# *Lithium Ion Battery Life Predictor using Convolutional Neural Networks*

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**Abstract**

**The modelling of Non-Linear Data has always been a challenging task for analysts and researchers for a long time. While some techniques have been developed to model complex systems by studying their physical characteristics and statistical data. With the rise of Machine Learning and Deep Learning techniques it is imperative to develop a technique which can learn from the past telemetry data of the system and use it to make accurate predictions about the system. One such use case is to predict the Remaining Useful life (RUL) of Li-Ion Batteries. In this study, we aim to develop a model that uses deep learning to predict the RUL of Li-Ion batteries by the analysis of its charging and discharging data over a certain number of cycles.**

**Keywords: Remaining Useful Life (RUL), Lithium-Ion Battery (Li-ion), Charging Cycle, Battery Degradation.**

## 1 INTRODUCTION

Lithium-ion batteries are extensively being used nowadays to power almost the entirety of electronic gadgets deployed in our daily lives due to the fact that they have high energy density, long life and low cost. They are an integral part of renewable energy and the upcoming electric vehicles industry. The obstacle with long battery life is that it experiences delayed feedback of performance (Severson et al.). A lot of effort has been made in order to predict how many charging cycles a battery will survive before becoming unfit to be used. Better predictions about lifetime via early-cycle data would facilitate better quality standards, improve long-term planning and introduce new opportunities in battery production. For instance, manufacturers would be able to enhance the cell development cycle and select new cells according to their expected lifetime. One such application of early prediction becoming apparent is through the optimization of processes such as multistep fast charging and formation cycle. These processes cannot be configured due to constraints they put up (*Predicting Battery Lifetime with CNNs - Towards Data Science*).

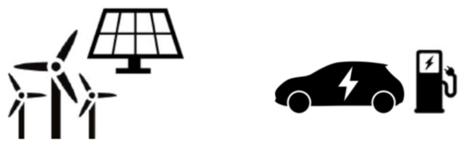

**Fig. 1**: Some use cases of Li-Ion Batteries

Since each battery ages differently owing to its usage and condition during its manufacturing process, it becomes difficult to predict its life cycle. Previously also many studies have been conducted to model lithium-ion battery life. (Broussely et al.) and (Bloom et al.) worked on semi-empirical models which were helpful in the estimation of power and capacity loss. Ever since many studies have been conducted in this field of which the mechanical and semi-empirical model for analysing the state and the specialised diagnostic measurement like coulombic efficiency and impedance spectroscopy for estimating the life of the battery is considered the best (Severson et al.).

(Severson et al.) discusses the solution to this nonlinear degradation and wide variability problem by combining the comprehensive experimental data and artificial intelligence. The enhancement in algorithmic power and data generation have made such methods feasible. In general, such algorithms make estimations about the life cycle of a battery only after collecting and analysing the data corresponding to at least 25% degradation or via specialised measurements at the very start of life (Deng et al.). Predicting the life cycle with comparatively less degradation precisely is a challenging task but this combination somewhat enables us to do so. The results obtained from this hybrid approach come out to be better than the traditional methods. Although in this method the team focused more on the electrical domain than on the machine learning part (*Predicting Battery Lifetime with CNNs - Towards Data Science*).

RUL predictions methods can be done in two ways- **data driven methods** and **model based prognostic methods**. Mathematical models such as model based ones, include practical rules that show the degradation of the performance of the system in a lithium -ion battery.

According to (Ramadan et al.), the capacities of the lithium ion battery was predicted according to extended Kalman

filtering method (EKF), which provides promising results. Also, due to complex internal structure of lithium-ion batteries, it is difficult to achieve the generalization using model based prognostic methods. Data driven models on the other hand, can prevent these problems posed by the model-based method by keeping an eye on the position of the system, analysing the behaviour according to the data collected over the years and changing it to the predictable models used for predication of the future state of the system. This is the approach applied in this study(Hussein). The benefit of using a data driven models allows us to present features that are domain specific and of varying complexity while being easy to interpret. These models have very low computational costs as they can be trained offline whereas training these online would require a single dot product after the processing of data(Mosallam et al.; Ma et al.). For this study we aim to include the characteristic features of the Li-ion battery such as Charge time, temperature of the cell body, initial discharge rates and capacities.

## 2 REVIEW OF LITERATURE

**2.1 Physical Model** – Several attempts have made to study the deterioration of Li-Ion battery life in the past. These studies were based on the physical features of the battery. Some of these approaches include estimating the degradation of the lithium inventory, loss of active material in the cell and increase in internal resistance based on many degradation models [5][6][7]. They do the work and have been successful in predicting the same, but their working is not up to the mark, because of the complicated internal structure of these systems. These early studies used semi-empirical models to predict the capacity and power loss. These models were based on diverse mechanisms like growth of solid-electrolyte interphase, impendence loss, active material loss and lithium plating (Severson et al.). It was also observed that special types of measurements such as columbic efficiency and impendence spectral analysis can also be taken into account while calculating RUL.

**2.2 *Data Driven Models*** – Another popular way to predict RUL is using data driven mechanisms. This uses machine learning and complex statistical methods with huge amounts of data. Instead of building a very cumbersome physical model, which work to relate the charge-discharge cycles of the battery (Choi et al.). These methods are mechanism -agnostic alternatives. Due to the advances in the computational power and the generation of data, it has become an easy process to predict several properties such as the properties of a material, the routes its chemistry would take and catalysis. The accurate prediction of the early life cycles with less degradation is quite challenging due to non-linear degradation processes (Cadini et al.). Data driven RUL can be achieved by two methods: Feature Engineering based RUL prediction and autoregressive capacity fade prediction.

**2.3 *Feature Engineering*:** There are many studies that have tried to bring consider the other aspects of the features like voltage, current, charge of the cell, temperature of an li-ion battery etc. (Zhao et al.) used 21 features of li-ion batteries and Support Vector Regression (SVR) technique to determine the RUL of batteries. Recent work has observed that when the discharge voltage across multiple cycles is used as a characteristic, a model can predict the RUL with the data from around 100 cycles (Severson et al.; Attia et al.; Hong et al.). It must also be noted that the life of the battery detoriates when it's not in use due to calendar aging. Another factor to be notes is cyclic aging, that is caused due to the repetitive charging and discharging cycle.

**2.4 *Autoregressive Techniques And Deep Learning:***

Several studies have been published focusing on the capacity degradation characteristics of the battery to predict the RUL. Exponential Empirical models used with advanced filters such as Kalman filter. To predict capacity degradation, Relevance Vector Machine(RVM) ,Box Cox Transform and Gaussian Process Regression (GPR) have been used by several studies.(Cadini et al.; Liu et al.)(Zhang et al.; Richardson et al.). To increase the probability of accurate results, deep learning can also be applied on the same. Deep Learning networks like Long Short-Term Memory (LSTM) or Recurrent Neural Networks (RNN) are deployed to predict the rate at which the battery degrades. In order to do away with the complexity of the above said methods, (Ma et al.) developed a hybrid model which had both CNN and RNN in it. Through vast studies, it has been observed that Li-ion batteries have insignificant differences in discharge capacity at the beginning of their life cycle, thus the data required in such a process has to be from at least 25% discharge of the battery to predict the RUL correctly.

The health estimation of a battery depends upon its aging process. Three major factors that degrade the life of a Li-ion battery: increase in cell resistance , the loss of lithium inventory (LLI) and the loss of active material (LAM) (Li et al.). The increase of resistance in the battery occurs due to the formation of energy draining phases at the surface of the electrodes and the reduction in the electrical contact inside the electrode. This process makes the Li-ions unavailable for the charge-discharge process , thus weaking the battery (Barré et al.). LAM occurs due to a summation of several physical and chemical factors. The structural degradation of the electrodes because of the changes in the volumes of the active materials during the cycles. These lead to mechanical stress, causing the cracking of particle and reduction in the density of sites for Li-ion collection (Barré et al.).
High and low temperatures of storage and usage also play a very critical role in the reduction of the battery life. While high temperatures accelerate the rate of LLI, low temperatures slow down the rate of rate of movement of the Li-ions in both electrolyte and electrode. High temperature increases the resistance, electrolyte decomposition and the metal dilution from the cathode. All these factors pave way for thermal runaway. Low temperatures may cause the overcrowding of the Li-ions and this leads to the growth of lithium dendrites which penetrates the separator and causes short circuit (Finegan et al.; Jaguemont et al.).
High currents occur within the cell due to the excessive charge-discharge currents. High currents lead to more heat wastage, which causes the degradation of the lifetime of the cell. The electrolytes made up of organic materials have low thermal intake which makes them vulnerable to rapid increase of temperature ,leading to high flow of current within the cell.(Chandrasekaran)

## 3 METHODOLOGY

We aim at formulating a deep learning framework to predict the RUL of Li-ion batteries from the telemetric data of the batteries. We have taken the MIT Stanford Dataset [8] which encompasses the following characteristics over different cycles-

1. Current Density
2. Voltage Changes
3. Temperature of the Cell.

The initial Data Pre-processing step involved taking the voltage range during discharging as the reference instead of time and then Interpolating the charge and temperature over voltage. The entire data was then resampled 1000 equidistant voltage steps to make the measurements uniform. After this, the data was used to train a neural network which gave predictions about the current cycle and remaining no. of cycles of the battery.

The features used in this work can be concluded directly from the models used in our framework, while they correspond to actual feature-based RUL. This proposed deep leaning model brings to light the distinct patterns in electrical engineering and determines the most ideal features required for RUL prediction. The proposed model includes a Convolutional Neural Network (CNN) and Long-Short Term Memory (LSTM).

A neural network is a collection of artificial neurons that have the aim to identify patterns and relations depicted by a set of data with the help of a process that mimics the way that the human brain operates. These networks represent an entire system of neurons that are artificial or organic in nature. These networks can adapt themselves to rapidly evolving input, and they produce the best results without the need of reconstructing the output criteria. They consist of layers or nodes which are interconnected by data points.

For this study we have deicide to use convolution neural networks or CNN. The measurements from the batteries, system, current, cell temperature and terminal voltage are fed as inputs to the developed network and the algorithms of neural networks is used to predict the RUL of the battery under study. However, the model suffers one drawback, i.e. at times it can give inaccurate results when the testing data distribution has some is disjoint from the train data distribution. This prompts us to use a large dataset.
The lifetime of the battery degrades as we use it. Even similar Li-ion batteries have varying degradation curves, due to the varying conditions in the production process and the also the conditions in which the battery operates. These factors made the RUL prediction difficult. It is known from studies that the battery becomes when its quality degrades to 80% of its initial value.
Thus, the RUL can be characterized by the following equation:

$$R_{UL}=C_{EOL}-C_M$$

$C_{EOL}$: the total number of charge-discharge cycles that the battery undergoes before End of Life

$C_M$: the total number of cycles the battery has undergone during usage when the last measurement was taken.

This method uses ‘L’ seconds of the current, temperature and terminal voltage. Here, L represents the time under of observation. The input to this NN is given by-

$$\mathbf{x}_{i,j} = \begin{bmatrix} V_{i,c_j} & V_{i,c_j+1} & \cdots & V_{i,c_j+L-1} \\ I_{i,c_j} & I_{i,c_j+1} & \cdots & I_{i,c_j+L-1} \\ T_{i,c_j} & T_{i,c_j+1} & \cdots & T_{i,c_j+L-1} \end{bmatrix}_{3\times L}$$

The $V_I$, $I_I$ and $T_I$ represents the terminal voltage, current and cell temperature.

The dataset is represented by –

$D = \{\boldsymbol{d}_{i,j} := (\boldsymbol{x}_{i,j}, y_{i,j}) \mid i \in [0, \boldsymbol{I}\text{-}1], j\in[0,\boldsymbol{J}\text{-}1]\}$

This entire dataset is divided into 3 parts -

Training – $\mathbf{D}_{train} = \{\boldsymbol{d}_{i,j} \mid i \in D_{train}\}$

Validation – $\mathbf{D}_{valid} = \{ \boldsymbol{d}_{i,j} \mid i \in D_{valid}\}$

Test – $\mathbf{D}_{test} = \{ \boldsymbol{d}_{i,j} \mid i \in D_{test}\}$

The operations of the CNN are defined by –

$$S(i,j)=(X*W)(i,j)=\sum m \sum n X(i-m,j-n)W(m,n)$$

Where X is defined as the input given and W is described as the kernel matrix. A typical CNN have a sequence of layers stacked together. Mainly, a convolutional layer, a ReLU Layer, a pooling layer and a fully connected layer. In the I$^{st}$ layer, the convolutional procedure is followed wherein the exact features are extracted. Then an activation function is used to give the final result. The pooling layer has the purpose of reducing the spatial size of the map of features and gives the most feasible learning results for the data that is provided as input. The output is then passed through the next layer where the entire process is repeated. This ensures that the most optimal solutions are received at every stage. Finally, the classification and regression are obtained through the fully connected layer.

## 4 EXPERIMENTAL RESULTS

We trained and tested our model on the MIT-Stanford dataset which has the data of 124 batteries across 3 batches. We were able to predict the current cycle as well as the remaining no. of cycles of the battery which in turn gave us information about the RUL. The original paper used feature engineering but, in our study, we opted to work with the raw data itself to begin with in order to build a comprehensive and robust model. Initial pre-processing and outlier removal was done to remove any noise and then the data was resampled.

We use deep learning instead on any 20 cycles window to account for the uneven decrease in capacity.

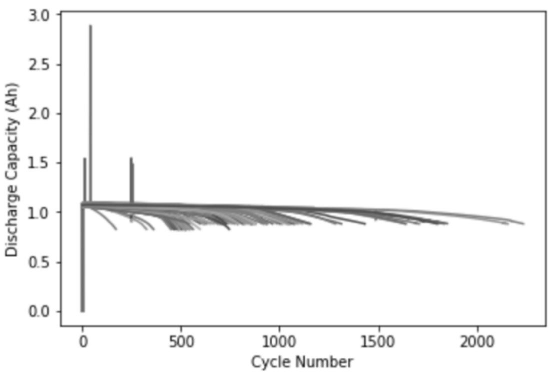


**Fig. 2:** Discharge capacity of batteries

Fig 2. shows us the discharge capacity of the batteries over their usage cycles. Some batteries exhibited extremely high or low no. of cycles due to anomalies in manufacturing and difference in physical conditions.

We then train our model on the dataset. It is a hybrid model of CNN and LSTM as the characteristics of both these NNs were needed to make accurate predictions about the RUL of the batteries.

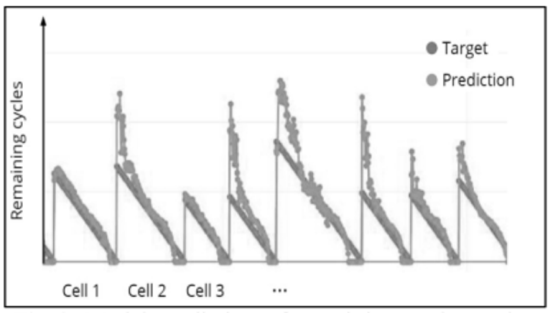


**Fig. 3:** Model prediction of remaining cycles and actual target value.

Fig 3. gives the model prediction for the no. of remaining cycles and the actual target value. The graph conveys that the model was able to predict the no. of cycles remaining. In some cases, the predicted value was higher than the target and this can be attributed to the fact that the degree of degradation of a cell increases with time, justifying its non- linear nature.

Overall, our model performed relatively better than the original work both in terms of Mean Absolute

Error (MAE) in predicting both current cycle as well as remaining number of cycles. The model was tested for different window sizes and performance was found to be better for each window size.

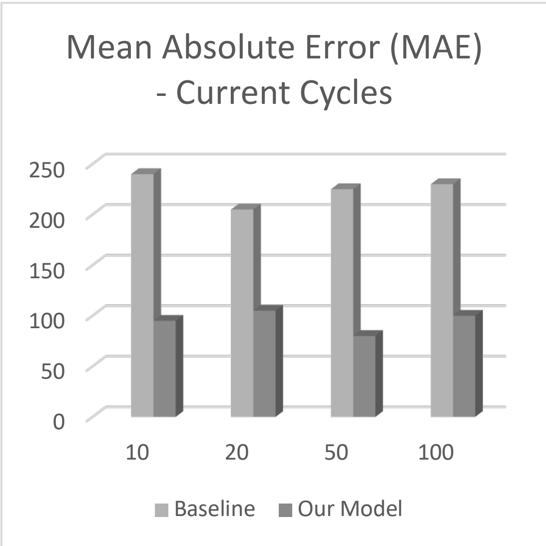


**Fig. 4:** Mean absolute error prediction of current cycle

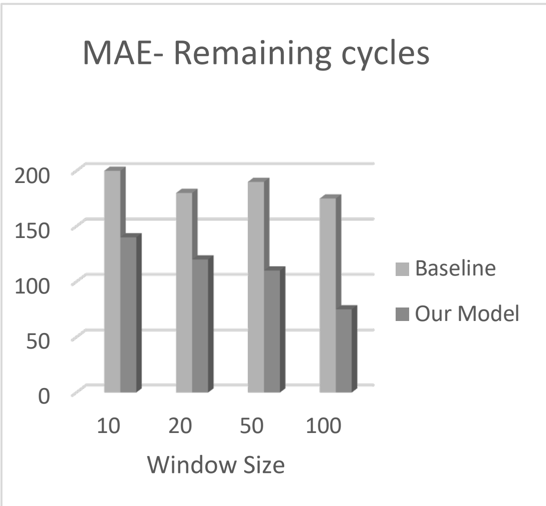


**Fig. 5:** Mean absolute error prediction of current cycle

Fig. 4 & 5 compare the error in predicting the remaining cycles between the model used in the original study and the model used in our study.

## 5 CONCLUSION AND FUTURE SCOPE OF WORK

A deep learning-based model seems to be an effective way of predicting the Remaining Useful Life of Lithium-Ion Batteries. The study has shown that the convolutional neural network performs better than the Physical, Statistical and other Data driven models when it comes to predicting RUL of Li-Ion batteries. However, With the increase in the installation and use of Li-Ion batteries and their usage in mobile technology and electric vehicles a more accurate and real-time framework to predict RUL of batteries can be developed. Another important study can be to relate the usage patterns of various electronic devices with the degradation of their battery capacity.

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