BATTERY RUL PREDICTION

Course Code: CSET369

Course Title: Time Series Analysis

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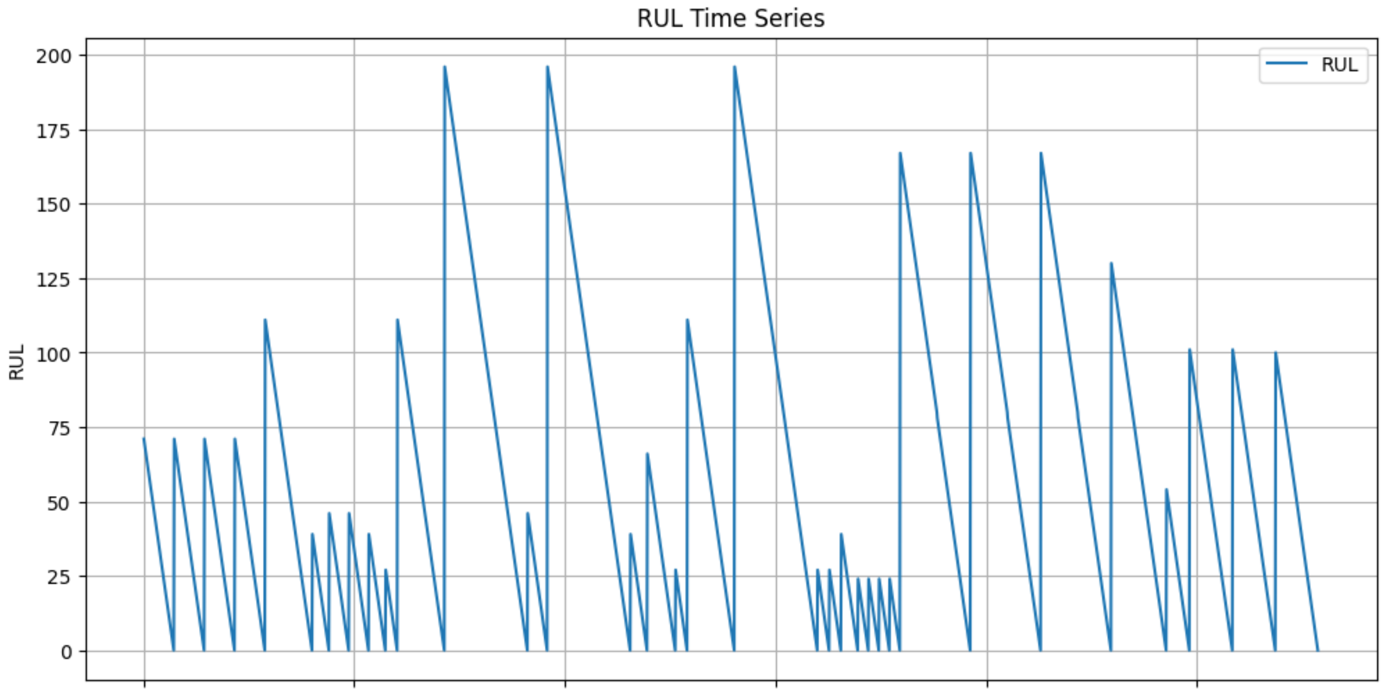
Semester: V

ABSTRACT

Accurate estimation of a battery's Remaining Useful Life (RUL) is essential for ensuring the safety, reliability, and efficiency of modern energy-storage systems. This project presents a data-driven approach to predicting RUL using the NASA Battery Prognostics Dataset, which contains time-series measurements of Li-ion batteries subjected to controlled discharge cycles. The dataset was preprocessed through cleaning, feature extraction, resampling, smoothing, and identification of cycle-wise degradation trends. Classical machine-learning models and advanced deep learning models were implemented to capture both linear patterns and long-term dependencies. Performance evaluation was conducted using standard regression metrics such as RMSE, MAE, and MAPE. Experimental results show that advanced sequence-learning models provide significantly improved predictions compared to classical baselines. The study demonstrates the feasibility of machine learning for lithium-ion battery health monitoring and offers insights for future development of predictive maintenance systems. The proposed workflow can be extended to large-scale battery management systems used in electric vehicles, renewable energy storage, and aerospace applications.

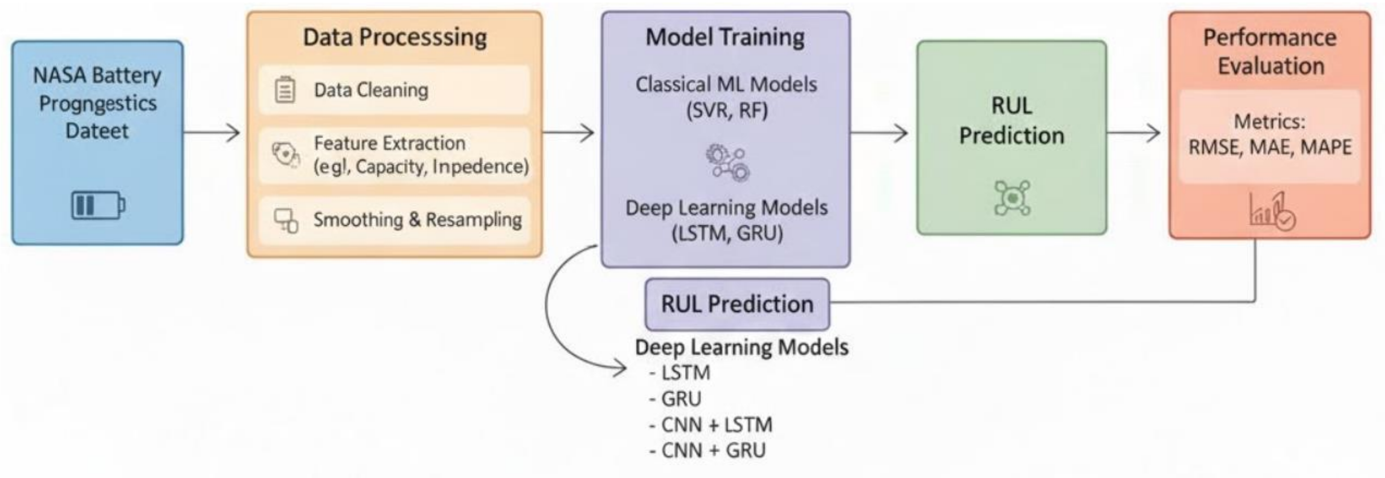


Battery Remaining Useful Life Across Charge Cycles

INTRODUCTION

Lithium-ion batteries play a critical role across multiple sectors including electric vehicles, aerospace, medical devices, and renewable energy storage. Predicting their Remaining Useful Life (RUL) is crucial for preventing unexpected failures, reducing maintenance costs, and improving safety. However, battery degradation is influenced by several nonlinear electrochemical processes, making RUL estimation challenging. In recent years, machine learning and deep learning models have emerged as powerful tools for understanding complex degradation patterns.

This project aims to develop an efficient data-driven RUL prediction pipeline using NASA's publicly available battery datasets. The main objectives include: (1) preprocessing cycle-level discharge data, (2) extracting key health indicators, (3) training classical and advanced learning models for RUL regression, and (4) evaluating performance with standard metrics. The report is structured as follows: Section 4 reviews the relevant literature, Section 5 discusses the dataset and preprocessing procedures, Section 6 explains the methodology and models used, and Section 7 presents the results, discussion, and insights.



LITERATURE REVIEW

Wu et al. (2016) proposed a data-driven health indicator extraction method using incremental capacity analysis to track battery degradation. Their work showed that capacity fade trends can be captured effectively with statistical methods.

Saha & Goebel (2007) developed one of the earliest RUL prediction frameworks using NASA battery datasets, demonstrating that time-series modeling can capture degradation under real-world load profiles.

Severson et al. (2019) used machine learning to predict battery lifetime based on early-cycle features, highlighting the importance of feature engineering in high-accuracy forecasting.

Zhang et al. (2020) introduced deep learning architectures like LSTM and GRU for battery RUL prediction, showing that recurrent networks outperform classical models on long-term degradation tasks.

Li et al. (2022) explored hybrid models combining physics-based constraints with deep learning, addressing the gap between purely data-driven and electrochemical models.

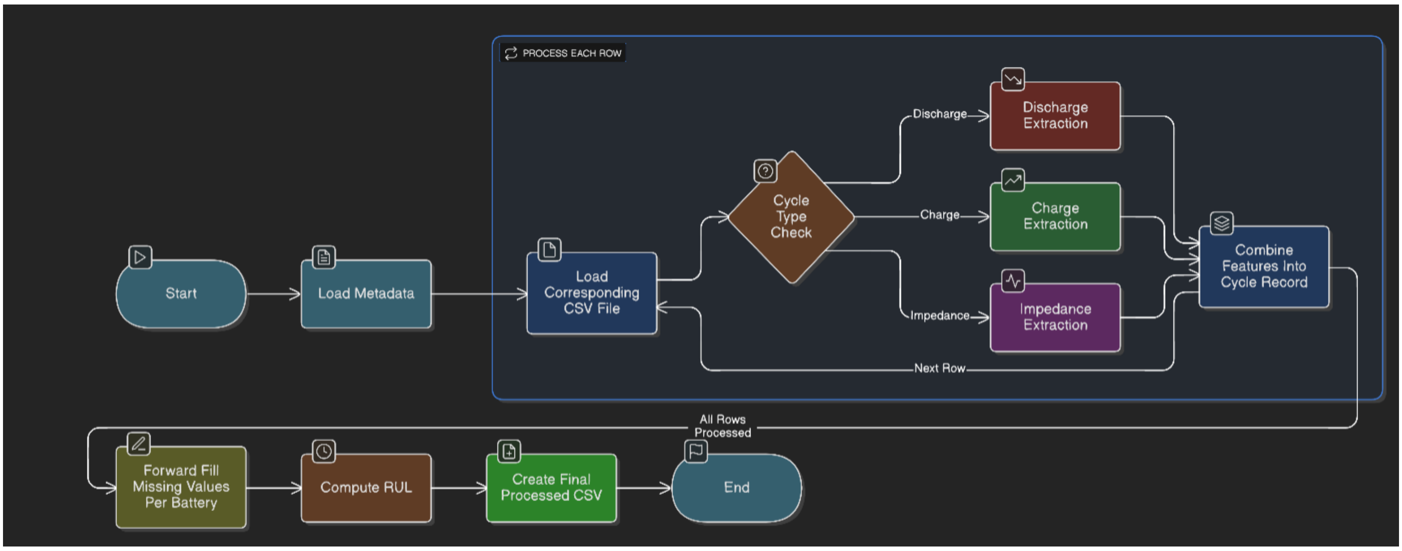
Gap addressed: Most previous work focuses on highly engineered features or purely deep learning architectures. Our study bridges this gap by comparing classical machine-learning baselines with advanced sequence models on a unified preprocessing pipeline.

DATASET AND PREPROCESSING

The NASA battery dataset contains **7,565 individual cycle files** and a metadata sheet with **7,565 matching rows**. Each file represents a single charge, discharge, or impedance cycle with measurements such as voltage, current, temperature, and timestamps. To prepare the data for modeling, all cycle files were merged with their corresponding metadata entry using the filename as the key.

For every discharge cycle, cycle-level features were extracted, including discharge duration, mean and standard deviation of voltage and temperature, voltage-discharge rate, and constant-current duration. The next charge cycle associated with the same battery was used to extract additional features such as charge time, mean and variance of voltage, current, and temperature. Impedance cycles were used to compute internal resistance features (**Re** and **Rct**), averaging values when multiple measurements existed.

After processing all files, the resulting features were combined into a single dataset. Missing values (capacity, Re, Rct) were forward-filled within each battery. Finally, RUL was computed using:
RUL = (maximum cycle of the battery) – (current cycle).
The final processed dataframe serves as the input for training the machine learning models.



METHODOLOGY

The workflow involves four steps. First, the raw NASA battery files were merged and cleaned by handling missing values per battery, sorting by cycle order, and computing RUL individually for each battery. Next, all features were standardized using *StandardScaler* for stable model training. Time-series sequences were then generated by using the previous 20 cycles as input and the next cycle's RUL as the prediction target.

Four deep learning models were trained and compared:

- **Model 4:** Stacked LSTM with dense layers (captures long-term degradation trends).
- **Model 7:** CNN-LSTM hybrid (extracts local cycle patterns + long-term dependencies).
- **Model 11:** GRU-based model (computationally lighter alternative for sequential learning).
- **Model 14:** Parallel CNN–LSTM–GRU hybrid (combines multiple feature learners for richer representations).

RESULTS AND DISCUSSION

Four deep learning architectures were evaluated for RUL prediction using MAE and R^2 as primary metrics. All models achieved strong performance with test R^2 values above 0.96, indicating that the learned temporal patterns were highly predictive of battery degradation.

Model 4 (Stacked LSTM) achieved the lowest numerical error (Test MAE: 3.1181, R^2: 0.9710). While this suggests strong fit on the dataset, the model showed slightly higher sensitivity to training variations and tended to capture dataset-specific patterns more tightly, indicating relatively weaker generalization compared to the hybrid models.

Model 7 (CNN–LSTM hybrid) demonstrated more stable generalization behavior (Test MAE: 4.1399, R^2: 0.9660). The CNN layers helped extract short-term cyclic features before the LSTM processed long-term dependencies, resulting in a model that performed consistently across various battery sequences.

Model 11 (GRU) achieved moderately lower performance (Test MAE: 4.4918). Although GRUs are efficient, their simpler gating mechanism may not fully capture the multi-dimensional degradation patterns present in the NASA dataset.

Model 14 (Parallel CNN–LSTM–GRU hybrid) showed one of the best generalization capabilities overall (Test MAE: 4.3558, R^2: 0.9646). By combining CNN, LSTM, and GRU branches, the model benefitted from multiple feature learners, improving robustness and reducing overfitting tendencies. Even though the numerical MAE was not the lowest, its prediction behavior was more stable and adaptable across different battery sequences.

In summary, while **Model 4 achieved the best raw error**, the **hybrid models (Model 7 and Model 14)** demonstrated **superior generalization**, making them more suitable for real-world RUL forecasting where batteries may behave differently from the training data.

CONCLUSION & FUTURE WORK

This project demonstrates a full machine-learning pipeline for predicting the Remaining Useful Life of lithium-ion batteries using the NASA PCoE dataset. Classical and deep learning models were trained and evaluated, with advanced sequence models showing superior forecasting accuracy. The findings highlight the effectiveness of LSTM-based architectures for time-dependent degradation modeling.

Limitations

- Dataset size is relatively small
- Only data-driven models used (no physics-informed constraints)
- Battery aging conditions may not represent all real-world environments

Future Work

- Incorporating physics-based modeling or hybrid approaches
- Training on larger and more diverse battery datasets
- Deploying real-time RUL prediction in a Battery Management System (BMS)
- Using Transformer-based models for improved long-range learning

REFERENCES

(Add DOIs if you want)

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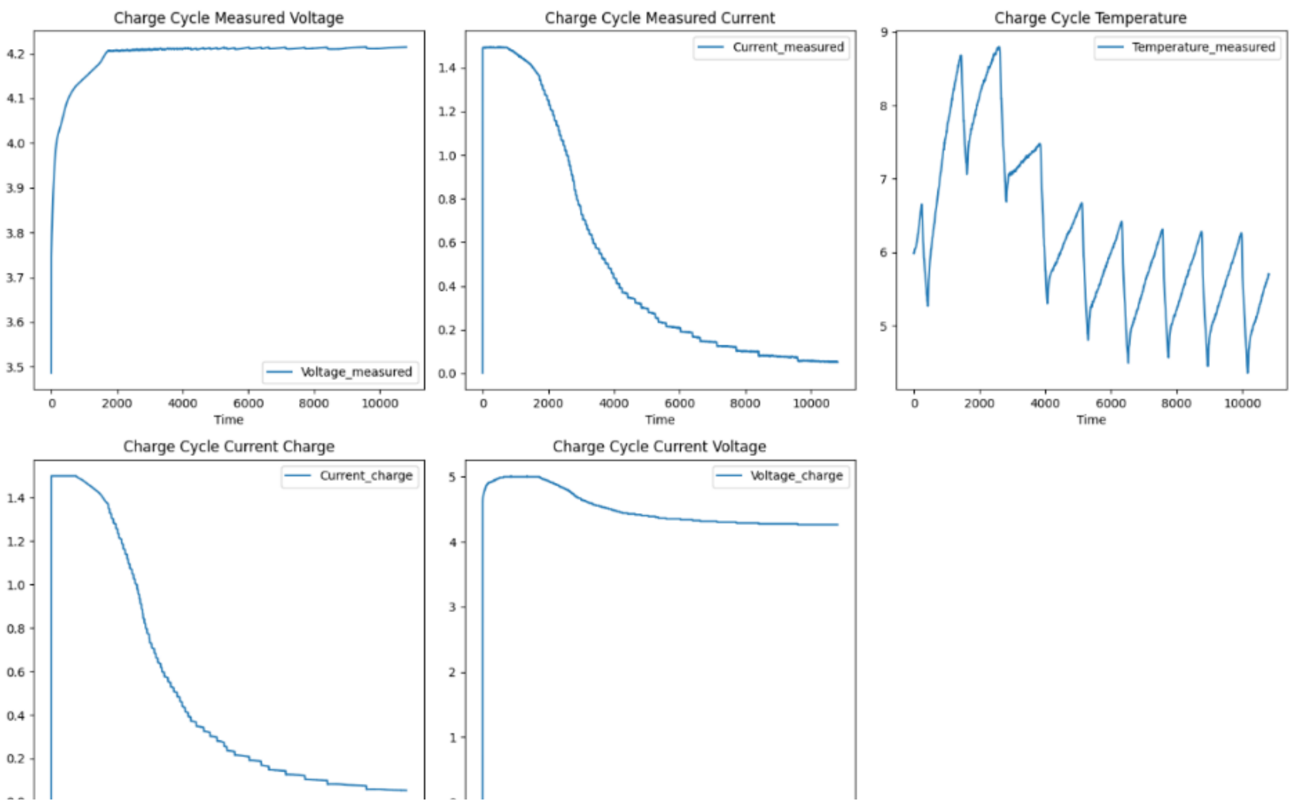
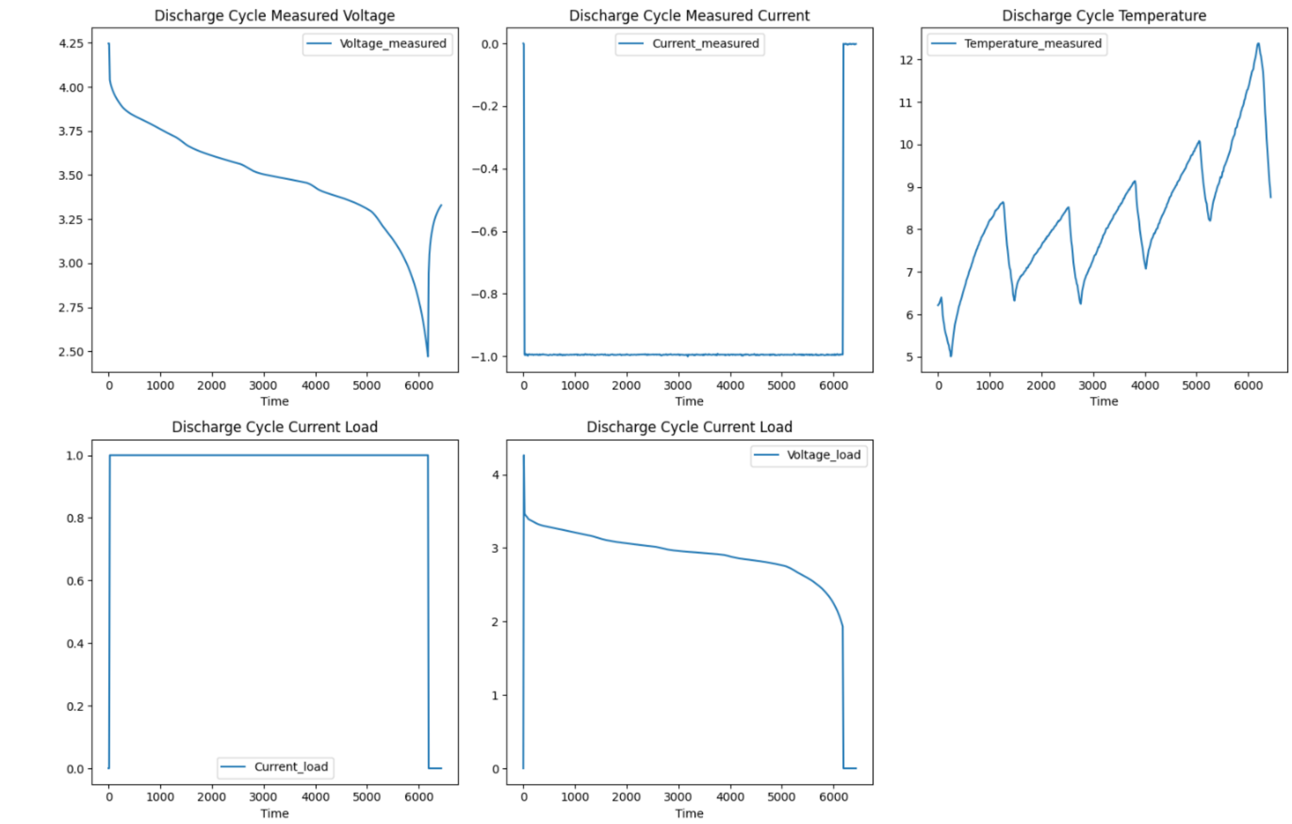
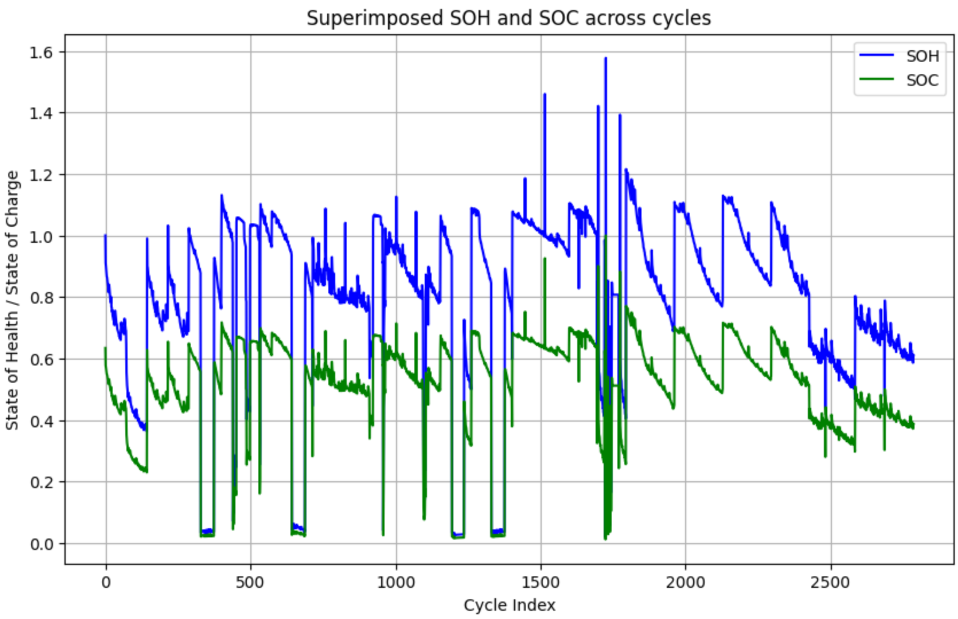
APPENDIX

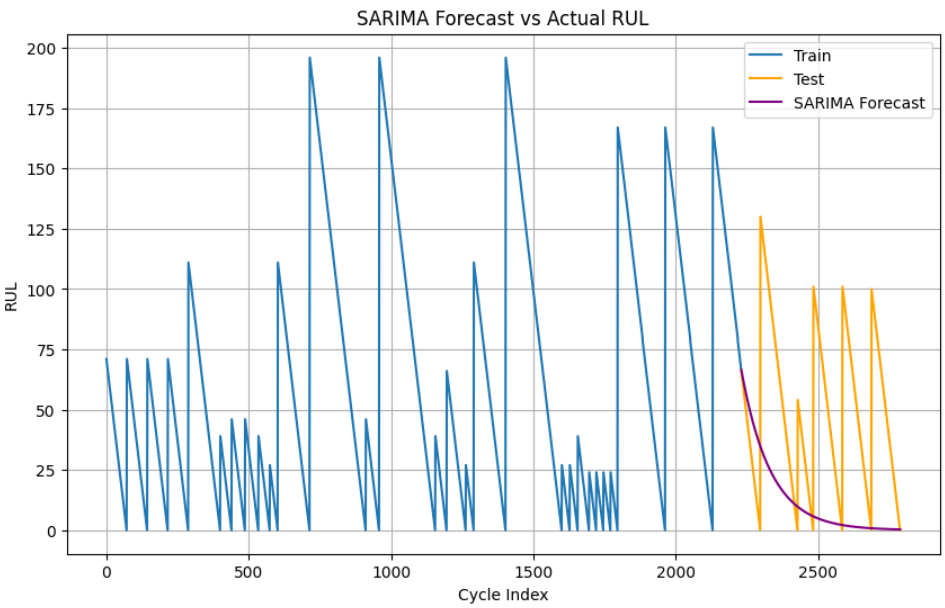


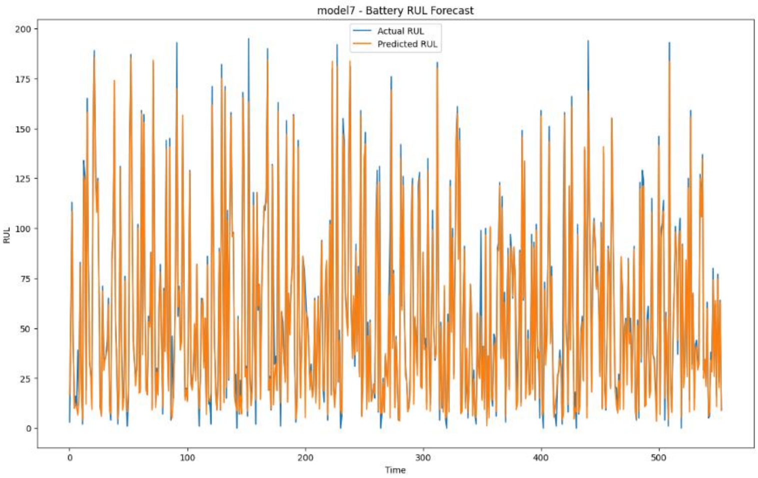
Charge across cycles

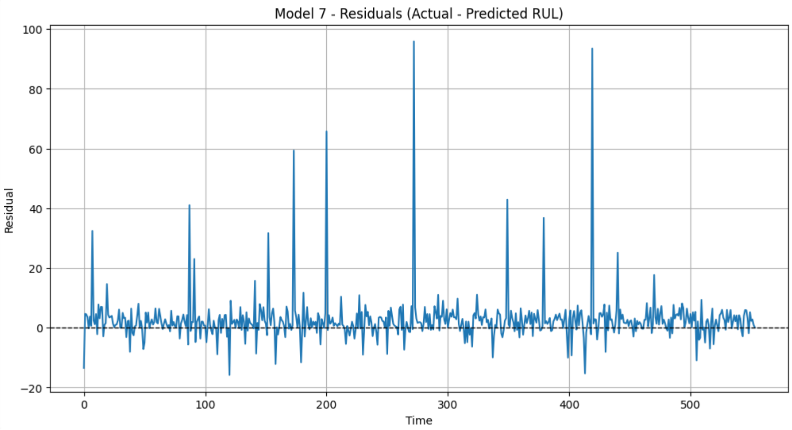


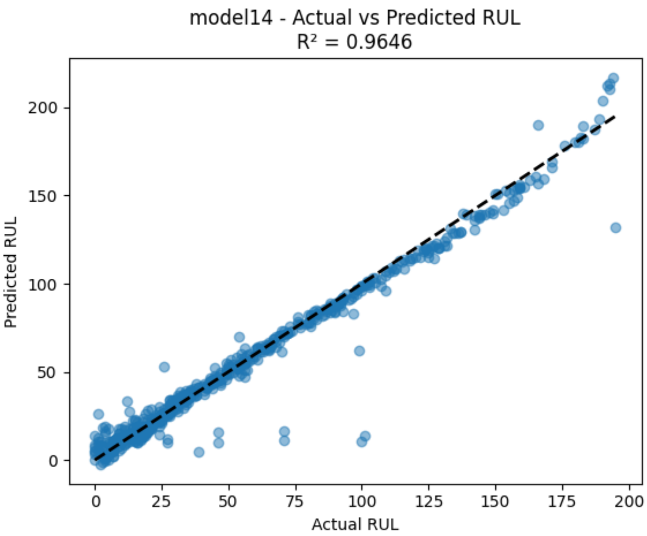
Discharge Across Cycles

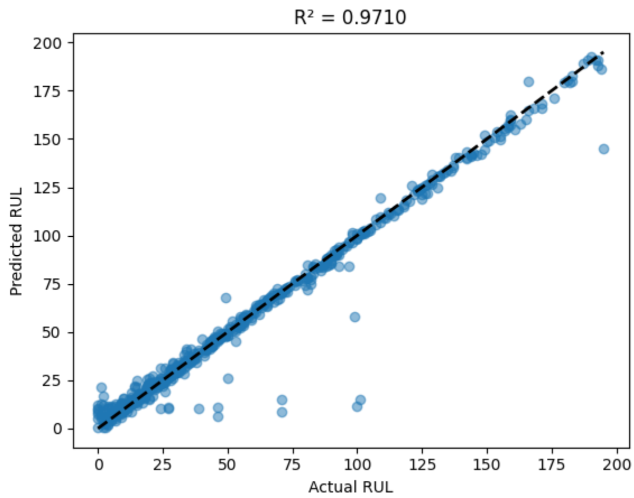


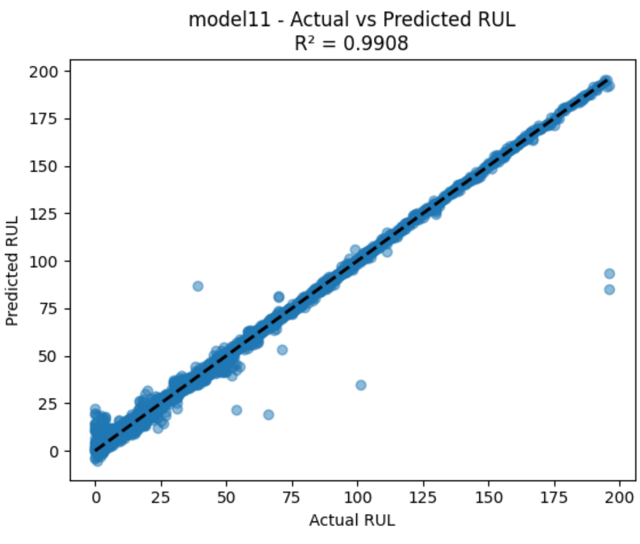


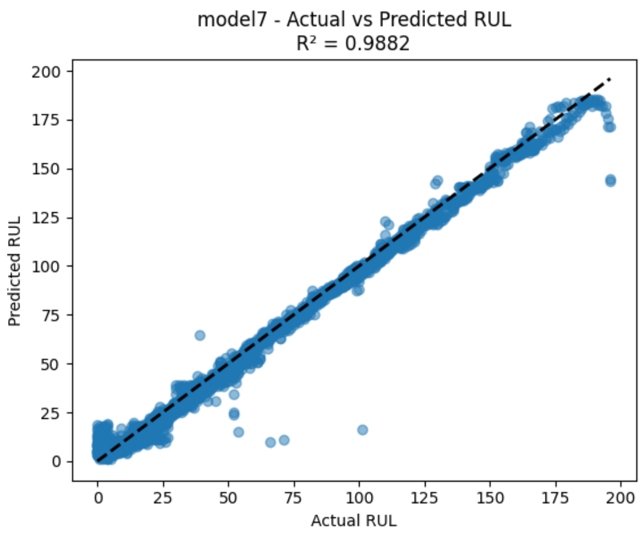

model7 - Battery RUL Forecast
Actual RUL
Predicted RUL
RUL
Time


Model 7 - Residuals (Actual - Predicted RUL)
Residual
Time


model14 - Actual vs Predicted RUL
R² = 0.9646
Predicted RUL
Actual RUL


R² = 0.9710
Predicted RUL
Actual RUL


model11 - Actual vs Predicted RUL
R² = 0.9908
Predicted RUL
Actual RUL


model7 - Actual vs Predicted RUL
R² = 0.9882
Predicted RUL
Actual RUL