

Remaining useful life prediction of lithium-ion batteries with limited historical data

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ABSTRACT

The lithium-ion battery system has strong coupling and nonlinear characteristics, bringing great challenges to its online failure prediction and life estimation. Several studies have shown the potential of deep learning methods on remaining useful life (RUL) prediction of lithium-ion batteries, these methods mostly use historical cycling data from beginning to the prediction point. However, long-term cycling data can be costly and difficult to obtain in practical applications. This article presents a data-driven algorithm using a combination of deep convolutional neural network (DCNN) and long short-term memory (LSTM) to predict the RUL of lithium batteries based on the data of the past 10 continuous cycles. Here the DCNN processes time-series data including capacity, temperature, and capacity difference at the same voltage during discharging, the LSTM is used to process the scalar data of each cycle including internal resistance, discharge time, and discharge capacity. The proposed network uses an open dataset with 124 batteries for training and validation. The generalization ability of the model for batteries under different charging/discharging strategies is also validated. The proposed DCNN-LSTM network demonstrates well performance on capturing the life changes of batteries with different life lengths and working conditions using limited historical cycling data with an average root mean square error of 5%.

Keywords: remaining useful life prediction, lithium-ion battery, convolutional neural network, long short-term memory, deep learning.

1. INTRODUCTION

As one of the most expensive components in energy storage devices and electric vehicles, lithium-ion batteries play an important role and they should be carefully monitored and manipulated. It is important to achieve an accurate prediction of the remaining battery life under various operating conditions. Due to complex degradation mechanisms, battery life can vary greatly under different operating conditions. A lot of research on RUL prediction with deep learning methods have been reported[1]. Some strategies use CNN[2] or LSTM[3] to extract features from the capacity decay curves over cycles or voltage curves during charge/discharge duration, Ma et al.[4] used a hybrid neural network that combines the advantages of CNN and LSTM to make RUL predictions. Most methods are depending on the historical data from the beginning of the battery life to the prediction point and needed a re-train to fit a new battery decay curve, which brings a lot of difficulty to practical use especially when facing unknown batteries with unusable historical data. Few existing methods have the ability to predict the remaining battery life based on a small amount of recent cycling data meantime have the universality of different batteries once trained.

In this article, we refer to the latest research on the use of deep learning techniques to predict battery RUL to achieve the goal mentioned above. We propose a combined DCNN and LSTM network in which CNN part process time-series data and LSTM for scalar data. Depending on these two different data scales which characterize battery life, the proposed network can only rely on the data of the most recent 10 cycles to predict the RUL in percentage without a separate feature extraction step.

2. IMPLEMENTATION OF DCNN-LSTM NETWORK

2.1 Input and output structures

The purpose of this study is to estimate the remaining life of a lithium-ion battery based on the battery temperature, current and capacity difference curves measured during the discharge cycle and the internal resistance, capacity, and time measured after each cycle. It is worth mentioning that the sampling frequency of different battery test devices is various. In

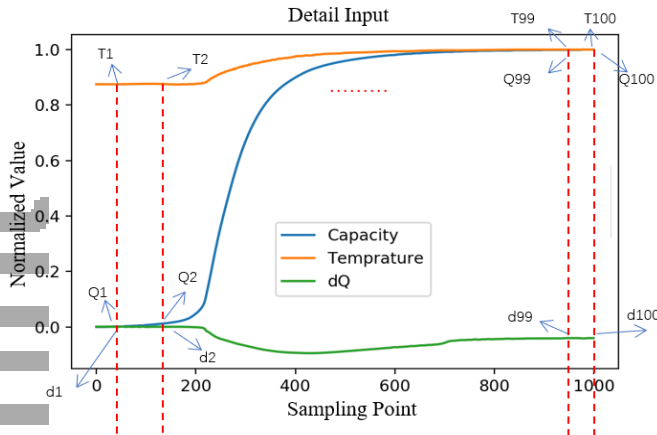


Fig 1 Resample data from the original temperature, capacity, and capacity-difference curves

the data processing of this article, all discrete data collected by the sensor is firstly serialized using cubic spline interpolation, and then average resample the curve into 100 sampling points. To better display the input of the time series, the temperature, current and capacity difference interpolation curves are shown in Figure 1. According to Severson et.al[5], the variance of the difference in discharge capacity at the same voltage with different cycle numbers has a strong linear correlation with the battery life. Here, we do not calculate its variance but directly take the capacity difference(dQ) curve at the same discharge voltage between last and first cycle of the ten cycles as input, and the scalar data of internal resistance, capacity and discharge time are measured and counted after completing each charge and discharge cycle.

Resampled temperature, capacity and discharge differences data are arranged in channel, 10 consecutive cycling data are arranged in the width as shown in Figure 2. In this way, the time series input to the model is a matrix of fixed size $100 \times 10 \times 3$, where the first dimension is 100 temperature data for 10 consecutive cycles, with temperature, current and discharge voltage differences in the second and third dimensions respectively. All data are normalized by maximum normalization.

Where T_n , Q_n and dQ_n respectively represent the temperature, capacity, and capacity difference of the

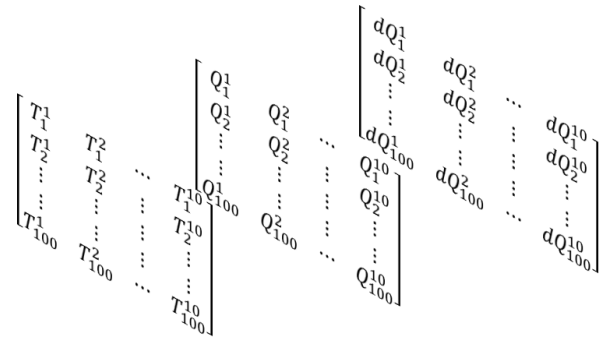


Fig 2 The structure of input matrix for serial data n th segment of the discharge cycle.

The input matrix of scalar data is defined as:

$$\begin{bmatrix} IR^1 & Q_d^1 & t_d^1 \\ IR^2 & Q_d^2 & t_d^2 \\ \vdots & \vdots & \vdots \\ IR^{10} & Q_d^{10} & t_d^{10} \end{bmatrix} \quad (1)$$

Where IR^i , Q_d^i and t_d^i respectively represent the internal resistance, capacity and discharge time after the end of the i th discharge cycle.

This study proposed to give the remaining useful life of the current cycle battery in percent. The output of the network is defined as the RUL in the form of a percentage, which is defined as:

$$RUL = \left(1 - \frac{n_{present}}{n_{end}}\right) \times 100\% \quad (2)$$

Where n_{end} is the number of cycles when the battery degrade to 80% of the nominal capacity, and $n_{present}$ is the current number of cycles.

2.2 Overall architecture of DCNN-LSTM

The DCNN-LSTM structure implemented in this study is shown in Figure 3. The model is composed of a five-layer convolutional network and a two-layer LSTM network, and then the features are combined through a splicing layer to enter the fully connected (FC) layer.

Convolutional layers are used to execute a special kind of linear operation named convolution. In the context of deep learning, convolution is an operation on the inputs and kernels. Specifically, each unit of a convolutional layer is connected to local patches in the feature maps of the previous layer through a set of weights called filter banks. The result of this locally weighted sum is then passed through a variety of layers, such as a rectified linear unit (ReLU) and batch normalization (BN), to form the feature maps of the next layer.

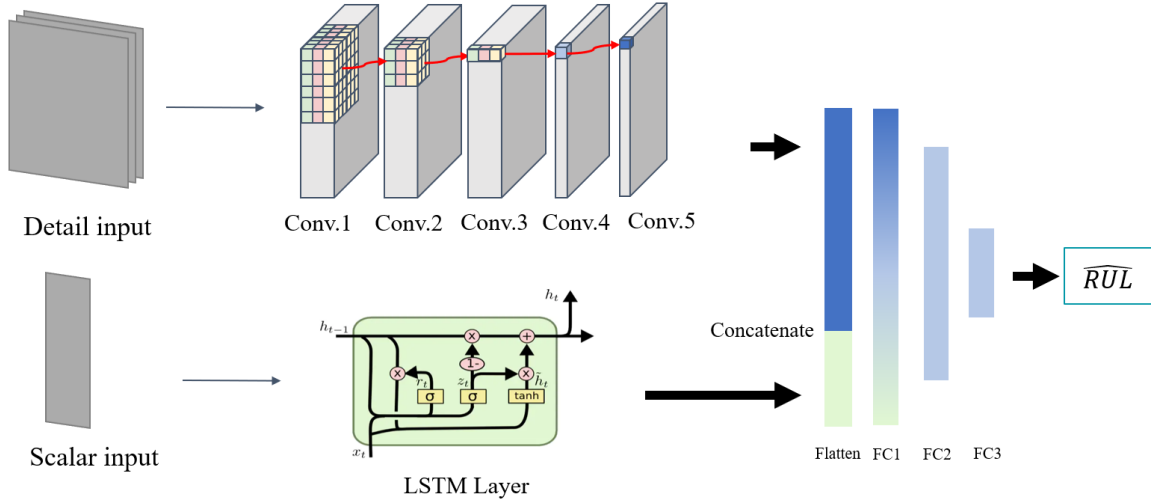


Fig 3 Overall achitecture of CNN-LSTM RUL prediction network

As a variant of recurrent neural network (RNN), LSTM can solve the problem of gradient disappearance and gradient explosion caused by original RNN. LSTM mainly works through the following three steps. First, the LSTMs forget irrelevant parts of the previous state by using the forget gate. Then, the LSTMs selectively update the cell state values, and finally, the LSTMs use an output gate to output certain parts of the cell state for the next cell. LSTM retains the error to reverse transmission along with time and layer. In addition, LSTM can keep errors at a more constant level, allowing RNNs to learn many time steps, thus opening the way for establishing long-term causality. The high-level features captured by the convolutional layer and the parameters obtained from the LSTM layer are concatenated before entering the FC layer.

The proposed DCNN-LSTM model has about 14M parameters and consists of five convolutional layers and three fully connected layers.

2.3 Training algorithm and error measures

The goal of the optimization algorithm Adam is to reduce the expected generalization error given by the equation. To achieve this, the DCNN-LSTM model was trained for 30 epochs with a mini-batch of 32 examples. For all convolutional layers, LSTM layers and fully connected layers, the initial learning rate α is set to 0.001, and the learning rate drops by half every 5 epochs. Table 1 summarizes several important parameters used to train the DCNN-LSTM model.

We randomly initialize the weights of each layer using mean 0 and standard deviation 0.01 and deviation 0. With the support of the GPU, we can simultaneously calculate updates that minimize $J_R(\theta)$ based on 32 samples.

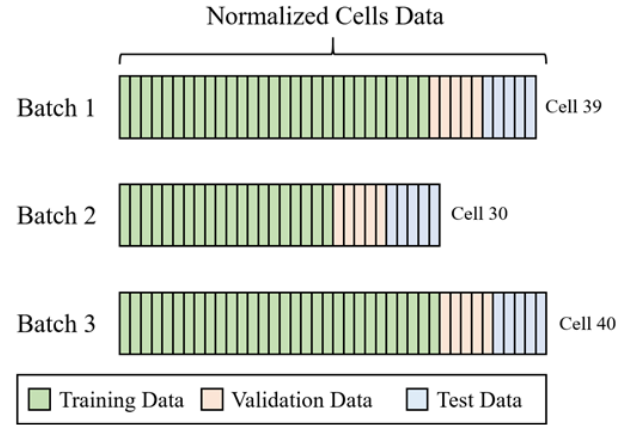


Fig 4 Segmentation of the cycling data from 109 Li-ion batteries

The 109 batteries are screened from original dataset[5] and divided into Batch1, Batch2, and Batch3 according to the charge/discharge protocol and test time as Figure 4 shown. For each batch, we randomly select 5 cells as the validation set and the test set respectively, and the remaining cells as the training set. Repeat five times to get five prediction models and results.

After performing all tests, the overall test error ϵ_{RMS}^{All} of DCNN-LSTM model is estimated by taking the average value of each test error ϵ_{RMS}^k from 5 trials.

$$\epsilon_{RMS}^k = \sqrt{\frac{1}{N_k} \sum_{i=1}^{N_k} (y^k(x_i^k) - \widehat{y}^k(x_i^k))^2} \quad (3)$$

$$\epsilon_{RMS}^{All} = \sqrt{\frac{1}{\sum_{k=1}^5 N_k} \sum_{k=1}^5 \sum_{i=1}^{N_k} (y^k(x_i^k) - \widehat{y}^k(x_i^k))^2} \quad (4)$$

Where N_k denotes the number of samples for the k th test, y^k and \widehat{y}^k respectively denotes the estimated capacity and measured(true) capacity of the i th sample in the k th trial, x_i^k denotes the i th sample matrix in the k th experiment. The overall test error

defined according to the equation (4) reflects the performance of the proposed DCNN-LSTM model.

3. EXPERIMENT RESULTS AND DISCUSSION

3.1 RUL prediction result of the open dataset

Table 1. RUL estimation results achieved by DCNN-LSTM

Item	Batch1	Batch2	Batch3
RMSE _{ALL}	0.061	0.052	0.037
MaxE	0.150	0.148	0.089

Table 1 shows the RUL prediction result of the proposed model. RMSE_{ALL} is the average RMSE value of five randomly selected cross-validation. MaxE is the maximum RMSE value of all predictions in the five cross-validation. Figure 5 shows the statistical distribution of RMSE for three batches. The MaxE values of Batch1 and Batch2 are much higher than Batch 3, reaching about 15% error. This error caused by the disparity between the life of the battery used for training and for testing. If the shorter life batteries in the training set account for a larger portion, the model's generalization ability for long-life batteries will be poor, as the prediction results in the middle life span is higher than the actual results, but sharply converge to zero near the end, forming an arc-like predicted result curve. That the life span of batteries in Batch 3 is close may be the reason for the relatively small RMSE value model performed.

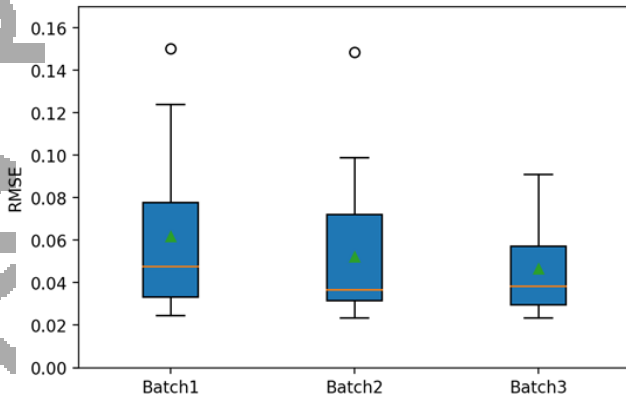


Fig 5 Root Mean Square Error box plot of the DCNN-LSTM predictions for the three batches

Figure 6 shows the RUL estimation results of DCNN-LSTM for the 45th cell in Batch 3. Its actual life was measured using a two-step charge and fixed discharge protocol. The RMSE of this battery prediction is 0.022 and max error reaches 0.043. The model has good

performance for battery RUL prediction, and the RMSE can reach as low as 2%.

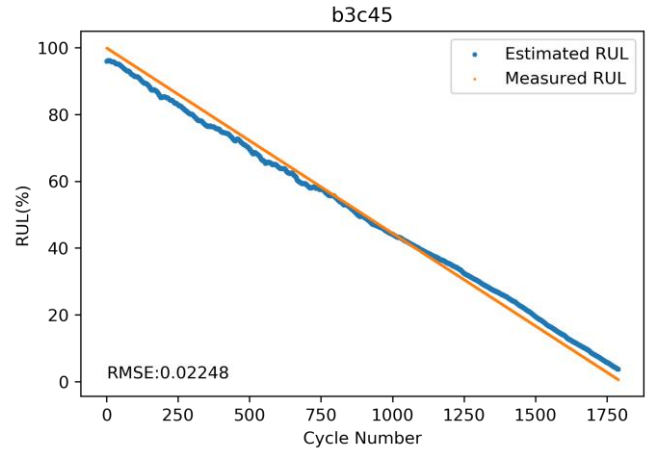


Fig 6 RUL prediction result of Cell 45 in Batch 3

To further examine the generalization ability of the model for batteries under different charging/discharging strategies, we use a model trained by Batch 3 to predict the RUL of Cell 9 in Batch 1, their voltage ranges are the same. As shown in Figure 3, the RMSE is 0.022 with a max error of 0.074, which indicates the model has good generalization ability for batteries with different charge/discharge currents but in the same operating voltage window. The DCNN-LSTM model can predict their RUL with only the last 10 cycles of discharging data. Similar observations can be made for the remaining cells.

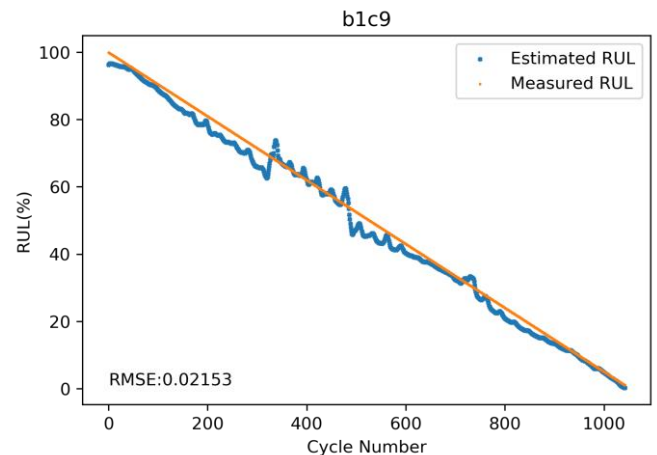


Fig 7 RUL prediction result of Cell 9 in Batch 1, model trained by Cells in Batch 3

The proposed method no longer requires a complex and time-consuming feature extraction process. In contrast to other studies, our network supports both the input of time series data as well as scalar data, which means that deep learning algorithms will learn from battery cycle data and subsequent resting data. The deep

learning algorithm automatically learns information related to the remaining useful life from these two most easily accessible and characterizing data and combines them to make predictions.

This model percentages the output, which gives the model better generalization than outputting the number of remaining cycles or capacity. Once trained on the training set, the RUL predictions can be obtained in 10 cycles for cells of different capacities and SOH degrees.

4. CONCLUSION

We developed a combined DCNN-LSTM deep learning model to predict the Li-ion battery RUL in percentage based on the last 10 cycles of measurements of temperature, capacity, capacity difference curves and internal resistance, discharge time. The effectiveness of the proposed deep learning method was verified using a public battery dataset of LiFePO₄ batteries. The verification results demonstrate that the proposed deep learning model achieves promising accuracy in the battery life estimation. Trained on a selected training set, the proposed model can reach an average RMSE of 5% and the best of 2%. The proposed model is capable of approximating the complex data-health relationship of battery cells from large-scale datasets. This brings to the model the potential to predict any unknown battery at the cost of performing 10 cycles. We have initially validated this in the same dataset with an RMSE of ideally 2%.

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