USING MACHINE LEARNING TO TRANSLATE IN-SITU BATTERY MEASUREMENTS TO OPTIMIZE BATTERY PERFORMANCE

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Motivation

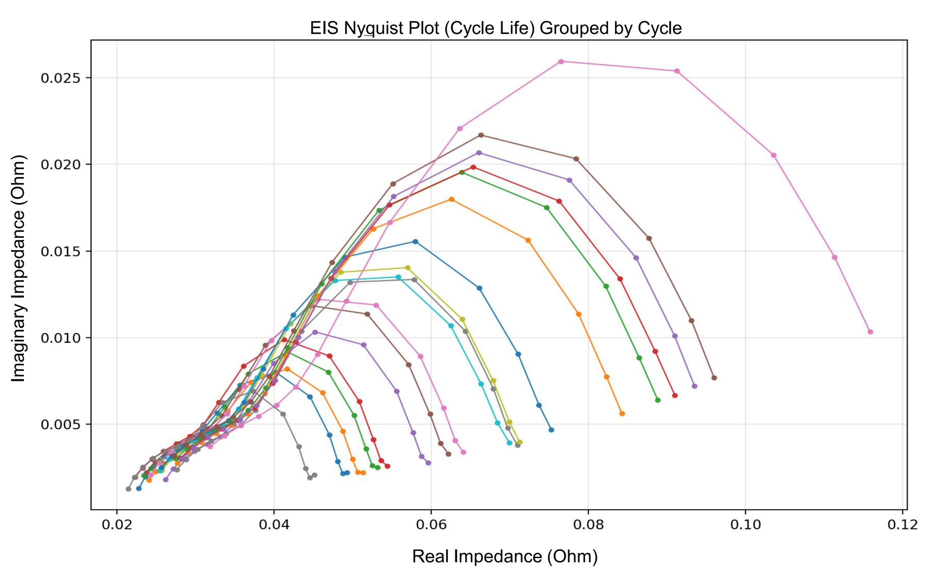
- **Battery swell**, the slight expansion of the battery due to internal battery chemistry and electrical characteristics, is a persistent issue within LCO batteries that current methods are unable to accurately predict on-device
- This project aims to develop a **machine-learning model** that can estimate battery swell with on-device resources, allowing optimization of the available battery energy within laptops and tablets. and enable strategies to mitigate battery swell with real-time battery swell prediction

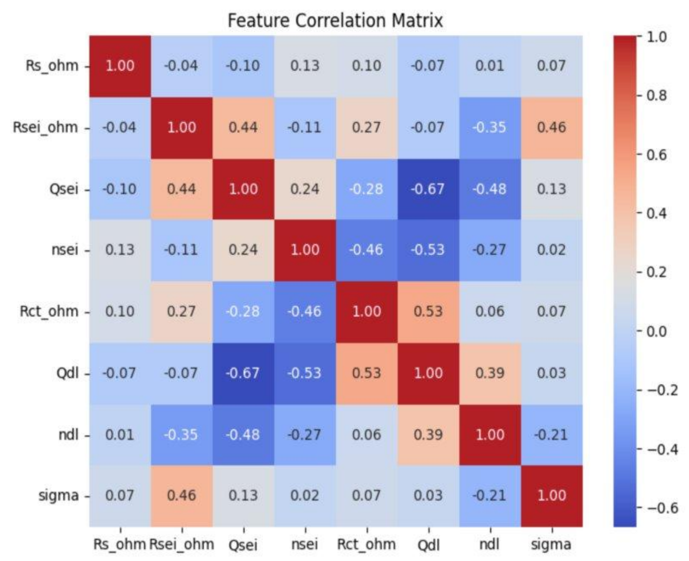
Requirements

- **Acquire battery telemetry data** with the existing battery gas gauge and embedded system interfaces with minimal hardware modifications
- Collect battery data from multiple devices and during various usage conditions to extract features related to battery degradation and obtain data for model training/testing/validation
- Predict swell with high accuracy on laboratory datasets **(target: MAE < 0.1)** covering solid, gaseous, and combined swelling mechanisms

Feature Engineering

- Analyzed **EIS (Electronic Impedance Spectroscopy)** parameters including resistance, sigma, and total resistance across multiple battery aging cycles
- EIS data yields Nyquist plots in frequency domain, captures a rich variety of internal battery processes
- Generated **feature-feature** and **feature-label** correlation analyses to evaluate relationships between impedance parameters and battery thickness growth.
- Performed **outlier filtering** using parameter threshold constraints to improve dataset consistency and model reliability.
- Investigated additional features including discharge capacity, OCV, ACIR, cycle count, and delta impedance trends for swell prediction modeling

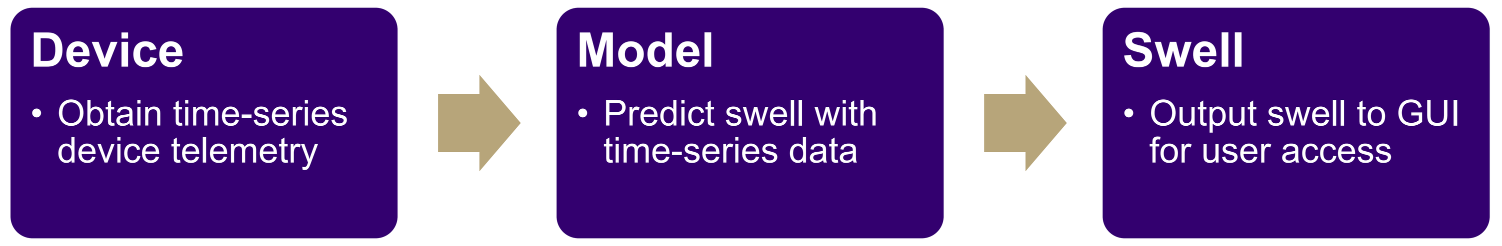




Machine Learning Models

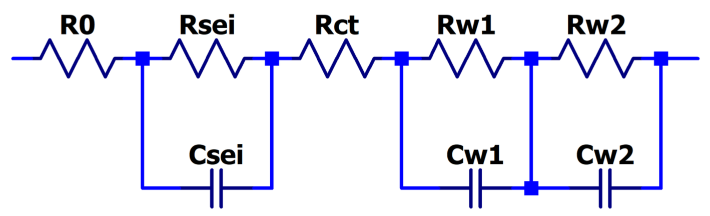
1-Stage Model

- Extracted features including resistance growth, diffusion behavior, and impedance evolution across aging cycles
- **Evaluated multiple regression approaches** including Ridge Regression, Random Forest, Gradient Boosting, and Neural Networks, with Gradient Boosting models having the most stable performance on the current dataset
- Compared model performance using RMSE, MAE, residual analysis, and pred. scatter plots.
- **Traditional machine learning models currently outperform sequence-based neural network** approaches due to dataset size limitations



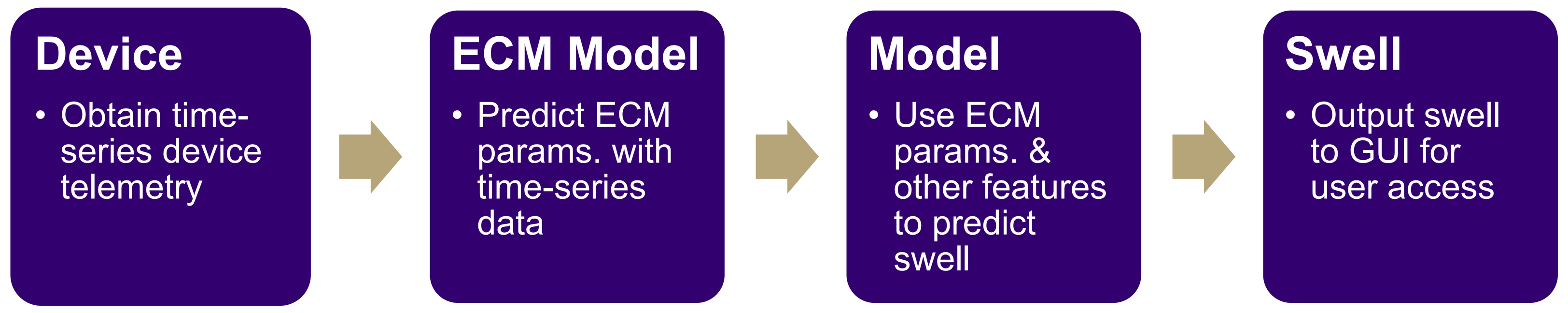
2-Stage Model

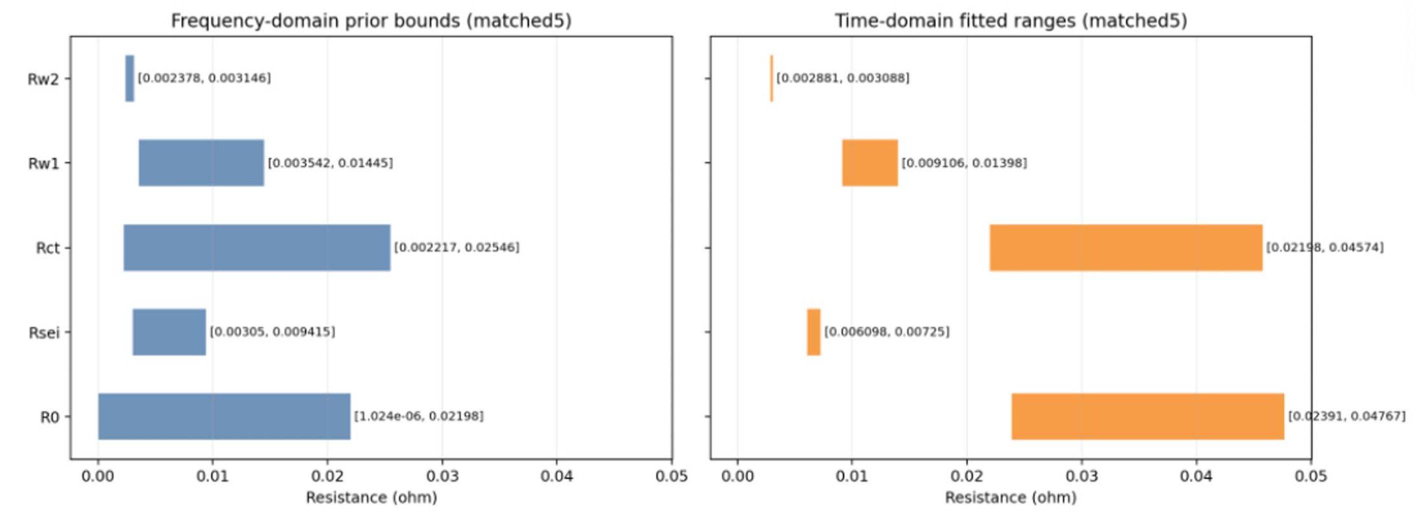
- **Equivalent Circuit Modeling (ECM)** uses circuit components to model battery behavior such as EIS from Nyquist plots in the frequency domain
- The 2-stage model uses ECM parameters to predict battery thickness growth and swelling behavior



- **R0** – Ohmic resistance
- **SEI** – SEI layer res./cap.
- **CT** – Charge transfer resistance
- **Warburg** – RC stages to approx. Warburg impedance

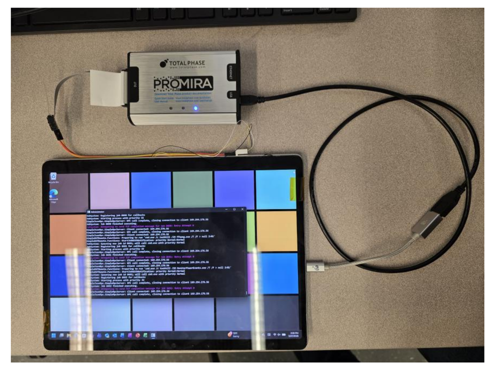
- Obtaining Nyquist plots on-device is difficult due to limitations with battery telemetry: lower frequency response for EIS Nyquist plots (only lower frequency diffusion tail available) and higher noise levels on-device than in lab
- Instead, ECM parameters are predicted using time-series device data and kept in bounds through analyzing frequency domain ECM parameters obtained from lab data

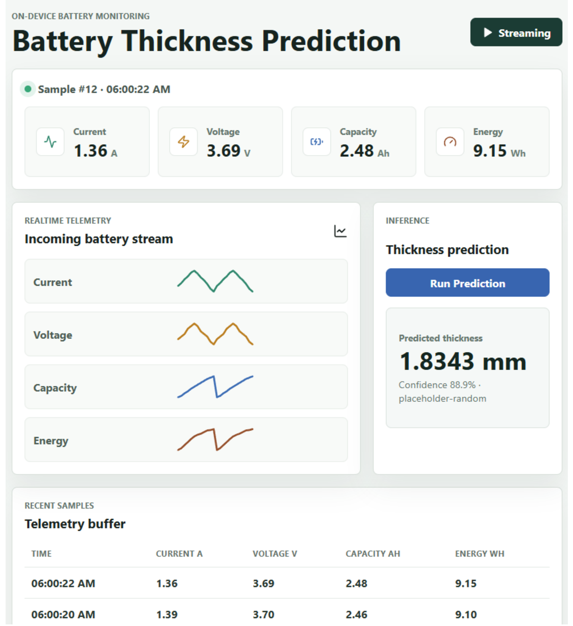




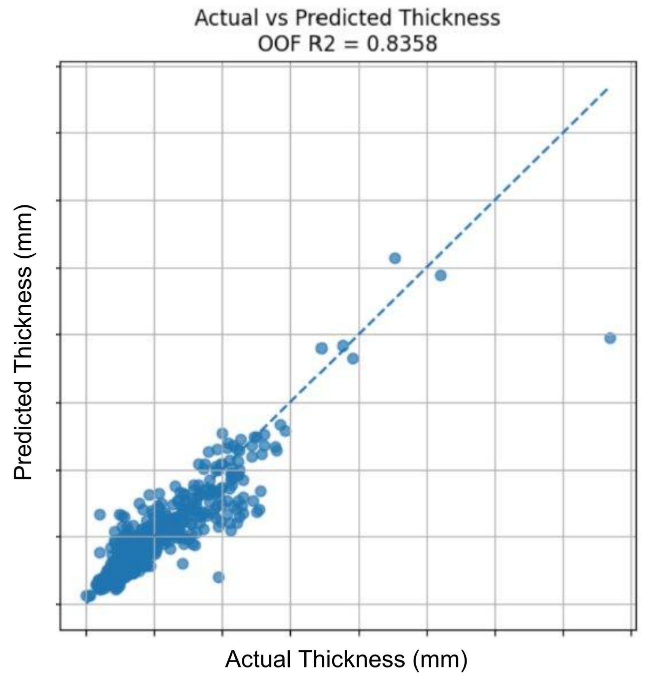
Integration

- Utilized **Microsoft Surface Pro 11 devices** with original batteries replaced with aged and intentionally swollen battery packs at controlled swell percentages from the lab
- Configured **Promira** (I2C master-slave emulator and analyzer) to communicate with the battery management system to read battery telemetry from devices through SMB/I2C
- Set up **HOBL** (Hours of Battery Life), Microsoft's internal automation and testing software, to simulate real-world user activity while continuously capturing battery telemetry through Promira
- **Automated data collection** with Python scripts to gather large volumes of data over extended durations and feed them into the models for battery swell prediction

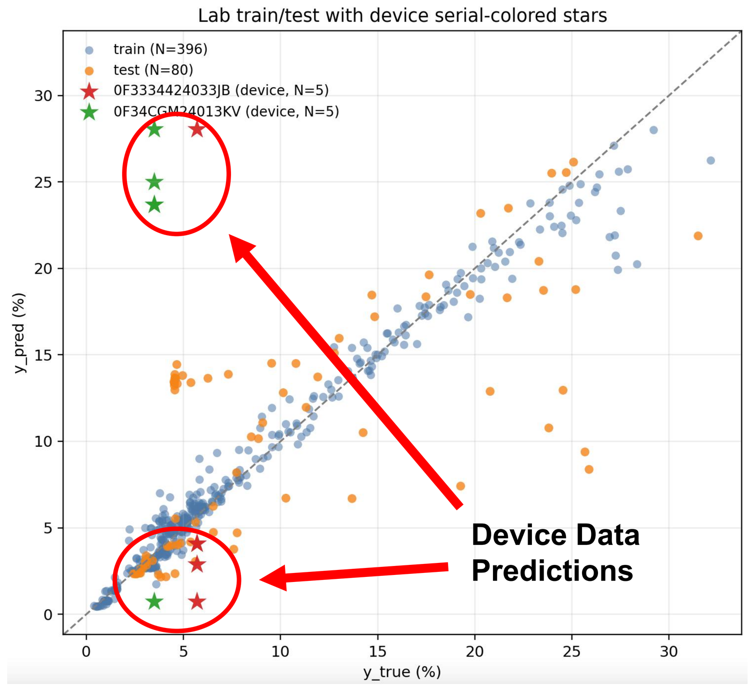




Results



Prediction Accuracy of 1-Stage Model with Lab Data



Prediction Accuracy of 2-Stage Model with Device Data

Future Work

- Further developing the GUI to include both models and enhanced data visualization
- Collecting device data under different charging conditions for more diverse datasets
- Create protocols that activate depending on the battery swell estimation to mitigate battery swell conditions on device

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