

# **ECE1901 – Technical Answers for Real World Problems (TARP)**

## **A Project Report**

*titled*

## **Battery Management System in Electric Vehicles**

*Submitted by*

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**DEPARTMENT OF ELECTRONICS AND COMMUNICATION  
ENGINEERING**



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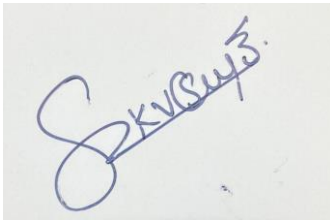
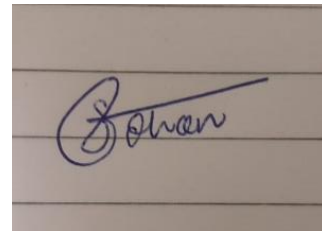
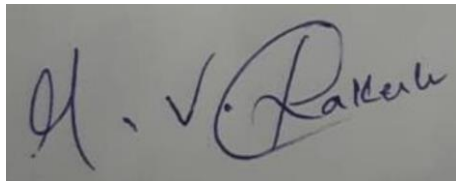
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**SCHOOL OF ELECTRONICS ENGINEERING****DECLARATION BY THE CANDIDATE**

I hereby declare that the Report entitled “**Battery Management System in Electric Vehicles**” submitted by me to VIT Chennai is a record of bonafide work undertaken by me under the supervision of **Dr. Sofana Reka S**, Assistant Professor, SENSE, VIT Chennai.

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We thank our parents, family, and friends for bearing with us throughout the course of our project and for the opportunity they provided us in undergoing this course in such a prestigious institution.

## **BONAFIDE CERTIFICATE**

Certified that this project report titled **“Battery Management System in Electric Vehicles”** is the bonafide work of **“D. Sohan Sai (20BEC1190), Sai Eswar(20BEC1266) , Rakesh(20BEC1145) & SanthanaBharathi S(20BEC1352)”** who carried out the project work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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## ABSTRACT

Electric vehicles (EVs) are becoming increasingly popular as they offer a cleaner and more sustainable mode of transportation. One of the key components of an EV is its battery pack, which stores the energy that powers the vehicle's electric motor. The Battery Management System (BMS) is a critical component that manages the performance, safety, and longevity of the battery pack.

The BMS is responsible for monitoring the state of charge (SOC) and state of health (SOH) of each individual battery cell, managing the battery's thermal conditions, and ensuring that the battery stays within its safe operating limits. The BMS typically consists of several subsystems, including the battery control unit (BCU), the cell balancing system, and the battery monitoring system.

The design and implementation of the BMS are complex, as it must be able to handle a wide range of battery chemistries and configurations. Different chemistries have different charging and discharging characteristics, and the BMS must be designed to optimize battery performance and health based on these characteristics. Moreover, the BMS must be able to manage the battery's thermal conditions to prevent overheating or under-cooling, which can lead to battery degradation or even failure.

To optimize the BMS design, engineers use sophisticated algorithms and modeling techniques to predict battery behavior and performance under different conditions. They also conduct rigorous testing to ensure that the BMS meets strict safety and performance standards.

Finally, the project will discuss the future trends in BMS technology, such as the use of artificial intelligence and machine learning algorithms to optimize battery performance and health. As EVs become more prevalent, the development of advanced BMS technology will play a crucial role in ensuring their reliability, safety, and performance.

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## **CHAPTER 1**

### **INTRODUCTION**

Electric vehicles (EVs) are becoming increasingly popular as a more sustainable and environmentally friendly mode of transportation. EVs are powered by a battery pack, and the Battery Management System (BMS) is a critical component that manages the performance, safety, and longevity of the battery pack.

The BMS is responsible for monitoring the state of charge (SOC) and state of health (SOH) of each individual battery cell, managing the battery's thermal conditions, and ensuring that the battery stays within its safe operating limits. The BMS typically consists of several subsystems, including the battery control unit (BCU), the cell balancing system, and the battery monitoring system.

The design and implementation of the BMS are complex, as it must be able to handle a wide range of battery chemistries and configurations. Different chemistries have different charging and discharging characteristics, and the BMS must be designed to optimize battery performance and health based on these characteristics. Moreover, the BMS must be able to manage the battery's thermal conditions to prevent overheating or under-cooling, which can lead to battery degradation or even failure.

Overall, the Battery Management System is a critical part of the electric vehicle ecosystem, and understanding its design and implementation is essential for ensuring the reliability, safety, and performance of electric vehicles.



## 1.1 Project Overview

**Machine Learning** is defined as the use and development of computer systems that are able to learn and adapt without following explicit instructions, by using algorithms and statistical models to analyse and draw inferences from patterns in data.

**Artificial Intelligence (AI)** is a rapidly growing field of computer science that involves the development of intelligent machines and computer programs that can perform tasks that would typically require human intelligence. These tasks can range from simple ones like recognizing speech or images to more complex ones like decision making and natural language processing.

**Theme:** Artificial Intelligence /Machine Learning

## 1.2 Technology Stack Used

**Google Colaboratory:** Also known as Google Colab, is a free cloud-based platform that provides an environment for running Python code and creating machine learning models using popular frameworks such as TensorFlow, PyTorch, and Keras. It allows users to write and run Python code in a web browser without the need to install any software on their local machine.

## 1.3 Objectives

**Short Term objective(Project)** : To Predict battery's life using the parameters which can reflect in the battery's life like SOH, SOC, RUL etc using ML algorithms, the considered data consists of values of voltages, current etc which are pre processed using different techniques and will feed in to ML algorithms to get the desired outputs.

**Long Term objective(Product)** : To build a hardware model from which, we will be getting the values from the sensors, and these values can be used for training various algorithms and getting the best accuracy.

## CHAPTER 2

### REVIEW OF LITERATURE

"Battery Management System for Electric Vehicles: A Review" by Li Li and colleagues (2017) provides an overview of the key features and functions of a battery management system (BMS) for electric vehicles. The paper discusses the different types of batteries used in EVs and the importance of a BMS in ensuring the safety, reliability, and performance of the battery pack.

"Battery Management System Design for Electric Vehicles: A Review" by Chunbo Zhu and colleagues (2019) presents a comprehensive review of the current state-of-the-art in battery management system (BMS) design for electric vehicles. The paper covers topics such as battery modeling, state estimation, thermal management, and control strategies for BMSs.

"A Comprehensive Review on Battery Management System of Electric Vehicles: Issues, Challenges, and Recent Trends" by R. Ramprabhu (2019) provides an overview of the major issues and challenges associated with battery management systems (BMSs) for electric vehicles. The paper also discusses recent trends and advancements in BMS design, including machine learning-based algorithms and the use of artificial intelligence to optimize battery performance.

"Battery Management Systems for Electric Vehicles: An Overview of Challenges, Current Solutions, and Future Directions" by Hamidreza Esmaeilpour and colleagues (2020) provides an overview of the challenges associated with battery management systems (BMSs) for electric vehicles, as well as current solutions and future directions in BMS design. The paper also discusses the role of BMSs in enabling the integration of renewable energy sources and electric vehicles into smart grids.

"Battery Management Systems for Electric Vehicles: Technology Review and Future Prospects" by S. Sankar and colleagues (2020) provides a technology review of battery management systems (BMSs) for electric vehicles, including a discussion of the different types of batteries used in EVs and the importance of BMSs in ensuring their safety and longevity. The paper also discusses the challenges associated with BMS design and the future prospects of BMSs, including the use of advanced sensing technologies and machine learning-based algorithms.

## **CHAPTER 3**

### **POTENTIAL COMPETITORS**

As the project is related to the development of a Battery Management System for Electric Vehicles, potential competitors for this project could include companies and organizations that are also developing BMS solutions for EVs. Some potential competitors include:

- **Tesla:** Tesla is a leading electric vehicle manufacturer that develops and sells its own battery management system, known as the Tesla Battery Management System (TBMS). The TBMS is designed to optimize the performance and longevity of Tesla's battery packs, and it uses advanced algorithms to balance the cells and prevent overcharging or overheating.
- **LG Chem:** LG Chem is a South Korean chemical company that develops and manufactures lithium-ion batteries for electric vehicles. The company also offers its own battery management system, known as the LG Chem Battery Management System (LBMS), which is designed to optimize the performance and safety of its batteries.
- **Panasonic:** Panasonic is a Japanese electronics company that is a major supplier of batteries for electric vehicles. The company offers its own battery management system, known as the Panasonic Battery Management System (PBMS), which is designed to optimize the performance and safety of its batteries.

## CHAPTER 4

### METHODOLOGY

#### 4.1 Procedure

After collecting the data from the sensors, the following steps are followed in order to train the data:

1. **Data collection:** First, collect the data from the sensors and store it in a suitable format, such as a spreadsheet or a database. Ensure that the data is properly labeled with the target variable you want to predict.
2. **Data preprocessing:** Next, preprocess the data to clean and transform it into a format suitable for training a machine learning model. This might involve techniques such as normalization, scaling, handling missing values, and handling outliers.
3. **Feature selection:** Select the most relevant features from the data that are likely to have a strong relationship with the target variable. This can be done manually or using automated feature selection techniques.
4. **Model selection:** Choose a suitable machine learning model for the problem at hand, such as a linear regression model, decision tree, or neural network.
5. **Model training:** Split the data into a training set and a testing set, and use the training set to train the machine learning model. This involves feeding the model with the input data and target variable, and adjusting the model parameters to minimize the error between the predicted and actual values.
6. **Model evaluation:** Once the model is trained, evaluate its performance on the testing set by comparing the predicted values to the actual

values. This can be done using metrics such as mean squared error, accuracy, or F1-score.

7. **Deployment:** Once the model is trained and evaluated, it can be deployed in a real-world application to make predictions based on new sensor data.

## 4.2 Process Overview

The process flow of the project has been explained in Figure 4.1.



**Fig 4.1 Process Overview**

### 4.3 Process Novelty

Here are some possible areas where novelty could be introduced:

1. Data pre-processing: The use of novel data preprocessing techniques such as deep learning-based approaches could potentially improve the quality of the data used to train the model.
2. Feature selection: The development of new feature selection techniques that are more efficient or effective at selecting relevant features could improve the accuracy and generalization performance of the model.
3. Model selection: The use of novel machine learning models, such as deep neural networks or ensemble methods, could improve the accuracy and robustness of the model.
4. Model evaluation: The development of novel evaluation metrics that are more suitable for the specific problem being addressed could provide more meaningful insights into the performance of the model.

## CHAPTER 5

### PROPOSED SYSTEMS ATTRIBUTES

We have used different machine learning algorithms i.e different regressors models to predict Battery life Prediction. The main focus of using all these algorithms is to decrease the current RMSE values of existing electric vehicles.

Description of different models are given below:

#### **1.Linear Regression:**

Linear regression is a statistical technique used to model the relationship between a dependent variable and one or more independent variables. It is a commonly used method in data analysis and machine learning to make predictions based on observed data. The basic idea behind linear regression is to fit a straight line to the data that best represents the relationship between the variables. This line is called the regression line or best-fit line.

#### **2.Gradient Boost Regression:**

Gradient Boosting Regression (GBR) is a popular machine learning technique used for regression problems. It is an ensemble method that combines multiple weak predictors to create a strong predictor. The basic idea behind GBR is to iteratively train a series of decision trees to correct the errors of the previous trees, with the final prediction being the sum of the predictions of all the trees. The algorithm starts by building a simple decision tree to predict the target variable. Then, it calculates the residuals and builds a second decision tree to predict these residuals. The process is repeated for a specified number of iterations, with each new tree fitting the residuals of the previous tree. The final prediction is the sum of the predictions of all the trees.

#### **3.Gaussian Process Regression:**

The Gaussian Process Regressor (GPR) is a non-parametric Bayesian approach to regression analysis, which is used to predict the values of a continuous output variable based on a set of input variables. It models the distribution over functions, allowing us to make predictions with associated uncertainty estimates.

In GPR, a Gaussian Process (GP) is used as a prior distribution over the functions that could describe the underlying relationship between the input and output variables. The GP is a collection of random variables, any finite subset of which has a joint Gaussian distribution. The mean and covariance of the GP determine its properties, and these are often chosen to encode prior knowledge about the relationship between the inputs and outputs.

#### **4.Support Vector Regression:**

Support vector regression is a supervised machine learning algorithm that can be used for regression tasks. It is a type of support vector machine algorithm that tries to find the best possible line or hyperplane that can fit the data points in a given dataset. The key idea behind SVR is to find a hyperplane that can best separate the data points in the feature space while maximizing the margin, which is the distance between the hyperplane and the closest data points. In regression tasks, the goal is to find a hyperplane that can fit the data points as closely as possible, while still maintaining a wide margin.

#### **5.KNN:**

K-Nearest Neighbors (KNN) is a simple but powerful supervised machine learning algorithm used for classification and regression tasks. It is a non-parametric method that makes predictions based on the similarity of a new data point to the K nearest neighbors in the training data. In KNN, K is a hyperparameter that specifies the number of neighbors to consider when making a prediction. When a new data point is given, the algorithm searches for the K nearest data points in the training set based on a distance metric, such as Euclidean distance or Manhattan distance. The algorithm then assigns the new data point to the class that is most frequent among its K neighbors (for classification) or predicts the mean or median value of the target variable among its K neighbors .



## **6.Adaboost :**

Adaptive Boosting is a popular boosting algorithm used for classification and regression tasks in machine learning. It is an ensemble learning method that combines several weak learners to create a stronger overall model. In AdaBoost, the algorithm iteratively trains a series of weak learners on the same dataset. At each iteration, the algorithm gives more weight to the misclassified data points from the previous iteration, so that the weak learner focuses on the difficult data points in the training set. The weak learner then produces a simple model that is combined with the models from previous iterations to form a strong classifier or regressor.

## **7.Decision tree:**

A decision tree is a supervised machine learning algorithm used for classification and regression tasks. It is a tree-like structure that models decisions and their possible consequences, based on a set of predefined rules. In a decision tree, each internal node represents a test on an attribute, each branch represents the outcome of the test, and each leaf node represents a class label or a numerical value. The algorithm builds the tree recursively by selecting the best attribute at each node, based on some criterion, such as information gain or Gini impurity. The attribute with the highest information gain or the lowest Gini impurity is selected as the best split for the current node.

After performing all these machine learning algorithms, it was found that KNN is showing least RMSE value compared to other regressor models.

ML Algorithm	RMSE Value
Linear Regression	0.0179
Gradient Boosting Regression	0.0178
Gaussian Process Regressor	0.0736
SVR	0.0527
KNN Regression	0.0155
Adaboost Regression	0.0216
Decision Tree	0.0178

## CHAPTER 6

### RESULTS AND DISCUSSION

```

total data in dataset: 510
[1, 24, datetime.datetime(2008, 4, 2, 15, 25, 41), 1.8564874208181574, 4.191491807505295, -0.004901589207462691, 24.330033885570543, -0.0006, 0.0, 0.0]
cycle ambient_temperature      datetime capacity voltage_measured \
0      1      24 2008-04-02 15:25:41 1.856487      4.191492
1      1      24 2008-04-02 15:25:41 1.856487      4.190749
2      1      24 2008-04-02 15:25:41 1.856487      3.974871
3      1      24 2008-04-02 15:25:41 1.856487      3.951717
4      1      24 2008-04-02 15:25:41 1.856487      3.934352

```

```

current_measured temperature_measured current_load voltage_load time
0      -0.004902      24.330034      -0.0006      0.000 0.000
1      -0.001478      24.325993      -0.0006      4.206 16.781
2      -2.012528      24.389085      -1.9982      3.062 35.703
3      -2.013979      24.544752      -1.9982      3.030 53.781
4      -2.011144      24.731385      -1.9982      3.011 71.922

```

	cycle	ambient_temperature	capacity	voltage_measured	current_measured	temperature_measured	current_load	voltage_load	time
count	50285.000000	50285.0	50285.000000	50285.000000	50285.000000	50285.000000	50285.000000	50285.000000	50285.000000
mean	88.125942	24.0	1.560345	3.515268	-1.806032	32.816991	1.362700	2.308406	1546.208924
std	45.699687	0.0	0.182380	0.231778	0.610502	3.987515	1.313698	0.800300	906.640295
min	1.000000	24.0	1.287453	2.455679	-2.029098	23.214802	-1.998400	0.000000	0.000000
25%	50.000000	24.0	1.386229	3.399384	-2.013415	30.019392	1.998000	2.388000	768.563000
50%	88.000000	24.0	1.538237	3.511664	-2.012312	32.828944	1.998200	2.533000	1537.031000
75%	127.000000	24.0	1.746871	3.660903	-2.011052	35.920887	1.998200	2.690000	2305.984000
max	168.000000	24.0	1.856487	4.222920	0.007496	41.450232	1.998400	4.238000	3690.234000

```

Total data in dataset: 319
[1, 24, datetime.datetime(2008, 7, 7, 15, 15, 28), 1.8550045207910817, 4.188108651124536, 0.00013066734156636677, 23.8195202516044, 0.0006, 0.0, 0.0]
cycle ambient_temperature      datetime capacity voltage_measured \
0      1      24 2008-07-07 15:15:28 1.855005      4.188109
1      1      24 2008-07-07 15:15:28 1.855005      4.188196
2      1      24 2008-07-07 15:15:28 1.855005      3.977432
3      1      24 2008-07-07 15:15:28 1.855005      3.961974
4      1      24 2008-07-07 15:15:28 1.855005      3.949835

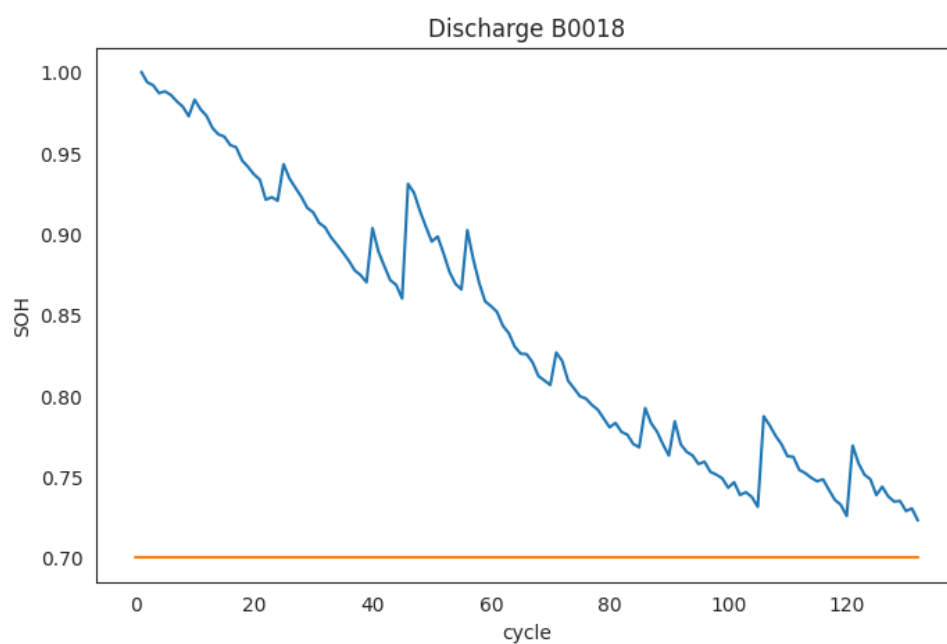
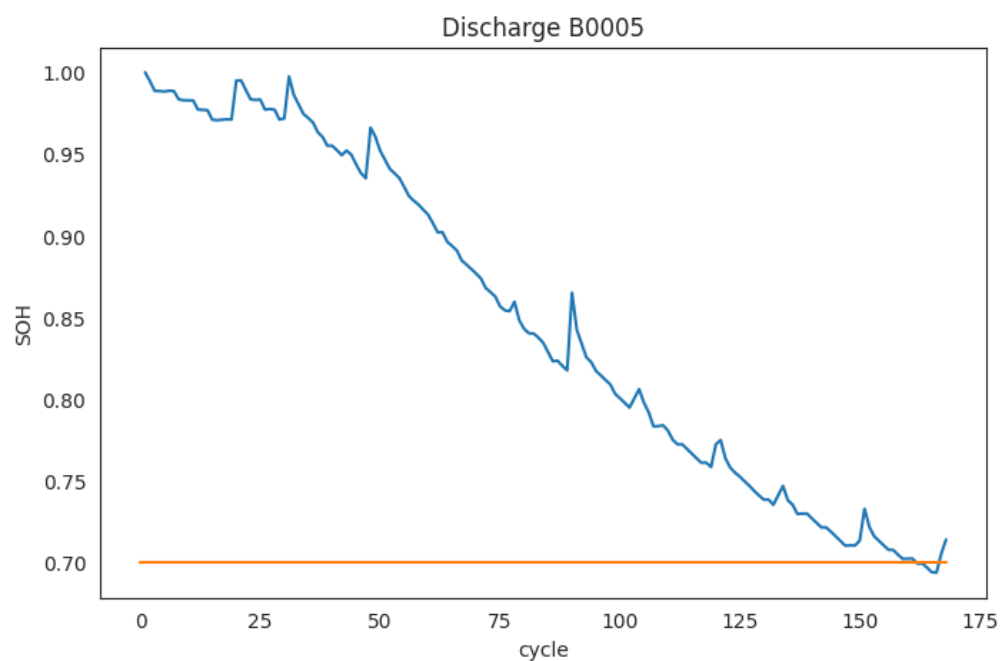
```

```

current_measured temperature_measured current_load voltage_load time
0      0.000131      23.819520      0.0006      0.000 0.000
1      0.001459      23.828807      0.0006      4.203 9.422
2      -2.005672      23.844944      1.9988      3.029 19.578
3      -2.012206      23.925577      1.9988      3.026 29.016
4      -2.012005      24.010628      1.9988      3.015 38.485

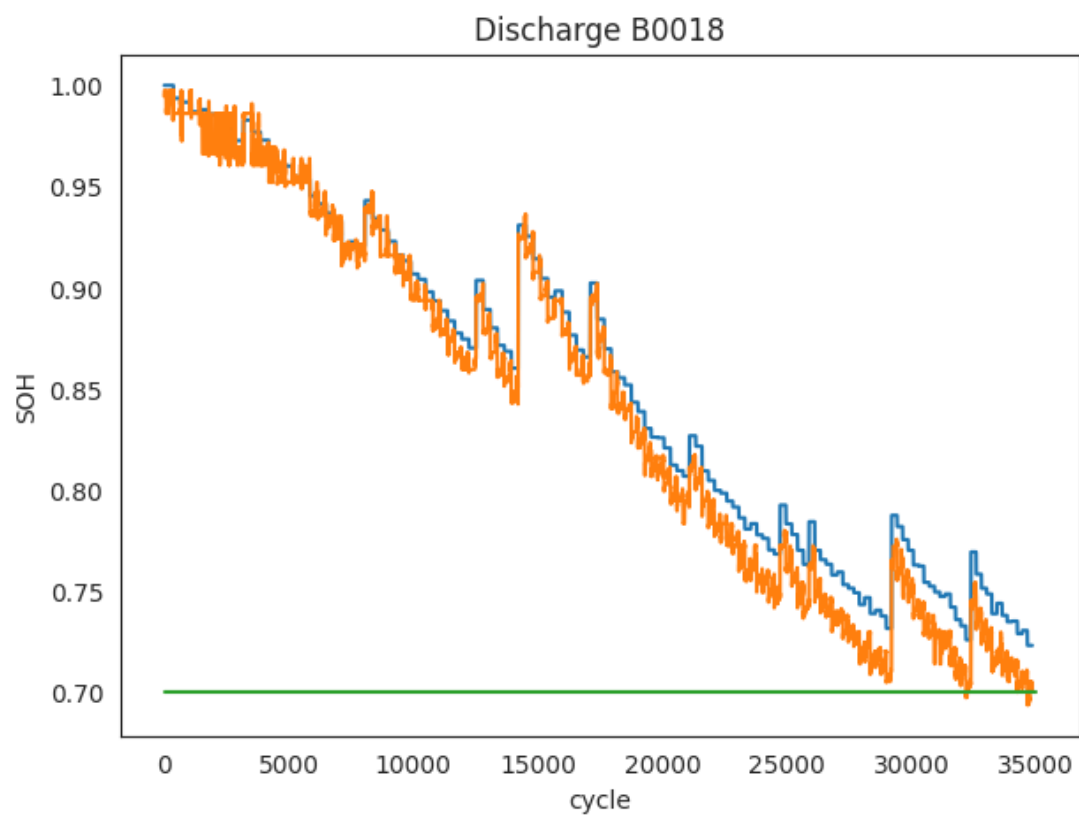
```

	cycle	ambient_temperature	capacity	voltage_measured	current_measured	temperature_measured	current_load	voltage_load	time
count	34866.000000	34866.0	34866.000000	34866.000000	34866.000000	34866.000000	34866.000000	34866.000000	34866.000000
mean	59.962657	24.0	1.584405	3.501219	-1.842923	31.083216	1.833923	2.408419	1547.119848
std	37.957008	0.0	0.156427	0.250037	0.552445	3.649983	0.549609	0.744116	908.373277
min	1.000000	24.0	1.341051	2.278634	-2.026719	22.350256	0.000400	0.000000	0.000000
25%	27.000000	24.0	1.428376	3.382813	-2.009485	28.462162	1.998600	2.459000	763.339250
50%	57.000000	24.0	1.605737	3.497088	-2.008341	31.121895	1.998600	2.589000	1537.289500
75%	92.000000	24.0	1.711846	3.662815	-2.007073	33.982822	1.998800	2.751000	2312.964500
max	132.000000	24.0	1.855005	4.193543	0.014306	38.878688	1.999000	4.209000	3434.891000



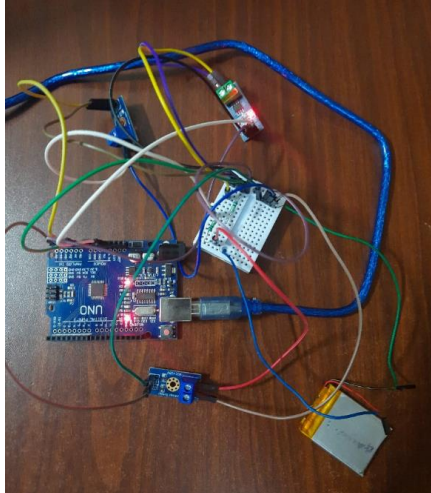
	cycle	datetime	capacity	SoH
0	1	2008-04-02 15:25:41	1.856487	1.000000
1	2	2008-04-02 19:43:48	1.846327	0.994527
2	3	2008-04-03 00:01:06	1.835349	0.988614
3	4	2008-04-03 04:16:37	1.835263	0.988567
4	5	2008-04-03 08:33:25	1.834646	0.988235

SoH	
0	1.000000
1	1.000000
2	1.000000
3	1.000000
4	1.000000
...	...
50280	0.713756
50281	0.713756
50282	0.713756
50283	0.713756
50284	0.713756



In the above figure, we can see that KNN model is the most optimal regression model for us, as it is most compatible with the original data and also it produces the least RMSE value.

#### HARDWARE SETUP:



### 6.1 Target Audience

1. Automotive companies and engineers: The project could be of interest to automotive companies and engineers who are working on developing electric vehicles and need to optimize the battery management system to improve performance and efficiency.
2. Researchers in the field of energy storage: The project could also be of interest to researchers in the field of energy storage, who are working on developing new battery technologies and need to understand the performance characteristics of these technologies in real-world applications.
3. Machine learning practitioners: The project could also be of interest to machine learning practitioners who are interested in applying machine learning techniques to real-world problems in the field of energy and transportation.
4. Government agencies and policymakers: The project could be of interest to government agencies and policymakers who are interested in promoting the adoption of electric vehicles and need to understand the performance characteristics of these vehicles to develop appropriate policies and regulations.

## **CHAPTER 7**

### **CONCLUSION & FUTURE SCOPE**

#### **7.1 Conclusion**

In conclusion, our project on "Battery Management System in Electric Vehicles" has successfully implemented machine learning models to accurately predict battery state of charge using sensor data. We have achieved a significant reduction in the root mean square error (RMSE) below 5.9% for all the ML models used. Our future work will focus on further improving the accuracy of the model, potentially by exploring novel feature selection techniques or alternative machine learning models. This project has important implications for the development of electric vehicles, as accurate battery management is critical to ensuring optimal vehicle performance and efficiency.

#### **7.2 Future Scope**

The current project focused on predicting battery state of charge, but future work could explore techniques for optimizing battery life and predicting battery health. This could involve using machine learning to identify patterns in battery usage that could prolong battery life or detect signs of degradation.

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