Supervised Learning for Electro-thermal Lithium-ion Battery Modeling via Hybrid Pulse Power Characterization

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

[1]University of South Carolina, Department of Mechanical Engineering, Columbia, SC
[2]University of South Carolina, Department of Civil and Environmental Engineering, Columbia, SC
[3]University of South Carolina, Department of Electrical Engineering, Columbia, SC

Introduction

- Accurate modeling of lithium-ion batteries is critical for energy storage systems in dynamic applications like shipboard power, where fluctuations degrade system performance
- Traditional physics-based models are often computationally expensive to deploy and require detailed electrochemical knowledge to parameterize
- This work employs a deep neural network ensemble (DNNE) trained on HPPC data for fast, low cost, predictive modeling

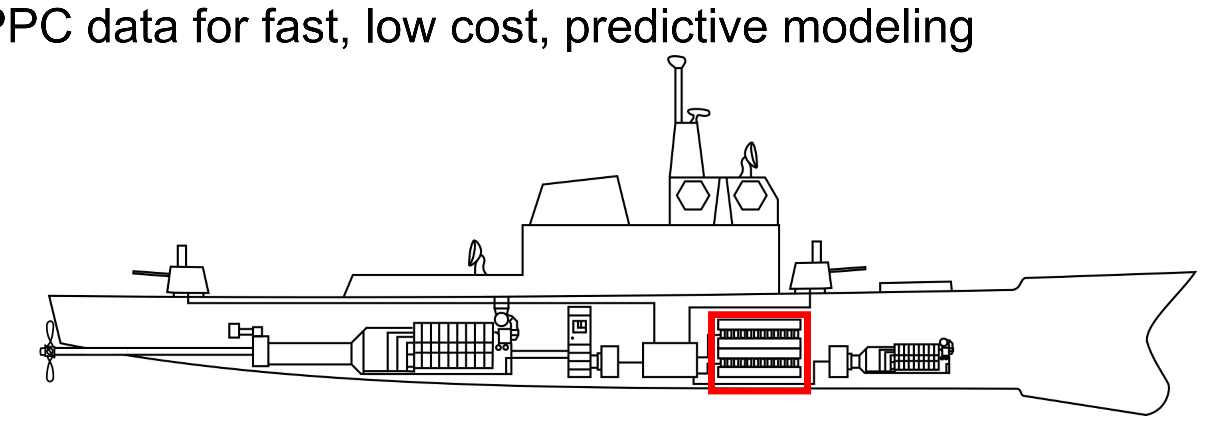
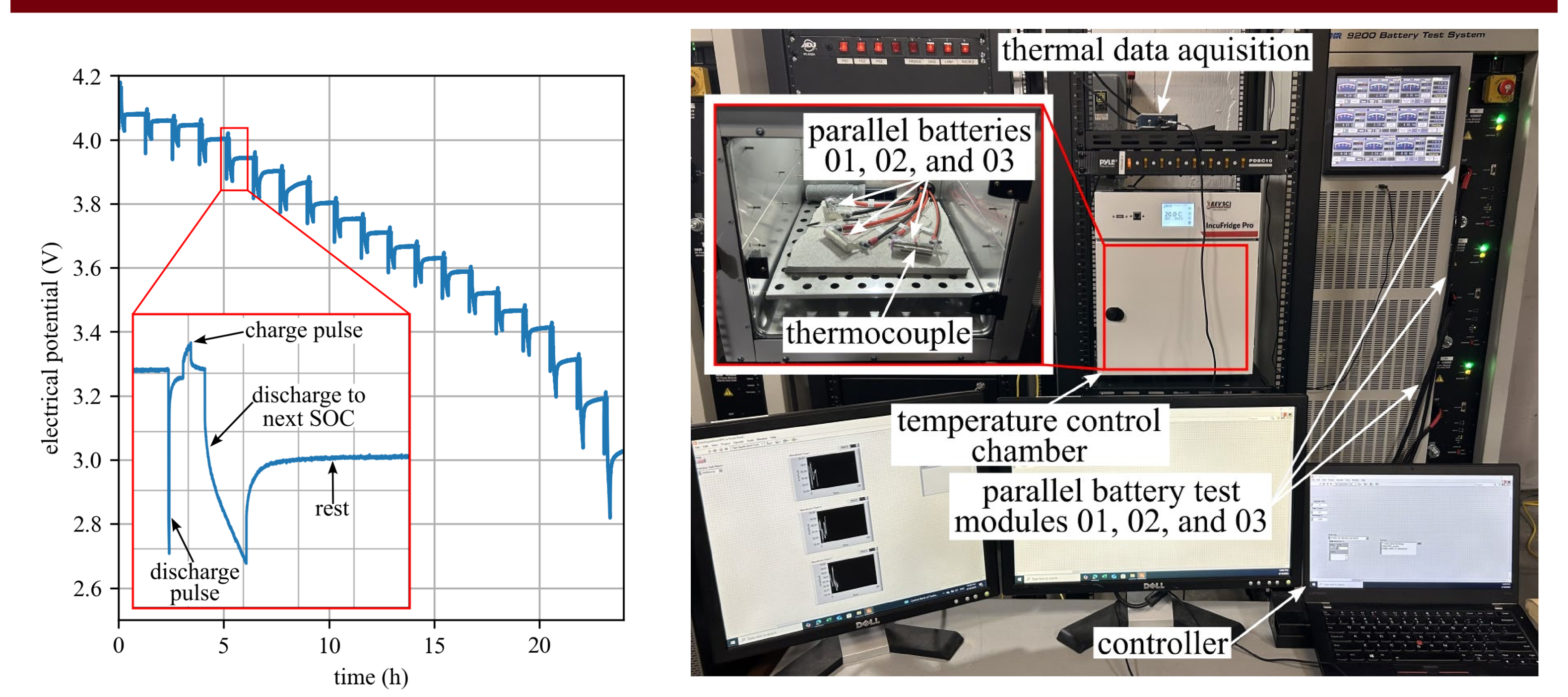


Diagram of a hybrid shipboard microgrid highlighting the battery energy storage

Data Collection



The voltage throughout an HPPC protocol (left) and the test setup used (right)

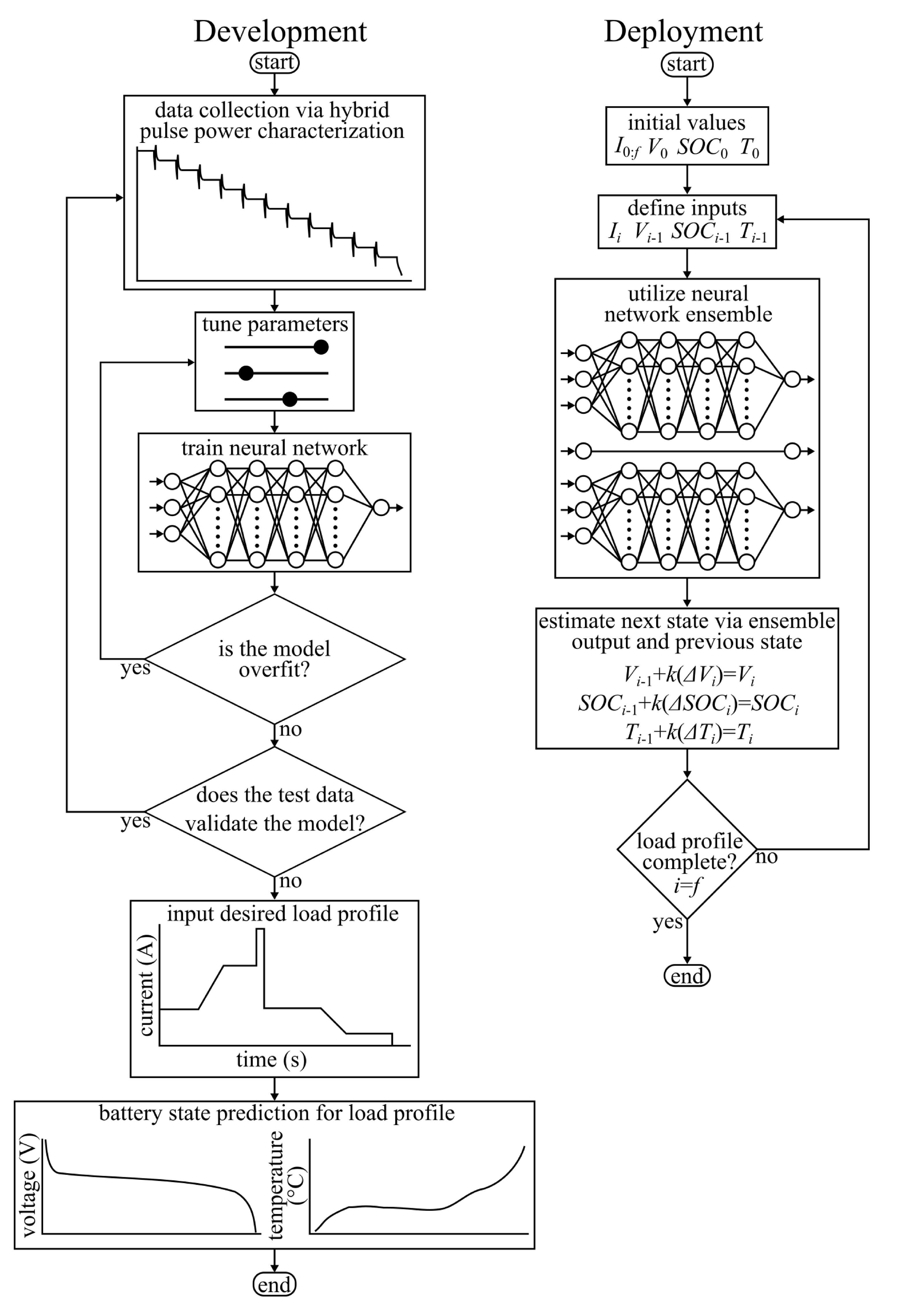
- Data is trained on HPPC at 5% SOC steps from 100-0% to capture dynamic behavior necessary for pulse load emulation
- Each HPPC protocol is run on three different batteries at three C-rates and three temperatures for operational variability
- Tests are conducted in Incufridge Pro temperature control chambers using NHR 9200 battery testers
- Data is collected at 1 Hz then averaged at 0.1 Hz to filter noise

HPPC data set distribution			
	discharge pulse rate		
T_{amb}	C/2	1C	2C
20°C	3 tests	3 tests	3 tests
30°C	3 tests	3 tests	3 tests
40°C	3 tests	3 tests	3 tests

Distribution of the hybrid pulse power characterization tests conducted at each rate and temperature to build the training dataset

Neural Network Development

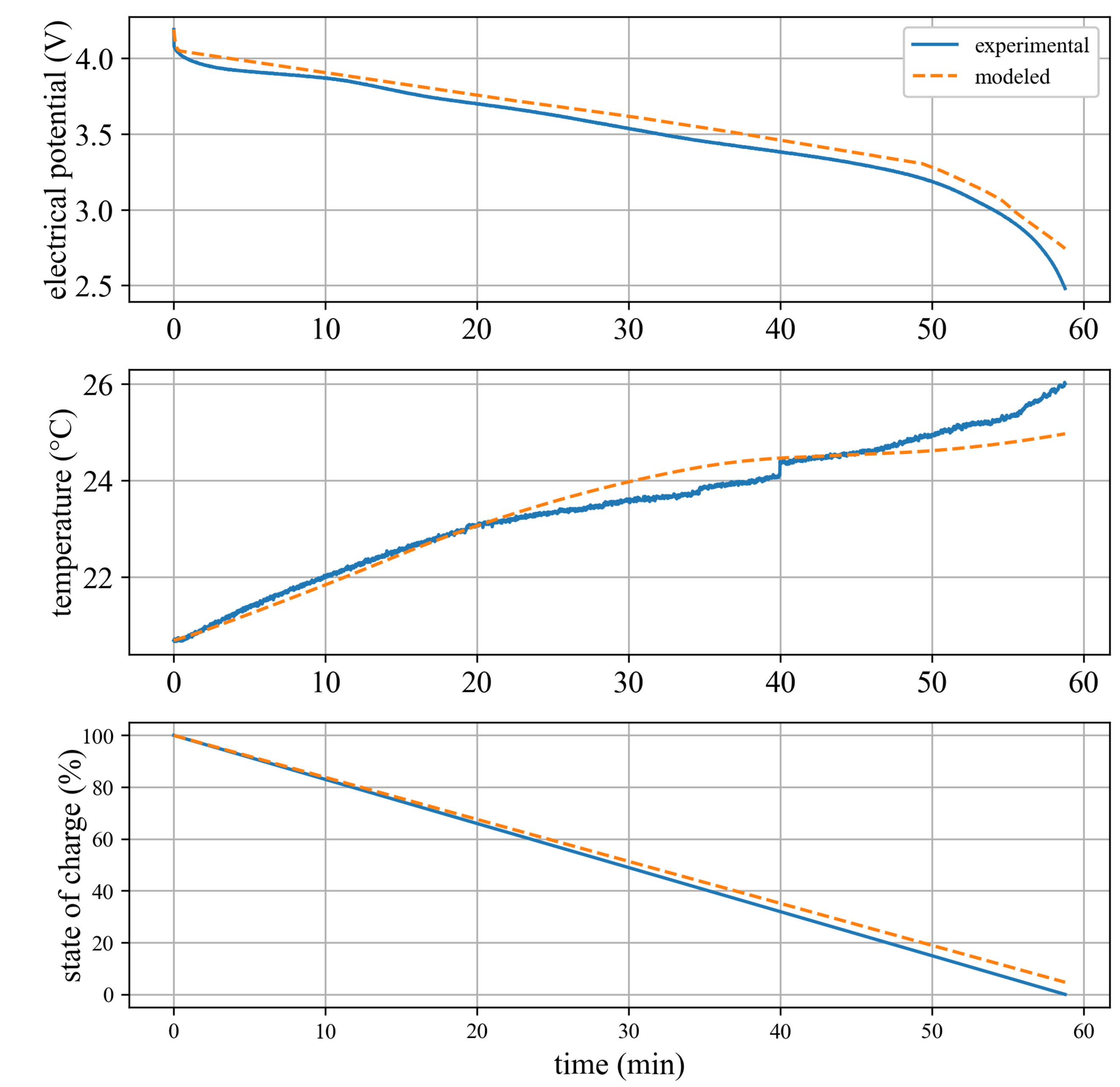
- Predicts battery behavior over 10 second intervals using prior state and input to estimate the next output
- A scaling factor k adapts to time steps as output is fed back into input for continuous simulation across a load profile
- Three separate submodels – for voltage, temperature and SOC – are combined to predict behavior in multiple domains



The process pipeline to develop a and train a neural network ensemble based on HPPC data (left) and the iterative loop to predict battery behavior using the model (right)

Results

- The model's predictions for voltage, temperature, and SOC during a 1C discharge closely match experimental results, with average absolute errors of 0.07 V, 0.25 °C, 2.35% respectively
- The DNNE successfully replicates key nonlinear behaviors such as rapid voltage drops at the start and end of the discharge cycle, and accelerated heating at low SOC due to higher DC internal resistance and entropic effects



The results for a 1C constant current discharge displaying the voltage (top), temperature (middle), and state of charge (bottom), comparing the model to experimental data

- This framework provides a low computation alternative to physics-based models, enabling accessible electrothermal emulation for optimal energy system design
- Future work will focus on online learning for continuous model adaptation, improved architecture turning, and expanded training datasets to improve model generalizability

Data

ARTS-Lab, "Dataset Electrothermal Deformation Characterization for Samsung 30Q Cell," GitHub repository, 2024. [Online]. Available: https://github.com/ARTS-Laboratory/dataset-electrothermal-deformation-characterization-for-samsung-30Q-cell.

This work was supported by the Office of Naval Research under contract NOs. N00014-23-C-1012, and N00014-24-C-1301. The support of the ONR is gratefully acknowledged. The views expressed are those of the authors and do not reflect the official policy or position of the Department of Defense or the U.S. Government.

UNIVERSITY OF South Carolina