Thermal Data-driven Model Reduction for Enhanced Battery Health Monitoring

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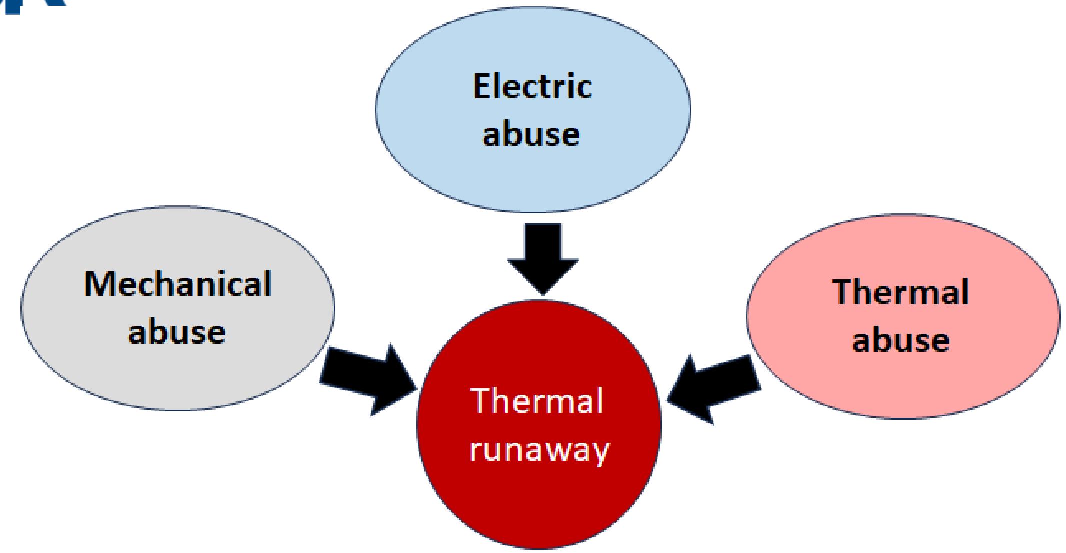
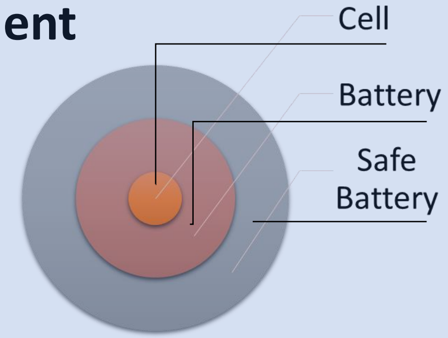
Need for Thermal Anomaly Detection



- Mechanical abuse: deformation, crash
- Electric abuse: over-charging, over-discharging
- Thermal abuse: overheating

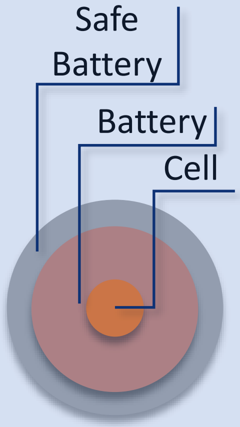
- SOA approach: containment



Alternative

(CAS: SPARRCI)

Smart BMS:
- ✓ In-situ sensors
- ✓ Predictive framework



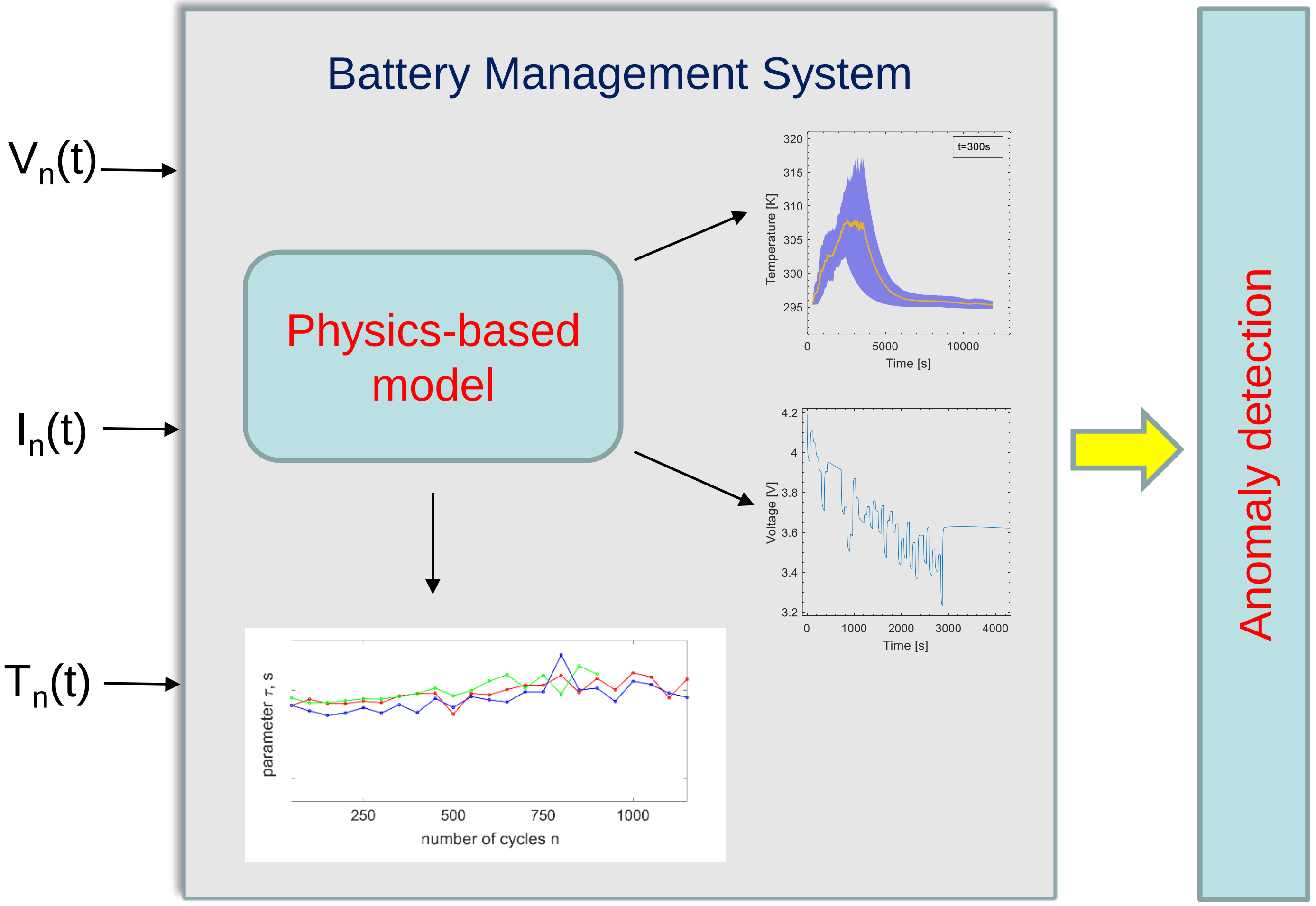
- Cons: Weight Penalty for Safety
- Smart BMS: reduction of the battery weight

SMART BMS for Aviation Batteries

Problem: Thermal anomalies can deteriorate into faults and become a major safety concern

Approach:
Use *physics-based models* for the measured battery's state variables V(t),T(t) to:

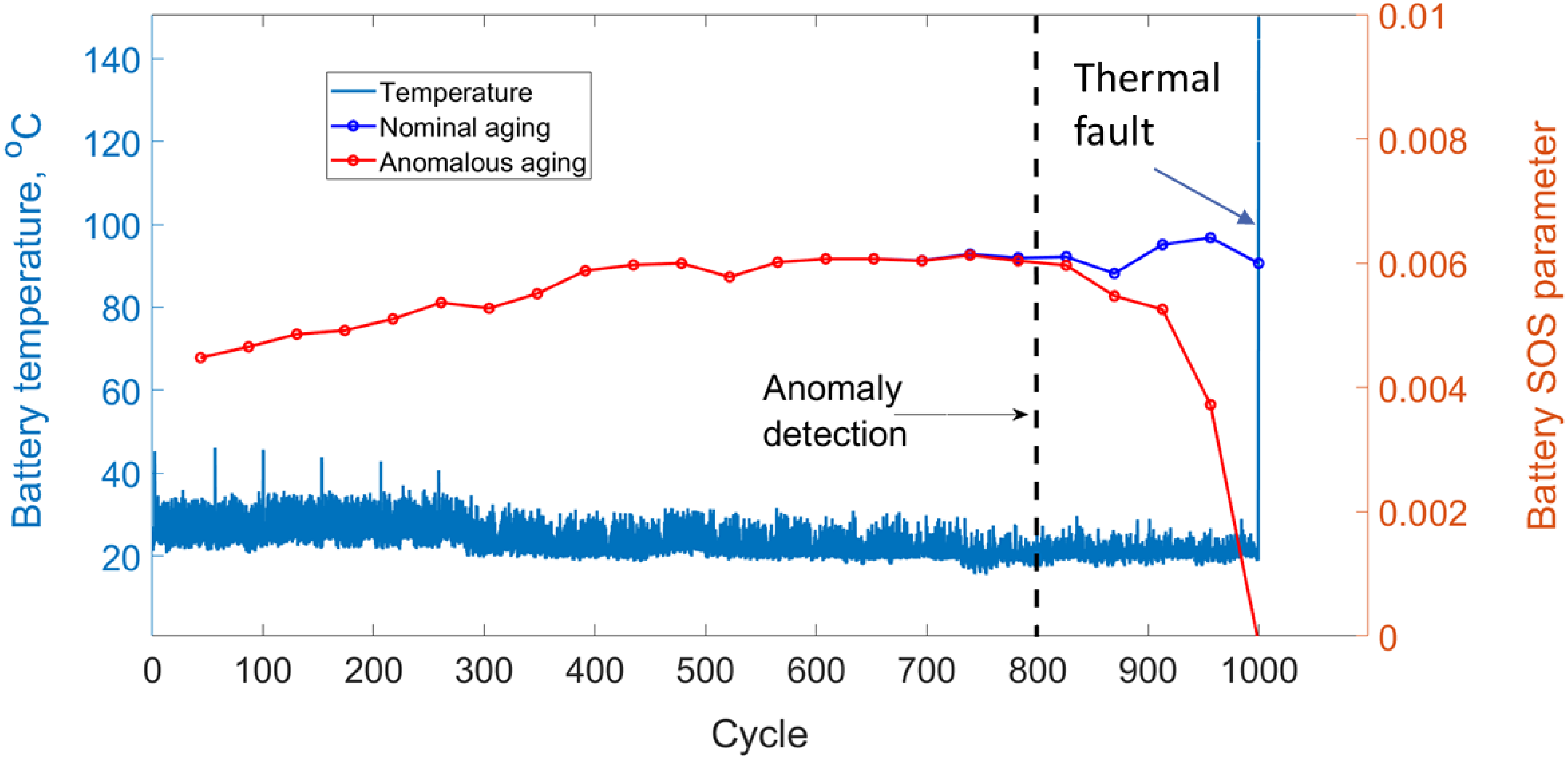
- ✓ Infer the *maximal set* of battery's SOH/SOS parameters;
- ✓ Predict the near-term cycling performance;
- ✓ Build empirical model for the parameter evolution (aging, degradation);
- ✓ Detect anomalies the parameter evolution;
- ✓ Correlate those anomalies to TR or other failures.



Outcome: The ability to predict thermal anomaly will increase safety and reduce battery weight

Thermal Anomalies in Batteries

Schematic of a thermal anomaly detection



Common faults: sensor faults, cooling system faults, overcharge abuse, and manufacturing defects.

- Thermal anomalies can reflect faults which can become catastrophic over time
- SOA BMS track anomalies in just two parameters: capacity and typical maximal temperature
- Field (flight) thermal data contains more information
- Retrieving this information is challenging

Battery State Variables vs Parameters

Electrochemical Model

$$V(t) = U_p^0(x_p) - U_n^0(x_n) - \eta_R' - \eta_p' - \eta_n'$$

$$x_i = \frac{(C_{s,i} + C_{b,i})}{C_{max}}$$

$$\dot{C}_{s,p/n} = \pm\frac{\mathrm{i_{app}}}{F} + \frac{(C_{b,p/n} - C_{s,p/n})}{\tau_D}, \quad \dot{C}_{b,i} = \frac{(C_{s,i} - C_{b,i})}{\tau_D}$$

$$\dot{\eta}_R' = \frac{\mathrm{i_{app}} R_0 - \eta_R'}{\tau_R}, \qquad \dot{\eta}_i' = \frac{2V_t \sinh^{-1}\left(\frac{J_i}{J_i^0(C_{s,i})}\right) - \eta_i'}{\tau_i}$$

Thermal Model

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

Physics-based Model reduction

3pTROM: $$\frac{dT}{dt} = \frac{I(t)}{C_b}\left(V_0 - V(t)\right) + \frac{T - T_a}{\tau}$$

Data-driven Model reduction

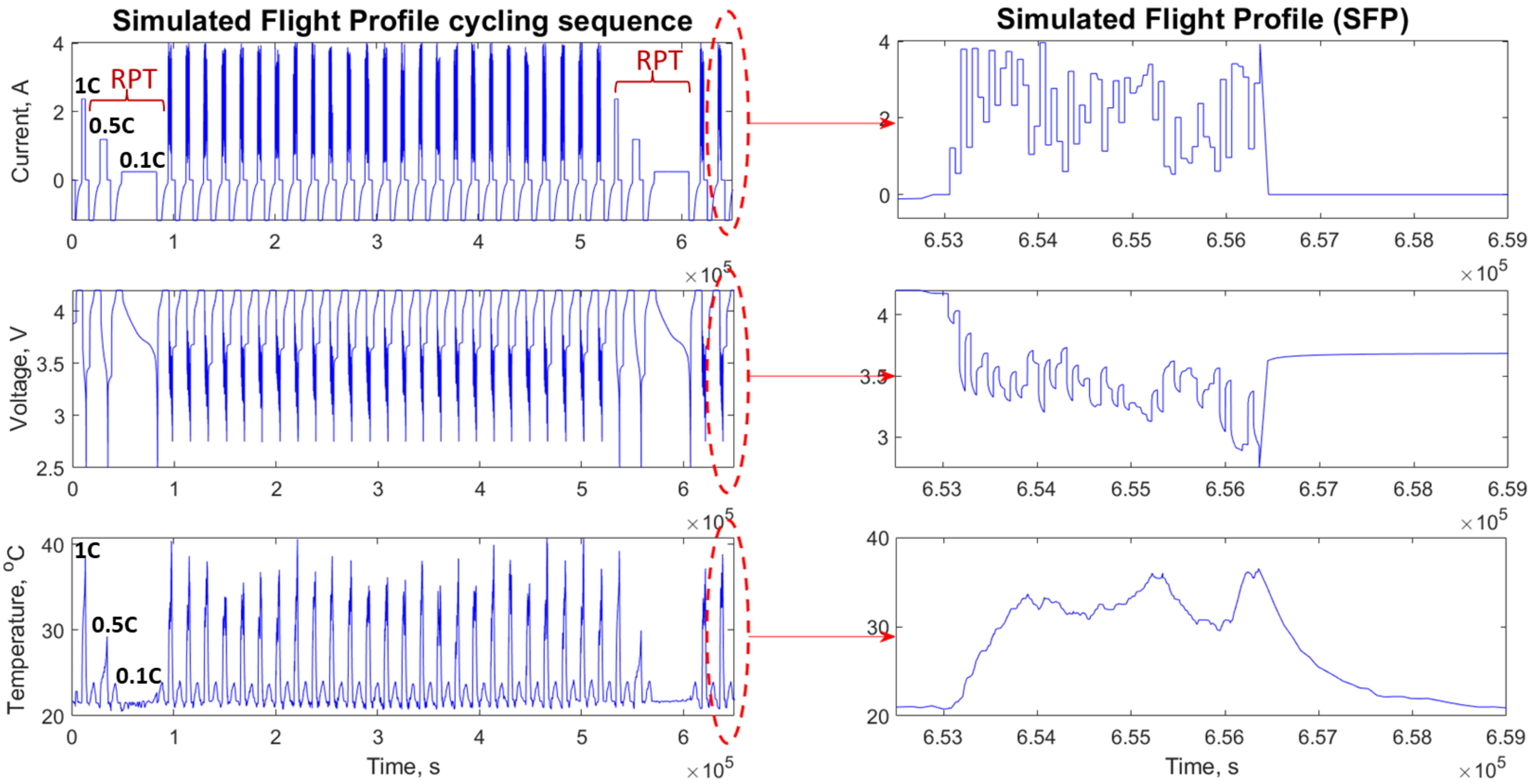
2pTROM: $$\frac{dT}{dt} = \beta I(t) + \frac{T - T_a}{\tau}$$

- State variables *(black)* change during a cycle: fast dynamics (charging/discharging)
- Battery parameters *(red)* evolve over many cycles: slow dynamics (aging , degradation)

Battery State Variables vs Parameters

	Electrochemical Model			Thermal Model		
Model Parameter	C_{max}	τ_D	R_0	C_b / β	V_0 / β	τ
Interpretation	Total cell capacity	Effective diffusion time	Effective resistance	Effective heat capacity / Reduced thermal parameter	Offset OCV voltage / Reduced thermal parameter	Cooling time
Measured variable	***V(t)***			***T(t)***		
Interpretation	Terminal voltage			Cell temperature		

Testing protocol: RPT + SFP



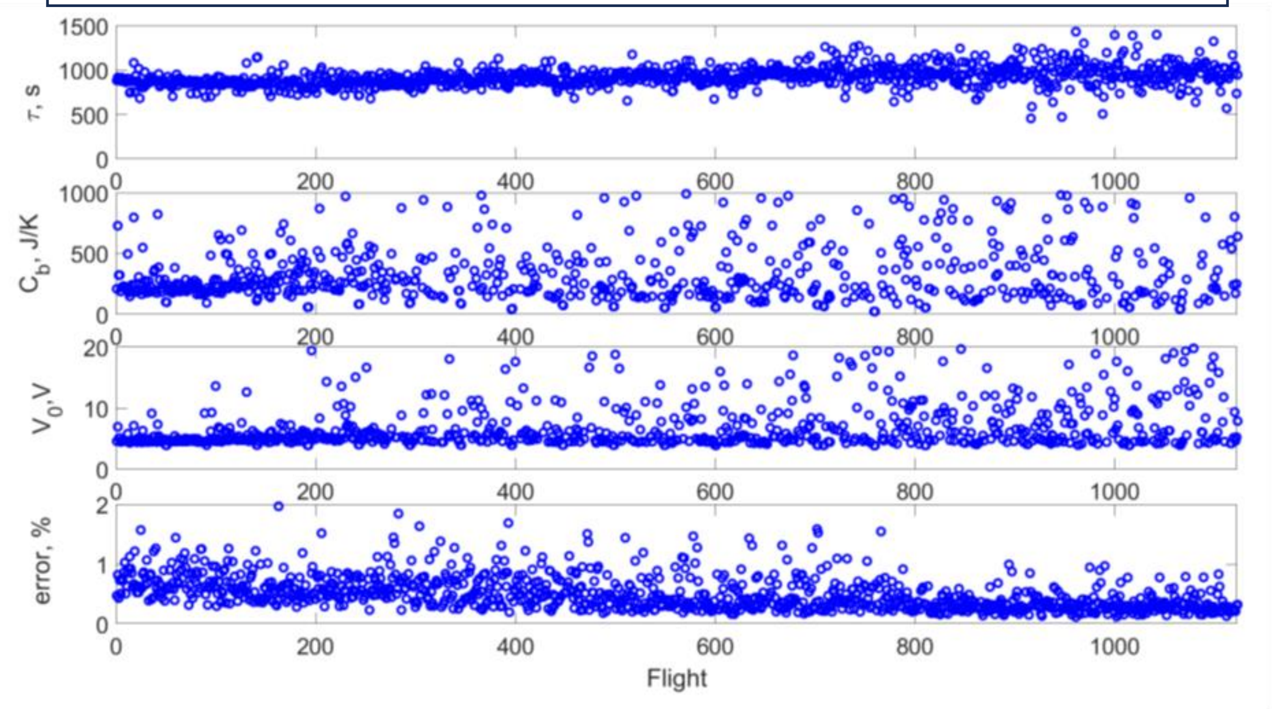
Question: Need for Identifiable models

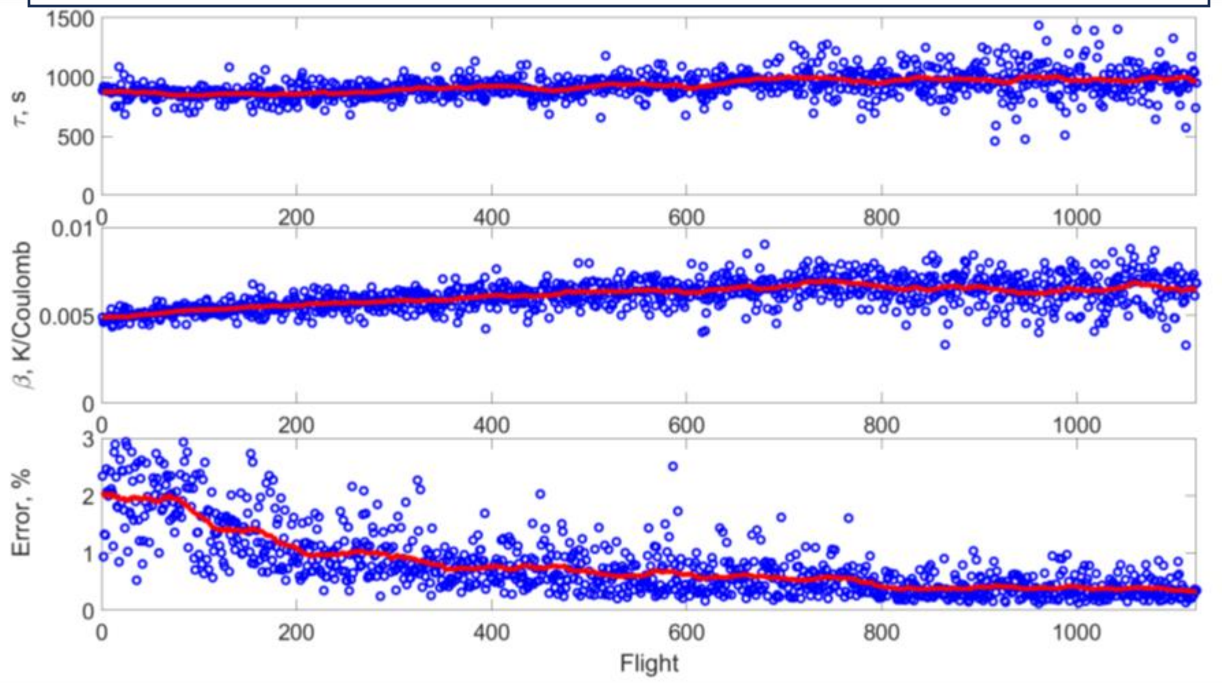
3pTROM:

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

2pTROM:

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





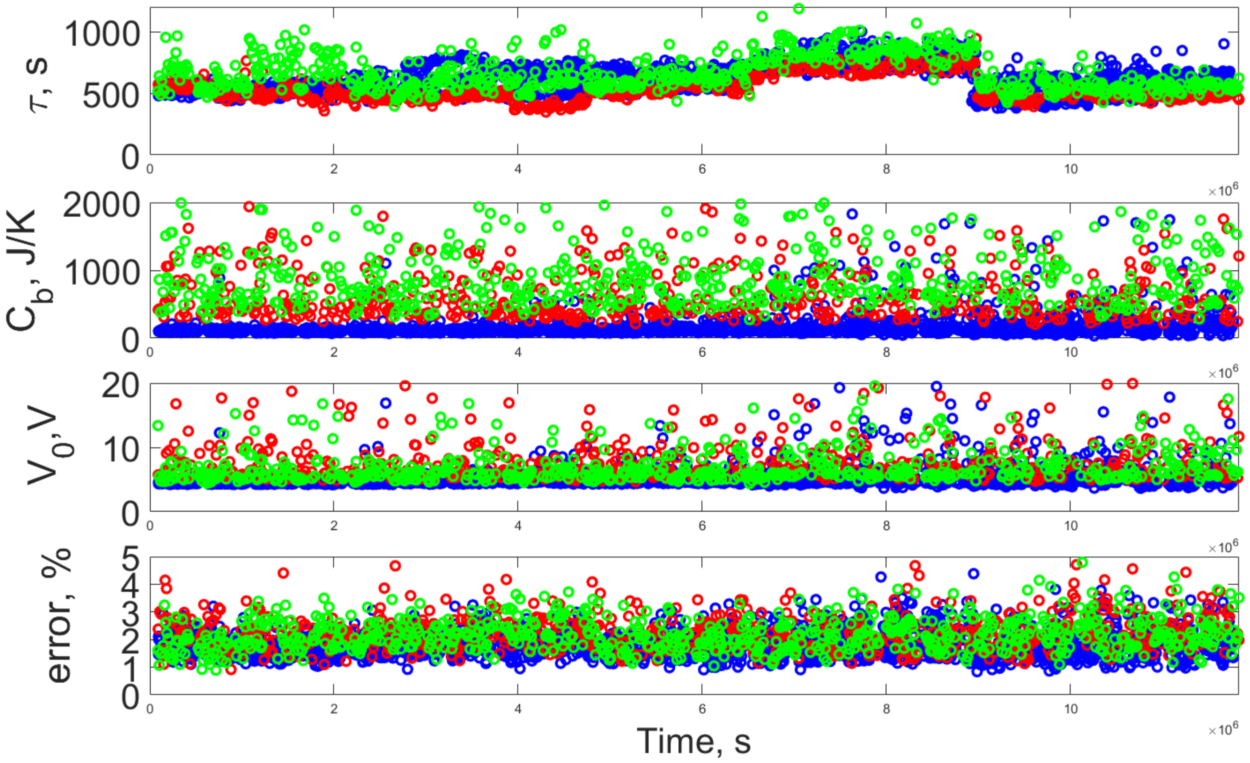
The 3-parameter TM is practically non-identifiable from SFP data at older age.

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

Model validated on 9 cells (3 chemistries)

3pTROM:

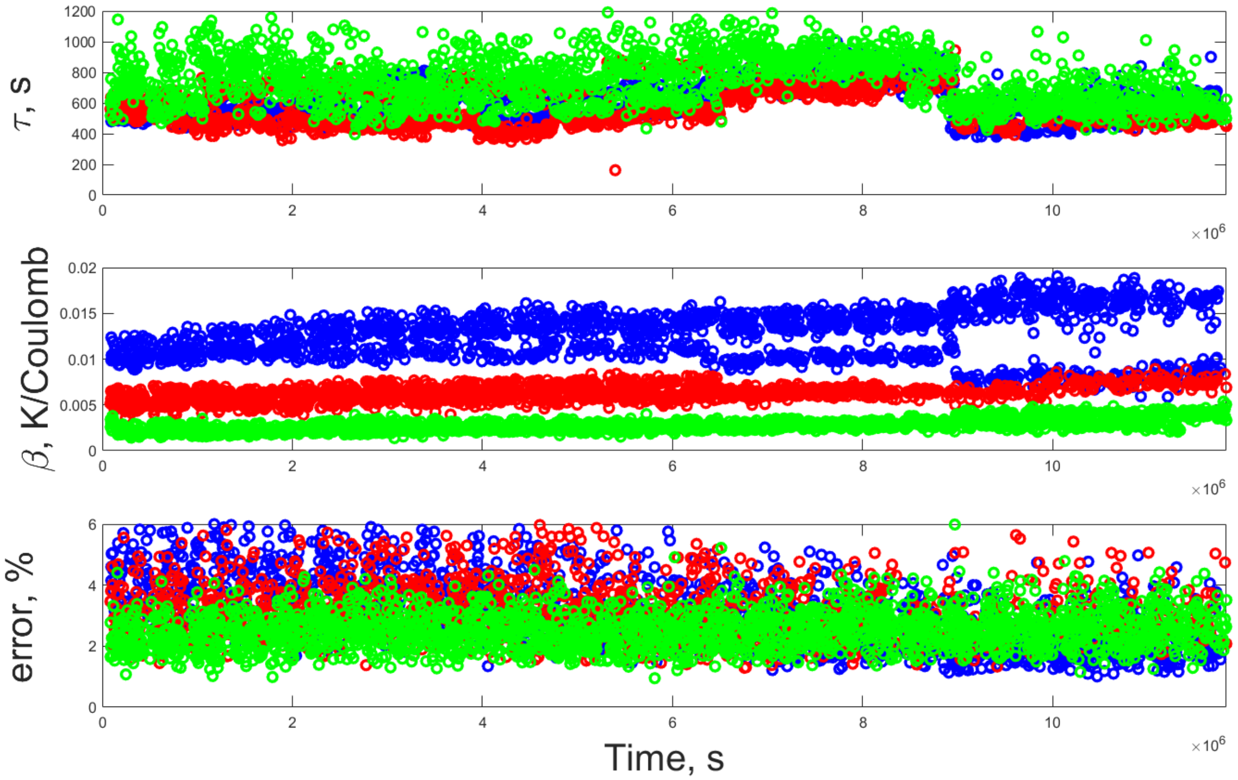
$$T(t) = T_a + [T(0) - T_a]e^{-t/\tau} + C_b^{-1} \int_0^t I(t')[V_0 - V(t')]e^{\frac{t'-t}{\tau}} dt'$$



3pTROM is *practically non-identifiable* from SFP data for NMC (red) and NCA (green) and LCO (blue).

2pTROM:

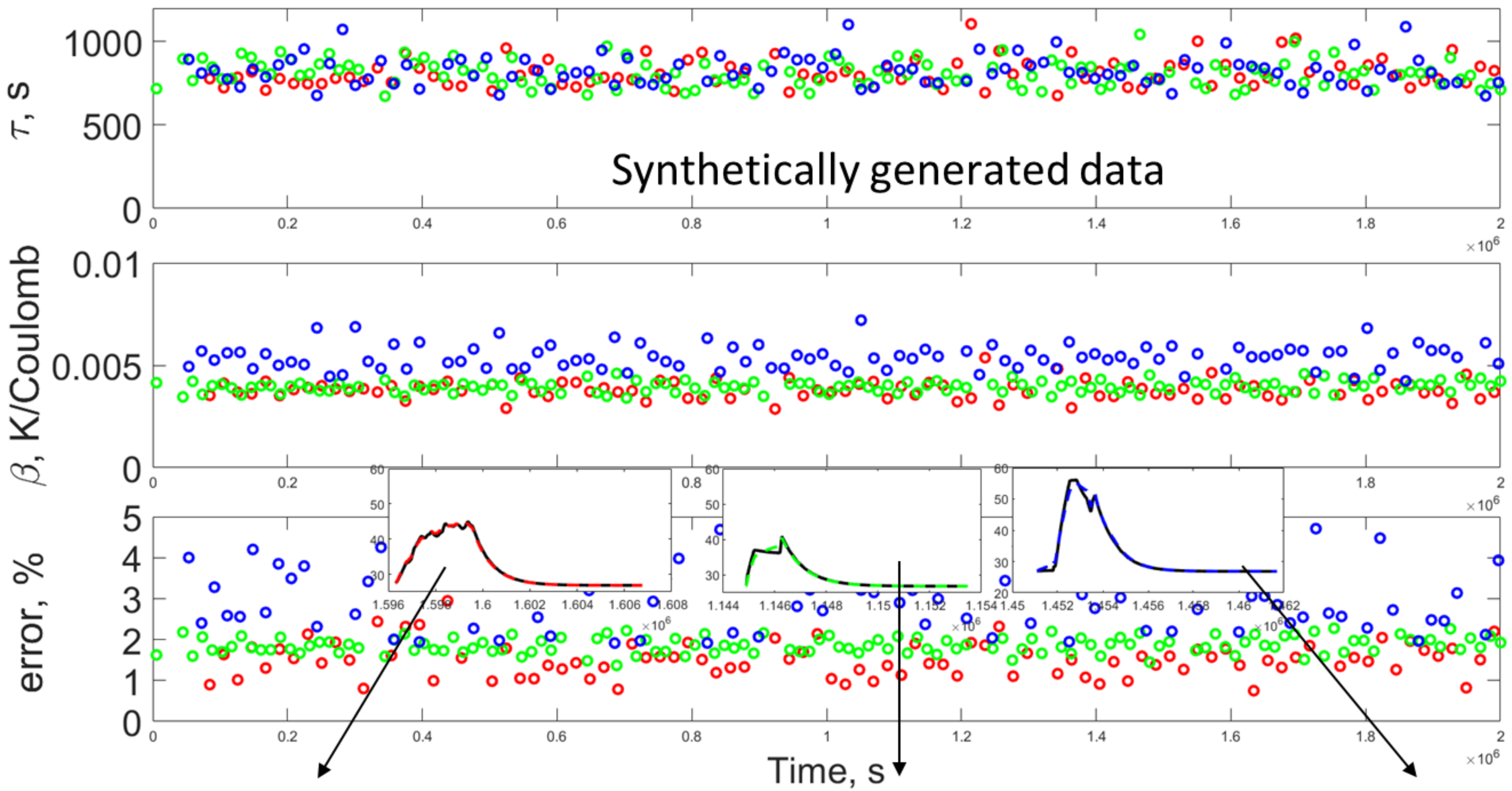
$$T(t) = T_a + [T(0) - T_a]e^{-t/\tau} + \beta \int_0^t I(t')e^{\frac{t'-t}{\tau}} dt'$$



2pTROM is *practically identifiable* from SFP data for all three chemistries.

Validation on Various Flight Profiles

$$\textbf{2pTROM:}\quad T(t) = T_a + [T(0) - T_a]e^{-t/\tau} + \beta \int_0^t I(t')e^{\frac{t'-t}{\tau}}dt'$$



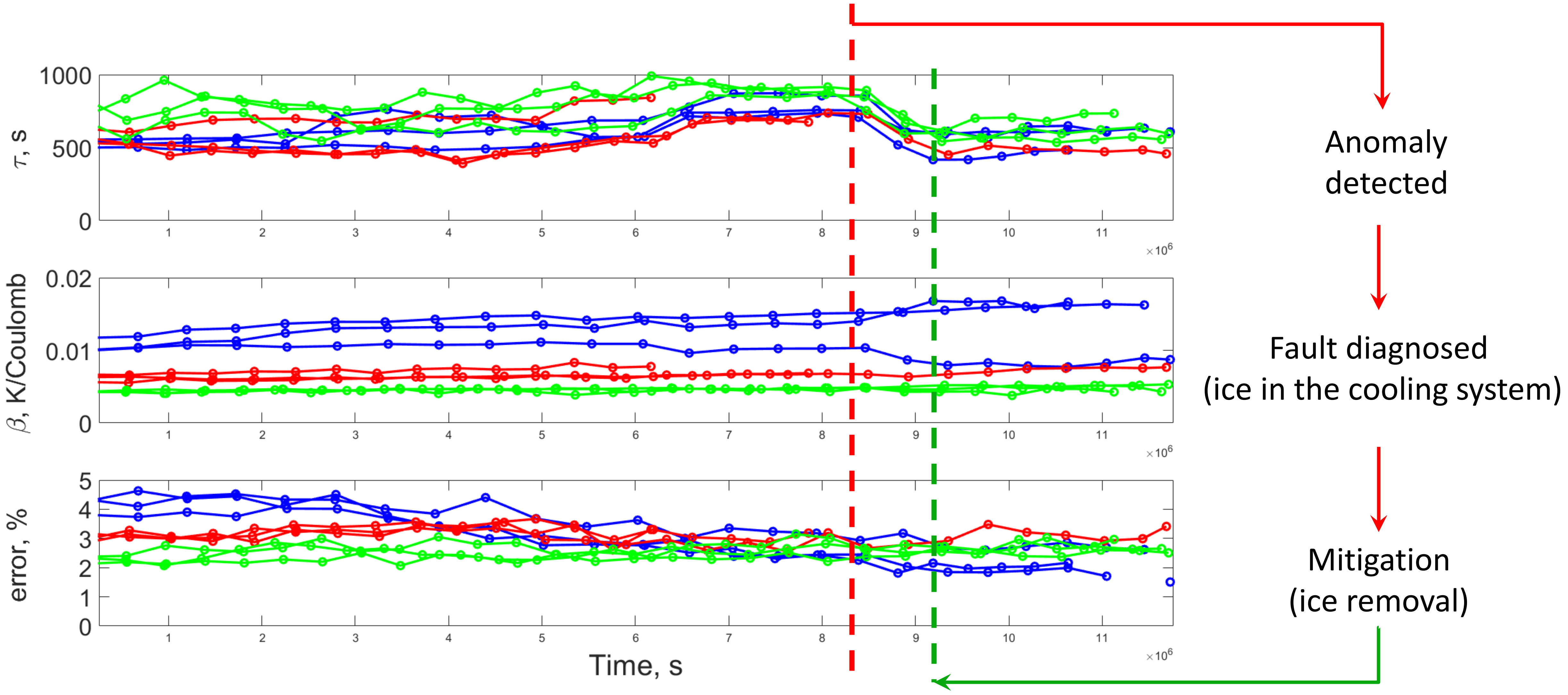
Random Walk UAV (<50lbs)

UAM (eVTOL) Flight Profile

X-57 Flight Profile

- The model fits thermal data accurately (1-3% RMSE) for all three flight profiles
- The model is identifiable (limited variance of the inferred parameters)
- The RW and UAM profiles belong to the same data class (the model can be trained and tested on the data from either profile)

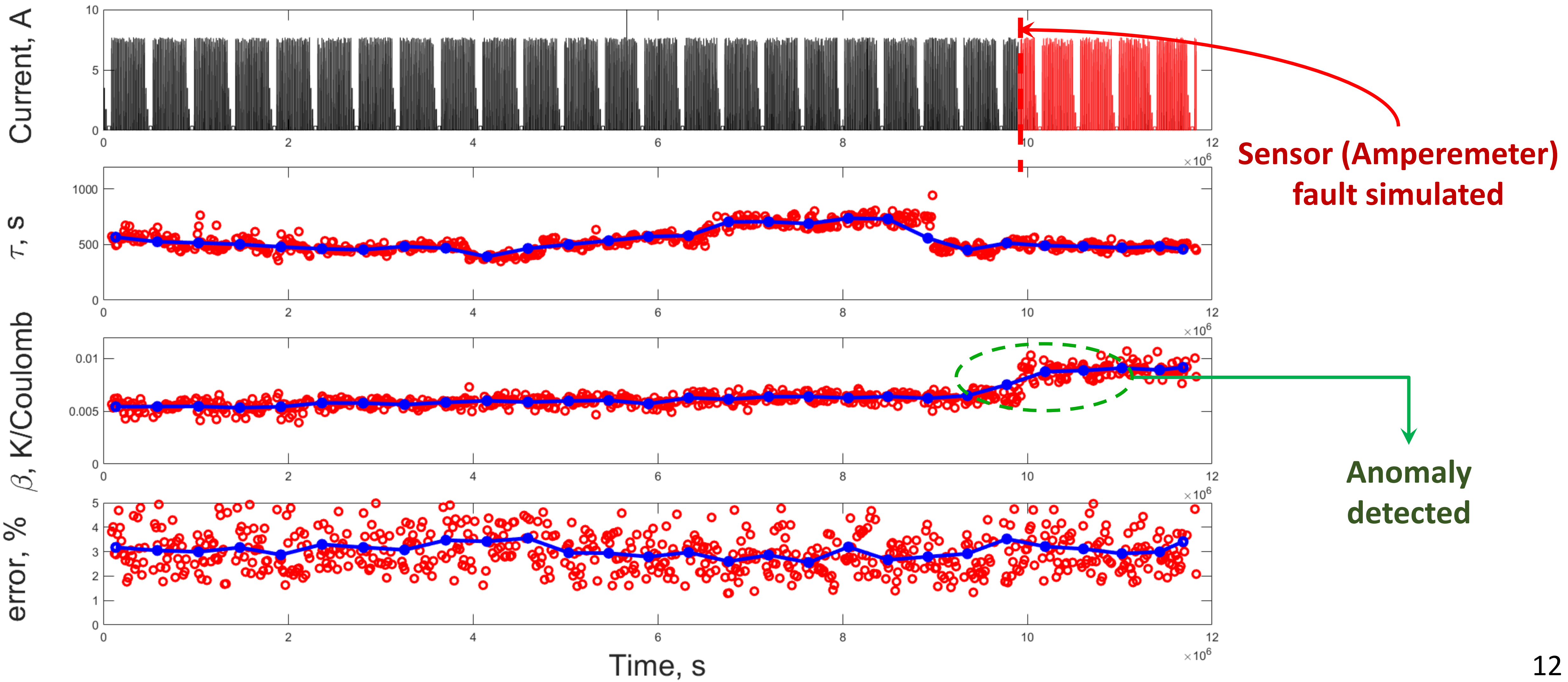
Detection of the cooling anomaly (Expt.)



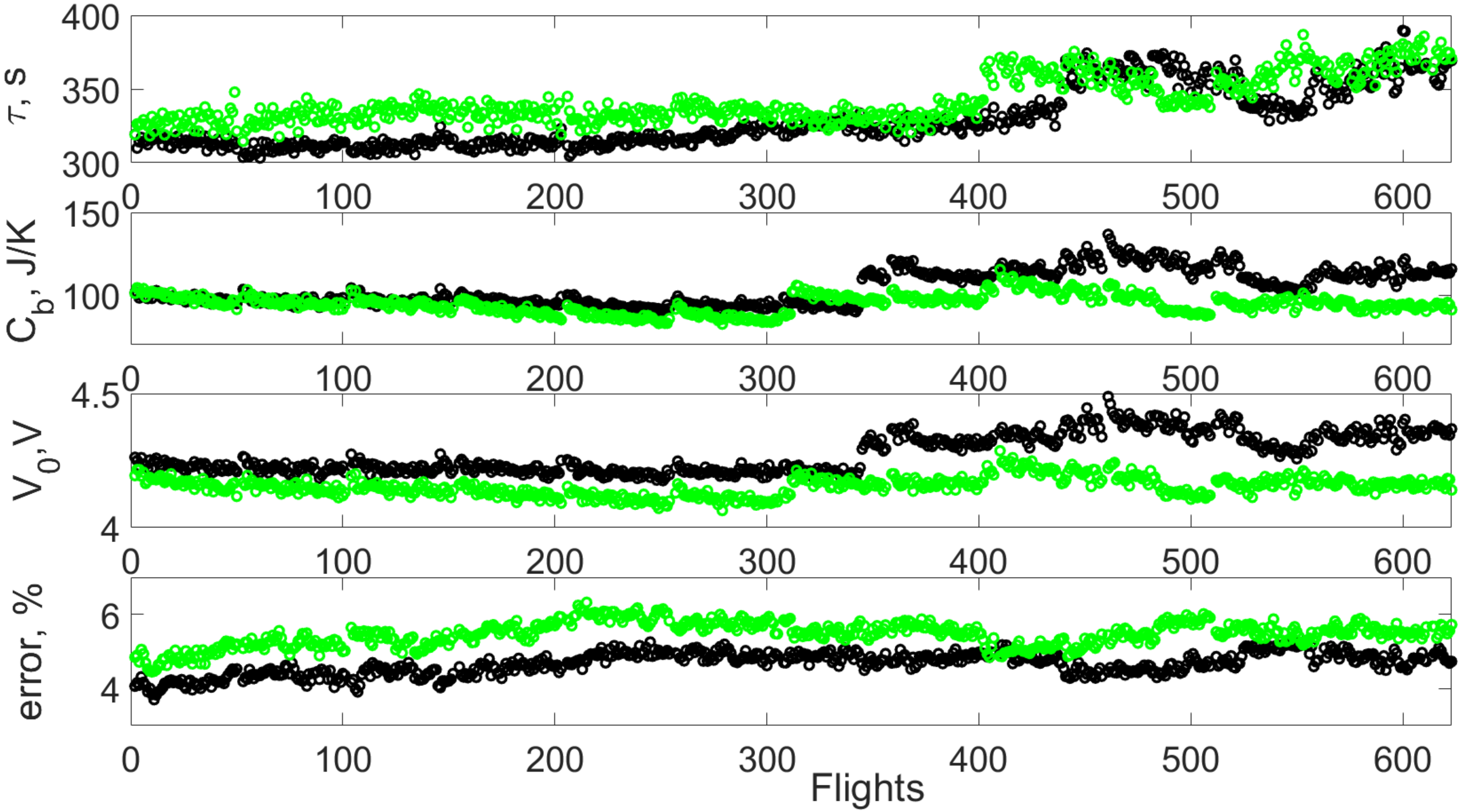
Error in the estimated parameters is <5%

Detecting Sensor Faults (expt.)

2pTROM: $T(t) = T_a + [T(0) - T_a]e^{-t/\tau} + \beta \int_0^t I(t')e^{\frac{t'-t}{\tau}} dt'$



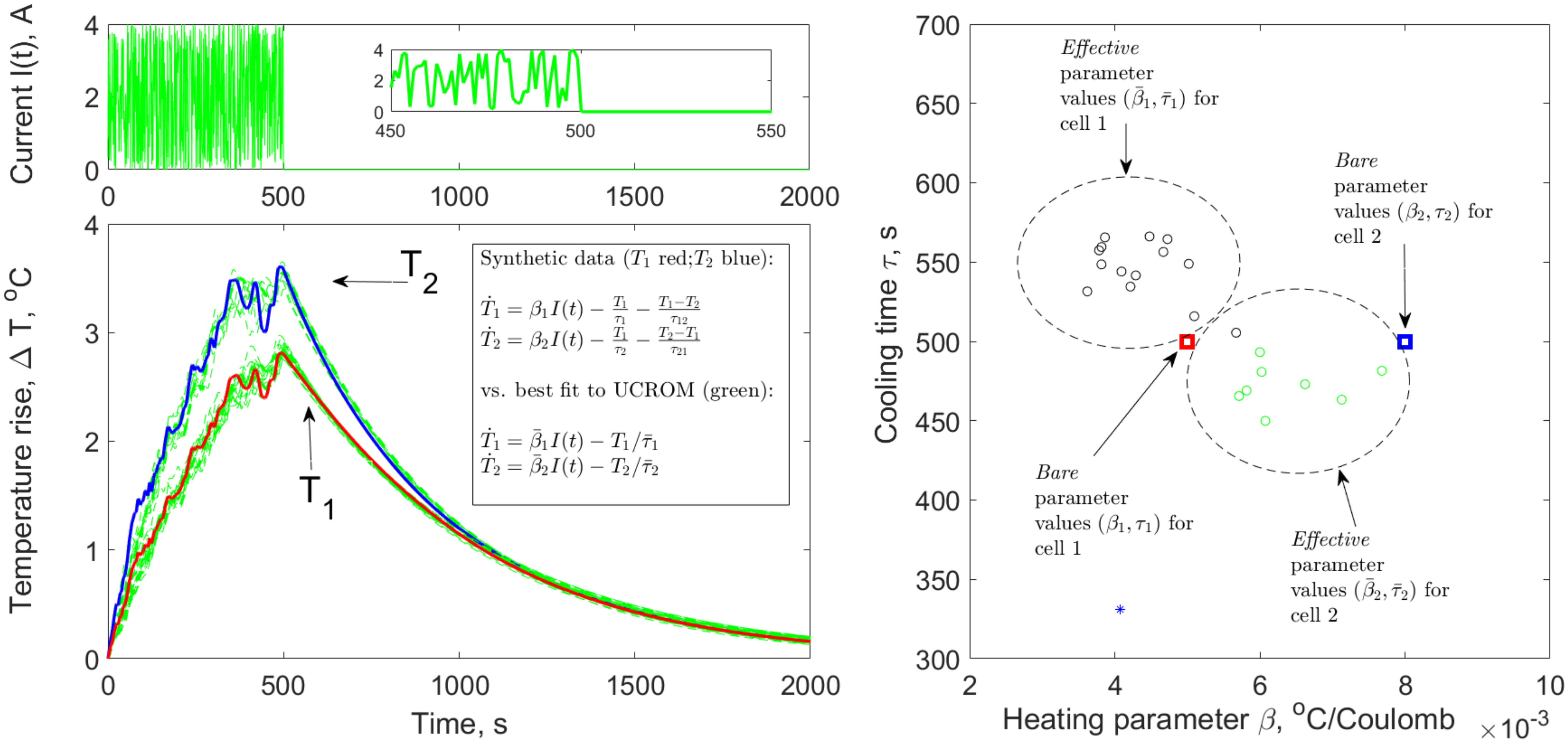
Detecting Unseen Faults



Is any discontinuity an anomaly? More data is needed to establish the nominal behavior

Thermal modeling of in-series packs

Synthetic data for two coupled cells vs. uncoupled cells ROM (UCROM): $\dot{T}_{1,2} = \bar{\beta}_{1,2} I(t) - T_{1,2}/\bar{\tau}_{1,2}$



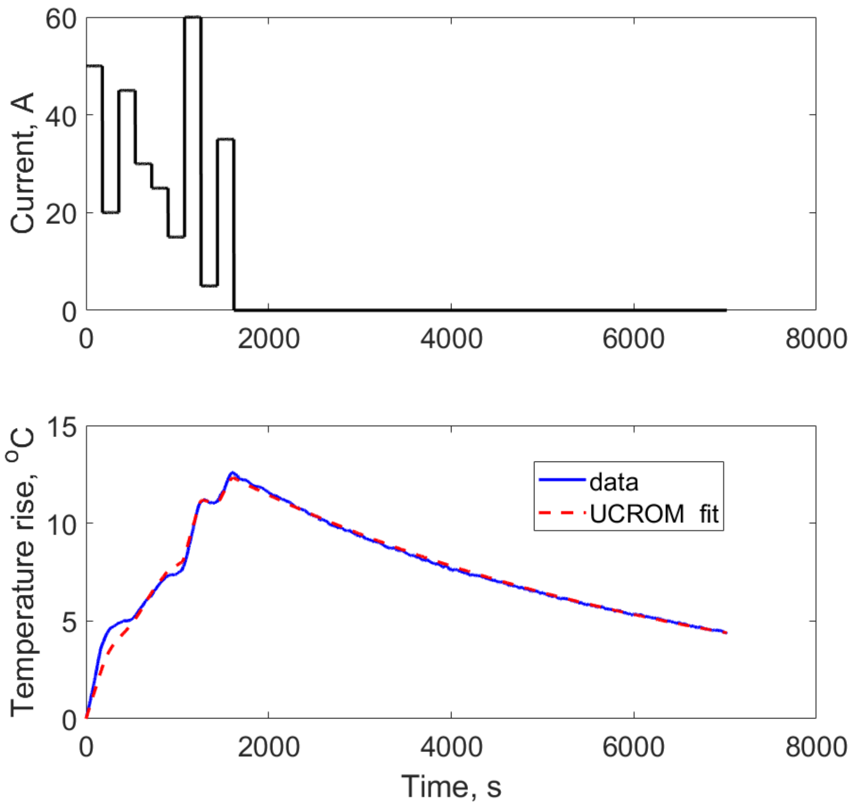
Thermal modeling of in-series packs.

Lab data

Specifications:
- Minimum Capacity: 22000mAh
- Configuration: 6S1P / 22.2V / 6 cells
- Discharge Rate: 30C
- Max Burst Discharge Rate: 150C
- Net Weight(±20g): 2460g
- Dimensions: 206mm Length x 91mm Width x 61mm Height
- Balancer Connector Type: JST-XHR

UCROM:

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



Summary and next steps

Summary:

- We developed an approach to derive identifiable thermal ROMs of Li ion cells;
- Identifiable ROMs allow:
  - ✓ Unique characterization of the cell’s aging and degradation
  - ✓ Anomaly detection

Next steps:

1. Further extension of the model-reduction approach to battery packs;
2. Searching for bigger datasets and in-field datasets for packs and cells.
3. Analysis of aging and degradation data for battery packs and cells to identify nominal and anomalous signatures in terms of the ROM parameters.