A Deep Learning Model for the Prediction of Remaining Useful Life of Lithium-Ion Batteries

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Abstract.

Accurate state of Health (SOH) and remaining useful life (RUL) prediction is the key to ensure safety and reliability of Lithium-Ion Batteries (LIBs). Recent advances in deep learning algorithms have led to data-driven estimation approaches with improved accuracy. This paper employs data-driven technique for SOH prediction by utilizing multiple battery datasets that are multivariate time series (MTS) that are packed with dynamical information of the battery ageing system. In this paper, authors have proposed a hybrid method, namely the CNN-LSTM model, which improves the prediction accuracy by exploiting advantages of both Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) methods, for the prediction of SOH and RUL of the LIBs. A comparison against relevant deep learning forecasting algorithms is carried out by utilizing various statistical indicators like the MAE, MAPE and RMSE, to numerically evaluate the prediction results. The proposed hybrid estimation approach outperforms other relevant deep learning techniques. Authors have validated the results experimentally by utilizing multiple NASA battery datasets at different temperatures.

Keywords. Convolutional Neural Network, CNN-LSTM network, Deep Neural Network, Long-short term memory network, State of Health Estimation and Remaining Useful Life estimation of batteries

1. INTRODUCTION

The rapid endorsement of electric vehicles (EVs) has led to significant rise in the demand of LIBs [1]. In the meantime, EV batteries have started to reach their end-of-life condition and it is expected to observe an exponential growth of these retired EV batteries in the nearing decades. Consequently, the world would be in risk from potential waste of retired EV LIBs. Bloomberg New Energy Finance predicts that the incremental addition of the retired EV batteries can show up at 185.5 GWh/year in capacity by 2025 [2]. A second study estimates the cumulative retired EV batteries capacity could hit approximately 1000 GWh by 2030 [3]. IDTechEX predicts that the total amount of EV batteries retiring from vehicles will reach 7.8 million tonnes per year by 2040 [4]. These retired EV batteries can either be reutilized for a second life in stationary applications or it can be recycled to procure the raw materials.

Theoretically, recycling is marginal sustainable measure taken in circular economy and therefore, recycling should be the final step, only in the case when batteries are not utilizable anymore. Hence, before recycling retired EV batteries, they should be taken into consideration for remanufacturing or repurposing for second life. The LIBs retired from EVs retain 70-80% of their initial capacity unlike the batteries used in consumer electronics [5]. These retired EV batteries are ineffective for EV service as decline in battery capacity limits the driving range. But these retired EV batteries, with lower SOH, can still meet the requirements of less demanding stationary applications like energy storage [6]. Therefore, second life becomes an attractive option for retired EV batteries having LFP chemistry.

However, estimating SOH is complex because numerous internal and external factors causing degradation of batteries are involved in calculation. Estimates of capacity and power degradation of ageing battery could reasonably estimate SOH [7]. SOH prediction methods are categorized into experimental methods and adaptive battery methods. Experimental techniques include model-based measurements and direct measurements. Merits of these experimental techniques are lesser computational power and easier Battery Management System (BMS) implementation [8]. Demerits like lower accuracy and time consuming make these methods less popular. Alternatively, adaptive methods like Kalman Filters need high computational effort and integration to BMS is difficult [9]. Recent method of combining electrochemical and mathematical models yields better results at cost of increased complexity and computational resources [10].

The data-driven method being the state-of-the-art method can be utilized if data from the battery's previous life can be gained. These methods are asserted to be more powerful as statistical and machine learning approaches are incorporated, without depending on complete understanding of the various degradation mechanisms like solid electrolyte interphase formation, dendrite formation, lithium plating, physical changes like particle cracking and fragmentation. Considering these aspects, data-driven approaches have an edge over conventional SOH estimation methods, as data-driven methods use historical data for prediction and do not need understanding of complex physical, chemical and mathematical models of LIBs capacity degradation. Hence, authors have considered data driven methods for estimating SOH of ageing LIBs. Data driven approaches are machine learning techniques, evolutionary algorithms, artificial neural network and deep neural networks. Various researchers have proposed different data driven methods for RUL prediction of LIBs, like recurrent neural network [11], LSTM [11], support vector machine [12], etc. LSTM models and CNNs are widely accepted, efficacious and established deep learning methods [13]. [14]-[16] are the recent research papers which have employed CNN-LSTM technique to estimate RUL of LIBs. The essential ideology supporting the implementation of CNN and LSTM techniques on time-series forecasting is the ability of LSTM networks to proficiently apprehend sequence pattern information of long sequential data owing to their distinct architecture design which constitutes internal memory. Whereas CNN networks can efficiently filter the noise of sequential data and can draw significant features of multivariate time series data. Standard CNNs are suitable for addressing spatial autocorrelation data, and LSTM models are tailored to deal with temporal correlations. Therefore, authors have proposed a deep learning network which exploits the merits of both LSTM and CNN techniques to enhance the SOH and RUL prediction performance of ageing LIBs. Authors have employed multiple battery datasets at different temperatures that are multivariate time series for SOH and RUL estimation, which are unlikely to be seen in available literatures.

The paper is organized in following manner: Section 1 presents a brief survey of retired EV lithium-ion batteries and its current literatures concerning the second life application various data-driven techniques in SOH and RUL prediction of ageing LIBs. Section 2 describes the details of the proposed CNN-LSTM deep learning technique. Section 3 discusses the data of ageing lithium-ion battery. Section 4 presents results obtained and related discussions. Section 5 summarizes the findings of the research undertaken.

2. PROPOSED MODEL

The primary idea of the proposed model is to effectively integrate the merits of the two established and efficient deep leaning techniques namely CNN and LSTM.

2.1. Convolutional and pooling layers

These layers are particularly made for data pre-processing; hence it filters noises from input data and extract input features i.e., important information which is usually utilized as an input for next network layer [17]. These convolutional layers perform convolution operation on convolution kernels and input data generate some feature values. This necessitates that input to be organised in matrix form, as CNN was essentially developed to extract features of image. Convolution kernel can be thought of as a small window containing coefficient values in matrix for (for comparison with the input matrix). This tiny window performs convolution operation on every patch met by the specified window across the input matrix as the window slides over the input data. The resulting convolved matrix corresponds to a feature value. By employing various convolution kernels on the input datasets, several corresponding features are developed. These convolved features are better than the actual features of the input datasets and hence, the model performance is improved. The convolutional layers are generally accompanied by a nonlinear activation function to introduce some amount of non-linearity. These layers are then followed pooling layers to decrease dimensionality of feature maps. Consequently, the pooling layer provides matrices which comprehend the convolved features. The pooling operation assists in making the system more robust

2.2. LSTM layers

LSTM models are specialized recurrent neural networks (RNNs) that learn the long-term dependencies by employing feedback connections [18]. Conventional RNNs are feed forward neural networks, and its lack of memory causes underperformance on long temporal sequences and time-series problems. RNNs use recurring connections on their hidden layers to obtain information from time-series sequential data and attain short term memory. However, RNNs are inefficient in learning long-term dependencies of sequential data as it’s affected by vanishing gradient problem. LSTM resolves this issue by learning long term dependencies by managing controlled flow of information by storing important data on memory cells and deleting insignificant information.

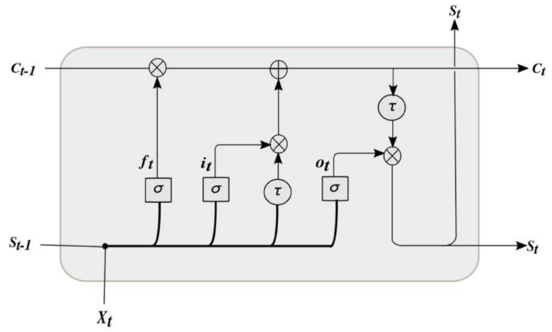


Fig. 1: LSTM block and f_t, i_t, o_t are forget, input and output gates respectively

As exhibited in Fig. 1 the LSTM cell is comprised of different gates, which are input gate, output gate, forget gate and self-recurrent neuron. The inter activeness among various memory units are controlled by these gates. The input gate checks if the input data can change memory cell's state or not. The output gate manages the modification of other memory cells' state. In contrast the forget gate can decide to discard or retain its past information. Various gates, cell states, hidden states and outputs can be represented as follows:

$$f_t = \sigma(X_t U^f + S_{t-1} W^f + b_f) \quad (1)$$
$$i_t = \sigma(X_t U^i + S_{t-1} W^i + b_i) \quad (2)$$
$$o_t = \sigma(X_t U^o + S_{t-1} W^o + b_0) \quad (3)$$
$$C_t^{\sim} = \tanh(X_t U^c + S_{t-1} W^c + b_c) \quad (4)$$
$$C_t = C_{t-1} \otimes f_t \oplus i_t \otimes C_t^{\sim} \quad (5)$$
$$S_t = o_t \otimes tanhC_t \quad (6)$$

where(U^f, U^i, U^o, U^c),(b_f, b_i, b_0, b_c) and (W^f, W^i, W^o, W^c) are input weights, biases and recurrent weights respectively. C_t, X_t and S_t and are cell, input and hidden states respectively at time step t. While at time step t − 1, C_{t-1} and S_{t-1} are cell state and hidden respectively. ⨂, σ, ⨁ and are pointwise multiplication, sigmoid activation and pointwise addition respectively.

2.3. CNN–LSTM model

The objective of the research undertaken is to attain RUL prediction with improved accuracy and acceptable execution time by combining CNN and LSTM. CNN-LSTM is employed for multivariate time series ageing Li-ion batteries datasets for prediction of the RUL. The architecture of CNN-LSTM comprising its building blocks is as shown in Fig. 2. The CNNLSTM model exploits the usefulness and merits of both CNN model and LSTM model. Here both spatial and temporal features are extracted. The interrelations within present inputs are the spatial features and these are extracted by CNNs. Whereas LSTM bring out the correlations between present SOH and previous inputs which can be understood as the temporal (time domain) features. By recursive execution of the input vectors processing, the LSTM networks become better at treatment of time-series information [19].

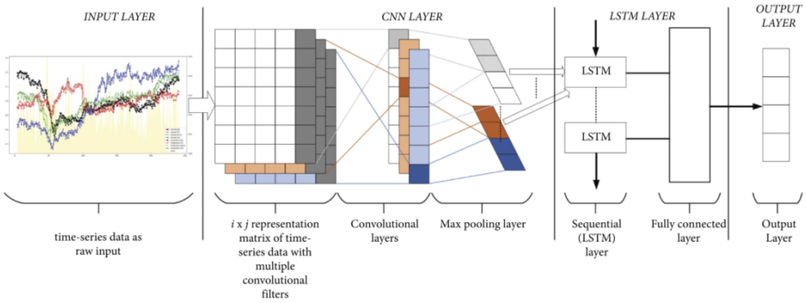


Fig. 2: Proposed architecture of CNN-LSTM network

3. DATASETS

The experimental datasets are considered by extracting different batteries of NASA Prognostics Centre of Excellence Battery ageing datasets that consists of aging data for LIBs [20]. All the LIBs were examined through 3 distinct operational processes namely: charge, discharge and impedance. For all the LIBs, charging was carried out at a constant current (CC) mode at 1.5A till the LIB voltage hit 4.2V, following this a constant voltage (CV) mode was carried out until the charging current decreased to 20mA. A set of four LIBs (# 05, 06, 07 and 18) were run at room temperature (24 deg C), another set of four LIBs (# 29, 30, 31 and 32) were run at elevated ambient temperature (43 deg C) and yet another set of four LIBs (# 53 - 56) were run at reduced temperature of 4 deg C. Table I illustrates the information about LIBs used.

Table I: Experimental Dataset, Comprising 3 Groups of Cells at Different Temperature

File Name	Included Cell	Discharge	Temperature Cycled	Cycled until
Battery Aging ARCFY08Q4	Three cells numbering #05 and #6	Discharge was conducted with CC level of 2A till LIB voltage dropped to 2.7V and 2.5V for batteries #05 and #06 respectively	24 deg C	30% fade
Battery Aging ARC 25-44	Three cells numbering #29 and #30	Discharge was conducted with CC level of 4A till LIB voltage dropped to 2.0Vand 2.2V for batteries #29 and #30 respectively	43 deg C	30% fade
Battery Aging ARC 53 54 55 56	Three cells numbering #55 and #56	Discharge was conducted at fixed load current of 2A and distinct stop voltages 2.5V and 2.7V for batteries #55 and #56 respectively	4 deg C	30% fade

Sustained charge discharge cycles caused accelerated aging of LIBs. These experiments were discontinued when LIBs reached 30% fade in rated capacity which is End-of- Life (EOL) criteria. Fig. 3 depicts capacity degradation over time for all the LIBs considered for testing and implementation. By data pre-processing, authors can obtain the datasets of particular LIBs. These datasets constitute the fields like impedance, charge and discharge. Among these fields, authors have selected the discharge data as discharge datasets are more relevant in case of capacity degradation. In discharge datasets we have considered all relevant features like cycle number, battery capacity (Ahr), terminal battery voltage, battery current, battery temperature, load current, voltage under load. These parameters are highly reliable, and they characterize the actual performance and degradation LIBs accurately under different cell aging conditions.

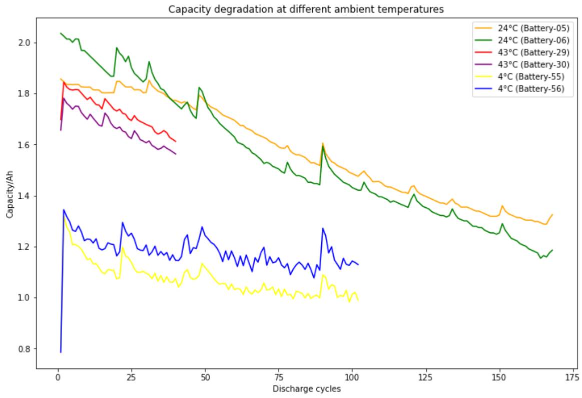


Fig. 3: Capacity Degradation over Charge/Discharge Cycles

4. RESULTS AND DISCUSSIONS

This section summarizes SOH and RUL estimation methods and various performance metrics that are adopted for the comparisons and validation. Further, we evaluate the effectiveness of the proposed CNN–LSTM model in comparison with the state-of-the-art methods namely LSTM and CNN.

4.1. SOH and RUL Estimation

In literature, there are various definitions for battery SOH. For understanding, we used the SOH [%] , which can be defined as:

$$SOH(\%) = \frac{C_{bat}}{C_{nom}} * 100\ [\%] \tag{7}$$

Where: SOH [%] is the battery SOH, C_{bat} is the current LIB capacity and C_{nom} is the LIB nominal capacity. RUL is stated as the length of remaining charge/discharge cycles to reach the threshold of failure of the LIBs. Threshold of failure can be considered as the EOL of LIBs when the remaining output capacity hits to 70–80% of the nominal output capacity of LIB. This is established as:

$$RUL = T_{EOL} - T_{CC} \tag{8}$$

T_{EOL} is the cycle number at which output capacity hits the failure threshold i.e. EOL and T_{CC} is the current capacity's cycle number.

4.2. Performance Measures

Besides, evaluation of RUL prediction performance, we have used the mean absolute error (MAE), mean absolute percentage error (MAPE), and the root mean square error (RMSE) as performance metrics for SOH estimation:

$$MAE = \frac{1}{n}\sum_{1}^{n} |C_k - C_k^{\wedge}| \tag{9}$$

$$MAPE = \frac{100}{n}\sum_{k}^{n} |\frac{C_k - C_k^{\wedge}}{C_k}| \tag{10}$$

$$RMSE(\%) = \sqrt{\frac{1}{n}\sum_{k}^{n}(C_k - C_k^{\wedge})^2} \tag{11}$$

Where k is the cycle number, $C_k^{\wedge}$ is estimated LIB capacity, C_k is the true capacity of LIB and n is total number of cycles. The MAE measures how close the predictions are to the corresponding true observations without sign consideration. MAE is insensitive to outliers as it gives less weight to outliers. MAPE is closer to MAE, but it is normalized by true observation. RMSE refers to Root of MSE which is a combination measurement of variance and bias of the prediction. The unit is brought back to actual unit by RMSE and makes model accuracy interpretation is made easier. When these indicators are close to zero, then it can be stated that capacity prediction accuracy is higher.

4.3. Experimental Results

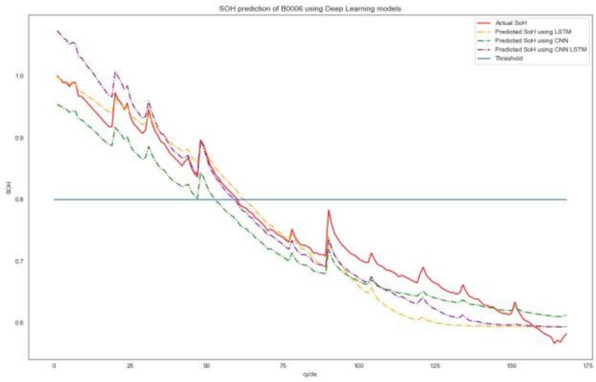
The code was implemented in Python by using open-source distribution for programming namely Anaconda 3.0. The deep learning models were developed using Keras library [21] with Tensorflow 2.0 as backend. All the models (LSTM, CNN and CNNLSTM) were trained for maximum of 500 epochs with early stopping. Adaptive moment estimation (ADAM) is used as optimizer and the batch size used was 72. The activation function employed is rectified linear unit (ReLU) and the loss function is mean-squared loss.

We have adopted multi battery datasets for SOH estimation. Since training and testing datasets should have similar operational profiles, therefore one battery from each temperature group is considered for training and other battery is utilized for testing. For batteries at 24 deg C, #05 is used for training the model and #06 is employed for testing. For batteries at 43 deg C, #29 is employed for training and #30 is utilized for validating the model. Similarly for batteries at 4 deg C, #55 is adopted for training the models and #56 is used for testing. Various performance metrics results are displayed in Table II.

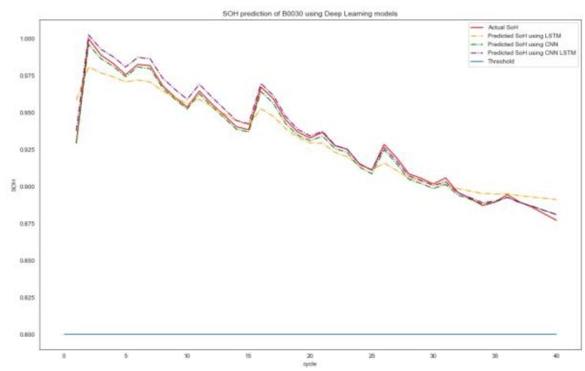
Table II: SOH Estimation Results for Various Batteries

Battery	**Model**	**MAE**	**MAPE**	**RMSE**
B0006	LSTM	0.115316	0.076345	0.12709
	CNN	0.0872128	0.058788	0.098374
	CNNLSTM	**0.080202**	**0.054259**	**0.089557**
B0030	LSTM	0.059344	0.034233	0.06207
	CNN	0.058901	0.034158	0.059317
	CNNLSTM	**0.051973**	**0.030214**	**0.052244**
B0056	LSTM	0.043546	0.036565	0.050271
	CNN	0.031195	0.026098	0.037071
	CNNLSTM	**0.027973**	**0.023428**	**0.033831**

Fig. 4a, 4b and 4c show the prediction results for batteries at 24 deg C, 43 deg C and 4 deg C respectively. Battery #30 at 43 deg C has a smaller number of cycles than batteries at 24 deg C during capacity degradation. It can be evidently seen that it’s challenging to forecast with the battery datasets. Despite that, the CNN-LSTM algorithm achieved better results in comparison of simpler LSTM and CNN networks. Further, RUL errors at 80% capacity degrade for #06 is 2, -8 and -1 cycles for LSTM, CNN and CNN-LSTM networks respectively. For other batteries, as per given datasets capacity degrade does not reach 80%, which can be observed in Fig. 4b and Fig. 4c. Hence, it is seen that RUL is significantly less for CNN-LSTM technique. The aforesaid experiments declare that the proposed CNN-LSTM based algorithm has effectively captured the dynamic features of LIBs with efficient learning.



a.



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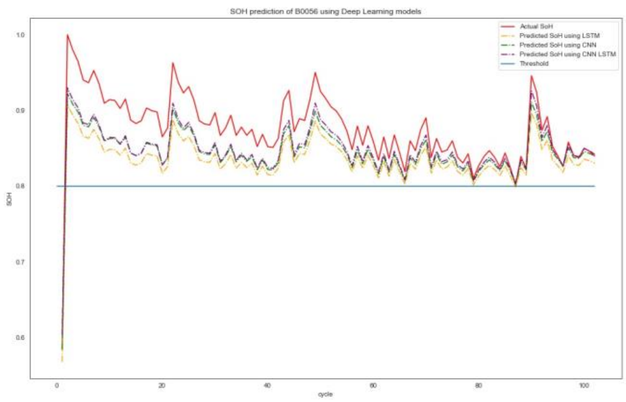

c.

Fig. 4: SOH Estimation Results for Battery (a.) #6, (b.) #30 and (c.) #56

The proposed methods, particularly CNN-LSTM has improved estimation performance with significant prediction accuracy. MAPE of CNNLSTM is 0.05, 0.03 and 0.02 for batteries #06, #30 and #56 respectively. Hence it is observed that improved values are obtained

5. CONCLUSION

In the research undertaken, authors have presented multi battery SOH prediction method based on state-of-the-art CNNLSTM neural networks. The proposed deep learning framework has been implemented and tested on different LIBs dataset, for three different temperature ranges (24 deg C, 43 deg C, and 4 deg C). The estimation performance of the proposed method has been assessed using various performance metrics. Comparisons performed against different relevant deep neural networks CNN and LSTM show the superior performances of the CNN-LSTM. The estimation errors of the hybrid CNNLSTM method are lesser than the ones obtained with the single deep learning algorithm. Hence, CNN-LSTM-based estimation method is a very suitable candidate for multi battery SOH and RUL prediction.

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