

# Estimating State of Health SOH and Remaining useful life RUL of Lithium-Ion Batteries

## INTRODUCTION

Lithium-ion (Li-ion) batteries, known for their high voltage, energy density, and long cycle life, are essential in various applications, including electronic devices and electric vehicles. However, they degrade over time through repeated charge and discharge cycles, leading to diminished capacity and increased safety risks such as thermal runaway. This study explores the use of machine learning techniques to monitor battery health, estimate the State of Health (SoH), and predict the Remaining Useful Life (RUL) of Li-ion batteries. By employing data-driven methods and Exploratory Data Analysis (EDA), we aim to develop a robust framework for effective battery health monitoring and preventive maintenance.



## EDA

The EDA aims to understand the characteristics of a dataset from four Li-ion batteries, focusing on parameters like terminal voltage, output current, and temperature. Key findings include a consistent decrease in capacity over time, with a normalized distribution, and trends such as decreasing voltage in increasing temperature. The analysis reveals that SoH is inversely correlated with cycles but positively correlated with capacity and time, with SoH and RUL showing a strong positive correlation. Redundant features, like voltage load, were identified for removal to enhance model efficiency.



## AIMS

The aim of this study is to develop a robust and adaptable framework for monitoring the health and predicting the lifespan of Lithium-ion (Li-ion) batteries using machine learning techniques.

- Identify features influencing battery performance and degradation through EDA.
- Comparing different machine learning techniques to make a robust model for predicting RUL and SOH accurately.
- Implement predictive maintenance strategies to enhance battery performance, prolong battery lifespan, and ensure user safety.

## METHODS

For the research purposed we used the NASA's Li-ion Battery Aging Dataset. Based on our research this was the most comprehensive dataset publicly available.

The dataset has the data for different batteries under different environmental conditions, for creating a robust model and gathering insight we will combine the data for the different batteries under different condition.

We will also need to calculate the SOH and RUL from the data given. Using this the EDA should give useful insight as well as allow us to accurately train and test different models. The models will be compared in order to choose the best possible solution.

## MODELLING

Data Normalization:

- We used Min-Max Scaler to normalize in the dataset to enhances model stability, convergence efficiency, and resistance to outliers.

Initial Deep Neural Network (DNN) Models:

- SoH Prediction: MSE: 0.000295
- RUL Prediction: MSE: 0.000256

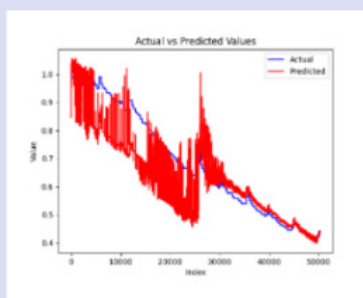
Integration of SoH into RUL Prediction:

- Testing Our approach: We Included SoH data in the RUL prediction model to as the BMS can predict or keep track of SoH and since they have a high coloration the models accuracy should improve.
- MSE: 4.695e-08
- Outcome: The integration led to improved RUL prediction performance with a close linear relationship between actual and predicted values.

Comparison of DNN and LSTM Models for SoH Prediction:

- DNN Model: MSE: 0.001895
- LSTM Model: MSE: 0.000252
- Comparison:
- LSTM showed superior accuracy due to its ability to capture temporal dependencies in sequential data.
- Considerations: LSTM models are more complex and computationally intensive than DNNs. DNNs are simpler and may be preferable if efficiency are prioritized.

## RESULTS OF LSTM MODEL



## DISCUSSION

Our research enhances the accuracy of battery State of Health (SoH) and Remaining Useful Life (RUL) predictions by analyzing data from Lithium-ion batteries and applying machine learning models. Notably, integrating SoH data into RUL predictions and using Long Short-Term Memory (LSTM) models improved accuracy. Future work will focus on integrating these models into Battery Management Systems (BMS), optimizing preventive maintenance, enhancing safety, and validating models in real-world scenarios. This research advances battery health monitoring and aims to improve proactive management and operational efficiency.

## REFERENCES

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