Estimating the Health of Lithium-Ion Batteries Online Using a Data-Driven Ensemble Learning Approach

Tirunagiri Kavitha[1], Ch.Nikitha[2],N. Jahnavi[3],E. Pooja[4]

[1]Assistant Professor, Computer Science and Engineering, Sridevi Women's Engineering College Hyderabad, India

[1]Computer Science and Engineering, Sridevi Women's Engineering College, B.Tech IV Year Hyderabad, India

[2]Computer Science and Engineering, Sridevi Women's Engineering College, B.Tech IV Year Hyderabad, India

3Computer Science and Engineering, Sridevi Women's Engineering College, B.Tech IV Year, Hyderabad, India

Abstract

Estimating a state of health (SOH) of lithium-ion batteries is crucial to ensure the security of related systems. In this study, we offer a unique ensemble learning approach to state of health estimation for LIBs. To determine the LIB's overall health, we use a metric called "same charging voltage range duration" (DSCVR). The prediction model's inputs are narrowed down to four variables using a Pearson correlation analysis. To further minimise the calculation errors of the individual ELM models, an ensemble learning framework is developed. To additional growth in the precision and dependability of the estimate findings, a trustworthy conclusion-making procedure is developed to assess the reliability of the results of each ELM model and to exclude the unreliable output. The results of the proposed method's testing on two publicly available datasets demonstrate its ability to reliably estimate the state of health in 1ms while being resistant to changes in temperature during the operation and load profile. There is as little as a 0.78% RMSE on average. The suggested solution is well-suited for ongoing practical applications since it does not need any extra hardware or system downtime.

1. INTRODUCTION

Since batteries made with lithium ion have low self-discharge rates, long useful lives, minimal maintenance needs, and high energy densities, they have found widespread use in electric cars and energy storage systems. But as time went on, LIB's performance would decline due to wear and tear and the effects of the running environment. The breakdown might need urgent repair and a sudden shutdown of the system, both of which would be disastrous. That's why it's crucial to have a good read on LIBs' SOH if you want their performance to meet your expectations. LIB ageing is notoriously difficult to understand. Reduced capacity and increased impedance are the end outcomes of the interface of solid electrolytes decomposing, precipitating, and plating with lithium metal. As a result, LIB capacity and impedance are useful measures for quantifying health. Multiple methods have been described in recent years for SOH estimate of LIB. There are three broad types of these techniques: Direct measurement, model-based, and data-driven. Measurements taken directly from a battery may be second-hand to determine the cell's capacity or impedance. Using the OCV relaxing curve and the capacity, the capacity may be predictable using the open-circuit voltage approach. To learn more about how lithium-ion batteries degrade nonlinearly with use, the coulomb-counting technique is presented in. In addition, SOH may be reflected by measuring the increase in battery impedance due to electrochemical reactions throughout the ageing process. Most battery impedance readings are done using electrochemical impedance spectroscopy. Internal resistance is measured using a number of techniques, including EIS, current pulses, and the Joule effect. In conclusion, a direct measuring approach often requires less hardware and has less computing complexity, but it is difficult to apply online. The SOH may also be estimated by analysing the battery's charging and discharging data, for which a density function the probabilities is provided. Model-based techniques all need a physical understanding of battery behaviours as their starting point. While the electrochemical model approaches are reliable, their complexity prevents them from being used in a battery management system with relatively modest computational resources. Simple and well-suited for onboard applications, observer approaches based on the comparable circuit model may not have sufficient precision to characterise the battery ageing behaviours. Therefore, rather being seen as a functional mathematical model, the battery is treated as a mysterious unknown. In order toreliably estimate SOH of LIBs, we need the correlative health indicator. It is taken from real-time readings of variables like electrical current, voltage, and temperature. The most often-utilised indication in current practises is the charging/discharging voltage. Liu et al., for example, determined that the capacity loss could be quantified by comparing the voltages attained while discharging at equally spaced time periods. The capacity drop is modelled in the sample using the entropy of a voltage sequence resulting from a brief discharge. In most cases, the system that manages the battery will be able to regulate the charging process, whereas the draining process will be largely dependent on load profiles. To determine the health indicator, we use the incremental ability curve in. The computational load, however, is higher due to the use of derivative and filter techniques. In, four charging-voltage-derived characteristics are chosen to estimate SOH. It's important to note that additional health indicators may not always lead to more precise estimates when using data-driven approaches. Once an appropriate indicator has been developed, many data-driven approaches are used to approximateLIB SOH.Neural autoregressive with external inputs is an architecture created for SOC and sulphur dioxide estimation in a recurrent network that is dynamically driven. A similar support vector reversion-particle filter strategy for SOH monitoring was suggested inAdditionally, practical applications are worried about estimate accuracy and dependability. The following are the specific contributions:

First, state-of-charge (SOC) estimates may be calculated using an enhanced health indicator derived from the battery's terminal voltage. With the use of a chance-based learning method called Extreme Learning Machine (ELM), we are able to determine the correspondence between our chosen health metrics and SOH. ELM is well-suited for battery management platforms because to its substantially quicker learning speed, better generalisation its limit, and computationally effective tuning mechanism. After validating the ELM with a number of test cases over a broad variety of situations, we develop an ensemble learning the framework to further improve the SOH estimate accuracy. (2) In this study, we provide a trustworthy method for making decisions on the "credibility" of particular ELMs' results. This allows the individual ELMs to correct for each other, which in turn allows the ensemble model to lower aggregated variance and, perhaps, improve accuracy. Third, using cross-validation testing, we ensure the robustness or scalable of the proposed technique by verifying and analysing the impacts of health gauge, temperatures, and load profile variables on the state of health estimate findings.

2. RELATED WORK

“Prognostics of lithium-ion batteries based on Dempster–Shafer theory and the Bayesian Monte Carlo method”

Dempster-Shafer theories and the Bayes Monte Carlo (BMC) technique are offered as a novel way for calculating lithium-ion batteries' state of health and RUL. An empirical model is constructed herein that makes use of the physical deterioration behaviour of lithium-ion batteries. RUL predictions made by the model grow more precise as more data are collected. Two examples are given to prove the usefulness of this method.

“Data-driven prediction of battery cycle life before capacity degradation,”

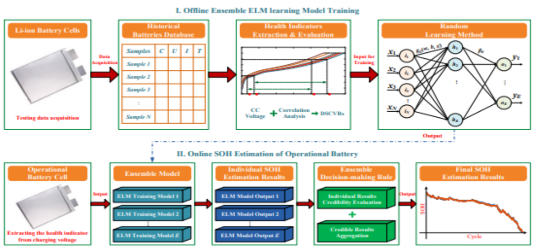
As per expense performance, the ratio of lithium-ion batteries steadily drops in a competitive market, there is a window of opportunity to investigate cost-cutting measures. Electric car and mobile phone manufacturers, among others, have a vested interest in lithium-ion battery lifespan estimates. This requires costly testing to comprehend. This work utilises the data and procedures established by Kristin A.. The primary goal is to determine whether the machine learning methods can be educated on preliminary life cycle data to reliably estimate battery capacity throughout the battery's life cycle. Gaussian process regression and elastic network regression (ENR) are compared, with major data aspects from the large dataset utilised in Severson's study being highlighted.

“Prognostics of lithium-ion batteries based on relevance vectors and a conditional three-parameter capacity degradation model”

Commercial devices rely heavily on lithium-ion batteries for electricity, including laptops, EVs, and UAVs (unmanned aerial vehicles). Significant effort has been put into refining the performance and dependability of lithium-ion batteries to guarantee a steady flow of energy. In this research, we create a prognosis approach for lithium-ion battery capacity to predict how long these batteries have left before they become useless In order to account for the prediction values at every cycle of the significance vectors, an arbitrary three-parameter capacity decline model is created. Results demonstrate the presented method's efficacy in foreseeing lithium-ion batteries' future health status.

3. METHODOLOGY

The framework of the proposed randomised learning driven ensemble, data-driven technique for estimating LIB SOH under cycle ageing is shown in Fig. 1. There are two phases for this procedure: training an ensemble learning model offline and estimating SOH in actual. During the offline phase, a database is constructed from gathered operational data, including voltage, current, and temperature. Measurements from accelerated ageing tests are used to determine each cycle's realistic capabilities, which in turn serve as standards for further development and testing. Indicators of health are selected from characteristics with a high quantitative association to real-world SOH.Extracting the new battery's health indicators from the online data and feeding them into the properly educated ELM ensemble model acquired in the offline step yields an online SOH calculation. To assess the "credibility" of the results produced by each ELM model, a trustworthy decision-making rule has been developed. The battery's SOH is calculated using only reliable readings. This allows for better generalisationand estimate as a result.



Exsisting System

In existing, load profiles play a vital character in determining the discharging procedure of batteries. Consequently, the charging voltage curves are utilized to calculate various health indicators. A research study introduced a novel model that consisted of three separate relations of network architecture: convolutional neural network (CNN), thefeed-forward neural network (FNN), and long short-term memory (LSTM) neural network. The results of the study indicated that the LSTM network exhibited superior performance compared to the other model designs. By leveraging its unique architecture, the LSTM network demonstrated exceptional capability in approximating battery capacity.

Disadvantages

- They are frequently created under exact assumptions and application limitations.
- Consequently, it is hard to determine which technique has the best estimation presentation in each submission.
- Availability is difficult.
- Cost is high.

Proposed System

An unexplored approach in the field involves exploring the correlation between adapted data and the state of health (SOH) of batteries. This can be achieved by using the machine learning methods such as the Extreme Learning Machine (ELM), Support Vector Machine (SVM), and Pearson correlation.

Advantages

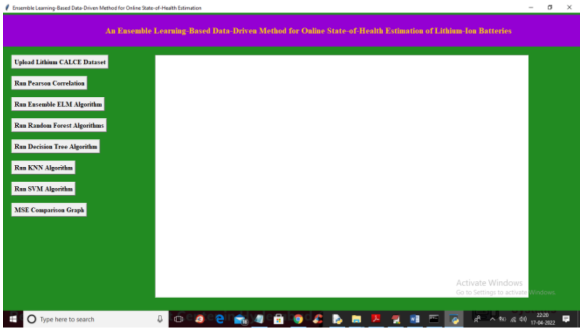
- ELM is a fast and robust machine learning algorithm and high precision and high self-flexibility.
- 2.The ELM can meaningly decrease the quantity of time

Modules

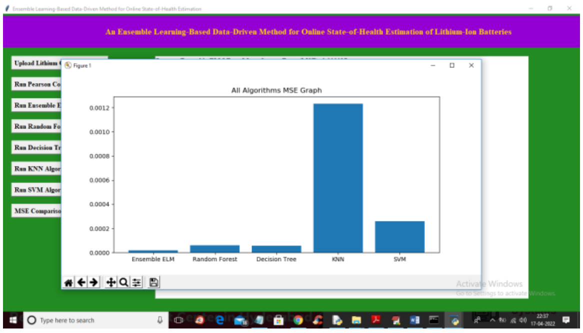
- Upload Lithium CALCE Dataset; using this module we will upload dataset to application
- Run Pearson Correlation: using this module we run the Pearson formula to calculate important attributes from the dataset and the attributes/column names which give score as 1 will consider as important attribute
- Run Ensemble ELM Algorithm: using this module we will input above dataset to group or ensemble of ELM to train a model and then perform the prediction of battery health and then check its prediction error rate with the original estimated values to get RMSE
- Run Random Forest Algorithm: using this module we will input above dataset to Random Forest train a model and then perform the prediction of battery health and then check its prediction error rate with the original estimated values to get RMSE
- Run Decision Tree Algorithm: using this module we will input above dataset to Decision Tree to train a model and then perform the prediction of battery health and then check its prediction error rate with the original estimated values to get RMSE
- Run SVM Algorithm: using this module we will input above dataset to SVM to train a model and then perform the prediction of battery health and then check its prediction error rate with the original estimated values to get RMSE
- Run KNN Algorithm: using this module we will input above dataset to KNN to train a model and then perform the prediction of battery health and then check its prediction error rate with the original estimated values to get RMSE
- Comparison Graph: using this module we will plot RMSE comparison between all algorithms and the algorithm with less RMSE is the better one

4. RESULT AND DISCUSSION:

This is the interface that appears when our programme is active.



The operations can be carried out in a sequential fashion: first, the dataset is uploaded; then, pre-processing is carried out; the data is separated into training and testing groups; the algorithm is trained using the training information; and finally, the accuracy of the methods is determined using the test data; however, in this case, the RSME of the methods is determined.



We propose which algorithms provide the lowest RSME so that future battery estimate times may be predicted with more accuracy.

5. CONCLUSION

In this learning, we offer a novel data-driven technique that utilises ensemble Lsm for the state of health estimate of lithium-ion batteries. The state of health (SOH) of a battery may be accurately reflected by a health marker retrieved from the voltage of the charging signal. ELM has the ability to learn quickly and accurately, it is used as a predictor to understand the connection between DSCVRs and the state of health. To further enhance the reliability of the predictions, a collaborative ELM learning framework has been developed Finally, the suggested SOH estimate technique is tested using both CALCE's average data and NASA's random walk data. The approximation results demonstrate that the suggested ensemble ELM driven data-driven technique exceeds the state-of-the-art learning procedures in its ability to properly and consistently predict the SOH utilising a health pointer derived from a narrow voltage series of 3.84V to 3.86V in 1ms. In addition, the suggested method is shown to be stable throughout a wide range of load profiles and temperatures.

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