# Model Based Diagnostics and Prognostics Framework for Systems Health Management

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**Advanced Composites Technology Review**

**Stanford University**

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# Overview

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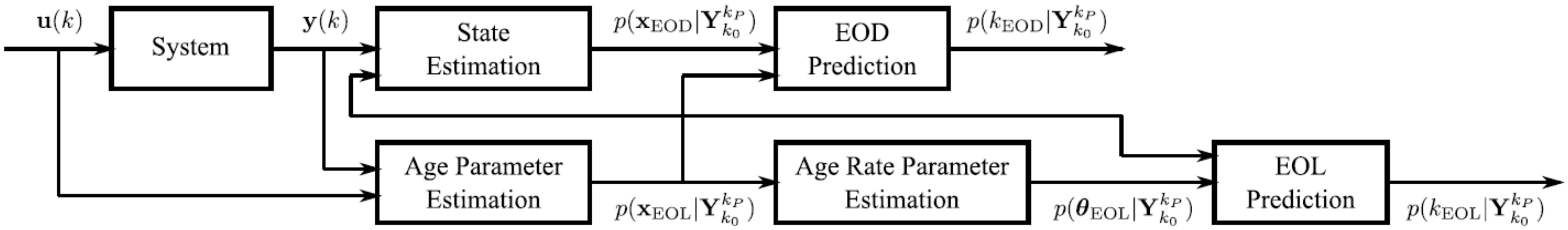
- Goals
  - Understand system behavior through dynamic models
  - Develop model-based algorithms for state estimation, end of discharge (EOD) prediction, and end of life (EOL) prediction
  - Validate algorithms in the lab and fielded applications
- Algorithms
  - Dynamic state and parameter estimation
  - Uncertainty Representation
  - Prognostics
- Models
  - Electric circuit equivalent (for EOD prediction)
  - Electrochemistry-based model (for EOD and EOL prediction)
- Laboratory capabilities and fielded systems
  - MACCOR battery tester, environmental test chamber
  - Planetary rover testbed
  - Subscale electric aircraft (Edge 540)
  - UAVs vehicles and testbed

# Prognostics Architecture






- System gets input and produces output
- Estimation module estimates the states and parameters, given system inputs and outputs
  - Must handle sensor noise
  - Must handle process noise
- For some event $E$, e.g., end-of-discharge or end-of-life, prediction module predicts $k_E$
  - Must handle state-parameter uncertainty at $k_P$
  - Must handle future process noise trajectories
  - Must handle future input trajectories
  - A diagnosis module can inform the prognostics what model to use
- In model-based approaches, require a dynamic model of the battery

# State Estimation

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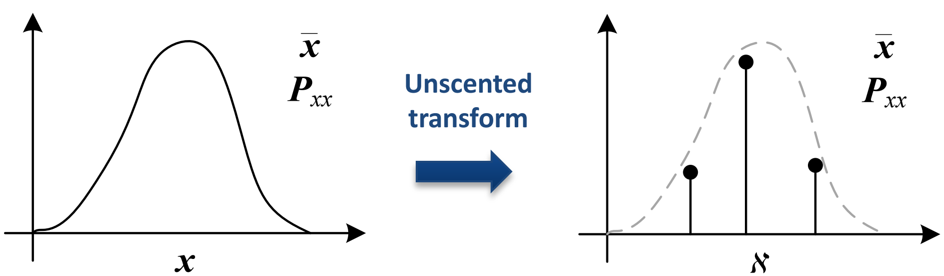
- What is the current system state and its associated uncertainty?
  - Input: system outputs $y$ from $k_0$ to $k$, $y(k_0{:}k)$
  - Output: $p(x(k),\theta(k)|y(k_0{:}k))$
- Most of the models are nonlinear e.g battery, so require nonlinear state estimator (e.g., extended Kalman filter, particle filter, unscented Kalman filter)
- Use unscented Kalman filter (UKF)
  - Straightforward to implement and tune performance
  - Computationally efficient (number of samples linear in size of state space)

# Unscented Kalman Filter

- The UKF is an approximate nonlinear filter, and assumes additive, Gaussian process and sensor noise
- Handles nonlinearity by using the concept of sigma points
  - Transform mean and covariance of state into set of samples, called sigma points, selected deterministically to preserve mean and covariance
  - Sigma points are transformed through the nonlinear function and recover mean and covariance of transformed sigma points




$$w^i = \begin{cases} \dfrac{\kappa}{(n_x + \kappa)}, & i = 0 \\ \dfrac{1}{2(n_x + \kappa)}, & i = 1, \ldots, 2n_x \end{cases}$$

$$\mathcal{X}^i = \begin{cases} \bar{\mathbf{x}}, & i = 0 \\ \bar{\mathbf{x}} + \left(\sqrt{(n_x+\kappa)\mathbf{P}_{xx}}\right)^i, & i = 1, \ldots, n_x \\ \bar{\mathbf{x}} - \left(\sqrt{(n_x+\kappa)\mathbf{P}_{xx}}\right)^i, & i = n_x+1, \ldots, 2n_x \end{cases}$$

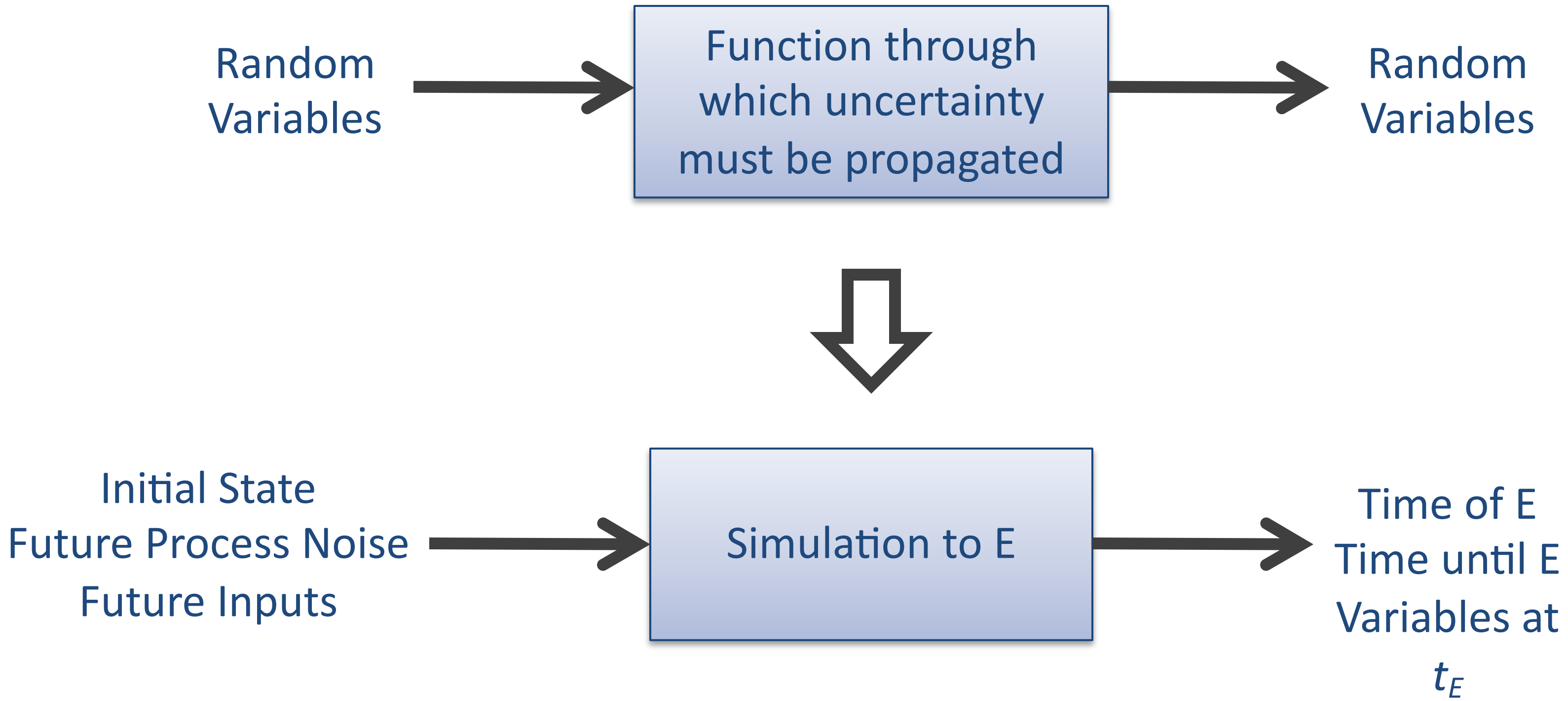
**Symmetric Unscented Transform**

- Number of sigma points is linear in the size of the state dimension

# Prediction

- What is $k_E$ and what is its uncertainty?
  – Input: $p(x(k),\theta(k)|y(k_0:k))$
  – Output: $p(k_E)$
- Most algorithms operate by simulating samples forward in time until $E$
- Algorithms must account for several sources of uncertainty besides that in the initial state
  – A representation of that uncertainty is required for the selected prediction algorithm
  – A specific description of that uncertainty is required (e.g., mean, variance)

# Uncertainty Quantification



# Uncertainty Representation

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- To predict $k_E$, need to account for following sources of uncertainty:
  - Initial state at $k_P$: $\mathbf{x}(k_p)$
  - Parameter values for $k_P$ to $k_E$: $\mathbf{\Theta}_{k_P}$
  - Inputs for $k_P$ to $k_E$: $\mathbf{U}_{k_P}$
  - Process noise for $k_P$ to $k_E$: $\mathbf{V}_{k_P}$
- Trajectories represented indirectly through parameterized equations describing the trajectories, where probability distributions for the parameters are specified
  - Sample these parameter variables to sample a trajectory
  - For example, constant power trajectory represented through $u(k) = c$, for all $k > k_P$, where $c$ is random

# Prediction Algorithm



- The $\mathtt{P}$ function takes an initial state, and a parameter, an input, and a process noise trajectory
  - Simulates state forward using $\mathbf{f}$ until $E$ is reached to computes $k_E$ for a single sample
- Top-level prediction algorithm calls $\mathtt{P}$
  - These algorithms differ by how they compute samples upon which to call $\mathtt{P}$
- Monte Carlo algorithm ($\mathtt{MC}$) takes as input
  - Initial state-parameter estimate
  - Probability distributions for the surrogate variables for the parameter, input, and process noise trajectories
  - Number of samples, $N$
- $\mathtt{MC}$ samples from its input distributions, and computes $k_E$
- The "$\mathtt{construct}$" functions describe how to construct a trajectory given trajectory parameters

**Algorithm 1** $k_E(k_P) \leftarrow \mathtt{P}(\mathbf{x}(k_P), \mathbf{\Theta}_{k_P}, \mathbf{U}_{k_P}, \mathbf{V}_{k_P})$

$k \leftarrow k_P$

$\mathbf{x}(k) \leftarrow \mathbf{x}(k_P)$

**while** $T_E(\mathbf{x}(k), \mathbf{\Theta}_{k_P}(k), \mathbf{U}_{k_P}(k)) = 0$ **do**

    $\mathbf{x}(k+1) \leftarrow \mathbf{f}(k, \mathbf{x}(k), \mathbf{\Theta}_{k_P}(k), \mathbf{U}_{k_P}(k), \mathbf{V}_{k_P}(k))$

    $k \leftarrow k + 1$

    $\mathbf{x}(k) \leftarrow \mathbf{x}(k+1)$

**end while**

$k_E(k_P) \leftarrow k$

**Algorithm 2** $\{k_E^{(i)}\}_{i=1}^N = \mathtt{MC}(p(\mathbf{x}(k_P), \boldsymbol{\theta}(k_P)|\mathbf{y}(k_0{:}k_P)), p(\boldsymbol{\lambda}_\theta), p(\boldsymbol{\lambda}_u), p(\boldsymbol{\lambda}_v), N)$

**for** $i = 1$ **to** $N$ **do**

    $(\mathbf{x}^{(i)}(k_P), \boldsymbol{\theta}^{(i)}(k_P)) \sim p(\mathbf{x}(k_P), \boldsymbol{\theta}(k_P)|\mathbf{y}(k_0{:}k_P))$

    $\boldsymbol{\lambda}_\theta^{(i)} \sim p(\boldsymbol{\lambda}_\theta)$

    $\mathbf{\Theta}_{k_P}^{(i)} \leftarrow \mathtt{construct\Theta}(\boldsymbol{\lambda}_\theta^{(i)}, \boldsymbol{\theta}^{(i)}(k_P))$

    $\boldsymbol{\lambda}_u^{(i)} \sim p(\boldsymbol{\lambda}_u)$

    $\mathbf{U}_{k_P}^{(i)} \leftarrow \mathtt{constructU}(\boldsymbol{\lambda}_u^{(i)})$

    $\boldsymbol{\lambda}_v^{(i)} \sim p(\boldsymbol{\lambda}_v)$

    $\mathbf{V}_{k_P}^{(i)} \leftarrow \mathtt{constructV}(\boldsymbol{\lambda}_v^{(i)})$

    $k_E^{(i)} \leftarrow \mathtt{P}(\mathbf{x}^{(i)}(k_P), \mathbf{\Theta}_{k_P}^{(i)}, \mathbf{U}_{k_P}^{(i)}, \mathbf{V}_{k_P}^{(i)})$

**end for**

# Battery Prognostics

# Electrochemistry Battery Modeling

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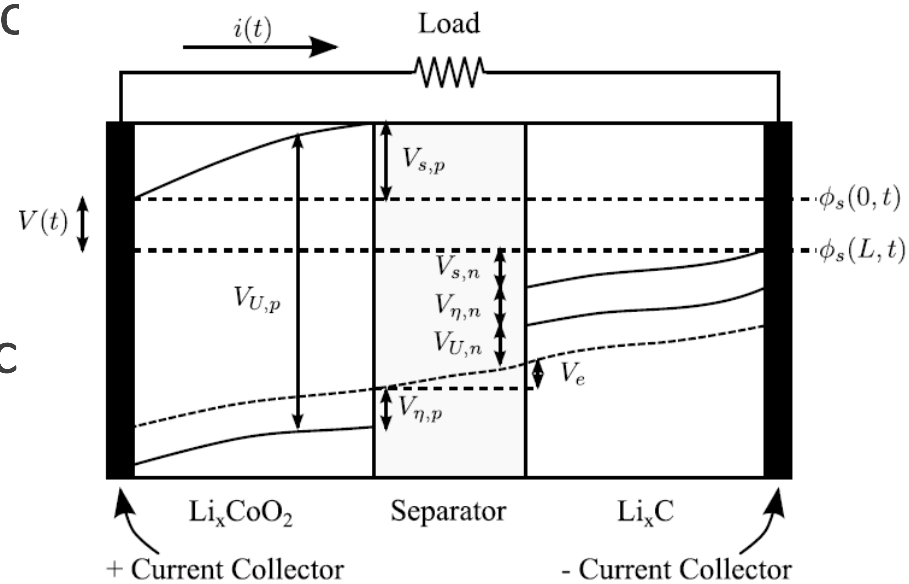
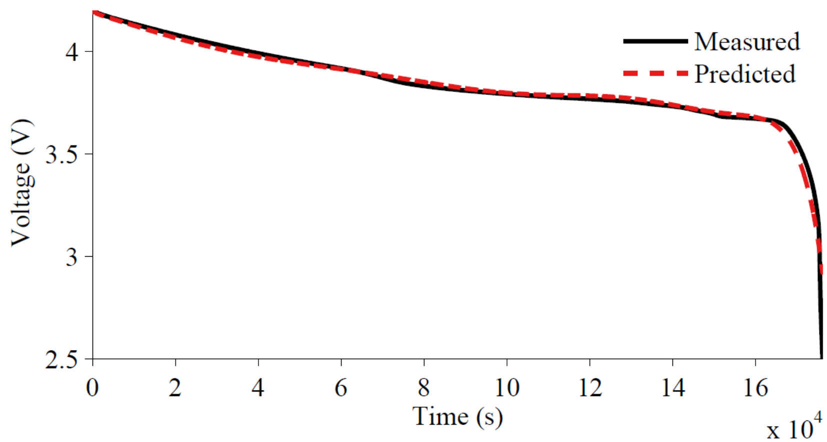
- Lumped-parameter, ordinary differential equations
- Capture voltage contributions from different sources
  - Equilibrium potential → Nernst equation with Redlich-Kister expansion
  - Concentration overpotential → split electrodes into surface and bulk control vc
  - Surface overpotential → Butler-Volmer equation applied at surface layers
  - Ohmic overpotential → Constant lumped resistanc accounting for current collector resistances, electrolyte resistance, solid-phase ohmic resistan

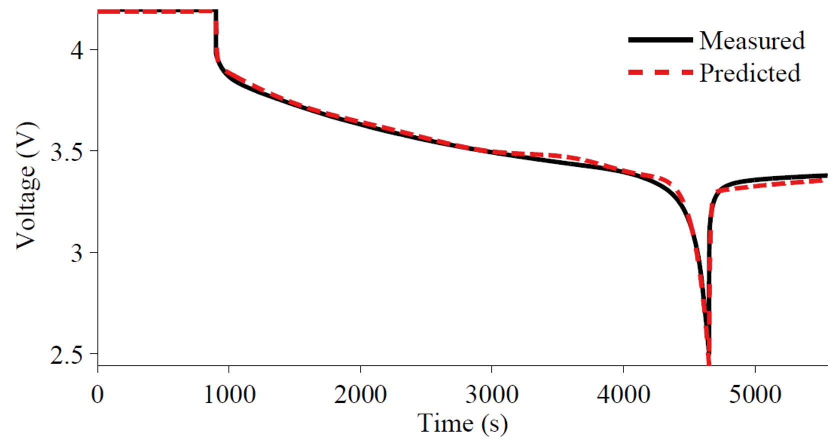


# Battery Model Validation



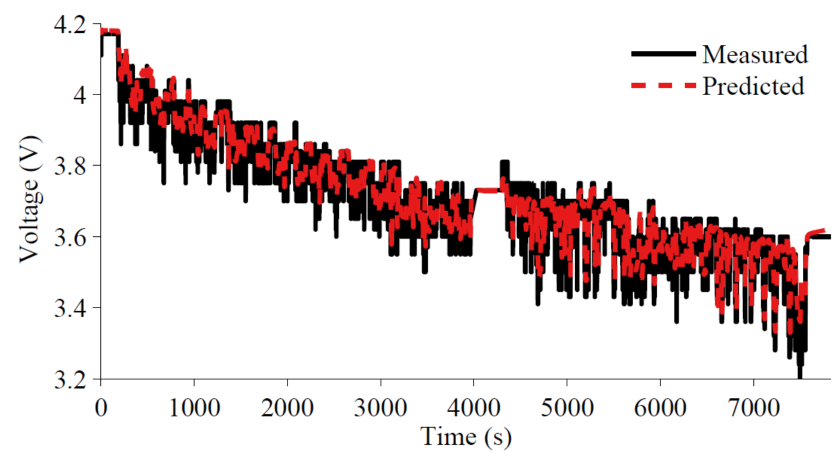



"Open-Circuit" Discharge Curve




Nominal 2A Discharge Curve

Model matches well for open-circuit, nominal discharge, and variable-load discharges on the rover.



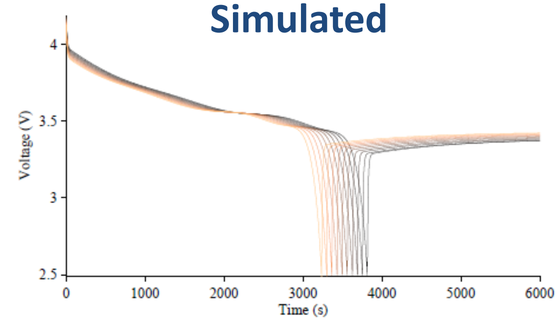

Rover Battery Discharge Curve

# Battery Aging

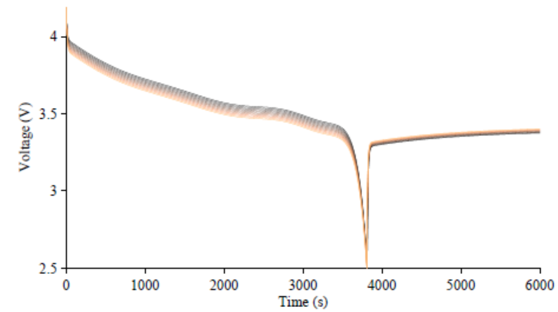


- Contributions from both decrease in mobile Li ions (lost due to side reactions related to aging) and increase in internal resistance
  - Modeled with decrease in "$q^{max}$" parameter, used to compute mole fraction
  - Modeled with increase in "$R_o$" parameter capturing lumped resistances

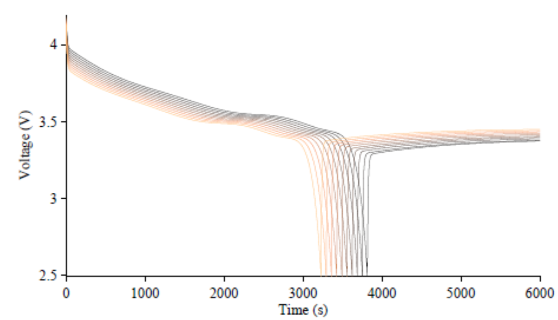
Simulated



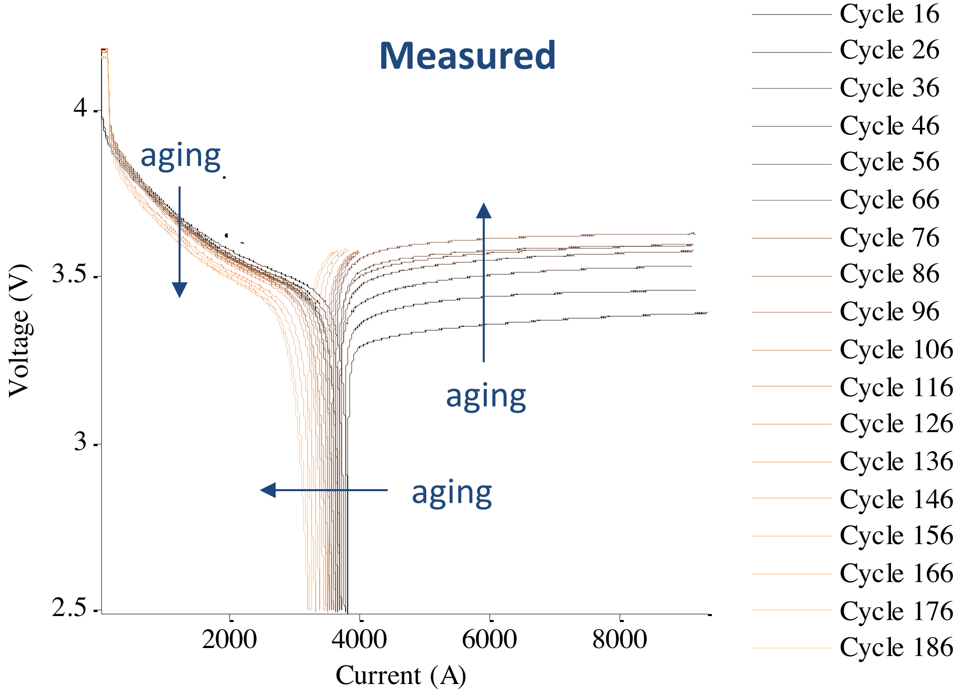

(a) Decreasing $q^{max}$.




(b) Decreasing $R_o$.



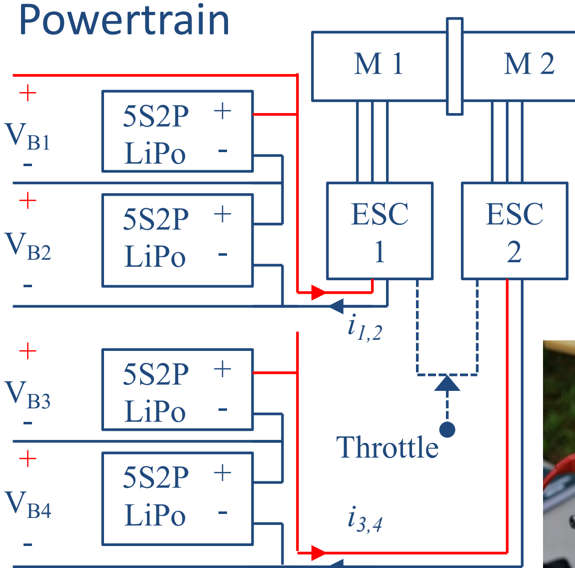

(c) Decreasing $q^{max}$ and $R_o$.

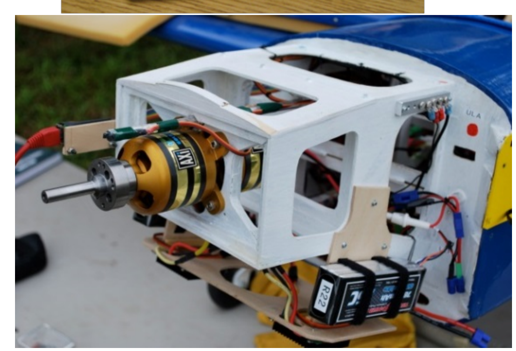


# Edge 540-T

- Subscale electric aircraft operated at NASA Langley Research Center
- Powered by four sets of Li-polymer batteries
- Estimate SOC online and provide EOD and remaining flight time predictions for ground-based pilots

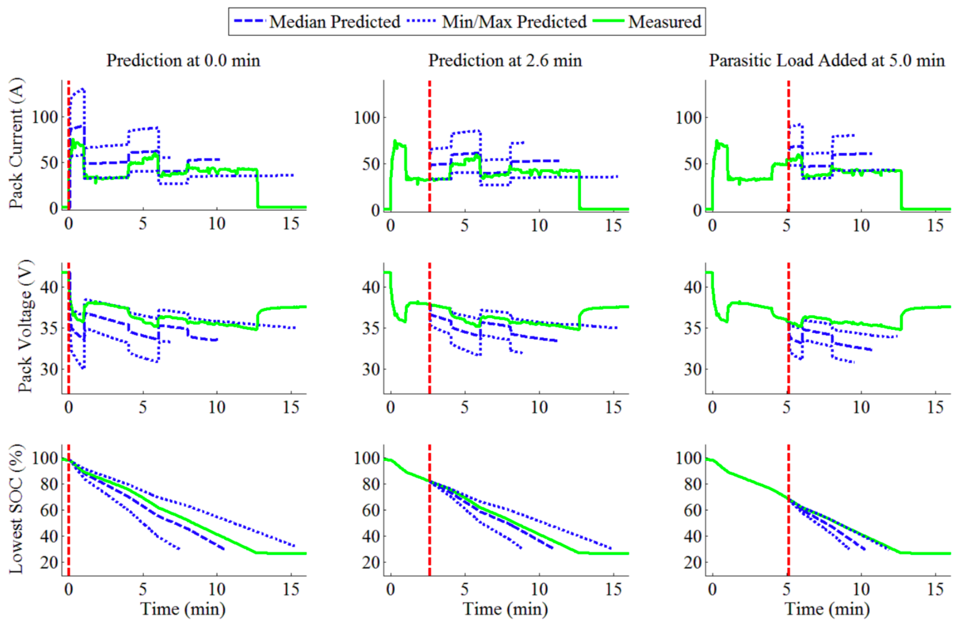
Powertrain



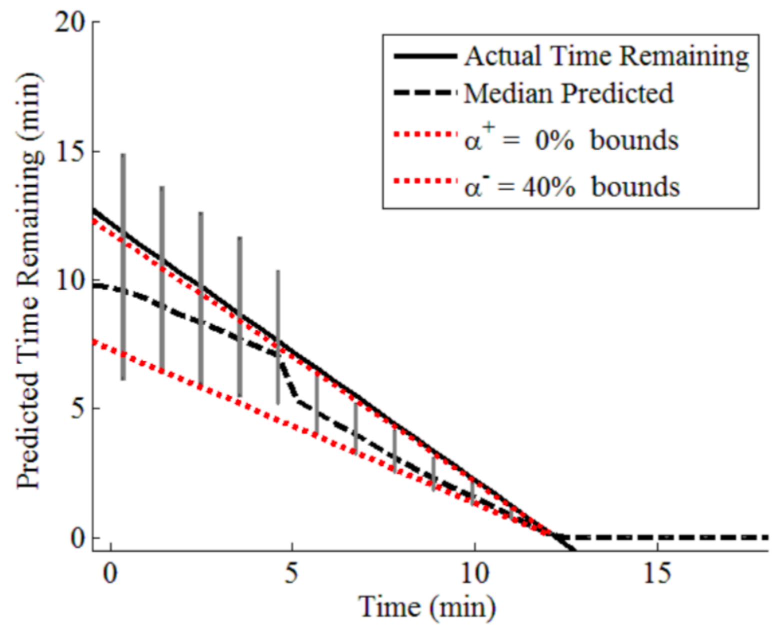



# Results: Edge

- Use UKF for state estimation with electrochemistry model



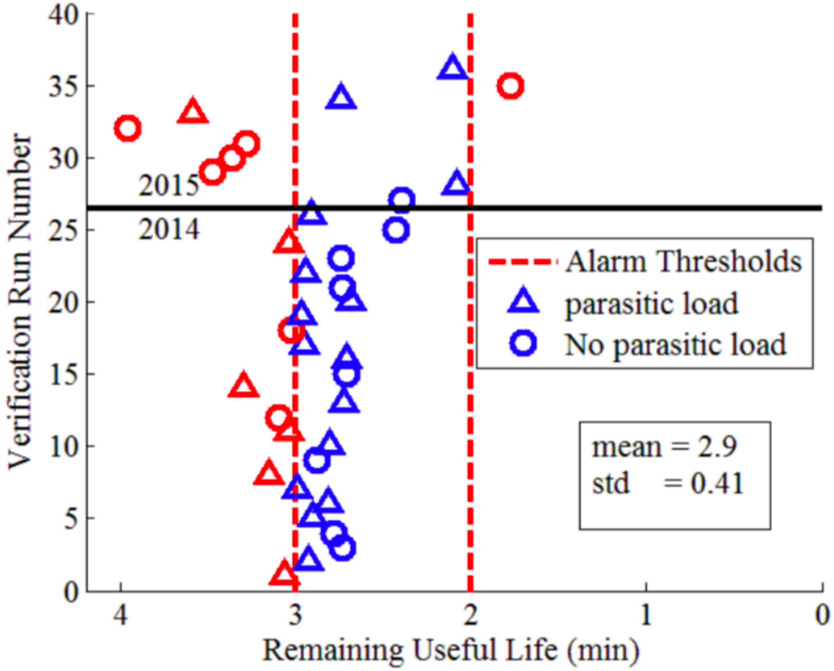

Example plot of measured and predicted battery current (top) and voltage (bottom) shown at three sample times over a trial battery discharge run



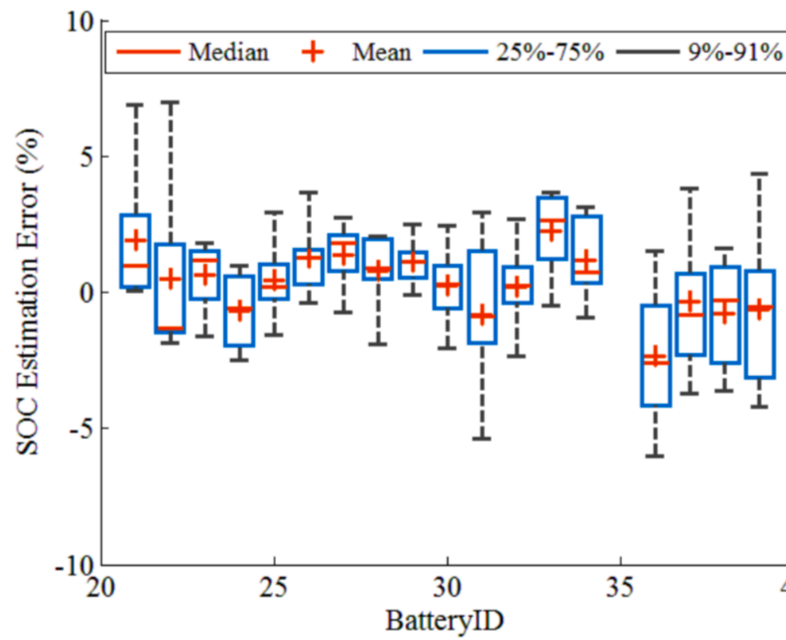

Predicted remaining flying time

# Results: Edge






Two-minute alarms for additional runs done a year later using revised battery capacity parameters.




SOC estimation error from 10 additional verification runs in 2015 (36 runs that each use 4 batteries)

# NDE Analysis and Prognostics

# NDE/SHM of Composites

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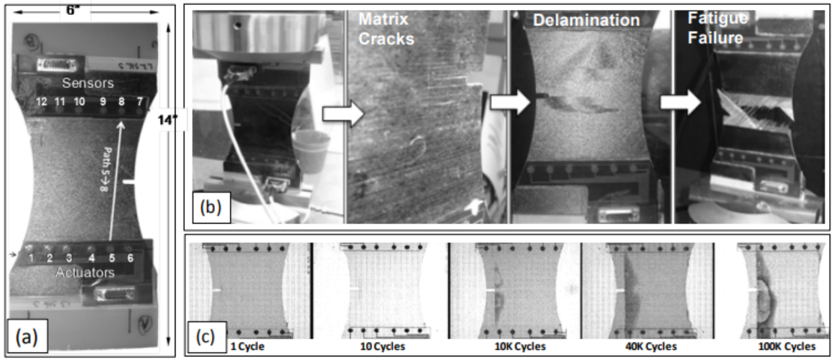
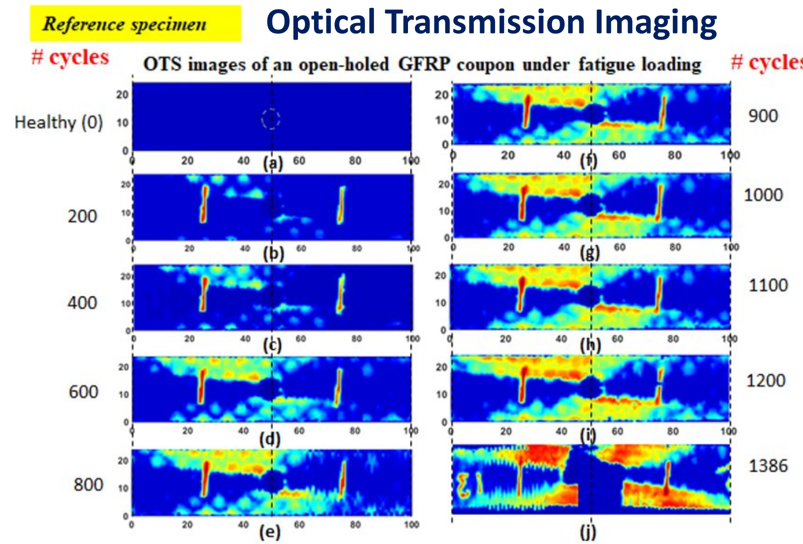
## X-ray Imaging

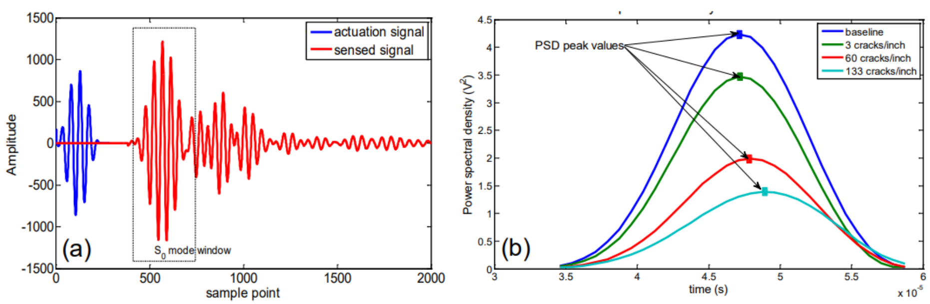



(a) Coupon specimen, SMART Layers location, and diagnostic path from actuator 5 to sensor 8. (b) Development of matrix cracks and delamination leading to fatigue failure. (c) Growth in delamination area in X-ray images.

## Optical Transmission Imaging

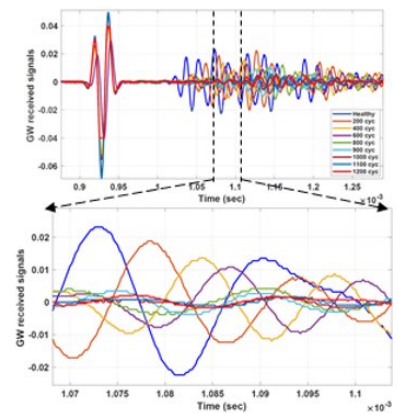



## Guided Wave Sensing




a) Isolating the first S0 mode by windowing the sensed signal. (b) Change in Power Spectral Density curves with increasing matrix crack density

## Guided Wave Sensing




Change in TOF with increasing delamination.

*Data extracted from Stanford SACL's fatigue tests on dog-bone CFRP specimens.

**Thanks to Prof. Fu-Kuo Chang, Dr. Cecilia Larrosa.**

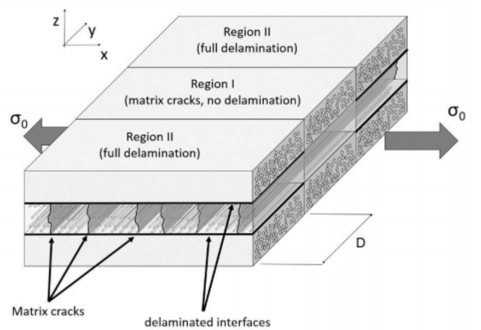
*Data extracted from Michigan State University NDE Lab's fatigue tests on notched GFRP specimens.

**Thanks to Prof. Yiming Deng, Prof. Mahmoodul Haq and Prof. Lalita Udpa.**

# Damage growth prediction in composites



- Investigate simple (yet robust) damage accumulation models for fiber-reinforced polymers that can be adopted in model-based prognostics.




**Zhang's model for a partially-delaminated cross-ply laminate**

**SERR and growth rates**

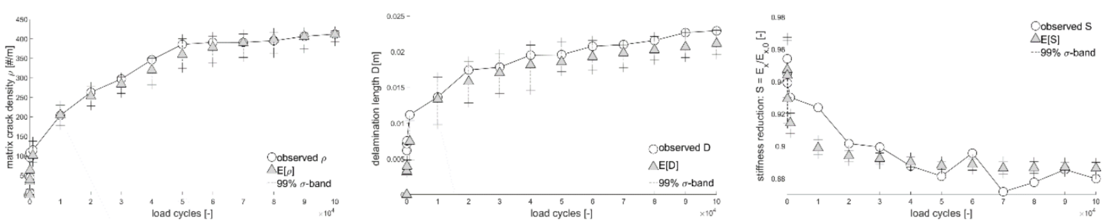
$$G = -\frac{\partial U}{\partial A} = f(\rho, D_x, D_y); \qquad \frac{d\rho}{dN} = f(G), \frac{dD_x}{dN} = f(G), \frac{dD_y}{dN} = f(G)$$

**State-space formulation**

$$\boldsymbol{x}_k = \begin{bmatrix} \rho_k \\ D_{y,k} \\ S_k \end{bmatrix} = \begin{bmatrix} \rho_k = \rho_{k-1} + \frac{d\rho}{dN}(\boldsymbol{\theta})\Big|_{k-1} e^{\omega_{\rho,k}} \\ D_{y,k} = D_{y,k-1} + \frac{dD_y}{dN}(\boldsymbol{\theta})\Big|_{k-1} e^{\omega_{D_y,k}} \\ S_k = \frac{E_{x,k}(\rho_k, D_{y,k})}{E_{x,0}} + \omega_{S,k} \end{bmatrix}$$

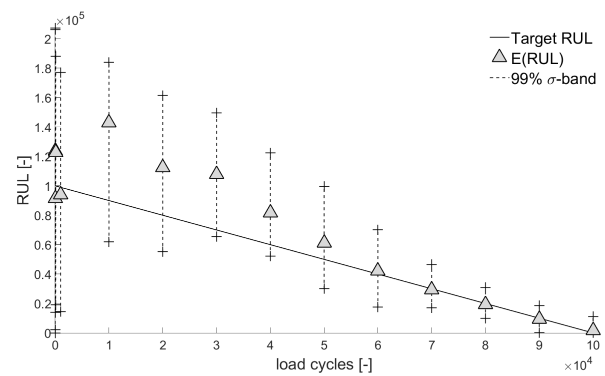
$$\boldsymbol{z}_k = \begin{bmatrix} \hat{\rho}_k \\ \hat{D}_{y,k} \\ \hat{S}_k \end{bmatrix} = \begin{bmatrix} \rho_k + \eta_{\rho,k} \\ D_{y,k} + \eta_{D_y,k} \\ S_k + \eta_{S,k} \end{bmatrix}$$

- Application of Bayesian filtering to fatigue damage progression




(a) (b) (c)

**Posterior estimation of the damage growth against load cycles; matrix crack density (a), delamination (b) and normalized stiffness (c)**




**RUL Prediction**

# Conclusions

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- Focus on model-based approaches for system  state estimation and prediction
- Hybrid approaches
- Validate models and algorithms with data from lab experiments and fielded systems
- Future work involves
  - Thermal models
  - Higher fidelity models
  - More efficient algorithms