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

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**Funded By**

NASA Aeronautics Research Mission Directorate (ARMD) Convergent Aeronautics Solutions (CAS) Project, SPARRCI sub-project.

**Presentation date**: 11/17/2022

# Overview

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

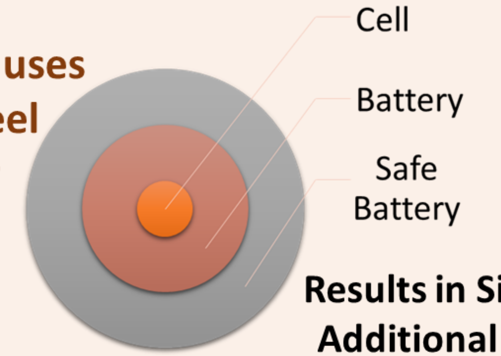
# SPARRCI to Improve Specific Energy for a Safe Electric Aircraft Battery

## 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**

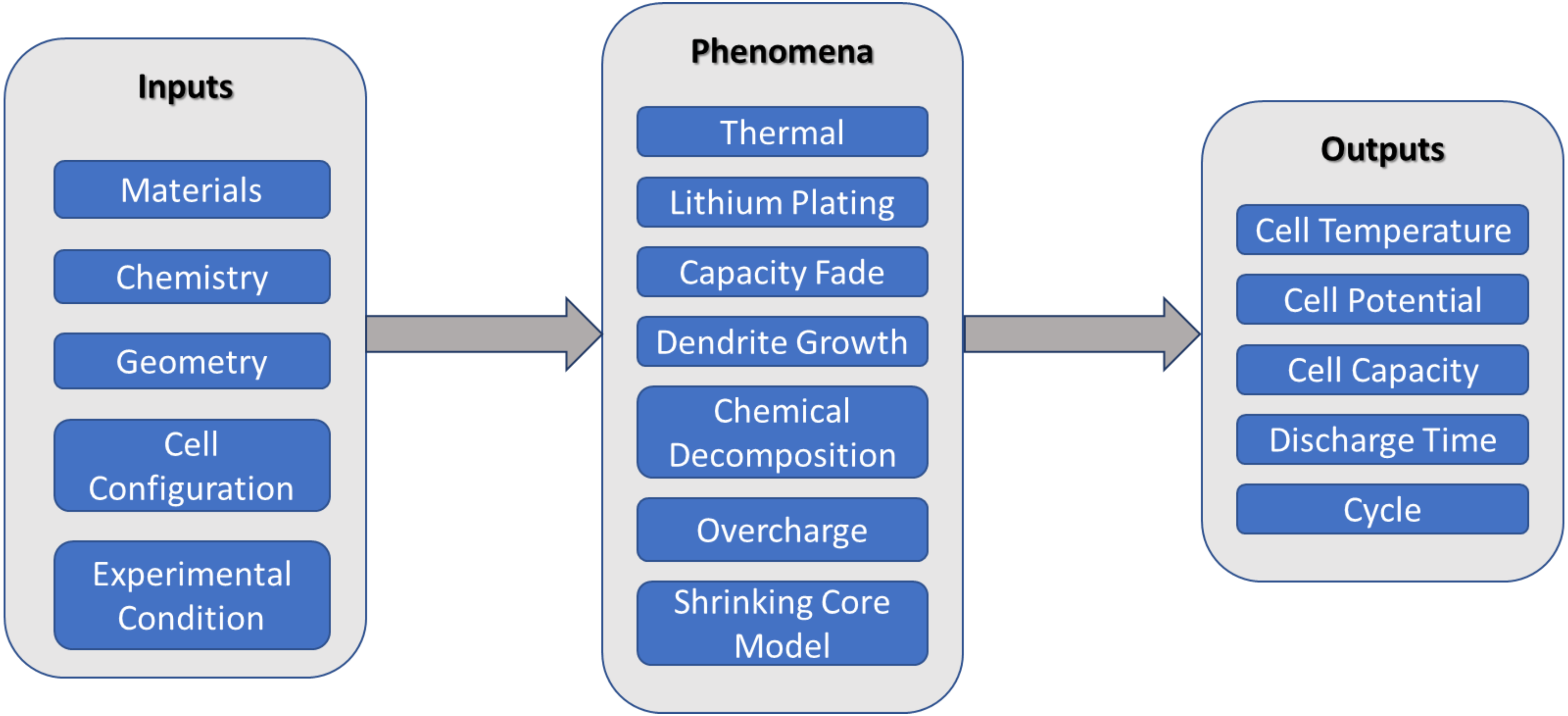
**SOA Safe Battery uses honeycomb steel structures or containers**




**Results in Significant Additional Weight!**

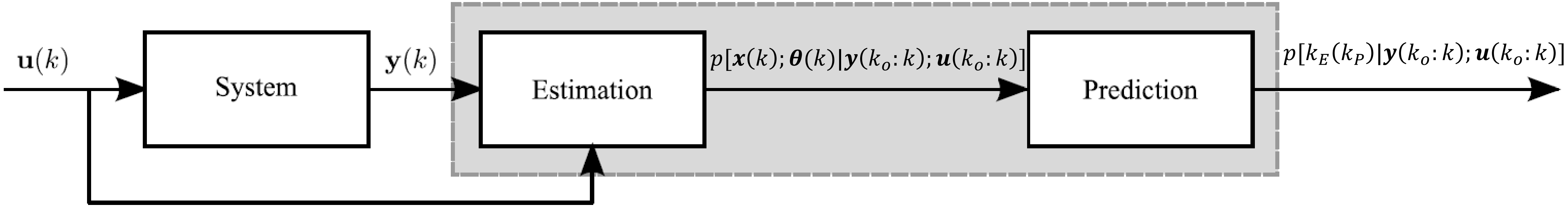
- ***Alternative Solution is* reducing the non-battery chemistry mass with the development of:**
  - Better Internal Battery Monitoring Tools
  - Developing internal fault detection & mitigation strategies

# Overview for Complexity in Modeling Nominal Cell Behavior



# Prognostics Introduction

## Simplified Prognostics Architecture

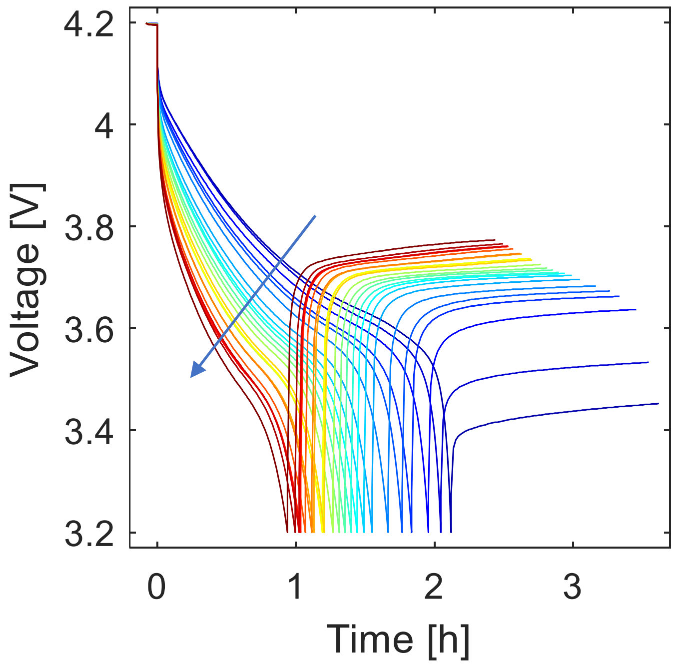



We use two such architectures 1: For Predicting Properties T, V, and EOD

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

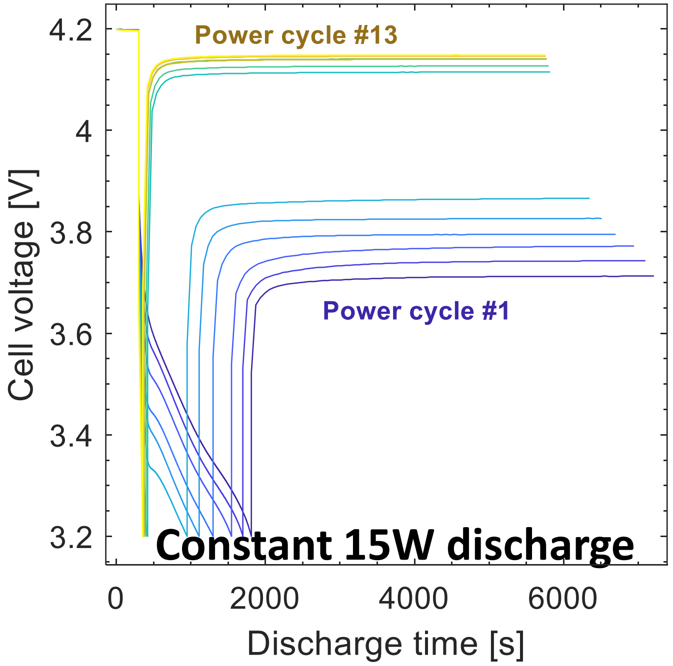
# Dataset Used (Battery: LG ICR18650S3)

## Reference Discharge Cycle



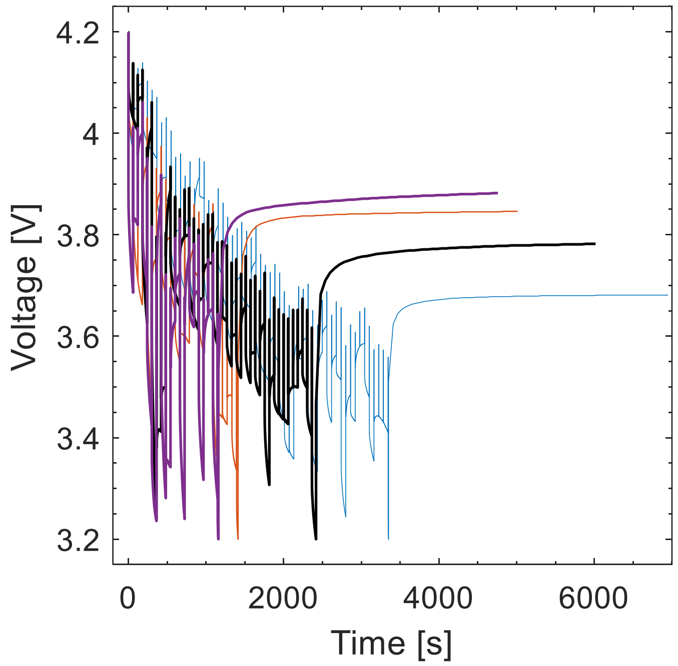

22 Ref. cycles with decreasing SOH

## Power Discharge Cycle




A Power cycle is measured after each Ref. cycle

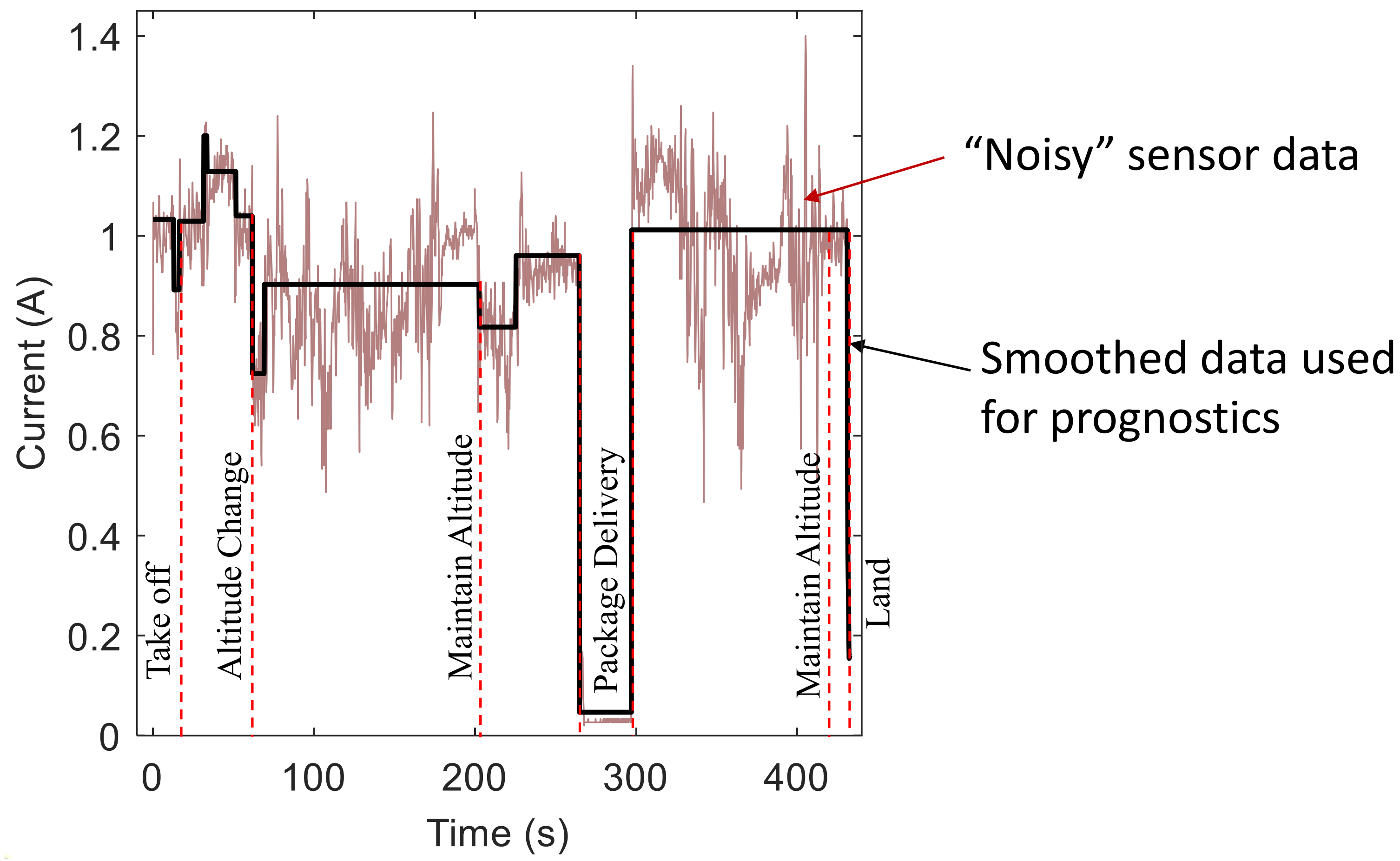
## Random Discharge Cycle




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

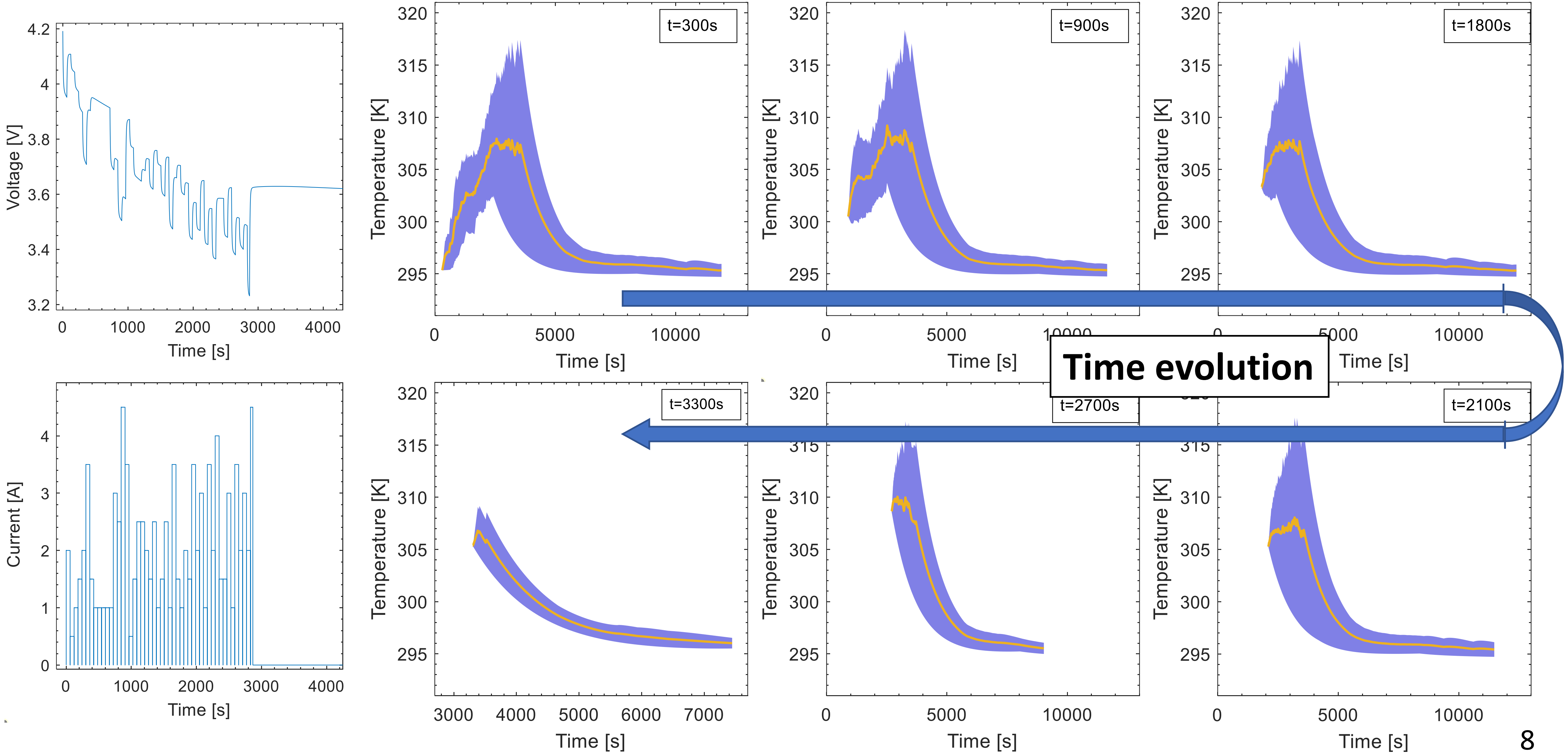
# Data from a Short Test Flight



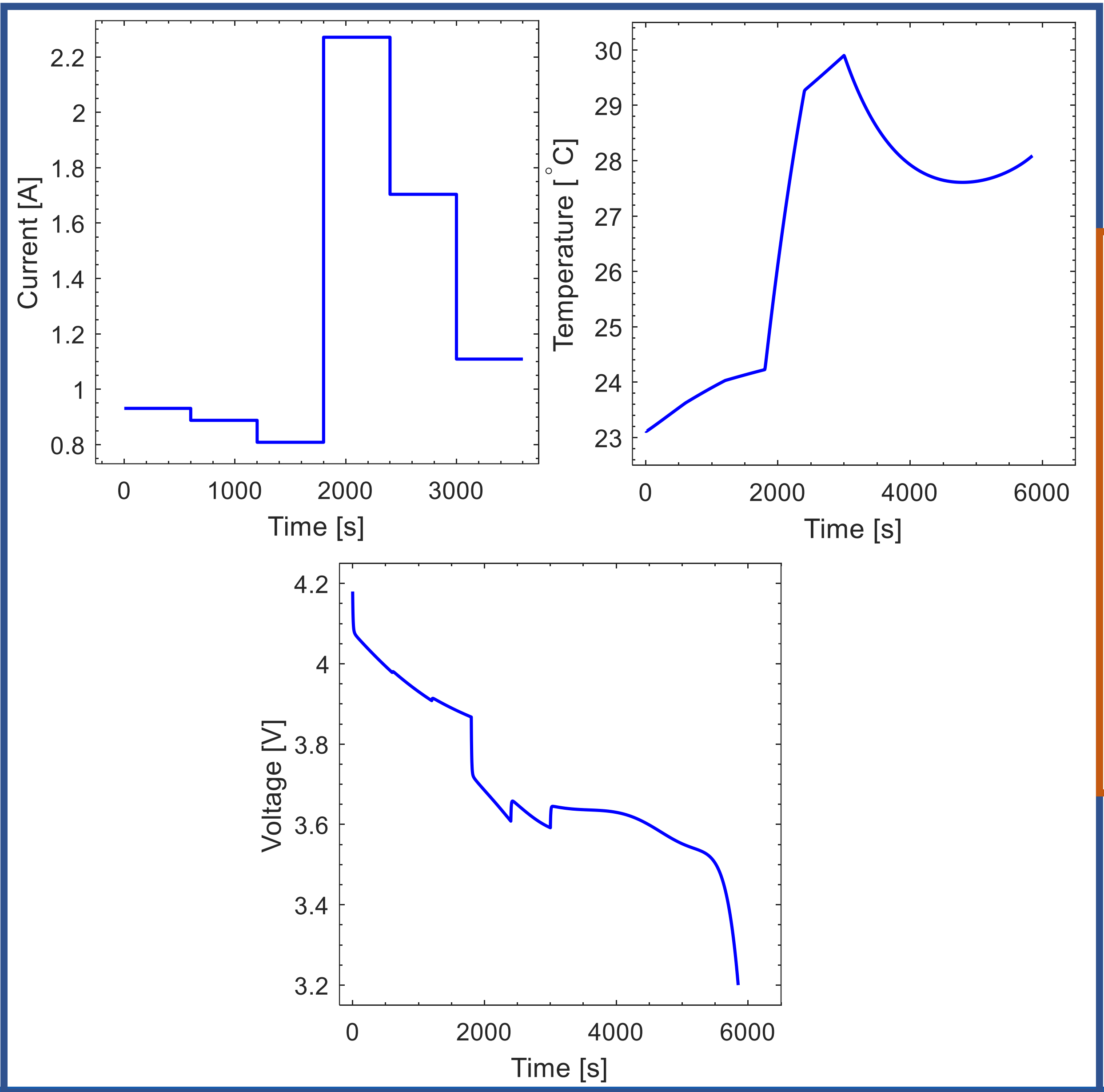

**Data pre-processing is needed for accurate estimation**

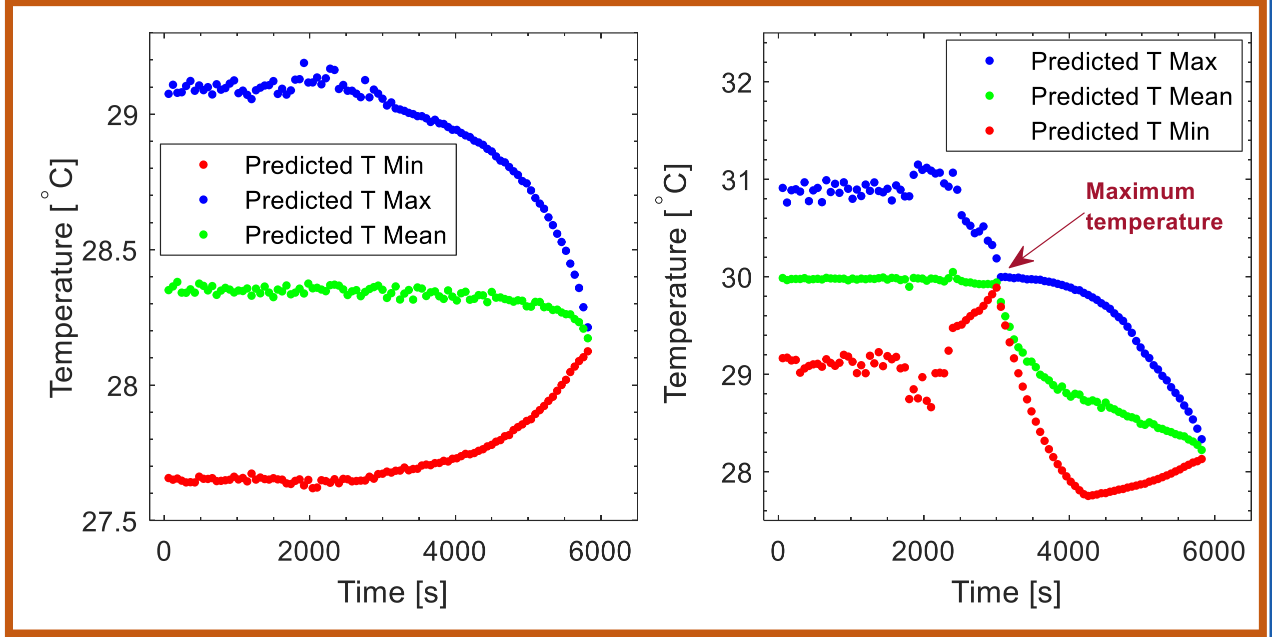
**Random Walk is used as a substitute for Simulated Flight Profile**

# Prognostics on SFP



# Two Temperature Metrics for SFP

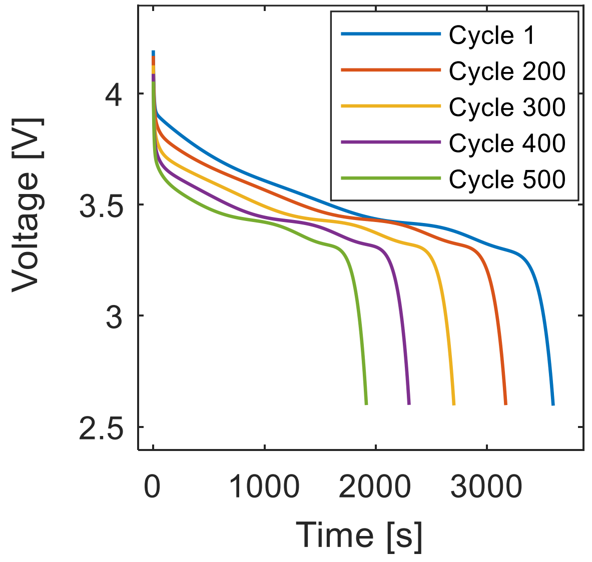


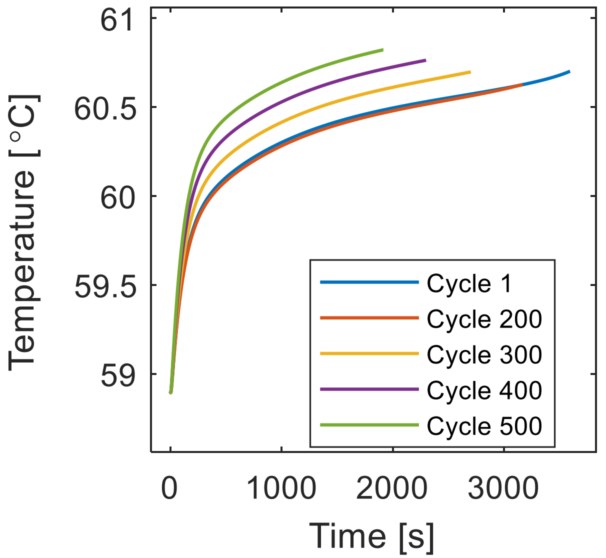




Predicting EOF Temperature

Predicting Maximum Temperature

# Hybrid Model-Based Aging

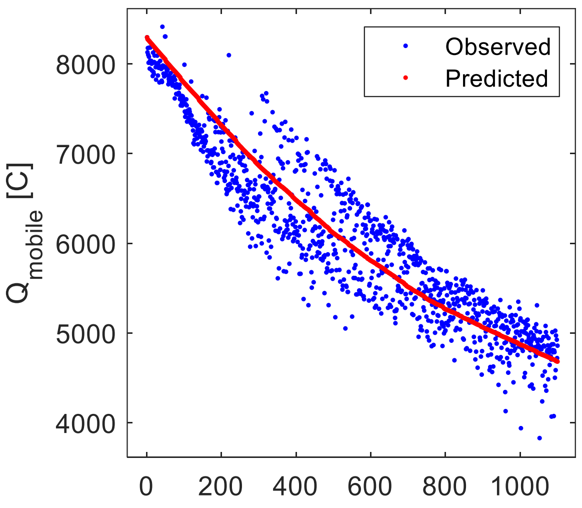


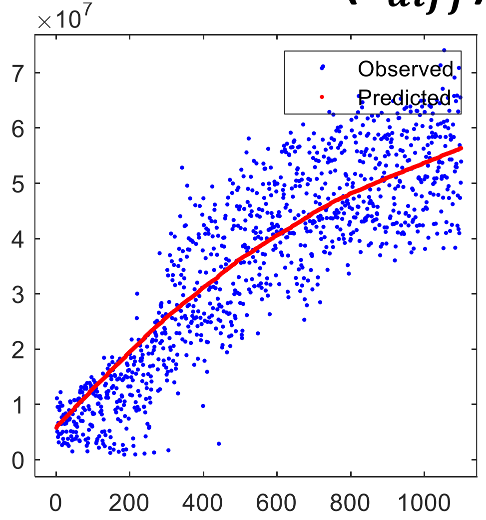

## Empirical Aging Model

- 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

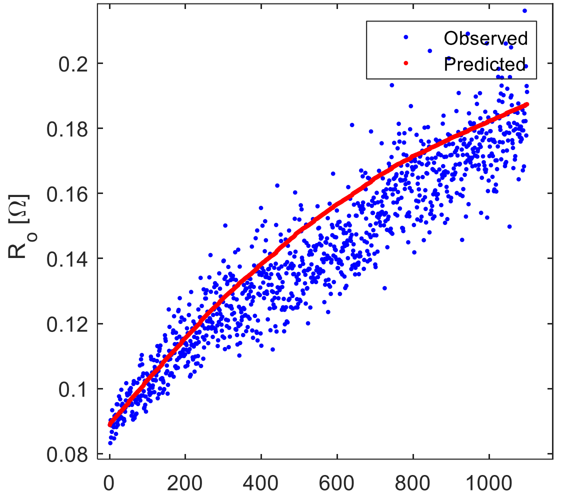
**Usable Li-ion ($Q_{mobile}$)**




**Diffusion time ($\tau_{diff}$)**

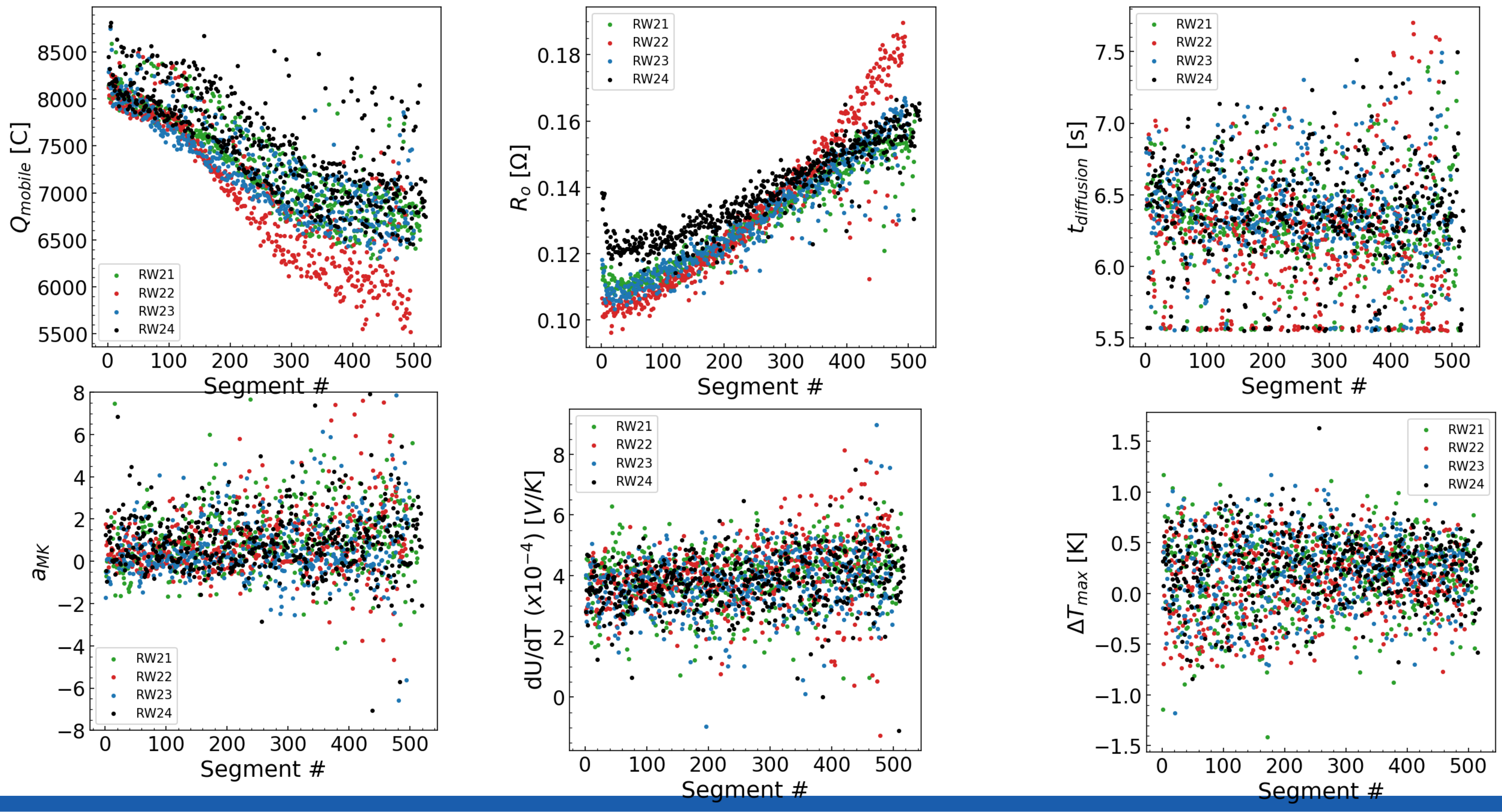



**Ohmic Resistance ($R_o$)**




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**

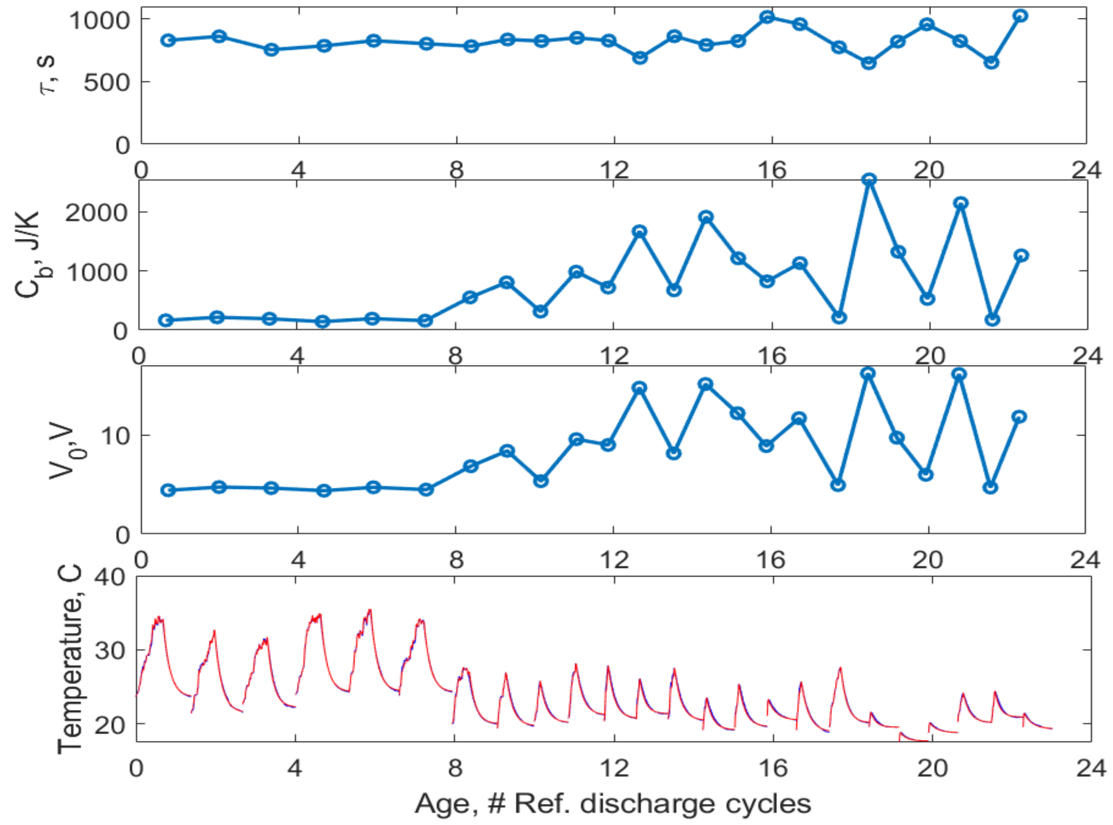
**For realistic flight profiles with varying values of the discharge currents**

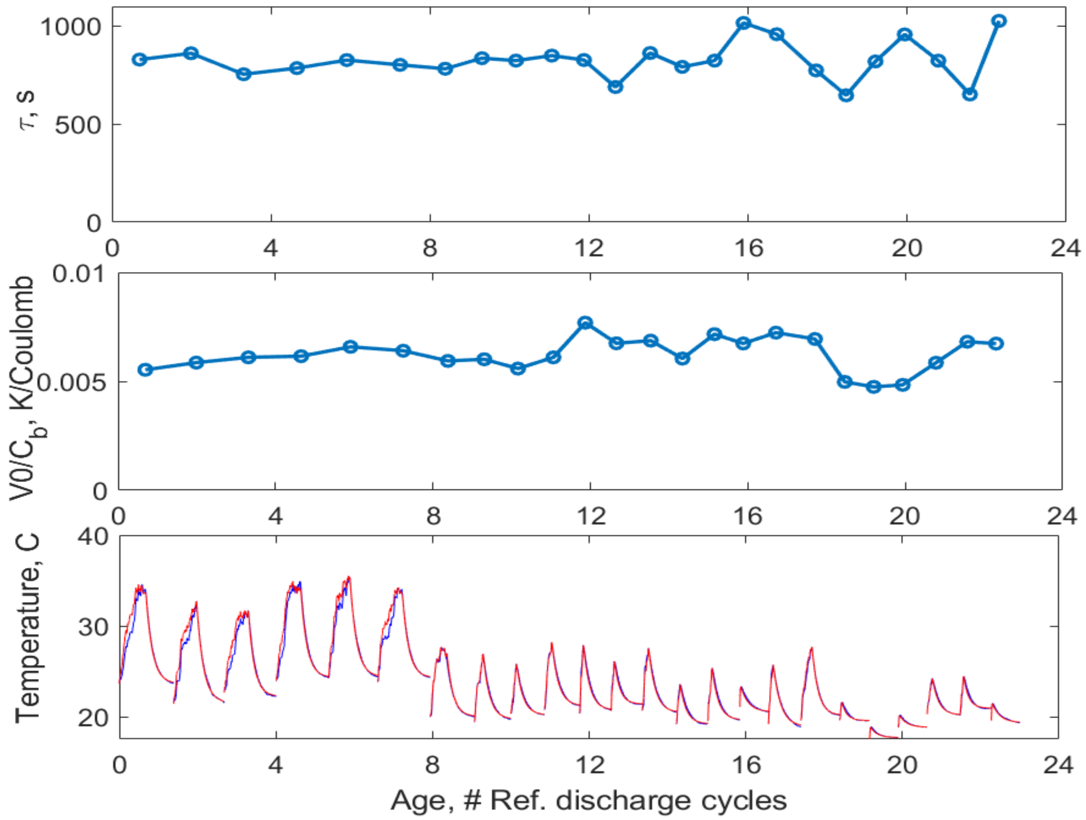
$$T(t) = T_a + [T(0) - T_a]e^{-t/\tau} + \frac{V_0}{C_b}\int_0^t I(t')e^{\frac{t'-t}{\tau}}dt'$$

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



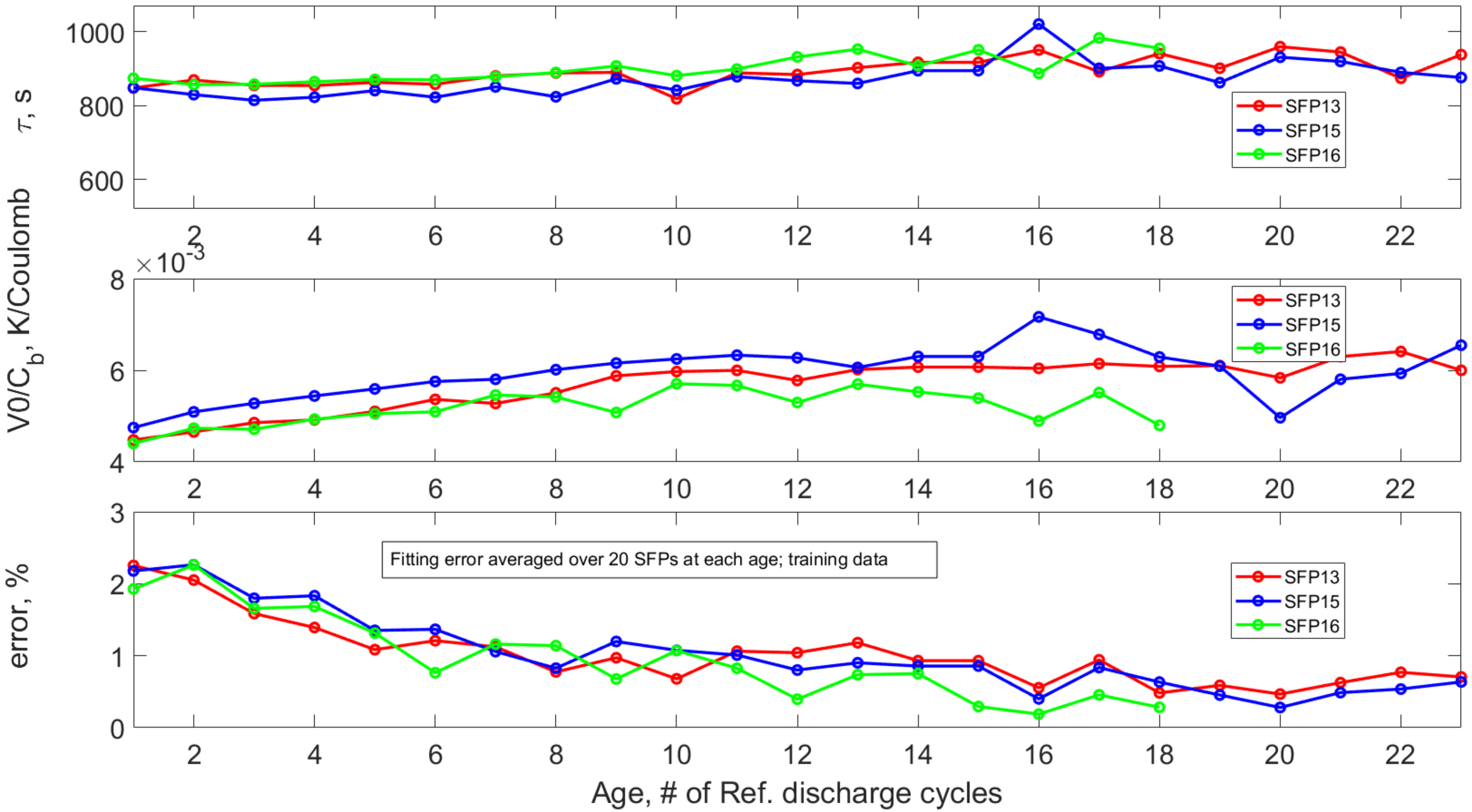




The 3-parameter TM is practically *non-identifiable* from SFP data at older age.

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 <u>cannot be identified</u> from SFPs alone, therefore it cannot be used for predicting aging parameters**

3. **Thermal ROM with two model parameters <u>is identifiable</u> 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

# Acknowledgments


**NASA Glenn Research Center**
Brianne DeMattia
Gary Hunter
Donald L. Simon
Daniel F. Perey
William C. Schneck

**NASA Langley Research Center**
Erik L. Frankforter
William C. Schneck
Peter W. Spaeth
Yi Lin
Daniel F. Perey

**Purdue University**
Conner Fear
Venkatesh Kabra
Partha Mukherjee




## Funding

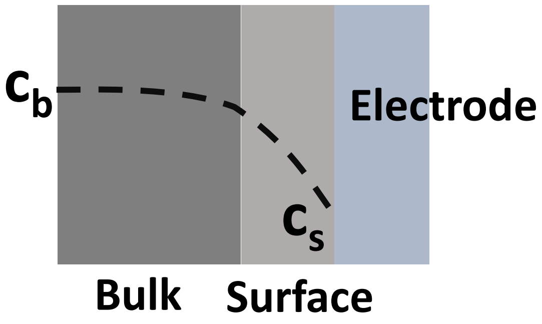
NASA Aeronautics Research Mission Directorate (ARMD) Convergent Aeronautics Solutions (CAS) Project, ***SPARRCI*** sub-project.

# Backup Slides

# Hybrid Electrochemical Model

## Hybrid Echem Model (SPM + ECM):

**concentration distribution assumption**




**Cell Voltage:**

$$\boxed{\boldsymbol{V = E_p^0 - E_n^0 - \dot{V}_o - \dot{\eta}_p - \dot{\eta}_n}}$$

M. Daigle, C.S. Kulkarni, Electrochemistry-based Battery Modeling for Prognostics, in: Annual Conference of the Prognostics and Health Management Society, 2013: p. 13.

$\boldsymbol{V_o}$ Voltage across ohmic resistance

$\boldsymbol{\eta}$ Butler-Volmer Kinetics

$$\boldsymbol{\dot{c} = \frac{c_b - c_s}{\tau_{diff}}}$$ $Li^+$ concentration in a electrode

$$\dot{\{\cdot\}}^{k} = \frac{\{\cdot\}^{k} - \{\cdot\}^{k-1}}{\tau_{\cdot}}$$ State Evolution

## Lumped Thermal Model:

$$\frac{\partial \mathrm{T}}{\partial \mathrm{t}} = \underbrace{\boxed{\frac{Q}{m_{\mathrm{cell}}\mathrm{C_p}}}}_{\text{Heat generated}} - \underbrace{\boxed{\epsilon_{conv}(T - T_{amb})}}_{\text{Heat loss}}$$

Non-linearity in EOD temperature can be attributed to the 5th phase

Modified Scaling Parameter based on Birkl's model

$$x_{NE}\left(E_{NE}^{OC}\right) = \frac{\Delta x_{NE}}{1 + e^{\frac{\alpha\left(E_{NE}^{OC} - E_{0,NE,5}\right)}{V_T}}}$$

$$\epsilon_{\mathrm{conv}} = \frac{\mathrm{A_{surf}}}{\mathrm{C}_p m_{\mathrm{cell}}} h_{\mathrm{conv}}$$

$$Q = \mathrm{I}\left(U_c - \alpha U_a - V - T\frac{dU}{\mathrm{dT}}\right)$$

# Battery Modeling (ROM and P2D)

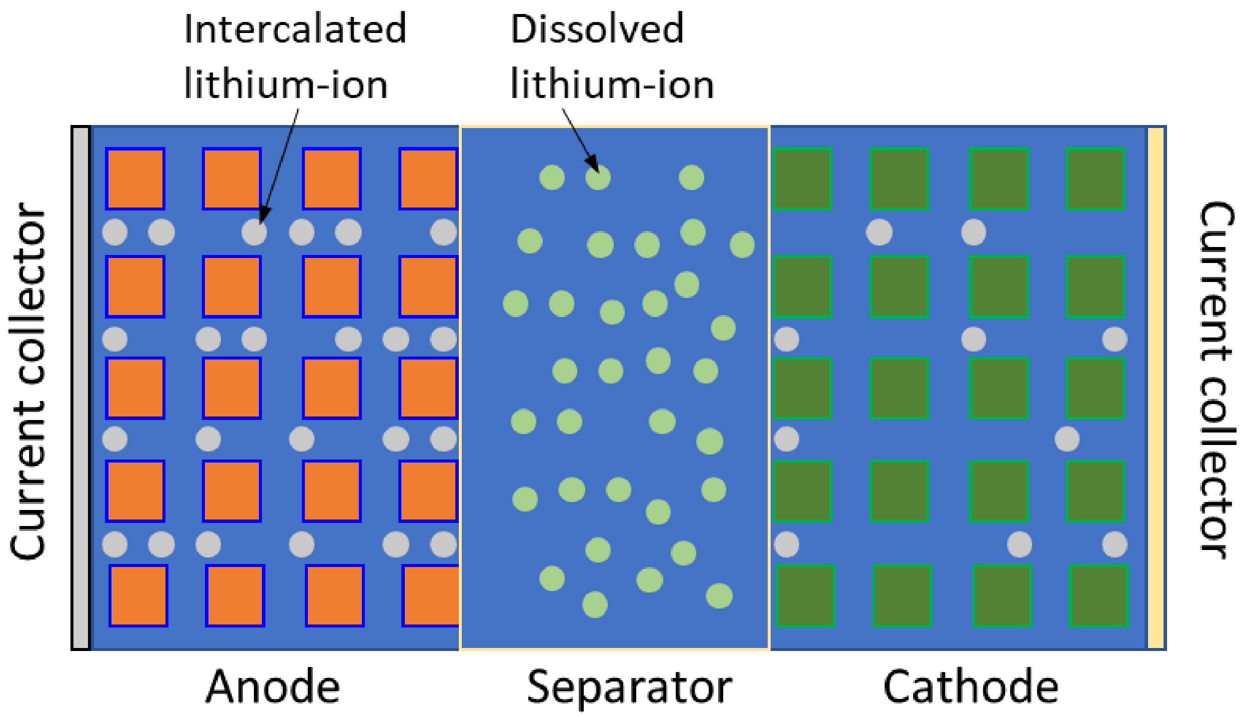
- Li-ion Chemistry

  Cathode (LCO/NMC/LFP)

  Anode (Graphite/Lithium)

  Electrolyte ($LiCF_3SO_3$, $LiPF_6$ in EC/DMC)

  Separator ($PP/Al_2O_3$)




**Anode reaction**

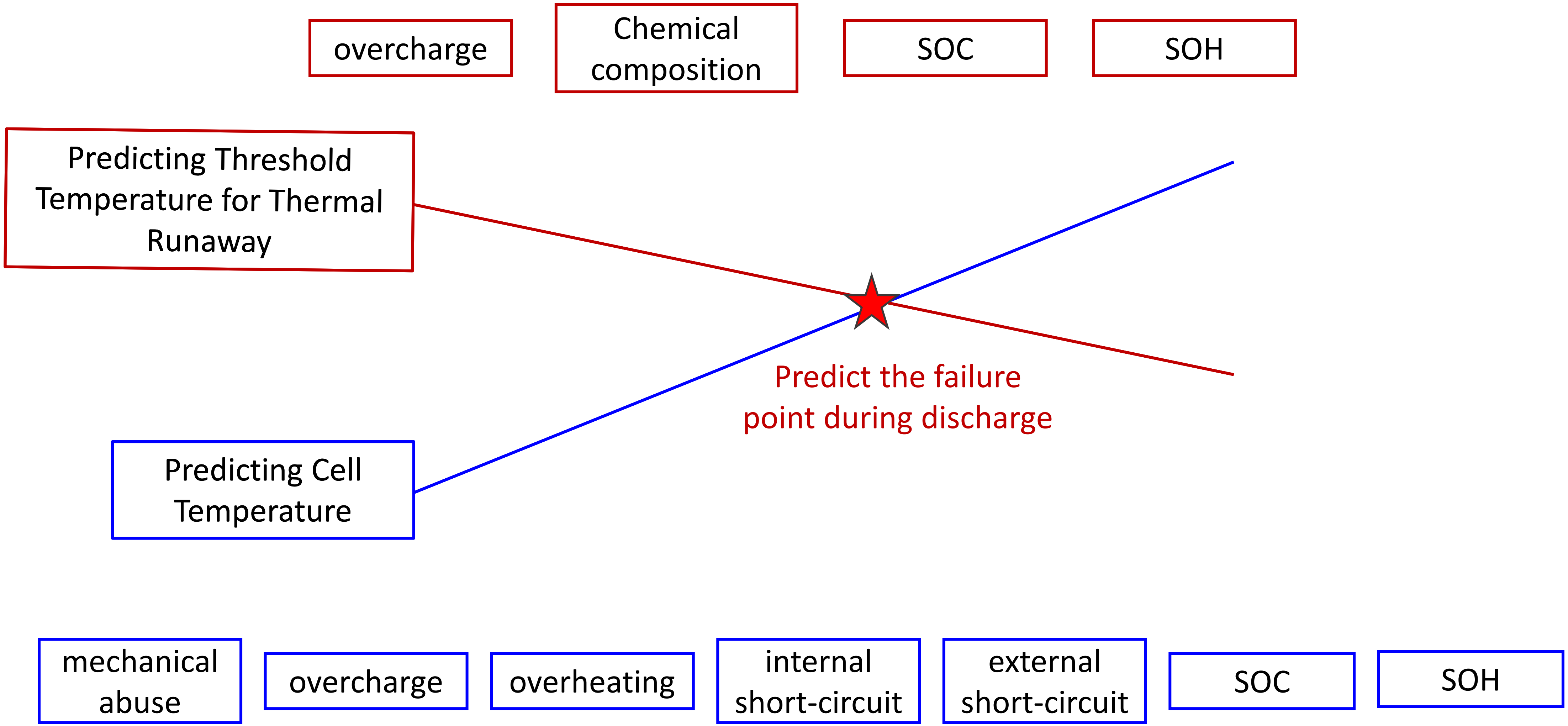
$$\mathrm{Li}_x\mathrm{C} \rightarrow \mathrm{C} + x\mathrm{Li}^+ + x\mathrm{e}^-$$

**Cathode reaction**

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

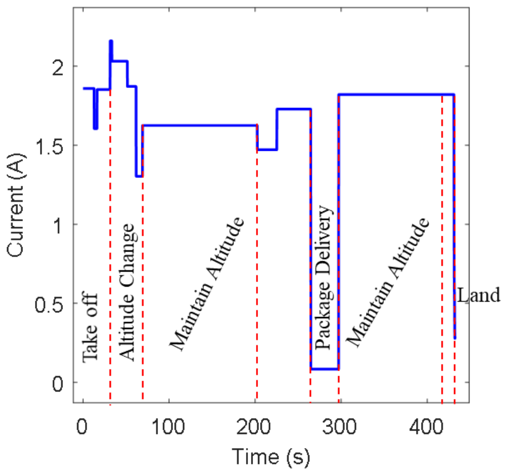
Full Multiphysics Models Allows us to identify Important Mechanisms for capturing Thermal and Battery Performance with Aging over High C flight profiles

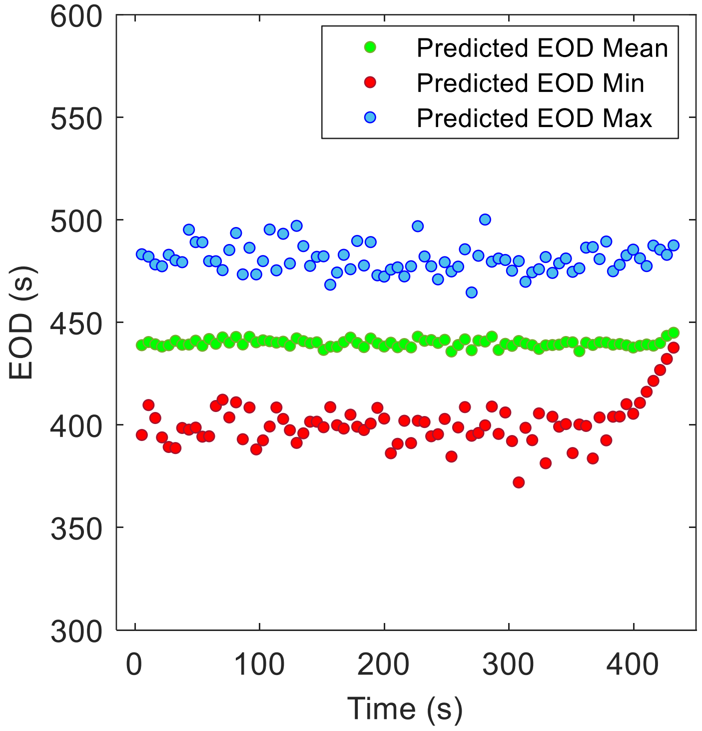
# Simplified Picture of Complexity in Modeling Thermal Runaway

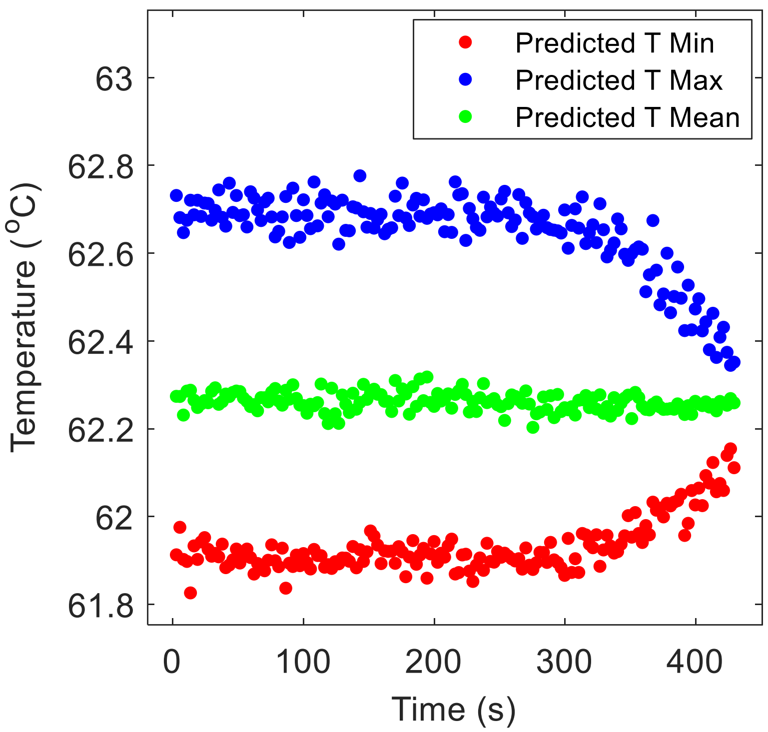


# Preliminary Results for EOD Estimation

## Applying Prognostics Algorithm on a Short Test Flight Profile

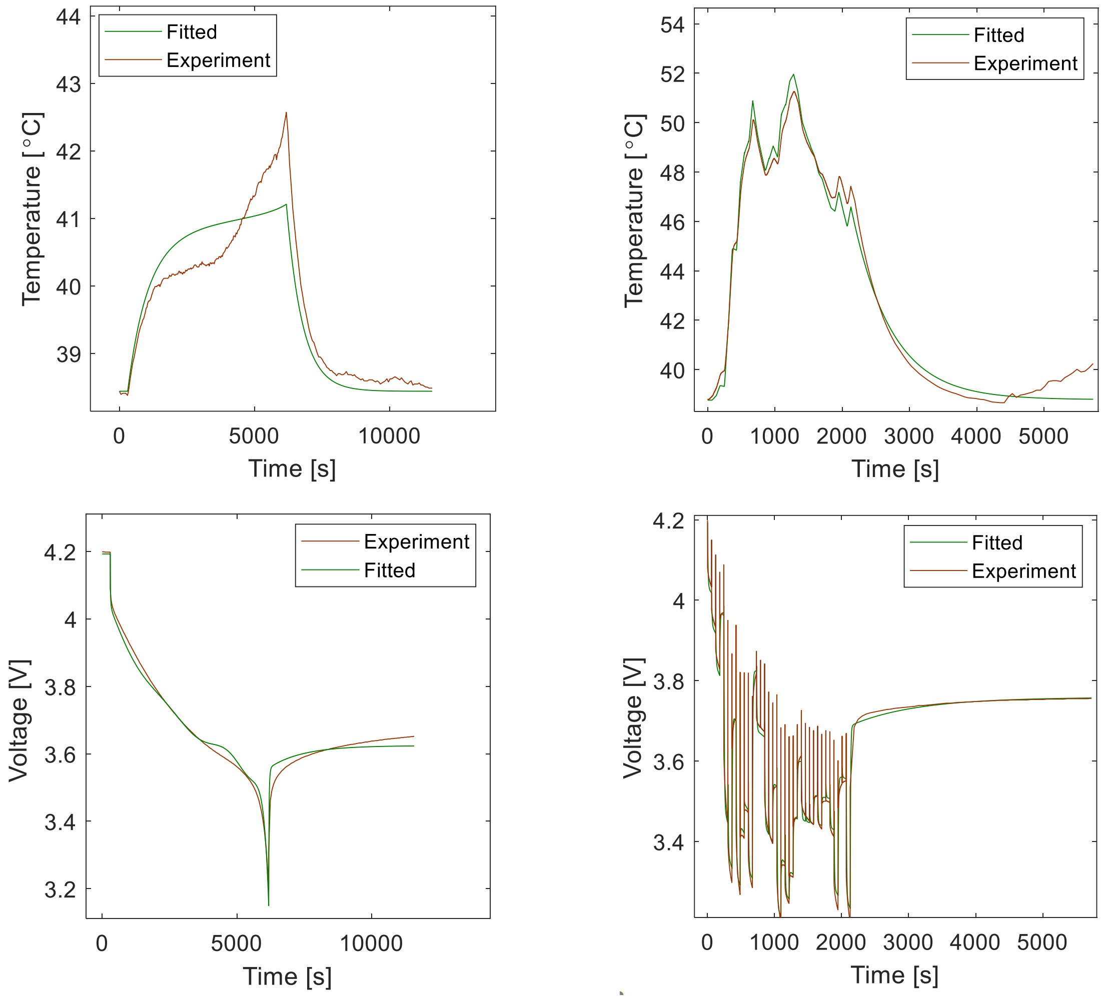


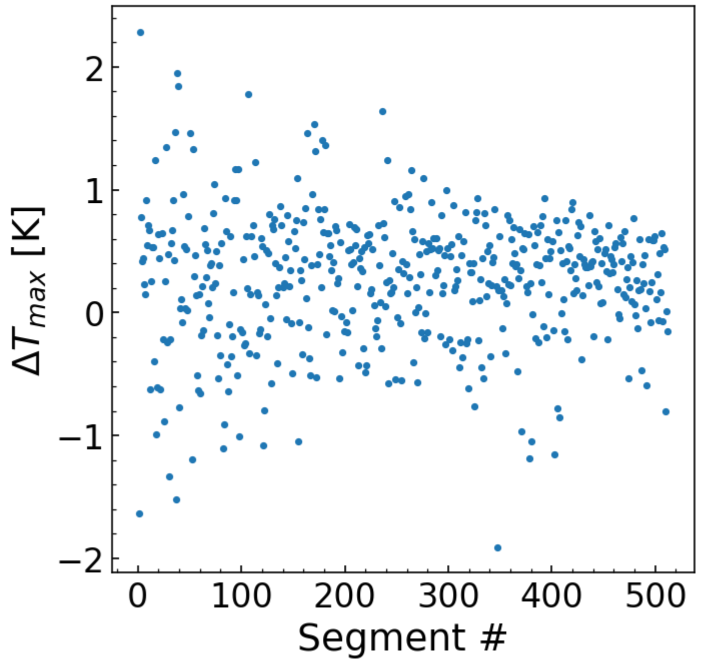




**The Distribution of the End-of-Discharge Estimation shows that the Algorithm is working correctly.**

# Part I: Effect of Discharge Protocol




**Estimating entropic term (dU/dT) in addition to $Q_{mobile}$, $R_o$, $\tau_{diff}$ improves temperature prediction for RW but not Reference discharges**

# 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:**

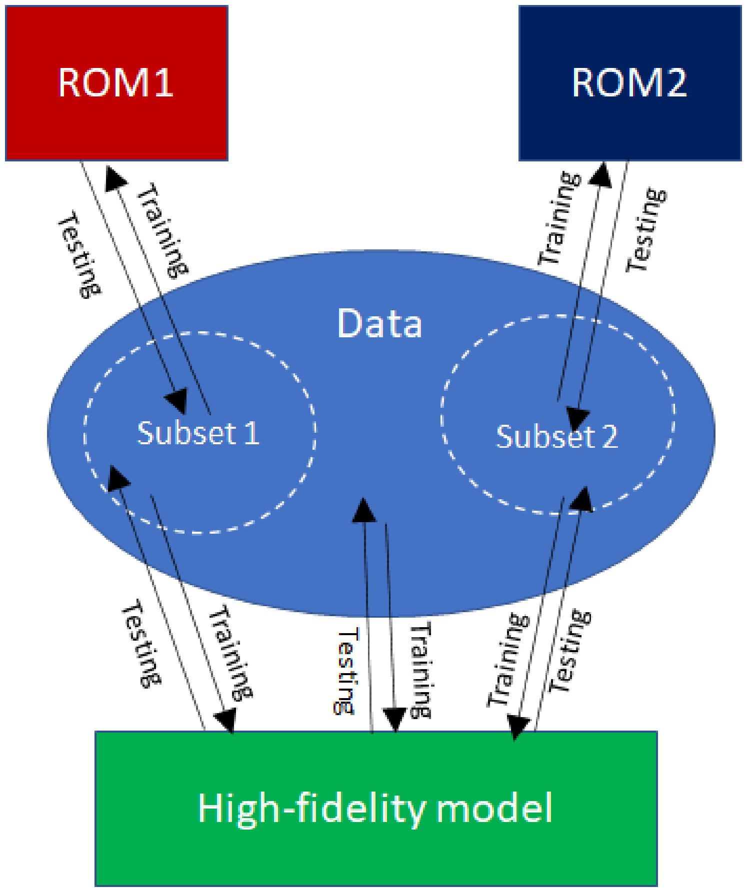
- The computational complexity of a ROM is lower than that of a high-fidelity model.
- A ROM can be practically identifiable, i.e., its parameters can be uniquely fit to data.

**Disadvantages of ROMs:**

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

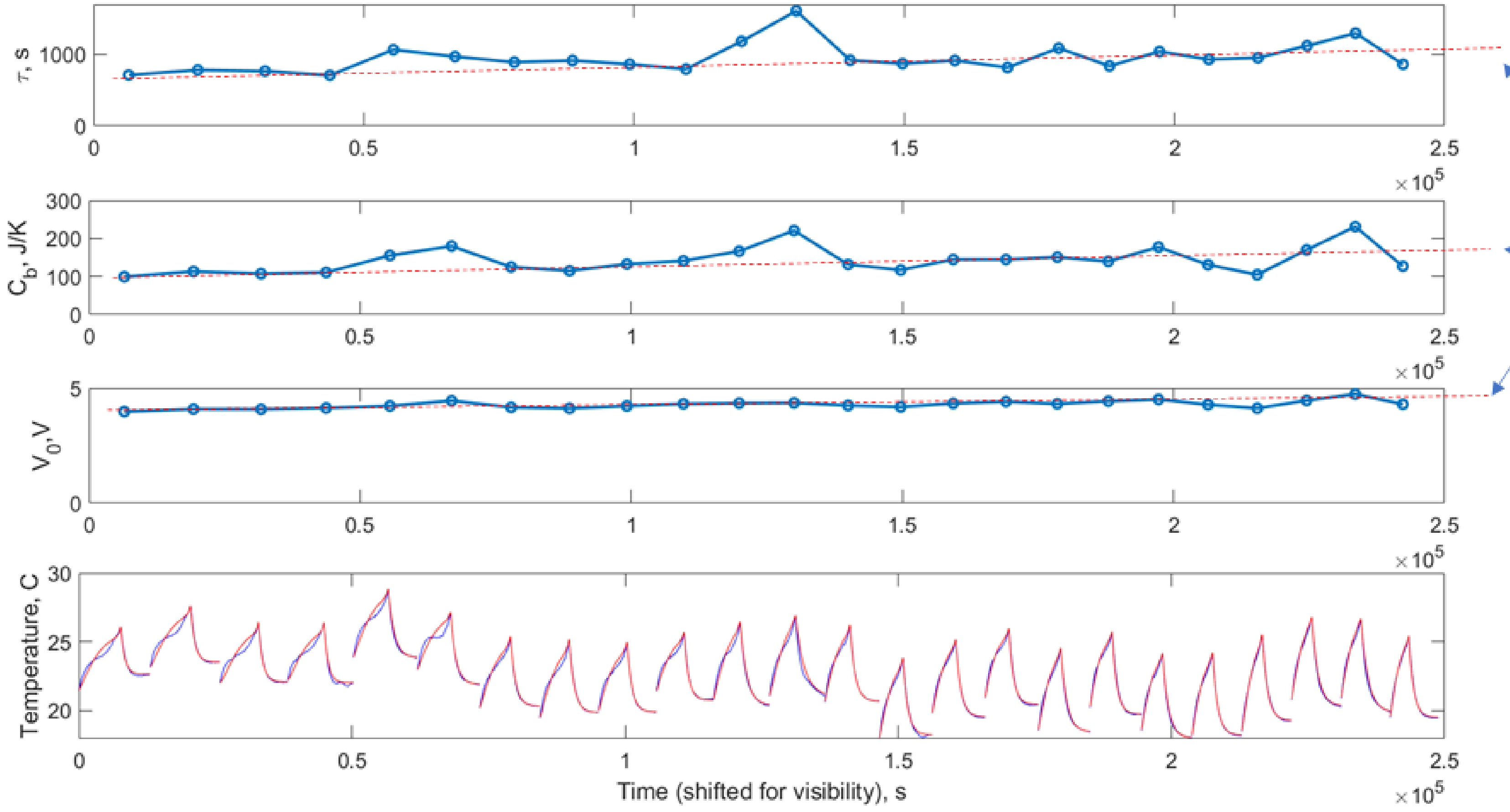
**How to derive ROM?**

- 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.



# Fitting the TM to galvanostatic discharge data

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



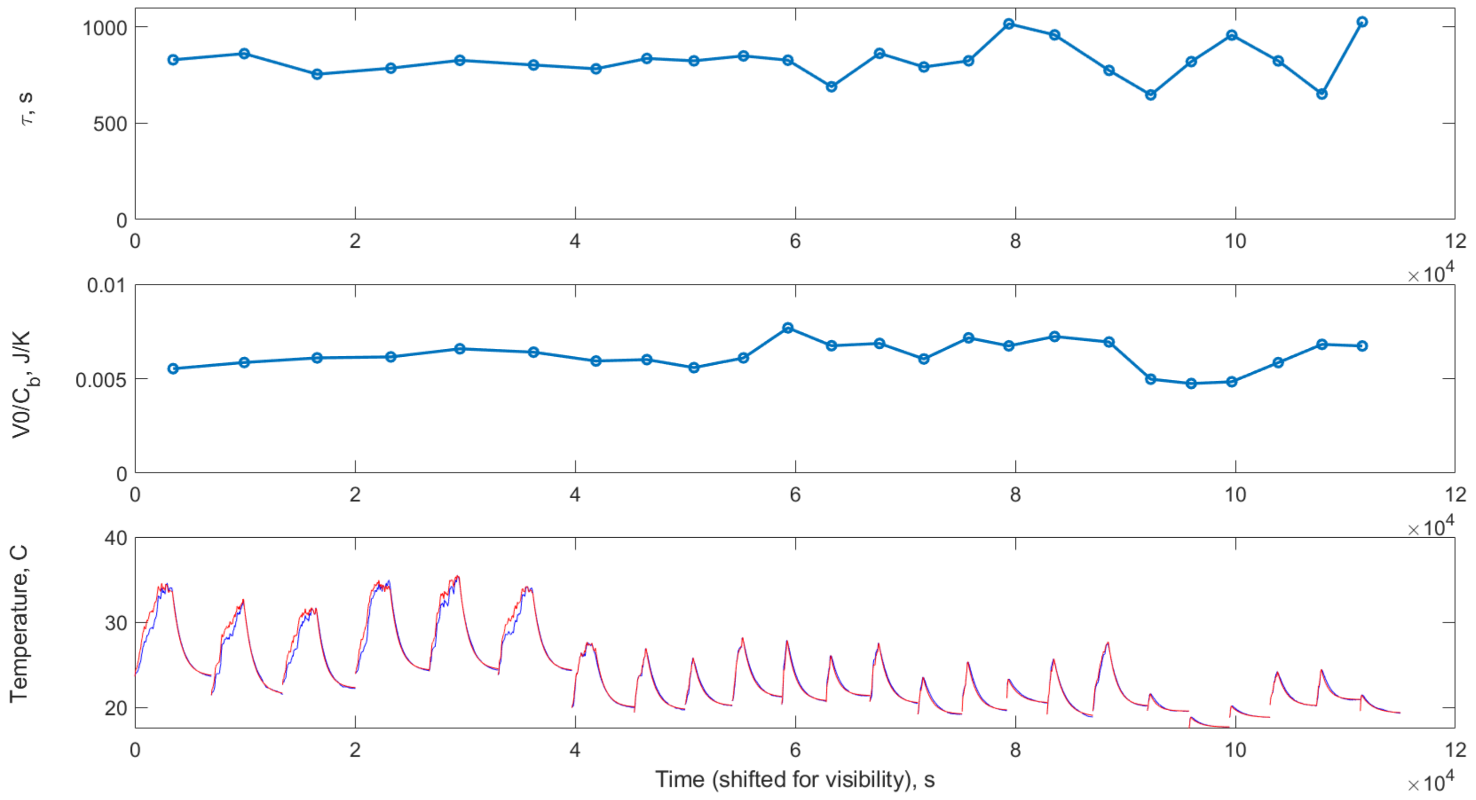

Weak trend to increase

The TM is identifiable from galvanostatic discharges data.

# Thermal ROM for RW data

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

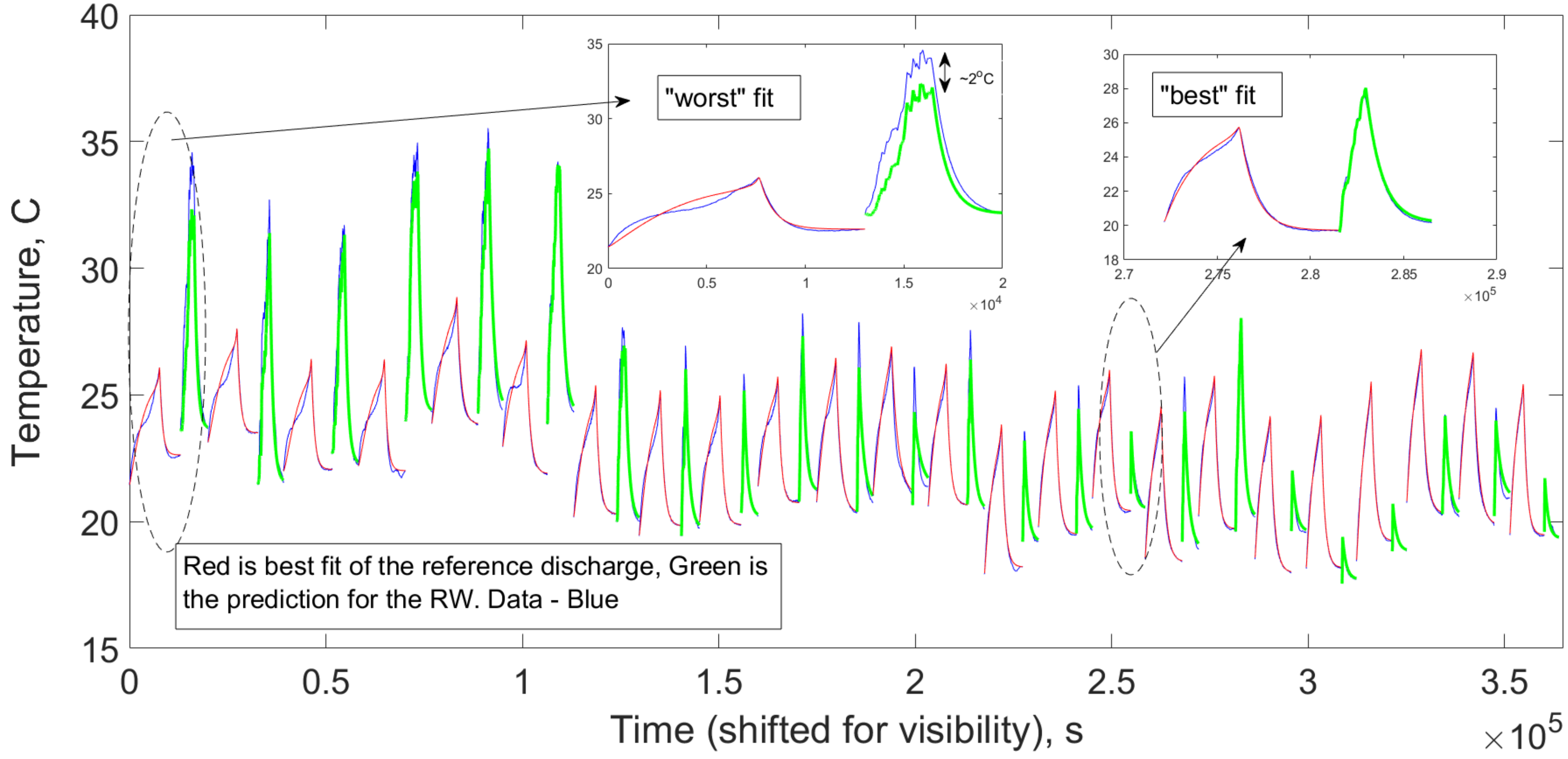
$\rightarrow$ ROM: $T(t) = T_a + [T(0) - T_a]e^{-t/\tau} + \frac{V_0}{C_b}\int_0^t I(t')e^{\frac{t'-t}{\tau}}dt'$




- The ROM is accurate for and is identifiable from the RW data;
- The temperature evolution decouples from the voltage evolution.

# 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.