Indian Institute of Technology, Roorkee

Department of Physics

Internship Project Report

Li-ion Battery Fault Analysis using Novel Deep Learning Approach

Prepared For

Prof. Yogesh Kumar Sharma

Prepared By

Vardan Popli

B.tech Chemical Engineering
IIT (BHU) Varanasi

Project synopsis submitted during SPARK'24
20 May to 5 July, 2024

Abstract

Lithium-ion (Li-ion) batteries are critical components in electric vehicles (EVs) and require accurate health monitoring for safety and performance optimization. This project investigates a novel deep-learning approach for predicting Li-ion battery SoH while incorporating degradation mechanisms. The initial phase involved understanding battery fundamentals, including SoH, State of Charge (SoC), and fault types. A literature review explored degradation mechanisms and physical parameters for their measurement. Subsequently, various deep learning approaches were studied, with a focus on the Long Short-Term Memory (LSTM) model.

The project then transitioned to model development and testing. An LSTM model was trained on a dataset of Li-ion 18650 Cell discharged over power drive-cycle*, achieving a high accuracy of 99.68%. However, a temperature measurement system was constructed using an NTC thermistor, resistor, and Arduino Uno. This system enabled the acquisition of temperature data alongside voltage and current measurements during power cycle testing on a single cell.

The proposed approach leverages voltage, current, and temperature data from discharge cycles to predict SoH. This approach differentiates itself from traditional methods by incorporating a degradation model within the deep learning framework. A previous study by a senior researcher used an Artificial Neural Network (ANN) for SoC prediction in discharge cycles but neglected the crucial factor of battery degradation. This project addresses this gap by considering degradation mechanisms, leading to a more comprehensive and accurate SoH prediction.

This report details the project methodology, including the literature review, model development, data acquisition, and experimental setup. The results section will present the SoH prediction performance and model again trained and tested over sodium ion cells prepared in laboratory. Finally, the discussion section will analyze the findings, limitations, and potential future directions.

*Representative of RMSE 23 drive-cycle, Motorsports Team IIT Roorkee over an EV battery pack.

Table of Contents

Introduction

1.1 Background and Motivation

The adoption of lithium-ion batteries in electric vehicles (EVs) and electric vertical take-off and landing (eVTOL) aircraft is revolutionizing the transportation industry. These batteries offer a high energy density, long cycle life, and low self-discharge rate, making them ideal for such applications. Furthermore, Li-ion batteries find applications beyond transportation and consumer electronics. They are used in grid storage systems for renewable energy integration, medical devices, and power tools.

The increasing demand for clean energy with longer dependence fueled the development of Li-ion batteries to overcome the limitations of previous battery technologies. Therefore, Accurate prediction of State of Health (SoH) and State of Charge (SoC) is crucial for the reliable and safe operation of these batteries.

1.2 Significance of State-of-Health (SoH) and State-of-Charge (SoC) [1]

The health and performance of an Li-ion battery are crucial for safe and efficient EV operation. Two key parameters define battery health:

- **State of Health (SoH):** SoH reflects the remaining capacity of a battery compared to its original capacity rated when new. It essentially indicates the battery's overall health and degradation level. A lower SoH signifies reduced capacity and potential performance limitations.

$$SoH = \frac{C_{max}}{C_{rated}} \times 100\%$$

- **State of Charge (SoC):** SoC represents the remaining amount of energy stored in a battery relative to its full capacity. Unlike SoH, SoC fluctuates with use and recharging. Understanding both SoH and SoC is essential for optimal battery management in EVs.

$$SoC = \frac{C_{releasable}}{C_{rated}} \times 100\%$$

1.3 Overview of battery fault and their impact [2]

Li-ion batteries are susceptible to various faults that can impact performance, safety, and lifespan. Early detection and diagnosis of battery faults are critical for ensuring safe and reliable EV operation. Common fault types include:

Overcharge/Overdischarge: Exceeding the recommended voltage limits during charging or discharging can damage the battery and lead to reduced capacity or even thermal runaway, a dangerous condition where the battery heats up rapidly and poses a fire risk.

Internal Short Circuit: Internal short circuits occur when the positive and negative electrodes come into contact, causing rapid discharge and overheating.

Temperature Extremes: Extreme temperatures, both high and low, can accelerate battery degradation and reduce lifespan.

1.4 Project Objectives

1. To develop a deep learning model, specifically an LSTM model, for SoH prediction in Li-ion batteries.
2. To incorporate a degradation model within the deep learning framework to account for the impact of aging on battery health.
3. To validate the model's performance using experimental data collected during discharge cycles on a single Li-ion cell

Literature Review

2.1 Previous Work Over SoC Prediction (By Kamal Utla [6] and Kunal Shaw[7])

The report titled "Novel Deep Learning Techniques to Predict the State of Charge of Lithium-Ion Batteries in Electric Vehicles" presents extensive research conducted to develop a deep learning model for accurately predicting the State of Charge (SoC) of lithium-ion batteries. This model leverages real-time data such as temperature, voltage, and current collected from drive cycles of electric vehicles (EVs) simulated in a controlled laboratory environment. The project demonstrates a successful implementation of a feed-forward neural network model, which was trained and tested with various drive cycle profiles to ensure high accuracy and generalizability. The trained model achieved a maximum deviation of 2% from the actual SoC, showcasing its effectiveness and reliability for real-world applications.

The report concludes that the deep learning model developed for SoC estimation has achieved state-of-the-art accuracy by incorporating regularization layers and applying low-pass filters to smooth the output. The model's performance was validated through custom and standard drive cycles, demonstrating robustness and precision with an R2 score exceeding 99.9%. This research lays the groundwork for further advancements in battery management systems, emphasizing the importance of accurate SoC prediction for optimizing EV performance and longevity

Building upon the work done on SoC estimation, the current project aims to extend the research to include the prediction of the State of Health (SoH) of lithium-ion batteries. Accurate SoH prediction is crucial for assessing the long-term performance and safety of batteries, which directly impacts the reliability and efficiency of EVs. The work presented in this report uses the same power cycle generated for previous work on SoC.

2.2 Type of Faults and Degradation Mechanism

Lithium-ion battery degradation is influenced by various physical and chemical processes that affect different components of the cell. One key degradation mechanism is the formation and growth of the Solid Electrolyte Interphase (SEI). The SEI layer forms on the anode surface during the initial charging cycles, and its continuous growth consumes lithium ions and electrolyte, thereby reducing the battery's capacity over time. Another critical mechanism is the loss of active material (LAM) from both the cathode (LAMPE) and the anode (LAMNE). This loss can occur due to structural disordering, particle cracking, or the loss of electrical contact, all of which lead to capacity fade and increased cell resistance.[3]

Lithium plating is another significant degradation mechanism, where overcharging or operating at low temperatures causes lithium to deposit on the anode surface instead of intercalating into it. This metallic lithium can lead to internal short circuits and capacity loss. Electrolyte degradation also plays a vital role; the electrolyte can decompose due to high temperatures, overcharging, or prolonged cycling. This degradation results in gas formation, increased cell impedance, and further capacity loss. Additionally, repeated charging and discharging induce mechanical deformation, causing mechanical stress that leads to electrode cracking, separator deformation, and potential internal short circuits.

Finally, thermal degradation accelerates chemical reactions that degrade the electrolyte and electrode materials, especially at elevated temperatures, further reducing battery life and performance[2]. Understanding these degradation mechanisms is essential for developing more durable and efficient lithium-ion batteries.

Methodology

3.1 Data Description

The dataset used in this project comprises detailed metadata and time series data collected from Lithium ion cells and power cycle data from electric vehicles (EVs). The Lithium ion coin cells dataset includes metadata such as end and start voltage, energy, capacitance, capacity, and other averaged parameters evaluated at the end of each cycle. Additionally, the time series data contains voltage, temperature, and current measurements recorded at regular intervals throughout each cycle. This data is stored in multiple CSV files, each representing a single cycle, with corresponding capacity values for each cycle as shown in Fig 1 (*Dark for initial cycles, lighter for preceding cycles*). The power cycle data from EVs is collected similarly, providing essential information for modeling and predicting the state of health (SoH) and state of charge (SoC) of the battery.

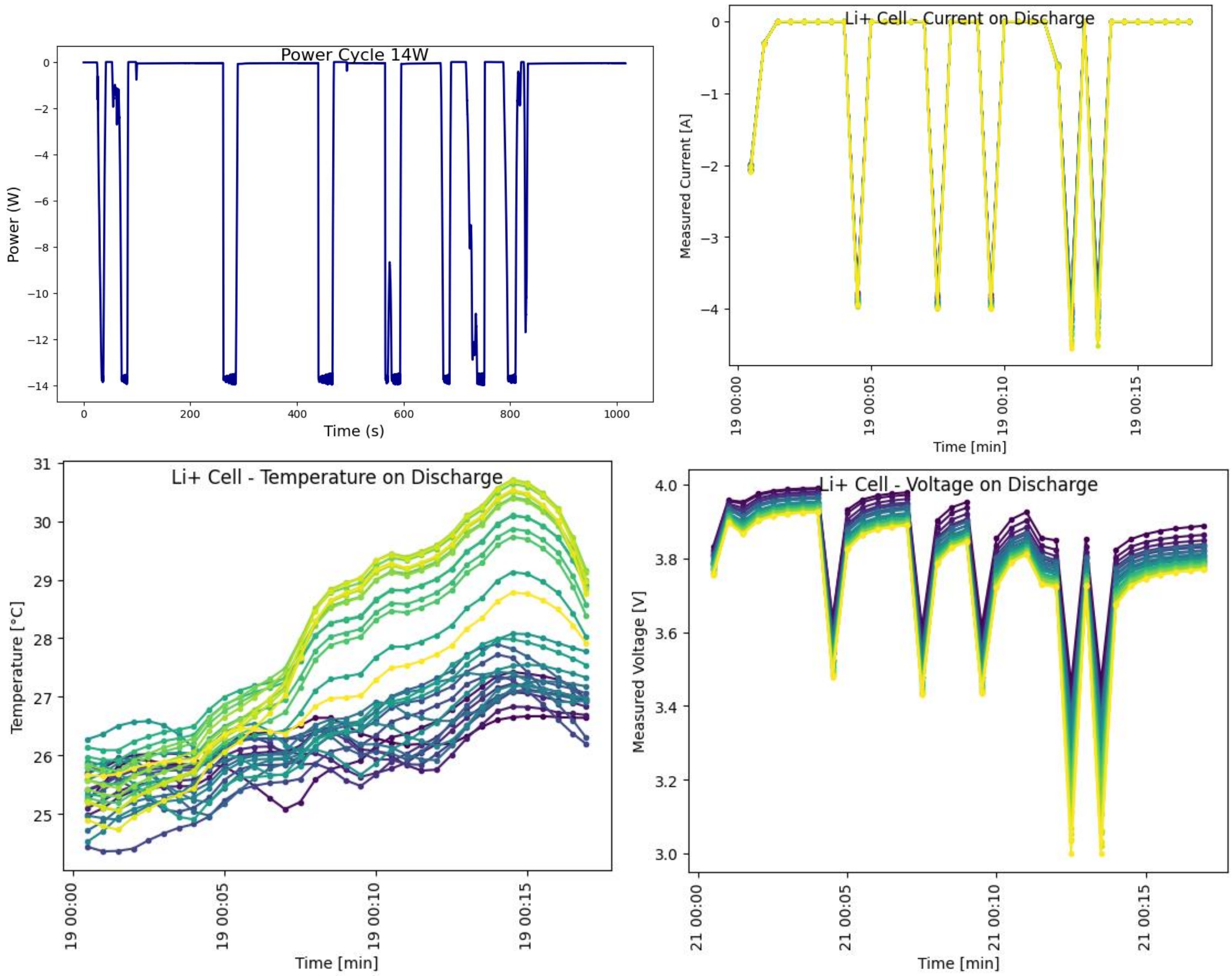

Fig.1 Discharge Power Cycle calibrated for single cell against Battery Pack

3.2 Data Pre-processing

Preprocessing involves splitting and normalizing (upto 35 data points) of the voltage, current, and temperature data from each CSV file into a fixed number of rows representing time steps. This normalized data is then fed into a 3D LSTM model, with each time step considered a single input sequence. The dataset is split into training and validation sets, with 70% of the data used for training. Although data collection was limited to 30 cycles due to technical difficulties, it is recommended to train on at least 60 to 70 cycles for optimal LSTM model performance.

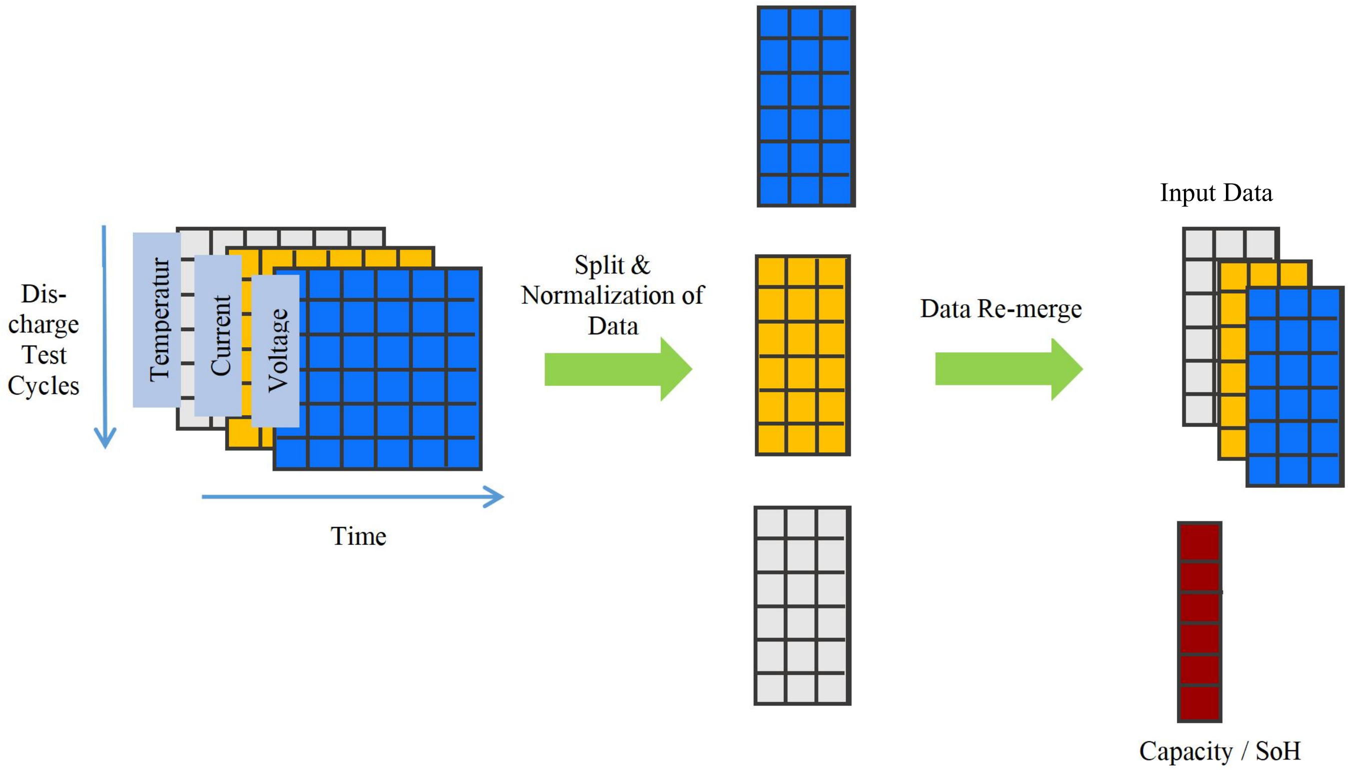

Fig 2 Illustration of organizing and normalizing experimental data to create input/output data for training LSTM networks for estimating SoH

3.3 Temperature Measurement Setup

Temperature data is measured using an Arduino and an NTC thermistor setup, where the thermistor has a resistance of 10K ohms, and the Arduino UNO microcontroller reads the resistance values and converts them to temperature readings.

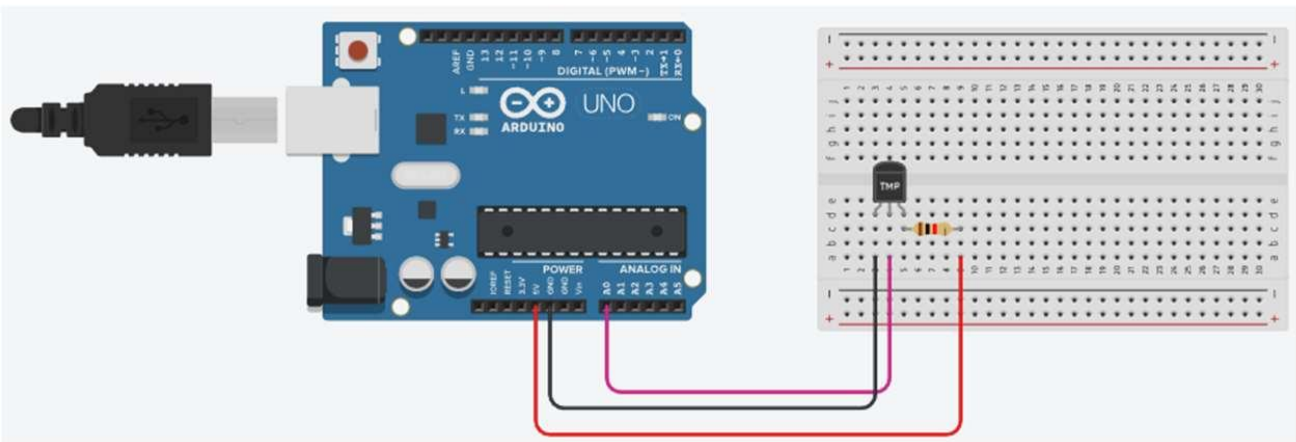

Fig 3 Temperature Measurement Setup using Arduino UNO and 10K ohm NTC Thermistor

Experimental Setup

The battery discharge experiment is set up using the Neware Battery Cycler, programmed through the Neware BTS Client software. The current and voltage sensors are integrated into the Battery Cycler, while temperature sensing is achieved using an NTC 103 Thermistor, which is suitable for the operating temperatures.

4.1 Calibration of the Thermistor

Fig 4 NTC 103 Thermistord

To ensure accurate readings from the thermistor, calibration is necessary. The NTC 103 Thermistor (Fig 4) operates based on the Steinhart-Hart Equation:

$$\frac{1}{T} = A + Bln(R) + C(ln(R))^3$$

where T is the temperature in Kelvin providing a direct relationship with the thermodynamic properties of the materials involved, R is the resistance, and A, B, and C are the empirical Steinhart-Hart coefficients.

The thermistor is attached to the target to monitor its temperature, and as the temperature changes, the thermistor's resistance changes accordingly. The resistance can be measured to determine the temperature using the Steinhart-Hart Equation.

4.2 Interfacing with Arduino

The thermistor circuit is interfaced with a microcontroller (Fig 3), the Arduino Uno, which is programmed to sample the thermistor at a given rate and log the data to a PC (Fig 5). The Arduino is connected to the PC via a serial port. By accessing the specific serial port to which the Arduino is connected, the data transmitted over the serial port can be logged. For this purpose, PuTTY software is used on the PC, facilitating the logging of serial port data.

Fig 5 Battery Cycler (5V6A) and Interfacing with Arduino

4.3 Programming with Battery Cycler

Once the temperature sensor is set up, the battery cycler is programmed with generated power profiles. The BTS Client software includes a "SIM" mode, allowing the input of a specific power profile for discharging/charging according to the profile.

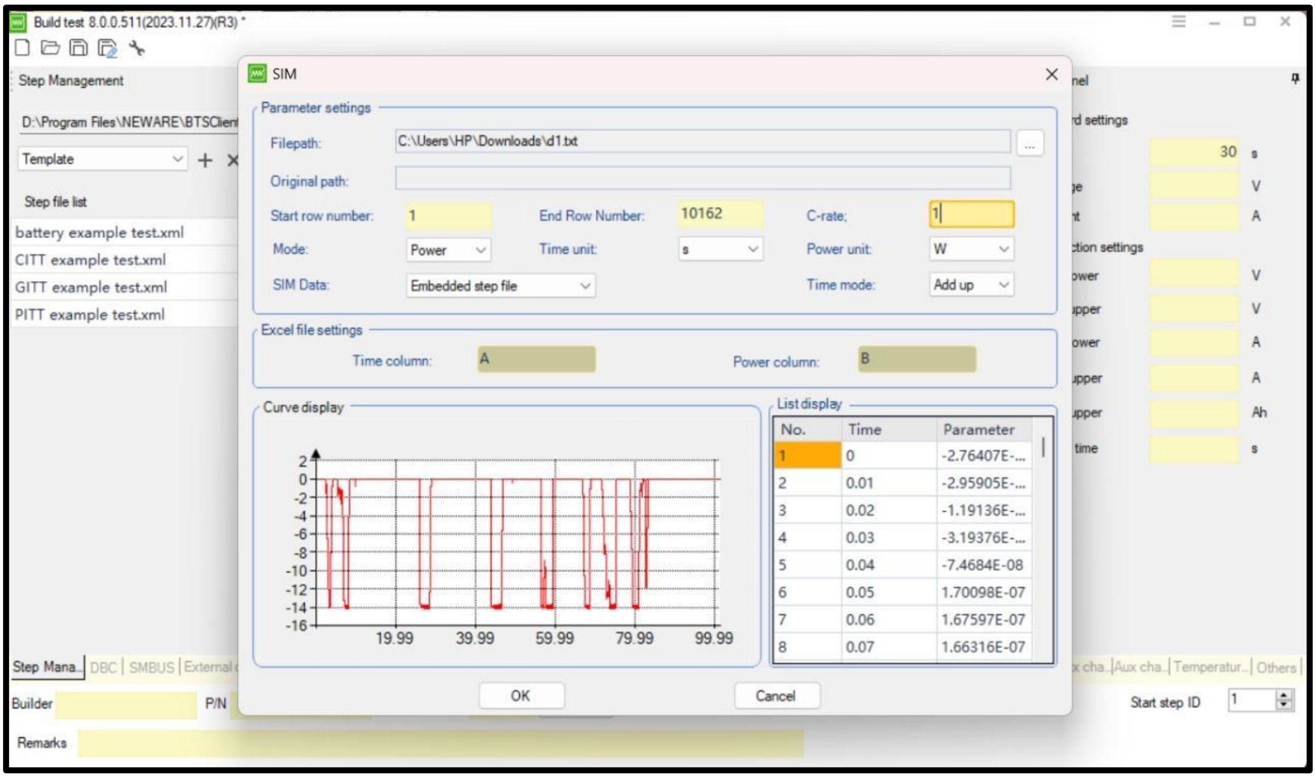

Fig 6 UI of loading the power profile in Neware BTS Client software

Model Development

5.1 Description of the Model

The LSTM (Long Short-Term Memory) network used in this project is designed to estimate the State of Health (SoH) of batteries. The structure of the LSTM network consists of N (= 2) layers, as illustrated in Fig7. The input data for the network includes current, voltage,and temperature time-series data with m (= 35) Averaged data points, while the output data includes the capacity, further can be transformed to SoH as discussed earlier.

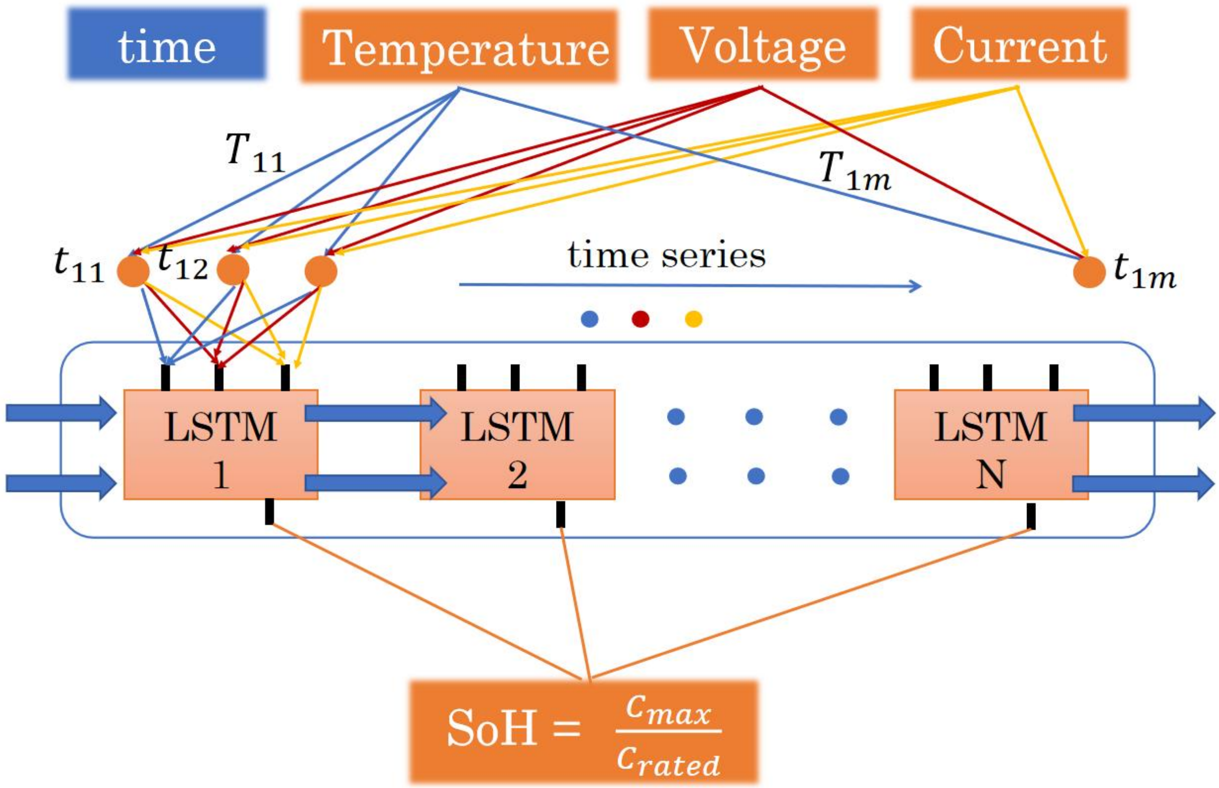

Fig 7 Graphical structure of the 3D LSTM network used for SoH estimation. (m =35, N = 2)

5.2 Model Architecture

Key configuration of the LSTM model include: 2 LSTM layers, first with units of 27, Activation function ReLU (Rectified Linear Unit), Return Sequences is set True (to ensure that the next LSTM layer receives the full sequence of outputs), input shape is matrix (35,3), where Three input parameters includes Temperature, Voltage, Current and each has Thirty-Five averaged time-series data points.

Second Layer consists of 95 units. The activation function is ReLU. Return Sequences is set to False (since this is the final LSTM layer before the Dense layer). Finally, there is one dense output prediction layer.

The optimizer chosen is Adam (Adaptive Moment Estimation) for its efficient gradient-based optimization and adaptive learning rate capabilities. Loss is evaluated by Mean Squared Error (MSE), which measures the average of the squares of the errors between the predicted and actual values. The model is trained for 250 epochs using a batch size of 12.

5.3 Training Process and Hyper-parameter Tuning

The data used to train the LSTM network is divided into three sets:

- Training Set: 70%
- Test Set: 30%

These ratios are determined through numerous tests to prevent overfitting, accurately measure the model's performance on unseen data, and ensure the generalization of the model. The learning rate and the number of iterations are critical hyperparameters. The optimal learning rate is discovered through trial and error. A higher number of iterations can improve performance but may also lead to overfitting. Monitoring the validation loss helps in determining the appropriate stopping point for training.

Results and Discussion

To evaluate the accuracy of SoH, the following metrics are used:

- Mean Absolute Percentage Error (MAPE): Measures the average magnitude of the errors between predicted and actual values, expressed as a percentage.
- Mean Absolute Error (MAE): Measures the average magnitude of the errors in a set of predictions, without considering their direction.
- Root Mean Square Error (RMSE): Measures the square root of the average of squared differences between predicted and actual values.

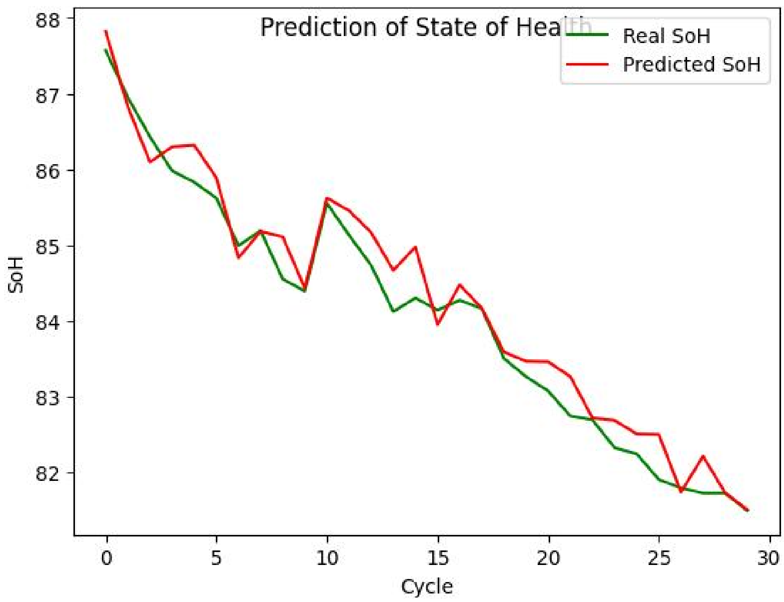

Fig 8 Comparison of predicted to actual SoH Vs No. of discharge cycle

Mean Absolute Percentage Error (MAPE): 0.32%
Mean Absolute Error (MAE): 0.27
Root Mean Squared Error (RMSE): 0.33
Accuracy: 99.60% (100 - 0.32%)

The results demonstrate that the model has effectively traced the actual state of health (SoH) of the battery. This indicates that such a model can be perfectly applied to electric vehicles (EVs) or other transportation systems where real-time prediction of SoH is necessary. It can further be used to predict internal resistance and identify potential faults within the battery.

The presented method successfully models essential parameters of the battery, such as temperature, current, and voltage. This is crucial for analyzing the real-world effects on the battery during operation.

While there are simple laboratory methods to determine the SoH of a battery, such as Electrochemical Impedance Spectroscopy (EIS) and the Open Circuit Voltage method (OCV), they fail when a user-friendly and immediate prediction method is required, such as in EVs or eVTOLs.

Other models, such as Electrical Equivalent Circuit Models (EECM) and Electrochemical Models, also exist. However, they are not optimal when fast and accurate predictions are required. Electrochemical models show high accuracy and cover almost all possible faults and degradation within the cell, but their high computational complexity makes them unsuitable for use in EVs. On the other hand, EECM models are easier to compute but show less accuracy compared to advanced deep learning models like Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) networks.

Future Perspective

- Forecasting resistance and temperature rise to determine maximum heat capacity of degraded cells.
- Incorporating ambient temperature, humidity, gas evolution, stress, and coolant metrics to enhance the model.
- Preparing generalized model using various cells and power cycles data.
- Interpolating Voltage, Current, Temperature and predicting SoH after set of training cycles.
- Combining Electrochemical models and Deep learning models for better accuracy in optimal time complexity.

Conclusion

This project successfully developed and validated a novel deep-learning approach for predicting the State of Health (SoH) of lithium-ion (Li-ion) batteries, emphasizing the incorporation of degradation mechanisms. Utilizing Long Short-Term Memory (LSTM) networks, the model achieved an impressive accuracy of 99.68% in predicting the SoH of Li-ion 18650 cells during power drive cycles. The inclusion of temperature data, alongside voltage and current measurements, significantly enhanced the prediction accuracy, differentiating this approach from traditional methods that often overlook degradation factors.

The constructed temperature measurement system using an NTC thermistor and Arduino Uno facilitated precise temperature data acquisition, essential for accurate SoH predictions. This project's innovative approach, combining deep learning with degradation modeling, addresses a critical gap in existing research and provides a comprehensive solution for real-time battery health monitoring in electric vehicles (EVs) and other applications.

This project showcases a significant advancement in battery health monitoring, with potential implications for improving the safety, performance, and reliability of batteries in modern transportation and other sectors.

References

1. A Closer Look at State of Charge (SOC) and State of Health (SOH) Estimation Techniques for Batteries by Martin Murnane

2. Lithium-ion Batteries used in Electrified Vehicles – General Risk Assessment and Construction Guidelines from a Fire and Gas Release Perspective By Fredrik Larsson & Bengt-Erik Mellander

3. Degradation diagnostics for lithium ion cells By Christoph R. Birkl & Matthew R. Roberts

4. EVBattery: A Large-Scale Electric Vehicle Dataset for Battery Health and Capacity Estimation

5. Estimation of SoH and internal resistances of Lithium ion battery based on LSTM network

6. BTP Thesis Final Kamal Utla 20122018

7. Final_LBP_Report_Kunal