Predicting Maximum Temperatures of a Li-ion Battery on a Simulated Flight Profile using a Model-based Prognostics

Mohit Mehta (KBR, Inc.), Michael Khasin (NASA Research Center),
Chetan Kulkarni (KBR, Inc.), and John Lawson (NASA Research Center)

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Overview

- Introduction
- Prognostics Architecture
- Results
- Challenges and Future Work

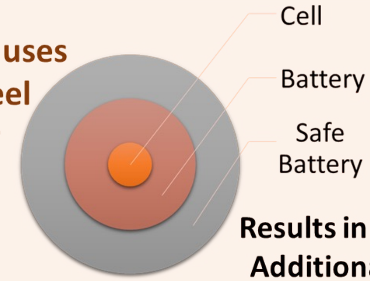
SPARRCI to Improve Specific Energy for a Safe Electric Aircraft Battery

Electric Aircraft need Better and Safer Batteries

- **Consequence of Unmitigated Cell Thermal Runaway Events**
  - Fire
  - Explosion
  - Debris

- ***Current Solution*** **Results in Low Specific Energy and Specific Power for a Current Li-ion Battery**

SOA Safe Battery uses honeycomb steel structures or containers



Results in Significant Additional Weight!

- ***Alternative Solution is*** **reducing the non-battery chemistry mass with the development of:**
  - Better Internal Battery Monitoring Tools
  - Developing internal fault detection & mitigation strategies

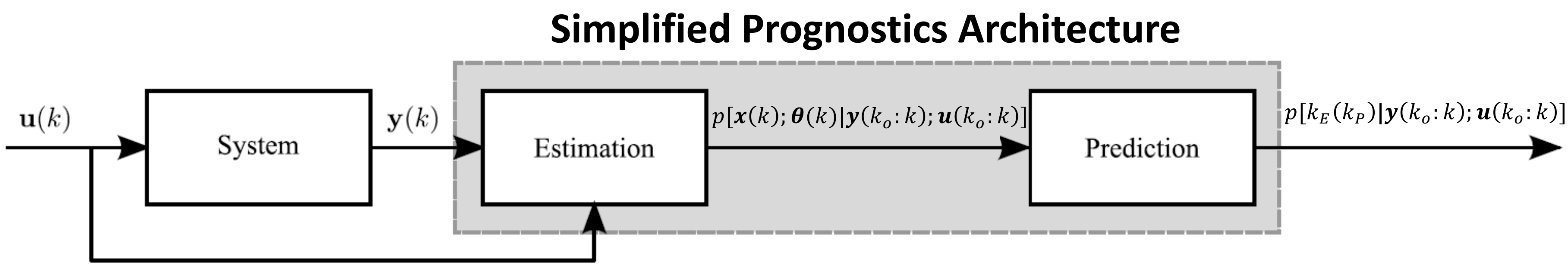
Overview for Complexity in Modeling Nominal Cell Behavior

Inputs
- Materials
- Chemistry
- Geometry
- Cell Configuration
- Experimental Condition

Phenomena
- Thermal
- Lithium Plating
- Capacity Fade
- Dendrite Growth
- Chemical Decomposition
- Overcharge
- Shrinking Core Model

Outputs
- Cell Temperature
- Cell Potential
- Cell Capacity
- Discharge Time
- Cycle

Prognostics Introduction

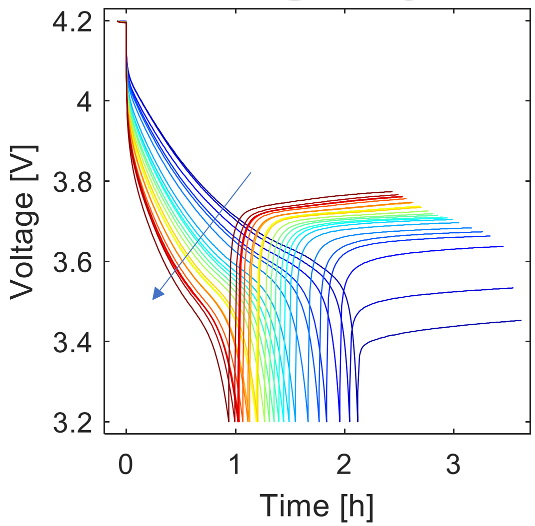


We use two such architectures 1: For Predicting Properties T, V, and EOD

2: For Predicting Aging Parameters and hence, T and EOL

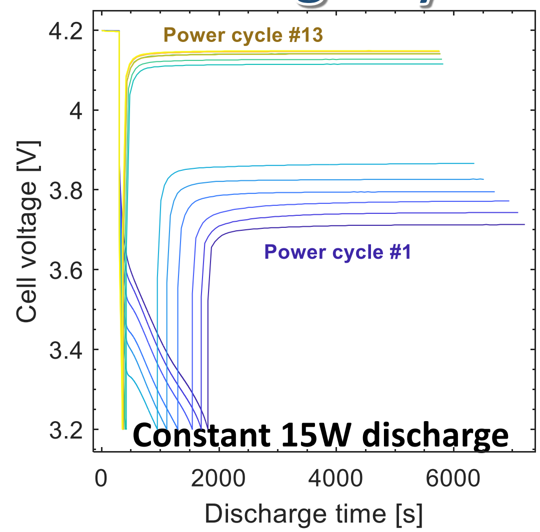
Dataset Used (Battery: LG ICR18650S3)

Reference Discharge Cycle



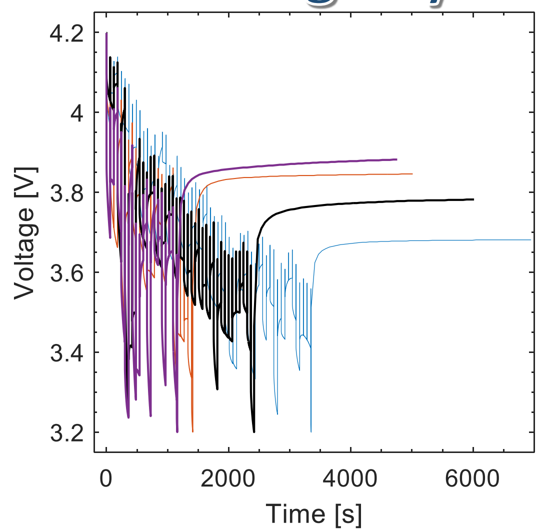
22 Ref. cycles with decreasing SOH

Power Discharge Cycle



A Power cycle is measured after each Ref. cycle

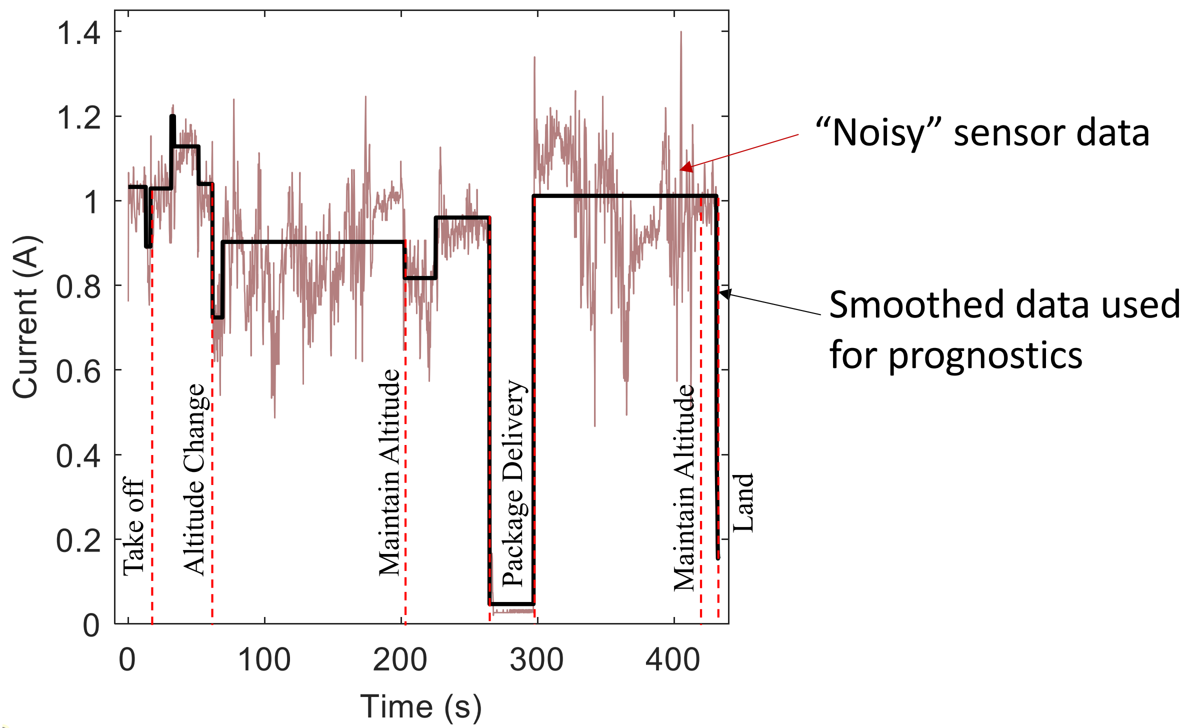
Random Discharge Cycle



Approximate 50 RW cycles between any two Ref. cycles

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

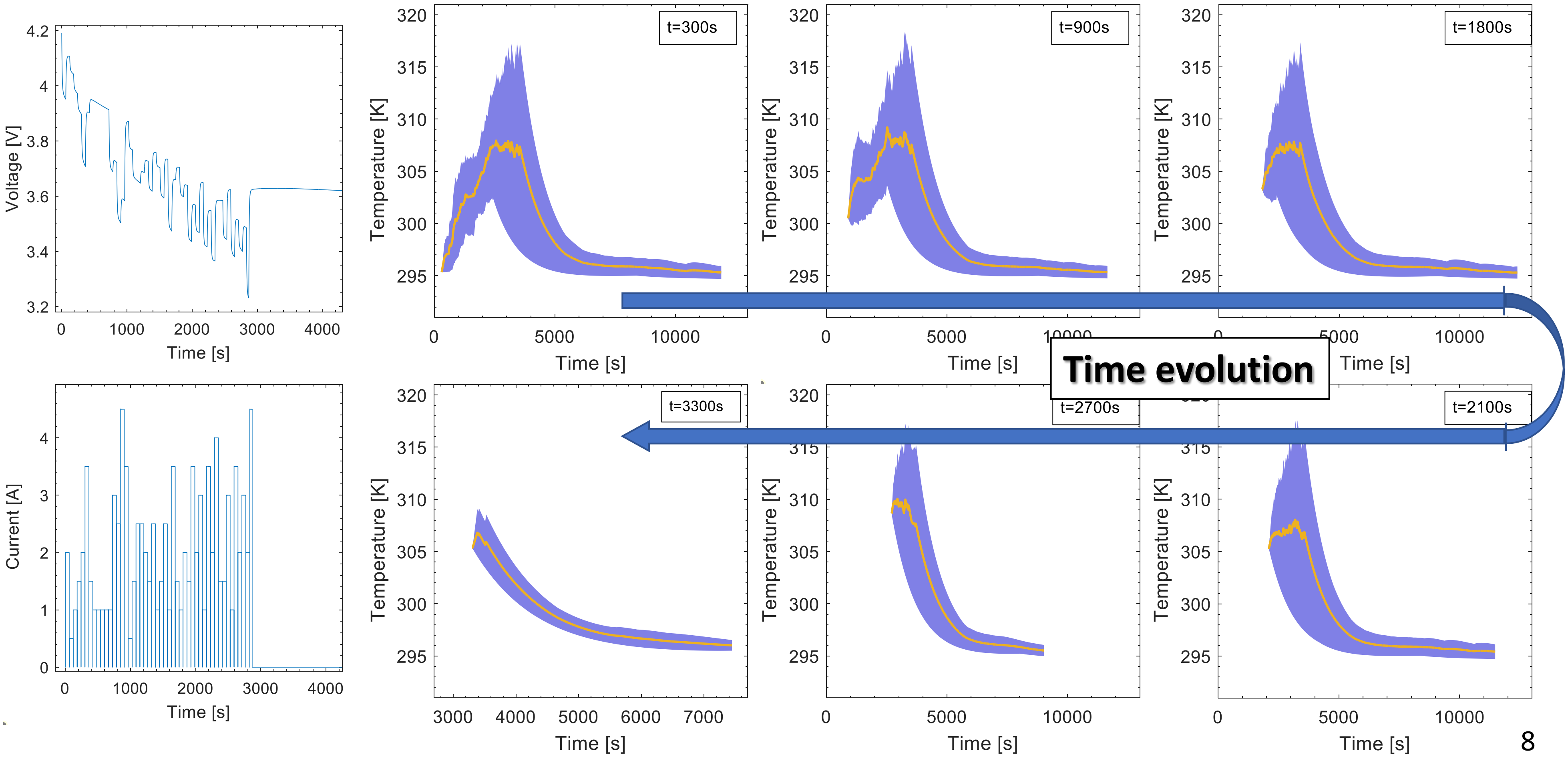
Data from a Short Test Flight



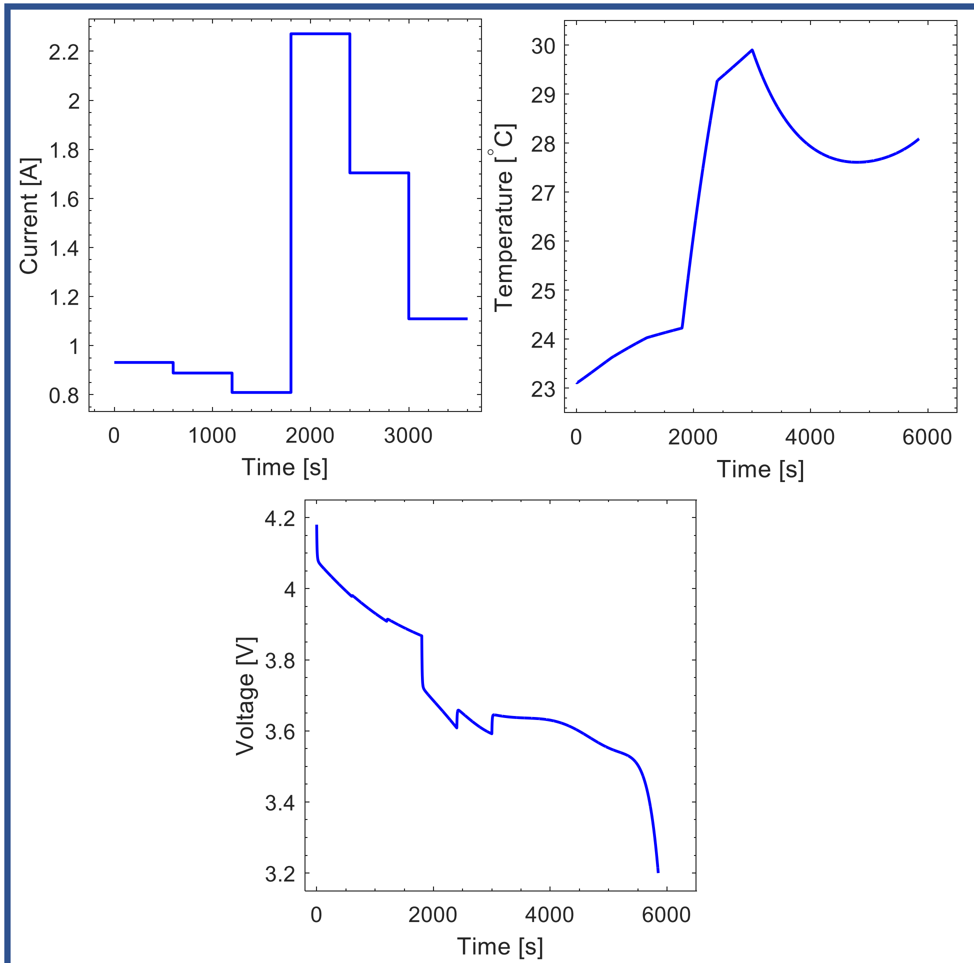
Data pre-processing is needed for accurate estimation

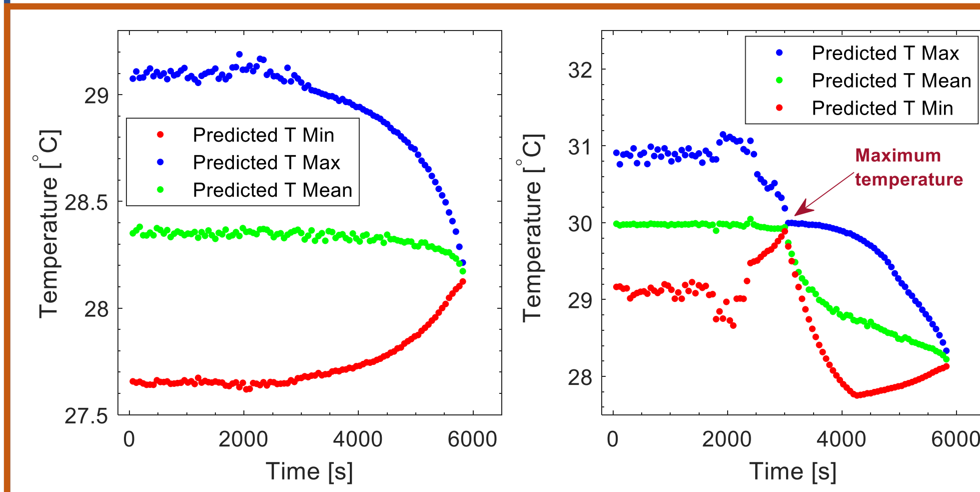
Random Walk is used as a substitute for Simulated Flight Profile

Prognostics on SFP



Two Temperature Metrics for SFP

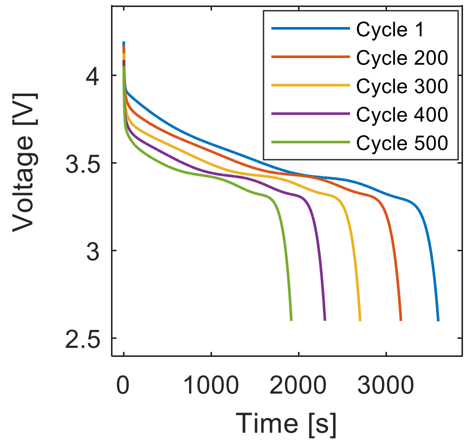


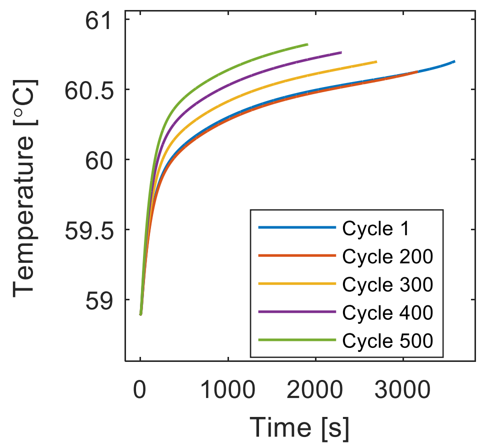


Predicting EOF Temperature

Predicting Maximum Temperature

Hybrid Model-Based Aging

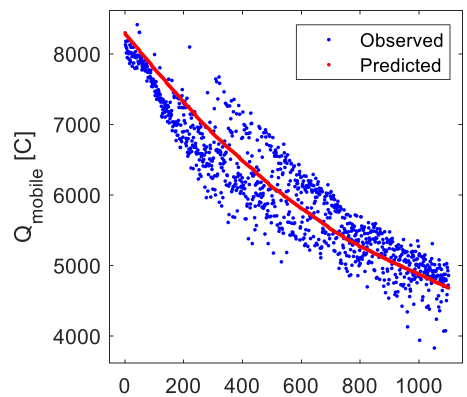




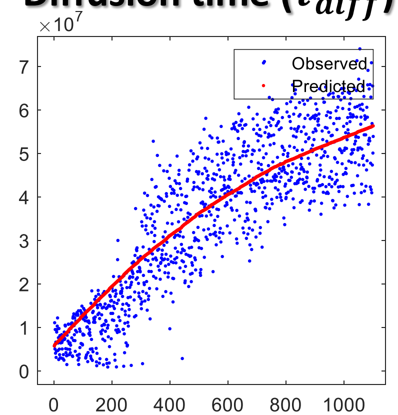
Empirical Aging Model

- Parameters are estimated using Simulated Flight discharge cycles
- C-rate ranges from 0.2-2.2C
- Each Simulated Flight Profile is stopped after V_{min} is reached

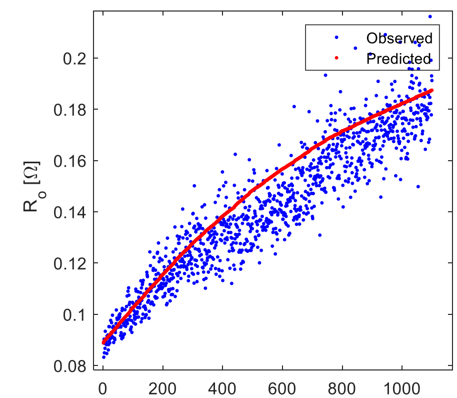
Usable Li-ion (Q_{mobile})



Diffusion time (τ_{diff})

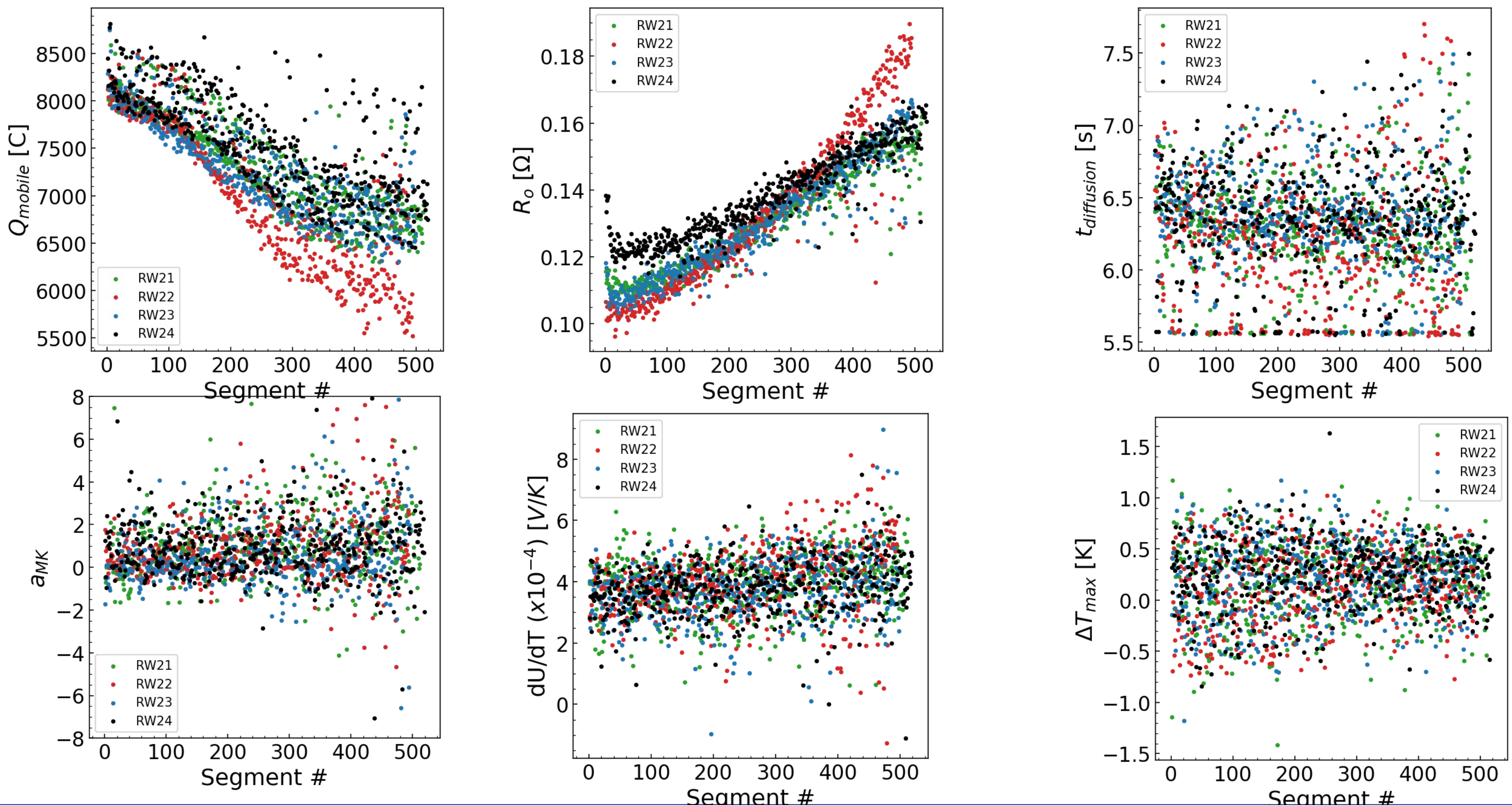


Ohmic Resistance (R_o)



Temperature increases qualitatively on voltage parameterized data

Challenge in Aging Related Temperature Prediction



Voltage Decoupled Thermal Models

$$\frac{dT}{dt} = I(t)C_b^{-1}\left(U - T\frac{dU}{dT} - V(t)\right) - \frac{T - T_a}{\tau}$$

Decoupled voltage
(sensor input or model output)

$$T(t) = T_a + [T(0) - T_a]e^{-t/\tau} + C_b^{-1}\int_0^t I(t')[V_0 - V(t')]e^{\frac{t'-t}{\tau}}dt'$$

ROM

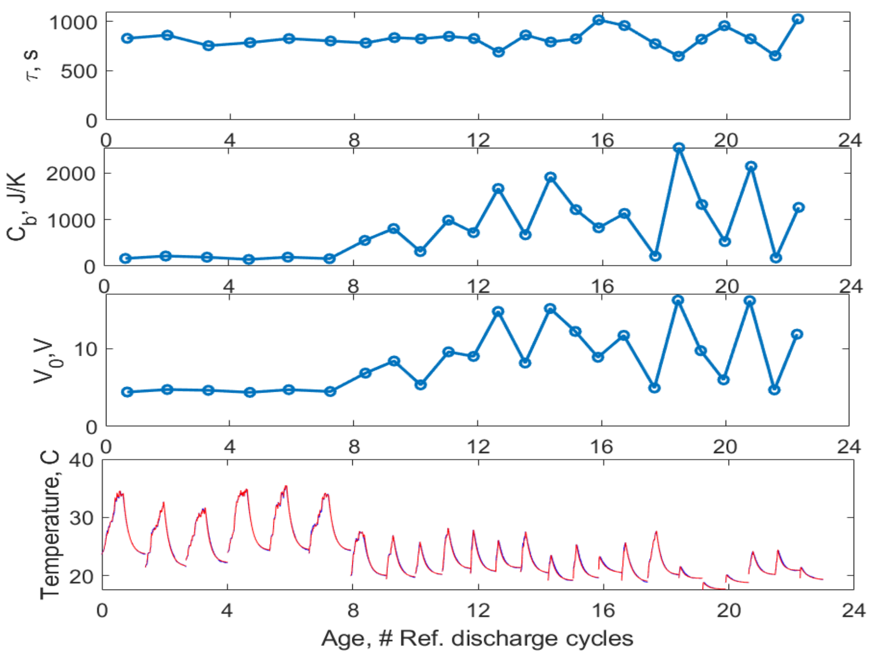
For realistic flight profiles with varying values of the discharge currents

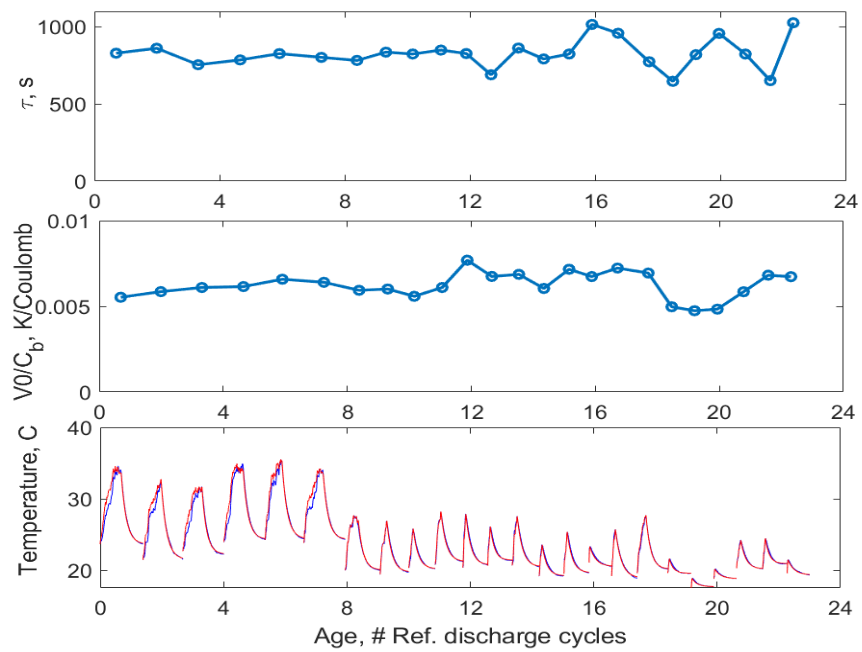
$$T(t) = T_a + [T(0) - T_a]e^{-t/\tau} + \frac{V_0}{C_b}\int_0^t I(t')e^{\frac{t'-t}{\tau}}dt'$$

Overcompensation can be tested by decoupling voltage and temperature parameter estimation

Fitting TM and ROM to SFP data

TM: $T(t) = T_a + [T(0) - T_a]e^{-t/\tau} + C_b^{-1}\int_0^t I(t')[V_0 - V(t')]e^{\frac{t'-t}{\tau}}dt' \rightarrow$ **ROM**: $T(t) = T_a + [T(0) - T_a]e^{-t/\tau} + \frac{V_0}{C_b}\int_0^t I(t')e^{\frac{t'-t}{\tau}}dt'$



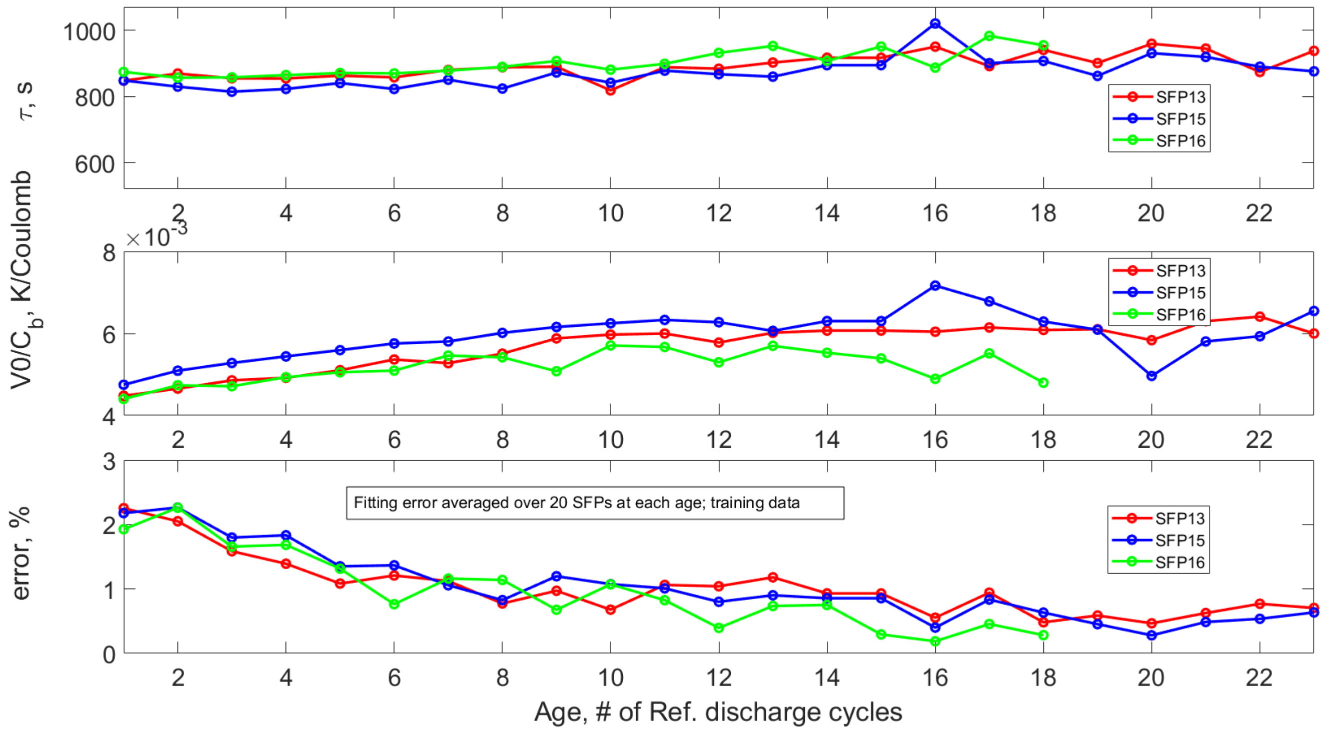


The 3-parameter TM is practically *non-identifiable* from SFP data at older age.

The 2-parameter ROM is *practically identifiable* from SFP data at each age.

Fitting ROM to SFP datasets

ROM: $T(t) = T_a + [T(0) - T_a]e^{-t/\tau} + \frac{V_0}{C_b}\int_0^t I(t')e^{\frac{t'-t}{\tau}}dt'$



The 2-parameter ROM is *practically identifiable* from SFP data at each age.

Summary

1. **Hybrid-ECM-based prognostics can predict temperatures for a "simulated" flight profile with noise** (assuming Poisson noise and Gaussian noise)

2. **Hybrid-ECM thermal model cannot be identified from SFPs alone, therefore it cannot be used for predicting aging parameters**

3. **Thermal ROM with two model parameters is identifiable and can be used to** predict the aging parameters

4. **Collecting experimental data with four datatypes (OCV, galvanostatic with range of "usable" C-rates, and "expected" loading profile)** can provide better insights and provide a flexible path to model reduction for a targeted observable property

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Backup Slides

Battery Modeling (ROM and P2D)

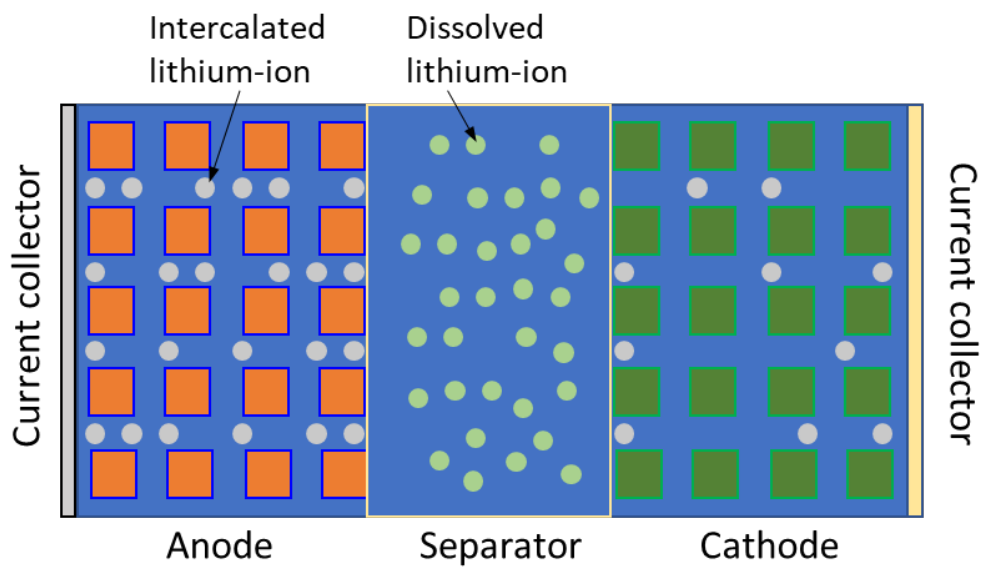
- Li-ion Chemistry
  - Cathode (LCO/NMC/LFP)
  - Anode (Graphite/Lithium)
  - Electrolyte ($LiCF_3SO_3$, $LiPF_6$ in EC/DMC)
  - Separator (PP/Al_2O_3)

Anode reaction

$$\mathrm{Li}_x\mathrm{C} \rightarrow \mathrm{C} + x\mathrm{Li}^{+} + x\mathrm{e}^{-}$$

Cathode reaction

$$\mathrm{Li}_{1-x}\mathrm{CoO}_2 + x\mathrm{Li}^{+} + x\mathrm{e}^{-} \rightarrow \mathrm{LiCoO}_2$$



Full Multiphysics Models Allows us to identify Important Mechanisms for capturing Thermal and Battery Performance with Aging over High C flight profiles

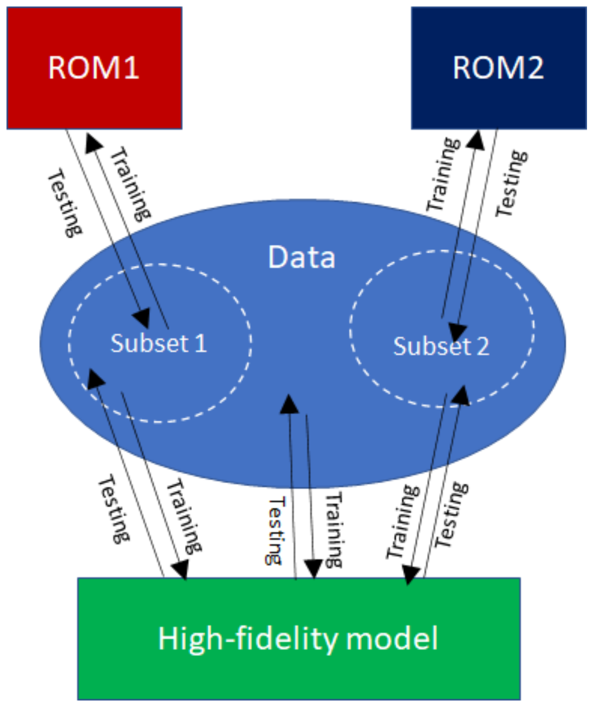
Reduced-Order-Models (ROMs)

What are ROMs?
- A ROM is a simplified model of the system which interpolates in a subset of data.
- Different subsets of data will be associated with different ROMs. For example, ROM1 may predict a battery's voltage while ROM2 may predict its temperature.
- A ROM can be physics-based or purely data-driven.

Advantages of ROMs:
- The computational complexity of a ROM is lower than that of a high-fidelity model.
- A ROM can be practically identifiable, i.e., its parameters can be uniquely fit to data.

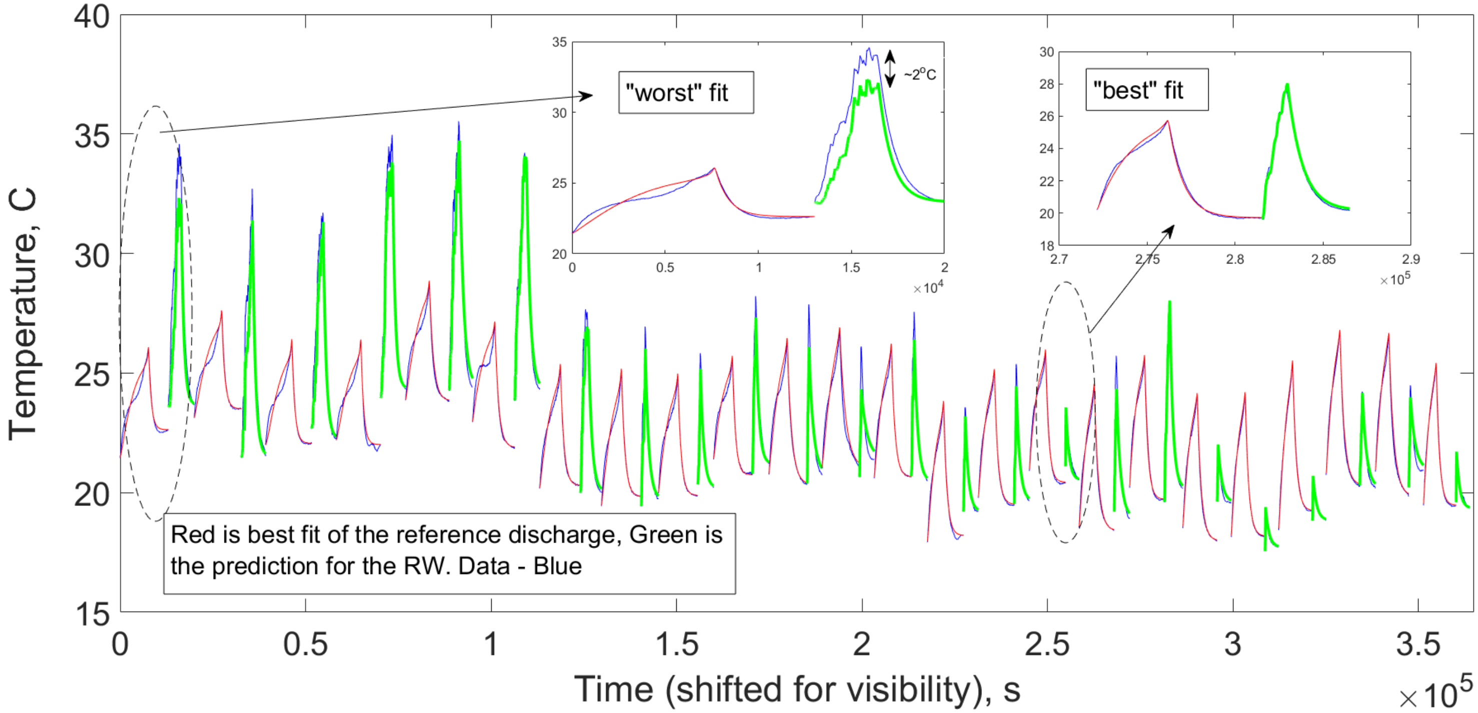
Disadvantages of ROMs:
- Limited range of validity compared to a high-fidelity model.

How to derive ROM?
- Our approach is inspired by [Manifold Boundary Approximation Method]:
  - Parameter sensitivity applied to high-fidelity model is used eliminate some parameters from the model
  - The resulting ROM is fitted to the data. If it's not completely identifiable, the reduction is repeated, until the final ROM is completely identifiable.



Using the TM to predict RW data.

TM: $T(t) = T_a + [T(0) - T_a]e^{-t/\tau} + C_b^{-1}\int_0^t I(t')[V_0 - V(t')]e^{\frac{t'-t}{\tau}}dt'$



Fitting the TM to galvanostatic discharge data gives a decent prediction for RW data.