

OPTIMAL ENERGY UTILIZATION OF GRID ENERGY STORAGE SYSTEMS

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Background and Objectives

PROJECT PROFILE

Topic: Power Electronics
Vertical: Safety & Reliability
Strategic Pathway: Optimize
Project Duration: FY25-FY26

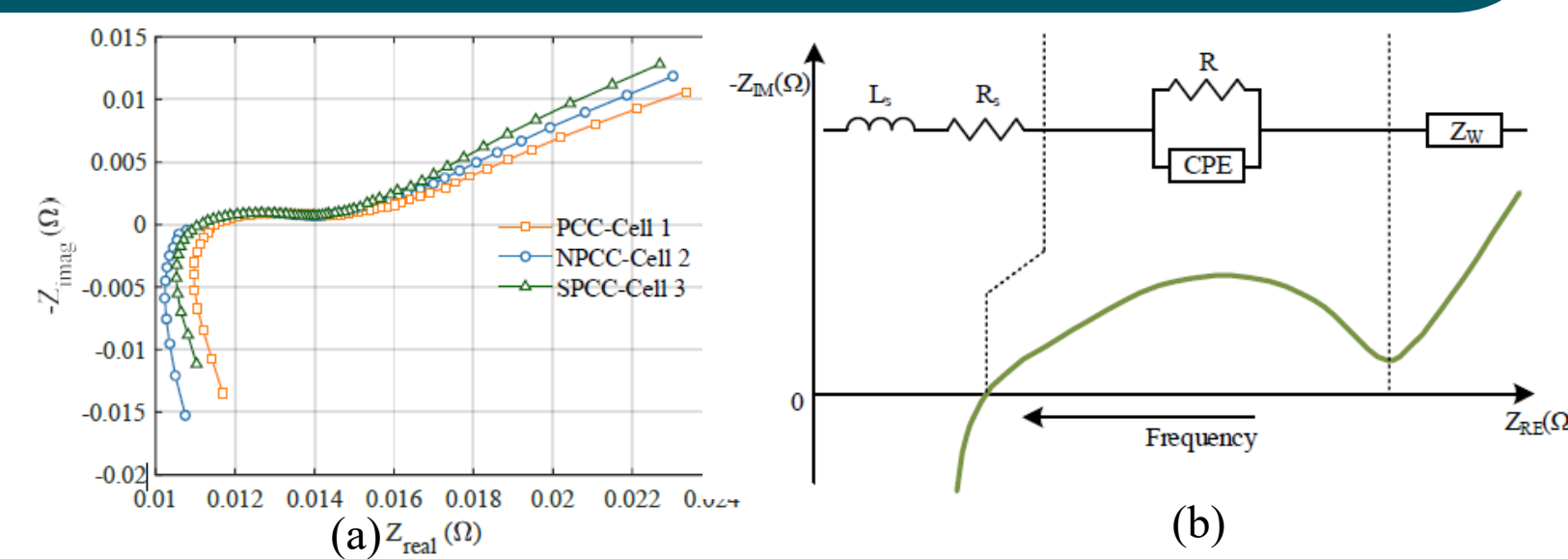
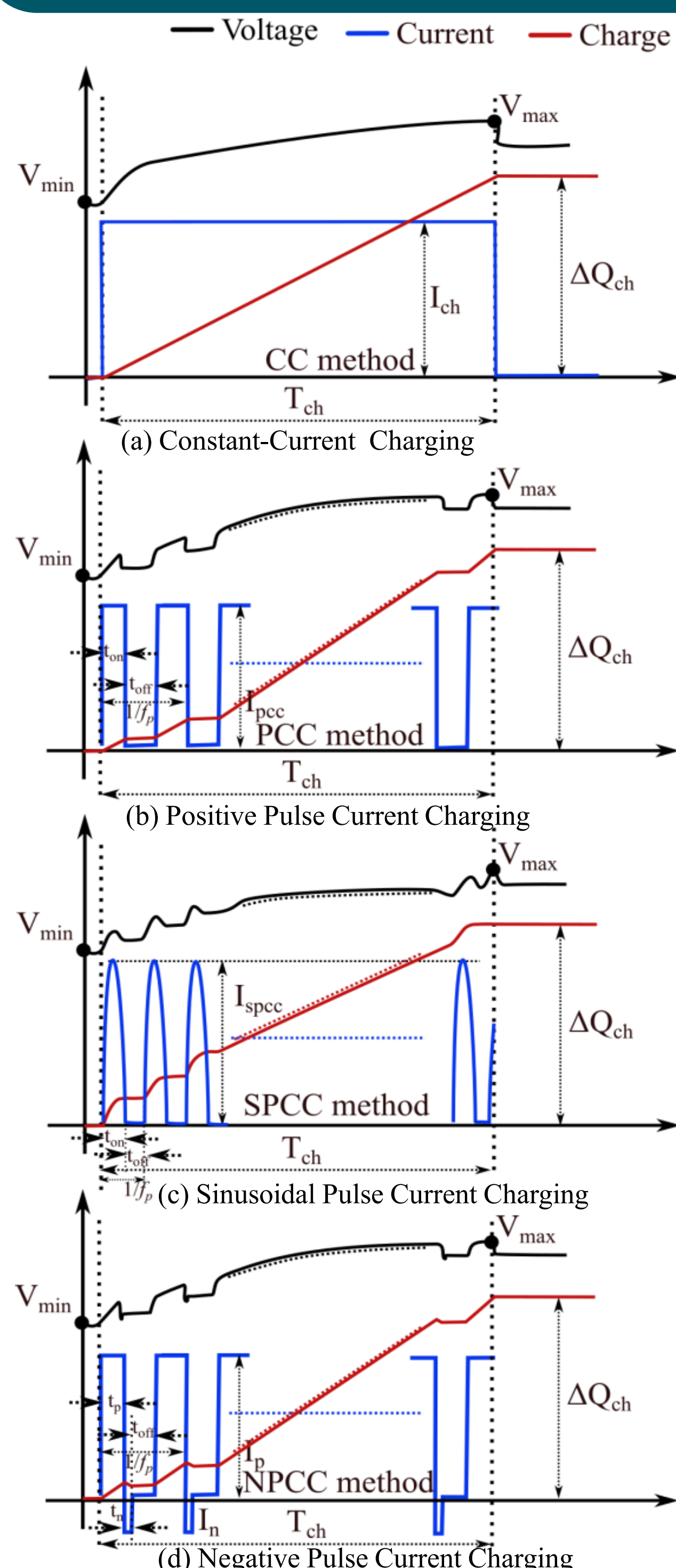


Fig. 1. (a) Protocol-dependent impedance variation under pulsed-charging aging motivates robust SOH estimation. (b) ECM model (Equivalent Circuit Model)

- High C-rate and pulsed charging can accelerate Li-ion battery degradation, causing capacity fade, impedance growth, and reduced State of Health (SOH). Reliable SOH estimation is important for long-life grid-integrated Battery Energy Storage Systems (BESS).
- The key problem is protocol-dependent impedance variation: pulsed-charging waveforms introduce transient polarization and relaxation effects, so batteries with similar aging levels can show different Electrochemical Impedance Spectroscopy (EIS) responses. This reduces the reliability of conventional EIS-based SOH estimation.
- The problem is difficult because EIS depends on both State of Charge (SOC) and SOH. Different frequency regions contain different aging information, and purely data-driven models may overfit one charging protocol and fail when the waveform changes.
- Current practice uses offline capacity tests, EIS measurements, equivalent-circuit models, and data-driven estimators, but these methods can require long relaxation time, interrupt operation, or lack robustness under dynamic pulsed-charging conditions.
- Objective: Develop a degradation-aware energy utilization framework for grid energy storage systems by combining physics-aware machine-learning-based State of Health estimation, optimized terminal-voltage constraints, and future power-converter-based charging control to improve battery lifetime, reliability, and system performance.

Charging Protocols and Methodology



- Evaluate charging waveforms: Compare Constant Current Charging (CC), Positive Pulsed Current Charging (PCC), Negative Pulsed Current Charging (NPCC), Sinusoidal Pulsed Current Charging (SPCC), and High-Frequency PCC (HFPCC) to study waveform-dependent battery aging.
- Use multi-chemistry battery data (NCA, NMC)
- Extract degradation features: Use capacity measurements and EIS to identify impedance features linked to SOH, impedance growth, and capacity fade.
- Develop physics-aware ML model: Integrate equivalent-circuit-model behavior with machine learning to estimate SOH under pulsed-charging conditions and reduce protocol-dependent error.
- Support practical SOH estimation: Use two estimation modes: EIS + SOC when SOC is available and EIS-only when SOC is unavailable.
- Enable converter implementation: Bidirectional BESS converter topologies for implementing degradation-aware charging control.
- Leverage unique lab capabilities: Use Arbin battery cycling, Gamry EIS measurement (cell- and pack level), Typhoon Hardware In loop (HIL) testing, Digital Signal Processing (DSP)-based embedded validation.

Fig. 2. Charging waveforms used to evaluate degradation under constant-current and pulsed-charging conditions

Protocol-Robust SOH Estimation

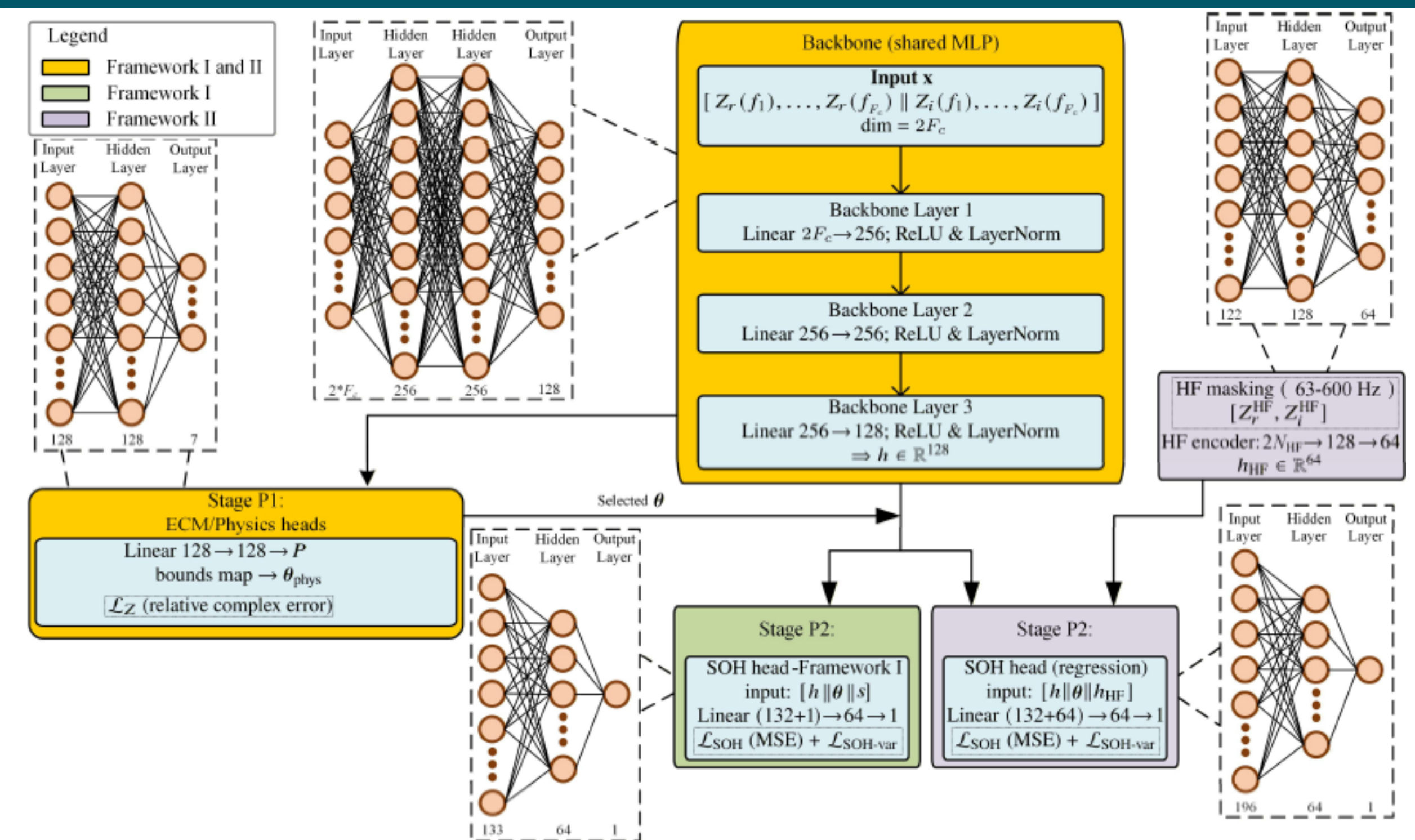


Fig. 3. Physics-aware ML framework for EIS + SOC and EIS-only SOH estimation.

- Figure 3 shows the proposed physics-aware machine-learning framework for battery SOH estimation. The model combines EIS features with equivalent-circuit-model-based physical constraints to improve robustness under pulsed-charging aging.
- The framework supports two practical SOH estimation cases: Case 1: EIS + SOC input when SOC information is available. Case 2: EIS-only input when SOC information is unavailable.
- Figure 4 illustrates the experimental platforms used for online implementation and edge deployment.

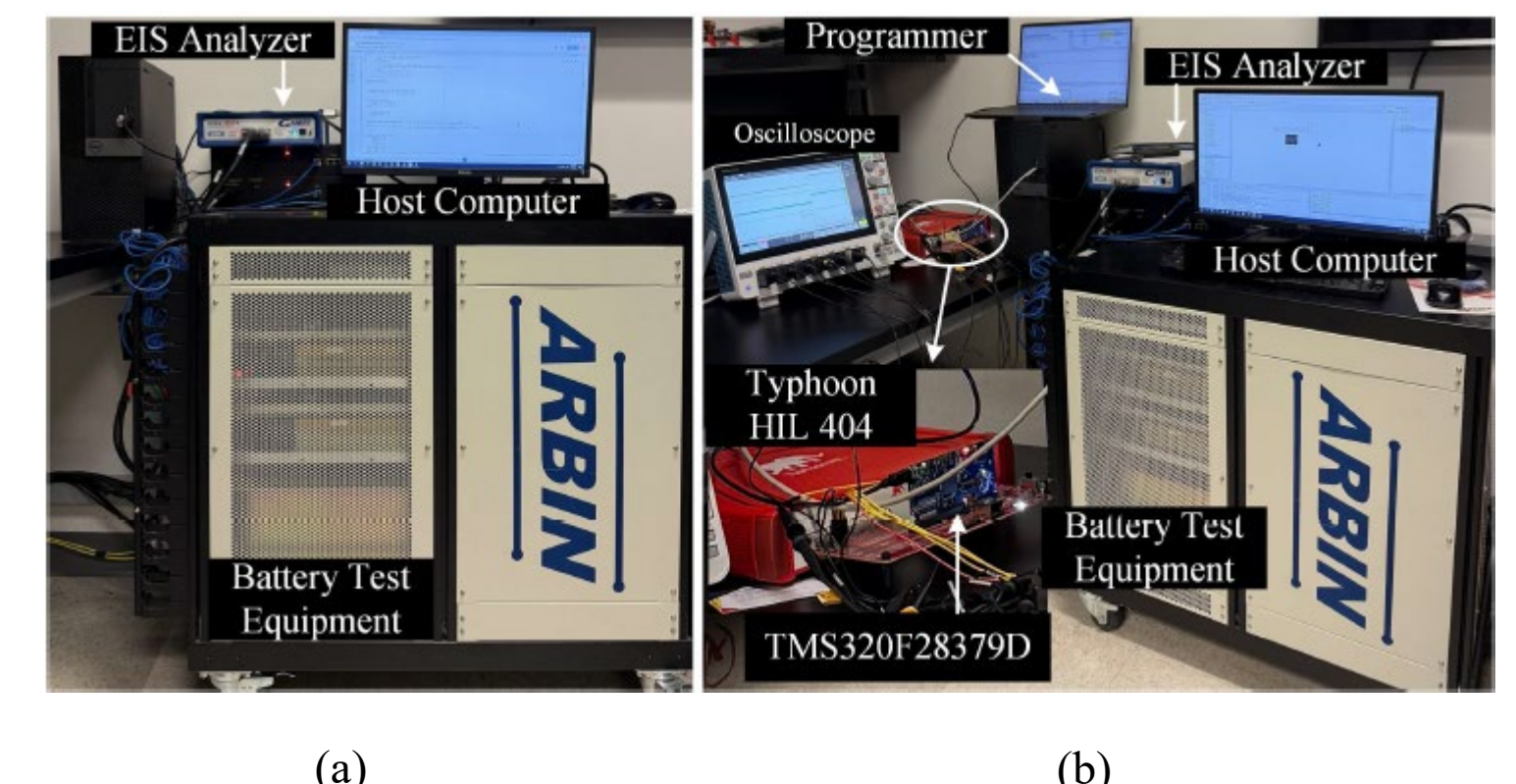


Fig. 4. (a) Experiment setup for online implementation. (b) Experiment setup for edge deployment.

- Figure 5 presents SOH estimation results on the test cell over 1000 aging cycles.
- Figure 6 shows online SOH estimation results using additional cells connected to the Arbin-Gamry platform. The results validate that the proposed model maintains reliable prediction performance under practical experimental conditions.

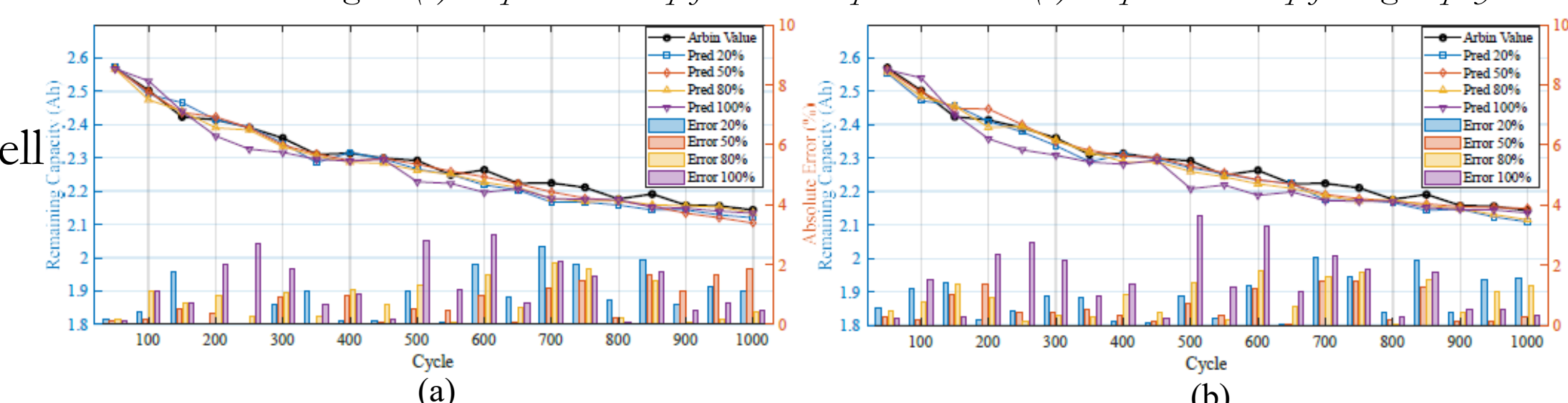


Fig. 5. SOH estimation results on test cell. (a) Framework I. (b) Framework II.

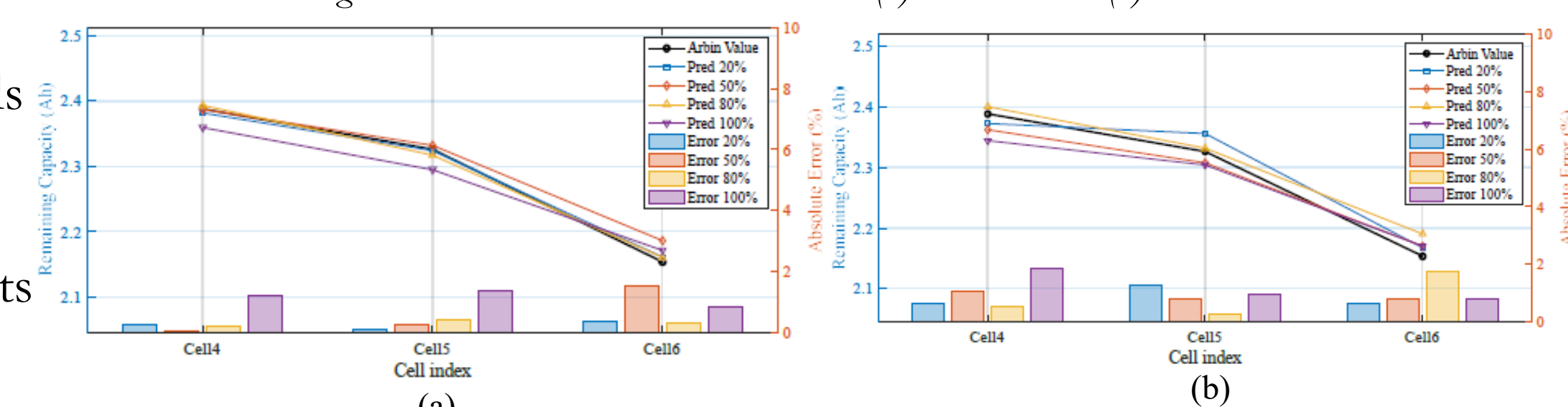


Fig. 6. SOH estimation results of online implementation. (a) Framework I. (b) Framework II.

TABLE 1: PERFORMANCE COMPARISON

Method	MAPE	RMSE	R2
Proposed Framework I	0.94%	0.0268	0.9443
Proposed Framework II	0.96%	0.0270	0.9403

Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), Coefficient of Determination (R^2)

Conclusions and Future Work

- The physics-aware ML framework accurately estimates battery SOH. Framework I and Framework II achieved **0.94%** and **0.96%** MAPE. DSP deployment achieved **1.2 ms** inference time for embedded BMS implementation.
- BESS operators, battery management system developers, and power-converter designers can use this framework to improve battery health tracking and degradation-aware charging control.
- This work enables future converter-integrated **in-situ EIS**, where the BESS power converter performs both charging control and impedance-based SOH monitoring without requiring a separate EIS instrument.