Battery Management for Lithium-Ion EV Batteries

BACHARAM PADMARAO,
Student, Department of Electrical and Electronics Engineering,
Vagdevi College of Engineering and Technology.

RAJESH THOTA,
Associate Professor
Department of Electrical and Electronics Engineering,
Vagdevi College of Engineering and Technology.

Abstract: As there is exponential growth in EV market, demand of EV with proper maintenance and reliable battery is increasing. In this application, different AI (Artificial Intelligence) based techniques are utilized for performance analysis of State of Health (SOH) and Remaining Useful Life (RUL) calculation of lithium-ion battery which is used in electrical vehicles. In the proposed work different AI based techniques, machine learning methods such as K-Nearest Neighbours (KNN), Support Vector Regression (SVR), Random Forest (RF), Decision Tree (DT), Naive Bayes (NB) and deep learning methods such as Long Short-Term Memory (LSTM) are used. The dataset is obtained from real world three battery models from Kaggle. The dataset is pre-processed and then used for dataset splitting. Performance analysis of all the methods for both SOH estimation and RUL prediction are calculated using different performance metrics such as R2-Score, Mean Absolute Error (MAE), Mean Squared Error (MSE). From the performance analysis of different machine learning and deep learning models it is observed that random forest algorithm having superior performance compared to the other different methods for both SOH estimation and RUL prediction. Perform analysis is shown both in tabular format as well as in graphical format using bar graphs. Web framework using flask is used for web application. For system safety improvement and monitoring the lifespan of lithium-ion battery Which helps in predictive maintenance, ai based techniques are giving scalable as well as reliable solution.

Keywords: AI based techniques, SOH estimation, RUL prediction, Machine Learning, Deep Learning, Random Forest (RF), Web Application.

I. Introduction

The shift toward electric mobility and smart energy system in recent years has only enhanced the need to have dependable and high-performance lithium-ion batteries (LiBs). This, along with their high density of energy, long cycle life, and decreasing cost, make them the technology of choice in electric vehicles (EVs) and energy storage applications. But, estimating the state of health (SoH) and capacity of these batteries is a key issue that is difficult to estimate. Conventional electrochemical models, despite the exactness in theory, have specific material parameters and are computationally expensive, and can only be utilized in real-time under specific conditions. Conversely, data-driven modeling techniques involve the use of quantifiable quantities of voltage, current, and temperature to simulate intricate battery behaviors with an efficient manner. As the field of artificial intelligence (AI) and deep learning has grown, data-based models have become effective instruments of predicting battery health and performance without the requirement of deep electrochemical understanding.

Recent developments in deep neural network designs have increased the accuracy of battery capacity estimation to a large extent. The researchers in [1] tested three models (feed-forward neural network (FNN), convolutional neural network (CNN), and long short-term memory (LSTM) steam) on the basis of quantifiable Li-ion battery signals. The findings showed that the LSTM model offered the most optimal performance in terms of decreasing root mean square error (RMSE) up to 19 percent as compared to CNN. The study further noted that the learning and efficiency of the model is maximized when signals are sparsely sampled, thus simpler neural network structures can produce reliable results with low computational cost.

A number of machine learning (ML) methods have also been trained to estimate SoH in EV batteries. In [2], such algorithms as K-nearest neighbours (KNN), support vector regression (SVR), and decision tree (DT) as well as random forest (RF) were tested on a dataset provided by Sandia National Laboratories. The result indicated that KNN and DT were more precise in different temperature variations and had small mean absolute error (MAE) and RMSE. The results of this paper demonstrate that classical ML techniques that are trained on quality data can offer precise and interpretable battery health estimates that can be integrated into embedded systems and online health monitoring.

In addition to the individual model research, review articles have also studied the inclusion of machine learning in the estimation of SoH and SoC in electric vehicles. The analysis of ML in [3] was the review of the approaches applied to various Li-ion chemistries and datasets, with a particular focus on the impact of the input features and tuning of hyperparameters on the model performance. A case of data-driven ML solution, combining big data, AI, and Internet of Things (IoT) was proposed in [4] to predict battery health in real-time. The proposed approach obtained an R 2 close to one, and a very small mean squared error (MSE), demonstrating that the data-driven AI models can be as accurate and flexibility as conventional models.

More has also added deep learning and digital twin technology to simulate nonlinear battery degradation. The techniques reviewed in studies [5] and [6] included feed-forward neural networks, recurrent neural networks, and support vector machine to estimate SoH and SoC. The results of these works were that hybrid methods that are trained on physics-based knowledge, in addition to ML, are capable of increasing interpretability and preserving the predictive power. Similarly, [7] explored the application of ML algorithms to predicting the remaining useful life (RUL), in which data-driven methods could be utilized to solve nonlinear and time-dependent degradation patterns in EV batteries.

In spite of this great advance, there are still problems in the generation of models that are at the same time accurate, interpretable and generalizable to a variety of battery chemistries and operating conditions. Most of the current strategies are based on a specific set of data or a predefined architecture, which restricts their ability to adapt to new environments. As such, the proposed paper will present a new hybrid deep learning framework that will combine data-driven modeling and intelligent feature extraction to enhance the accuracy and adaptability of Li-ion battery capacity estimation. Our proposed method is used machine learning and deep learning for frameworks for SOH estimation and RUL prediction. The proposed system will help minimize the estimation error, improve learning with sparse signals, and provide a scalable model that can be used to monitor and manage the battery of electric vehicles in real-time.

II. Literature Survey

This research aims at applying the data-driven modeling methods to estimate the battery capacity with proper accuracy without depending on the electrochemical modeling. The authors compared the feed-forward neural networks (FNN), convolutional neural networks (CNN) and long short-term memory (LSTM) models on measurable signals using Li-ion batteries. The results reveal that LSTM is the most suitable because of its capabilities to process time-series data and long-term relationships, which yield lower levels of RMSE in comparison with FNN and CNN. It also established that sparse sampling enhances the efficiency of learning and that temperature has a lower contribution to the accuracy of prediction of capacity. [1]

The paper will discuss some machine learning algorithms, including K-nearest neighbors (KNN), support vector regression (SVR), decision tree (DT), and random forest (RF) to predict the state of the health of lithium-ion batteries. Each method was compared with the data in Sandia National Laboratories with the help of the MAPE, MSE, RMSE, and MAE metrics at different temperatures. The findings showed that KNN and DT had the best accuracy, making them to be robust in the estimation of the battery health of electric vehicles. The research finding is that the integration of data analytics and hardware partnerships can be used to improve predictive battery surveillance.[2]

The authors provide a detailed overview of machine learning methods of predicting state-of-charge (SoC) and state-of-health (SoH) in electric vehicle batteries. The paper systematically compares the popular ML algorithms, input features, datasets, and evaluation metrics applied to various battery chemistries. It highlights the role of high-quality datasets, hyperparameters choice, and stable modeling in the accurate estimation of SoH and SoC. The review identifies gaps in research and offers future directions of the ML-based advancements of Li-ion battery management systems.[3]

The study presents a machine learning model based on the use of big data, artificial intelligence, and IoT technologies to predict the state of the health of electric vehicle batteries. The proposed system is quite accurate with high values of R 2 and low values of mean square error indicating the effectiveness of the system. The model integrates both real-time battery data and machine learning algorithms to provide an effective online monitoring service on battery condition analysis. This paper demonstrates that information-based models are less expensive and accurate compared to conventional physical models.[4]

The paper surveys some of the machine learning techniques in estimating battery state parameters, which include SoC and SoH, as neural networks (feed-forward and recurrent), support vectors machines and radial basis function models. These models are compared in the analysis in terms of the quality of data set, conditions of test, and accuracy of estimation. The authors emphasize that training randomness and parameterization can influence the performance of neural networks, and to be able to compare them fairly, it is required that the experiments will be conducted in a consistent manner. In general, the article presents considerations of important aspects when choosing suitable ML architectures to estimate battery states.[5]

This work is a detailed survey on machine learning, deep learning, and the application of the digital twin technologies in predicting and controlling the state of health of the electric vehicle batteries. The paper summarizes the advantages of data-based approaches to the limitations posed by traditional experimental and physics-based approaches by modeling nonlinear battery dynamics in a more efficient way. It also talks about incorporating domain knowledge with physics in ML models to achieve improved interpretability. The review also includes comments on the existing gaps in the research with an accent on the upward trend of hybrid data-driven models in the future battery management system. [6]

The issue explored in this paper involves the use of machine learning to determine the condition of health and remaining useful life of lithium-ion batteries. It gives a detailed explanation of machine learning algorithms applied to determine age, estimate states, and analyse degradation. One of the challenges that are common and are discussed in the study includes non-linear behavior, temperature sensitivity, and data inconsistency in EV battery management. It concludes that machine learning methods can be successfully used to cope with these problems and offer more stable lifetime predictors of electric vehicles. [7]

IV. Proposed Method

Proposed method is designed for estimation of SOH and Prediction of RUL using different machine learning and deep learning techniques. Proposed method steps are discussed below,

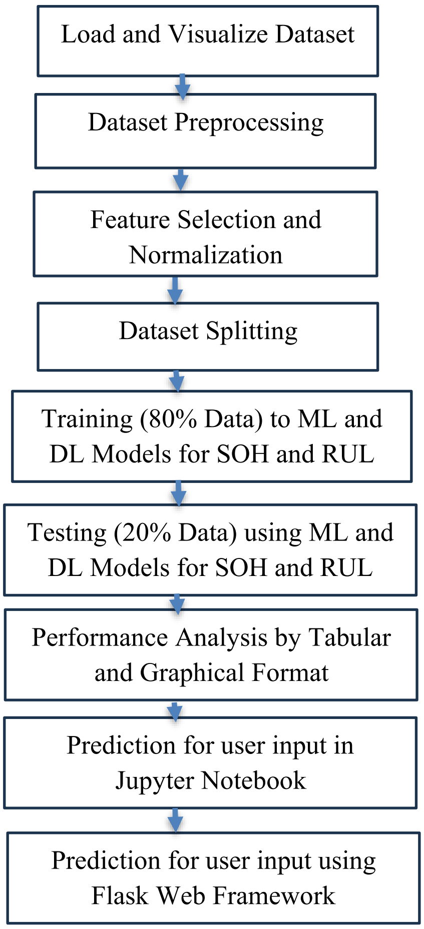

Fig. 4.1 Proposed Method Block Diagram

In the proposed method, the dataset is collected from Kaggle.com and it was originally collected from the NASA organization. The dataset link is : https://www.kaggle.com/datasets/programmer3/lithium-ion-battery-degradation-dataset?resource=download

This dataset contains total 3 different battery data which has 680 experimental data , and 11 different feature columns.
In the preprocessing stage, the dataset with missing values is treated well so model will get perfect training. Dataset with preprocessing gives better training and prediction performance compared to the original raw dataset as model understand clean data good way.

The features which are not much relevant to the final prediction are removed from the dataset which comes under feature selection. The main features which are important for classification or prediction are selected for further training and testing steps. Normalization brings the pixels value range to 0 to 1 from original range.

The dataset used in this application is not fed as it is to for training. The dataset is divided into 80% (for training) and 20% (for testing).

The selected machine learning and deep learning methods such as Naïve Bayes, Random Forest, Decision Tree, KNN, SVR and LSTM are first trained with 80% of the data from the dataset. The data and respective labels are used.

The trained models of machine learning and deep learning will be loaded for performing testing. After performing testing on testing data the predicted results are then given to performance metrics which compares predicted results and actual results.

Flask web framework is used for taking inputs from user interface from browser. For user inputs the random forest is used in background to predict the SOH and RUL for a given battery. The predicted results are displayed on same web page.

V. Results Analysis

Proposed method is designed using Jupyter notebook and flask framework. Results are explained in detail below,

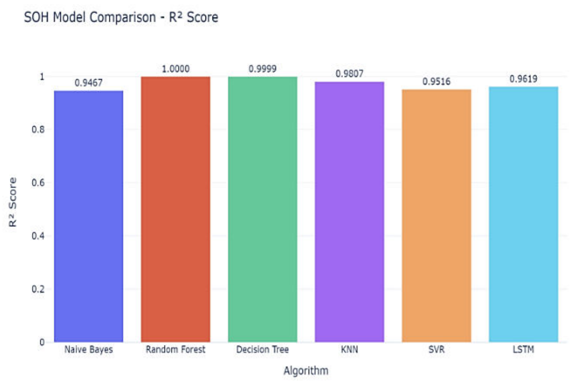

Fig.5.1 SOH Estimation Model Comparison with different Algorithm

The obtained performance in tabular format is plotted using bar graph. X-axis presents algorithm names while deep learning algorithms shows the performance metric R2_score. In graph, it is observed that random forest algorithm performs better than other algorithms.

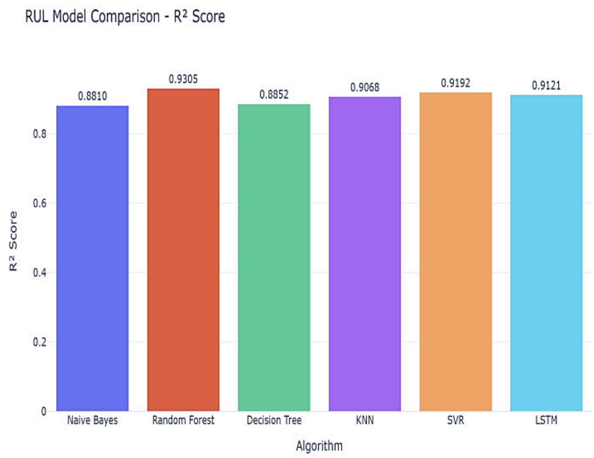

Fig.5.5 RUL Prediction Model Comparison with different Algorithm

In the above graph x-axis represents the algorithm names while on y-axis R2_score is represented. In the above graph Random Forest works better with higher R2 score for RUL prediction.

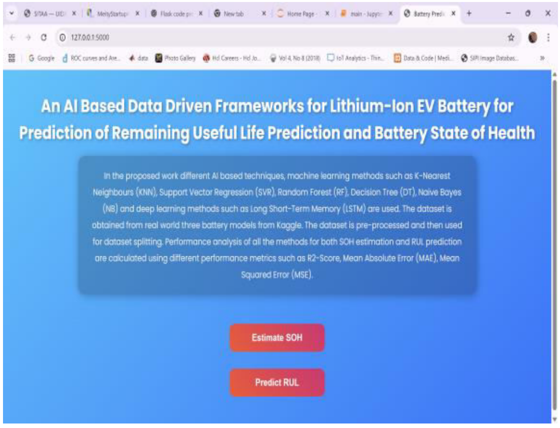

Fig. 5.2 Web Application designed for SOH Estimation and RUL Prediction

Above is the main page of web application which is prepared using flask web framework. The page has two options like Estimate SOH and Predict RUL.

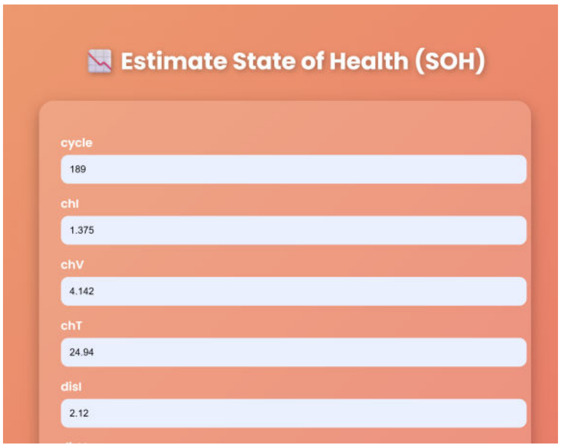

Fig. 5.3 SOH estimation from user input

In the above web page, all inputs are taken from user to predict the SOH of the battery. In the background random forest classifier is used for SOH estimation.

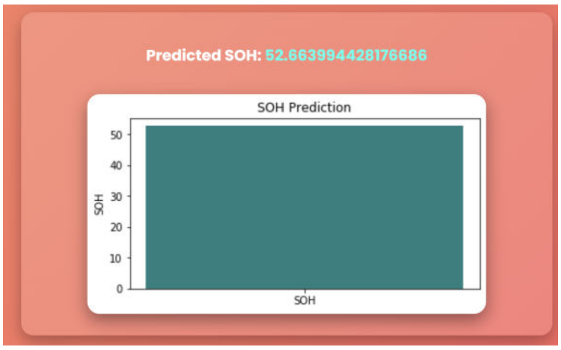

Fig. 5.4 Predicted results of SOH

The predicted SOH value for given input by user is displayed on same screen. Predicted values are very near and matching to actual values.

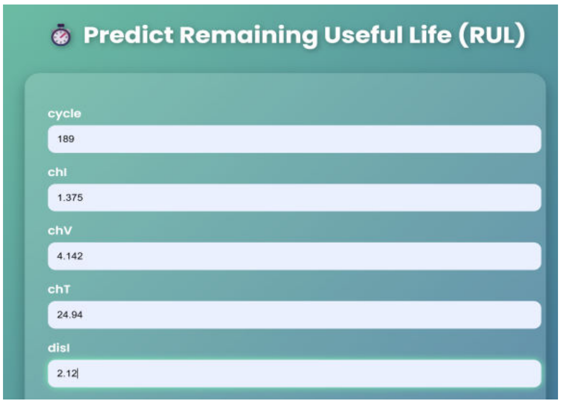

Fig. 5.5 RUL prediction from user input

Inputs given by the user to predict RUL is shown in the above figure. In the background , random forest classifier is used for prediction of RUL value.

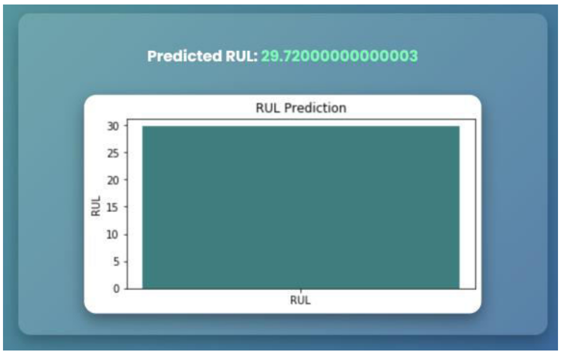

Fig. 5.6 Predicted Result of RUL for user inputs

Predicted results of RUL by random forest classifier is shown in above figure. RUL value graph is shown for visual interaction with user.

Conclusion

As there is exponential growth in the electrical vehicle market demand of electrical vehicles with proper maintenance and good life of the electrical vehicle's battery is required to fulfil. In proposed method successfully designed different AI based techniques such as machine learning and deep learning methods for estimation of SOH and prediction of RUL of lithium-Ion battery which is used in electric vehicle. In proposed method three batteries information is used for SOH estimation and RUL prediction.

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