Predicting Lifespan of Lithium-Ion Cells

Jack Landers, June 6, 2025

***Abstract*—Accurate prediction of the remaining useful life (RUL) of lithium-ion batteries is essential for battery management systems in electric vehicles, consumer electronics, and energy storage. This paper presents a machine learning approach trained on the open-source NASA battery aging dataset on Kaggle. A complex feature engineering strategy combines discharge, charge, and calculated impedance from current sensing measurements. With this, the model achieves a mean absolute error of 8.45 cycles and an R^2 error of 0.962.**

I. Introduction

Lithium-ion batteries degrade over time due to irreversible electrochemical processes. Predicting their remaining useful life (RUL) helps with proactive maintenance and safer operation. Among publicly available sources, the NASA Prognostics Center data offers high-resolution discharge, charge, and impedance values collected under controlled conditions, at the local AMES Research Center. The variety of this dataset is utilized to build a regression model using a decision tree with 22 layers and 1818 leaf nodes.

II. Dataset

The dataset consists of 24 commercial-grade 18650 cells cycled at three temperatures ($24°\text{C}, 43°\text{C}, 4°\text{C}$). For each cell, every charge, discharge, and impedance test is stored in an individual CSV. These include terminal voltage, current, temperature, and timestamp with current sweeps storing complex values for impedance. Altogether, these variables represent the electrochemical properties of the battery which determine its remaining lifespan. To make this data suitable for modeling, scalar impedance features are extracted by parsing the complex values and computing the average real and imaginary components:

$$Z_{\text{real}} = \frac{1}{N}\sum_{i=1}^{N}\text{Re}(Z_i), \quad Z_{\text{imag}} = \frac{1}{N}\sum_{i=1}^{N}\text{Im}(Z_i), \tag{1}$$

where Z_i are the complex impedance values from each measurement point in the sweep.

Although the dataset stops recording shortly after a battery reaches its end-of-life (EOL) condition, we define *useful* end-of-life as the point where the battery's measured capacity drops below 80% of its initial value. This threshold is widely used in literature and industry to indicate the end of a battery's practical service life. Accordingly, the label for each discharge cycle n is defined as:

$$\text{RUL}_n = N_{\text{EOL}} - n, \tag{2}$$

where N_{EOL} is the index of the first cycle that falls below the 80% capacity threshold. While the full dataset extends beyond this point, the model focuses on predicting the remaining *useful* life leading up to this degradation boundary.

III. Methodology

A. Input Features

- **Cycle Index**: test id captures how many usage cycles the battery has been through.
- **Discharge Features**: Duration and energy throughput, which is computed as the integral of instantaneous power.
- **Charge Features**: Duration and energy throughput from the preceding charge.
- **Impedance Features**: Mean real (R_{e}) and imaginary (X_{e}) parts from the latest impedance spectrum.
- **Ambient Temperature**: Logged chamber temperature.

The final design matrix contains ten numerical predictors after dropping identifiers.

The raw CSVs are parsed per-cycle from over 7500 files using NumPy and pandas. Complex impedance strings such as 0.162-0.024j could be cast with Python's complex constructor from sense current. Missing impedance samples are imputed with forward filling.

B. Model Choice

I employed a Decision Tree Regressor from the scikit-learn library with default Gini splitting. This model is well-suited for battery Remaining Useful Life (RUL) prediction due to several key advantages. First, the tree structure allows us to trace the impact of features directly along the prediction path. Secondly, decision trees inherently capture non-linear relationships and complex feature interactions, which are common in the battery degradation processes.

Unlike linear models, which assume additive and independent contributions from each feature, decision trees are capable of modeling conditional dependencies. For instance, the effect of impedance may be significant only when the voltage is below a certain threshold, a structure naturally learned through recursive partitioning. Moreover, decision trees handle missing values and heterogeneous feature scales without the need for normalization or imputation.

While decision trees are prone to overfitting, this risk can be mitigated through train-test validation and feature selection. The ability to reveal the data's structure and provide fast inference with low computational overhead, makes it a strong baseline choice for this task.

C. Training and Testing

Sparce impedance measurements made the model difficult to effectively train. They were sampled at a lower frequency and only occur every 50 cycles. By forward-filling the latest sweep to subsequent cycles, MAE improved by 7 %, and no data was falsified by interpolation.

There were also slight inconsistencies in the data such as an i instead of j caused parsing failures. Robust pre-processing to normalize all the entries was required before complex casting.

The dataset is partitioned with an 80/20 shuffle split separated by cell ID to avoid learning cell-specific artifacts. Evaluation metrics include mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination (R^2).

IV. Evaluation and Analysis

Multiple analyses validate the model's performance reliability and generalization. The distribution shows that most samples cluster around RUL values close to zero, with relatively fewer examples in both early-life (positive RUL) and post-EOL (negative RUL) regions. The following plots and metrics summarize the Decision Tree model's behavior in predicting remaining useful life.

A. Feature Relationships and Importance

Figure 1 displays feature importances extracted from the trained tree. The model ranks charge energy and discharge energy highest, followed by impedance features and test id, indicating the model captures both electrochemical and chronological degradation factors.

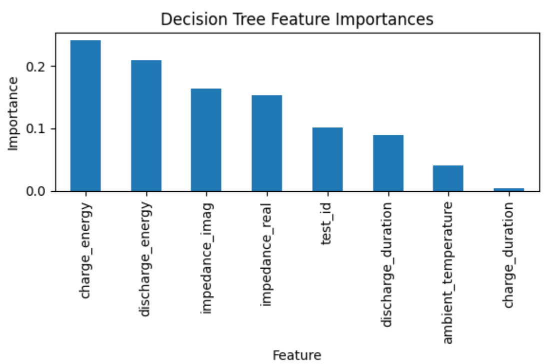

Fig. 1. Decision Tree feature importances.

B. Prediction Accuracy

Figure 2 compares predicted versus actual RUL. The near-diagonal alignment of points and tight scatter suggest that the model captures both high and low RUL values effectively, with only a few outliers.

C. Residual Analysis

The residual distribution (Figure 3) is nearly symmetric and tightly centered at zero, indicating unbiased predictions. A few extreme errors inflate the RMSE metric relative to the MAE, which is expected in a real-world dataset containing outlier behavior.

When residuals are plotted against true RUL values the scatter remains balanced, but more variance appears in the mid-to-late life range. This suggests that as batteries degrade, the system becomes less predictable with physical degradation dynamics, making it a heteroskedastic distribution.

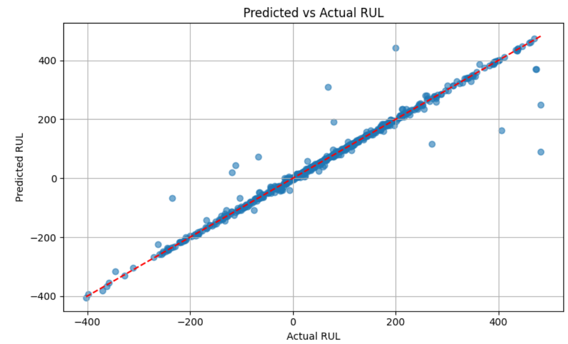

Fig. 2. Predicted vs. actual RUL on test set.

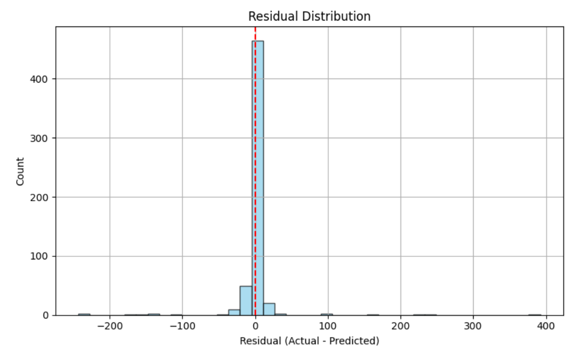

Fig. 3. Histogram of residuals (actual - predicted).

V. Conclusion

This model demonstrates a strong ability to predict RUL with an R^2 of 0.962, an MAE of 8.45 cycles, and an RMSE of 31.6 cycles. It performs well across most of the data range, but is sensitive to outliers and imbalance in long-life examples. The tree's ability to exploit nonlinear features like impedance, while retaining interpretability, makes it a strong candidate for prognostic applications like battery degradation.