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Hybrid Neural Network Method for Predicting the SOH and RUL of Lithium-Ion Batteries

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ABSTRACT

The use of a battery to power an electrical or electronic system is accompanied by battery management, i.e. a set of measures intended to preserve it for preventative maintenance, thus the cost reduction. This management is generally based on two key parameters, the (remaining useful life) RUL and the (State-of-health) SOH, which relate respectively to the charge output and the aging of the Lithium-ion battery. The issue will be resolved and advances in production, battery utilization, and optimization will be made possible by accurate SOH determination and dependable RUL prediction. The CNN-BGRU-DNN hybrid strategy, which we suggest in this study, integrates Convolutional Neural Networks (CNN), Bidirectional Gated Recurrent Units (BGRU), and Deep Neural Networks (DNN) to increase the precision of SOH and RUL estimates for Lithium-ion batteries. To that purpose, the performance of the prediction findings is assessed using the MAE, RMSE, AE, and RE as well as the NASA datasets of lithium-ion batteries for experimental validation. The verification tests' findings show that, in comparison to existing approaches in the literature, the suggested method may greatly reduce prediction error and achieve high estimation accuracy of the battery's state of health.

1. Introduction

Electric vehicles are a promising technology for reducing the increasing air pollution such as decreasing CO2 emission from worldwide transportation. They are operated by battery packs [1]. The accelerated electrification of vehicles is significantly facilitated by batteries [2]. There are five key considerations for EV batteries: longevity, specific energy, specific power, cost, and safety. Over the past ten years, the first four factors have greatly aided in the optimization of electrode and electrolyte materials. Many researchers worldwide, however, have not fully addressed the question of safety [3]. The repeated operation of batteries leads to loss of capacity and increase the resistance, which allow some catastrophes to happen like explosion and combustion resulted on the excessive usage. The solution will enable advancements in battery production, use, and optimization through accurate state of health (SOH) determination and reliable remaining useful life (RUL) prediction. For instance, end users can make an estimation of the predicted battery life to ensure that batteries are used to their greatest capability before being replaced or discarded. To expedite the testing, validation, and production processes, manufacturers might group new cells according to their anticipated lifetime [4]. As a result, the complete electrification system requires an intelligent BMS capable of forecasting and monitoring battery behavior, which are very important for the safety and reliability of EVs and ESS [5]. Among different batteries, Li-Bs are widely regarded as potential options for a variety of applications, owing to their high energy density, power density, low self-discharge rate, and extended lifespan. Recently, many researches have started to focus on parameters of the BMS battery to estimate each of them. Many factors, including the state of charge (SOC), SOH, RUL, the charge capacity, and the internal resistance, must be monitored to ensure that Li-ion batteries are used efficiently and safely [6] [7]. Throughout the life cycle of lithium batteries in electrified vehicles, SOH is an essential parameter for problem diagnostics and safety early warnings in addition to its capacity to precisely predict the remaining mileage of EVs [8]. The RUL prediction of Li-Bs considers a significant choice for reliability, safety, and efficient battery operations, which is the number of cycles (charge/discharge) left before the battery fails, which is between 70 and 80% of its maximum capacity [7], [9], [10]. The equivalent circuit model [11], electrochemical model, data-driven model, and hybrid method

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model are the four primary models that have been used in recent decades to perform substantial research on RUL estimate and SOH prediction of lithium batteries. The approach of the data model is receiving increasing amounts of attention as a result of the growth in lithium battery data [12], [13].

An accurate state of health (SOH) estimate helps ensure dependability and safety while the battery is operating. There are several ways to estimate it, including hybrid techniques based on neural networks [14], [15]. In 2017 [16], the author proposed the OS-ELM method and they utilized the discharge time of equal voltage interval as the HI. In 2019 [17], the author focused on their paper on the SOH estimation of lithium-ion battery using PKNN and Markov Chain. For verification, they compared the PKNN with other methods, which it obtained a high prediction accuracy. Besides, in [18], the author propose a method that combines the partial incremental capacity and ANN. Additionally, in [19], the author combine the ANN method with the PF algorithm for estimating the SOH, where they obtained an accurate estimation. In 2020 [20], the author integrated the deep Boltzmann machines and LSTM for obtaining the health prediction of a medical Li-ion battery. The empirical results obtain a good of SOH prediction. In [21], the author proposed a combination between GRU and CNN. While, in [8], the author combined the WNN with UPF. The performance results demonstrate their capability in improving the accuracy of SOH prediction.

The goal of this paper is to estimate the SOH and RUL of a lithium-ion battery using a hybrid method named CNN-BGRU-DNN. The comparison is performed between the proposed hybrid method and various prediction methods. The experiment obtained good results for the proposed method that achieved high predictive accuracy for the SOH and estimation compared to the other results.

The remaining parts of this essay are written as follows: The tools and methods for forecasting the RUL and SOH of battery lithium-ion batteries using the suggested method are presented in Section 2. A comparison of the SOH estimate accuracy is shown in Section 3. A conclusion is then offered.

2. RUL and SOH Prediction

2.1. CNN-BGRU-DNN architecture

The SOH and RUL of Li-ion batteries have been predicted using the CNN, BGRU, and DNN methods in prior literary works, where they performed well. By merging CNN, BGRU, and DNN, our study aims to enhance and attain high accuracy of SOH and RUL estimate.

In terms of feature extraction, CNN is proficient and benefits from both scale invariance and local dependence. Its feature extraction process is organized hierarchically. Through the use of many feature planes and neurons, the first layer of convolution extracts various input characteristics. In order to acquire continuous spatial features, the second layer, known as secondary feature extraction, decreases the feature surface dimension and its resolution. The outputs of the convolution layer are the inputs of the pooling layer, and the two layers are mapped one to one and each to the other. The data from the first two levels can be combined in the third layer. Full connection outputs are delivered to the last layer. [22].

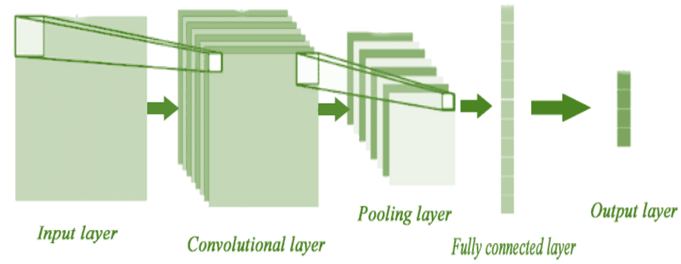

Figure 1: CNN structure

The RNN is one of the most well-liked deep learning (DL) algorithms since it makes use of the temporal correlations between neurons, although it suffers from the gradient vanishing issue [23]. Two RNN variations, LSTM and GRU, are utilized to regulate the propagation of gradient information and remember the parameters as successive inputs during the long-term sequence in order to solve this problem. [13].

GRU is classified as one of the RNN's variants. Its ability to regulate the propagation of gradient information and retain the parameters as future inputs over the long-term sequence is a core element. GRU consists of two gates: update gate z, which regulates the updating of the hidden state, and reset gate r, which determines whether or not to ignore the prior hidden state.

GRU's equations can be defined as follow:

$$z_t = \sigma(W_z[h_{t-1}, x_t])$$
$$r_t = \sigma(W_r[h_{t-1}, x_t]) \quad (1)$$
$$\tilde{h}_t = \tanh(W_h[r_t * h_{t-1}, x_t])$$
$$h_t = ((1 - z_t) * h_{t-1}) + (z_t * \tilde{h}_t)$$

where, $\tilde{h}_t$ is the candidate gate and h_t is output activation, the unit output as (h), W is the weight matrices, and σ is the sigmoid function represented [24].

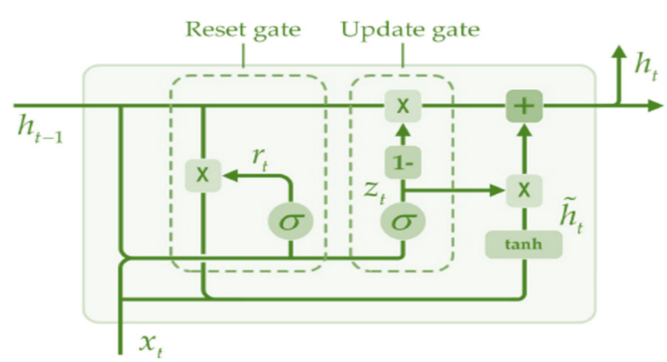

Figure 2: GRU structure

A GRU neural network with a two-layer structure is known as a Bidirectional Gate Recurrent Unit (BGRU) neural network. They have the ability to process the data inputs in both directions, i.e. the forward and backward temporal sequences, with the outputs of both connected in the same output layer, allowing these bidirectional algorithms to be more efficient with defining the relationship between the sequences and its model. BGRU can save cost and time by reducing the amount of calculations required.

To benefit from the advantages of each algorithm and enhance the performance, they were combined with each other. The results of the integration of CNN, bidirectional of GRU, and DNN into one framework obtained good performance. The DL technology uses multiple layers to extract higher-level features from the raw input progressively.

Data processing is the initial step. We chose the discharge data from datasets that we extract from specific batteries that comprise charge, discharge, and impedance features. For each cycle of our experiment, where the input is the prior capacity and the output is the current capacity, we only choose one feature from this data, the capacity. We then used a window size of eight values to organize this data for the training step, which predicts data sequences. Finally, we split the data into test and training sets using the same split ratios for each battery. To predict the RUL of the Li-ion battery, we used the CNN-BGRU-DNN technique based on univariate time series.

We try to profit from their advantages where CNN is applied to extract local features, capture the spatial relationship, and use shared weights structure to reduce the amount of the weights and try to find the shared information from the measurement of data. Where we use one convolutional layer with 64 filters inclusive of the kernel size of 4, also we employ in this structure one default stride, causal padding, and Relu activation function. Then, the BGRU is applied to understand the temporal relationships in the feature sequence and it uses their internal state (memory) to learn features and time dependencies from the sequential data, and capture temporal features. Where we utilize two layers from each of them, which consist of 160 nodes then a flatten layer comes next. While DNN maps the features by choosing 3 dense layers, containing the Relu activation functions of each layer, with 128 nodes. Then we use one dense layer with one node to employ as a regression layer for getting the final SOH output and contribute to accurate prediction. Thus, the architecture of the proposed method shown in figure 3 is chosen after numerous experiments.

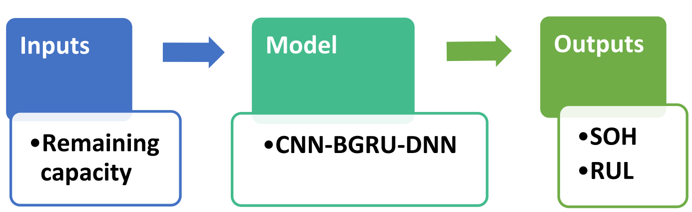

Figure 3 : The framework of proposed method

2.2. Experiment description

This research validates its findings using experimental data from the NASA Prognostics Center of Excellence [25], which includes of aging information 18650 Li-ion batteries. Where Table 1 provides the following information regarding these batteries:

Table 1: NASA Lithium-Ion Batteries description

Batteries	NASA
Temperature (C)	24
Constant charge current	1.5 (A)
Cut-off voltage of Charge/Discharge	4.2 / 2.5 (V)
Minimum charge current	20 (mA)
Rated capacity (Ah)	2
Cycles	168 (B5,B6,B7)

The proposed approach, CNN-BGRU-DNN, was implemented using the hyper-parameters presented in table 2 and using the following environment and tools:

- Google Colaboratory notebook
- 1 CPU Core: Intel(R) Xeon(R) CPU @ 2.20GHz
- Physical memory: 12G
- GPU: Tesla K80 - 11441MiB memory
- CUDA Version: 11.2
- TensorFlow version: 2.7.0
- Python version: 3.7.12.

Table 2: Hyper-parameters values

Hyper parameters	values
Window size	8
Batch size	32
Shuffle buffer size	1000
Epochs	1400
Learning rate	8e-4
Regularization	without
Activation function	ReLU
Optimizer	Adam
Loss function	Huber

We utilize MAE and RMSE [24] to assess how well the algorithms execute SOH estimation, while AE and RE are used to assess RUL prediction accuracy. These are their definitions [26] :

$$MAE = \frac{1}{K}\sum_{k=1}^{k}|y_k - \widehat{y_k}| \quad (2)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_k - \widehat{y_k})^2} \quad (3)$$

$$AE = |RULreal - RULpredicted\,| \quad (4)$$

$$RE = |RULreal - RULpredicted\,| / RULreal \times 100\%.\,| \quad (5)$$

Where $\widehat{y_k}$ is the predicted value and y_k is the actual value. The accuracy of the SOH forecast is greater when the MAE and RMSE are near to zero.

2.3. RUL and SOH estimation

The major of this section is to present the ability of the proposed hybrid method CNN-BGRU-DNN to estimate the SOH and RUL of different Li-ion batteries; it is also for confirming our method's prediction accuracy.

The battery's capacity, performance, and state of health are shown by SOH indicator. It is the ratio of a battery's actual capacity (Ca) to its rated capacity (Cr), where actual capacity refers to how much of the battery's capacity is actually used when it is fully charged. The rated capacity of a totally charged battery is 100%, whereas the capacity of a totally failed battery is 0%. The battery's SOH is defined as follows [27]:

$$SOH = \frac{Ca}{Cr} \tag{6}$$

The remaining number of cycles of battery capacity to reach at its failure threshold that means the time between now and the end-of-life "EOL" is defined as RUL, showing as follows [7]:

$$RUL = C_{EOL} - C_{cc} \tag{7}$$

C_{cc} is the number of cycle at the actual capacity and C_{EOL} is the cycle number when the capacity of battery arrives at the EOL.

The experiment were terminated only when battery attained their EOL, as seen in figure 4, where the line of EOL represented by a red color, which considered as the time when the capacity reaches 70% in rated capacity for the NASA batteries. The EOL is calculated as:

$$EOL = Cr * 0.7 = 1.4\ Ah \tag{8}$$

In this study, we separated the datasets into training and prediction data with the identical beginning prediction point of each dataset, which is 80 cycles. We utilized three batteries, B0005, B0006, and B0007, to establish the degradation sample of the battery's capacity.

Figure 4 above displays the outcomes of the SOH and RUL predictions, where Real values are displayed in blue and predicted values are shown in orange. The SOH and RUL predictions for NASA batteries demonstrate how the suggested hybrid technique, CNN-BGRU-DNN, practically always results in almost identical actual and predicted curves for all batteries. As a result, the hybrid method's SOH estimation accuracy is good. The point of failure at the end of life (EOL) for all batteries is when both curves almost exactly meet. As a result, CNN-BGRU-DNN achieves the maximum level of RUL prediction accuracy.

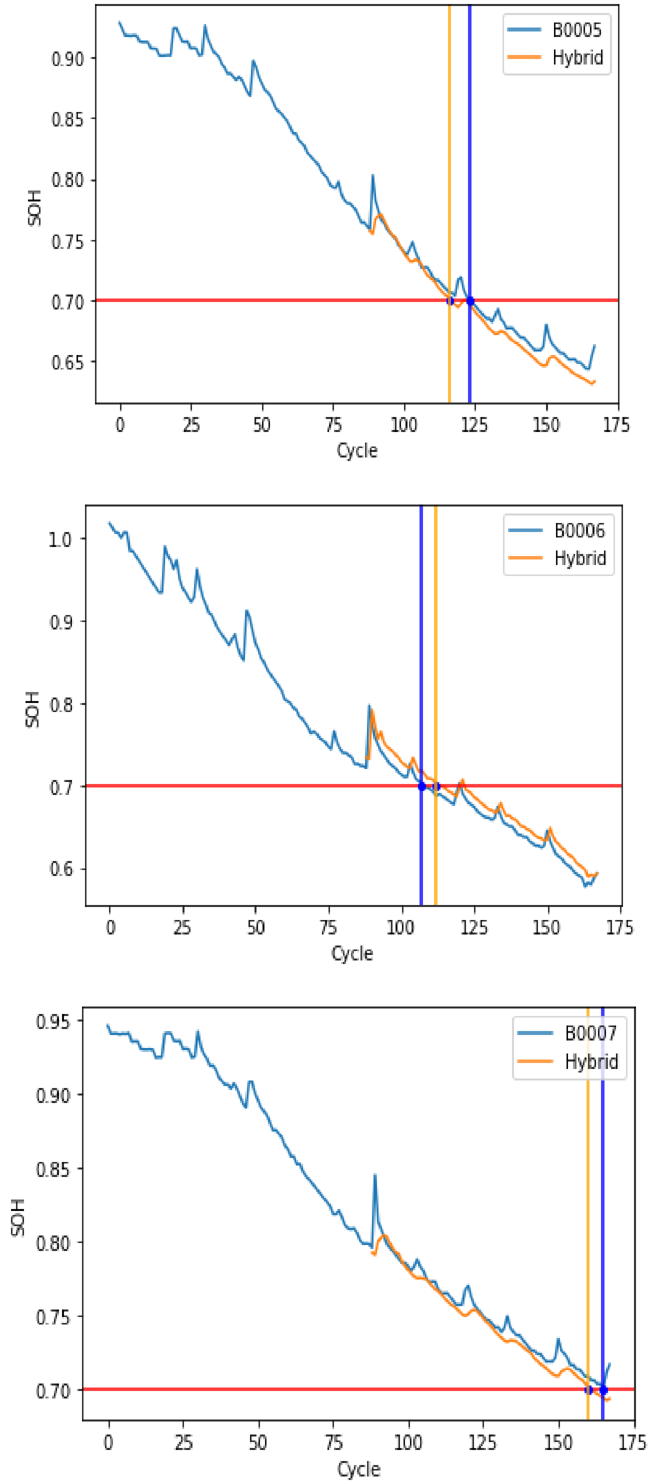

Figure 4: The SOH and RULprediction results using CNN-BGRU-DNN.

Table 3: SOH estimation results

Batteries	Methods	RMSE	MAE
B0005	CNN-BGRU-DNN	0.01165	0.00884
B0006	CNN-BGRU-DNN	0.00884	0.01334

B0007	CNN-BGRU-DNN	0.00990	0.00667

Table 4: RUL estimation results

CNN-BGRU-DNN				
Batteries	RUL_{real}	$RUL_{predicted}$	**AE**	**RE %**
B0005	123	116	7	5.69
B0006	107	112	5	4.67
B0007	165	160	5	3.03

The values for MAE, AE, and RMSE are extremely low, as seen in Tables 3 and 4. The CNN-BGRU-DNN approach helps minimize error during SOH deterioration, as this experiment shows. Furthermore, the Li-ion battery RUL estimation using the CNN-BGRU-DNN method is accurate. This demonstrates that CNN-BGRU-DNN approach is the best at predicting battery SOH, and the experiment illustrates perfectly the hybrid method's capacity for having greater forecast accuracy.

3. Comparison between proposed method and other methods in literature

This subsection provides a comparison of the SOH prediction accuracy of different other studies' predictions. We use performance method findings from earlier papers to compare more widely with other forms of prediction, since these approaches use the same NASA datasets and performance measures.

Table 5: SOH estimation results of some papers

Batteries	**Methods**	**RMSE**
B0005	UPF Elman NN WNN-UPF [8]	1.088 0.210 0.027
	GPR- LSTM [28]	0.012
	CNN-BGRU-DNN	0.011
B0006	CGTSSA_Cat_Boost [29] SSA_Cat_Boost PSO_Cat_Boost Cat_Boost CGTSSA-SVM CGTSSA-ELM	0.0268 0.0317 0.0531 0.0708 0.0362 0.0579
	UPF Elman NN WNN-UPF [8]	1.115 0.223 0.050
	GPR- LSTM [28]	0.013
	CNN-BGRU-DNN	0.008
B0007	UPF Elman NN WNN-UPF [8]	1.161 0.145 0.024
	CGTSSA_Cat_Boost [29] SSA_Cat_Boost PSO_Cat_Boost Cat_Boost CGTSSA-SVM CGTSSA-ELM	0.0118 0.0147 0.0263 0.0465 0.0178 0.0447
	GPR- LSTM [28]	0.009
	CNN-BGRU-DNN	0.009

From the results of table 5, we can clearly see that the RMSE value of our proposed method is smaller than the values reported by the studies, the RMSE metric is widely used in regression problems where we predict continues values, which is the case is the prediction of the SOH of Ion-Lithium batteries.

We can conclude based on the results of table 5 that the proposed suggested named CNN-BGRU-DNN is a good estimator with its high accuracy for predicting the RUL and SOH.

Conclusion

This study proposes a hybrid approach known as CNN-BGRU-DNN to predict Li-ion battery SOH and RUL. A dataset received from NASA is used to experimentally validate the suggested strategy. The results of the proposed hybrid method demonstrate that we achieved a big performance improvement and satisfying results evaluated by the performance indicators called MAE, RE %, AE and RMSE, where error rates are reduced and accuracy increased. In comparison to the outcomes of previous publications, four prediction performance indices show that CNN-BGRU-DNN has the greatest accuracy.

Nomenclature

AE	absolute error
ANN	artificial neural network
BMS	battery management system
BGRU	bidirectional gated recurrent units
CNN	convolutional neural network
DNN	deep neural networks
DL	deep Learning
ELM	extreme learning machine
LSTM	long short-term memory
Li-B	lithium-ion battery
MAE	mean absolute error
ML	machine learning
NASA	national aeronautics and space administration
PF	particle filter
RE	relative error
RNN	recurrent neural network
RMSE	root mean square error
RUL	remaining useful life
ReLU	rectified linear unit
UKF	unscented Kalman filter
WNN	wavelet neural network
UPF	unscented Kalman particle filter

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