State-Of-Health Estimation for Lithium-Ion Battery Using Bidirectional Gated Recurrent Unit

Report submitted to the SASTRA Deemed to be University as the requirement for the course

Course Code: INT500R01: PROJECT WORK & VIVA VOCE

Submitted by

NAME: POOVARASAN V
(Reg. No: 124150032)

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SCHOOL OF ARTS, SCIENCES, HUMANITIES AND EDUCATION
THANJAVUR, TAMIL NADU, INDIA – 613 401

SCHOOL OF ARTS, SCIENCES, HUMANITIES AND EDUCATION

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<u>Bonafide Certificate</u>

This is to certify that the report titled "**State-Of-Health Estimation for Lithium-Ion Battery Using Bidirectional Gated Recurrent Unit**" submitted as a requirement for the course, **Course Code: INT500R01: PROJECT WORK & VIVA VOCE** for M.Sc. Data Science programme, is a bona fide record of the work done by **Mr. Poovarasan V (124150032)** during the academic year 2023-2024, in the School of Arts, Sciences, Humanities and Education, under my supervision.

Signature of Project Supervisor:

Name with Affiliation : Dr. Manivannan. R, Asst. Professor II, Department of Mathematics, SASHE, SASTRA Deemed to be University.

Date : **02.05.2024**

Project *Viva voc*e held on _02.05.2024_______________

Examiner 1 **Examiner 2**

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Declaration

I declare that the report titled **"State-Of-Health Estimation for Lithium-Ion Battery Using Bidirectional Gated Recurrent Unit"** submitted by me is an original work done by me under the guidance of **Dr. Manivannan. R, Asst. Professor II, Department of Mathematics, SASHE, SASTRA Deemed to be University** during the fourth semester of the academic year 2023-24, in the **School of Arts, Sciences, Humanities and Education**. The work is original and wherever I have used materials from other sources, I have given due credit and cited them in the text of the report. This report has not formed the basis for the award of any degree, diploma, associate-ship, fellowship or other similar title to any candidate of any University.

Signature of the candidate(s) : V. Pohj

Name of the candidate(s) : Poovarasan. V

Date : **02.05.2024**

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Abstract

Lithium-ion batteries (LIBs) are widely used in industries for their numerous benefits, such as an extensive life cycle, high energy density, low self-discharge, and fast charging. The state of health (SOH) of a battery represents a measurement of a battery's ability to store and deliver electrical energy. Accurate estimation of SOH is essential for capacity estimation and the remaining useful life (RUL) time prediction of the battery.

In this project, we've decided to calculate a battery's SOH using a data-driven model. A data-driven model makes decisions by utilizing data. We have selected a benchmark dataset, the Oxford Battery Degradation dataset from the University of Oxford. By analysing the dataset using capacity degradation analysis, we have determined the battery's capacity degradation. Based on that, we have estimated the SOH of the battery. We've chosen to employ a Bidirectional Gated Recurrent Unit (Bi-GRU) to develop a predictive model that forecasts the SOH of the battery. Bi-GRU is well-regarded for its ability to capture intricate, non-linear relationships within data. The model has been trained effectively, yielding experimental results that demonstrate a low root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) value, indicating its robust performance.

Keywords: State of Health (SOH), Lithium-ion batteries (LIBs), Capacity Degradation Analysis, Bidirectional Gated Recurrent Unit (Bi-GRU).

CHAPTER 1

INTRODUCTION

Lithium-ion batteries (LIBs) are a type of rechargeable battery that is used to store and release energy. They are widely used in many industrial applications due to their extensive life cycle, high energy density and high efficiency. For effective and environmentally friendly transportation, LIBs are mostly utilized in electric vehicles. They are also necessary for consumer electronics since they offer laptops and smartphones with portable, long-lasting power. Clean energy from renewable energy sources, such as solar and wind power, is made quicker to store and distribute with the help of LIBs.

Recent research on LIBs is focused on enhancing safety features, increasing energy density for longer-lasting power, exploring sustainable materials and recycling methods, and developing advanced technologies like solid-state batteries. These initiatives seek to meet the world's rising energy needs, enhance environmental sustainability, and promote the transition to greener energy sources.

1.1 Battery Management System (BMS)

A BMS plays an essential role in the safe and efficient operation of rechargeable batteries. It monitors and controls several critical parameters, and it also balances the voltages and temperatures of individual cells in multiple-cell configurations. The BMS protects the battery from overcharging or over discharging. It actively controls the temperature during operation. It optimizes the battery’s performance, efficiency, and longevity.

BMS are used in a wide range of applications where rechargeable batteries are employed to ensure their safe and efficient operation. Some common applications of BMS include:

- Electric Vehicles
- Renewable Energy Systems
- Uninterruptible Power Supplies (UPS)
- Portable Electronics
- Medical Devices
- Aerospace and Aviation

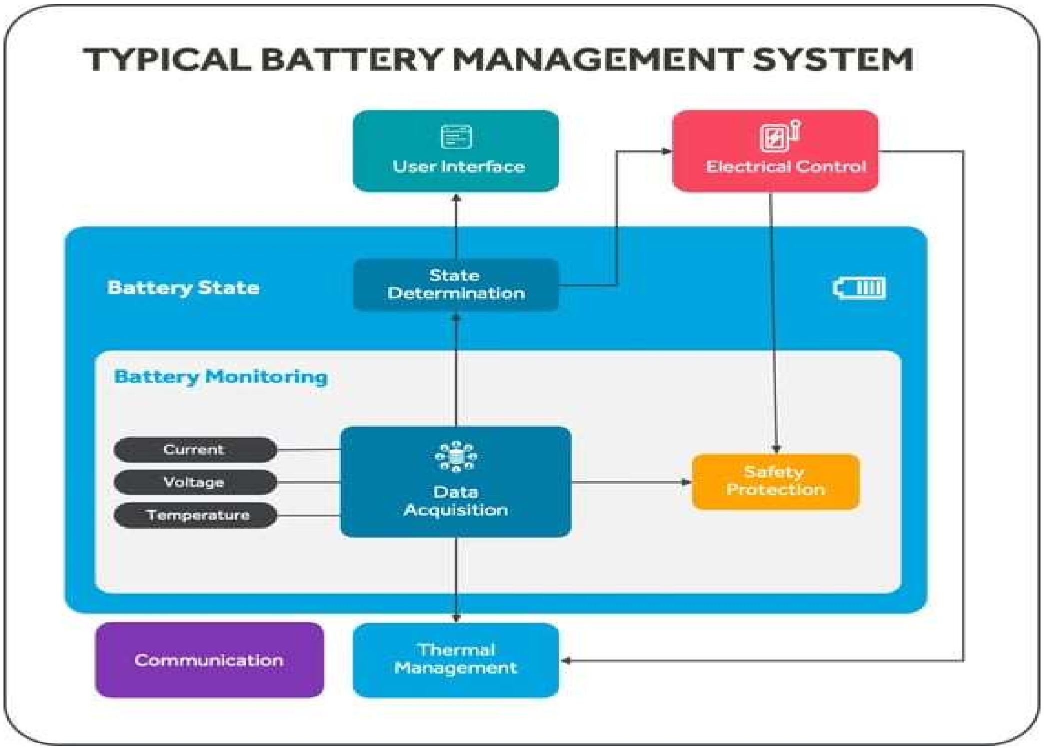


Fig.1 Battery Management System

1.2 Battery States

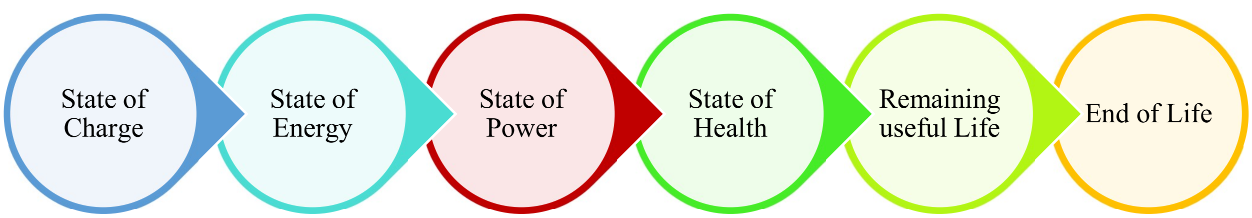


Fig.2 Battery States

State Of Charge (SOC): The BMS continuously monitors the SOC, indicating how much charge is left in the battery. It helps prevent overcharging or deep discharging, which can degrade battery life.

State of Health (SOH): The SOH of a battery represents a measurement of a battery's ability to store and deliver electrical energy.

State Of Energy (SOE): The SOE represents the amount of energy stored in a battery or energy storage system, crucial for understanding available capacity and optimizing energy use.

State Of Power (SOP): It's the batteries present ability to provide power under certain voltage and current limit.

Remaining Useful Life (RUL): It represents the estimated remaining operational lifespan or durability of a component or system, often used in predictive maintenance and reliability analysis.

End-Of-Life State (EOL): When a battery can no longer provide sufficient energy storage or has reached the end of its useful life, it enters the end-of-life state. Proper disposal and recycling are crucial for environmentally responsible handling of batteries in this state.

1.3 State of Health (SOH)

The SOH is a measurement of a battery's ability to store and deliver electrical energy, indicates the battery's overall health and performance. It is a vital indicator in a BMS that ensures efficient use of energy, accurate fault diagnosis, and a decrease in unscheduled maintenance costs.

Fig.3 State of Health

The SOH of a battery can be determined using the following methods. They are,

- Capacity Degradation analysis
- Internal resistance - increment analysis

Capacity reduction indicates how much a LIBs energy storage capacity has decreased as it ages. Resistance increment measures the increase in internal resistance within the battery, reflecting its declining efficiency and performance. In order to evaluate a battery's condition and determine when maintenance or replacement is required, both characteristics are crucial. The capacity degradation analysis will be used in this study to determine the battery's state of health.

1.4 Motivation

The motivation for estimating and predicting the SOH for lithium-ion batteries is driven by several crucial criteria and considerations:

Sustainable Energy: Battery technology plays a vital role in the transition to sustainable and renewable energy sources, making it an exciting area to contribute to environmental preservation.

Electric Vehicles: The booming electric vehicle market offers a platform to work on batteries that can transform transportation and reduce carbon emissions.

Research and Development: The SOH estimation is essential for battery manufacturers and researchers to improve battery technology and design.

Industry Relevance: Working on SOH is relevant and valuable in a wide range of industrial applications, including, electric vehicles, energy, aerospace, and consumer electronics.

Medical Devices and Healthcare: Battery-powered medical devices such as implantable medical devices, wearable health monitors, and portable medical equipment rely on lithium-ion batteries for power. Predicting the SOH of these batteries is essential to ensure the safety and effectiveness of medical devices, especially in life-critical situations where reliable power sources are paramount.

Remote Monitoring and IoT Devices: The widespread adoption of Internet of Things (IoT) devices and remote monitoring systems across various industries has led to the common use of lithium-ion batteries to power sensors, data loggers, and other IoT devices. Accurate estimation of battery State of Health (SOH) is crucial for enhancing the performance and reliability of these devices, particularly in remote or inaccessible locations where battery replacement poses challenges.

CHAPTER 2

LITERATURE SURVEY

Assessing SOH is crucial for battery system reliability and longevity. Various methodologies, such as data-driven models and empirical techniques, are used to estimate SOH accurately. Maintaining optimal SOH is vital for enhanced battery performance and preventing premature degradation. Ongoing research aims to advance SOH estimation methods to meet diverse application demands, including electric vehicles and renewable energy storage.

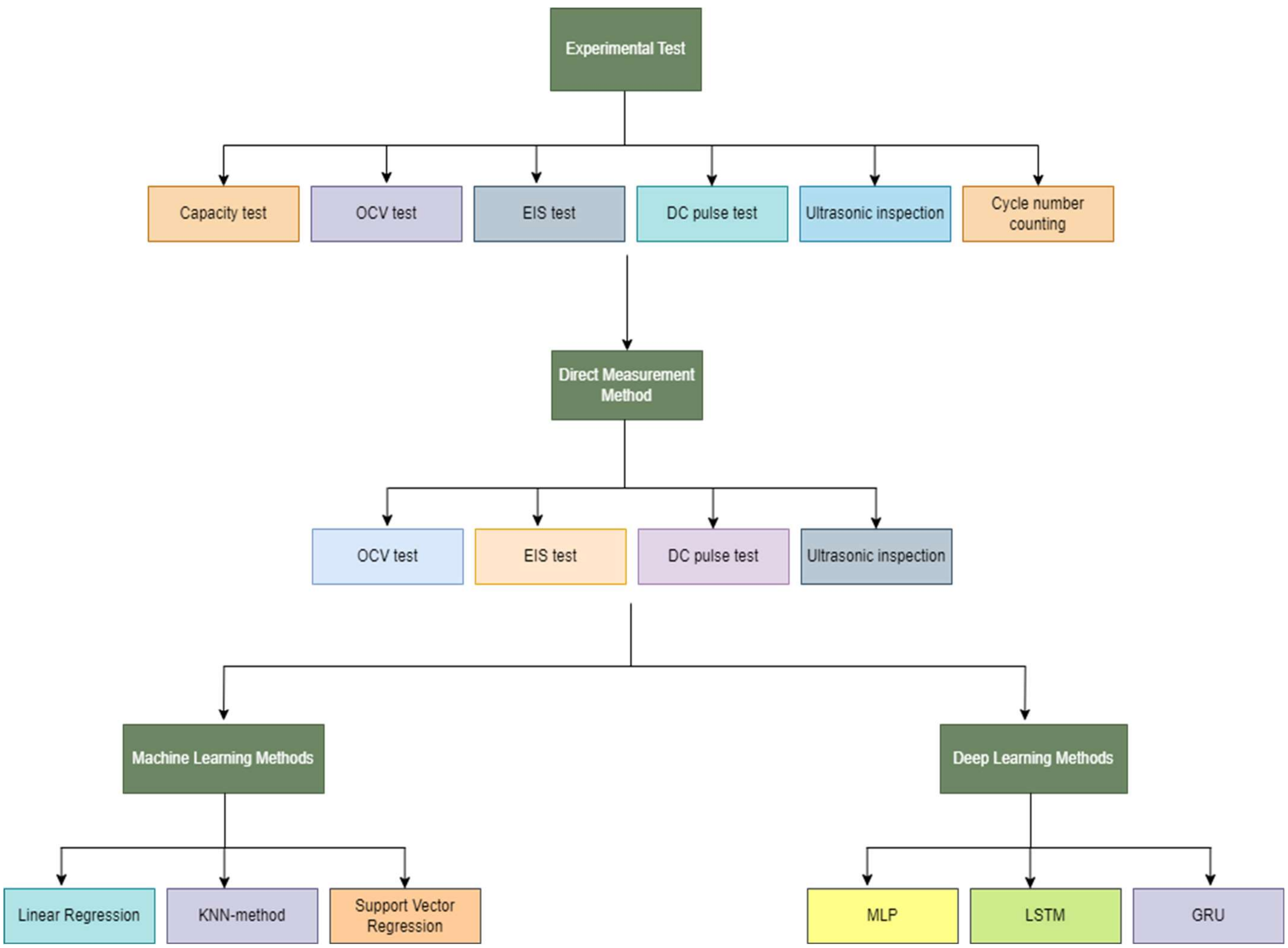


Fig.4 Methodologies in Literature [5]

The techniques mentioned above are presently utilized to extract data from the battery and estimate its SOH via a data-driven approach.

The literature on state of health estimation in lithium-ion batteries for electric vehicle (EV) applications underscores the critical importance of accurately assessing battery health for optimal vehicle performance and longevity. Various methodologies have been explored to achieve this, with a primary focus on deep learning techniques, wearable sensors, machine learning approaches, and real-time monitoring systems.

Deep learning methods have emerged as promising tools for SOH estimation in lithium-ion batteries, leveraging complex neural networks to analyze extensive datasets generated during battery operation. These techniques enable accurate prediction of battery degradation and remaining useful life, crucial for ensuring reliable performance and safety in EVs. However, challenges such as data scarcity and interpretability need to be addressed to enhance the robustness of deep learning-based estimations.

Research in SOH estimation for lithium-ion EV batteries has witnessed significant advancements across various methodologies. Machine learning approaches have been extensively explored, with studies focusing on the application of algorithms such as neural networks, support vector machines, and random forests. These approaches aim to predict battery degradation and remaining useful life accurately. Challenges like data scarcity and model interpretability persist, necessitating further research to enhance the reliability of machine learning-based SOH estimations.

Data-driven approaches have been a prominent in SOH estimation research for lithium-ion EV batteries. Techniques such as statistical modelling and artificial intelligence have been employed to analyze battery performance data and predict degradation. These methods play a crucial role in optimizing battery management systems and extending battery lifespan. However, challenges related to data quality and scalability remain, underscoring the need for robust data-driven methodologies.

The integration of deep learning techniques has shown promise in enhancing SOH estimation accuracy. Deep learning architectures such as convolutional neural networks and recurrent neural networks offer the capability to process large volumes of battery data and extract meaningful features for degradation prediction. Despite their potential, challenges regarding model complexity and training data availability need to be addressed to fully leverage deep learning-based SOH estimation in practical EV applications.

Real-time SOH estimation techniques have also been a focus of research, aiming to provide timely insights into battery health during EV operation. These techniques leverage model-based approaches, data-driven algorithms, and hybrid models to estimate battery degradation and remaining capacity in real-time. However, ensuring accuracy and reliability in real-time estimations poses significant challenges, particularly in dynamic EV operating conditions. Addressing these challenges is crucial for the practical deployment of real-time SOH estimation techniques in EVs, ultimately contributing to improved battery management and vehicle performance.[5][7][8][9]

2.1 OBJECTIVES

Safety Assurance: Safety assurance in battery systems, utilizing SOH estimations, helps to avoid thermal runaway issues, Ensuring secure and reliable operation and safeguarding lives and assets.

Historical Analysis: Analysing past data to spot patterns and trends that might point to modifications in the battery's condition.

Predictive Modelling: Using advanced machine learning algorithms, develop a predictive model that can forecast the battery's future behaviour, aiding in proactive maintenance and replacement decisions.

Optimization: Optimize battery performance by fine-tuning charging and discharging strategies, ensuring a balance between achieving desired operational goals and preserving SoH.

Consumer Confidence Enhancement: Providing transparent information on battery health through SOH estimations can enhance consumer confidence in products incorporating battery technology. Clear documentation of battery performance and longevity can instill trust in consumers regarding the reliability and safety of devices, leading to increased customer satisfaction and brand loyalty.

Research Advancement: Continuous refinement and validation of SOH estimation techniques contribute to the advancement of battery research and development. Insights gained from analyzing battery behaviour and degradation patterns can drive innovation in battery materials, design, and manufacturing processes, leading to the development of more efficient, durable, and sustainable battery technologies.

CHAPTER 3

METHODOLOGY

3.1 Dataset Description

The Oxford Battery Degradation dataset, compiled by the University of Oxford, focuses on eight lithium-ion pouch cell batteries. Through rigorous testing across multiple charging and discharging cycles, the data was extracted. Key parameters such as voltage, current, temperature and capacity are measured over time. This dataset enables the examination of degradation patterns in batteries and facilitates the development of predictive models to estimate battery health.[10]

TYPE	INFORMATION
Battery Type	Lithium Cobalt Oxide Battery - Pouch Cell
Battery Quantity	8
Rated Capacity	740mah
Charging Mode	1c
Charging Temperature	40 Degrees Celsius
Nominal Voltage	2.7
Cutoff Voltage	4.2

Table-1 Battery Description

The above table represents the information about the battery that was utilised by the University of Oxford.

Cycle	Voltage	Capacity	Temperature
0	2.719213	0.000049	41.295536
0	2.856135	0.206339	41.000046
0	2.877108	0.412724	40.962608
0	2.892908	0.619110	40.987579
0	2.906382	0.825497	41.049992

Table-2 Raw Data

3.2 Data-Preprocessing

First, I selected the essential features from the dataset required for the analysis and extracted the relevant data. Subsequently, I addressed missing values using a linear interpolation method to ensure the dataset's completeness. This method maintains the temporal integrity of the data while filling in the gaps. By doing so, the dataset becomes complete and ready for analysis.

3.3 Data-Driven Models

Data-driven models refer to computational algorithms and techniques that utilize large volumes of data to make predictions, identify the patterns, and optimize decision-making processes [11]. In the context of battery management, data-driven models analyse extensive datasets from batteries, considering factors such as charge-discharge cycles, Capacity, temperature variations and voltages.

These models employ machine learning, deep learning algorithms and statistical methods to enhance battery performance and enable intelligent management strategies. Data-driven models make a substantial contribution to improving battery efficiency, extending lifespan, and guaranteeing dependable and sustainable energy storage solutions by utilizing data. Their integration into battery management systems revolutionizes the approach to energy storage, offering smarter and more sustainable solutions for various industries and applications.

3.4 Capacity Degradation Analysis

The capacity degradation of lithium-ion (Li-ion) batteries over time and cycles is primarily due to several factors:

Chemical Changes: During charging and discharging cycles, chemical reactions occur within the battery electrodes and electrolyte. These reactions can cause the formation of unwanted compounds or structural changes within the electrodes, leading to a decrease in the battery's ability to store and release energy efficiently.

Electrode Degradation: Over repeated charge and discharge cycles, the active materials in the positive and negative electrodes of the battery can degrade. This degradation may involve physical changes such as particle cracking, loss of active material, or the formation of a passivation layer on the electrode surfaces, all of which contribute to reduced capacity.

Electrolyte Decomposition: The electrolyte in a Li-ion battery can also degrade over time due to chemical reactions with the electrodes or exposure to high temperatures. This degradation can lead to a decrease in the electrolyte's ability to transport lithium ions, which affects the battery's overall performance and capacity.

Formation of Solid-Electrolyte Interface (SEI): When a Li-ion battery is initially charged, a thin layer called the solid-electrolyte interface (SEI) forms on the surface of the electrodes. While the SEI layer is necessary for the battery's operation, it can continue to grow and change over time, which can increase the internal resistance of the battery and decrease its capacity.

Mechanical Stress: Expansion and contraction of the electrodes during charge and discharge cycles can cause mechanical stress on the battery's components. This stress can lead to the degradation of electrode materials and the breakdown of electrical connections within the battery, further contributing to capacity loss.

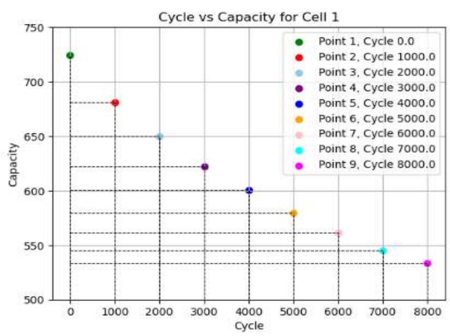
Overall, these various factors contribute to the gradual degradation of a Li-ion battery's capacity over time and cycles. The rate of degradation can depend on factors such as the battery's design, operating conditions, charging/discharging protocols, and the quality of its materials. So, analyzing the capacity degradation of the battery over time or cycles is also an effective method for estimating the SOH of the battery[12].

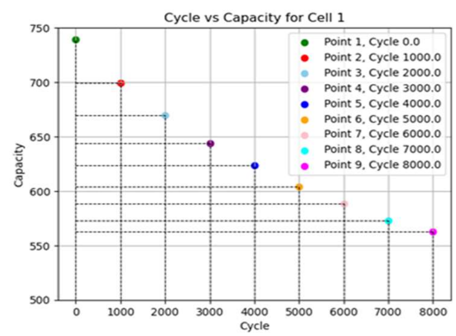
In the realm of charging and discharging lithium-ion batteries, two key capacities are at play:

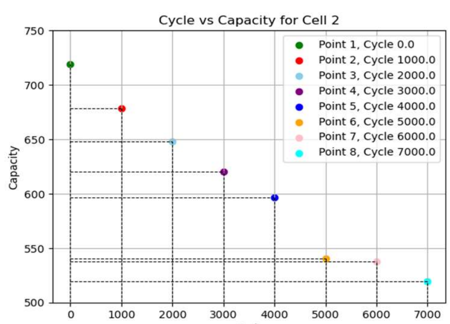
Charging Capacity: This refers to the amount of charge that can be added to the battery during the charging process. It is typically measured in ampere-hours (Ah) or watt-hours (Wh) and represents the maximum amount of energy that the battery can store when fully charged.

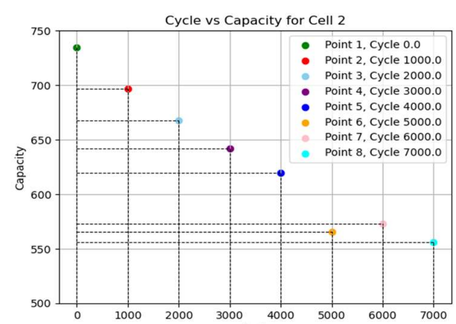
Discharging Capacity: This represents the amount of charge that can be extracted from the battery during the discharging process. Similar to charging capacity, it is measured in ampere-hours (Ah) or watt-hours (Wh) and indicates the usable energy available from the battery when it is being used to power a device or system.

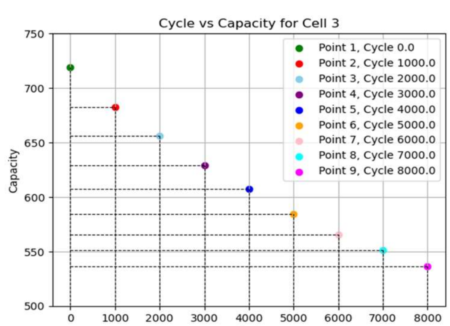
Both charging and discharging capacities are important parameters for assessing the performance and efficiency of lithium-ion batteries. Understanding how these capacities change over time and cycles can provide valuable insights into battery degradation and state of health estimation.

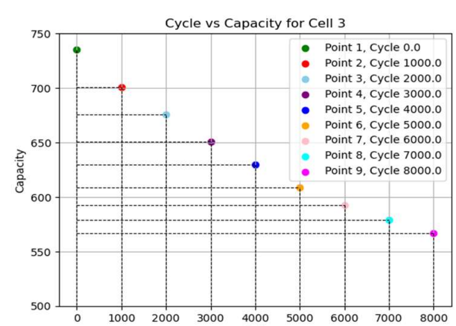


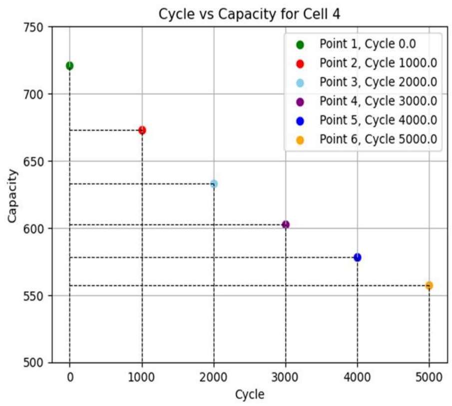


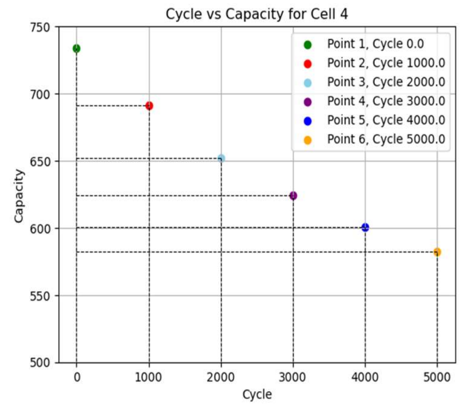


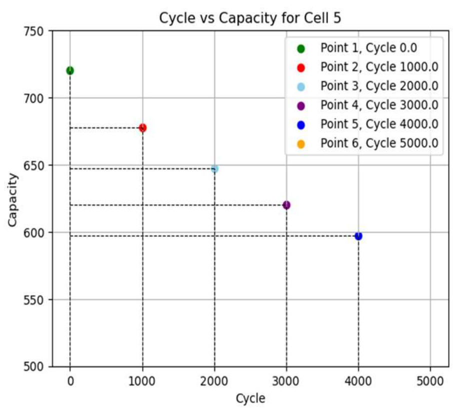


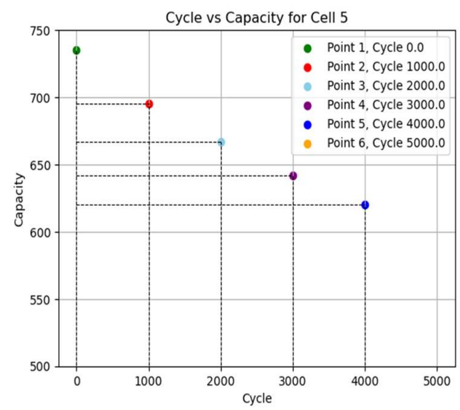





Cycle vs Capacity for Cell 4
Point 1, Cycle 0.0
Point 2, Cycle 1000.0
Point 3, Cycle 2000.0
Point 4, Cycle 3000.0
Point 5, Cycle 4000.0
Point 6, Cycle 5000.0
Capacity
Cycle


Cycle vs Capacity for Cell 4
Point 1, Cycle 0.0
Point 2, Cycle 1000.0
Point 3, Cycle 2000.0
Point 4, Cycle 3000.0
Point 5, Cycle 4000.0
Point 6, Cycle 5000.0
Capacity
Cycle


Cycle vs Capacity for Cell 5
Point 1, Cycle 0.0
Point 2, Cycle 1000.0
Point 3, Cycle 2000.0
Point 4, Cycle 3000.0
Point 5, Cycle 4000.0
Point 6, Cycle 5000.0
Capacity
Cycle


Cycle vs Capacity for Cell 5
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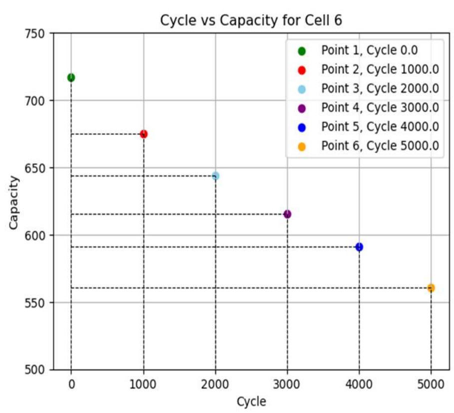
Point 2, Cycle 1000.0
Point 3, Cycle 2000.0
Point 4, Cycle 3000.0
Point 5, Cycle 4000.0
Point 6, Cycle 5000.0
Capacity
Cycle


Cycle vs Capacity for Cell 6
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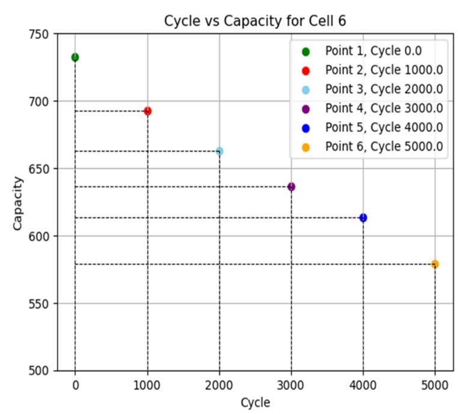
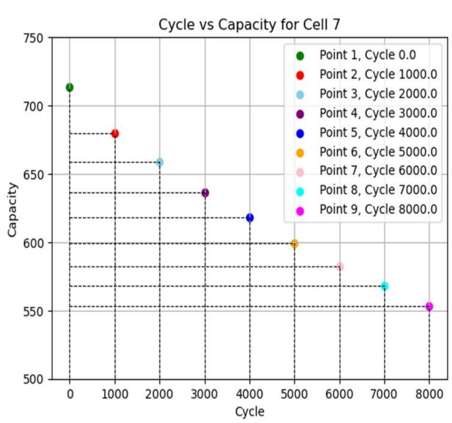
Point 2, Cycle 1000.0
Point 3, Cycle 2000.0
Point 4, Cycle 3000.0
Point 5, Cycle 4000.0
Point 6, Cycle 5000.0
Capacity
Cycle


Cycle vs Capacity for Cell 6
Point 1, Cycle 0.0
Point 2, Cycle 1000.0
Point 3, Cycle 2000.0
Point 4, Cycle 3000.0
Point 5, Cycle 4000.0
Point 6, Cycle 5000.0
Capacity
Cycle


Cycle vs Capacity for Cell 7
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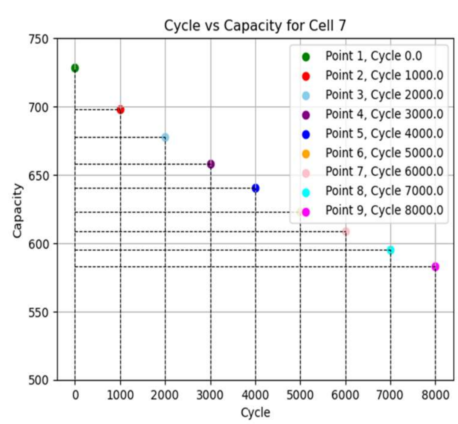
Point 2, Cycle 1000.0
Point 3, Cycle 2000.0
Point 4, Cycle 3000.0
Point 5, Cycle 4000.0
Point 6, Cycle 5000.0
Point 7, Cycle 6000.0
Point 8, Cycle 7000.0
Point 9, Cycle 8000.0
Capacity
Cycle


Cycle vs Capacity for Cell 7
Point 1, Cycle 0.0
Point 2, Cycle 1000.0
Point 3, Cycle 2000.0
Point 4, Cycle 3000.0
Point 5, Cycle 4000.0
Point 6, Cycle 5000.0
Point 7, Cycle 6000.0
Point 8, Cycle 7000.0
Point 9, Cycle 8000.0
Capacity
Cycle

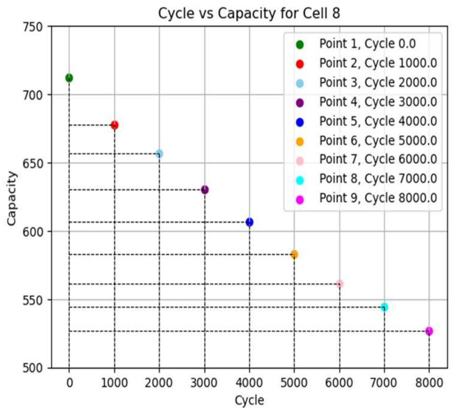


Fig.5 Degradation of Charge Sheet

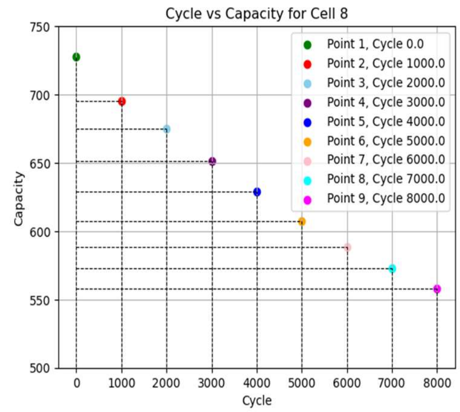


Fig.6 Degradation of Discharge Sheet

After successfully analyzing the capacity degradation, we have successfully estimated the state of health (SOH) of the battery and obtained a new data frame.

Cell	Cycle	Capacity	Degradation	Battery Health
1	0	724.120891	2.145825	97.854175
1	100	714.535043	3.441210	96.558790
….	….	….	….	….
1	8200	530.596118	28.297822	71.702178

Table-3 Final Data Frame Charge Sheet

Cell	Cycle	Capacity	Degradation	Battery Health
1	0	739.110921	0.120146	99.879854
1	100	730.192949	1.325277	98.674723
….	….	….	….	….
1	8200	560.649583	24.236543	75.763457

Table-4 Final Data Frame Discharge Sheet

3.5 Bi-directional Gated Recurrent Unit (Bi-GRU)

Bidirectional Gated Recurrent Unit (Bi-GRU) is a sophisticated neural network architecture renowned for its efficacy in sequence modelling tasks, particularly in the realm of natural language processing and time series analysis. Unlike traditional recurrent neural networks (RNNs), which process input sequences in a single direction, Bi-GRU incorporates two GRU layers, each processing the input sequence in opposite directions one from past to future and the other from future to past. This bidirectional processing allows the model to capture both past and future context, enabling more comprehensive understanding and representation of sequential data.

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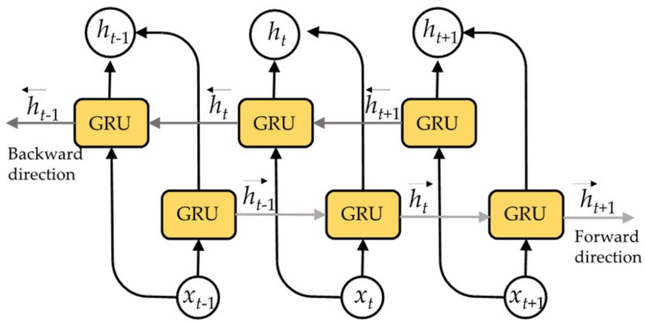

Fig.7 Gated Recurrent Unit [13]

Bi-GRU has demonstrated remarkable performance in various applications, including sentiment analysis, machine translation, and speech recognition. In the context of battery health estimation, Bi-GRU excels in capturing the temporal dependencies and intricate patterns inherent in battery degradation processes. By analyzing historical data of battery performance, Bi-GRU can effectively learn the underlying dynamics and predict the State of Health (SOH) with high accuracy.

3.6 Rectified Linear Unit (ReLU) Activation Function

ReLU is one of the most widely used activation functions in deep learning models due to its simplicity and effectiveness. It addresses the vanishing gradient problem encountered with other activation functions like sigmoid and tanh by allowing the model to learn faster and converge more quickly during training.

ReLU sets all negative values to zero and passes positive values unchanged, making it computationally efficient and easy to implement. Its non-linearity enables the model to learn complex relationships between features, resulting in improved model performance.

3.7 Adam Optimizer

Adam (Adaptive Moment Estimation) is a popular optimization algorithm widely used in training deep neural networks. It combines the benefits of both AdaGrad and RMSProp optimization algorithms. Adam maintains per-parameter learning rates that are adapted based on the estimates of the first and second moments of the gradients.

It performs well on a wide range of deep learning tasks and is particularly effective for models with large datasets and high-dimensional parameter spaces. Adam optimizes the learning process by adjusting the learning rates dynamically for each parameter, resulting in faster convergence and better generalization performance.

In our experimentation, the combination of ReLU activation function and Adam optimizer consistently outperformed other combinations of activation functions and optimizers. This pairing not only accelerated convergence but also enhanced model performance, yielding superior results in terms of accuracy and efficiency. Furthermore, our observations suggest that ReLU's ability to mitigate vanishing gradients and Adam's adaptive learning rate mechanism synergistically contribute to the success of this combination, making it the preferred choice for optimizing deep learning models in our context.

3.8 Model Architecture

In this Bi-GRU model, we input the cycle, capacity, and degradation values to predict the battery's health. The model architecture comprises:

Input Layer:

- Bi-GRU with 512 units, which enables the model to capture bidirectional temporal dependencies in the input data.

Hidden Layers:

- Bi-GRU with 256 units, providing a balance between model complexity and computational efficiency while capturing deeper temporal features.

Fully Connected Layers:

- Dense layer with 128 units and ReLU activation function, facilitating nonlinear transformations and feature extraction from the GRU output.
- Dense layer with 1 unit and Linear activation function, serving as the output layer for predicting the battery's health.

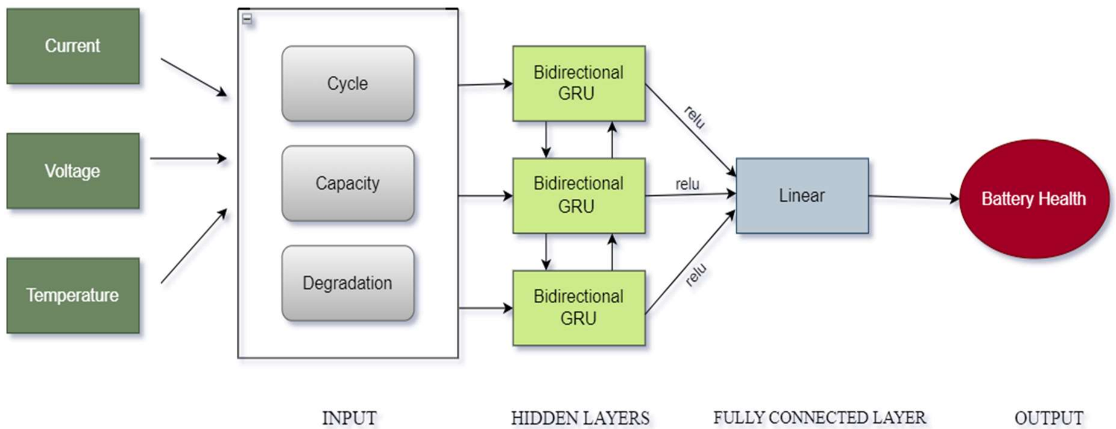

Fig.8 Model Architecture

Model Interpretation:

- The bidirectional nature of the GRU layers allows the model to capture both past and future dependencies in the input sequences, enhancing its ability to predict the battery's health based on historical data.
- The presence of hidden layers with decreasing units helps the model extract hierarchical features and patterns from the input data, leading to improved predictive performance.
- Utilizing ReLU activation functions within the hidden layers introduces non-linearity, enabling the model to capture complex patterns and relationships in the input data more effectively, enhancing its predictive capacity for battery health estimation.
- The final dense layer with linear activation provides a continuous output representing the estimated health of the battery, allowing for direct interpretation and comparison with ground truth values.
- Incorporating the Adam optimizer during model training facilitates faster convergence by dynamically adjusting learning rates for each parameter based on past gradients, thereby accelerating the optimization process and improving the overall efficiency and effectiveness of the training procedure.
- Overall, this model architecture is designed to effectively leverage the sequential nature of the input data and capture complex relationships between cycle, capacity, degradation, and battery health.

3.9 Workflow

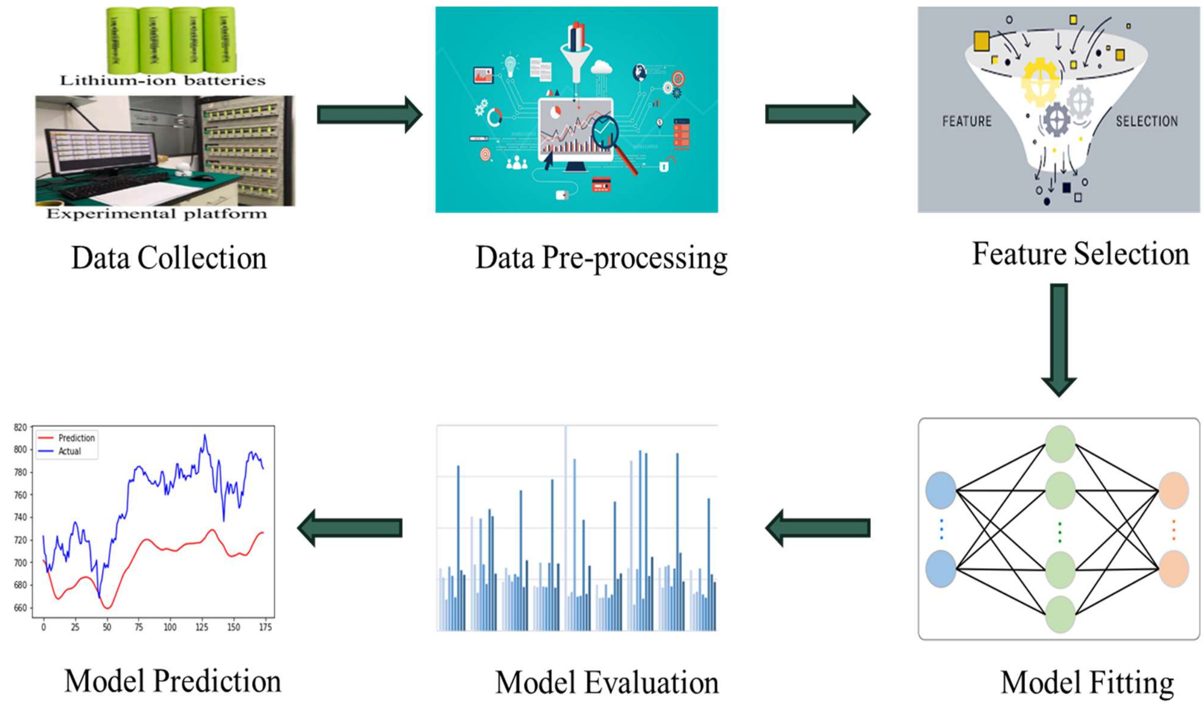

Fig.9 Workflow

- Initially, the Oxford Battery Degradation dataset benchmark data was acquired from the University of Oxford.
- Select and extract the required features from the raw data, including cycle number, capacity. Select and extract the required features from the raw data, including cycle number and capacity. To make sure the dataset is complete, the linear interpolation approach is used to fill in any missing values, and a new data frame was created for the pre-processed data for additional investigation.
- After conducting thorough capacity degradation analysis, the battery's degradation values were obtained. Utilizing these values, SOH is estimated, resulting in the creation of a new data frame.
- The Bidirectional GRU is employed to develop a predictive model for forecasting the SOH of the battery. The deployed model is evaluated using metrics such as MAE, RMSE, MAPE.

CHAPTER 4

RESULTS AND DISCUSSION

Based on capacity degradation analysis the SOH of the battery is calculated:

SOH = CP/CN × 100%

where CP denotes the current practical capacity and CN is the nominal capacity of the battery.

The Bi-GRU is employed to develop a predictive model for forecasting the SOH of the battery. The deployed model is evaluated using metrics such as mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE).

The RMSE is the squared differences between predicted and actual values. The RMSE is defined as follow:

$$\text{RMSE} = \sqrt{\sum_{i=1}^{n} |x' - x|^2 / \text{n}}$$

x'- Predicted SOH value, x-Actual SOH value and n- number of predicted points.

MAE is calculated as the average of the absolute differences between the predicted values (x') and the actual values (x). The MAE is defined as follow:

$$\text{MAE} = \frac{\sum_{i=1}^{n} |\hat{x}_i - x|}{n}$$

$\hat{x}_i$ - Predicted SOH value, x-Actual SOH value and n- number of predicted points.

The MAPE is the average absolute percentage difference between the predicted and actual values. The MAPE is defined as follows:

$$\text{MAPE} = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{x_i - x}{x} \right|$$

x_i- Predicted SOH value, x-Actual SOH value and n- number of predicted points.

RESULTS OBTAINED IN BIDIRECTIONAL GRU MODEL	
Metrics	**Results**
Mean Absolute Percentage Error (MAPE)	0.2936
Mean Absolute Error (MAE)	0.2385
Root Mean Squared Error (RMSE)	0.2826

Table-5 Charge Sheet Results

RESULTS OBTAINED IN BIDIRECTIONAL GRU MODEL	
Metrics	**Results**
Mean Absolute Percentage Error (MAPE)	0.0963
Mean Absolute Error (MAE)	0.0823
Root Mean Squared Error (RMSE)	0.0975

Table-6 Discharge Sheet Results

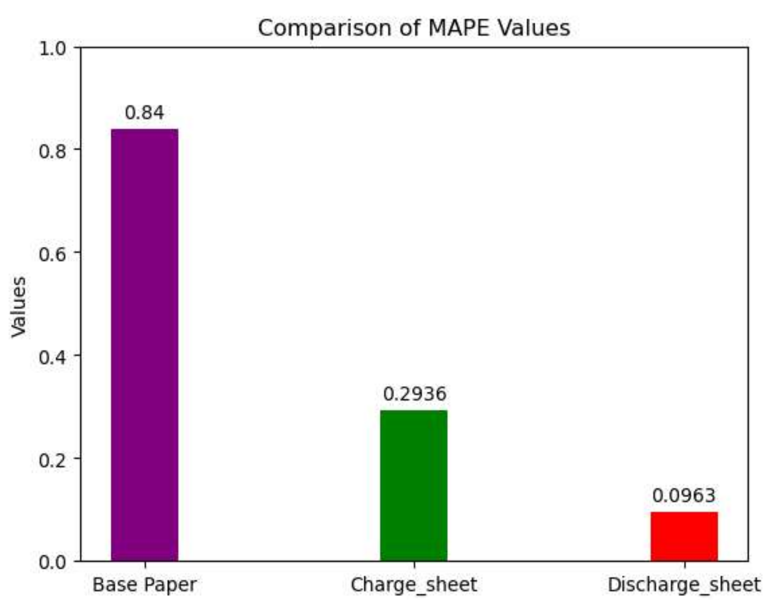

Fig.10 Comparison of Results

The above results were obtained from the Bi-GRU model, employing ReLU activation and the Adam optimizer, indicating a notable improvement in accuracy. The proposed model achieved a MAPE value of 0.2936 for charge sheet prediction, surpassing the reported value of 0.84 in the base paper. This outcome demonstrates the effectiveness of the chosen model architecture and optimization strategy.

The model exhibited high precision in discharge sheet prediction, yielding a MAPE value of 0.0963, showcasing its effectiveness. Additional error metrics, including MAE and RMSE, provide valuable insights into the model's accuracy and performance characteristics, enhancing our understanding about the model.

From the above, it's evident that we have achieved promising results, indicating that the deep learning model has excelled in capturing essential patterns and providing dependable predictions. This demonstrates the model's robust ability to generalize its knowledge to unseen data.

CHAPTER 5

CONCLUSION AND FUTURE WORK

5.1 Conclusion

In conclusion, our utilization of the bidirectional-GRU model represents a significant advancement in battery health monitoring and management. By exploring capacity degradation analysis and comprehending the underlying dynamics, we have developed a model that exceeds the capabilities of the base paper. The bidirectional-GRU's adeptness at capturing intricate patterns and temporal dependencies has yielded promising results. This success not only underscores the effectiveness of our approach but also hints at the potential for substantial progress in ensuring the reliability and longevity of battery systems across various applications.

5.2 Future Work

- Our current research is centred on estimating the battery's State of Health (SOH) through capacity degradation analysis, showcasing promising results.
- We aim to advance this by integrating joint estimation methods, incorporating estimations of the battery's remaining useful life (RUL) for a more comprehensive assessment.
- This comprehensive approach would provide a more thorough understanding of the battery's condition and its expected lifespan, enabling better maintenance planning and ensuring reliable performance.
- The results obtained from these methodologies will be compared and more robust machine learning/deep learning models will be developed for the accurate estimation and prediction of SOH and RUL.

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