Enhancing Battery Degradation Analysis and Thermal Runaway Prediction

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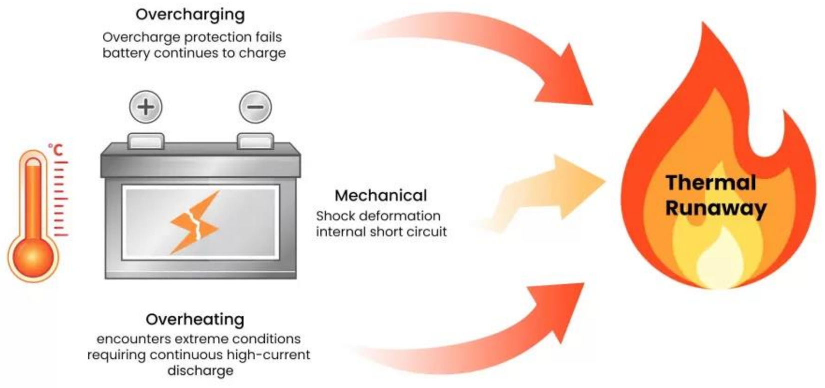
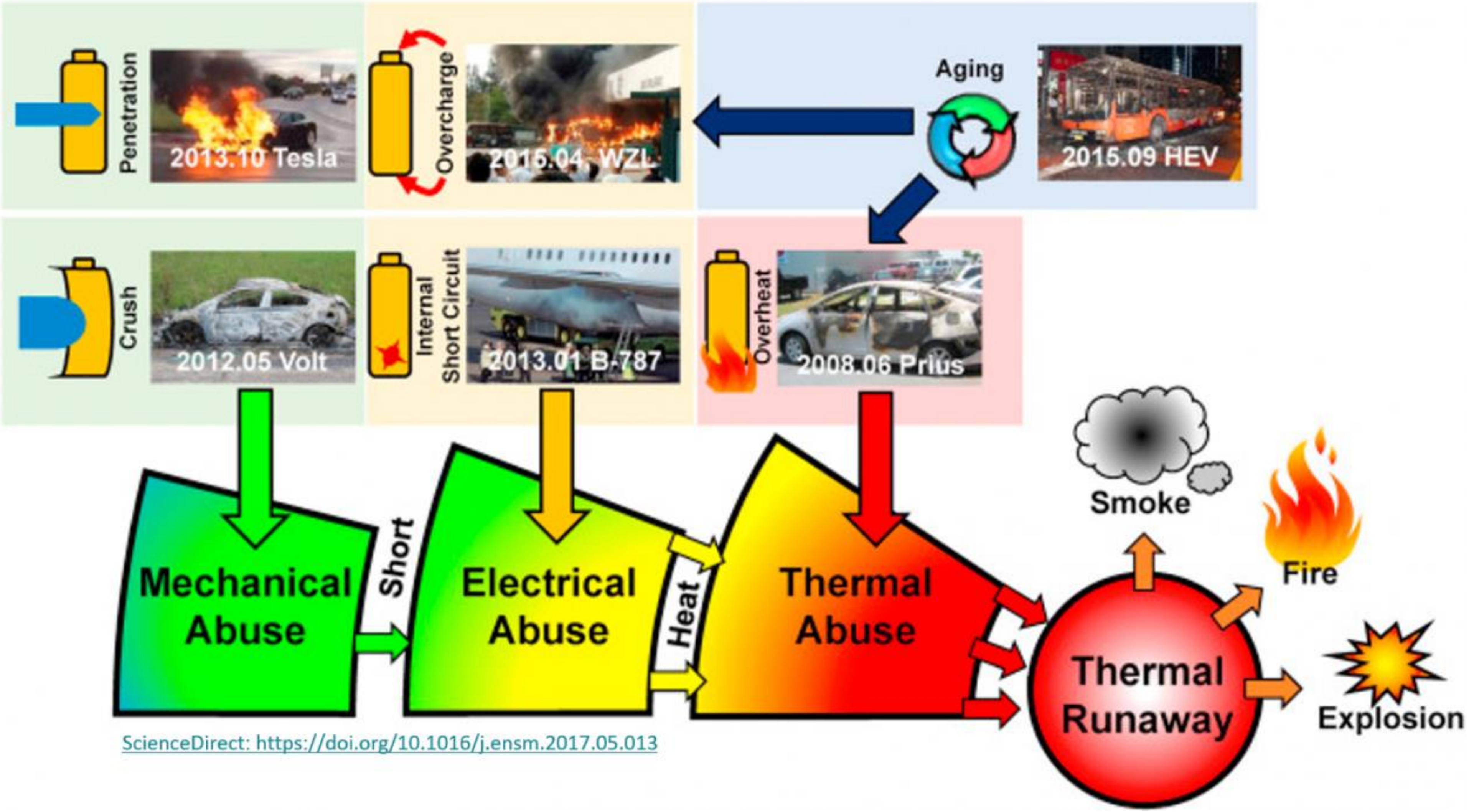
Thermal Runaway: Background



- Thermal runaway (TR) is an uncontrollable, self-accelerating failure in batteries.
- Triggered by internal short circuits, overcharge, or mechanical/thermal abuse.
- Leads to rapid temperature rise, gas venting, fire, or explosion
- Rare but catastrophic, with strong cell-to-cell propagation risks
- Key message: TR is the endpoint of a gradual degradation process.

Thermal Runaway in EV Batteries: When a Small Fault Becomes Catastrophic



ScienceDirect: https://doi.org/10.1016/j.ensm.2017.05.013

Thermal Runaway in EV Batteries: When a Small Fault Becomes Catastrophic

Samsung Recalls Galaxy Note7 Smartphones Due to Serious Fire and Burn Hazards

Share:

Recalled Samsung Galaxy Note7 phone

Hazard:

The **lithium-ion battery** in the Galaxy Note7 **smartphones** can overheat and catch fire, posing a serious burn hazard to consumers.

Remedy:

Refund

Replace

Repor
unsafe p

Boeing 787 aircraft grounded after battery problem in Japan

14 January 2014

Heathrow fire on Boeing Dreamliner 'started in battery component'

Investigators say crew would have struggled to contain blaze once plane was in mid-air

The Ethiopian Airlines Boeing 787 Dreamliner at Heathrow after it caught fire last week. Photograph: Anthony Devlin/PA

New Data: Battery Thermal Runaway Incidents on Board Passenger and Cargo Aircraft Hit Record High as Passengers Remain Largely Unaware of Risks

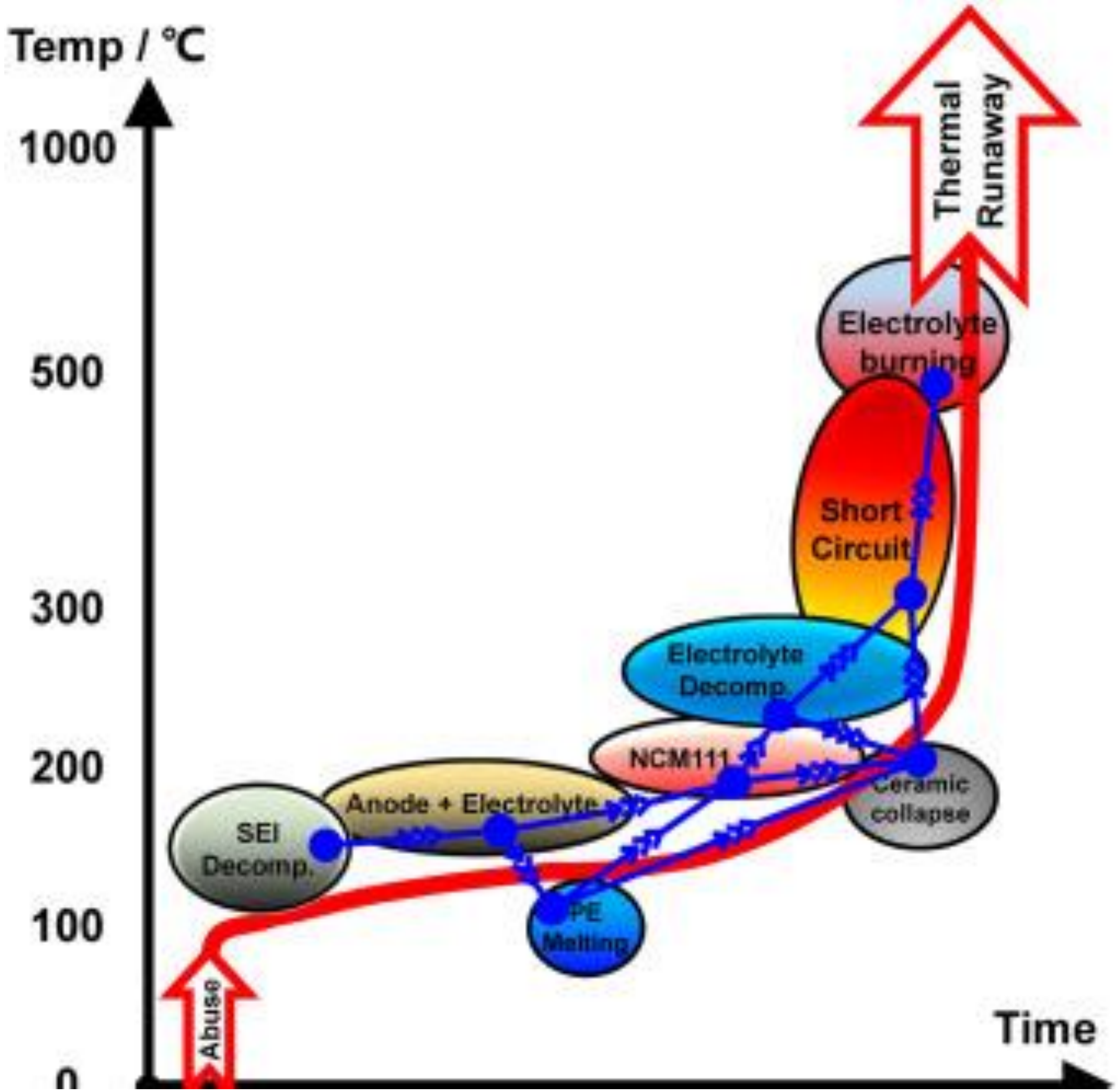
News | September 9, 2024 Connect:

Fire department urges caution after lithium ion battery starts fire at London school

No injuries were reported in the fire, which happened at Northridge Public School

CBC News · Posted: Feb 06, 2026 7:42 PM EST | Last Updated: February 6

Thermal Runaway has precursors!



Data-Driven Solution makes a difference

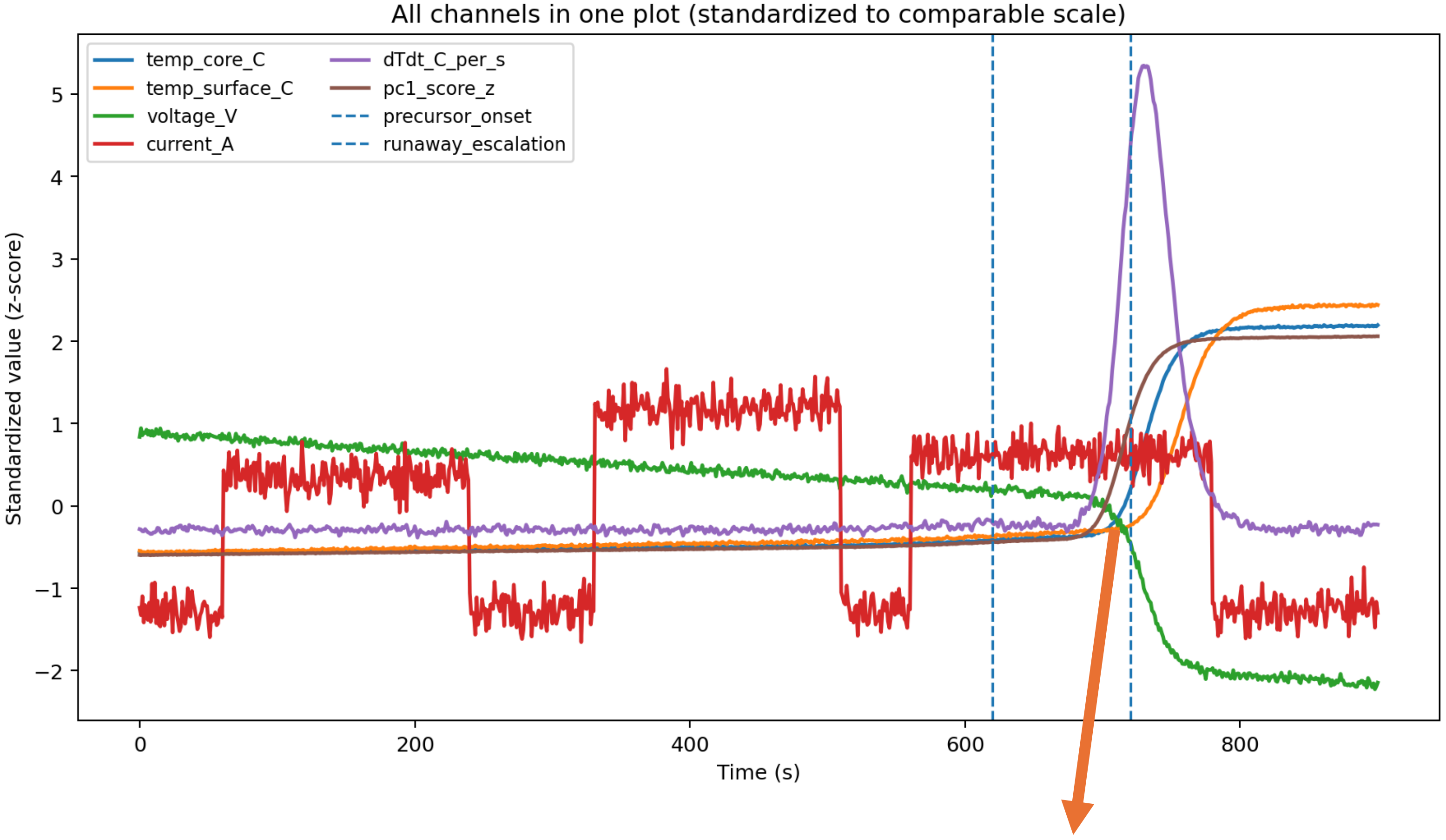
- **Observed Signals:**

- **Temperature Gradient**
- **Current Spikes**
- **Voltage Drops**
- **Latent (gradual) degradation patterns**

- **Key challenge**

TR (Thermal Runaway) Precursors are often *weak, hidden, distributed, and context-dependent*

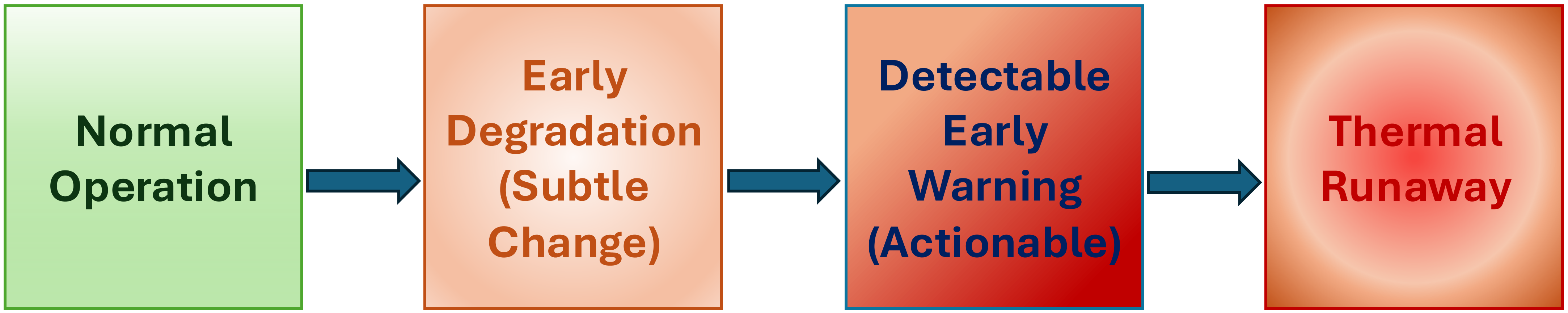
Thermal Runaway Data: Multivariate Time-Series



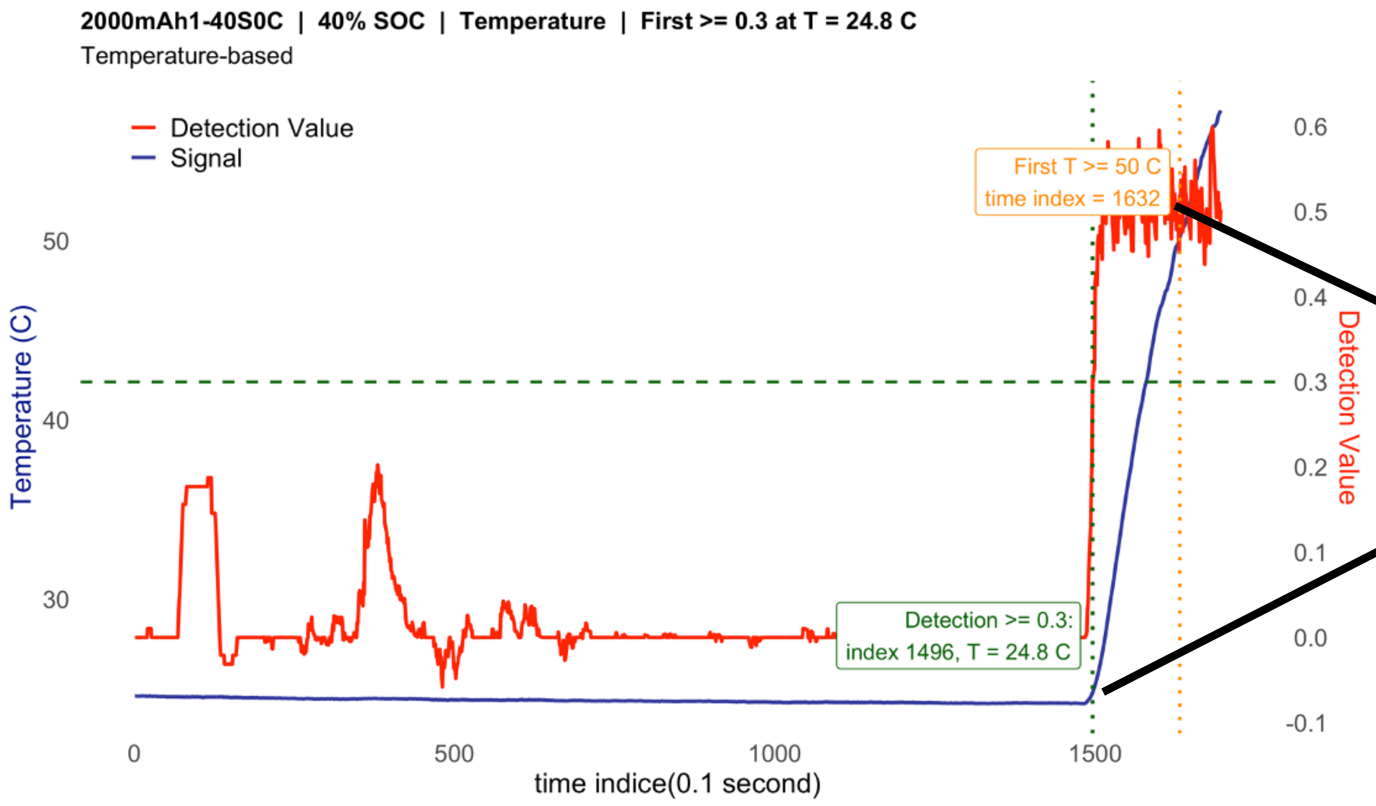
Highly Nonlinear, Complex Patterns

Why Early-Warning Signal Generation Matters

- Thermal Runaway are nonlinear and non-stationary.
- Intervention in only effective before critical thresholds.
- Threshold-based alarms are reactive and often too late.



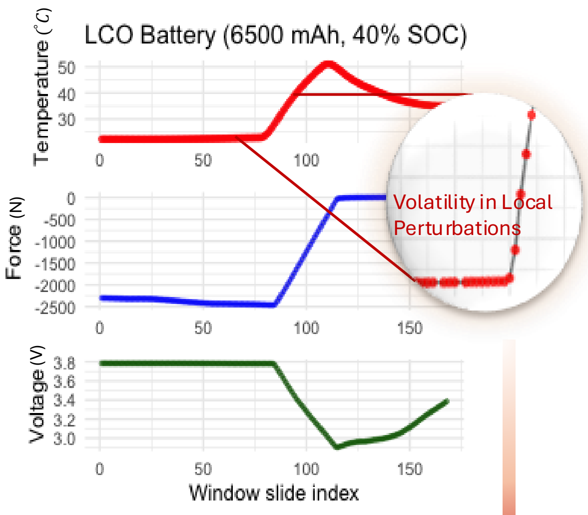
Generate early warning signal and take actions to prevent it

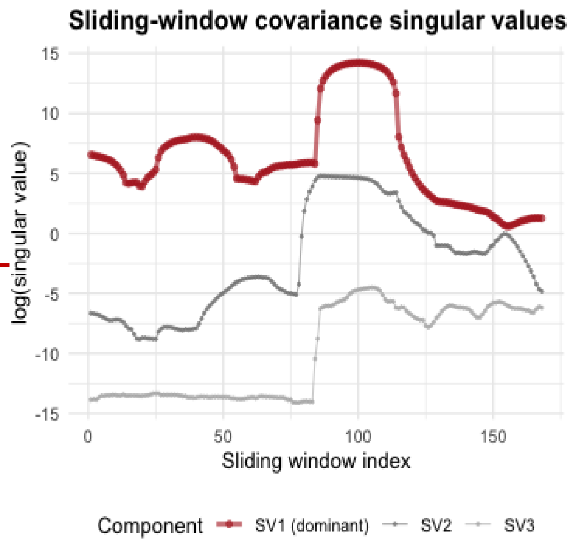


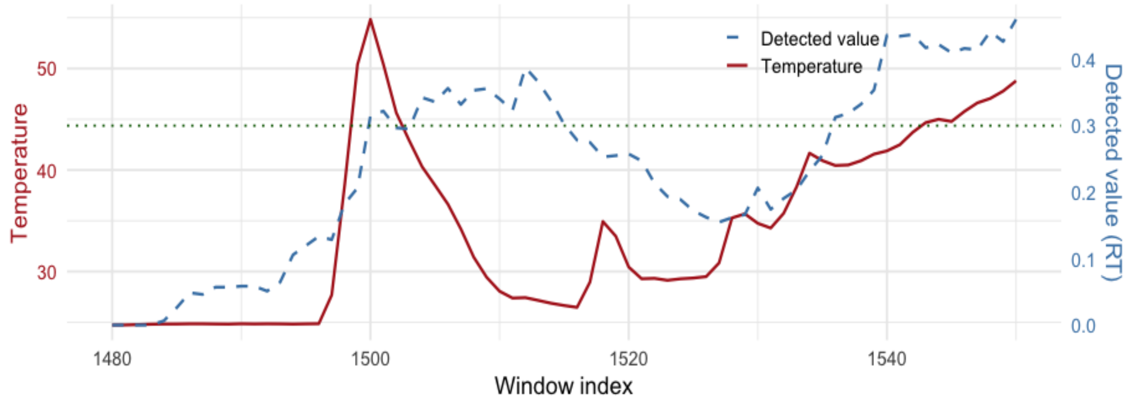
Drastic Increase - Detect before the temperature exceeds an alerting threshold.

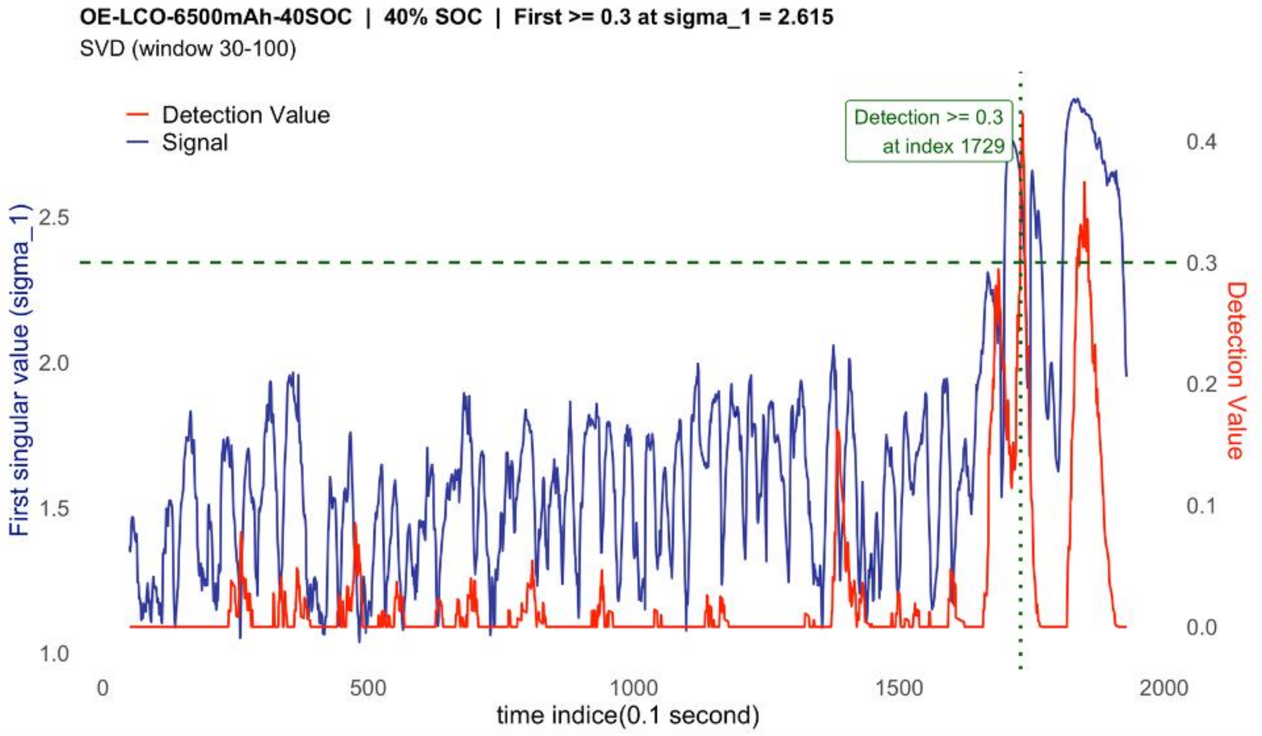
Detect shift via searching for gradient change that occurs over a range of **time window**

Heuristics of our algorithm









Trust & Actionability: Beyond the Black Box

The Interpretability Gap

- **Engineers:** Need root-cause logic to fix triggered alerts.
- **Operators:** Need actionable diagnostics, not just "anomaly scores."
- **Compliance:** Safety and regulatory contexts mandate explainability.

Three Pillars of Actionable Output

- **Signal Attribution:** Which specific sensors drove the alarm?
- **Temporal Scale:** How fast did the anomaly emerge?
- **Robustness:** Is the warning stable or just noise?

Trust & Actionability: Beyond the Black Box

Our Solution: Bridging Theory & Practice

- **The Problem:** Existing literature lacks reproducible open-source software.
- **The Goal:** Peel back the "black box" using internal interpretability methods.
- **The Deliverable:** A unified, accurate, and reproducible library in **R & Python**.
- **Takeaway:** Detection is only as valuable as it is **trustworthy and actionable.**

NREL Dataset

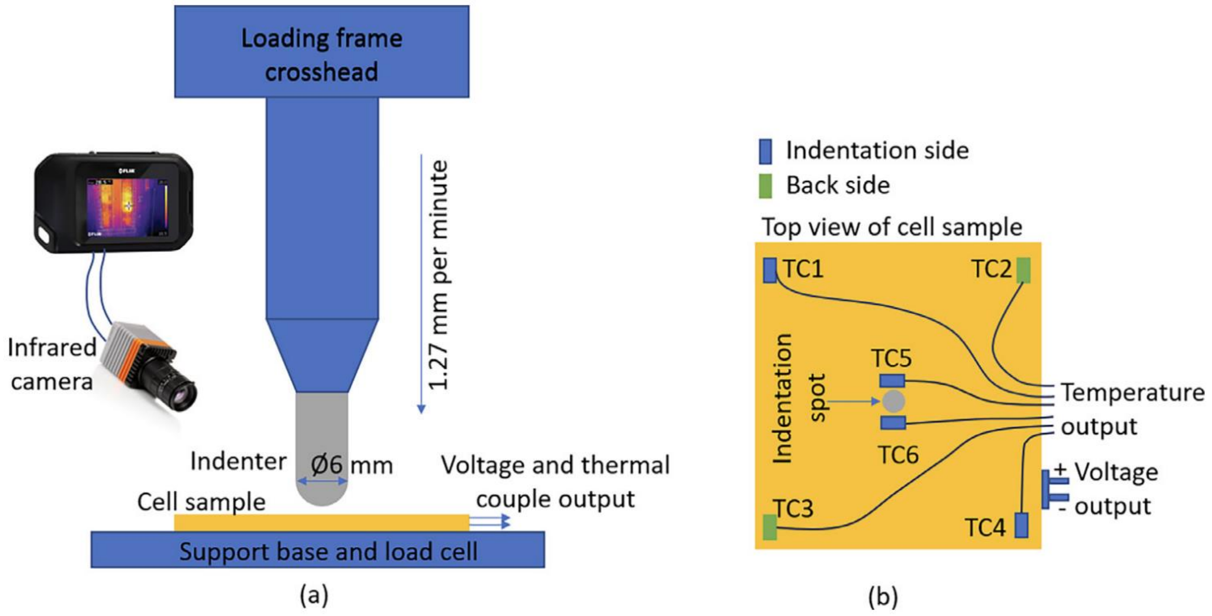
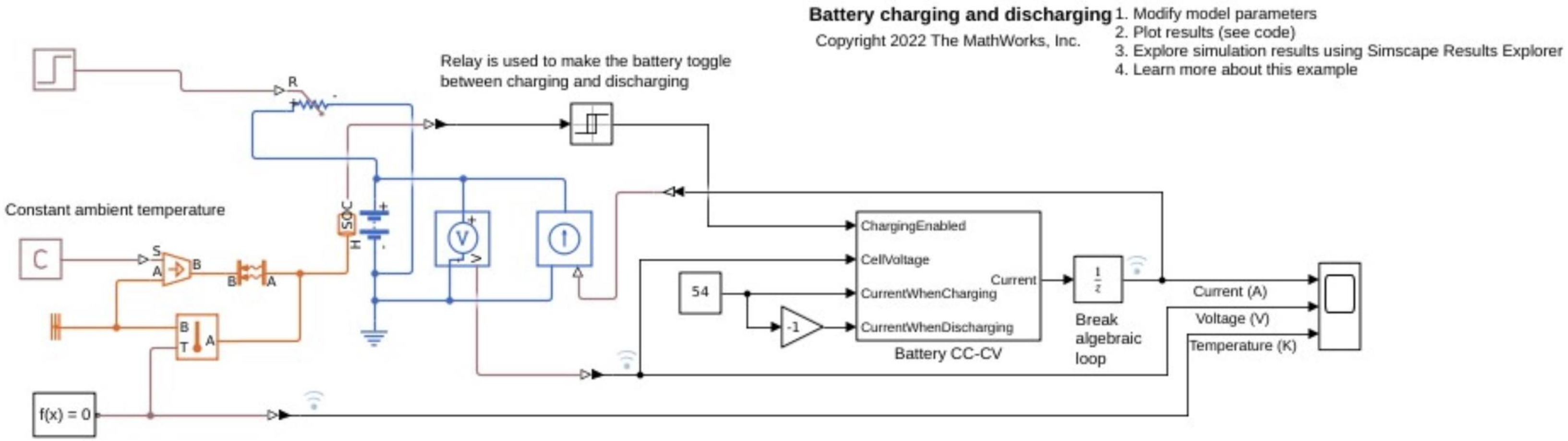


Fig. 5. Illustration of single-side indentation test (a) front view of test frame and cell sample; (b) top view of cell sample with thermocouples (TC1~TC6) attached.

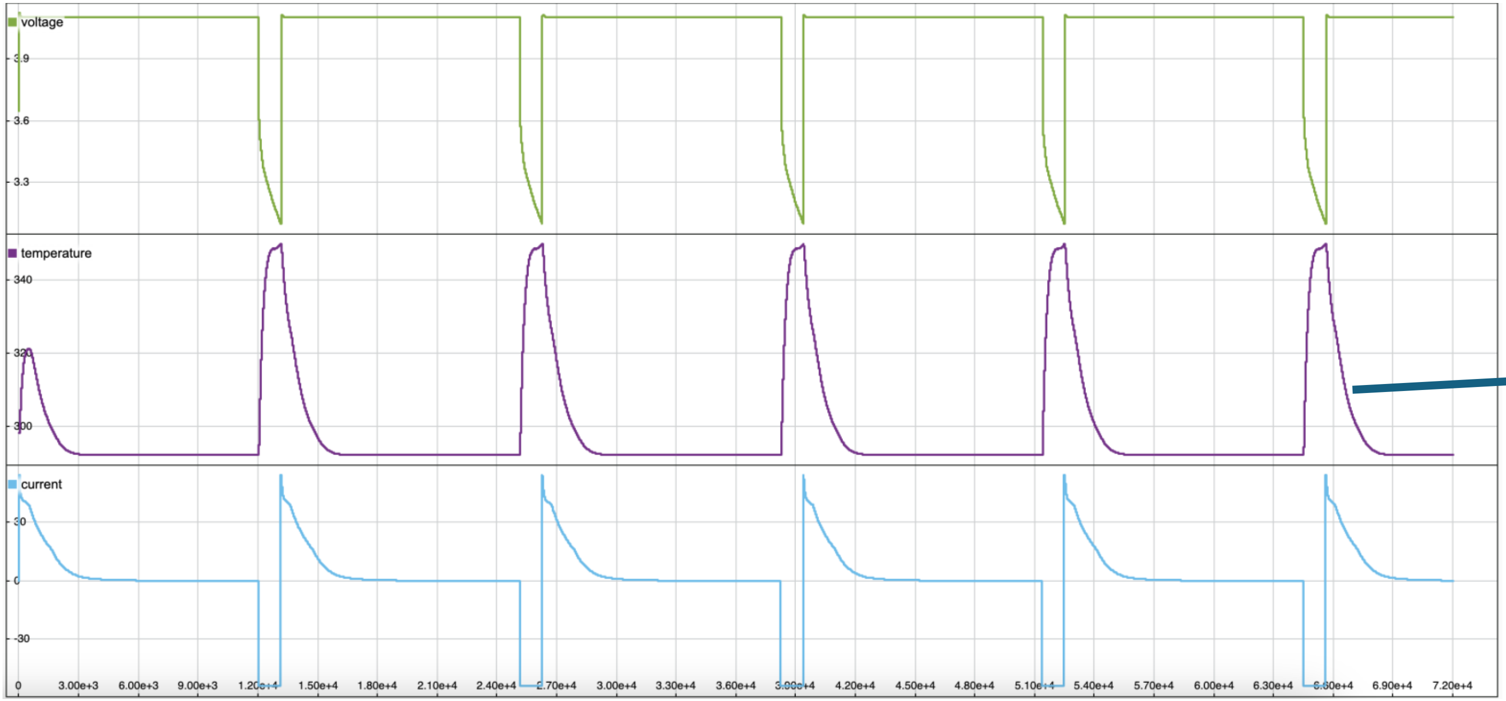
- Standardized mechanical abuse (single-side indentation) is applied to Li-ion cells to induce an **internal short circuit(ISC)**, while recording time-series measurements of cell voltage, compressive load, indenter stroke (**displacement**), and temperature at the **indentation** point.
- Measurements: Voltage, Current, Temperature and Penetration Force, 118 battery cells in total

https://www.sciencedirect.com/science/article/pii/S2352340924005766

Synthetic Dataset: Matlab Simulink



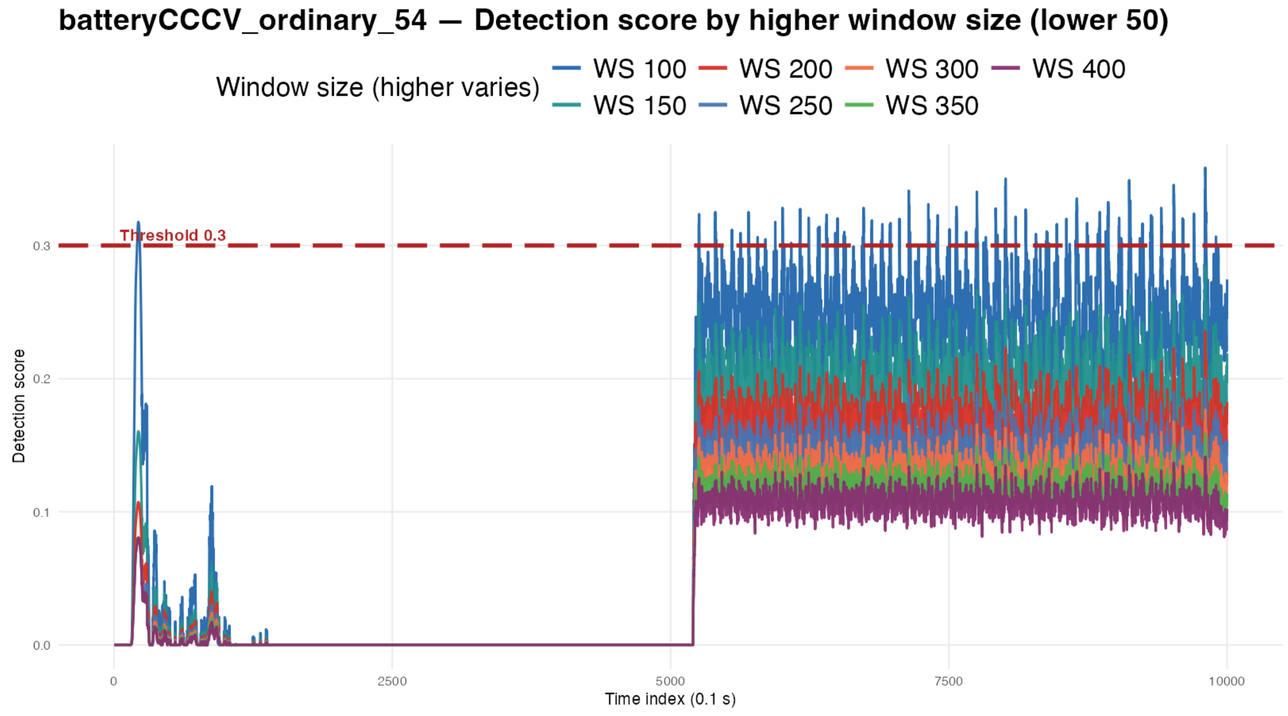
Battery CCCV Internal Short Circuit

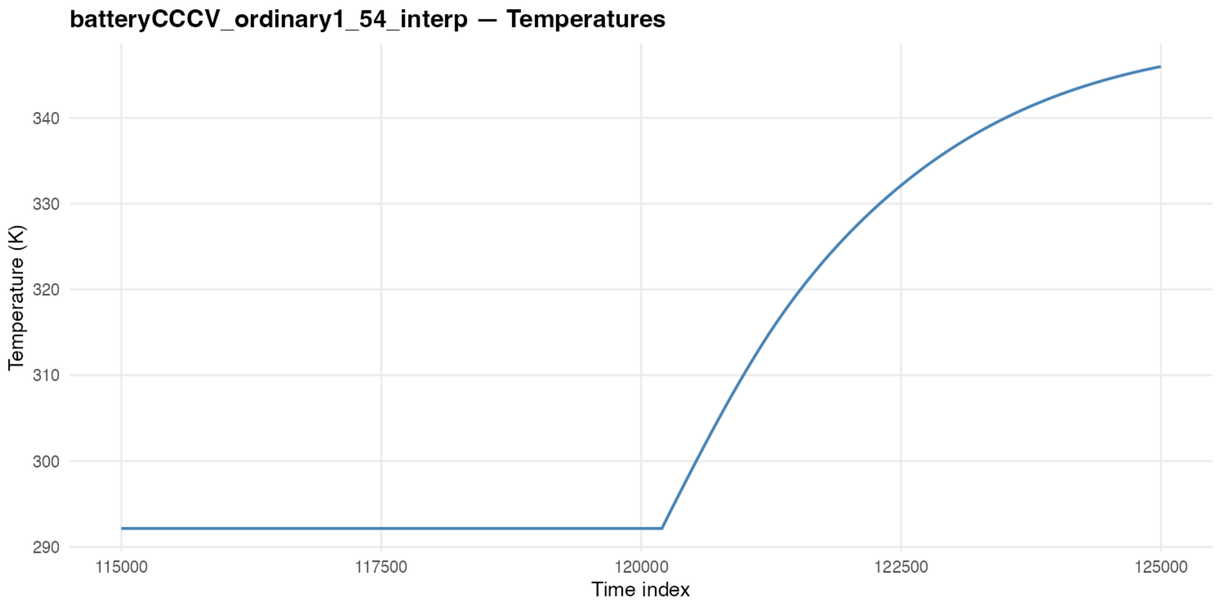


Multiple Charging Cycles

https://www.mathworks.com/help/simscape-battery/ref/batterycccv.html

Threshold sensitivity: Window-Sizes

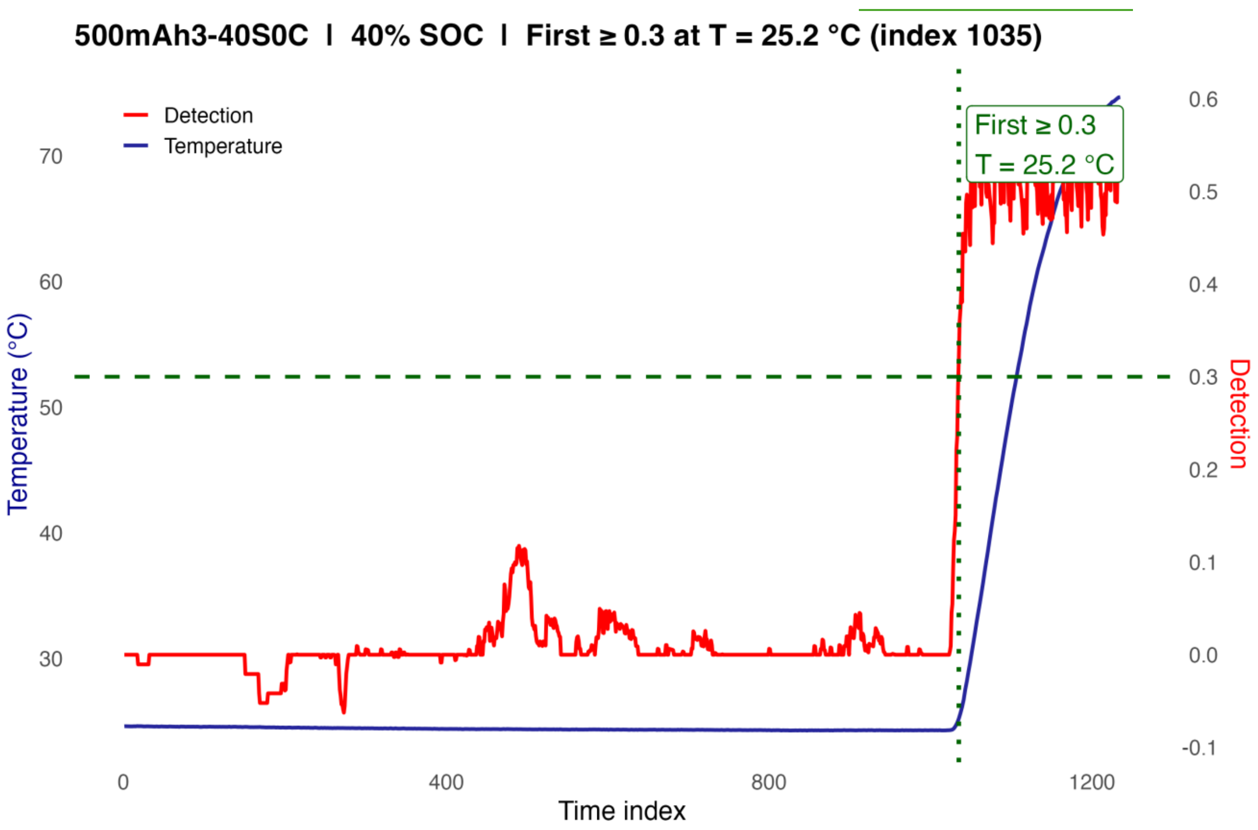


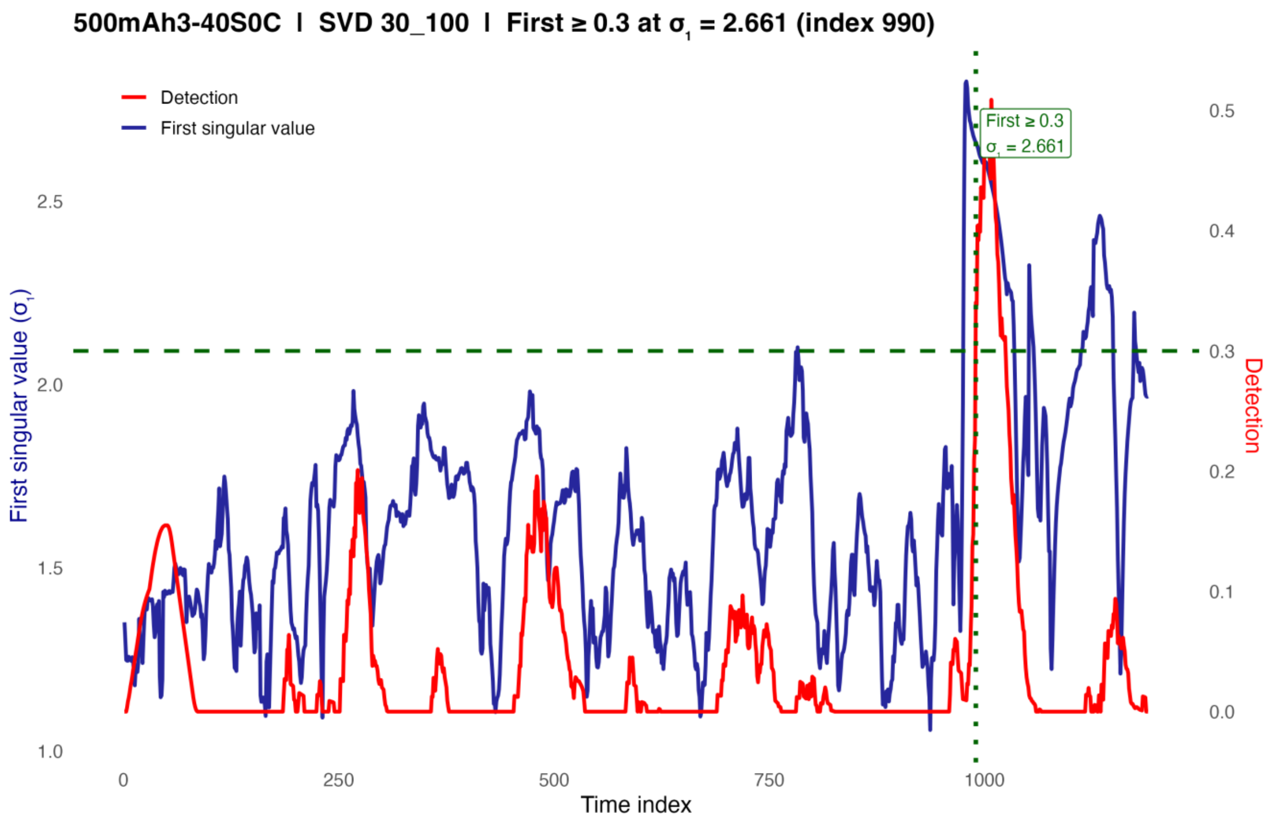


Window size:

- **Lower Range (w_{low}):** Capture local volatility; sensitive to early, short-horizon precursors.
- **Higher Range (w_{high}):** Capture long-term trends; robust to transient fluctuations.
- In practice, balances early warning (detecting incipient thermal runaway or abnormal heating) against nuisance alarms driven by current steps or sensor noise.

Multivariate SVD Procedure can enhance earlier detection





NREL Dataset: Accuracy across different window-sizes

Lower/Higher Window-Size	**60**	**75**	**100**	**125**	**150**
5	0.739	0.721	0.721	0.711	0.703
10	0.739	0.748	0.703	0.693	0.693
20	0.739	0.739	0.711	0.703	0.693
30	0.712	0.703	0.703	0.693	0.693
40	0.721	0.693	0.703	0.703	0.676

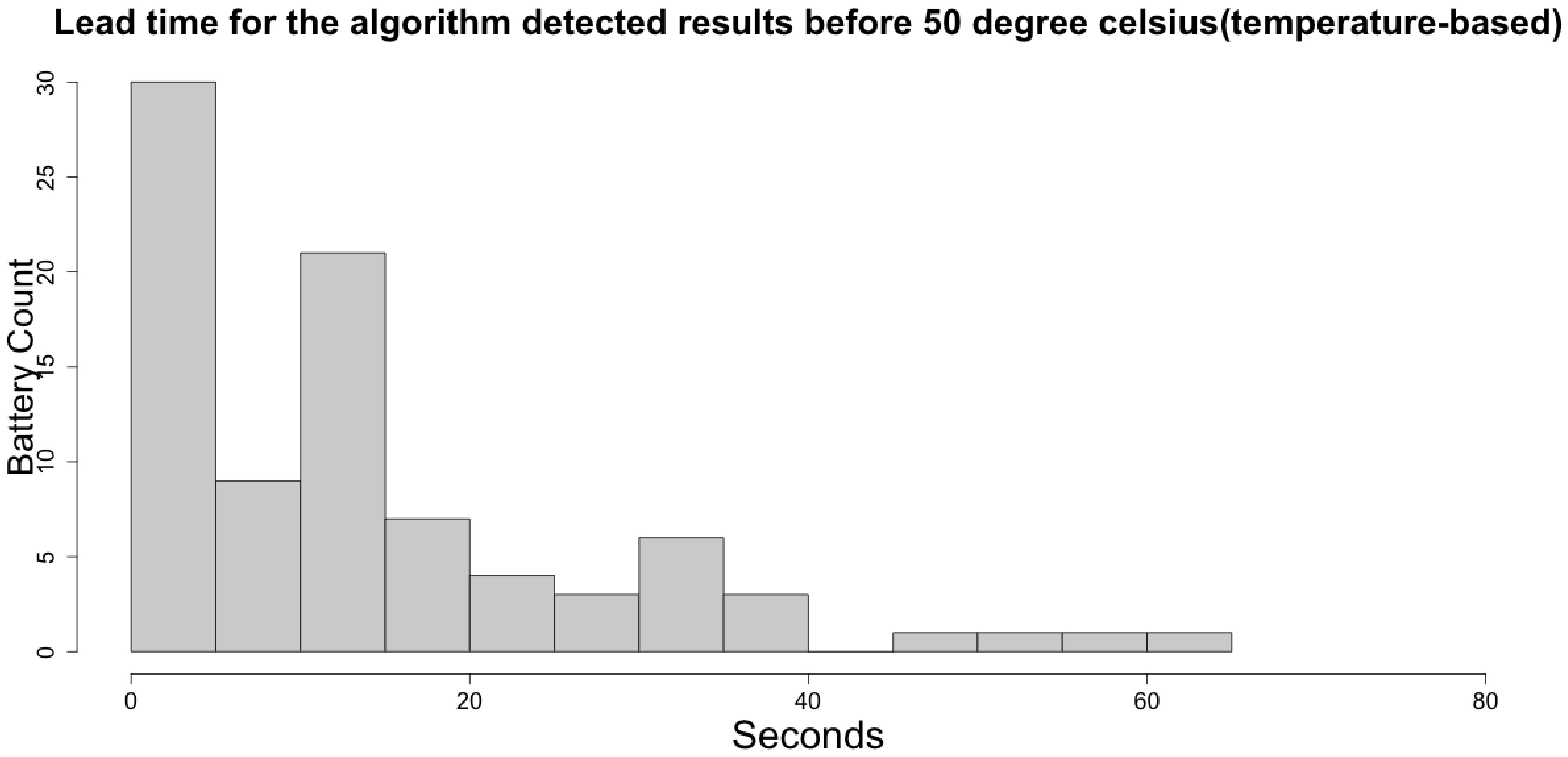
Univariate Algorithm on Temperature

$$Accuracy = \frac{\#\ Corrected\ detected\ TR\ in\ Battery\ cells}{\#\ Battery\ cells}$$

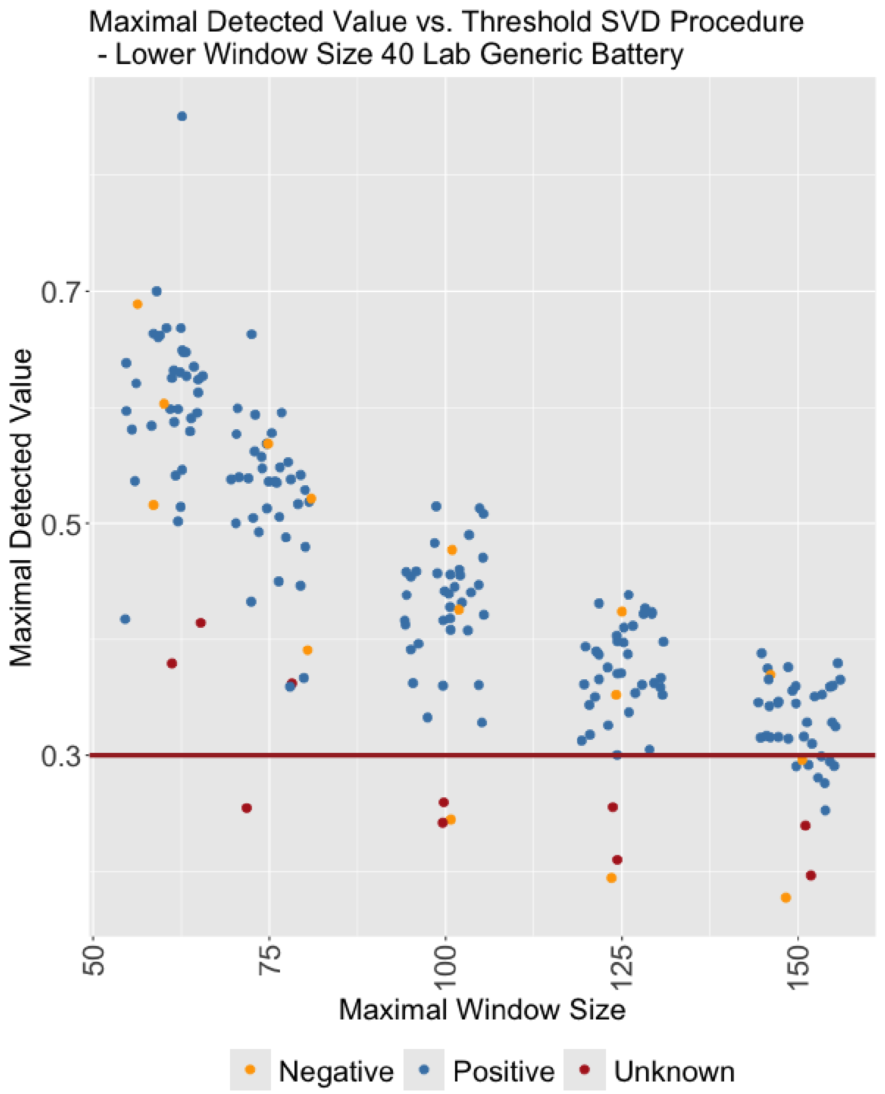
Lower/Higher Window-Size	**60**	**75**	**100**	**125**	**150**
5	0.730	0.730	0.711	0.711	0.703
10	0.748	0.748	0.712	0.693	0.703
20	0.739	0.748	0.711	0.693	0.676
30	0.721	0.703	0.703	0.693	0.676
40	0.721	0.703	0.693	0.676	0.640

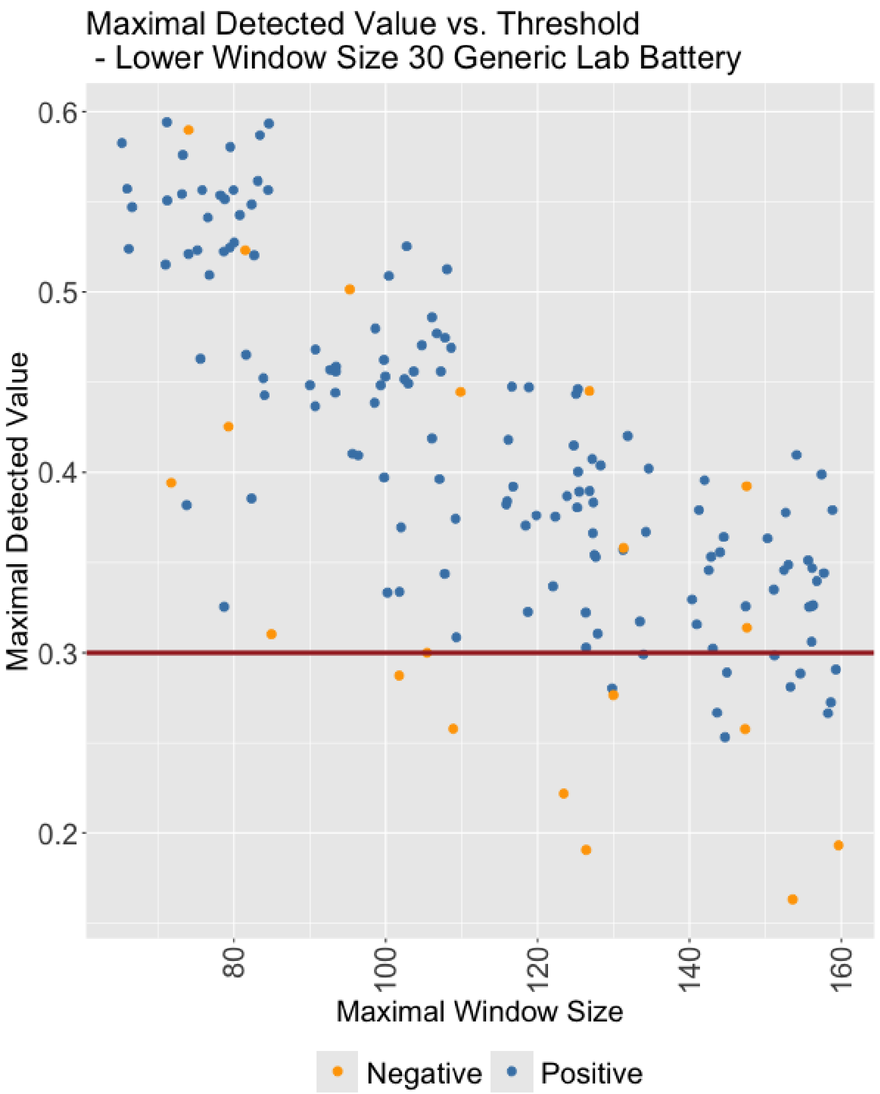
SVD Based-Procedure on "Temperature, Current and Voltage"

NREL Dataset: Detect earlier than threshold based method

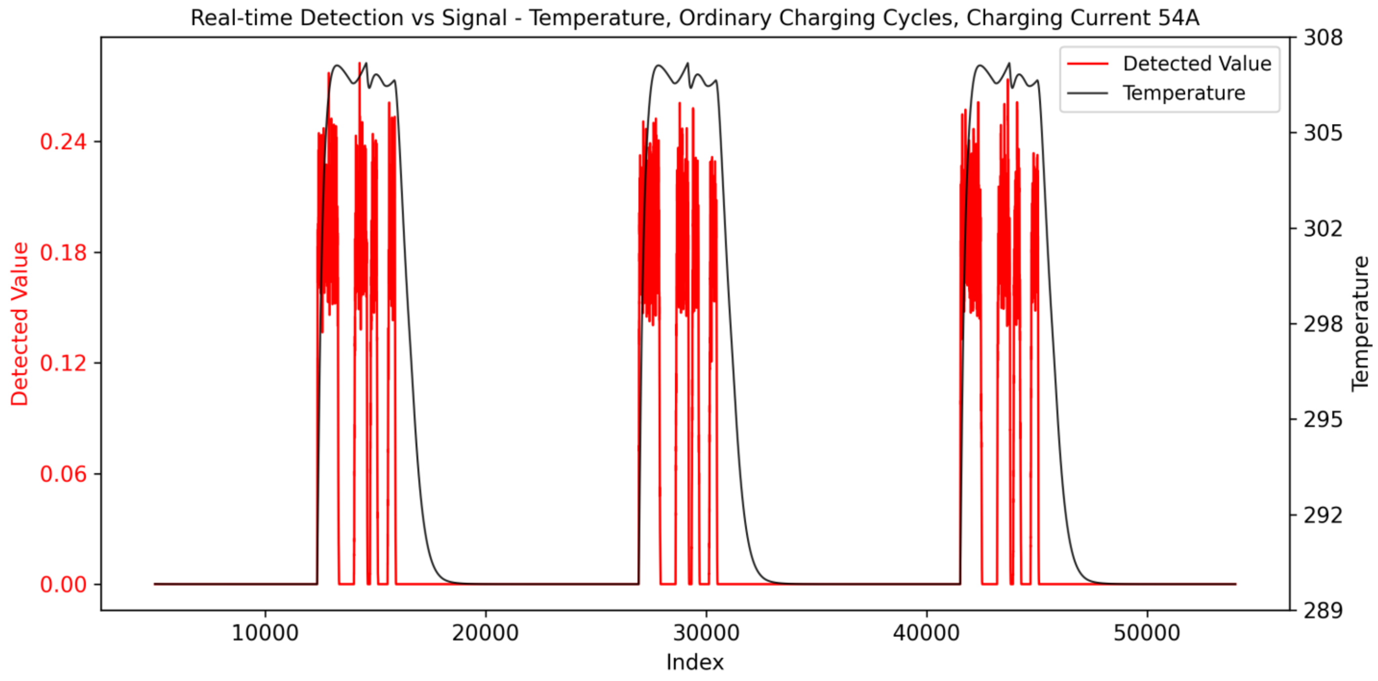


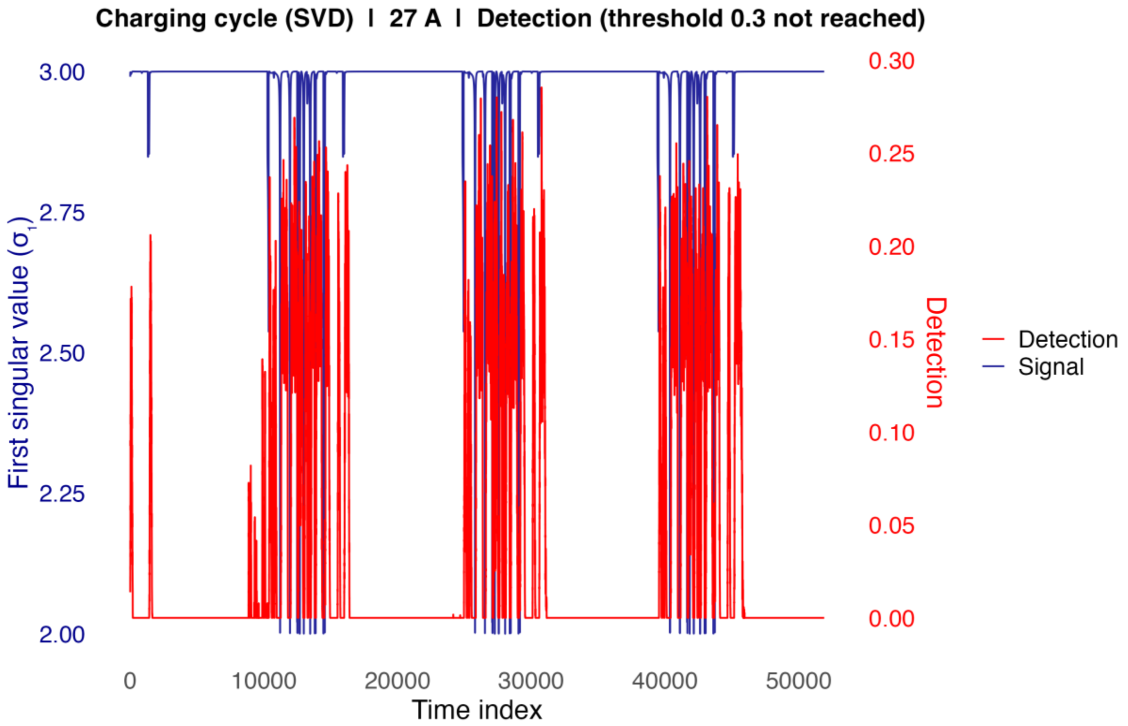
NREL Dataset: Sensitivity Analysis for Varying Window-Size





Simulated Data: Ordinary Charging Cycles, real-time detection





Capable of preventing False Alarms

Scalability & Generalizability

- **Battery-agnostic deployment:** Can this framework generalize across battery chemistries, form factors, and operating regimes (e.g., LFP vs NMC; pouch vs cylindrical; EV vs BESS) with minimal manual intervention?

- **Beyond thermal runaway:** Can the same real-time procedure detect and localize other abnormal behaviors in battery telemetry.

- **Deployment in real-world systems** with **multi-cycle operation** to support periodic **evaluation and validation**.

Discussion & Summary

- **Slope-based detection is inherently interpretable** and can generate **earlier warning signals** than traditional CUSUM methods.

- The **SVD-based aggregation** captures **latent cross-sensor (panel) structure**, delivering **consistent gains** over the baseline **TRpred** pipeline.

- Best suited for **moderate-complexity regimes**, where patterns are structured but not dominated by extreme nonlinearity

- **Broadly generalizable** to a wide range of multivariate time-series monitoring tasks

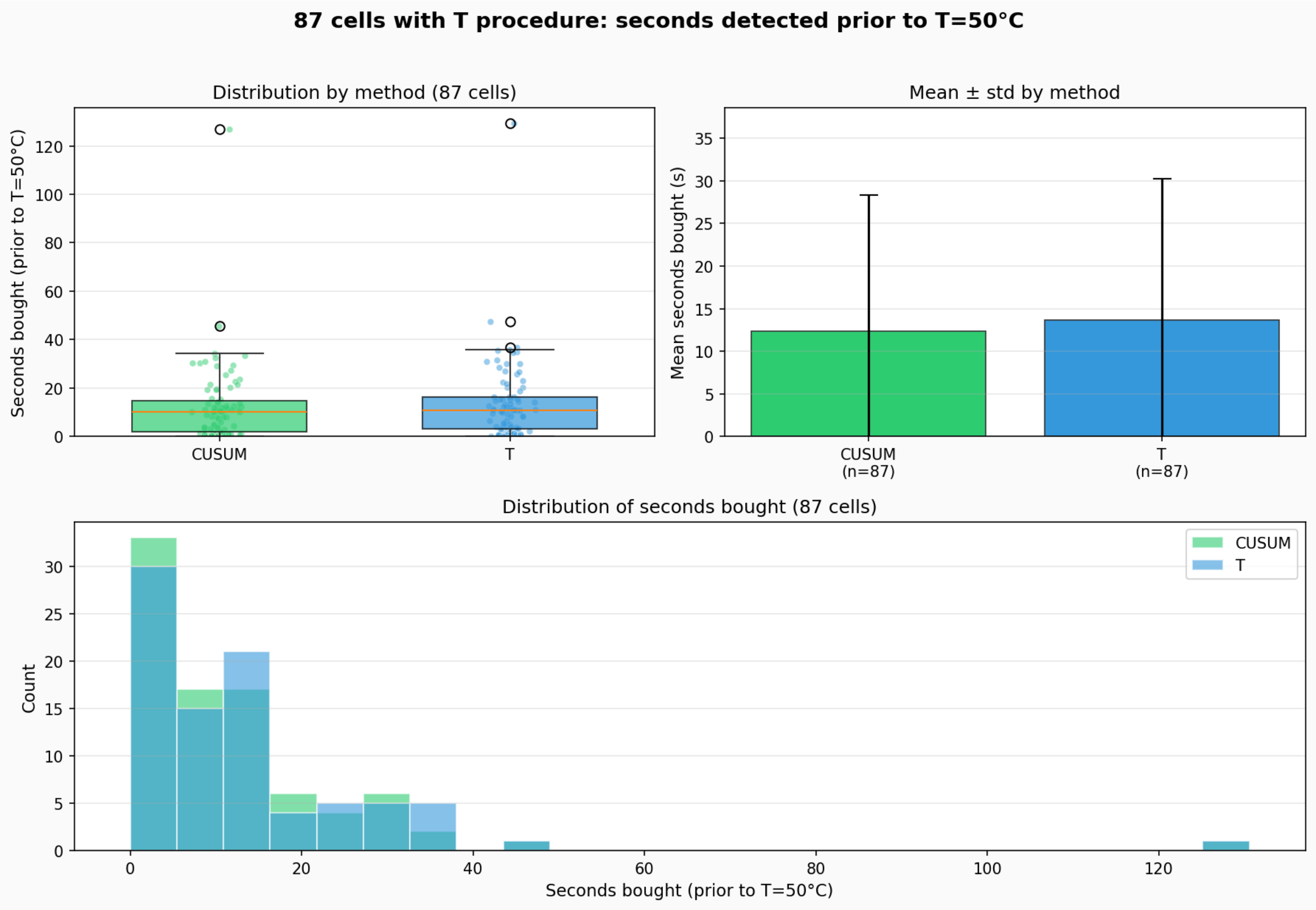
Acknowledgements

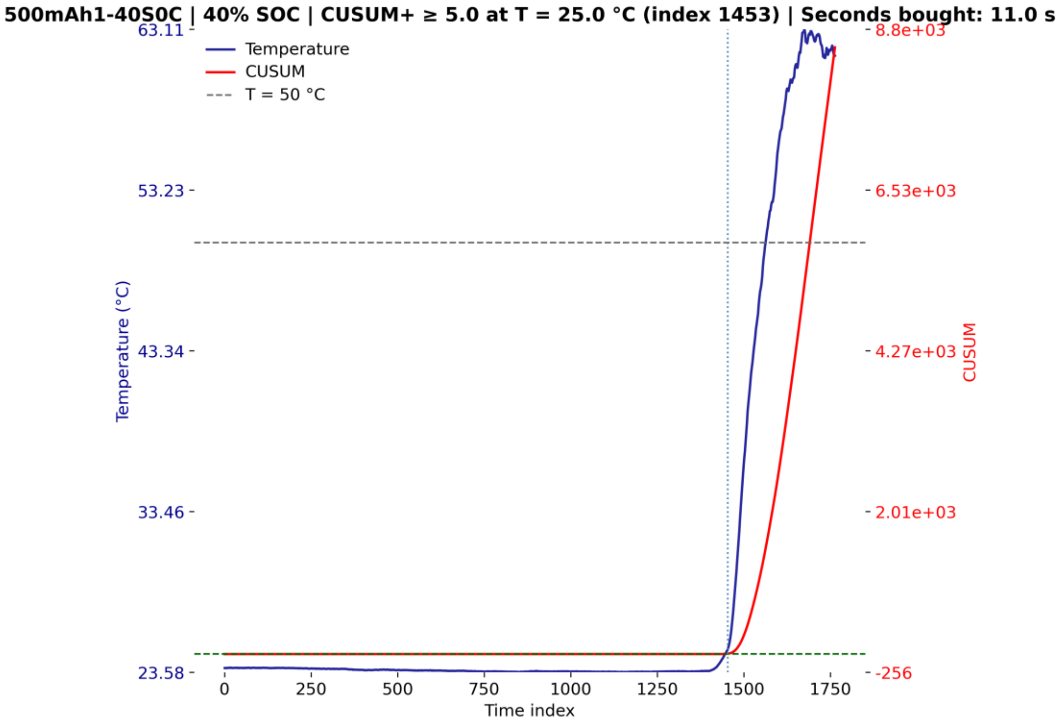
- We highly appreciate Dr. Mustapha Makki for guidance and thoughtful insights into the aspects of thermal runaway and lithium-ion batteries.
- Eaton for membership support and sharing datasets.

- We have developed packages in R and Python, which is available for members to try. The algorithm is broadly generalizable to a wide range of multivariate time-series monitoring tasks.

Supplementary Slides

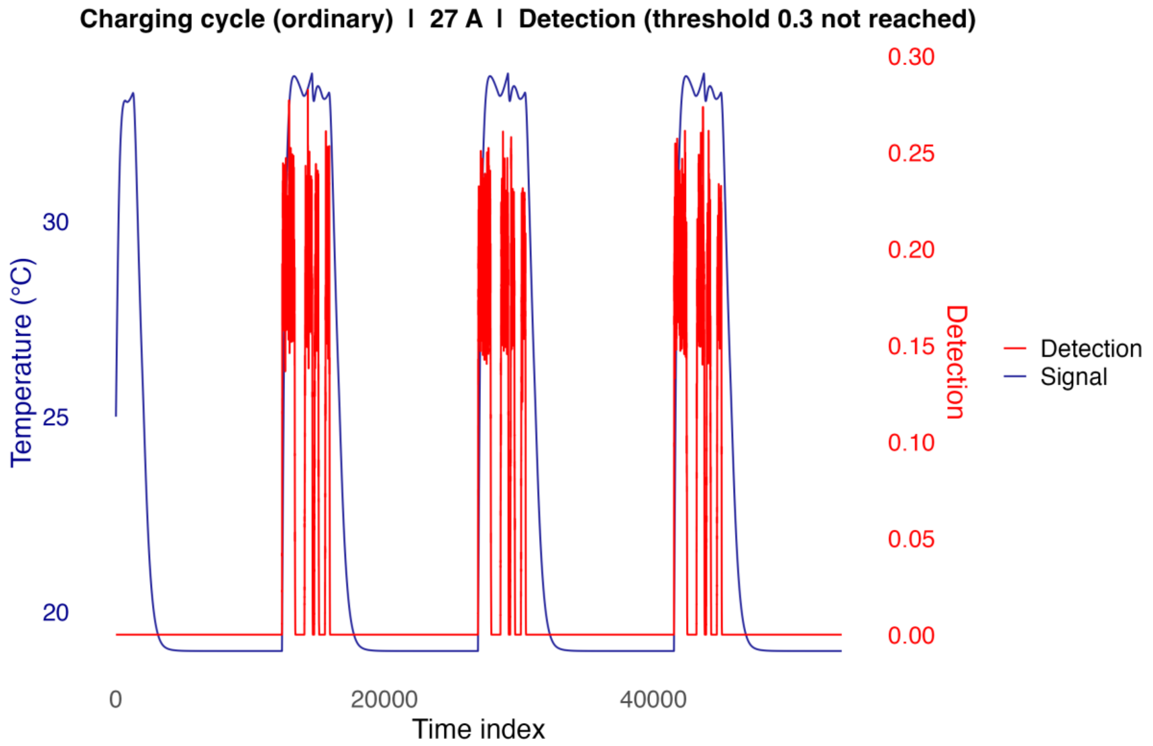
Benchmark Comparison - CUSUM

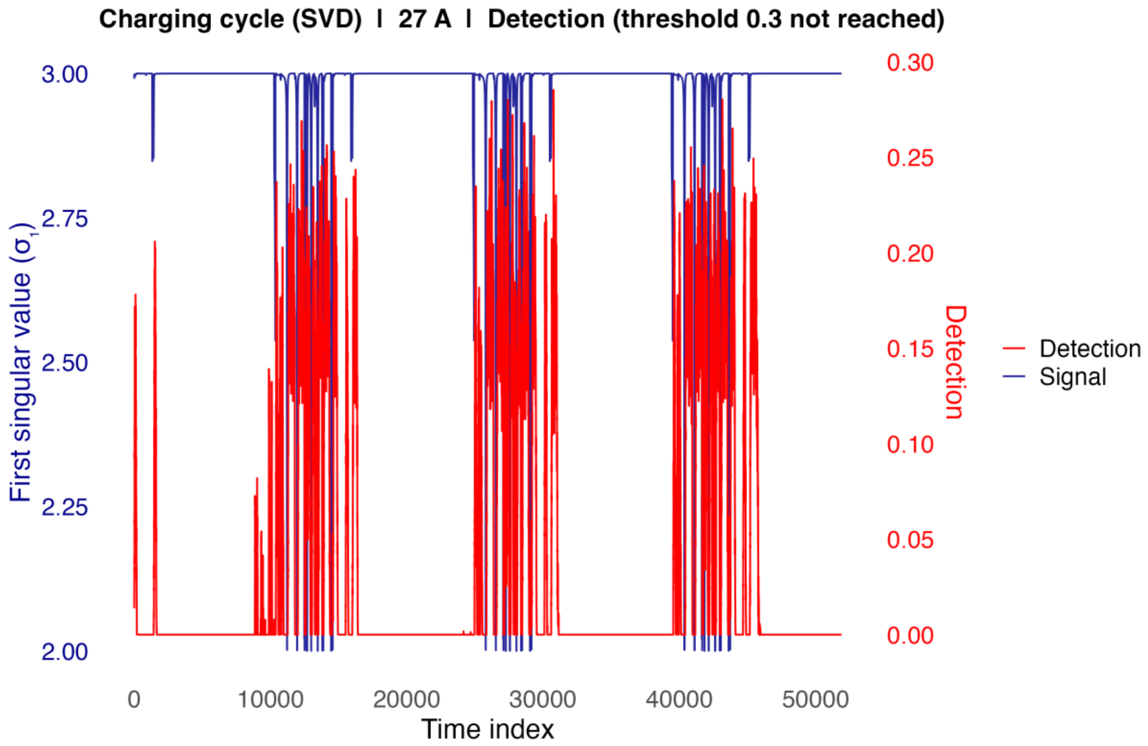


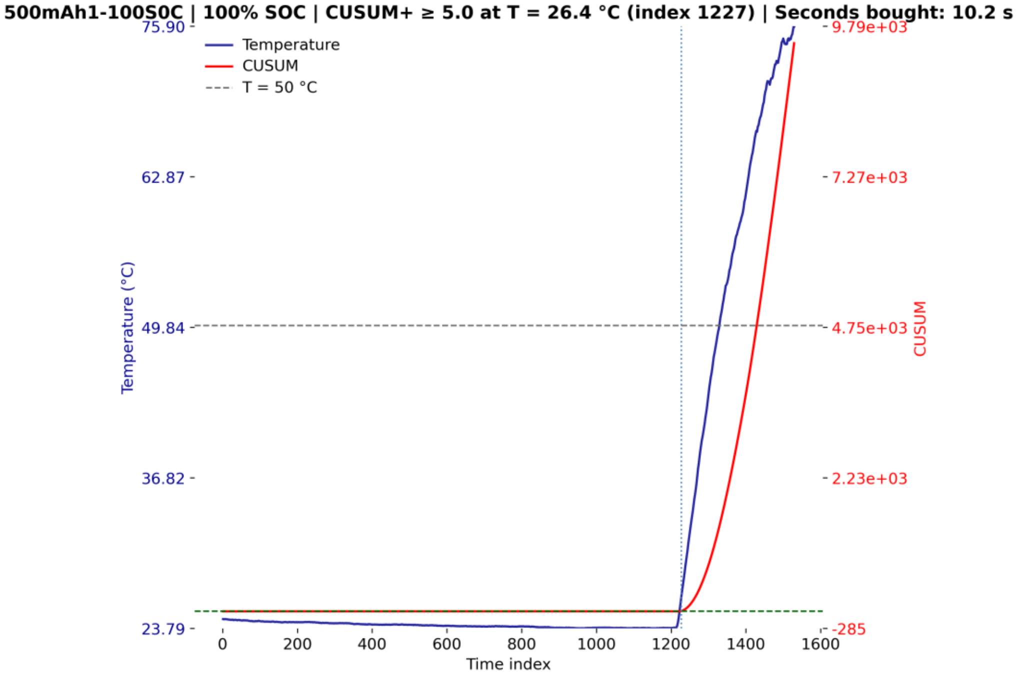


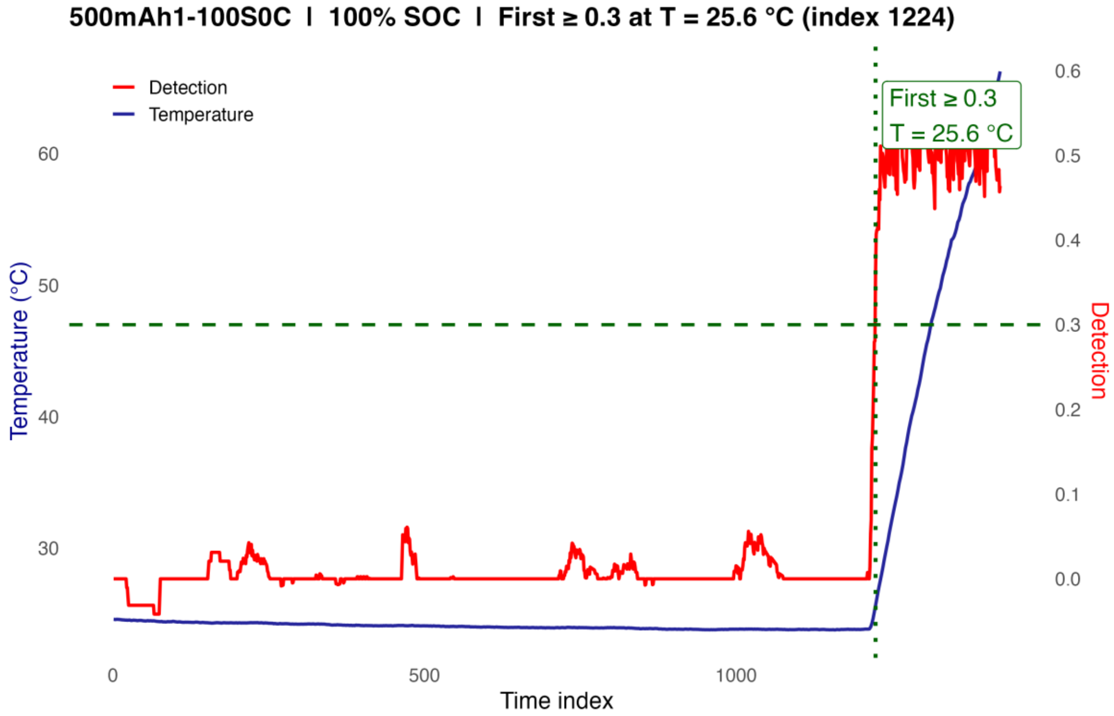
https://www.jstor.org/stable/1266472

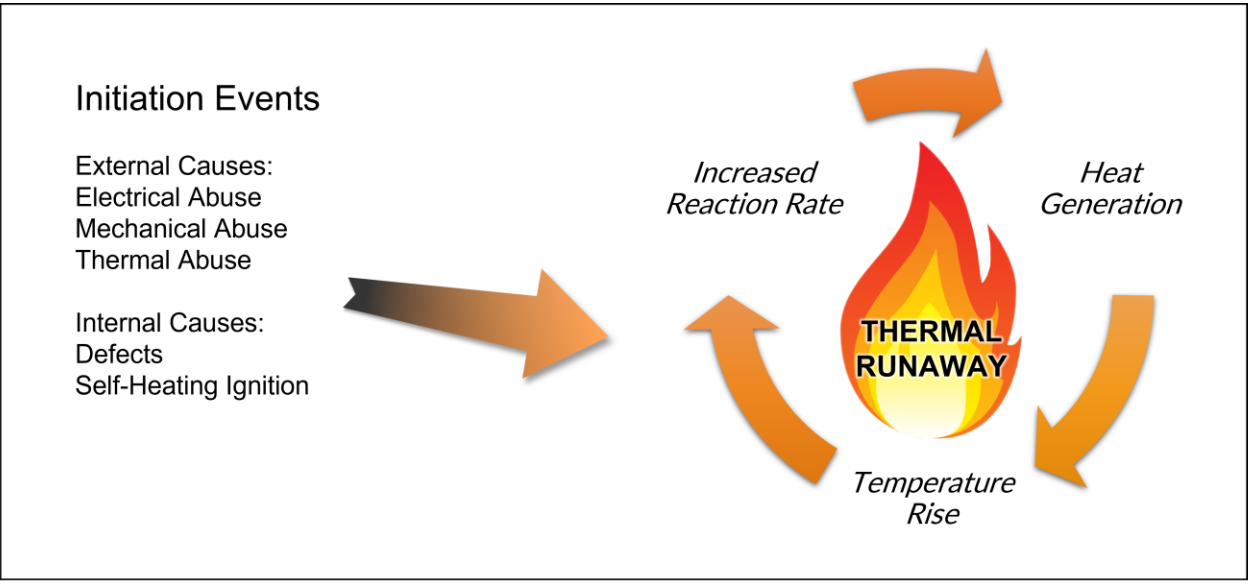
Sensitivity Analysis: Charging Cycles with varying charging current

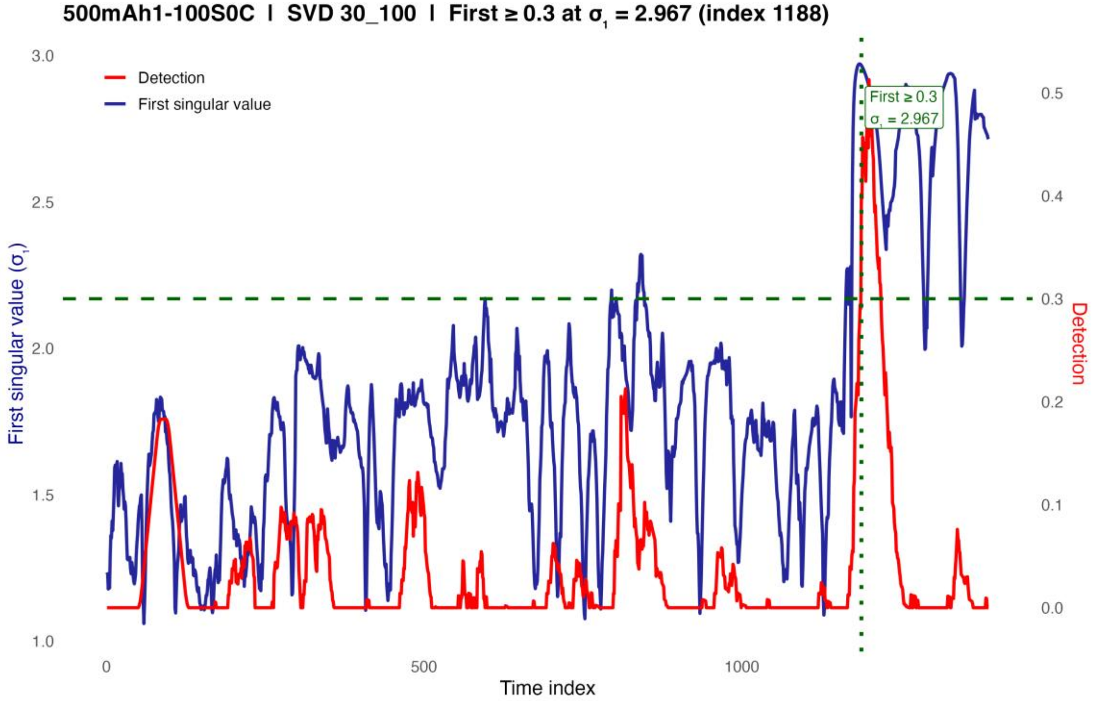





500mAh1-100SOC | 100% SOC | CUSUM+ ≥ 5.0 at T = 26.4 °C (index 1227) | Seconds bought: 10.2 s
Temperature
CUSUM
T = 50 °C
Temperature (°C)
CUSUM
Time index
75.90
62.87
49.84
36.82
23.79
9.79e+03
7.27e+03
4.75e+03
2.23e+03
-285
0
200
400
600
800
1000
1200
1400
1600


500mAh1-100S0C I 100% SOC I First ≥ 0.3 at T = 25.6 °C (index 1224)
Detection
Temperature
First ≥ 0.3
T = 25.6 °C
Temperature (°C)
Detection
Time index
60
50
40
30
0.6
0.5
0.4
0.3
0.2
0.1
0.0
0
500
1000


Initiation Events
External Causes:
Electrical Abuse
Mechanical Abuse
Thermal Abuse
Internal Causes:
Defects
Self-Heating Ignition
Increased Reaction Rate
Heat Generation
THERMAL RUNAWAY
Temperature Rise

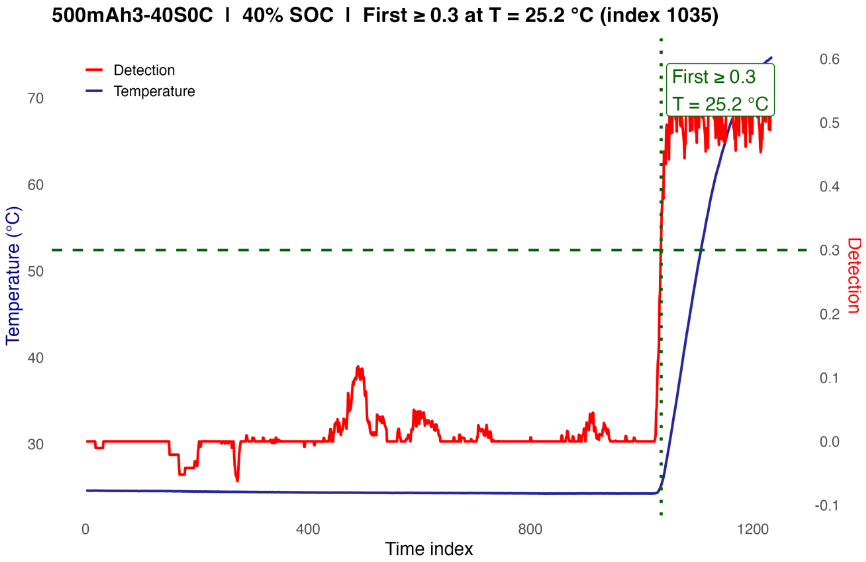

500mAh1-100S0C I SVD 30_100 I First ≥ 0.3 at σ1 = 2.967 (index 1188)
Detection
First singular value
First ≥ 0.3
σ1 = 2.967
First singular value (σ1)
Detection
Time index
3.0
2.5
2.0
1.5
1.0
0.5
0.4
0.3
0.2
0.1
0.0
0
500
1000

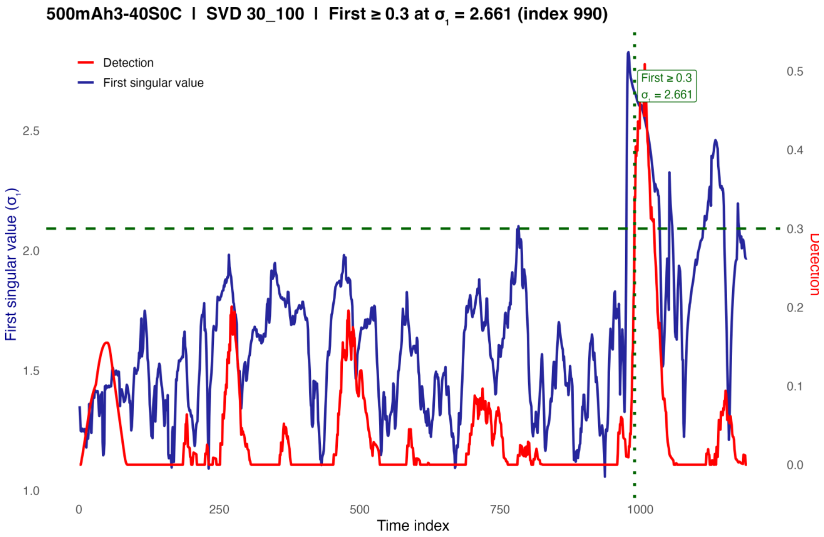
Backup Slides: Nonlinear Kernel Method

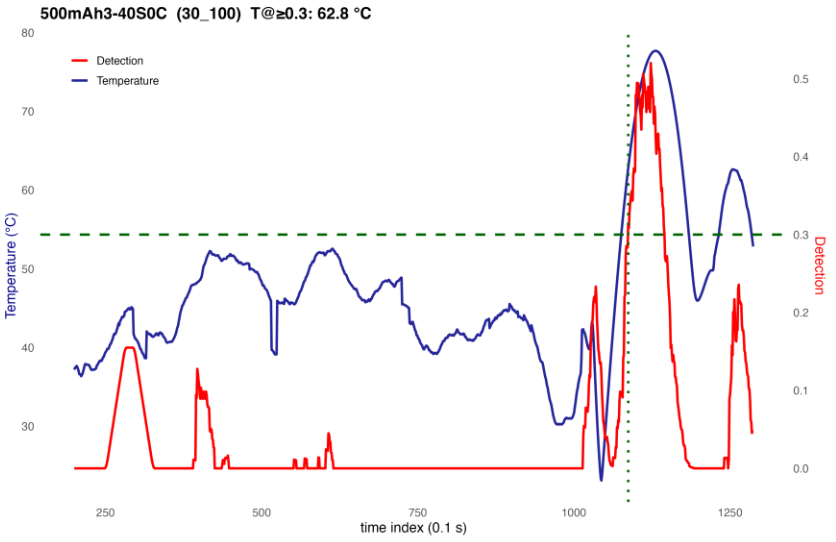
Lower/Higher Window-Size	**60**	**75**	**100**	**125**	**150**
5	0.730	0.730	0.721	0.730	0.711
10	0.748	0.730	0.730	0.730	0.721
20	0.739	0.739	0.721	0.703	0.711
30	0.730	0.721	0.711	0.711	0.730
40	0.721	0.711	0.730	0.711	0.703

Kernel PCA on the running window, Slightly higher accuracy.

Backup Slides: Nonlinear Kernel Method

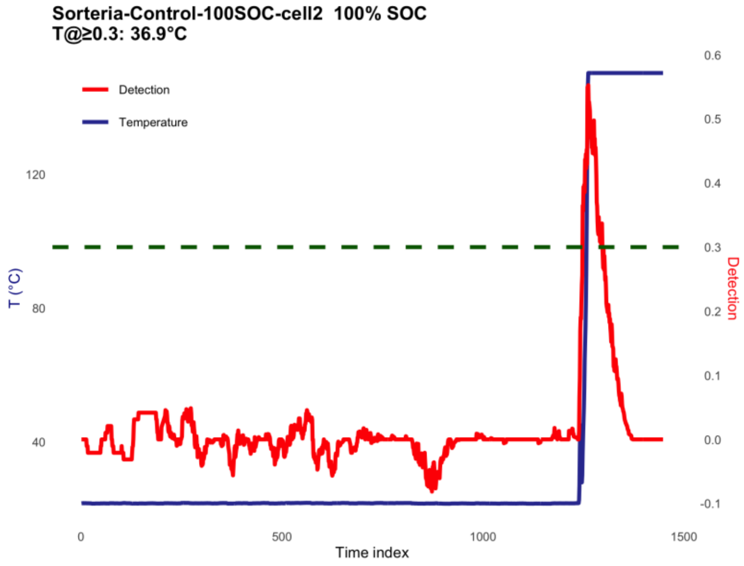


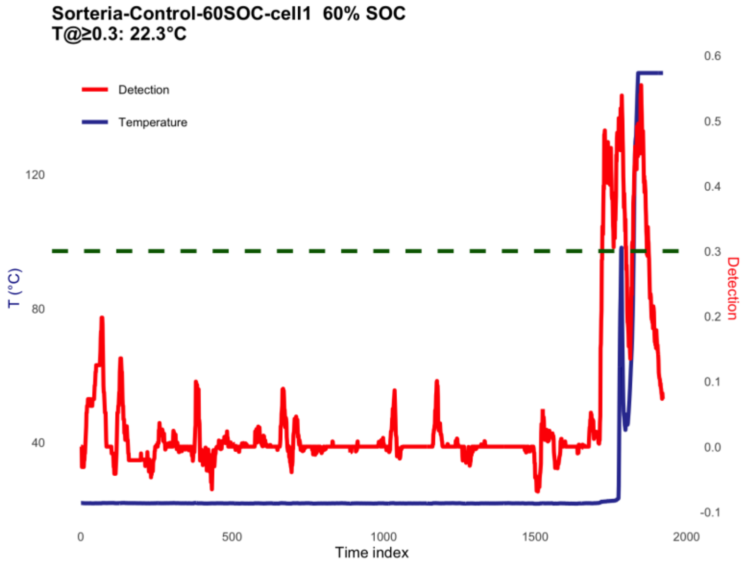


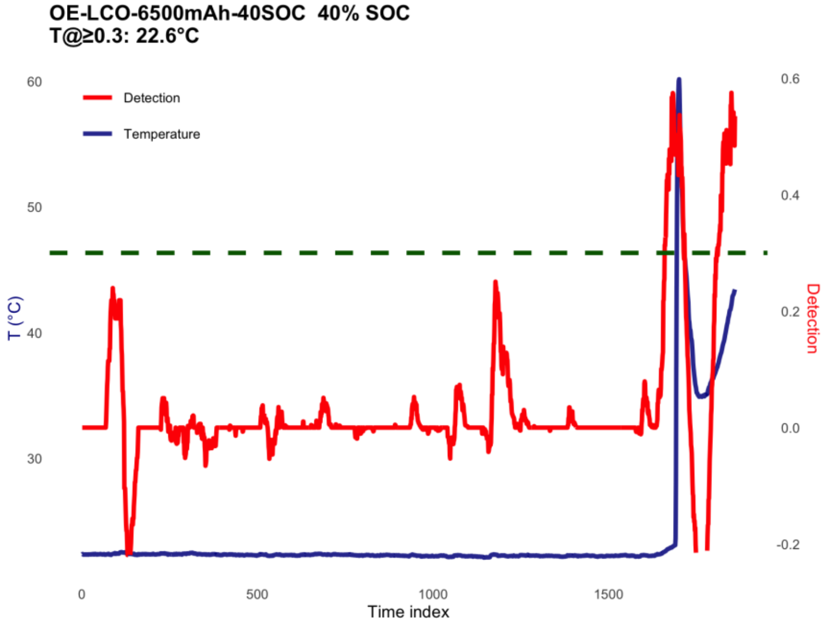


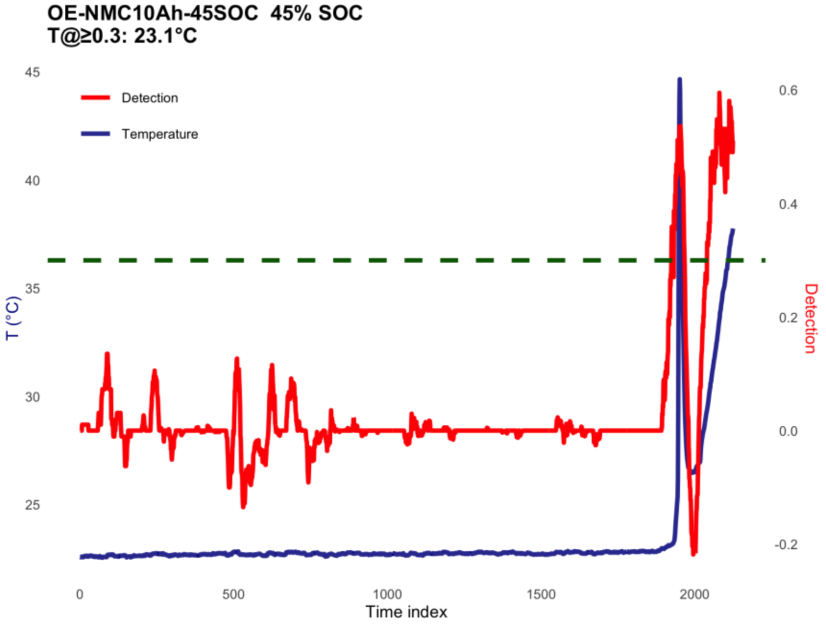
Slightly higher accuracy, won't enhance the earlier detection

SVD based Procedure captures the Panel Information









Thresholding Sensitivity

- **Multi-Scale Windowing & Thresholding (**τ = 0.3**)**
- **Small windows (w_{low}):** Capture local volatility; sensitive to early, short-horizon precursors.
- **Large windows (w_{high}):** Capture long-term trends; robust to transient fluctuations.

- **Threshold rule (**0.3)
- Enforces moderate multi-scale consensus: an alarm triggers only when a nontrivial fraction of window scales simultaneously detect an anomaly.
- With 20–30 scales, τ = 0.3 corresponds to agreement across ~6–9 scales.

- **Practical implication**
- Balances early warning (detecting incipient thermal runaway or abnormal heating) against nuisance alarms driven by current steps or sensor noise.
- Plot to illustrate how we choose(small & large window, algorithm)