various input parameters
- Policy design for contract based service providers to assess which components is PHM most profitable for

**3) PHM Design – for integrating into a legacy system or incorporating into the new system**

- Sensor selection and placement
- Determine detection thresholds (e.g. on a RoC curve) for a cost effective PHM
- Down select and prioritize list of faults/subsystems/components for PHM capability

**4) Assess effectiveness of PHM to reduce costs and improve reliability**

- Evaluate the economic promise of PHM compared to the cost (value) of the system itself
- Assess safety and reliability benefits of PHM
- Assess savings in the overall Life Cycle Costs for an asset

**5) Compare various PHM approaches**

- Compare based on ROI in a given period of performance
- Compare payback periods for various alternatives

***Source:*** Saxena, A., Celaya, J., Saha, B., Saha, H., Roychoudhury, I., Goebel, K., "Requirements Specification for Prognostics Performance – An Overview", AIAA Infotech @ Aerospace, Atlanta GA, Apr. 2010

# Cost Benefit Analysis (CBA)



- Two main ideas for CBA
  - Return on Investment (ROI)
    - ROI = (Return – Investment) / Investment
  - Cost Savings by Implementing PHM
    - $\text{Savings}_{\text{PHM}} = \text{Cost}_{\text{without PHM}} - \text{Cost}_{\text{with PHM}}$
  - Cost assignments based on past maintenance records, account logs etc.
    - Cost incurred due to similar components in legacy systems
    - Cost of man hours based on data on direct/indirect staffing requirements in the past
    - Inflation adjustments, etc.
- CBA should be formulated into a multi-objective optimization problem
- One factor usually not considered is “when to take an action”
  - Cost of early replacement – *a function of Prediction Horizon*
  - Confidence in prognostic algorithm – *a function of uncertainty management*
  - Risk absorbing capacity – *a function of criticality & confidence in prognostic algorithm*

***Source:*** Saxena, A., Celaya, J., Saha, B., Saha, H., Roychoudhury, I., Goebel, K., “Requirements Specification for Prognostics Performance – An Overview”, AIAA Infotech @ Aerospace, Atlanta GA, Apr. 2010

# Cost Benefit Analysis: Review Summary

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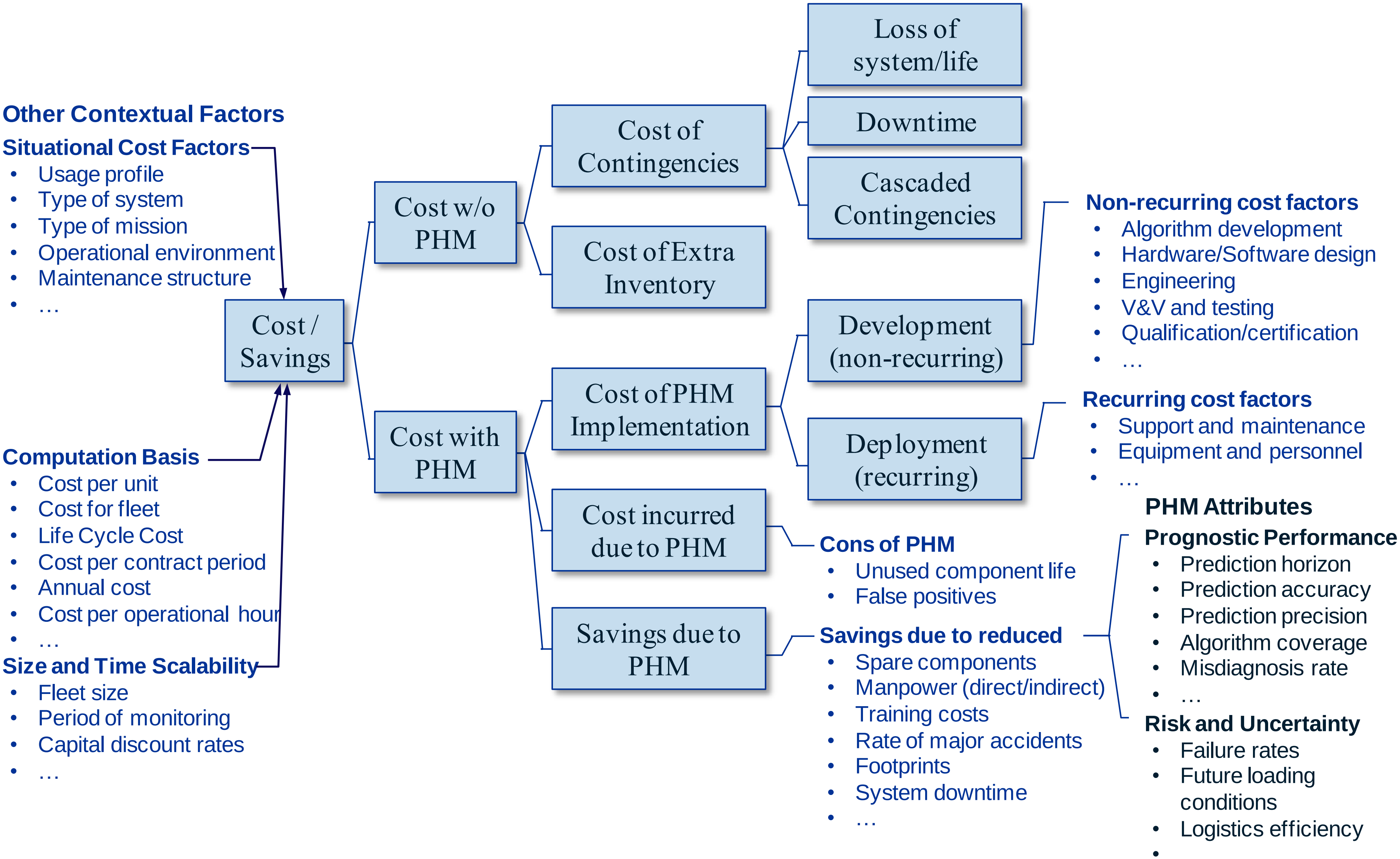


***Source:*** Saxena, A., Celaya, J., Saha, B., Saha, H., Roychoudhury, I., Goebel, K., "Requirements Specification for Prognostics Performance – An Overview", AIAA Infotech @ Aerospace, Atlanta GA, Apr. 2010

# Requirements Engineering and Flowdown

1. Requirement definition and gathering
2. Requirement prioritization
3. Requirement flowdown

# Requirements



- Requirement definition & gathering
  - Interactively determine what customer wants
    1. Scope of the health management system by defining needs, goals, mission, constraints, schedules, budgets, and responsibility
    2. Operational concepts that cover scenarios for how the health management system might behave and be used
    3. Interfaces between the health management system and rest of the world
    4. Health management design requirements
    5. Rationale for each requirement
    6. Assignment of requirements to the right levels
    7. Verifying each requirement
    8. Provide proper documentation for all requirements
    9. Check requirements for completeness and correctness
- Requirement analysis
  - Determine if requirements are unclear, incomplete, ambiguous, or contradictory
  - Resolve above issues by further customer interaction

***Source:*** Ivy F. Hooks; Kristin A. Farry ,"*Customer Centered Products: Creating Successful Products Through Smart Requirements Management*", AMACOM American Management Association, 2000

# Requirement Prioritization

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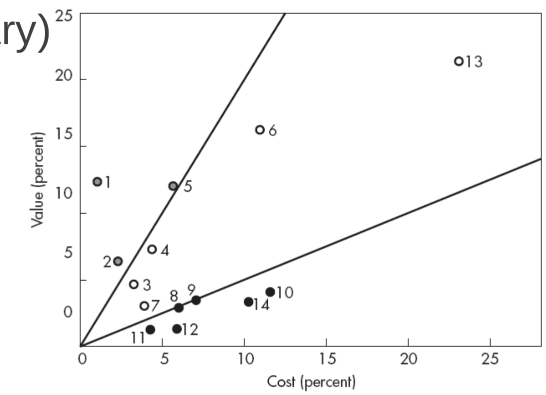
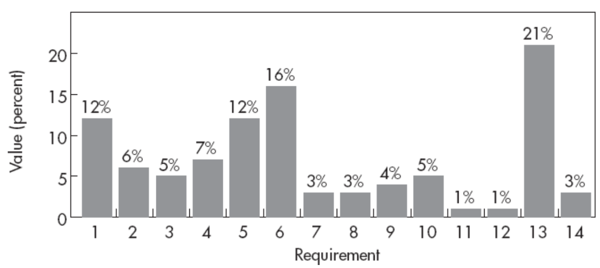
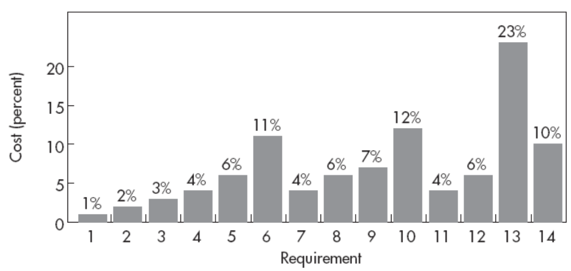
- Resolve conflicting requirements
- Mostly based on cost-benefit analysis
- Requirement attributes[a]
  - Type (Functional vs. non-Functional, primary vs. secondary)
  - Estimated benefit to customer
  - Estimated size of software that embeds the requirement
  - Estimated cost of building what embeds it
  - Priority
  - Requirement dependencies
- Analytic Hierarchy Process (AHP)[b]
  - Pair wise comparison among all requirements according to a standard scale
  - Obtain normalized aggregates to indicate relative order of priority (value)

Cost-Value Plot




*Source:* [a] J. Karlsson, and K. Ryan, "A Cost-Value Approach for Prioritizing Requirements," *IEEE Software, vol. 14, no. 5, pp. 67-74, 1997*
[b] T.L. Saaty, *The Analytic Hierarchy Process, McGraw-Hill, New York, 1980*

# Requirement Flowdown

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Translate broad customer requirements into more easily quantified requirements

- Customer oriented view
  - E.g. CTQ and QFD
- Designer/developer oriented view
  - E.g. “Vee” Model and NASA’s System Engineering Engine
- Most popular methods
  - **CTQ Tree**: Critical-to-Quality tree for quality focused methodology e.g. six-sigma
  - **QFD:** Quality Function Deployment to translate customer requirement into engineering specifications

QFD Tools

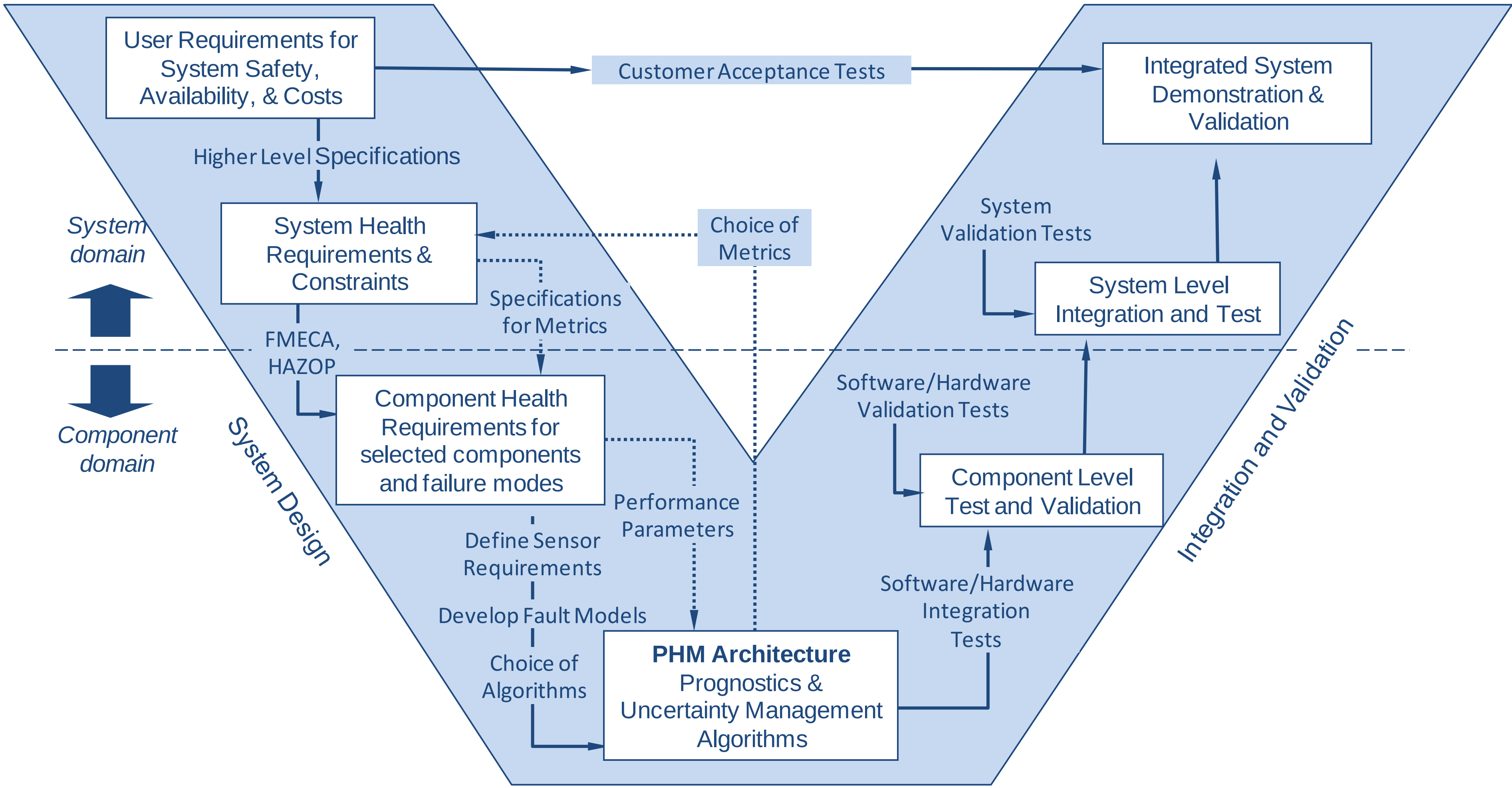
- Affinity diagrams
- Relations diagrams
- Hierarchy trees
- Process decision program diagrams
- Analytic hierarchy process
- Blueprinting
- House of quality

House of Quality

- Customer requirements
- Technical requirements
- Planning matrix
- Interrelationship matrix
- Technical correlation (roof) matrix
- Technical priorities, benchmarks, and targets

# Requirement Flowdown

- "Vee" Model for PHM system design




***Source:*** Saxena, A., Celaya, J., Saha, B., Saha, H., Roychoudhury, I., Goebel, K., "Requirements Specification for Prognostics Performance – An Overview", AIAA Infotech @ Aerospace, Atlanta GA, Apr. 2010

# Simulation Approaches to Derive Performance Parameters

*Discrete Event Simulation Examples*

# Discrete Event Simulation – Example 1

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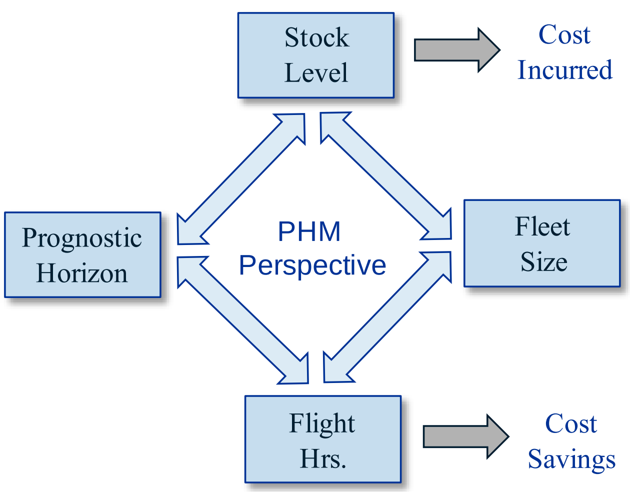
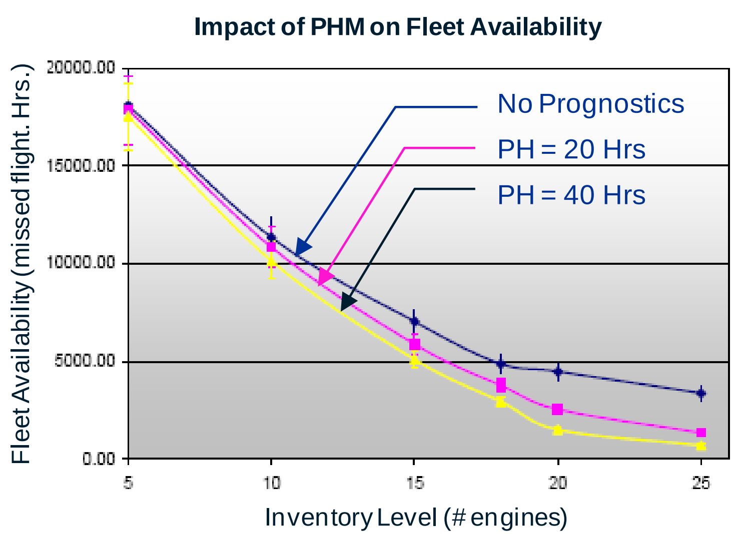
- **Case:** Spare supplier for a fleet network
  - A maintenance, repair, and overhaul (MRO) network for helicopter engines
  - Engines are swapped between fleets (varying size) of different operators
- **Task:** Forecast demand to strike Lean-Agile balance in the MRO network
  - Strike a cost-effective balance between inventory level and prognostic horizon
    - Long term PH – helps in scaling the resources in a network of aging fleet or incorporating any changes in the operating environment
    - Short term PH – forecasting maintenance demand and allocate resources accordingly




**DES inputs**

- Helicopter Usage (probabilistic)
- HUMS data (Monitoring data)
- LRU reliability data (weibull distribution)
- LRU MTTR (log normal)
- Production capacities
- Prediction horizon
- Inventory size
- Fleet availability
- Fleet size
- Network structure
- ...




***Source:*** Pipe, K. "Practical Prognostics for Condition Based Maintenance," *International Conference on Prognostics and Health Management*. Denver, CO, 2008.

# Discrete Event Simulation – Example 2

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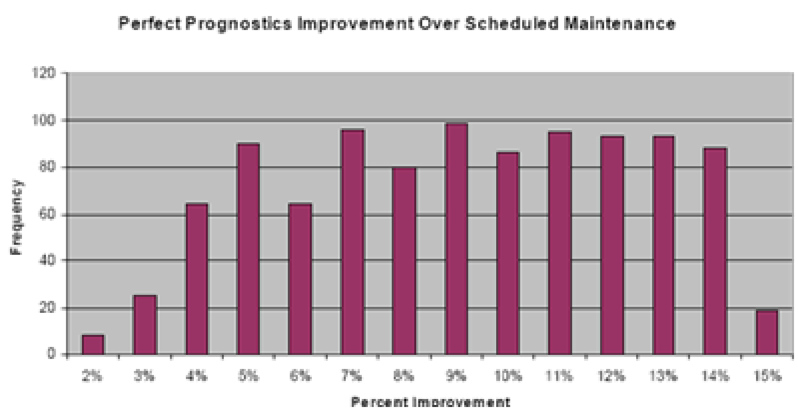
- A DES to evaluate
  - Improvement in over scheduled maintenance due to perfect prognosis
  - Limits on prognostics performance to break even
    - with scheduled maintenance – minimum desirable performance for cost effectiveness
    - with run-to-failure maintenance – maximum limit on prognostic errors
- Black box model for a single component system considered

**DES inputs considered**

- Length of mission (probabilistic)
- Number of Missions (requirement)
- Failure Distribution weibull distribution f($\beta$,$\eta$)
- LRU MTTR log normal distribution
- Time between scheduled maintenance
- Prognostic Error on RUL ($\varepsilon$)
- Standard deviation of RUL error ($\alpha$)
- …

| Exptt. Factors | Factor levels | Improvement (%) | |
|---|---|---|---|
| $\beta$ | 1.25, 1.50, …, 3.25, 3.50 | *min* | 1.23 |
| $m$ | 10, 15, …, 50, 55 | *median* | 8.71 |
| $t_m/m$ (%) | 5, 10, …, 45, 50 | *mean* | 8.63 |
| $\alpha$ | 0, 10, …, 140, 150 | *max* | 14.55 |




| $\alpha$ | PHM > PM | PHM < PM | PHM = PM |
|---|---|---|---|
| 10 | 971 | 22 | 7 |
| 20 | 910 | 79 | 11 |
| 30 | 860 | 123 | 17 |
| 40 | 814 | 171 | 15 |
| 50 | 737 | 232 | 31 |
| 60 | 651 | 322 | 27 |
| 70 | 569 | 395 | 36 |
| 80 | 502 | 459 | 39 |
| 90 | 437 | 518 | 45 |
| 100 | 388 | 575 | 37 |
| 110 | 340 | 617 | 43 |
| 120 | 301 | 661 | 38 |
| 130 | 259 | 699 | 42 |
| 140 | 233 | 733 | 34 |
| 150 | 208 | 753 | 39 |

***Source:*** Carrasco, M.; Cassady, C.R., "*A study of the impact of prognostic errors on system performance*", Annual Reliability and Maintainability Symposium, RAMS06, pp.1 - 6, 23-26 Jan. 2006

# Uncertainty Management and Representation

*Establishing Confidence in Prognostic Estimates*

# Dealing with Uncertainties



- Uncertainties
  - arise from a variety of sources
  - are injected at different steps of the prognostic process
  - combine and get filtered through complex non-linear system dynamics
  - often do not exhibit known distribution characteristics
- Uncertainty Representations
  - Interval mathematics
    - Deals with error bounds only
  - Fuzzy theory
    - Incorporates uncertainties due to vagueness in addition to uncertainties due to randomness
  - Probability theory
    - Most widely used
    - Deals with distributions

Reference: http://www.ccl.rutgers.edu/~ssi/thesis/thesis-node13.html

# Uncertainty Management Methods



- Risk Sensitive Particle Filter (RSPF) approach
  - RSPF for uncertainty representation
  - Outer correction loop for uncertainty management

**Non-Linear State Equation**

$$\begin{cases} x_1(t+1) = x_1(t) \pm a \cdot x_3(t) \cdot (b + e \cdot x_2(t) + c x_2(t)^2)^d + \omega_1(t) \\ x_2(t+1) = x_2(t) + 1 \\ x_3(t+1) = x_3(t) + \omega_2(t) \end{cases}$$

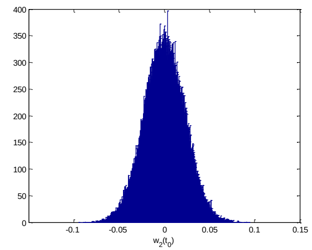
$$y(t) = x_1(t) + \nu(t)$$

**Model Noise: as a Gaussian sum**

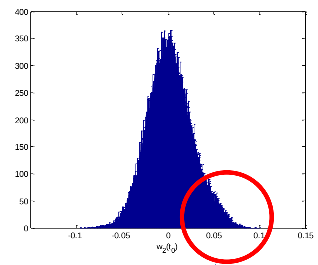
$$\omega_1(t) \sim \delta \cdot \omega_1^{'}(t) + (1-\delta) \cdot \omega_1^{*}(t)$$

$$\omega_1^{'}(t) \sim N\left(0, \sigma'^2\right)$$

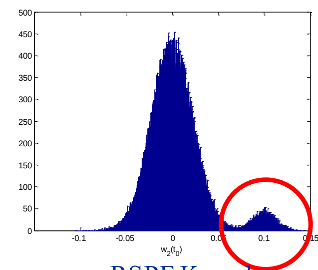
$$\omega_1^{*}(t) \sim N\left(d, \sigma^{*2}\right) \quad d = E\left\{\omega_1^{*}(t)\right\} \neq 0$$



RSPF Kernel
$E\{\omega_1 *\} = 0.00$



RSPF Kernel
$E\{\omega_1 *\} = 0.05$



RSPF Kernel
$E\{\omega_1 *\} = 0.10$

| Metric | Definition $\delta = 0.95$ | PF | RSPF |
|---|---|---|---|
| ***Length of CI*** | | 32 | 28 |
| ***Online Precision Index*** | $RUL\_OPI(t) = \lim_{t \to t_p} \exp\left\{-\frac{\sup(CI_t) - \inf(CI_t)}{E_t\{EoL\} - t}\right\}$ | 0.4582 | 0.5134 |
| ***Online Steadiness index*** | $RUL\_OSI(t) = \lim_{t \to EoL} \sqrt{\operatorname{var}(E_t\{EoL\})}$ | 3.15 | 1.55 |

***Source:*** Orchard, M. E., Tang, L., Goebel, K., and G. Vachtsevanos. "A Novel RSPF Approach to Prediction of High-Risk, Low-Probability Failure Events," *Annual Conference of the Prognostics and Health Management Society (PHM09)*. San Diego, CA, p. 0 2009.

# Uncertainty Management Methods

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- Uncertainty Quantification
  - Loading uncertainty
    - Current and future load uncertainty
  - Initial state estimation uncertainty – diagnostic uncertainty
    - EIFS~LN(λ,ζ)
  - Data uncertainty – assumptions about distributions
    - Loading: $\mu_1$, $\sigma_1$, $\mu_2$, $\sigma_2$ - uniform random variables
    - EIFS: λ, ζ - normal random variables
  - Crack growth model uncertainty:
    - Modified Paris Law with wheeler model
    - C, $\Delta K_{th}$ and $\varepsilon_{cg}$ are lognormal random variables
  - Prediction algorithm uncertainty
    - Gaussian process or particle filters
  - FEA discretization error
- Global sensitivity analysis
  - Decomposition of variance
    - Total Variance = estimate of variance + variance of estimates
  - Standardized regression coefficients (*β*) as a robust measure of sensitivity
    - Applicable to non-linear models
    - Measure of linearity of sensitivity w.r.t. input parameters in a non-linear model
    - Multi-dimension averaged measure
    - Explores entire domain of input
    - Statistical significance tests available

## Modified Paris' Law

Fault Propagation Model

$$\frac{da}{dN} = \varphi^r C(\Delta K)^n \left(1 - \frac{\Delta K_{th}}{\Delta K}\right)^m \varepsilon_{cg}$$

| No. Load Cycles | EIFS (θ) | Model (C) | Material ($\Delta K_{th}$) | Load (σ) | Linearity |
|---|---|---|---|---|---|
| 100 | 0.9922 | 0.0044 | -0.0018 | 0.0197 | 98.5 % |
| 500 | 0.9661 | 0.2430 | -0.0180 | 0.0810 | 99.2 % |
| 1000 | 0.8512 | 0.4985 | -0.0203 | 0.1806 | 99.3 % |
| 5000 | 0.6071 | 0.6387 | -0.2659 | 0.3915 | 99.9 % |

***Source:*** Sankararaman, S., Ling, Y., Shantz, C., and Mahadevan, S. "Uncertainty Quantification in Fatigue Damage Prognosis," *Annual Conference of the Prognostics and Health Management Society (PHM09)*. San Diego, CA, p. 13 2009

# Research Activities and Results

Ames Research Center

## Validation Data

| Experiments | Simulation models | Monte-Carlo Simulation |
|---|---|---|
| 2024-T351 Al – lit.<br>7075-T6 Al – expt.<br>4340 Steel – expt.<br>CCComposites–expt.<br>Semiconductor devices – expt. | FEM<br>NASTRAN | Benes Model |
| | Impact Technologies, Clarkson University, Vanderbilt University, ARC | |

## Fault-Growth Model

Paris' Model + retardation
Small Time Scale model
Surrogate model
Finite Element model

Impact Technologies
Vanderbilt University

## Algorithm Mathematics

Uncertainty representation and propagation methods

Bayesian – Particle filters, Sequential Bayesian update – load, material
Max Relative Entropy
GPR, Monte-Carlo
Trans-Dimension MCMC for model fusion/selection

Impact Technologies
Clarkson University
ARC

## Measurement uncertainties

Intrinsic mode decomposition method

Vanderbilt University

## Future Load Uncertainties

Equivalent Stress model
GPR model
Rainflow counting
Markov chain method
ARMA model
DSI: dispersion sensitivity
CSI: confidence interval

Impact Technologies
Vanderbilt University

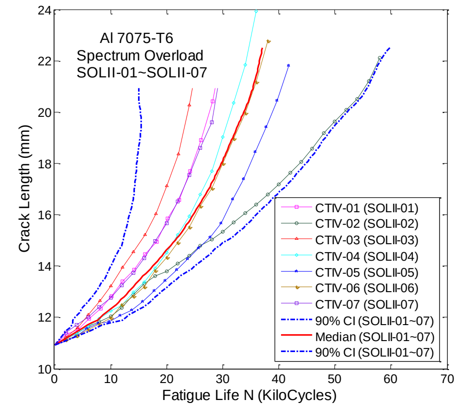
## Accounting for High-Risk Low-Probability events

Risk Sensitive Particle Filter (RSPF)

Impact Technologies, ARC

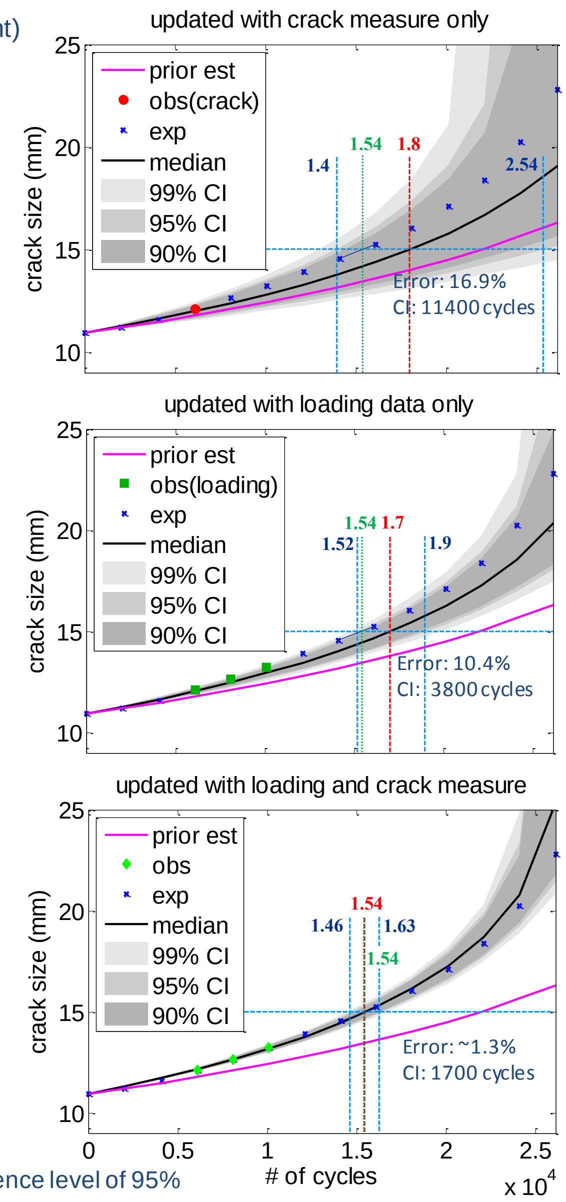
## Improving Prognostic Uncertainties

Al-7075-T6 alloy
Loading Spectrum (experiment)




Failure Threshold: **15mm**

$t_{\lambda=0}$ = 0 cycles
$t_{\lambda=1/2}$ ~ 7,500 cycles
$t_{\lambda=2/3}$ ~ 10,000 cycles
$T_{\lambda=1}$ ~ 15,400 cycles




**Results**

1. Accuracy measured halfway is better than 25% in all cases
2. Improvement in uncertainty bounds is more than 10% from initial prediction to the end of life

Note: All results are reported at a confidence level of 95%

Thanks!

# Questions?