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Applying NASA Data sets to Battery Prognostics and Health Management (PHM)

The State-of-Health (SoH) of a lithium-ion battery is one of the most complex and critical parameters for the Battery Management System. Essentially, there are two ways to estimate the state of health of

formulas that represent the system. Over a period of time, they become highly complex and require extensive time and resources, which may not be suitable in real-world applications. However, the data-driven models are less complex and are based on empirical lifetime data of the operation of the system. In this report, we have used both the approaches on public data sets made available by NASA.

About the data set:

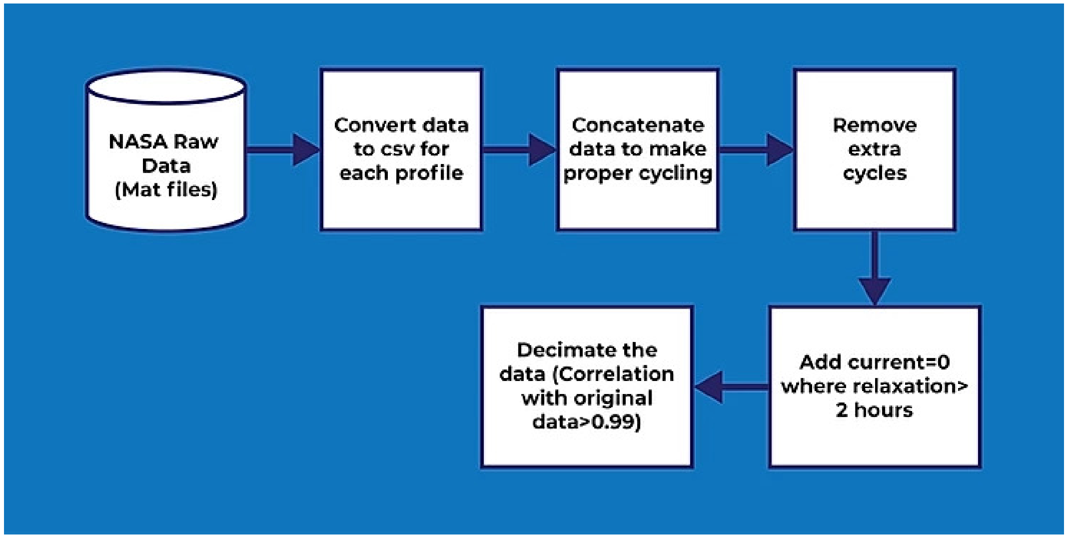
The data set has been collected from a custom-built battery prognostics testbed at the NASA Ames Prognostics Center of Excellence (PCoE). Lithium-ion batteries were run through 3 different operational profiles (charge, discharge, and Electrochemical Impedance Spectroscopy), at different temperatures. Discharges were carried out at different current load levels until the battery voltage fell to preset voltage thresholds. Some of these thresholds were lower than those recommended by the OEM (2.7 V) in order to induce deep discharge aging effects.

Charging was carried out in constant current (CC) mode at 1.5A until the battery voltage reached 4.2V and then continued in a constant voltage (CV) mode until the charge current dropped to 20mA. The discharge was carried out at a constant current (CC) level of 2A until the battery voltage fell to 2.7V, 2.5V, 2.2V and 2.5V for batteries 5, 6, 7 and 18 respectively.

Impedance measurement was carried out through electrochemical impedance spectroscopy (EIS) frequency sweep from 0.1 Hz to 5 kHz. Repeated charge and discharge cycles result in accelerated aging of the batteries while impedance measurements provide insight into the internal battery parameters that change as aging progresses. The experiments were stopped when the batteries reached end-of-life (EOL) criteria, which was a 30% fade in rated capacity (from 2Ahr to 1.4Ahr).

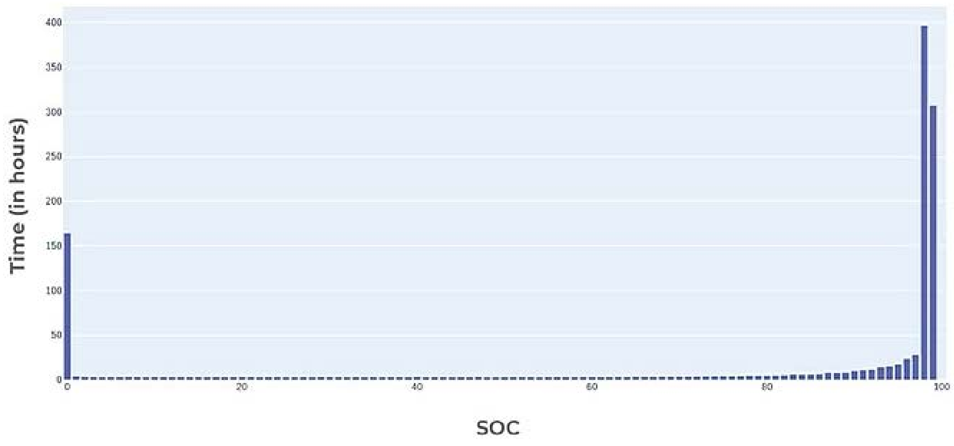
Data Preprocessing

The raw data set provided by NASA was not in a structured format as required for preprocessing. We followed the process as shown in the diagram below.



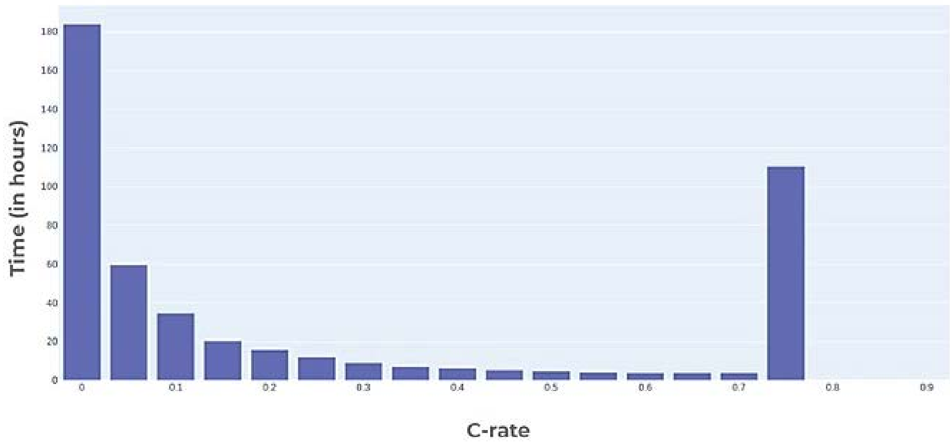
Exploratory Data Analysis

State of Charge-time Distribution



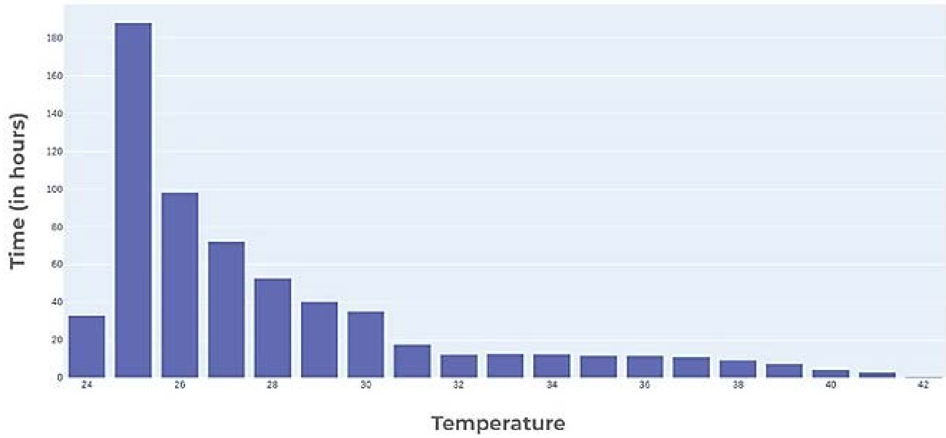
The graph clearly indicates how the battery was used. Mostly, the battery remained in a fully charged state. Also, it is interesting to note that the battery was in a fully discharged state for a significant amount of time. Since the battery's depth of discharge (DoD) level was to operate at extremes, it is evident that battery will face accelerated aging.

Charge C-rate Distribution



As mentioned above in the data description, the battery was charged in two phases, constant current (CC) and constant voltage (CV) phase. The above plot shows the manner in which the current is drawn out from the batteries. When the battery is charged in the CC phase, the C- rate is around 0.75, however, as the battery enters in the CV phase the C-rate decreases; and the battery spends most of the time in the CV phase.

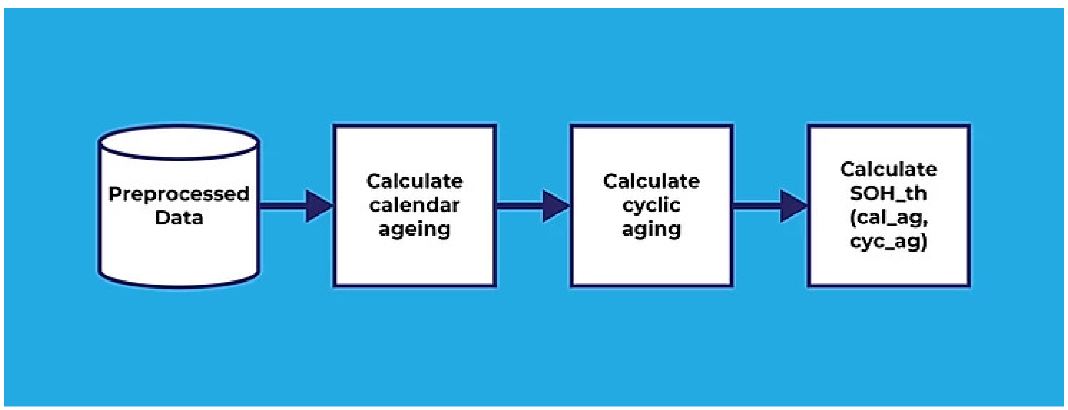
Temperature Distribution



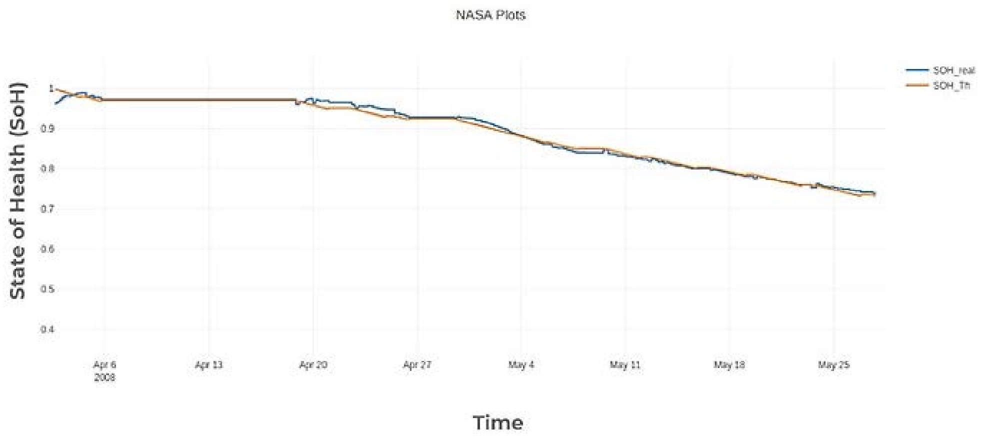
The batteries were mostly kept in an ambient temperature of 24°C, however, it is important to note that during the cycling process the temperature can go as high as 42°C.

Physics-based Modelling for Battery Prognostics

Modelling



Result



The temperature was found to have almost no effect on the capacity for the given datasets, to the best of our knowledge. However, relaxation time between and after cycling was found to have a profound impact on battery capacity, which mostly leads to capacity regeneration. To tackle this effect of relaxation, we used an RC low pass filter.

Data-driven methods

Feature Engineered

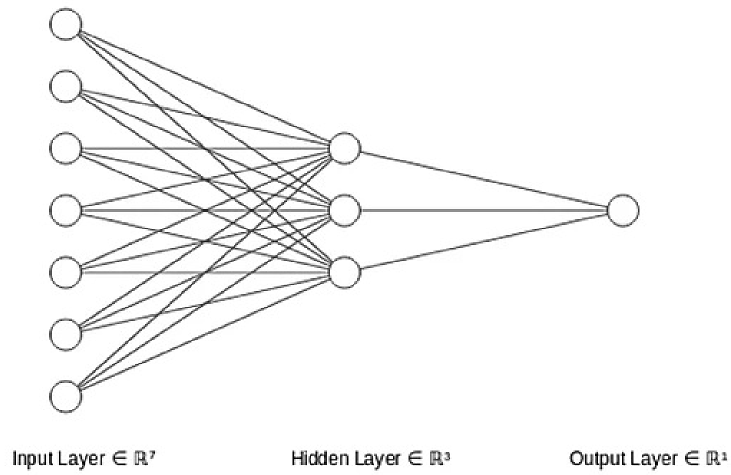
1. Rest time

2. Age

3. Equal Voltage Drop

Modelling

Model Architecture



Hyperparameters:

- Activation Functions

  – Hidden Layer: relu

  – Output layer: linear

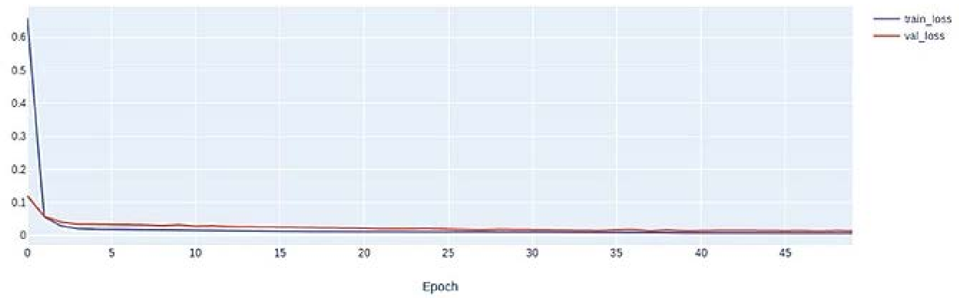
- Optimizer: ‘adam’
- Error function: ’mean absolute error’
- Epochs: 50
- Batch size: 128

Results

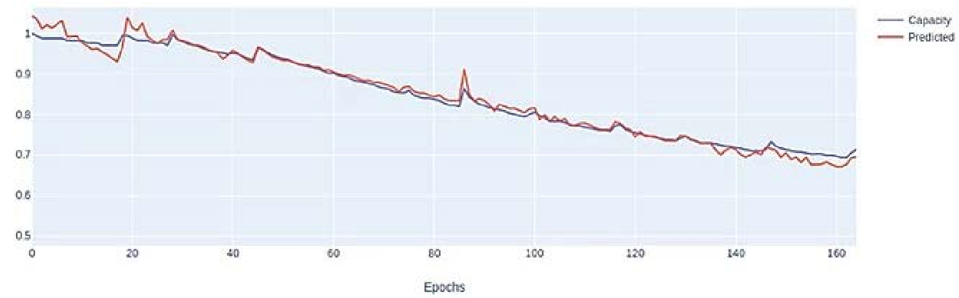
NASA has provided the capacity at the end of discharge of each cycle. We use this capacity as a label for predicting the capacity. We performed 5-fold cross-validations to check the robustness of our model and the mean root mean square error (RSME) was 0.0087.

Battery #5

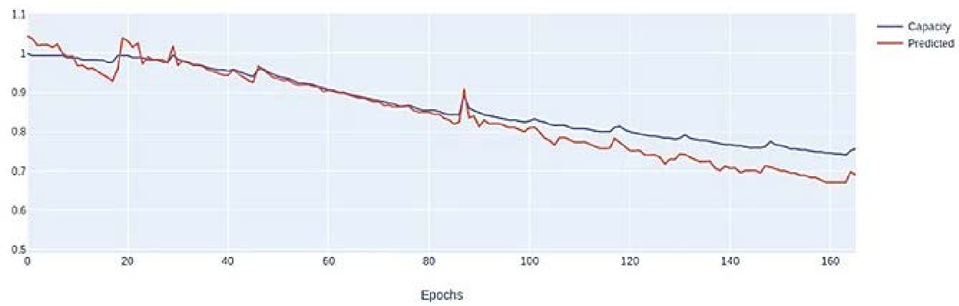
Error rate with epochs:



Predictions:



Testing the model trained on battery #5, to predict SOH of battery #7



The NASA dataset is one of the few algorithms that we've assessed, although the analysis is at a nascent stage. The data models used in this blogpost provided the essential model for Edison