Enhanced Capacity Predictive Model of Li-Ion Batteries

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Introduction

Li-Ion batteries are widely used as they provide better performance at low temperature and due to its high power ratings. Capacity monitoring and prediction is a crucial step for effective usage of battery in order to replace the battery before it reaches its end-of-life. This is also measured in terms of remaining useful life (RUL) of the battery. Generally, it is replaced when it reaches 80% of its beginning-of-life or factory setting. Data-based prediction models have gained popularity as they are easy to deploy and provides greater accuracy. Adequate selection of feature plays a vital role in prediction models,. Better the features elected, better is the accuracy.

Data-driven RUL

For the project, open sourced battery data set from NASA prognostic centre has been used. For experiment, data set number 5 is selected. Failure threshold is considered 30% of the lowest capacity value after which it is evident the lifecycle of the battery in use is reaching and the battery could no longer be in operation and must be replaced.

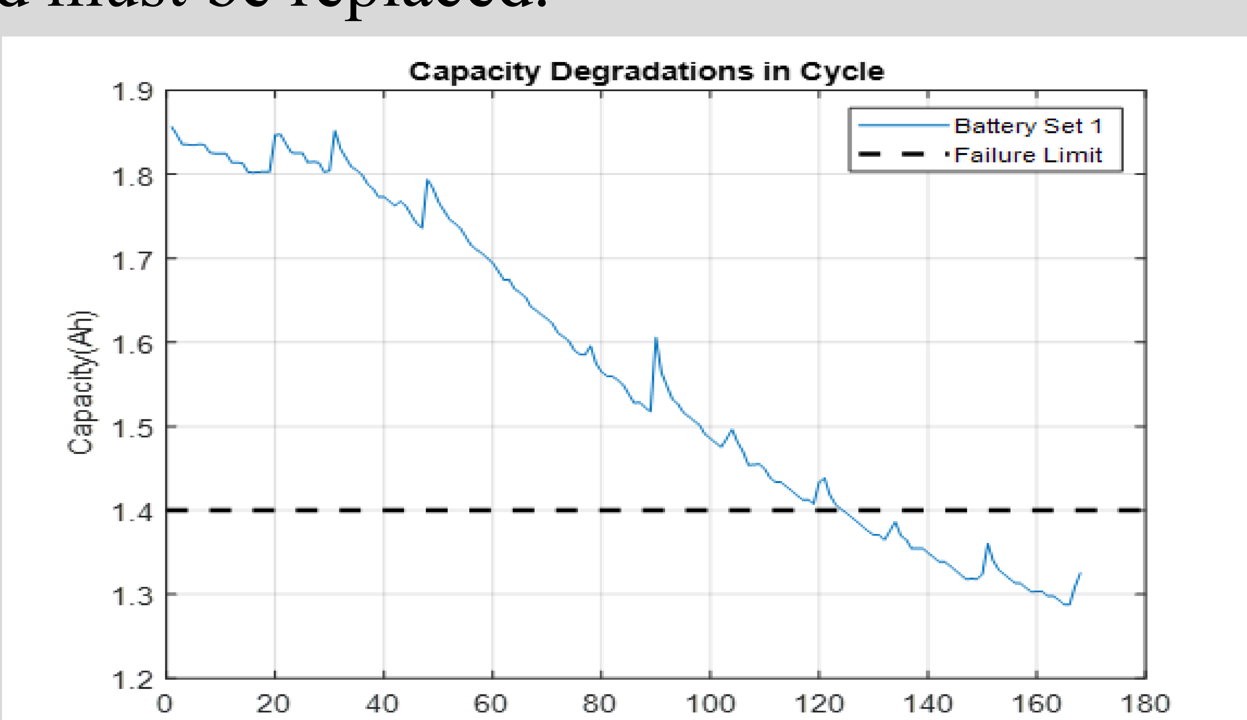

Fig. I. Capacity Degradation cycle of battery set 05

Objectives

- To assess the existing model and suggest an improvement in the feature selection.
- Design the predictive models based on different machine learning algorithms.
- Trian the predictive model with new features.
- Compare the results.

Methodology

The original model is limited to individual values of measured voltage & current and temperature as data selection. The modified model takes account of both measured and terminal voltage as a reference.
Voltage ΔV = Voltage charged - Voltage measured.
Current ΔI = Current charged - Current measured.
Following machine learning models were used to validate both the models.
1.Feedforward neural network (10/40 neurons)
2.Convolution neural network (filter size 10,1 and 30,15)
3.Long short-term memory with 5 hidden unit.

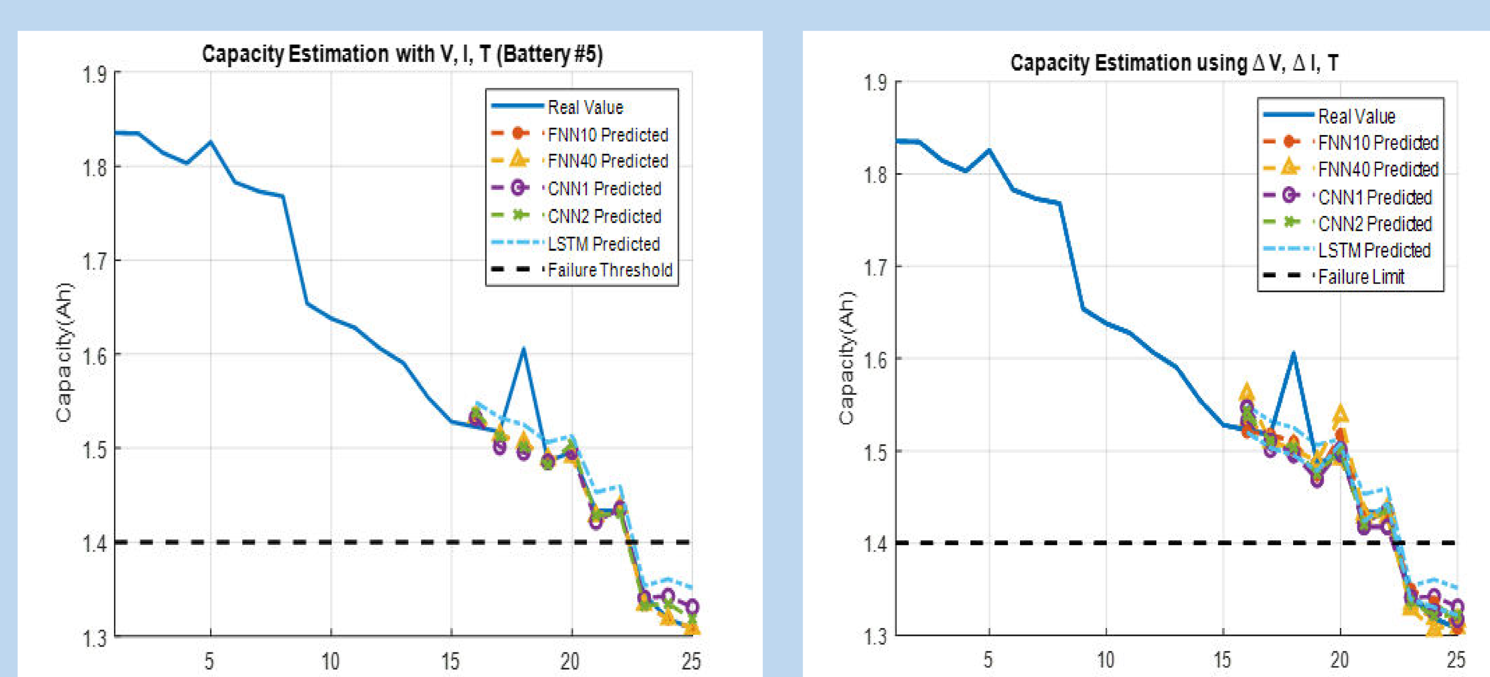

Fig. II. Capacity prediction using FNN, CNN, LSTM (right: original model, left: modified model)

Result

To differentiate the performance, RMSE criteria is used and Table I differentiates the values of different predictive models employed. It is evident the former model has a greater capability of performance, but the modified model gives almost a better performance.

Models	Feedforward N/w (10 neurons)	Feedforward N/w (40 neurons)	Convolution Layer with filter size [1, 2] and number of filter 10,5	Convolution Layer with filter size [1, 2] and number of filter 30,15	LSTM layer with 5 hidden unit
RMSE (Original)	0.0320	0.0320	0.0372	0.0343	0.0360
RMSE (Modified)	0.0319	0.0384	0.0366	0.0343	0.0363

Table. I. RMSE comparison of original model and modified model

In comparison, the CNN model gives same results whereas LSTM provides nearly satisfied results. Feedforward models with less neurons give same result for both the models but considering the size of the data, the second model of 40 neurons is highly recommended to phase out the better weighting of the neurons.

Acknowledgement

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