Predicting Battery Remaining Useful-A data driven approach

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Abstract

Accurate prediction of the lifetime of lithium-ion batteries is crucial for technological advancement and clean energy solutions. Diverse aging mechanisms, device variability and dynamic conditions make this task complicated. A dataset of 124 commercial lithium ion cycled under charging conditions with life spans ranging from 150 to 2300 cycles is used. The discharge and charge cycles are analysed with data driven approaches in order to provide insights about the degradation patterns. Lasso regression is observed to perform the best with a percentage error of 7 percent.

Introduction

Lithium-ion batteries are widely used due to their low costs, high energy densities and long battery life. Predicting battery lifetime using early cycle data can help in improving the rate of battery production and utilisation. Data driven models are developed in order to accurately predict the remaining useful life of lithium-ion cells. RUL is defined as the difference between the total cycles to reach 80 percent of the nominal capacity and the current cycle count. By leveraging early cycle data to forecast the RUL of battery, we aim to understand the degradation battery mechanisms in a better way and also improve the efficiency of battery usage in various applications.

Methods

Our dataset comprises of three batches with 46,48 and 46 cells respectively. Each cell was cycled under different charging conditions over 1000 charging and discharging cycles. A feature-based approach was employed in order to build an early prediction model. The features synthesised include i**nitial discharge(Q_in), discharge at the 200th cycle(QD_200), difference between the initial and the 200th cycle discharge(QD_delta), initial resistance(IR_in), resistance at 200th cycle(IR_200), time to charge 100% (charge_time), minimum Value in the voltage range 2.2-2.6 and 3-3.3 V respectively(dqdv_1 and dqdv_2),rate of change of discharge(QD_slope) intercept of the discharge curve(QD_intercept),rate of change of internal resistance(IR_slope),variance of Q_discharge between cycle 10 and 100(dQ_var) and intercept of the internal resistance curve (IR_intercept).** Multiple machine learning models including Linear Regression, Elastic Net regression,Lasso Regression and XGBoost Regression were used to predict RUL. Models were evaluated using RMSE and percentage error metrics.

Results and Discussion

The xgboost regression model is observed to demonstrate superior performance on the test dataset. The results across various models are summarised below.

Model	RMSE	R^2
Linear Regression	316.76	0.28
Elastic Net	372.5	0.06
Lasso	316.05	0.28
XGBoost	187.85	0.74

Discussion of Features

Qd_in – Provides a baseline capacity of the battery indicating the initial performance and manufacturing quality.

Qd_200- Monitoring capacity at 200th cycle helps understand how battery capacity retains over the initial cycles

Qd_delta- Measures the early capacity loss. Higher value indicates faster degradation.

Qd_slope and Qd_intercept- Represent the rate of change and baseline trend of capacity degradation.

IR_in and IR_200- Similar to Qd_in and Qd_200, Measures the internal resistance. Lower value indicates better performance.

IR_slope and IR_intercept- Similar to Qd_slope and Qd_intercept. Help in quantifying the rate of increase in internal resistance.

Dqdv_1 and dqdv_2-Capture specific characteristics of the voltage-capacity curve, indicating phase transformations within the battery during discharge.

Deltaq_var-captures the variability in discharge capacity over a range of cycles, providing a measure of the stability.

Charge_time-Measures impact of charging policies on battery performance.

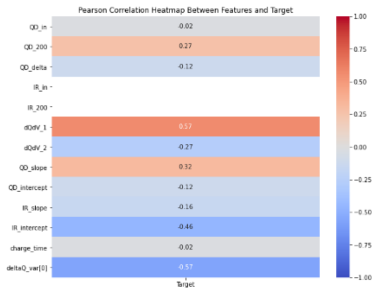

Fig1.Pearson correlation was used to find the important features and It was observed that dqdv_1 and deltaq_var has the strongest correlation.

Conclusion

This study predicts the remaining useful life (RUL) of lithium-ion batteries using data from 46 cells per batch across three batches. Linear regression achieved a test r^2 of 0.28, improved to 0.74 with XGBoost regression. Hyperparameter-tuned XGBoost achieved an RMSE of 187.85.

Future Work

We will generate more features combining more data and fine-tuning models to predict lower percentage error within 8% and compare data driven results with experimental battery degradation based on physical and semi-empirical models and how batteries degrade with real-time monitoring.

References:

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