Health Monitoring and Prognostics for More Electric Aircrafts

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http://prognostics.nasa.gov

Motivation

- Aircrafts with all electric powertrain are increasingly being used for long missions
- Electrical and Electronic components have increasingly critical role in on-board, autonomous functions for decision making
- We need understanding of behavior of deteriorated components to develop capability to anticipate failures/predict remaining RUL
- Safe Flight under failure operating conditions.

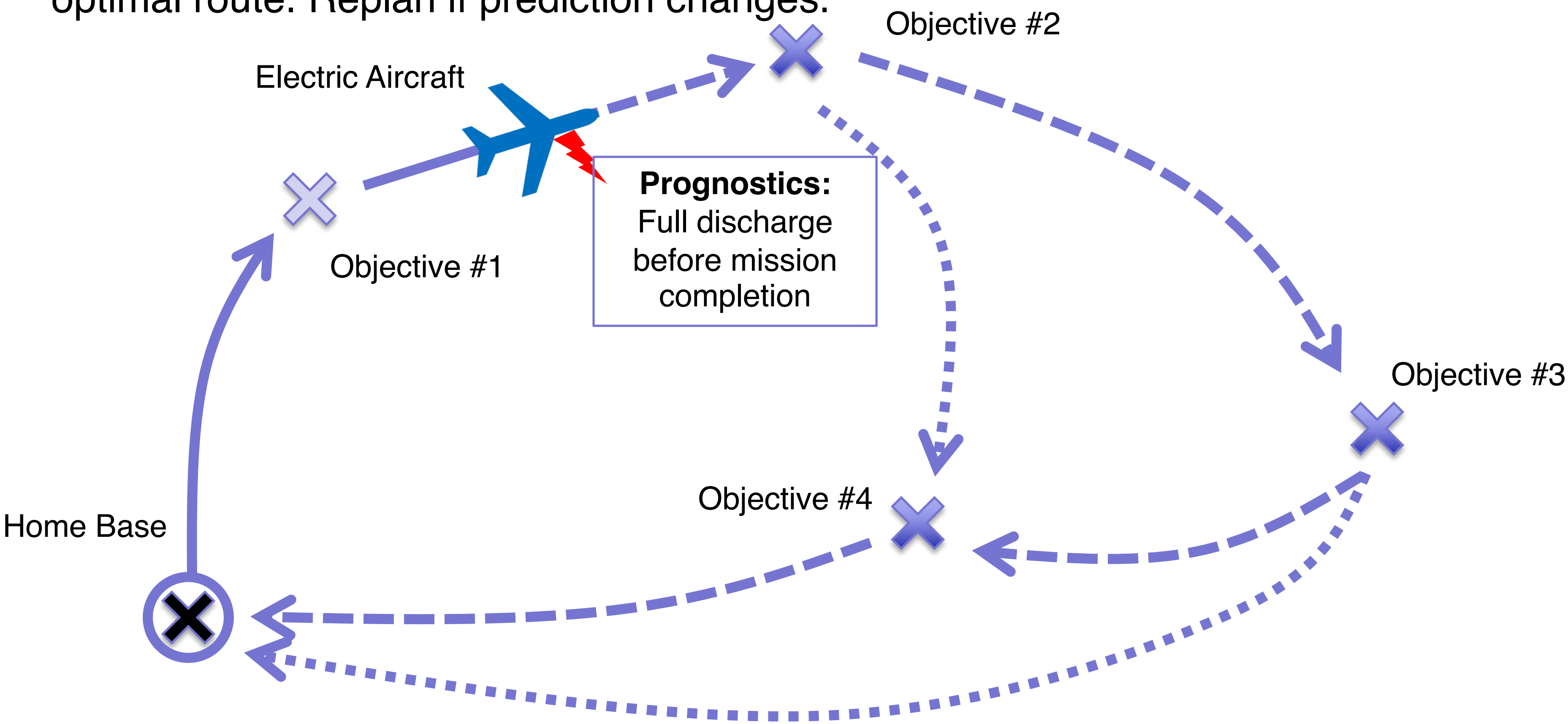
Motivation

- Health Monitoring of Energy Systems is key to EA systems
- Batteries increasingly used in more and more systems as a power source
- Prediction of Remaining useful life (RUL) 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.

Why Prognostics?

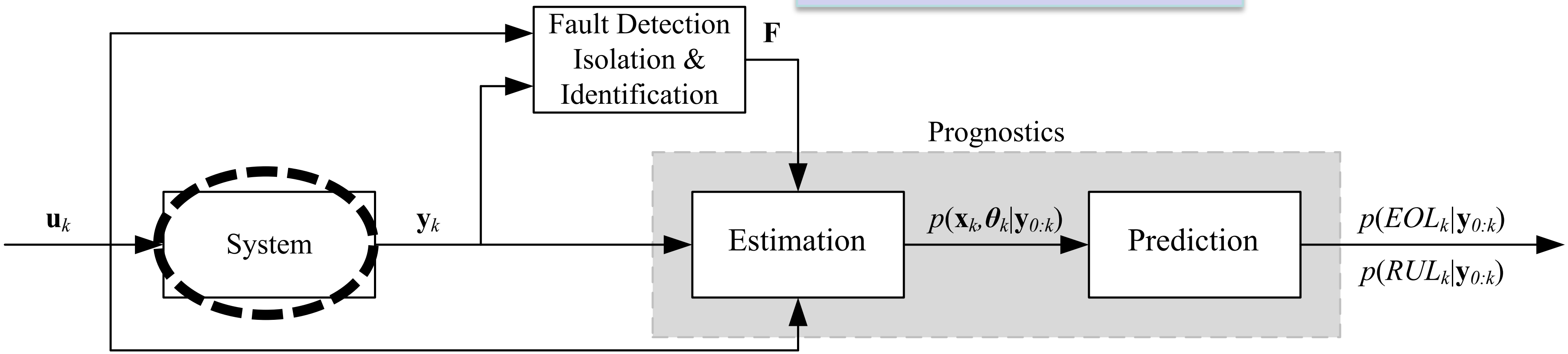
Example: UAV Mission
Visit waypoints to accomplish science objectives. Predict aircraft battery end of discharge to determine which objectives can be met. Based on prediction, plan optimal route. Replan if prediction changes.



Model-Based Architecture

1 System receives inputs, produces outputs

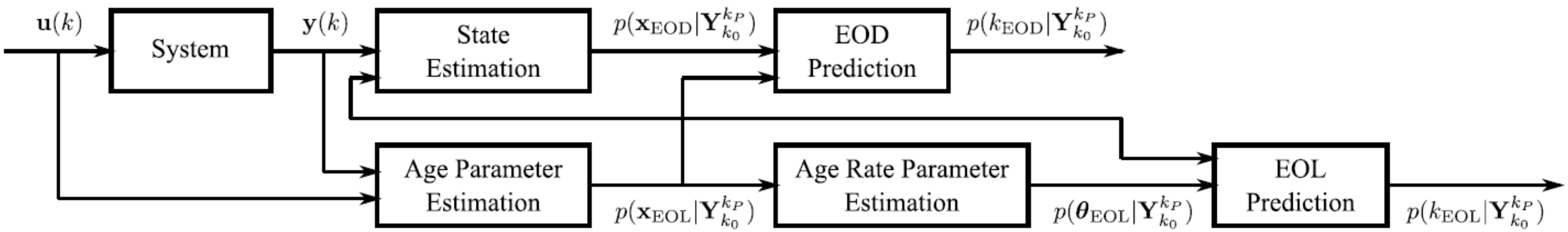
2 Identify active damage mechanisms



3 Estimate current state and parameter values

4 Predict EOL and RUL as probability distributions

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 system i.e. battery
- 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

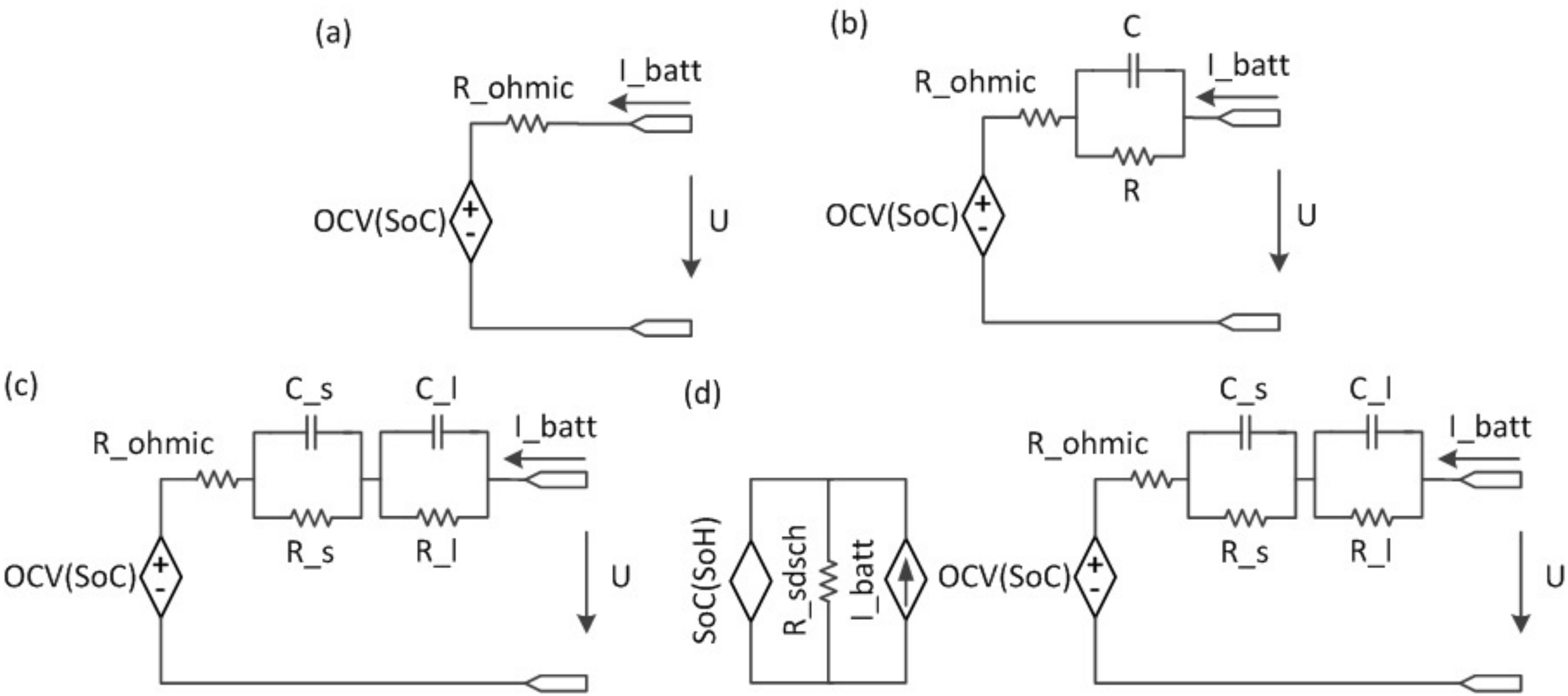
- What is the current system state and its associated uncertainty?
  - Input: system outputs y from k_0 to k, $y(k_0:k)$
  - Output: $p(x(k),\theta(k)|y(k_0:k))$
- Battery models are nonlinear, so require nonlinear state estimator (e.g., extended Kalman filter, particle filter, unscented Kalman filter)
- 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)

Battery Modeling

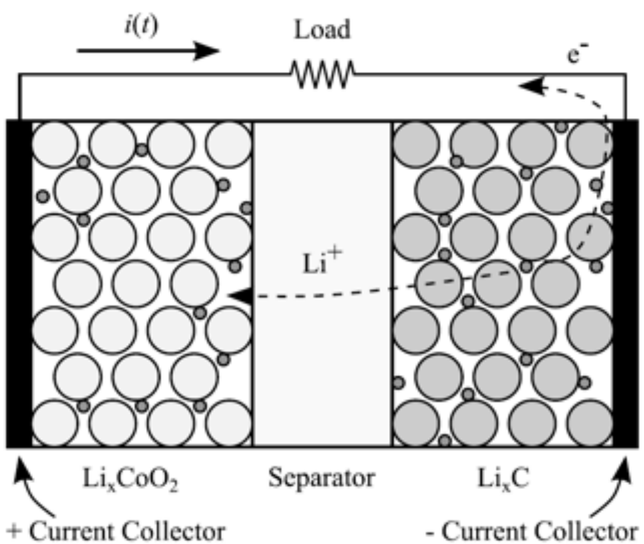
– <u>Equivalent Circuit Empirical Models</u>
  - Most common approach
  - Various model complexities used
  - Difficulty in incorporating aging effects



Battery Modeling

– <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



Discharge

Reduction at pos. electrode:

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

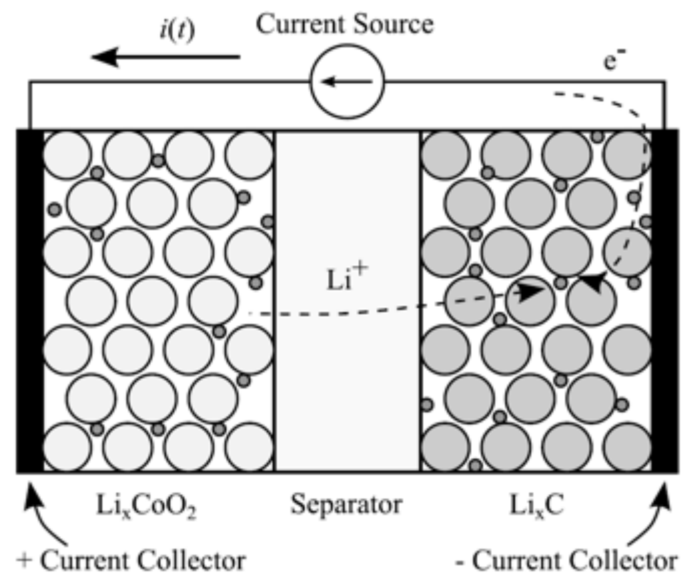
Oxidation at neg. electrode:

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

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:

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

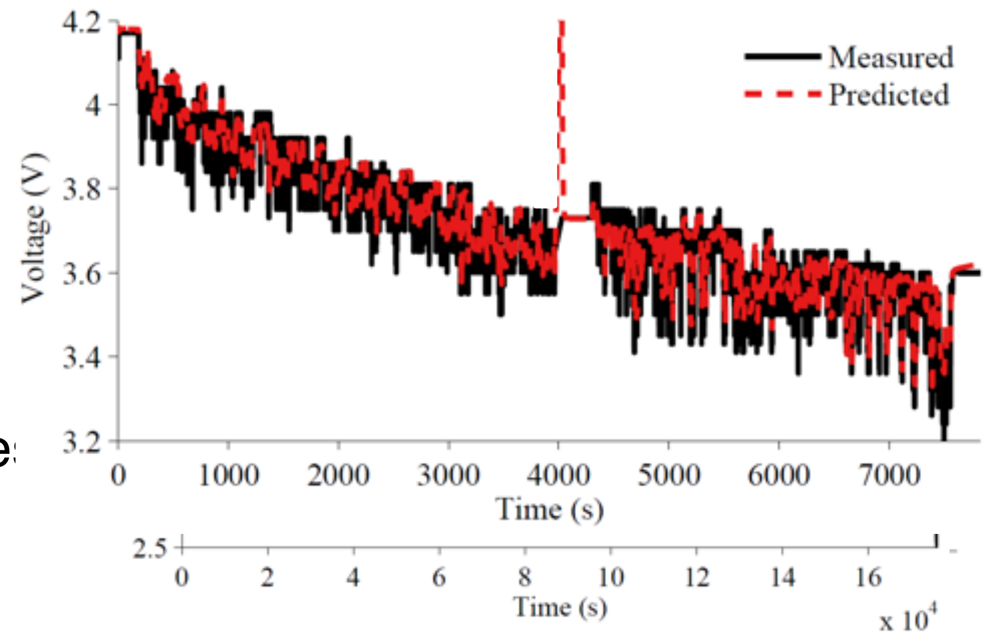
Current flows – to +

Electrons flow + to –

Lithium ions flow + to –

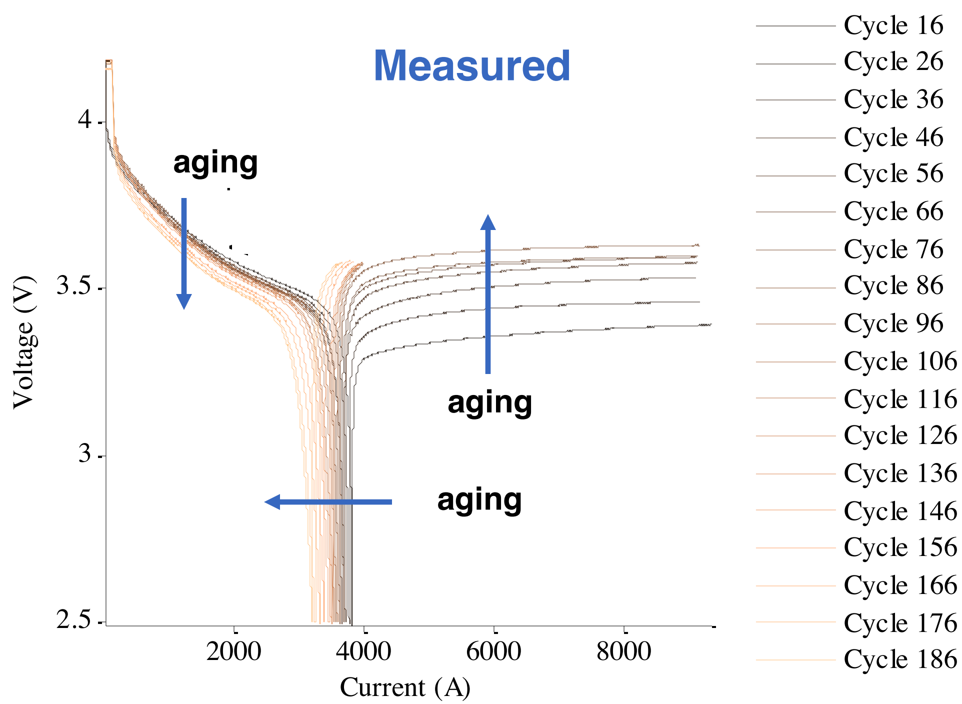
Electrochemical Li-ion Model

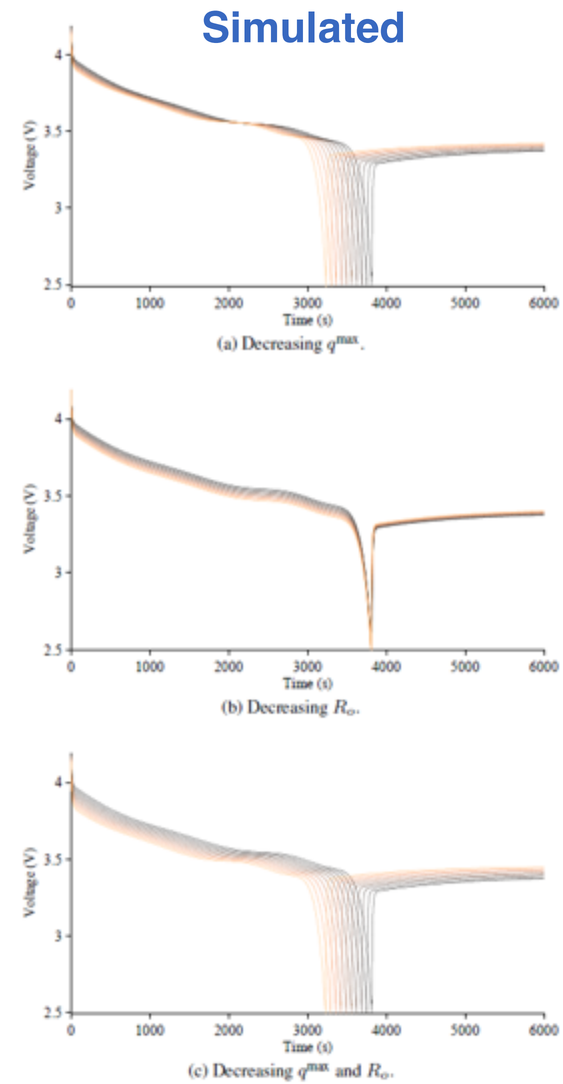
- Lumped-parameter, ordinary differential equations
- Capture voltage contributions from different sources
  - Equilibrium potential →Nernst equation with Redlich-Kister expansion
  - Concentration overpotential → split electrodes into surface and bulk control volumes
  - Surface overpotential → Butler-Volmer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



Battery Aging

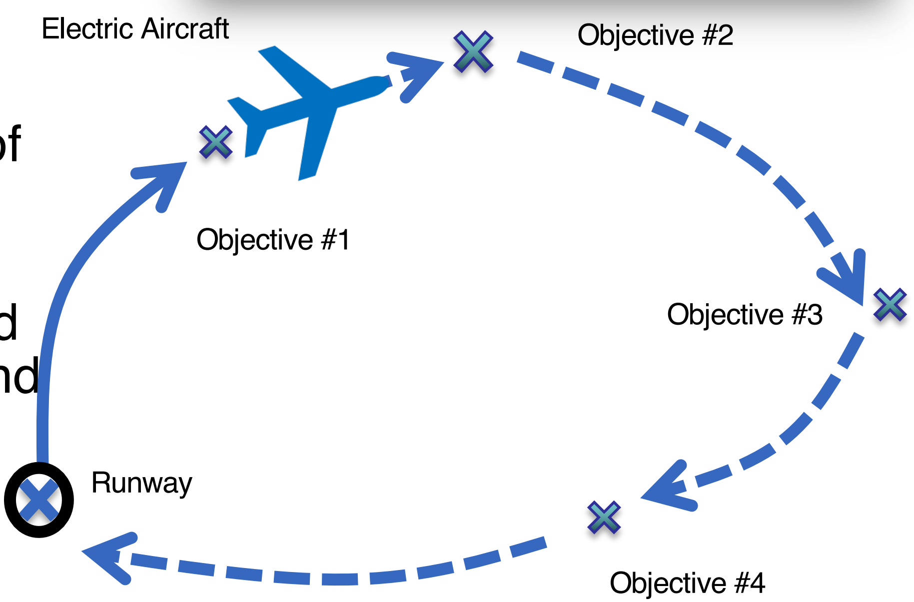
- Contributions from both decrease in mobile Li ions (lost due to side reactions related to aging) and increase in internal resistance
  - Modeled with decrease in "q^{max}" parameter, used to compute mole fraction
  - Modeled with increase in "R_o" parameter capturing lumped resistances





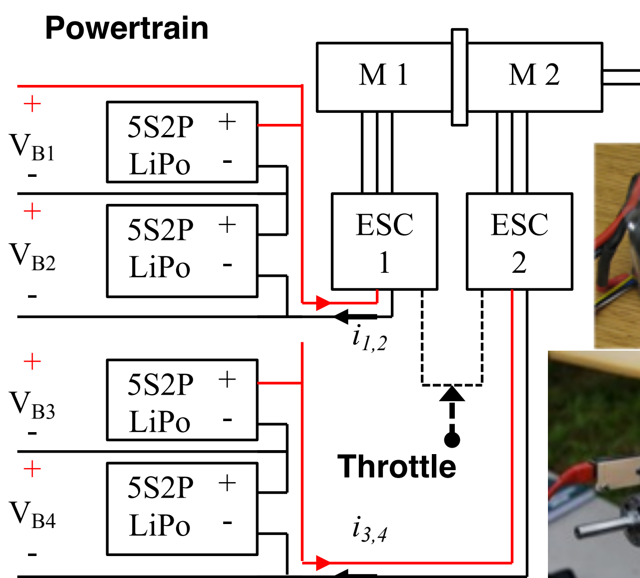
Case 1 - Edge Aircraft

- Electric aircraft operated at NASA Langley
- Piloted and autonomous missions, visiting waypoints
- 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



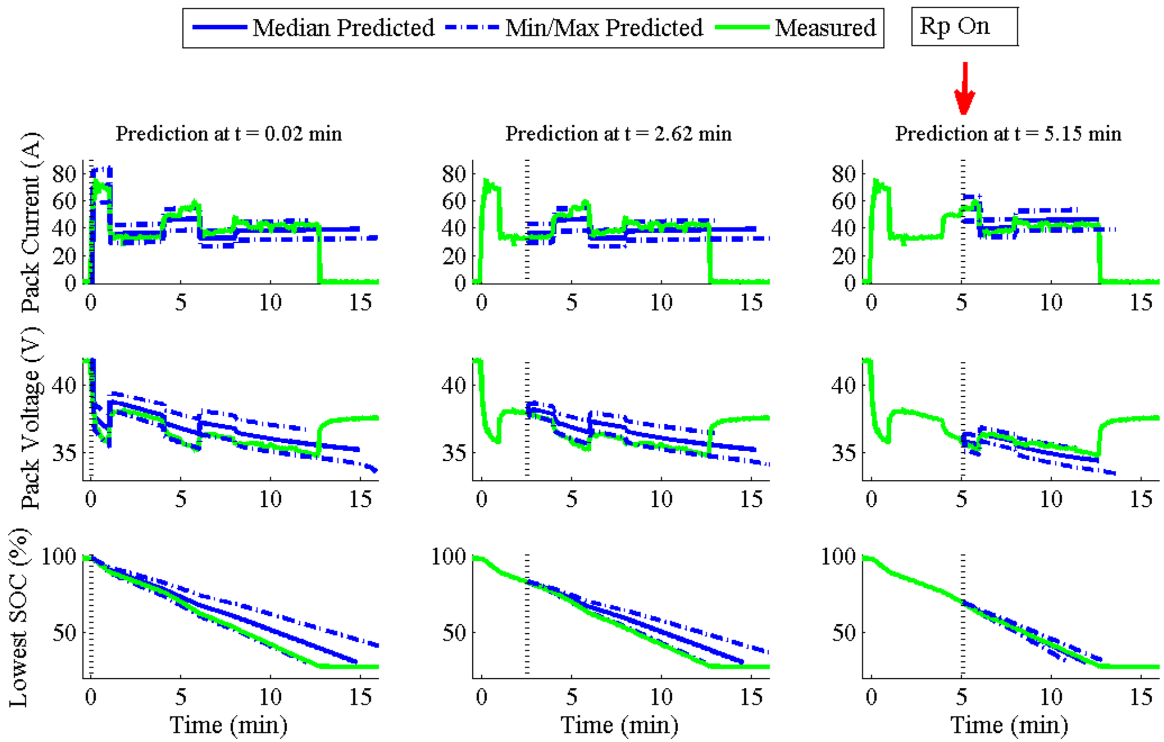
Edge 540-T

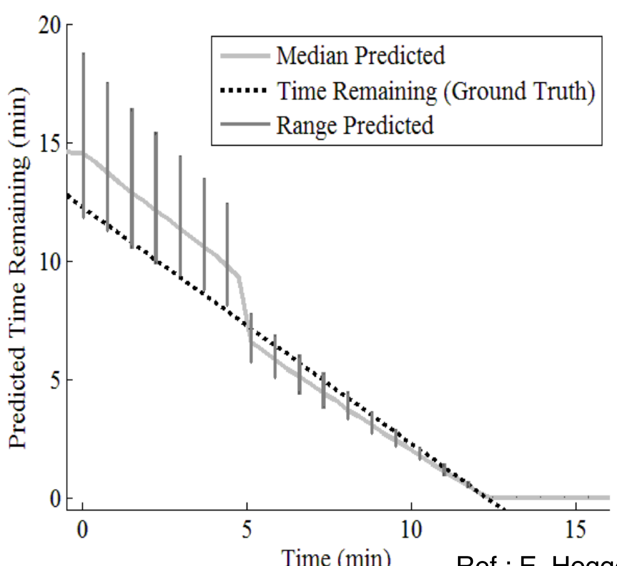
- Subscale electric aircraft operated at NASA Langley Research Center
- Powered by four sets of Li-polymer batteries
- Estimate SOC online and provide EOD and remaining flight time predictions for ground-based pilots



Predication over Flight Plan

- 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%

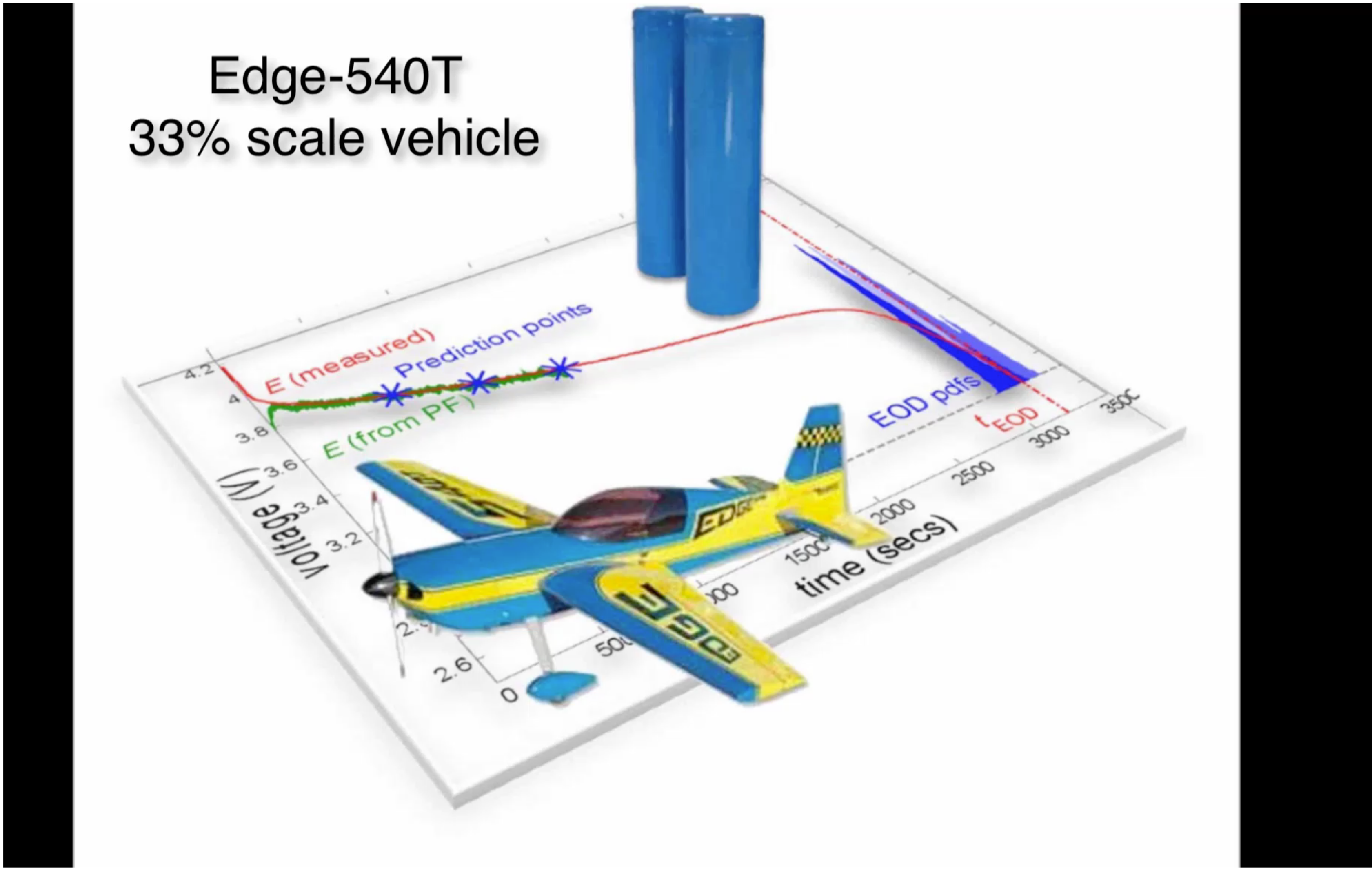




- Predictions for remaining flight time for entire flight plan
- Overestimate till parasitic load is injected
- Once the parasitic load is detected the remaining flying time time prediction shifts down.

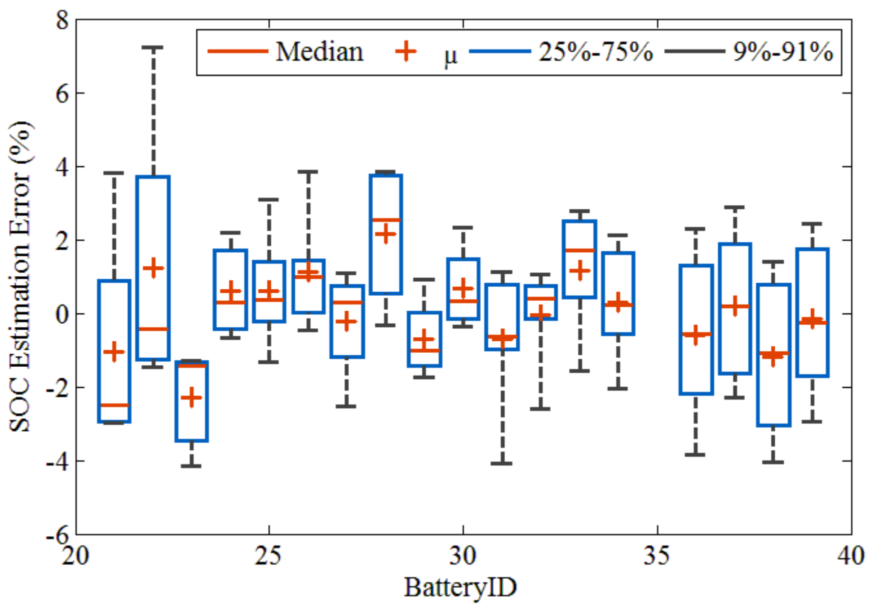
Ref : E. Hogge et al, "Verification of a Remaining Flying Time Prediction System for Small Electric Aircraft", PHM 2015

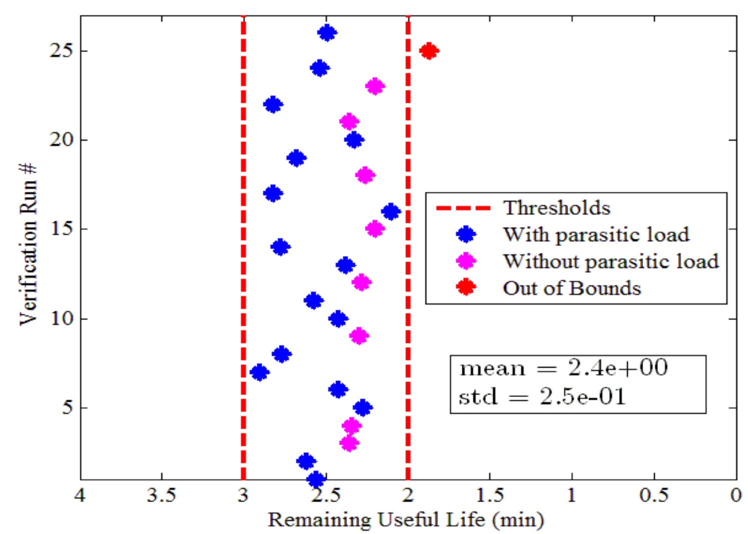
Edge-540 Flight - Demo



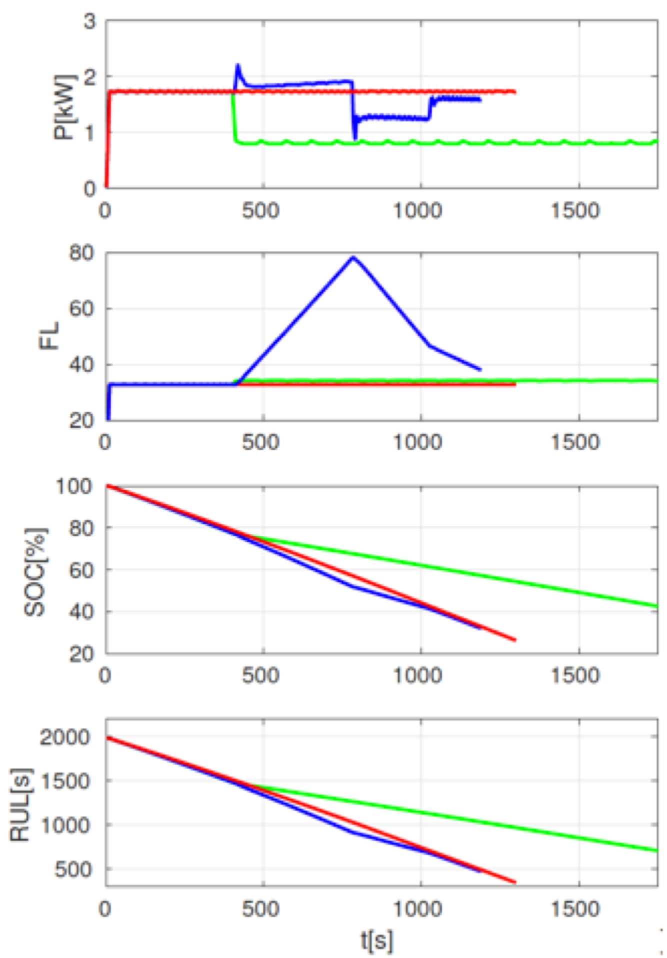
Performance Requirements

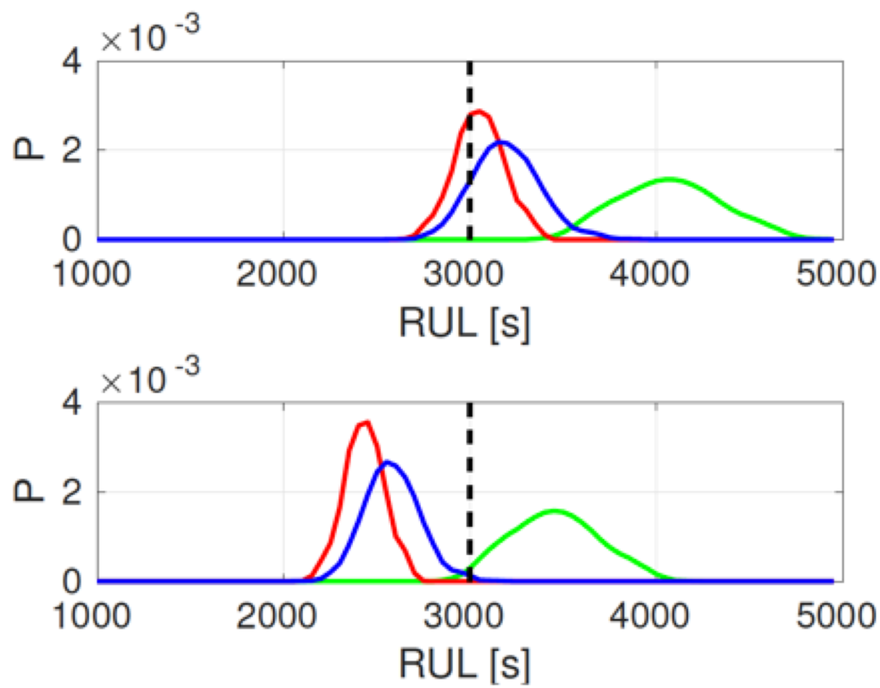
- Accuracy requirements for the two minute warning were specified as:
  - *The prognostic algorithm shall raise an alarm no later than two minutes before the lowest battery SOC estimate falls below 30% for at least 90% of verification trial runs.*
  - *The prognostic algorithm shall raise an alarm no 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*





Case 2 : RUL Prognosis for a fixed-wing Electric Aircraft





Probability densities for RUL at the beginning of the flight t = 0s and at the decision point t = 400s with pwr = 0:1

Ref : Kulkarni, Roychoudhury, and Schumann. "On-board Battery Monitoring and Prognostics for Electric-Propulsion Aircraft", 2018 AIAA/IEEE Electric Aircraft Technologies Symposium, AIAA Propulsion and Energy Forum, (AIAA 2018-5034)

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

- Prognostics enables the pilot/operator to estimate future health state of the system
- Known future health state helps is taking better decisions
- Both combined can help in keeping the EA system as well as airspace safe
- 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

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http://prognostics.nasa.gov