Prognostics and Health Monitoring: Application to Electric Vehicles

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Motivation (1/2)

- Future aircraft systems will rely more on electrical and electronic components
- UAV’s 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
  - Vehicle controls, communications, navigation, radar systems
  - Power electronic devices such as power MOSFETs and IGBTs are frequently used in high-power switching circuits
  - Batteries are the sole energy storage
  - The integrated navigation (INAV) module combines output of the GPS model and inertial measurement unit.
- Assumption of new functionality increases number of faults with perhaps unanticipated fault modes
- We need understanding of behavior of deteriorated components to develop capability to anticipate failures/predict remaining RUL
Motivation (2/2)

Images courtesy: Boeing

Line Replaceable Unit: Power Controller

Component: Power Transistor

Sceptor

Ref: www.nasa.gov

GL-10

Ref: www.nasa.gov

Edge 540

Ref: www.nasa.gov
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
  – Rover
  – Edge 540-T electric aircraft
Outline

• Introduction to Prognostics
• Introduction to Model-based Prognostics
• Research Approach
• Electric Vehicle Powertrain
• Algorithms
  – Prognostic Architecture
  – Dynamic state and state-of-charge estimation
• Applications
  – Rover
  – Edge 540-T electric aircraft
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
The Basic

Threshold as a Function of System State

Not necessarily a one-dimensional problem!
… This schematic is oversimplified!
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.

**Objective #1**

**Objective #2**

**Objective #3**

**Objective #4**

**Prognostics:** Full discharge before mission completion.

Electric Aircraft

Home Base
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
The Basic Idea: Batteries Example

E = End of Discharge (EOD)

Voltage Threshold

Cell Voltage

Time

$t_eod$

$\Delta t_{EOD}$
The Basic Idea: Batteries Example

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

- **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.
  - Ex: Weibull Analysis

- **Type II: Stress-based**
  - Use population based fault growth model – learned 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.
  - Ex: 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.
  - Ex: Cumulative Damage Model, Filtering and State Estimation
Physics-Based Methods

- Description of a system’s underlying physics using suitable representation
- Some examples:
  - Model derived from “First Principles”
    - Encapsulate fundamental laws of physics
      - PDEs
      - Euler-Lagrange Equations
  - Empirical model chosen based on an understanding of the dynamics of a system
    - Lumped Parameter Model
    - Classical 1st (or higher) order response curves
  - Mappings of stressors onto damage accumulation
    - Finite Element Model
    - High-fidelity Simulation Model
- Something in the model correlates to the failure mode(s) of interest
Physics-Based Models

• Pros
  – Results tend to be intuitive
    • Based on modeled phenomenon
    • And when they’re not, they’re still instructive (e.g., identifying needs for more fidelity or unmodeled effects)
  – Models can be reused
    • Tuning of parameters can be used to account for differences in design
  – If incorporated early enough in the design process, can drive sensor requirements (adding or removing)
  – Computationally efficient to implement

• Cons
  – Model development requires a thorough understanding of the system
  – High-fidelity models can be computationally intensive

• Examples
  – Paris-Erdogan Crack Growth Model
  – Taylor tool wear model
  – Corrosion model
  – Abrasion model
INTRODUCTION TO MODEL-BASED PROGNOSTICS
Model-based prognostics (1/2)

\[
\dot{x}(t) = f(x(t), u(t)) + w(t) \\
y(t) = h(x(t)), u(t)) + v(k)
\]

\[
R(t_p) = t_{EOL} - t_p
\]

- State vector includes dynamics of the degradation process
- It might include nominal operation dynamics
- EOL defined at time in which performance variable cross failure threshold
- Failure threshold could be crisp or also a random variable
Model-based prognostics (2/2)

- Tracking of health state based on measurements
- Forecasting of health state until failure threshold is crossed
- Compute RUL as function of EOL defined at time failure threshold is crossed
Prognostics Center of Excellence

Methodology

\[ x_k = A x_{k-1} + B u_{k-1} + w_{k-1} \]
\[ y_k = H x_k + v_k \]
RESEARCH APPROACH
High level research efforts

• Prognostics models and algorithms
  – Identification of precursors of failure for MOSFETs under different failure mechanism conditions
  – Identification of precursors of failure for different IGBT technologies (CALCE)
  – Modeling of degradation process MOSFETs
  – Development of prognostics algorithms
• Prognostics for output capacitor in power supplies (Vanderbilt University)
  – Electrical overstress and thermal overstress
  – Development of prognostics algorithms
• Accelerated Life Testing
  – Thermal overstress aging of MOSFETs and IGBTs
  – Electrical overstress aging testbed MOSFETs
  – Electrical overstress aging testbed for Capacitors
• Effects of lightning events of MOSFETS (LaRC)
• Battery Degradation and ageing (ARC – LaRC)
• Ageing Effecting on ESC’s (ARC – LaRC)
Research Approach

- Identification of failure modes and their relationship to their particular failure mechanisms
- Identification of precursors of failure which play an essential role in the prediction of remaining life
- Development of accelerated aging testbeds that facilitate the exploration of different failure mechanisms and aid the understanding of damage progression
- Development of degradation models based on the physics of the device and the failure mechanisms
- Development of remaining life prediction algorithms that take into account the different sources of uncertainty while leveraging physics-based degradation models that considers future operational and environmental conditions
Prognostics Algorithm Maturation through Validation Experiments
Aging under thermal and electric stresses

\[ C(t) = \left( \frac{2\varepsilon R \varepsilon_0}{dC} \right) \left( \frac{V_e - V_e(t)}{j_e o t w_e} \right) \]

\[ ESR(t) = \frac{1}{2} (\rho_E d_C P_E) \left( \frac{j_e o t w_e}{V_e - V_e(t)} \right) \]

First Principles Model for multiple failure modes

TRL 4

Aging under thermal stresses

\[ C(t) = e^{\alpha t} + \beta \]

Physics inspired empirical Model

TRL 2

Aging under electric stresses

TRL 3

Prognostics Algorithm Maturation through Validation Experiments
ELECTRIC VEHICLE POWERTRAIN
System Level Prognostics

Component Level Prognostics – System Level Prognostics

- Batteries
- Power Conditioning Circuit – Capacitors, MOSFETs
- Electronic Speed Controllers (ESC) – MOSFETs
- BLDC

- Study Cascading faults
- Effects of component level aging/degradation on system performance
Hardware in Test Loop

- Laboratory Workstation
  - Voltages
  - Temperatures
  - Battery Banks
  - PWM Signal
  - Temperatures
  - Electronic Speed Controllers
  - Temperature
  - Stator Cover Temperature
  - Motor Under Test
  - Slave Motor
  - Full Bridge Rectifier & Power Load

- DAQ
- arduino
Accelerated Aging

• Traditionally used to assess the reliability of products with expected lifetimes in the order of thousands of hours
  – in a considerably shorter amount of time
• Provides opportunities for the development and validation of prognostic algorithms
• Such experiments are invaluable since run-to-failure data for prognostics is rarely or never available
• Unlike reliability studies, prognostics is concerned not only with time to failure of devices but with the degradation process leading to an irreversible failure
  – This requires in-situ measurements of key output variables and observable parameters in the accelerated aging process with the associated time information
• Thermal, electrical and mechanical overstresses are commonly used for accelerated aging tests of electronics
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)
Prediction Algorithm

• The $P$ function takes an initial state, and a parameter, an input, and a process noise trajectory
  – Simulates state forward using $f$ until $E$ is reached to computes $k_E$ for a single sample

• Top-level prediction algorithm calls $P$
  – These algorithms differ by how they compute samples upon which to call $P$

• Monte Carlo algorithm (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, $N$

• MC samples from its input distributions, and computes $k_E$

• The “construct” functions describe how to construct a trajectory given trajectory parameters
POWER TRANSISTORS
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Modeling for Power MOSFET under electrical overstress

- Two-transistor model is shown to be a good candidate for a degradation model for model-based prognostics.
- The model parameters $K$, and $W_1$ could be varied as the device degrades as a function of usage time, loading and environmental conditions.
- Parameter $W_1$ defines the area of the healthy transistors, the lower this area, the larger the degradation in the two-transistor model. In addition, parameter $K$ serves as a scaling factor for the thermal resistance of the degraded transistors, the larger this factor, the larger the degradation in the model.
Precursor of Failure

- As case temperature increases, ON-resistance increases.
- This relationship shifts as the degradation of the device increases.
- For a degraded state, ON-resistance will be higher at any given case temperature.
- This is consistent with the die-attach damage since it results in increased junction temperature operation.
- This plot can be used directly for fault detection and diagnostics of the die-attach failure mechanism.
Degradation process data

- Normalized ON-state resistance ($\Delta R_{DS(ON)}$) and filtered trajectory for device #36

• Cases #08, #09, #11, #12 and #14 are used for algorithm development purposes.
• Case #36 is used to test the algorithms.
Empirical Degradation Model

- An empirical degradation model was selected for the model-based algorithms
- Exponential based function to capture degradation process
- Two parameters in the model which will be estimated on-line

\[ \Delta R_{DS(ON)} = \alpha (e^{\beta t} - 1) \]
Prediction of Remaining Life
A single feature is used to assess the health state of the device \( \Delta R_{DS(ON)} \).

It is assumed that the die-attached failure mechanism is the only active degradation during the accelerated aging experiment.

Furthermore, \( \Delta R_{DS(ON)} \) accounts for the degradation progression from nominal condition through failure.

Periodic measurements with fixed sampling rate are available for \( \Delta R_{DS(ON)} \).

A crisp failure threshold of 0.05 increase in \( \Delta R_{DS(ON)} \) is used.

The prognostics algorithm will make a prediction of the remaining useful life at time \( t_p \), using all the measurements up to this point either to estimate the health state at time \( t_p \) in a regression framework or in a Bayesian state tracking framework.

It is also assumed that the future load conditions do not vary significantly from past load conditions.
RUL Prediction Algorithms

• Gaussian Process Regression
  – Algorithm development cases used to select covariance matrix structure and values

• Extended Kalman filter
  – Empirical degradation model
  – State variable: Normalized ON-resistance and degradation model parameters
  – Arbitrary values for measurement and process noise variance

• Particle filter
  – Empirical degradation model
  – State variable: Normalized ON-resistance, degradation model parameters
  – Exponential growth model used for degradation model parameters
  – Arbitrary values for measurement and process noise variance
RUL estimation results

![Graph showing RUL estimation results for different methods: GPR, EKF, and PF. The x-axis represents time in minutes, ranging from 140 to 230, while the y-axis represents RUL. The graph includes markers and lines for each method, showing the estimated RUL over time.](image-url)
CAPACITORS
Degradation Mechanisms

Degradation Causes\ Mechanisms

- Degradation of Oxide Film

Failure Modes

- Decrease in capacitance
- Increase in ESR

Degradation in Anode foil

- Over Voltage Stress
- Excess Ripple Current
- Charging\Discharging Cycles
- High Ambient Temperature

Degradation in Cathode foil

- Over Voltage Stress
- Excess Ripple Current
- Charging\Discharging Cycles
- High Ambient Temperature

Prolonged Use -Nominal Degradation

- Increase in internal Temperature
- Over Voltage Stress
- Excess Ripple Current
- Charging\Discharging Cycles
- High Ambient Temperature

Electrolyte Evaporation

- Prolonged Use
- Electrical Stress
Degradation Model: Electrical Circuit Equivalent

Granularity of Degradation Models

\[ R_{pao} \geq 10K \]
\[ C_E \]
\[ R_{pc0} \geq 10K \]

\[ 1m\Omega \]
\[ R_{ao} \]
\[ 2m\Omega \]
\[ R_1 \]

\[ C_{ao} \]
\[ R_{co} \]
\[ C_{co} \]

\[ \text{cathode} \]
\[ \text{anode} \]
\[ \text{dielectric Layer} \]
\[ \text{highly etched aluminum foil} \]
\[ \text{Al}_2\text{O}_3 \text{– oxide layer(forming)} \]
\[ \text{Al}_2\text{O}_3 \text{– oxide layer(natural)} \]
\[ \text{electrolyte} \]
\[ \text{etched aluminum foil} \]
\[ \text{leakage current} \]

\[ \text{ESR} \]

\[ \text{ESR} \]

\[ \text{ESR} \]
Capacitance Degradation Model

• Decrease in electrolyte volume:

\[ Ve(t) = V_{e0} - (w_e A_s j_{eo} t) \]  

where:
- \( V \): dispersed volume at time \( t \), \( V_e \): initial electrolyte volume
- \( A_s \): surface area of evaporation, \( j_{eo} \): evaporation rate
- \( t \): time in minutes, \( w_e \) = volume of ethyl glycol molecule

• Capacitance (C) ): Physics-Based Model:

\[ C = \left( \frac{2\epsilon_R \epsilon_O A_s}{d_C} \right) \]

where:
- \( \mathcal{D}_1 : C(t) = \left( \frac{2\epsilon_R \epsilon_0}{d_C} \right) \left( \frac{V_{e0} - V_e(t)}{j_{eo} t w_e} \right) \)

• Electrolyte evaporation dominant degradation phenomenon
  – First principles: Capacitance degradation as a function of electrolyte loss
Capacitance Degradation Model

- Oxide breakdown observed - experimental data
- The breakdown factor is exp. function of electrolyte evaporation

\[ C_{bk(t)} = \exp f(V_{eo} - V_e(t)) \]

- Updated in capacitance degradation model:

\[
C = \frac{(2\varepsilon_R\varepsilon_0 A_s c_{bk})}{d_C}, \\
D_{11}: C(t) = c_{bk(t)} \left( \frac{2\varepsilon_R\varepsilon_0}{d_C} \right) \left( \frac{V_{eo} - V_e(t)}{j_{eo} t w_e} \right)
\]
Dynamic Model of ESR

- Decrease in electrolyte volume:
  \[ V_e(t) = V_{e0} - (w_e A_s j_{eo} t) \]

- ESR
  - Based on mechanical structure and electrochemistry.
  - With changes in \( R_E \) (electrolyte resistance)

\[
ESR = \frac{1}{2} \left( \frac{\rho_{EdC} P_E e_{bk}(t)}{A_s} \right)
\]

\[
D_2 : ESR(t) = \frac{1}{2} (\rho_E dC P_E) \left( \frac{j_{eo} t w_e e_{bk}(t)}{V_e(t)} \right)
\]

Dynamic ESR degradation Model:

\[
D_5 : \frac{1}{ESR_{k+1}} = \frac{1}{ESR_k} - \left( \frac{2 w_e A_s j_{eo}}{\rho_E P_E d_C^2 e_{bk}(t)} \right) \Delta t
\]

where:
- \( \rho_E \) : electrolyte resistivity,
- \( P_E \) : correlation factor related to electrolyte spacer porosity and average liquid pathway,
- \( e_{bk}(t) \) : resistance dependence oxide breakdown factor
Process Flow

Experiments

Monitor degradation behavior

Physics-based / Empirical Degradation models

Offline Parameter Estimation

Health State

Tracking Health State / Parameter Estimation

Forecasting

Compute RUL

Performance Assessment

\[ D_1 : C(t) = \left( \frac{2 \varepsilon R \varepsilon_0 c_{bk}}{d_C} \right) \left( \frac{V_0 - V_e(t)}{j_{eo} t w_e} \right) \]

\[ D_4 : C_{k+1} = C_k - \left( \frac{2 \varepsilon R \varepsilon_0 w_e A_s j_{eo} c_{bk}}{d_C^2} \right) \Delta t, \]

\[ (\alpha, \beta) \]

\[ (C_i) \]

\[ (C_i, j_{eo(i)}, c_{bk(i)}) \]

\[ tp = EOL \]

\[ RA = 100 \left( 1 - \frac{RUL^* - RUL}{RUL^*} \right) \]
RUL and Validation – EOS -Experiment – ESR Degradation Model $D_5$

Tracking

Predictions at different aging time

Alpha Lambda

$\alpha = 0.3$, $\beta = 0.5$

Measured

Predicted

$t_p = 24$

$t_p = 47$

$t_p = 94$

$t_p = 149$

$t_p = 171$
RUL and Validation – TOS -Experiment - Capacitance

Tracking

Cap #1

Output Error - Cap #1

Aging Time (Hours)

Predictions at different aging time

Alpha Lambda

Predictions at different aging time

\[ \text{Predicted} = \text{Measured} + \text{Filter Data} \]

\[ t_p = 87 \]

\[ t_p = 607 \]

\[ t_p = 1495 \]

\[ t_p = 2131 \]

\[ t_p = 2800 \]

\[ \alpha = 0.3, \beta = 0.5 \]
LI-ION BATTERIES
Electrochemical Li-ion Model

- **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

- **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

![Graph showing measured and predicted voltage over time](image)
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 “$q^{\text{max}}$” parameter, used to compute mole fraction
  - Modeled with increase in “$R_o$” parameter capturing lumped resistances

Simulated

Measured

Cycle 16
Cycle 26
Cycle 36
Cycle 46
Cycle 56
Cycle 66
Cycle 76
Cycle 86
Cycle 96
Cycle 106
Cycle 116
Cycle 126
Cycle 136
Cycle 146
Cycle 156
Cycle 166
Cycle 176
Cycle 186
Rover

- Planetary rover testbed at NASA Ames Research Center
  - 24 lithium ion batteries, two parallel sets of 12 in series
  - Batteries power 4 motors, one for each wheel (skid steering)
- Rover operated in two driving modes
  - Unstructured driving
    - Rover is driven freely by an operator, without prior knowledge of actions
  - Structured driving
    - Rover has a given mission, to visit a set of waypoints
    - Rover moves along, visiting waypoints
    - End-of-discharge prediction is required in order to ensure the given set of waypoints can be visited, and if not, to replan the route to optimize mission value

Results: Structured Driving

Predictions are very accurate since rover travels at a known fixed average speed, and waypoints are known. Uncertainty in predictions is significantly less than for unstructured driving, since more information about future inputs are known. Predictions are under at the start because power drawn for first 500 s is half the average.
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.

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
Data Sets Available for Download

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

### Randomized Battery Usage Data Set

<table>
<thead>
<tr>
<th>Description</th>
<th>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.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Format</td>
<td></td>
</tr>
<tr>
<td>Datasets</td>
<td>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)</td>
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<tr>
<td>Dataset Citation</td>
<td>B. Bole, C. Kulkarni, and M. Daigle &quot;Randomized Battery Usage Data Set&quot;, NASA Ames Prognostics Data Repository (<a href="http://ti.arc.nasa.gov/project/prognostic-data-repository">http://ti.arc.nasa.gov/project/prognostic-data-repository</a>), NASA Ames Research Center, Moffett Field, CA</td>
</tr>
<tr>
<td>Publication Citation</td>
<td>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</td>
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</tbody>
</table>

### HIRF Battery Data Set

<table>
<thead>
<tr>
<th>Description</th>
<th>Battery Data collected from the Experiments on the Edge 540 Aircraft in HIRF Chamber. Reference document can be downloaded here</th>
</tr>
</thead>
<tbody>
<tr>
<td>Format</td>
<td>The set is in .mat format and has been zipped.</td>
</tr>
<tr>
<td>Datasets</td>
<td>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)</td>
</tr>
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<td>C. Kulkarni, E. Hogge, C. Quach and K. Goebel &quot;HIRF Battery Data Set&quot;, NASA Ames Prognostics Data Repository (<a href="http://ti.arc.nasa.gov/project/prognostic-data-repository">http://ti.arc.nasa.gov/project/prognostic-data-repository</a>), NASA Ames Research Center, Moffett Field, CA</td>
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<td>Publication Citation</td>
<td>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</td>
</tr>
</tbody>
</table>
Remarks (1/2)

- Electrical and Electronics PHM Maturity - scientific and engineering challenges
- Research approach challenges
  - How to balance lack of knowledge of the system vs own expertise on particular PHM tools
  - Data-driven or model-based?
    - Data is always needed but more important, information about degradation/aging processes is key
    - Experiments and field data
• Aging systems as a research tool
  – Value in terms of exploration of precursors of failure and their measurements is evident
  – Still an open question on how degradation models and algorithms are translated to the real usage timescale

• In the use of physics
  – It should be embraced

• Validate models and algorithms with data from lab experiments and fielded systems

• A success in developing PHM methodologies in an real usage application will require the right team
Acknowledgments

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  – NASA SMART –NAS Project
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