Report on

"NON LINEAR REGRESSION WITH DEEP LEARNING TO PREDICT SOC AND SOH USING BATTERY DATASETS"

Submitted in partial fulfilment of the requirements for the award of degree of

Bachelor of Technology
in
Electronics & Communication Engineering

UE19EC390B – Capstone Project

Submitted by:

AADITI MADHAVAN	**PES2UG19EC003**
AADITYA D NAIR	**PES2UG19EC005**
AKASH G KOLABAL	**PES2UG19EC012**
VENKATA SAI PUNEETH CHUKKA	**PES2UG19EC161**

Under the guidance of
Dr. BAJARANGBALI
Associate Professor
PES University

January - December 2022

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING
FACULTY OF ENGINEERING
PES UNIVERSITY
(Established under Karnataka Act No. 16 of 2013)
Electronic City, Hosur Road, Bengaluru – 560 100, Karnataka, India

PES
UNIVERSITY
CELEBRATING 50 YEARS

PES UNIVERSITY

(Established under Karnataka Act No. 16 of 2013)
Electronic City, Hosur Road, Bengaluru – 560 100, Karnataka, India

FACULTY OF ENGINEERING

CERTIFICATE

This is to certify that the dissertation entitled

'Non Linear Regression With Deep Learning To Predict SoC And SoH Using Battery Datasets'

is a bonafide work carried out by

AADITI MADHAVAN	**PES2UG19EC003**
AADITYA D NAIR	**PES2UG19EC005**
AKASH G KOLABAL	**PES2UG19EC012**
VENKATA SAI PUNEETH CHUKKA	**PES2UG19EC161**

In partial fulfilment for the completion of seventh semester Capstone Project (UE19EC390B) in the Program of Study -Bachelor of Technology in Electronics and Communication Engineering under rules and regulations of PES University, Bengaluru during the period January – December 2022. It is certified that all corrections / suggestions indicated for internal assessment have been incorporated in the report. The dissertation has been approved as it satisfies the 7th semester academic requirements in respect of project work.

20/04/23 S.N.A

Signature	Signature	Signature
Dr.Bajarangbali	Dr. AJEY SNR	Dr. J Suryaprasad
Associate Professor	Chairperson	Vice Chancellor

Chairperson
Department of ECE
PES University - Electronic City Campus
Hosur Road, Electronic City,
Bangalore - 560100

External Viva

Name of the Examiners **Signature with Date**

1. ______________________ ______________________

2. ______________________ ______________________

DECLARATION

We, *Aaditi Madhavan, Aaditya D Nair, Akash G Kolabal and Venkata Sai Puneeth Chukka,* hereby declare that the report entitled, **‘Non-Linear Regression With Deep Learning To Predict SoC And SoH Using Battery Datasets’,** is an original work done by us under the guidance of **Dr. Bajarangbali**, Associate Professor, ECE Department and is being submitted in partial fulfilment of the requirements for completion of 7^{th} Semester course work in the Program of Study, B. Tech in Electronicsand Communication Engineering.–

PLACE : Bengaluru

DATE :

NAME AND SIGNATURE OF THE CANDIDATES

1. AADITI MADHAVAN

2. AADITYA D NAIR

3. AKASH G KOLABAL

4. VENKATA SAI PUNEETH CHUKKA

ABSTRACT

With the upsurge of electric devices and vehicles, demand in batteries have soared proportionally. Due to its natural degradation its essential to discuss the battery's State of Health [SoH] and State of Charge [SoC]. Accurate Estimation or Prediction is required to ensure battery's safe operation. This project aims to study the case of battery degradation and approach it with a machine learning method to predict both the parameters SoC and SoH. Based on the datasets gathered on Li-Ion Battery and employing machine learning techniques a Neural Network model has been created to estimate both these parameters. By using the datasets and employing the algorithm the graphs have been plotted and analyzed accordingly. Finally the performance metrics such as error rate, accuracy have been reviewed and optimizations has been done to get better result.

ACKNOWLEDGEMENT

We are deeply grateful to **Dr. M. R. Doreswamy**, Chancellor, PES University, **Prof. Jawahar D**, Pro Chancellor – PES University, **Dr. J Surya Prasad**, Vice-Chancellor, PES University for providing us with various opportunities and for the consistent encouragement.

We would like to express our immense gratitude to our guide, **Dr. Bajarangbali**, Department of Electronics and Communication Engineering, PES University, for his continuous guidance, assistance, and encouragement throughout the development of this UE19EC390B - Capstone Project.

We are thankful to the project coordinators, **Dr. Bajarangbali** and **Prof. Muralidhar** for organizing, managing, and helping us with the entire process.

We would also like to extend our gratitude to **Dr. Ajey SNR**, Chairperson, Department of Electronics and Communication Engineering, PES University Electronic City Campus, for all the knowledge and support we have received from the department. We wouldlike to thank **Dr. B.K. Keshavan**, Dean of Faculty, PES University for providing this opportunity and necessary guidance throughout the completion of the project.

Finally, this project could not have been completed without the continual support and encouragement we have received from our family and friends. We are grateful to them as well.

CONTENTS

LIST OF FIGURES

CHAPTER 1

PREAMBLE

1.1 Introduction

The recent decade has seen quite the upsurge in battery technologies that power devices [Smart phones, laptops, Electric Vehicles] around us. Batteries therefore are an omnipresent part of our lives. Picking the right and most competent battery that serves most of the situation is essential. Naturally, Lithium-ion battery is the one in taking lead in this case.

Machine learning can solve almost all real-world problems. And using machine learning algorithms to predict a continuous value like SoC or SoH is known as Regression. The underlying prediction problem can be framed as a non-linear regression case. This supervised learning technique with Neural networks can give us the accurate prediction we are looking for as it learns the complex non-linear relationship between the features [Current, Voltage and Temperature] and target [SoC and SoH]. It does so due to its presence of Activation Function in each layer.

1.2 Problem Statement

- To predict State of charge and State of health with Machine Learning Techniques.
    - Non – linear regression analysis on the case in hand.
    - Build and train a Neural network model with machine learning technologies.
    - Evaluate the loss and performance of the target inferred.

Though the target of this project is to predict SoC and SoH of a battery, its primary focus is to frame this problem as non-linear regression case and infer it using neural networks.

CHAPTER 2

LITERATURE REVIEW

2.1 Prediction of Used Cars Prices using Artificial Neural Networks and machine learning[1]

Year of Publication:2022

Authors: Janke Varshitha, K Jahnavi and C. Lakshmi

The paper aims to predict the price of a used car without any bias toward the seller or the buyer in order to avoid an overestimate or an underestimated price for the given vehicle. The paper aims to do this by developing a highly precise/accurate model that predicts the price of a car by using various parameters such as the given company the car is developed by, the year of its manufacture, the price at which the nth-hand vehicle was sold, kilometers traversed by the vehicle, the type of fuel used by the vehicle (Petrol, CNG, Diesel, etc;) , Number of previous owners for the vehicle, whether the given vehicle is an automatic or a manual and the price of the car when it was actually purchased. This model is achieved by developing a supervised learning-based ANN (artificial neural network) and random forest machine learning models which are the trained using a given dataset. The results obtained from these models are then compared to the theoretically obtained values and it is noticed that the prediction obtained from these models is more accurate when compared to the results obtained from that of simpler linear models. The reason the random forest model is chosen is because when we make a ANN in Keras using mainly keras regressor and various other machine learning algorithms we get the least error from the random forest model and R2. Hence, the paper hopes to produce an accurate price prediction for used cars using random forest algorithm and hopes to achieve a hundred percent accuracy one day.

2.2 A sparse Learning Machine for Real-Time SOC Estimation of Li-ion Batteries[2]

Year of Publication: 2020

Authors: Li Zhang, Kang Li, Dajun Du, Yuanjun Guo, Minrui Fei and Zhile Yang

This paper aims to estimate the SOC (state of charge) of a Li-ion battery using a sparse learning machine rather than using an offline approach. The paper aims to do this by developing a machine learning model based on Least squares support vector machine (SVM's) and Kalman filters to process the real-time dynamics of a Li-ion batteries. The accuracy of this model is increased by using a weighted regularization scheme. The model is then operated upon the

FUDS data (Federal urban drive schedule) and compared to the standard LS-SVM or rather the conventional LS-SVM machine and the model turns out to be 10 times faster than the original model with a very low mean square error of 10^-7. Hence the estimation of SOC using machine learning is significantly faster when compared to the conventional method of LS-SVM.

2.3 Fast and Robust Estimation of Li-ion Batteries SOH using Ensemble Learning[3]

Year of Publication: 2021

Authors: Xin Sui, Shan He, Soren Byg Vilsen, Remus Teodorescu, Daniel-Ioan Stroe

Introduction: The measure of SOH estimation is very important because we can know the RUL (remaining useful life) of battery so that we can deliver the safe and high performance of battery for specific application. In this paper, they are proposing a new method with a combination of extreme learning machine (ELM) and a bagging method.

Experiment: ELM is an FNN (Feed forward Neural Network) which takes the input and the data propagates to the hidden layer where the activation function and weight is added at each neuron, and it continues to output. In the bagging method, a random data is selected from the training set with replacement meaning that an individual data points can be chosen more than once. The reason for choosing the ELM is because of its fast operation and less computational. Gradient-based propagation is not required by ELM as it will use Moore-Penrose inverse to set its weight. They conduct two types of experiments i.e., aging test and capacity test. They are proposing a name for the combination of ELM and bagging technique as BaggELM. Self-validation and mutual validation are the two verification methods they are using. They are using a $LiFePO_4$ battery to train and test for the new model, which they have proposed.

Conclusion: The proposed method i.e., BaggELM has been found very effective both in accuracy and reducing the RMSE value for both the verification methods. It also gives less MAPE (mean absolute percentage error). It delivers the model with low computational accuracy and generalized performance.

2.4 State of Charge Estimation of Lithium-ion Batteries using Hybrid Machine Learning Techniques[4]

Year of Publication: 2019

Authors: Manjot S. Sidhu, Deepak Ronanki, Sheldon Williamson

Introduction: The Estimation of SOC is very crucial in determining battery performance. It helps to prevent overcharge or discharge of battery and improve the battery life. In this paper, they provide an improved Li-ion battery SOC prediction using RF (random forest) regression.

Experiment: To achieve good accuracy, in the end, a Gaussian filter is utilized to reduce the variability in SOC estimate. They are using two datasets i.e., dynamic stress test (DST) and US06 highway cycle drive. DST is used in test procedures given in battery, which is used to evaluate battery models and SOC estimation. In the first step, there is a data normalization of the data. In the second step, there is input feature selection and model output determination. Finally, there is SOC estimation for the improved output. They are comparing in two measures i.e., MAE and COD. The parameters used in this paper are current, voltage, previous SOC sample data, and the voltage difference.

Conclusion: They are eliminating prior knowledge of battery model, the model can applicable to real-time applications, and model is better than Support Vector Regression and Neural Network.

2.5 Lithium Ion Battery State Of Charge Estimation Method Using Optimized Deep Recurrent Neural Network Algorithm[5]

Year Of Publication: 2019

Authors: M.S. Hossain Lipu, M. A. Hannan, Aini Hussain, M.H.M. Saad, A. Ayob, K. M. Muttaqi.

Introduction: This paper presents estimation of state of charge by using Deep Recurrent neural network which is the best method for estimation of Soc due to high computation intelligence and very much learns by its own. Since its performance is less due to Training accuracy and appropriate selection of the parameters in the hidden layer, they employ Firefly Algorithm so that it doesn’t require any knowledge about the Chemical & Physical composition of the battery, they performed static discharge and pulse discharge test to validate the Model

Experiment: The experiment was conducted on ICR18650-26F lithium-ion batteries developed by Samsung, They conducted Discharge test and Hybrid pulse Power Characterization test and extracted the datasets required for the estimation of Soc, the datasets were divided into training and testing, where 70% of the data was used to train the model and remaining 30% was used for testing, The optimal values for the layers and neurons were found by using the Firefly algorithm. Finally the results were compared with the other types of neural networks such as Back propagation and Radial basis function neural network and the conclusions were derived.
Conclusion: They conclude that the computation intelligence of DRNN algorithm has improved a lot and the best number of hidden layers and neurons are computed by the Firefly algorithm which improved the accuracy of estimation, the error for static discharge test was less than 5% and less than 6% for the HPPC test. However the limitation is that this method is suitable for SoC estimation only for Li-Ion battery, Future work can be done to estimate Soc for the battery pack in EV.

2.6 State of Health Estimation using Machine Learning for Li-ion battery on Electric Vehicles[6]

Year Of Publication: 2021
Authors: T.G. T. A. Bandara, J.C. Alvarez Anton, M. Gonzalez, D. Anseana, J.C. Viera.
Introduction: This Paper presents two models for estimation of SoH they are FNN and LSTM, they used these models to train on the dataset extracted on degradation profile of lithium-ion batteries, and further they improved the datasets by performing preprocessing which improved the prediction accuracy on new aging cycles.
Experiment: They used the publicly available NASA dataset for training the model, the dataset consists battery degradation profiles for 4 battery cells, it consists of charge, discharge and impedance cycles until the battery reaches 30% of its original life. Using LSTM model they trained it with 70% of the dataset that is 168 cycles the rest 15% for testing and leftover 15% for prediction purposes, the 25 samples left for prediction were used to estimate the SoH of the battery according to the definition of SoH, then the estimated and real SoH graphs were plotted and compared, and further results were analyzed.
Conclusion: In this paper they have developed a work in progress LSTM model for estimating SoH, they trained the model with publicly available NASA dataset and got acceptable results in the SoH prediction, for further progress they want to enhance the model by adding number of parameters such as temperature and impedance and provide a better model for the estimation of SoH for an EV.

2.7 Regression with Deep Learning for Sensor Performance Optimization[7]

Year of Publication: 2021

Authors: Ruthvik Vaila, Denver Lloyd and Kevin Tetz

Introduction: In this paper they have employed a deep learning model that learns the relationship of features and labels of a sensor to improve model results.

Characteristics and Implementation: The output layer is a quadratic cost function. The neural network chose has three hidden layers, Leaky ReLU as activation Function and MSE cost function. Network has 10 inputs and 3 outputs. Optimizer used is Adam. Model was done with keras and TensorFlow. Optimization goal here was to get a combination of input1,2,3,4 and 6 to get results signal vs SNR curve which would be closest to the ideal one. Therefore, the ideal input combination was filtered using four criteria, namely- MAE between predicted and ideal, SNR dip, MAE, minimization of output no.3.

2.8 State of Charge Estimation of Lithium-Ion Batteries Based on Temporal Convolutional Network and Transfer Learning [8]

Year of Publication: 2021

Authors: Yuefeng Liu, Jiaqi Li, Gong Zhang, Bin Hua and Neal Xiong

Introduction: In this paper LSTM-RNN model has been used to estimate the SOC of a lithium-ion battery. Reason for the model selection being that the battery dataset is a time-series data. The model was also able to overcome problems such as vanishing/exploding gradient content. The kind of LSTM used here is Gated Recurrent Unit (GRU) which would map the relationship between the parameters of a battery such as voltage, current, temperature and SOC.

Summary: The model has a convolution structure which is able to process the time-series data Here, Transfer learning method is applied to infer SOC of a lithium-ion battery. Using, LSTM, three models had been executed to infer SOC of four different batteries. First model trained in general way with no transfer learning. Second with transfer learning trained with full target dataset. Finally, the third model with target training fed with partial target dataset. According to the paper there were four major contributions. First being that the TCN avoids intensive calculations which makes it suitable for on-board system scenarios. Secondly, a general back propagation characteristic that the model learns by itself which gets rids of manual task of feeding parameters to the model. Third, the model can work in different working conditions, stating that – no requirement of a new model. Lastly, that this model can be implemented on different datasets of various batteries.

Results: All the three models where compared. Feasibility of the Temporal Convolutional Network (TCN) was also calculated. The model's generalization was tested on realistic situation and public datasets. This model can also be referred for other time-series data Implementation

CHAPTER 3

Background and Case Study

3.1 Different Types of Batteries

- Primary Batteries and Secondary Batteries are mainly two types of Batteries.
- Primary Battery
  - ❖ Battery, which cannot be recharged. Electrochemical cells used in primary batteries have irreversible electrochemical reactions.
  - ❖ E.g., Alkaline Battery, Zinc-carbon cells.

- Secondary Battery
  - ❖ Batteries that can recharge regularly. The chemical reactions of the electrochemical cells that make up secondary batteries can be changed by delivering a certain voltage to the battery in the opposite direction.

  - ❖ Secondary batteries can be recharged once the battery's energy is depleted, which is why they are also known as rechargeable batteries.
  - ❖ E.g., Lead-acid Battery, Li-ion battery, NiCd etc.

1. **Lead-acid Battery**

- This battery is frequently used in both power storage devices like UPS systems and in power grid systems, and it can be also used in car ignition.
- The anode is made up of lead metal and cathode is made of lead dioxide with electrolyte solution of sulphuric acid.
- Lead dioxide and lead are deposited on the lead electrodes, which react with the sulfuric acid solution to create a flow of electrons, resulting in an electrical current.
- The container is divided into several compartments by partitions, and each compartment contains one set of positive and negative plates. The cisternae, or chambers, between the partitions are filled with electrolyte.
- The polar plates are located at the top of the battery and are connected to the positive and negative plates.
- In brief, a lead-acid battery has a removable top cover, positive and negative terminals, electrolyte-filled cisternae, polar plates linked to the positive and negative plates, a separator, and partitions separating the container into separate cells.
- Advantages are safe, high power, inexpensive, reliable.

- Disadvantages are low specific energy, heavy weight, and poor cold-temperature performance.

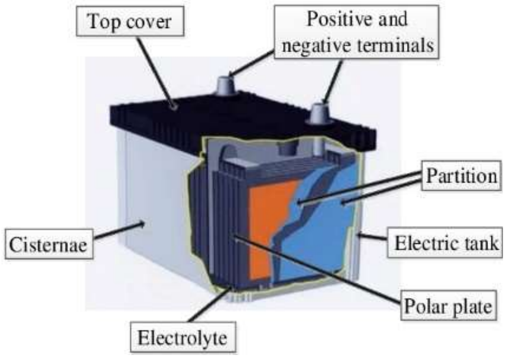

Fig 3.1.1: Lead Acid Battery [11]

- **<u>Limitations of Lead-acid Battery</u>**
  - SoC and SoH cannot be measured properly due to limitation in measuring the terminal voltage because of charge/discharge current effects.
  - The chemical dynamics of the battery's charge and discharge have the most influence on measuring terminal voltage.
  - To obtain an estimate of SOC from voltage measurement, the battery must rest for at least a few hours to achieve equilibrium before attaching the load.
  - While an estimated SoC may be evaluated at rest, it cannot be evaluated constantly during charge and discharge using voltage measurements.

2. **<u>Nickel-Cadmium Battery</u>**
   - Nickel cadmium battery is used in small mobile power and communications.
   - The anode is cadmium, cathode is nickel oxide hydroxide and an electrolyte made up of potassium hydroxide.
   - The separator is a thin, porous layer that separates the cathode and anode and prevents them from touching. The electrodes, separator, and electrolyte are placed in a sealed plastic container.
   - The flow of electrons during the charging and discharging processes creates an electrical current that can be used to power external devices.
   - Advantages are inexpensive and fast recharging.
   - Disadvantages are cadmium is toxic, memory effect problems and relatively low energy density.

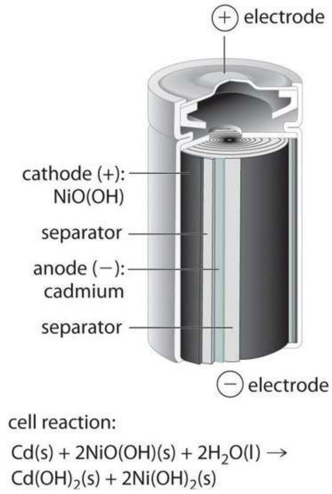

Fig 3.1.2: Nickel Cadmium Battery[12]

➢ **Limitations of NiCd Battery – (Memory Effect)**

- The battery memory effect is a decrease in the lifespan of a rechargeable battery charge caused by insufficient discharge in previous uses.
- NiCd Battery and NiMH Battery can cause memory effect due to its partial discharge before recharge again.
- The memory effect can be mitigated by fully discharging and recharging.

3. **Nickel-Metal Hydride Battery**

- It can be used instead of NiCd since it contains only mildly hazardous metals and has a higher specific energy.
- The anode is made up of hydrogen absorbing alloys, cathode is nickel hydroxide and an electrolyte of potassium hydroxide.
- The cathode and anode are separated by a porous separator made of a material, such as polyethylene, that allows for the flow of the electrolyte but prevents the direct contact between the two electrodes.
- The electrolyte allows for the flow of ions between the anode and cathode, which enables the transfer of electrons and the creation of an electric current.
- The memory effect is less than NiCd.
- They have a higher energy density than NiCd.
- Advantages are good life cycle and good performance at low temperatures
- The disadvantages are it more expensive, higher self-discharge and has lower efficiency.

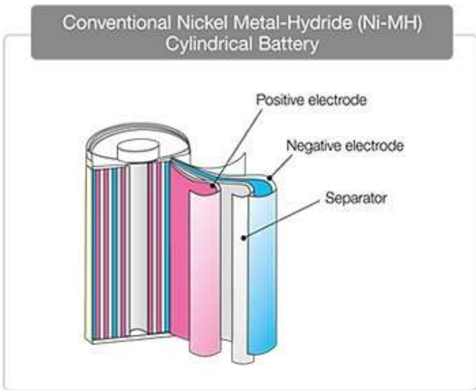

Fig 3.1.3: Nickel Metal-Hydride Battery[13]

- **Limitations of Nickel-Metal Hydride battery**
  - Charge efficiency drops off when the SOC reaches 70%, until then there is normal SOC.
  - The cells begin to produce gases, then the gases builds pressure, and the pressure makes temperature increase rapidly.
  - SoC charge efficiency is up to 70%. Charge efficiency is comparable to coulombic efficiency in that it measures the battery's ability to take charge.
  - NiMH is comparable to NiCd.

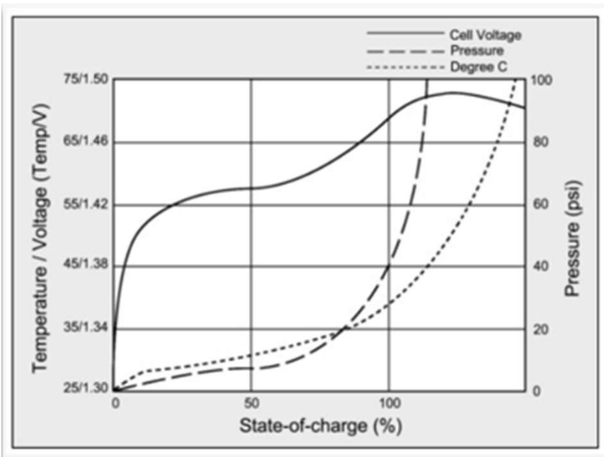

Fig 3.1.4: Charge Characteristics of NiCd Cell[14]

4. **Lithium-ion Battery**
   - These are widely used rechargeable types of because of its best low self-discharge rate and high OCV and it used in different portable electronics, also it has good energy to weight ratios.
   - Advantages include safety, high energy density, no memory effect and Do not contain toxic elements like cadmium or lead
   - The disadvantages are expensive and, in some cases, overheated.

- As a result of its quick charging, extended life cycle, and high energy density, lithium-ion batteries' SOC estimate has received a lot of attention.
- SOC is an important statistic used in the assessment of electric vehicle (EV) battery storage systems.

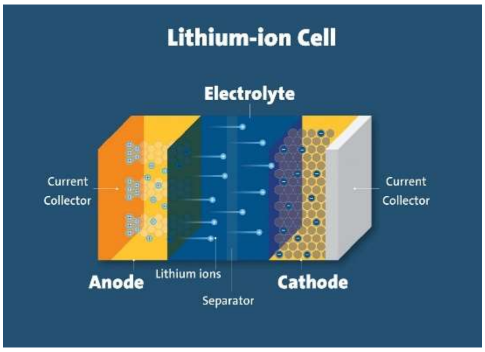

Fig 3.1.5: Lithium Ion Battery[15]

3.2 Why Li-ion Battery?

Li-ion battery has the three essential and major characteristics of choosing an energy source:

1. Low cost
2. High Energy density
3. Longer life

These characteristics are in comparison to other kinds of electrical batteries. They provide higher energy density than any other battery tech but are majorly inferior to petrol and diesel. Because the most crucial part that effects this is the storage medium in which the lithium ions and electrons are stored. Commonly its graphite. Latest technological improvements include mixing silicon with graphite which gives increase in the energy density.

Apart from this there is another factor called conversion efficiency which in terms of li-ion batteries are high i.e., around 80-90%. It is the ratio between energy converting machine and input which is electric power in this case.

3.3 Parameters for SOC and SOH estimation

1. Voltage

- The voltage technique uses battery voltage versus state-of-charge (SOC) discharge curve is used to convert a battery voltage data into the matching SOC value.
- Due to the battery's temperature and electrochemical kinetics, the voltage is more influenced by the battery current.
- To determine a battery's state of charge while it is draining, the battery's current and terminal voltage must both be monitored (SOC)
- Due to the nature of Lithium-ion batteries, connection between state of charge ("SOC") and voltage is mostly linear across the discharge range of the battery.

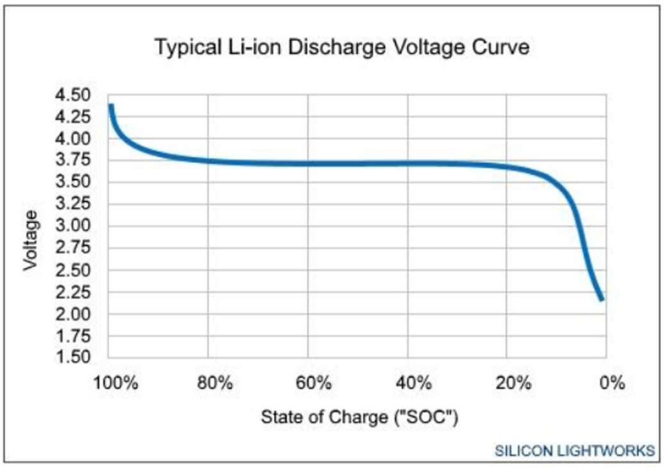

Fig 3.3.1: Voltage vs SOC graph[16]

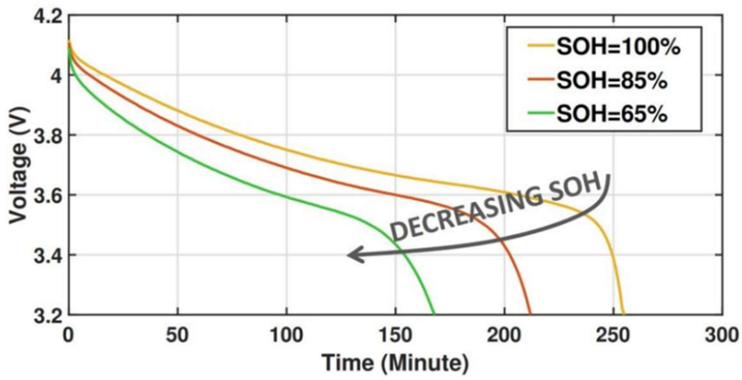

Fig 3.3.2: Voltage vs SOH graph[17]

2. Current

- The standard method for measuring SOC is to measure the current individually and cell voltages in and out of the cell stack under all operating situations.
- To create a precise SOC estimate, this data is combined with previously loaded cell pack data.

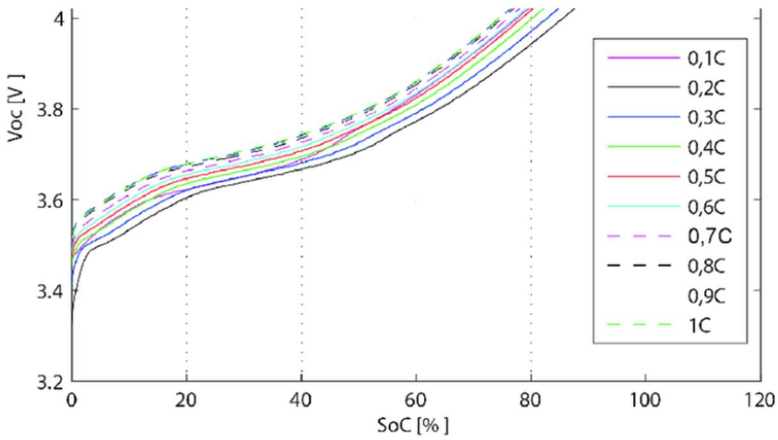

Fig 3.3.3: VOC vs SOC graph with different currents[18]

3. Temperature

- The temperature and current rate have a significant impact on SOC/SOH.
- The estimator can retain excellent accuracy over a range of temperatures since capacity, resistance and the OCV are temperature dependent.
- The OCV is a linear function with temperature dependent, but the internal resistance is dependent on temperature with a three-order polynomial.

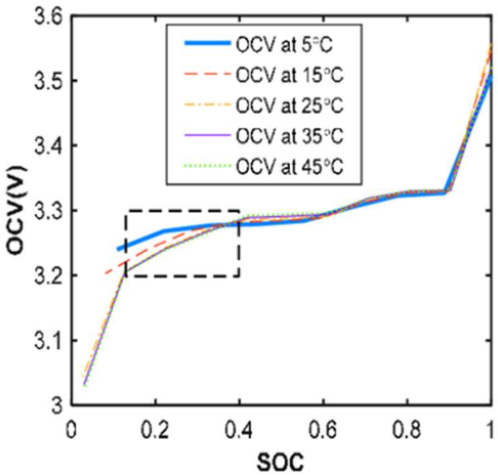

Fig 3.3.4: OCV vs SOC graph with different temperature[19]

3.4 What is SoC and SoH

STATE OF CHARGE (SoC): The State Of Charge Of any battery tells us the difference between a fully charged or full capacity battery and the same battery in use.

$$\text{STATE OF CHARGE} = \frac{\textit{Remaining Charge in the Battery}}{\textit{Maximum Charge that can be Deliverd by the Battery}}$$

Qmax =Full capacity
Of a Battery

Q = Remaining
Charge in battery

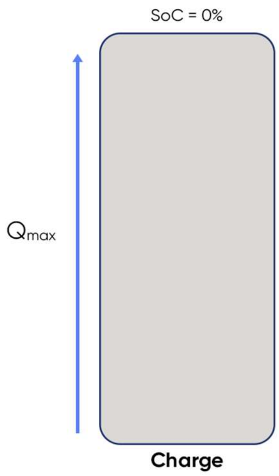

Fig 3.4.1: State of charge of Battey During Charge and Discharge

STATE OF HEALTH (SoH): The State Of Health Of any battery tells us the difference between a battery in use and the new battery considering external factors and cell aging.

$$\text{STATE OF HEALTH} = \frac{\textit{Maximum Battery Charge}}{\textit{Rated Capacty}}$$

Qmax=Max Capacity of
battery considering
Aging

Cr=Max Capacity of New
Battery

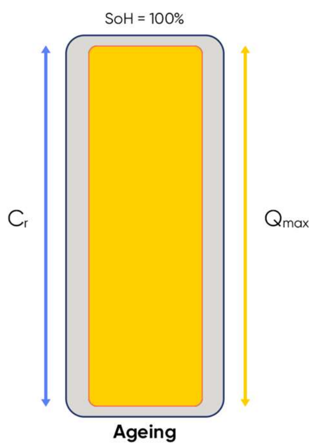

Fig 3.4.2: State of Health Of A Battery During Aging

3.5 Degradation of Li-ion battery

i) Schematic of a Li-ion battery

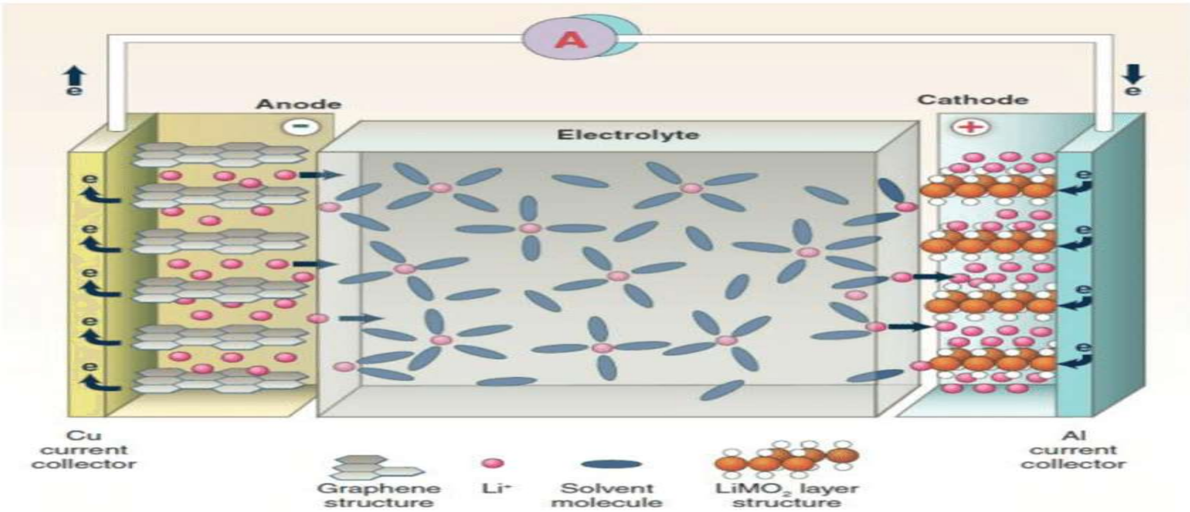

Fig 3.5.1: Structure of Li-Ion Battery

Current collector: It is a device that is used to provide the conduction of electrons that is used to transfer electrons from the inside of an electrochemical reaction to the outside without taking part in any chemical reaction within an operation window. The commonly available current collectors for anode and cathode are copper and aluminum.

Anode: The anode is a copper current collector. The cathode’s job is to hold the charged Li-ion’s as when the battery is in the charging state the Li-ions travel from the cathode to the anode and interpolate in the graphite sheet.

Cathode: The cathode is used to hold the Li-ion’s in the uncharged state and the material it is made out of depends on the manufacturers.

Electrolyte: It is present between cathode and anode with some Li-ion in it. The electrolyte only allows Li-ions to pass through it and prevents electrons from doing so.

ii)Working

During Charging: When the battery is charged the Li-ion travels from the cathode through the organic material to the anode where the Cu current collector hold the ions.

During Discharge: The Li-ion tend to want to travel back to the cathode since that is where the ions are stable and the electrons go to the cathode using the wire since they cannot travel through the electrolyte.

iii)Mechanisms of Battery Degradation:

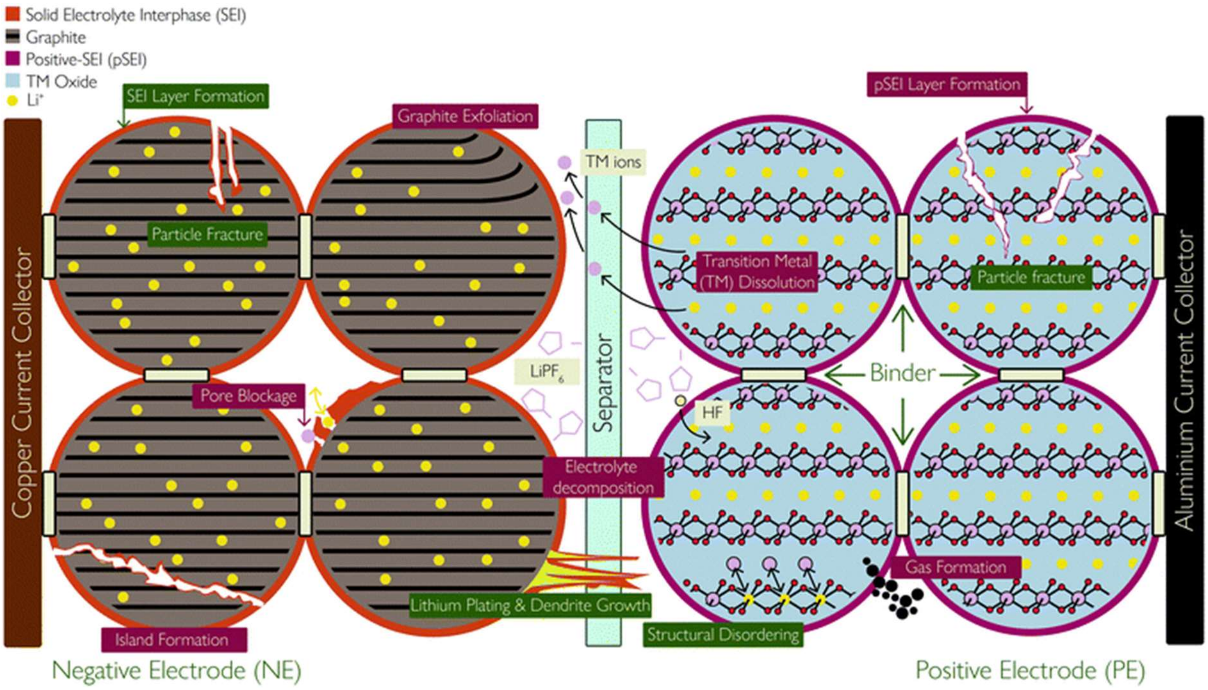

Fig 3.5.2: Internal Structure of Li-Ion Battery

- The Green Blocks Are The Major Reasons Whereas The Purple Blocks Are The Secondary Factors.

The two directly observable effects of degradation of a Li-ion battery are capacity fade and power fade respectively. Reduction in the usable capacity of a given battery is considered capacity fade whereas the reduction in the power deliverability of the battery is called power fade.

SEI layer growth: The SEI (solid electrolyte interface) is an interface that is formed on the surface of the negative electrode (anode), this occurs when the Li+ ions interact with the graphite plating around the anode and end up forming a surface, thereby the battery looses Li+ ions to work with and also increases the overall impedance of the battery thereby leading to power fade as well.

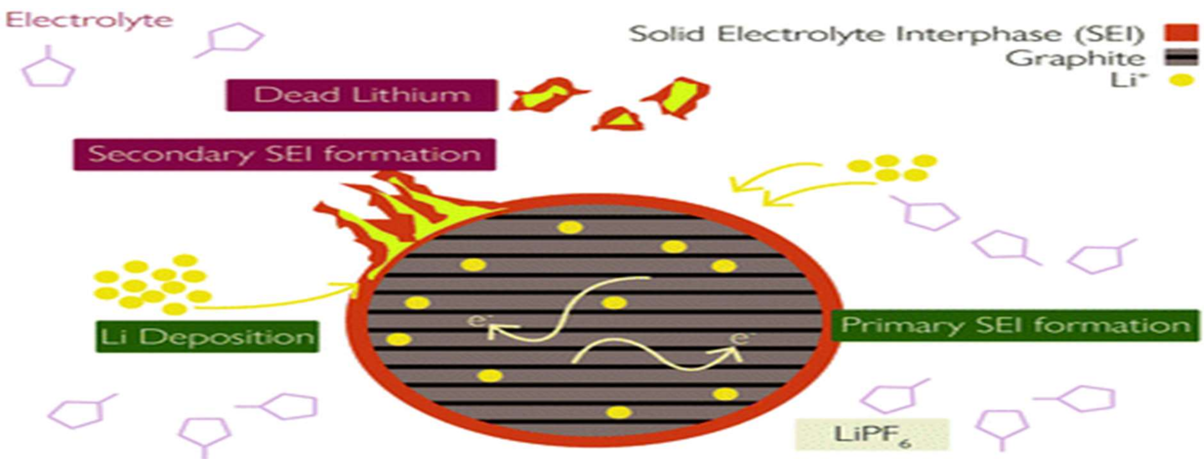

Fig 3.5.3: Representation of SEI Formation

Lithium plating: this is a phenomenon that occurs when the Li-ion forms a layer on the anode by intercalating into it and forming a Li plate around anode. This usually occurs when the negative electrode surface becomes fully lithiated leading to nowhere for the Li-ions to go. Lithium plating has both reversible and irreversible components.

Particle fracture: This is caused by a substantial change in the volume of the electrodes which leads to stress during electrochemical operation. Particle fractures occurs in both the electrodes and this leads to a disruption in electrical contact between active particles and current collectors which leads to an overall loss in conductivity.

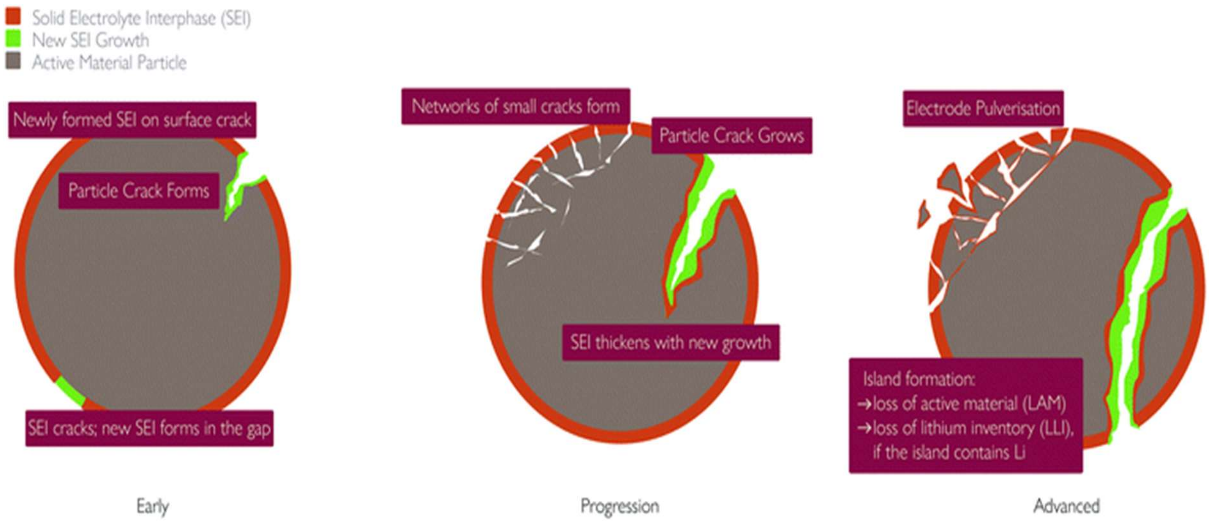

Fig 3.5.4: Pictorial Representation of Particle Fracture

Dendrite formation: this is the increase in the surface area of the metal anode which leads to the metal surface poking into the electrolyte which will lead to the rapture of the electrolyte and therefore cause an internal short circuit.

Structural Disordering: Oxidation of the electrolyte leads to the formation of HF (hydrofluoric acid) which in turn reacts to with the Lithium from the positive electrode and thereby leading to a lesser amount of Li ions available for charging/discharge.

PSEI formation: its is the formation of a layer on the positive electrode (cathode) the same way an SEI layer forms on a negative electrode.

3.6 Case as Non-linear Regression

Framing a real-world problem as a Machine Learning problem is essential as it helps us to decide if Machine learning is a good approach to solve it. Problem framing is the process of studying a problem to segregate and extract parameters that would influence the target. Extracting parameter in this case is a non-linear optimization task due to the nonlinearity in battery degradation. Therefore, SOC and SOH are approximated using non linear features-Current, Voltage and Temperature. Almost all other real-world forecasting and predication problems are framed as non-linear regression models.

CHAPTER 4

DESIGN AND IMPLEMENTATION

4.1 BLOCK DIAGRAM REPRESENTATION

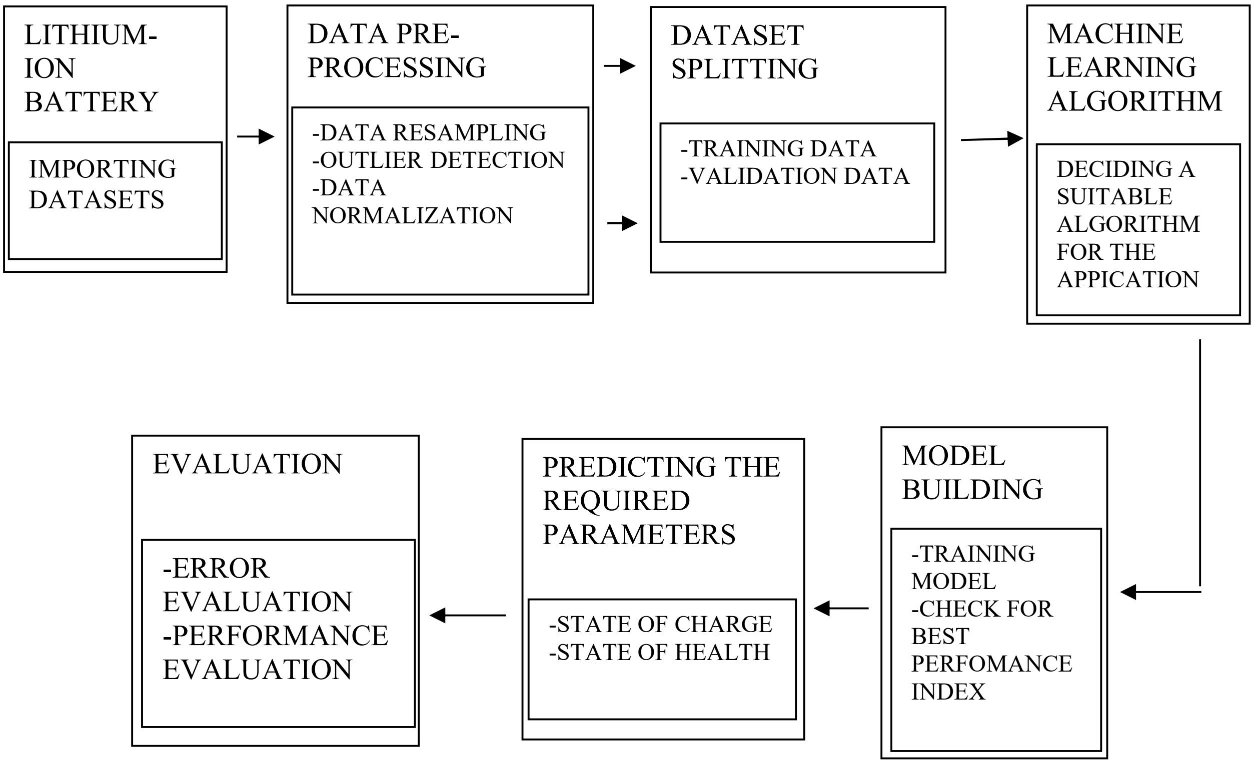

Fig 4.1.1: Block Diagram Representation of The Design Architecture

1) The First Step Is Importing the Datasets Extracted from the Experimental Setup done for the battery used in our application (Datasets: - Terminal voltage, Terminal current, Temperature, Charge current, Charge voltage, Time, Cycle, Measured Voltage, Measured Current, Load Voltage Load Current)
2) The Next Step Is Data Pre-processing where the necessary steps such as Resampling, Outlier Detection and Normalization are done this step is done to remove missing or inconsistent data and to improve the accuracy of the dataset.
3) In the Next Step We split the Data into Training and Validation To avoid Overfitting.
4) Next step is to Decide a Suitable Algorithm in our case it is Feed Forward Neural Network.
5) Then We Build A Suitable Model, for example Nonlinear Regression in our Application.
6) After Building The model we predict the required Parameters which Are SoC and SoH and fine tune the code until we get a best possible value.
7) Then we check for Performance by handling the errors and calculating the Performance indices such as Co-efficient of determination (R^2), RMSE, MAE.

4.2 Implementation

4.2.1 Why Machine Learning?

Machine learning is a field or rather a subfield of Artificial intelligence which is defined the ability of a machine to imitate human intelligence. We need machine learning here because machine learning can be used to solve complex problems which would otherwise take longer to solve whilst using conventional methods.

In the case of SOC/SOH estimation it is proven that machine learning approaches are significantly faster than conventional methods and may even incur lesser absolute errors, as said in “A Sparse Learning Machine for Real-time SOC Estimation of Li-ion batteries” the maximum absolute error received from the algorithm/machine learning approach is only one sixth of the mean absolute error of that obtained by the conventional LS-SVM’s and the result is obtained by the algorithm almost 10 times faster than the conventional method.

4.2.2 Neural networks

A Neural network is a set of algorithms that aims to recognize the relationship between data through processes that mimic the working of the human mind. They help computers make intelligent decisions with limited human assistance.

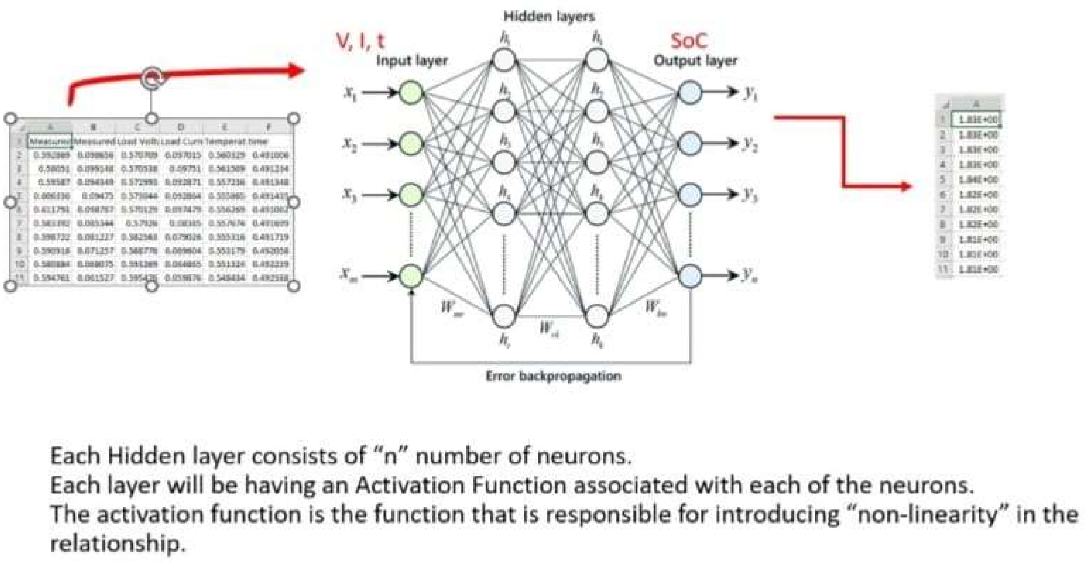

Fig 4.2.2.1: Supervised Deep Learning Neural Network

To compute interesting functions, a neural network needs to pick a non-linear activation function. Non-linearity means that the neural networks can successfully approximate functions that do not follow linearity or it can successfully predict the class of a given function that is divided by a decision boundary that is not linear. Since estimation of SOC/SOH has non-linear characteristics this ability of neural networks come in handy.

There are various types of non-linear activation function like,

Sigmoid: It is an activation function that mainly exists between 0 and 1. Therefore it is mainly utilized in models where we require the prediction of a probability of as an output since probability only lies between 0 and 1. It is mainly used in the output layer.
Mathematical equation for sigmoid: f(x)=1/(1+e^-x)

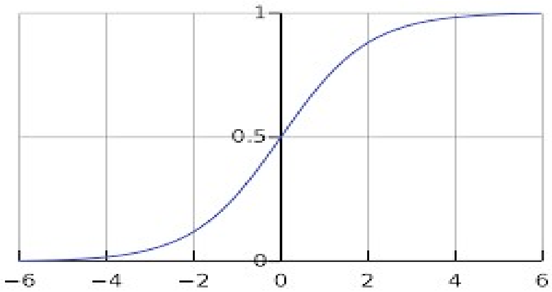

Fig 4.2.2.2: Sigmoid Activation Function

Tanh: tanh is like a shifted version of sigmoid function where its range is between -1 and 1 rather than between 0 and 1 like sigmoid. Since the mean for the given hidden layer will be closer to zero it makes learning for the next layer easier.
Tanh can be defined as: tanh(x)=(2/(1+e^(-2x)))-1

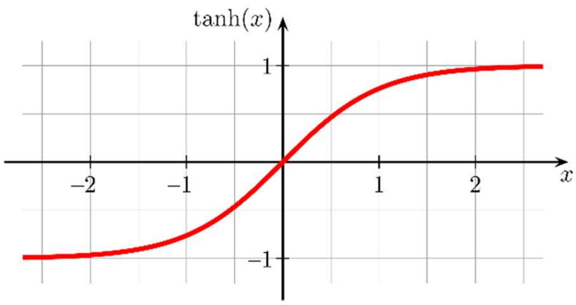

Fig 4.2.2.3: Tanh Activation Function

Relu: It is comparatively faster to compute and is used as a default choice for an activation function. Relu's gradient decent does not get stuck much on plateaus thanks to the fact that it does not saturate much for large input values as opposed to those of logistic function or hyperbolic tangent function.

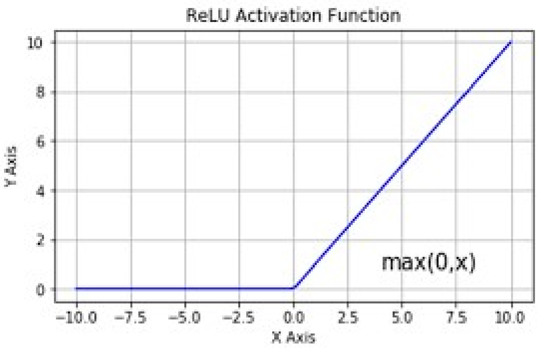

Fig 4.2.2.4: Relu Activation Function

Leaky Relu: It is used to overcome some issues faced by relu (such as the dying relu problem). It was proposed in order to tackle the dead neuron problem by adding a little bit of a negative slope to sustain and keep the weighted updates alive during the entire propagation process.

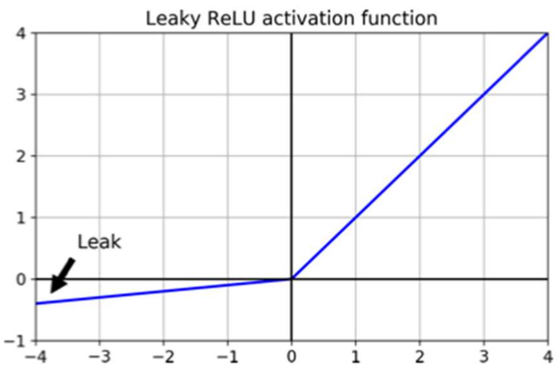

Fig 4.2.2.5: Leaky Relu activation function

Softmax: It is used in Neural networks when we want to build a multi-class classifier which solves the problem of assigning an instance to a class when the number of probable classes is more than two. Its application is based on use case and user preference as sigmoid can also be used for multi-class classifier problems.

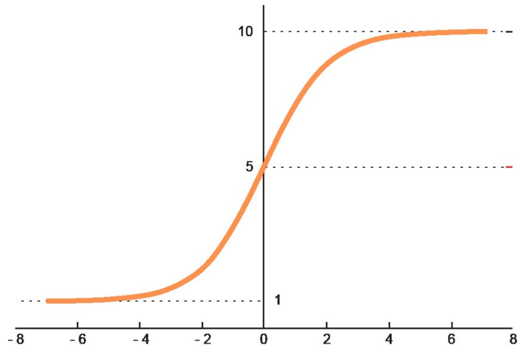

Fig 4.2.2.6: Softmax activation function

Out of these we use Relu because it does not utilize all the neuron simultaneously, that is if the given function value is below 0 then the neurons are turned off, hence we use Relu as it is computationally efficient, simple and fast.

4.2.3 TENSORFLOW and KERAS:

TensorFlow

- TensorFlow is an open-source toolkit for large-scale machine learning and numerical computing. It is a symbolic math toolbox that uses differentiable programming and dataflow to perform numerous operations used for deep neural network training and inference.

- **Why are we using TensorFlow?**

- Scalable

TensorFlow is not constrained to a single type of gadget. It functions just as effectively on a mobile device as it does on any other sophisticated equipment. The library is so well specified that any device may use it.

- Open-Source Platform

It is free of cost. Any user can utilize this module whenever and wherever they required

- Graphs

TensorFlow can visualize data more effectively than any other accessible framework.

- Debugging

TensorFlow has a Tensor board, which enables simple node debugging. This reduces the overhead of accessing the entire code.

- **Introduction to TensorFlow**

  An end-to-end platform for machine learning

- Prepare and load data for successful machine learning outputs.
- With the TensorFlow environment, you can create and fine-tune models.
- Models can be deployed on devices, in browsers or in the cloud.
- Use MLOps for production machine learning

Keras

- Keras is a deep learning API that runs on top of TensorFlow which is a framework of machine learning.
- It is a deep learning API based on Python.
- It was developed with the intention of facilitating fast experimentation.

- Why are we using Keras?
- Simple

Keras reduces developer cognitive burden, allowing you to concentrate on the most crucial aspects of the problem.

- Flexible

Keras follows the notion of progressive complexity disclosure: in which basic processes should be very clear, while complex workflows should be possible via a clear path.

- Powerful

Keras delivers industry-leading performance and scalability.

- Advantages of Keras
- It is extremely simple to comprehend and include quicker network model implementation.
- It supports several backends, which means you may use TensorFlow with Keras as a backend. It also supports cross-platform due to its ease of deployment.
- It allows data parallelism, which implies that Keras may be taught on several GPUs at the same time, shortening training time and processing large amounts of data.

- Disadvantages of Keras
- The main drawback is that Keras has its own pre-configured layers and will not let you construct an abstract layer since it cannot handle low-level APIs. It just allows high-level API to operate on top of the backend engine.

4.2.4 Optimizer

- Optimizers is an algorithm or function that is used to attune the characteristics of the neural network, such as weights and learning rate to minimize losses.

- There are several types of Optimizers: -

1. Gradient Descent
    - It specifies how the values should be adjusted in order for the function to achieve a minimum. It is a first-order optimization approach based on the first order derivative of a loss function.

2. Stochastic Gradient Descent (SGD)
    - It is an updated version of GD. Every iteration involves updating the model's parameters. It involves updating the model after every epoch and testing the loss function.

3. Mini-Batch Gradient Descent
    - The model's parameters are updated after every batch. So, the dataset is split up into several batches, and the parameters are changed between each batch.

4. Adagrad
    - The learning rate is altered by this optimizer. At each time step 't' and for each parameter, it modifies the learning rate **'η'**.

5. RMSProp
    - It enhances the Adagrad optimizer. By choosing the average value of gradient which is an exponential rather than the sum of squared gradients, this aims to reduce the learning rate.

6. Adam

- The combination of momentum-based GD and root mean square prop are estimated. Adam optimizers are an effective technique because of the ability of adaptative learning rate of RMSProp and momentum.

- The objective of Adam is that we do not want to go too rapidly because we can pass over the minimum; rather, we want to slow down the careful search
- m(t) = $\frac{m}{1-\beta 1}$ and v(t) = $\frac{v}{1-\beta 2}$ where m(t) is mean and v(t) is variance and the value for $\beta 1 = 0.9$ and β2 = 0.999
- To update the parameter:

$$\theta(t+1) = \theta(t) - \frac{\eta}{\sqrt{v(t)} + \epsilon} m(t)$$

where θ(t) – parameters, ε - (10 x exp(-8)) , η – learning rate

4.2.5 Loss Function

- Loss functions are used to determine the amount that a model should try to minimize during training.

- Mean Squared Error
- The Mean Squared Error is a metric that measures a regression line which is used to set of data points. It represents as loss of the risk function, which is the expected value of the squared error.
- Mean Squared Error is calculated by taking average of the mean of squared errors from data.

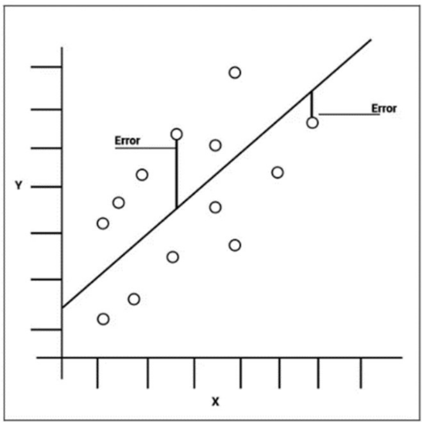

Fig 4.2.5.1: Mean Squared Error Graph

- $MSE = \frac{\sum(y-yi)^2}{n}$ where y – value, which is given,

  yi – value, which is predicted

  n - number of observations

- e.g., tf.keras.losses.MeanSquaredError(reduction="auto",name="mean_squared_error)
  It results in the mean of squares of errors between labels and predictions.

- Usage with compile() API:
  model.compile(optimizer = 'sgd' , loss= tf.keras.losses.MeanSquaredError())

4.3 Performance and Evaluation metrics:

One of the tools to calculate model parameters- weights and biases is Loss Function. Depending upon the different models we get the most appropriate is chosen using a loss function. We choose optimal values for the parameters such that the loss function is minimized. To optimize this further, optimizers are used.

4.3.1 R2 Performance Value

R^2 Performance value -R^2 is coefficient of determination, a statistical measure of how good the model fits and how well the regression predictions are. R Square value lies between values 0 and 1. The more positive the number and towards 1 better is the model performance.

$$\boldsymbol{R2 = 1 - \frac{RSS}{TSS}}$$

Where RSS = sum of squares of the residual (squared sum of error in regression line)
TSS = sum of squares (squared sum of the mean line)

4.3.2 Evaluation Metrics

Evaluation methods are required to study how generalized the models are. Using different evaluation methods helps us to fine tune the results and optimize it. There are three major evaluation metrics that are specifically chosen to analyze regression predictions.

RMSE – Root Mean Square Error and MSE – Mean Square Error: As R2 performance value is a statistical and Relative measure, RMSE and MSE are absolute measures for evaluation. MSE is calculated by taking the sum of squares of the prediction error which is the real output subtracted by the predicted output and that is divided by the number of data points. Whereas, Root Mean Square Error (RMSE) is the square root of MSE.

$$\boldsymbol{RMSE = \sqrt{}(\frac{\sum_{i=1}^{N}(Predicted_i - Actual_i)^2}{N})}$$

$$\boldsymbol{MSE = \frac{\sum_{i=1}^{N}(Predicted_i - Actual_i)^2}{N}}$$

MAE – Mean Absolute Error Difference between MSE and MAE is that - sum of the absolute values of errors are considered instead of sum of the square of the error. MSE gives larger penalty to larger prediction value error by squaring whereas MAE treats all the errors equally.

$$\boldsymbol{MSE = \frac{\sum_{i=1}^{N}(Predicted_i - Actual_i)}{N}}$$

CHAPTER 5

CODING / ALGORITHM

5.1 Libraries Required

```
# imports
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import Dropout
from sklearn.metrics import r2_score
import matplotlib.pyplot as plt
import numpy
from keras.optimizers import Adam
import keras
from matplotlib import pyplot
from keras.callbacks import EarlyStopping
import pandas as pd
from sklearn.preprocessing import LabelEncoder
print('check')
import math
```

Keras' models: they offer user-friendly way to define a neural network, which will then be built by TensorFlow.

Sequential: the sequential API's main idea/core use is to arrange the keras layers in a sequential order.

Dense: is used to create dense layers whose neurons all get their inputs from all the other layers in a previous network.

Dropout: it is used to create dropout layers which randomly sets the input units to 0 with a frequency of rate at each step during training time. This prevents all the weights from synchronizing simultaneously.

R2_score: it is a regression score function with the best possible score of 1 and it can be negative if the given model is arbitrarily worse.

Matplotlib: it is used to create static, animated and interactive visualizations in python. Mainly to plot graphs.

Numpy: It is a library that is used to support large multidimensional arrays and matrices, numpy also supplies the user with many mathematical operations to operate on these arrays.

Adam: the adam optimizer provides a stochastic gradient method which is used mainly for training deep learning models.

Keras: is a software library that provides a interface for artificial neural networks in python.

Pyplot: it is a plotting library that is used in python to make 2 dimensional graphics in python.

Earlystopping: it is a method that allows the user to specify a large number of epochs and stop the training once the given model's performance stops improving on a given validation set.

Pandas: it is a package that offers functions for data manipulation.

Sklearn: it is a python machine learning library that offers various classification, clustering and regression algorithms.

Labelencoder: it is used to normalize labels, for example it can be used to convert non-numerical labels to numerical labels.

5.2 Pseudo Code Explanation:

```
In [3]:

model = Sequential()
model.add(Dense(512, activation="relu", input_dim=6))
model.add(Dense(128, activation="relu"))
model.add(Dense(32, activation="relu"))
model.add(Dense(8, activation="relu"))

model.add(Dense(1, activation="linear"))

model.compile(loss='mean_squared_error', optimizer=Adam(lr=1e-3, decay=1e-3 / 200))

# early stopping
es = EarlyStopping(monitor='val_loss', mode='min', verbose=1, patience=200)

history = model.fit(X1, Y1, validation_data=(X2, Y2), epochs=10000000, batch_size=1000, verbose=2, callbacks=[es])

PredTestSet = model.predict(X1)
PredValSet = model.predict(X2)

numpy.savetxt("trainresults.csv", PredTestSet, delimiter=",")
numpy.savetxt("valresults.csv", PredValSet, delimiter=",")
```

- We use sequential model for our application which helps us to specify the neural network which is convenient for our application.
- The Model.add() function helps us to pass a list of layers to the sequential function.
- The compile function checks for format errors and helps us to debug the code before running the model.
- Early stopping function stops executing the model when the specified or selected metric has stopped improving this helps to reduce the loss.
- Fit function helps us to train the model for specified number of cycles or epochs.
- Predict function helps to strategize the whole model into a class along its parameters and attributes and the selected variables that fit into the selected class.

```
model.compile(loss='mean_squared_error', optimizer=Adam(lr=1e-3, decay=1e-3 / 200))
```

- The optimizer used in the code is Adam optimizer .
- The Loss function used in the code is Mean Squared Error.

➢

```
In [14]:
MSE = numpy.square(numpy.subtract(Y1,PredictedTestSet)).mean()
RMSE = math.sqrt(MSE)
print(RMSE)

0.07907971685319741
```

- Calculating the root mean squared error.

CHAPTER 6

RESULTS AND VERIFICATION

6.1 SOC RESULTS:

In [65]:
```
# Plot actual vs prediction for training set
TestResults = numpy.genfromtxt("trainresults.csv", delimiter=",")
plt.plot(Y1,TestResults,'r-')
plt.title('Training Set')
plt.xlabel('Actual')
plt.ylabel('Predicted')

# Compute R-Square value for training set
TestR2Value = r2_score(Y1,TestResults)
print("Training Set R-Square=", TestR2Value)
```

```
Training Set R-Square= 0.9901440346497656
```

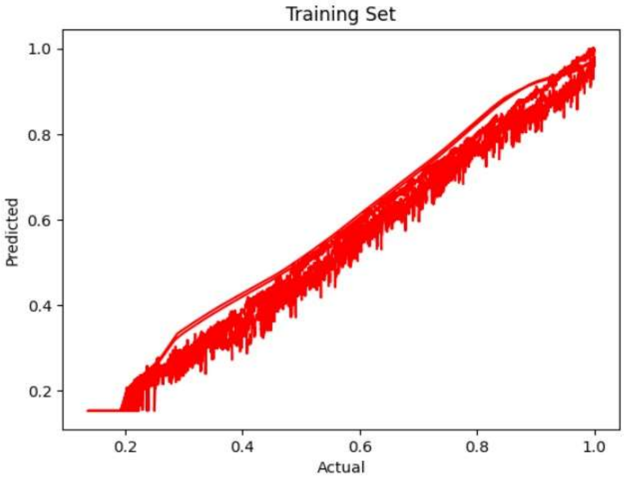

Fig 6.1.1: Plot of Training the model using the Datasets

The R^2 value would be a measure of how well the predicted values of the state of charge of the battery match the actual values. An R-squared value of 0.9901 indicates a very strong relationship between the independent variables and the dependent variable in the regression model. This means that 99% of the variation in the dependent variable (in this case, the state of charge of the battery) can be explained by the independent variable(s) (the input data).

In [67]:
```
f1 = plt.figure(figsize=(30,10))
ax10 = f1.add_subplot(2,3,1)
ax10.plot(XX1['time'],Y1, label = 'Curve 1', color = "r", marker='o')
ax10.plot(XX1['time'],PredTestSet, label = 'Curve 7', color="g", marker='o',linestyle ='--')
ax10.set_xlabel('time')
ax10.set_ylabel('SoC')
```

```
Out[67]: Text(0, 0.5, 'SoC')
```

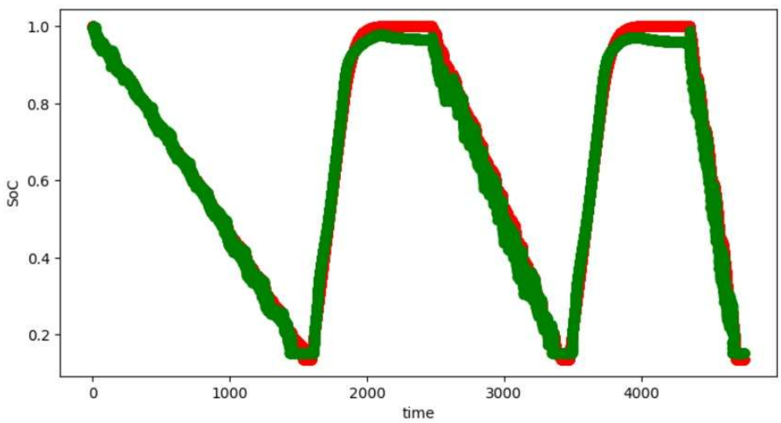

Fig 6.1.2: Plot of Predicted Vs Actual Values for SoC

The graph shows the SOC of a battery over a period of charge-discharge cycles. The x-axis represents time, and the y-axis represents the SOC of the battery. The graph includes two lines: one representing the actual SOC values (shown in red), and the other representing the predicted SOC values (shown in green).

```
In [37]: MSE = numpy.square(numpy.subtract(Y1,PredictedTestSet)).mean()
         RMSE = math.sqrt(MSE)
         print(RMSE)

         0.02535502131613562
```

Fig 6.1.3: RMSE of SoC

- For the Model we built we get an RMSE of 0.025 that is 2.5%.

6.2 SOH RESULTS:

```
Training Set R-Square= 0.811702062374119
```

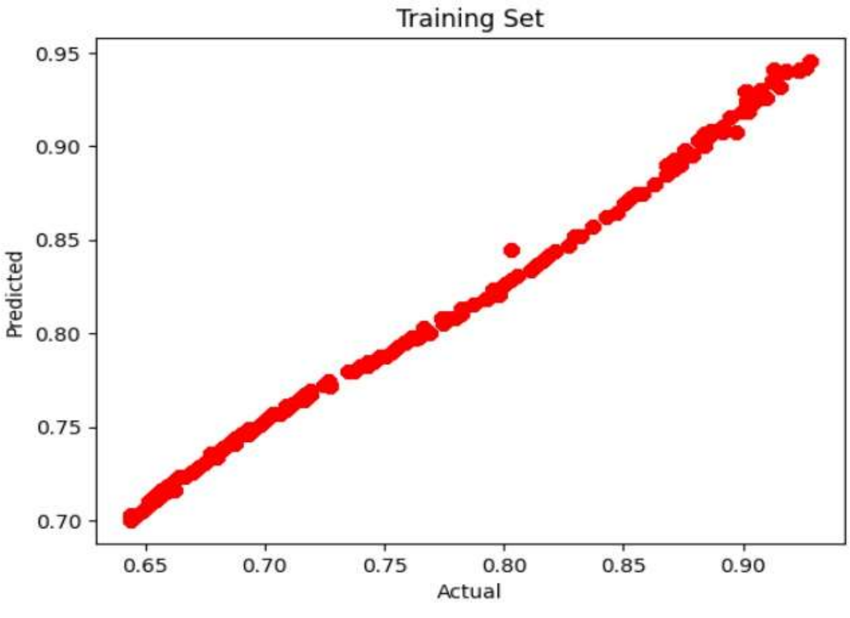

Fig 6.2.1: Plot of R^2 value for SOH

The dotted R^2 graph of the state of health of a battery with an R^2 value of 0.81170 indicates a relatively strong linear relationship between the battery's state of health and the measured variables. The R^2 value of 0.81170 indicates that the measured variable(s) used to determine the state of health of the battery are strongly correlated with the actual state of health, and can be used to make reasonably accurate predictions or assessments of the battery's condition.

Out[11]: Text(0, 0.5, 'SoC')

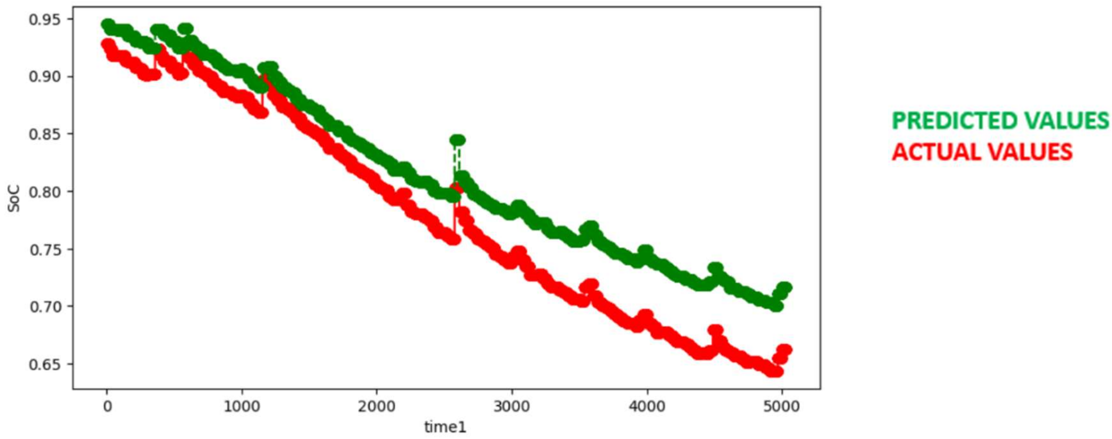

Fig 6.2.2: Plot of Predicted Vs Actual Values For SoH

The SOH (State of Health) battery graph shows the battery's capacity degradation over time. The x-axis represents time, and the y-axis represents the battery's State of Health. The graph includes two lines: one representing the actual SOH values (shown in red), and the other representing the predicted SOH values (shown in green). They show a gradual decrease in the battery's SOH over time, indicating a natural capacity degradation that occurs with use. Alternatively, there may be abrupt changes in the SOH values due to various factors such as environmental conditions, operating conditions, or maintenance issues.

CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1 CONCLUSIONS:

- From the above results obtained we observe that the Root mean squared error obtained for SoC is 2.5% and the R^2 value obtained for SoH is 81.1.
- A neural network model has been created to estimate the SOC and SOH values of a battery. The project mainly dealt with predicting values of a non-linear regression problem. The case was approached from a Machine learning point of view by using Keras API with TensorFlow backend
- Numerous cases where the model has to be fit in variety of curves can be done by optimizing it and designing it appropriately. Hence the model can be used as prediction model for SOC and SOH for other batteries. The model can also be trained for other cases which are non-linear in nature like inflation, biological process and agriculture research.

7.2 FUTURE WORK:

- In continuation with the work done we can improve the model to get more precise results by adding many other parameters along with the existing ones such as pressure change, different datasets of other types of batteries, increasing the load etc.
- The above work can be made Real time estimation by constructing a experimental setup which extracts all the required datasets in real time which can be used serially to estimate the required parameters.
- The accuracy of the work can be increased by using other types of models suitable for estimating the listed parameters, and results may be compared.
- With recent development in neural networks, model train time can be reduced. This project can be further developed with a customer point-of-view by building a GUI. Therefore, this can be made into an app or website where the data is fed by the user and relevant results are displayed with its accuracy.

7.3 PUBLICATION:

This work has been accepted to be presented in the International Conference On Advances In Engineering And Technology For Intelligent Systems (ICAETIS -2023) organized By Dayanand Sagar College Of Engineering, Bangalore. Later to be published in SCOPUS Indexed Journals.

GROUP 18 2022 REPORT DECEMBER.pdf

ORIGINALITY REPORT

15%	11%	10%	8%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	medium.com Internet Source	2%
2	Submitted to Sheffield Hallam University Student Paper	1%
3	Submitted to Universiti Malaysia Pahang Student Paper	1%
4	jpinfotech.org Internet Source	1%
5	www.researchgate.net Internet Source	1%
6	eprints.whiterose.ac.uk Internet Source	<1%
7	researchr.org Internet Source	<1%
8	Yuefeng Liu, Jiaqi Li, Gong Zhang, Bin Hua, Neal Xiong. "State of Charge Estimation of Lithium-ion Batteries Based on Temporal Convolutional Network and Transfer Learning", IEEE Access, 2021 Publication	<1%

9	Submitted to Coventry University Student Paper	<1 %
10	huggingface.co Internet Source	<1 %
11	T.G. T. A. Bandara, J.C. Alvarez Anton, M. Gonzalez, D. Anseana, J.C. Viera. "State of Health Estimation using Machine Learning for Li-ion battery on Electric Vehicles", 2021 IEEE Vehicle Power and Propulsion Conference (VPPC), 2021 Publication	<1 %
12	Submitted to Liverpool John Moores University Student Paper	<1 %
13	dspace.uniten.edu.my Internet Source	<1 %
14	jglobal.jst.go.jp Internet Source	<1 %
15	Submitted to University of Wales Institute, Cardiff Student Paper	<1 %
16	rivm.openrepository.com Internet Source	<1 %
17	Submitted to Babes-Bolyai University Student Paper	<1 %

REFERENCES

[1] J. Varshitha, K. Jahnavi and C. Lakshmi, "Prediction Of Used Car Prices Using Artificial Neural Networks And Machine Learning," *2022 International Conference on Computer Communication and Informatics (ICCCI)*,Coimbatore,India,2022, pp. 1-4, doi:10.1109/ICCCI54379.2022.9740817.

[2] L. Zhang, K. Li, D. Du, Y. Guo, M. Fei and Z. Yang, "A Sparse Learning Machine for Real-Time SOC Estimation of Li-ion Batteries," in *IEEE Access*, vol. 8, pp. 156165-156176, 2020, doi: 10.1109/ACCESS.2020.3017774.

[3] X. Sui, S. He, S. B. Vilsen, R. Teodorescu and D. -I. Stroe, "Fast and Robust Estimation of Lithium-ion Batteries State of Health Using Ensemble Learning," 2021 IEEE Energy Conversion Congress and Exposition (ECCE), 2021, pp. 1393-1399, doi: 10.1109/ECCE47101.2021.9595113.

[4] M. S. Sidhu, D. Ronanki and S. Williamson, "State of Charge Estimation of Lithium-Ion Batteries Using Hybrid Machine Learning Technique," IECON 2019 - 45th Annual Conference of the IEEE Industrial Electronics Society,New York,NY,USA, 2019, pp. 2732-2737, doi: 10.1109/IECON.2019.8927066.

[5] M. S. H. Lipu, M. A. Hannan, A. Hussain, M. H. M. Saad, A. Ayob and K. M. Muttaqi, "Lithium-ion Battery State of Charge Estimation Method Using Optimized Deep Recurrent Neural Network Algorithm," 2019 IEEE Industry Applications Society Annual Meeting, Baltimore, MD, USA, 2019, pp. 1-9, doi: 10.1109/IAS.2019.8912322.

[6] T. G. T. A. Bandara, J. C. Á. Antón, M. González, D. Anseána and J. C. Viera, "State of Health Estimation using Machine Learning for Li-ion battery on Electric Vehicles," *2021 IEEE Vehicle Power and Propulsion Conference (VPPC)*, 2021, pp. 1-4, doi: 10.1109/VPPC53923.2021.9699273.

[7] R. Vaila, D. Lloyd and K. Tetz, "Regression with Deep Learning for Sensor Performance Optimization," 2021 IEEE Workshop on Microelectronics and Electron Devices (WMED), Boise, ID, USA, 2021, pp. 1-4, doi: 10.1109/WMED49473.2021.9425222.

[8] Y. Liu, J. Li, G. Zhang, B. Hua and N. Xiong, "State of Charge Estimation of Lithium-Ion Batteries Based on Temporal Convolutional Network and Transfer Learning," in IEEE Access, vol. 9, pp. 34177-34187, 2021, doi: 10.1109/ACCESS.2021.3057371.

[9] G. Vennam, A. Sahoo and S. Ahmed, "A Novel Coupled Electro-thermal-aging Model for Simultaneous SOC, SOH, and Parameter Estimation of Lithium-ion Batteries," 2022 American Control Conference (ACC), Atlanta, GA, USA, 2022, pp. 5259-5264, doi: 10.23919/ACC53348.2022.9867320.

[10] J. Wu, H. Su, J. Meng and M. Lin, "State of Health Estimation for Lithium-Ion Battery via Recursive Feature Elimination on Partial Charging Curves," in IEEE Journal of Emerging and Selected Topics in Power Electronics, vol. 11, no. 1, pp. 131-142, Feb. 2023, doi: 10.1109/JESTPE.2022.3177451.

[11] Sun, R & Hu, P & Wang, R & Qi, L. (2020). A new method for charging and repairing Lead-acid batteries. IOP Conference Series: Earth and Environmental Science. 461. 012031. 10.1088/1755-1315/461/1/012031.

[12] khatab, ahmed, and A.abd elhakeem elhakeem. “Electro-chemistry / Secondary Cells /Nickel Cadmium Battery/Lead–acid Storage Battery.” YouTube, 22 Mar. 2017, www.youtube.com/watch?v=Q0VSVy-_IIM.

[13] Structure. Kawasaki Heavy Industries. (n.d.). Retrieved April 15, 2023, from https://global.kawasaki.com/en/energy/solutions/battery_energy/about_gigacell/structure.html

[14] University, Battery. “BU-407: Charging Nickel-cadmium.” Battery University, 12 Feb. 2011, batteryuniversity.com/article/bu-407-charging-nickel-cadmium.

[15] “What Are Lithium-Ion Batteries? | UL Research Institutes.” What Are Lithium-Ion Batteries? | UL Research Institutes, 14 Sept. 2021, ul.org/research/electrochemical-safety/getting-started-electrochemical-safety/what-are-lithium-ion.

[16] “Silicon Lightworks.” Li-ion Voltage Analysis, 27 Oct. 2016, siliconlightworks.com/li-ion-voltage.

[17] Alamin, Khaled Sidahmed Sidahmed & Chen, Yukai & Macii, Enrico & Poncino, Massimo & Vinco, Sara. (2022). A Machine Learning-based Digital Twin for Electric Vehicle Battery Modeling. 10.48550/arXiv.2206.08080.

[18] Rivera-Barrera, Juan & Munoz, Nicolas & Sarmiento, Henry. (2017). SoC Estimation for Lithium-ion Batteries: Review and Future Challenges. Electronics. 6. 102. 10.3390/electronics6040102.

[19] Chin, Cheng Siong & Gao, Zuchang. (2018). State-of-Charge Estimation of Battery Pack under Varying Ambient Temperature Using an Adaptive Sequential Extreme Learning Machine. Energies. 11. 711. 10.3390/en11040711.