INTEGER TECHNOLOGIES

UNIVERSITY OF South Carolina

Strain Sensing and Intelligent Load Management to Enhance Battery Lifespan and Safety in Electric Vehicle Applications.

George Anthony

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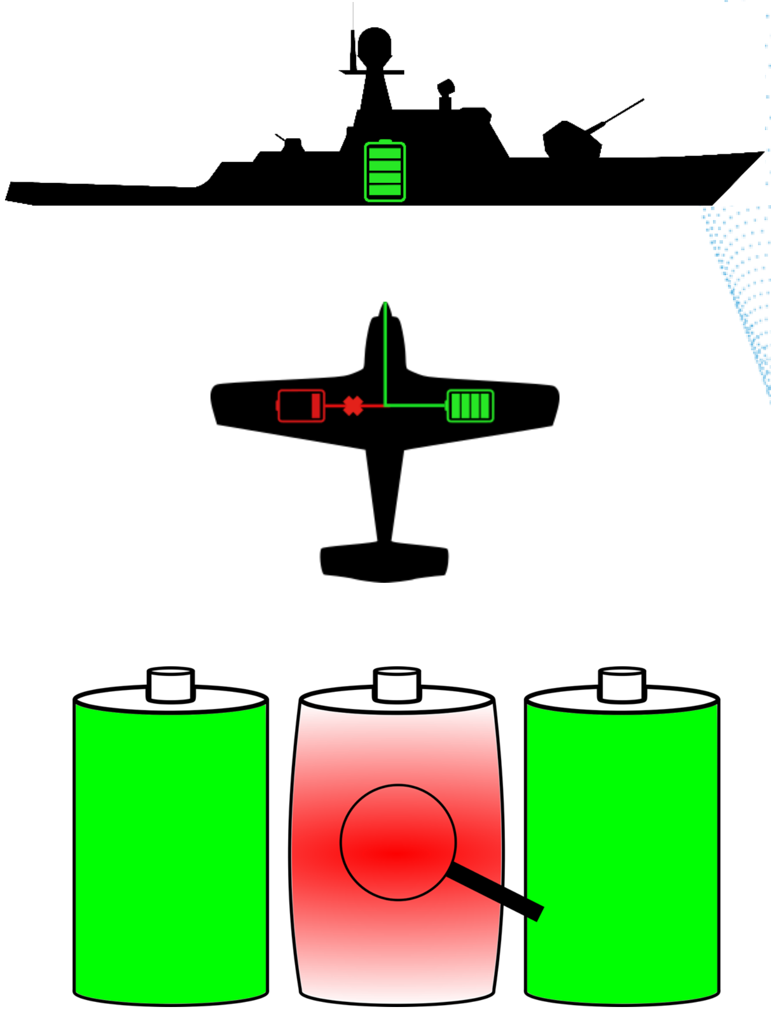
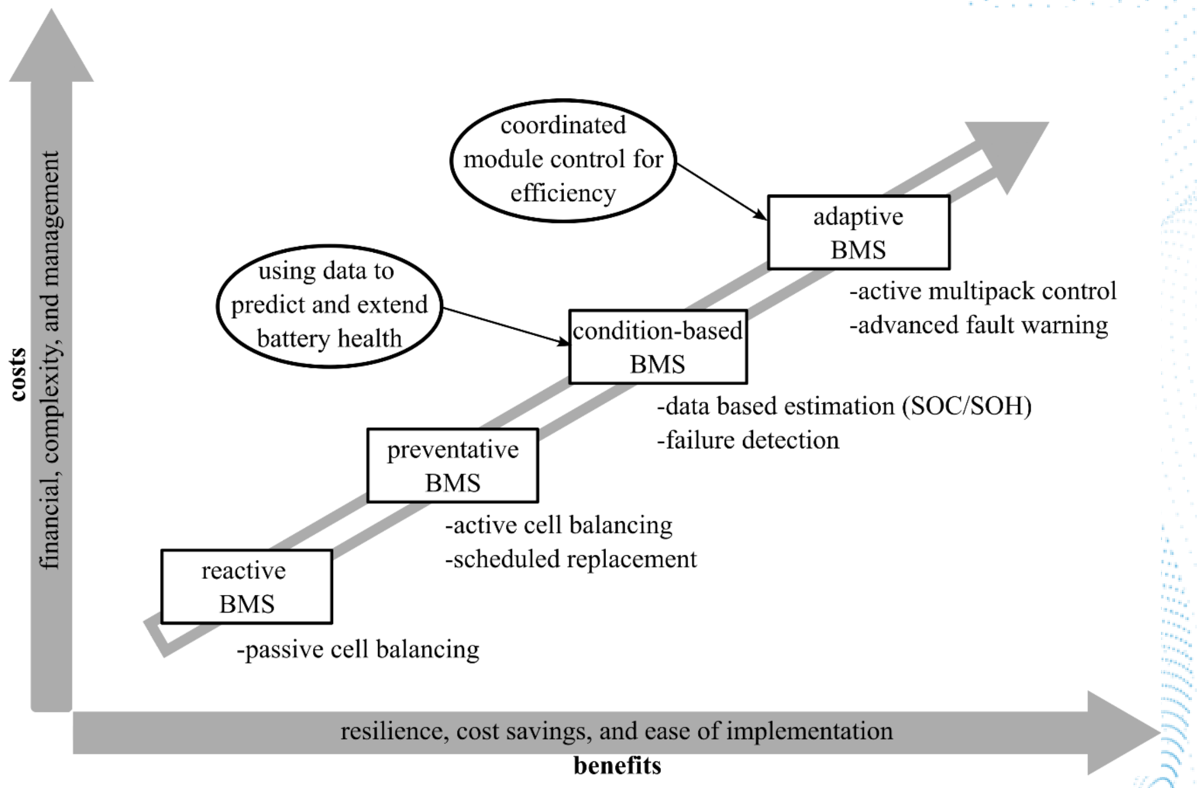
Outline

- Introduction and contributions
- Extending Battery Life with Load Sharing
- Early detection of CID failure via Strain
- Inferring SOC using Strain and Machine Learning
- Current imbalance between parallel cells
- Conclusions



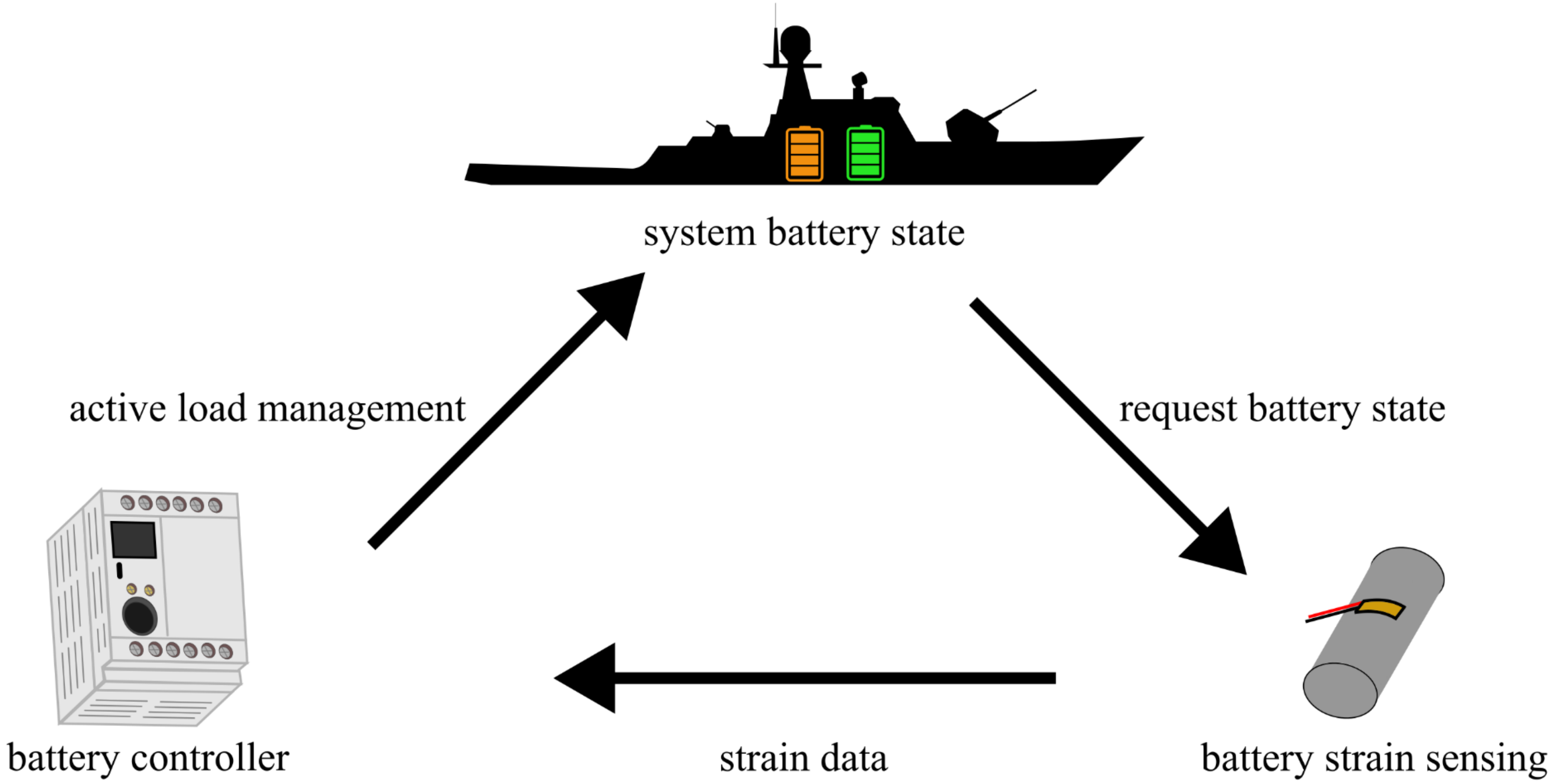
Introduction

- Lithium-ion batteries are central to electrification of ships, aircraft and vehicles
- High reliability and longevity are essential for mission critical systems
- As the install base increases for vehicles the demand for enhanced safety and control increases
- Smart BMS strategies
  - Load sharing for degradation management
  - Strain as internal diagnostic
  - Strain-informed state estimation



Goals

- Use strain data to inform the BMS to estimate and predict battery state



Contributions

Main:

- Load sharing strategy for equalizing battery degradation maintenance cycles
- Trained a Neural network for strain-based SOC prediction
- Investigated strain-based detection of catastrophic failure under high-C Discharge

Supporting:

- Helped build the software library for the battery testing facility in 300 Main
- Built Parallel testbed to observe current imbalance of cells in parallel

Publications

- Peer-Reviewed Conference proceedings:
  - **George Anthony**, Ryan Yount, Austin R.J. Downey, and Kerry Sado. Inferring battery state of charge using strain sensing and machine learning. IMECE 2025 (Reviewed awaiting publication)
  - **George Anthony**, Andrew Weng, Austin R.J Downey, Ralph White, and Kerry Sado. Strain Based investigation of current imbalance and lithium intercalation stages in parallel-connected lithium-ion cells. AIAA SCITECH 2026 (under review)
  - Korebami Adebajo, **George Anthony**, Jarett Peskar, Austin R Downey, Yuche Chen, and Chao Hu. Impact of charging rate and state of charge on electric aircraft battery degradation using a multi-domain model with realistic southeastern us flight paths. In AIAA SCITECH 2025 Forum, page 2705, 2025. doi:10.2514/6.2025-2705
  - Nathaniel Cooper, **George Anthony**, Jarett Peskar, Austin R Downey, and Kristen Booth. Data assimilation in a Modelica framework for optimizing battery longevity in electric aircraft. In AIAA SCITECH 2025 Forum, page 2706, 2025. doi:10.2514/6.2025-2706
  - Jack Hannum, Kerry Sado, Aqarib Hussain, **George Anthony**, Jason Bakos, Austin Downey, and Kristen Booth. Remaining useful life digital shadow for an eVTOL powertrain. In 2024 IEEE Sixth International Conference on DC Microgrids (ICDCM), pages 1–5. IEEE, August 2024. doi:10.1109/icdcm60322.2024.10665005
  - **George Anthony**, Nathaniel Cooper, Jarrett Peskar, Austin R.J. Downey, and Kristen Booth. Extending battery life via load sharing in electric aircraft. In AIAA SCITECH 2024 Forum. American Institute of Aeronautics and Astronautics, January 2024. doi: 10.2514/6.2024-2154
- Conference Proceedings
  - **George Anthony**, Connor Madden, Emmanuel A. Ogunniyi, Austin R. J. Downey, Ryan Limbaugh, Jarret Peskar, Jingjing Bao, and Xinyu Huang. Exploratory investigation of early detection for high-c discharge-induced failure in 18650 lithium-ion batteries. In Piervincenzo Rizzo, Zhongqing Su, Fabrizio Ricci, and Kara J. Peters, editors, Health Monitoring of Structural and Biological Systems XVIII. SPIE, May 2024. doi: 10.1117/12.3011097

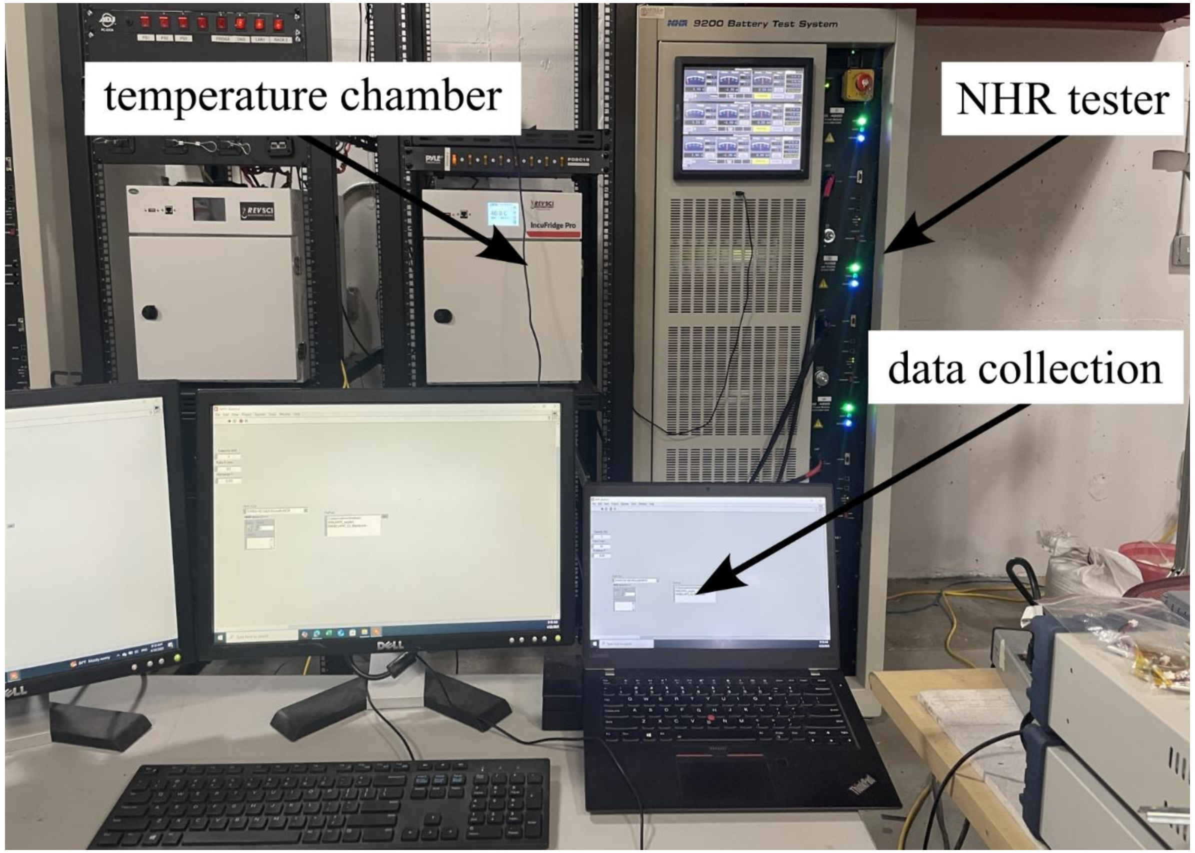
Publications

- Posters:
  - **George Anthony**, Ryan Limbaugh, Jarrett Peskar, Thomas Stubbs, and Austin R.J. Downey. Full-scale battery pack degradation monitoring. 2024 Battery Safety Workshop, August 2024
  - Jarrett Peskar, **George Anthony**, Kerry Sado, Austin R.J. Downey, Jamil Khan, and Kristen Booth. Enabling safe battery system design through electro-thermal emulation. 2024 Battery Safety Workshop, August 2024
  - Ryan Limbaugh, **George Anthony**, and Austin Downey. 30Q lithium-ion cell cycling with strain monitoring. 2024 Battery Safety Workshop, August 2024
  - Korebami Adebajo, Austin Downey, Peskar Jarett, and **Anthony George**. Multi-domain modeling of an electric aircraft. Discover USC, March 2024
  - John White, Connor Madden, **George Anthony**, and Austin Downey. Battery expansion measured with digital image correlation. Discover USC, March 2024
  - Jarrett Peskar, Nicholas Liger, **George Anthony**, Austin R.J. Downey, and Jamil Khan. Coupled electro-thermo battery emulator. 2023 Battery Safety Workshop, June 2023
  - **George Anthony**, Korebami Adebajo, Austin Downey, and Nathaniel Cooper. Power electronics testbed of evtol vehicles. 2023 Battery Safety Workshop, June 2023

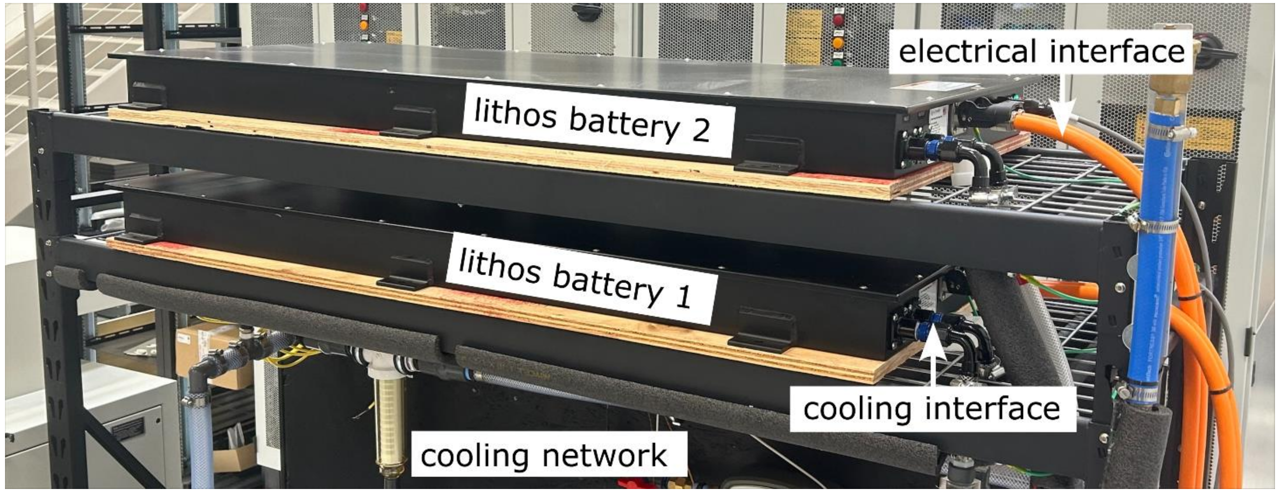
Battery Testing Facility

Battery Testing Facility

- 9 NHR 9200 Battery Test system modules
  - 6 12kW 600V 40A modules
  - 3 12kW 120V 120A modules
- 3 Itech bi-directional power supplies
- 3 temperature chambers 10-80C
- Data and control performed with LabVIEW

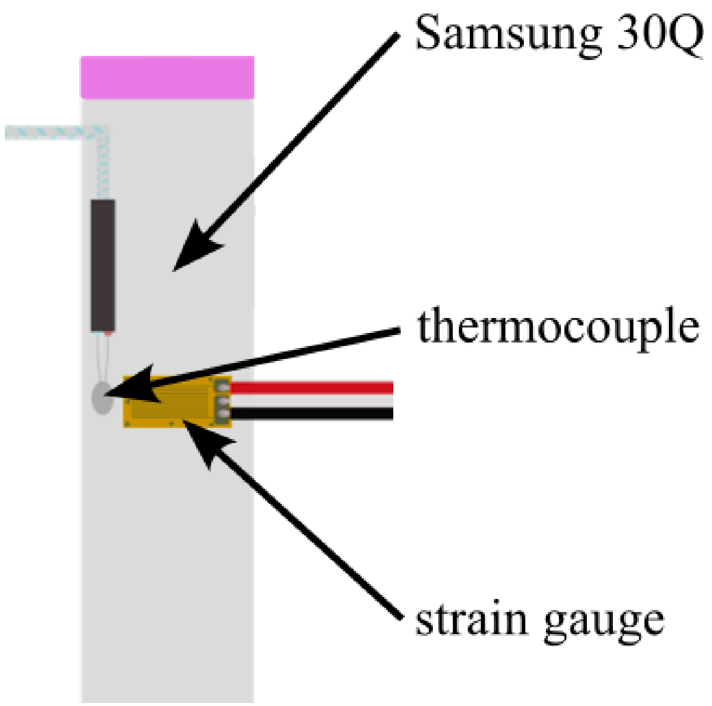


Lithos and Testbed



Typical Battery Test

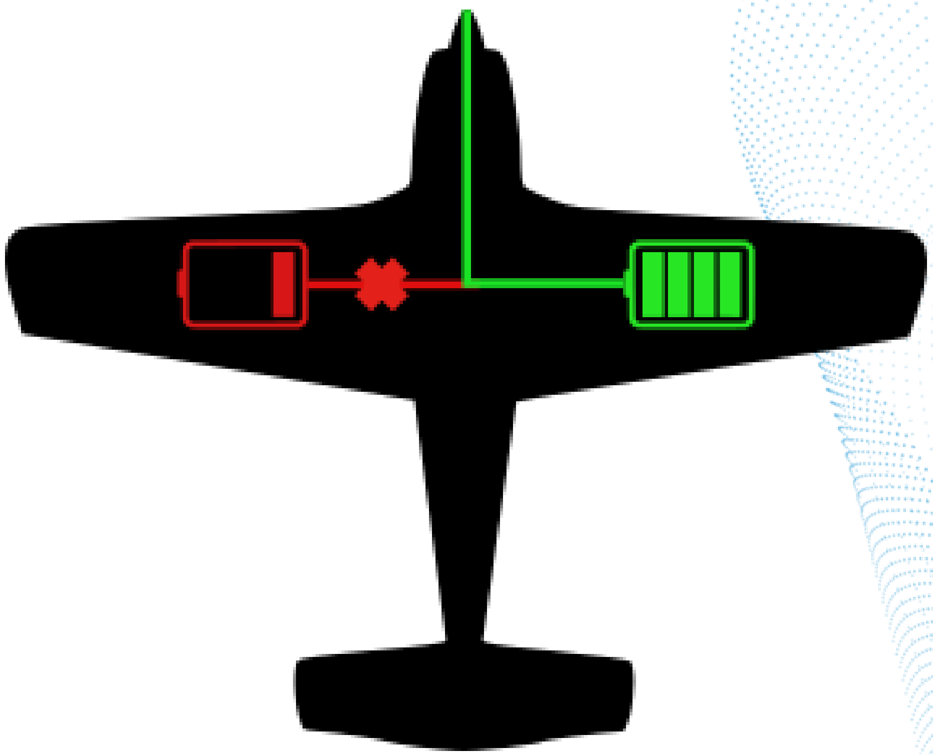
- Primarily Samsung 30Q NMC 18650 cells
- Type K thermocouple
- 350Ω strain gauges
- Other Cells include
  - LFP 22650 Cells
  - NMC 21700 Cells



Extending Battery Life via Load Sharing

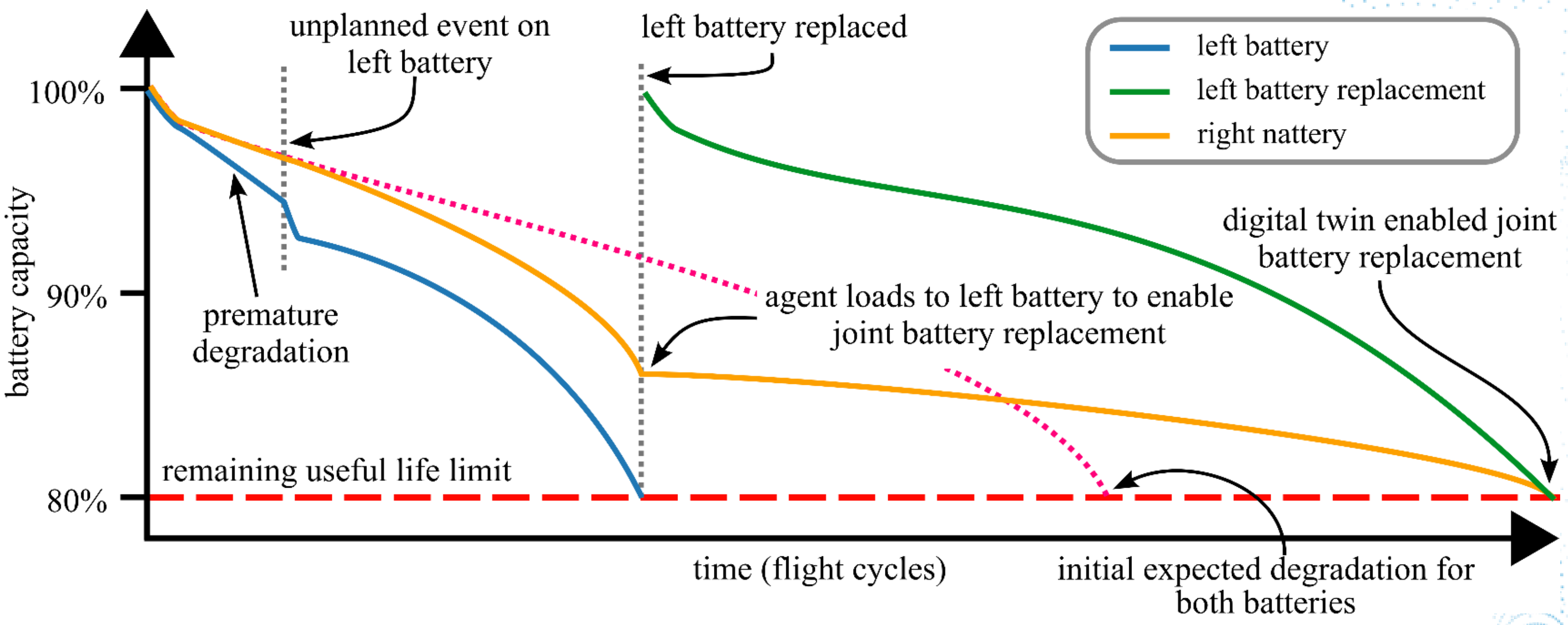
Goals of Load Sharing Model

- Importance: Reducing battery replacement costs.
- Problem: When one battery fails early, it disrupts synchronized maintenance cycles in multi-battery systems.
- Proposal: Use a control agent to adjust load sharing and balance future degradation between remaining batteries.
- Objective: Align battery health trajectories to restore synchronized maintenance and reduce long-term cost.



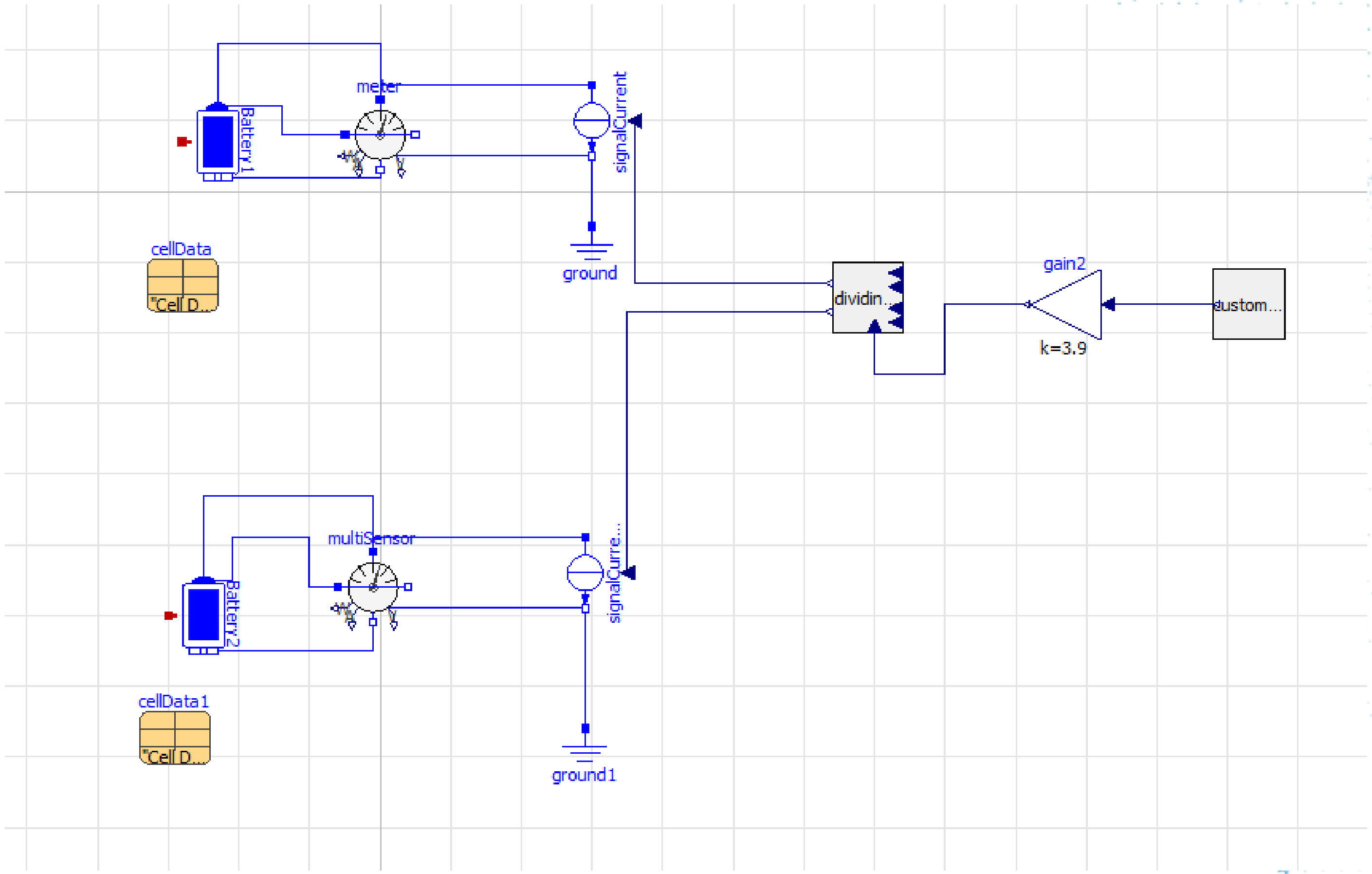
Load Sharing Scenario

- A single battery fails prematurely causing the 2-battery system to have different maintenance cycles
- The agent helps equalize the batteries for future maintenance



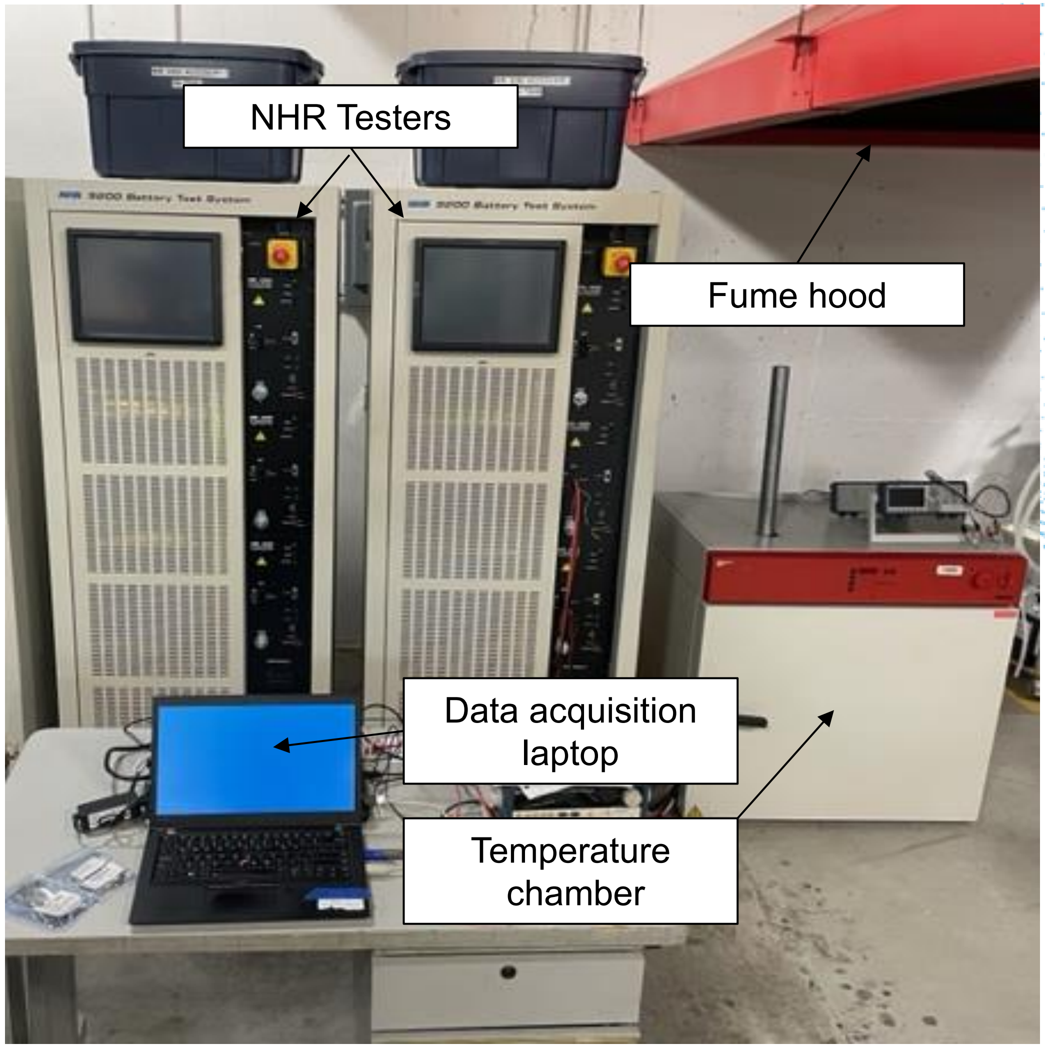
Model implementation

- OpenModelica was used for the modelling of the agent
- Two one load is distributed between two battery stack models by dividing model
- Coloumb counting was the primary method of determining RUL



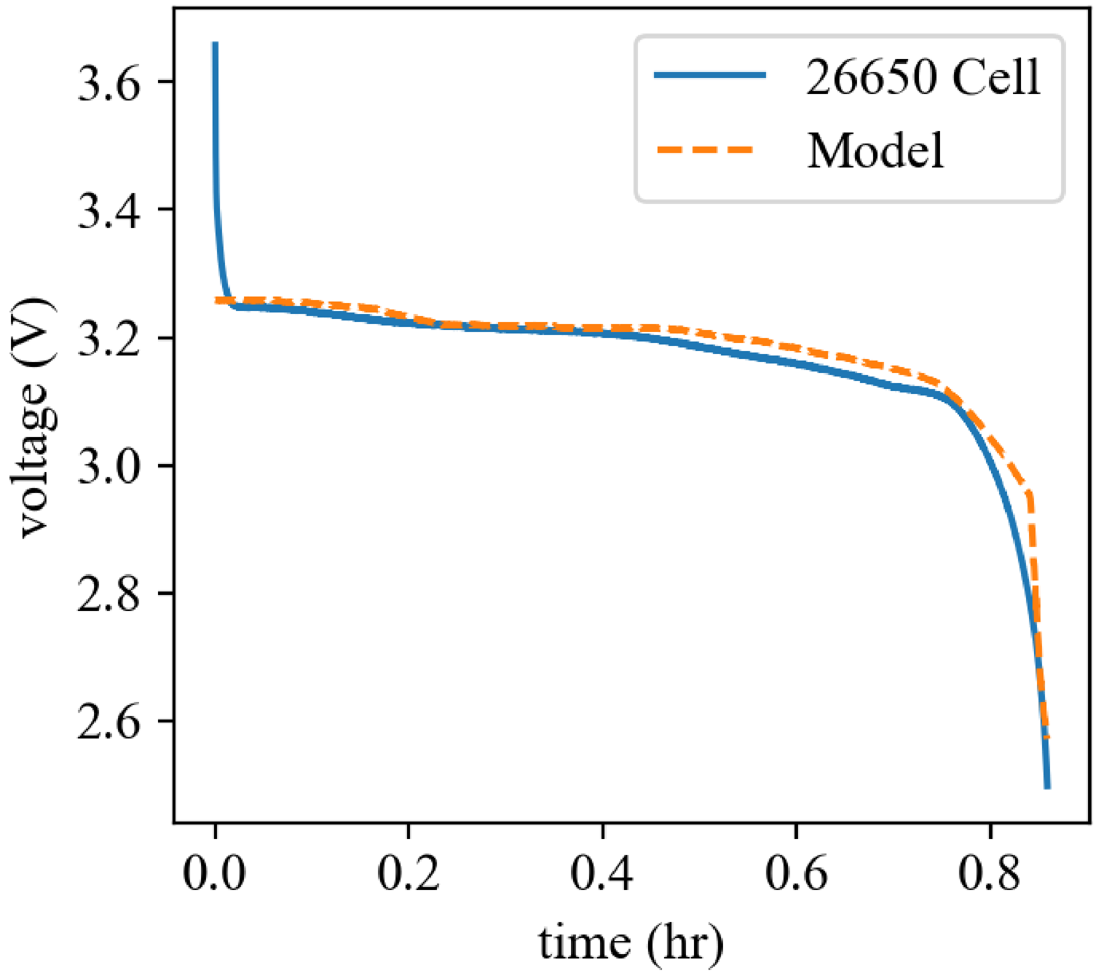
Battery Characterization

- Used NHR 9200 Battery Test system to run tests to characterize batteries
- Controlled using LabVIEW
- Batteries were kept in temperature chamber to provide constant ambient temperature
- Characterized LiFePO4 22650 Battery Cell for the model
- LiFePO4 was chosen for its chemical stability in a test environment



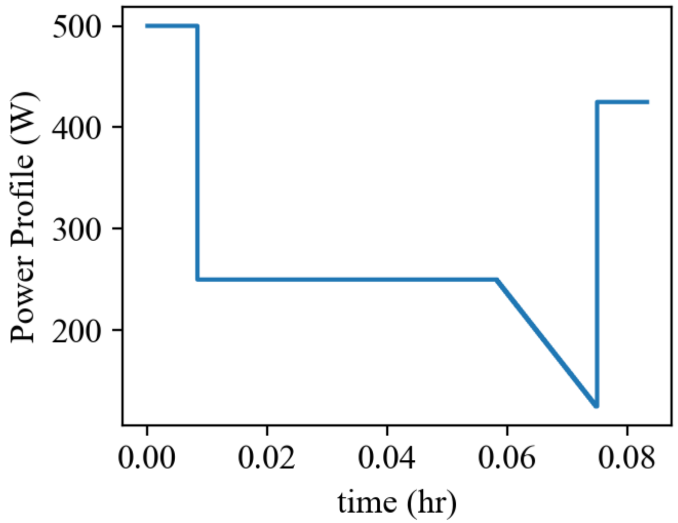
Battery Characterization

- Parameterized LiFeP 22650 cell based on literature and internal data collected
- Graph compares a 1 C discharge of the model vs a single 26650 cell

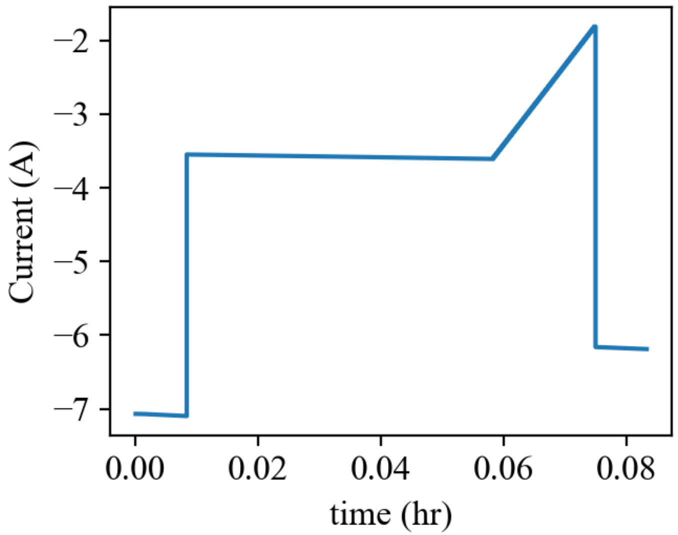


Battery

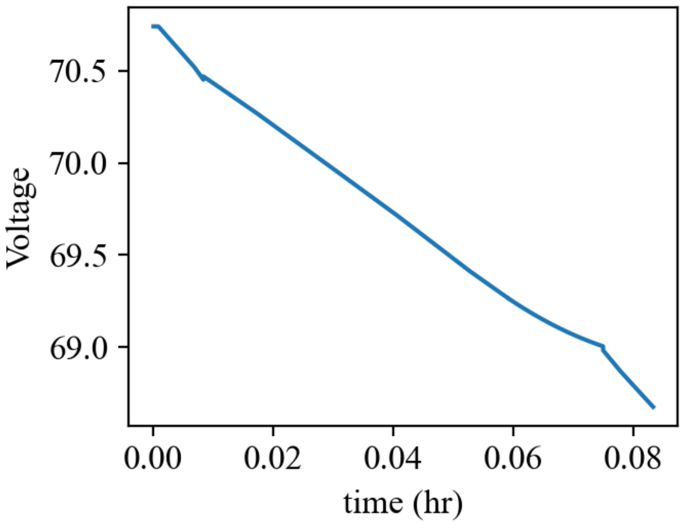
- Response to eVTOL load profile
- Model response scaled as predicted for a larger Battery pack



Power profile



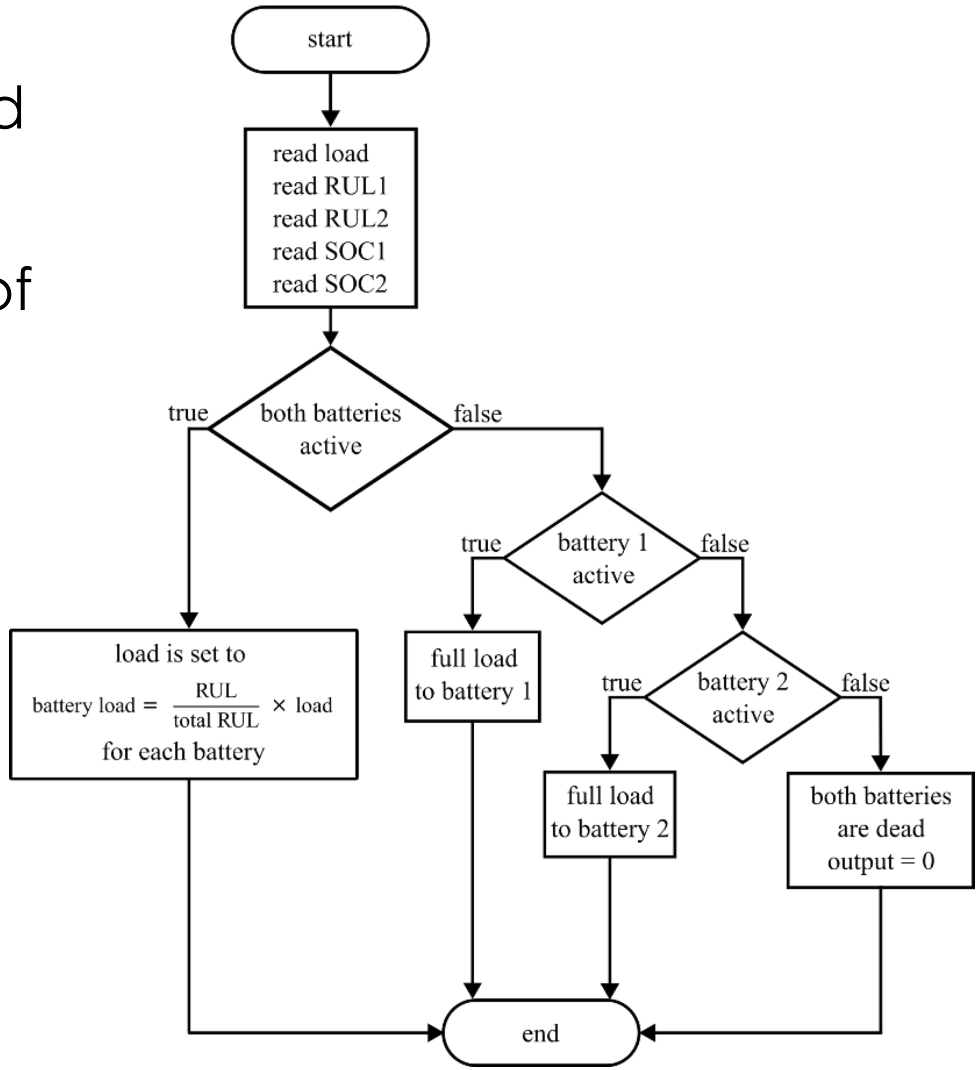
Current response(negative)



Voltage response

Load sharing logic

- After reading the status of both batteries the model distributes the load based on the health of the batteries
- The load is scaled based on the ratio of the current RUL to the total RUL of the system



Results

- 3 of the 5 scenarios ended in success
- The load sharing method was able to get the batteries to equalize at 0 when RUL2 was > 0.5

RUL equalization results.

RUL1 Start Value	RUL2 Start Value	Equalization Result	Final RUL1	Final RUL2
1	0.8	Success	0	0
1	0.6	Success	0	0
1	0.5	Success	0	0
1	0.4	Fail	0.2	0
1	0.2	Fail	0.6	0

Approved, DCN# 2025-7-30-1227
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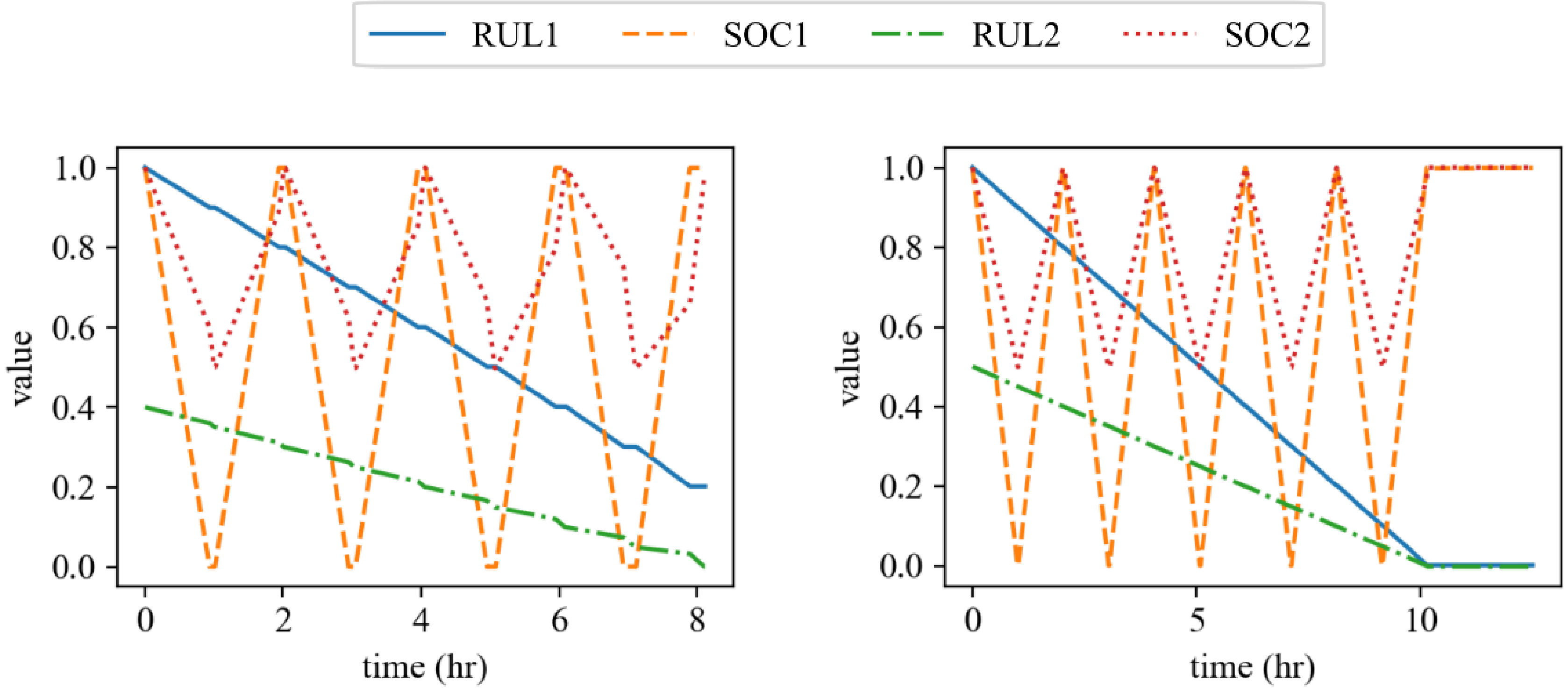
Load Sharing Results



Limits to the model were shown at large RUL differentials

If the difference is manageable, it can equalize in one cycle.

Load Sharing Outcomes

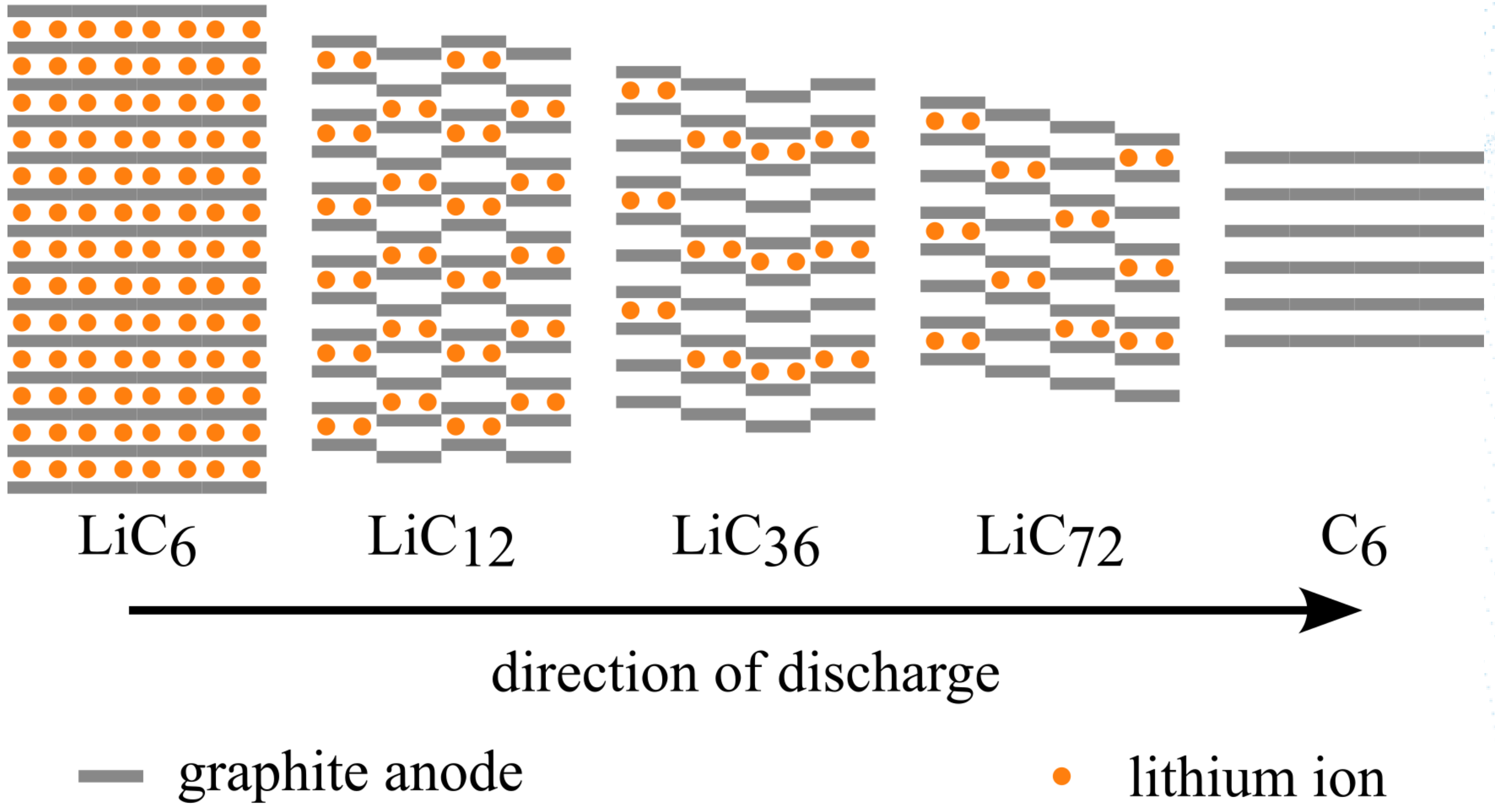
- Extended battery life by up to 50% through intelligent load redistribution
- Partial success in aligning battery RULs—equalization not always achievable in a single maintenance cycle
- Large RUL differences (>0.5) limit equalization, requiring additional replacements or more advanced control

Image Credit: https://www.pipistrel-aircraft.com/wp-content/uploads/2020/05/Velis_Electro_horizontalSlider2.jpg

Strain Informed Battery Management

Introduction to strain in NMC lithium-ion cell

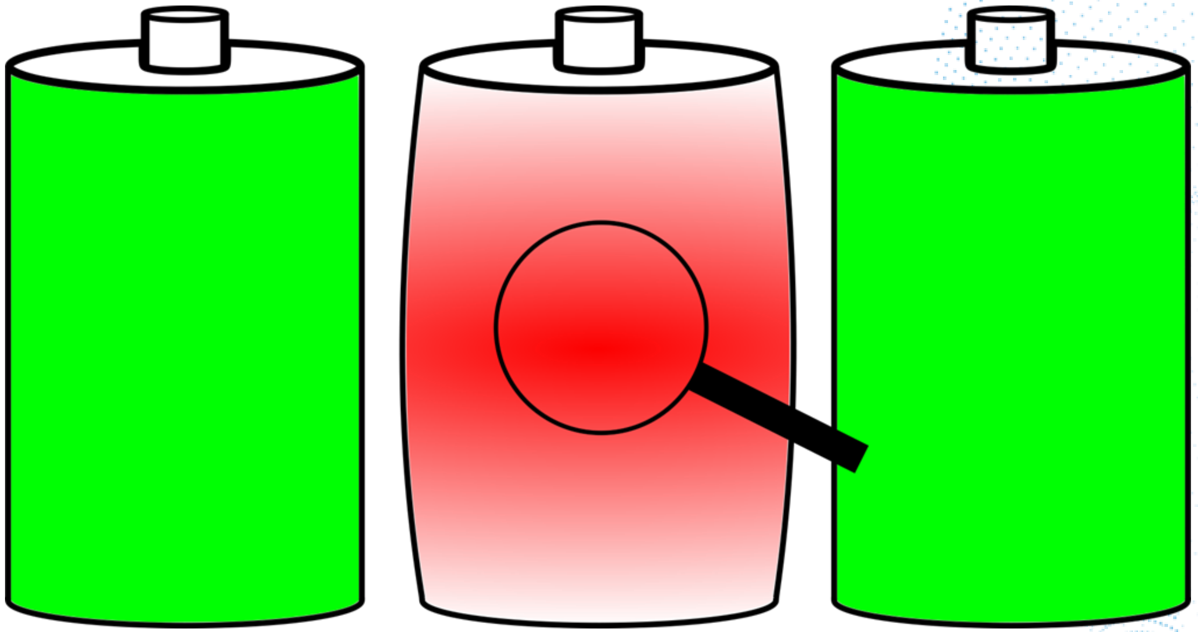
- During charge and discharge, lithium ions intercalate in and out of the graphite anode.
- This reversible intercalation process causes measurable expansion and contraction of the cell.
- As the cell ages, non-reversible expansion also occurs due to side reactions, gas generation, and other degradation.



Strain in High-C Discharge Failure

Early Detection of High-C Induced Cell Failure

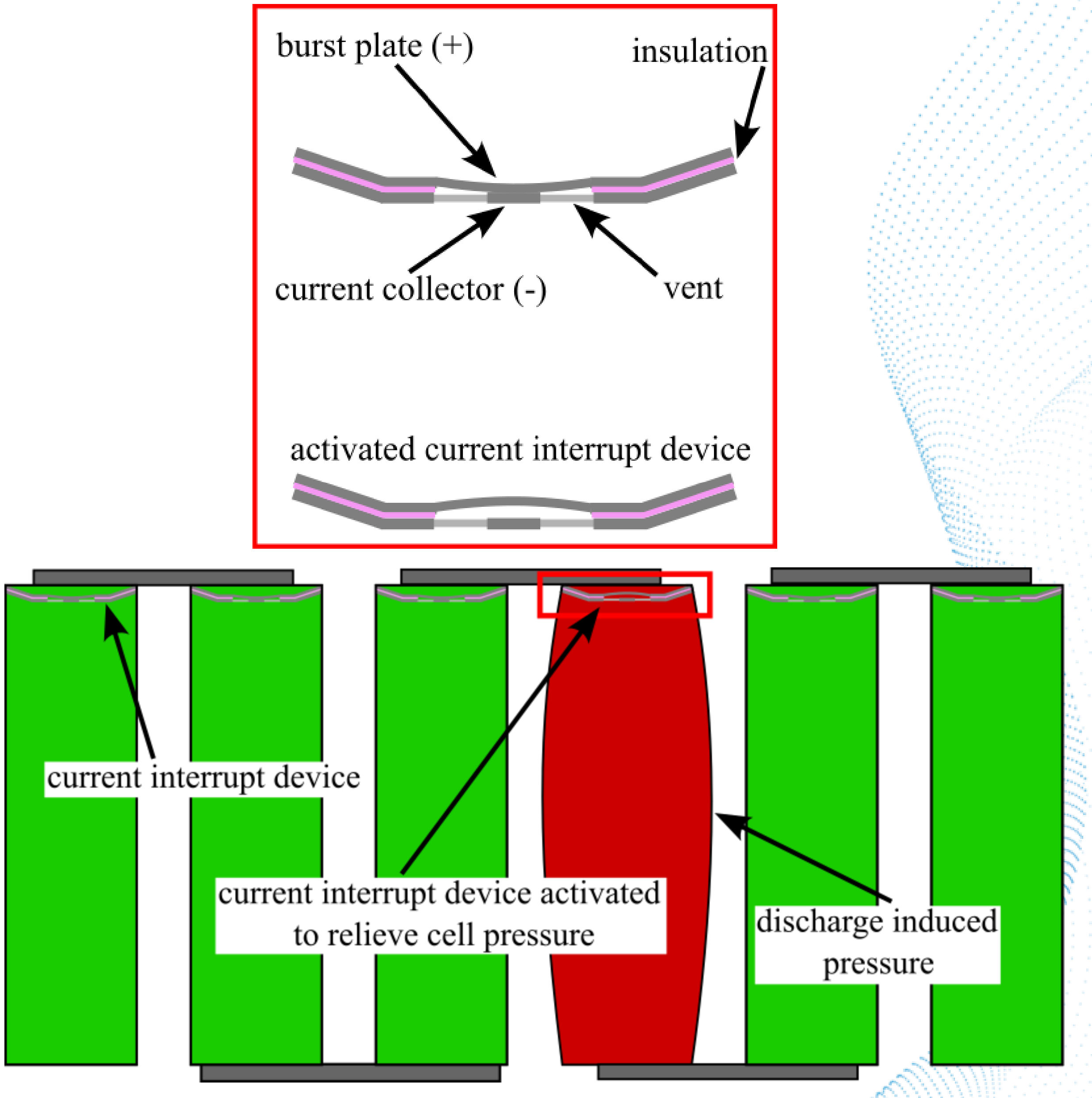
- Importance: High-current loads in aviation and defense demand robust, safe battery operation
- Problem: Conventional safety devices react too late, after internal pressure becomes critical rendering cells inert.
- Proposal: Use strain measurements to detect mechanical warning signs before failure
- Objective: Enable predictive failure detection to improve safety in high-rate discharge scenarios



The battery that experiences excessive strain should be identified to reduce the likelihood of failure

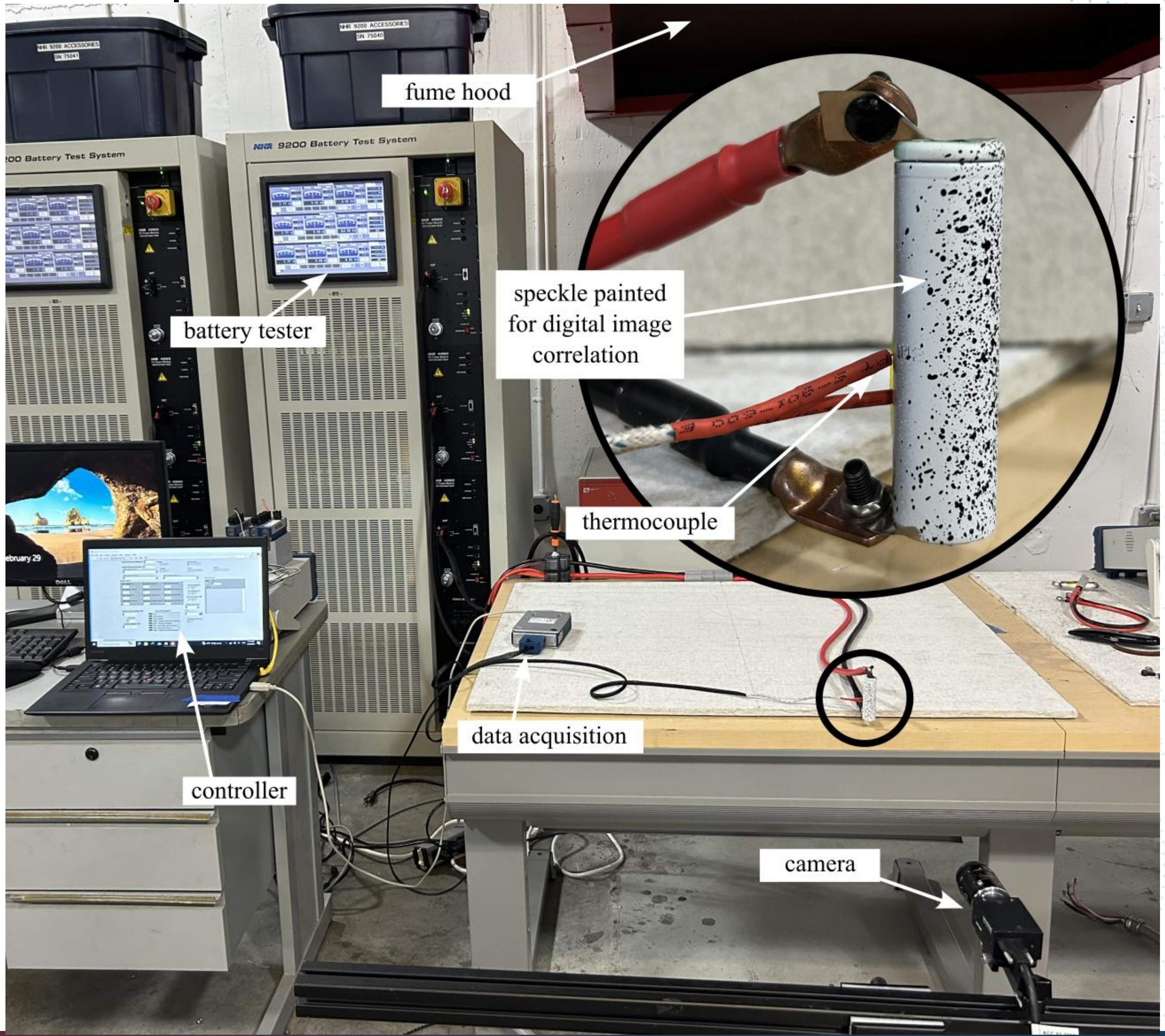
CID activation

- High-C discharge causes gas generation within the cell, increasing internal pressure
- When pressure exceeds a threshold, the current interrupt device (CID) breaks the internal circuit.
- CID activation is irreversible permanently disabling the battery



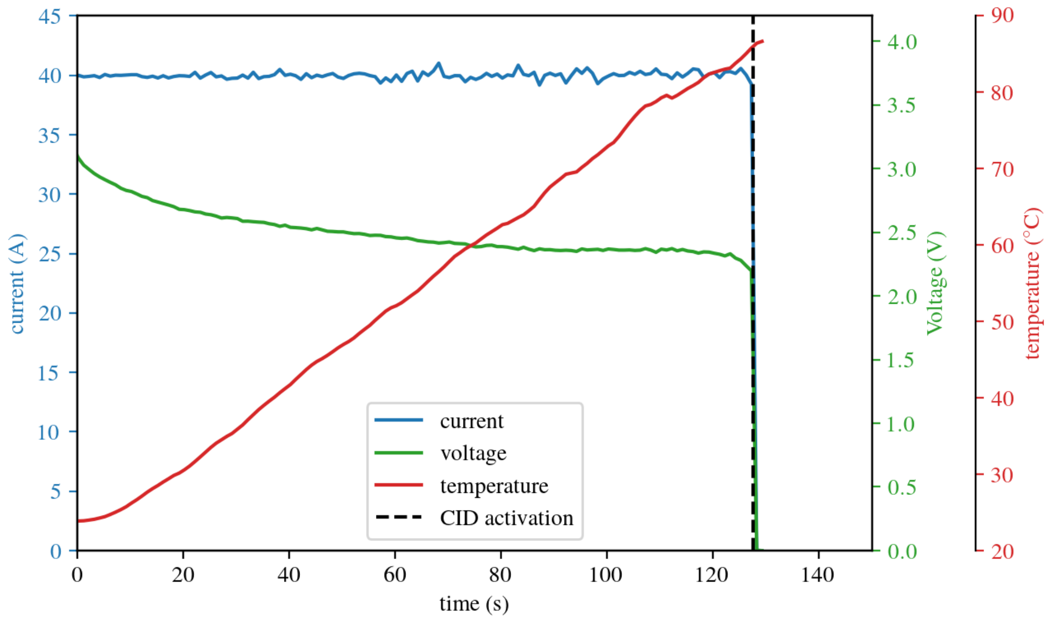
Digital Image Correlation Setup

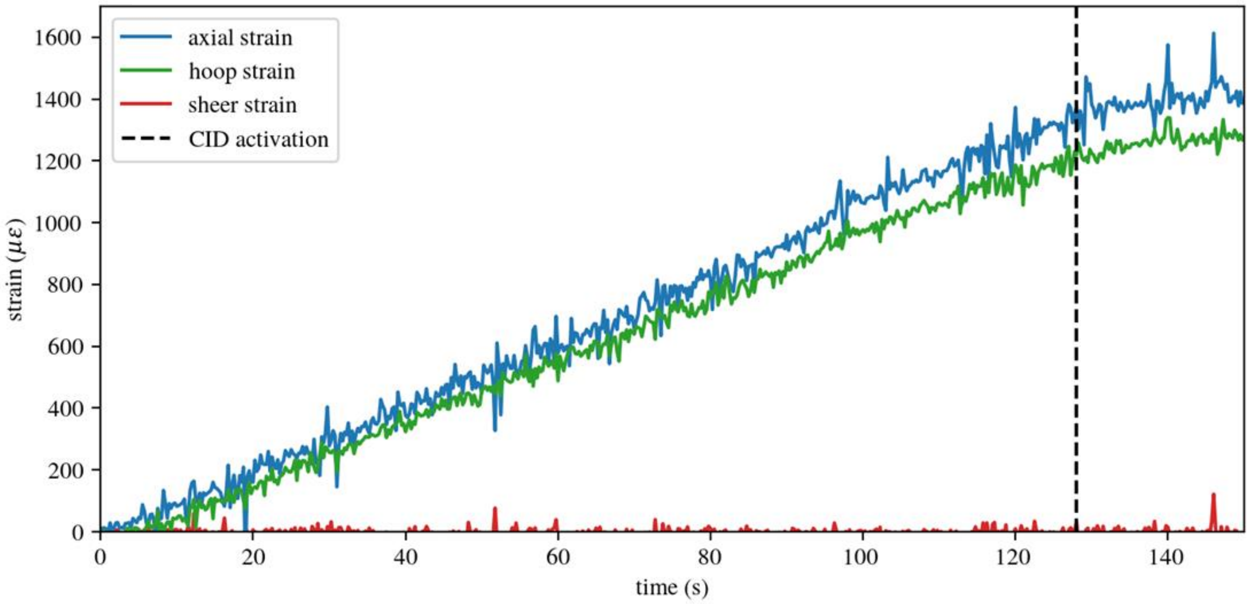
- 3 module battery tester applies a 40 A High-C discharge to the cell
- Cell is speckle painted for strain tracking with digital image correlation
- Syncronized Control of:
  - digital image correlation cameras
  - battery tester
  - thermal data acquisition



High-C Experimental outcomes

- Strain increase from temperature should be isotropic and we see that for the first minute
- As the test progresses divergence of axial and hoop strain can be observed
- Evidence of a force besides the temperature expansion
- could be the gas generation leading to CID failure

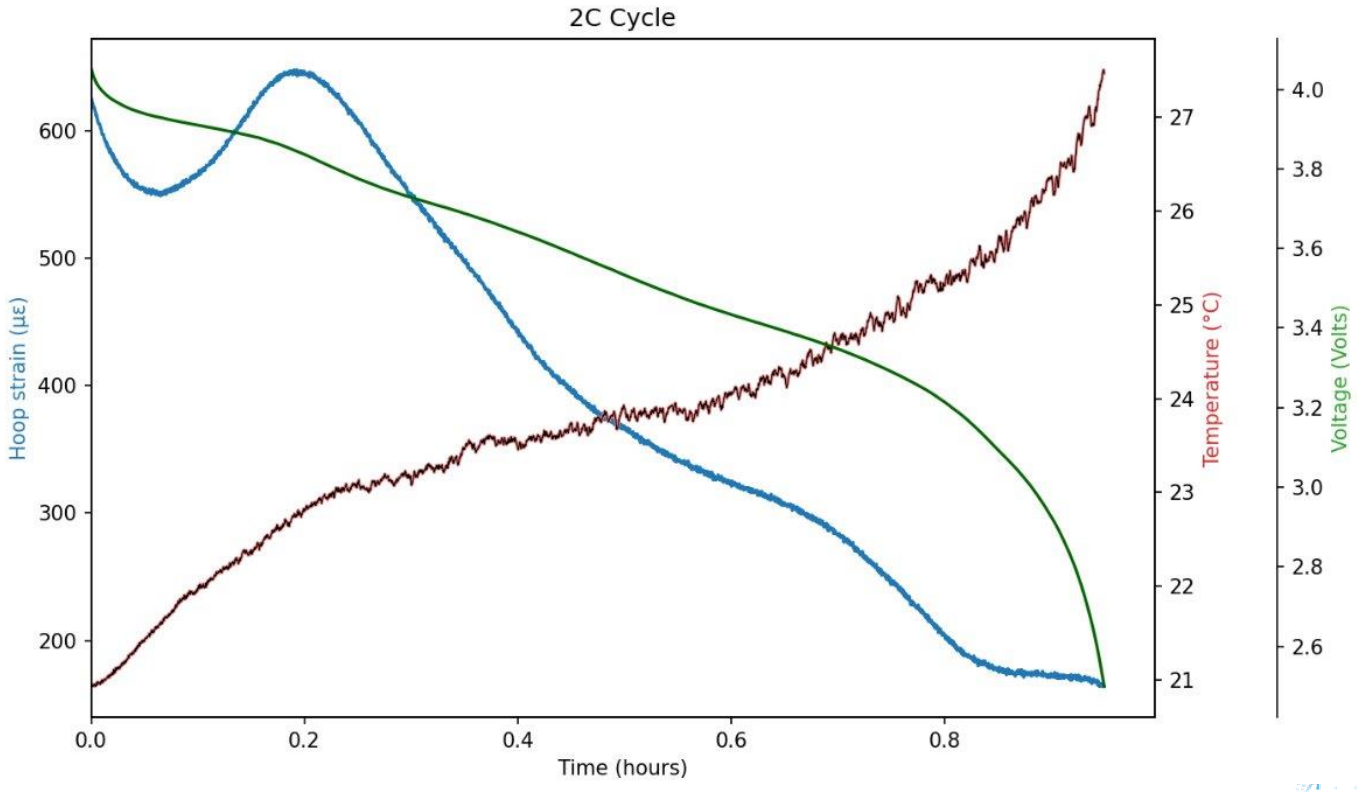




Strain-Based SOC prediction

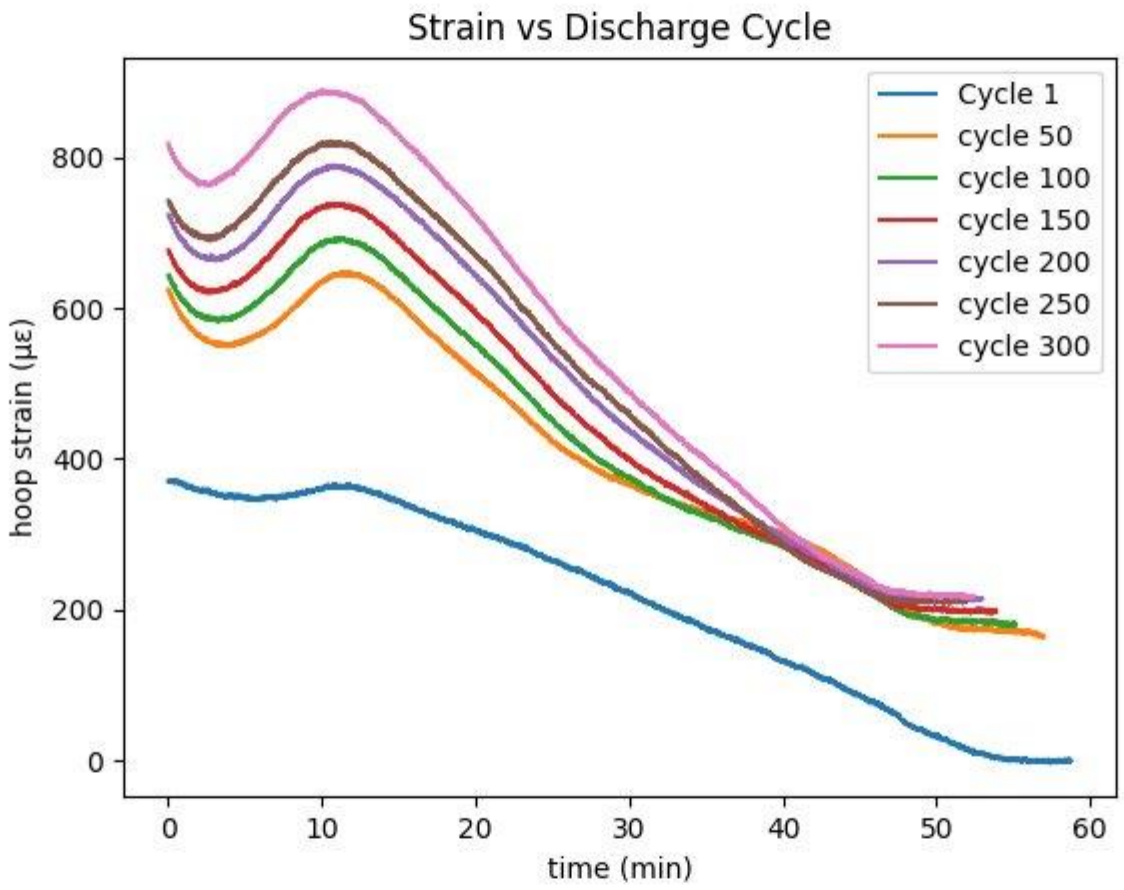
Strain Gauge Measurement on 18650 Cell

- A strain gauge was affixed to the outer casing of an 18650 to monitor mechanical expansion.
- The measured strain correlates with voltage but not as much with temperature reflecting lithium intercalation and cell dynamics.
- This data enables non-invasive, real-time insight into cell behavior.



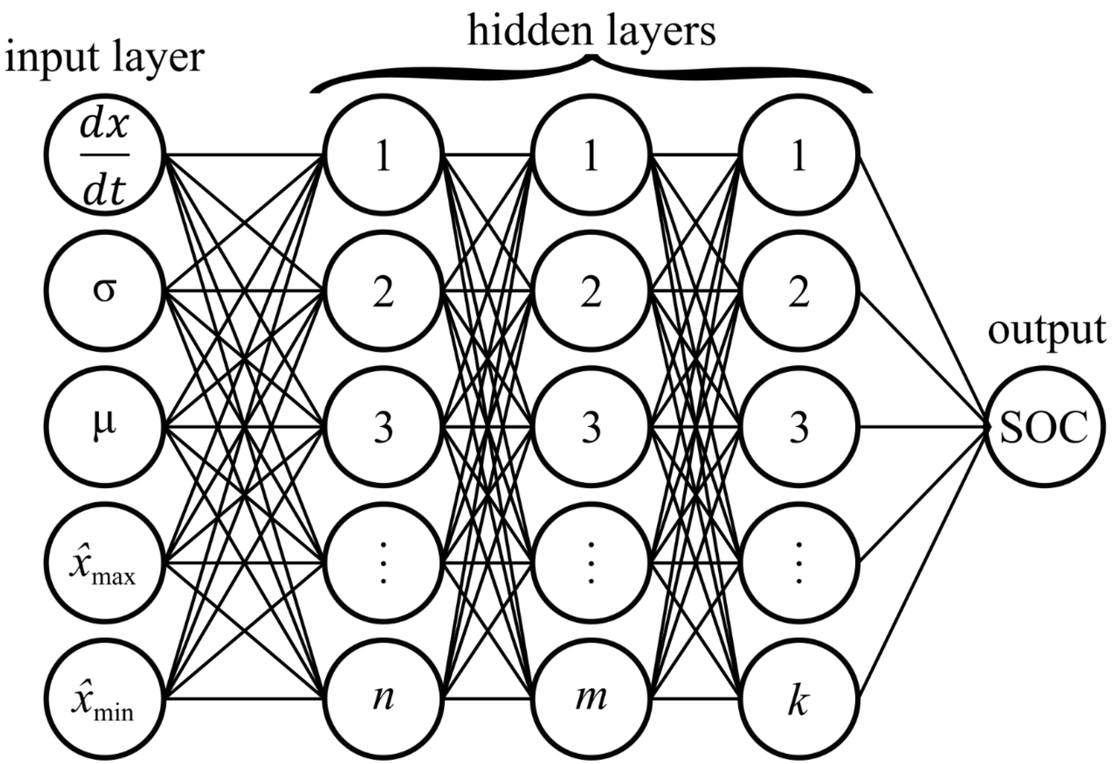
Strain Evolution Over Battery Lifecycle

- Cyclic strain measurements reveal both reversible, and non-reversible expansion
- As the battery degrades non-reversible strain accumulates shifting the baseline at complete discharge up over time.
- Strain shows electrochemical and mechanical changes, adding additional insight to cell health.
- Strain data from 3 NMC 18650 cells were used to train the neural network.



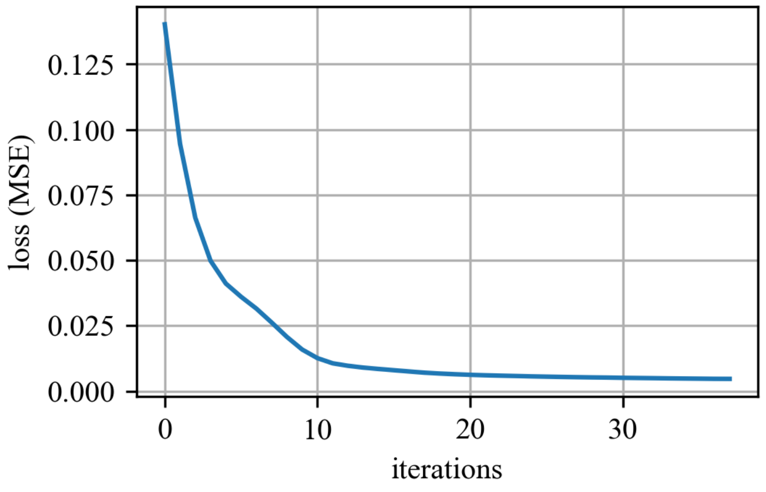
Neural Network Methodology for SOC Prediction

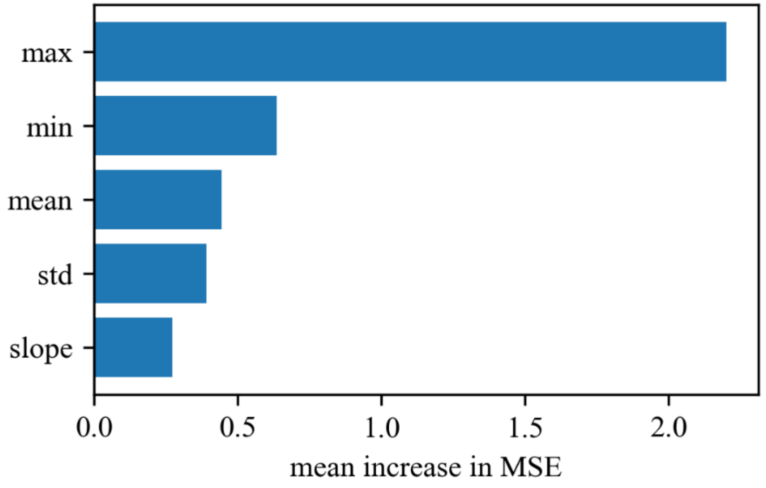
- Rather than single point strain a windowed segment of strain was processed into statistical features: mean, max, min, std dev, and slope.
- These features capture the dynamic strain behavior and reduce sensor noise.
- These features form the input later of a multi-layer perceptron (MLP) neural network that outputs state of charge SOC.



Model Training and Feature importance

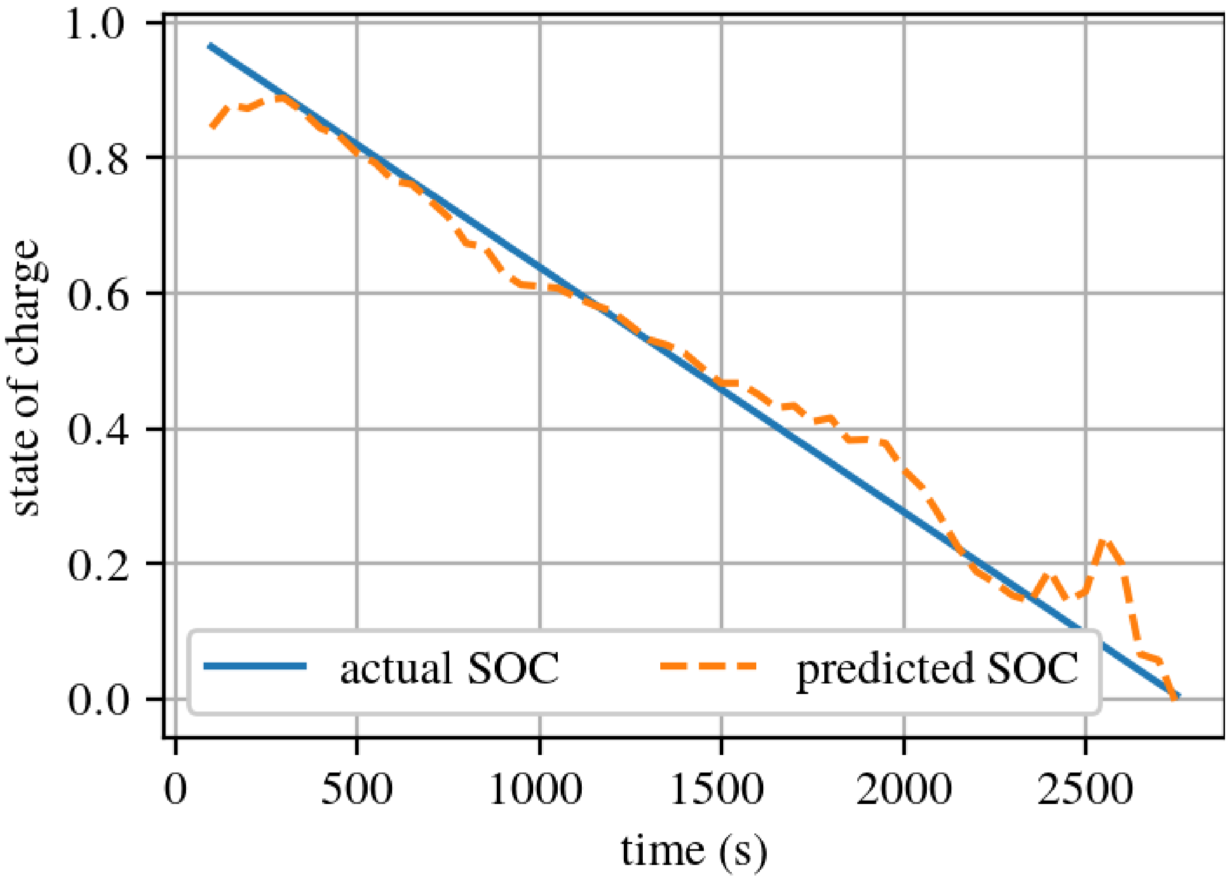
- Model trained using mean squared error (MSE) as the loss function.
- Training converged in under 40 iterations indicating stable learning.
- Feature analysis shows that max, min, and mean were the primary predictors of SOC.





Model Prediction Accuracy

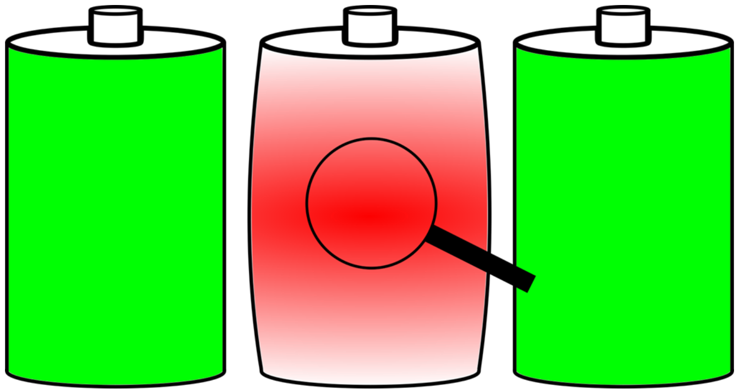
- Model successfully predicts SOC using strain alone.
- Prediction follows the actual adjusted SOC based on the capacity of the battery at that cycle.
- The more cycles trained reduced the error of the system.
- 10 cycles produced RMSE of 0.129, 100 produced RMSE of 0.101, and 631 cycles produced RMSE of 0.0886
- For the shown case (Cycle 578), the model achieved an RMSE of 0.0475

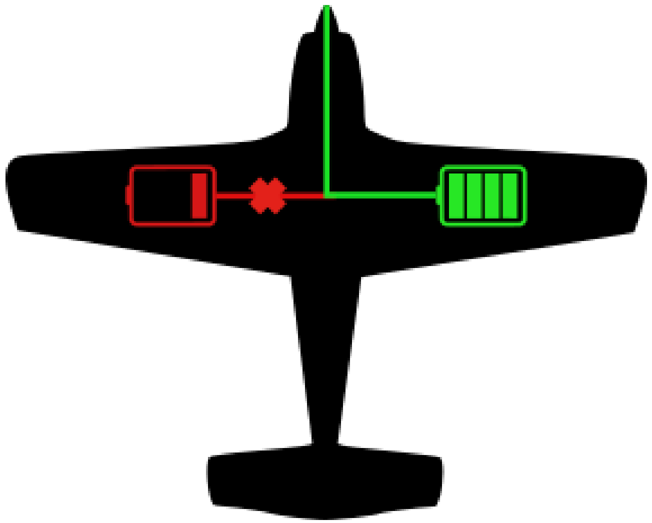


Current Imbalance in Parallel Cells

Investigating Imbalance in Parallel-Connected Cells

- Importance: Parallel cell configurations are used to increase capacity and power in all large battery systems.
- Problem: Variations in internal resistance and SOC can lead to uneven current distribution, Accelerating degradation and reducing efficiency.
- Proposal: Using a custom testbed to measure current, voltage, strain, and temperature at the cell level in parallel configurations.
- Objective: Understand the electromechanical behavior of cells in parallel and identify strain-based indicators of imbalance.





Expected strain behavior and Electrochemical imbalance

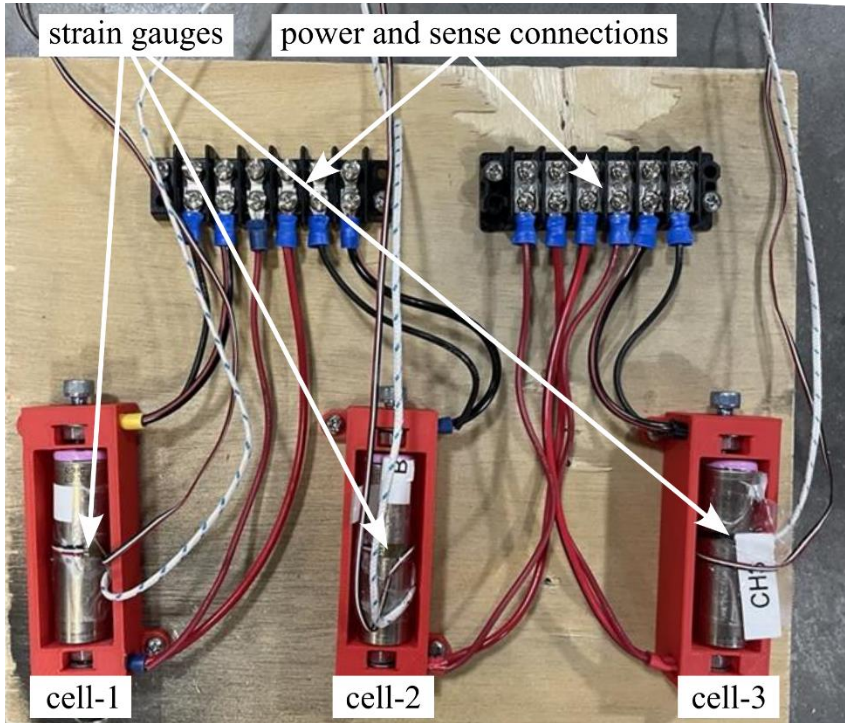
- Previous models explain imbalance using OCV mismatch and ohmic resistance
- This study adds strain-based observation to capture electrochemical-mechanical features
- Strain is assumed to track reversible expansion, more directly tying it to lithium concentration.

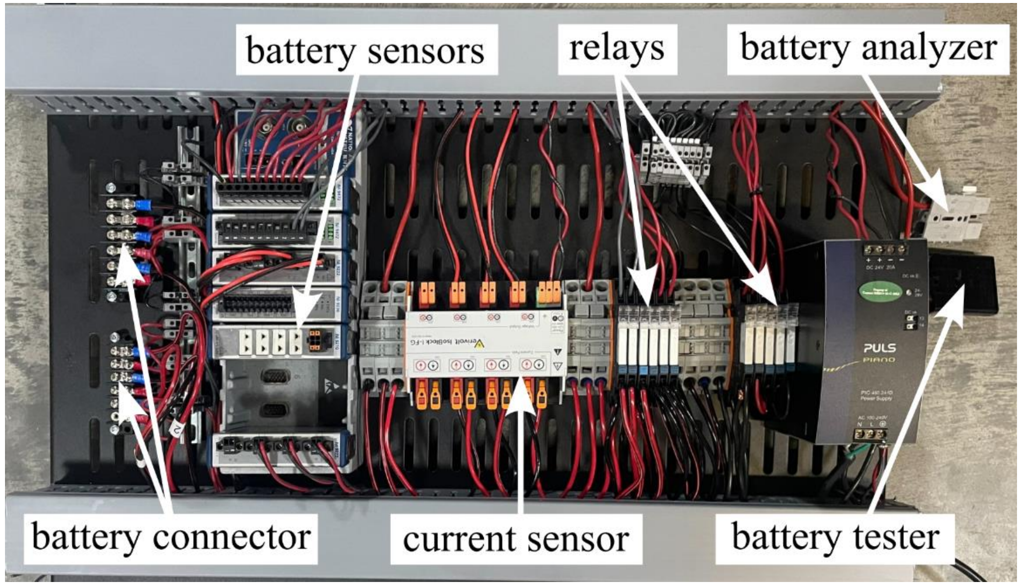
$$\Delta I(t) = \Delta I_{OCV\ imbalance}(t) + \Delta I_{ohmic}(t)$$

$$\Delta L = \Delta L_{reversible} + \cancel{\Delta L_{non\_reversible}} + \cancel{\Delta L_{thermal}}$$

Testbed Hardware

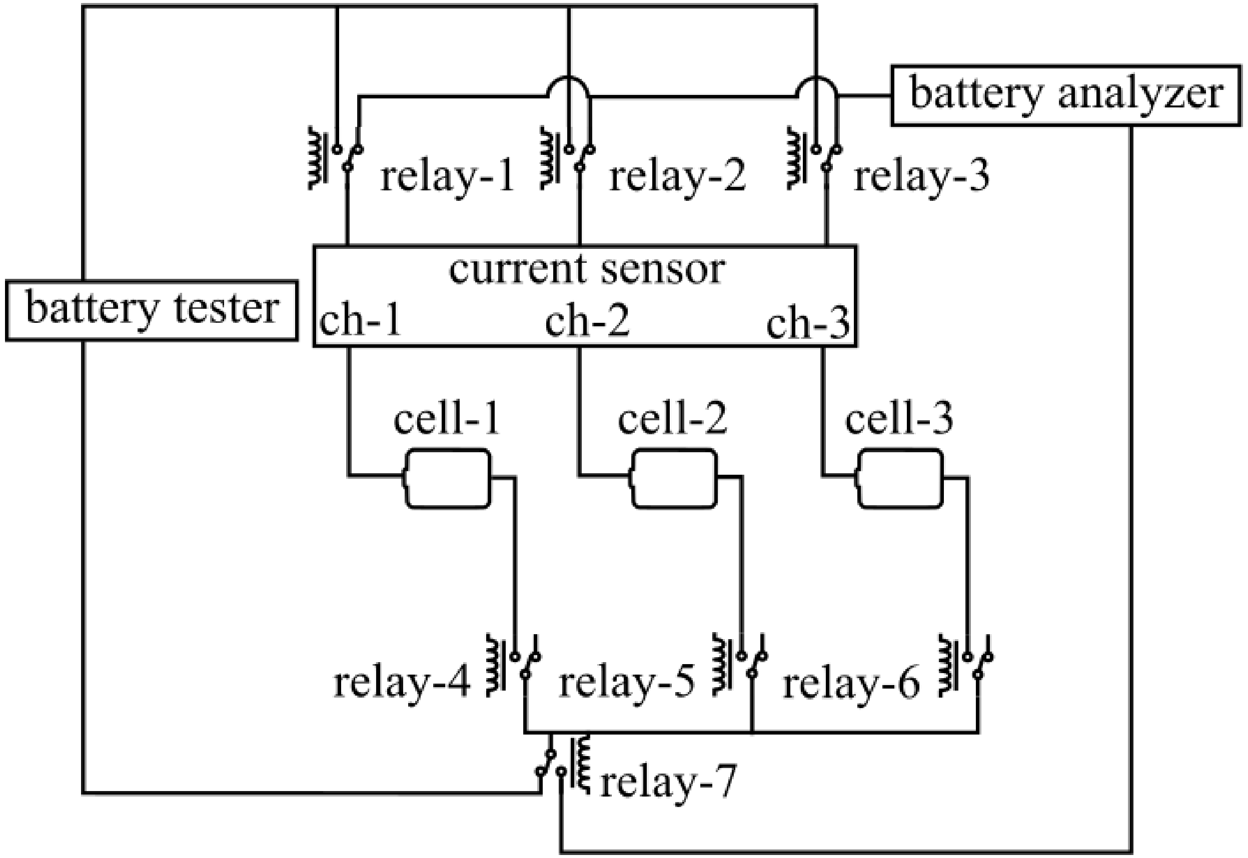
- Three Samsung 30Q NMC 18650 cells in parallel.
- Each cell monitored independently for:
  - Current (Verivolt flux-gate sensor)
  - Voltage (cDAQ)
  - Strain (350Ω foil gauges)
  - Temperature (type-K thermocouples)
- Testbed uses NI cDAQ driven with labVIEW for data collection.





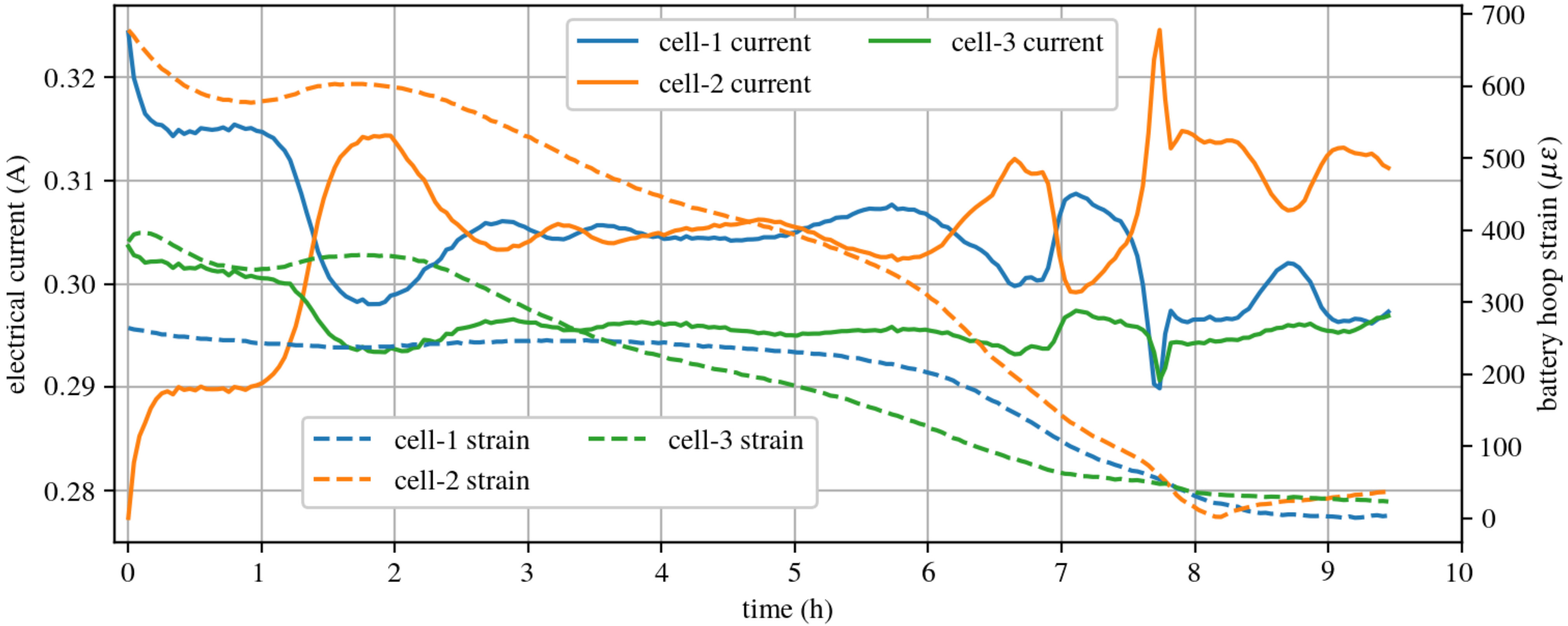
Testbed Wiring and Isolation

- Each cell connected through independent sense and power lines.
- Relays allow cells to be tested individually or in parallel.
- Enables measurement of:
  - Internal resistance from BK analyzer
  - Individual open circuit voltage (OCV)
  - Individual capacity
- Isolation relays allow for assessment of OCV imbalance and resistive differences.



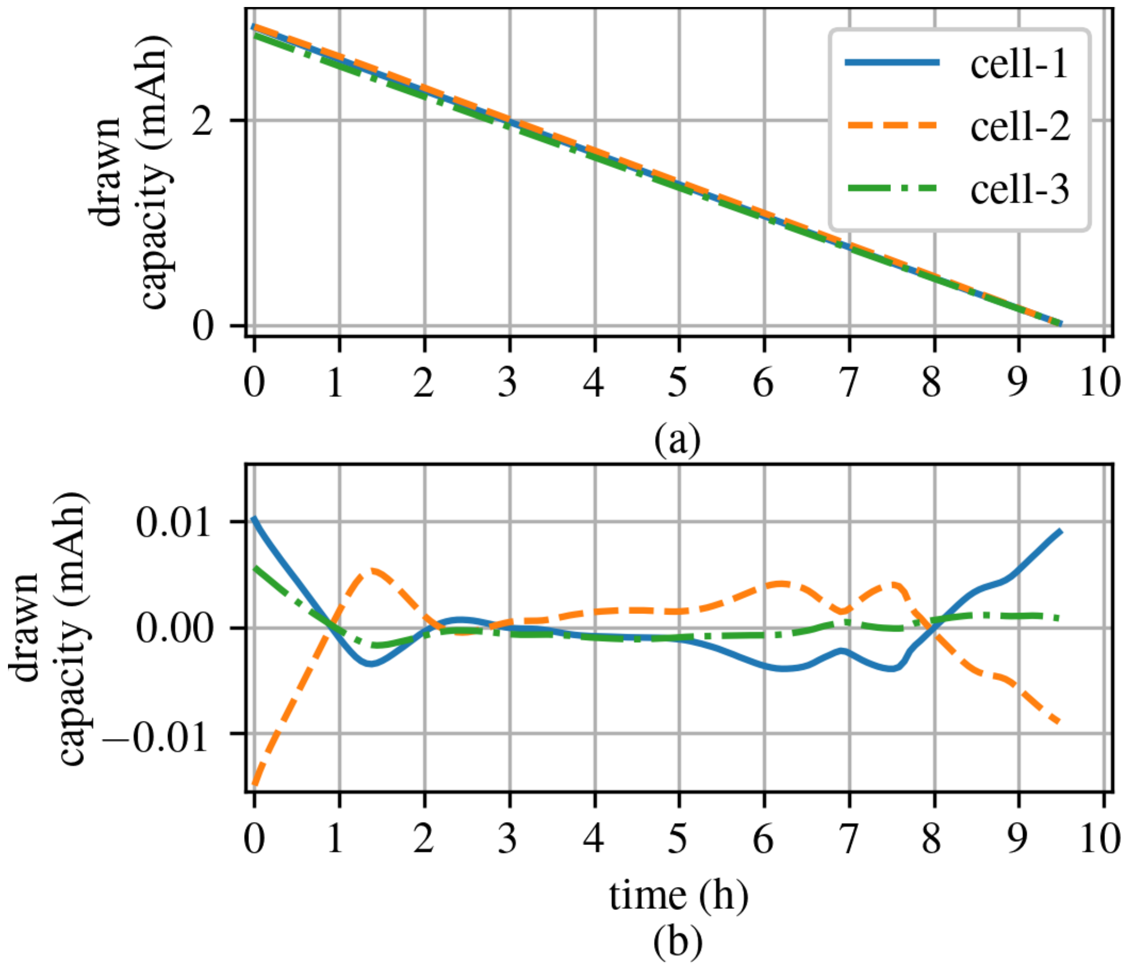
Initial Results Current and Strain

- Despite same starting Soc, the three cells immediately draw uneven current throughout discharge
- Cell-2 drew 15% more current than average



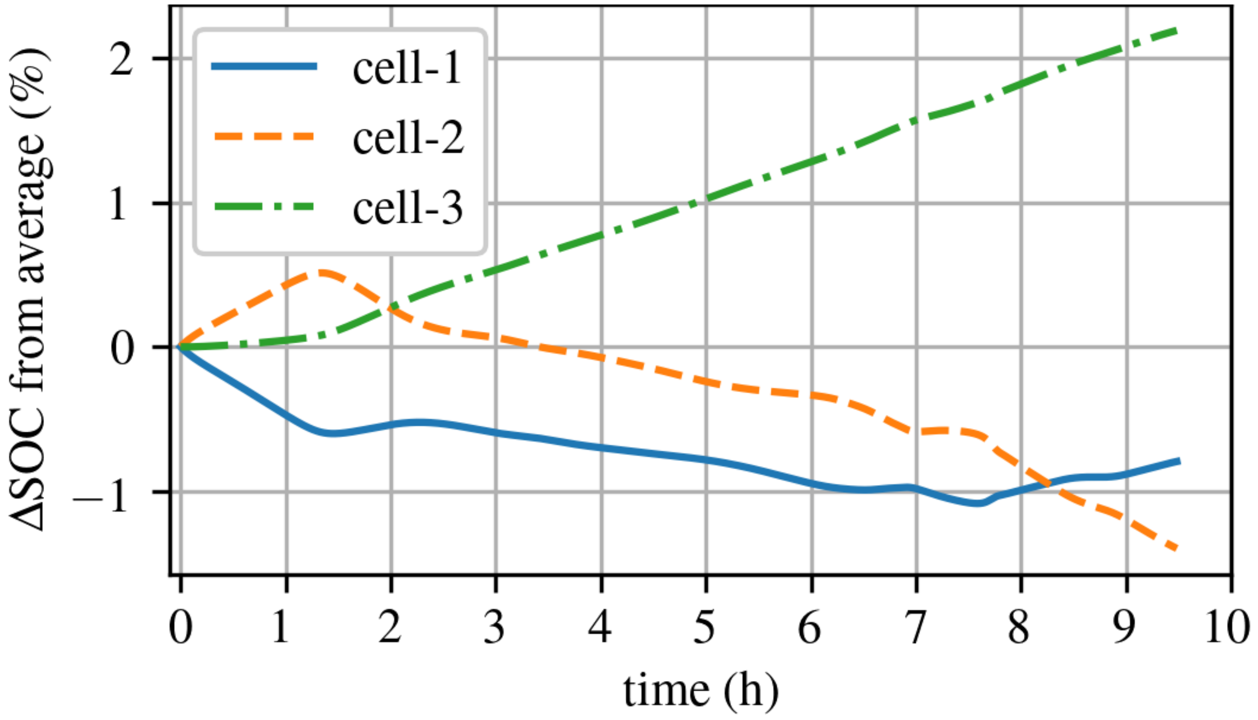
Initial Current Imbalance Results

- Capacity curves were detrended from their average to highlight deviation from ideal constant current behavior.
- (a) shows the drawn capacity from each cell during the test
- (b) plots the deviation from average capacity across cells.
    - Cell-2 consistently shows a positive deviation indicating it supplies more current than others throughout discharge
- This imbalance suggests a cell-to-cell mismatch in internal resistance or state, of charge, leading to accelerated degradation if uncorrected.



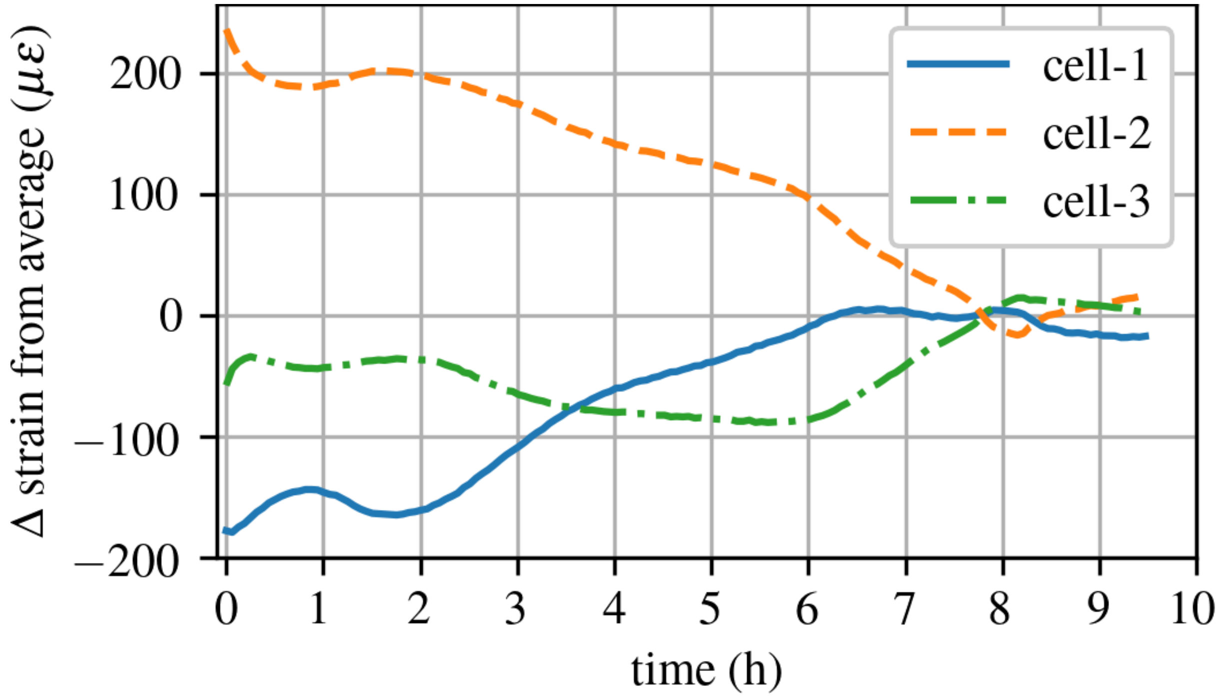
SOC Imbalance

- Figure shows State of Charge (SOC) for all three cells during discharge.
- This divergence is driven by:
  - Slight differences in cell capacity or resistance
  - Current sharing imbalance from earlier shown results
- SOC mismatch becomes more pronounced in the second half of the test, which could limit usable capacity or trigger early protection events in battery management systems.



Strain divergence

- Figure shows difference in hoop strain between cells over the discharge cycle.
- At low SOC, strain values converge as the intercalation of the cells reach a near empty state
- At higher SOC, strain varies significantly between cells:
  - Reflects imbalance in cell loading
  - Suggests strain could be a useful marker for early imbalance detection



Conclusion

- Extending battery useful life is critical for high-performance applications like electric vehicles and electric aircraft.
- Smart load sharing can reduce stress and improve longevity by managing imbalances dynamically, streamlining maintenance.
- Early fault detection (e.g., via CID strain signature) has potential to enable proactive maintenance and improved safety.
- Strain-based models offer a promising path to non-invasive state-of-health and state-of-charge prediction.
- Together, these strategies support more reliable, efficient, and maintainable electrified systems.

Future Direction

- Expanded cycling studies across multiple chemistries, aging conditions, and temperatures will allow more advanced models
- Real-time strain-based diagnostics to integrate strain measurements into embedded BMS architectures.
- Create more advanced machine learning models to predict SOC and SOH using strain data.
- Parallel cell modeling & optimization for load distribution and scale them from cell to pack level.

acknowledgements

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- Austin Downey, Jamil Khan, Kerry Sado for support.

Thanks

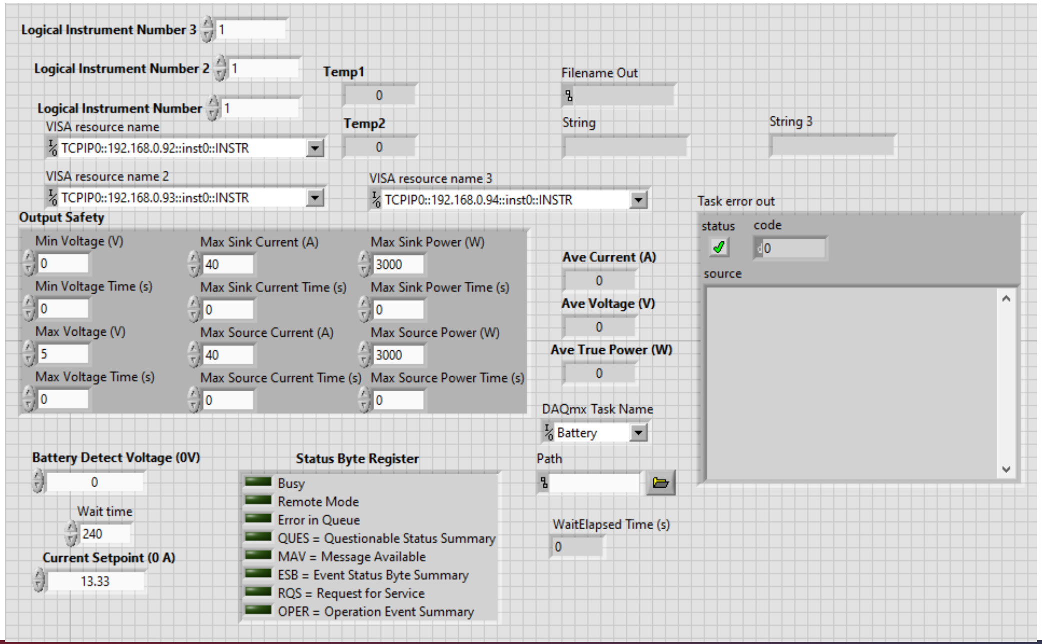
Questions?

Load sharing Conclusions

While we made progress in extending the life of the batteries and equalizing the maintenance schedule, more work needs to be done to prevent the loss of redundancy of the current system

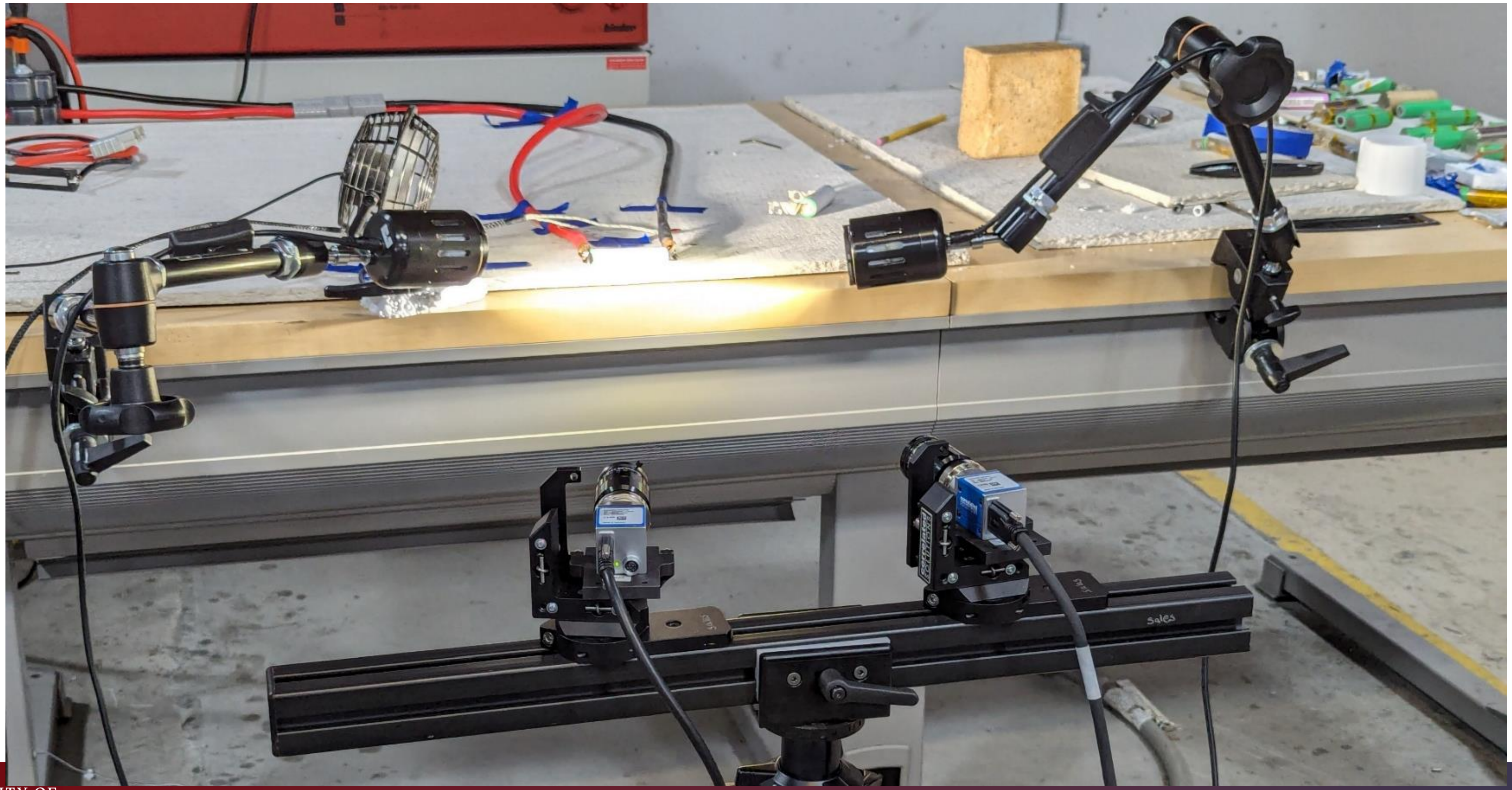
Digital Image Correlation Setup

- Hardware:
- Samsung 25R nickel cobalt aluminum (NCA) 18650 Cell
- NHR-9200 battery tester
- NI-9210 compact data acquisition
- J type thermocouple
- ThinkPad T470s
- 5MP Cameras
- Software:
- LabVIEW 2020 SP1
- NI-MAX 2022 Q3
- VIC-Snap



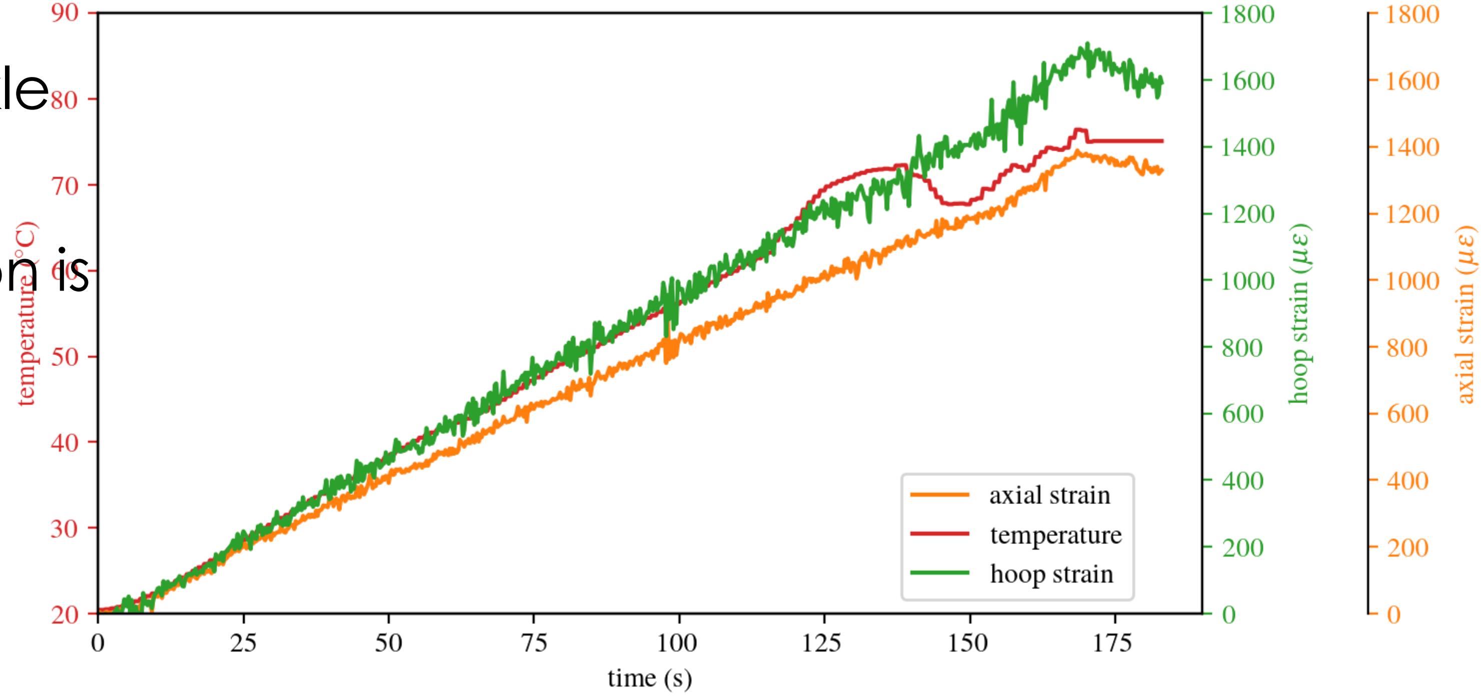
Digital Image Correlation Setup

- Improved speckle painting methods
- Added better lighting for speckle detection
- Added fan to mitigate heat waves



High-C Experimental outcomes

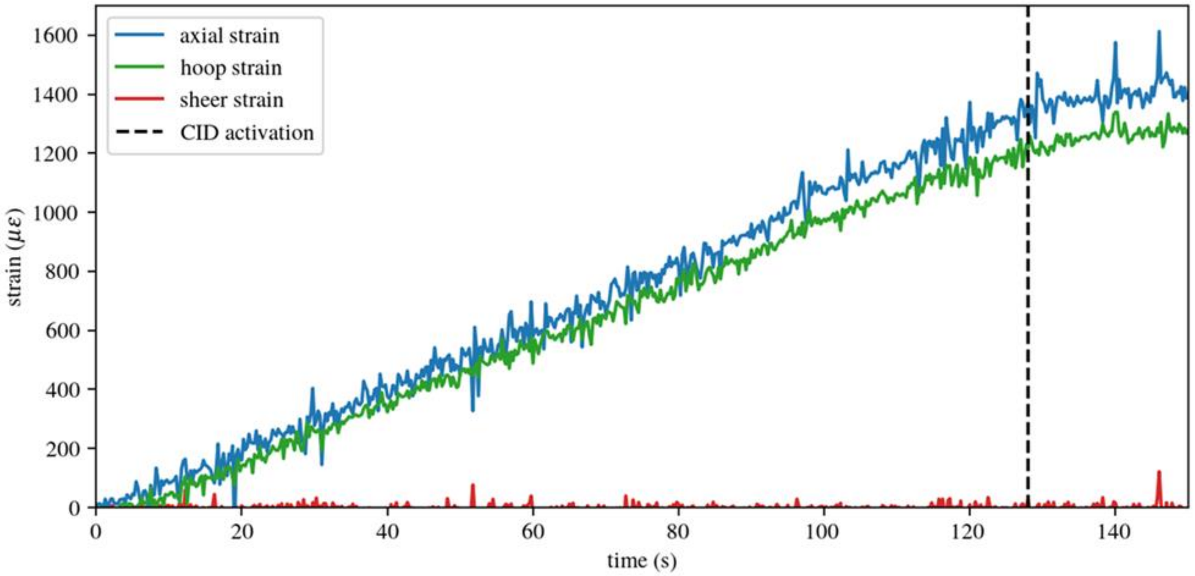
- Experimental outcomes
- Improved Digital Image Correlation setup
- Less noise likely due to new speckle method
- Current Interrupt Device activation is more pronounced

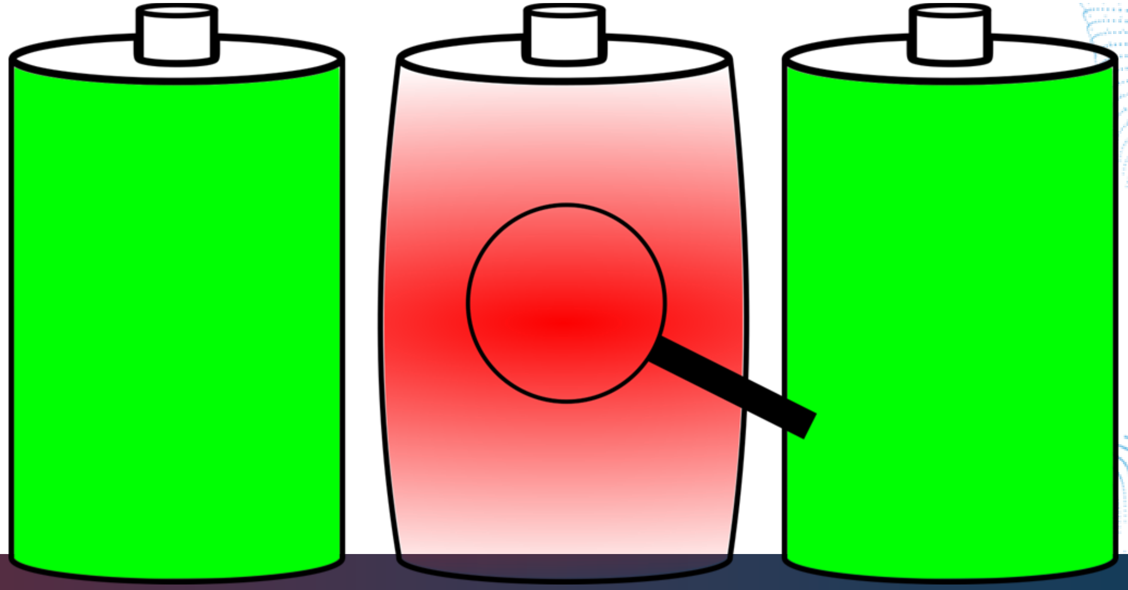


High-C overview

Conclusions and Overview

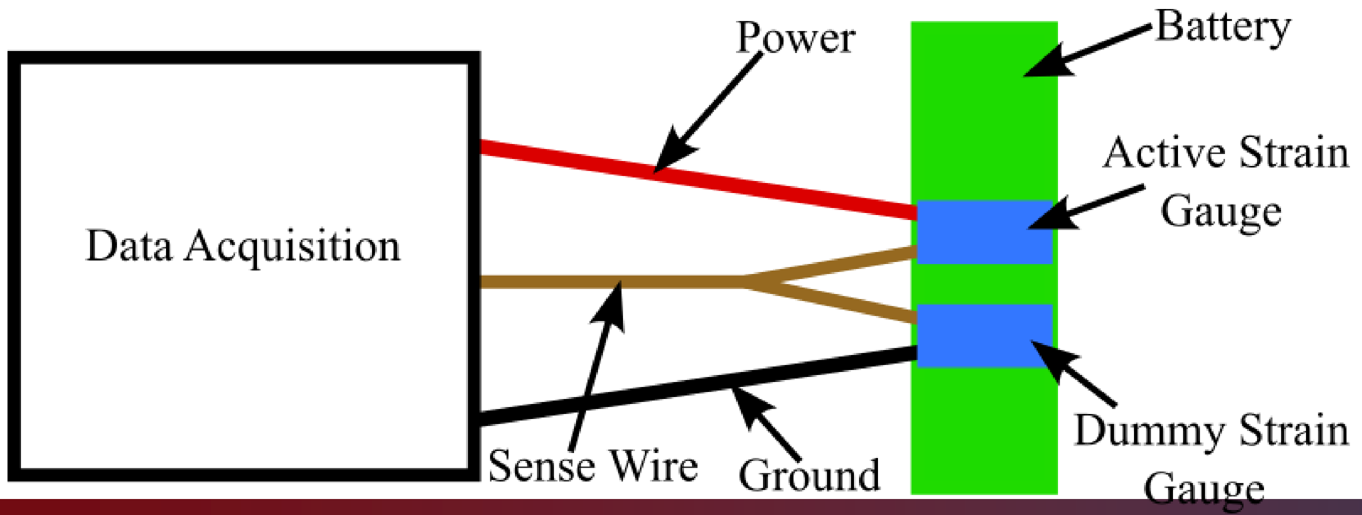
- Potential for using battery deformation as a method of detecting CID failure is evident
- Potential for the integration of non-destructive strain evaluation methods into battery monitoring systems needs further exploration
- Future work will refine current methods and explore alternatives to digital image correlation

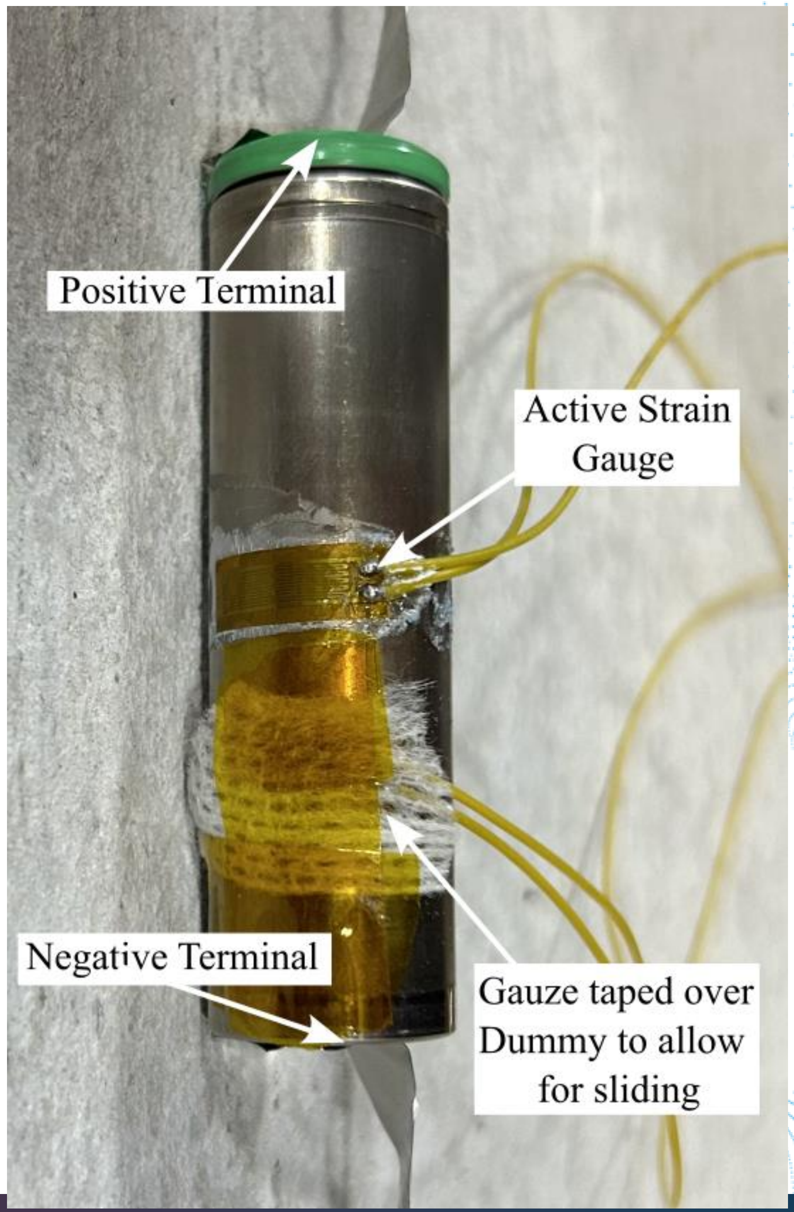




Future work

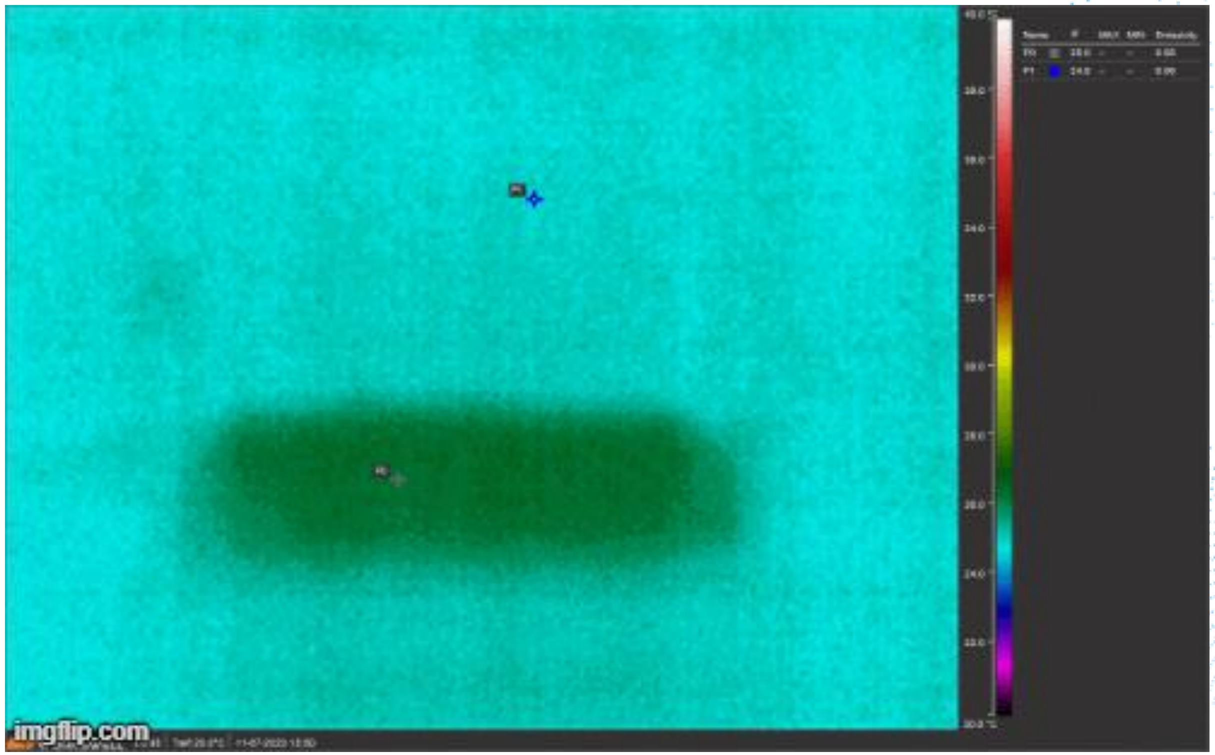
- Implementation of strain gauge will be explored as an alternate deformation detection method
- More applicable to battery management systems
- Will need temperature compensation
- Will run strain gauge and Digital Image Correlation simultaneously

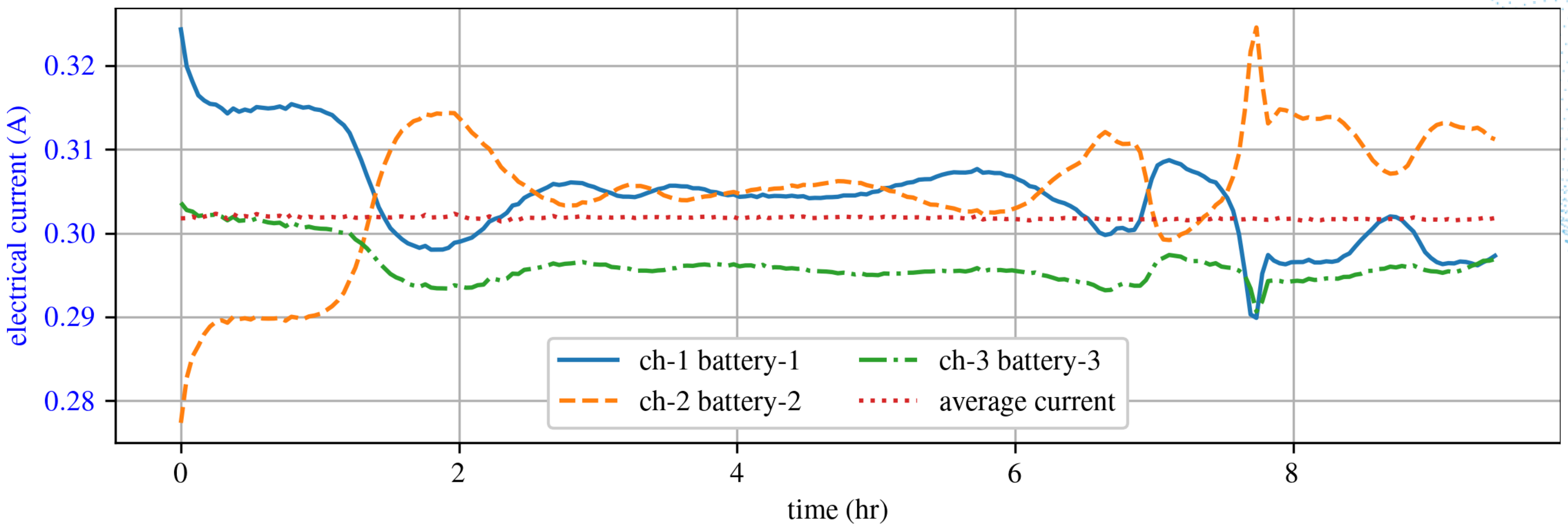




Future work

- Add high resolution thermal camera to understand temperature gradient during battery discharge
- Understanding the temperature gradient of the battery will assist in compensating for the strain generated by temperature





0.32
0.31
0.30
0.29
0.28
electrical current (A)
0
2
4
6
8
time (hr)
ch-1 battery-1
ch-2 battery-2
ch-3 battery-3
average current

Table data

Range (percent difference)	cell-1	cell-2	cell-3
max current (mA)	324	325	304
min current (mA)	289	278	290
mean current (mA)	304	305	296
range of current-to-mean (%)	11.7	15.6	4.54
max Δcapacity from mean (mAh)	0.010	-0.015	0.0057
max current from mean (mA)	324	325	290
max ΔSOC (%)	-1.09	-1.40	2.19
max Δstrain (με)	-179.3	236.0	-88.67
max strain (με)	265.0	678.0	398.0