Performance Prediction in Battery Energy Storage System

BTP Report Submitted by

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Contents

Chapter 1

Introduction to BESS and Problem Statement

1.1 Introduction to Battery Energy Storage Systems (BESS)

Battery Energy Storage Systems (BESS) are advanced electrical systems that capture energy from the grid or a power source, store it in electrochemical batteries, and then release it later when the power is needed. These systems are critical components of the modern energy infrastructure, enabling higher integration of renewable energy sources and enhancing grid resilience.

The presentation introduces Stationary Storage Systems, which are fixed BESS installations used for large-scale applications.

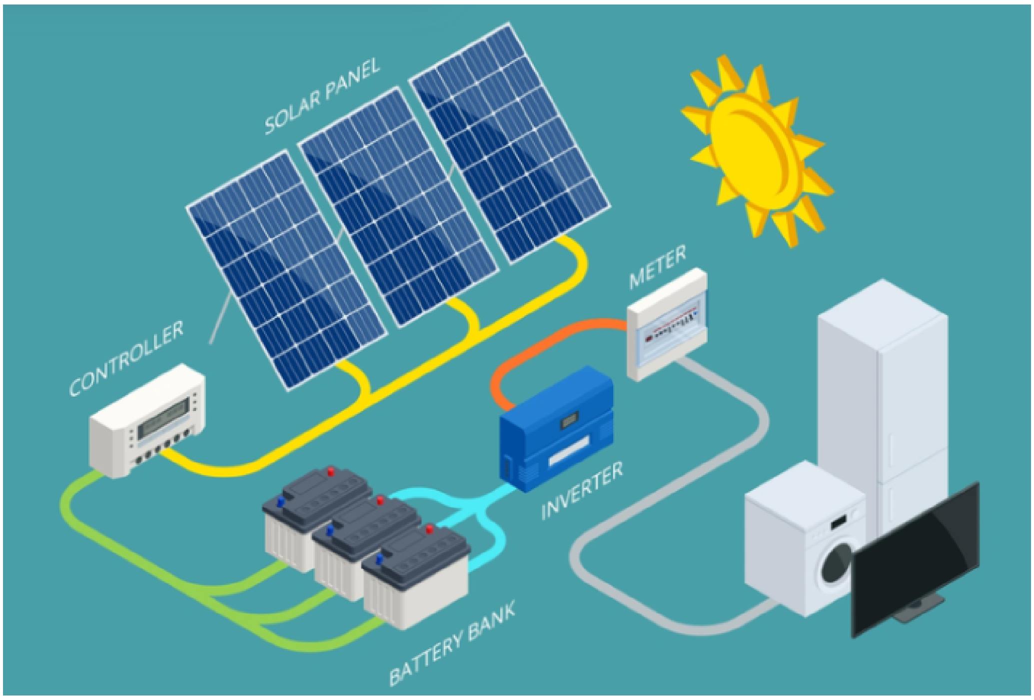

Figure 1.1: Diagram illustrating a typical stationary solar BESS setup, including the solar panel, controller, battery bank, inverter, and meter.

1.2 Applications of Stationary Storage

Stationary BESS provides essential services across the energy value chain, from generation to transmission and distribution. The primary applications include:

1. **Renewable Energy Smoothing:** Renewable sources like solar and wind are inherently intermittent. BESS absorbs excess energy during peak generation and injects power during dips, effectively balancing fluctuations to provide a steady, predictable power output to the grid. This makes renewable energy sources more reliable and grid-friendly.

2. **Frequency Regulation:** The electrical grid must operate at a precise frequency (e.g., 50 Hz or 60 Hz). Any imbalance between power generation and consumption causes the frequency to fluctuate. BESS can respond within milliseconds to absorb or inject power, acting as a dynamic buffer to maintain grid frequency within safe operating limits, thereby preventing blackouts.

3. **Peak Shaving:** Energy consumption patterns often show sharp peaks, typically in the morning and evening. By storing cheaper, off-peak energy and discharging it during these high-demand (and high-cost) periods, BESS effectively reduces the overall peak demand. This minimizes operating costs and alleviates stress on transmission and generation assets.

4. **Grid Stability and Ancillary Services:** Beyond frequency, BESS supports general grid stability by providing services like voltage support and reactive power compensation. This helps prevent localized voltage drops and ensures the reliable flow of power across the network.

1.3 Problem Statement: The Challenge of Degradation

While BESS is essential, the core challenge lies in the degradation of the battery cells. All batteries lose performance over time, and this degradation directly impacts system efficiency, profitability, and lifespan.

The primary problem is predicting and managing this degradation. Without an accurate measure of a battery's State of Health (SOH) and Remaining Useful Life (RUL), operators cannot optimize usage schedules or plan for maintenance and replacement, leading to financial risks and system downtime. This report aims to address this by:

- Analyzing the fundamental degradation mechanisms.
- Exploring advanced data processing techniques (PCA and Feature Analysis) on real-world battery datasets.
- Developing and evaluating machine learning models for accurate capacity prediction.

Chapter 2

Li-ion Battery Chemistry & Key Terms

2.1 Lithium-ion Battery Electrochemistry

Lithium-ion (Li-ion) batteries are the most common choice for BESS due to their high energy density and long cycle life. Their operation relies on the reversible movement of lithium ions (Li^+) between two electrodes.

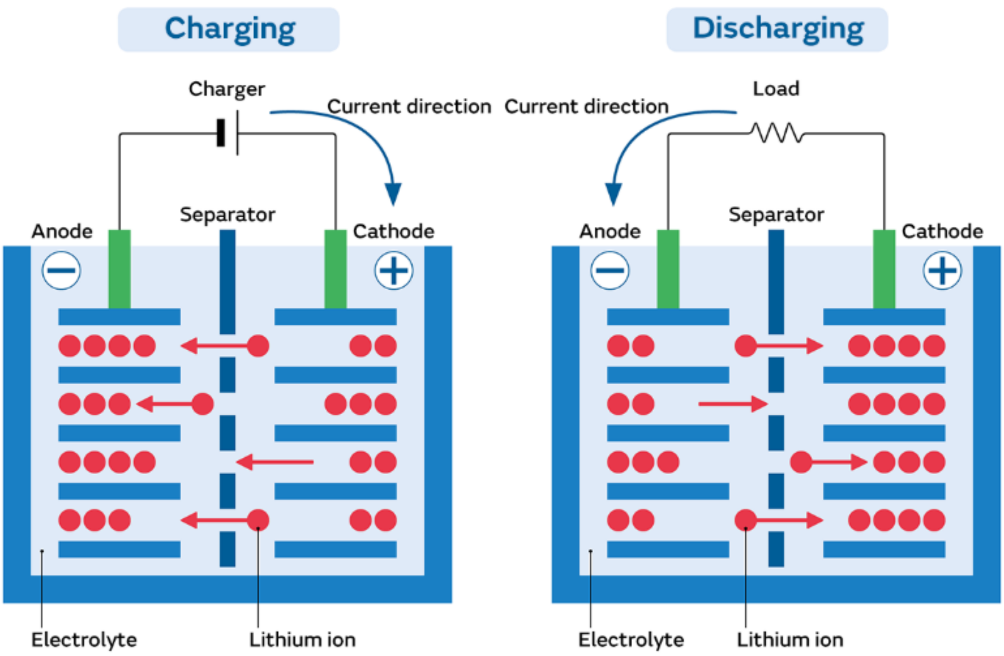

Figure 2.1: Schematic of Li-ion movement during charging and discharging.

Ion Movement During Operation

- **Discharge Process:** When the battery is powering an external device (load), Li^+ ions flow from the anode (the negative electrode, typically made of graphite) through the electrolyte and the separator to the cathode (the positive electrode, typically a lithium metal oxide). Simultaneously, electrons are released from the anode and travel through the external circuit to the cathode, creating the electric current that powers the device.

- **Charging Process:** An external power source (charger) applies a voltage, driving the reaction in reverse. Electrons are forced into the anode, and Li^+ ions are driven back from the cathode, through the electrolyte, and re-intercalated into the anode material, thus storing energy.

2.2 Battery Energy Storage System (BESS) and Battery Management System (BMS)

A BESS is more than just a battery bank; it is an integrated system:

- **BESS:** The complete system that stores electrical energy. It includes the battery cells, power electronics (inverters/converters), and the control unit.
- **Battery Management System (BMS):** The "brain" of the BESS. It is an electronic control unit that continuously monitors and manages the battery to ensure safe and efficient operation.

Primary Functions of the BMS:

1. **Monitoring:** Tracks essential cell parameters: voltage, current, and temperature.
2. **Protection:** Actively prevents hazardous conditions, such as overcharge, over-discharge, and overheating, which can lead to irreversible damage or thermal runaway.
3. **Cell Balancing:** Ensures all individual cells within a module or pack maintain a uniform State of Charge (SOC), maximizing overall pack capacity and lifespan.
4. **Data Logging:** Records operational data for health assessment and diagnostic analysis.

2.3 Key Terminology for Battery Operation and Health

Refer to Table 2.1.

2.4 BESS Components and Hierarchy

Larger BESS installations are built up from multiple units:

- **Cell Geometries:** Individual battery cells come in various forms, including cylindrical (e.g., 18650, 21700), prismatic (rectangular hard-cased), and pouch (flexible foil casing). The choice of geometry impacts thermal management and energy density.
- **Module:** A module is a collection of interconnected cells (wired in series, parallel, or both) housed in a protective case. Modules are the fundamental building blocks for large systems.
- **Pack:** A pack is an assembly of multiple modules, integrated with the BMS, cooling/heating systems, and structural supports. The pack is the final, deployable unit within the BESS.

Term	Definition and Importance
Cell Voltage (V)	The potential difference between the electrodes. Directly relates to the battery's SOC.
Current (A)	The rate of flow of electric charge. Dictates the charging/discharging speed.
Capacity (mAh/Ah)	The total amount of charge the cell can store and deliver. Capacity fade is the key indicator of degradation.
Energy (Wh/kWh)	The total energy stored, calculated as the product of voltage and capacity.
C-rate	The rate of charge or discharge relative to the battery's maximum capacity (e.g., $1C$ rate means fully charging/discharging in 1 hour). Higher C-rates accelerate degradation.
State of Charge (SOC)	The percentage of the battery's remaining capacity relative to its maximum capacity (0% to 100%).
State of Health (SOH)	A measure of the battery's overall condition and performance compared to its original, fresh state (typically based on capacity retention).
Depth of Discharge (DOD)	The percentage of the capacity that has been discharged. High DOD cycles (deep cycles) typically reduce cycle life.
Power Density (W/L or W/kg)	The amount of power the battery can deliver per unit volume or mass.
Cycle Life	The number of complete charge-discharge cycles a battery can undergo before its capacity drops below a predefined threshold (e.g., 80% of original capacity).
Calendar Life	The total lifespan (in years) of a battery, independent of cycling, influenced by storage conditions (temperature, SOC).
Internal Resistance (Ω)	The opposition to current flow within the battery. Degradation causes internal resistance to increase, reducing efficiency and power output.

Table 2.1: Key Battery Terminology

Chapter 3

Degradation of a Li-ion Battery and Data Analysis

3.1 Degradation of a Li-ion Battery

Battery degradation is the irreversible loss of performance and capacity over time, leading to reduced efficiency, shorter lifespan, and decreased reliability. Degradation occurs through various simultaneous electrochemical and mechanical processes.

Factors Leading to Accelerated Degradation:

1. **High Temperature:** Elevated temperatures drastically accelerate unwanted chemical side reactions within the cell, particularly electrolyte decomposition and SEI growth, leading to faster capacity and power loss.
2. **High C-Rates:** High charge and discharge currents cause significant mechanical stress on the electrode materials (due to rapid volume changes during intercalation/de-intercalation) and promote side reactions like lithium plating.
3. **Solvent and Electrolyte Breakdown:** The organic solvent in the electrolyte can decompose due to high temperatures or voltages, contributing to gaseous side products and active material consumption.

Major Degradation Mechanisms

The analysis focuses on two critical and interconnected degradation mechanisms:

Mechanism 1: Solid Electrolyte Interface (SEI) Formation and Degradation

Formation: The Solid Electrolyte Interface (SEI) is a passivation layer that forms on the surface of the anode (graphite) during the very first charge cycle. This is an unavoidable side reaction where the electrolyte components are reduced by electrons at the anode surface.

Reaction Example:

$$\mathrm{EC} + \mathrm{Li}^+ + e^- \longrightarrow (\mathrm{CH_2OCO_2Li})_2 + \mathrm{C_2H_4}$$

Equation 1: Simplified reaction showing the reduction of Ethylene Carbonate (EC) to form components of the SEI layer.

Function: The SEI is a double-edged sword:

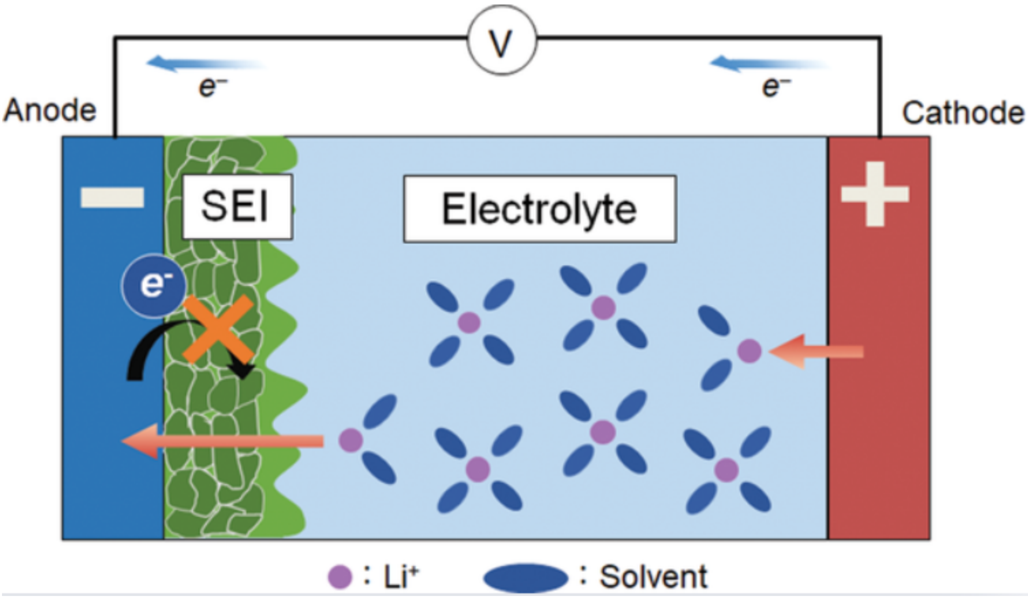

Figure 3.1: Diagram illustrating the SEI layer between the anode and electrolyte. It is electronically insulating but ionically conductive, allowing Li^+ ions to pass while blocking electrons.

- **Protection (Good):** It is electronically insulating, preventing the continuous reduction of the electrolyte by blocking electrons.
- **Passage (Good):** It is ionically conductive, allowing the essential Li^+ ions to pass through for charging and discharging.

Degradation Problem (SRP and Unwanted Reduction): Under stress (high C-rates, extreme temperature, or high voltage), the SEI layer can break down and reform. The problem is that the Standard Reduction Potential (SRP) of organic solvents and electrolytes is often more favorable than that of lithium intercalation. When the SEI degrades, the electrolyte reduction becomes the dominant reaction instead of the desired intercalation.

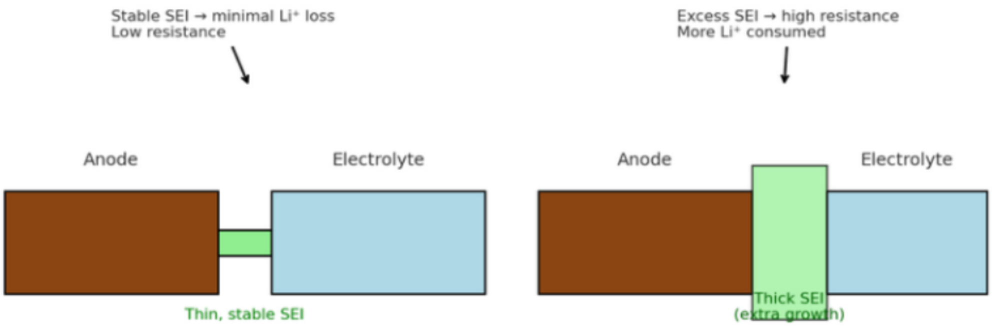

Figure 3.2: Comparison of a stable, thin SEI layer (low resistance) and a thick, unstable SEI layer (high resistance and increased Li^+ consumption).

This leads to:

- **Wasted Active Material (Lithium Loss):** Li^+ ions are permanently consumed in the continuous, irreversible formation of SEI components, leading directly to Capacity Fade.
- **Increased Internal Resistance:** A thick, unstable SEI layer acts as a barrier, slowing the movement of Li^+ ions and increasing the battery's internal resistance, which reduces its power capability and efficiency.

Mechanism 2: Lithium Plating

Definition: Lithium plating is a critical degradation mechanism where metallic lithium is deposited on the surface of the anode instead of being safely intercalated (fitting into the lattice structure of the graphite).

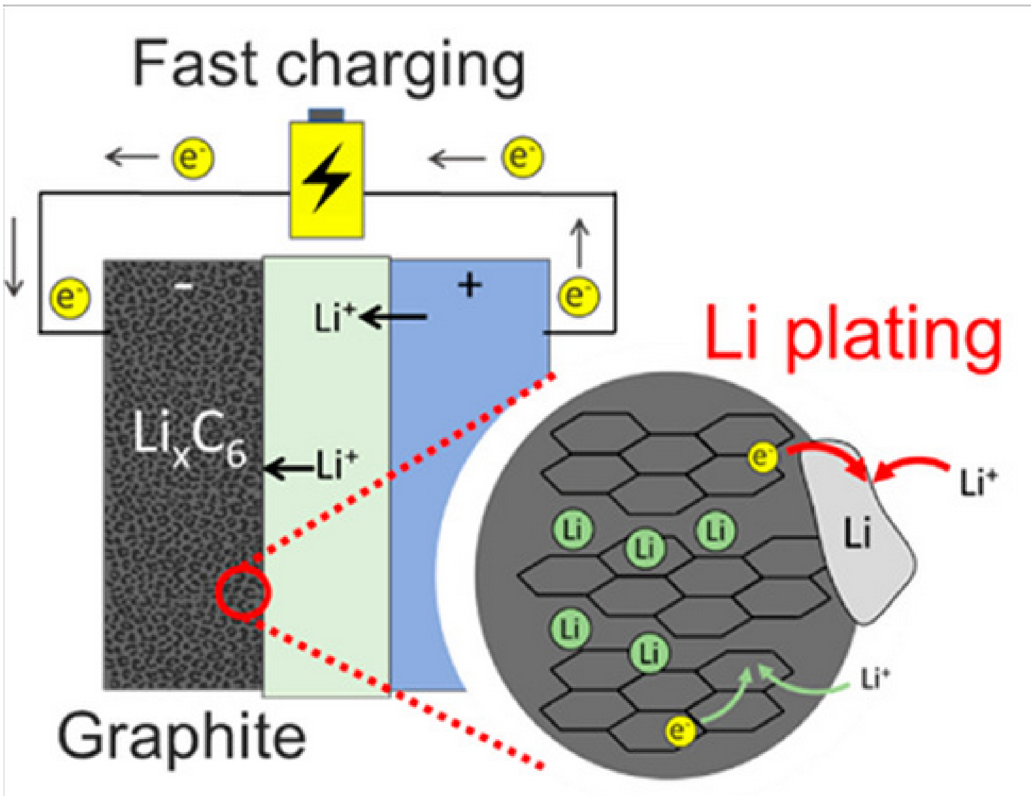

Figure 3.3: Illustration of metallic lithium plating on the graphite anode, showing Li^+ ions failing to intercalate.

Causes: Plating occurs when the rate of Li^+ arrival at the anode exceeds the rate at which the ions can intercalate.

1. **Fast Charging/High C-Rates:** High currents push Li^+ ions to the anode too quickly.
2. **Low Temperatures:** Low temperatures slow down the kinetics of intercalation, reducing the anode's ability to absorb Li^+.
3. **Over-Discharge/Deep Cycling:** This can deform the anode structure, making it harder for Li^+ to intercalate on subsequent charges.

Impacts of Degradation and Why Health Prediction is Critical:

1. **Material Loss & Capacity Fade:** Plated lithium that loses electrical contact with the anode becomes electrochemically inactive (dead lithium). This permanently removes Li^+ from the cycling process, directly causing capacity fade.
2. **Increased Internal Resistance:** The layer of plated lithium acts as a resistive barrier, impeding ionic movement.
3. **Dendrite Formation and Safety Hazard:** Plated lithium can grow into sharp, needle-like structures called dendrites. These dendrites can pierce the separator, causing an internal short circuit that leads to rapid heat generation (thermal runaway) and potential fire or explosion.

Health Prediction Necessity: Predicting the SOH and RUL is critical to ensure battery safety (by identifying conditions that promote plating) and maximizing economic return (by optimizing usage to slow capacity fade).

3.2 NASA Degradation Dataset

The study utilizes the publicly available NASA Battery Dataset, which contains comprehensive charge and discharge data for multiple Li-ion batteries cycled under different conditions (e.g., B0005, B0006, B0007, B0018).

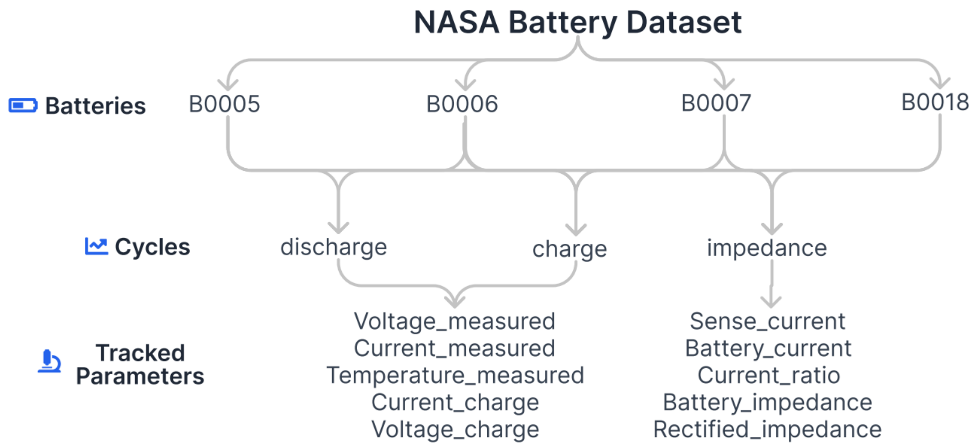

Figure 3.4: Hierarchy of the NASA Dataset showing batteries, cycles, and tracked parameters.

3.2.1 Data: Basic Measurements

The dataset comprises four Li-ion batteries (B0005, B0006, B0007, and B0018) cycled at room temperature. Charging followed a Constant Current-Constant Voltage (CC-CV) protocol (1.5A to 4.2V, cutoff at 20mA), while discharge was maintained at a constant current of 2A until specific voltage thresholds (2.2V–2.7V) were reached. Electrochemical Impedance Spectroscopy (EIS) was performed from 0.1Hz to 5kHz to monitor internal parameter changes. The experiments concluded upon reaching the End-of-Life (EOL) criteria, defined as a 30% capacity fade (from 2Ahr to 1.4Ahr).

The raw data recorded by the BMS for each cycle includes:

- **Charge/Discharge Cycles:** Voltage_measured, Current_measured, Current_charge, Voltage_charge, Temperature_measured, .
- **Impedance Data:** Sense_current, Battery_current, Battery_impedance, etc.

3.2.2 Inferred Variable: Q(V)

A significant challenge in analyzing raw time-series data is that the time duration of a discharge cycle changes as the battery degrades (a healthier battery takes longer to discharge than a degraded one).

To address this, the dependent variable is changed from time to Voltage (V), which remains within a fixed range (e.g., 4.2V to 2.7V) across all cycles.

- **Voltage Analysis Approach:** A fixed voltage grid (e.g., 0.01V increments) is established, and all features (Time, Temperature, Current) are interpolated onto this uniform voltage grid using techniques like Univariate Spline Interpolation. This effectively synchronizes the data across cycles based on the state of the battery, not the time taken.
- **The Q(V) Feature:** This inferred variable, Q(V) (Charge vs. Voltage), is calculated to quantify the change in discharge time (or charge capacity) at specific voltage points relative to the first cycle.
  - Q(V) depicts the difference in time taken for the battery to reach a certain voltage in the given cycle compared to the time taken in the first cycle. A higher Q(V) value for a degraded battery indicates that it took much less time (has less capacity) to reach that voltage level compared to the healthy reference cycle.

3.2.3 Feature Extraction and Selection

To prepare the data for machine learning, a comprehensive feature extraction and selection process was conducted. This involved calculating various statistical features from the processed voltage-based discharge curves to capture signal characteristics in the time and frequency domains:

- **Statistical Parameters:** Standard Deviation (STD), Root Mean Square (RMS), Mean, Peak.
- **Shape Parameters:** Shape Factor, Kurtosis, Skewness, SINAD.
- **Frequency Parameters:** Impulse Factor, Crest Factor, THD, SNR, Clearance Factor.

These 13 parameters were calculated for the three main discharge curves: Q(V), Temperature (Temp), and Voltage Levels (VL), resulting in an initial set of $3 \times 13 = 39$ statistical features.

Feature Selection Methodology: To identify the most influential features for capacity prediction, One-way ANOVA (Analysis of Variance) and Pearson Correlation Coefficient (PCC) were utilized:

- **Pearson Correlation Coefficient (PCC):** This was used to measure the strength of the linear relationship between each individual feature and the target variable (capacity).
- **Analysis of Variance (ANOVA):** This was employed to assess the variance of features across different groups of data (specifically, different SOH levels) to determine their discriminative power.

The top 4 features according to the ANOVA and PCC values were obtained:

1. Q(V) - STD
2. Q(V) - Mean
3. Q(V) - Peak
4. Q(V) - RMS

This finding strongly suggests that the change in the shape and spread of the Q(V) curve captures most of the degradation information.

3.2.4 Heat Map Analysis

A Magnitude Correlation Heatmap was used to visualize the relationships between the 39 initial features.

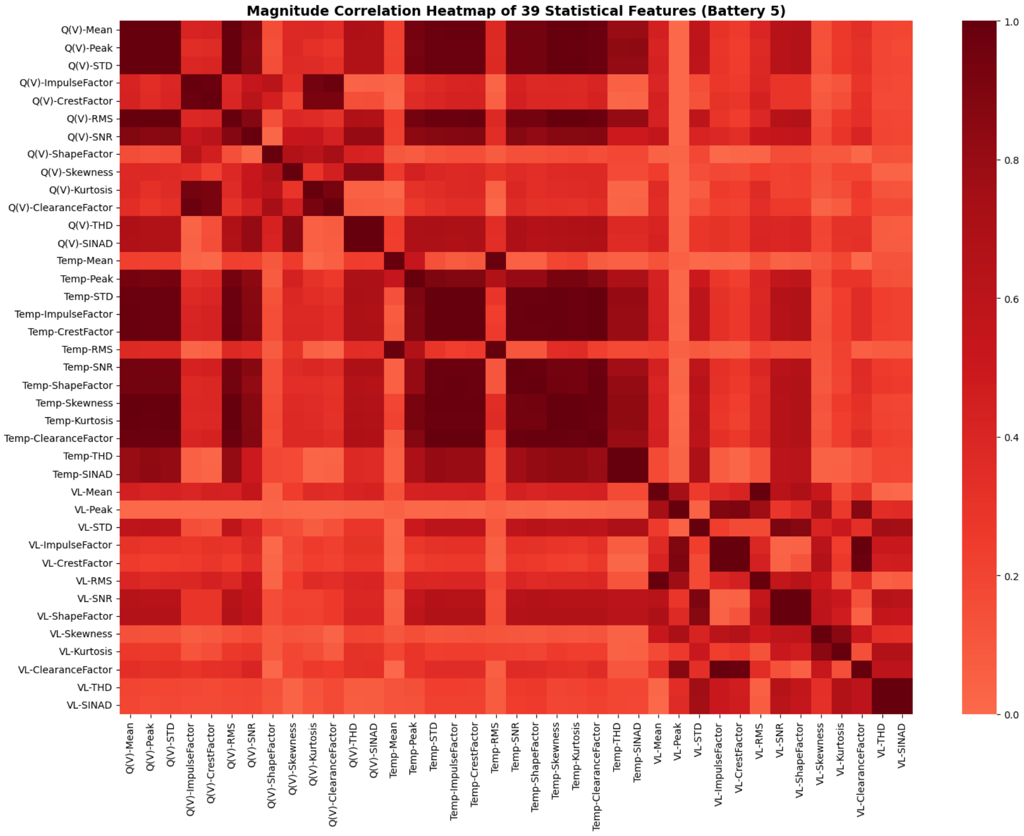

Figure 3.5: Initial Heatmap of 39 Statistical Features.

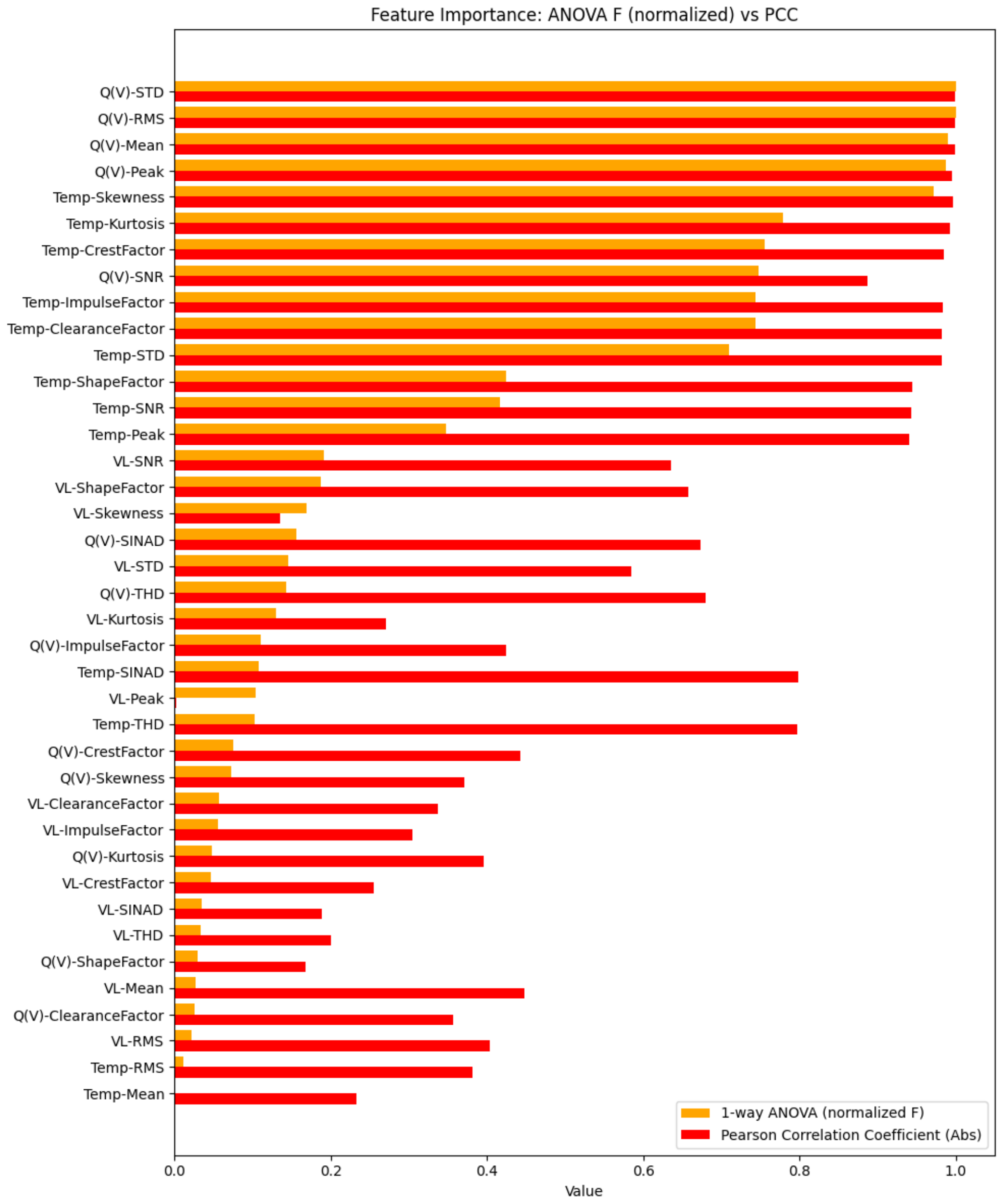

Figure 3.6: PCA conducted on all 39 features

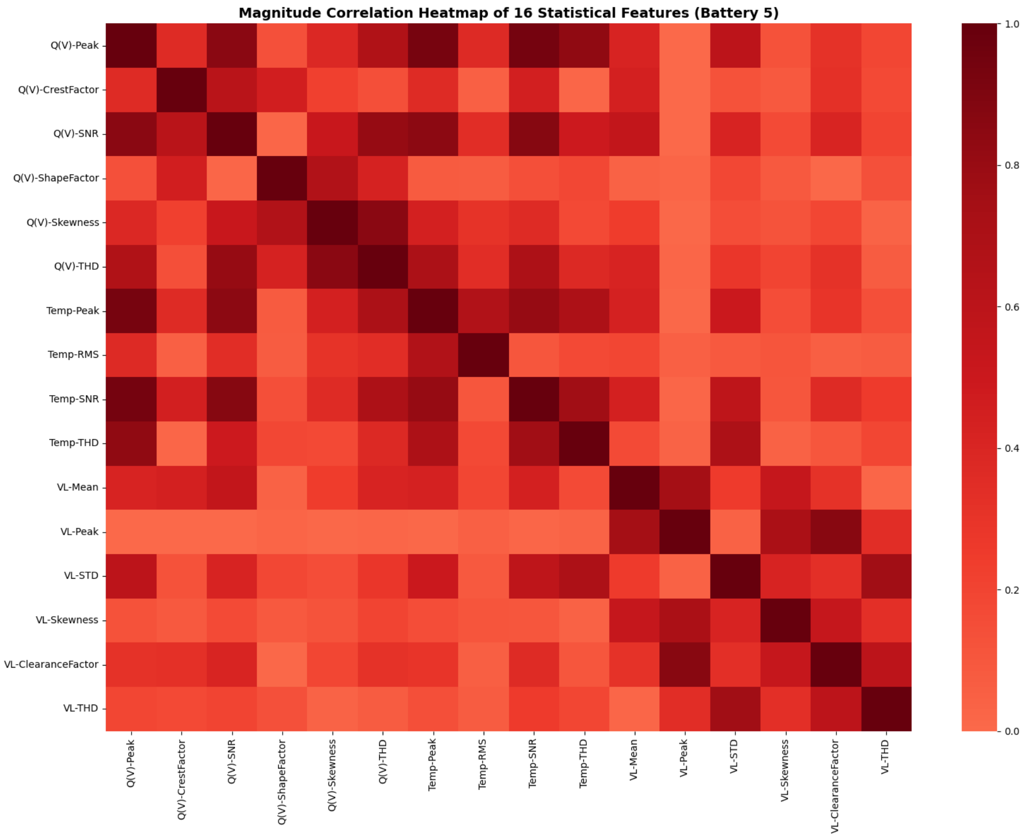

Figure 3.7: Heatmap after elimination of correlated features

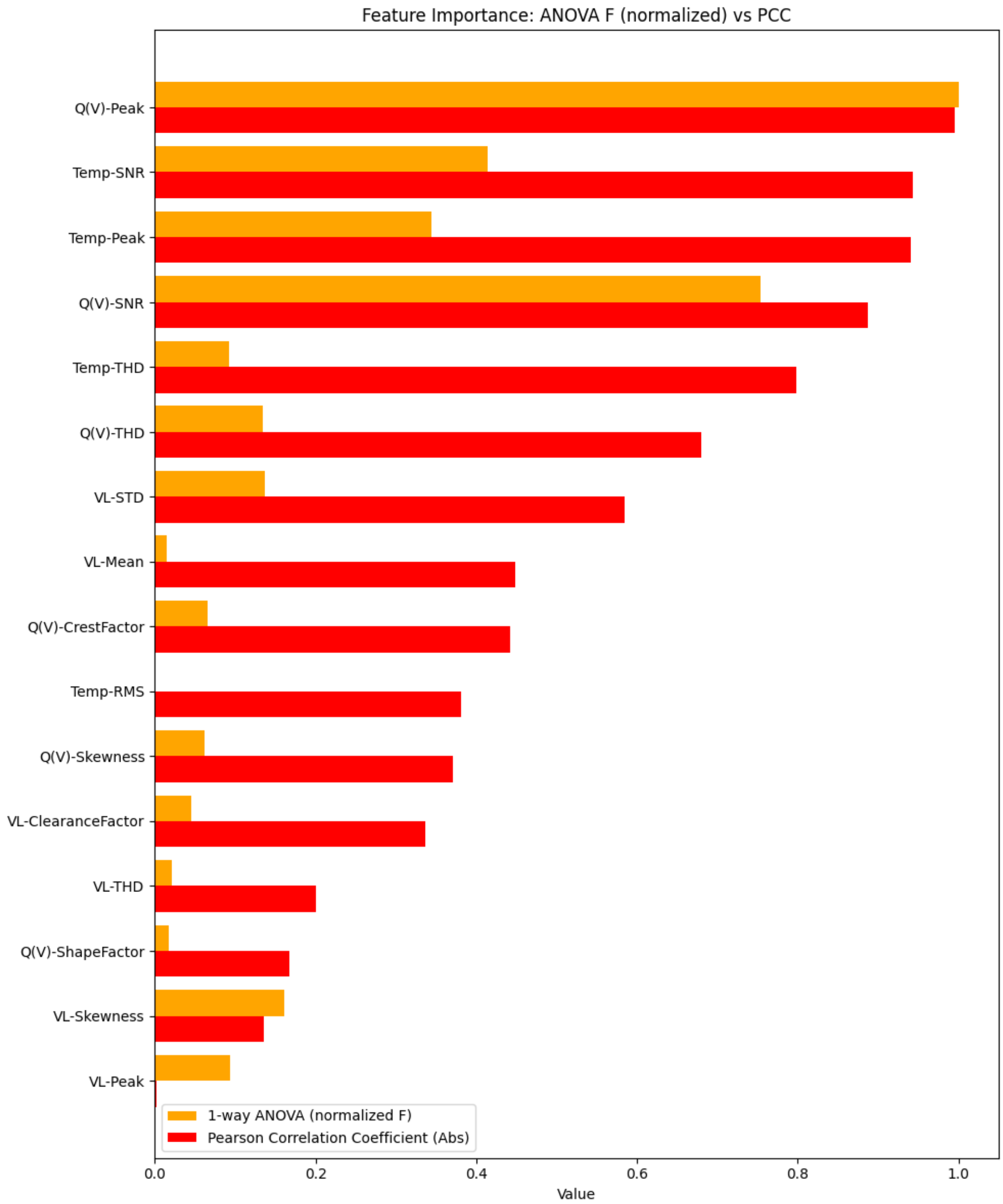

Figure 3.8: Bar chart comparing feature importance based on normalized ANOVA F-statistic and absolute Pearson Correlation Coefficient for the reduced feature set.

Chapter 4

Linear Regression Analysis

Linear Regression serves as a baseline model for predicting battery capacity. It assumes a linear relationship between the input features and the target variable (Remaining Capacity).

The model was tested using two feature sets:

1. **Full Feature Set** (as used in the reference paper): Using the top 19 features from PCA, as performed in the reference paper. Note that we have used 18 features instead of 19, as one of the features (VL-Crest Factor) had a completely different range of values for battery 5 & 7 while the target ranges were roughly similar, causing model accuracy to decrease.
2. **Top 4 Features** (Q(V) - Mean, Q(V) - Peak, Q(V) - STD, Q(V) - RMS): The selection was capped at four features to ensure the model relies exclusively on descriptors of a single variable type: Q(V). The feature ranking analysis indicated that the fifth most significant feature was 'TEMP-skewness', a temperature-derived metric. Excluding this allowes us to create a model that is fed only descriptors the Q(V) parameter.

4.1 Exception of Battery 6

Before modeling, we found a difference between the metadata and the actual data regarding initial capacity. The metadata states a capacity fade from 2 Ah to 1.4 Ah for all batteries. However, actual data showed that Batteries 5, 7, and 18 started with an initial capacity of roughly 1.85 Ah to 1.88 Ah, whereas Battery 6 started at 2.0 Ah. This difference in starting conditions caused the test results for Battery 6 to be significantly abnormal.

To fix this, we ignored the first 28 cycles of Battery 6 during pre-processing. We only considered data from the 29th cycle onwards, where the capacity was approximately 1.85 Ah. This brought all batteries to a common starting point and significantly improved the results.

4.2 Model Evaluation Results

Model Performance using Full Feature Set (as used in the Reference Paper)

Battery	B0005 (Training)	B0006 (Testing)	B0007 (Testing)	B0018 (Testing)
R^2 Score	0.9999	0.9465	0.9721	0.9968

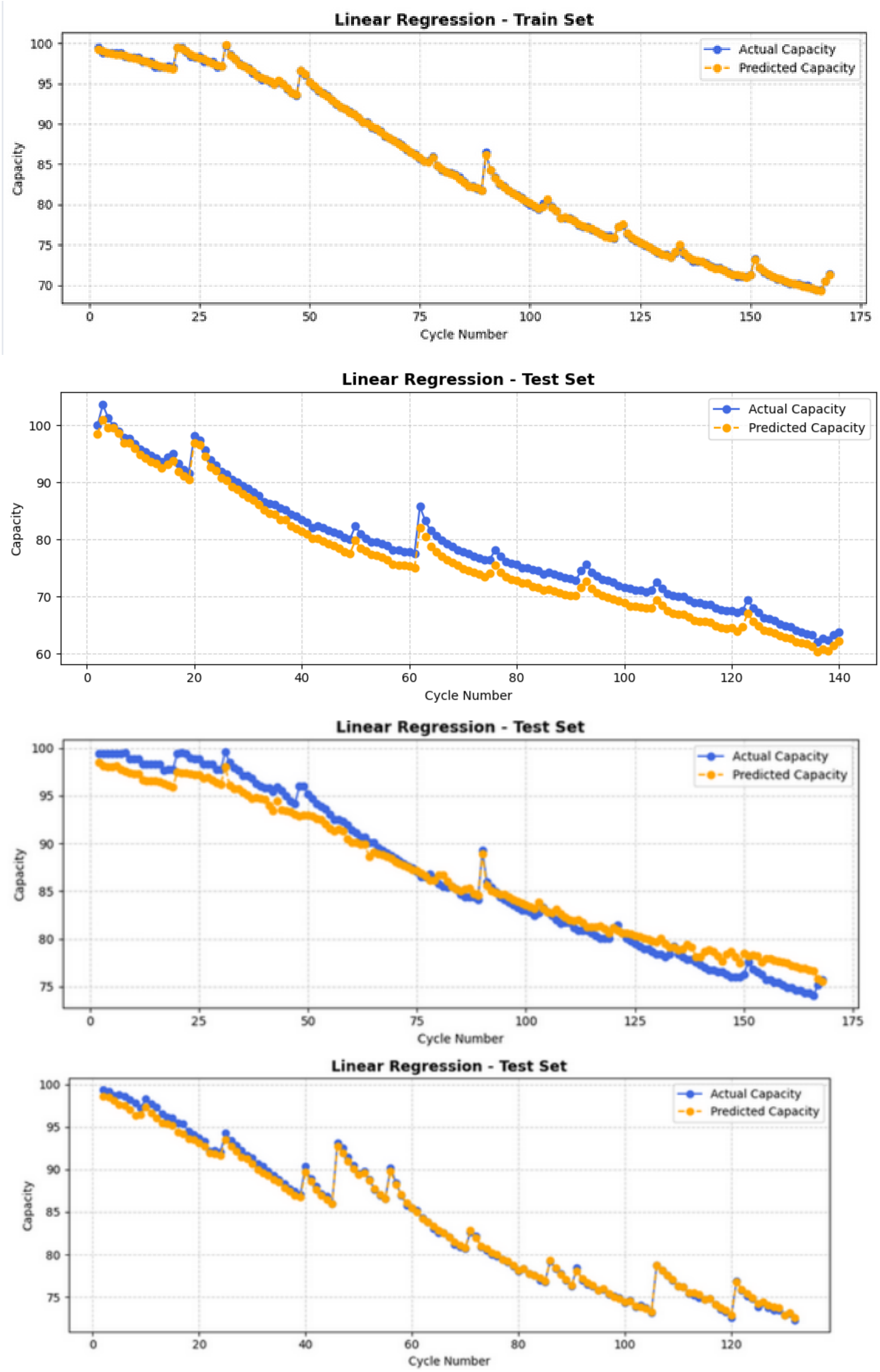

Figure 4.1: Linear Regression (Full Feature Set as per reference paper) plots for Actual Capacity vs. Predicted Capacity across test batteries B0006, B0007, B0018 and Training performance on B0005.

Battery	B0005 (Training)	B0006 (Testing)	B0007 (Testing)	B0018 (Testing)
R^2 Score	0.9999	**0.9785**	**0.9988**	**0.9990**

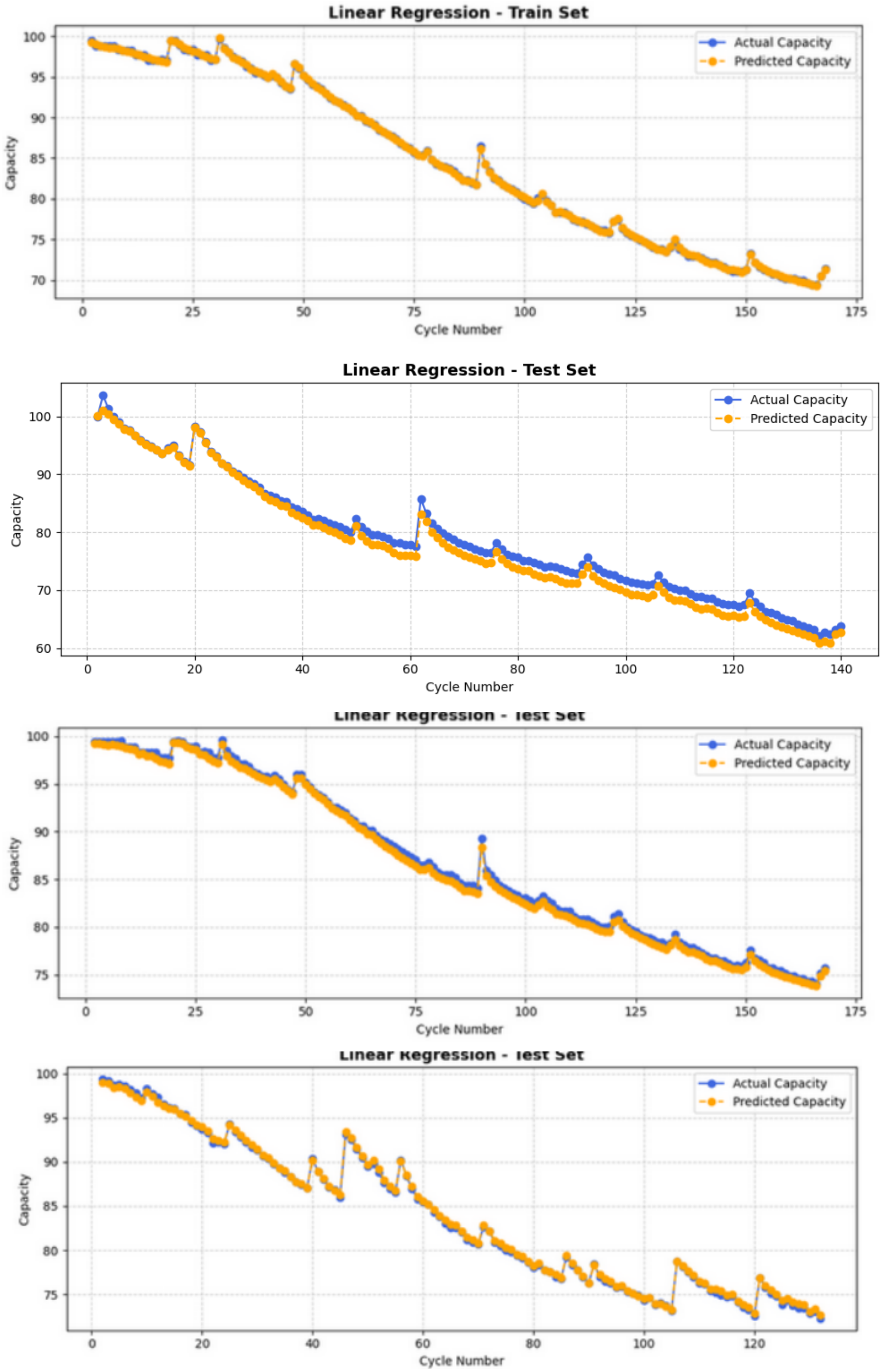

Figure 4.2: Linear Regression (Top 4 Feature Set) plots for Actual Capacity vs. Predicted Capacity across test batteries B0006, B0007, B0018 and Training performance on B0005.

Model Performance using Top 4 Features (Significantly Better Results)

4.3 Results Interpretation - Linear Regression

The superior performance of the model utilizing only the top 4 features compared to the extensive 18-feature set serves as a classic example of the trade-off between model complexity and generalization, specifically highlighting the issue of **overfitting**.

In machine learning, overfitting occurs when a model learns the training data too well, capturing not just the underlying signal (the actual degradation trend) but also the random noise and specific idiosyncrasies unique to that specific dataset (in this case, the training battery B0005). When the model was trained with 18 features, many of which likely contained redundant information or noise with low correlation to capacity fade, the regression algorithm assigned weights to these less relevant variables to minimize the training error.

While this might result in a near-perfect fit for the training battery, these specific noise patterns and minor fluctuations do not exist in the test batteries (B0006, B0007, and B0018). Consequently, the complex model failed to generalize its learning to new data, leading to a drop in prediction accuracy.

In contrast, by restricting the model to the top 4 highly domain-informed features (Q(V) - Mean, Peak, STD, RMS), we effectively forced the model to focus only on the most robust and universal indicators of degradation. This simpler model filtered out the noise and captured the fundamental capacity fade trend shared across all batteries, thereby achieving significantly higher accuracy when applied to the unseen test data.

Chapter 5

Advanced Regression Models

To explore whether non-linear models can capture more complex degradation patterns, advanced regression techniques, including ensemble methods and neural networks, were deployed.

5.1 Ridge Regression

Ridge Regression is an extension of linear regression that includes a regularization term. This term adds a penalty equal to the square of the magnitude of coefficients. The goal is to prevent overfitting by shrinking the coefficients of less important features towards zero. While still linear, Ridge Regression can be more stable than standard linear regression when dealing with a high number of slightly correlated features.

5.2 Decision Trees

A Decision Tree is a non-linear model that partitions the data space into smaller, more manageable subsets based on a sequence of simple feature-based questions.

- **Mechanism:** The tree recursively selects the split point (a feature and a threshold) that best reduces entropy (randomness/impurity) in the resulting child nodes. The process continues until a stopping criterion is met, and the final prediction is made at the leaf node.

- **Stopping Criteria:** These are pre-defined rules used to halt the growth of the tree to prevent complex, overfitted structures. Common examples include setting a maximum depth for the tree or requiring a minimum number of samples in a leaf node.

- **Prediction:** For regression, a leaf node's prediction is often the average capacity of all training samples that fall into that node.

- **Advantages:** Handles non-linear relationships, is easy to interpret, and requires minimal data preprocessing.

- **Disadvantage:** A single tree can be highly sensitive to noise in the training data and prone to overfitting.

5.3 Ensemble Models: Random Forest and XGBoost

Ensemble methods combine multiple simple models to improve overall prediction accuracy and stability.

5.3.1 Random Forest (Regression)

A Random Forest mitigates the overfitting issue of a single decision tree by building an ensemble of many trees.

- **Mechanism:** It builds hundreds of decision trees, where each tree is trained on a random subset of the training data and uses a random subset of the features at each split point.
- **Prediction:** The final prediction is the average of the predictions made by all individual trees (ensemble averaging). This significantly reduces variance and overfitting, leading to a more robust model.

5.3.2 XG Boost Model (Extreme Gradient Boosting)

XGBoost is a highly efficient and accurate implementation of Gradient Boosting. Unlike Random Forest (which builds trees in parallel), XGBoost builds trees sequentially and iteratively.

- **Mechanism:** It starts with a simple initial prediction. Each subsequent tree is a "weak learner" built to model and correct the residual errors (mistakes) of the collective previous trees. It focuses more heavily on the data points that were previously misclassified or poorly predicted.
- **Why it's Powerful:** This sequential error-correction process allows the model to achieve extremely high accuracy and is generally very robust. It also incorporates regularization to prevent overfitting.

XGBoost Model Performance Evaluation

Battery	B0005 (Training)	B0006 (Testing)	B0007 (Testing)	B0018 (Testing)
R^2 Score	0.9999	0.8928	0.9657	0.9971

5.4 Neural Network (NN) Models

Neural Networks are powerful models for complex pattern recognition, particularly useful for time-series data due to the sequential nature of battery degradation.

5.4.1 Recurrent Neural Network (RNN)

Traditional models assume data points are independent. However, battery degradation is a sequential process where the health of cycle n depends on the conditions of cycle $n-1$.

RNNs are specifically designed for sequential data.

- **Mechanism:** An RNN contains a "memory" or hidden state that is passed from one time step to the next. At each step, it takes the new input data (X_t) and the previous memory (h_{t-1}) to calculate a new output (h_t) and update the memory.

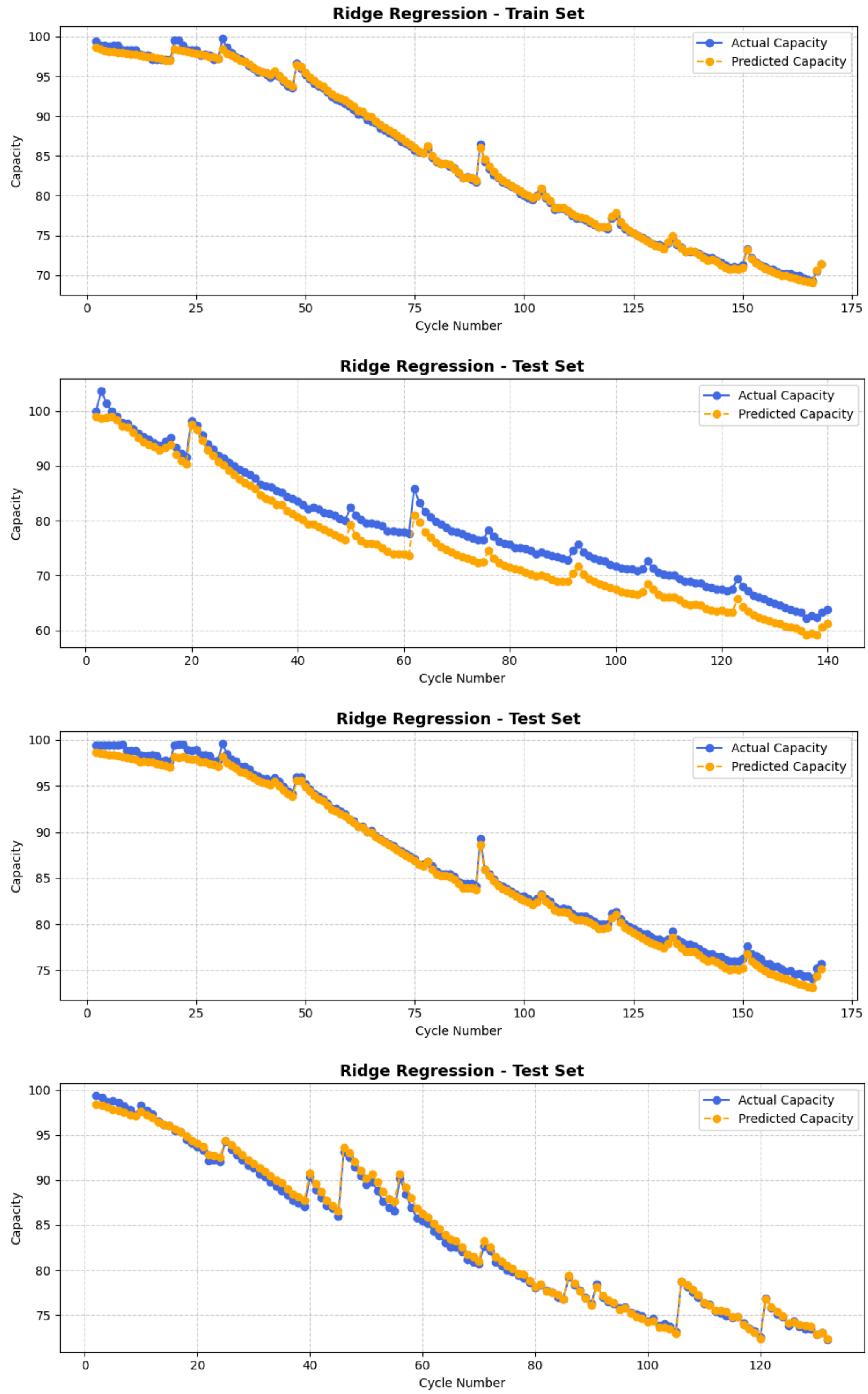

Figure 5.1: Ridge Regression plots for Actual Capacity vs. Predicted Capacity for the test set.

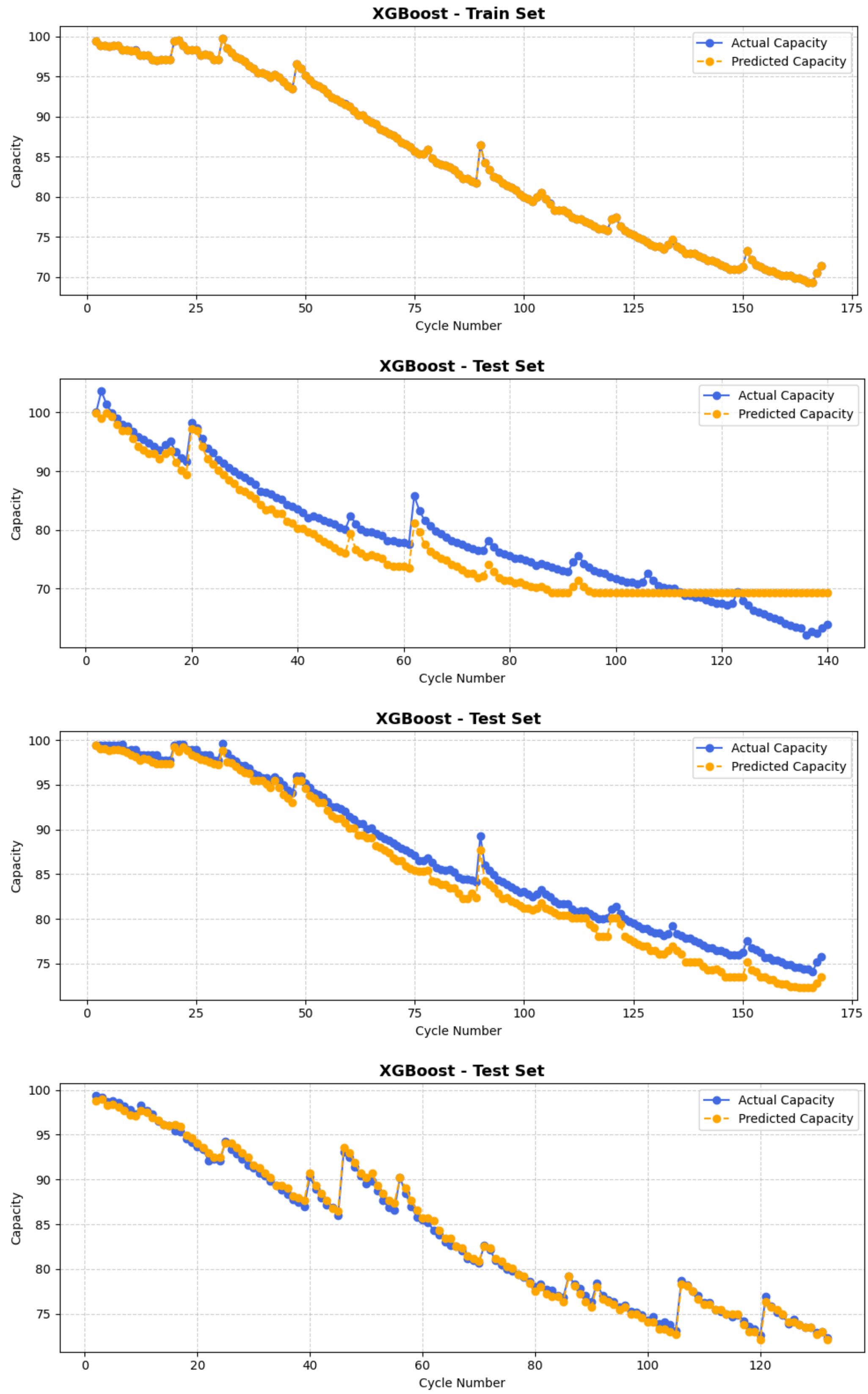

Figure 5.2: XGBoost plots for Actual Capacity vs. Predicted Capacity for the test set.

- **Limitation:** Basic RNNs suffer from the "vanishing gradient problem," making it difficult to remember information from very distant past steps. When sequences are long (like full discharge curves), the model quickly "forgets" older information.

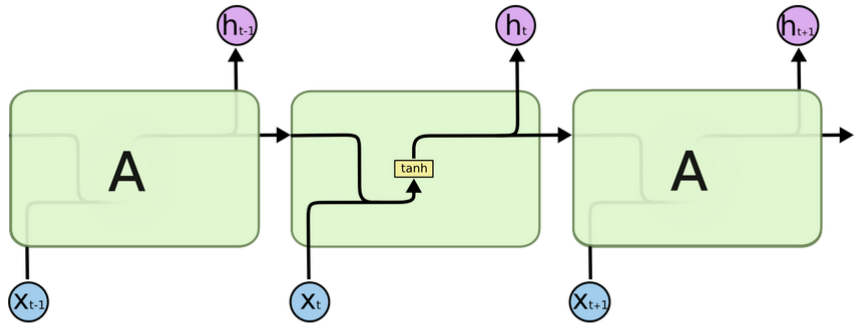

Figure 5.3: Schematic of an unrolled Recurrent Neural Network showing the memory state passing from X_{t-1} to X_t.

5.4.2 Long Short-Term Memory Networks (LSTMs)

LSTMs are a special type of RNN specifically engineered to overcome the RNN memory limitation and learn long-term dependencies.

- **Mechanism:** Instead of a simple memory, LSTMs use a dedicated Cell State and a set of internal control mechanisms called gates (Forget Gate, Input Gate, Output Gate). These gates intelligently regulate the flow of information:
  1. **Forget Gate:** Decides what information to discard from the previous cell state.
  2. **Input Gate:** Decides which new information from the current input is relevant to add to the cell state.
  3. **Output Gate:** Decides what part of the cell state to output as the prediction or the new hidden state.

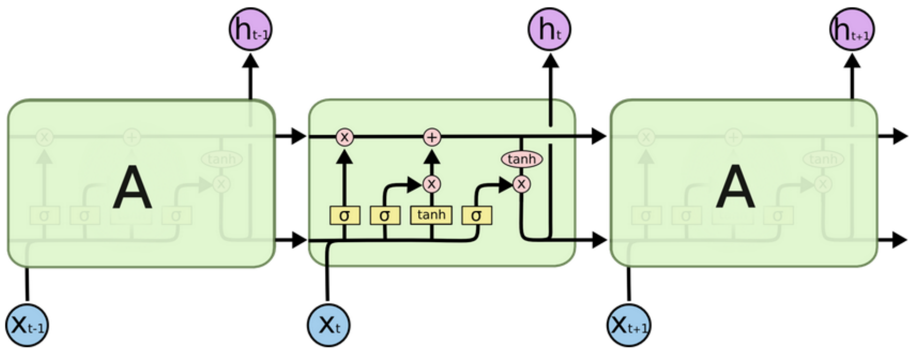

Figure 5.4: Schematic of the internal structure of a Long Short-Term Memory cell, highlighting the cell state and the three controlling gates.

Power for Battery Health: LSTMs are theoretically ideal for battery SOH prediction because they can capture intricate, long-term degradation trends across hundreds of cycles, making them highly suitable for predicting the capacity curve.

5.4.3 LSTM Model Architecture

The Long Short-Term Memory network implemented for this study utilizes a standard architecture optimized for time-series capacity prediction:

- **Sequence Length:** The input sequence length was set to 15. This means the model processes data from 15 consecutive, pre-processed discharge cycles to predict the capacity of the 16th cycle.
- **Layer Structure:** The model consists of two main components:
  1. **Stacked LSTM Layers:** Two (num_layers $= 2$) LSTM layers are stacked on top of each other. Stacking increases the model's complexity and ability to learn hierarchical features from the sequential data.
     - **Hidden Dimension:** Each LSTM layer has a hidden dimension of 128. This defines the size of the internal memory state passed between the time steps, offering a rich capacity for learning.
     - **Dropout:** A Dropout rate of 0.2 was applied. Dropout is a regularization technique that randomly ignores a fraction of neurons during training, which helps prevent the model from overfitting the training data.
  2. **Fully Connected Layer (FC):** The output from the final LSTM layer's hidden state is passed to a single Fully Connected Layer. This layer maps the 128-dimensional hidden state into a single output value, which is the predicted capacity (SOH) for the next cycle.

LSTM Model Performance Evaluation

Battery	B0005 (Training)	B0006 (Testing)	B0007 (Testing)	B0018 (Testing)
R^2 Score	0.9999	0.9387	0.9876	0.9619

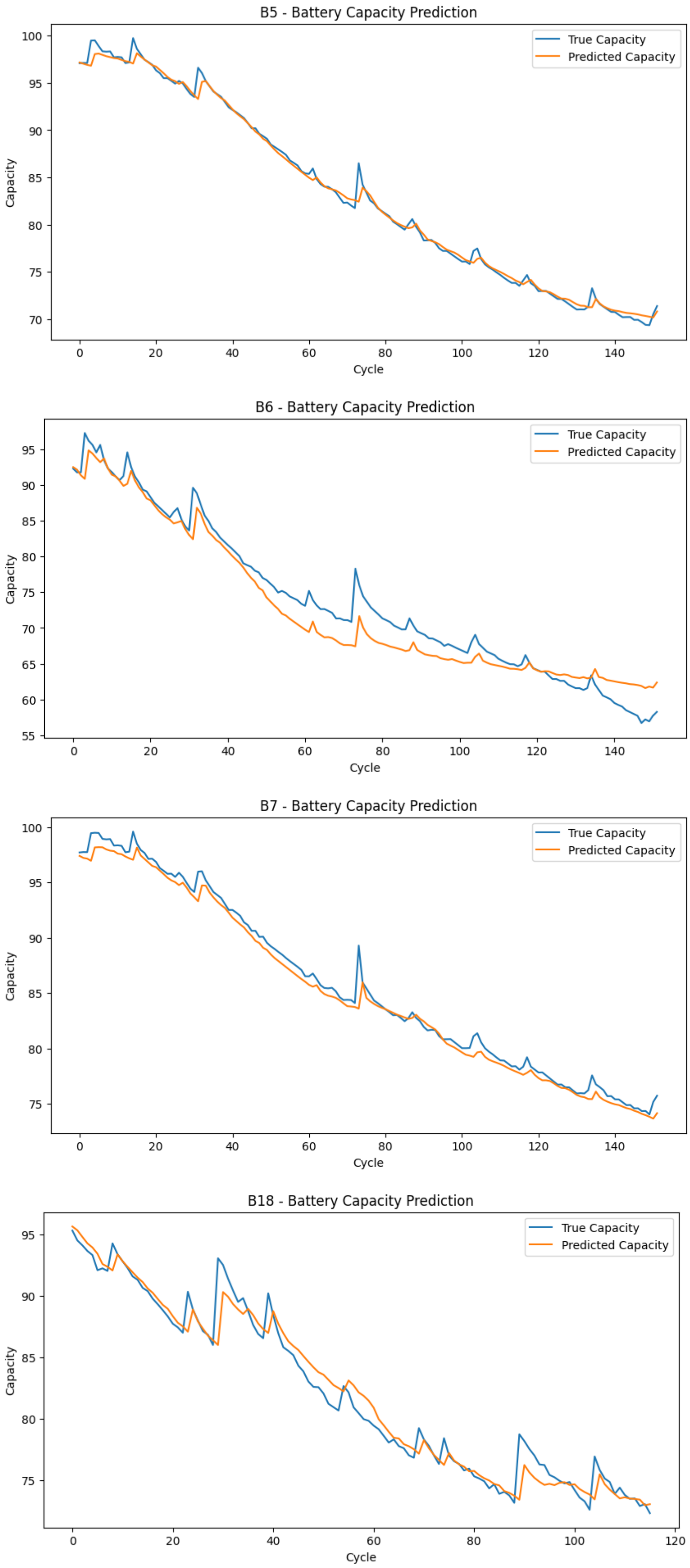

Figure 5.5: LSTM plots for Actual Capacity vs. Predicted Capacity for the test set.

Chapter 6

Conclusion and Future Work

6.1 Conclusion

The study led to several key findings regarding data processing and model selection for battery health prediction:

1. **Fewer Features Improve Model Performance:** Counterintuitively, models performed significantly better when provided with only the top 4 Q(V)-derived features (Mean, Peak, STD, RMS) compared to a much larger feature set. This confirms that the Q(V) transformation is an excellent, domain-informed indicator for battery health, and that redundant features only introduce noise, confusing the model.
2. **Simple Linear Regression Outperforms Ensemble Methods:** The simple Linear Regression model, especially with the reduced feature set, yielded higher R^2 scores than XGBoost. This is primarily because tree-based models like XGBoost are inherently interpolative (they predict within the range of the training data) and struggle to extrapolate the capacity decay curve accurately to predict health far into the future. Linear models are better suited for simple extrapolation.
3. **Linear Models Slightly Better than LSTMs:** Simple Linear Regression also performed marginally better than the complex LSTM network. This suggests that for the extracted features, the relationship with capacity fade is relatively linear, and introducing deep, nonlinear architecture adds unnecessary complexity that the model struggles to learn effectively.
4. **Temporal Dependencies Lost During Pre-processing:** LSTMs are designed for temporal analysis. The fact that the LSTM did not overwhelmingly outperform the linear model suggests that the pre-processing step—which summarized full cycles into single data points (Mean, STD, etc.)—may have resulted in the loss of critical temporal dependencies that LSTMs are best equipped to leverage.

6.2 Scope for Future Work

To further advance the accuracy and robustness of battery health prediction models, the following avenues of research are recommended:

1. **Scope for New Domain-Informed Features:** Since Q(V) proved to be such a rich feature, future work should focus on creating additional domain-knowledge-driven features that use Q(V) data. For instance, calculating the slope of the differential capacity curve

(dQ/dV) peaks could capture more subtle electrochemical changes than simple statistical summaries.

2. **Need for Extensive LSTM Hyperparameter Tuning:** Given the potential of LSTM networks, conducting in-depth optimization of hyperparameters (e.g., number of layers, neurons per layer, learning rate, sequence length) is crucial. A better-tuned LSTM network may be able to overcome the limitations observed in the current study.

3. **Revisiting Pre-processing to Preserve Temporal Dependencies:** The current approach summarized each cycle. A critical future modification would involve changing the pre-processing to feed the full voltage and temperature curves for the entire cycle (or a significant portion of it) directly to the LSTM as a sequence. This would allow the LSTM to model the temporal relationship between the raw measurements and the overall capacity fade, which may unlock its true predictive power.

References

[1] Efficient linear predictive model with short term features for lithium-ion batteries state of health estimation.
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