Deep Neural Network-Based Electro-thermal Modeling of Lithium-ion Batteries

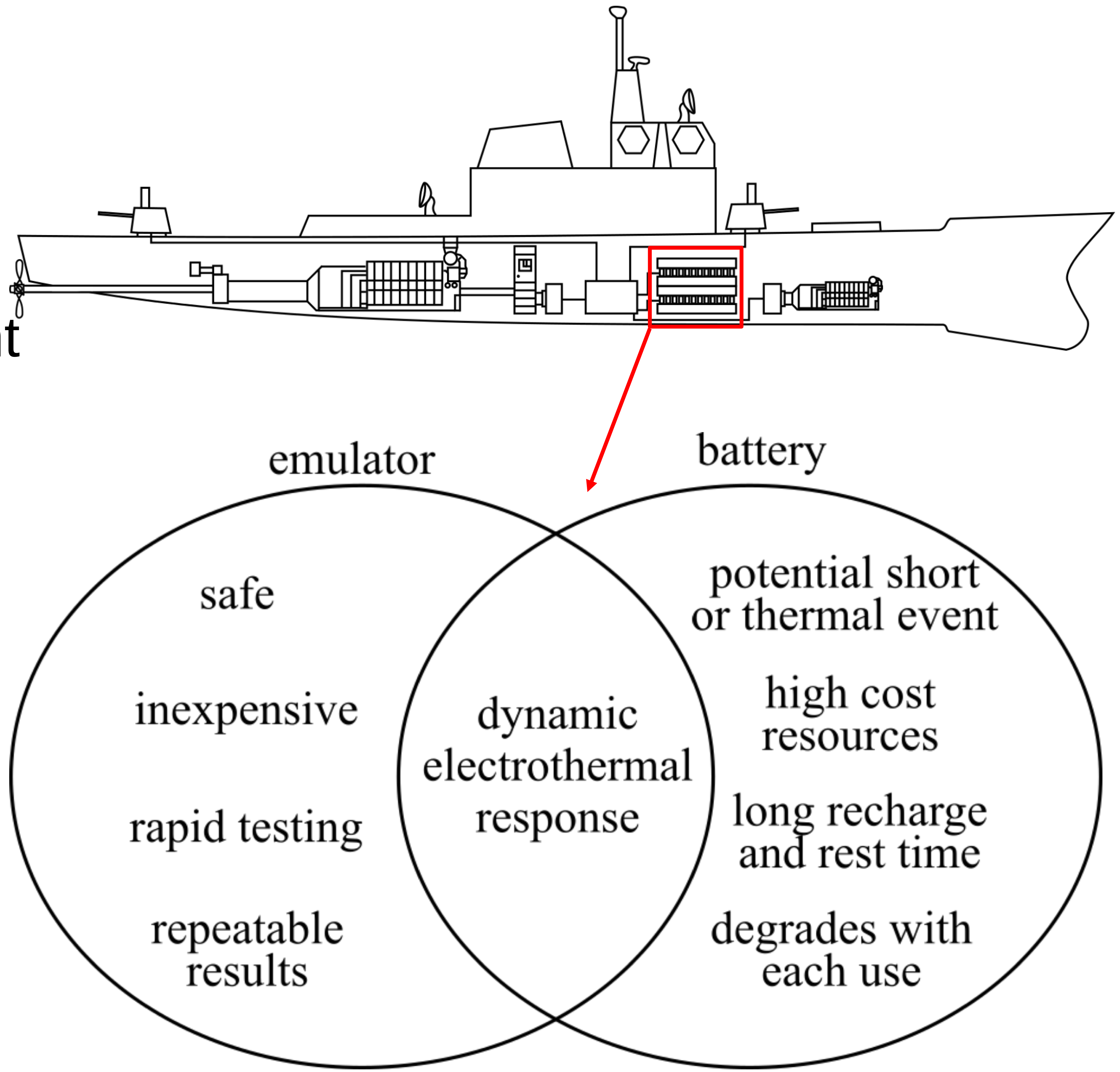
Connor Madden[1], Jarrett Peskar[1], Austin R.J. Downey[1,2], Kerry Sado[3], Jamil Khan[1]

[1]Department of Mechanical Engineering
[2]Department of Civil and Environmental Engineering
[3]Department of Electrical Engineering

This work was supported by the Office of Naval Research (ONR) under contract NOs. N00014-22-C-1003, N00014-23-C-1012,and N00014-24-C-1301

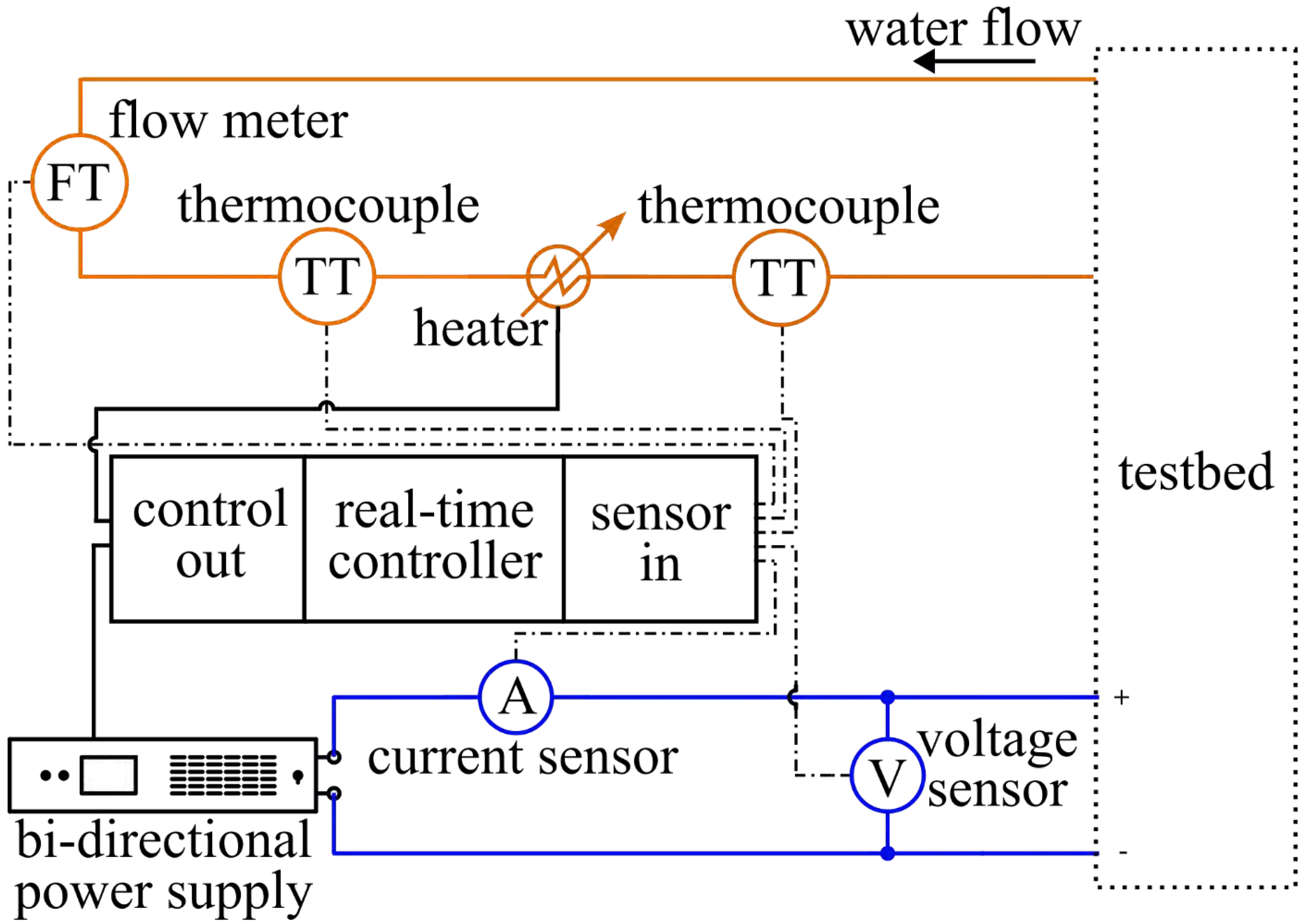
Intro

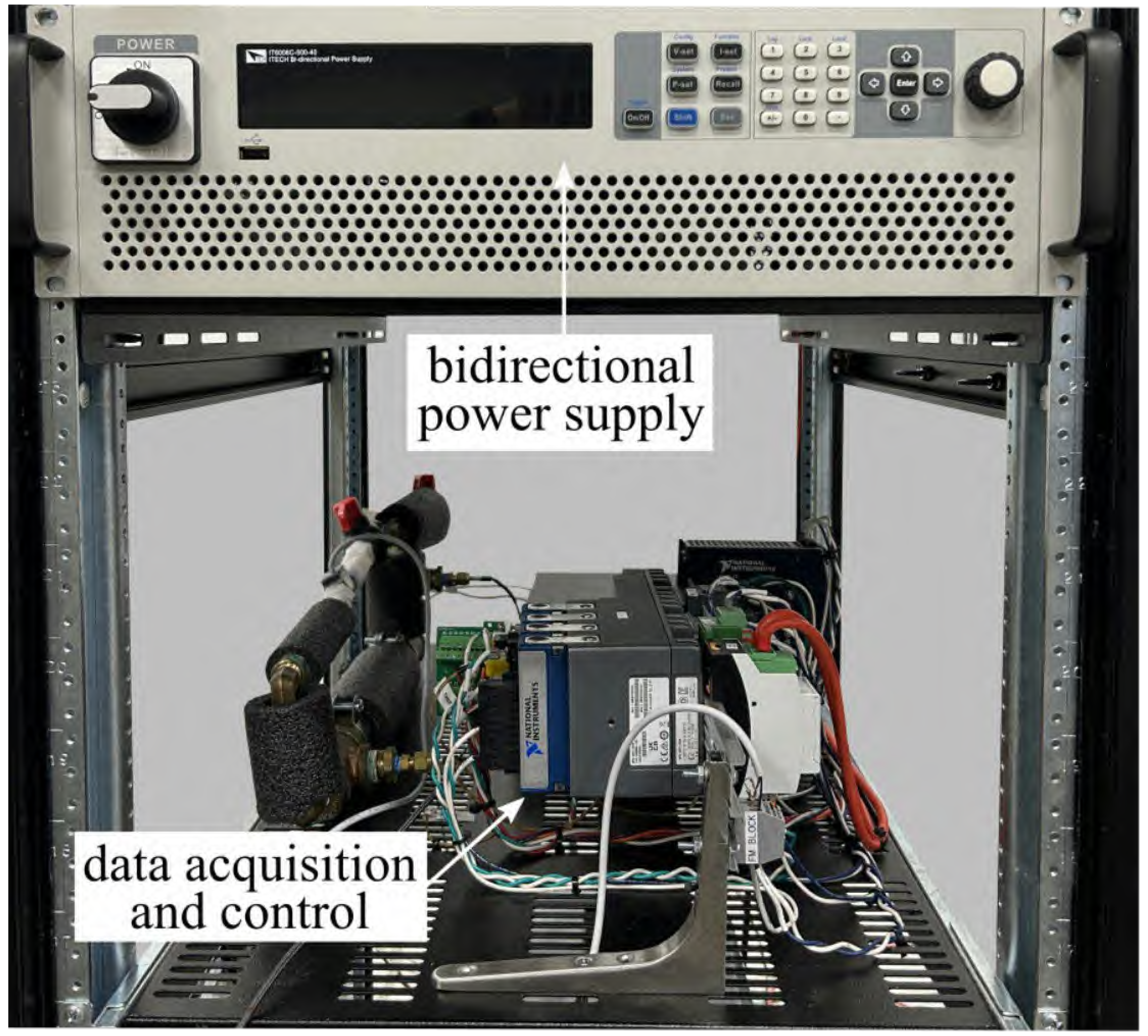
- Electrification In Naval Ships requires energy storage for buffering and supplying pulsed power
- Lithium-ion batteries provide dense and efficient energy storage but are impractical for frequent testing
- Emulation provides:
  - Repeatable conditions
  - limits cost
  - saves time
  - safety



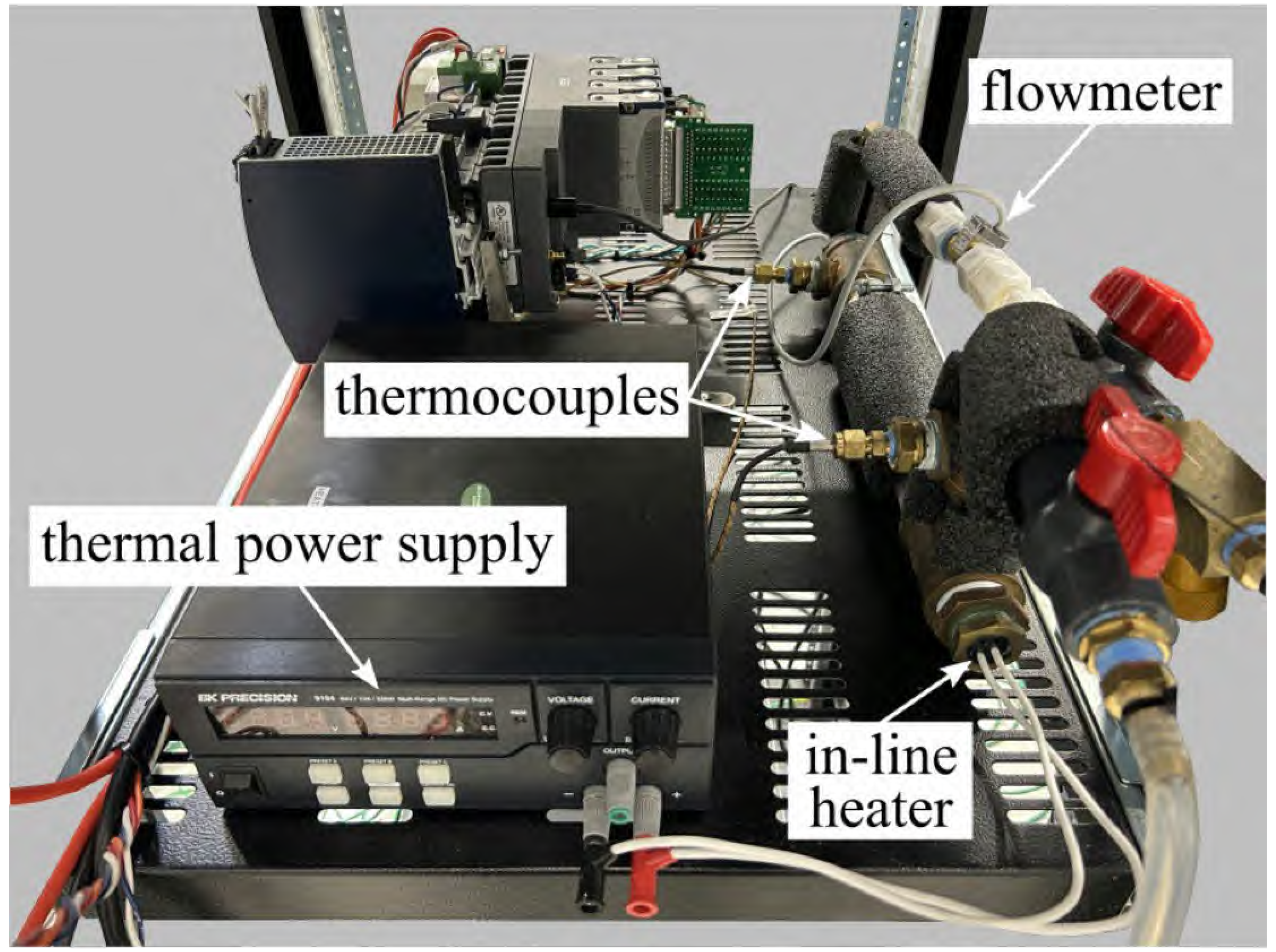
Hardware in the loop Battery Emulator

- Sensors feed the testbed state, such as coolant temperature and current load, to the real-time controller (RTC)
- Model running on the RTC sets a heater and bi-directional power supply to match the calculated thermal and electrical response of a battery





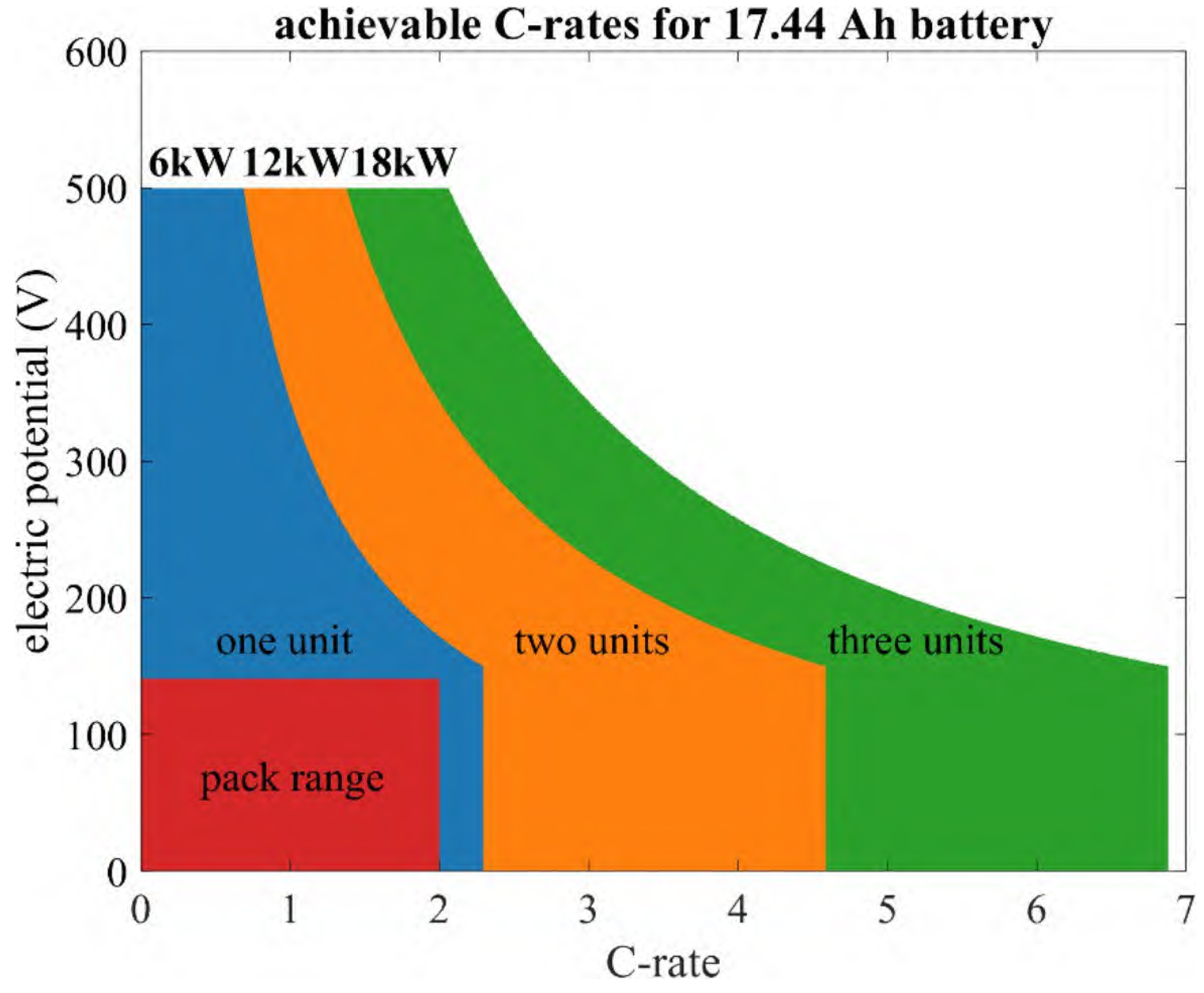
front view

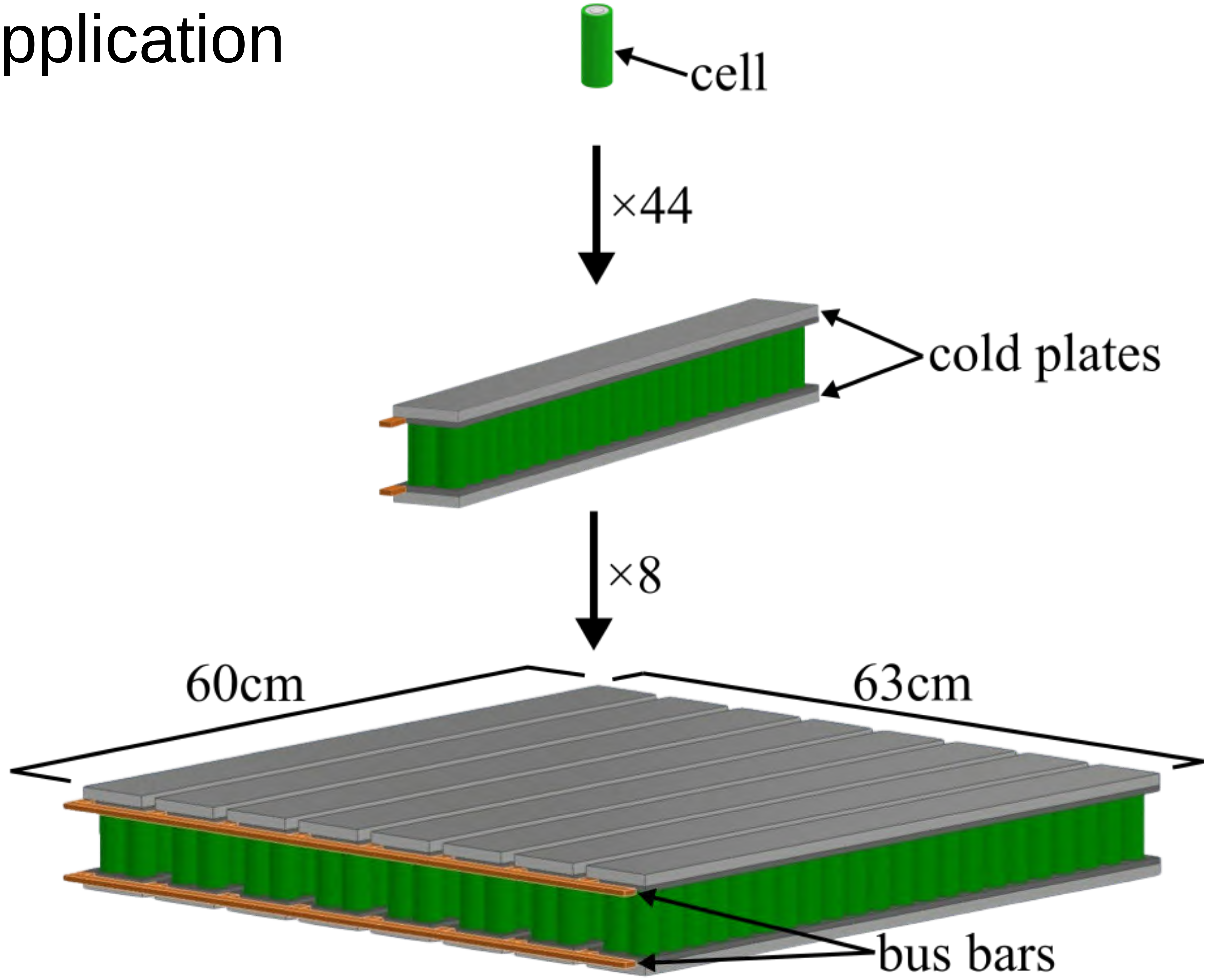


rear view

Scales to High Power Application

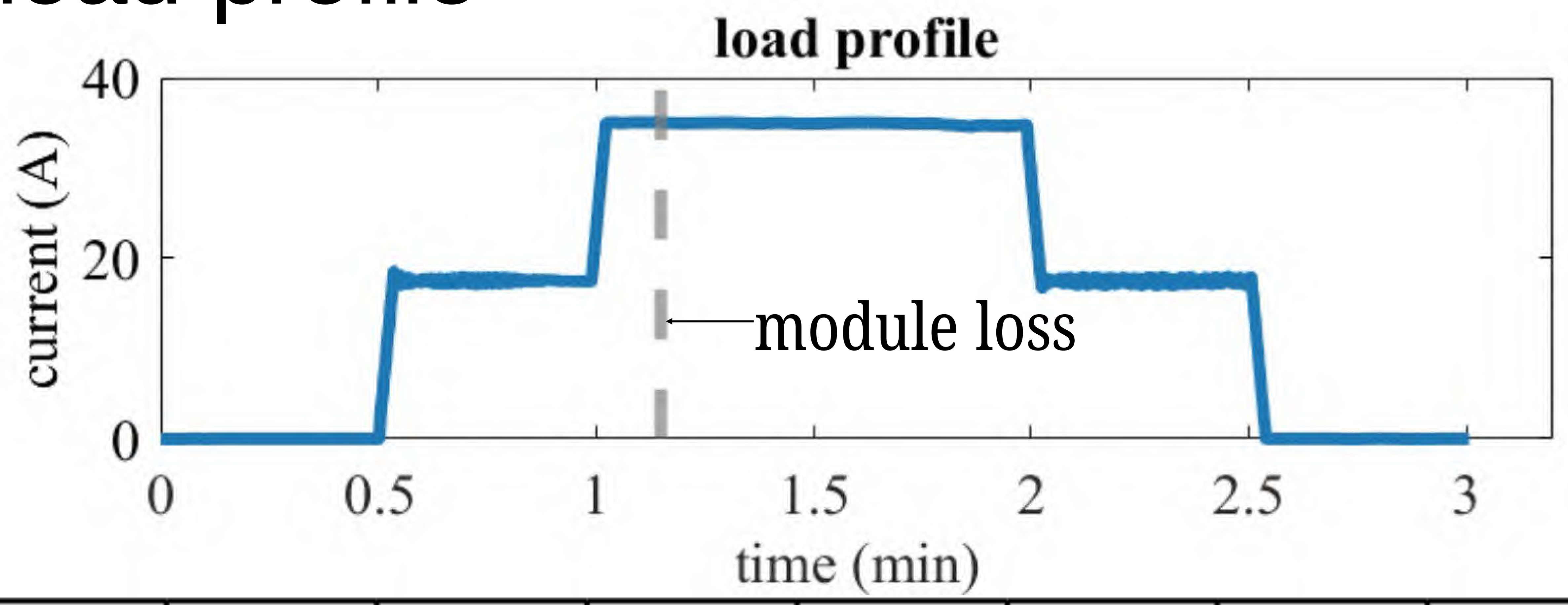
- Battery Pack
  - 44S8P
  - Nominal Voltage = 140.8 V
  - Capacity = 17.44 Ah
  - Power @ 1C = 2.456 kW
  - Power @ 2C =4.911 kW

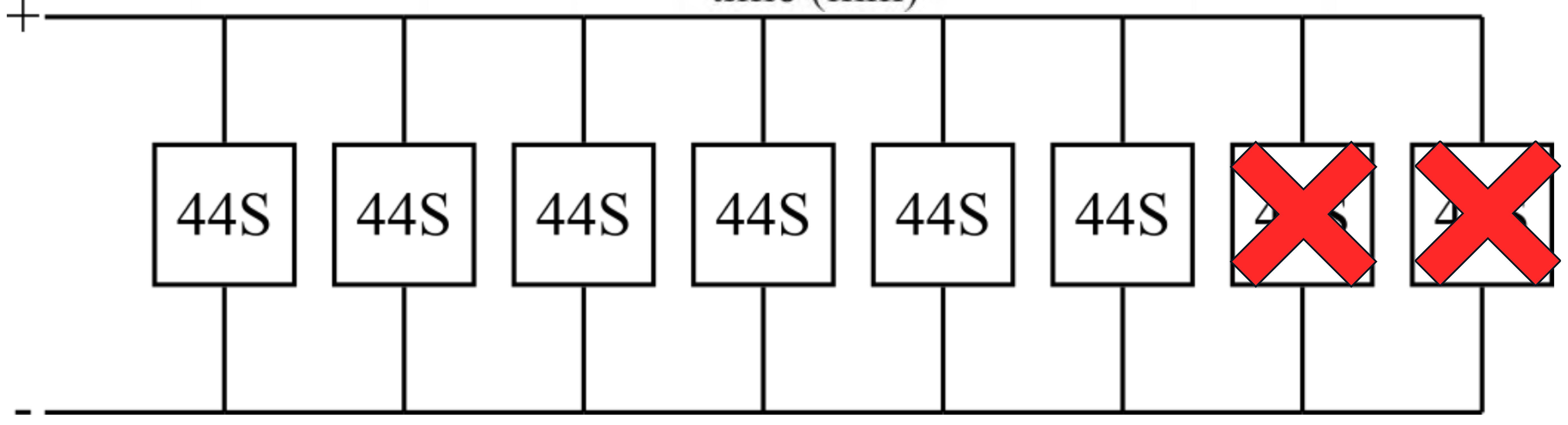


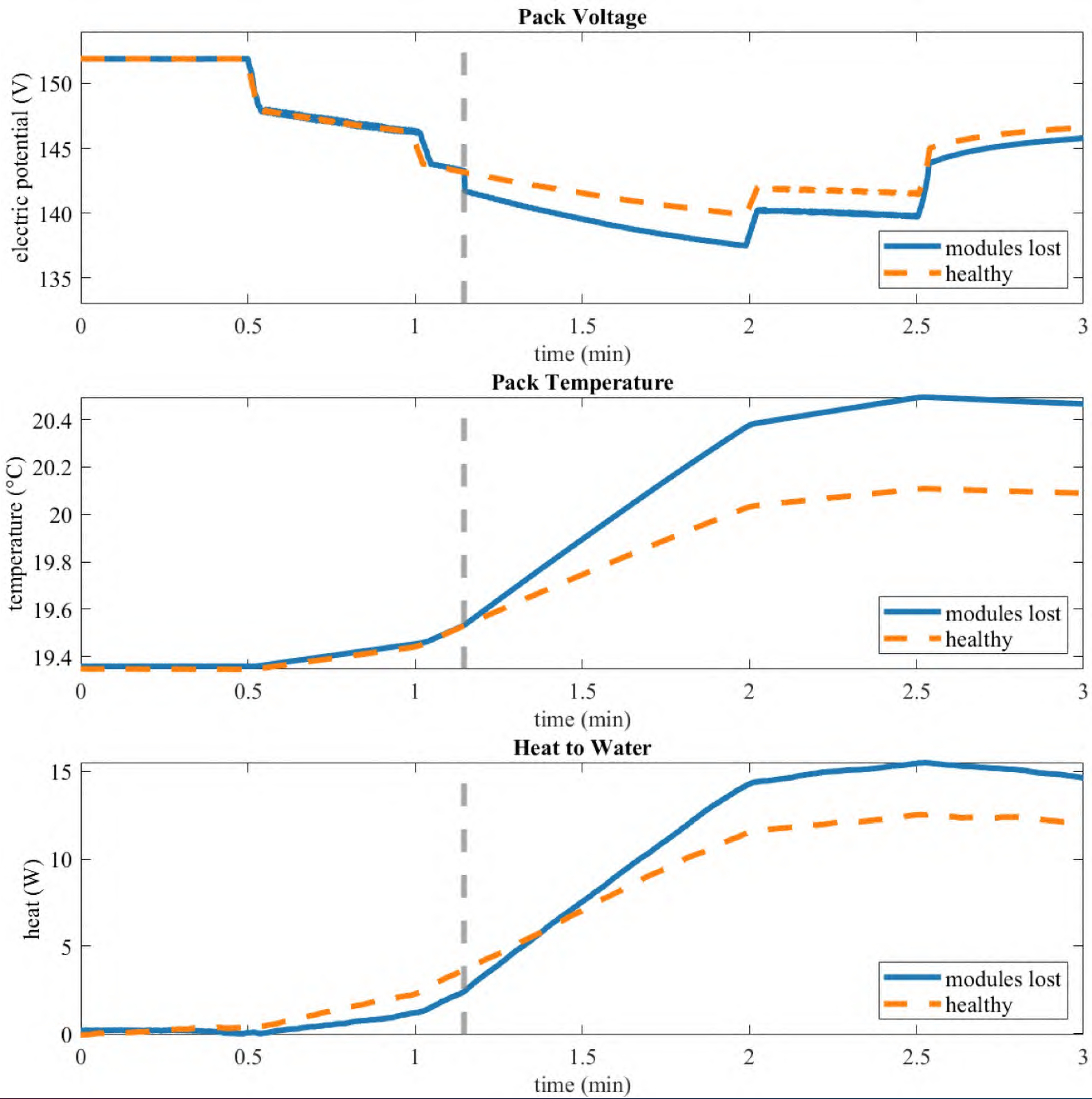


Previous Testing

- Emulator supports fault injection/abuse scenario that would not be tested on a real battery pack
- Disconnecting two parallel modules from a 44S8P pack during a stepped 1-2 C-rate load profile

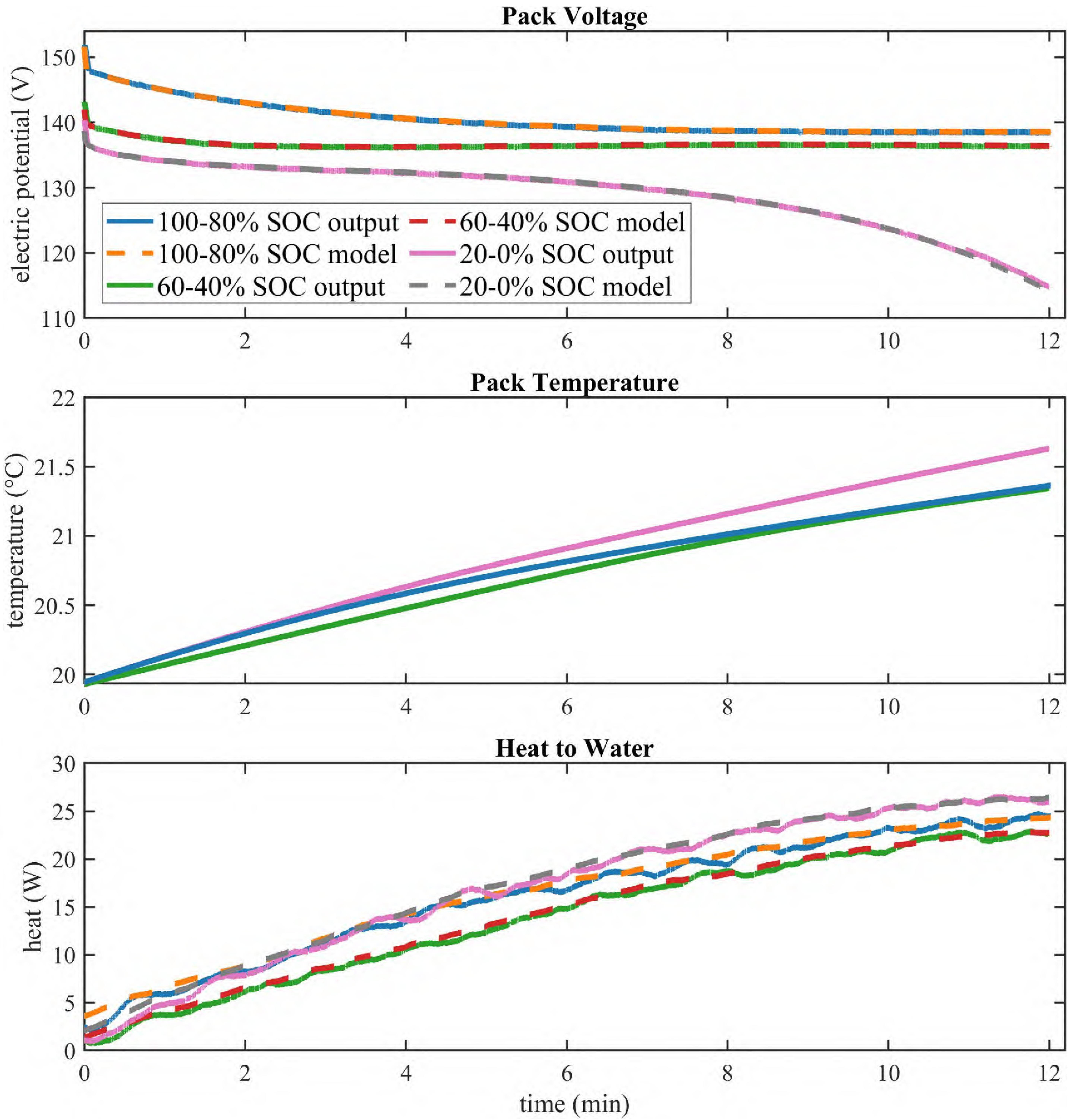


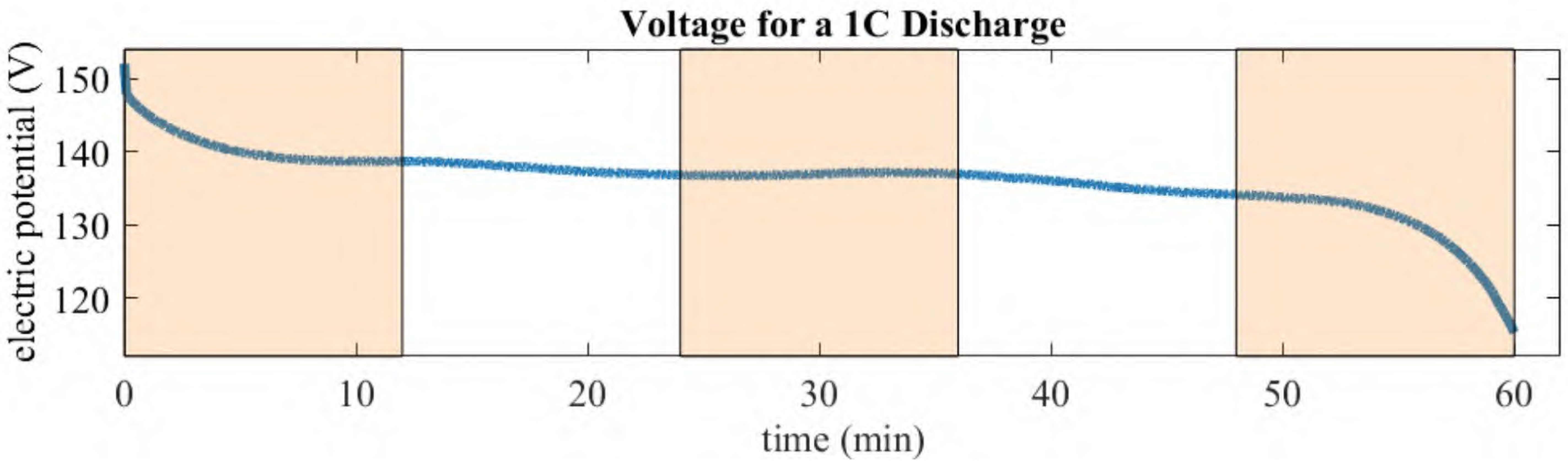




Previous Testing cont.

- A 1C-rate discharge was performed at 100-80%, 60-40%, and 20-0% SOC
  - Captures regions of highest and lowest DC Internal Resistance
- Rapid testing capability
  - No recharge, discharge to desired SOC, or rest necessary between tests





Previously Used Cell Model

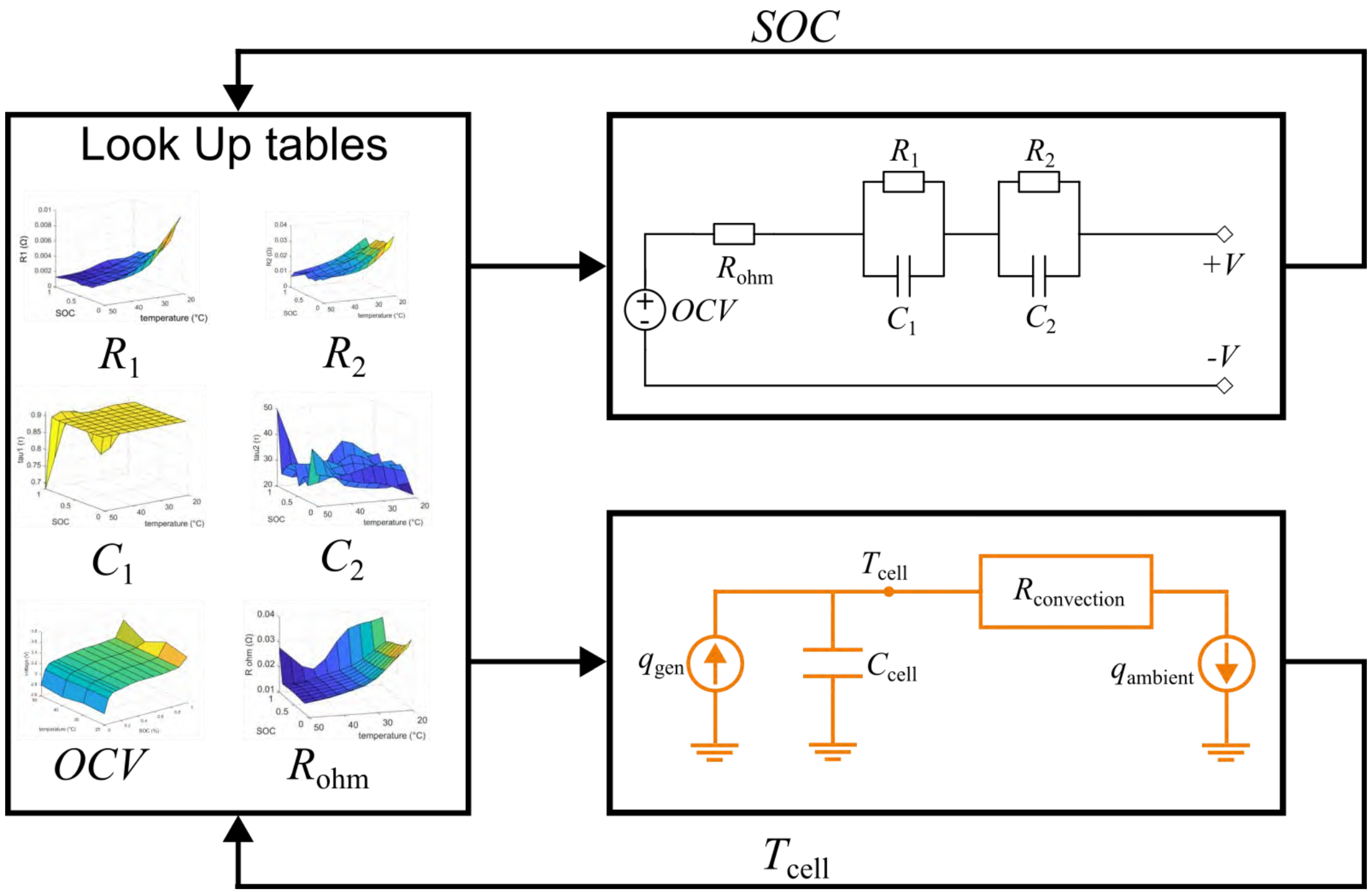
- Coupled Electrothermal Model
  - 2nd order equivalent circuit

$$\frac{dV}{dt} = OCV(\mathrm{SOC}) - IR_{\mathrm{ohm}} - V_{R_1C_1} - V_{R_2C_2}$$

  - 1st order 1-D heat transfer

$$C_{\mathrm{pack}}\frac{dT_{\mathrm{pack}}}{dt} = \underbrace{-UA_{\mathrm{liquid\ conv}}\,LMTD}_{Q_{\mathrm{out}}} + \underbrace{I_{\mathrm{mod}}^2 R_{\mathrm{ohm}} n_{\mathrm{cell}}}_{Q_{\mathrm{gen}}}$$

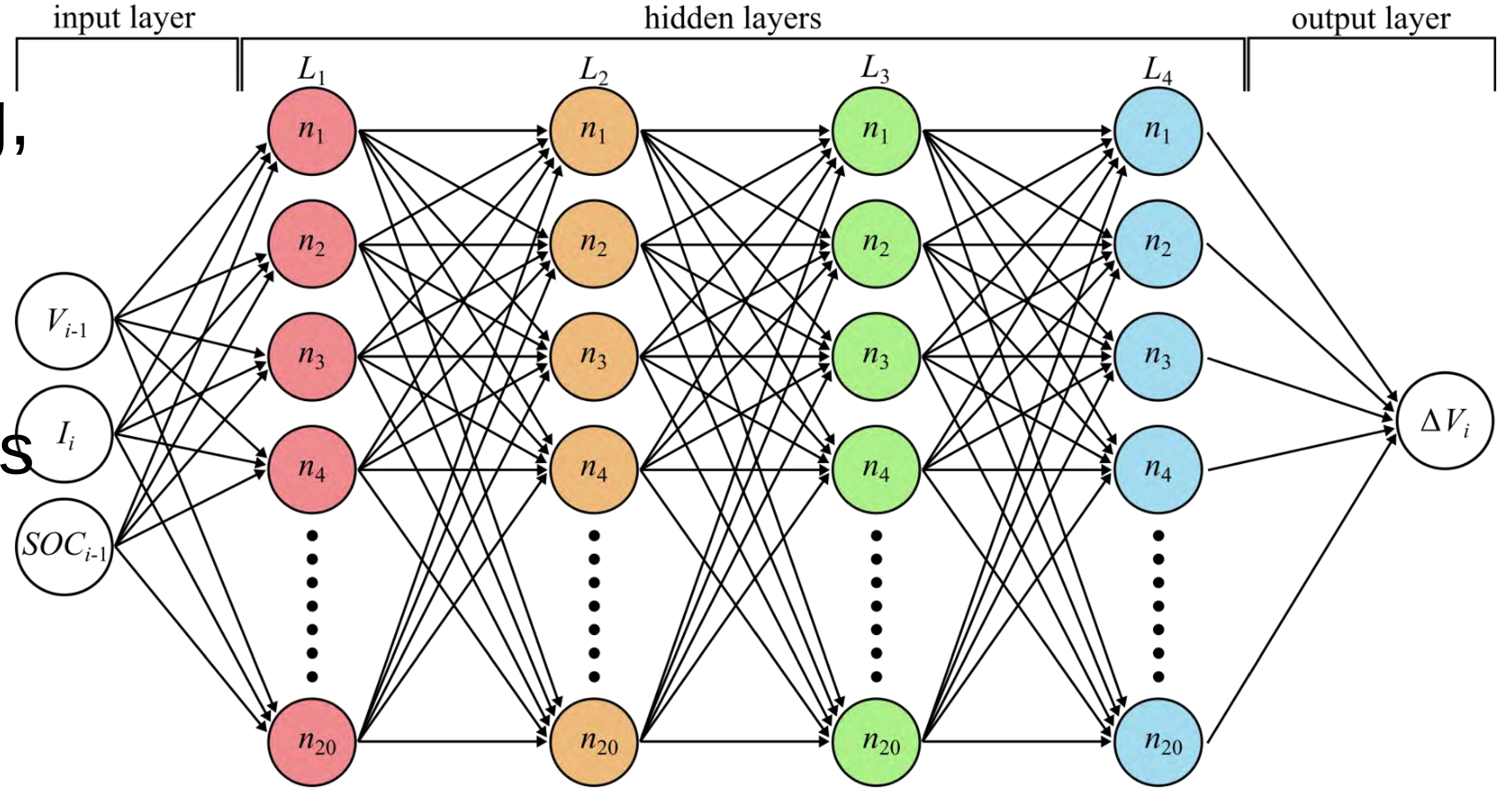
- Challenges of physics-based modeling:
  - Time consuming to parameterize
  - High cost of computation
    - Limits real-time application



Proposed Data-Driven Method

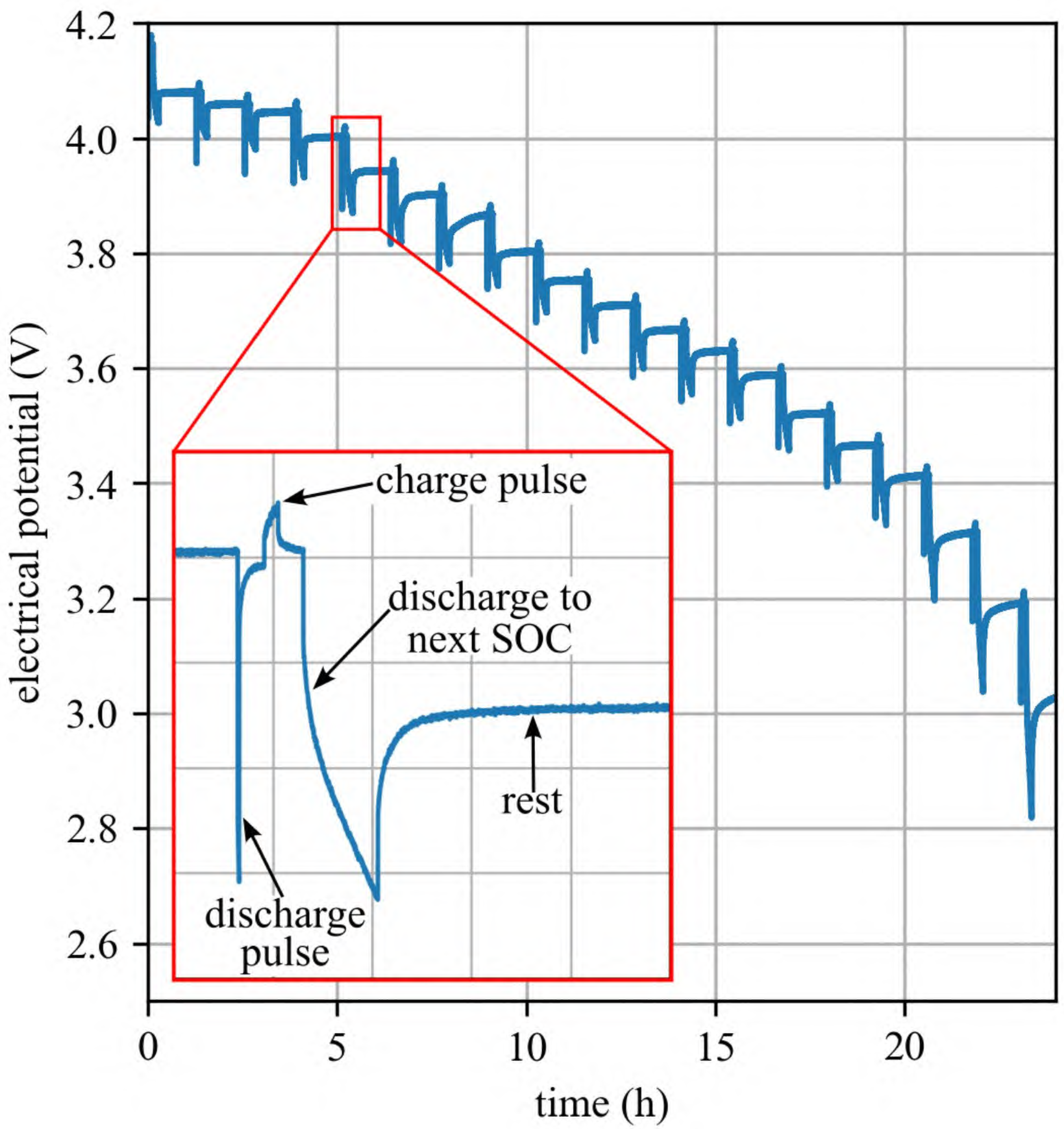
- To address physics-based limitations, a data-driven modeling approach using deep neural networks is pursued
- The model will consist of three networks predicting, for a given time step, the change in:
  - State of charge based on current
  - Voltage from current, previous voltage, and previous state of charge
  - Temperature from current, previous temperature, and previous state of charge

network to predict change in voltage



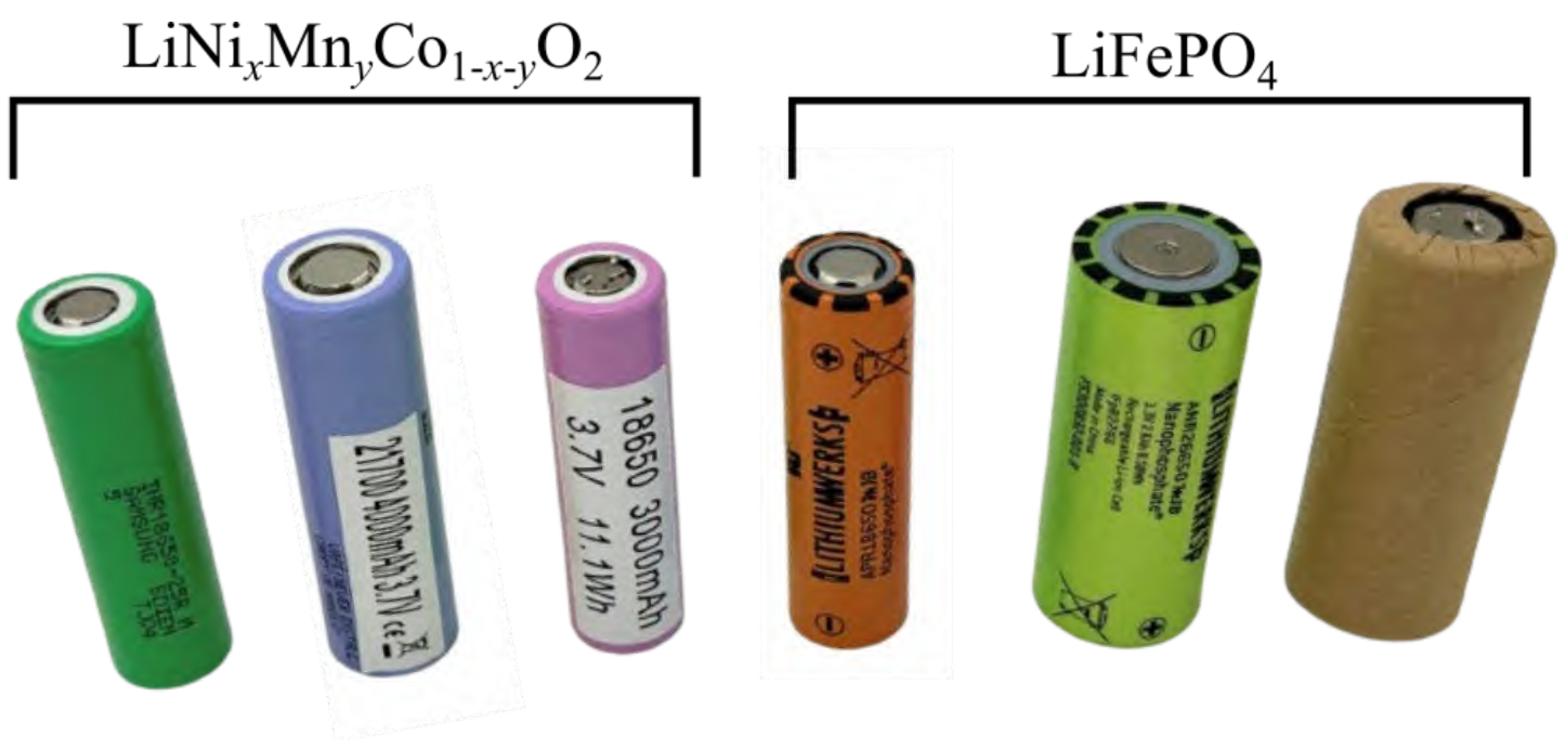
Data Collection

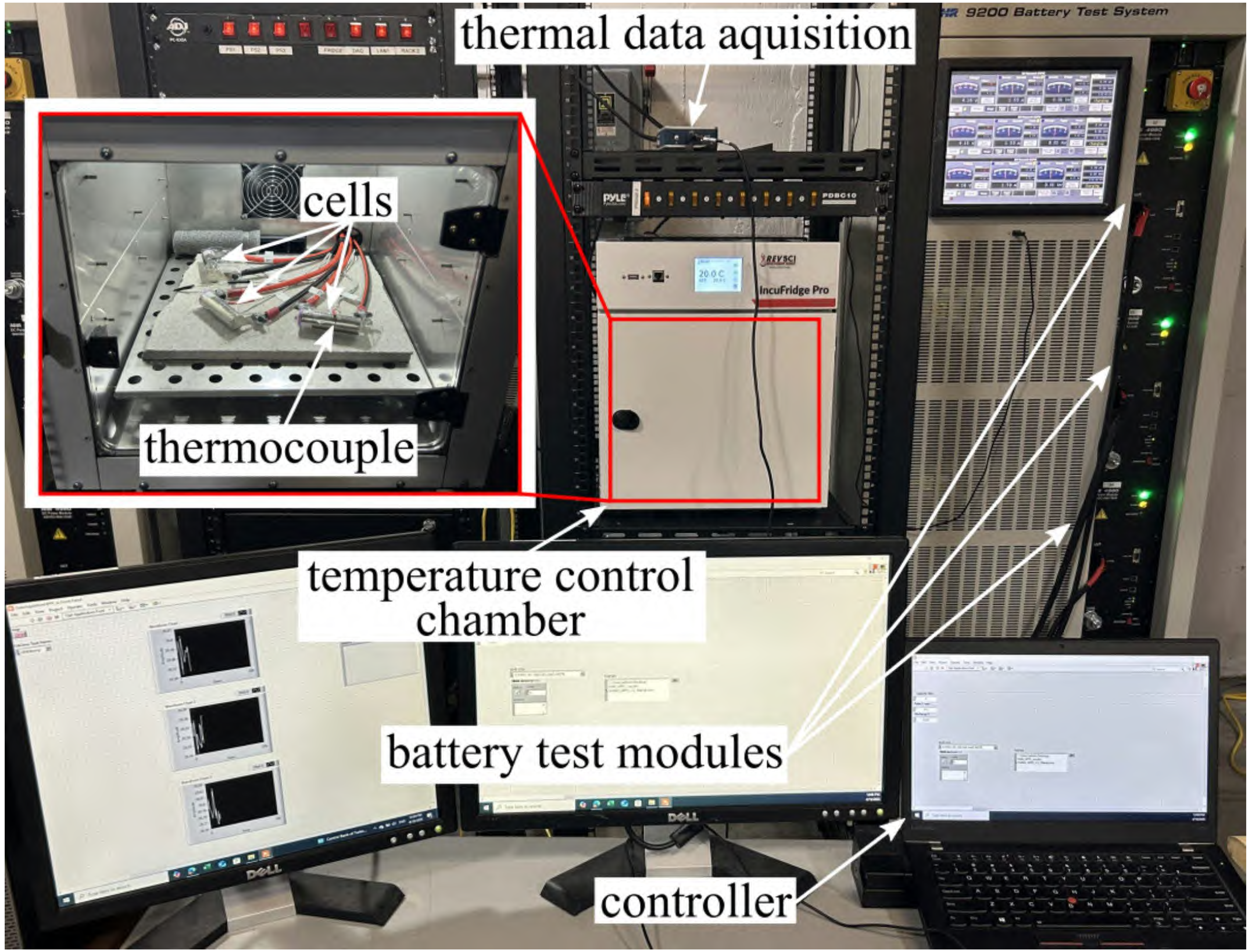
- Training data from Samsung 30Q 18650 3000mAh NMC batteries
- Hybrid Pulsed Power Characterization run on 3 cells each run at:
  - Discharge pulses at every 5% SOC
  - pulse rates 0.5C, 1C, and 2C
  - ambient temperatures of 20°C, 30°C, and 40°C
- Captures dynamic battery behavior under transient load
- Enables learning of nonlinear electrical and thermal behavior



Battery Testing

- NHR 9200 Battery Tester
  - Machine is controlled using LabVIEW on a laptop
- Incufridge
  - Regulates the temperature of the battery
  - Temperature is tracked by two thermocouples





Data Processing

- Due to noise, data is down-sampled to 0.1 Hz and segmented into 10 s windows to capture short-term dynamics while filtering measurement noise
- Feature generation:
  - Compute state of charge (SOC) via Coulomb counting

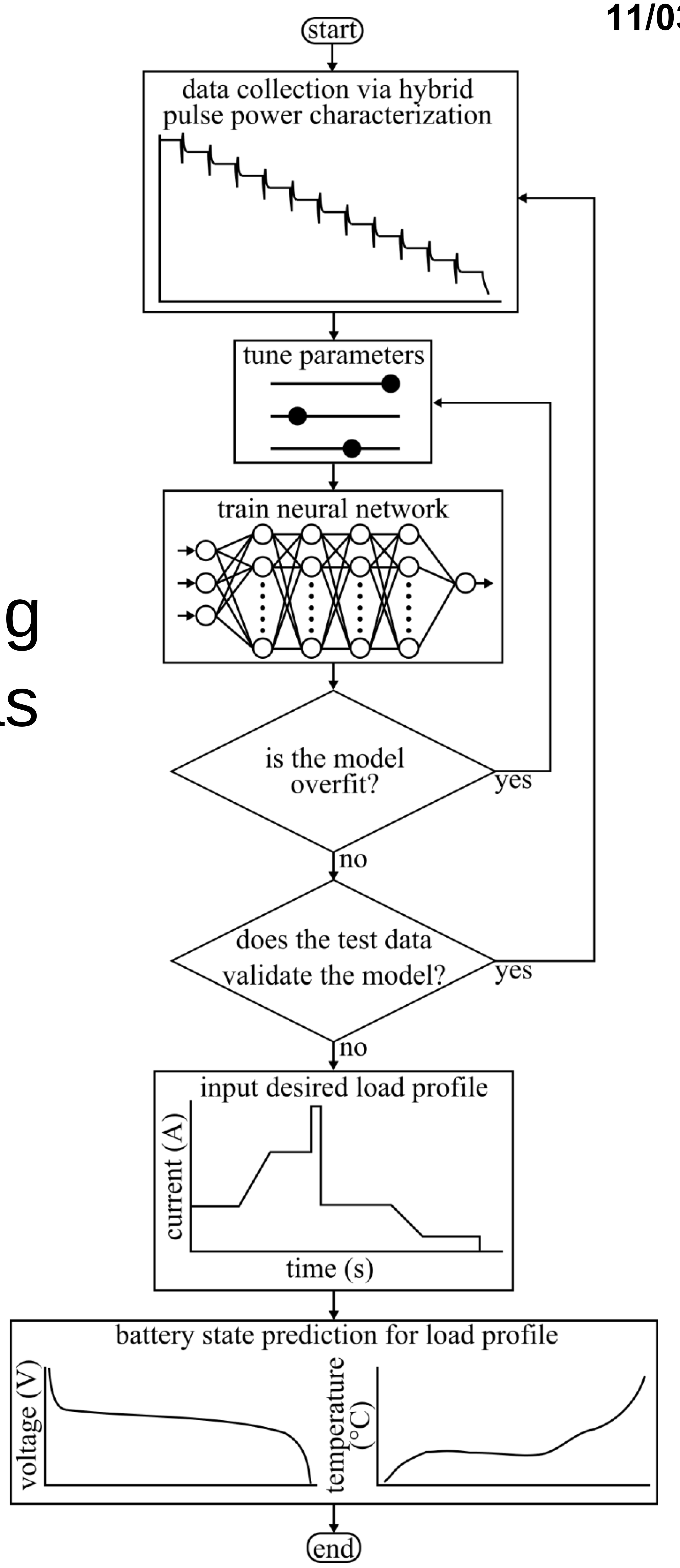
$$SOC(i) = SOC_{i-1} - \frac{1}{Q_{nom}} \int I(t)dt$$

  - Calculate ΔV, ΔSOC, and ΔT for each window
- Relaxation periods (avg current > −0.9 A) are excluded to avoid positive ΔV after discharge
- Output dataset: structured input–output pairs for supervised learning

(I, V, SOC, T → ΔV, ΔSOC, ΔT)

Data-Driven Model Development

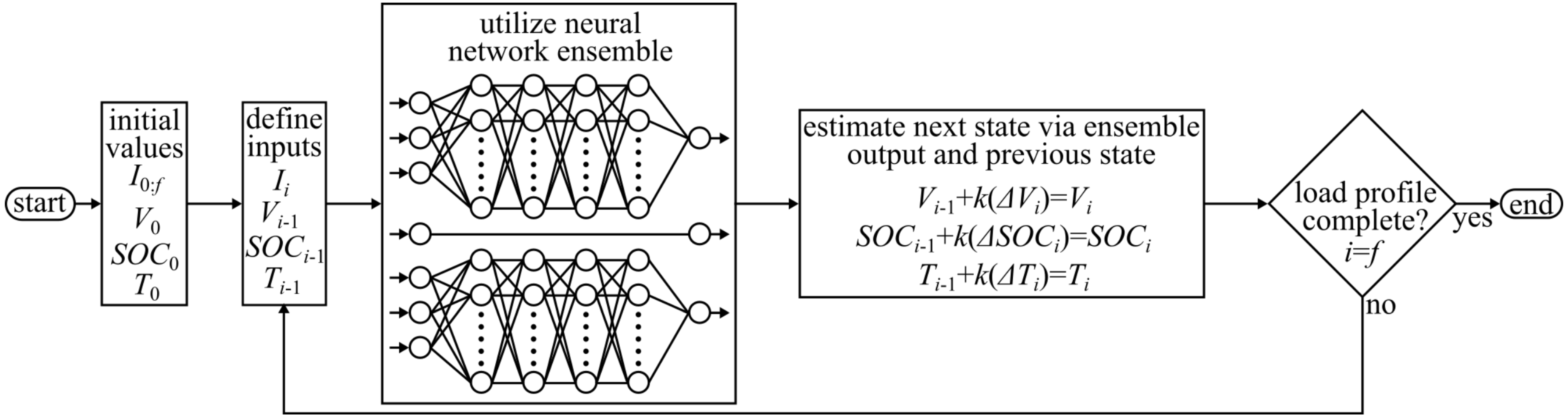
- Deep Neural Network Ensemble (DNNE) composed of three sub-models for ΔV, ΔSOC, and ΔT using SciKit-Learn MLPRegressor
- Independent training improves robustness and limits overfitting across temperatures and C-rates using mean squared error as the loss function
- ReLU-activated multilayer perceptrons (4×20 for voltage, 3×[10-10-9] for temperature, linear for SOC) optimized using Adam
- Provides a lightweight, data-driven framework that captures nonlinear electro-thermal behavior.



Model Implementation

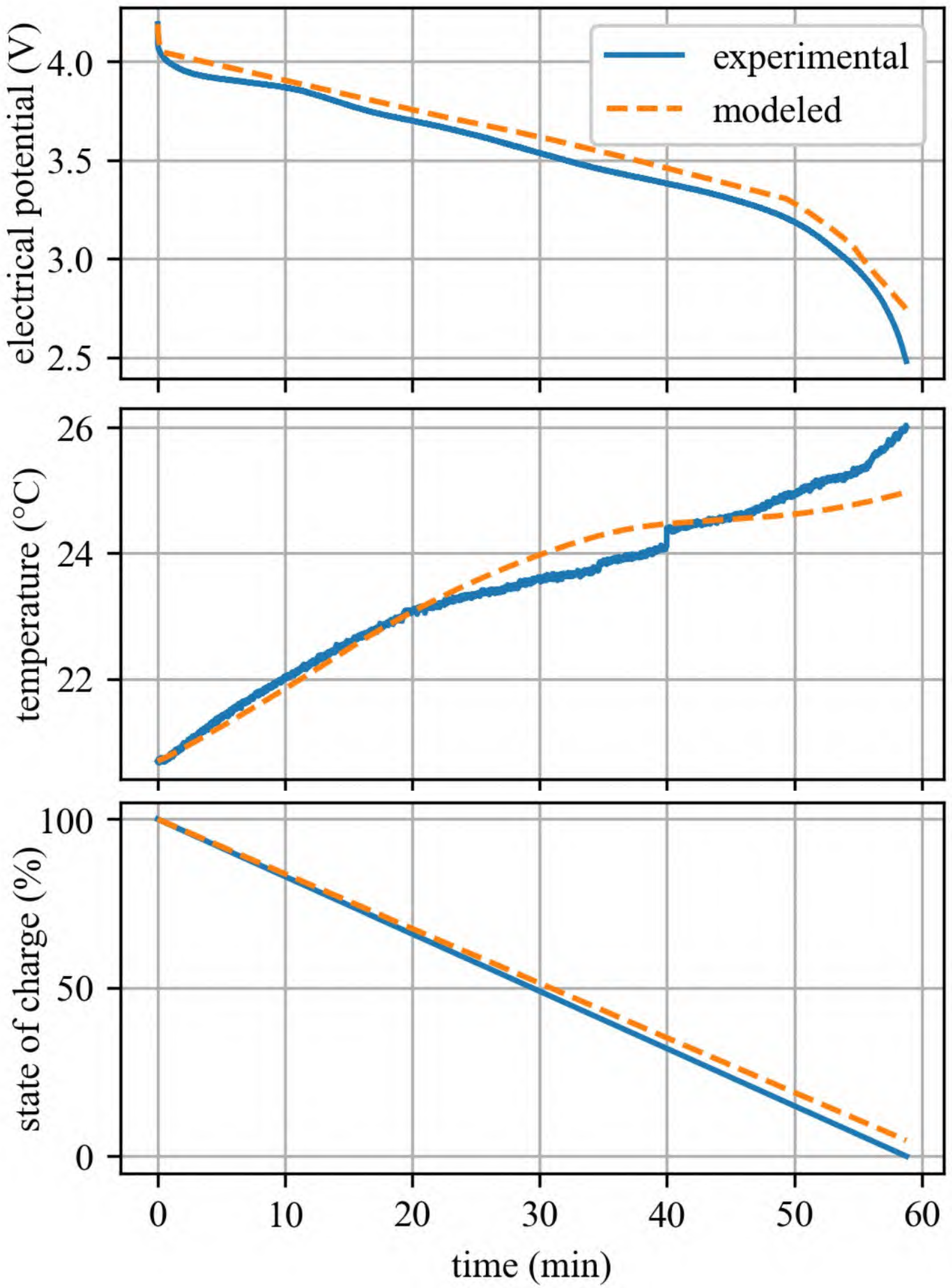
- Inputs per time step:
  - Applied current (I_i)
  - Previous voltage (V_{i-1}), SOC (SOC_{i-1}), temperature (T_{i-1})
- Ensemble inference:
  - Sub-models (neural networks) independently output predicted ΔV_i, ΔSOC_i, ΔT_i
- State update equation: $x_i = x_{i-1} + k(\Delta x_i)$

where k linearly scales predictions to actual time step



Results

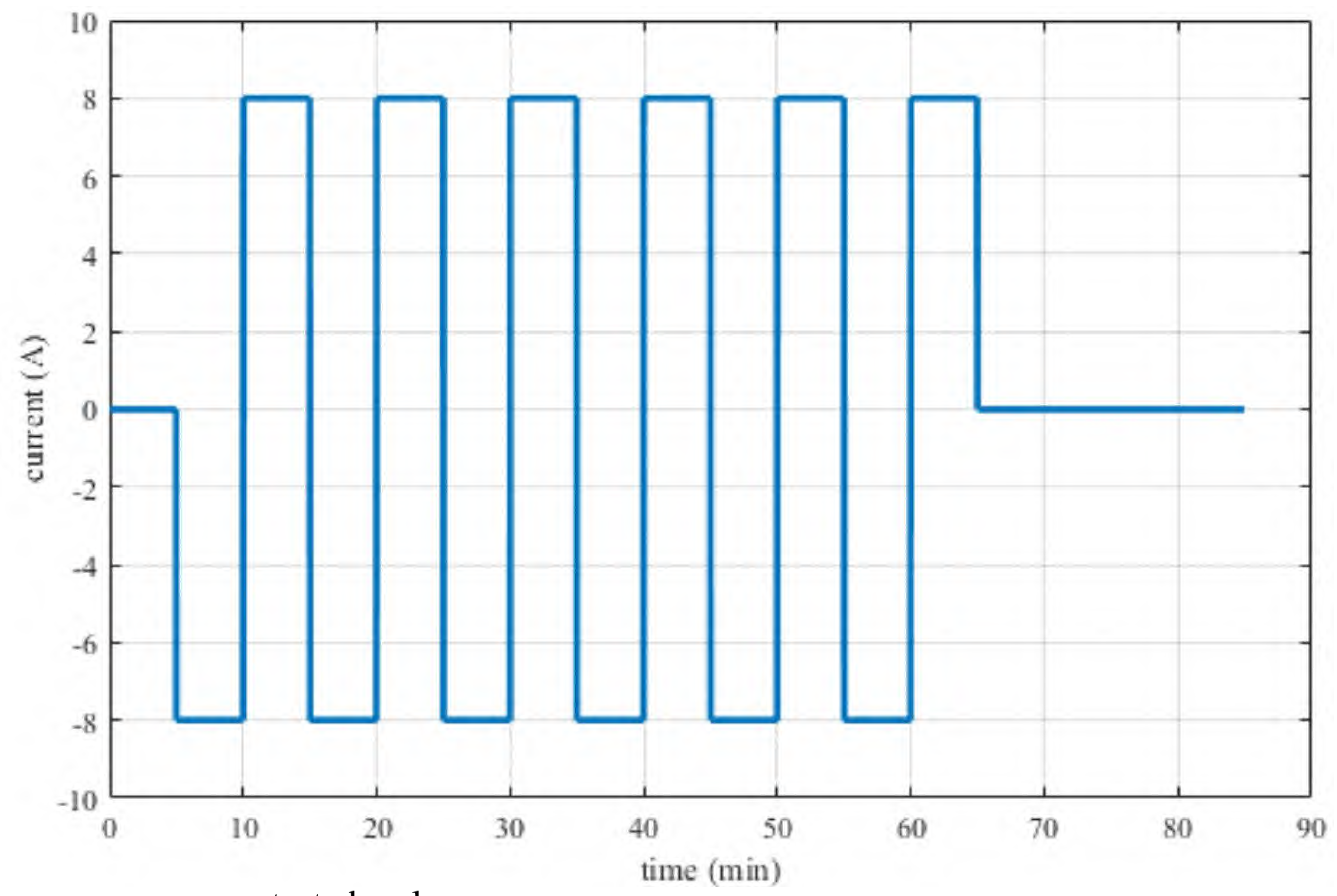
- Under constant current 1C discharge the model reproduces both electrical and thermal nonlinearities
- Noise filtering (windowing) likely contributes to disagreement in temperature prediction
  - Measurement error can be observed causing two jumps in temperature
- Nominal capacity assumption introduces SOC bias
  - SOC bias propagates to error in voltage and temperature

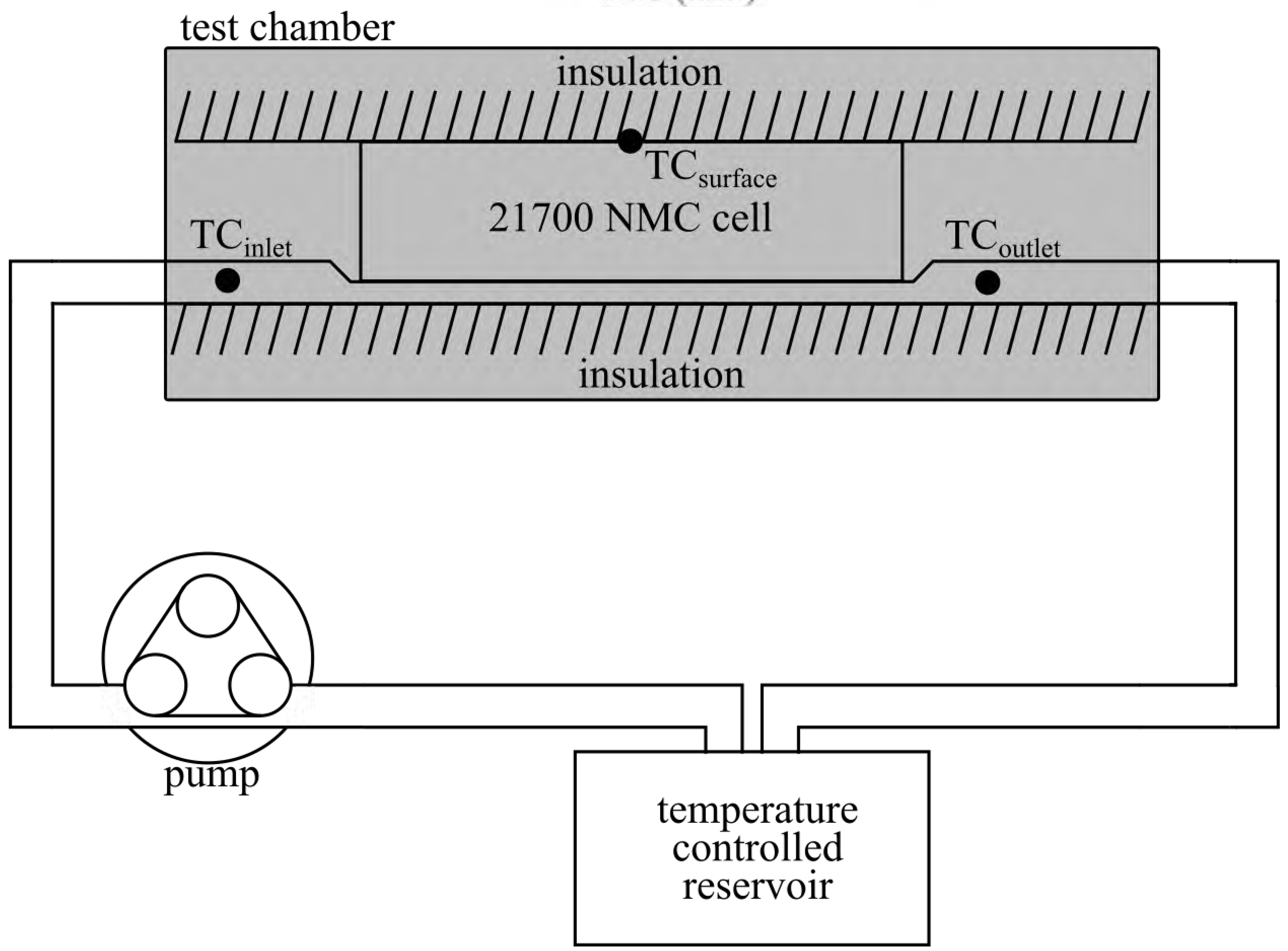


Metric	Average Error
electrical potential	0.07 V
state of charge	2.35 %
temperature	0.25 °C

Battery Thermal Testbed

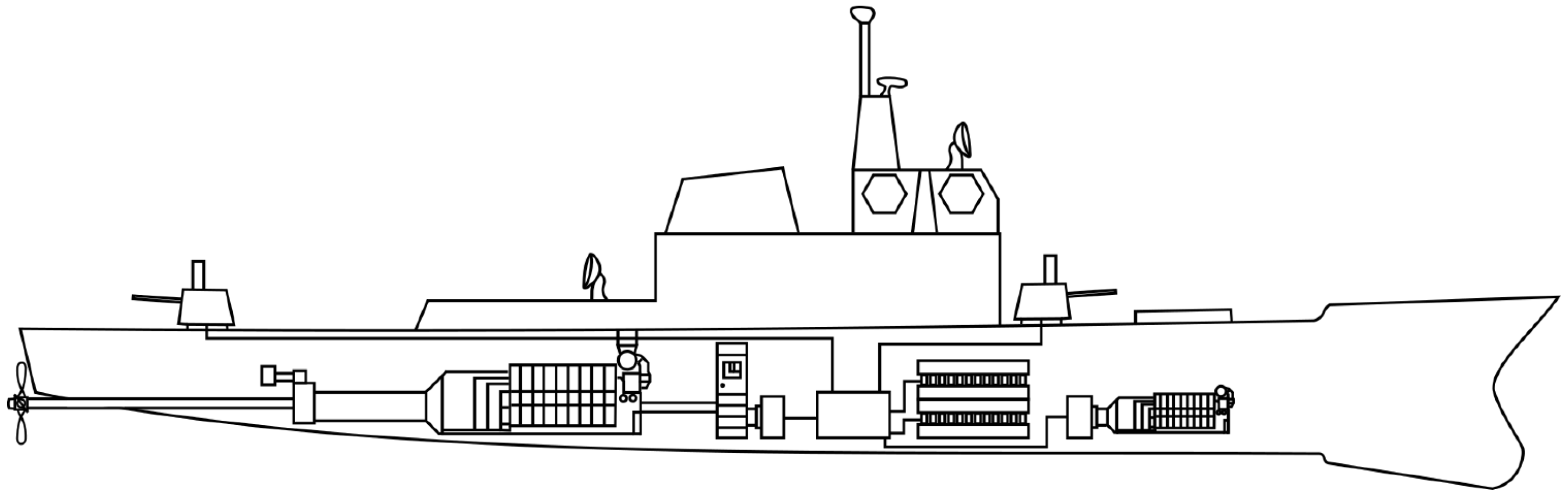
- To improve temperature prediction, a thermally focused test setup is necessary
- Temperature evolves much slower across a load than voltage response
    - a more suitable load profile will be used to collect thermal training data
    - Constant current discharging around each desired state of charge until oscillating around a steady state
- The new thermal testbed is liquid cooled, which is likely the case for any large pack that would be on a ship
    - Previously natural convection in a thermal chamber drove heat transfer





Conclusion and Future Work

- Neural Network Ensemble captures nonlinear behavior in electrical and thermal responses
- A liquid cooled single cell test setup has been developed and a lower rate load profile is being explored for higher quality thermal training data
- Deployment of the developed models onto hardware will be pursued
- Physics constrained machine learning models are being developed by training to predict parameters of physics-based equations



Acknowledgement

This work was supported by the Office of Naval Research under contracts N00014-22-C-1003, N00014-23-C-1012,and N00014-24-C-1301. The views expressed are those of the author and do not reflect the official policy or position of the Department of War or the U.S. Government.

Thank you!

Austin RJ Downey

austindowney@sc.edu