Deep Learning Based Remaining Useful Life Prediction of Lithium-Ion Batteries Using Early Cycle Degradation Features

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ABSTRACT

The failure of a lithium-ion battery (LiB), which is used as an energy storage system (ESS) in the mobility industry, such as electric vehicles and aircraft, can lead to substantial loss of life and property, thereby causing significant problems. Therefore, it is essential to monitor the capacity degradation of the mobility battery and accurately predict the remaining useful life (RUL) from the early cycle stage. Particularly, RUL prediction is the main objective of the Battery Management System (BMS) and is important for guaranteeing the safety of the mobility system (Wu *et al.*, 2016). This research introduces a hybrid deep learning model for RUL prediction, using LSTM-attention and Multi-Layer Perceptron (MLP) methodologies. The proposed model uses statistical degradation features and domain knowledge-based features as input data acquired from the early 100 cycles of charge/discharge data of a lithium-ion battery. The model's performance evaluation was divided into two phases: primary and secondary, providing root mean square errors of 158.4 and 168.67, respectively. This study's results aim to contribute to the advancement of Prognostic and Health Management (PHM) technology, Condition-Based Maintenance (CBM) strategies, and BMS-based life prediction technology for mobility battery systems.

1. INTRODUCTION

Batteries are principally used in mobility systems to store electricity and provide power to motors and driving devices. Lithium-ion batteries are used as a conventional energy source in E-mobility devices due to their long lifespan, efficiency, and high energy density. Nonetheless, despite these advantages, if the battery's available capacity drops below 80% of its initial capacity at the end of its lifespan, it could lead to severe safety incidents, including explosions and fires. Therefore, predicting the end-of-life point of the battery during the early cycle is an important technical challenge that is directly related to improving the safety of mobility systems.

The lithium-ion battery shows a slow degradation rate during the early cycle due to its longevity, making it challenging to assess its lifespan over a short period of time. For this reason, an approach for predicting the battery's RUL by analyzing degradation-related variables from early charging and discharging cycle data is being researched.

(Severson *et al.*, 2019) pioneered data-driven cycle life prediction for lithium-ion batteries, introducing an elastic network-based learning approach that leverages a subset of variance (Elastic-V), discharged (Elastic-D), and full (Elastic-F) variables. (Yu *et al.*, 2025) proposed a hybrid RUL prediction model that combines Transformer-CNN and MLP, integrating domain knowledge-based and statistical features into Intra-cycle Features and Inter-cycle Features to achieve superior predictive performance.

In this study, we advance the methodology of (Yu *et al.*, 2025) by introducing a hybrid input structure that integrates domain knowledge-based features with clear physical significance, including Coulombic Efficiency and Charge–discharge Voltage Difference, alongside statistical features such as discharge capacity, incremental capacity (dQ/dV), temperature, and internal resistance (IR). These features are categorized into Intra-cycle Features and Inter-cycle Features, serving as input data for LSTM-Attention and MLP models, respectively, to perform RUL prediction. This research offers a deep learning neural network methodology based on battery degradation characteristics, which offers the following contributions:

- We quantitatively characterize the changes in energy efficiency during charge–discharge processes and the increase in overpotential associated with cycle degradation through Coulombic Efficiency and Charge–discharge

Voltage Difference, thereby enhancing the physical interpretability and improving the reliability of the prediction results.

- We apply a physics-guided feature engineering approach to organically integrate the physicochemical behavior of the battery with the data-driven learning model, thereby improving the generalizability of the model.

2. DATASET DESCRIPTION

2.1. MIT-Stanford dataset

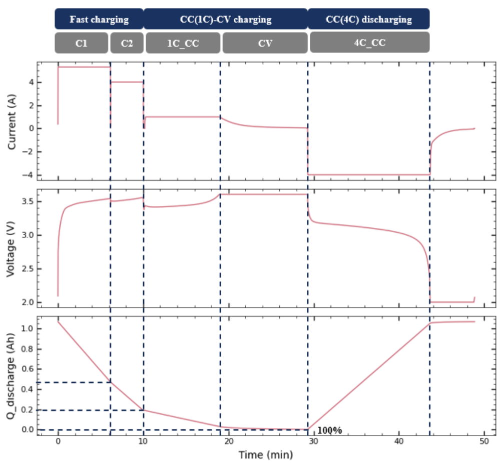

Figure 1. Battery charge/discharge protocol

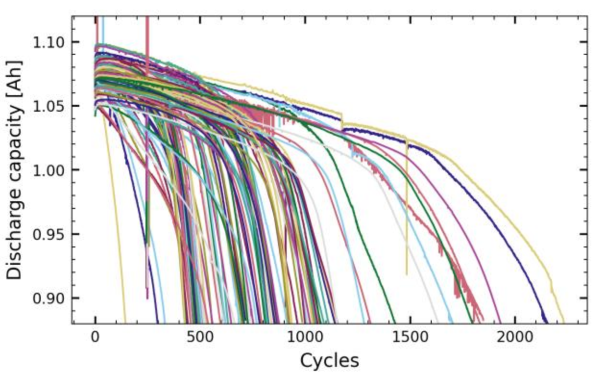

Figure 2. Battery capacity degradation

In this study, we used the open-access, MIT-Stanford battery dataset(Severson *et al.*, 2019). This dataset contains $LiFePO_4$ (LFP) battery cycle data as experimental. The tested cells are APR18650M1A commercial cells produced by A123 Systems, with a nominal capacity of 1.1Ah, a nominal voltage of 3.3V, and a LFP/graphite electrode configuration. The C1(Q1)-C2 fast charging strategy was used for the battery, with C1 and C2 representing constant current values in steps 1 and 2, respectively, and the average charging rate ranging from 3.6C to 6C. After fast charging, the battery was fully charged in CC (Constant Current) mode of 1C and CV (Constant Voltage) mode. All cells were discharged in CC mode of 4 C, with a lower cut-off voltage of 2.0 V. The dataset includes data from 124 battery cells, displaying an extensive variety of lifespans. Figure 1 shows the charge/discharge protocol of an arbitrary battery, and Figure 2 shows the discharge capacity degradation curve included in the dataset.

3. METHODOLOGY

3.1. Degradation feature generation

The statistical features related to battery degradation, extracted with reference to the feature extraction method proposed by (Severson *et al.*, 2019), together with the domain knowledge-based features, Coulombic Efficiency and Charge–discharge Voltage Difference, are used to generate features.

3.2. Inter-feature extraction

The inter-feature set consists of the statistical characteristics of the discharge capacity difference between the 100th and 10th cycles, as well as the mean value of the Coulombic Efficiency difference between the 100th and 50th cycles. Detailed information on the feature transformation process is provided in Table 1.

Table 1. Inter feature transformation function.

Descriptions	Feature formulations (Log scale)
$Min\_\Delta Q_{100-10}(V)$	$log\ (\lvert min\ (\Delta Q(V))\rvert)$
$Mean\_\Delta Q_{100-10}(V)$	$log\ (\lvert(\overline{\Delta Q}(V))\rvert)$
$Var\_\Delta Q_{100-10}(V)$	$log\ (\left\lvert\frac{1}{p-1}\sum_{i=1}^{p}\left(\Delta Q(V)-\overline{\Delta Q}(V)\right)^2\right\rvert)$
$Mean(\Delta\eta CE_{100-50})$	$log\left(\left\lvert\frac{1}{p-1}\sum_{i=1}^{p}\eta CE(k)\right\rvert\right); \eta =\ Q_{dis}^{max}\ /\ Q_{dis}^{min}$

3.3. Intra-feature extraction

The intra-feature set was constructed by utilizing the cycle-wise statistical characteristics of discharge capacity, incremental capacity, and temperature to form time-series data capturing the degradation behavior of each battery. In addition, the incorporation of cycle-wise Coulombic Efficiency, Charge–discharge Voltage Difference, and IR values further enhanced the explanatory power of the degradation characteristics. Detailed information on the Charge–discharge Voltage Difference transformation function is provided in Table 2.

Table 2. Charge–discharge Voltage Difference function.

Descriptions	Feature formulations (Log scale)
$\bar{V}_c\ /\ \bar{V}_d$	$\frac{1}{n_c}\sum_{i=1}^{n_c}V_{c,i}\ /\ \frac{1}{n_d}\sum_{i=1}^{n_d}V_{d,i}$
ΔV	$log\ (\bar{V}_c - \bar{V}_d)$

3.4. Correlation analysis

The inter-feature set was analyzed for its correlation with the battery's RUL cycle. Figure 3 illustrates the correlation coefficients between the four inter-features and the RUL cycle on a log scale.

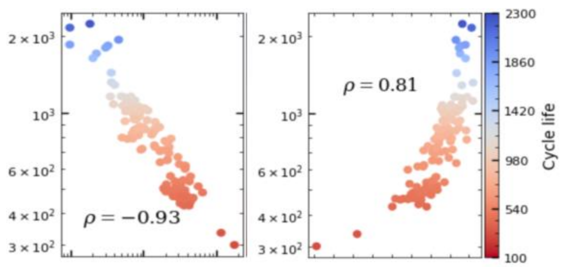

Figure 3. Correlation between Discharge Capacity Difference, Coulombic Efficiency, and RUL

3.5. LSTM-Attention & MLP model

The proposed early cycle RUL prediction model employs a hybrid architecture combining a sequence LSTM–attention branch with a static-feature MLP branch. Time-series inputs are processed by a 3-layer bidirectional LSTM (hidden layer=32), followed by an attention mechanism that assigns weights to salient time steps, and the weighted context is projected to 16 dimensions.

Static inputs containing features such as Coulombic Efficiency and Charge–discharge Voltage Difference are fed into an MLP (4, 16, 32, 64, 32, 16) where Sigmoid and SiLU activations are alternately applied to enhance nonlinearity. The resulting 16-dimensional embedding is concatenated with the LSTM branch embedding and passed to a prediction head MLP (32, 64, 32, 1) to produce the RUL prediction.

4. RESULTS AND DISCUSSION

In this study, we evaluated the regression-based RUL prediction model performance on both the Primary and Secondary test datasets using RMSE and MAPE metrics, as shown in Table 3. Compared to (Severson *et al.*, 2019)'s results, the RMSE for the Primary test was 74.07% worse, whereas the Secondary test showed a 2.5% improvement. Figure 4 qualitatively illustrates the prediction results for both datasets, providing visual insight into the model's performance.

The reduced performance in the Primary test is attributed to larger prediction errors for long-lifetime battery cells. The Secondary test exhibited a similar trend, with reduced accuracy for long-lifetime cells, consistent with the patterns observed in (Severson *et al.*, 2019)'s results. This suggests that the data-driven prediction model, which maps the relationship between degradation history and RUL, tends to be biased toward cells with rapid degradation under high-rate cycling conditions. Such data imbalance led to limited extrapolation capability for long-lifetime cells. Nevertheless, the comparable performance across both test datasets demonstrates the consistency of the model, which can be interpreted as a positive indicator that reduces the likelihood of overfitting.

Future work will focus on improving prediction accuracy for long-lifetime battery cells by incorporating data imbalance mitigation techniques and enhancing extrapolation performance. The goal is to develop a generalized prediction model applicable to cells with diverse lifetime characteristics.

Table 3. Prediction performance metrics.

	RMSE (cycles)	MAPE (%)
Primary	158.40	11.18
Secondary	168.67	11.96

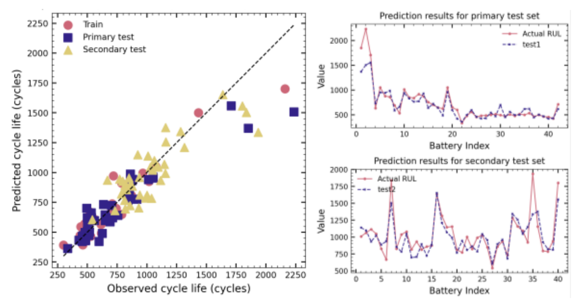

Figure 4. Early cycle prediction results

5. CONCLUSION

This study proposed a method for predicting the RUL of mobility batteries and validated its performance through two stages of testing. The proposed model demonstrated consistent prediction trends across both test datasets, indicating stable performance. However, for a subset of long-lifetime battery cells, the prediction accuracy was reduced, likely due to insufficient consideration of slow degradation characteristics. Future work will focus on incorporating novel domain knowledge–based feature extraction techniques tailored to slow degradation to enhance prediction accuracy for long-lifetime cells.

ACKNOWLEDGEMENT

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