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.

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
  – 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

Cell Voltage

Time

E = End of Discharge (EOD)

Δt_{EOD}

Voltage Threshold

t_{EOD}

t
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 $k_P$: $x(k_P)$
  – Parameter values for $k_P$ to $k_E$: $\Theta_{k_P}$
  – Inputs for $k_P$ to $k_E$: $U_{k_P}$
  – Process noise for $k_P$ to $k_E$: $V_{k_P}$

• 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
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:

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

\[ \dot{x} = \begin{bmatrix}
0 & 0 & 0 \\
0 & -\frac{1}{R_{cp}C_{cp}} & 0 \\
0 & 0 & -\frac{1}{R_sC_s}
\end{bmatrix} x + \begin{bmatrix}
-1 \\
1 \\
1
\end{bmatrix} i + \xi \]

\[ y = V = \left[ \frac{1}{C_b} - \frac{1}{C_{cp}} - \frac{1}{C_{s}} \right] \cdot x \]

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

\[ \text{SOC} = 1 - \frac{q_{max} - q_b}{C_{max}} \]

\[ C_b = C_{b0} + C_{b1} \cdot \text{SOC} + C_{b2} \cdot \text{SOC}^2 + C_{b3} \cdot \text{SOC}^3 \]

\[ C_{cp} = C_{cp0} + C_{cp1} \cdot \exp(C_{cp2} (1 - \text{SOC})) \]

\[ R_{cp} = R_{cp0} + R_{cp1} \cdot \exp(R_{cp2} (1 - \text{SOC})) \]
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:
\[ \text{Li}_{1-n}\text{CoO}_2 + n\text{Li}^+ + n\text{e}^- \rightarrow \text{LiCoO}_2 \]
Oxidation at neg. electrode:
\[ \text{Li}_n\text{C} \rightarrow n\text{Li}^+ + n\text{e}^- + \text{C} \]
Current flows + to –
Electrons flow – to +
Lithium ions flow – to +

Charge
Oxidation at pos. electrode:
\[ \text{LiCoO}_2 \rightarrow \text{Li}_{1-n}\text{CoO}_2 + n\text{Li}^+ + n\text{e}^- \]
Reduction at neg. electrode:
\[ n\text{Li}^+ + n\text{e}^- + \text{C} \rightarrow \text{Li}_n\text{C} \]
Current flows – to +
Electrons flow + to –
Lithium ions flow + to –

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.
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 $\rightarrow$ Nernst equation with Redlich-Kister expansion
    - Concentration overpotential $\rightarrow$ split electrodes into surface and bulk control volumes
    - Surface overpotential $\rightarrow$ Butler-Volmer equation applied at surface layers
    - Ohmic overpotential $\rightarrow$ 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 “$q_{max}$” parameter, used to compute mole fraction
  - Modeled with increase in “$R_o$” parameter capturing lumped resistances
• 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
• 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 predicted SOC reaches 30%

Battery parameters deterioration with Aging

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

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

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/

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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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