Remaining Useful Life Assessment for Lithium-Ion Batteries Using CNN-LSTM-DNN Hybrid Method

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***Abstract*—The prediction of a Lithium-ion battery's lifetime is very important for ensuring safety and reliability. In addition, it is utilized as an early warning system to prevent the battery's failure. Recent advance in Machine Learning (ML) is an enabler for new data-driven estimation approaches. In this paper, we suggest a hybrid method, named the CNN-LSTM-DNN, which is a combination of Convolutional Neural Network (CNN), Long Short Term Memory (LSTM), and Deep Neural Networks (DNN), for the estimation of the battery's remaining useful life (RUL) and improving prediction accuracy with acceptable execution time. A comparison against various ML estimation algorithms is carried out to show the superiority of the proposed hybrid estimation approach. For that, three statistical indicators, i.e., the MAE, R^2, and RMSE, are selected to assess numerically the prediction results. Experimental validation is performed using two datasets of different lithium-ion batteries from NASA and CALCE. Thus, results reveal that hybrid methods perform better than the single ones, also the effectiveness of the suggested method in reducing the prediction error and in achieving better RUL prediction performance compared to the other methods.**

***Index Terms*—Lithium-ion batteries, machine learning, remaining useful life, long short term memory, deep neural network, convolutional neural network.**

List of Abbreviations

ANN	artificial neural network
CNN	convolutional neural network
DNN	deep neural network
DBN	deep belief networks
EOL	end of life
ESS	energy storage system
FOSELM	forgetting online sequential extreme learning
GPR	gaussian process regression
LSTM	long short-term memory
MAE	mean absolute error
ML	machine learning
MLR	multiscale logistic regression
ND–AR	nonlinear degradation autoregressive
NASA	national aeronautics and space administration
PF	particle filter
R^2	R-squared
RNN	recurrent neural network
RUL	remaining useful life
RMSE	root mean square error
RVM	relevance vector machine
SP	starting point of prediction
TPN	temporal convolutional network

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I. Introduction

The ENERGY storage system (ESS) is one of the essential components of electric vehicles (EVs) that is anticipated to penetrate the current transport market because of the constant increase in the environmental pollution and the oil prices [1]. Thus far, lithium-ion (Li-ion) batteries remain the main source of energy for EVs [2] and consumer electronics [3]. They have exceptional advantages, like a long life cycle and high power /energy density, as they can be considered the perfect choice for the ESS [4], [5]. However, the battery performance degrades progressively with time leading to some potential disasters (e.g., battery explosion in cell phones and EVs). Consequently, additional efforts are required to effectively assess the Li-ion battery's health and to predict its lifetime (e.g., battery replacement time and control of degradation precursors) to improve the reliability of the overall energy system [6]. Subsequently, a battery management system (BMS) is necessary to ensure the safety of Li-ion batteries which is generally based on three essential elements: remaining useful life (RUL), state of charge (SOC), and state of health (SOH), which have a relationship respectively to the charge of the batteries and their aging [7]. Additionally, accurate RUL estimation of batteries would contribute to the reduction of their frequent maintenance [8].

The Li-ion battery's RUL prediction that that depends on the data-driven method can be partitioned into three categories: fitting (e.g., linear model, single-exponential model, polynomials model, etc.), sequence prediction (e.g., neural network, relevance rector machine, gray prediction, etc.) and filter observation (e.g., unscented particle filter, spherical cubature particle filter, etc.). There is a difficulty in establishing an analytic model that tracks the battery's capacity degradation by model-based and data-driven methods. This latter analyzes the complex chemical and physical changes during some cycles making its application a popular choice to estimate the battery's RUL [9].

Obtaining the RUL forecast of a battery is usually carried out, as a first choice, by a capacity check [4]. Among the advantages of data-driven methods, using historical data to avoid the need for complex physical or mathematical models for battery capacity degradation. Data-driven methods include evolutionary algorithms, Machine Learning (ML), artificial neural network (ANN), etc. Therefore, several researchers used a combination of known algorithms or single algorithms with additional features from various models [10].

Hu *et al.* [11] present an estimator based on sparse Bayesian predictive modeling (SBPM) with a model of the third degree as thus, it is able to estimate the RUL with a developed SOH estimator. Richardson *et al.* [12] propose a regression of the Gaussian process (GP) to predict the battery's RUL. It shows the predictive capacity for short and long-term forecasts of RUL on capacity datasets for Li-ion battery's RUL prediction. Then, Zhang *et al.* [13] use the hybrid algorithm LSTM-RNN for the RUL prediction of Li-ion batteries. Wang *et al.* [14] introduce the difference between mixed algorithms, i.e., quantum particle swarm optimization – support vector regression (QPSO–SVR) and particle swarm optimization and support vector regression (PSO–SVR), and single algorithm, i.e., support vector regression (SVR), where they demonstrate that hybrid methods are able to better estimate the RUL compared to single algorithms. Both Chen *et al.* [15] and Zhang *et al.* [16] also used a hybrid prognosis model for RUL estimation, where the first method fuses the variational mode decomposition (VMD), autoregressive integrated moving average (ARIMA), and gray model (GM) models and the second method combines the ANN with partial incremental capacity (PIC) method during constant current (CC) discharge. Moreover, Zhao *et al.* [17] propose a hybrid method (RVM-GM) combining the relevance vector machine (RVM) and the gray model (GM) that only relies on historical data to estimate the RUL and it achieves better performance for various kinds of batteries. Zhu *et al.* [18] propose another method that contributes to a significant improvement to the estimation accuracy for the battery's RUL. It combines extreme learning machine (ELM), gray wolf optimization (GWO), and differential evolution (DE) to design a DGWO-ELM algorithm. For the Li-ion battery's RUL prediction, there are also typical techniques that combine filter-based methods and machine learning methods. Zhang *et al.* [19] propose an improved unscented particle filter (IUPF) method based on Markov chain Monte Carlo (MCMC). Xue *et al.* [20] propose the combination between Adaptive unscented Kalman filter (AUKF), Genetic algorithm (GA), and Support vector regression (SVR). This technique has a much better filtering effect than UKF and RVR-UKF methods. Zheng *et al.* [21] suggest a developed method combing the unscented Kalman filter (UKF) and relevance vector regression (RVR).

As it is shown, many researchers have proposed several ML algorithms for RUL estimation of Li-ion batteries, such as RNN [13], VMD-ARIMA-GM [15], support vector machine (SVM) [11], LSTM [13], QPSO–SVR [22], DGWO-ELM [18], etc. Despite these algorithms show acceptable performance in the RUL prediction for a battery of Li-ion, their accuracy is still not satisfactory for all life cycle stages.

ANNs have become recently popular in the area of time series forecasting. Their success in several domains is due to their numerous advantages (e.g., they are data-driven, self-adaptive, and nonlinear). Recently, several studies have been reported on their application to time series forecasting and modeling. Therefore, in this article we focus our study on different variants of ANN forecasting models [23].

Several researchers have used the new hybrid method named CNN-LSTM-DNN in some fields such as cyberbullying [24], social media [25], sarcasm sentences [26], [27], speech signal of emotion [28] and voice [29], [30]. This algorithm has shown its potential with good results in the aforementioned applications.

The present work capitalizes on the merits of the CNN-LSTM-DNN hybrid algorithm and the latest developments of ANNs in general to achieve high prediction accuracy for the RUL of the Li-ion battery. This is among the scarce attempts, if any, in implementing the hybrid algorithm for such application.

In the last few years, the CNN-LSTM hybrid method is applied successfully to many classification and prediction problems as medicine [31], agriculture [32]. It is also able to recognize the different headlines of Clickbait and classify them [33]. Moreover, it was used for air quality and energy structure prediction [34], [35] as well as a tool to predict the volatility of gold which is considered a kind of financial asset [36]. It is also utilized to estimate traffic [37]. More importantly, this method is proposed to estimate the battery's RUL [5] and SOC [38]. In this paper, the CNN-LSTM method is used as a benchmark to assess the performance of the proposed hybrid algorithm in RUL prediction of the Li-ion battery.

The main challenging issues of this study are summarized as follows:

1. The prediction accuracy for the RUL results. Accuracy is always an ambition of all researchers for achieving the best results.
2. Reducing Overall time of execution (i.e., data extraction, data formatting, training, validation, and performance computing) for a hybrid method, which is more complex and requires more time to obtain the prediction results.

To overcome these issues, the proposed method CNN-LSTM-DNN is designed, to benefit from combining the CNN, LSTM, and DNN, along with univariate time series for achieving high accuracy of RUL prediction with acceptable time-execution.

Our main contributions of this study are summarized as follows:

1. The hybrid model named CNN-LSTM-DNN is created by combining basic NN namely CNN, LSTM, and DNN to take their advantages with a single-channel (i.e., capacity) for predicting the RUL of Li-ion batteries. Based on referenced literature, as far as we know, this combination has never been used for predicting RUL of Li-ion battery with univariate time series before.
2. Providing deeper insights on the single and hybrid methods for predicting the RUL of Li-ion batteries by the comparison of these methods LSTM, CNN-LSTM, and

CNN-LSTM-DNN. The CNN-LSTM-DNN method demonstrates the superiority in the RUL prediction compared to them, where it provides improvement of RMSE between 10% and 38%.

3. The results of the proposed hybrid method achieved higher accuracy compared to the other methods in the literature. It demonstrates that it is able to achieve a huge performance improvement and long-term predictive capability with an acceptable time of execution, where its average values are around 300s for all steps (i.e., data extraction, data formatting, training, validation, and performance computing).

The other sections of this paper are prepared as follows: Section II explains the architecture of CNN-LSTM-DNN. Section III presents the RUL estimation techniques using three different algorithms with two kinds of datasets. Section IV shows the experiment results of our proposed method and the comparison between it and the algorithms in other papers. Finally, a conclusion is given.

II. CNN-LSTM-DNN ALGORITHM

Each CNN, LSTM, and DNN algorithm have been applied for predicting RUL of the Li-ion batteries in the previous works where they gave a good performance [5]. The aim of our paper is to improve and achieve high accuracy with acceptable time-execution of RUL prediction by combining CNN, LSTM, and DNN. To the best of our knowledge, this is the first attempt at using CNN-LSTM-DNN with univariate time series for predicting the RUL of Li-ion batteries.

The CNN-LSTM algorithm combines the advantages of CNN and LSTM, where two kinds of features are extracted: the spatial features and temporal features. The first ones are the interrelations within current inputs, which will be taken out by CNN, while the temporal features are the correlations between current RUL and past inputs, which will be bringing out by LSTM. The LSTM layers are good at treating time-series information, where are capable to process the input vectors through the method of recursive execution [27], this execution process is dependent on the past hidden state and present input. Then we come to the DNN layers, which can be used to obtain features of the raw data from linear and nonlinear operations. With CNN and LSTM features, which contain sequential informations, the DNN is capable of improving accuracy and efficiency for RUL estimation. Thus, the proposed method is designed to take advantage of all of them, this architecture shown in Fig. 1 was chosen after numerous experiments.

The first part is data preprocessing, we extract the datasets from specific batteries, which contain the charge, discharge, and impedance fields. Then we select the discharge data. Among this data, we choose only one feature i.e., the capacity for each cycle in this experiment, where the input is the previous capacity and output is the actual capacity [5], [39], [40]. Next, we formatted this data using a window size equal to eight, to prepare it for the training step that expects sequences of data. Finally, we split the data into training and validation sets using different split ratios for each battery type.

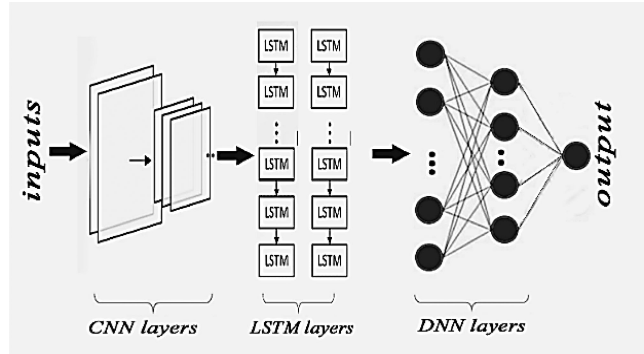


Fig. 1. The Proposed architecture of CNN-LSTM-DNN network.

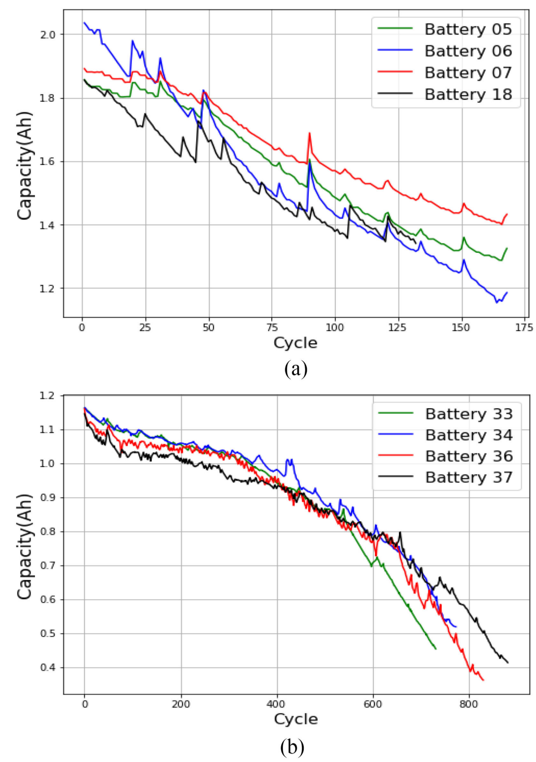


Fig. 2. (a) Capacity degradation curve of NASA batteries. (b) Capacity degradation curve of CALCE batteries.

The second part shows the structure of CNN, which consists of convolution, pooling, and fully connected layers. This convolution is performed using a filter or kernel "K", which is utilized to obtain a feature map S from the input vector A [41]. The formula is:

$$S\,(\mathrm{i},\mathrm{j}) \;=\sum_m\sum_n A\,(i-m, i-n)\,.\,K\,(m,n) \qquad (1)$$

We chose the most appropriate CNN structure, where we use a one-dimension CNN layer with 64 kernels of size 5. We avoid using pooling layers since we have a limited spatial feature. Besides we maintain one as default strides and we choose the causal padding and Rectified Linear Unit (ReLU) activation function.

The third part represents the LSTM, the cell of the LSTM consists of a long-term state of "c_t" and a short-term state "h_t". In addition, it relies on three control gates: forget gate "f_t", input gate "i_t", and output gate "o_t". When data sequentially input into the network, the calculation of the hidden layer nodes depends on the input of the current layer and the activation values of nodes at the previous moment [42]. The calculation formula is as follows:

$$\begin{aligned} f_t &= \sigma\left(W_f\left[h_{t-1},\ x_t\right]+b_f\right) \\ i_t &= \sigma(W_i\left[h_{t-1},\ x_t\right]+b_i \\ q_t &= \tanh\left(W_q\left[h_{t-1},\ x_t\right]+b_q\right) \\ o_t &= \sigma(W_o\left[h_{t-1},\ x_t\right]+b_o \\ c_t &= f_t * c_{t-1}+i_t * q_t \\ h_t &= o_t * \tanh(c_t) \end{aligned} \tag{2}$$

Where, W is the weight matrices, b is the bias, σ is the sigmoid function, x_t is the unit input at time t, h_{t-1} is the unit output of the previous LSTM cell, c_t and c_{t-1} are the cell states at time t and t-1, respectively. The q_t is the hyperbolic function where the state of the previous step and tanh is used to calculate the current input state cell.

After many assays, we select two LSTM layers with true return sequences, and the same return for the 32 nodes. We selected the LSTM because each record in the data sequence of Li-ion batteries in this experiment depends on the records that came before it.

The fourth part is the DNN. Where the LSTM outputs will be inputs into the DNN for the final prediction of the RUL, two dense layers were carefully chosen with the Rectified Linear Unit activation function. They have 16 and 8 nodes, respectively.

The final part of our algorithm is one dense layer with one node.

III. RUL Estimation

RUL is defined as the remaining number of cycles (charge/discharge) to get to the failure threshold of the battery with a specific output capacity [17], (i.e., the length of time from the current time to the end of life "EOL"). The EOL is considered as the time when the capacity gets to 70–80% of the nominal capacity, which can be expressed as [5], [16]:

$$\mathrm{RUL} = \mathrm{T_{EOL}} - -\mathrm{T_{cc}} \tag{3}$$

T_{cc} is the cycle number of current capacity and T_{EOL} is the cycle number when the capacity reaches the EOL threshold [5], [43], [44].

The experimental datasets are presented extracting from two groups with different batteries. The first group is the NASA Prognostics Center of Excellence [51]. It consists of aging data for 18650 Li-ion batteries. They are examined at room temperature 24 degrees Celsius during three different operational processes (i.e., charge, discharge, and impedance). The second datasets are from the Center for Advanced Life Cycle Engineering (CALCE) at the University of Maryland [52]. Four Li-ion batteries used in this experiment were cycled utilizing an ArbinBT2000 battery test system. When the measured actual capacity of the Li-ion battery of NASA and CALCE became lower than the 70% and 80% of rated capacity, respectively, the experiment stopped. Two

TABLE I
The Description of NASA Lithium-Ion Batteries

Battery	Type	Constant charge current	Minimal charge current	Discharge current	Rated capacity	Charge/Discharge cut-off voltage
B5	18650 NMC	1.5A	20mA	2A	2Ah	4.2/2.7V
B6	18650 NMC	1.5A	20mA	2A	2Ah	4.2/2.5V
B7	18650 NMC	1.5A	20mA	2A	2Ah	4.2/2.3V
B18	18650 NMC	1.5A	20mA	2A	2Ah	4.2/2.5V

TABLE II
The Description of CALCE Lithium-Ion Batteries

Battery	Constant current rate CC	Minimal charge current	Constant current discharge	Rated capacity	Charge/discharge Cut-off voltage
CS2_33	0.5C	0.05A	0.5C	1.1Ah	4.2/2.7V
CS2_34	0.5C	0.05C	0.5C	1.1Ah	4.2/2.7V
CS2_36	0.5C	0.05C	1C	1.1Ah	4.2/2.7V
CS2_37	0.5C	0.05C	1C	1.1Ah	4.2/2.7V

Tables I and II introduce information about these batteries as follow:

Three algorithms, i.e., LSTM, CNN-LSTM, and CNN-LSTM-DNN, were implemented using Tensorflow 2.0. A Server with Intel(R) Xeon(R) CPU ES-2687W 03.10GHz (2 processors) and 256 GB memory is used with Anaconda 3.0 as is an open-source distribution for programming in Python. The rectified linear unit (ReLU) activation function is used along with Adam optimizer. Huber loss, a loss function used in robust regression, is also employed. Besides, to evaluate the RUL prediction performance of the algorithms, we use the mean absolute error (MAE) [9], root mean square error (RMSE), and R square (R^2) [20]. They are defined as follow:

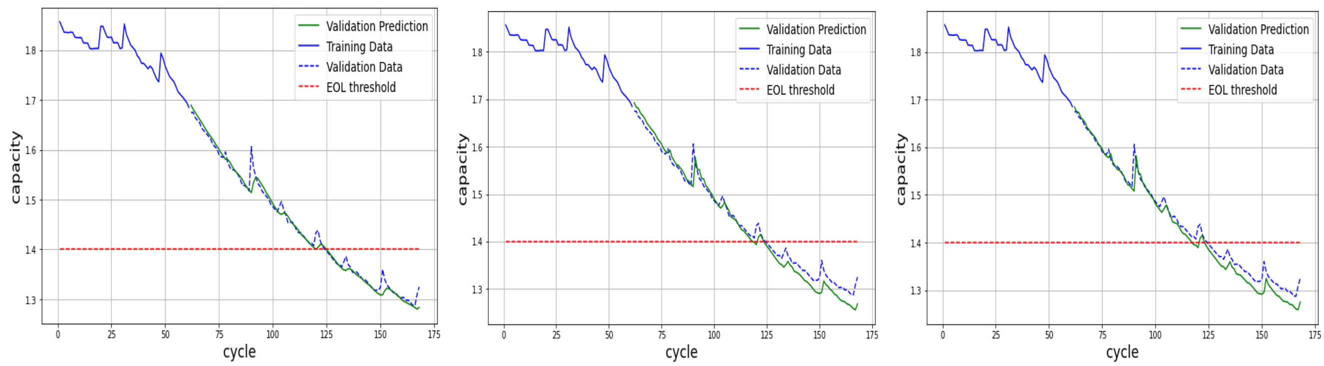
$$MAE = \sum_{k=1}^{k} \left|y_k - \widehat{y_k}\right| \tag{4}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_k - \widehat{y_k}\right)^2} \tag{5}$$

$$R^2 = 1 - \frac{\sum_{K=1}^{n}\left(y_k - \widehat{y_k}\right)^2}{\sum_{K=1}^{n}\left(y_k - \widehat{\overline{y_k}}\right)^2} \tag{6}$$

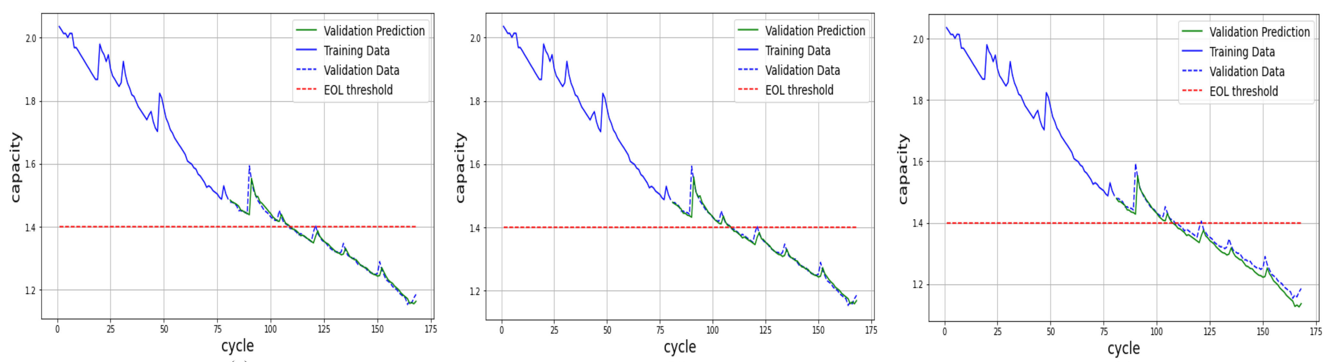
Where y_k is the true value battery capacity, while $\widehat{y_k}$ is the estimated value battery capacity, $\widehat{y_k}$represents the average of actual battery capacity; The MAE measures how estimates are close to the corresponding outcomes without considering the sign. For the indicator MAE and RMSE, when it is close to zero, then the capacity prediction accuracy is higher. As for R^2, a value close to one yields better accurate RUL prediction results.

Each algorithm consists of three steps: data preprocessing, training, and validation. After many attempts, we choose these hyper-parameters for all the three algorithms (window_size = 8, batch_size = 8, shuffle_buffer_size = 1000, epochs = 1500,



(a) (b) (c)

Fig. 3. RUL prediction results for B0005 using: (a) CNN-LSTM-DNN (b) CNN-LSTM (c) LSTM.



(a) (b) (c)

Fig. 4. RUL prediction results for B0006 using: (a) CNN-LSTM-DNN (b) CNN-LSTM (c) LSTM.

learning_rate = 8e-4, without regularization). The average algorithms time execution is equal to 300s for each NASA and CALCE data. This time includes all steps i.e., data extraction, data formatting, training, validation, and performance computing. After several repetitive training phases, these algorithms give approximately the same performance and seem to be consistent. Below, the RUL prediction results are presented for three algorithms the real value is represented in blue color, validation data in blue dotted color, validation prediction in green color, and EOL threshold of these algorithms in red dotted color.

A. NASA Datasets Prediction

The main of this sub-section is to compare the proposed method i.e., CNN-LSTM-DNN with other ones, i.e., LSTM, CNN-LSTM, for predicting RUL of different Li-ion batteries, it is also for verifying the prediction performance of our method. We use four batteries (i.e., B0005, B0006, B0007, and B0018) to predict the RUL. we divided the datasets into training and validation data with different starting validation points of each battery.

First, Three LSTM, CNN-LSTM, and CNN-LSTM-DNN algorithms are implemented for the RUL estimation of the B0005 Li-ion battery. RUL prediction results of the LSTM algorithm for battery B0005 is shown in Fig. 3(c). As it is shown an acceptable estimation performance is achieved in the validation phase. While Fig. 3(b) presents the results of prediction for the CNN-LSTM algorithm, where it shows splitting the training and the validation curve which start at 61 cycles. These two curves are close to each other. Additionally, the MAE, RMSE, and R^2 values indicate 0.0153, 0.0204, and 96.687, respectively. In spite of a good estimation performance, it still observed more poor accuracy. For that, we use the proposed method named CNN-LSTM-DNN showing in Fig. 3(a) to improve further the estimation performance and more importantly to achieve prediction accuracy. It is clear from it that there is a better consistency between the estimates and the true values. Moreover, good performance is finally obtained for the prediction.

A second Li-ion battery is B0006. We use the same three algorithms to predict the RUL with another start point that is 80. Fig. 4 reveals the degradation of the capacity of B0006 through some cycles using these algorithms. The MAE and RMSE values of CNN-LSTM-DNN are equal to 0.0087 and 0.0199, respectively, which is lower than those obtained with the LSTM and CNN-LSTM. In addition, the R^2 value of 96.096 is high with respect to the CNN-LSTM-DNN.

A third Li-ion battery is B0007. The same three algorithms are introduced for the RUL prediction of Li-ion battery where we start the validation prediction even 54 cycles. It is observed from Fig. 5(a) that there is a better consistency between the prediction curve and the true curve of CNN-LSTM-DNN compared to LSTM and CNN-LSTM. Moreover, The MAE, R^2, and RMSE

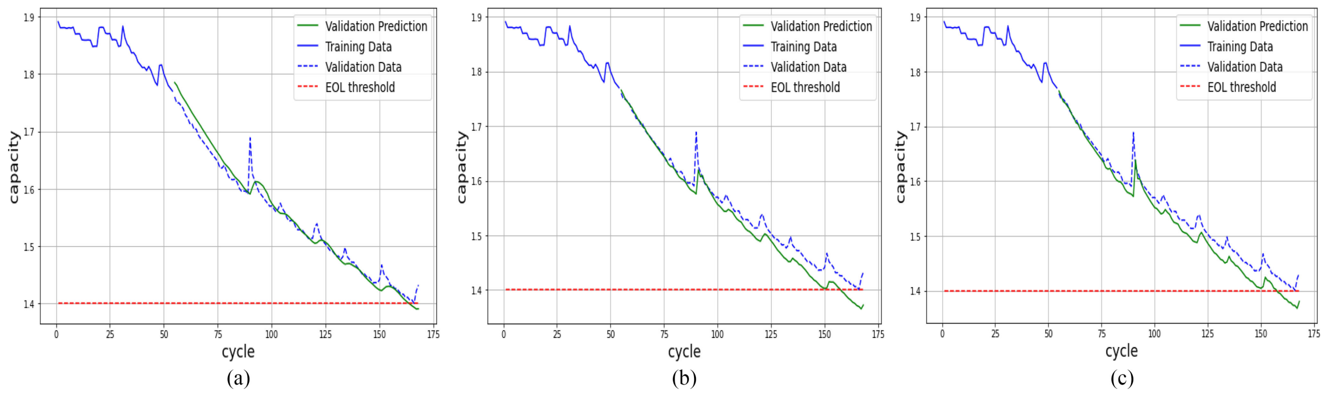


Fig. 5. RUL prediction results for B0007 using: (a) CNN-LSTM-DNN (b) CNN-LSTM (c) LSTM.

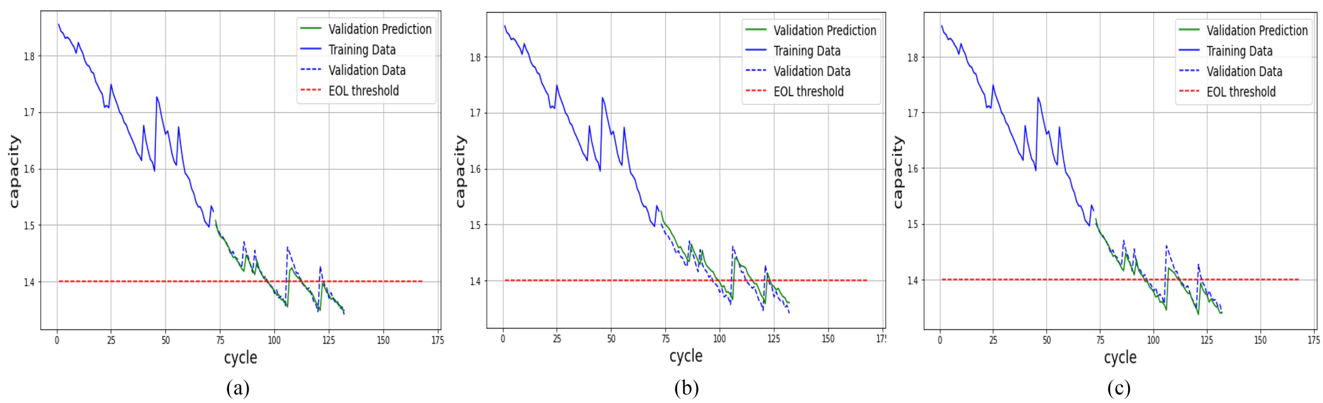


Fig. 6. RUL prediction results for B0018 using: (a) CNN-LSTM-DNN (b) CNN-LSTM (c) LSTM.

values of the proposed method are equal to 0.0119, 96.90, and 0.0172, respectively, which are the good values obtained.

A fourth Li-ion battery is B0018, which is characterized by much fluctuation and oscillation during degradation of capacity and its cycles are lower than previous batteries showing in Fig. 6. It is clearly observed that it is difficult to predict with these datasets. However, the CNN-LSTM-DNN obtained good results compared to other algorithms.

All figures illustrate the prediction curve of the hybrid approach is the closest to the real capacity degradation curve compared to a single algorithm with a different starting point of prediction (SP) for each battery. Thus, the CNN-LSTM-DNN algorithm shows a very accurate capacity estimation for these batteries.

Table III summarizes the numeric RUL prediction errors of three algorithms of B0005, B0006, B0007, and B0018 batteries. It shows that the RMSE and MAE values with hybrid methods are lower than that with a single one and the R^2 values with hybrid methods are higher than that with a single one. This confirms that the hybrid method improve substantially the capacity estimation. In addition, the RMSE and MAE of CNN-LSTM-DNN for B0005 are lower than that of CNN-LSTM by 0.00585 and 0.0071, respectively. This confirms that CNN-LSTM-DNN is better than CNN-LSTM for estimating the battery degradation.

Table IV shows that the hybrid methods outclass the single method for NASA datasets. In addition, the combination of

TABLE III
RUL ESTIMATION RESULTS FOR NASA BATTERIES

Batteries	Methods	SP	RMSE	R^2%	MAE
B5	CNN-LSTM-DNN CNN-LSTM LSTM	61	0.01457 0.02042 0.02363	98.313 96.687 92.648	0.00826 0.01536 0.01897
B6	CNN-LSTM-DNN CNN-LSTM LSTM	80	0.01992 0.02052 0.02641	96.096 95.859 93.141	0.00872 0.00892 0.01674
B7	CNN-LSTM-DNN CNN-LSTM LSTM	54	0.01722 0.02379 0.02420	96.900 94.082 93.874	0.01199 0.01763 0.01919
B18	CNN-LSTM-DNN CNN-LSTM LSTM	72	0.02033 0.02148 0.02266	74.686 71.743 68.551	0.00966 0.01634 0.01106

TABLE IV
RMSE IMPROVEMENT OF RUL ESTIMATION RESULTS

Bat	Hybrid Methods	RMSE	Single Method	RMSE	RMSE Improvement
B5	CNN-LSTM-DNN CNN-LSTM	0.01457 0.02042	LSTM	0.02363	38,34% 13,58%
B6	CNN-LSTM-DNN CNN-LSTM	0,01992 0.02052	LSTM	0,02641	24,57% 22.30%
B7	CNN-LSTM-DNN CNN-LSTM	0,01722 0.02379	LSTM	0,02420	28,84% 16.94%
B18	CNN-LSTM-DNN CNN-LSTM	0,02033 0.02148	LSTM	0,02266	10,28% 05.20%

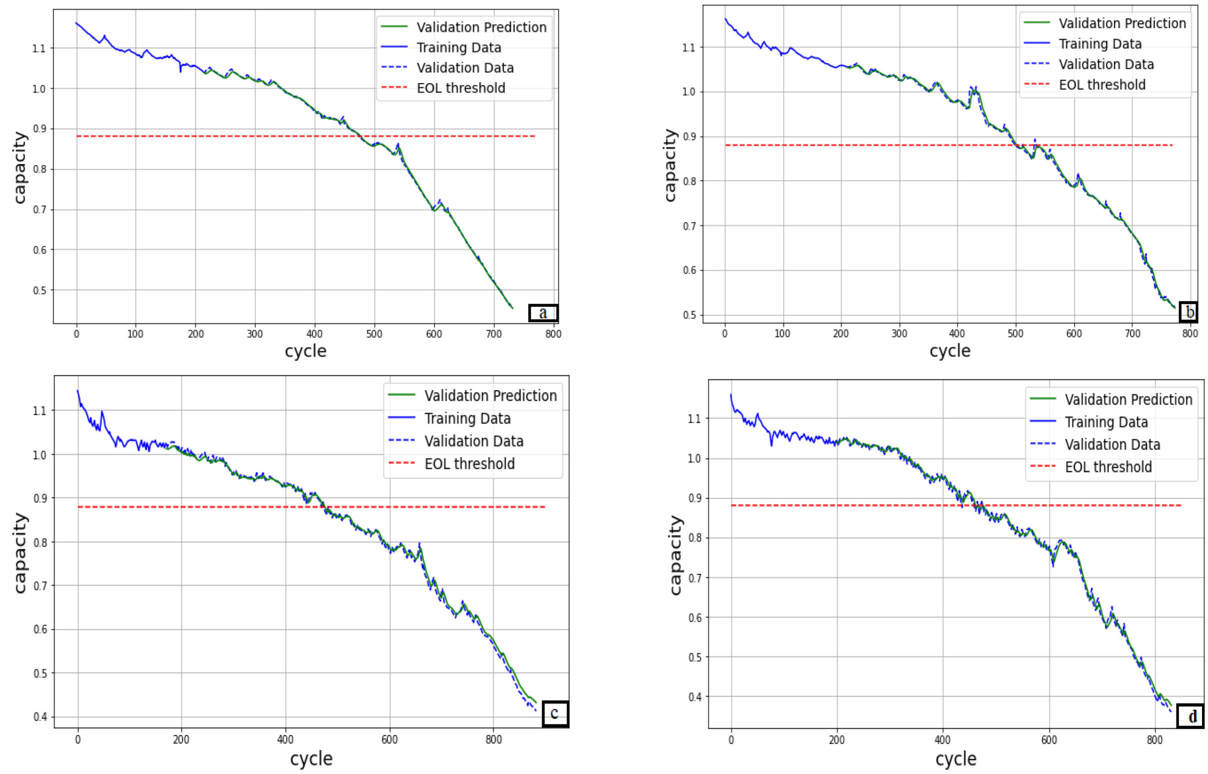


Fig. 7. RUL prediction results using CNN-LSTM-DNN for: (a) **CS2_33,** (b) **CS2_34,** (c) **CS2_36,** (d) **CS2_37.**

the three neural network topologies (CNN, LSTM, and DNN) gives a better improvement than the two topologies (CNN and LSTM). This experiment demonstrates clearly the superiority of the CNN-LSTM-DNN method which obtained the highest accuracy in the RUL prediction of Li-ion batteries.

B. CALCE Datasets Prediction

In this experiment, we use the CALCE datasets for confirming the good results obtained in the NASA datasets. The CNN-LSTM-DNN hybrid algorithm is implemented for RUL prediction of four batteries named CS2_33, CS2_34, CS2_36, and CS2_37.

Fig. 7 shows the accurate prediction results for CALCE batteries, which have more number of cycles than NASA batteries during capacity degradation. It illustrates that both the true and predictive curves are almost identical. Thus, the hybrid algorithm has a high estimation accuracy. Although we utilized the different training/validation split for these four batteries, CNN-LSTM-DNN obtains the highest accuracy in the RUL prediction and shows similar performance among Li-ion batteries. Therefore, this algorithm is suitable for the task. While similar values of R^2, MAE, and RMSE are observed for these four batteries, where MAE, and RMSE values are very low and R^2 is very high as described in Table V.

This table summarizes the numeric RUL prediction errors of CALCE datasets batteries. The experiment demonstrates clearly the good results of the proposed hybrid method in achieving high accuracy of prediction and more importantly in predicting different types of Li-ion batteries.

TABLE V
RUL Estimation Results of CNN-LSTM-DNN for CALCE Batteries

Batteries	**CS2_33**	**CS2_34**	**CS2_36**	**CS2_37**
SP	214	210	199	171
RMSE	0.00438	0.00649	0.00935	0.00848
MAE	0.00299	0.00455	0.00783	0.00682
R^2%	99.9354	99.8219	99.7721	99.7489

IV. Comparative Results Analysis

The above experiments reveal that the proposed hybrid method has successfully learned the dynamic nature of Li-ion batteries. Thus, in order to perform a valid benchmark study, this section focuses on the comparison of our prediction results against those from studies that have used single and hybrid methods using batteries B5, B6, B7, B18, CS2_33, CS2_34, CS2_36, and CS2_37 from NASA and CALCE datasets. These articles have also used almost the same starting point of prediction (SP) with the same indicators of performance. Table VI summarizes RUL prediction results sorted from worst to best for each battery. It is obvious that [4], [17], and [20] display better results than the other papers that used NASA data. The results obtained with proposed method outclass them all.

Table VII summarizes the comparative study between results obtained with the proposed method and the best RUL prediction results available in the literature with CALCE data. If the SP of RUL prediction shifts to early cycles, RUL prediction becomes harder because the model leverage a small training set [45]. In

TABLE VI
RUL ESTIMATION RESULTS OF SOME PAPERS FOR NASA BATTERIES

Battery	algorithms	SP	RMSE	R^2 %	MAE
B5 [15]	VMD-ARIMA-GM	60	0.0599		
	EMD-ARIMA		0.0593		
B5 [45]	RNN	66	0.0276		0.0219
	GRU		0.0286		0.0258
	SRU		0.0356		0.0303
	LSTM		0.0250		0.0215
B5 [20]	UKF	60	0.0399	67.45	0.0285
	AUKF		0.0265	82.35	0.0187
	AUKF-GASVR		0.0230	87.35	0.0148
B5	**CNN-LSTM-DNN**	**61**	**0.0145**	**98.313**	**0.00826**
B6 [46]	ELM	84		88.292	
	PSO-ELM			89.453	
	MPSO-ELM			95.142	
B6 [20]	UKF	80	0.1275		0.0994
	AUKF		0.0489		0.0371
	AUKF-GASVR		0.0483		0.0368
B6 [4]	RNN	78	0.1131		
	LSTM		0.1216		
	RVM		0.0784		
	HA-FOSELM		0.0434		
B6 [17]	RVM	80	0.0667		
	GM		0.0634		
	RVM-GM		0.0306		
B6	**CNN-LSTM-DNN**	**80**	**0.0199**	**96.096**	**0.00892**
B7 [4]	RNN	51	0.1132		
	LSTM		0.0284		
	RVM		0.1138		
	HA-FOSELM		0.1021		
B7	**CNN-LSTM-DNN**	**54**	**0.01722**	**96.900**	**0.01199**
B18 [45]	RNN	78	0.0645		0.0504
	GRU		0.0568		0.0453
	SRU		0.0800		0.0698
	LSTM		0.0449		0.0393
B18 [15]	VMD-ARIMA-GM	70	0.0917		
	EMD-ARIMA		0.0775		
B18 [7]	MLR-GPR	71			0.0345
B18 [47]	LSTM	70	0.0327		
	RNN		0.0466		
	RVM		0.0300		
	PA-LSTM		0.0287		
B18 [**4**]	RNN	71	0.0551		
	LSTM		0.0498		
	RVM		0.0601		
	HA-FOSELM		0.0274		
B18	**CNN-LSTM-DNN**	**72**	**0.02033**	**74.686**	**0.00966**

spite of the difference in prediction SP, the proposed method CNN-LSTM-DNN achieved a good performance with respect to other methods especially those that used almost the same prediction SP.

Table VIII shows the RMSE improvement in RUL prediction, our benchmark will focus on the best results of articles for showing improvement of RMSE using the CNN-LSTM-DNN method.

For each battery, the best RUL prediction result is selected amongst all algorithms in Table VIII, where prediction results show that RMSE improvement percentage increased starting from 25.91% even 83.15% for NASA data, and from 25.91% even 83.15% for CALCE data.

This shows the power of hybridization in achieving better results and confirms the findings presented in this manuscript. Besides, the proposed method CNN-LSTM-DNN obtained the best performance compared to the methods of other papers. According to the above analysis, we can conclude that the proposed CNN-LSTM-DNN RUL prediction approach is an excellent estimator with its high accuracy and long-term predictive capability with acceptable execution time.

TABLE VII
RUL ESTIMATION RESULTS OF SOME PAPERS FOR CALCE BATTERIES

CS2	ALGORITHMS	SP	RMSE	R^2 %	MAE
33 [39]	GPR	80	0.2373		
	HGPFR		0.0954		
	WD-HGPFR		0.0863		
33 [40]	AR	300	0.0397		0.0317
	AR-ND		0.0126		0.0066
33	**CNN-LSTM-DNN**	**214**	**0.0043**	**99.935**	**0.0029**
34 [48]	LSTM	174	0.988		0.045
	LSTM-ELMAN		0.915		0.042
34 [43]	TCN	360	0.018		0.014
34	**CNN-LSTM-DNN**	**210**	**0.0064**	**99.821**	**0.0045**
36 [49]	NN-PF	-	0.0138	99.17	
36	**CNN-LSTM-DNN**	**199**	**0.0093**	**99.772**	**0.0078**
37 [48]	LSTM	174	1.118		0.033
	LSTM-ELMAN		0.976		0.030
37 [50]	AR	460	0.2879		1.9732
	DBN		0.0979		0.6093
37 [49]	NN-PF	-	0.0132	99.13	
37	**CNN-LSTM-DNN**	**171**	**0.0084**	**99.748**	**0.0068**

TABLE VIII
RMSE IMPROVEMENT OF OUR RESULTS COMPARED TO RESULT OF OTHERS PAPERS

Battery	Algorithm	RMSE	RMSE Improvement
B5	CNN-LSTM-DNN AUKF-GASVR [20]	0,0145 0.0230	36,96%
B6	CNN-LSTM-DNN RVM-GM [17]	0,0199 0.0306	34,97%
B7	CNN-LSTM-DNN HA-FOSELM [4]	0,0172 0.1021	83,15%
B18	CNN-LSTM-DNN HA-FOSELM [4]	0,0203 0.0274	25,91%
CS2_33	CNN-LSTM-DNN AR-ND [40]	0.0043 0.0126	65.87%
CS2_34	CNN-LSTM-DNN TCN [43]	0.0064 0.0180	64.44%
CS2_36	CNN-LSTM-DNN NN-PF [49]	0.0093 0.0138	32.60%
CS2_37	CNN-LSTM-DNN NN-PF [49]	0.0084 0.0132	36.36%

V. CONCLUSION

In this paper, a hybrid CNN-LSTM-DNN algorithm is suggested by combining three well-known algorithms, i.e., Convolutional Neural Networks (CNNs), Deep Neural Networks (DNNs), and Long Short Term Memory (LSTM), to estimate the battery's remaining useful life (RUL) and improve the long-term prediction performance of lithium-ion batteries. The proposed algorithm is experimentally validated on two datasets obtained from NASA and CALCE with different batteries. Experimental results demonstrate a high RUL prediction accuracy with acceptable execution time of the Li-ion battery. Moreover, the prognostic of the proposed hybrid method is more accurate with respect to single ML methods. Furthermore, three prediction performance indices reveal higher accuracy and lower error rate using CNN-LSTM-DNN compared to LSTM, CNN-LSTM, and other existing ML algorithms.

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