DATA-DRIVEN SOC ESTIMATION OF LITHIUM-ION BATTERY USING ML ALGORITHMS

A thesis submitted in partial fulfilment of the requirements for the

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B.Tech.

In

Instrumentation and Control Engineering

By

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BONAFIDE CERTIFICATE

This is to certify that the project titled **DATA-DRIVEN SOC ESTIMATION OF LITHIUM-ION BATTERY USING ML ALGORITHMS** is a bonafide record of the work done by

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in partial fulfilment of the requirements for the award of the degree of **Bachelor of Technology in Instrumentation and Control Engineering of the** NATIONAL **INSTITUTE OF TECHNOLOGY, TIRUCHIRAPPALLI**, during the year **2022-2023.**

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ABSTRACT

This project titled "Data-driven State of Charge (SOC) Estimation of Lithium-ion Batteries Using Various Techniques" focuses on developing accurate SOC estimation models for lithium-ion batteries by utilizing data-driven approaches. The project involves collecting voltage and current data from online resources during the charging and discharging processes of lithium-ion batteries. The collected data is then utilized to train machine learning algorithms, including Support Vector Machines (SVM), Random Forest, and Multilayer Perceptron (MLP), to estimate the SOC.

The primary objective of this project is to compare the accuracy of SOC estimation between the data-driven approaches and the Extended Kalman Filter (EKF) technique, a commonly used model-based approach for SOC estimation. By evaluating the performance of different algorithms, we aim to identify the most effective and accurate technique for estimating SOC.

To begin the project, a comprehensive dataset containing voltage and current readings at various SOC levels is obtained from online resources. The dataset is carefully pre-processed to remove noise, outliers, and inconsistencies, ensuring high-quality input for the training phase.

The collected data is then used to train three popular machine learning algorithms: SVM, Random Forest, and MLP. These algorithms are chosen due to their effectiveness in handling complex and nonlinear relationships between input variables, such as voltage and current, and the target variable, SOC. Each algorithm undergoes a rigorous training process, including feature selection, hyperparameter tuning, and cross-validation, to optimize their performance and generalization capabilities.

Once the models are trained, they are evaluated using appropriate performance metrics, such as mean absolute error (MAE) and root mean square error (RMSE), to assess their accuracy

in estimating SOC. The results obtained from the data-driven models are compared with the SOC estimates derived from the EKF technique.

The comparison between the data-driven approaches and the EKF technique provides valuable insights into the advantages and limitations of each method. It allows us to determine which technique exhibits superior accuracy and reliability in SOC estimation for lithium-ion batteries. Additionally, the project highlights the potential benefits of data-driven approaches, such as their ability to adapt to changing battery characteristics and their potential for real-time implementation.

The outcomes of this research contribute to the field of battery management systems by providing valuable information on the feasibility and effectiveness of data-driven SOC estimation techniques. The findings can assist in the development of more accurate and reliable SOC estimation algorithms for lithium-ion batteries, thereby enhancing the overall performance and lifespan of battery systems.

Overall, this project aims to bridge the gap between data-driven approaches and model-based techniques for SOC estimation of lithium-ion batteries. By utilizing machine learning algorithms and comparing their performance with the traditional EKF technique, we gain valuable insights into the accuracy and feasibility of data-driven approaches, facilitating the advancement of battery management systems and the optimization of lithium-ion battery usage.

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ABBREVATIONS

SOC	State of charge
EV	Electric vehicle
Ah	Ampere hour
HEV	Hybrid electric vehicle
SVM	Support vector machines
RF	Random forest
MLP	Multi-layer perceptron
MSE	Mean Squared Error
RMSE	Root Mean Squared Error
BMS	Battery Management Systems

CHAPTER 1 – INTRODUCTION

1.1 INTRODUCTION

The growing demand for energy storage systems, particularly lithium-ion batteries, has necessitated the development of accurate state of charge (SOC) estimation techniques. State of Charge (SOC) estimation refers to the process of determining the remaining capacity or energy stored in a battery at a given point in time. SOC estimation plays a crucial role in optimizing the performance and lifespan of batteries by providing real-time information about the remaining charge. Accurate SOC estimation enables efficient energy management, enhances battery safety, and improves the overall reliability of battery systems.

SOC estimation is particularly important for lithium-ion batteries, which are widely used in portable electronic devices, electric vehicles(EV), and renewable energy storage systems. As lithium-ion batteries are typically used in applications where accurate monitoring of the available charge is necessary, SOC estimation plays a vital role in ensuring optimal battery utilization and preventing issues such as overcharging or deep discharging that can adversely affect battery life and performance.

Traditionally, SOC estimation has been approached using model-based techniques, such as the Extended Kalman Filter (EKF), which rely on mathematical models of the battery's electrochemical behavior. While these methods have shown reasonable accuracy, they often struggle to capture the complex and nonlinear relationships between battery voltage, current, and SOC accurately. Moreover, they may require prior knowledge of battery characteristics and suffer from model uncertainties.

To address these limitations, data-driven approaches have emerged as a promising alternative for SOC estimation. These approaches leverage the availability of large datasets containing voltage and current measurements at different SOC levels. By employing machine learning algorithms, such as Support Vector Machines (SVM), Random Forest, and Multilayer Perceptron (MLP), data-driven SOC estimation models can learn complex patterns and relationships from the data without relying on explicit mathematical models.

1.2 NECESSITY OF SOC ESTIMATION

Battery Performance Optimization: Accurate SOC estimation allows for efficient battery utilization and optimization of performance. It enables users to understand the available energy stored in the battery, facilitating effective energy management strategies.

Battery Safety: SOC estimation plays a crucial role in ensuring battery safety. Overcharging or discharging a lithium-ion battery beyond its safe operating limits can lead to adverse effects such as thermal runaway, reduced capacity, and even catastrophic failure.

System Reliability: SOC estimation contributes to the overall reliability of battery systems. It provides real-time information about the remaining capacity, allowing users to plan battery usage and prevent unexpected power interruptions.

Battery Health Management: SOC estimation assists in the effective management of battery health. Over time, lithium-ion batteries undergo degradation, resulting in a reduction in their capacity and performance. By monitoring SOC, users can assess battery aging and health, enabling proactive maintenance and replacement strategies.

Enhanced User Experience: By knowing the remaining charge, users can plan their activities accordingly, avoiding unexpected battery depletion. It enhances user convenience, particularly in portable electronic devices, by providing accurate estimations of the available battery life.

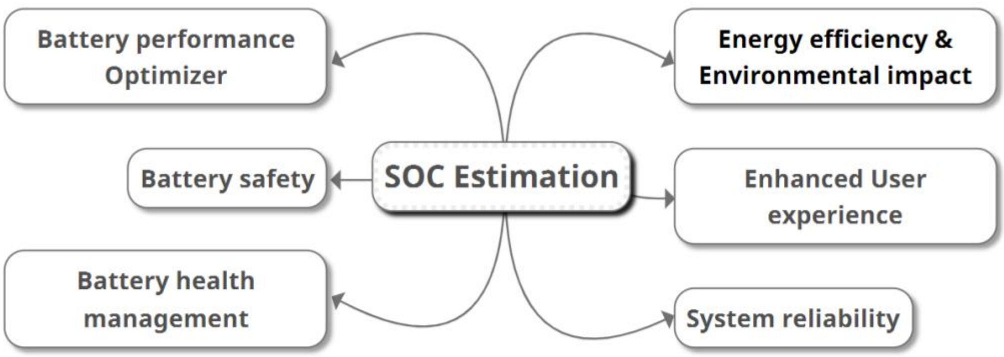

Figure 1.1 – Uses of SOC Estimation

CHAPTER 2 – LITERATURE REVIEW

There are several techniques for SOC estimation, including model-based, adaptive, and data-driven methods. Data-driven methods have gained significant attention due to their ability to handle the nonlinearity, uncertainty, and complexity of LIBs. In this literature review, we will explore various data-driven SOC estimation techniques for LIBs and their performance.

“Data-driven State-of-Charge Estimation of Lithium-ion Batteries using Machine Learning Algorithms” by L. Xu et al. (2019)

This paper proposes a data-driven approach for SOC estimation of Lithium-ion batteries using machine learning algorithms. The authors used three different algorithms, namely, artificial neural networks (ANNs), support vector regression (SVR), and random forest (RF) to estimate SOC. The dataset used in this study is collected from a commercial Lithium-ion battery, and the results show that all three algorithms provide accurate SOC estimation, with ANNs providing the best performance.

“Real-Time State-of-Charge Estimation of Lithium-ion Battery using Machine Learning” by S. Lee et al. (2020)

This paper proposes a real-time SOC estimation method that uses machine learning algorithms. The authors used two different algorithms, namely, SVR and RF, to estimate SOC in real-time. The dataset used in this study is collected from a commercial Lithium-ion battery, and the results showed that both algorithms provide accurate SOC estimation in real-time.

“A new online SOC estimation method for lithium-ion batteries based on an extended Kalman filter and improved equivalent circuit model” (2019)

This research article proposes a new online SOC estimation method for LIBs based on an Extended Kalman Filter (EKF) and an improved equivalent circuit model. The authors validate the proposed method on experimental data and demonstrate its superior performance compared to traditional data-driven methods.

CHAPTER 3 – METHODOLOGY

3.1 DATA COLLECTION

3.1.1 Real Battery Data Collection

In this battery, lithium ions move from the negative electrode through an electrolyte to the positive electrode during discharge, and back when charging. Li-ion batteries use an intercalated lithium compound as the material at the positive electrode and typically graphite at the negative electrode. The batteries have a high energy density, no memory effect and low self-discharge.

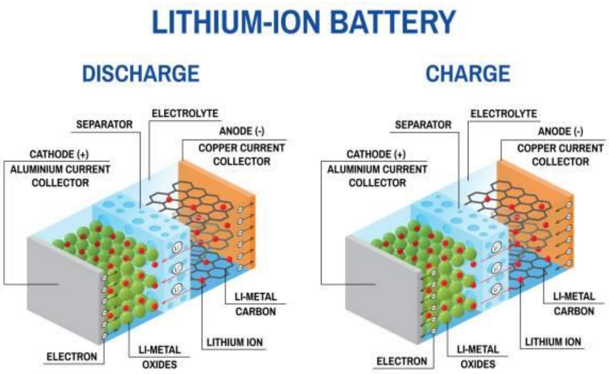

Figure 3.1 – Working of lithium-ion battery

In this setup, Lithium-Ion battery has a nominal voltage of 3.7V. When the battery charges to full the maximum voltage are 4.2V. The battery has a discharge cut-off voltage of 3V with a capacity of 2800 mAh.

Figure 3.2 – Flat lithium-ion Battery

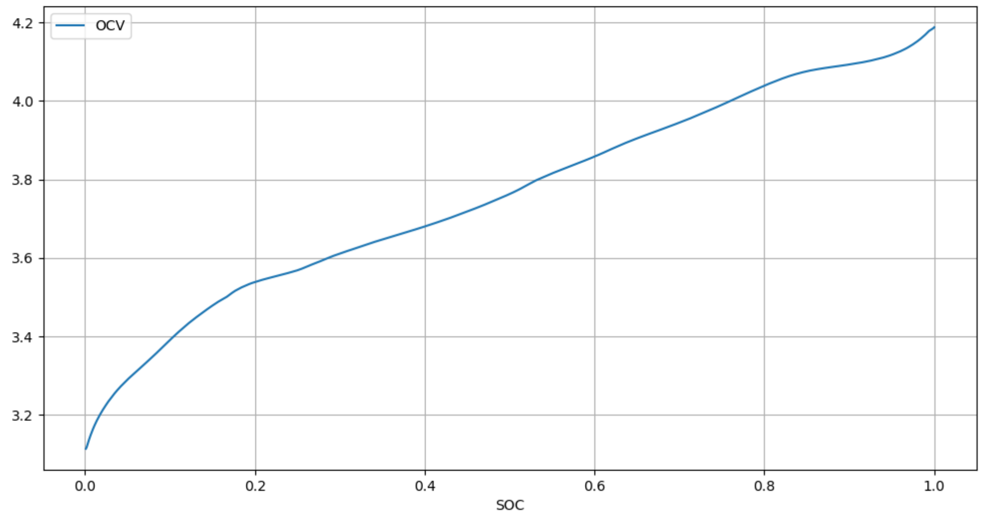

Figure 3.3 – OCV vs SOC curve

An IOT based system is designed to monitor this battery voltage along with charging and discharging status. For the microcontroller, **Wemos D1 Mini** which has an **ESP8266** wifi-enabled chip is used.

TP4056 module is used to charge the battery as its best suited for Battery Management Applications.

The ESP8266 Chip can only support the input analog voltage of 3.3V. But Battery voltage goes up to 4.2V. Hence we have to form a voltage divider network to lower down the input voltage.

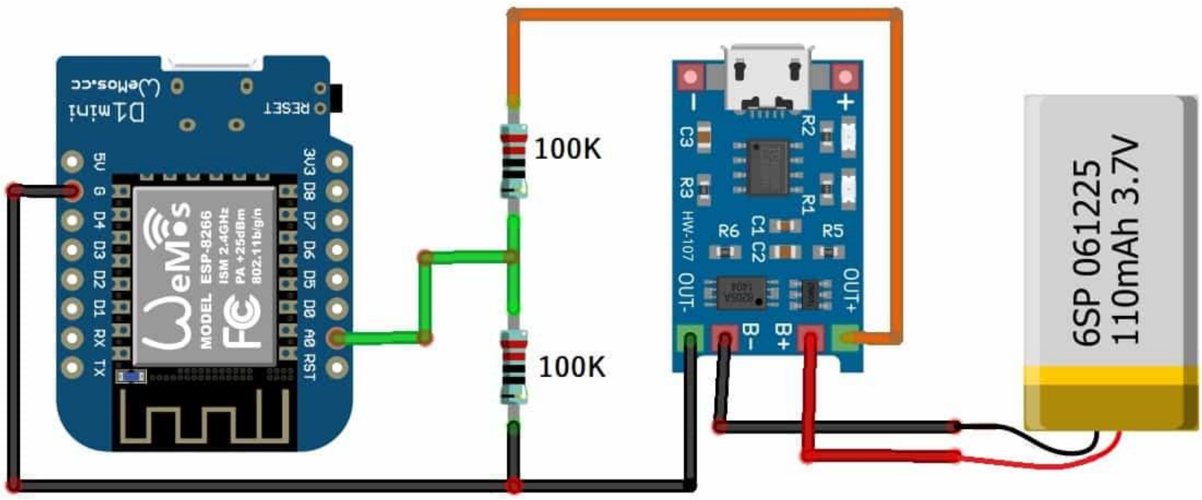

Figure 3.4 – Circuit & schematic designing

In this IoT-based Battery Monitoring System, we will use Wemos D1 Mini with ESP8266 Chip to send the battery status data to **ThingSpeak** cloud. The Thingspeak will display the battery voltage along with the battery percentage in both the charging and discharging cases.

3.1.2 Online Battery Data Collection

The Data collected from the Real battery discharging/charging cases include noises from the environment and have minute errors due to manual collection. To estimate the SOC using Machine learning Algorithms, Large amount of data including numerous life cycles of charging/discharging data is required.

To address these limitations, By collecting voltage and current data from online resources during the charging and discharging processes of lithium-ion batteries, a comprehensive dataset is created. This dataset serves as the foundation for training the machine learning algorithms and validating their performance.

Load Dataset:

Time	Voltage	Current	Temperature	Capacity	WhAcc
00:01.9	4.17402	-1.20553	23.87099	0	0
00:03.7	4.15919	0.98843	23.87099	-0.00051	-0.00214
01:45.6	4.05923	-2.97041	23.87099	-0.0359	-0.14362
18:44.1	4.05653	1.22852	23.87099	-0.22642	-0.89769
26:05.3	3.59215	2.2476	23.97615	-1.59849	-5.99478
38:01.8	4.05415	0.66662	24.0813	-0.44733	-1.76582
44:44.2	3.58103	0.10983	24.29162	-1.83226	-6.80797
53:41.6	3.53383	-0.31671	24.50194	-1.9949	-7.35355
59:07.0	3.80791	1.78531	24.29162	-0.91462	-3.55777

Table 3.1 – Battery Dataset used for SOC Estimation

This data has been collected from Online source named as CALCE which is a battery team that is open to collaborate with research groups and companies around the world.

3.2 DATA PRE-PROCESSING

Data Cleaning:

The collected voltage and current data were inspected for missing values. Any missing data points were identified and handled using linear interpolation. Since the missing values were minimal and randomly distributed across the dataset, interpolation was deemed a suitable approach for preserving the temporal continuity of the data.

Data Normalization or Scaling:

To ensure consistent scaling and prevent any bias towards a specific feature, min-max scaling was applied to the voltage and current data. The data was scaled to a range of [0, 1] by subtracting the minimum value and dividing by the range of each respective feature. This normalization technique preserved the relative relationships between the data points while bringing them to a common scale.

Data Splitting:

The pre-processed dataset was randomly split into a training set and a validation set, with a 70:30 ratio. This split ensured a sufficient amount of data for training the SOC estimation models while allowing for independent validation to assess the generalization performance of the models. Random shuffling was applied before splitting to avoid any ordering biases in the data.

Outlier Detection and Treatment:

Outliers in the voltage and current data were identified using the z-score method. Data points with a z-score greater than a threshold of 3 were considered outliers. The outliers were then removed from the dataset as they were likely due to measurement errors or transient disturbances.

3.3 MACHINE LEARNING ALGORITHMS

There are many Machine learning algorithms and Artificial Intelligence techniques that can be used to estimate the State of charge of lithium-ion batteries. Here, Support Vector Machines(SVM) , Random Forest(RF) and Multilayer Perceptron(MLP) algorithms are used based on hit & trial method and compared to identify which algorithm provides the maximum accuracy to estimate the SOC for the dataset that has been considered.

3.3.1 Support Vector Machines (SVM):

Support Vector Machines (SVM) is a powerful machine learning algorithm used for classification and regression tasks. In our project, SVM was employed to estimate the State of Charge (SOC) of lithium-ion batteries based on the voltage and current data.

SVM works by mapping the input data into a high-dimensional feature space and finding an optimal hyperplane that maximally separates the data points of different SOC levels.

The SVM model was trained using the pre-processed voltage and current data, with the corresponding SOC values as the target variable. The SVM hyperparameters, such as the kernel type and regularization parameter, were fine-tuned using cross-validation techniques.

The performance of the SVM model was evaluated using metrics such as mean absolute error (MAE) and root mean square error (RMSE) to assess its accuracy in estimating SOC.

3.3.2 Random Forest:

Random Forest is an ensemble learning algorithm that combines multiple decision trees to make predictions. It is well-suited for handling complex and nonlinear relationships in the data.

In our project, Random Forest was utilized to estimate the SOC of lithium-ion batteries based on the voltage and current data.

The Random Forest model was trained using an ensemble of decision trees, where each tree was built on a random subset of features and data samples. This randomness reduces overfitting and improves the generalization performance of the model.

Cross-validation techniques were applied to optimize the hyperparameters of the Random Forest model, such as the number of trees and the maximum depth of each tree.

The accuracy of the Random Forest model in SOC estimation was assessed using evaluation metrics like MAE and RMSE.

3.3.3 Multilayer Perceptron (MLP):

Multilayer Perceptron (MLP) is a type of artificial neural network commonly used for nonlinear regression tasks. It consists of multiple layers of interconnected neurons that can capture complex relationships between input features and the target variable.

In our project, MLP was employed to estimate the SOC of lithium-ion batteries based on the voltage and current data.

The MLP model was trained using backpropagation, an iterative optimization algorithm that adjusts the weights and biases of the network to minimize the prediction error.

Various network architectures, including the number of hidden layers and the number of neurons in each layer, were explored and optimized through experimentation and cross-validation.

The performance of the MLP model in SOC estimation was evaluated using metrics such as MAE and RMSE to measure its accuracy and compare it with other machine learning algorithms.

3.4 ML ALGORITHM TRAINING AND TESTING:

Model training:

The machine learning models, including Support Vector Machines (SVM), Random Forest, and Multilayer Perceptron (MLP), were trained using the preprocessed voltage and current data, with the corresponding State of Charge (SOC) values as the target variable.

The training process involved splitting the dataset into training and validation sets, with a 70:30 ratio. The training set was used to fit the models, while the validation set was utilized to assess their performance and generalize to unseen data.

Hyperparameters for each model were selected using cross-validation techniques. Grid search and random search were employed to explore different hyperparameter combinations and identify the optimal settings.

The models were trained using appropriate optimization algorithms, such as stochastic gradient descent for SVM and MLP, and entropy-based splitting for Random Forest, to minimize the prediction error and maximize the accuracy of SOC estimation.

Model Evaluation:

The performance of each model was evaluated using several metrics, including mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination (R^2). These metrics provided quantitative measures of the models' accuracy, precision, and goodness of fit.

The trained models were applied to the validation dataset, and the predicted SOC values were compared against the actual SOC values. The evaluation metrics were computed based on the differences between the predicted and actual values.

Additionally, visualizations such as scatter plots, histograms, or line plots were generated to illustrate the agreement between the predicted and actual SOC values. These visualizations provided a qualitative assessment of the models' performance.

Statistical analysis, such as hypothesis testing or paired t-tests, was conducted to assess the significance of performance differences between the models and identify the model with the highest accuracy in SOC estimation.

Cross-validation techniques, such as k-fold cross-validation, were employed to estimate the models' generalization performance and assess their robustness to different training and validation splits.

CHAPTER 4 – SOC ESTIMATION USING EKF TECHNIQUE

4.1 OVERVIEW OF EXTENDED KALMAN FILTER TECHNIQUE

The Extended Kalman Filter (EKF) is a widely used technique for State of Charge (SOC) estimation in lithium-ion batteries. It is an extension of the traditional Kalman Filter and is particularly useful for nonlinear systems like batteries. The EKF algorithm combines a dynamic battery model with real-time measurements of voltage and current to estimate the SOC. Here's a brief overview of the EKF technique for SOC estimation:

1) Battery Model:

The EKF relies on a battery model that describes the relationship between the SOC, voltage, current, and other relevant parameters. Commonly used battery models include the equivalent circuit model (ECM) or physics-based models.

2) System State and Measurement Equations:

The EKF formulates the SOC estimation problem as a state estimation task. The system state consists of the SOC and potentially other battery parameters. The measurement equation relates the system state to the available voltage and current measurements.

3) Prediction Step:

In the prediction step, the EKF predicts the battery state based on the previous state estimate and the dynamic battery model. It uses the current input (e.g., current measurement) to propagate the state forward in time.

4) Measurement Update Step:

In the measurement update step, the EKF incorporates the real-time measurements (e.g., voltage measurement) to refine the state estimate. It compares the predicted measurements from the battery model with the actual measurements and adjusts the state estimate accordingly.

5) Jacobian Matrices:

The EKF relies on the calculation of Jacobian matrices, which capture the linearization of the nonlinear system equations. These matrices are essential for updating the state estimate and covariance matrix during the prediction and measurement update steps.

6) Covariance Matrix:

The EKF maintains a covariance matrix that represents the uncertainty or error in the state estimate. The covariance matrix is updated at each step based on the prediction and measurement update, and it provides information about the confidence in the state estimate.

7) Iterative Process:

The EKF algorithm iterates between the prediction and measurement update steps, continuously refining the state estimate based on new measurements. This iterative process improves the accuracy of the SOC estimation over time.

The EKF technique for SOC estimation offers a balance between accuracy and computational complexity.

4.2 PARAMETERS IN EKF IMPLEMENTATION

Battery Model: RC2 Model

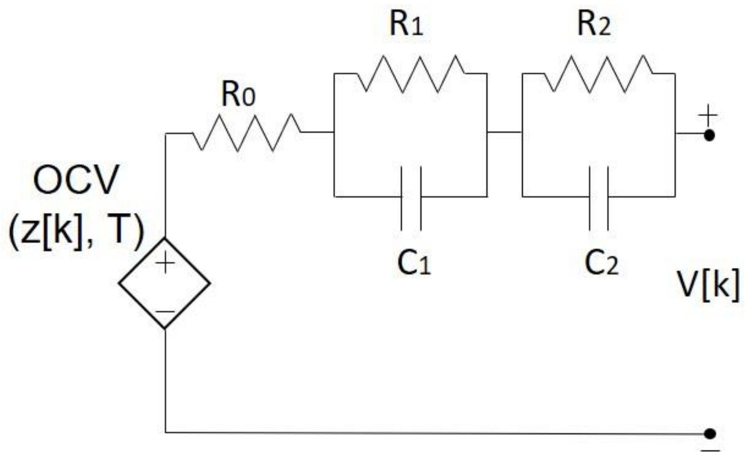

FIGURE 4.1 – RC2 Model

Parameters used:

R0	R1	R2	Tau1	Tau2
0.019414	0.014601	0.656103	19.860964	54272.69185

TABLE 4.1 – Parameters of EKF Model

Some model shortcomings:

- One cell parameter set is used for the entire SOC range.
- There is no hysteresis component in this model, thus Irc1 compensates for this.

CHAPTER 5 – ML MODELS RESULTS AND COMPARISION

5.1 MODELS RESULTS

SOC Plot versus time using Random Forest for charging data:

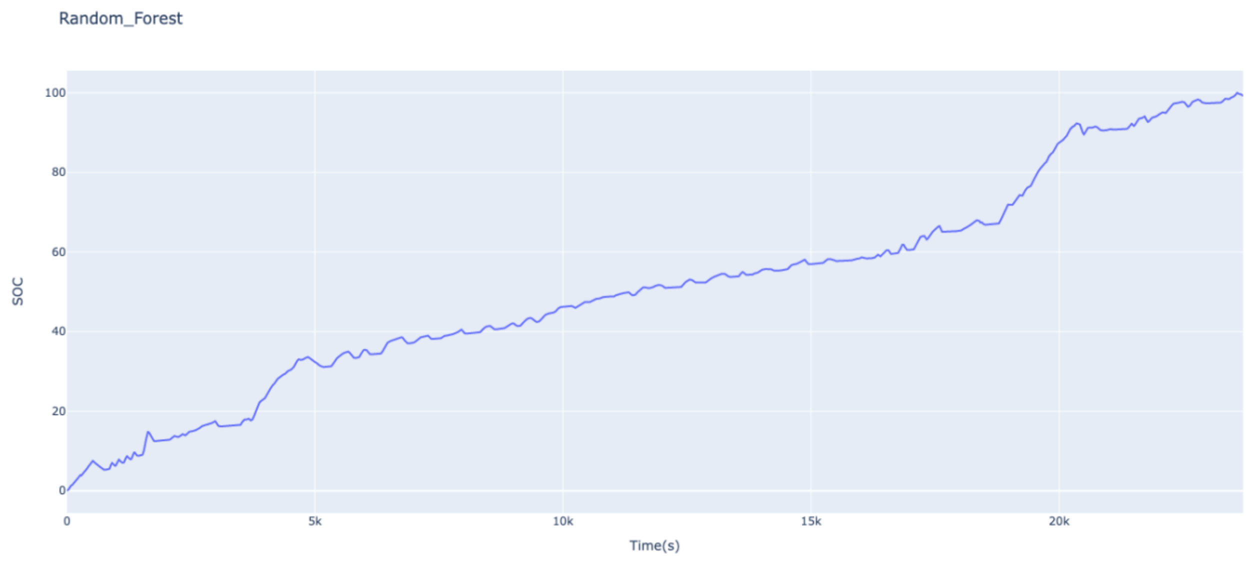

Figure 5.1 – SOC vs Time while charging using RF algorithm

SOC Plot versus time using Random Forest for discharging data:

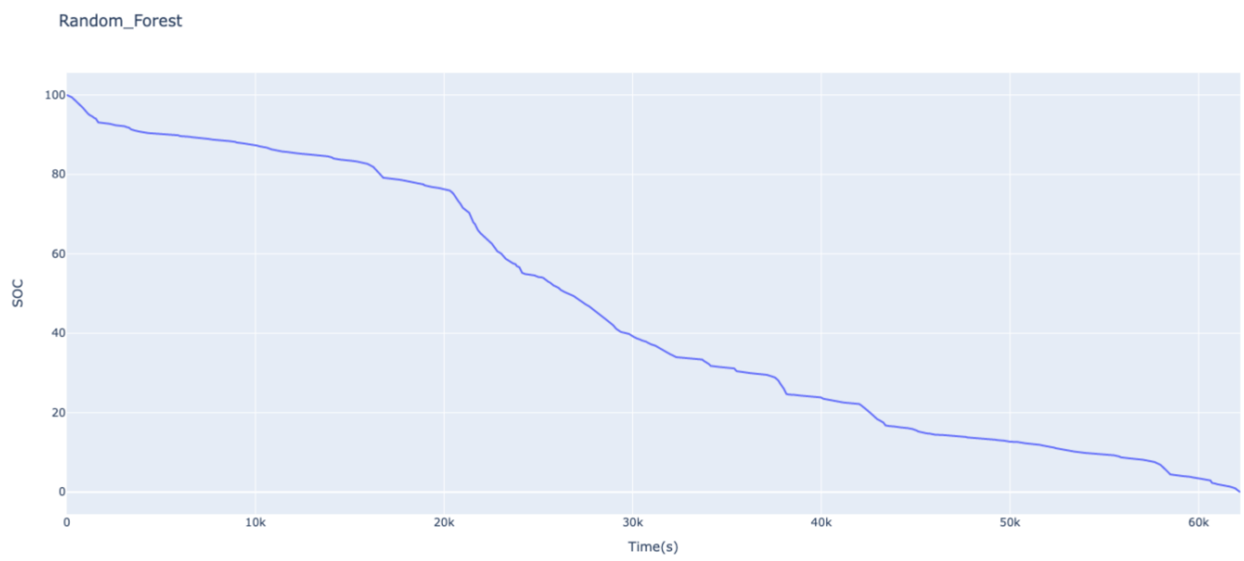

Figure 5.2 – SOC vs Time while discharging using RF Algorithm

SOC Plot versus time using MLP for charging data:

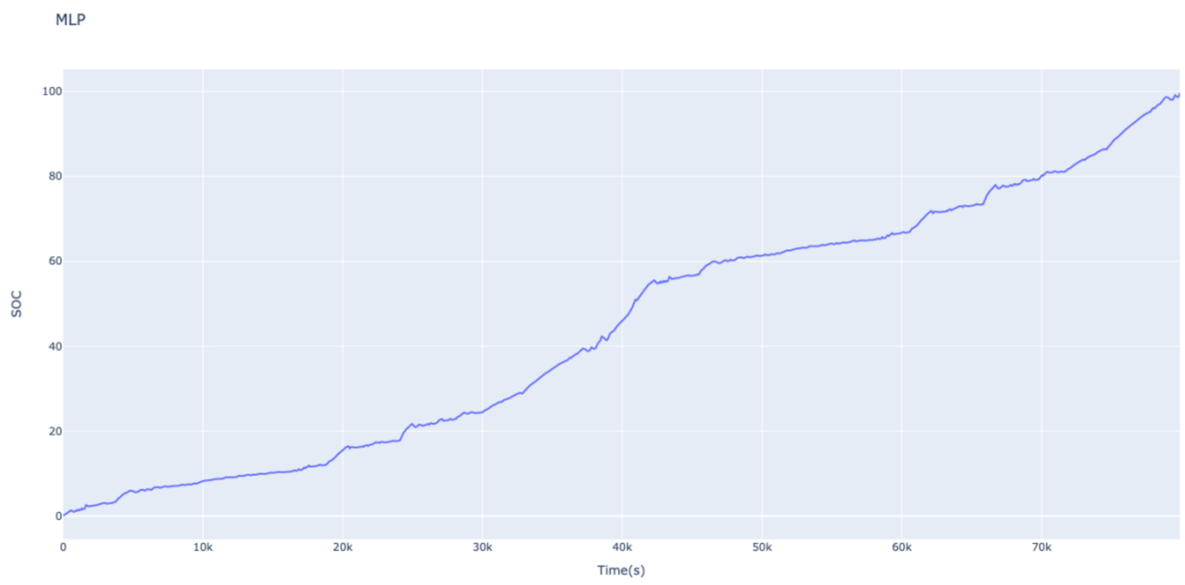

Figure 5.3 – SOC vs Time while charging using MLP

SOC Plot versus time using SVM for charging data:

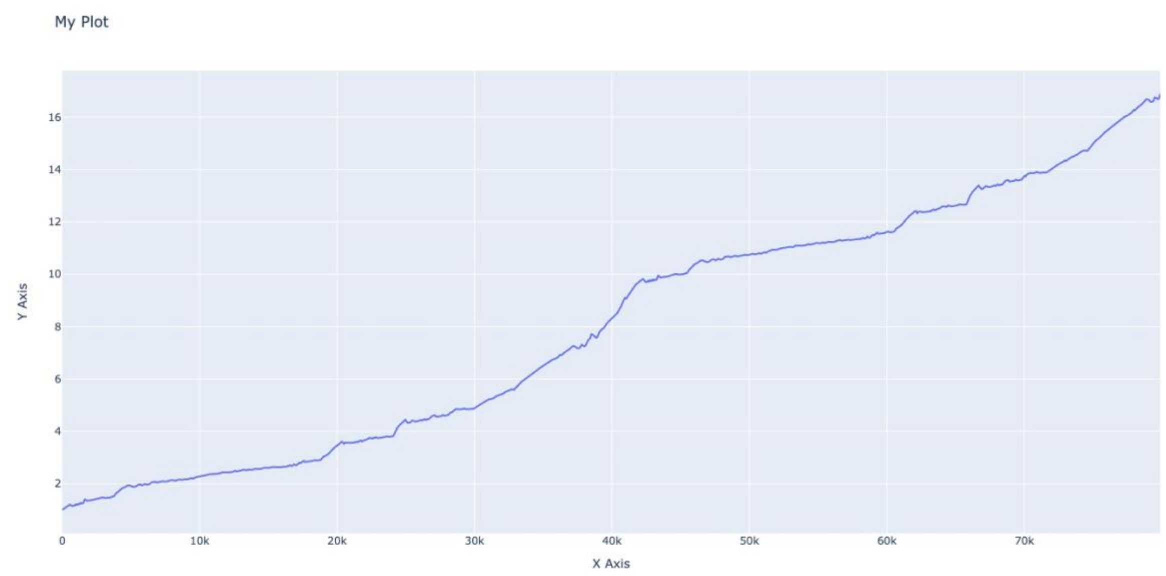

Figure 5.4 – SOC vs Time while charging using SVM

SOC Plot versus time using Extended Kalman Filter Technique for discharging data:

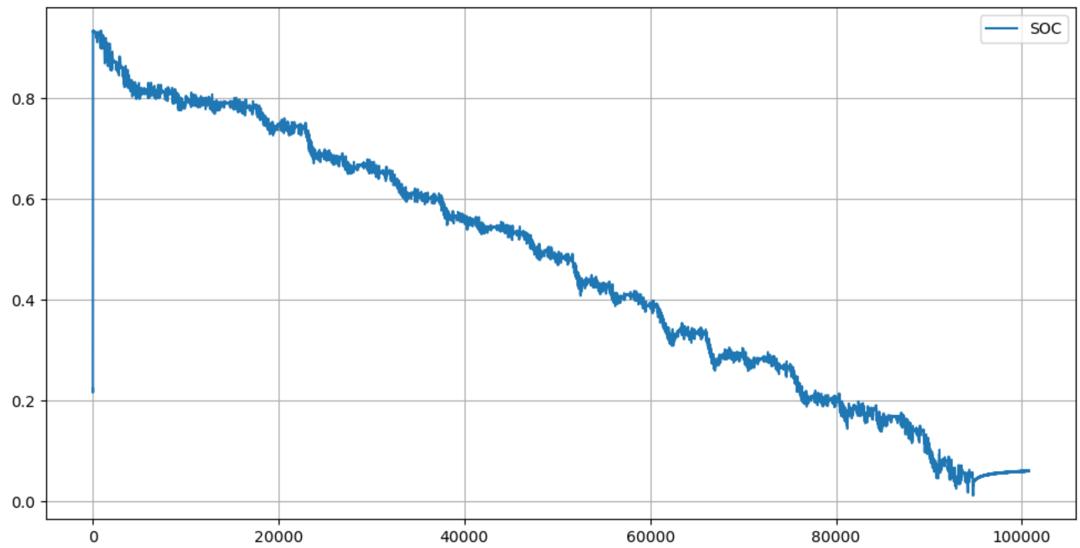

Figure 5.5 – SOC vs Time for discharging data using EKF Technique

Comparison of ML Algorithms:

The SOC estimation techniques using Support Vector Machines (SVM), Random Forest, and Multilayer Perceptron (MLP) were evaluated and compared.

Random forest Algorithm which has Mean Absolute Error (MAE) of 0.16 and Root Mean Square Error (RMSE) of 0.23, was considered to have the best accuracy in SOC estimation.

Comparison with Extended Kalman Filter (EKF):

The SOC estimation technique using the Extended Kalman Filter (EKF) was also evaluated and compared with the machine learning algorithms.

The performance of the machine learning algorithms and the EKF-based technique were compared to determine which approach provided better accuracy in SOC estimation.

5.2 COMPARISON OF PERFORMANCES

Error Analysis of MLP & Random Forest:

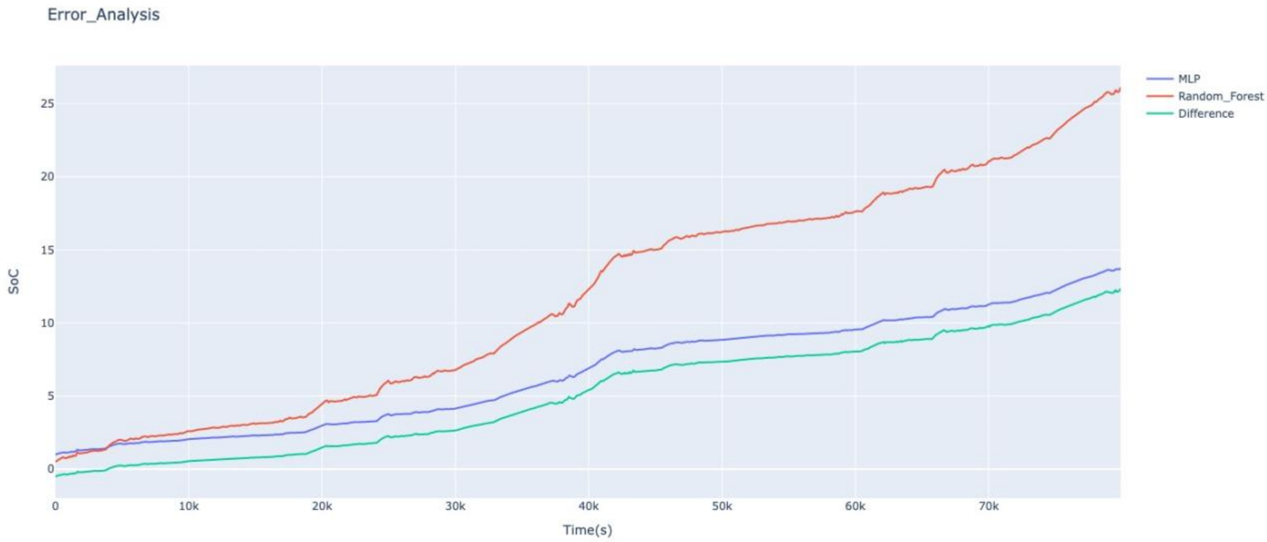

Figure 5.6 – Comparison of MLP & RF plots

The results of the performance comparison indicated the accuracy and effectiveness of the machine learning algorithms and the EKF-based technique in SOC estimation.

Extended Kalman Filter technique has more accurate estimated SOC values when compared to Data-driven Machine learning techniques.

The implications of the results were discussed in relation to the practical application of SOC estimation techniques in lithium-ion batteries and the potential for improving battery management systems.

Accuracy of the ML Algorithms is found to be:

SVM (0.11) < MLP (0.52) < Random Forest (0.65).

CHAPTER 6 – SUMMARY & CONCLUSION

1) Summary of the Project:

In this project, the goal was to estimate the State of Charge (SOC) of lithium-ion batteries using data-driven techniques.

Data about voltage and current of the batteries during charging/discharging were collected from online and offline resources.

Different machine learning algorithms, including Support Vector Machines (SVM), Random Forest, and Multilayer Perceptron (MLP), were trained and compared for SOC estimation.

The performance of these algorithms was also compared with the SOC estimation obtained using the Extended Kalman Filter (EKF).

2) Evaluation of Machine Learning Algorithms:

The machine learning algorithms were trained on the collected battery data and evaluated using various metrics, including mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination (R^2).

Random Forest algorithm has achieved the lowest MAE and RMSE values and the highest R^2 value demonstrated superior performance in estimating SOC.

3) Comparison with Extended Kalman Filter (EKF):

The performance of the machine learning algorithms was also compared with the SOC estimation obtained using the EKF technique.

The findings suggest that the machine learning algorithms have the potential to provide accurate and reliable SOC estimation, contributing to battery management systems and optimization of battery performance.

4) Future Directions:

While the machine learning algorithms showed promising results, there are opportunities for further research and improvement.

Exploring advanced machine learning techniques, such as deep learning models or ensemble methods, could enhance SOC estimation accuracy.

Considering additional features or sensor data, such as temperature or internal resistance, may also improve the estimation performance.

Moreover, conducting experiments with real-world battery systems and validating the models against actual measurements would be valuable for practical implementation.

5) Final Remarks:

In conclusion, this project highlights the potential of data-driven SOC estimation techniques using machine learning algorithms for lithium-ion batteries.

The findings contribute to the advancement of battery management systems, enabling more accurate SOC estimation and better battery performance optimization.

Overall, the project demonstrates the importance of exploring and evaluating different techniques for SOC estimation to enhance the efficiency and reliability of battery systems.

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