ML DRIVEN BATTERY LONGEVITY ESTIMATION FOR ELECTRIC VECHICLES USING KNN ALGORITHM

Dr Mohanraj M
Electrical and Electronics Engineering
Kumaraguru College of Technology
Coimbatore, India
mohanraj.m.eee@kct.ac.in

Sanjay P
Electrical and Electronics Engineering
Kumaraguru College of Technology
Coimbatore, India
sanjay.20ee@kct.ac.in

Kavin M
Electrical and Electronics Engineering
Kumaraguru College of Technology
Coimbatore, India
kavin.20ee@kct.ac.in

Suriya Prasad S
Electrical and Electronics Engineering
Kumaraguru College of Technology
Coimbatore, India
suriyaprasad.20ee@kct.ac.in

***Abstract* - The rapid adoption of electric vehicles (EVs) has spurred a pressing need for effective battery management strategies to ensure prolonged battery life and optimal performance. In this context, this project introduces an innovative approach to extend the lifespan of EV batteries by harnessing the power of artificial intelligence (AI). The proposed methodology revolves around a comprehensive analysis of battery charging and discharging characteristics, facilitated by AI-driven techniques.**

The primary objective of this project is to develop a predictive model that can accurately estimate the remaining lifetime of an EV battery based on real-time battery behaviour. Leveraging AI algorithms such as machine learning and neural networks, the model integrates data from various sensors, including voltage, current, temperature, and state of charge. By processing and learning from this diverse dataset, the AI model can recognize patterns, anomalies, and stress factors that impact battery health. Furthermore, the project emphasizes the development of an adaptive battery management system that takes insights from the AI model to optimize charging and discharging processes. This approach ensures that the battery operates within safe limits while maintaining efficient performance.

Consequently, the overall EV system benefits from extended battery life, reduced maintenance costs, and increased sustainability. The significance of this project lies in its potential to revolutionize the EV industry's approach to battery management. By proactively identifying potential battery degradation factors, optimizing charging patterns, and mitigating risks, this AI-driven solution contributes to a more robust and reliable EV ecosystem. As governments, industries, and individuals alike strive for greener transportation options, the findings of this research can significantly contribute to a more sustainable and efficient future of electric mobility.

***Keywords* -KNN Algorithm, ML-driven techniques, Battery Longevity, AI Model**

I. INTRODUCTION

A lithium-ion battery or Li-ion battery (abbreviated as LIB) can store electric energy as chemical energy. Both non-rechargeable and rechargeable LIBs are commercially available. The non-rechargeable LIBs (also called primary cells) have long shelf-life and low self-discharge rates and are typically fabricated as small button cells for e.g., portable consumer electronics, arm watches and hearing aids. Rechargeable LIBs (also named secondary cells) are applied in all kinds of consumer electronics and is currently entering new markets such as electric vehicles and large-scale electricity storage. The rechargeable LIBs can be used to supply system level services such as primary frequency regulation, voltage regulation and load shifting, as well as for local electricity storage at individual households. Below we only focus on the rechargeable LIBs.

A LIB contains two porous electrodes separated by a porous membrane. A liquid electrolyte fills the pores in the electrodes and membrane. Lithium salt (e.g., $LiPF_6$) is dissolved in the electrolyte to form Li^+ and PF_6^- ions. The ions can move from one electrode to the other via the pores in the electrolyte and membrane. Both the positive and negative electrode materials can react with the Li^+ ions. The negative electrode in a LIB is typically made of carbon and the positive of a Lithium metal oxide. Electrons cannot migrate through the electrolyte and the membrane physically separates the two electrodes to avoid electrons crossing from the negative to the positive electrode and thereby internally short circuiting the battery.

When the two electrodes are connected via an external circuit the battery start to discharge. During the discharge process electrons flow via the external circuit from the negative electrode to the positive. At the same time Li+ ions leave the negative electrode and flows through the electrolyte towards the positive electrode where they react with the positive electrode. The process runs spontaneously since the two electrodes are made of different materials. In popular terms the positive electrode "likes" the electrons and the Li+ ions better than the negative electrode.

The energy released by having one Li+ ion, and one electron, leaving the negative electrode and entering the positive electrode is measured as the battery voltage times the charge of the electron. In other words, the battery voltage -

also known as the electromotive force: EMF - measures the energy per electron released during the discharge process. EMF is typically at around 3-4 Volts and depends on the LIB cell chemistry, the temperature, and the state of charge (SOC – see below). When e.g., a light bulb is inserted in the external circuit the voltage primarily drops across the light bulb and therefore the energy released in the LIB is dissipated in the light bulb. If the light bulb is substituted with a voltage source (e.g., a power supply) the process in the battery can be reversed and thereby electric energy can be stored in the battery.

The battery is fully discharged when nearly all the Lithium have left the negative electrode and reacted with the positive electrode. If the battery is discharged beyond this point the electrode chemistries become unstable and start degrading. When the LIB is fully discharged the EMF is low compared to when it is fully charged. Each LIB chemistry has a safe voltage range for the EMF and the endpoints of the range typically define 0% and 100% state of charge (SOC). The discharge capacity is measured in units of Ampere times hours, Ah, and depends on the type and amount of material in the electrodes.

The first lithium batteries were developed in the early 1970's and Sony released the first commercial lithium-ion battery in 1991. During the 90's and early 2000's the LIBs gradually matured via the pull from the cell-phone market. The Tesla Roadster was released to customers in 2008 and was the first highway legal serial production all-electric car to use lithium-ion battery cells. Further, around 2010 the LIBs expanded into the energy storage sector.

II. PROBLEM STATEMENT

The problem at hand is the need to predict the remaining lifespan of Li-ion batteries in Electric Vehicles (EVs) to prevent the premature degradation of these batteries. Li-ion batteries in EVs often consist of multiple cells connected in series and parallel, where the failure of one cell can lead to the deterioration of others, potentially rendering the entire battery pack unusable. Additionally, with the growth of the second-use EV battery market, understanding the state of health and performance of these batteries is crucial for repurposing them for applications like energy storage. This poster aims to address these challenges through data-driven analysis of used EV battery packs to optimize their secondary use and reduce waste.

III. EXISTING METHODOLOGIES

There are 3 approaches to estimate the SOH of the batteries - direct measurement, model-based and data-driven methods.

DIRECT MEASUREMENT APPROACH

The direct measurement approach uses variables such as internal resistance, impedance, open circuit voltage (OCV) and charge/discharge current to estimate the battery SOH. Although these approaches are usually less computationally complex, they are either time consuming or they are not directly provided by the BMS as mentioned in, making them unsuitable for online estimation.

MODEL - BASED APPROACH

In model-based approach, electrochemical models (EM) are used to model chemical and physical aging mechanisms of the battery using a series of non-linear and partial differential equations. To estimate the SOH of the battery, the number of cyclable Li-ions in the electrodes is calculated, considering multiple factors depending on its complexity, such as the loss of Li-ions due to the growth of the Solid Electrolyte Interface (SEI). However, these models are simplified and may not be able to reflect the changes in SOH that the battery faces in real-time.

DATA - DRIVEN APPROACH

Data-driven methods work by fitting huge amounts of past experimental data of key HIs and their associated SOH to predict the SOH of the battery. These HIs could be provided by the BMS in real time, allowing for online estimation as opposed to direct measurement approach. It also does not require any information on the aging mechanisms of the Li-Ion battery, allowing it to make more complex mapping between the HIs and SOH that are not picked up by EMs.

IV. PROPOSED SOLUTION

A lithium-ion life estimation system consists of Node MCU as a main controller which monitors the charging and discharging status of the battery, and these values are recorded and sends the data to cloud using ESP8266 Wi-Fi module. The current status of lithium-ion battery is displayed through lcd display. The charging and discharging rate is stored in the form of ampere per hour. Moreover, our system uses KNN algorithm which classifies the number of used cycles of the battery by comparing the hardware data from cloud with the existing dataset from the number of used cycles the remaining cycles and life is calculate. The project was planned on the basis that, in the future E-Vehicles will play a major part in transportation and this project can be useful for that.

The project commences at the foundational level, drawing power from a 230V AC supply, which is meticulously rectified to establish a stable DC supply. This DC power serves as the backbone for a sophisticated sensor network, incorporating temperature, current, and voltage sensors strategically placed to monitor critical battery parameters. To facilitate the dynamic charging and discharging of the lithium-ion battery, a specialized circuit is employed, governed by relay mechanisms. The relay system, comprising two relays one dedicated to charging and the other to discharging provides precise control over the energy flow within the system.

The operational sequence is orchestrated by a microcontroller, the linchpin of the entire setup, initially establishing connectivity to WiFi or the internet for seamless

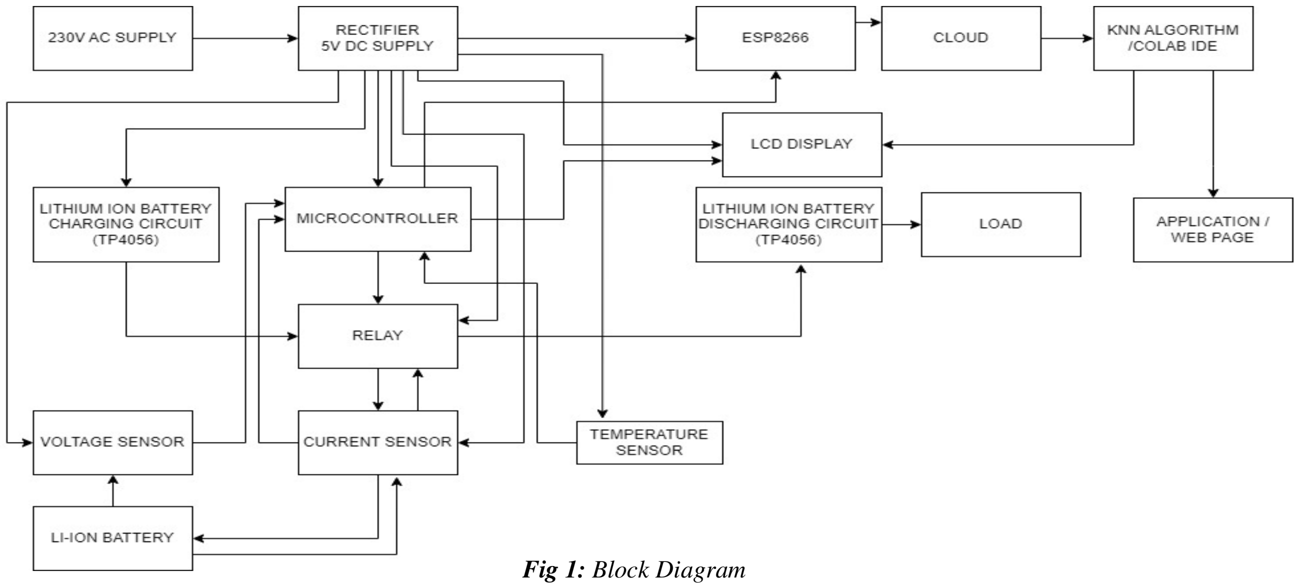

Fig 1: *Block Diagram*

data transfer to the cloud. Once the cloud interface is established, the relay system is activated, initializing both the charging and discharging processes. As the charging commences, sensors meticulously measure the charging current and voltage, capturing real-time data that is subsequently transmitted to the cloud via the microcontroller. A parallel process is executed during discharging, where sensors diligently record discharging current and voltage, sending this valuable dataset to the cloud infrastructure.

The culmination of this data in the cloud serves as the foundation for the application of the KNN algorithm, a machine learning technique chosen for its aptitude in predicting battery longevity. Leveraging historical data, the algorithm computes and forecasts the remaining cycles or useful time of the lithium-ion battery. The outcome of this computational endeavor is then seamlessly integrated into two distinct interfaces - the vehicle displays and a user-accessible website. The vehicle display offers an instantaneous snapshot of the predicted useful cycles, providing drivers with crucial insights into their battery's health. Simultaneously, the website interface extends this information to the user, fostering transparency and enabling remote monitoring of the electric vehicle's battery status. In essence, this methodology not only encapsulates a cutting-edge technical approach but also underscores the imperative of providing users with accessible and actionable insights into the longevity of their electric vehicle batteries.

The primary components used in this system are:

NodeMCU Controller: The NodeMCU serves as the central controller responsible for monitoring the battery's charging and discharging status. It is connected to various sensors and modules to collect data.

ESP8266 Wi-Fi Module: The ESP8266 module enables wireless communication between the system and the cloud platform. It sends the collected data to the cloud for analysis.

LCD Display: The system utilizes an LCD display to present real-time information about the Li-ion battery's current status, such as voltage, temperature, and state of charge.

Current Sensors: Current sensors are used to measure the charging and discharging rates of the battery. These values are collected in ampere-hours (Ah).

Data Acquisition and Monitoring: The NodeMCU continuously monitors the Li-ion battery's charging and discharging status. It collects data on voltage, temperature, charging rate, and discharging rate. The data is then stored and processed for further analysis.

Data Transmission to the Cloud: The ESP8266 Wi-Fi module facilitates the transfer of data to a cloud-based platform. The collected data is sent to the cloud server for storage and analysis.

Data Display on LCD: The real-time data, including voltage, temperature, and current status, is displayed on the LCD connected to the NodeMCU. This allows users to observe the battery's condition at a glance.

Data Preprocessing: Before applying the KNN algorithm, the collected data is pre-processed to ensure its quality and relevance. This step may involve data cleaning, normalization, and feature selection.

V. ML ALGORITHM

The KNN algorithm is employed to classify the number of used cycles of the battery. It does this by comparing the hardware data from the cloud with an existing dataset. The KNN algorithm calculates the similarity between the current battery's data and historical data to estimate its state of health.

The K- Nearest Neighbors (KNN) algorithm is an on-parametric supervised machine learning algorithm used for both bracket and retrogression tasks. It's a simple yet effective algorithm that relies on the conception of similarity to make prognostications. The KNN algorithm works by chancing the K nearest neighbors to a given data point in the point space. The value of K is a stoner- defined parameter that determines the number of neighbors to consider. The algorithm also assigns a class or predicts a value for the data point grounded on the maturity class or average value of its K nearest neighbors.

VI. WORKING OF ALGORITHM

Loading the training dataset: The algorithm begins by loading a labelled training dataset, comprising feature vectors and their corresponding class labels or target values. This dataset serves as the foundation for making predictions.

Choosing the value of K: The selection of an appropriate value for K is crucial, as it significantly impacts the algorithm's performance. This paper investigates the influence of different K values on the accuracy, precision, and recall of the KNN algorithm.

Calculating distances: To determine the similarity between data points, the algorithm employs distance metrics such as Euclidean distance, Manhattan distance, or Minkowski distance. This study explores the impact of different distance metrics on the algorithm's performance.

Finding K nearest neighbor's: By calculating the distances between the target point and all data points in the training dataset, the algorithm identifies the K data points with the shortest distances. These data points are considered the K nearest neighbors.

Making predictions: For classification tasks, the algorithm assigns the class label that is most frequent among the K nearest neighbors to the target point. In regression tasks, the algorithm calculates the average value of the target variable among the K nearest neighbor's and assigns it as the predicted value.

Performance evaluation: To assess the algorithm's performance, various evaluation metrics such as accuracy, precision, recall, and F1 score are employed. This paper investigates the impact of different factors, including dataset characteristics and parameter settings, on these performance metrics.

VII. PROPOSED METHODOLOGY

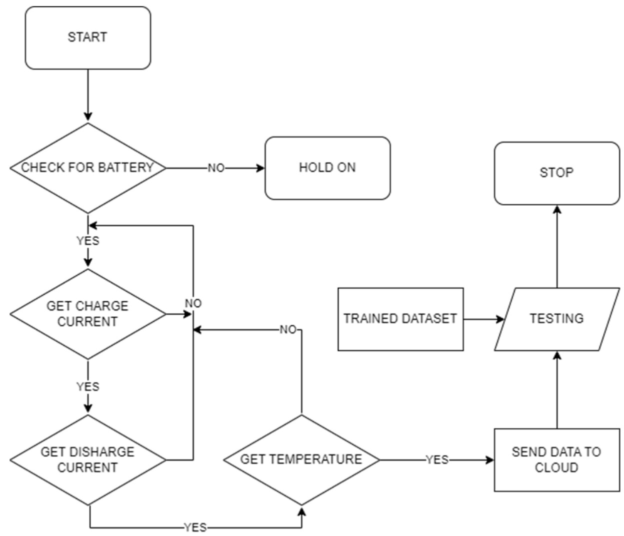

Fig 2: *Flowchart*

Data Collection: Collect charge current and discharge current data from hardware sensors installed in EV batteries. Record corresponding battery life cycle data and battery life in percentage at each data point.

Data Preprocessing: Clean the collected data to handle missing values and outliers. Normalize or standardize the data to ensure consistent scaling. Split the dataset into training and testing sets for model evaluation.

Feature Engineering: Extract relevant features from the charge and discharge current data. Consider time-series features or statistical aggregates to capture battery behaviour effectively.

K-Nearest Neighbors (KNN) Model: Implement the KNN algorithm for regression to predict battery life percentage and remaining life cycles. Choose an appropriate value of 'k' through hyperparameter tuning (e.g., cross-validation). Train the KNN model using the training dataset.
Model Evaluation: Evaluate the KNN model's performance using appropriate regression metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared. Use the testing dataset to assess the model's generalization ability.

Results Visualization: Visualize the predicted battery life percentage and remaining life cycles against actual values. Create graphs and charts to illustrate model performance.

Deployment: Implement the trained KNN model in a real-world environment for battery longevity prediction. Develop a user-friendly interface for users to input charge and discharge data and receive predictions.

VIII.SIMULATION AND RESULTS

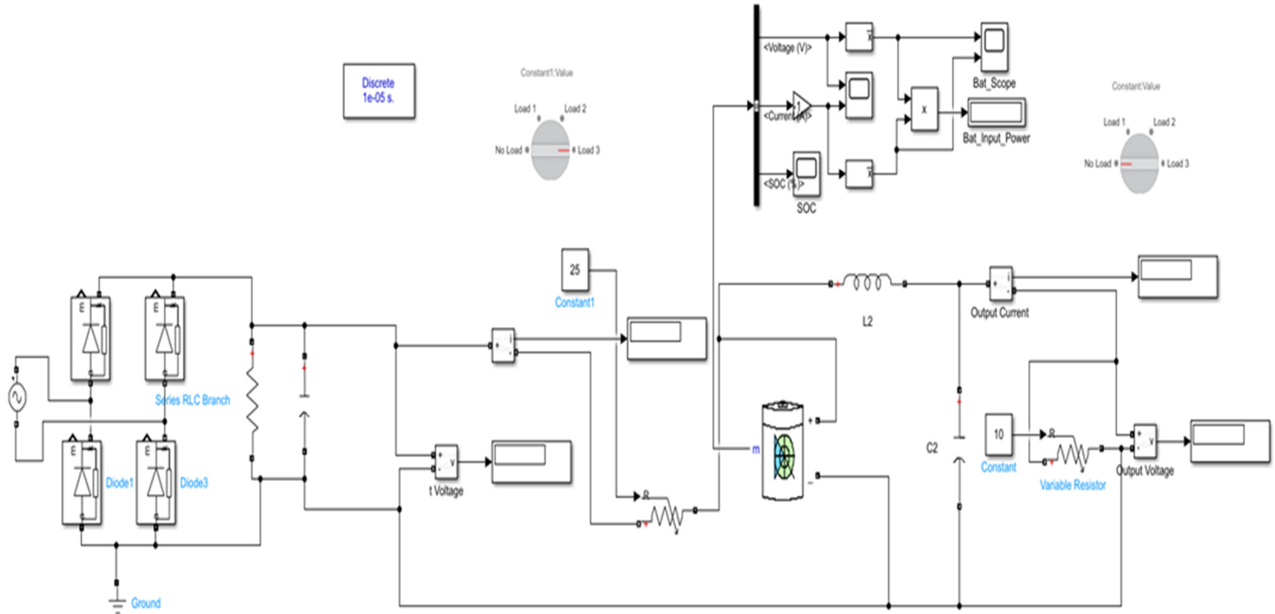

Fig 3: Charging and Discharging Circuit

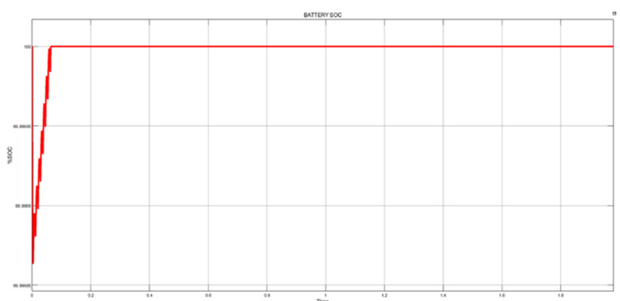

Fig 4: *SOC Graph*

The above figure represents the percentage of state of charge of battery while charging. It remains constant after the battery is fully charged up to 100%

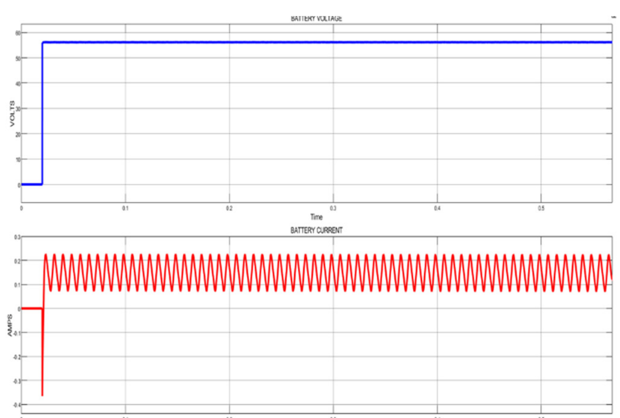

Fig 5: *Charging and Discharging Graph*

The above graph represents the behaviour of voltage and current of the battery while charging and discharging. After the voltage reaches the nominal value, it is kept constant while the current varies according to charging and discharge of the battery.

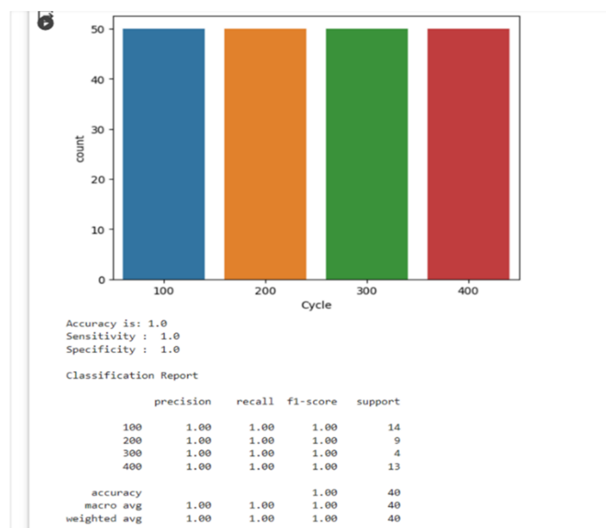

Fig 6: *Accuracy of Algorithm*

The above graph shows the accuracy and specificity of the model used which is trained with a dataset. The graph shows the relations between cycle and count.

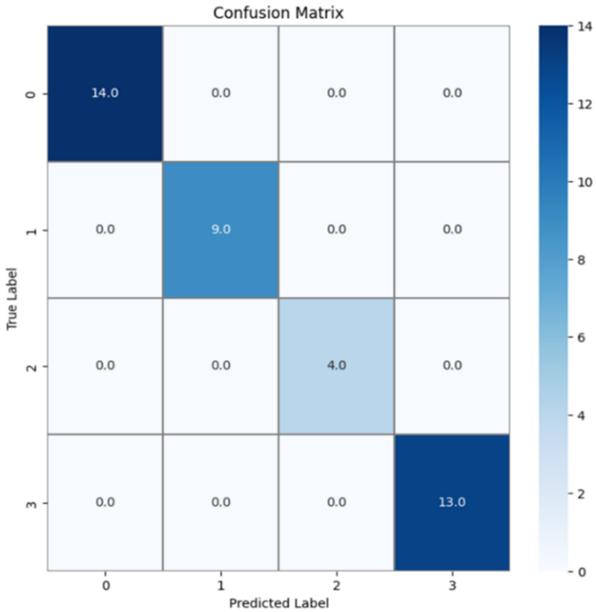

Fig 7: *Confusion Matrix*

The above figure represents the confusion matrix of the model. The diagonal value represents the accuracy of the model.

IX. CONCLUSION

The lifetime of Li-ion batteries is the key challenge to achieve sustainable battery performance. The application specific usage dominates the degradation path, and an accurate aging prediction is still a challenge. The precise forecasting of the battery life has a far-reaching consequence, which can help to understand the battery behavior under certain circumstances and perform diagnosis accordingly. In this project work, several techniques are developed following different methodologies, and model performances are compared with each other. The assessment is validated by using a common training dataset and tested/simulated on completely new cells.

X. FUTURE SCOPE

The future scope of research in this area is multifaceted. Further experiments are warranted to investigate the relationship between capacity fading and the frequency and duration of resting periods, while also exploring the impact of different initial State of Charges (SoCs) and State of Distributions (SoDs) on capacity fading models. Additionally, considering calendar losses in battery aging is crucial since electric vehicles spend significant time not in use, demanding a deeper exploration of the correlation between calendar and cycling losses. Moreover, the empirical equations for internal cell impedance, initially determined with unidirectional current, should be validated for dynamic current profiles, and research into the interplay between these equations modelling temperature and rate dependencies of impedance is essential. Addressing variations in ohmic resistance, particularly during cycling without a discernible trend, requires additional investigations, including potential links to regenerative braking and the modelling of aging effects on ohmic resistance under various stress factors. These future research endeavours are essential for advancing our understanding of battery behaviour and improving battery management strategies.

REFRENCES

[1] M. Suresh,B Kalai Selvi,V. Geetha Priya,K Sekar,K. Srinivasan,R M Sathiya Moorthy,"AI based Battery Life Estimation of Electric Vehicle",2022 Sixth International Conference on I-SMAC (IoT in Social Mobile Analytics and Cloud) (I-SMAC)

[2] Zachary Bosire Omariba,Lijun Zhang,Dongbai Sun,"Remaining useful life prediction of electric vehicle lithium-ion battery based on particle filter method",2018 IEEE 3rd International Conference on Big Data Analysis (ICBDA)

[3] A. Affanni,A. Bellini,C. Concari,G. Franceschini,E. Lorenzani,C. Tassoni,"EV battery state of charge: neural network based estimation",IEEE International Electric Machines and Drives Conference 2003. IEMDC03.

[4] Marcantonio Catelani,Lorenzo Ciani,Francesco Grasso,Gabriele Patrizi,Alberto Reatti,"Remaining Useful Life estimation for electric vehicle batteries using a similarity-based approach",2022 IEEE International Workshop on Metrology for Automotive (MetroAutomotive)

[5] K. H. Chen,Z. D. Ding,"Lithium-ion battery lifespan estimation for hybrid electric vehicle",The 27th Chinese Control and Decision Conference (2015 CCDC)

[6] Mahesh S. Chitnis,Sachin P. Pandit,M. N. Shaikh,"Electric Vehicle Li-Ion Battery State of Charge Estimation Using Artificial Neural Network",2018 International Conference on Inventive Research in Computing Applications (ICIRCA)

[7] C. C. Lee,Panpan Hu,C. Y. Li,S. H. Wang,"State of Charge Estimation of the Lithium-ion Battery based on Neural Network in Electric Vehicles",2022 IEEE International Symposium on Product Compliance Engineering - Asia (ISPCE-ASIA)

[8] Paramet Wirasanti,Watcharin Srirattanawichaikul,Suttichai Premrudeepreechacham,"Online SoC and Battery Life Estimation: Results from Filed Test of Electric Bus Transit",2018 21st International Conference on Electrical Machines and Systems (ICEMS)

[9] "A life cycle assessment of a Li-ion urban electric vehicle battery",2013 World Electric Vehicle Symposium and Exhibition (EVS27)

[10] Mamoona Khalid,Shehzar Shahzad Sheikh,Abdul Kashif Janjua,Hassan Abdullah Khalid,"Performance Validation of Electric Vehicleu2019s Battery Management System under state of charge estimation for lithium-ion Battery",2018 International Conference on Computing Electronic and Electrical Engineering (ICE Cube)