Investigating Battery Degradation Patterns and Predictive Models for Sustainable Energy Systems

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1. Introduction

Lithium-ion batteries (LIBs) are widely used in energy storage systems in portable devices and electric vehicle applications. Amongst various Li-ion chemistries, Lithium iron phosphate (LFP) batteries stand out due to their thermal stability, long cycle life and high safety [1]. However, conventional degradation assessments rely on extensive cycling tests, which are both time-consuming and costly [2], [3]. To accelerate the testing process, this study employs a machine learning approach to analyze the relationship between early-cycle discharge characteristics and long-term cycle life, specifically predicting the 80% state-of-health (SOH) cycle.

2. Results

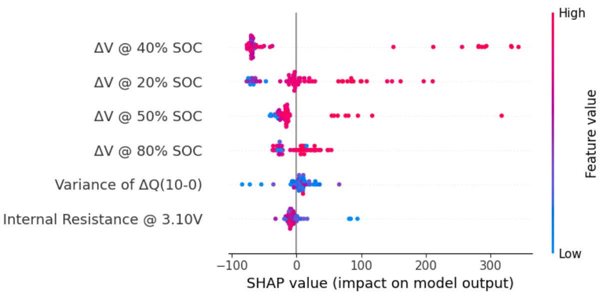

Fig. 1: SHAP-based feature importance for 80% SOH cycle prediction

By extracting key features such as current, discharge capacity trends, voltage and internal resistance variations at specific state-of-charge (SOC) or voltage levels, a predictive model is trained using XGBoost with recursive feature elimination (RFE) to identify the most important features.

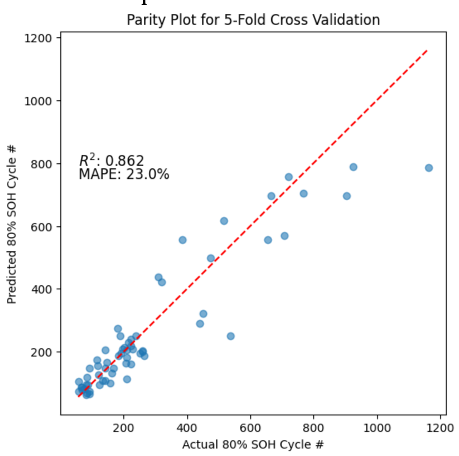

Fig. 2: Parity plot of test set predictions for 5-fold cross validation

The model demonstrates robust predictive performance of 0.862 R^2 and 23% mean absolute percentage error (MAPE) across different current levels, reducing the need for extensive cycling tests.

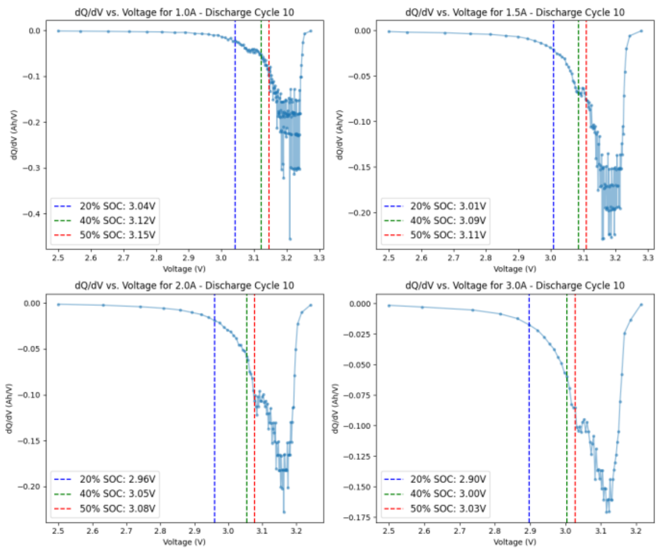

Fig. 3: Differential capacity (dQ/dV) curves with SOC reference lines (20%, 40%, 50%) for discharge cycle 10 at various currents

Finally, key insights are gained by mapping the key features onto the differential capacity analysis and discharge capacity plots to highlight the electrochemical signatures associated with degradation. This approach offers an interpretable framework, enabling a deeper understanding of battery degradation mechanisms. Furthermore, the methodology's transferability to other battery chemistries provides a scalable solution for accelerated battery health estimation across diverse energy storage applications.

References

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