Functional Life-Time Assessment for Lithium-Ion Batteries Based on Hybrid Deep Learning Model

SUSHANT CHAMOLI , Department of Comp. Sc. & Info. Tech., Graphic Era Hill University, Dehradun, Uttarakhand, India 248002

Abstract

For the purpose of assuring dependability and safety, the lifespan of a lithium-ion battery must be accurately predicted. It also serves as an advance warning mechanism for stopping battery from failing. New data-driven estimate techniques are made possible by recent advances in machine learning (ML). In this study, we propose a hybrid technique for estimating battery's remaining usable life and enhancing forecast accurateness while maintaining tolerable processing time. This hybrid method is called CNN-LSTM and merges Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM). To demonstrate advantages of the suggested hybrid estimation strategy, a comparison is made against several ML estimation algorithms. To test the accuracy of the predictions, two statistical indicators—the MSE, MAE, R2, and RMSE—are used. CNNs and LSTM are two well-known algorithms that may be used to create a hybrid algorithm that will calculate the battery's Remaining Usable Life (RUL) and enhance lithium-ion batteries' long-term prediction ability. Utilizing the CALCE dataset of several lithium-ion batteries, experimental validation is carried out. Results show that hybrid approaches outperform single ones and that the recommended strategy is successful in lowering prediction error and outperforming other methods in terms of RUL prediction performance.

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1. INTRODUCTION

The Energy Storage System is a vital part of electric vehicles (EVs), which are anticipated to overtake conventional cars on the road as a result of rising oil prices and environmental pollution. Lithium-ion (Li-ion) batteries continue to being primary energy source for EVs and consumer devices at this time. They are the ideal option for the ESS because of their remarkable benefits, including lengthy life cycle and high power efficiency. However, as time passes, the battery's performance gradually deteriorates, which might have disastrous effects (e.g.,mobile phone and electric vehicle batteries exploding). In order to increase the whole energy system's dependability, further work is needed to accurately analyse the Li-ion battery's condition as well as anticipate its lifetime (e.g. time for battery replacement and management of deterioration causes). The safety of Li-ion batteries must therefore be ensured by a Battery Management System, which is typically depend on 3 crucial factors: RUL, State Of Charge and State Of Health, which are related to the charge of the batteries and their ageing, respectively. Three categories may well be utilised to categorise RUL prediction for Li-ion batteries that is dependent on data-driven methods: fitting (e.g., single-exponential model, linear model, polynomials model), sequence prediction (e.g., neural network, grey prediction, relevance rector machine), and filter observation (e.g. spherical cubature particle filter, unscented particle filter, etc.). Developing a model-based and data-driven analytical approach that monitors battery capacity decline is challenging. This latter method is frequently used to calculate battery's RUL since it examines the intricate physical and chemical changes that occur throughout various cycles. In order to obtain excellent accuracy of prediction for RUL of Li-ion battery, current study makes utilisation of the advantages of the CNN-LSTM hybrid algorithm as well as most recent advancements in ANN technology in general. If any attempts have been made to implement the hybrid algorithm for such an operation, this is one of them. For the purpose of this study, we corroborate the positive outcomes from the NASA datasets using the CALCE datasets. For the RUL prediction of 4 batteries with model numbers CS2 33, CS2 34, CS2 36, and CS2 37, CNN-LSTM hybrid method is used. It displays the results of a correct forecast for CALCE batteries, which experience more cycles at the time of capacity decline in comparison to NASA batteries. It demonstrates how nearly alike the real and predicted curves are. As a result, the hybrid algorithm provides highly accurate estimate. Even though we used a distinct training/validation split for each of these 4 batteries, CNN-LSTM still outperforms Li-ion batteries with regards to RUL prediction accuracy. This approach is therefore appropriate for the purpose. Similar MAE, RMSE, and R2 values are shown for these four batteries, with R2 being very high and MAE, RMSE, and R2 values are very low.

2. LITERATURE SURVEY

Any smart battery management system must have the ability to calculate lithium-ion battery's RUL online with accuracy. A brand-new support vector machine (SVM) model for RUL prediction is put out in this research using partial discharge data (PDD). The suggested approach takes the PDD's voltage and temperature and extracts the essential characteristics for training the SVM models. To categorise and forecast correct RUL, the classification and regression properties of SVM are used. The best SVM model's training range was determined by analysing the various PDD ranges. The RUL is divided into six classes for gross estimation using SVM model developed with the best PDD characteristics, and support vector regression is utilised for determining precise value for final class. For publicly accessible data, comparisons are made between SVM models that were trained utilizing PDD and the entire set of discharge data for classification and predicting capabilities. The research findings demonstrate that SVM regression and classification model, developed using PDD characteristics, can successfully forecast RUL underlow storage pressure on BMS. SVM model built on PDD may be applied to electric car online RUL estimate. SOH estimation techniques are fairly straightforward to use, but they need extensive testing and precise measuring tools. An electric circuit model's parameters were also determined using the genetic algorithm [1].

The online study of EV batteries using dynamically driven recurrent networks (DDRNs) is presented in this research. For both state of health (SOH) and state of charge (SOC) estimates, a nonlinear autoregressive with exogenous inputs (NARX) architecture of the DDRN is created in this study. Unlike other methods, the global feedback theorem (GFT) applies to this estimating strategy, which retains a respectable level of simplicity while boosting computational intelligence and resilience. The suggested method leverages voltage of battery, charge/discharge currents and fluctuations in the surrounding temperature to precisely evaluate the battery's SOC and SOH at same time without the need for a model or prior information of the battery's internal properties. Utilizing two distinct batteries—lithium titanate (LT O) and lithium iron phosphate (LiFeP O4)—both susceptible to dynamic charge and discharge current profiles and changes in the surrounding temperature, the proposed approach is experimentally tested. Results show that this technique is resistant to the nonlinear dynamics, ageing, dynamic current profile, hysteresis, and parametric uncertainties of batteries. This technology is ideal and efficient for the battery management system of EVs due to its simplicity and resilience. The MLP fails when it comes to SOH estimate as well since it did not settle when examined with SOH data. This further supports DDRN's superiority over traditional MLP neural networks. This method's drawback is that it requires a precise battery model in order to work and is quite computationally intensive [2].

Lithium-ion battery-related safety incidents have become increasingly common in recent years. Hence, the health status monitoring and RUL forcast for Li-ion batteries have become more important. This study suggests a deep learning method that combines the Hybrid Grey Wolf Optimizer (HGWO) algorithm and attention mechanism with the Forgetting Online Sequential Extreme Learning Machine (FOS-ELM) for lithium-ion battery Prognostic and Health Management. We first design raw data prior to training using Variational Mode Decomposition (VMD). The FOS-ELM model's main parameters optimization built on the HGWO method is then presented. Finally, Researchers use attention method to raise algorithm's accuracy even higher. Method

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suggested in this study is more accurate and efficient than conventional neural network techniques. The VMD method is an adaptive Wiener filter group that has benefit of successfully migrating aliasing phenomena and minimising pseudo components, notably in the low-frequency component. HGWO method overcomes the shortcomings of early convergence, low stability, and propensity to slip in local optimum while combining the benefits of Grey Wolf Optimizer algorithms and Differential Evolution [3].

For electronic equipment, an accurate assessment of the lithium-ion battery's remaining usable life is essential. The complexity of the necessary electrochemical modelling restricts the widespread usage of model-based techniques for remaining useable battery life assessment in the literature. Additionally, incorrect sliding window widths are frequently defined empirically in data-driven algorithms for RUL assessment, and the prediction accuracy of these systems has to be increased. This research suggests using a hybrid neural network with the fake closest neighbours approach to overcome the aforementioned problems. The fake closest neighbours approach is initially used to determine the sliding window size needed to take prediction. Second, for model training and prediction, Convolutional neural networks and extensive short-term memories are combined to create a hybrid neural network that has both of their advantages. The efficiency of the suggested technique is tested using additional useful life prediction tests for batteries having various rated capabilities. The findings show that, when compared to previous state-of-the-art approaches, proposed method offers wide generality and decreased mistakes. The benefits of C-NN and LSTM are combined in the CNN technique. CNN is used to retrieve relevant feature information, while LSTM uses the derived features from CNN to forecast the unknowable sequences of capacity data. High energy density, low self-discharge rates, lengthy lives, and exceptional low-temperature performance are some benefits [4].

Scientific assessment and forecasting of the lithium-ion battery's SOH, particularly its RUL, is essential for guaranteeing battery reliability and safety throughout the battery's entire life cycle and minimising the risk of catastrophic incidents. This study initially analyses the issues with the typical particle filter so that it can appropriately anticipate the RUL of the battery. The extended Kalman filter (EKF) is then employed like a sample density function to improve the PF algorithm in a new extended Kalman particle filter (EKPF). Purpose of life cycle testing is to gather precise and trustworthy data for the RUL forecast. In-depth analysis is also done on the lithium-ion battery's ageing characteristics. The established capacity degradation model and suggested EKPF approach are used to forecast RUL. Results indicate that the suggested technique's RUL prediction error is less than 5%, making it more precise than the conventional PF method and suitable for offline as well as online application. This procedure might damage the battery irreparably in addition to taking a long time to test and costing a lot of money. The deterioration mechanism model is quite accurate; however it requires a lot of numerical calculations and has an excessive number of parameters [5].

3. PROPOSED SYSTEM

For the time being, forecasting the lithium-ion battery’s lifespan is essential to assure its dependability & safety. It also serves as an advance warning mechanism for stopping the battery from failing. New data-driven estimate techniques are made possible by recent advances in machine learning (ML). In the work, we provide a hybrid approach to estimate the battery's RUL and enhancing forecast accurateness with tolerable runtime. This hybrid method is called CNN-LSTM-DNN and combines CNN, Deep Neural Networks, and Long Short Term Memory. To demonstrate advantages of suggested hybrid estimation strategy, a comparison is made against several ML estimation algorithms. 3 statistical indicators are used to evaluate the forecasting outcomes numerically: the MAE, R2, and RMSE. Utilizing 2 datasets of various lithium-ion batteries from CALCE and NASA, experimental validation is carried out. Results show that hybrid approaches outperform single ones and that the recommended strategy is successful in lowering prediction error and outperforming other methods in terms of RUL prediction performance. Disadvantages: In this case, two datasets were employed, and one of them had poor results. It takes a lot of time and theoretical constraints are also there. The proposed system received its input from the CALCE dataset. The input data were obtained from the dataset repository.The 4 batteries, CS2 33, CS2 34, CS2 36, and CS2 37, must be taken. After that, the data preparation process must be put into action. To avoid inaccurate prediction at this step, we must deal with the missing data and remove any unnecessary columns from the process. After that, test and train groups for the dataset must be created.

Data is separated based on ratios. Most of the data will be available in train.

Fig 1: System Architecture

During the test, just a portion of the data will be available. At the time of training phase, model is evaluated then forecasts are produced during the testing phase. Next, we must put the deep learning classification method into practise. LSTM and CNN are two examples of deep learning algorithms. CNNs & LSTM are two famous methods that may be used to create a hybrid algorithm that will calculate the battery's RUL and enhance lithium-ion batteries' long-term prediction ability. Utilizing the CALCE dataset of several lithium-ion batteries, experimental validation is performed. Lastly, experimental data demonstrates that various performance indicators, including MAE, MSE, R squared, and RMSE, are useful. The findings for four batteries from our input dataset must then be evaluated.

There are several benefits of proposed system which are as follows:

- It works well with a lot of datasets.
- When compared to the current system, the experimental outcome is excellent.
- Low time commitment.

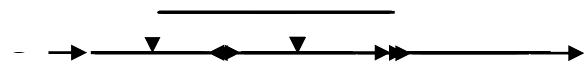


Fig. Flow Diagram

Following section explains several stages that are involved in putting the suggested technique into practice:

Data Selection: The input data was gathered via the dataset repository. CALCE dataset is used in this method. We must use the 4 batteries CS2 33, CS2 34, CS2 37, and CS2 38 in this dataset. The method of determining or foretelling a lithium ion battery's remaining usable life is known as data selection. Charging profile for all CS2 cells was the same, where the charging current was maintained at a constant rate of 0.5C until the voltage reached 4.2V after which the voltage was kept constant till the charging current fell below 0.05A. Unless otherwise stated, these batteries' discharge cut-off voltage was 2.7V. All of the CS2 cells were assigned random numbers and names. The nth numbered CS2 cell was given the name "CS2 n."

Data pre-processing: Data pre-processing is the process of deleting extraneous data from a dataset. To create a dataset with a structure that is suitable for machine learning, pre-processing data transformation techniques are utilised. The dataset is made more effective at this step by being cleaned of any inaccurate or superfluous data that can reduce the dataset's accuracy. Throughout this procedure, missing values and Nan values are removed from the data by replacing them with 0. Data was cleared of any errors and missing values as well as duplicates. Variables with a small number of label values are considered as categorical data. Input and output variables must be numbers for the most of machine learning algorithms.

Data splitting: Data availability is a requirement for machine learning to work. In addition to the data needed for training, test data are also necessary to assess the algorithm's performance and determine how effectively it functions. 30% of the input dataset was utilised as training data after splitting it into training and testing halves, according to our strategy. The process of breaking accessible data into 2 pieces, often for cross-validator needs, is known as data splitting. A portion of the data is utilised to create a prediction model, while another portion is utilised to assess model's performance. Splitting the data into training and testing sets is an important stage in reviewing data mining. When you split a data set into a training set and testing set, the large proportion of the data is typically employed for training while a smaller proportion is employed for testing.

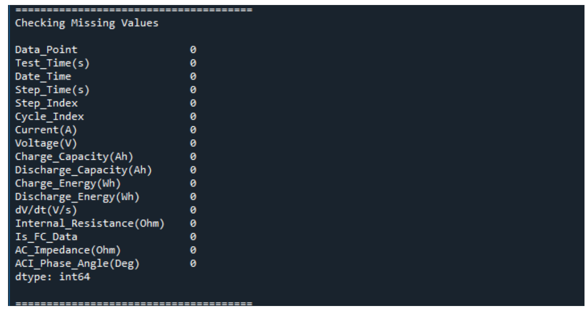
Classification: We use deep learning techniques such as CNN and LSTM in our approach. We use a hybrid model that combines CNN and LSTM. Deep learning uses an artificial recurrent neural network architecture called LSTM. In contrast to traditional feed-forward neural networks, LSTM has feedback connections. Together with single data points, it can analyse whole data streams. LSTM networks are ideally suited for classifying, studying, and forecasting on the basis of time series data as there may be delays of varying lengths between major events in a time series. A Deep Learning approach called ConvNet/CNN can acquire an input picture, give various objects and elements values and differentiate amongst them. With the help of a hierarchical model, the CNN creates a network in the form of a funnel that finally yields a fully connected layer in which all of the neurons are interconnected and the output is processed.

Result generation: Based on the overall categorization and prediction, the ultimate outcome will be created. The effectiveness of the recommended technique is evaluated using measures like MAE, MSE, and RMSE.

4. RESULTS

For the purpose of assuring dependability and safety, the lifespan of a lithium-ion battery must be accurately predicted. In the research, we present a hybrid technique for estimating the battery's remaining usable life that manages to merge Convolutional Neural Network and Long Short Term Memory. To demonstrate advantages of the suggested hybrid estimation strategy, a comparison is made against several ML estimation algorithms.

The suggested approach is experimentally verified using datasets from CALCE with various batteries. The accompanying screenshots from experimental findings indicate the Liion battery to have a good RUL prediction accuracy and an acceptable execution time. Additionally, the suggested hybrid method's prognosis is more precise than single ML approaches.



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Test_Time(s)               0
Date_Time                  0
Step_Time(s)               0
Step_Index                 0
Cycle_Index                0
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Voltage(V)                 0
Charge_Capacity(Ah)        0
Discharge_Capacity(Ah)     0
Charge_Energy(Wh)          0
Discharge_Energy(Wh)       0
dV/dt(V/s)                 0
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AC_Impedance(Ohm)          0
ACI_Phase_Angle(Deg)       0
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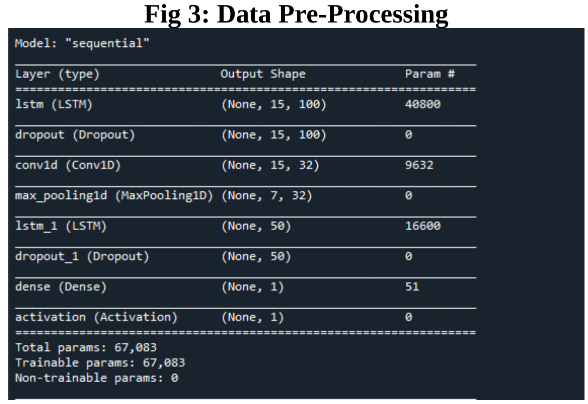
Fig 3: Data Pre-Processing



Model: "sequential"

Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 15, 100)	40800
dropout (Dropout)	(None, 15, 100)	0
conv1d (Conv1D)	(None, 15, 32)	9632
max_pooling1d (MaxPooling1D)	(None, 7, 32)	0
lstm_1 (LSTM)	(None, 50)	16600
dropout_1 (Dropout)	(None, 50)	0
dense (Dense)	(None, 1)	51
activation (Activation)	(None, 1)	0

Total params: 67,083
Trainable params: 67,083
Non-trainable params: 0

Fig 4: Classification

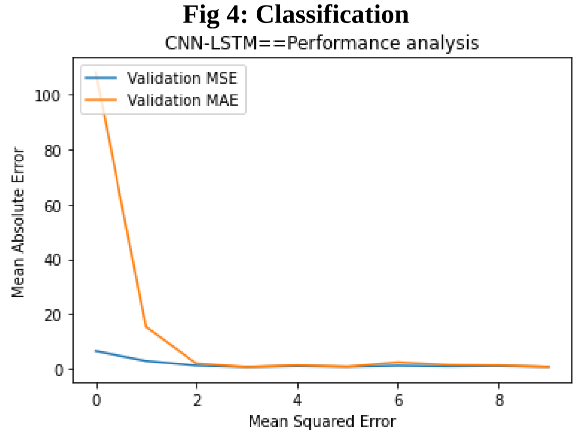


Fig 5: Performance Graph

5. CONCLUSION

In order to determine battery's RUL and enhance long-term prediction performance of lithium-ion

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batteries, a hybrid CNN-LSTM approach is proposed in this research by merging two popular algorithms, namely Convolutional Neural Networks and Long Short Term Memory. Suggested approach is experimentally verified using datasets from CALCE with various batteries. The Liion battery's strong RUL prediction accuracy and respectable execution time are demonstrated by experimental findings. Additionally, the suggested hybrid method's prognosis is more precise than single ML approaches.

6. FUTURE ENHANCEMENT

Future RUL prediction work is advised to focus on architectural optimization in order to shorten training times and improve the applicability to real-world operational circumstances. Additionally, the prediction technique will be used on more complex platforms with numerous components and assessed.

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