Prognostics

Prognostics Center of Excellence

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http://prognostics.nasa.gov

Prognostics CoE

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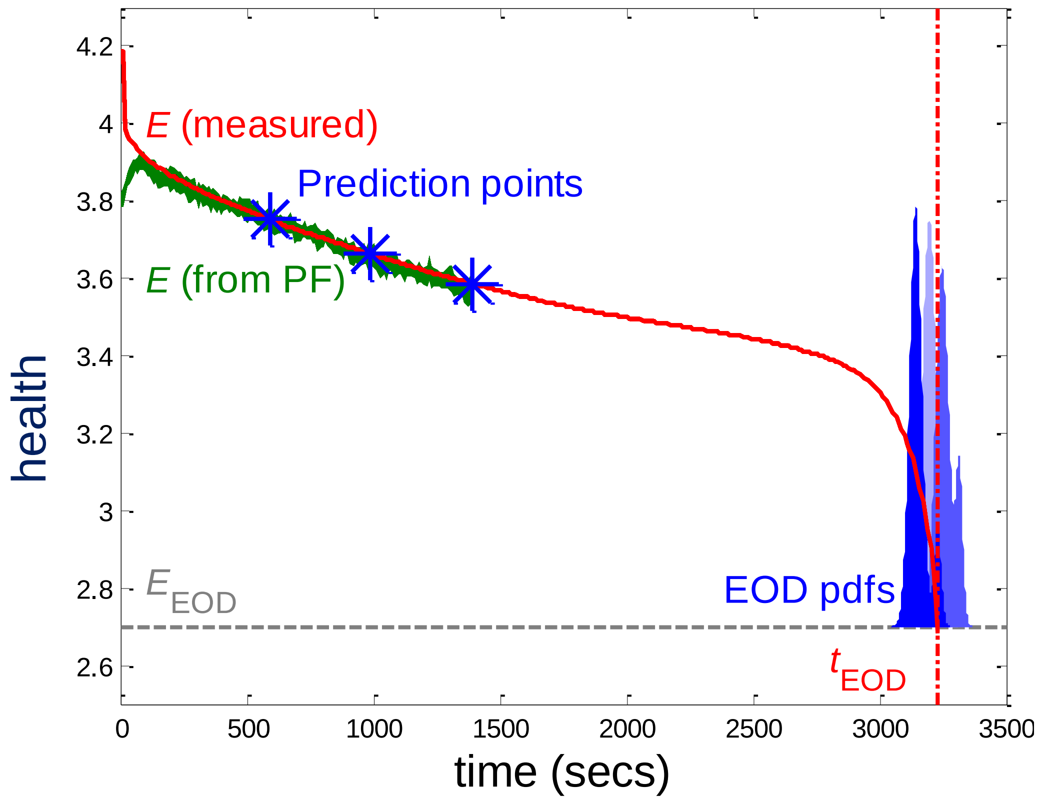
"The Prognostics Center of Excellence (PCoE) at Ames Research Center provides an umbrella for prognostic technology development, specifically addressing technology gaps within the application areas of aeronautics and space exploration."

- En route to becoming a **national asset**
- Expertise in prediction technology and uncertainty management for systems health monitoring

Prognostics



Definition: *Predict damage progression of a fault based on current and future operational and environmental conditions to estimate the time at which a component no longer fulfils its intended function within desired bounds ("Remaining Useful Life")*

Key Ingredients for Prognostics

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- Run-to-failure data
  - Measurement data
  - Ground truth data
  - Operational conditions
    - Load profiles
    - Environmental conditions
  - Failure threshold
- Physics of Failure models
  - For each fault in the fault catalogue
- Uncertainty information
  - Sources of uncertainty
  - Uncertainty characterization

Prognostics Algorithms

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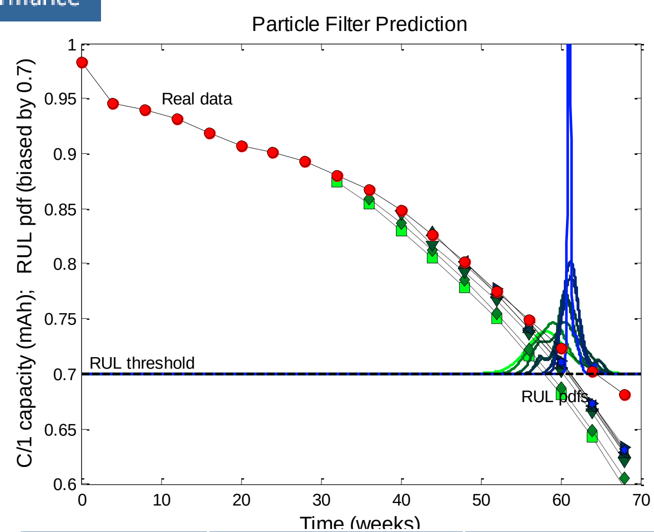
- Data Driven Algorithms
  - Gaussian Process Regression
  - Relevance Vector Machine
  - Neural Networks
  - Polynomial Regression
- Model Based Algorithms
- Hybrid Algorithms
  - Particle Filters
    - Classical PF
    - Rao-Blackwellized PF
    - Risk Sensitive PF
  - Kalman Filters
    - Classical KF
    - Extended KF

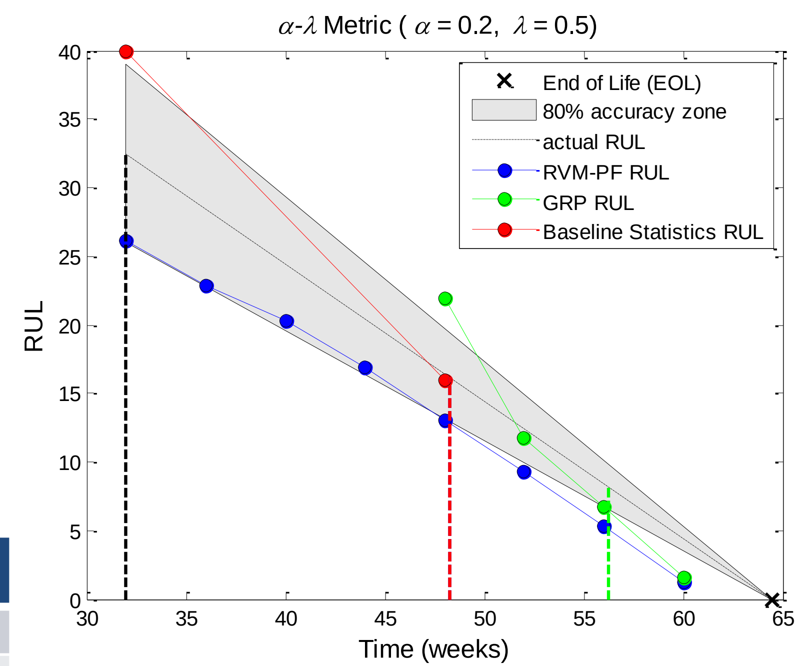
Metrics Example

- Performance Metrics
  - Algorithm Performance
    - Accuracy
    - Robustness
    - Precision
    - Trajectory
  - Computational Performance
  - Cost-benefit

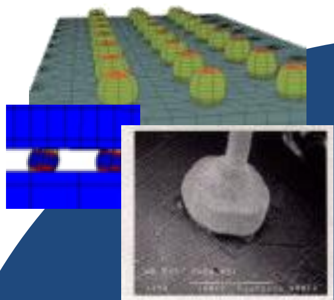
- Establishing a common ground to compare different prognostic efforts
- Metrics must not only measure accuracy and precision but also the convergence of both properties
- Data/time requirement of algorithms (prognostic horizon) before they produce consistent predictions is also important

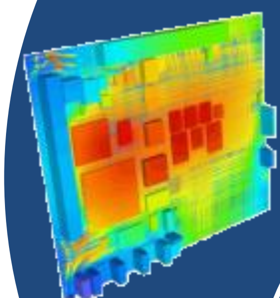


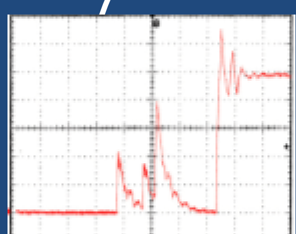
	Prediction Spread (weeks)	Prediction Horizon (weeks)
	4.23	32
	3.25	16
	5.34	32



Uncertainty Management







Sources of Uncertainty

- Model
  - System complexity
  - Insufficient knowledge
- Usage
  - Load profile
  - Temperature
- Noise
  - Internal, external
  - Electrical, mechanical, thermal
- Sensors

Uncertainty Management

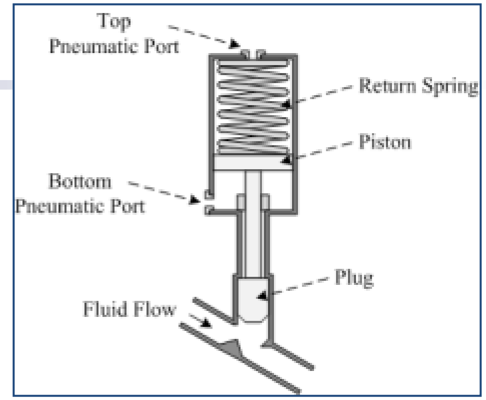
- Training data based extrapolation
- Probabilistic state space model
- Online model adaptation
- Noise modeling
- Probabilistic regression
- Hyperparameters to prevent overfitting

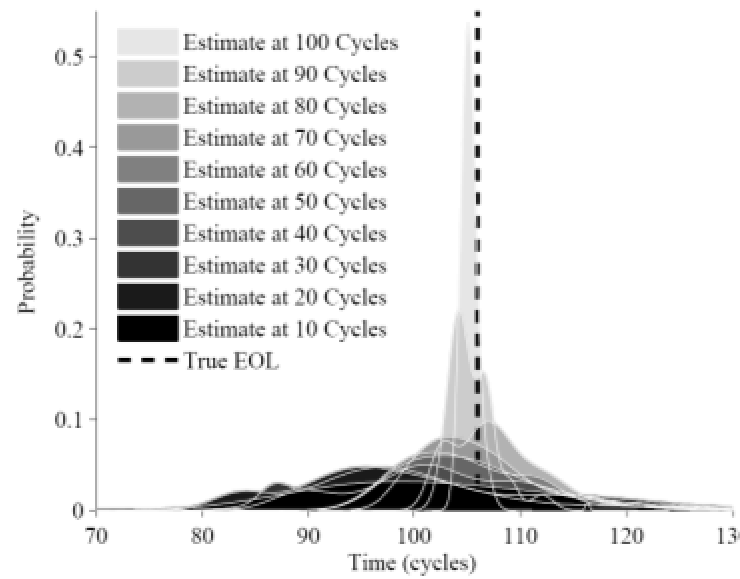
Modeling, Algorithms, Metrics

Application Example: Valves

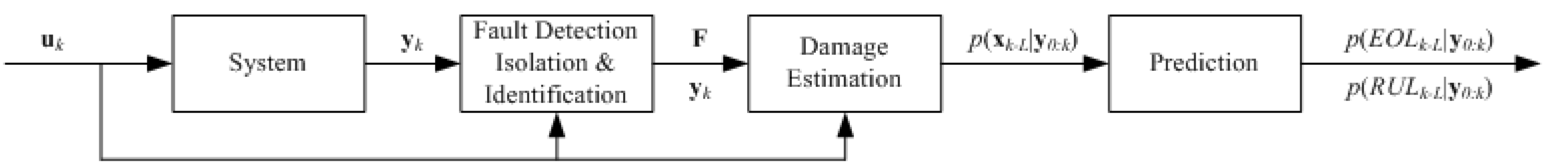
Valve Prognostics

- Apply model-based prognostics to pneumatic valves
- Develop high-fidelity simulation model
  - Progressive damage models include seal wear (internal and external leaks), spring degradation, and increase in friction.
- Investigate performance under different circumstances using prognostic performance metrics for comparison
  - Impact of using different filters
  - Effects of increased sensor noise
  - Effects of increased process noise and model uncertainty
  - Feasibility of different sensor sets (e.g. continuous position sensor vs. discrete open/closed indicators)





Computational Architecture



Source: *M. Daigle and K. Goebel, "Model-based Prognostics with Fixed-lag Particle Filters" Accepted for publication at PHM09*

Problem Formulation

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- Prognostics goal
  - Compute EOL = time point at which component no longer meets specified performance criteria
  - Compute RUL = time remaining until EOL
- System model

State Parameters Input Process Noise

$$\begin{aligned}\dot{\mathbf{x}}(t) &= \mathbf{f}(t, \mathbf{x}(t), \boldsymbol{\theta}(t), \mathbf{u}(t), \mathbf{v}(t))\\ \mathbf{y}(t) &= \mathbf{h}(t, \mathbf{x}(t), \boldsymbol{\theta}(t), \mathbf{u}(t), \mathbf{n}(t))\end{aligned}$$

Output Sensor Noise

- Define condition that determines if EOL has been reached

$$C_{EOL}(\mathbf{x}(t), \boldsymbol{\theta}(t)) = \begin{cases} 1, & \text{if EOL is reached} \\ 0, & \text{otherwise.} \end{cases}$$

- EOL and RUL defined as

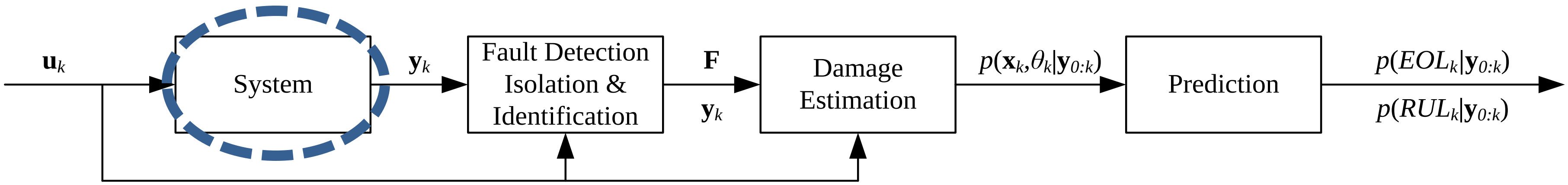
$$EOL(t_P) \triangleq \arg\min_{t \geq t_P} C_{EOL}(\mathbf{x}(t), \boldsymbol{\theta}(t)) = 1 \qquad RUL(t_P) \triangleq EOL(t_P) - t_P$$

Compute $p(EOL(t_P)|\mathbf{y}_{0:t_P})$ and/or $p(RUL(t_P)|\mathbf{y}_{0:t_P})$

Prognostics Architecture

1 System receives inputs, produces outputs

3 Estimate current state and parameter values

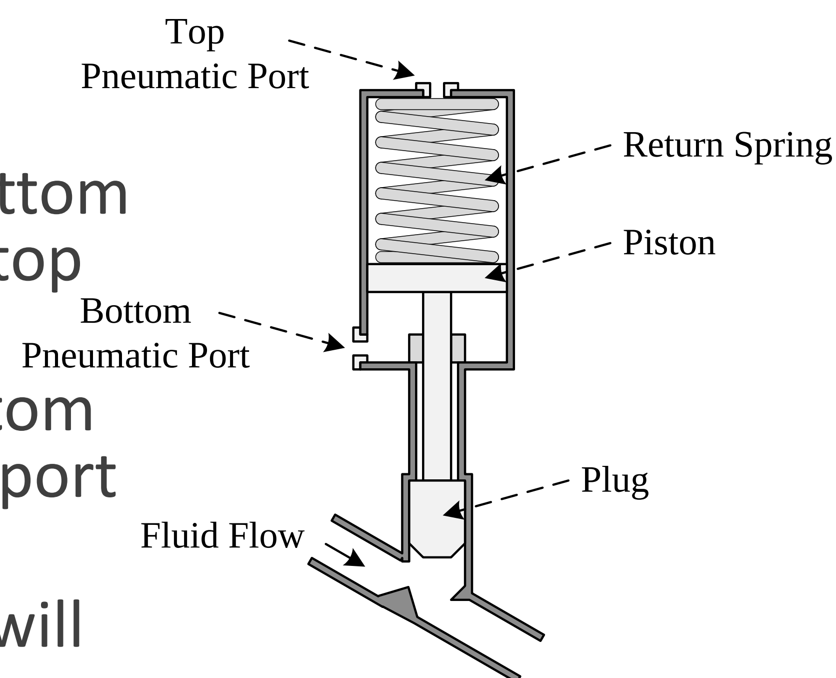


2 Identify active damage mechanisms

4 Predict EOL and RUL as probability distributions

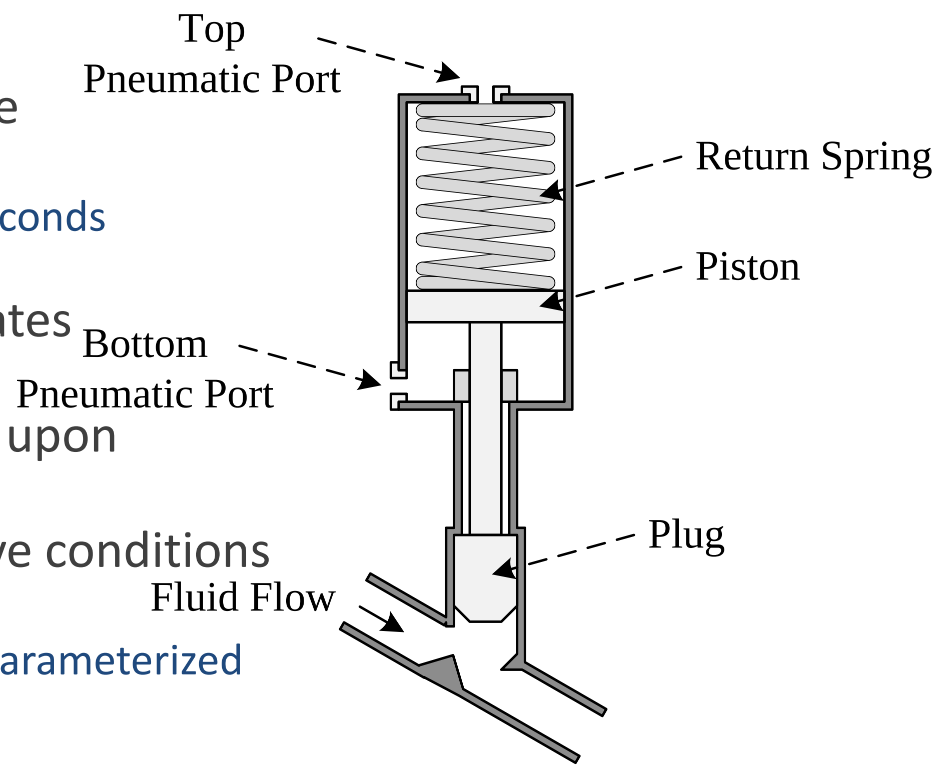
Case Study

- Apply framework to pneumatic valve
  - Complex mechanical devices used in many domains including aerospace
  - Failures of critical valves can cause significant effects on system function
- Pneumatic valve operation
  - Valve opened by opening bottom port to supply pressure and top **port to atmosphere**
  - Valve closed by opening bottom port to atmosphere and top port to supply pressure
  - Return spring ensures valve will close upon loss of supply pressure



Case Study

- Faults
  - External leaks at ports & internal leaks across piston
  - Friction buildup due to lubrication breakdown, sliding wear, buildup of particulate matter
  - Spring degradation
- Defining EOL
  - Limits defined for open and close times of valves
    - E.g., main fill valve opens in 20 seconds (26 req.), closes in 15 (20 req.)
  - Limits placed on valve leakage rates (pneumatic gas)
  - Valve must be able to fully close upon fail-safe
  - Valve is at EOL when any of above conditions violated (defines C_{EOL})
    - Function of amount of damage, parameterized in model



Physics-based Modeling

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- Valve state defined by

$$\mathbf{x}(t) = \begin{bmatrix} x(t) \\ v(t) \\ m_t(t) \\ m_b(t) \end{bmatrix} \begin{matrix} \text{Valve position} \\ \text{Valve velocity} \\ \text{Gas mass above piston} \\ \text{Gas mass below piston} \end{matrix}$$

- State derivatives given by

$$\dot{\mathbf{x}}(t) = \begin{bmatrix} v(t) \\ \frac{1}{m}\sum F(t) \\ f_t(t) \\ f_b(t) \end{bmatrix} \begin{matrix} \text{Velocity} \\ \text{Acceleration} \\ \text{Gas flow above piston} \\ \text{Gas flow below piston} \end{matrix}$$

- Inputs given by

$$\mathbf{u}(t) = \begin{bmatrix} p_l(t) \\ p_r(t) \\ u_t(t) \\ u_b(t) \end{bmatrix} \begin{matrix} \text{Fluid pressure (left)} \\ \text{Fluid pressure (right)} \\ \text{Input pressure at top port} \\ \text{Input pressure at bottom port} \end{matrix}$$

Physics-based Modeling: Forces

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- Piston movement governed by sum of forces, including
  - Pneumatic gas: $(p_b(t) - p_t(t))A_p$
  - Process fluid: $(p_r(t) - p_l(t))A_v$
  - Weight: $-mg$
  - Spring: $-k(x(t) - x_o)$
  - Friction: $-rv(t)$
  - Contact forces: $\begin{cases} k_c(-x), & x < 0 \\ 0, & 0 \le x \le L_s \\ -k_c(x - L_s), & x > L_s, \end{cases}$

$$\boxed{\begin{aligned} p_t(t) &= \frac{m_t(t) R_g T}{V_{t_0} + A_p(L_s - x(t))} \\ p_b(t) &= \frac{m_b(t) R_g T}{V_{b_0} + A_p x(t)} \end{aligned}}$$

Valve Stroke Length

Physics-based Modeling: Flows

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- Gas flows determined by choked/non-choked orifice flow equations:

$$f_t(t) = f_g(p_t(t), u_t(t))$$
$$f_b(t) = f_g(p_b(t), u_b(t))$$

$$f_g(p_1,p_2) = \begin{cases} C_s A_s p_1 \sqrt{\frac{\gamma}{Z R_g T}\left(\frac{2}{\gamma+1}\right)^{(\gamma+1)/(\gamma-1)}}, & p_1 \geq p_2 \wedge p_1/p_2 \geq \left(\frac{\gamma+1}{2}\right)^{\gamma/(\gamma-1)} \\ C_s A_s p_1 \sqrt{\frac{2}{Z R_g T}\left(\frac{\gamma}{\gamma-1}\right)\left(\left(\frac{p_2}{p_1}\right)^{2/\gamma} - \left(\frac{p_2}{p_1}\right)^{(\gamma+1)/\gamma}\right)}, & p_1 \geq p_2 \wedge p_1/p_2 < \left(\frac{\gamma+1}{2}\right)^{\gamma/(\gamma-1)} \\ C_s A_s p_2 \sqrt{\frac{\gamma}{Z R_g T}\left(\frac{2}{\gamma+1}\right)^{(\gamma+1)/(\gamma-1)}}, & p_1 < p_2 \wedge p_2/p_1 \geq \left(\frac{\gamma+1}{2}\right)^{\gamma/(\gamma-1)} \\ C_s A_s p_2 \sqrt{\frac{2}{Z R_g T}\left(\frac{\gamma}{\gamma-1}\right)\left(\left(\frac{p_1}{p_2}\right)^{2/\gamma} - \left(\frac{p_1}{p_2}\right)^{(\gamma+1)/\gamma}\right)}, & p_1 < p_2 \wedge p_2/p_1 < \left(\frac{\gamma+1}{2}\right)^{\gamma/(\gamma-1)} \end{cases}$$

- Fluid flow determined by orifice flow equation:

$$f_v(t) = \frac{x(t)}{L_s} C_v A_v \sqrt{\frac{2}{\rho}\left|p_{fl} - p_{fr}\right|}\,\mathrm{sign}(p_{fl} - p_{fr})$$

Pneumatic Valve Modeling

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- Possible sensors include

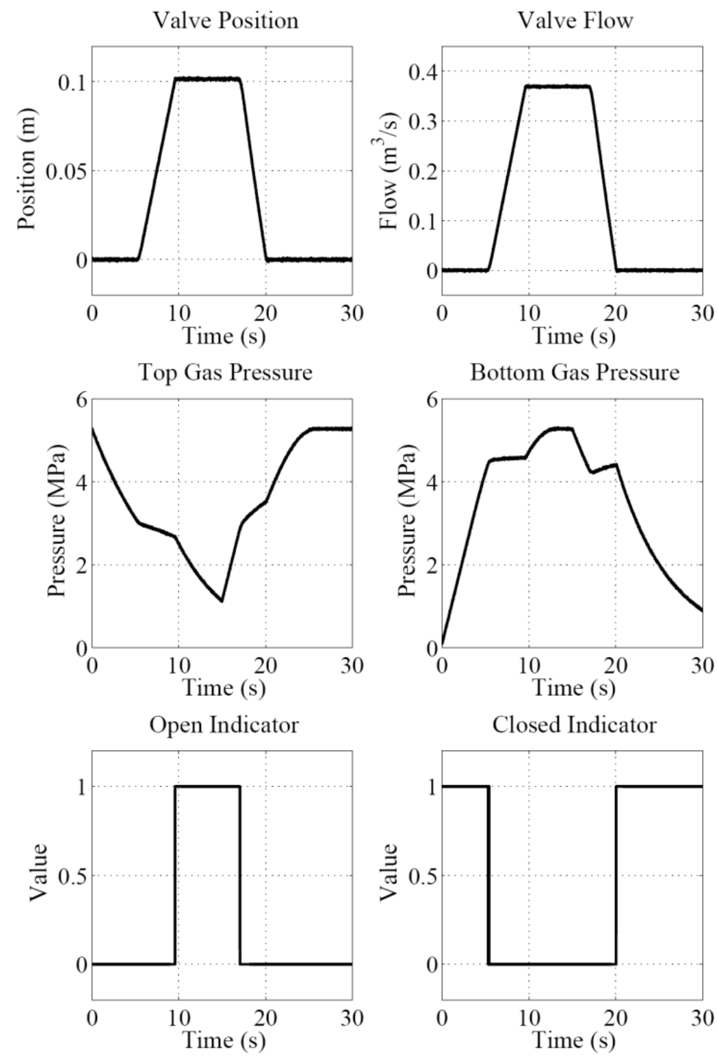
$$\mathbf{y}(t) = \begin{bmatrix} x(t) \\ p_t(t) \\ p_b(t) \\ f_v(t) \\ open(t) \\ closed(t) \end{bmatrix}$$

Valve position
Gas pressure (top)
Gas pressure (bottom)
Fluid flow
Open indicator
Closed Indicator

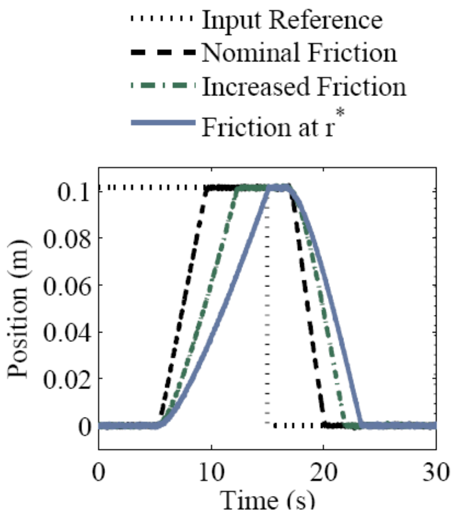
where,

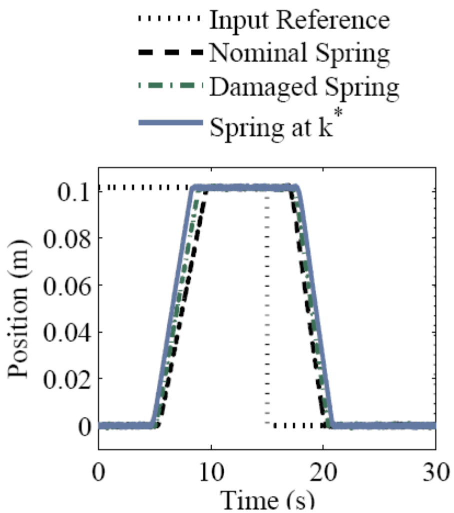
$$open(t) = \begin{cases} 1, & \text{if } x(t) \geq L_s \\ 0, & \text{otherwise} \end{cases}$$

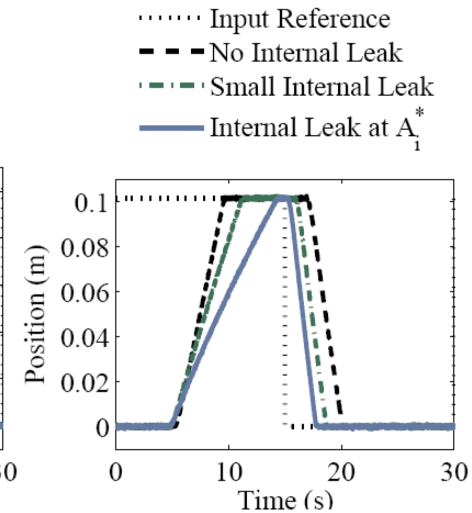
$$closed(t) = \begin{cases} 1, & \text{if } x(t) \leq 0 \\ 0, & \text{otherwise} \end{cases}$$

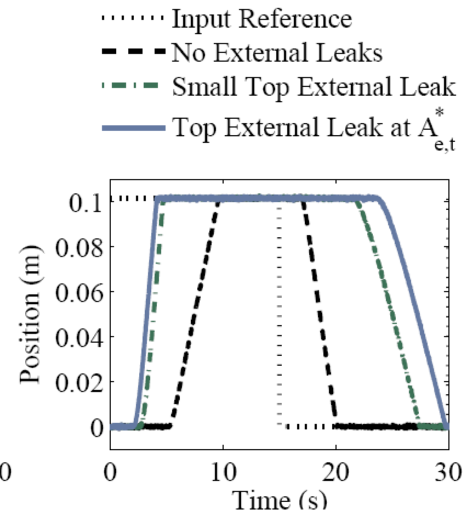


Modeling Damage









Increase in friction

- Based on sliding wear equation
- Describes how friction coefficient changes as function of friction force, piston velocity, and wear coefficient

$$\dot{r}(t) = w_r |F_f(t) v(t)|$$

Degradation of spring

- Assume form similar to sliding wear equation
- Describes how spring constant changes as function of spring force, piston velocity, and wear coefficient

$$\dot{k}(t) = -w_k |F_s(t) v(t)|$$

Growth of internal leak

- Based on sliding wear equation
- Describes how leak size changes as function of friction force, piston velocity, and wear coefficient

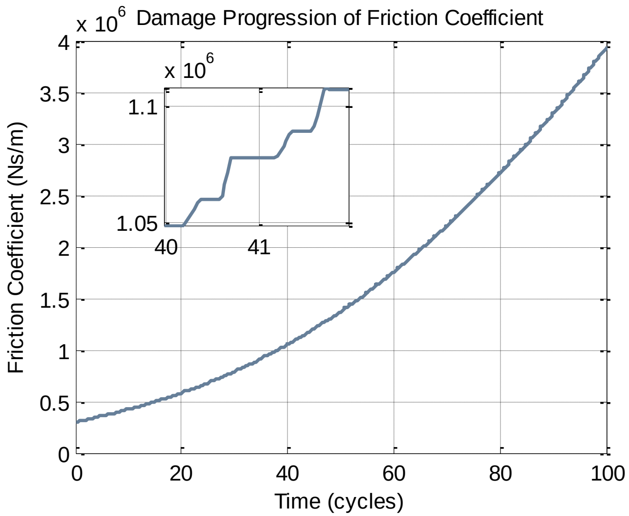
$$\dot{A}_i(t) = w_i |F_f(t) v(t)|$$

Growth of external leak

- Based on environmental factors such as corrosion
- Assume a linear change in absence of known model

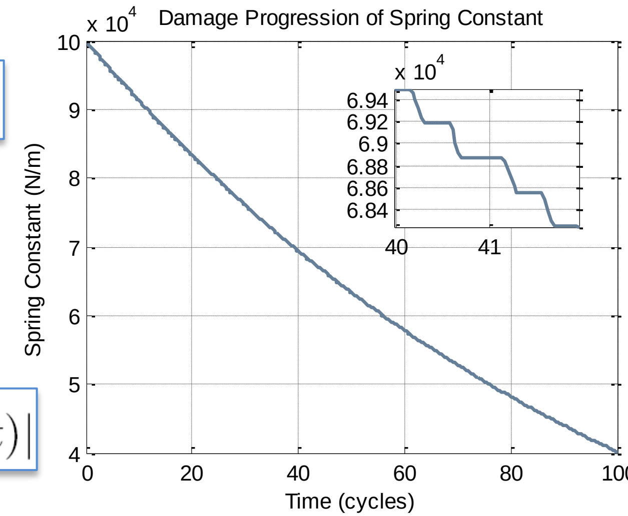
$$\dot{A}_e(t) = w_e$$

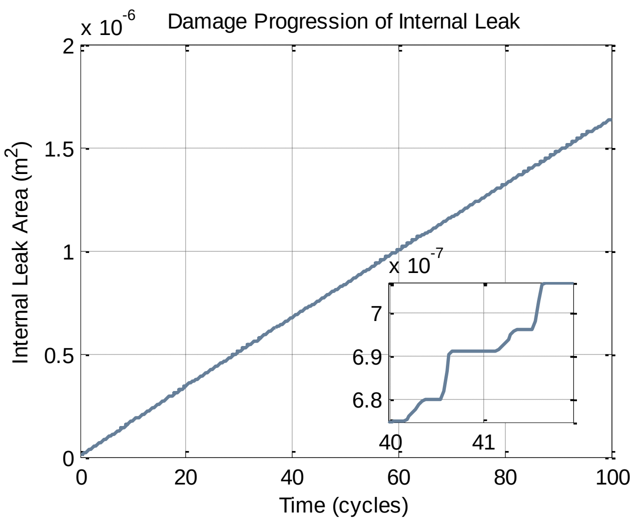
Damage Progression



$$\dot{r}(t) = w_r |F_f(t)v(t)|$$

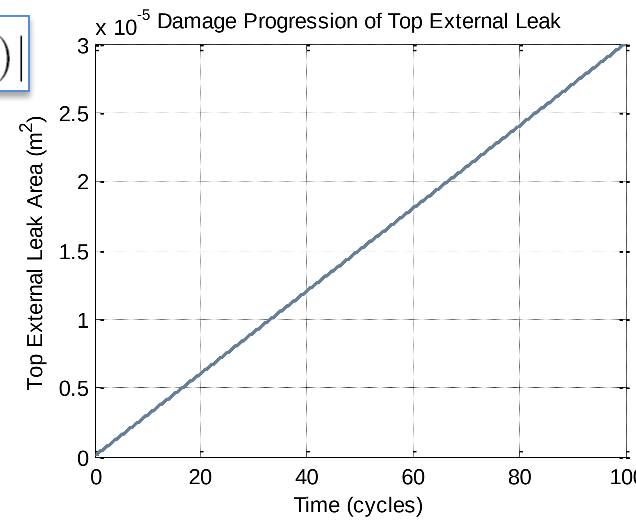
$$\dot{k}(t) = -w_k |F_s(t)v(t)|$$





$$\dot{A}_i(t) = w_i |F_f(t)v(t)|$$

$$\dot{A}_e(t) = w_e$$



Damage Estimation

- Wear parameters are unknown, and must be estimated along with system state

Augment system state with unknown parameters and use state observer

$$\mathbf{x}(t) = \begin{bmatrix} x(t) \\ v(t) \\ m_t(t) \\ m_b(t) \\ r(t) \\ k(t) \\ A_i(t) \\ A_{e,t}(t) \\ A_{e,b}(t) \end{bmatrix} \begin{array}{l} \text{Position} \\ \text{Velocity} \\ \text{Gas mass above piston} \\ \text{Gas mass below piston} \\ \text{Friction coefficient} \\ \text{Spring rate} \\ \text{Internal leak area} \\ \text{External leak area (top)} \\ \text{External leak area (bottom)} \end{array}$$

$$\boldsymbol{\theta}(t) = \begin{bmatrix} w_r(t) \\ w_k(t) \\ w_i(t) \\ w_{e,t}(t) \\ w_{e,b}(t) \end{bmatrix} \begin{array}{l} \text{Friction wear} \\ \text{Spring wear} \\ \text{Internal leak wear} \\ \text{External leak wear (top)} \\ \text{External leak wear (bottom)} \end{array}$$

Particle Filters

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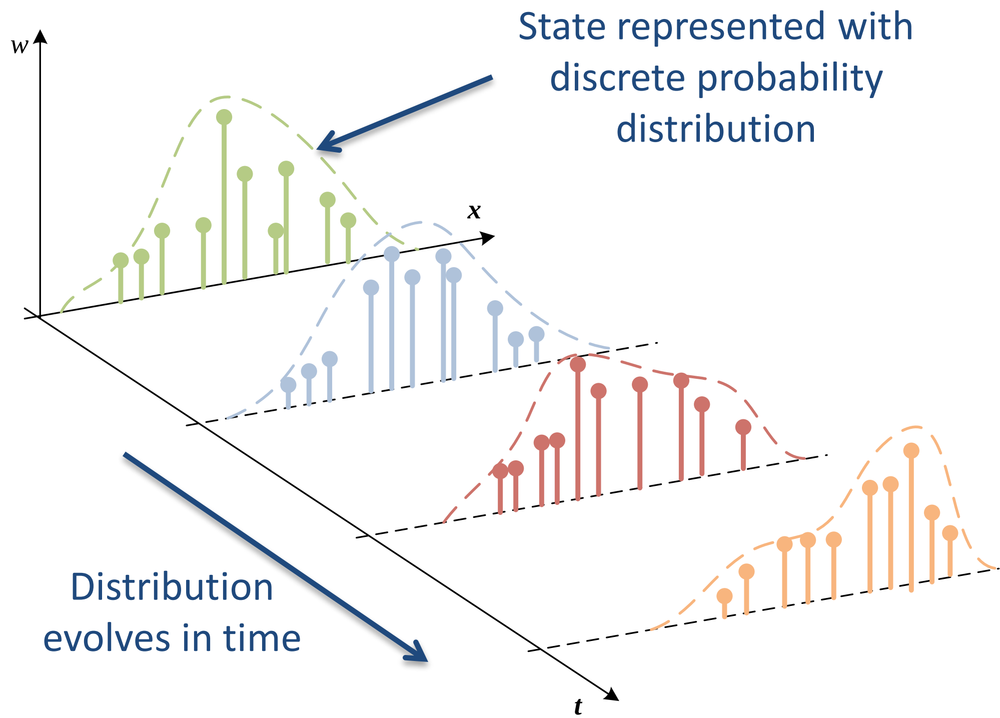
- Employ *particle filters* for joint state-parameter estimation
  - Represent probability distributions using set of weighted samples
  - Help manage uncertainty (e.g., sensor noise, process noise, etc.)
  - Similar approaches have been applied successfully to actuators, batteries, and other prognostics applications



Damage Estimation with PF

- Particle filters (PFs) are state observers that can be applied to general nonlinear processes with non-Gaussian noise
  - Approximate state distribution by set of discrete weighted samples:

$$\{(\mathbf{x}_k^i, \boldsymbol{\theta}_k^i), w_k^i\}_{i=1}^N$$

  - Suboptimal, but approach optimality as N→ ∞
- Parameter evolution described by random walk:

$$\theta_k = \theta_{k-1} + \xi_{k-1}$$

  - Selection of variance of random walk noise is important
  - Variance must be large enough to ensure convergence, but small enough to ensure precise tracking
- PF approximates posterior as

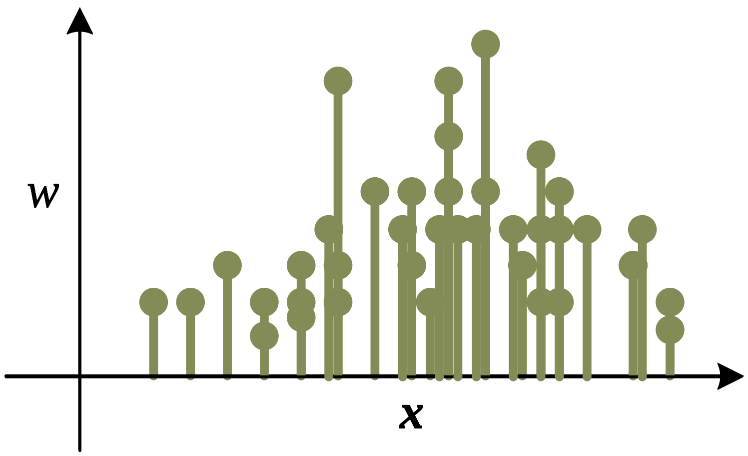
$$p(\mathbf{x}_k, \boldsymbol{\theta}_k | \mathbf{y}_{0:k}) \approx \sum_{i=1}^{N} w_k^i \delta_{(\mathbf{x}_k^i, \boldsymbol{\theta}_k^i)}(d\mathbf{x}_k d\boldsymbol{\theta}_k)$$

Sampling Importance Resampling

- Begin with initial particle population
- Predict evolution of particles one step ahead
- Compute particle weights based on likelihood of given observations
- Resample to avoid degeneracy issues
  - Degeneracy is when small number of particles have high weight and the rest have very low weight
  - Avoid wasting computation on particles that do not contribute to the approximation

Algorithm 1 SIR Filter

Inputs: $\{(\mathbf{x}_{k-1}^i, \boldsymbol{\theta}_{k-1}^i), w_{k-1}^i\}_{i=1}^N, \mathbf{u}_{k-1:k}, \mathbf{y}_k$
Outputs: $\{(\mathbf{x}_k^i, \boldsymbol{\theta}_k^i), w_k^i\}_{i=1}^N$
for $i = 1$ **to** N **do**
  $\boldsymbol{\theta}_k^i \sim p(\boldsymbol{\theta}_k | \boldsymbol{\theta}_{k-1}^i)$
  $\mathbf{x}_k^i \sim p(\mathbf{x}_k | \mathbf{x}_{k-1}^i, \boldsymbol{\theta}_{k-1}^i, \mathbf{u}_{k-1})$
  $w_k^i \leftarrow p(\mathbf{y}_k | \mathbf{x}_k^i, \boldsymbol{\theta}_k^i, \mathbf{u}_k)$
end for
$$W \leftarrow \sum_{i=1}^{N} w_k^i$$
for $i = 1$ to N **do**
  $w_k^i \leftarrow w_k^i / W$
end for
$\{\mathbf{x}_k^i, \boldsymbol{\theta}_k^i, w_k^i\}_{i=1}^N \leftarrow \texttt{Resample}(\{\mathbf{x}_k^i, \boldsymbol{\theta}_k^i, w_k^i\}_{i=1}^N)$



Prediction

- Particle filter computes

$$p(\mathbf{x}_{k_P}, \boldsymbol{\theta}_{k_P} | \mathbf{y}_{0:k_P}) \approx \sum_{i=1}^{N} w_{k_P}^i \delta_{(\mathbf{x}_{k_P}^i, \boldsymbol{\theta}_{k_P}^i)}(d\mathbf{x}_{k_P} d\boldsymbol{\theta}_{k_P})$$

- Prediction n steps ahead approximated as

$$p(\mathbf{x}_{k_P+n}, \boldsymbol{\theta}_{k_P+n} | \mathbf{y}_{0:k_P}) \approx \sum_{i=1}^{N} w_{k_P}^i \delta_{(\mathbf{x}_{k_P+n}^i, \boldsymbol{\theta}_{k_P+n}^i)}(d\mathbf{x}_{k_P+n} d\boldsymbol{\theta}_{k_P+n})$$

- Similarly, EOL prediction approximated as

$$p(EOL_{k_P} | \mathbf{y}_{0:k_P}) \approx \sum_{i=1}^{N} w_{k_P}^i \delta_{EOL_{k_P}^i}(dEOL_{k_P})$$

- General idea
  - Propagate each particle forward until EOL reached (condition on EOL evaluates to true)
  - Use particle weights for EOL weights

Prediction

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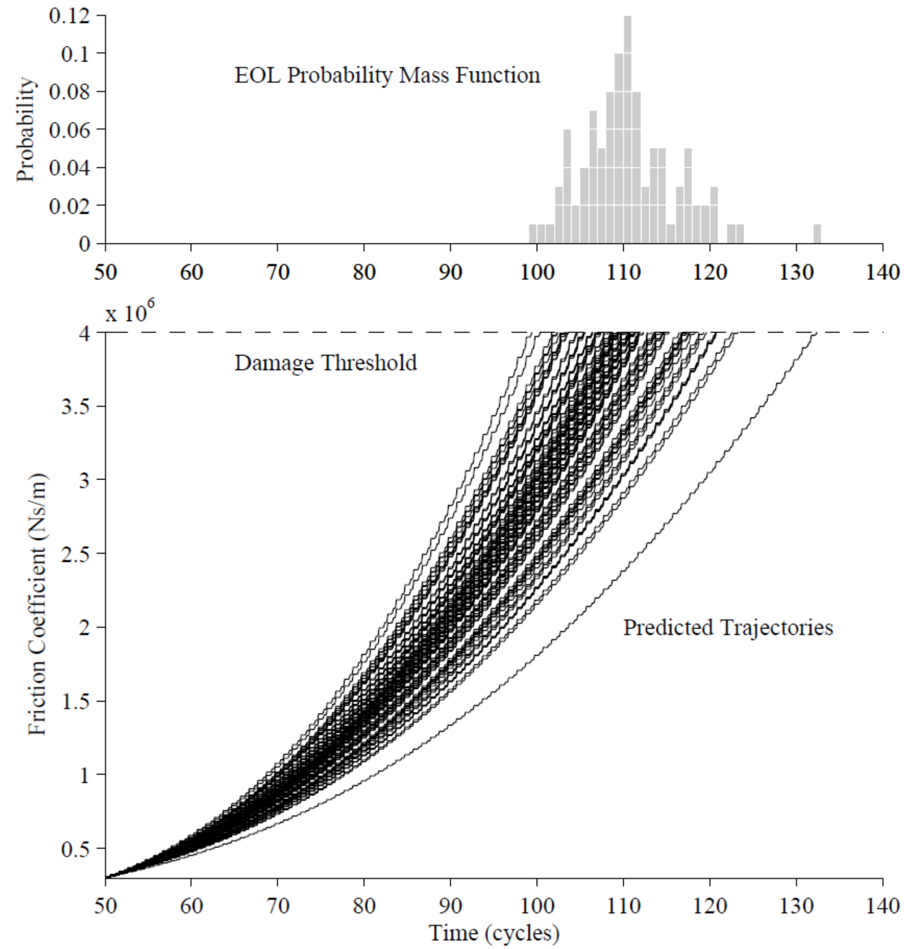
Algorithm 2 EOL Prediction

Inputs: $\{(\mathbf{x}^i_{k_P}, \boldsymbol{\theta}^i_k), w^i_{k_P}\}^N_{i=1}$
Outputs: $\{EOL^i_{k_P}, w^i_{k_P}\}^N_{i=1}$
for $i = 1$ **to** N **do**
  $k \leftarrow k_P$
  $\mathbf{x}^i_k \leftarrow \mathbf{x}^i_{k_P}$
  $\boldsymbol{\theta}^i_k \leftarrow \boldsymbol{\theta}^i_{k_P}$
  while $C_{EOL}(\mathbf{x}^i_k, \boldsymbol{\theta}^i_k) = 0$ **do**
    Predict $\hat{\mathbf{u}}_k$
    $\boldsymbol{\theta}^i_{k+1} \sim p(\boldsymbol{\theta}_{k+1} | \boldsymbol{\theta}^i_k)$
    $\mathbf{x}^i_{k+1} \sim p(\mathbf{x}_{k+1} | \mathbf{x}^i_k, \boldsymbol{\theta}^i_k, \hat{\mathbf{u}}_k)$
    $k \leftarrow k + 1$
    $\mathbf{x}^i_k \leftarrow \mathbf{x}^i_{k+1}$
    $\boldsymbol{\theta}^i_k \leftarrow \boldsymbol{\theta}^i_{k+1}$
  end while
  $EOL^i_{k_P} \leftarrow k$
end for

Hypothesized inputs



Friction progression EOL prediction

Validation of Methodology

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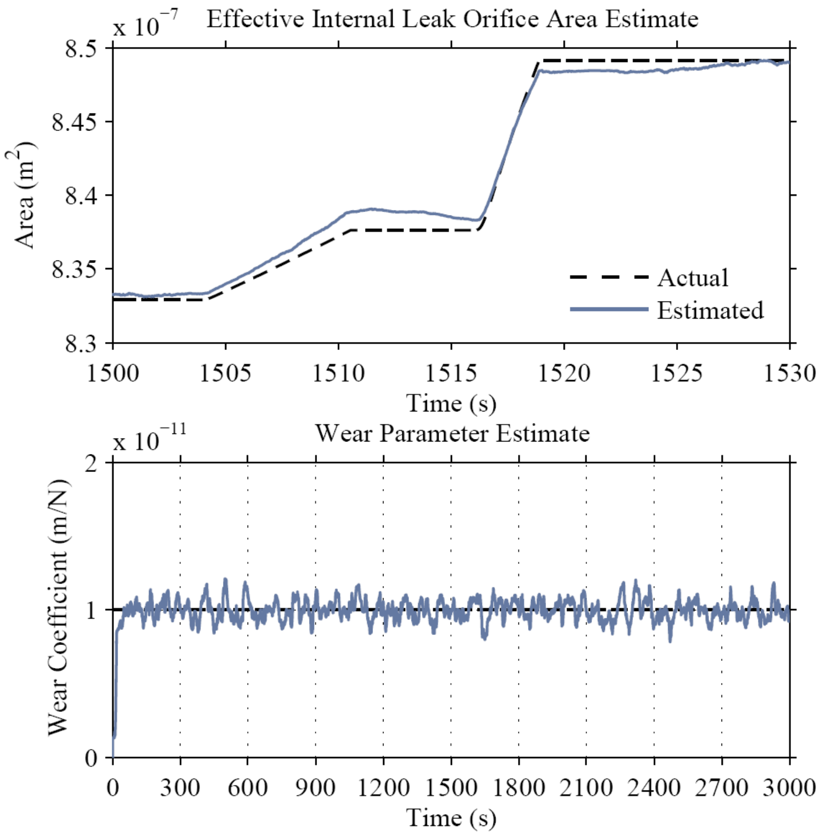

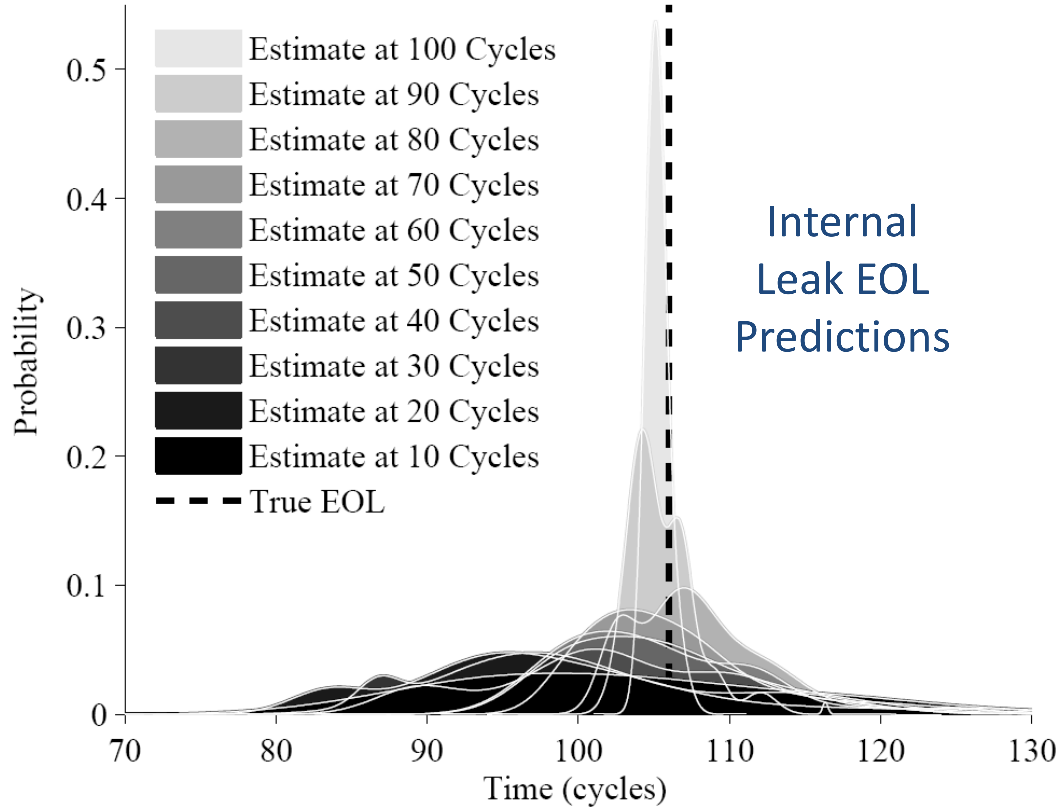

Internal Leak EOL Predictions

Estimate of wear parameter converges after a few cycles, after this, leak area can be tracked well.

EOL predictions all contain true EOL, and get more accurate and precise as EOL is approached.

α-λ Performance

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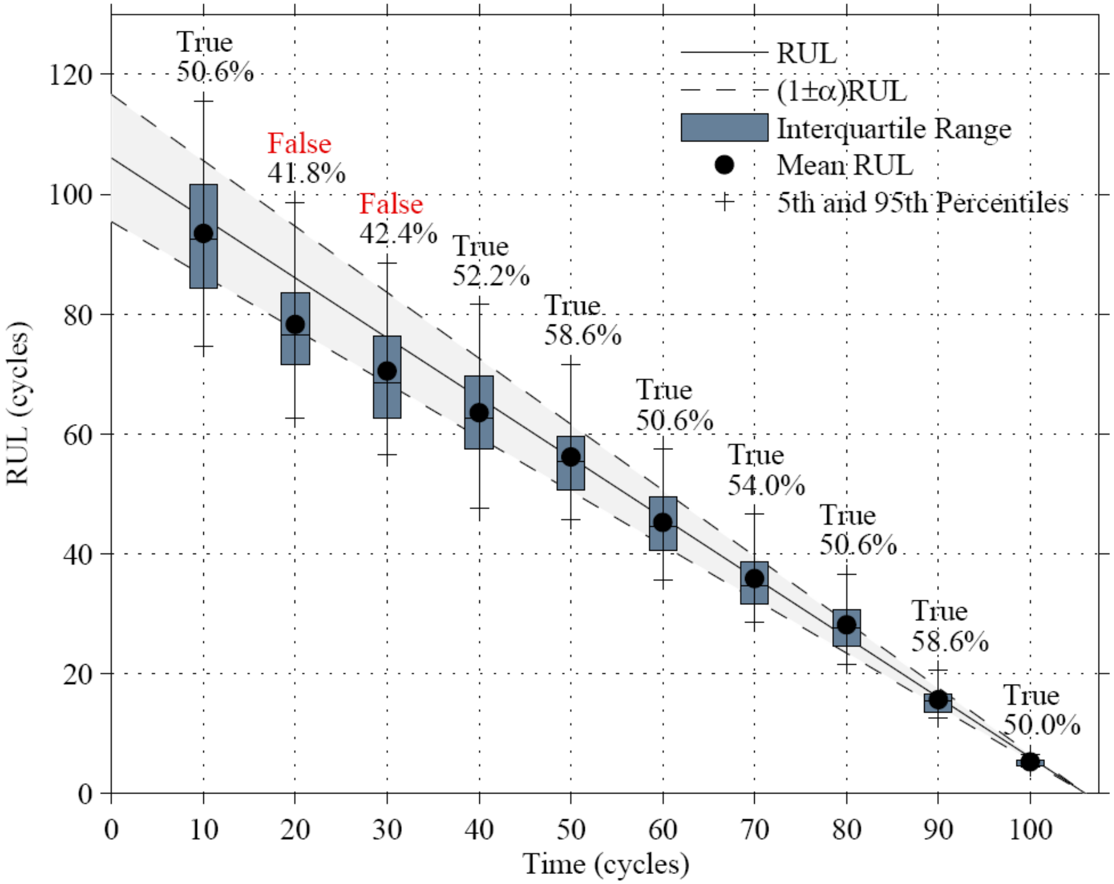
- Plot summarizes performance of internal leak prognosis
- Over 50% of probability mass concentrated within the bounds at all prediction points except at 20 and 30 cycles
  - Mean RULs are within the bounds at these points
- For α=0.122, metric is satisfied at all points

α=0.1, β=0.5



27

Prediction Performance

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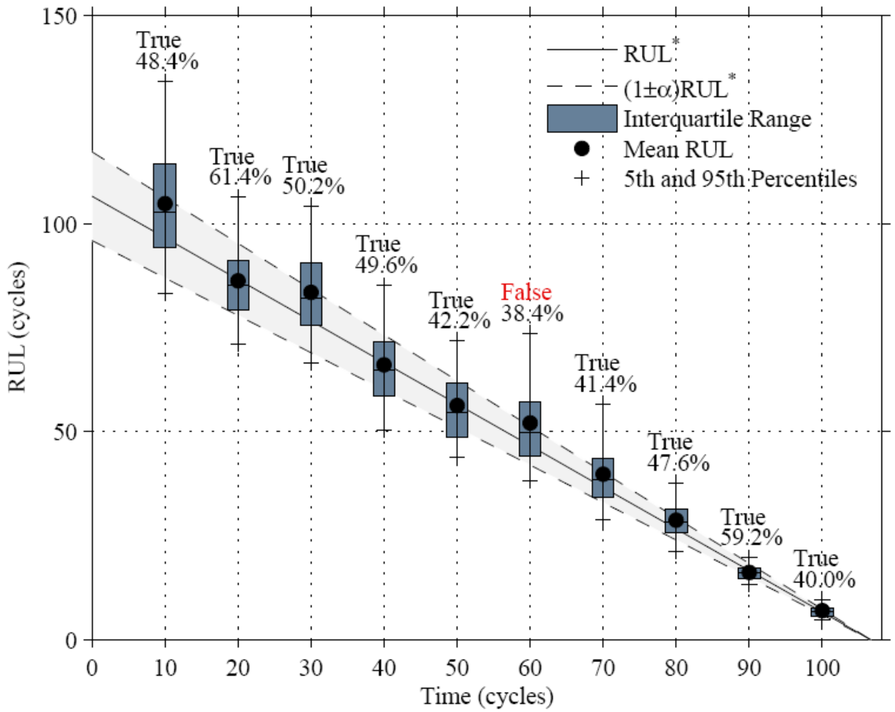
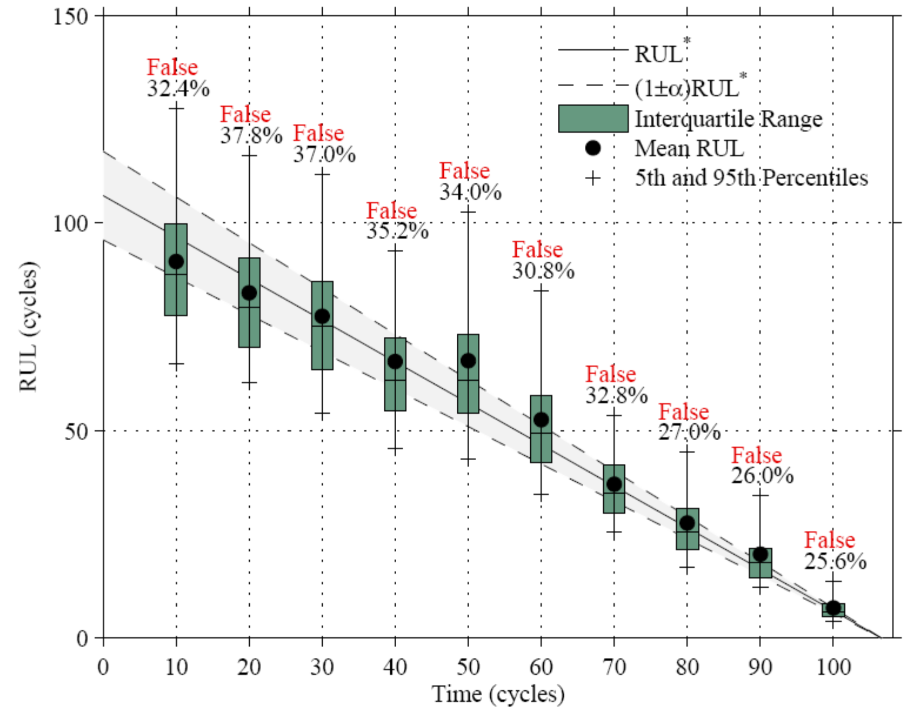
α-λ metric for spring damage prediction, where α =0.1, β=0.4, M={x,f,p_t,p_b}



α-λ metric for spring damage prediction, where α =0.1, β=0.4, M={*open,closed*}



Both cases have similar accuracy, but the case with continuous measurements has much better precision, as the metric evaluates to true for all but one λ point.

Discussion

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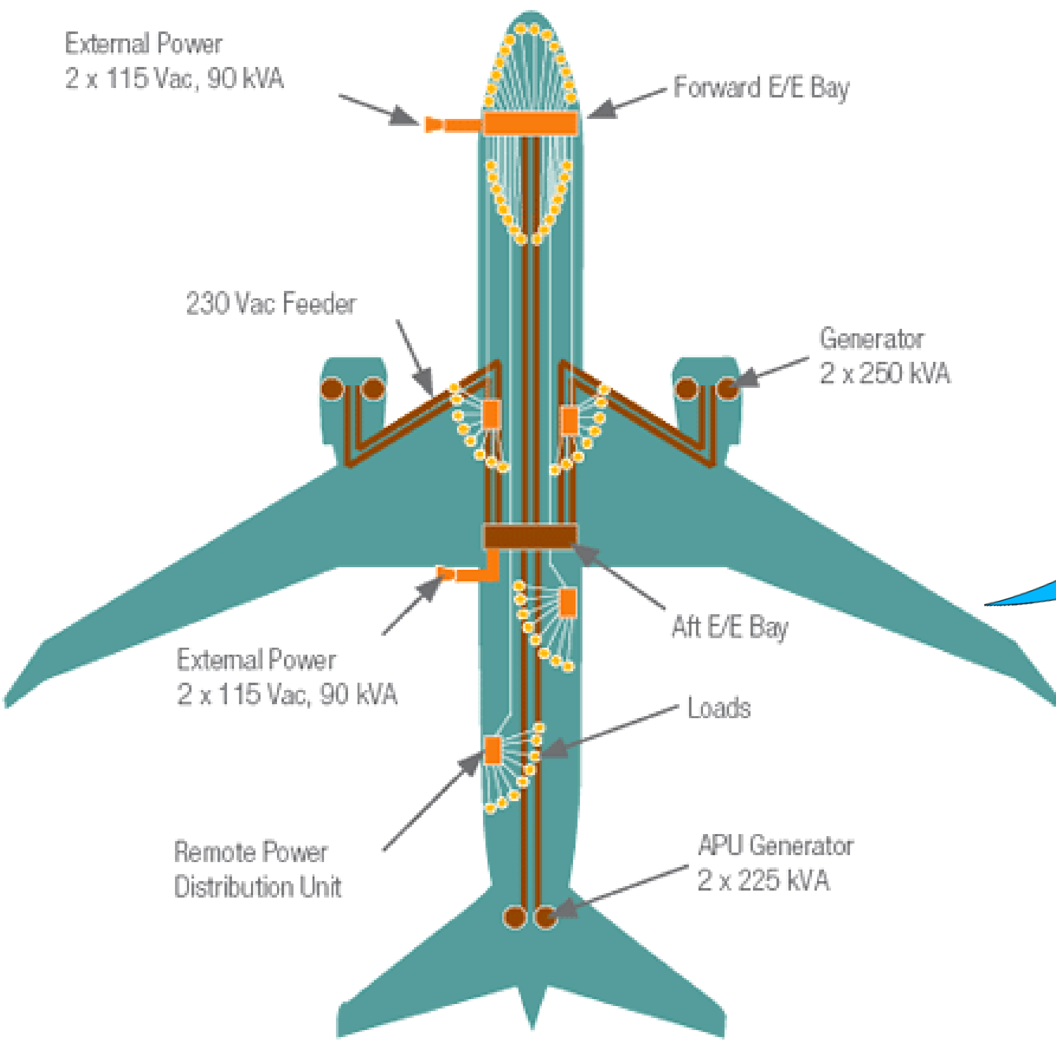
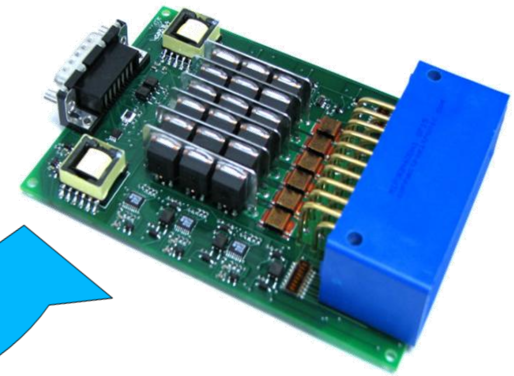
- Different sensor sets have comparable estimation and prediction accuracy, but some differences are observed
- Wide differences observed in precision of estimation and prediction
- Results reveal that some sensors are more useful for certain faults than others
  - Flow measurement can be dropped with little effect
  - For friction and spring faults, sensor sets with position measurement perform best
  - For leak faults, sensor sets with pressure measurements perform best
  - Helps decide importance of sensors based on which faults are most important
- Overall performance still reasonable with higher levels of noise
  - Sensor sets with continuous measurements impacted most

Application Example: Electronics

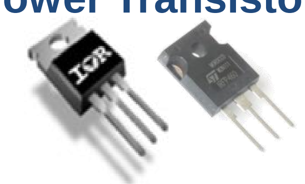
Prognostics for Electronics



Line Replaceable Unit:
Power Controller



Component:
Power Transistor



Motivation

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- Electronic components have increasingly critical role in on-board, autonomous functions for
  - Vehicle controls, Communications, Navigation, Radar systems
- Future aircraft systems will rely more on electric & electronic components
  - More electric aircraft
  - Next Generation Air Traffic System (NGATS)
- Move toward lead-free electronics and microelectromechanical devices (MEMS)
- Assumption of new functionality increases number of electronics faults with perhaps unanticipated fault modes
- Needed
  - Understanding of behavior of deteriorated components to
  - develop capability to anticipate failures/predict remaining RUL

Current Research Efforts

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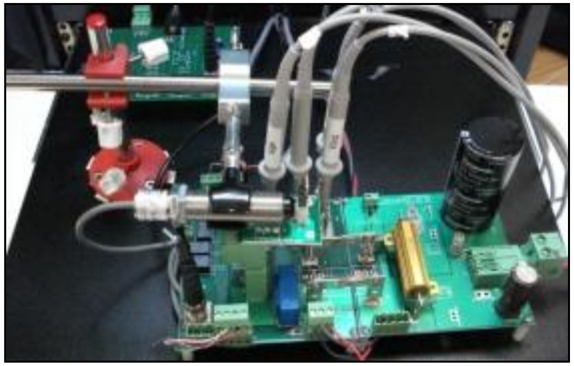
- Thermal overstress aging of MOSFETs and IGBTs
- Electrical overstress aging testbed (isothermal)
- Modeling of MOSFETs
- Identification of precursors of failure for different IGBT technologies*
- Prognostics for output capacitor in power supplies+
- Effects of lightning events of MOSFETS
- Effects of ESD events of MOSFETS and IGBTs
- Effects of radiation on MOSFETS and IGBTs

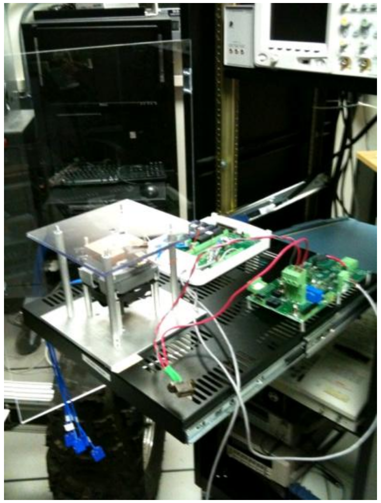
- In collaboration with
  ** University of Maryland*
  + Vanderbilt University

Accelerated aging system

Ames Research Center

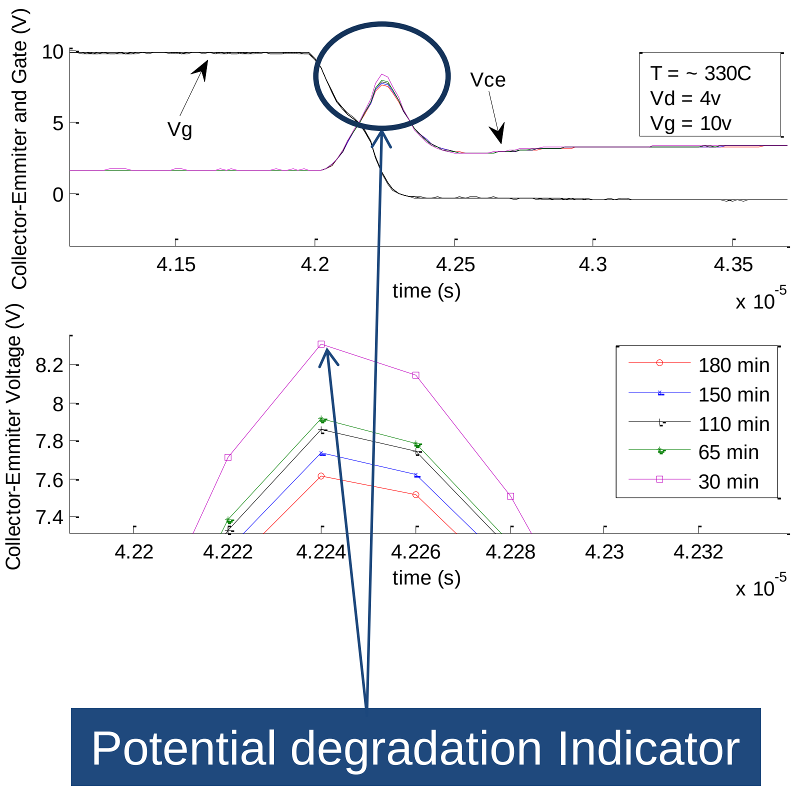
- A platform for aging, characterization, and scenario simulation of gate controlled power transistors.
- The platform supports:
  - Thermal cycling
  - Simulation of operation conditions
  - Isothermal aging
- In situ state monitoring is supported at varying gate and drain voltage levels.

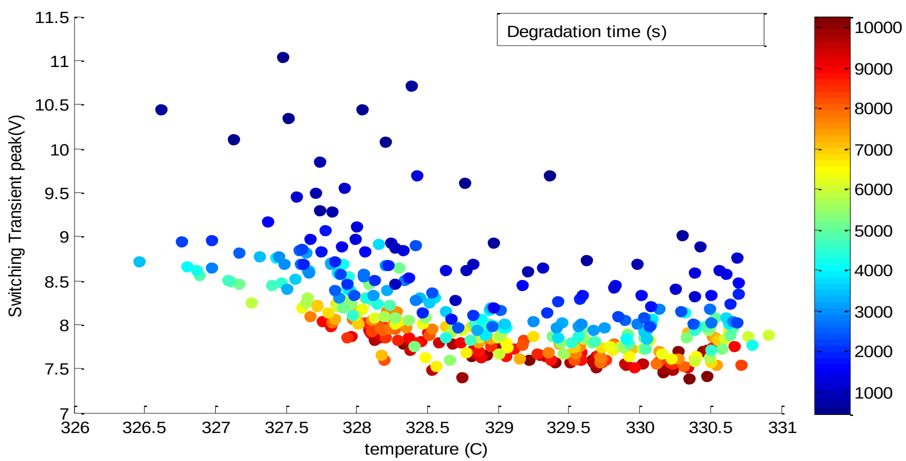




Experiment on IGBT

- Collector-emitter voltage turn-OFF transient





- Turn-OFF collector-emitter voltage transient decreased significantly with both increases in temperature and thermal overstress aging time

Electronics Aging

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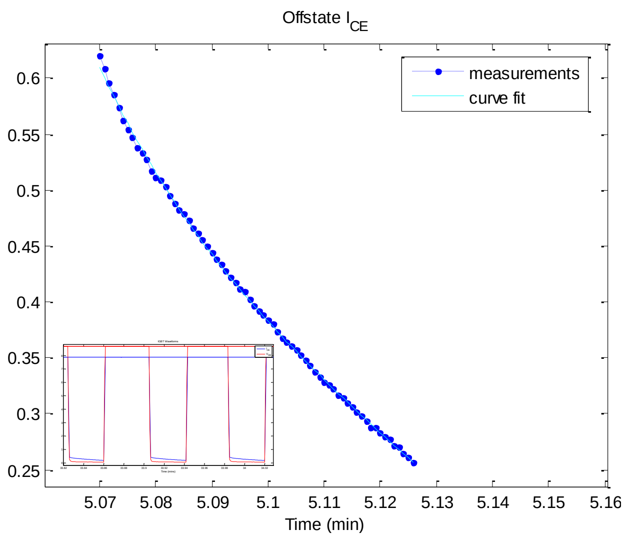
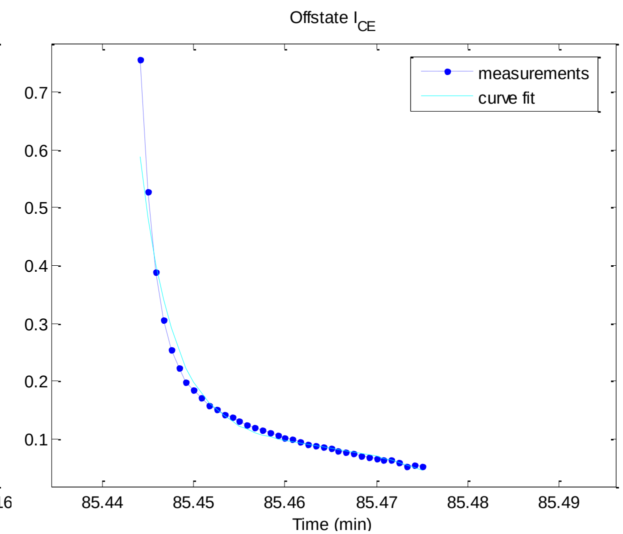
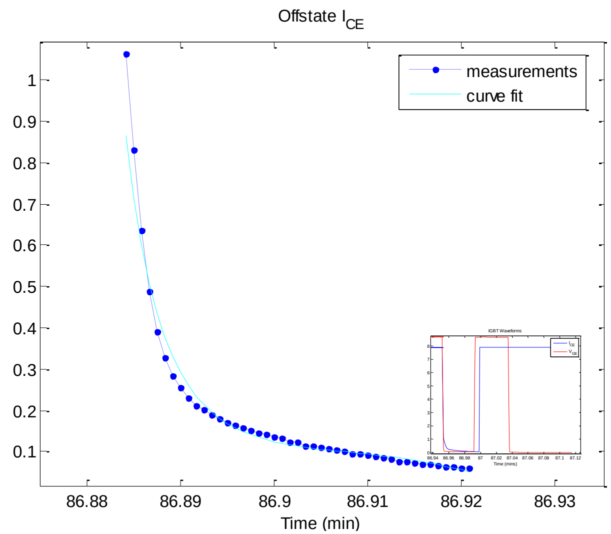
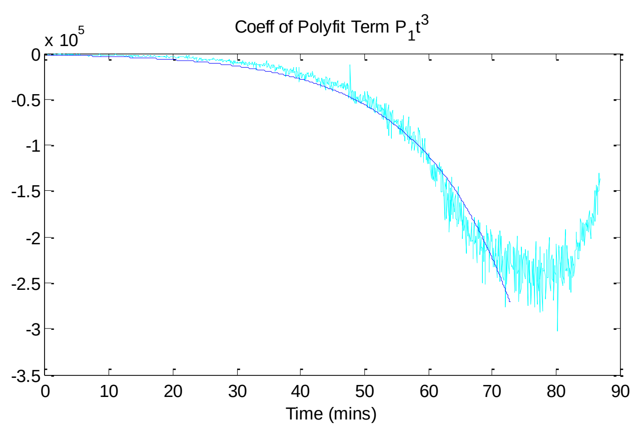
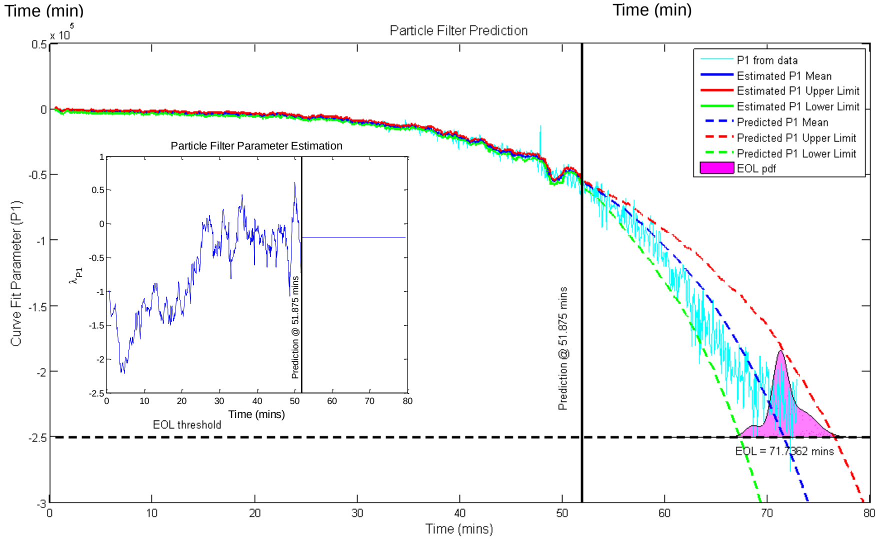










Application Example: EMA

Electro-Mechanical Actuators

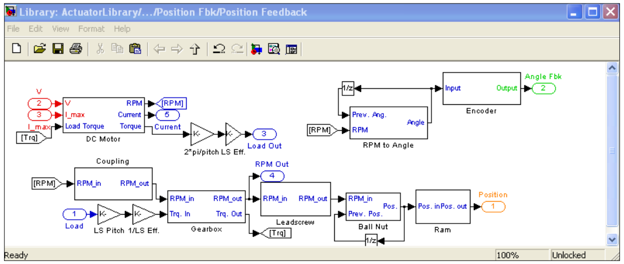
EMA

5 metric ton load capacity

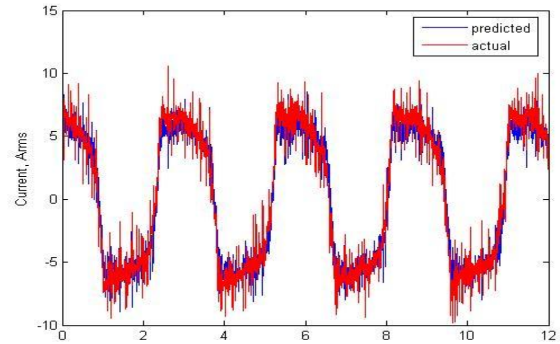
Data collection in laboratory…

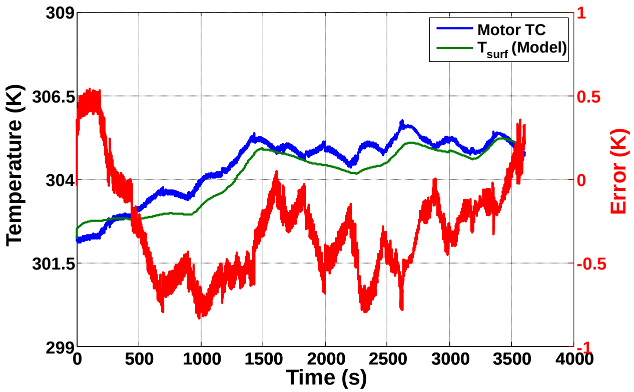
…and flight conditions

Physical Modeling



Model Verification





Flyable Electro-mechanical Actuator (FLEA) Testbed

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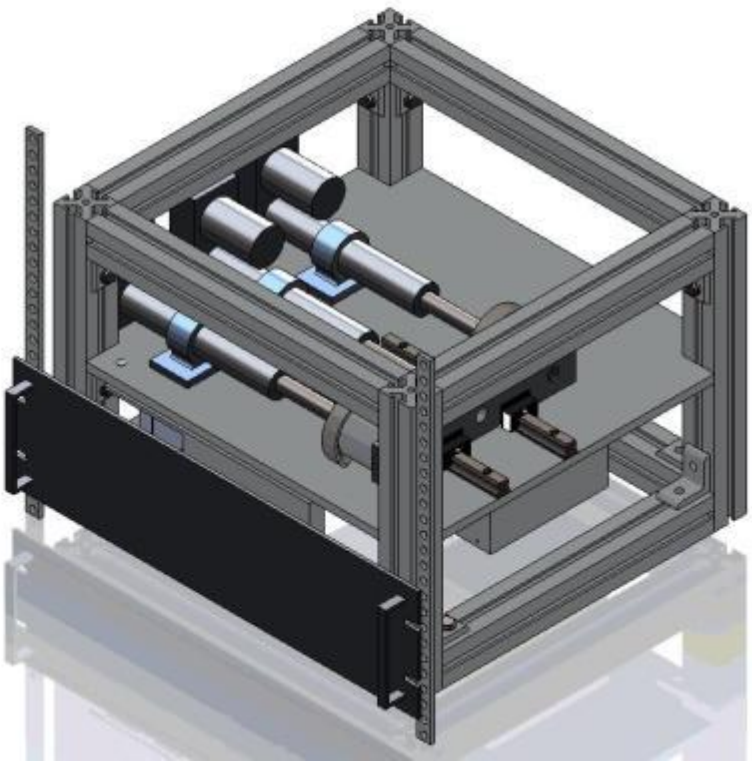
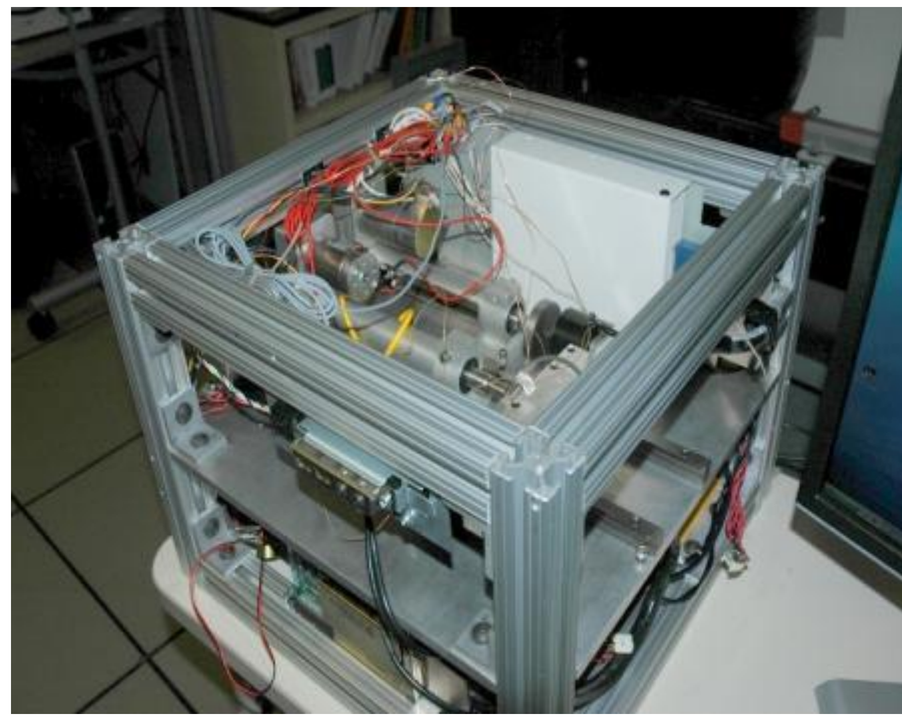


- Real-time flight surface loads simulation and data recording
- Data collection flights performed on C-17 (DFRC) and planned on UH-60 (ARC)

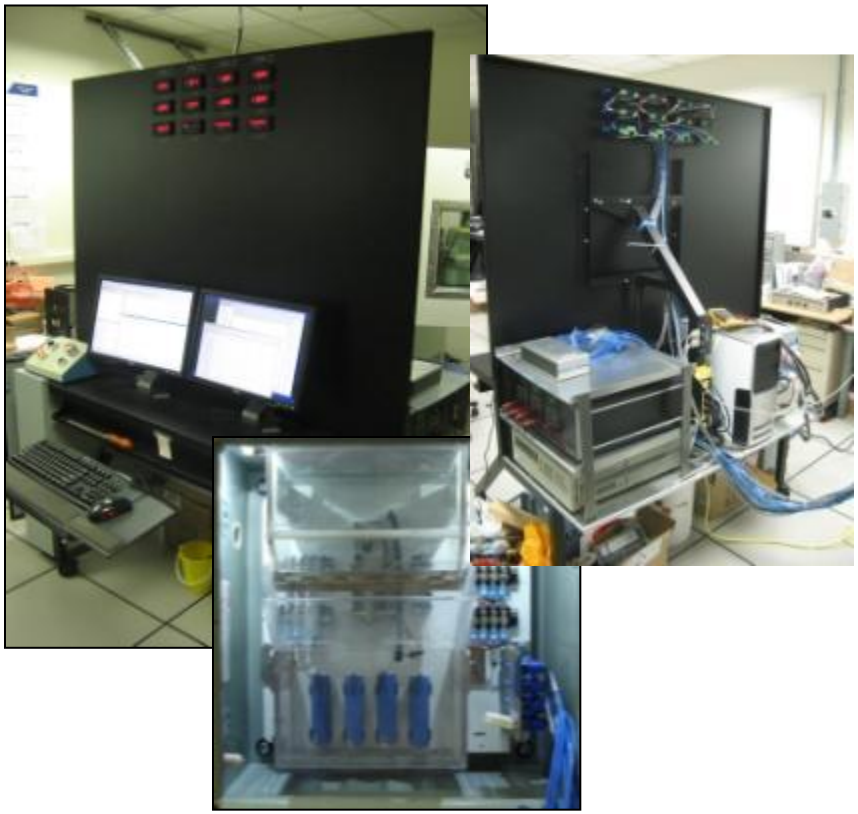
- One load actuator and two test actuators (nominal and faulty), switcheable in flight
- Sensor suite includes accelerometers, current sensors, position sensors, temperature sensors and a load cell



Demonstration

Application Example: Energy Storage Devices

Prognostics HIL Testbed



- Demonstrate prognostic algorithm performance
  - Fast
  - Inexpensive
  - Control of several run-to-failure parameters
  - Interesting dynamics
- Evaluate different prediction algorithms and uncertainty management schemes

Modeling Batteries

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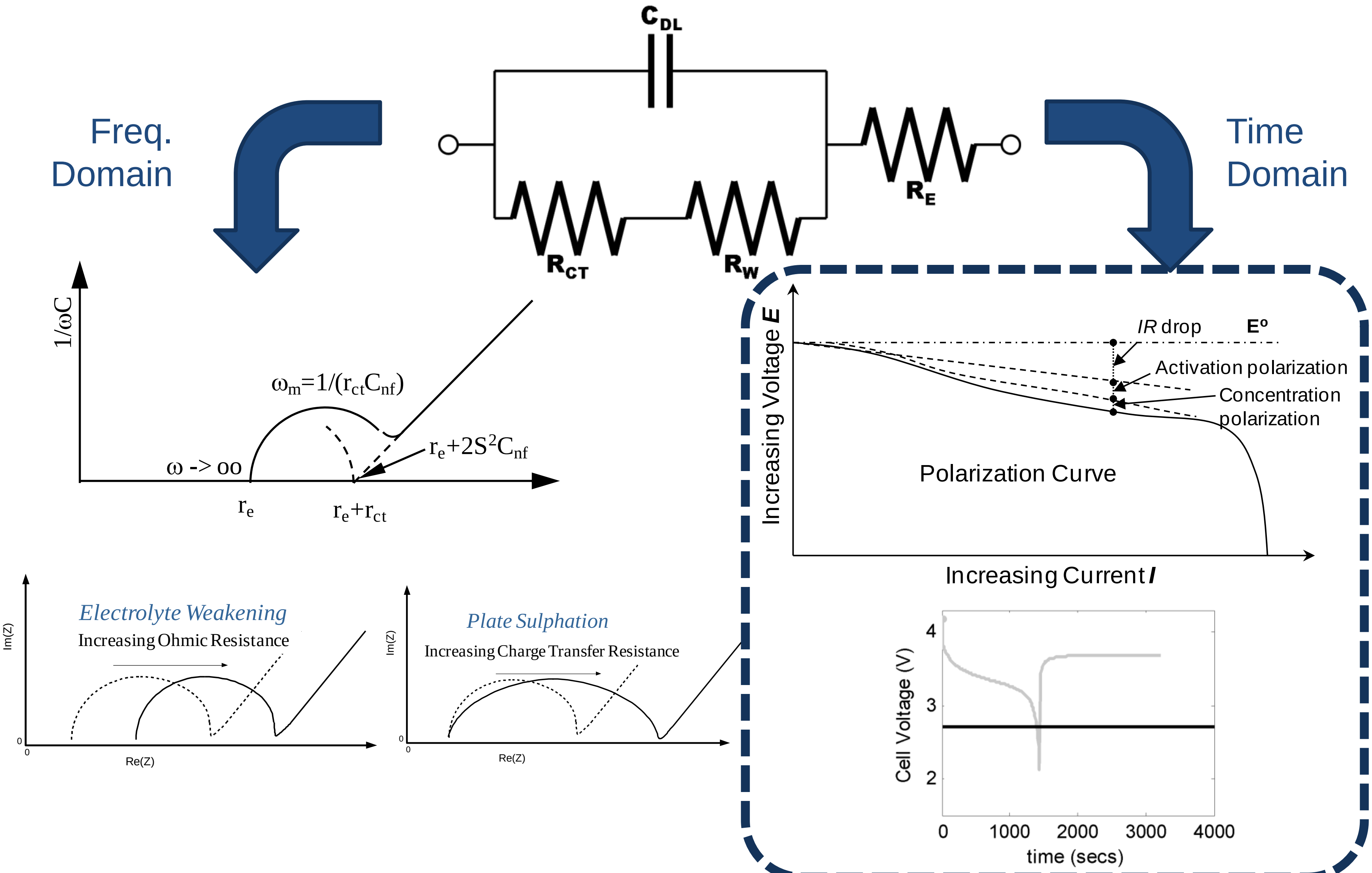

Modeling SOC

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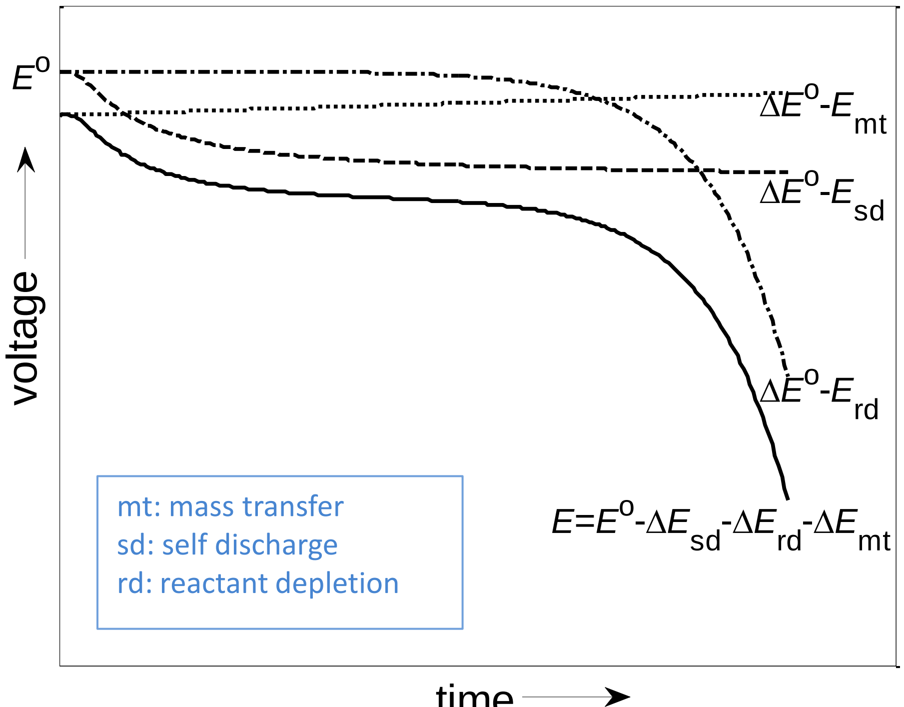
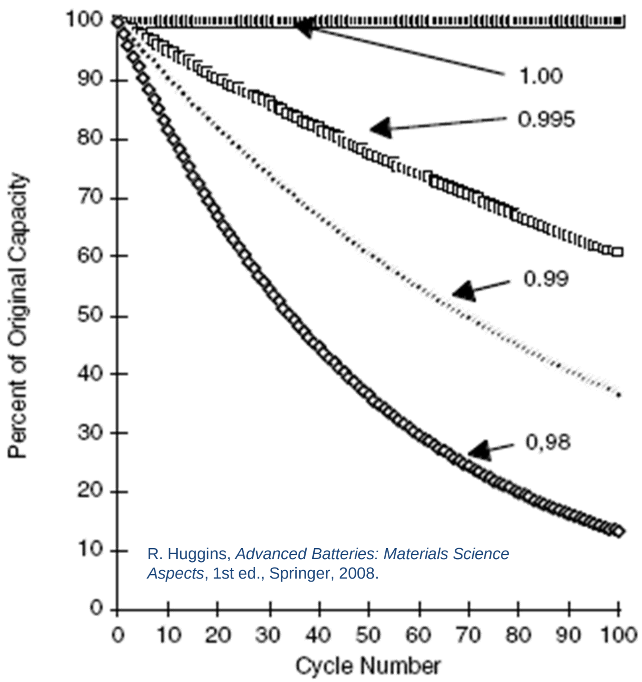
- Objective: Predict when Li-ion battery voltage will dip below 2.7V indicating end-of-discharge (EOD)
- Approach
  - Model non-linear electro-chemical phenomena that explain the discharge process
  - Learn model parameters from training data
  - Let the PF framework fine tune the model during the tracking phase
  - Use the tuned model to predict EOD



Modeling SOL

- Objective: Predict when Li-ion battery capacity will fade by 30% indicating life (EOL)
- Approach
  - Model self-recharge and Coulombic efficiency that explain the aging process
  - Learn model parameters from training data
  - Let the PF framework fine tune the model during a few initial cycles
  - Use the tuned model to predict EOL



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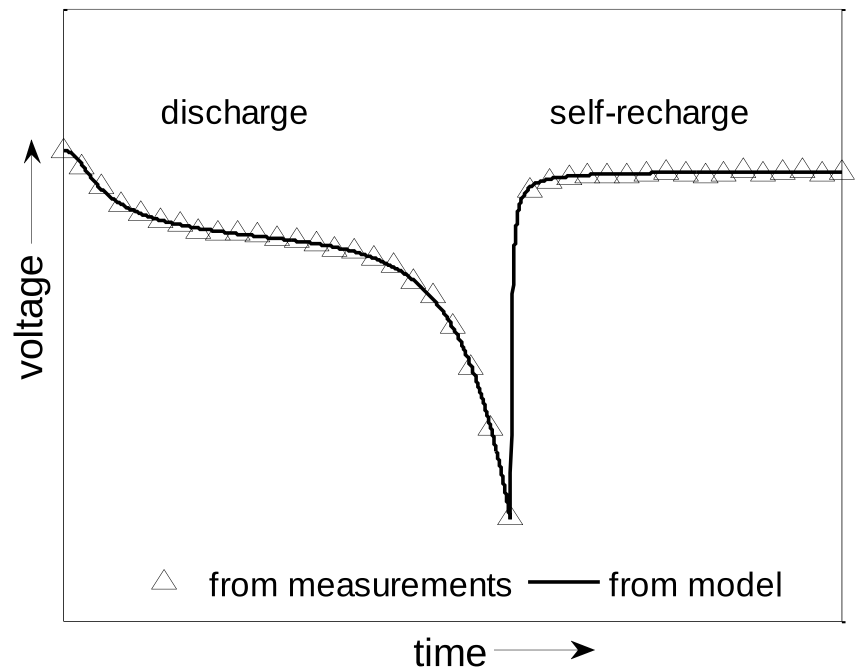
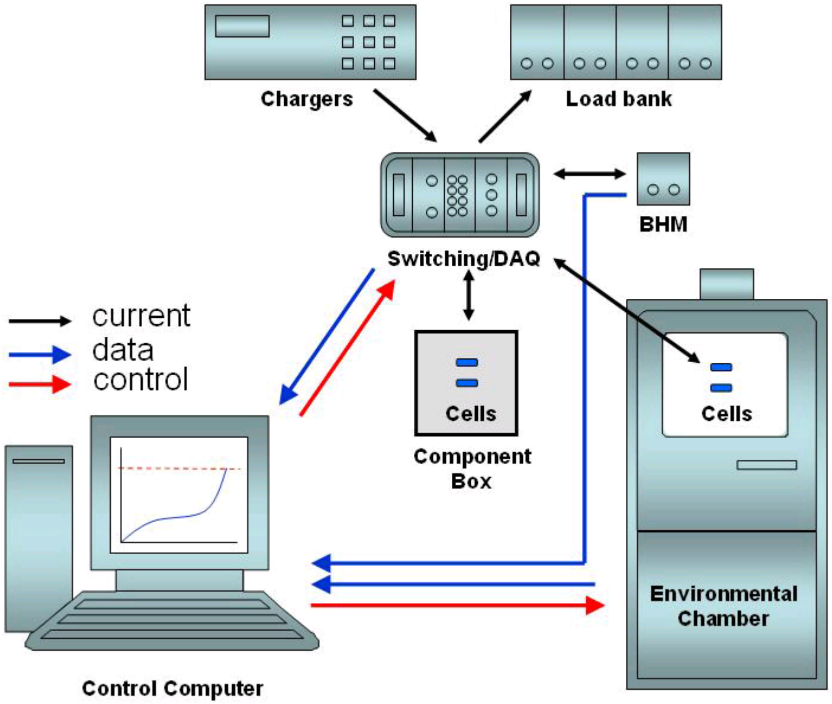
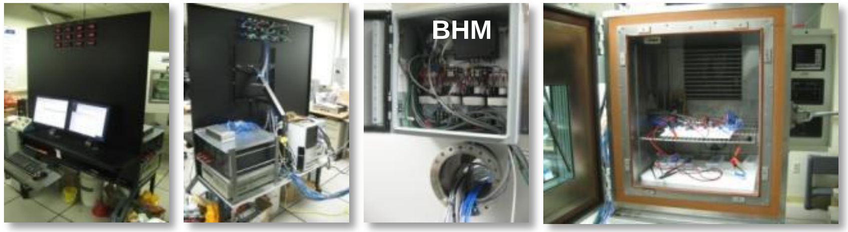


Battery Testbed

- Cells are cycled through charge and discharge under different load and environmental conditions set by the electronic load and environmental chamber respectively
- Periodically EIS measurements are taken to monitor the internal condition of the battery
- DAQ system collects externally observable parameters from the sensors
- Switching circuitry enables cells to be in the charge, discharge or EIS health monitoring state as dictated by the aging regime





EIS: Electro-chemical Impedance Spectroscopy

Prognostics in Action

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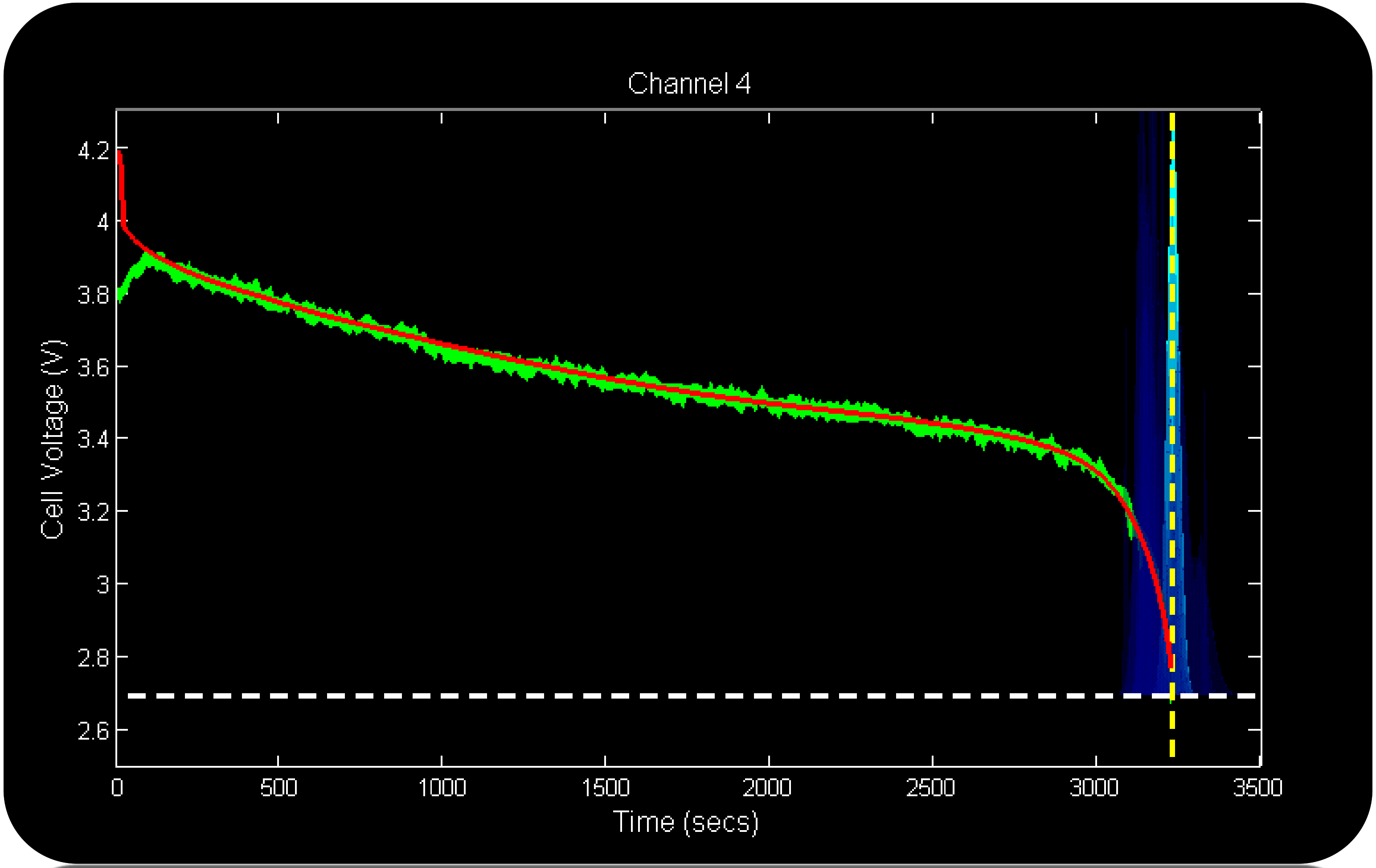

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