Study of Performance Characteristics of lithium ion battery in EV

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<u>Performance Characteristics</u>

Ageing characteristics

During its working lifetime, the output of a battery deteriorates, and once its capacity exceeds 80% of the initial value, it reaches the end of life (EOL). For reliability assessment and maintenance purposes, battery health should be controlled. Diagnosis of State of Health (SOH) and Remaining Useful Life (RUL) prognostics for lithium-ion batteries will help EV users monitor real-time battery health.
The study of life cycle and aging characteristics of a lithium ion battery was approached with two methods. We created a simulink model for monitoring the SOC, current and voltage variations for a lithium ion battery for a given time period in both serial and parallel combination of batteries. In the later part we also present an ML model that uses lithium ion battery data in order to train for prediction of SOH and RUL at any specific time of operation of a battery.

Simulation modelling

We can use a simulink model for understanding the performance characteristics of Li-ion batteries in EV's. In order to understand the HIgh voltage requirements in EV's, we are considering the series combination of lithium ion cells in a pack. Here we shall look at the effects of aging (due to cycling) in the form of SOC (State of Charge) of the battery. We also look at the Parallel combination and aging effects for that.

Nominal voltage for each of the Lithium ion batteries is taken 3.7 V and rated capacity of 2.6 Ah with an initial SOC of 96%.

Series Combination

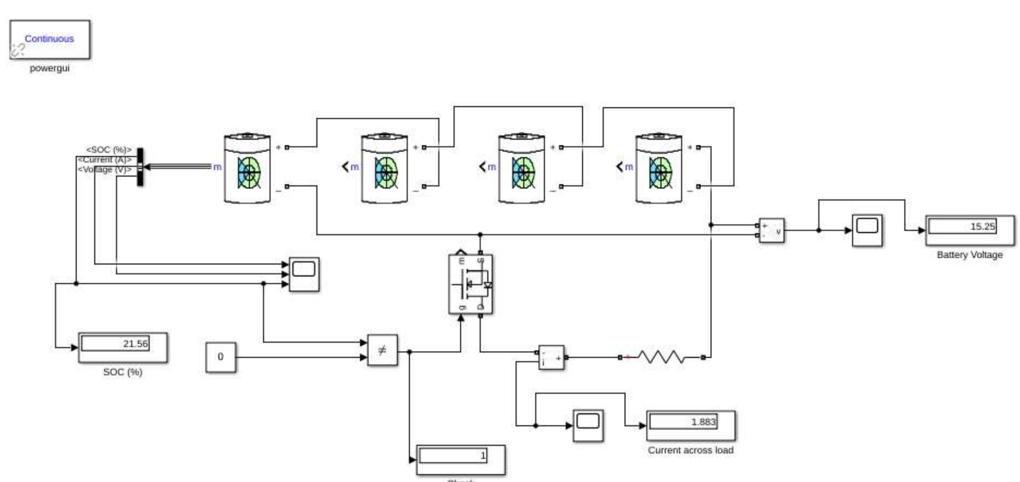
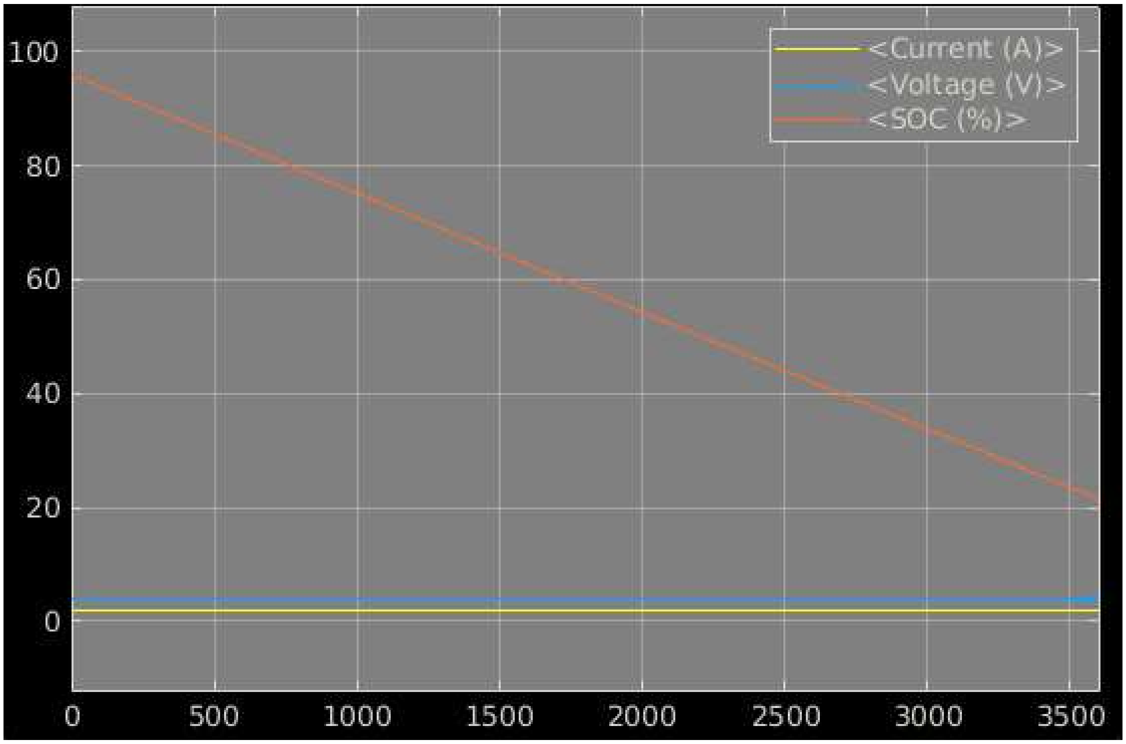


FIg.1 Series combination of batteries with SOC value for 3600 sec discharge



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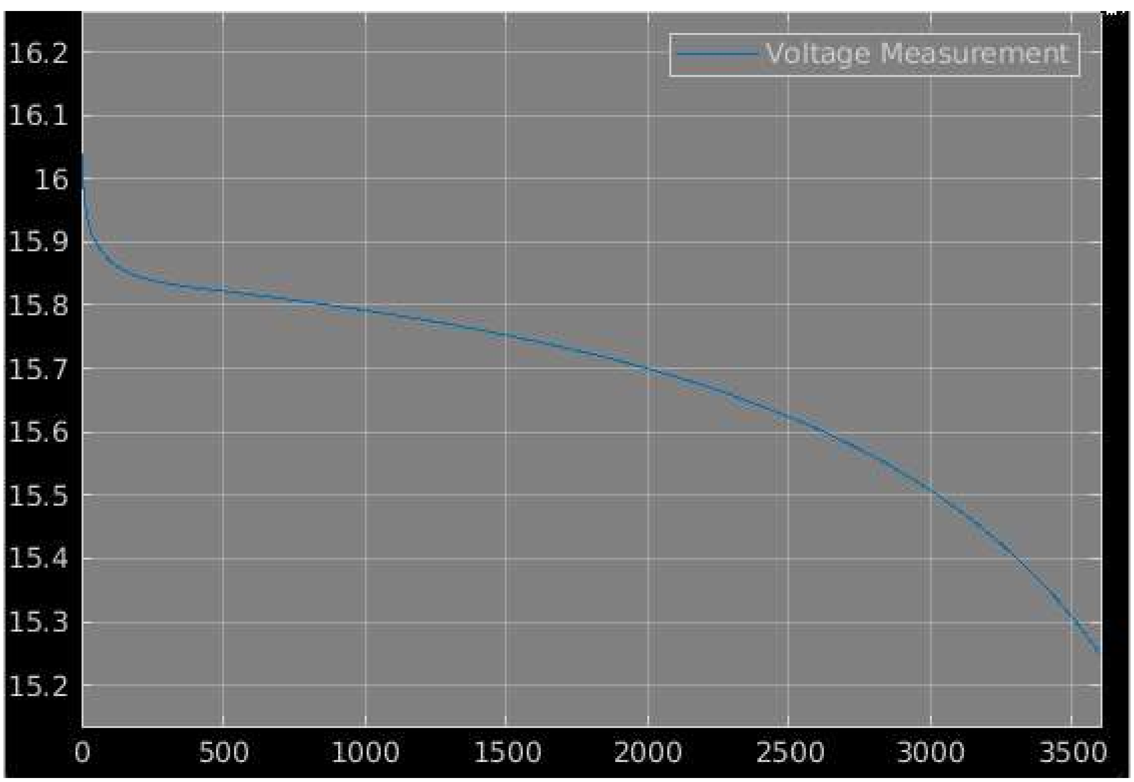
Battery SOC, Current, Voltage variation with time



Voltage across battery pack

Parallel Combination

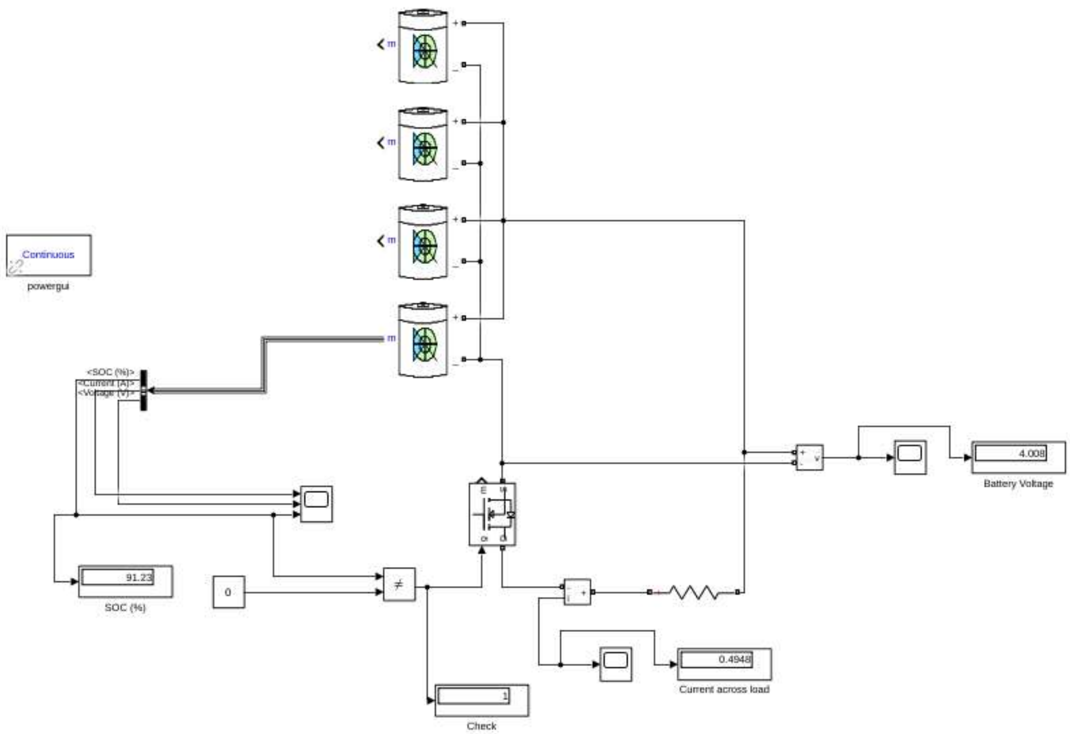
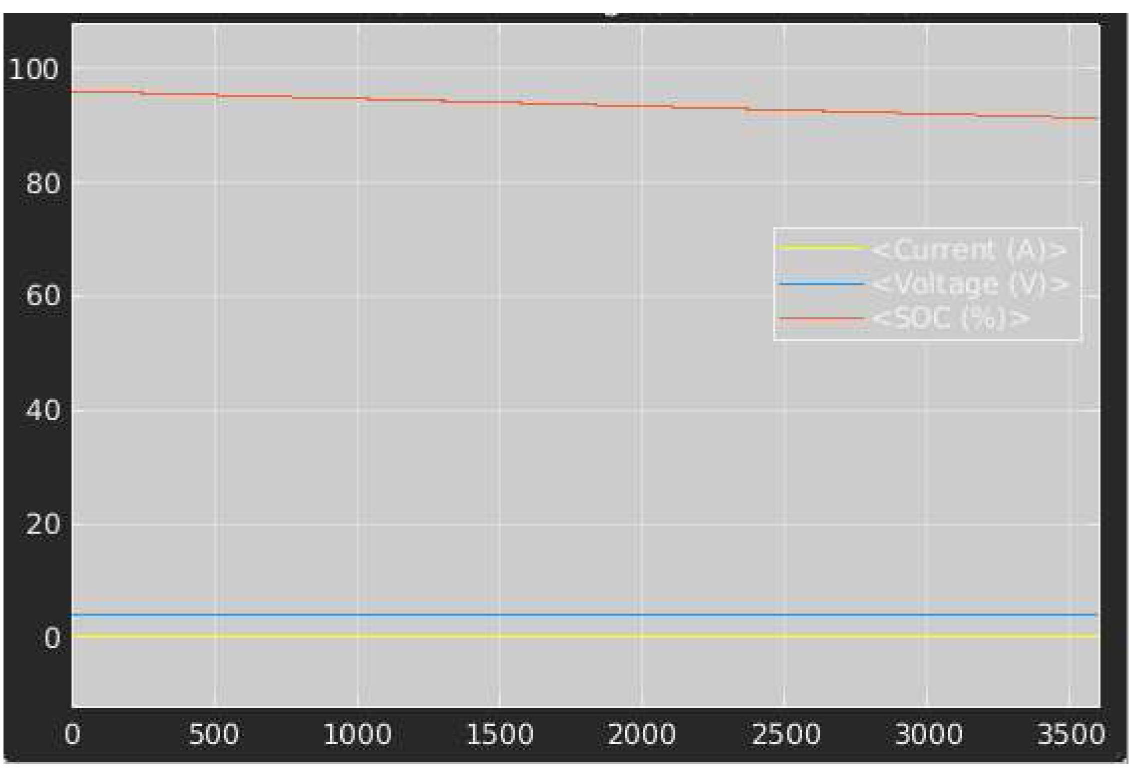
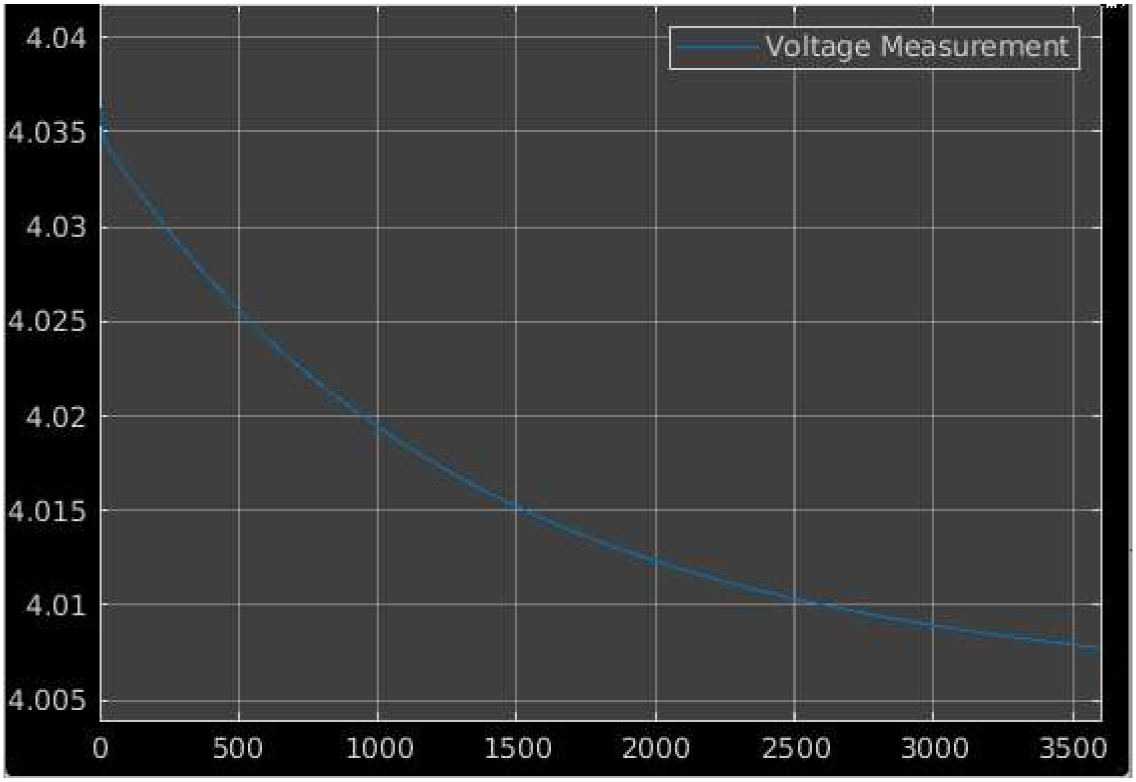


FIg.2 Parallel combination of batteries with SOC value for 3600 sec discharge



Battery SoC, Current, Voltage variation with time



Voltage across battery pack

The SOC plotted against time is a linear function in both the cases. The SOC plot has more rapid change in case of parallel combination but also provides a lower voltage and power.

Thermal Characteristics

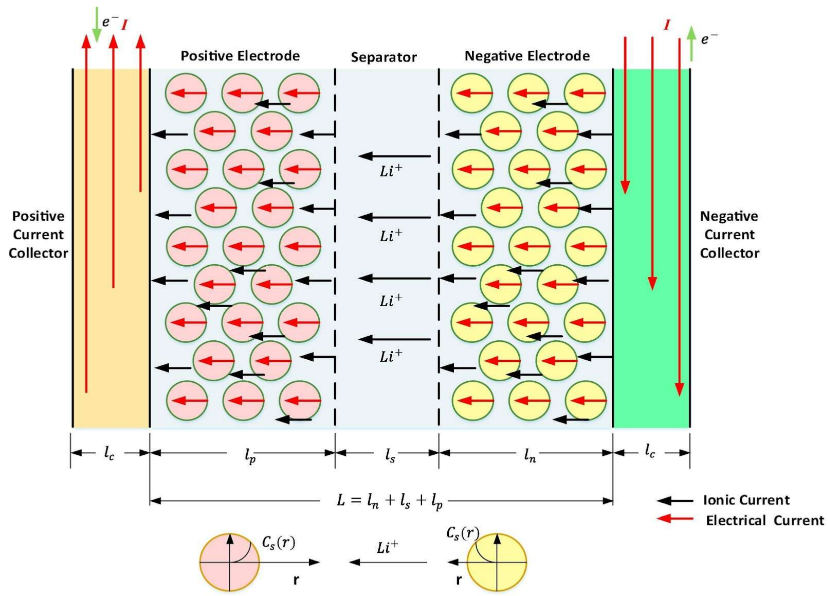
To extend the life of the battery, precautions must be taken during discharging and charging since, for example exceeding voltage, current or power limits may result in battery cell damage. In order to model that, the physics-based two-dimensional electrochemical models can be combined with the charge conservation and heat diffusion equations throughout the battery domain in order to calculate the temperature distributions.

During charging, an applied potential across the electrodes causes lithium ions (Li+) to diffuse from the cathode to the anode via the electrolyte. The ions fill voids in the cathode composite structure, and cause a charge potential to be established between the two electrodes. When all the available lithium ions intercalate into the positive electrode, the battery is considered to be fully charged. During discharge, an external circuit is used to connect the electrodes and electrical current flows until the charge potential is eliminated or the circuit is disconnected.

$$\text{Positive electrode :}\quad LiMO_2 \underset{Discharge}{\overset{Charge}{\rightleftarrows}} Li_{1-x}MO_2 + xLi^+ + xe^-$$

$$\text{Negative electrode :}\quad C + xLi^+ + xe^- + LiMO_2 \underset{Discharge}{\overset{Charge}{\rightleftarrows}} Li_xC$$

$$\text{Overall :}\quad LiMO_2 + C \underset{Discharge}{\overset{Charge}{\rightleftarrows}} Li_xC + Li_{1-x}MO_2$$



RUL Prediction Model

The state of health (SOH) and remaining useful life (RUL) of lithium-ion batteries are two important factors which are normally predicted using the battery capacity. Here we used NASA's NASA's Prognostics Center of Excellence Repository for the battery dataset. It can be accessed at the following link: https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognostic-data-repository/#battery

The ML model uses tensorflow libraries for SOH and RUL prediction for a specific battery.

The model is attached in the documents.

The RUL prediction

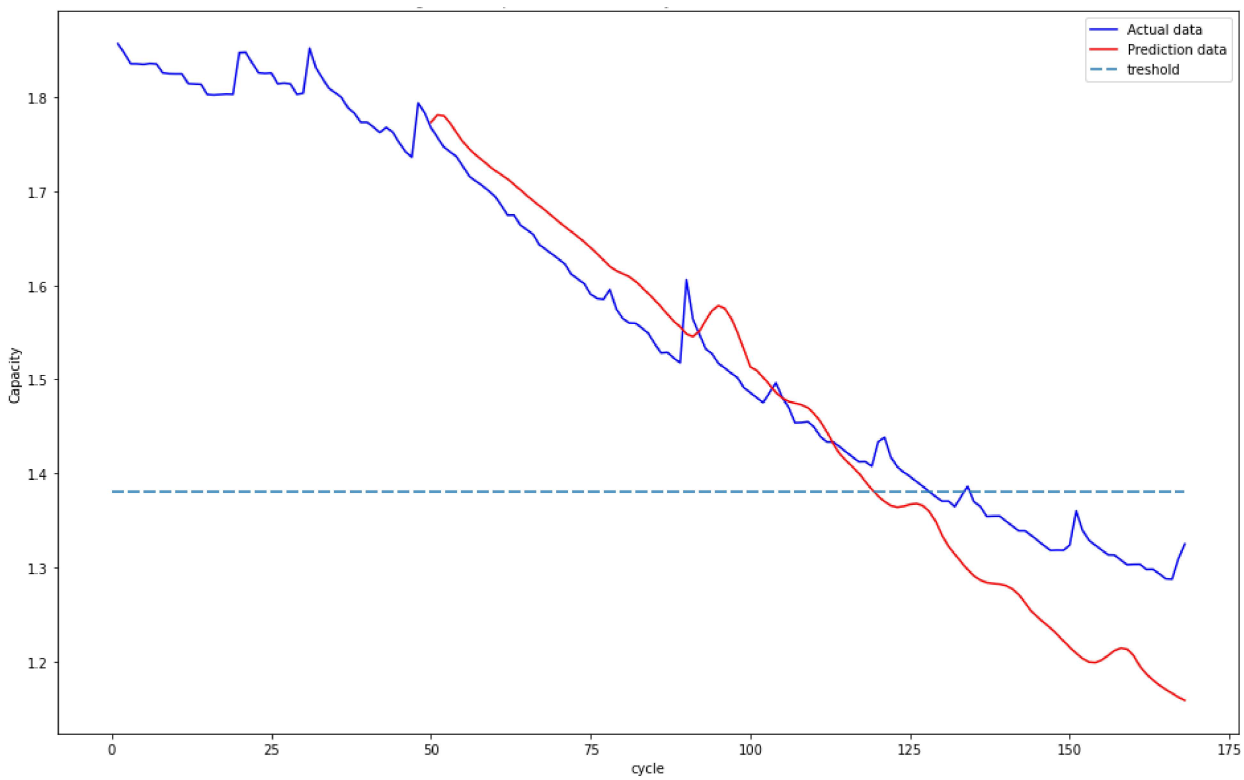
The battery dataset was divided into train and test parts. Data was converted into easy to use dataframe. Dataset description was such:

	cycle	ambient_temperature	capacity	voltage_measured	current_measured	temperature_measured	current_load	voltage_load	time
count	50285.000000	50285.0	50285.000000	50285.000000	50285.000000	50285.000000	50285.000000	50285.000000	50285.000000
mean	88.125942	24.0	1.560345	3.515268	-1.806032	32.816991	1.362700	2.308406	1546.208924
std	45.699687	0.0	0.182380	0.231778	0.610502	3.987515	1.313698	0.800300	906.640295
min	1.000000	24.0	1.287453	2.455679	-2.029098	23.214802	-1.998400	0.000000	0.000000
25%	50.000000	24.0	1.386229	3.399384	-2.013415	30.019392	1.998000	2.388000	768.563000
50%	88.000000	24.0	1.538237	3.511664	-2.012312	32.828944	1.998200	2.533000	1537.031000
75%	127.000000	24.0	1.746871	3.660903	-2.011052	35.920887	1.998200	2.690000	2305.984000
max	168.000000	24.0	1.856487	4.222920	0.007496	41.450232	1.998400	4.238000	3690.234000

In order to train the model, a neural network with the following architecture was created.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm (LSTM)                  (None, 10, 200)           161600
_________________________________________________________________
dropout (Dropout)            (None, 10, 200)           0
_________________________________________________________________
lstm_1 (LSTM)                (None, 10, 200)           320800
_________________________________________________________________
dropout_1 (Dropout)          (None, 10, 200)           0
_________________________________________________________________
lstm_2 (LSTM)                (None, 10, 200)           320800
_________________________________________________________________
dropout_2 (Dropout)          (None, 10, 200)           0
_________________________________________________________________
lstm_3 (LSTM)                (None, 200)               320800
_________________________________________________________________
dropout_3 (Dropout)          (None, 200)               0
_________________________________________________________________
dense (Dense)                (None, 1)                 201
=================================================================
Total params: 1,124,201
Trainable params: 1,124,201
Non-trainable params: 0
```

After training the model on train data, the comparison of actual RUL and predicted RUL on test data was following:



Results

The battery is considered in its EOL (End Of Life) state when its capacity exceeds 80% of its initial value or is less than 20% now. For the batteries we used as data, this threshold capacity is around 1.38 units. The model predicts the capacity for battery features like voltage, currents etc over an increasing number of cycles. The predicted

The Actual fail at cycle number: 128

The prediction fail at cycle number: 119

The error of RUL= -9 Cycle(s)

This model was able to predict the least allowable capacity fade with an error of 9 cycles for the given battery. This too was a negative error, showing that the prediction is conservative as well as efficient.

Results

Lithium-ion battery health for electric vehicles (EVs) must be monitored and prognosed in real time for reliability evaluation and maintenance purposes. This study looked at practical and effective battery state of health (SOH) diagnostic and remaining useful life (RUL) prognostic methods based on the aging characteristics analysis.
This study also tried to understand the SOC variations in a battery pack for series and parallel combinations and the thermal characteristics of the lithium ion batteries. Study helped in understanding battery data and implementing ML based prognostics on battery systems.

References:

1. Moshirvaziri_Andishe_201311_MASc_thesis.pdf (utoronto.ca)
2. Electrochemical thermal modeling and experimental measurements of 18650 cylindrical lithium-ion battery during discharge cycle for an EV - ScienceDirect
3. Development of a lithium-ion battery pack system for EV - ScienceDirect
4. A Review of Lithium-Ion Battery for Electric Vehicle Applications and Beyond - ScienceDirect
5. Aging characteristics-based health diagnosis and remaining useful life prognostics for lithium-ion batteries - ScienceDirect