ML Driven Battery Longevity Estimation for Electric Vehicles Using KNN Algorithm

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***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 main objective of the project is by developing a predictive model which can estimate remaining lifetime of an EV battery based on real-time battery behaviour. Leveraging AI algorithms like machine learning and neural networks, the model which integrates data from different 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 method assure whether the battery is operated under safe limits while maintaining efficient performance. Consequently, the overall EV system benefits from extended battery life, reduced maintenance costs, and increased sustainability. This project has the potential to revolutionize battery management in the EV industry. This project has the potential to revolutionize battery management in the EV industry. 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. The findings of this research could have a significant influence on a more efficient and sustainable future for electric mobility as companies, governments, and people strive for greener modes of transportation.**

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

I. INTRODUCTION

Lithium-ion batteries, commonly abbreviated as Li-ion batteries (LIB), play a pivotal role in the energy landscape by storing electrical energy in a chemical form. Within the market, one finds an assortment of LIBs, ranging from non-rechargeable to rechargeable variants. Non-rechargeable LIBs, also known as primary cells, boast extended longevity and minimal self-discharge rates, making them ideal for applications such as compact electronic devices like wristwatches and hearing aids. Conversely, rechargeable LIBs, referred to as secondary cells, offer versatility and find utility across a broad spectrum of consumer electronics and emerging sectors such as electric vehicles and large-scale energy storage. These rechargeable LIBs are instrumental in facilitating crucial functions such as primary frequency regulation, voltage stabilization, and load management, as well as enabling localized electricity storage in residential settings. For the purposes of this discussion, our focus will remain exclusively on rechargeable LIBs.

Typically, a rechargeable LIB consists of two porous electrodes separated by a porous membrane, with a liquid electrolyte saturating the interconnected pores. The electrolyte contains dissolved lithium salt, such as $LiPF_6$, which dissociates into Li^+ and PF_6^- ions. These ions facilitate the movement of charge carriers between the electrodes through the electrolyte and membrane. The negative electrode, usually comprising carbon, and the positive electrode, often composed of lithium metal oxide, engage in reversible reactions with the Li^+ ions. This electrochemical interplay is essential for the battery's operation and is facilitated by the physical separation of the electrodes by the membrane, which serves to prevent internal short-circuiting.

Upon establishing a connection between the electrodes via an external circuit, the discharge process of the battery is initiated. During discharge, electrons flow from the negative electrode to the positive electrode through the external circuit, while Li^+ ions migrate through the electrolyte towards the positive electrode, where they partake in electrochemical reactions. This discharge process occurs spontaneously due to the inherent disparities in electrochemical potentials between the electrodes. Essentially, the positive electrode exhibits a higher affinity for electrons and Li^+ ions compared to the negative electrode.

The energy released during the discharge process, characterized by the movement of one Li^+ ion and one electron from the negative to the positive electrode, is quantified by the product of the battery voltage and the charge of the electron. Known as electromotive force (EMF), this voltage represents the energy per electron released during the discharge. Typically ranging between 3 to 4 Volts, the EMF is influenced by various factors such as the LIB cell chemistry, temperature, and state of charge (SOC). For instance, when the battery is connected to an external load, such as a light bulb, the majority of the voltage drop occurs across the load, resulting in the release of energy from the LIB. Conversely, when the load is replaced by a voltage source, such as a power supply, the battery undergoes the charging process, allowing for the storage of electrical energy.

A rechargeable LIB reaches full discharge when nearly all lithium ions have migrated from the negative electrode to the positive electrode and participated in electrochemical reactions. Further discharging beyond this point can lead to instability in the electrode materials and subsequent degradation of battery performance. At full discharge, the EMF decreases compared to when the battery is fully charged. Each LIB chemistry defines a safe voltage range for the EMF, with the endpoints typically representing 0% and 100% state of charge (SOC). The discharge capacity, measured in Ampere-hours (Ah), varies depending on the type and quantity of active material present in the electrodes.

The evolution of lithium batteries can be traced back to the early 1970s, with significant milestones achieved over the years, including the commercial release of the first lithium-ion battery by Sony in 1991. The subsequent decades witnessed a gradual maturation of LIB technology, driven in part by the burgeoning demand from the consumer electronics market. Notably, the introduction of the Tesla Roadster in 2008 marked a significant leap forward, as it became the first commercially viable all-electric vehicle powered by lithium-ion battery cells. Furthermore, around 2010, LIBs began to gain traction in the energy storage sector, heralding a new era of sustainable energy solutions.

II. LITERERATURE SURVEY

LITERATURE REVIEW 1:

Electric vehicles (EVs) stand out as a valuable outcome of renewable technologies in the transportation sector, thanks to their environmentally friendly and user-friendly attributes. EVs equipped with lithium-ion (Li-ion) batteries capitalize on the latter's high energy capacity and extended lifespan. However, like any complex system, these batteries inevitably degrade over time or with continuous usage, leading to significant expenses in the case of failure. To enhance the reliability and safety of EVs, assessing battery health and predicting battery life emerge as crucial factors.

Because of the batteries non-linear capacity fading in the early cycles, previous research often provided inaccurate forecasts in future. An extensive Artificial Intelligence (AI) framework based on Convolutional Neural Networks (CNN) and Artificial Neural Networks (ANN) is presented in this study to ensure dependable predictions about battery life cycles. Obtaining data, removing features that aren't needed, and extracting the eight most relevant features are all steps in the methodology. Both ANN and CNN models undergo training with a total of 15 epochs, and their performance is evaluated using accuracy and loss functions. The CNN model demonstrates impressive accuracy at 97.21% and a minimal loss of 0.0913%.

LITERATURE REVIEW 2:

Many sectors, including portable devices, electric cars, military and aerospace applications, use lithium-ion batteries. Such batteries play a crucial role in the functionality of these systems, underscoring their significance. Predicting the remaining useful life is imperative to prevent diminished performance or catastrophic failure.Evaluating consecutive probability distributions of deteriorating states is part of this estimating method. For EVs, low battery capacity below the failure threshold leads to a huge concern. Degradation can cause the battery capacity to drop below the failure threshold, making it an important parameter for measuring the state of health (SOH). This study provides the observed data flow for estimating the remaining usable life by using NASA's battery dataset. After that, the particle filter (PF) method is used for estimating .

LITERATURE REVIEW 3:

Various types of electric vehicles (EVs) have been developed to address pollution issues stemming from gasoline-powered engines' emissions. The environmental benefits associated with EVs make them a favorable choice for urban transportation. However, the battery system remains a notable weak point in electric vehicles. Amongst the main hindrances to the widespread adoption of electric vehicles in the consumer market are the limitations in vehicle autonomy and the accuracy of battery state of charge detection.

This study focuses on analyzing the SOC of batteries, specifically assessing the performance of various battery sizes. Using a neural network (NN) based system, the state of charge is estimated. After that, a lithium-ion battery pack appropriate for electric vehicles is designed using the analysis's findings. The suggested system has characteristics like charge equalization and over/under voltage protection, and it is particularly good at recovering energy under braking situations.

Furthermore, the implementation of a neural network-based estimation for the state of charge of battery adds an optimization layer to enhance autonomy, depending on the journey's requirements, whether prioritizing performance or extending range.

III. PROBLEM STATEMENT

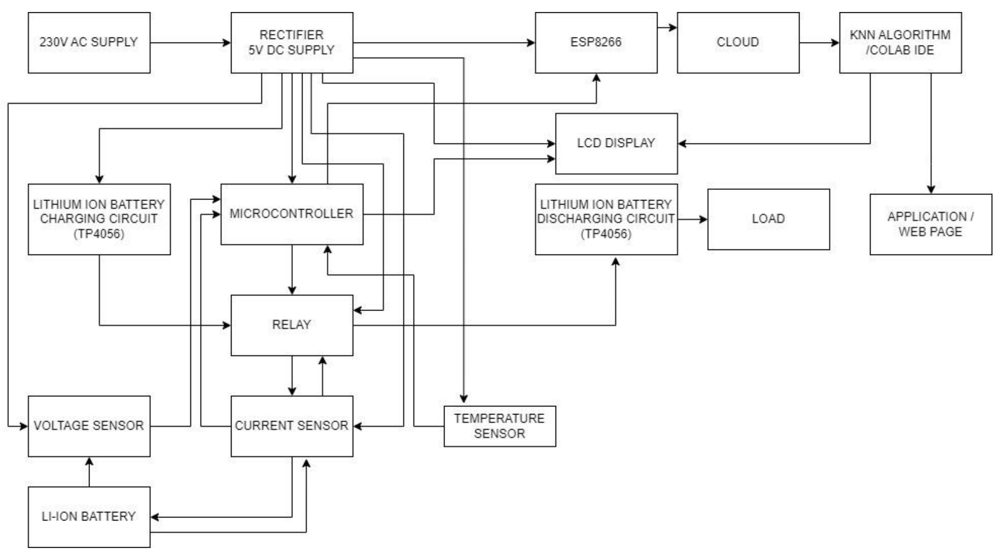
The challenge at hand is estimating how long Li-ion batteries in electric vehicles (EVs) will last in order to stop these batteries from degrading too soon.Li-ion batteries in EVs often consist of many cells connected in series and parallel method, where failure of one cell can lead to deterioration of others, potentially rendering the total battery pack unusable. Understanding the condition and performance of these batteries is also essential for repurposing them for uses like energy storage, as the market for used EV batteries is expanding. This poster aims to address these challenges through data-driven analysis of used EV battery packs to optimize their secondary use and reduce waste.

IV. EXISTING METHODOLOGIES

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

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 predict 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.

V. PROPOSED SOLUTION

A sophisticated lithium-ion battery longevity estimation system incorporates a Node MCU as its primary control unit, tasked with vigilant monitoring of both charging and discharging dynamics. This intricate data is meticulously logged and seamlessly relayed to the cloud infrastructure via an ESP8266 Wi-Fi module. Additionally, a vivid representation of the lithium-ion battery's current status is presented through an LCD display interface. Precise quantification of charging and discharging rates is facilitated in terms of ampere-hours. Moreover, the system employs an advanced K-nearest neighbors (KNN) algorithm to categorize the number of battery usage cycles. By juxtaposing real-time hardware metrics with an extensive preexisting dataset, the system adeptly computes the remaining cycles and overall battery life expectancy. This visionary project was conceived against the backdrop of an anticipated surge in the prominence of electric vehicles within the transportation landscape, underscoring its potential utility in shaping the future of sustainable mobility.

This project commences at a foundational level, drawing power from a 230V AC supply, which is meticulously rectified to establish a stable DC supply. This DC power forms the foundation of a intricate sensor network, with temperature, current, and voltage sensors perfectly positioned to monitor critical battery parameters. A specialized circuit that permits the dynamic charging and discharging of lithium-ion batteries is managed 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 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 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.

VI. ML ALGORITHM

The battery's number of used cycles is categorized using the KNN algorithm. It accomplishes this by contrasting an existing dataset with the hardware data retrieved from the cloud. The KNN algorithm calculates the similarity between the current battery's data and historical data to estimate its SOH.

A supervised machine learning algorithm that is on-parametric and utilized for bracket and retrogression tasks is K - Nearest Neighbors (KNN). This algorithm is straightforward but efficient, predicting outcomes by using the idea of similarity. Working with a given data point in point space, the KNN algorithm finds the K nearest neighbors by chance. To determine how many neighbors to take into account, a stoner-defined parameter called K is used. Based on the maturity class or average value of its K nearest neighbors, the algorithm additionally classifies the data point or predicts a value for it.

VII. 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 process of selecting the K value is crucial, as it impacts the algorithm's performance majorly. This paper investigates the influence of different K values on the accuracy, precision, and recall of the KNN algorithm. Calculating distances:The algorithm uses distance metrics like Minkowski, Manhattan, or Euclidean distance to find the similarity between data points. This paper investigates how various distance metrics affect the algorithm's efficiency. Finding K nearest neighbor's:The approach finds the K data points with the smallest distances by calculating the distances between the target point and every data point in the training dataset. The K nearest neighbors are these data points. Making predictions:The approach selects the class label that is most frequently used among the K closest neighbors to the target location for classification jobs.Once the regression task is finished, the algorithm determines the target variable's average value among its K closest neighbors and assigns that value as the expected value.

Performance evaluation:Several evaluation metrics, including accuracy, precision, recall, and F1 score, are used to evaluate the algorithm's performance. This paper investigates the impact of different factors, including dataset characteristics and parameter settings, on these performance metrics.

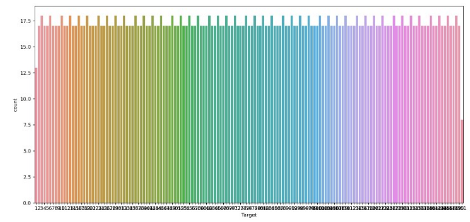


Fig 2: Count plot graph

VIII. PROPOSED METHODOLOGY

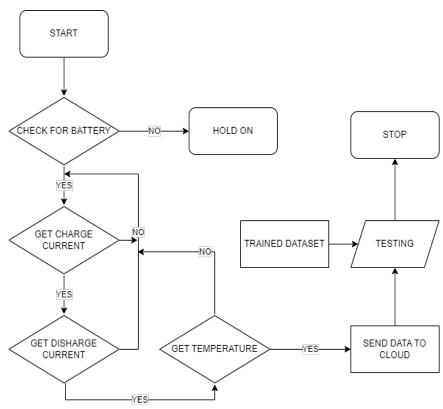
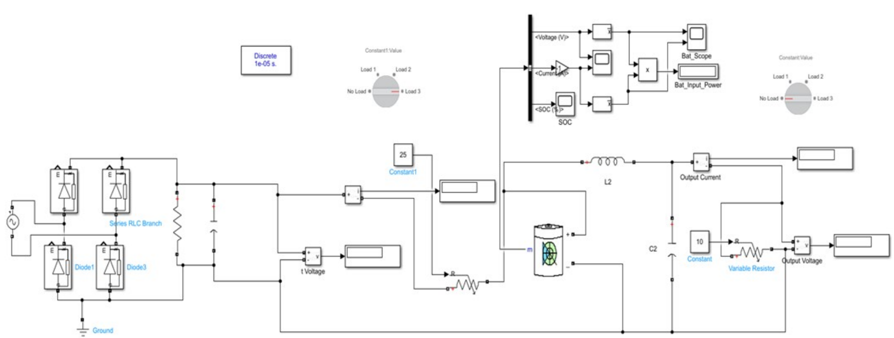


Fig 3: Flowchart



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:To interact with missing values and outliers, clean up the collected data. Ensure consistent scaling by normalizing or standardizing the data. To assess the model, divide the dataset into testing and training sets. 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). Then train the KNN model using the training dataset available.

Model Evaluation:Utilizing appropriate regression metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared, assess the performance of the KNN model. To evaluate the model's generalization capacity, use the testing dataset. Results Visualization: Visualize the predicted battery life percentage and remaining life cycles against actual values. Create graphs and charts to illustrate model performance. Deployment:To predict battery longevity in a real-world setting, implement the trained KNN model. Develop a user friendly interface for users to input charge and discharge data and receive predictions.

IX. HARDWARE AND RESULTS

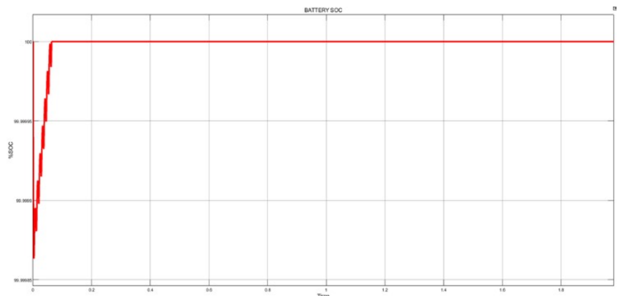


Fig 5: SOC Graph

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%

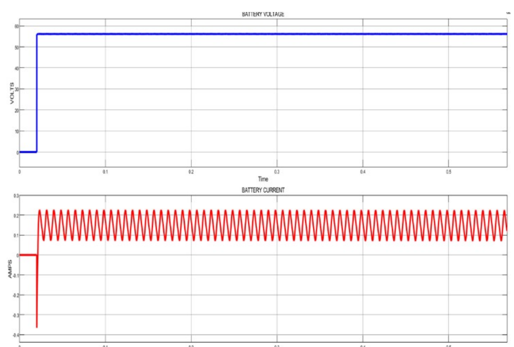


Fig 6:Charging and Discharging Graph

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

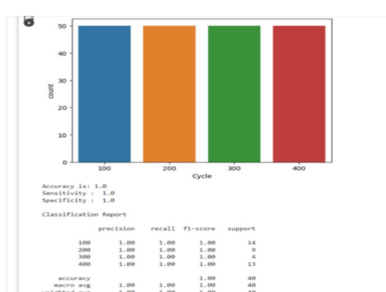


Fig 7: Accuracy of Algorithm

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

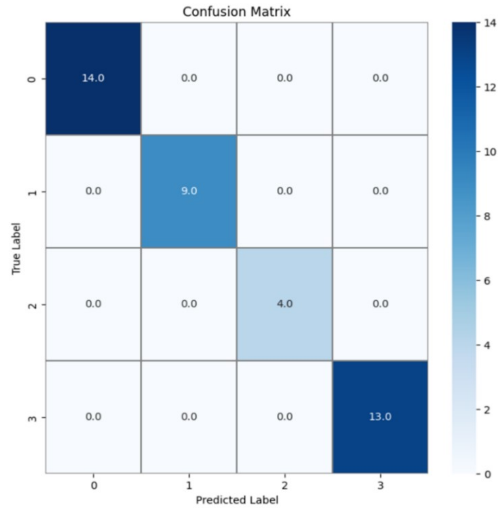


Fig 8:Confusion Matrix

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

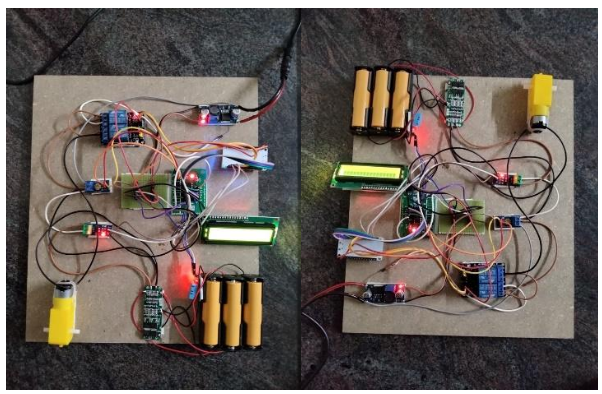


Fig 9: Hardware Images

X. CONCLUSION

To achieve good battery performance, the lifespan cycles of Li-ion batteries act as a main hustle factor.The application specific path determines the degradation path of the cells in the battery,the actual prediction of aging is somehow difficult to achieve.Exact battery life prediction is a vast reaching because the exact understanding of battery behaviour in some conditions becomes difficult.In this project we used several strategies and methodologies to compare the results of various models.The test is simulated on both new and used(old) cells and validated using a shared training dataset.

XI. 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.

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