REMAINING USEFUL LIFE AND STATE OF HEALTH ASSESSMENT FOR LITHIUM ION BATTERIES USING CNN-BILSTM-DNN HYBRID METHOD

Ansalnakhan N
PG Scholar
Centre for Artificial Intelligence
TKM College for Engineering kollam, kerala
21066@tkmce.ac.in

Fousia M Shamsudeen
Asst. Proffessor
Department of MCA
TKM College for Engineering kollam, kerala
fousiasahala@tkmce.ac.in

2022 IEEE International Power and Renewable Energy Conference (IPRECON) | 978-1-6654-9175-4/22/$31.00 ©2022 IEEE | DOI: 10.1109/IPRECON55716.2022.10059708

***Abstract*—Accurate prediction of Remaining Useful Life (RUL) and State of Health (SOH) of lithium-ion batteries play an increasingly crucial role in intelligent battery health management systems. It also serves as a battery failure early warning system. For electrical vehicles, lithium-ion batteries serve as the primary energy source. Li-ion battery safety requires the use of a battery management system (BMS), which typically rests on RUL and SOH. This work suggests a hybrid method, consisting of a Convolutional Neural Network (CNN), Bidirectional Long Short-Term Memory (BiLSTM), and Deep Neural Network (DNN), to estimate the remaining useful life (RUL) and state of health (SOH) of the battery. A comparative analysis has been done with another existing hybrid method consisting of a Convolutional Neural Network, Long Short-Term Memory, and Deep Neural Network. Three analytical indices are chosen to evaluate the prediction results numerically. They are MAE, R2, and RMSE. The suggested method is experimented with and validated on the NASA lithium-ion battery health dataset. When compared with the existing method, it is observed that the suggested technique has greater accuracy.**

***Index Terms*—Lithium-ion batteries, state of health, remaining useful life, bi-directional long short term memory, convolutional neural network, deep neural network.**

I. INTRODUCTION

Lithium-ion battery technology has been widely utilized in the rising modern industry, including vehicles, home appliances, communications, aerospace, and other fields. One of the crucial elements of electric vehicles that are projected to enter current transportation sector is the energy storage system (ESS). Lithium ion batteries continue to be the primary energy source for EVs and consumer devices so far. They are the ideal option for the ESS and offer great benefits including high power density and a lengthy life cycle. [1],[2]. The performance of the battery, however, gradually deteriorates over time, raising the risk of certain catastrophes (such as battery explosions in EVs and cell phones). To increase the whole energy system's reliability, further work is needed to accurately analyze the battery's health and therefore ensure its course of life [3]. Therefore to ensure the safety of lithium ion batteries a battery management system is maintained based on three factors. They are state of charge (SOC), remaining useful life (RUL) and state of health (SOH) respectively. Furthermore, timely maintienance of battery's RUL and SOH would reduce the need for frequent repairs.

Numerous types of research on SOH and RUL estimation have been done due to their importance to battery system operation. Model-based approaches and data-driven methods are two categories that can be applied to existing models, based on how their principles and structures differ. In model based approach because of the influence of the objective factors, it is challenging to precisely capture the maintenance of the battery.

Data driven techniques don't need a particular physical model. Instead, they develop pertinent models utilizing machine learning techniques employing a vast history of battery measurement data. As a result, these techniques are more adaptable and versatile and have more potential for use. Common data driven techniques include support vector machine, neural networks, ARMA models, regression models etc. Although these methods alone performe actively in the RUL and SOH prediction for a Lithium ion battery, their performance is still insufficient. The CNN-LSTM-DNN hybrid approach has been effectively utilized recently to resolve to solve a variety of classification and prediction issues in fields like health and agriculture. LSTM is a special case of recurrent neural network used for time series prediction [4]. The method's main purpose is to calculate the battery's RUL. In this research, the effectiveness of the suggested hybrid method for Lithium-ion battery SOH and RUL estimation is evaluated using the CNN-LSTM-DNN approach as a benchmark. The main challenging issues are summarised as follows.:

- The accuracy of prediction for RUL results. All researchers strive for accuracy to achieve the best results.

978-1-6654-9175-4/22/$31.00 ©2022 IEEE

- Reducing Overall execution time.

To overcome these challenges, a new hybrid model CNN-BiLSTM-DNN is proposed, which takes advantage of combining CNN, BiLSTM, and DNN. This proposed method can achieve good performance for RUL and SOH prediction with satisfactory timing.

II. RELATED WORKS

Zraibi et al. [5] 2021 proposed a CNN-LSTM-DNN hybrid method, which is a combination of Convolutional Neural Networks, deep neural Networks, and, Long Short Term Memory, for estimating the remaining useful life of battery and improving performance. Three statistical indicators are chosen to evaluate the prediction results numerically: the MAE, R2, and RMSE. The datasets used here is battery health dataset from NASA [6] and CALCE. This hybrid model has achieved better performance for RUL estimation when compared to other techniques.

Ren et al. [7] 2021 proposed Auto-CNN-LSTM method. It is an improved convolution neural network (CNN) and long short-term memory-based RUL prediction method (LSTM) for lithium-ion battery. This technique was developed based on deep CNN and LSTM to extract more detailed information from finite data. Various techniques are used to increase the dimensionality of the data for better CNN and LSTM training. The NASA PcoE datasets are chosen for both training and testing. In comparison to other models, it has an extremely high RMSE value of 4.8 per cent.

Cheng et al. [8] 2021 presented an EMD (empirical mode decomposition) method combined with a bidirectional LSTM (B-LSTM) for estimating SOH and RUL of lithium ion batteries. The many-to-one structure's BLSTM NN makes use of readily accessible battery data including current and to calculate the SOH, uses voltage. The EMD method is used to process SOH data to lessen the influence of capacity generation. The model has improved upon the present data-driven forecasting model in several with a clear framework and excellent accuracy. The experimental results have been validated using the datasets of lithium ion batteries from CALCE.

Ren et al. [9] 2018 proposed a deep learning approach for the RUL prediction of lithium ion batteries using an auto-encoder and a Deep Neural Network. First, to describe the decline in health of the battery, a multidimensional feature extraction model based on an auto-encoder is used. The suggested method is applied to the NASA dataset of lithium ion batteries. According to the experimental results, it has a higher RMSE value of 6.6 per cent.

Chen et al. [10] 2021 suggested a sequence decomposition with deep learning infused proposal for the prediction of remaining useful life of lithium ion batteries. To distinguish the local variations and the overall degradation trend from the battery ageing data, complementary ensemble mode decomposition and principal component analysis are used. As a transfer learning model, the long short-term memory neural network is paired with fully connected layers. The model's hyperparameter optimization and finetuning technique is based on offline training data. The suggested integrated approach's performance in deterioration modelling and RUL prediction is evaluated using three publically accessible lithium ion battery datasets.

III. METHODOLOGY

A. Dataset

The dataset used here is battery datasets from NASA Prognostics Center of Excellence data Repository. It has three different charging, discharging, and impedance operating profiles at room temperature. There are four lithium-ion batteries mainly. B0018, B0006, B0005 and B0007. The constant-current, constant-voltage principle is used to charge the batteries.

Charging is carried out at a constant current of 1.5A. The battery is charged until the voltage reaches 4.2V, at which point the voltage remains constant till the current drops to 20mA. Discharging is carried out at a constant current of 2A for batteries B0018, B0006, B0005, and B0007 until the cell voltage reaches 2.5V, 2.5V, 2.7V, and, 2.2V respectively. All the datasets are similar to each other, having the same number of rows and columns and the attributes of the rows and columns are also the same. The attributes in the dataset include cycle, capacity, voltage measured, current measured, temperature measured, date-time, ambient temperature, time, voltage at load and current at load. Each dataset consists of 50,285 rows and 11 columns. It has 168 cycles in total.

B. Dataset Preparation

1) For SOH estimation: For SOH estimation B0005 is used for both training and testing from the NASA dataset. For training, the first 90 cycles are taken and for testing remaining 78 cycles are chosen. The dataset is prepared in such a way that it can be used by Tensorflow in the training phase, for this, two structures are created corresponding to the input and output expected to be obtained. For the input data, the relevant characteristics of the dataset are filtered, which are:

- Battery capacity
- Voltage measured
- Current measured
- Temperature measured
- Voltage at load
- Current at load
- Instant of time (from the start of the download)

For the output data, the SOH of the battery is calculated and in both input and output cases, the values are normalized to a range of values between [0-1].

2) For RUL Estimation: For RUL estimation B0005 is used. B0005 is used in both training and testing. The input feature chosen is capacity taken with a window size of 10. The first 90 cycles are spent on training, while the remaining 78 cycles are spent on testing to predict the capacity in the following cycles in such a way as to be able to know when the threshold of the battery is reached and estimate the remaining cycles to reach the end of the battery.

C. Proposed Framework

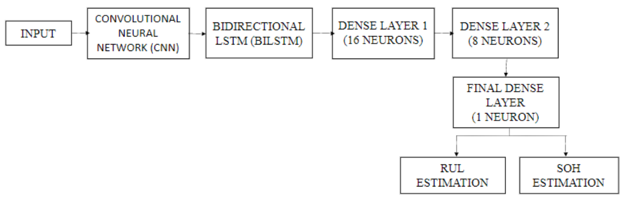

Fig. 1. CNN-BiLSTM-DNN architecture

The Model consists of a convolutional neural network, bidirectional LSTM and a deep neural network. The input is given to CNN. The output of the CNN is sequentially given to the bidirectional LSTM. The dense layers receive the output of the bidirectional LSTM. Finally, SOH and RUL are predicted by the dense layers.

The CNN-BiLSTM technique extracts two types of features. They are temporal features and spatial features. The temporal characteristics are the relationships between the present RUL and SOH and the historical inputs, which BiLSTM will reveal. The BiLSTM layers are effective at handling time-series data [11] because they can process input vectors using the recursive execution strategy, which depends on both the input and hidden state from the past. The DNN layers are the next to be discussed. Both linear and nonlinear techniques can be used to extract features from the raw data utilizing the DNN layers. The accuracy and effectiveness of the DNN can be increased for RUL and SOH estimates by utilizing CNN and BiLSTM features, which incorporate sequential information. As a result, the suggested strategy is set up to benefit from each one, as evidenced by the architecture in figure 1.

The model is made up of one convolutional layer, one bidirectional LSTM layer, and three dense layers. Firstly, the discharge battery data is taken. For SOH estimation, the attributes cycle, capacity, voltage measured, current measured, temperature measured, time, voltage at load and current at load are taken for training. For RUL estimation, only one feature is chosen, that is the capacity for each cycle in which the input is the previous capacity and the output is the actual capacity. Then the data is formatted by giving a window size of ten to prepare it for training. Finally, for both SOH and RUL, the data is split into training and testing sets. The formatted dataset is given in the CNN-BILSTM-DNN model. The one-dimensional convolution layer consists of 64 filters of size 3 with the same padding which is followed by a one-dimensional max-pooling of size 2. The bidirectional LSTM consists of 100 neurons with the same return sequence which is followed by a dropout of 20 percent. The feature maps from the current layer are flattened and fetched into the fully connected neural network. The first dense layer consists of 16 neurons, the second consists of 8 neurons, and the final one-node dense layer is for prediction. The models are optimized using Adam optimizer with a learning rate 8e-4. The epoch number is 200 and a batch size of 50 is used. The loss function used is Huber loss which is a loss function used in robust regression.

IV. PERFORMANCE EVALUATION METRICS

The following are the standard metrics that have been used in this work to measure the performance of the proposed method.

1. **Root Mean Square Error(RMSE):** It is defined as the standard deviation from the prediction error.

$$\mathrm{RMSD}=\sqrt{\frac{\sum_{i=1}^{N}\left(x_i-\hat{x}_i\right)^2}{N}} \tag{1}$$

2. **Mean Absolute Error(MAE):** It measures the average absolute value of the forecasting errors without taking into account their direction.

$$\mathrm{MAE}=\frac{\sum_{i=1}^{n}\left|y_i-x_i\right|}{n} \tag{2}$$

3. **R Squared:** R-squared is a measure of proportion of variance for a dependent variable that is predictable by an independent variable in a regression model.

$$R^2=1-\frac{RSS}{TSS} \tag{3}$$

where R squared is the coefficient of determination
RSS is Residual Sum Of Squares
TSS is Total Sum Of Squares

$$RSS=\sum_{i=1}^{n}\left(y_i-f\left(x_i\right)\right)^2 \tag{4}$$

$$\mathrm{TSS}=\sum_{i=1}^{n}\left(y_i-\bar{y}\right)^2 \tag{5}$$

V. EXPERIMENTAL SETUP

Python is used to implement the proposed model along with required libraries such as pandas, NumPy, Scikit-learn and others. The framework used is Keras with TensorFlow as background in the google colab. B0005 is used for both training and testing from the NASA dataset for SOH estimation. The dataset is prepared in such a way that it can be used by Tensorflow during the training phase; for this, two structures corresponding to the input and output are created. The datasets that have been filtered for input are battery capacity, voltage, current, temperature, charging voltage, charging current, and time. The SoH of the battery is calculated for the output data. In these cases, the values are normalized to a range of [0-1].

B0005 is used to estimate RUL. B0005 is used for training as well as testing. The first 90 cycle is used for training, and rest 78 cycle is used for validation to predict capacity in subsequent cycles to know when the battery's threshold is reached and estimate the remaining cycles to reach the battery's end of life. The models are optimized using Adam optimizer with learning rate 8e-4. The epoch number is 200 and a batch size of 50 is used. The loss function used is Huber loss which is a loss function used in robust regression.

VI. Experimental Analysis

A. Experiment on RUL Estimation

Firstly, all the necessary libraries for the treatment of the dataset are imported. The data preparation is done. The real RUL of the battery is calculated for each cycle. Next is training phase for calculating the predicted RUL. For RUL estimation B0005 is used. 90 cycle is used for training and remaining 78 cycle is used for testing. For training the model for predicting RUL, the attributes capacity is taken. First, the model is trained, 200 epochs and a batch size of 50 are used for training. To test the model's suitability, the information of the same battery is loaded and thus obtained the predicted RUL by the model. A table is created containing the real RUL and the RUL predicted by the network and the root of the mean square error(RMSE), Mean Absolute Error(MAE), and R Square is calculated. The graph comparing the real RUL and predicted RUL is shown.

B. Experiment on SOH Estimation

Firstly, all the libraries required for processing the dataset are imported. Then comes data preparation. For each cycle, the battery's actual SOH is determined. The training phase for determining the expected SOH comes next. B0005 is used for training and testing in SOH estimation. The attributes capacity, voltage measured, current measured, voltage at load, current at load, and time are used to train the model for forecasting SOH. The model must first be trained using 200 epochs and a batch size of 50. The same battery's information is loaded to evaluate the model's accuracy, and the anticipated SOH by the model is then obtained. Real SOH and SOH predicted by the network are entered into a table, and the R Square, mean absolute error (MAE), root mean square error (RMSE) is determined. The graph comparing the real SOH and predicted SOH is also taken into account.

VII. Results and Discussion

A. RUL Estimation Results

The experiment aimed to show that the proposed hybrid method predicts the data pattern of RUL estimation correctly as the real RUL. Table 1 shows the comparison of the real RUL and the predicted RUL. From the table, it is clear that real RUL and RUL estimated by the proposed CNN-BiLSTM-DNN hybrid method are similar which shows that the model predicts the battery's RUL correctly. Figure 2 shows the graph comparing the real RUL and estimated RUL. From the graph it is clear that the data pattern is learned by the model correctly, as predicted by the theory; since the shape and pattern of the curves are almost identical. A comparative analysis has been done with another existing hybrid method consisting of a Convolutional Neural Network, Deep Neural Network and, Long Short-Term Memory. For that, three analytical indices are selected. They are MAE, R^2, and RMSE. The proposed method has achieved an RMSE value of 0.023, an MAE value of 0.017, and an R square of 91.28 percent. Table 2 shows the comparison of the proposed method and the CNN-LSTM-DNN hybrid method using RMSE, MAE, and R square. From the table, it is clear that the proposed method outperforms the existing CNN-LSTM-DNN hybrid method.

TABLE I
Comparison of real RUL and predicted RUL

Cycles	Real RUL	Predicted RUL
90	**1.508654**	**1.511752**
91	**1.526599**	**1.511105**
92	**1.530590**	**1.511377**
93	**1.524837**	**1.512411**
94	**1.522765**	**1.512923**

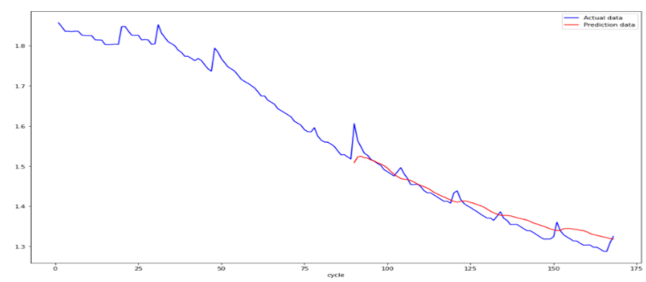

Fig. 2. The graph comparing real RUL and predicted RUL

TABLE II
Comparison of RUL estimation of the proposed method and CNN-LSTM-DNN hybrid method

Battery	Algorithm	RMSE	MAE	R Square
B0005	**CNN-BiLSTM-DNN**	**0.023**	**0.017**	**91.28**
B0005	**CNN-LSTM-DNN**	**0.041**	**0.0345**	**71.35**

B. SOH Estimation Results

The experiment demonstrated that the suggested hybrid method accurately predicts the data pattern of SOH estimation as the actual SOH. Table 3 contrasts the actual SOH with the expected SOH. The table demonstrates the similarity between the real SOH and the SOH predicted by the proposed CNN-BiLSTM-DNN hybrid technique, demonstrating the accuracy with which the model predicts the battery's SOH. Figure 3 contrasts the graph comparing actual SOH with the expected

SOH. Since the shape and pattern of the curves are nearly identical, it is evident from the graph that the model accurately learned the data pattern, as anticipated by the theory. A comparison with another hybrid method that is currently in use that uses a convolutional neural network, deep neural network and long and short term memory. Three analytical indices are chosen to evaluate the prediction results numerically: the MAE, R2, and RMSE. The RMSE, MAE, and R square for the suggested technique were 0.0804, 0.072, and 0.5749 percent respectively. The suggested approach and the CNN-LSTM-DNN hybrid method are compared using RMSE, MAE, and R square in table 4.

TABLE III
COMPARISON OF REAL SOH AND PREDICTED SOH

Cycles	Real SOH	Predicted SOH
1	**1.000000**	**1.003132**
2	**0.994990**	**0.999674**
3	**0.989185**	**0.995660**
4	**0.989165**	**0.995646**
5	**0.982898**	**0.991302**

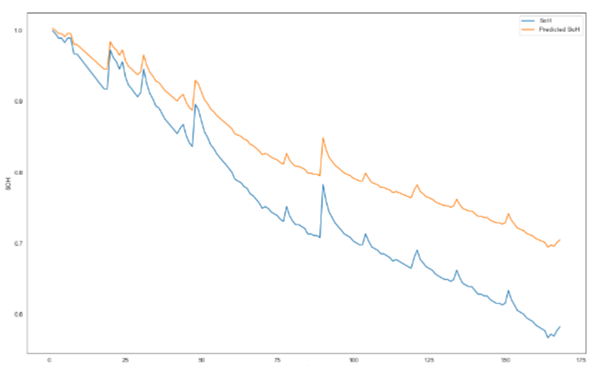

Fig. 3. The graph comparing real SOH and predicted SOH

TABLE IV
COMPARISON OF SOH ESTIMATION OF THE PROPOSED METHOD AND CNN-LSTM-DNN HYBRID METHOD

Battery	Algorithm	RMSE	MAE	R Square
B0005	**CNN-BiLSTM-DNN**	**0.080**	**0.072**	**57.49**
B0005	**CNN-LSTM-DNN**	**0.082**	**0.0745**	**55.67**

VIII. CONCLUSION

In this paper, a hybrid CNN-BiLSTM-DNN algorithm is suggested by combining three well-known algorithms, i.e., Convolutional Neural Networks (CNNs), Bidirectional Long Short Term Memory (BiLSTM), and Deep Neural Networks (DNNs), for the remaining useful life (RUL) and state of health (SOH) prediction of lithium ion batteries with better prediction accuracy. The proposed model has been experimentally tested on NASA battery health dataset of various lithium-ion batteries. Experimental results of RUL and SOH estimation demonstrate good performance with better execution time. To show the effectiveness of the proposed hybrid method a comparative analysis has been done with the existing CNN-LSTM-DNN hybrid model. The three prediction performance indices; RMSE, MAE, and R Square shows that the proposed method has very less error rate and high performance when compared with CNN-LSTM-DNN model. As for future scope, the proposed method will be tested by introducing the remaining NASA lithium-ion batteries i.e, B0007, B0006, and B0018. The technique will be evaluated using several other comparison algorithms.

REFERENCES

[1] J. Fan, J. Fan, F. Liu, J. Qu, and R. Li, "A novel machine learning method based approach for li-ion battery prognostic and health management," *Ieee Access*, vol. 7, pp. 160 043–160 061, 2019.

[2] G. Ma, Y. Zhang, C. Cheng, B. Zhou, P. Hu, and Y. Yuan, "Remaining useful life prediction of lithium-ion batteries based on false nearest neighbors and a hybrid neural network," *Applied Energy*, vol. 253, p. 113626, 2019.

[3] D. Liu, J. Pang, J. Zhou, and Y. Peng, "Data-driven prognostics for lithium-ion battery based on gaussian process regression," in *Proceedings of the IEEE 2012 prognostics and system health management conference (PHM-2012 Beijing)*. IEEE, 2012, pp. 1–5.

[4] Y. Zuo, Y. Wu, G. Min, C. Huang, and K. Pei, "An intelligent anomaly detection scheme for micro-services architectures with temporal and spatial data analysis," *IEEE Transactions on Cognitive Communications and Networking*, vol. 6, no. 2, pp. 548–561, 2020.

[5] B. Zraibi, C. Okar, H. Chaoui, and M. Mansouri, "Remaining useful life assessment for lithium-ion batteries using cnn-lstm-dnn hybrid method," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 5, pp. 4252–4261, 2021.

[6] B. Saha and K. Goebel, "Battery data set," *NASA AMES prognostics data repository*, 2007.

[7] L. Ren, J. Dong, X. Wang, Z. Meng, L. Zhao, and M. J. Deen, "A data-driven auto-cnn-lstm prediction model for lithium-ion battery remaining useful life," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 5, pp. 3478–3487, 2020.

[8] G. Cheng, X. Wang, and Y. He, "Remaining useful life and state of health prediction for lithium batteries based on empirical mode decomposition and a long and short memory neural network," *Energy*, vol. 232, p. 121022, 2021.

[9] L. Ren, L. Zhao, S. Hong, S. Zhao, H. Wang, and L. Zhang, "Remaining useful life prediction for lithium-ion battery: A deep learning approach," *Ieee Access*, vol. 6, pp. 50 587–50 598, 2018.

[10] Z. Chen, L. Chen, W. Shen, and K. Xu, "Remaining useful life prediction of lithium-ion battery via a sequence decomposition and deep learning integrated approach," *IEEE Transactions on Vehicular Technology*, vol. 71, no. 2, pp. 1466–1479, 2021.

[11] A. Ghosh and T. Veale, "Fracking sarcasm using neural network," in *Proceedings of the 7th workshop on computational approaches to subjectivity, sentiment and social media analysis*, 2016, pp. 161–169.