Modeling for Battery Prognostics

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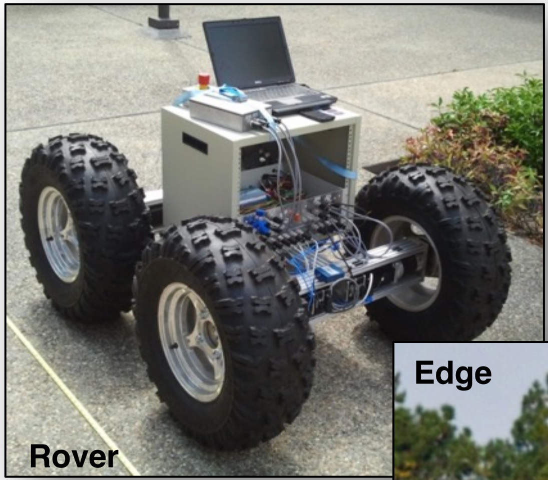
Motivation

- Batteries increasingly used in more and more systems as a power source
  - Electric cars
  - Electric aircraft
  - Space missions/small sats
  - Other electric utility vehicles
- Prediction of end-of-discharge (EOD) and end-of-life (EOL) are critical to system functions
  - How much longer can the system be used, given expected usage conditions?
  - How many more usage cycles until battery capacity is not sufficient for required system operations?

Solve using model-based prognostics approach.



Outline

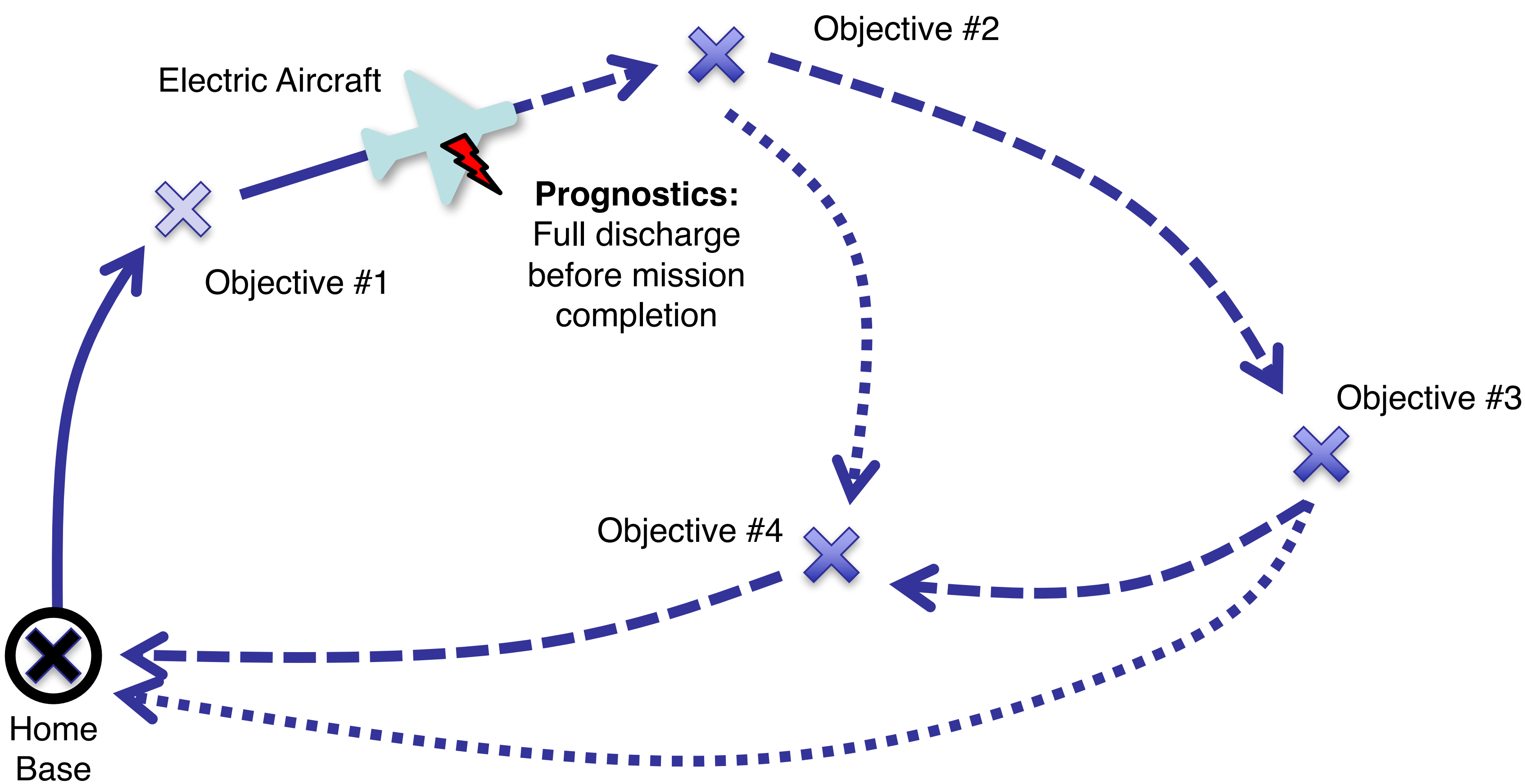
- Goals
  - Understand battery behavior through dynamic models
  - Develop model-based algorithms for state estimation, end of discharge (EOD) prediction, and end of life (EOL) prediction
  - Validate algorithms in the lab and fielded applications
- Algorithms
  - Prognostic Architecture
  - Dynamic state and state-of-charge estimation
- Modeling
  - Electric circuit equivalent (for EOD prediction)
  - Electrochemistry-based model (for EOD and EOL prediction)
- Applications
  - Edge 540-T electric UAV

Why Prognostics?

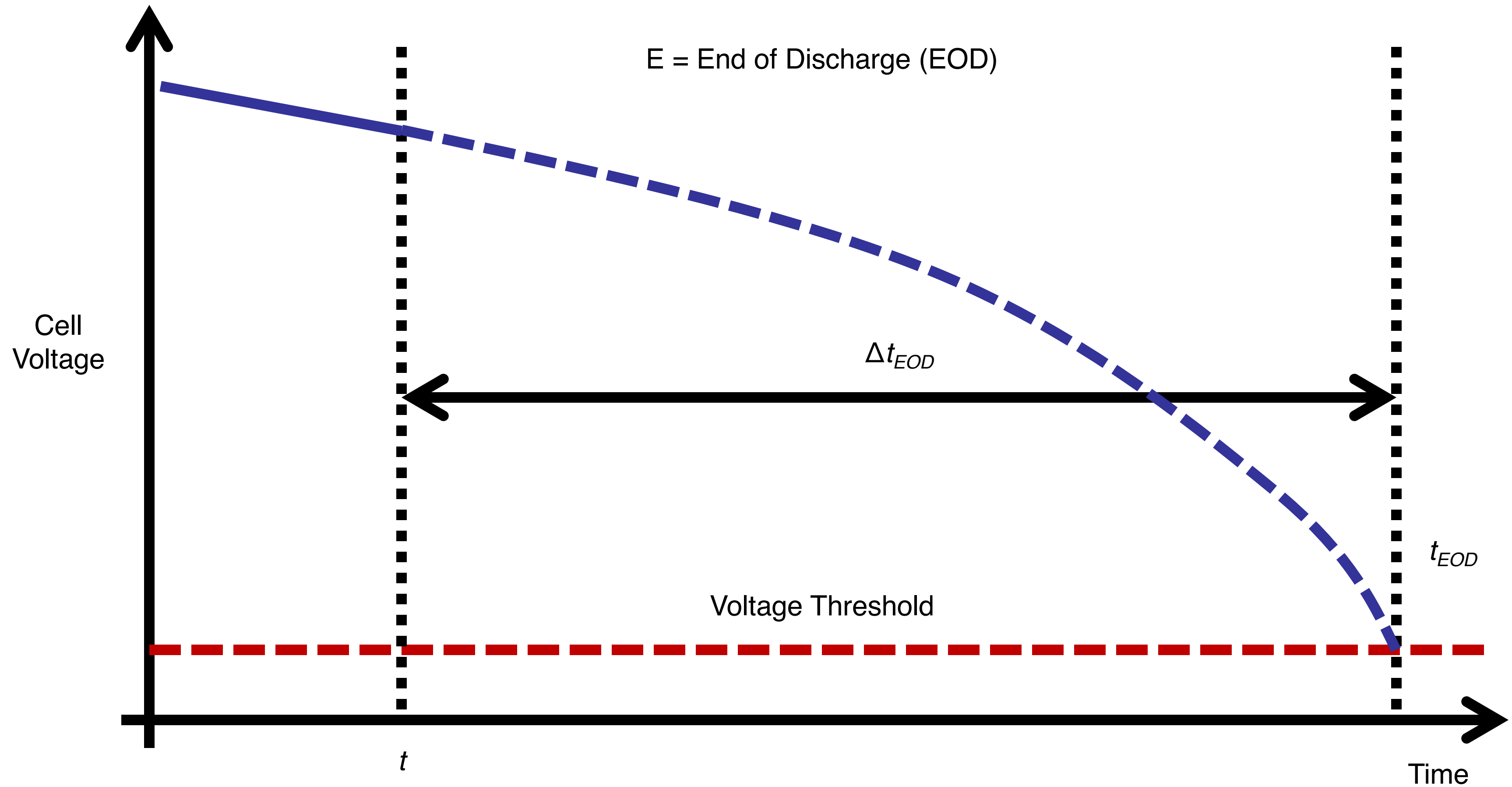
- Prognostics can enable:
  - Adopting condition-based maintenance strategies, instead of time-based maintenance
  - Optimally scheduling maintenance
  - Optimally planning for spare components
  - Reconfiguring the system to avoid using the component before it fails
  - Prolonging component life by modifying how the component is used (e.g., load shedding)
  - Optimally plan or replan a mission
- System operations can be optimized in a variety of ways

Why Prognostics?

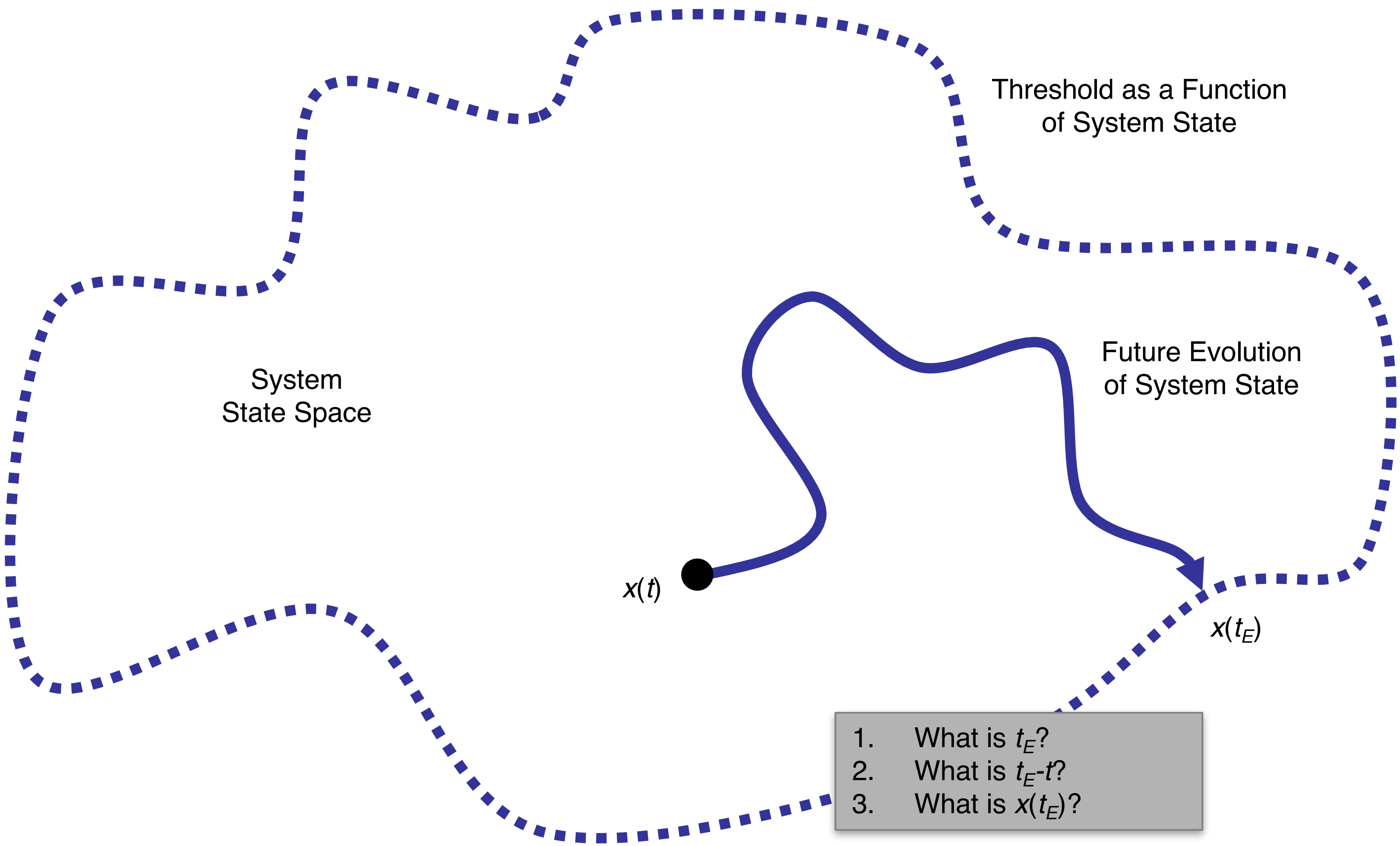
Example: UAV Mission
Visit waypoints to accomplish science objectives. Predict aircraft battery end of discharge to determine which objectives can be met. Based on prediction, plan optimal route. Replan if prediction changes.



The Basic Idea : Batteries Example



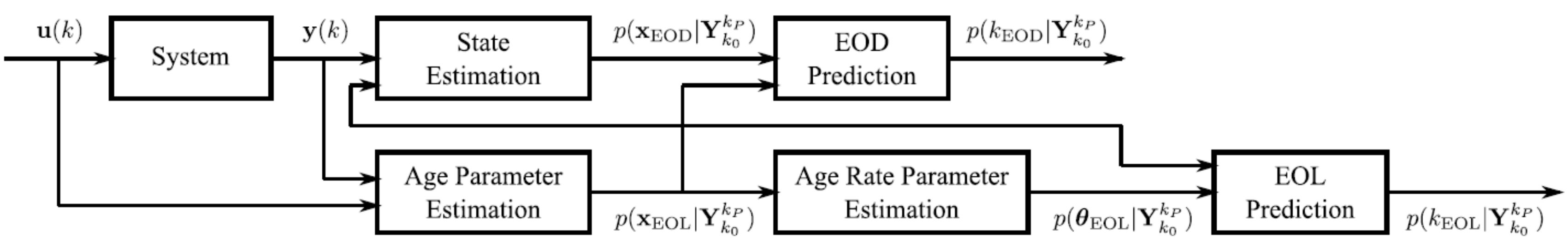
The Basic Idea : Batteries Example



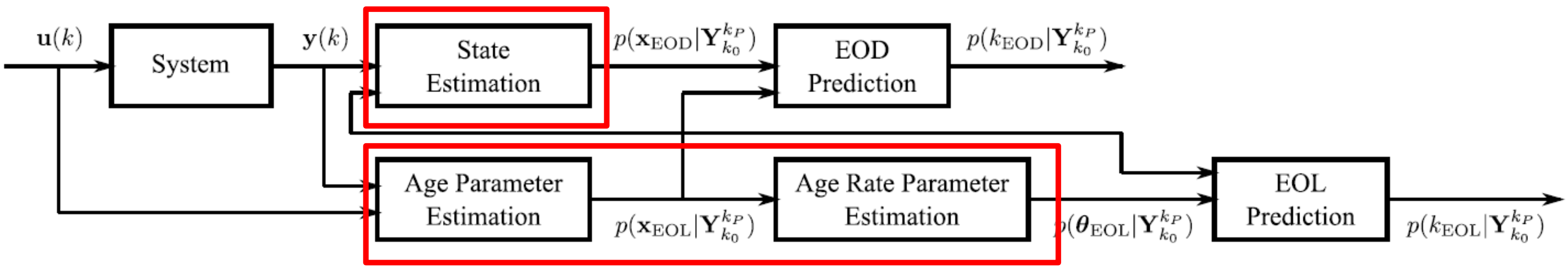
1. What is t_E?
2. What is t_E-t?
3. What is $x(t_E)$?

Integrated Prognostics Architecture

- System (battery) gets inputs (current) and produces outputs (voltage)
- State estimation computes estimate of state given estimates of age parameters
- EOD prediction computes prediction of time of EOD, given state and age parameter estimates
- Age parameter estimation computes estimates of age parameters
- Age rate parameter estimation computes parameters defining aging rate progression
- EOL prediction computes prediction of time of EOL, given age parameter and age rate parameter estimates

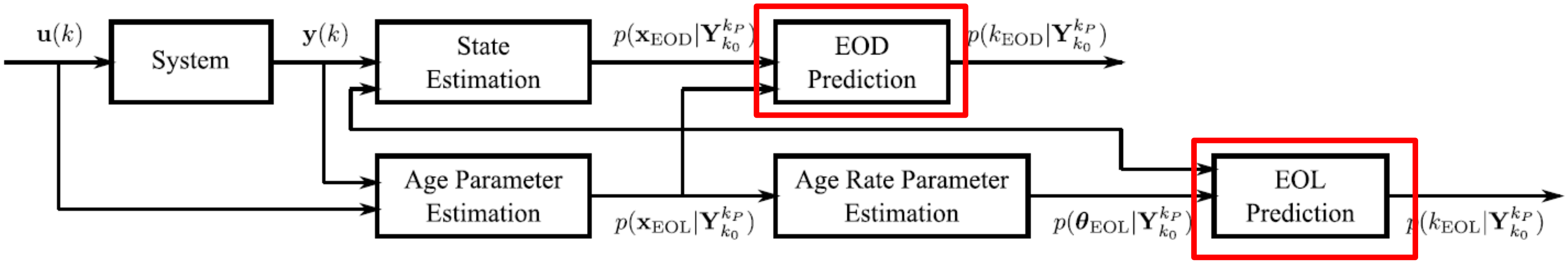


State Estimation



- Battery models are nonlinear, so require nonlinear state estimator (e.g., extended Kalman filter, particle filter, unscented Kalman filter)
- Estimate Aging/Degradation
- Use unscented Kalman filter (UKF)
  - Straight forward to implement and tune performance
  - Computationally efficient (number of samples linear in size of state space)

Prediction



- 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)

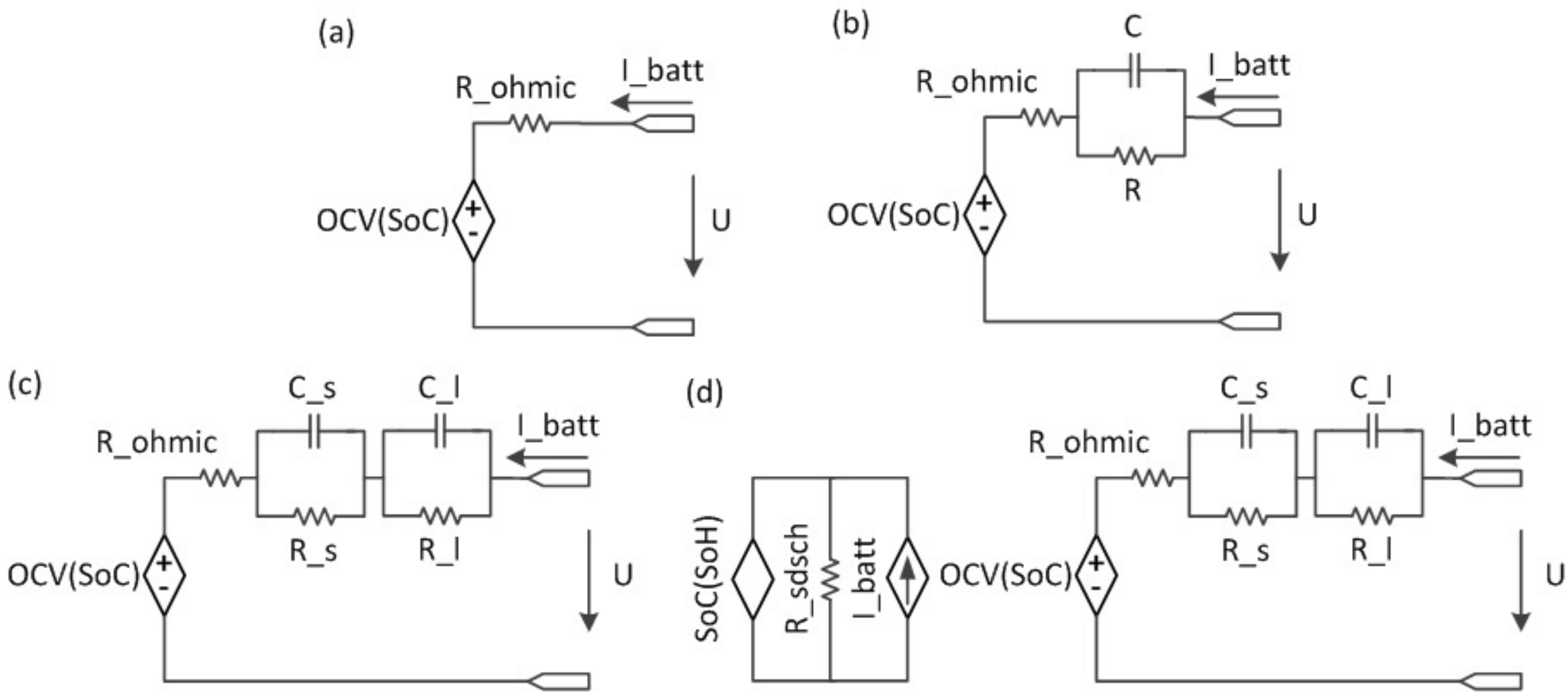
Uncertainty Representation

- 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

Battery Modeling

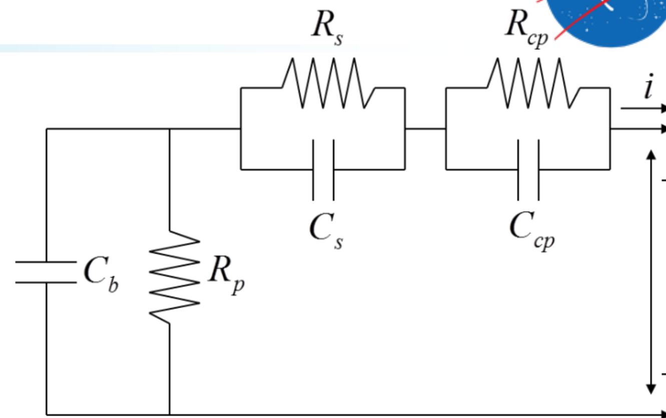
– Equivalent Circuit Empirical Models

- Most common approach
- Various model complexities used
- Difficulty in incorporating aging effects



Battery Model– Tuned using laboratory data

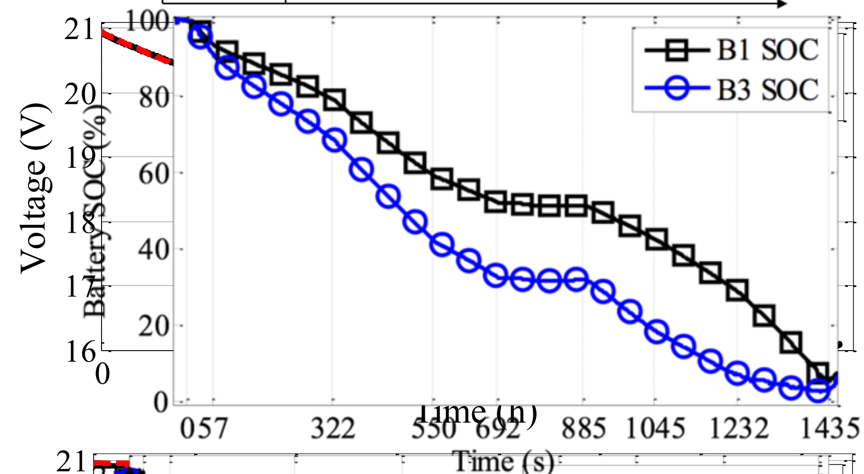
- An equivalent circuit battery model is used to represent the battery terminal voltage as a function of current and the charge stored in 3 capacitive elements



$$x = [q_b \; q_{cp} \; q_{Cs}]^T$$

$$\dot{x} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & -\frac{1}{R_{cp}C_{cp}} & 0 \\ 0 & 0 & -\frac{1}{R_s C_s} \end{bmatrix} x + \begin{bmatrix} -1 \\ 1 \\ 1 \end{bmatrix} i + \xi$$

$$y = V = \begin{bmatrix} \frac{1}{C_b} & -\frac{1}{C_{cp}} & -\frac{1}{C_s} \end{bmatrix} \cdot x$$



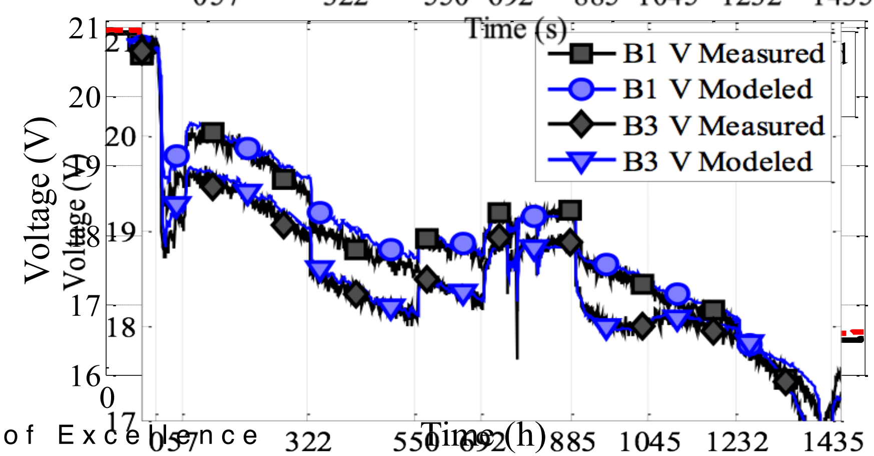
- Two laboratory loading experiments are used to fit the following parameterization coefficients

$$\mathrm{SOC} = 1 - \frac{q_{max} - q_b}{C_{max}}$$

$$C_b = C_{Cb0} + C_{Cb1} \cdot \mathrm{SOC} + C_{Cb2} \cdot \mathrm{SOC}^2 + C_{Cb3} \cdot \mathrm{SOC}^3$$

$$C_{cp} = C_{cp0} + C_{cp1} \cdot \exp\left(C_{cp2}\left(1 - \mathrm{SOC}\right)\right)$$

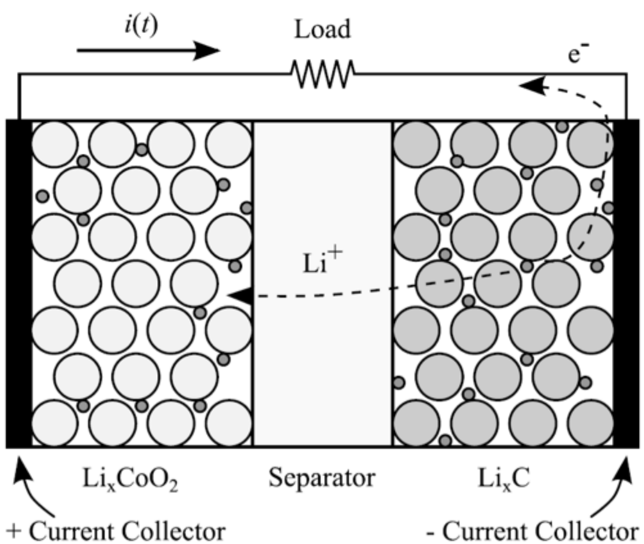
$$R_{cp} = R_{cp0} + R_{cp1} \cdot \exp\left(R_{cp2}\left(1 - \mathrm{SOC}\right)\right)$$

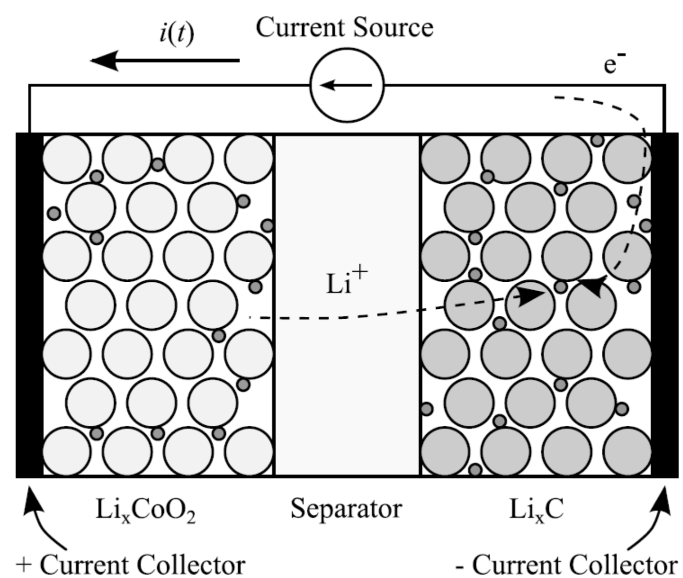


Battery Modeling

– Electrochemical Models vs. Empirical Models

- Battery physics models enable more direct representation of age-related changes in battery dynamics than empirical models
- Typically have a higher computational cost and more unknown parameters





Discharge

Reduction at pos. electrode:

$Li_{1-n}CoO_2 + nLi^+ + ne^- \rightarrow LiCoO_2$

Oxidation at neg. electrode:

$Li_nC \rightarrow nLi^+ + ne^- + C$

Current flows + to –

Electrons flow – to +

Lithium ions flow – to +

Charge

Oxidation at pos. electrode:

$LiCoO_2 \rightarrow Li_{1-n}CoO_2 + nLi^+ + ne^-$

Reduction at neg. electrode:

$nLi^+ + ne^- + C \rightarrow Li_nC$

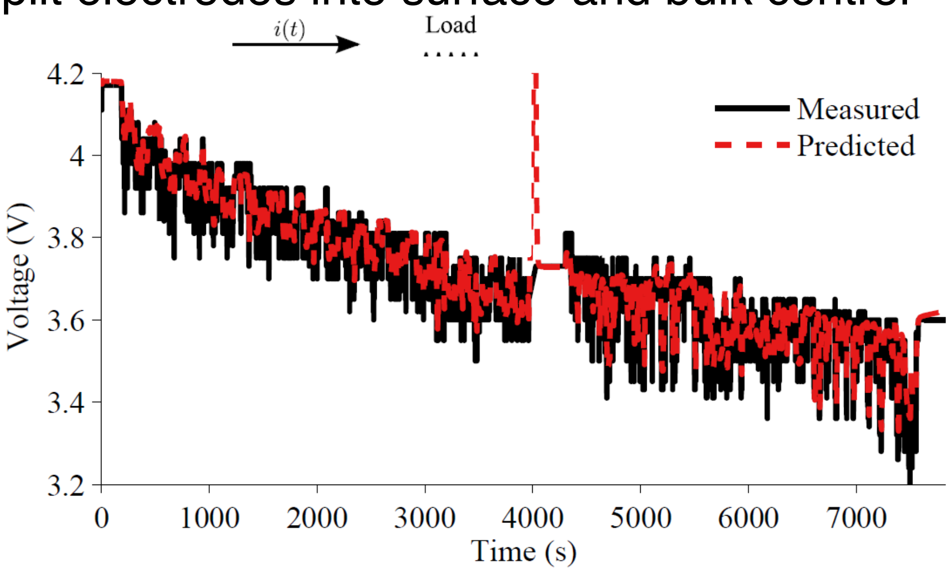
Current flows – to +

Electrons flow + to –

Lithium ions flow + to –

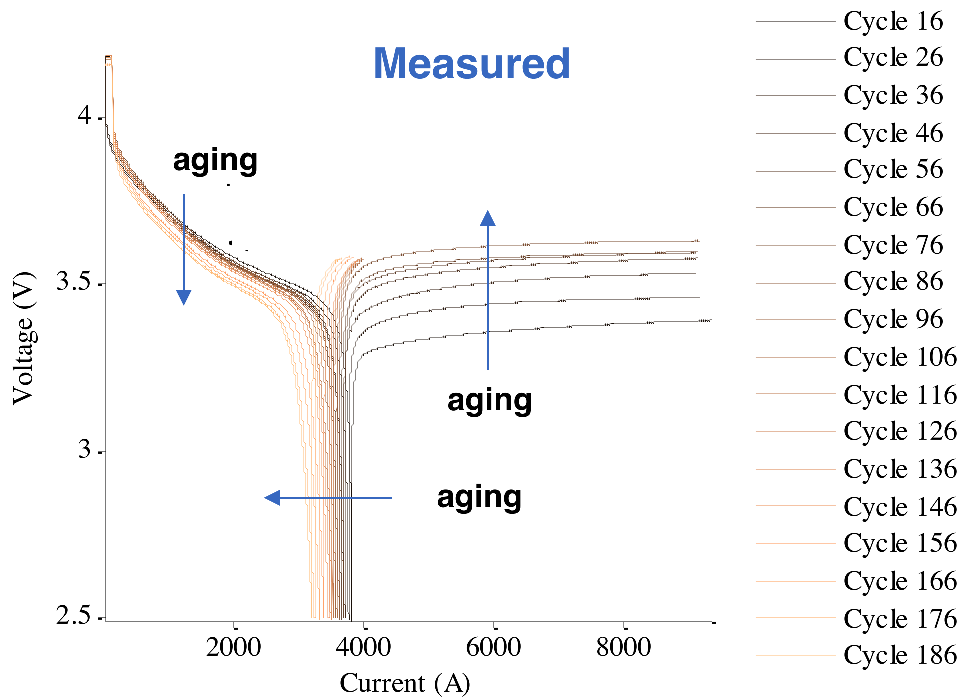
Electrochemical Li-ion Model

- <u>Electrochemical Models vs. Empirical Models</u>
  - Battery physics models enable more direct representation of age-related changes in battery dynamics than empirical models
  - Typically have a higher computational cost and more unknown parameters
  - 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 volumes
    - Surface overpotential → Butler-Volmer equation applied at surface layers
    - Ohmic overpotential → Constant lumped resistance accounting for current collector resistances, electrolyte resistance, solid-phase ohmic resistances

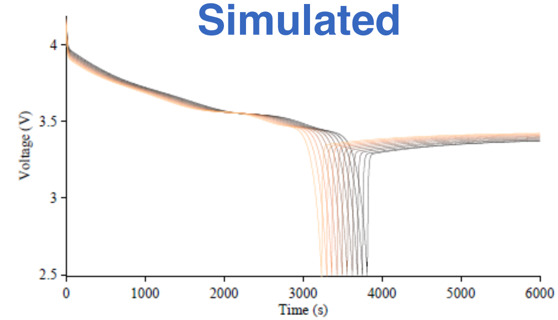


Battery Aging

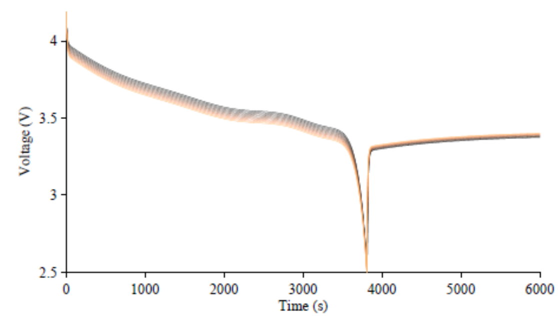
- Contributions from both decrease in mobile Li ions (lost due to side reactions related to aging) and increase in internal resistance
  - Modeled with decrease in "q^{max}" parameter, used to compute mole fraction
  - Modeled with increase in "R_o" parameter capturing lumped resistances



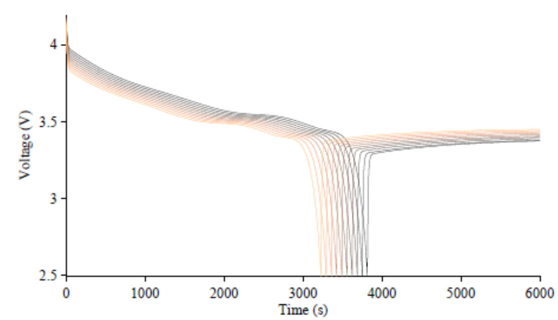
Simulated



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



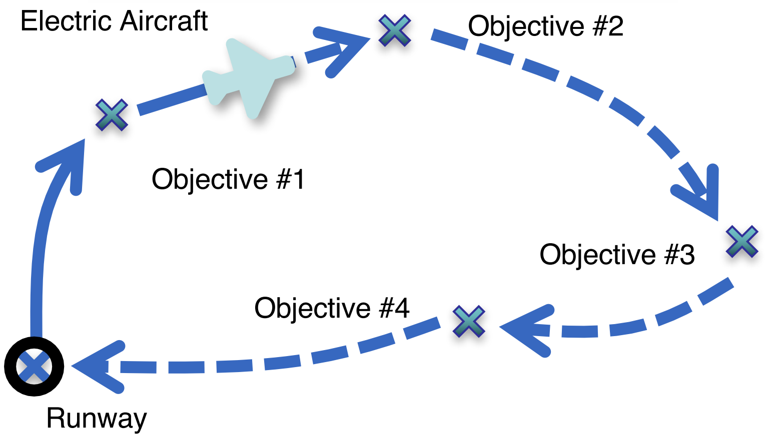
(b) Decreasing R_o.



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

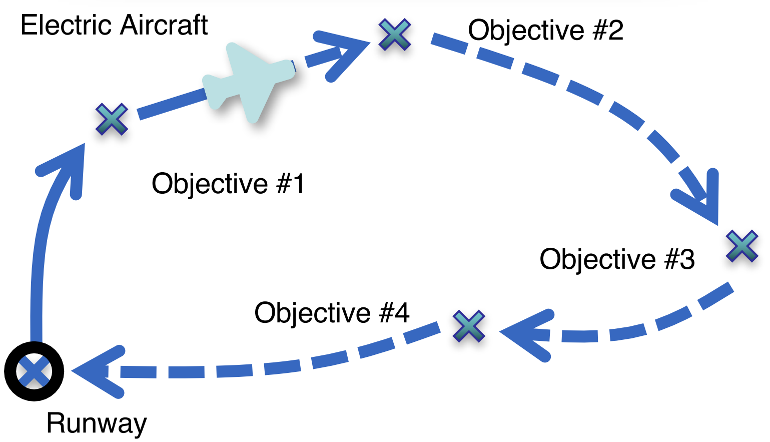
Edge 540-T

- Electric aircraft operated at NASA Langley
- Piloted and autonomous missions, visiting waypoints
- 50+ Flights with Battery Prognostics algorithm onboard
- 40+ HIRF chamber tests with Battery Prognostics algorithm
- Require 2-minute warning for EOD so pilot/autopilot has sufficient time to land safely
  - This answer depends on battery age
  - Need to track both current level of charge and current battery age
  - Based on current battery state, current battery age, and expected future usage, can predict EOD and correctly issue 2-minute warning



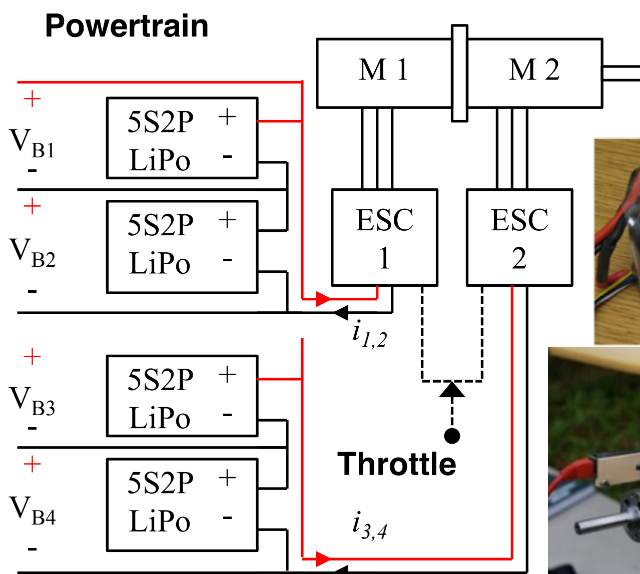
Edge 540-T

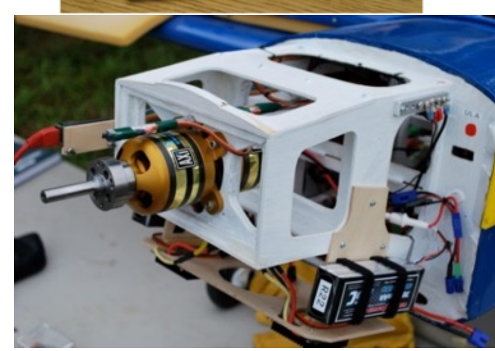
- Electric aircraft operated at NASA Langley
- Piloted and autonomous missions, visiting waypoints
- 50+ Flights with Battery Prognostics algorithm onboard
- 40+ HIRF chamber tests with Battery Prognostics algorithm
- Accuracy requirements for the two minute warning were specified as:
  – *The prognostic algorithm shall raise an alarm no later than two minutes before the lowest battery SOC estimate falls below 30% for at least 90% of verification trial runs.*
  – *The prognostic algorithm shall raise an alarm no earlier than three minutes before the lowest battery SOC estimate falls below 30% for at least 90% of verification trial runs.*
  – *Verification trial statistics must be computed using at least 20 experimental runs*



Edge 540-T

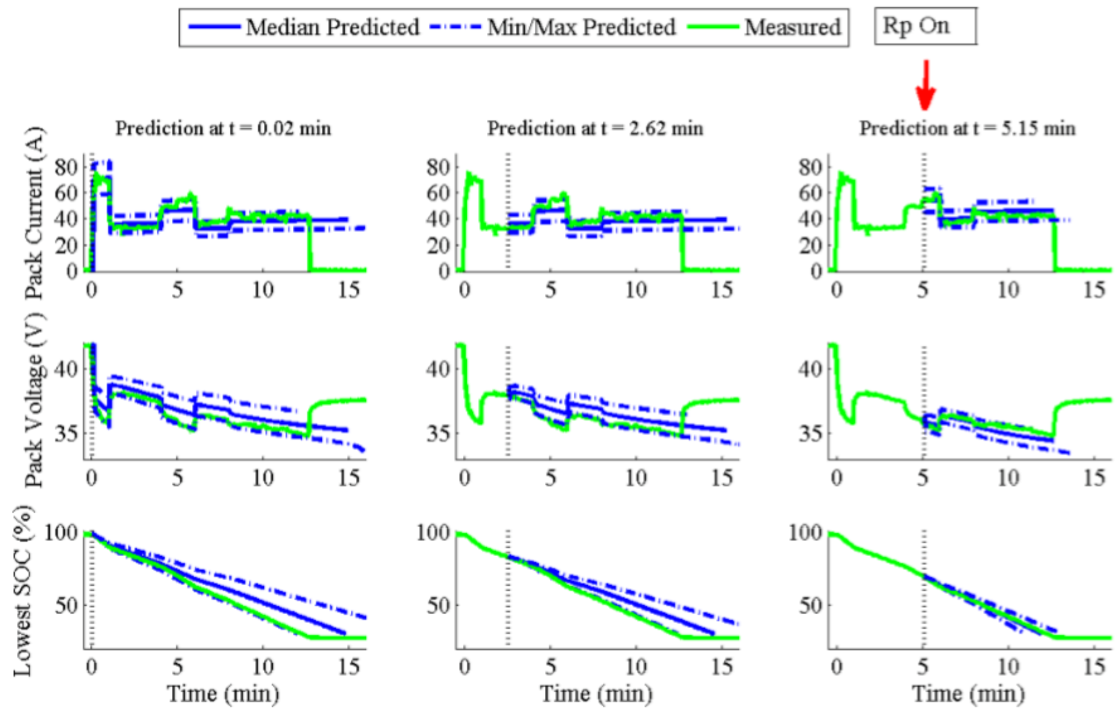
- Subscale electric aircraft operated at NASA Langley Research Center
- Powered by four sets of Li-polymer batteries
- Estimate SOC online and provide EOD and remaining flight time predictions for ground-based pilots

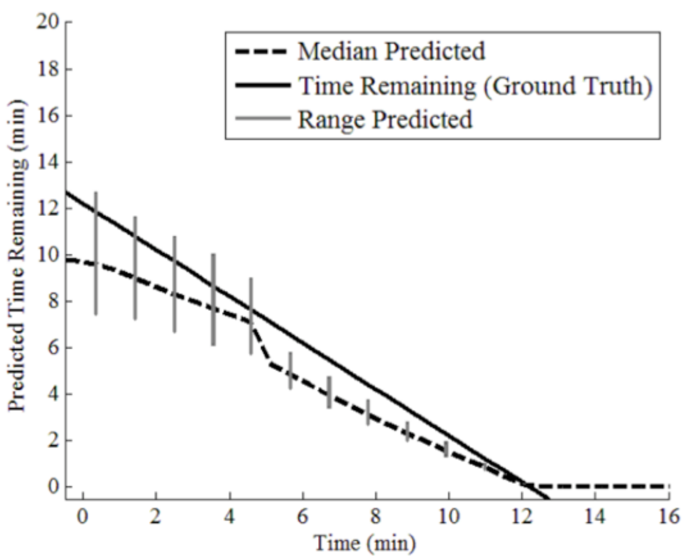




Predication over Flight Plan (HIRF Chamber Test)

- Measured and predicted battery current, voltage and SOC different time steps
- The min, max and median predictions are plotted from each sample time until the predicated SOC reaches 30%

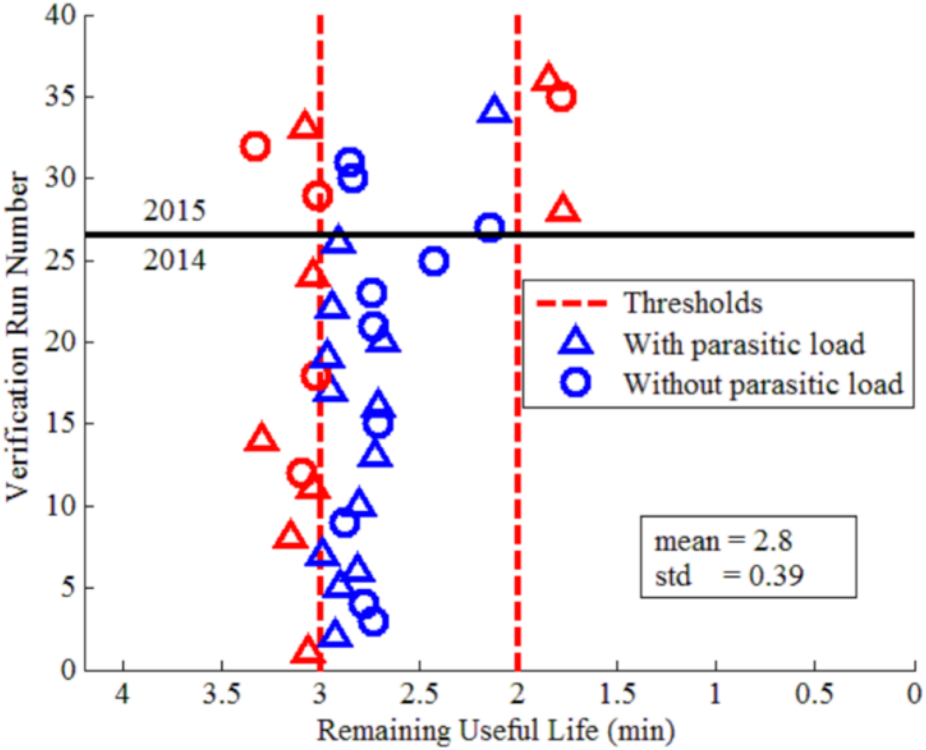




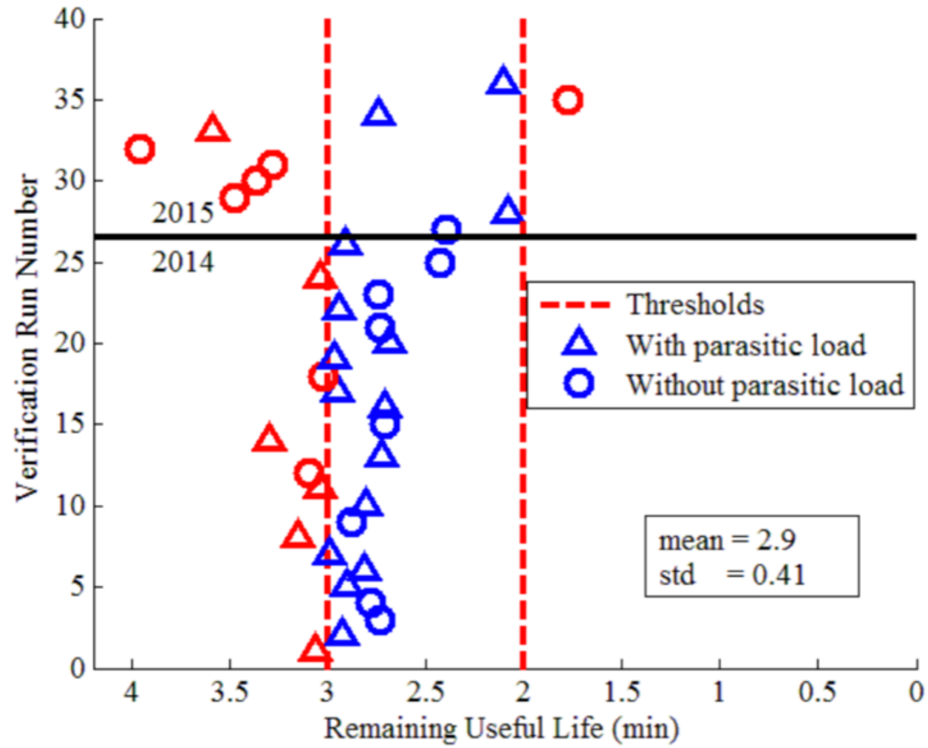
- Predictions for remaining flight time for entire flight plan
- Overestimate till parasitic load is injected
- Once the parasitic load is detected the remaining flying time time prediction shifts down.

Ref : E. Hogge, C. Kulkarni et al, “Verification of Prognostic Algorithms to Predict Remaining Flying Time for Electric Unmanned Vehicles”, IJPHM 2017 (accepted – in review)

Battery parameters deterioration with Aging



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



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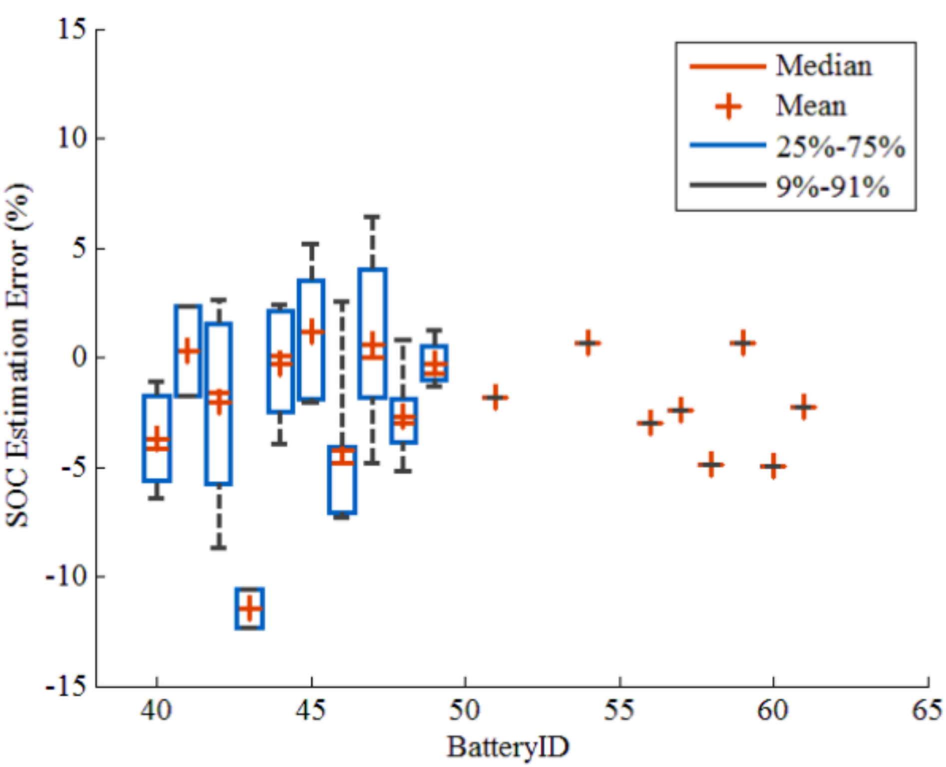
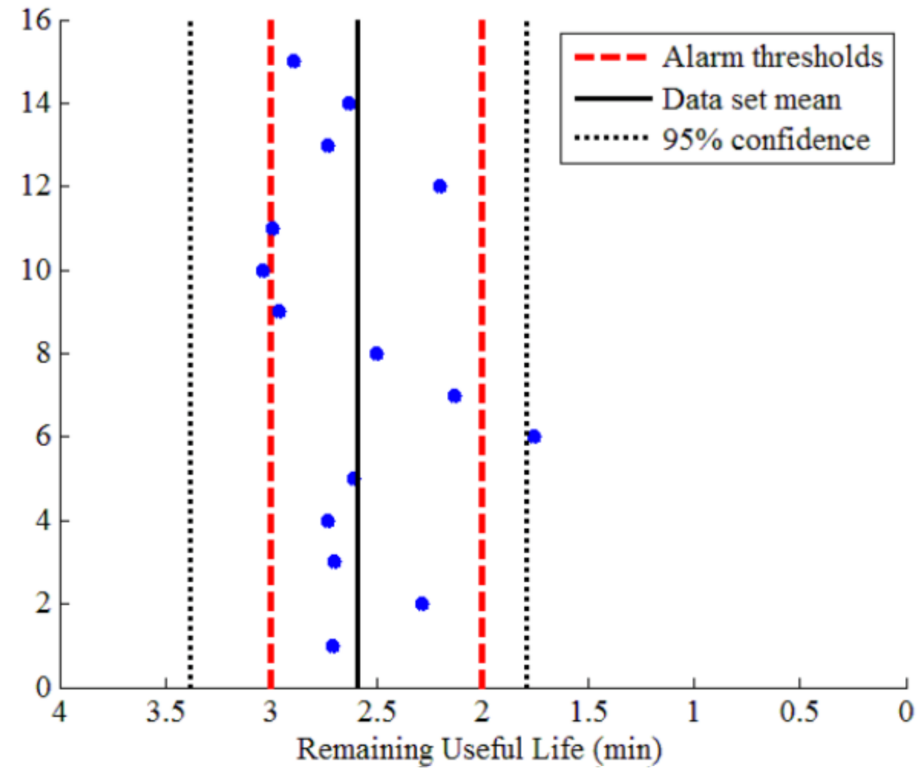
Performance of Predicted Flying Time Warning

- Use UKF for state estimation with electric circuit equivalent model
- Aerodynamics and powertrain kinematics modeling used to determine battery load predictions based on flight plan



Box plots of the SOC estimation error measured over 15 verification flights that each use 4 batteries

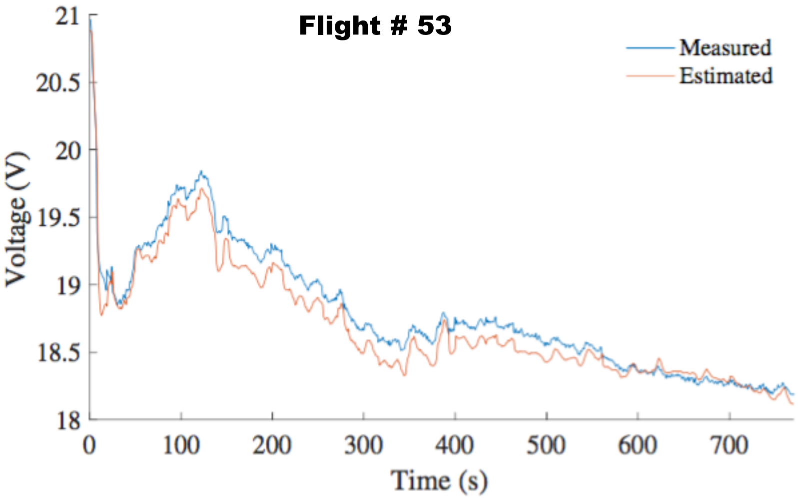


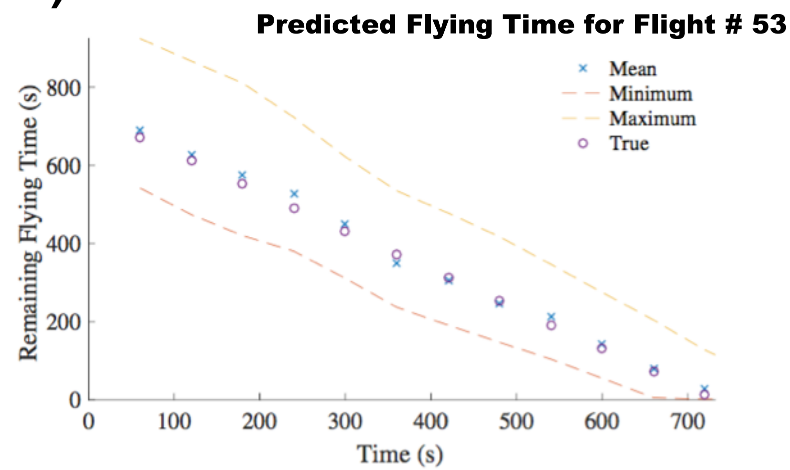
Two-minute alarms for 15 flights

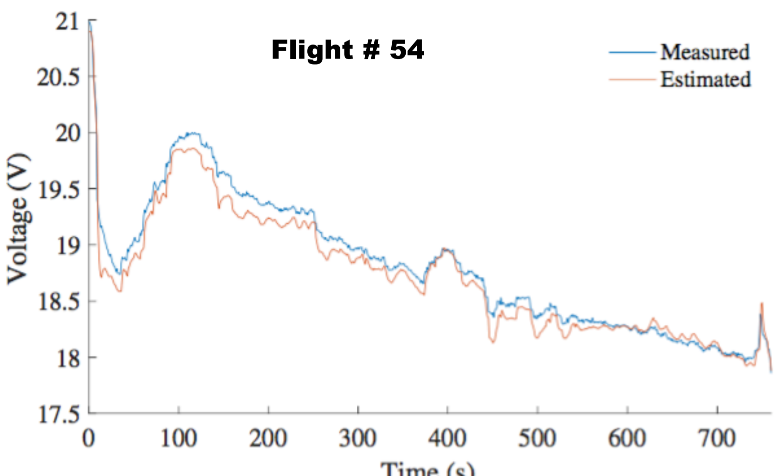
Ref : E. Hogge, C. Kulkarni et al, “Flight Tests of a Remaining Flying Time Prediction System for Small Electric Aircraft in the Presence of Faults”, PHM 2017

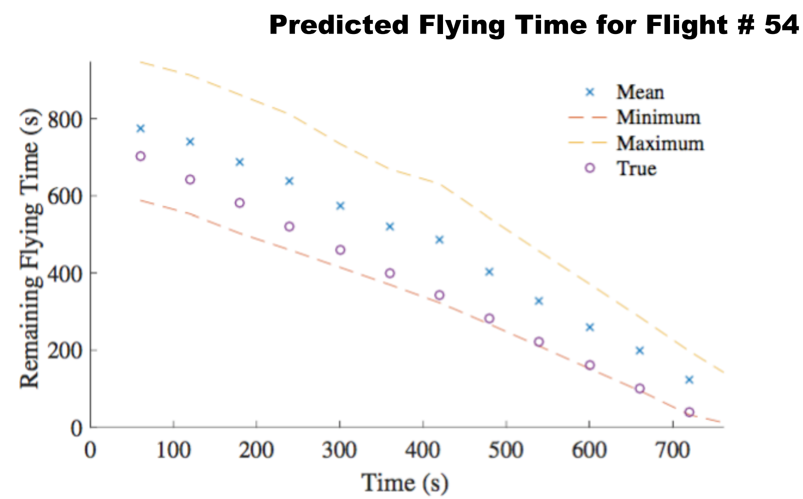
Offline Results over Flight Data

- Use UKF for state estimation with Battery Electro-chemistry (EC) model









Ref : C. Kulkarni et al, “Verification of Prognostic Algorithms to Predict Remaining Flying Time for Electric Unmanned Vehicles”, PHM 2017

Data Sets Available for Download

- https://ti.arc.nasa.gov/tech/dash/pcoe/prognostic-data-repository/

Randomized Battery Usage Data Set
Publications using this data set

Description	Batteries are continuously cycled with randomly generated current profiles. Reference charging and discharging cycles are also performed after a fixed interval of randomized usage in order to provide reference benchmarks for battery state of health.
Format	
Datasets	+ Download Randomized Battery Usage Data Set 1 (1285 downloads) + Download Randomized Battery Usage Data Set 2 (936 downloads) + Download Randomized Battery Usage Data Set 3 (906 downloads) + Download Randomized Battery Usage Data Set 4 (4217 downloads) + Download Randomized Battery Usage Data Set 5 (825 downloads) + Download Randomized Battery Usage Data Set 6 (890 downloads) + Download Randomized Battery Usage Data Set 7 (857 downloads)
Dataset Citation	B. Bole, C. Kulkarni, and M. Daigle "Randomized Battery Usage Data Set", NASA Ames Prognostics Data Repository (http://ti.arc.nasa.gov/project/prognostic-data-repository), NASA Ames Research Center, Moffett Field, CA
Publication Citation	B. Bole, C. Kulkarni, and M. Daigle, 'Adaptation of an Electrochemistry-based Li-Ion Battery Model to Account for Deterioration Observed Under Randomized Use', Annual Conference of the Prognostics and Health Management Society, 2014

HIRF Battery Data Set
Publications using this data set

Description	Battery Data collected from the Experiments on the Edge 540 Aircraft in HIRF Chamber. Refernce document can be downloaded here
Format	The set is in .mat format and has been zipped.
Datasets	+ Download HIRF Battery Data Set 1 (184 downloads) + Download HIRF Battery Data Set 2 (127 downloads) + Download HIRF Battery Data Set 3 (131 downloads) + Download HIRF Battery Data Set 4 (125 downloads) + Download HIRF Battery Data Set 5 (149 downloads) + Download HIRF Battery Data Set 6 (135 downloads)
Dataset Citation	C. Kulkarni, E. Hogge, C. Quach and K. Goebel "HIRF Battery Data Set", NASA Ames Prognostics Data Repository (http://ti.arc.nasa.gov/project/prognostic-data-repository), NASA Ames Research Center, Moffett Field, CA
Publication Citation	Verification of a Remaining Flying Time Prediction System for Small Electric Aircraft. Edward F. Hogge, Brian M. Bole, Sixto L. Vazquez, Jose R., Annual Conference of the Prognostics and Health Management, PHM 2015

Conclusions

- Focus on model-based approaches to battery state estimation and prediction
- Validate models and algorithms with data from lab experiments and fielded systems
- Defining operational requirements for different systems
- Future work in progress :
  - Temperature models
  - Higher fidelity models
  - More efficient algorithms
  - Additional applications

Thank you

Battery Prognostics Team

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