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Prognostics for Microgrid Components

Batteries, Capacitors, and Power Semiconductor Devices

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Prognostics CoE

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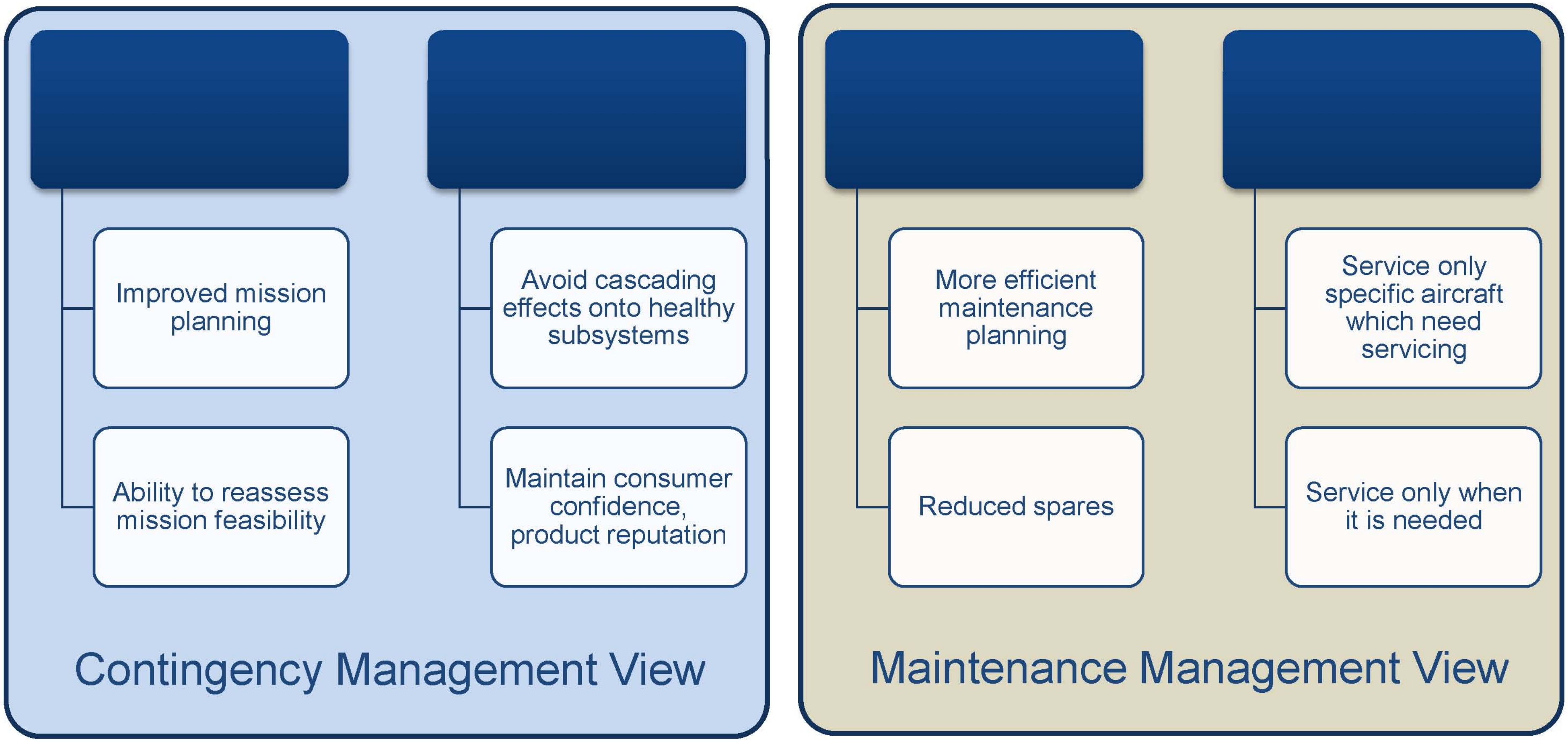
Prognostics and Health Management

In Perspective

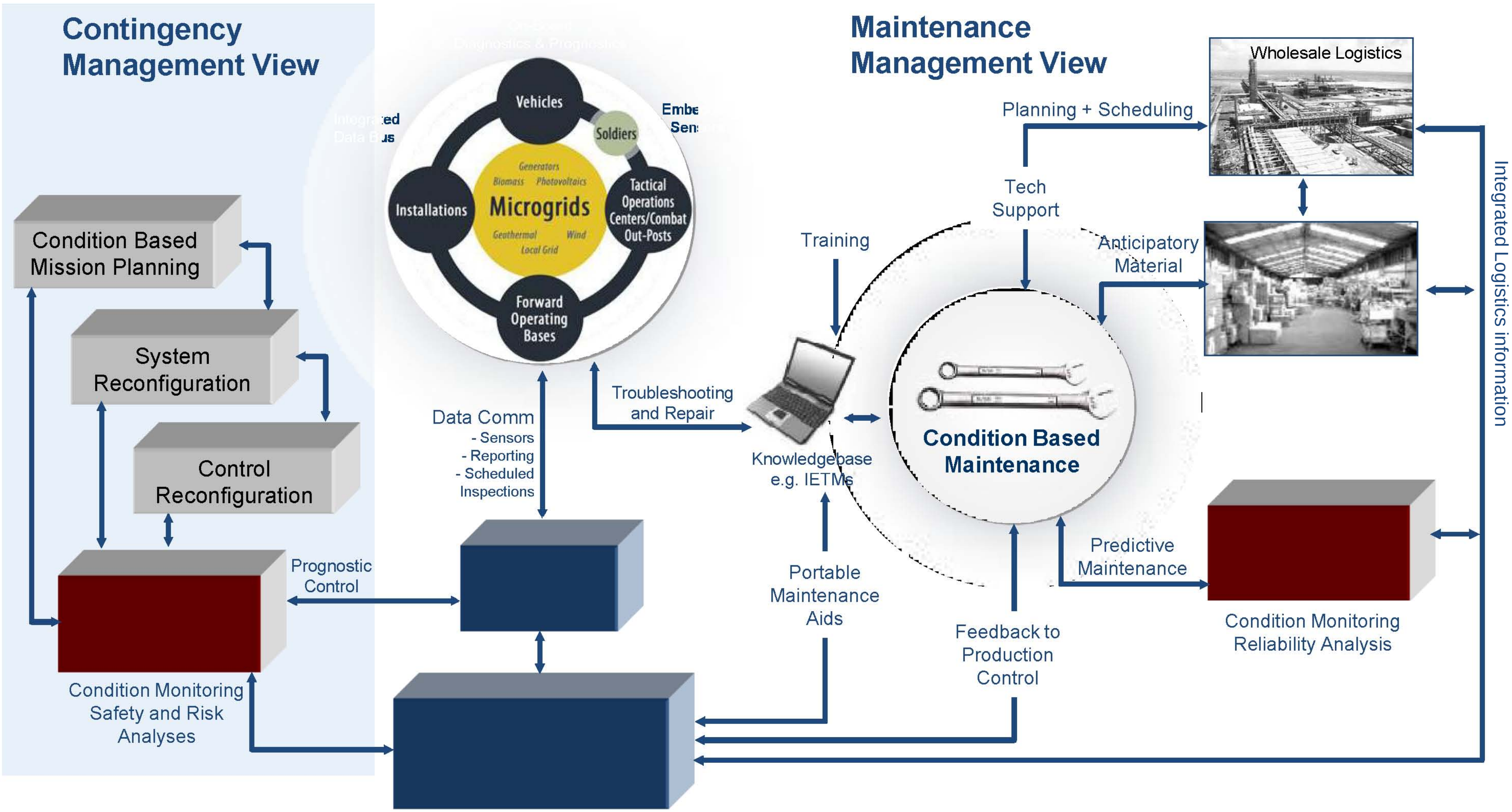
Goals for Prognostics

What does prognostics aim to achieve?



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

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.

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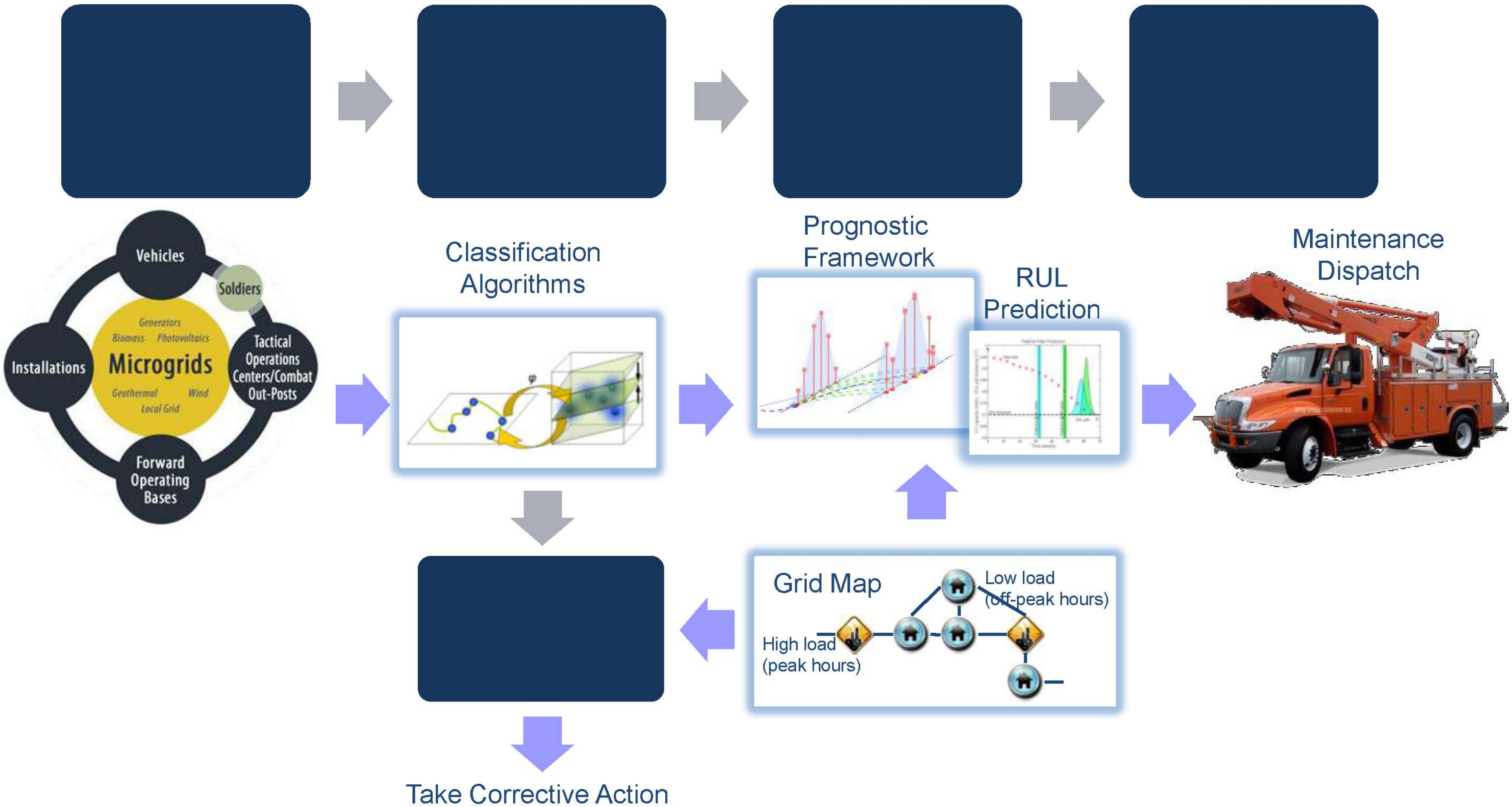
Prognostics for Microgrids

- Key components
  - Power storage
    - Batteries
    - Capacitors and SuperCapacitors
  - Power components and devices
    - Power switches (semiconductor switches and packaging)
    - Passive components (inductors, capacitors, high frequency transformers)
    - Controllers and Gate drivers
- Microgrids PHM – Potential benefits*
  - Advanced inverter controls for microgrids
  - Robust operation during fault conditions
  - More informed decision support

* Key R&D Areas for micro grid reliability as identified in 2011 DoE Microgrid Workshop, San Diego CA

Grid PHM Framework



Fundamentals of Predicting Remaining Useful Life

Understanding the Prognostic Process

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]

Prognostics Framework

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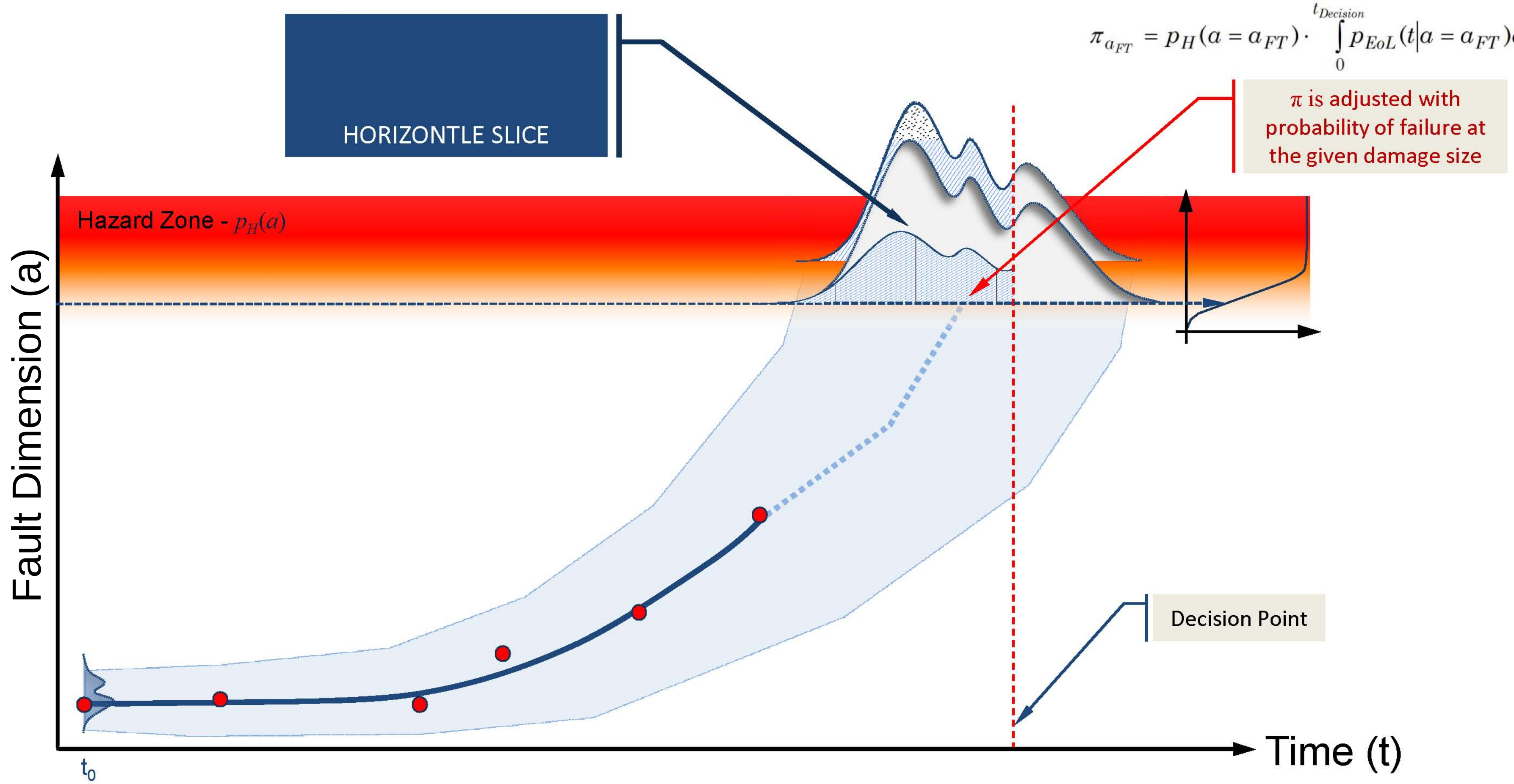
$$\pi_{a_{FT}} = p_H(a = a_{FT}) \cdot \int_0^{t_{Decision}} p_{EoL}(t \mid a = a_{FT})\,dt$$



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

Prognostics Framework

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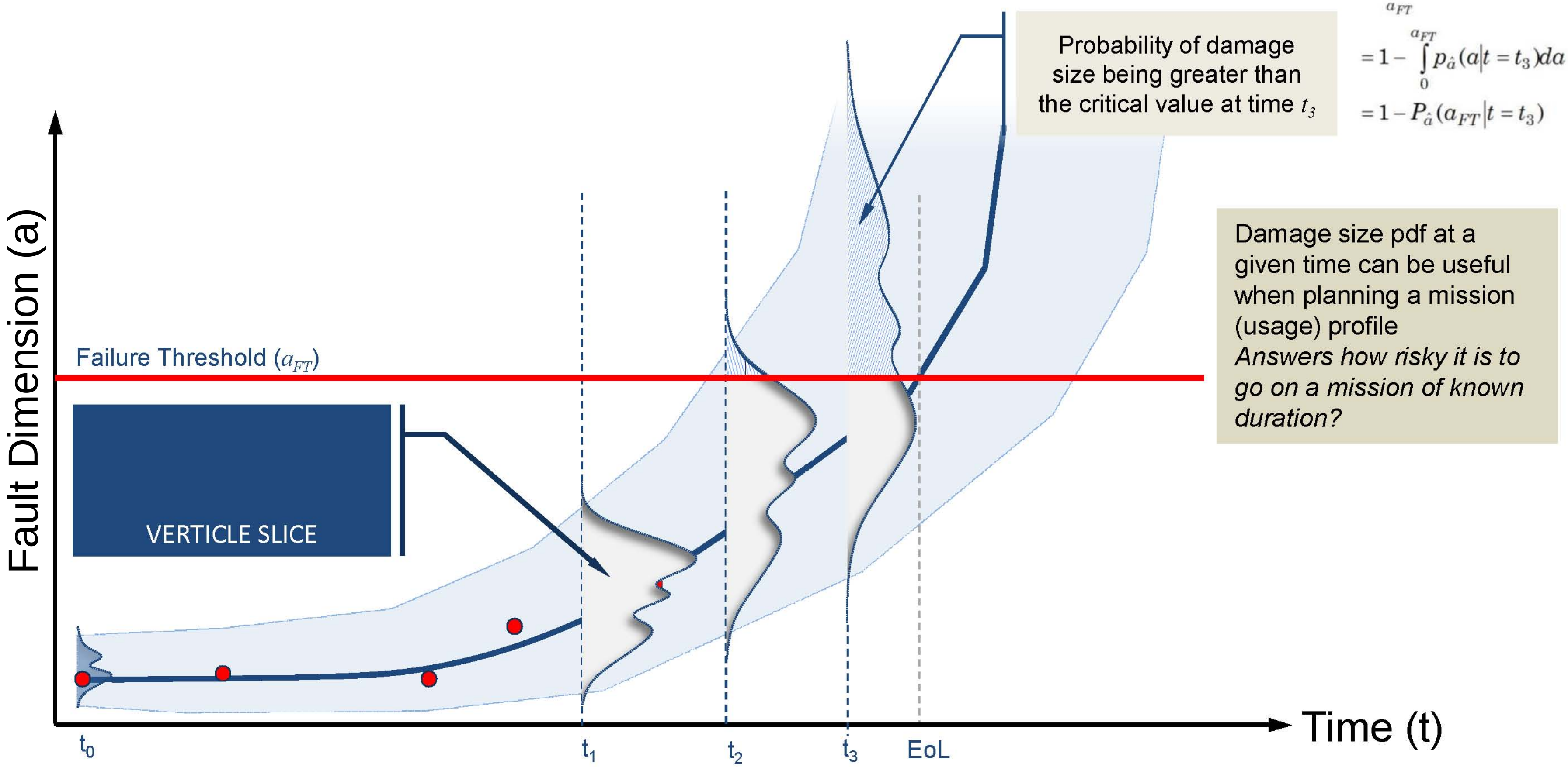
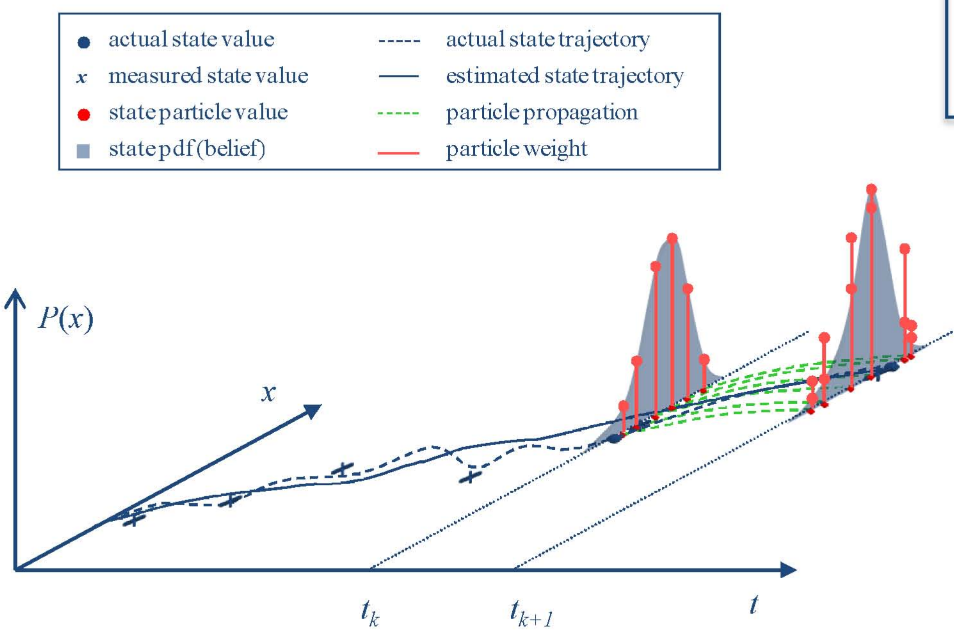


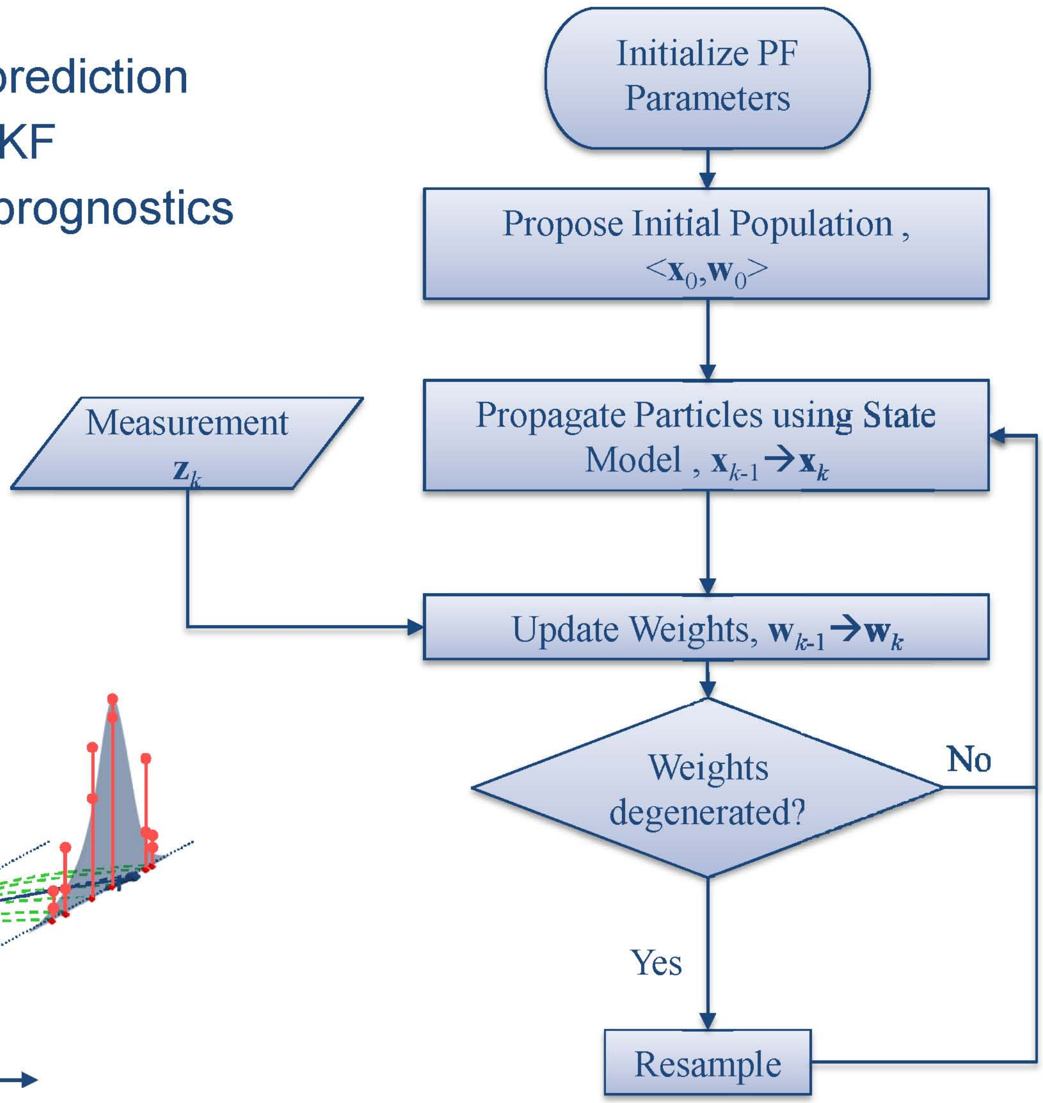
$$\pi_{t_3} = \int_{a_{FT}}^{\infty} p_{\hat{a}}(a|t = t_3)da$$
$$= 1 - \int_{0}^{a_{FT}} p_{\hat{a}}(a|t = t_3)da$$
$$= 1 - P_{\hat{a}}(a_{FT}|t = t_3)$$

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

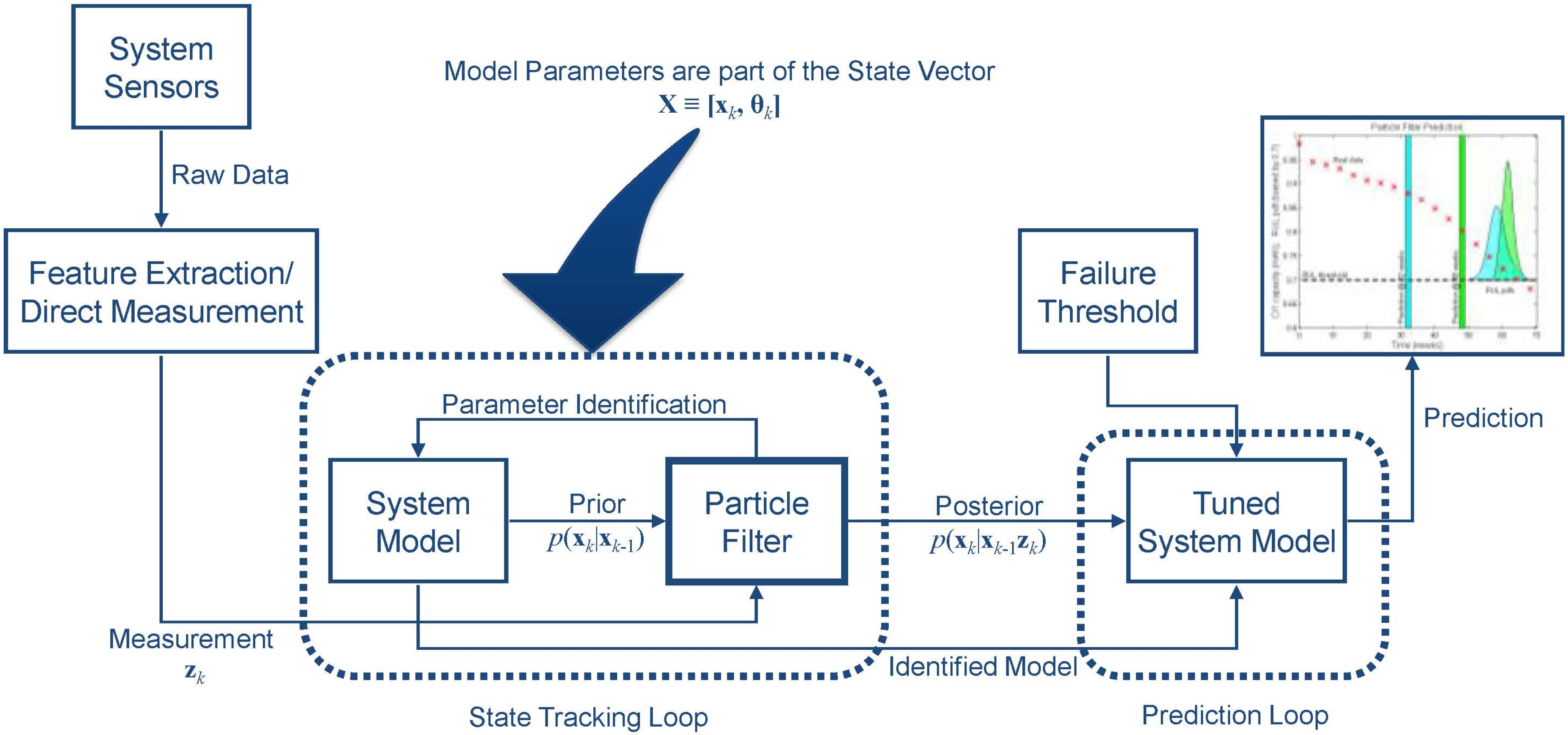
Particle Filters

- Allows model adaptation
- State estimation, tracking and prediction
- Nice tradeoff between MC and KF
- Useful in both diagnostics and prognostics
- Represents uncertainty
- Manages uncertainty





Particle Filter-Based Prognostics



Examples

Prognostics Applications

Power Storage Systems: Predicting Battery Discharge

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- Objective: Predict when the battery voltage will dip below 2.7 volts
  - Example: when to recharge laptop or cell phone batteries
- Approach
  - Model SOC as a sum of 3 sub-processes
    - mass transfer, self discharge and reactant depletion
  - Use PF algorithm to predict RUL

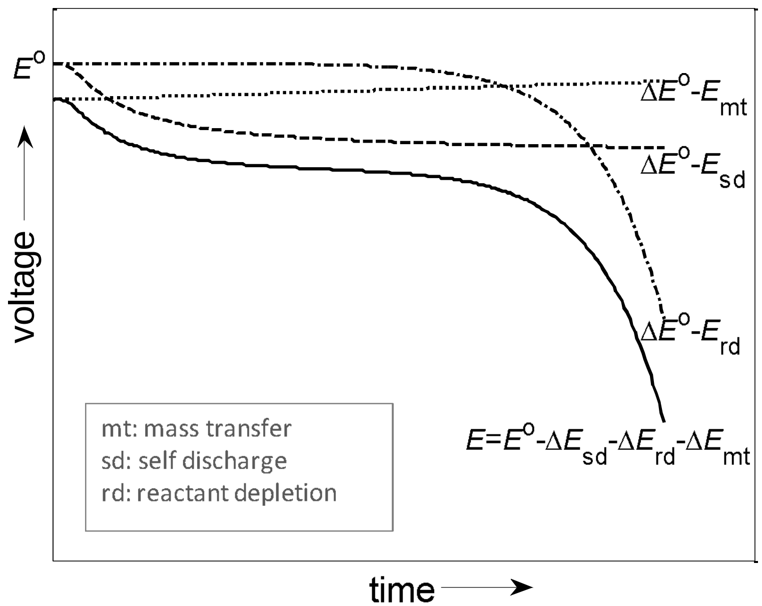
Cell voltage

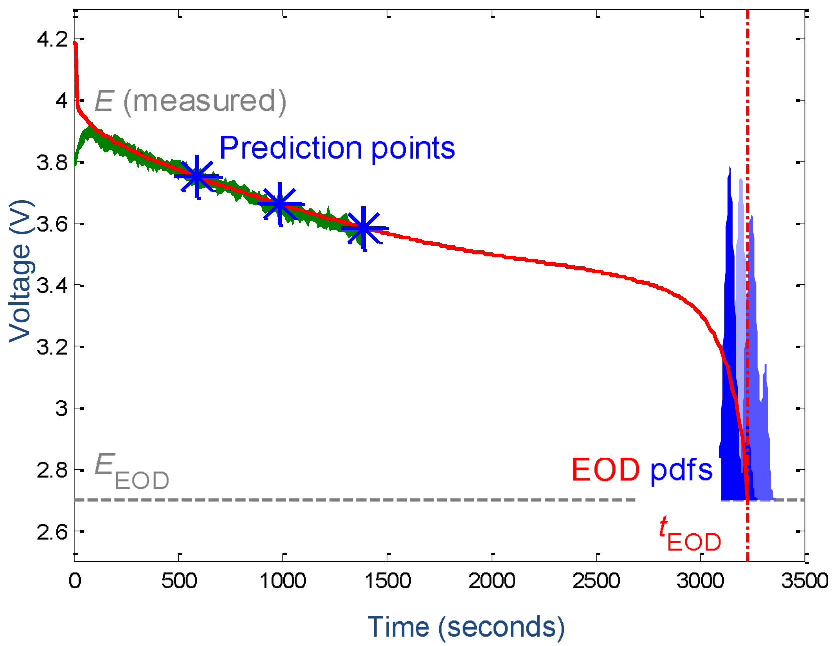
$$E(t_k) = E^o - \Delta E_{IR}(t_k) - \Delta E_{AP}(t_k) - \Delta E_{CP}(t_k)$$

where $\Delta E_{IR}(t_k) = \Delta I_k R - \alpha_{1,k} t_k$,

$$\Delta E_{AP}(t_k) = \alpha_{2,k} \exp(-\alpha_{3,k} / t_k),$$

$$\Delta E_{CP}(t_k) = \alpha_{4,k} \exp(\alpha_{5,k} t_k).$$





- 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

Model Validation in Realistic Environments

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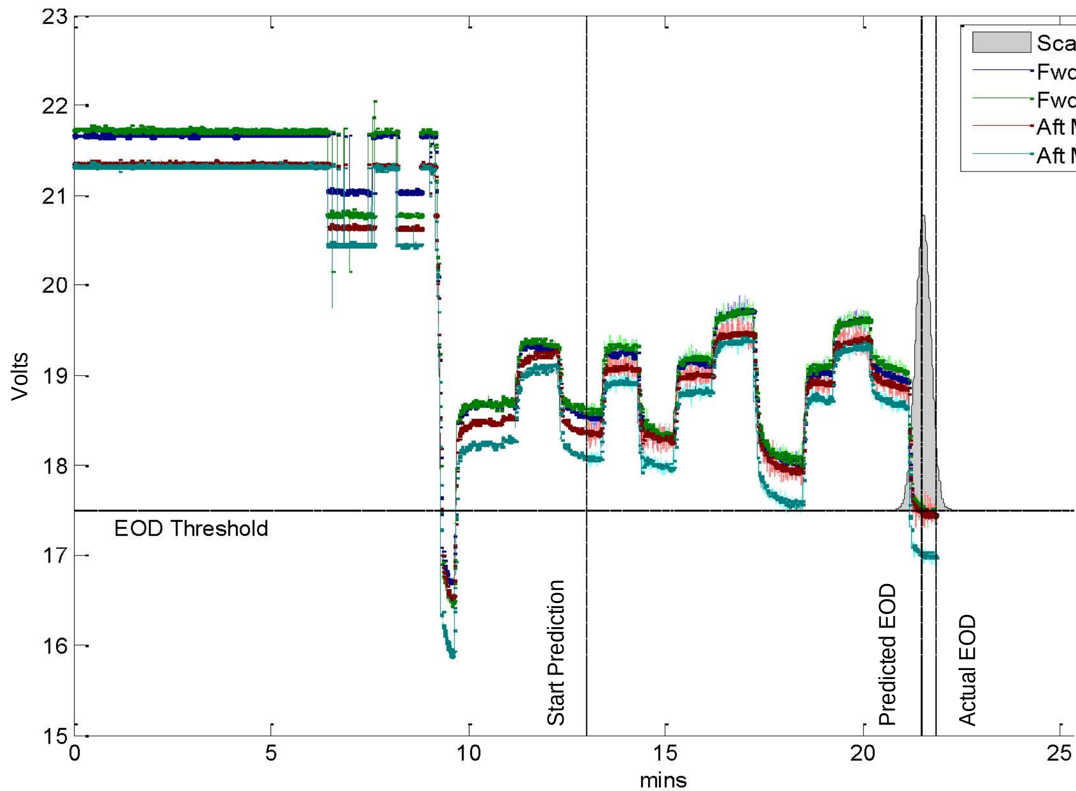
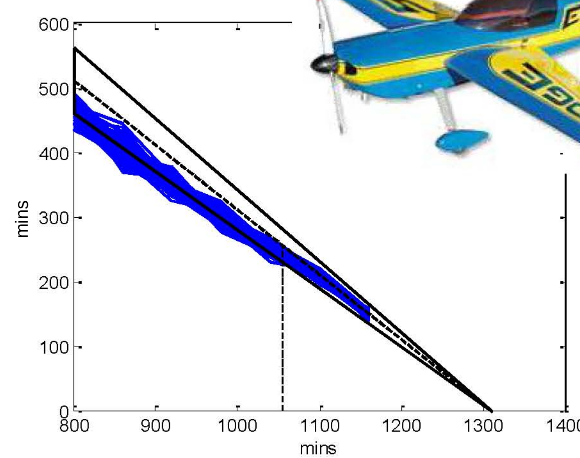
- Battery discharge algorithm was used in e-UAV BHM
- More than 3 dozen successful flights
  - Prediction update rates at 1Hz
  - Limited onboard computational power





Power Storage Systems - Predicting Battery Capacity

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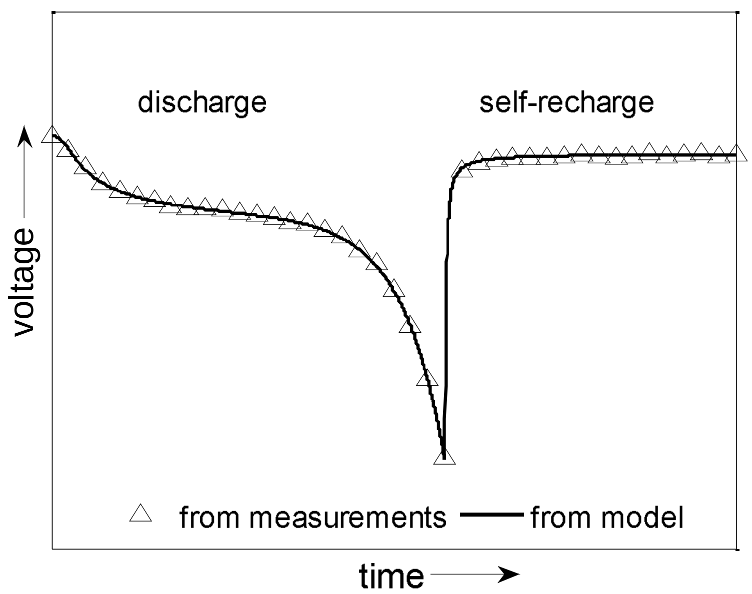
- Objective: Predict when Li-ion battery capacity will fade by 30% indicating life (EOL)
  - determine when to replace old batteries
- Approach:
  - Model self-recharge at rest and capacity loss due to Coulombic efficiency
  - Use PF algorithm to predict RUL

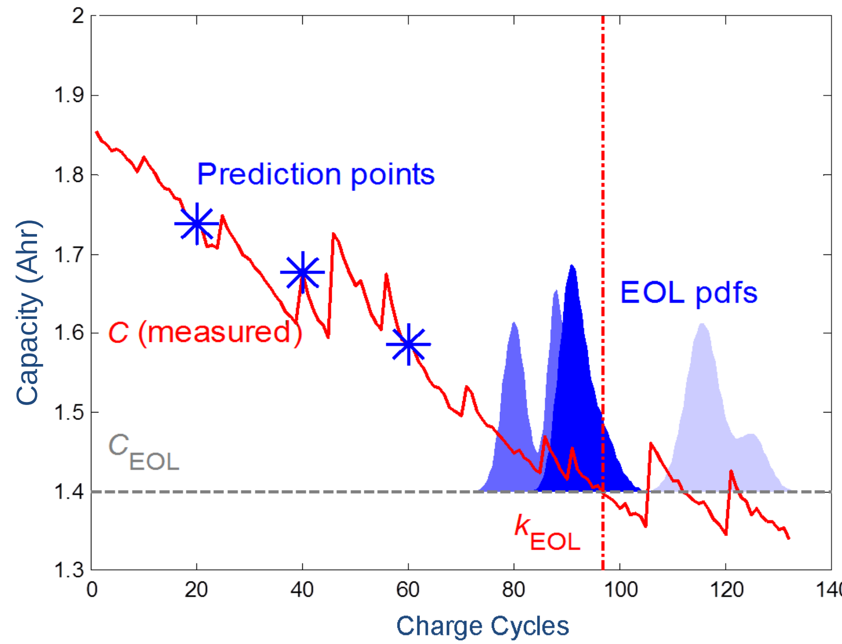
State transition model $\equiv$

$$\beta_{j,k+1} = \beta_{j,k} + \varphi_{j,k}\,,\; j = 1,2,$$

$$C_{k+1} = \eta_C\, C_k + \beta_{1,k} \exp(-\beta_{2,k}/\Delta t_k) + \varphi_k\,,$$

Measurement model $\equiv \tilde{C}_k = C_k + \psi_k\,,$





- 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

Power Electronics Failure - MOSFETs

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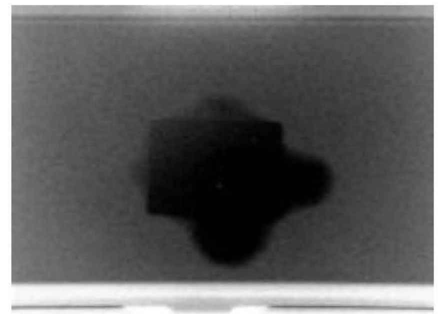
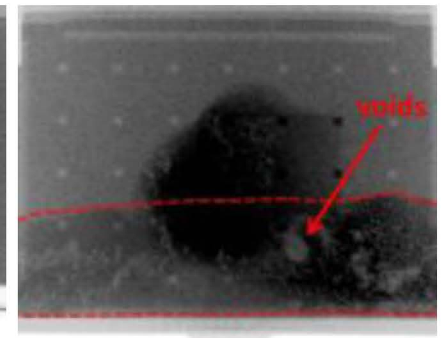
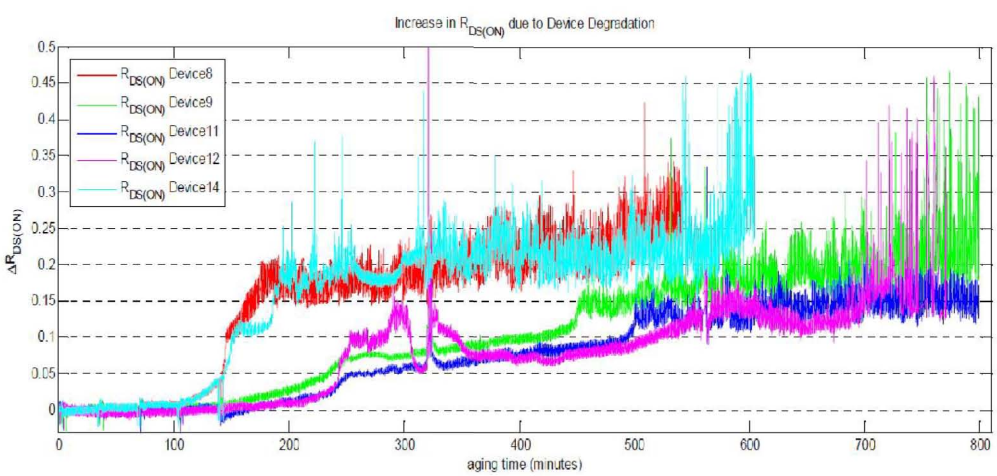
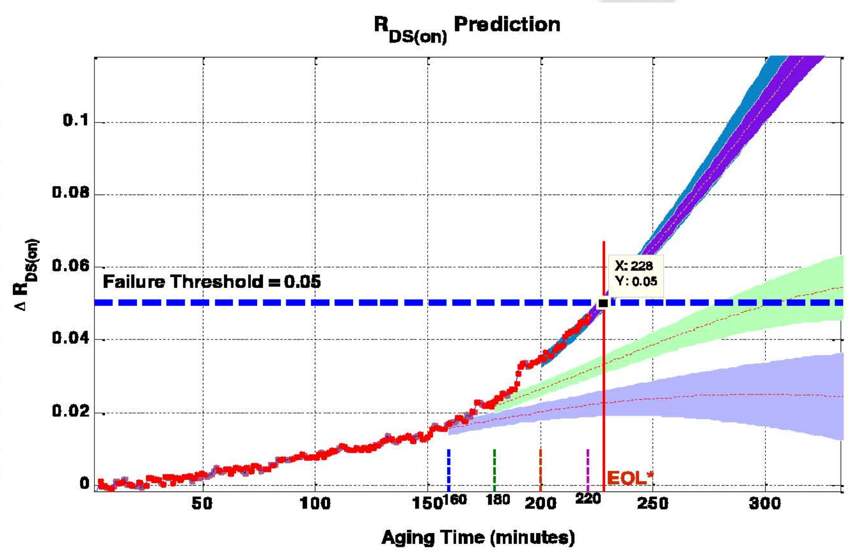
- Objective: predict abnormal functioning of power electronics devices
  - Prediction approach validated in data from 100V power MOSFETs
  - The failure mechanism for the stress conditions is determined to be die-attachment degradation
  - Change in ON-state resistance is used as a precursor of failure due to its dependence on junction temperature









- 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.

Power Component Failure - Capacitors

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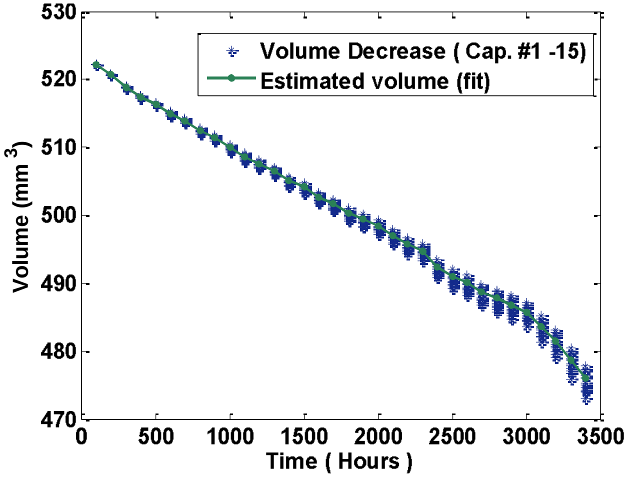
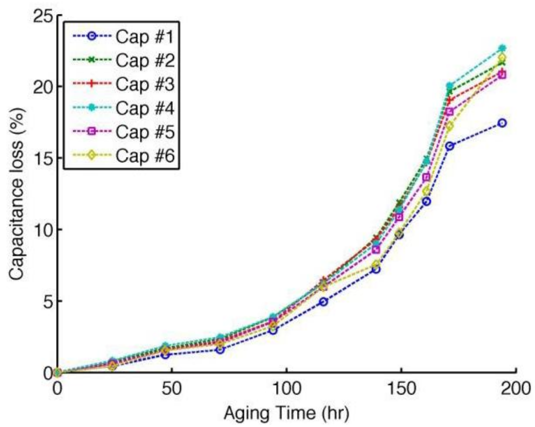
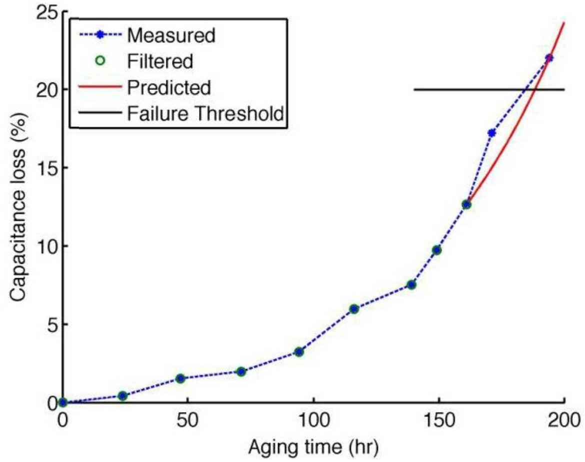
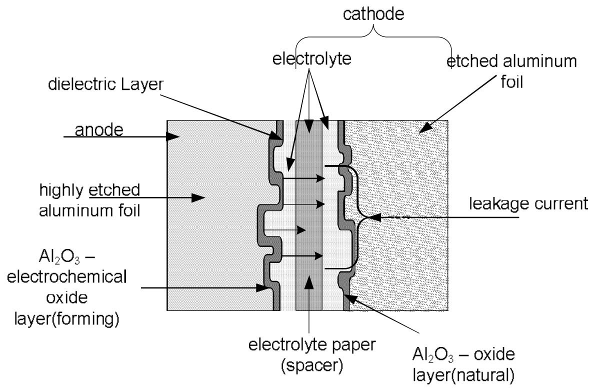
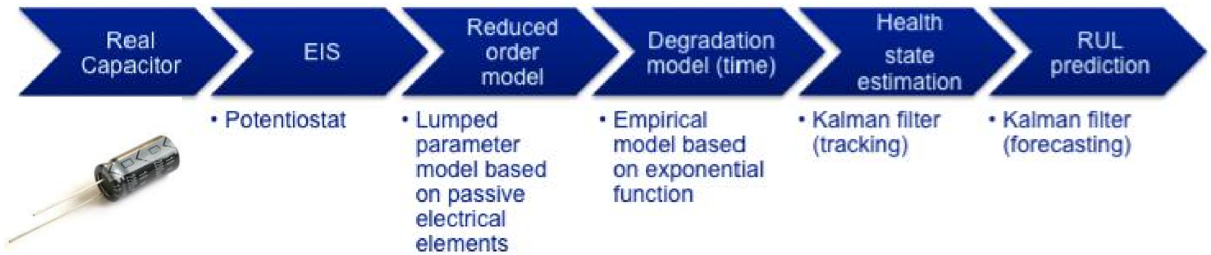
- Objective: Predict remaining useful life for capacitors
  - The failure mechanism is electrical overstresses via repeated charge/discharge of capacitors at high voltages
  - Lumped-parameter model identified as a viable reduced-order model for prognostics-algorithm development
  - Equivalent series resistance (ESR) and capacitance (C) \identified as precursor of failure feature parameters
  - Health state tracking and RUL prediction algorithm based on the Kalman filtering framework
  - Connect observations to physical models for a model based algorithm







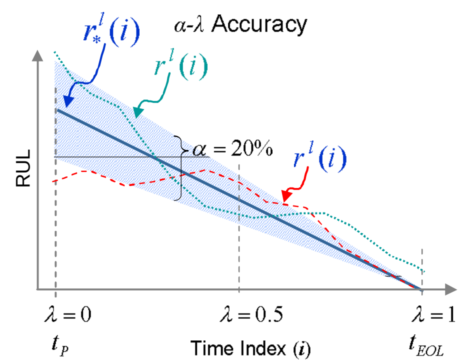


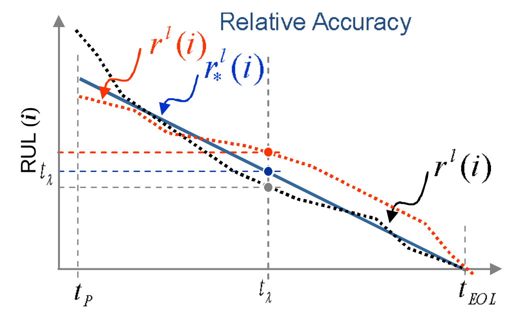


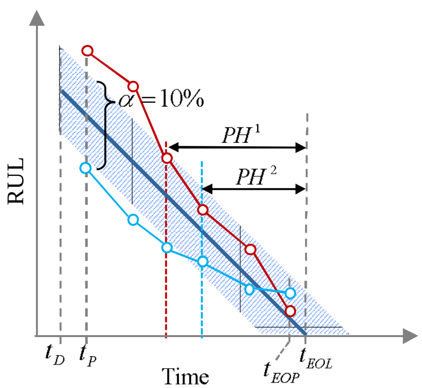
Prognostic Performance Metrics

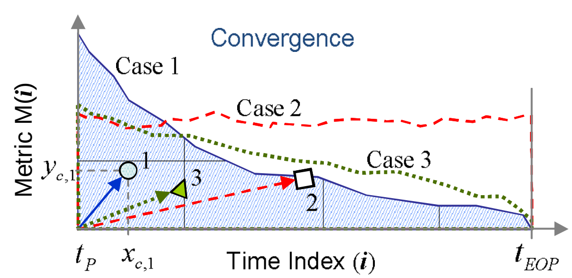
- New metrics were proposed specific to prognostics for PHM
- These metrics were applied to
  - a combination of different algorithms and different datasets
- Metrics were evaluated and refined

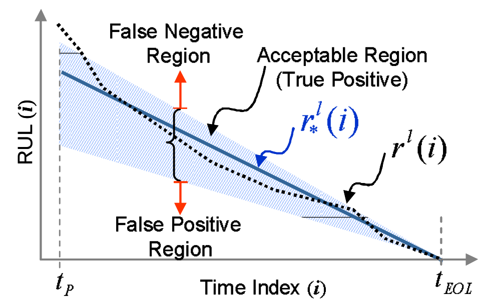
- Prognostics horizon
- *α-λ* performance
- Relative accuracy
- Cumulative relative accuracy
- Convergence











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

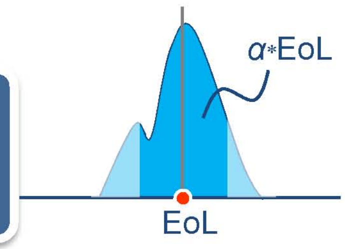
- Further does the algorithm stay within desired performance levels relative to RUL at a given time?

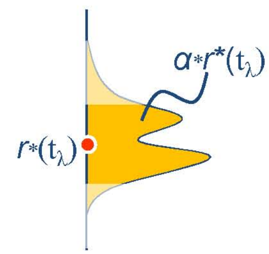
III. Relative Accuracy

- 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





Challenges in Prognostics

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- 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

Thanks!

Questions?