BATTERY MANAGEMENT SYSTEM FOR ELECTRICAL VEHICLES

DISSERTATION

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CANDIDATE'S DECLARATION

I, **AASHUTOSH VATS**, Roll No. – 2K20/PES/01 students of M.Tech (Power Electronics Systems, Electrical department),hereby declare that the project Dissertation titled "**Battery Management System for EVs**" which is submitted by me to the **Electrical Department**, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of degree of Masters of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma Associateship, Fellowship or other similartitle or recognition.

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I hereby certify that the Project Dissertation titled "**Battery Management System for EVs**" which is submitted by **Aashutosh Vats**, Roll No's – **2k20/PES/01, Power Electronics Systems**, Delhi TechnologicalUniversity, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is a record of the project work carried out by the students undermy supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

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ABSTRACT

Electric Vehicles are widely considered the future of the transportations industry, most developed nations are pushing towards cleaner modes of transportation. EVs are leading candidates for the same. One of the key components required for the economic and technological success of EVs is Battery Management System. A lot of research is being done on the topic, however the topic itself is very big, and the research is usually focused on some subtopic like SOH estimation. In this project, the target is to simulate the State Of Charge estimation, balancing technique and State Of Health estimation which are key functions of Battery Management System. Apart from this battery simulation is also done, there are many ways of doing it, they are briefly given in the report, the battery is simulated in two ways in the report, each model is specific to some estimation and hence is modelled with the details required. The ageing of battery is also simulated and the results under different conditions are compared. Different batteries are also compared for their usability specifically with respect to electrical vehicles.

Overall, this report rather than going into particular functions of BMS has tried present all the major functions. The techniques simulated to estimate the SOC involves basic techniques like Coulomb Counting and a little more complex technique like PIO. The purpose of doing the project this way is to highlight the practical problems with the basic technique and how a little complex method overcomes those issues. The SOH estimation is done with the help of PSO algorithm, and the empirical battery model is used to validate the results.

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LIST OF ABBREVIATIONS & SYMBOLS

S No	Abbreviated Name	Full Name
1	SOC	State of Charge
2	SOH	State of Health
3	Qn/Cn	Nominal Capacity
4	PSO	Particle Swarm Optimization
5	DOD	Depth of Discharge
6	SEI	Solid Electrolyte Interphase
7	V_{OC}/OCV	Open Circuit Voltage
8	z	Power Law Factor
9	Q_{loss}	Capacity Loss
10	Rn/Rnew	Initial Value of Series Resistance
11	R_ser/Ro	Series Resistance
12	N	Number of Cycles
13	Vt	Terminal Voltage of Battery
14	I/ I_B/i_discharge	Battery Current
15	BMS	Battery Management System
16	η	Coulombic efficiency
17	EIS	Electrochemical Impedance Spectroscopy
18	EVs	Electric Vehicles
19	KF/EKF	Kalman Filter/ Extended Kalman Filter
20	PIO	PI Controller Observer
21	Reol	End of Life Resistance of Battery
22	V_i	Velocity of Particle i
23	X_i	Position of Particle i
24	c_1,c_2	Acceleration Constant
25	w	Inertia Constant
26	R	Gas Constant
27	T	Temperature
28	Rp1, Cp1, Rp2, and Cp2	Thevenin Equivalent Circuit parameters
29	Ea	Activation Energy
30	ECM	Equivalent Circuit Model

CHAPTER 1: INTRODUCTION

1.1 Background:

The rise in levels of greenhouse gases and the limited supply of fossil fuels has pushed us to look for alternatives for conventional vehicles. In recent times the world have seen a steady shift towards Electric Vehicles. Electric vehicles (EVs) do not emit greenhouse gases and are not dependent on fossil fuels [2]. They also help in mitigating noise pollutionas they are basically noiseless compared to conventional vehicles. While the future with EVs looks bright but engineers are far from achieving that future as EVs are facing some major technological hurdles along the way. For starters, EVs are installed with a significantnumber of cells and their durability and range per charge possess a great challenge for engineers across the globe [2]. One of the key components for improving the life and utilization of battery packs is proper management of resources available to us. The batteryin an electric vehicle should be able to supply not just long-lasting energy but also high power. Li-ion batteries are the popular options for the EVS as they have many advantages over other potential candidates, but proper monitoring of the batteries is very important as they are sensitive to the overcharging [1]. Hence a system is needed which can properly monitor, analyze and utilize the battery pack and this system is called Battery ManagementSystem and this is what this project is based on. In this project the simulation and implementation the Battery management system for the EVs will take place.

1.2 **Objectives**:

1) To simulate the Battery management system for EVs in MATLAB Simulink.

2) To test the effectiveness of simulated model under controlled experimental conditions.

CHAPTER 2: LITERATURE SURVEY

2.1 Battery Terminology:

Battery: An electric battery is a device that produces electrical energy by converting chemical energy into electrical energy. It is made up of two or more cells connected in series or parallel to provide the required operating voltage and capacity.

Battery terminology:

1) **Nominal voltage:** Nominal voltage is the voltage supplied by a fully charged cell or battery when it delivers specified capacity at a specific discharge rate**.**

2) **SOC:** The ratio between the energy saved in the battery and the total energy that can be saved in the battery is known as SOC (State of Charge). Its value lies between 0 and 1.

   $SOC= Q(t)/Qn$ (1)

   Where $Q(t)$= present capacity

   Qn= nominal capacity

3) **DOD:** Depth of discharge tell us that how much energy is lost by the battery. It is 1-SOC.

4) **C rate:** The C-rate is the ratio of the charge or discharge current in Amperes to the rated capacity in Ah. For example, if the rated capacity is 10Ah, the C/2 rate is 5 A.

5) **Capacity:** Battery capacity is a measurement of the amount of energy a cell or battery can deliver during a single discharge. The capacity of a battery is usually expressed in amp-hours or watt-hours.

6) **Cycle Life:** The number of times a cell or battery may be charged and drained before itscapacity is depleted under specified conditions.

7) **Specific energy:** Specific energy (Wh/kg) is the weighted capacity of a battery. The capacity has to do with the amount of time it takes to complete a task. High specific energy is optimized for products that require lengthy runtimes at moderate load.

8) **Specific power**: Specific power refers to a device's ability to provide a large current and reflects its loading capacity. Power tool batteries are designed for high specific power and have a low specific energy.

2.2 Types of Batteries:

Ni-Cd Batteries:

Ni-Cd batteries have lower specific energy than Li-ion, However, but they have a steady discharge voltage and may be continuously overcharged if necessary, making them extremely dependable [3]. They can also be used in high-temperature conditions. But they are very costly, and cadmium initself is hazardous to environment.

Lead Acid Batteries:

Lead-acid batteries require lead plates as they act as electrodes and these electrodes are immersed in sulphuric acid. The main advantage of this type of battery is that Lead-acid batteries have the lowest cost of any rechargeable battery type for the same amount of power [3]. They are used where a large amount of power is needed suddenly which is why they are used in conventional cars. But they have lower specific energy, and they cannot be charged quickly. They are also very dangerous to deal with and are environmental hazard [3].

Li-ion Batteries:

In the present scenario, there are many options available for the batteries but for electric vehicles, none is more attractive than the Li-ion batteries and there are good reasons for it. Li-ion batteries have many advantages over conventional batteries. One of the major advantages of a Li-ion battery is that provides the best charge-to-weight ratio [16]. This helps in reducing the overall weight of the vehicle which is a game-changing feat for EVs. Apart from this They have a greater round-trip efficiency than many other options, which means they can last longer than other battery types like lead-acid [1].

The six lithium-ion battery types are lithium cobalt oxide, lithium manganese oxide, lithium nickel manganese cobalt oxide, lithium iron phosphate, lithium nickel cobalt aluminium oxide, and lithium titanate. [16].

Here is the comparison between Lithium Cobalt oxide, Lithium Manganese oxide, Lithium Iron Phosphate and Lithium Nickel cobalt [16].

Lithium Cobalt Oxide	**Lithium Manganese Oxide**	**Lithium Iron Phosphate**	**Lithium Nickel Cobalt Al Oxide**
1)Specific Energy is high	1) Specific Energy is higher	1) Low Specific Energy	1) Highest Specific Energy
2)Specific Power is low	2) Specific Power is high	2)Lowest Specific Power	2)Highest Specific Power
3)Life Span is low	3) Life Span is lower	3) High Lifespan	3) Medium Lifespan
4)Cost is high	4) Cost is high	4) High Cost	4) Lowest Cost
5)Performance is higher	5)Performance is lower	5) Highest Performance	5) Medium Performance
6)Safety is lowest	6) Safety is medium	6) Highest Safety	6) Medium Safety
7)Low thermal Stability	7)Low thermal Stability	7) Highest thermal stability among Li-ion Batteries	7)Low thermal stability
8)Low C- rate	8)Low C- rate	8)Low C- rate	8)Low C- rate

Table 2.1 Comparison of different Li-ion batteries

There are many other merits also such as temperature sensitivity and lower volume**.**

The most vital factor for EVs to succeed is the driving range of the vehicle per charge. To enhance the range one the most important thing is proper utilization of the battery pack. Particularly Li-ion battery pack is very sensitive to overcharging problems. Overcharging in Li-ion batteries leads to Shortening the life of the battery and operating at a high-power level overcharging can even lead to hazardous situations [**2].**

2.3 Battery Modelling:

Electrochemical battery modeling is very important to understand and predict the battery performance under different conditions. This technique is so fundamental for the development of the batteries for electrical vehicles that a lot of research has been going on now [11].

There are various methodology for battery modelling namely:

1) Physical First Principle Models or Electrochemical Models
2) Mathematical Modelling of battery
3) Electrical Modelling

Physical First Principle Models: They are based on the electrochemical reactions and incorporates thermal models, parasitic reactions, complex surface structure. Empirical relations are used to incorporate the ageing of the battery in the model [26]. They are the most accurate models for the battery, but the complexity and requirement of high computational power (days of simulation required) makes it method undesirable especially when on board estimation of parameters is required [26]. This method however can be used for ageing studies or to optimize the physical design of the batteries. It can also be used to relate the battery design parameters with voltage, current and concentration distribution [26].

Mathematical Modelling of Battery: This type of modelling is based on complex differential equation or state space equations [26]. Apart from being very complex, the error in the parameters estimation of the battery is very high compared to other methods [26]. The current and voltage information is not given and has to be obtained with great difficulty [26]. This model is useful in predicting the efficiency, capacity and battery run time. It is not used much owing to its complexity and error in estimation [26].

Electrical Modelling: In this type of modelling, the battery is replaced by the electrical equivalent circuit, the electrical components behavior is used to explain the functioning of the batteries [11]. The accuracy of these types of modes is more than what we get through mathematical modelling but less than first principle modelling [11]. These types of models are more intuitive to electrical engineers and are being widely used for their reasonable complexity and accuracy [26].

There are three types of Electrical Equivalent Model:

1)Thevenin Equivalent Model of Li-ion Battery:

The Thevenin equivalent model of Li-ion battery consists of open circuit voltage, Voc, internal resistance R_o, and one or two parallel RC circuits. The resistances and capacitances are function of SOC,Temperature and ageing of the cells. As the number of parallel branches increases, the accuracy of themodel also increases. But in general, it does not take more than two branches of RC circuit as they give satisfactorily results. The complexity of Battery increases a lot if there is further increase in the numberof RC branches [11]. In general, the Thevenin electrical equivalent models do not provide steady state battery voltage variations as well as runtime information.

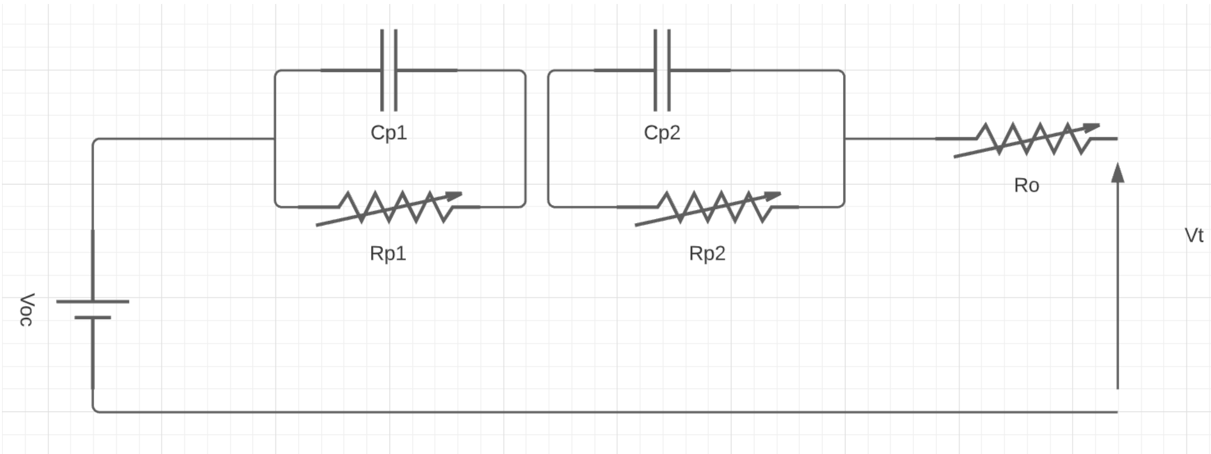

Fig. 2.1 Thevenin Equivalent Model for Lithium-ion Battery

2) Impedance- Based Electrical Model:

In this type of electrical equivalent models' electrochemical impedance spectroscopy is used to obtain an ac equivalent model [26]. The analysis is usually done in frequency domain and an equivalent impedance is used to represent the impedance spectra [26]. The whole procedure of representing battery with an impedance that can provide a satisfactory transient and ac response is complex [11]. These types of models do not work for variable temperature and SOC. Hence it is difficult to predict dc response or battery runtime [26]**.**

3) Runtime – Based Electrical Model:

Runtime-based models use a sophisticated electrical network to simulate battery endurance and dc voltage response with a constant discharge current in SPICE-compatible simulators. They can't predict runtime or voltage responsiveness for varying load currents with any accuracy [26].

2.4 Battery Ageing Mechanism:

Ageing means degradation of battery capabilities over time. This results in a decrease of capacity, also known as capacity fading, as well as an increase in impedance, resulting in a decrease in efficiency and energy supplying capabilities of battery. The main reason behind capacity fading over time is due to the loss of cyclable Li ion due to formation of Solid electrolyte interphase (SEI). This led to overall increase in resistance of the batter [21].

Factors affecting battery ageing:

1) Time: As chemical reactions are taking place in the battery overtime the SEI layer formed on the anode and cathode which limits the active lithium ion which in turns increases the resistance and it also reduces the ability of the cell to supply energy [23].

2) Temperature: It is one of the most important factors affecting the ageing mechanisms in the battery. The capacity loss at idle state (i.e., calendar losses) follows Arrhenius equation. When the temperature rises above 25 degrees Celsius, the ageing rate tends to accelerate. When the temperature drops below 25 degrees Celsius, the pace of ageing accelerates. [22]

3) DOD: Depth of discharge do affect the battery ageing process as evident in the capacity loss during calendar ageing, but the impact of DOD is not as significant as temperature, time and Crate [22].

4) Crate: When charging or discharging a cell with a high Crate, the battery's ageing process is accelerated. Cell heating increases when the C rate increases, this results in rise in temperature of battery which in turn contributes to the ageing of the battery [22].

There are two types of ageing that occurs in Li ion batteries namely: 1) Calendar ageing

2) Cycle ageing

Calendar ageing: It is referred to as the capacity loss of battery at idle state at elevated temperatures. The capacity loss here (due to temperature) follows Arrhenius equation [23].

$$Q_{Loss=} B*e^{(-E_a+370.3*C\_rate)/R*T} *A^{z}$$

A= Cycle No. *DOD*Full cell capacity

R=Universal Gas Constant

T= Temperature (in K)

B=Constant

Z= Power Law factor

C_rate= C rate of the battery

Qloss= Capacity loss

Cycle Ageing: When the battery is charged or discharged, cycle ageing occurs. This is due to the charge level, utilization mode, temperature, and current of the battery. As a result, several factors play a role in this type of ageing [23]. It is simply represented as increase of resistance of the battery.

$$\mathbf{R\_ser = Ka * N^{b} + Rn}$$

Where,

Rn= initial value of series resistance

N= no of cycles

R_ser= Series Resistance of battery

2.5 Battery Management System:

The battery management system is crucial in this regard; it monitors several battery factors such as temperature and SOC. It also uses active or passive biassing to control the charging and discharging of the battery packs. Various analog/digital sensors with microcontrollers are utilized for monitoring purposes.

Block Diagram of BMS:

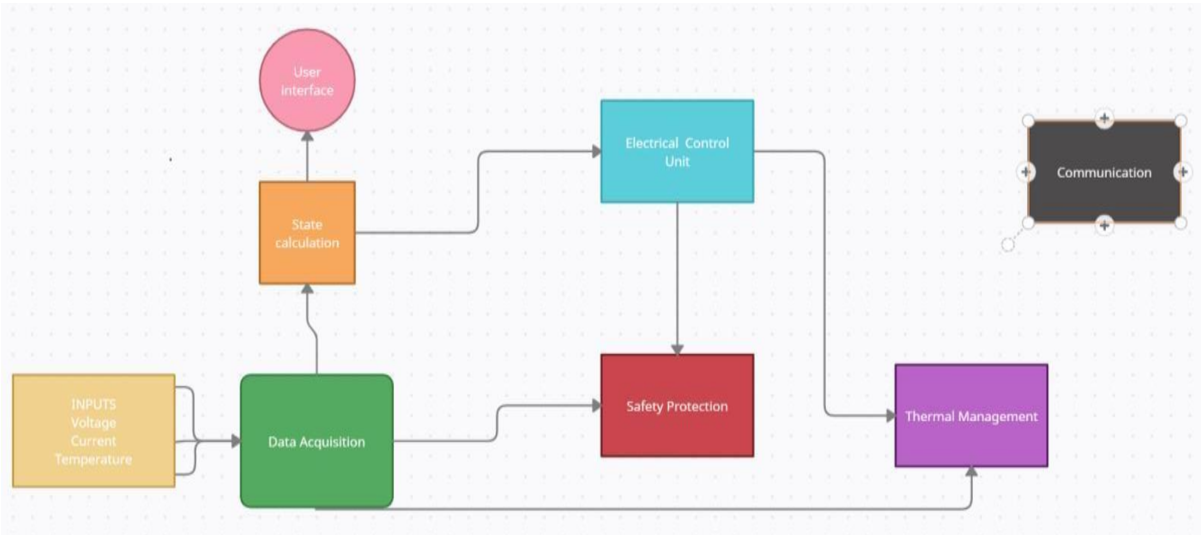

Fig. 2.2 Block diagram of BMS

Based on the topology, there are 3 types of BMS available

1. Modular BMS
2. Centralized BMS
3. Distributed BMS

They all are same with respect to their functionality but differ only in topology. They are following:

1 Modular BMS: A number of controllers, each controlling a certain number of cells, with communication between them.

2 Centralized BMS: The battery cells are connected to a single controller via a tangle of wires.

3 Distributed BMS: Each cell has its own BMS board, with only one communication wire connectingthe battery to the controller.

Functionality of BMS:

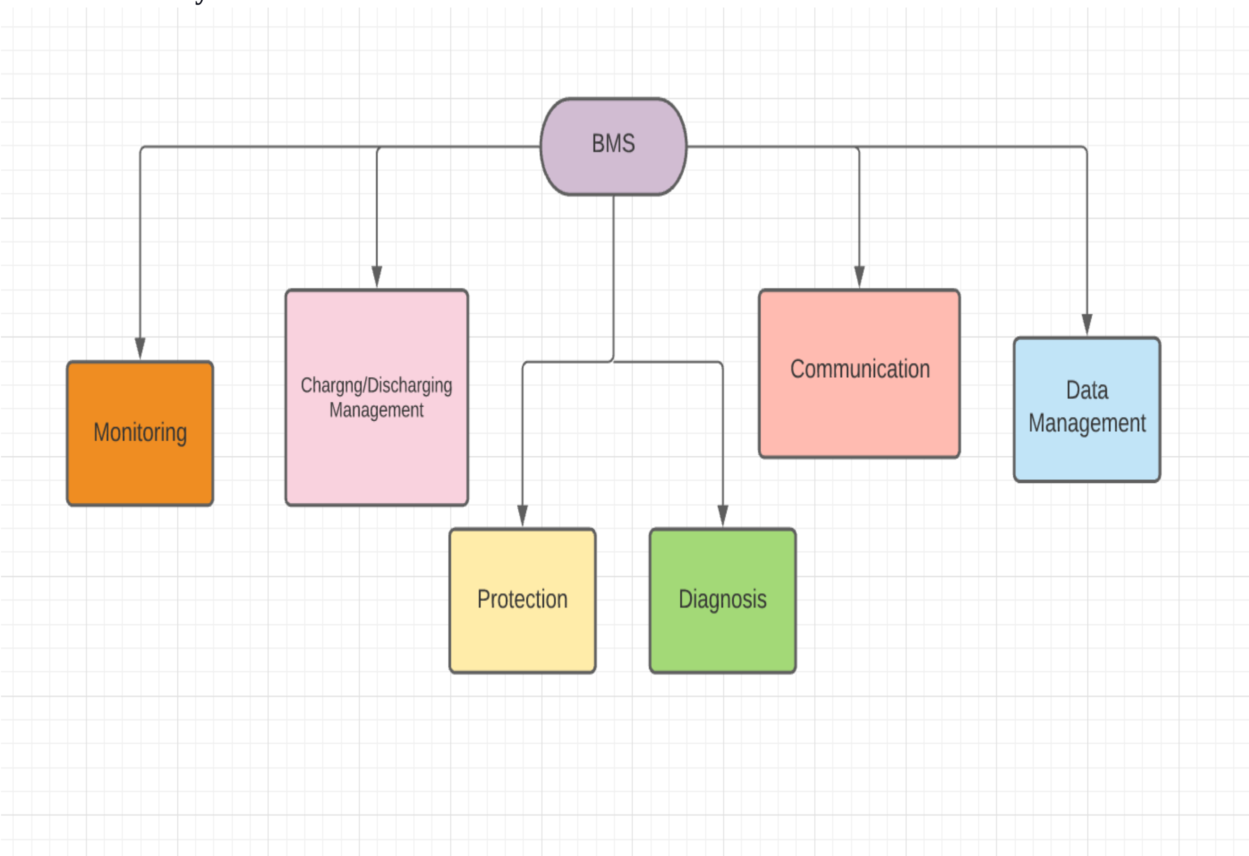

Fig. 2.3 Functionality of BMS

Input of BMS:

1) Cell Voltages
2) Cell Temperature
3) State Request
4) Output voltage of charger
5) Battery pack voltage &current

Output of BMS:

1) SOC
2) BMS State
3) Current limits
4) Balancing Command
5) Charging Current Requirement
6) Relay command
7) Contactor commands

BMS can be divided in four parts:

1. Main State Machine
2. Current Power Limits Calculation
3. SOC Estimation
4. Balancing Logic

CHAPTER 3: BMS Functions

3.1 State of Charge Estimation:

Since SOC is not a physical quantity. It is not possible to directly measure the state-of-charge. Only strongly correlated proxy quantities like as voltage, current, and temperature can be used to estimate it[5].

Categorizing SOC estimation methods:

1) Conventional Methods:
   - Look Up Table Method/OCV Method
   - Coulomb Counting Method
   - Electrochemical Impedance Spectroscopy
2) Model Based Approaches:
   - Electrical Circuit Model
   - Electrochemical Model
3) Adaptive Filter/Observer Based Methods:
   - Kalman filter Based Methods
   - H infinity-based Estimation
   - PIO
4) Data Driven Methods:
   - PSO Based Estimation
   - Artificial Neural Nets
   - Fuzzy Logic Based

Some of the different Methods of SOC Estimation:

1) **Open Circuit Voltage method/LOOK UP TABLE METHOD**:
   The look-up table makes use of the relationship between SOC and the open-circuit voltage (OCV), capacity, etc to establish some relation between them. By performing experiments on the battery, it tries to establish the relationship between the parameters and hence it tries to characterize how battery will behave in similar conditions. The look up table approach can be used to estimate the battery's SOC. [6].

Although there is a roughly linear relation between OCV and SOC for different batteries, this relationship is not accurate for lithium-ion batteries [13]. The capacity of the battery and the composition of the electrodes dictate this. With lithium-ion batteries, the relationship is fairly non-linear. The SOC-OCV connection in LFP batteries is fairly flat, and there is high OCV hysteresis. As a result, in LFPbatteries, the OCV approach is unreliable [15]. To reach the depolarization phase, LIB is first fully charged for a set period of time. After then,current pulses are used to fully discharge LIB. The battery is then held at rest for a set period of time, and the matching OCV of LIB is measured. The relationship between SOC and open circuit voltage is then mapped. One significant disadvantage of look-up table approaches is that they areonly relevant to batteries in a static condition, that is, batteries that have not been loaded and have had ample time to rest to achieve balance [5].

That's why there are not used for online prediction of SOC.

2) Coulomb Counting Method:

Because of its simplicity, it is the most widely used approach for estimating SOC. It is an open loop algorithm. Here it integrates the discharge current over a period and then subtract it from the initial value of SOC [8].

$$SOC = SOC_o - [\ \dot{\eta} * \int i\_discharge(t)*dt\ ]/C_n \quad (2)$$

here, SOC_o = initial state of charge

η = coulombic efficiency, C_n= nominal capacity,

i_discharge(t) = It is the battery's immediate discharge current.

In order to implement the above method, it is important to know the initial value of the state of charge,it also need to have properly calibrated current source [10]. This method is utilizing an open-loop system, so the probability of errors is very high, apart from this since the error will be accumulate in this method hence our final estimation could be far away from the actual value, so care must be taken in the measurement of parameters while implementing this method [15].

This method is not utilized directly because of the problems mentioned above. Several factors like ageing of battery, discharge rate and sensor precision also affect the accuracy of this method. Hence it cannot be used practically to measure SOC in BMS [15].

3) Electrochemical Impedance Spectroscopy:

The impedance of the battery is calculated using this method by adjusting the current for a short time while using the battery voltage and current. The temperature and C-rate have a big impact on the relationship between internal resistance and SOC [13].

Except for resistances, capacitors, and voltage sources, the approach is named Electrochemical Impedance Spectroscopy (EIS) for online applications, and it uses a Warburg element and a constant phase element (CPE) [13].

Only similar charging conditions are applicable for this estimation method. As a result, it is not ideal for EVs that may be charged in an inconsistent manner with varying current. This approach is limited to frequency of very high range because of the high temperature influence [14].

4) Electrical Circuit model-based estimation:

Model-based approaches use an advanced algorithm and a battery model to estimate the states of a battery based on measurable metrics like voltage, current, and temperature [14].

In this method, an equivalent electrical circuit is made to explain the battery processes. When a battery is discharged with a current pulse, a lot of the properties or qualities of the battery can be seen.Three distinct portions of the voltage drop can be identified: a sudden, a delayed or exponential reaction and finally towards the end of discharge. Here the Open Circuit Voltage is reduced due to lowered SOC [13].

The behavior of the separator inside the battery depends on temperature the most and causes the sudden drop, is represented by the internal resistance of an ECM [13].

A series of parallel RC elements influence a battery's overall dynamic responsiveness. A nonlinear or SOC-dependent voltage source is used to describe the voltage level [13].

A predefined SOC is employed in the modern control design technique to provide OCV data and to obtain the battery output voltage. The deployment of an algorithm is the final phase inthe SOC estimate process.

The main drawback of this method depending on how accurate the estimation of SOC, the accuracy of the battery model will be decided so, it is very difficult to achieve highly accurate model [11].

5) **Kalman filter-based SOC & SOH estimation**:

It's a clever tool for calculating a linear system's best state, and it is the most widely used used to estimate the battery dynamic state [13]. Based on linear quadratic estimation and under conditions of linear-gaussian uncertainty, KF method believes that the optimal solution to the Bayesian filter to be an extremely fast approach. [15]. However, it is restricted to linear and unimodal systems. Once the system is operational, KF the new state is estimated and corrected. The entire process has these two major steps:

- A state prediction step
- A state update step

The Kalman filter algorithm is self-correcting [15].

EKF (Extended Kalman Filter):

EKF linearizes the battery model using partial derivatives and a first-order Taylor series expansion. KF only utilises one point, the mean, and linearizes each time increment around that point. [13].

Unscented Kalman Filter:

The method makes use of a set of points (called sigma points) which includes the average and approximatesaround them. Approximation precision increases as number of points increases, but as the no. of points increases the method becomes more complex. The KF approach has the benefit of being able to accurately estimate the states that are impacted by external disturbances [13].

Disadvantages of KF:

High complexity, high computing expense, and instability plague the algorithms [14]. Complex matrix operations are used in the approach, which can cause numerical instabilities and make the process difficult to implement on a standard, cheap microcontroller [14]. KF techniques are constrained by Jacobian matrices' linearization accuracy and filter stability, and they rely largely on the battery model and sensor precision. [14].

6) **SOC estimation using PIO controller:**

In this method PI controller (as observer) is used. The feature of a PIO controller is to converge the predicted voltage to the measured voltage in an correct and rapid manner The outcomes display that the mistake is constrained to %2. But it requires trial and error methodfor tuning of the gains in the controller [16].

Here the algorithm compares the estimated terminal voltage with the actual terminal voltage, the error between the two will be fed to the PI controller. The output of PI controller is a control signal which is fed back to the model for estimation of SOC.

Here major drawback is it is difficult to tune the PIO [16].

7) **H∞ filter:**

H infinity (H∞) is an effective device to limit the impact of disturbances of external origin on output. The H∞-based approach is to assure that the noises remain under given level, so that error in SOC estimation is much less than tolerance levels [14].

This method is very similar to KF method here a strong design model which is robust under certain conditions is used. The next state of model is estimated by the H∞ filter like KF [16]. Essentially, it inherits all pitfalls of the KF primarily. Also, nonlinear constraints which include saturation aren't well-handled, and aging, hysteresis and temperature outcomes ought to vary the error offered by the method [16].

8) **SOC & SOH estimation using PSO algorithm:**

Particle Swarm Optimization (PSO) can be used to look for a global minimum and personal minimum iteratively looking to enhance candidate on the subject of a cost function [17]. It has been found that PSO is frequently utilized in aggregate with the model-primarily based on techniques for SOC prediction of batteries. PSO is used to optimize important elements of the model together with voltage, resistances, and temperature [17].

Main drawback of PSO based estimation is its complexity and poor convergence rate [14].

Cost function = Error in measured terminal voltage

Particles of PSO = Battery ECM parameters like Voltage, Resistance and Capacitor etc. [17].

3.2 SOH estimation:

State of Health (SOH) is used to measure the health of the battery. It is an extremely important parameter. The ability of a cell or battery to perform a specified discharge (or charge) function at a given point in the charge-discharge stand cycle regime is referred to as SOH [19].

To comment on SOH, we first need to establish the end of life (EOL) for the battery, EOL is taken as a period when the battery power is 60% of its initial maximum power at constant SOC and temperature. [19]

The maximum discharge or charge current at a given SOC and temperature depends mainly on resistance offered by the battery as OCV (open circuit voltage) is largely dependent on SOC which is kept constant.

So, in turn SOH is directly linked with the resistance offered by the battery.

$$\text{SOH} = (Reol - R) \div (Reol - \text{Rnew})$$

Where Reol is resistance offered by the battery at EOL & Rnew is resistance offered by the battery when the battery is brand new.

PSO Algorithm based battery parameter estimation and SOH estimation:

PSO: It is a metaheuristic algorithm which is based on the behavior of birds or fishes in group (swarm behavior). In this algorithm we iteratively tried to find the optimum solution to the problem by constantly trying to improve on the candidate solution based on personal best and global best solutions of the swarm particles. It is based on the principle of communication and learning [17].

The governing equations for PSO are given below:

$$X_i(t+1) = X_i(t) + V_i(t+1)$$

$$V_i(t+1) = w*V_i(t) + c_1*[P_i(t)-X_i(t)] + c_2*[G(t)-X_i(t)]$$

Where

V_i= Velocity of particle i

X_i= Position of particle i

t= Number of iteration

P_i= best position of particle i

G= Best Position for all the particles

c1 & c_2= Acceleration constant

w= Inertia constant

By comparing the model's terminal voltages to the genuine value, the PSO algorithm is utilised to optimise the equivalent circuit parameters of the battery model. [24]. As shown below first the SOC is calculate as all the parameters of Thevenin equivalent model depends on the SOC This model is being used to compare the result of PSO estimation , then PSO algorithm iteratively tries to obtained the components of the battery model according to the personal and global best solution until the error is minimum .After optimizing the parameters we use the series resistance of equivalent circuit to find the SOH of the battery as discussed before [25].

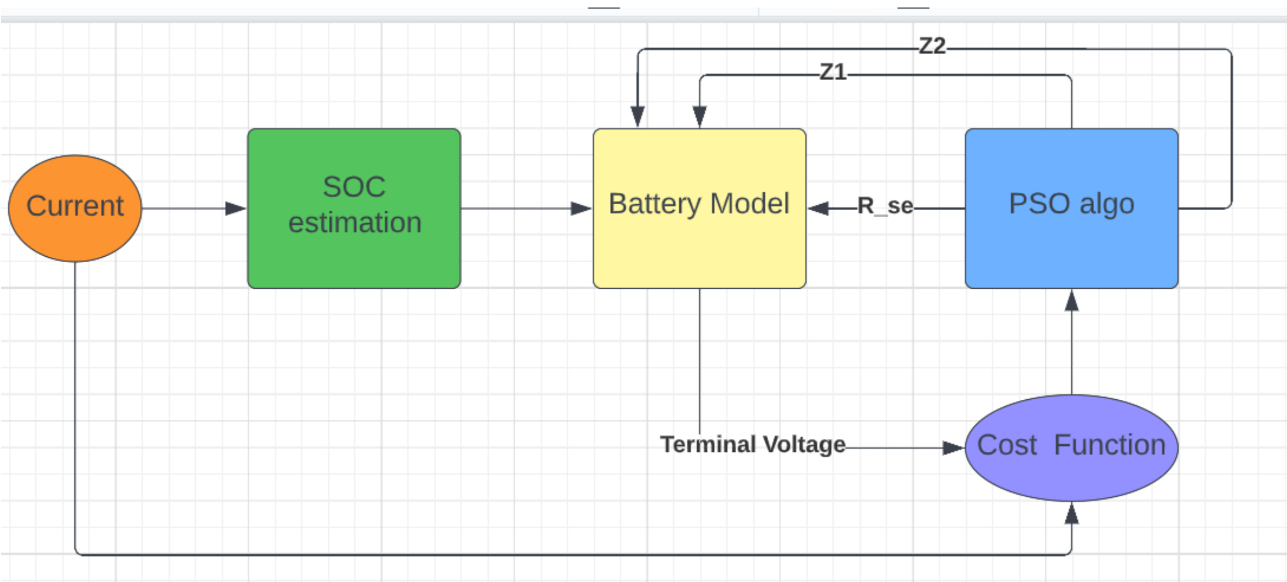

Fig. 3.1 SOH estimation using PSO algorithm

3.3 Balancing of Cells:

Inside the battery pack, a lot of cells are connected in different configuration according to the voltage and other requirements but mostly they are connected in series to achieve the high voltage requirementof the battery pack. Since every cell cannot be the same, they charge or discharge at different rates,hence over time their SOC differs a lot, they share different voltages in the string and this phenomenon is detrimental for the battery pack [2]. Hence it needs a system to maintain the SOC of the cells in the battery pack, at the same level. This system or process of balancing SOC to enhance of the utilization of cells in a battery pack is called cell balancing. The types of balancing used are:

1) Passive balancing:

The aim behind the passive cell balancing technique is to discharge the cells through a bypass route that is primarily dissipative [18]. Because the bypass can be external or integrated, it is simpler and easier to deploy than active balancing solutions, and it keeps the system more cost-effective in either case [18]. However, because all of the excess energy is wasted as heat, the battery's run time suffers, and it is less likely to be used during discharge [18].

2) Active balancing:

Charge is transferred between the cells with inductive charge shuttling or capacitive charge shuttling using active cell balancing [18]. This is an efficient method, as it transfers energy directly to where it is needed instead of wasting it. The downside of method is it demands additional components which in turn increase the cost [18].

Chapter 4: Simulations & Results

4.1 PASSIVE BIASING:

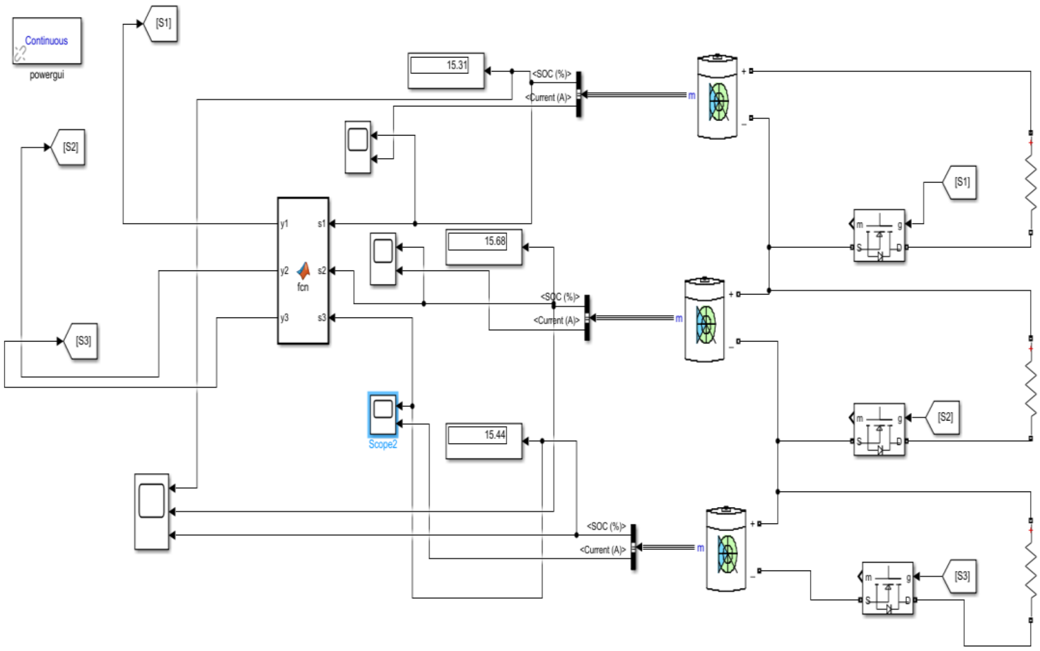

Fig. 4.01 Simulink Model for passive balancing

Initial SOC:

Battery 1 = 25%

Battery 2= 30%

Battery 3=20%

Final SOC of all batteries after 3600 sec =15%

In this Simulation, a passive balancing technique has been demonstrated here it is using external loads(resistances) to dissipate the energy to balance the SOC, generally in EV's the SOC of battery should not go below 70% but in this experiment a lower initial SOC is taken just to demonstrate the effectiveness of this model.

The logic for switches to close and open according to the respective SOC is provided in the Function block, the MATLAB code for the same is provided below.

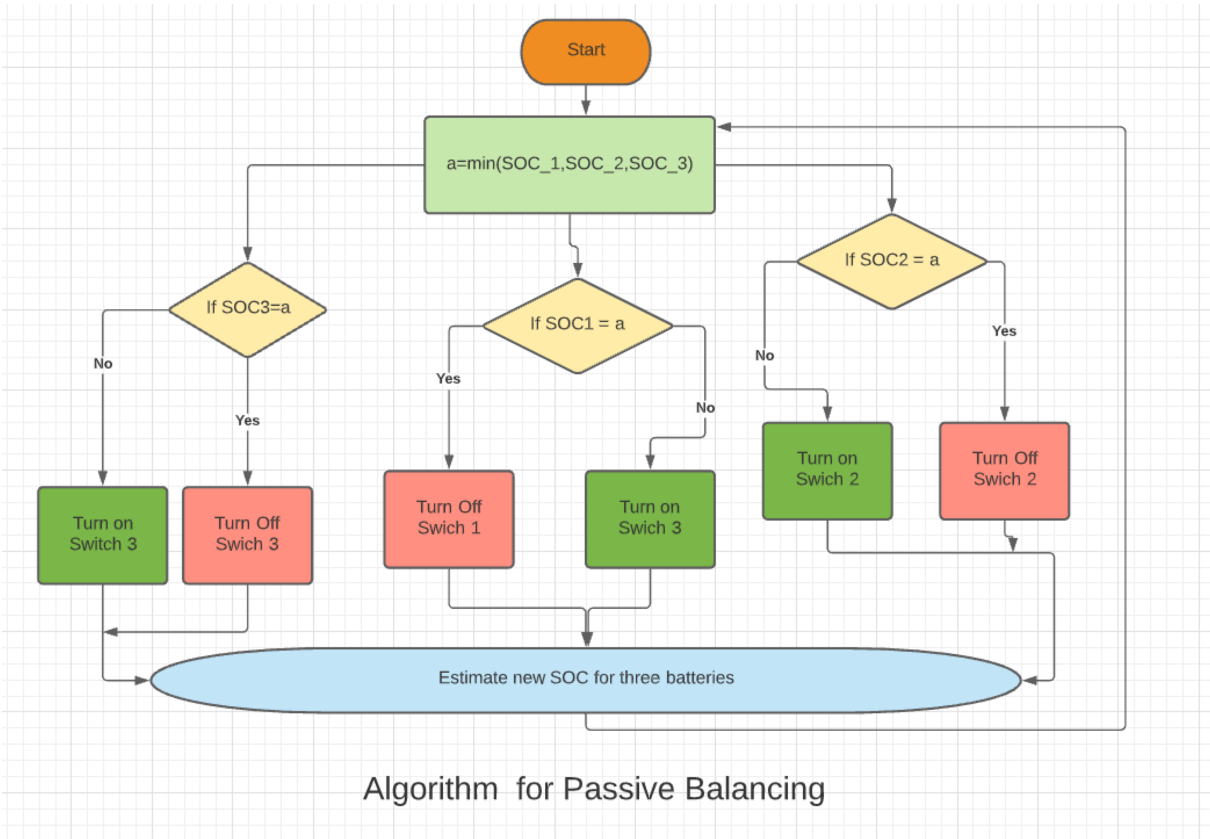

Fig. 4.02 Algorithm for passive balancing

The waveforms below show the SOC and discharging current of the battery 3. It can be seen clearly since the SOC is at 20% initially the battery is cutoff from the circuit.

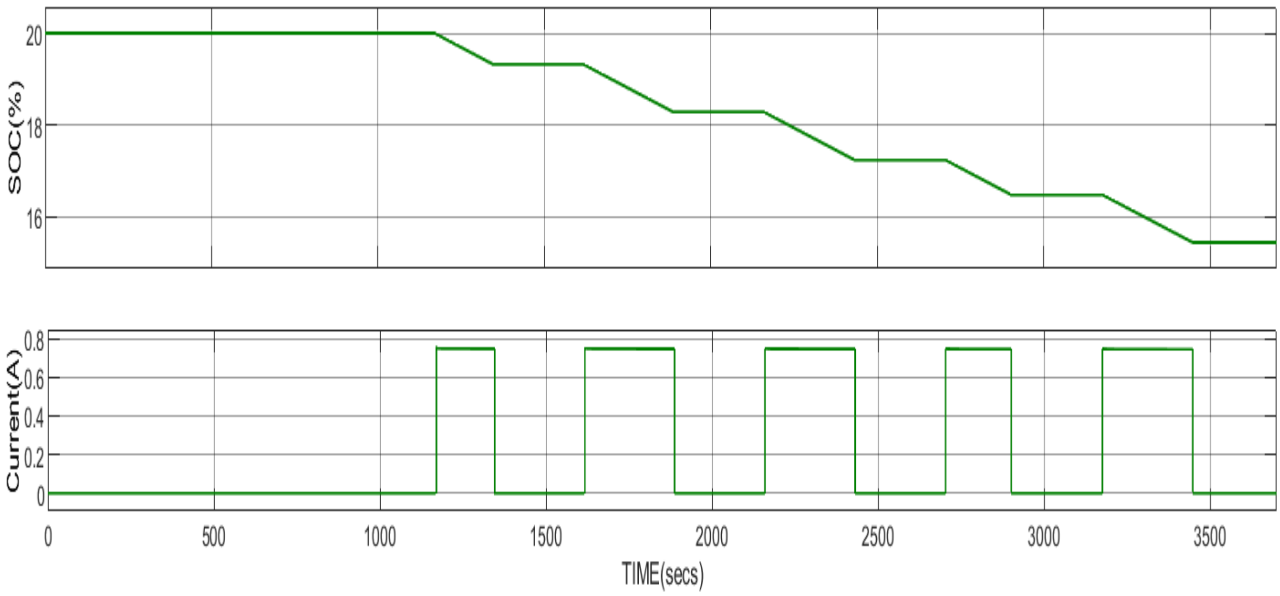

Fig. 4.03 Battery 3 parameters

In figure below it is showing SOC and Current waveforms for battery 1

Initial SOC=25%.

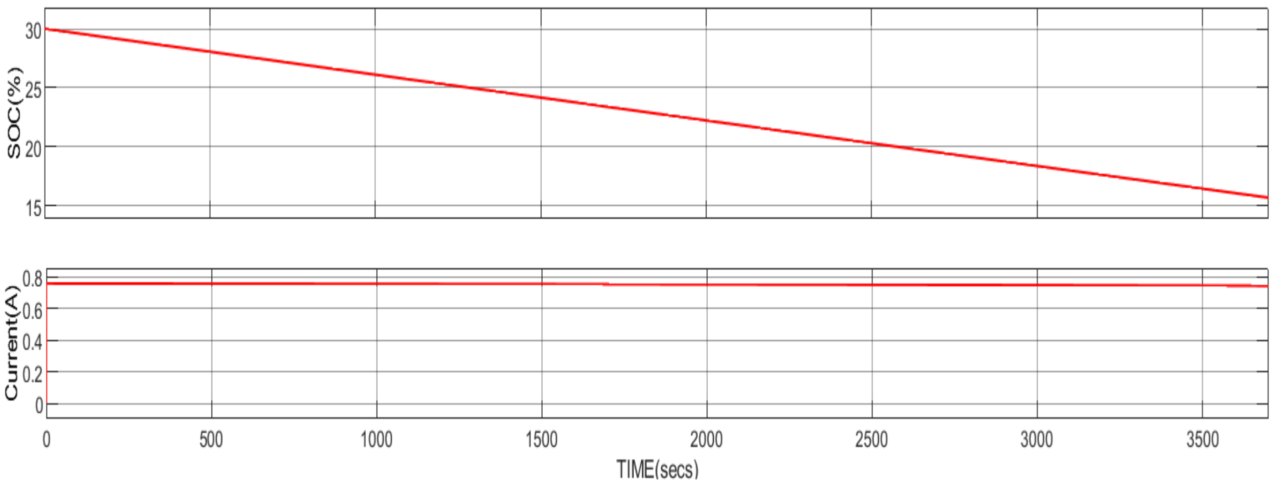

Fig. 4.04 Battery 1 parameters

In figure below it is showing SOC and Current waveforms for battery 2

Initial SOC=30%.

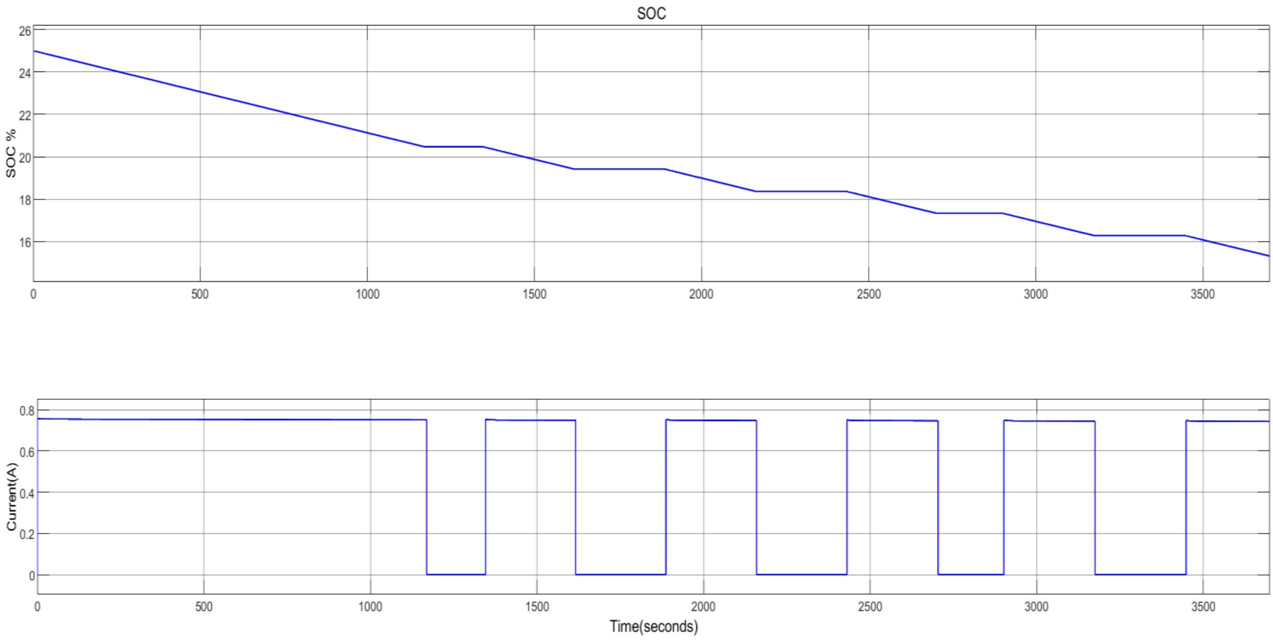

Fig. 4.05 Battery 3

The below Figure shows that SOC of three batteries is converging and becoming equal after 3500 seconds

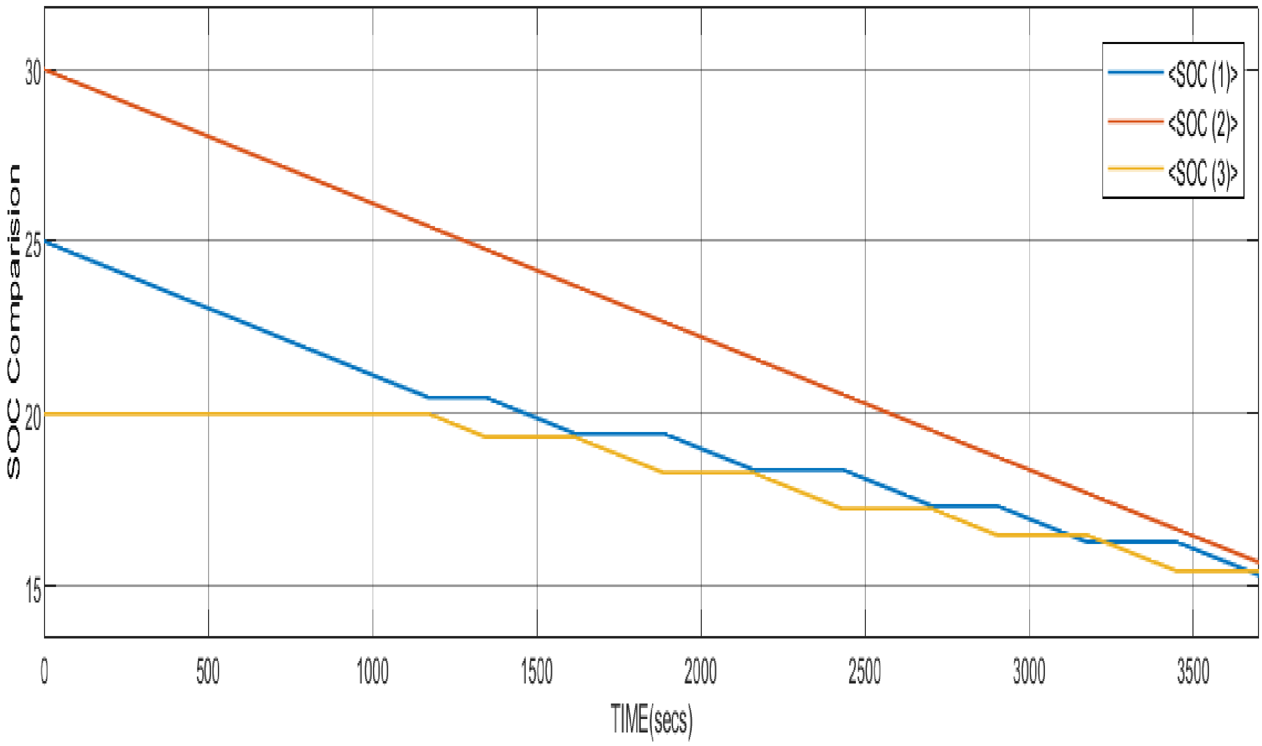

Fig. 4.06 SOC comparison

4.2 Battery simulation:

4.2.1 Look Up Table Method of battery simulation (used for SOC estimation using PIO method):

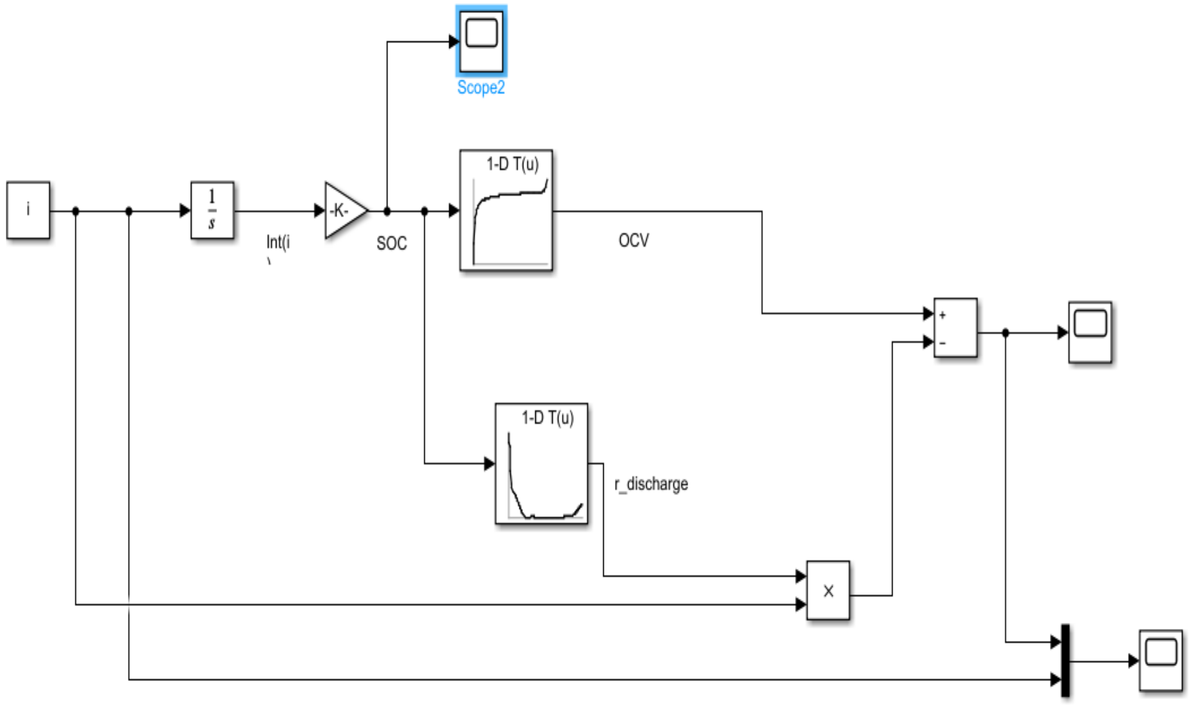

Fig. 4.07 MATLAB Simulink model for Li-ion batteries

The mathematical relation used to implement the model of battery:

SOC = SOCo + [ή* ∫i_charge(t)*dt]/Cn (1)

Vt = Voc(SOC)-i*R(T,SOC) (2)

The look up table is used to establish the relation between open circuit voltage and SOC. Similar method is used to establish relation between resistor and temperature. Finally, it obtained the terminal voltage and SOC curve as shown below.

The terminal voltage curve shows the average terminal voltage curve between charging and discharging of the battery.

The SOC is steadily rising over time as expected from the implementation of the equation (1), the SOCo (initial value of State of charge) is taken as 0.

Since the cells in a battery pack are in series the current remains constant, so it has taken current as constant.

The figure below shows the Terminal Voltage(V) over time(sec)

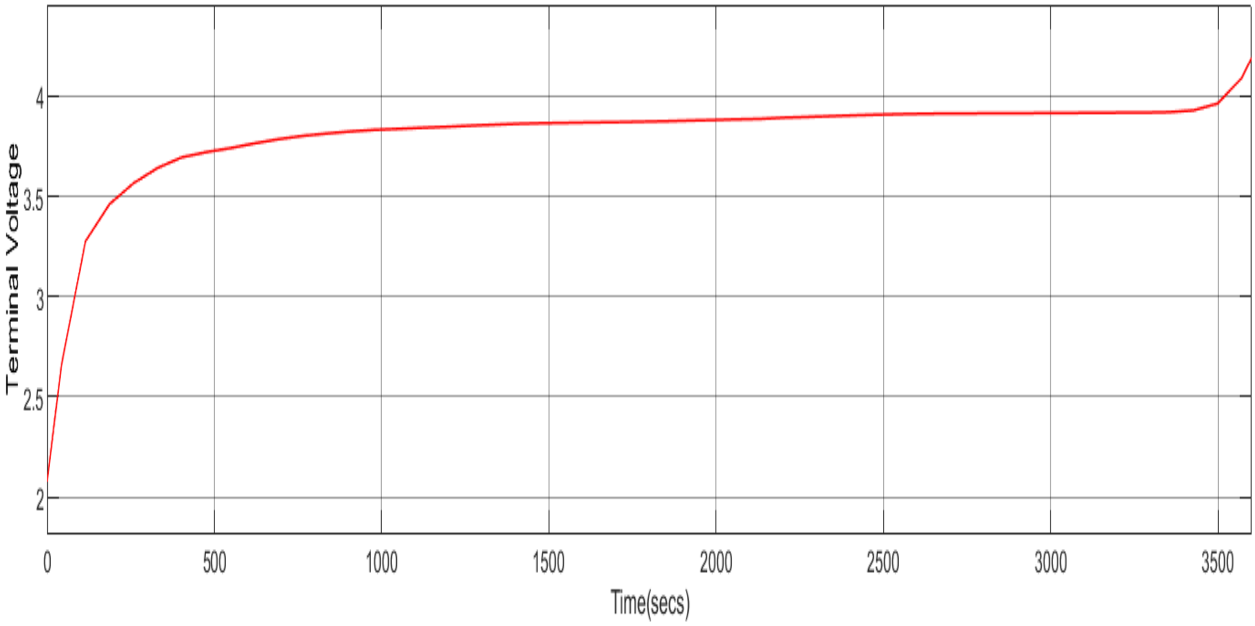

Fig. 4.08 Terminal Voltage

The figure below Shows SOC (0 to 1) over time(in sec):

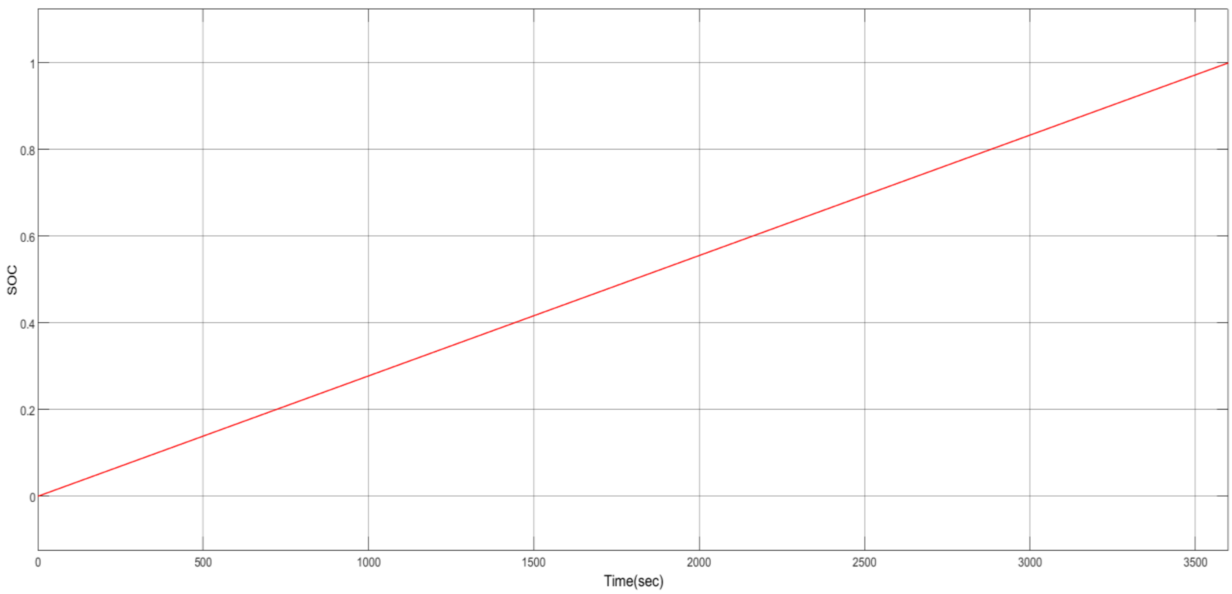

Fig. 4.09 SOC (during Charging)

4.2.2 Battery simulation using empirical modelling:

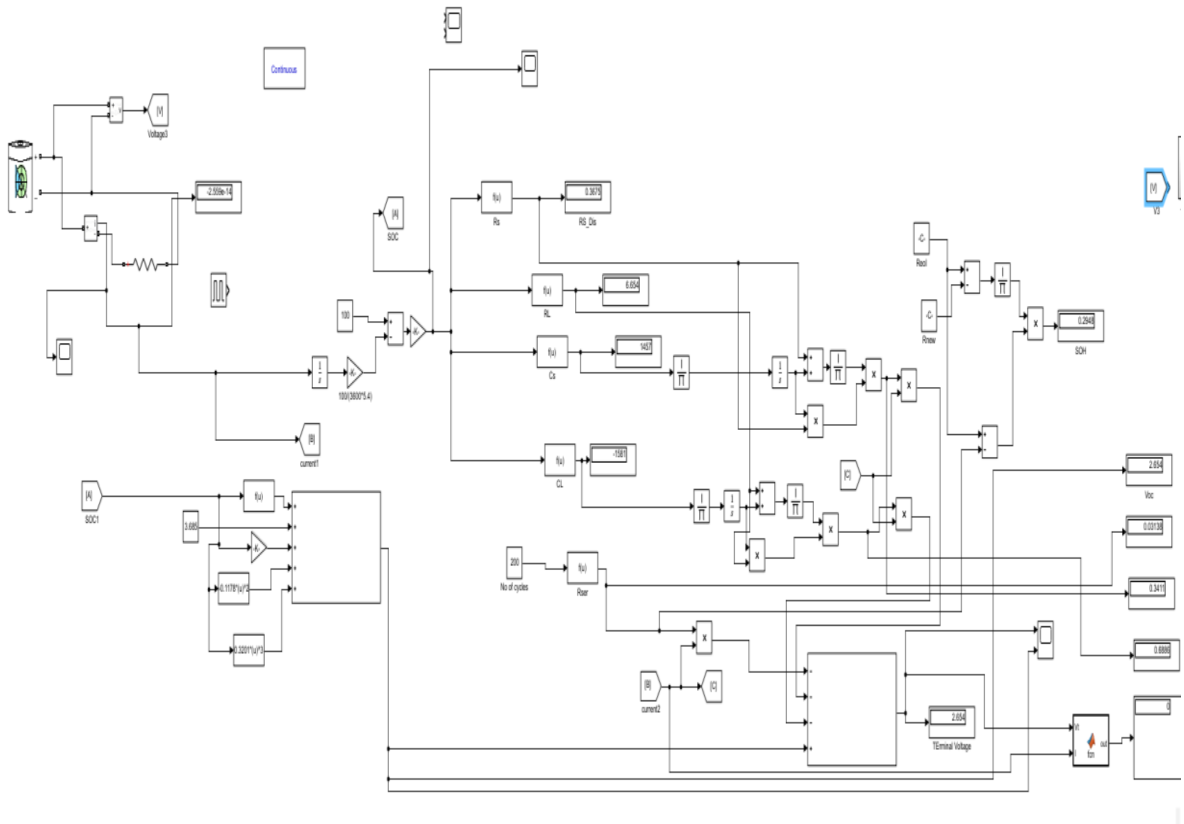

Fig. 4.10 Simulink model of Empirical battery model

Empirical Battery Model:

To obtain the relation between the battery parameters experiments on the battery are performed and with the help of curve fitting, the relation between parameters is obtained. Although to simplify the relationship approximation has been done.

R & C parameters of the battery model are almost constant between 20% and 100% of SOC and change exponentially between 0% and 20% SOC due to the electrochemical reaction inside the battery. However, the open-circuit voltage varies significantly with the SOC throughout.

The parameters were applied to the proposed model under similar conditions (temperature, etc.) to mimic the real battery voltage response for the same pulse discharge currents that were used to extract the parameters to ensure that the results were accurate.

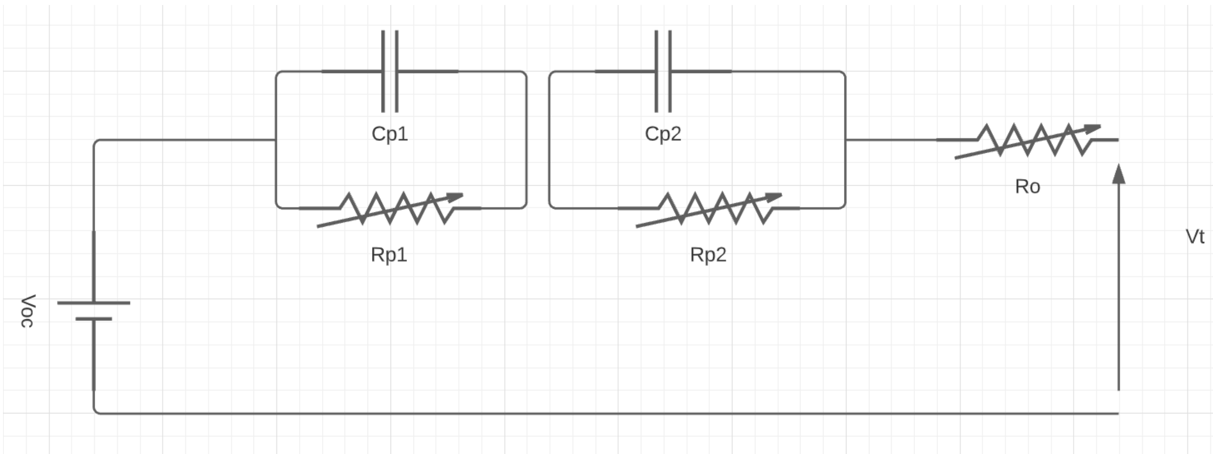

Fig. 4.11 Thevenin Equivalent Model for Lithium-ion Battery

The relationships between parameters are shown below:

$Voc = -1.031*e^{-35*SOC} + 3.685 + 0.1256*SOC-0.1178*SOC^2 +0.3201*SOC^3$

$R_{p1} = 0.3208*e^{-29.14*SOC} +0.04669$

$R_{P2} =6.603 * e^{-155.2*SOC} +0.04984$

$C_{p1}= 752.9*e^{-13.51*SOC} + 703.6$

$C_{p2=} -6056*e^{-27.12*SOC} + 4475$

$Ro= 0.001907\ N^{0.4699} +0.008391$

$Vt= Voc – I* (Ro +Z_{p1} +Z_{p2})$

The above equations show Voc(open circuit voltage), Rp1, Cp1, Rp2, and Cp2 branch impedances to capture the transient behavior of the battery as the nonlinear function of SOC. On the other hand, Ro is the series resistance of the battery used to capture the steady-state behavior of the battery it depends non-linearly on the number of cycles of the battery.

Finally, the terminal voltage is the function of all the above parameters and the discharging current/charging current of the battery.

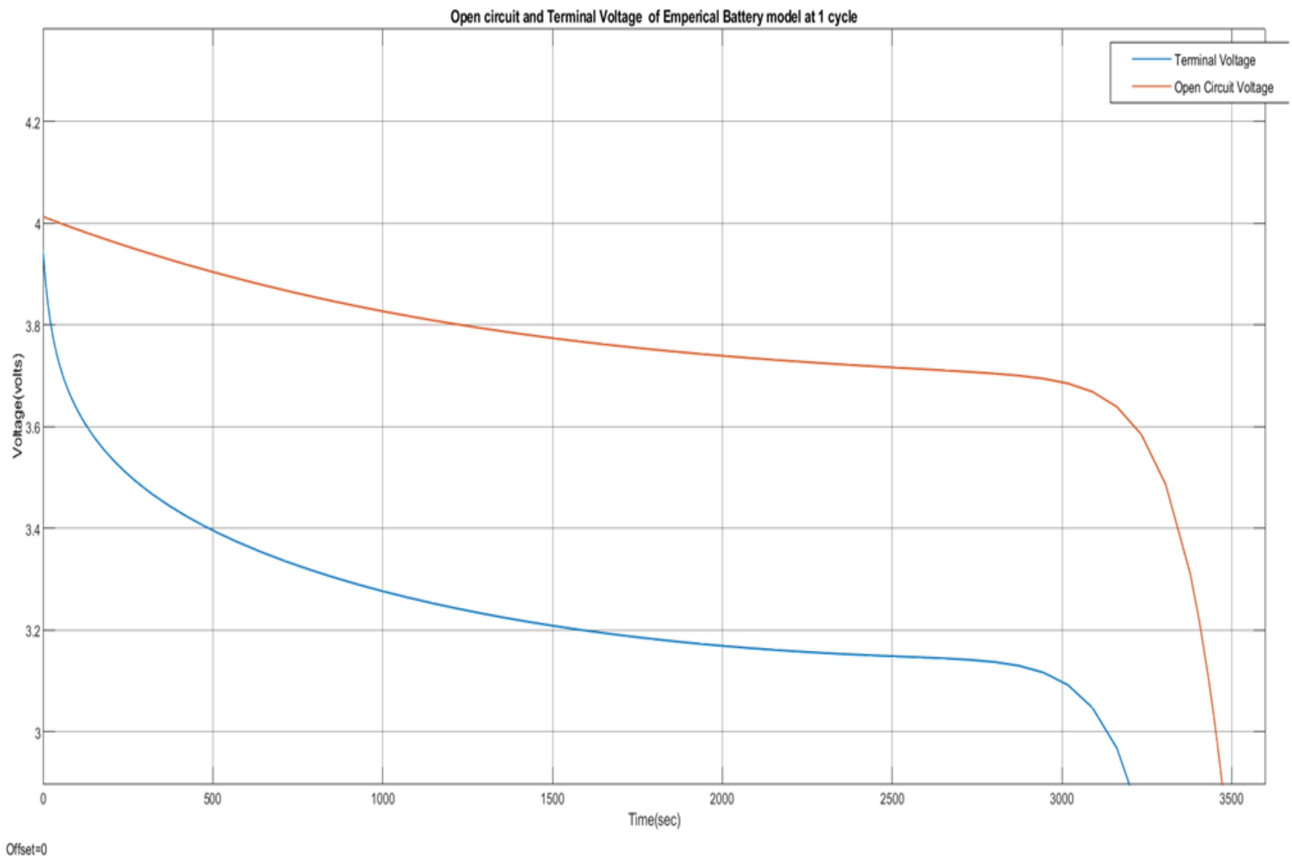

Fig. 4.12 Open Circuit and Terminal Voltage @ 1cycle

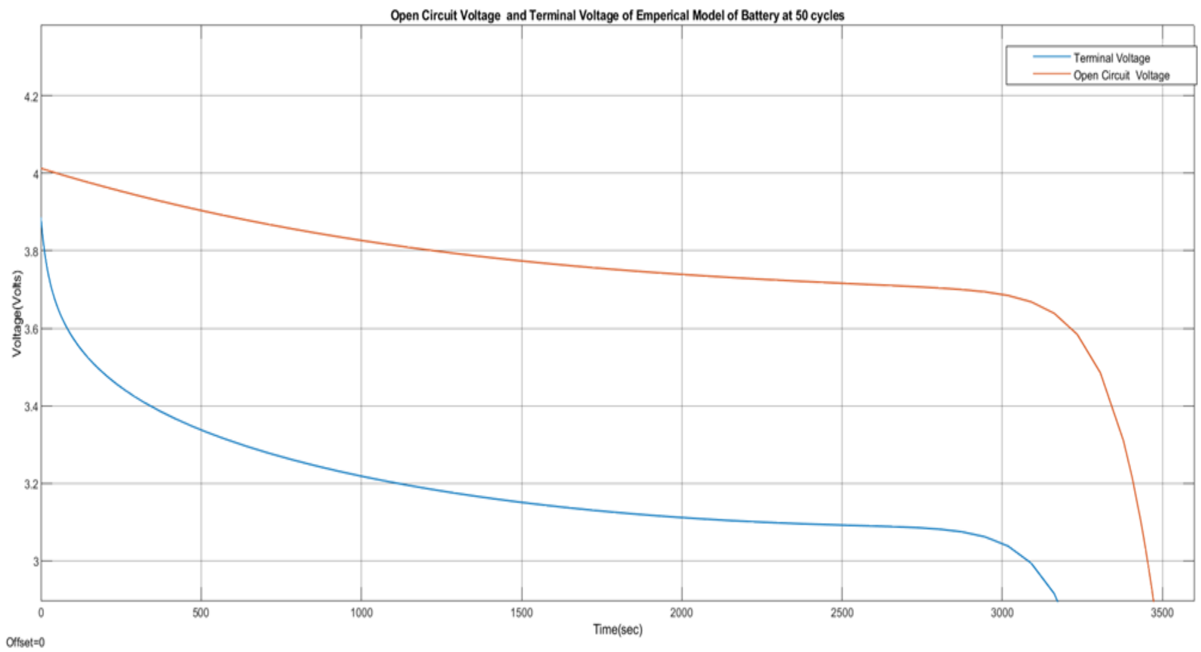

Fig. 4.13 Open Circuit and Terminal Voltage @ 50 cycles

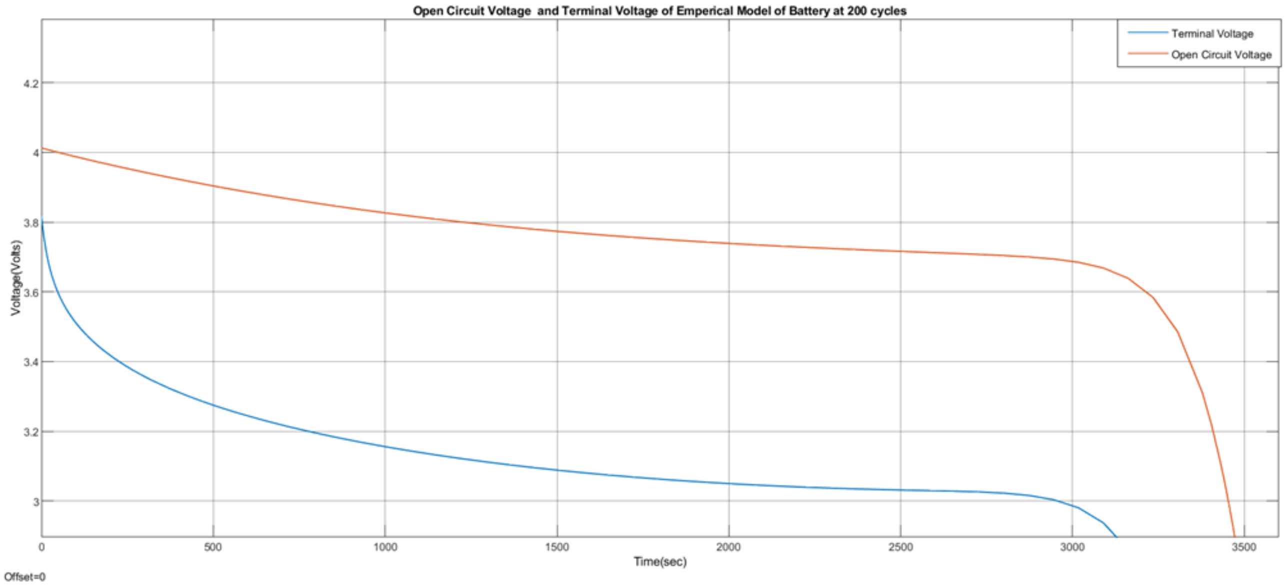

Fig. 4.14 Open Circuit and Terminal Voltage @ 200 cycles

4.2.3 Battery Capacity Fading Model (Ageing Model):

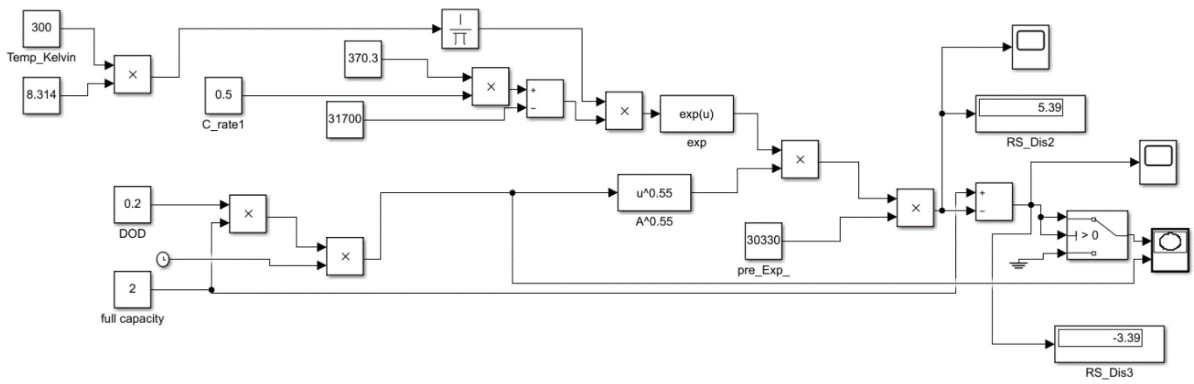

Fig. 4.15 Ageing Model

$$\mathbf{Q_{Loss} = B * e^{(-31700+370.3*C\_rate)/\ R*T} * A^{z}}$$

A= Cycle No. *DOD*Full cell capacity

R=8.314
T= Temperature in Kelvin
B=30330
Z=0.55
Ea= 31700

The above simulation shows capacity fading, it is based on power law equation described in Bloom et al. [28]
Here B is a constant whose value at C/2 is taken as 30,330 [27], the activation energy (Ea) and power law slope(z) is generalized for all values of C rate [27].

The capacity loss at different value of temperature and DOD is shown below:

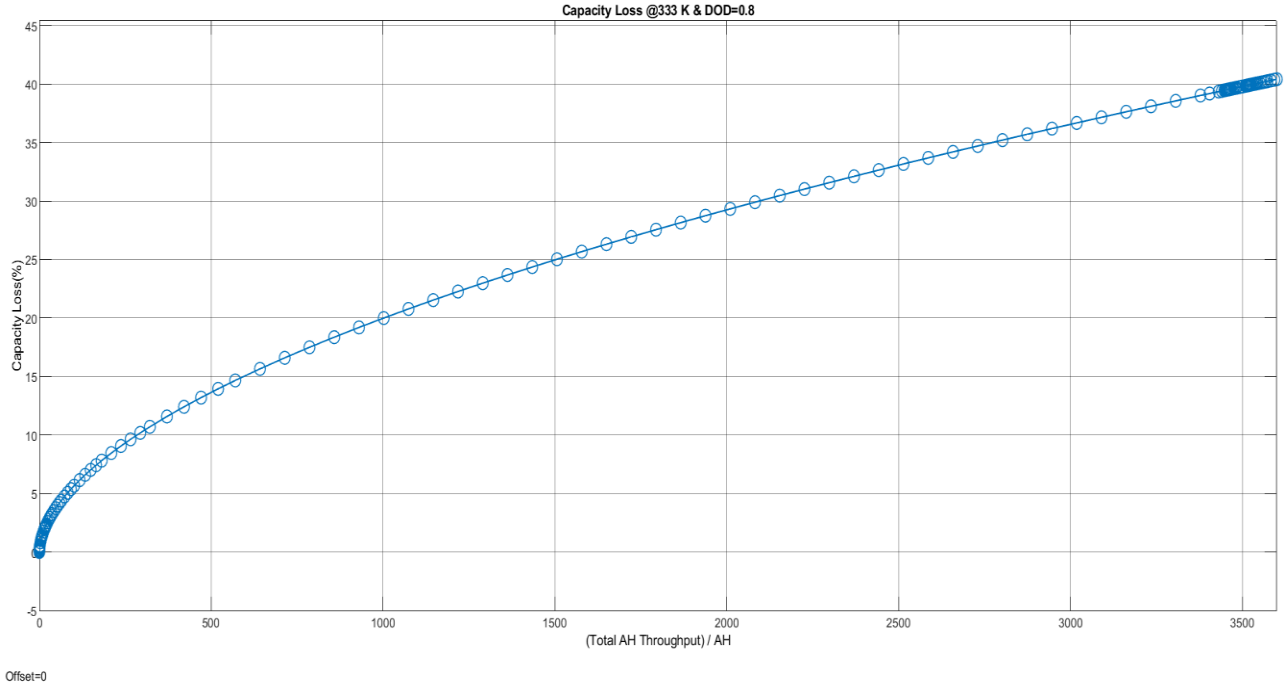

Fig. 4.16 Capacity fading @333 K and DOD=0.8

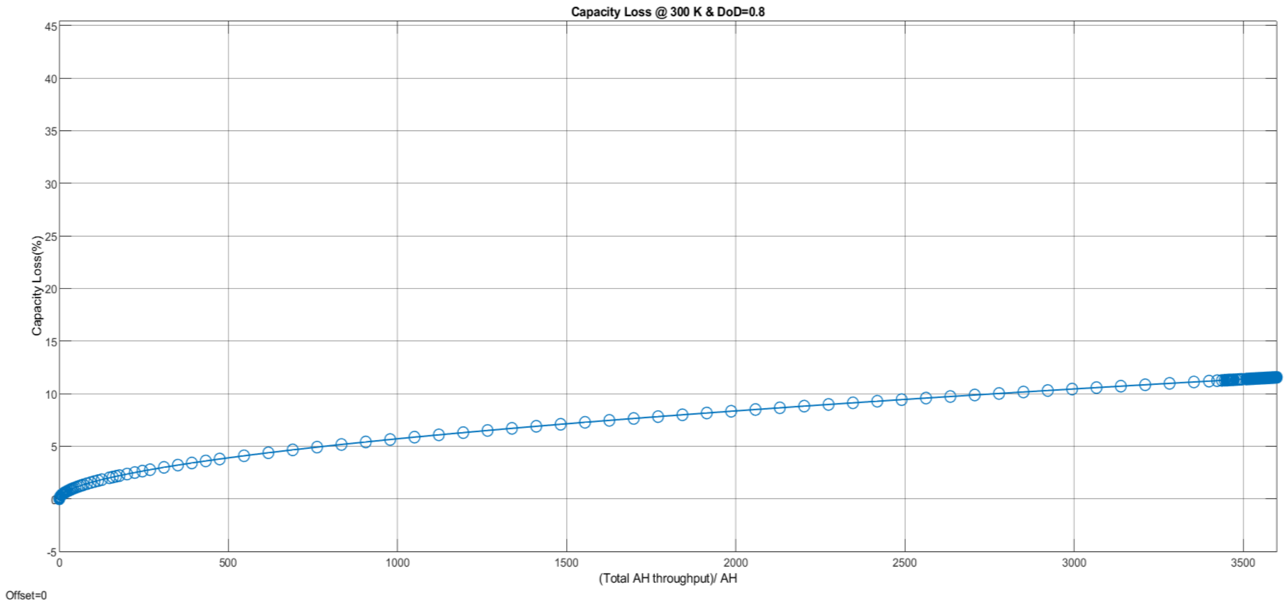

Fig. 4.17 Capacity fading @300 K and DOD=0.8

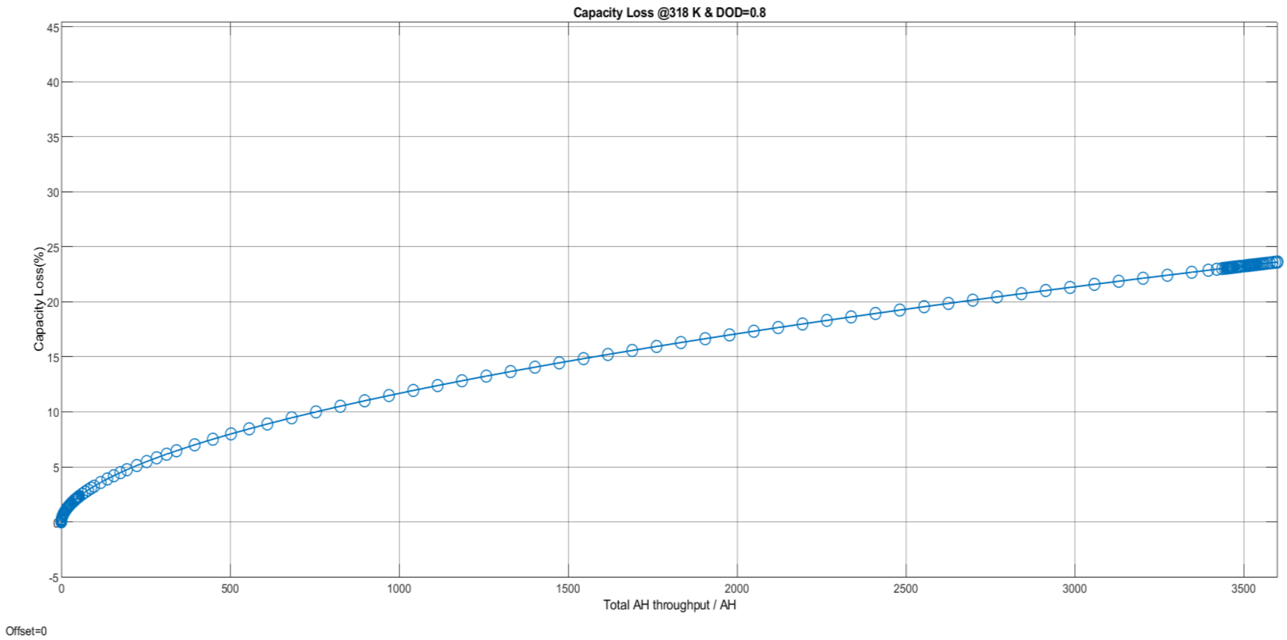

Fig. 4.18 Capacity fading @318 K and DOD=0.8

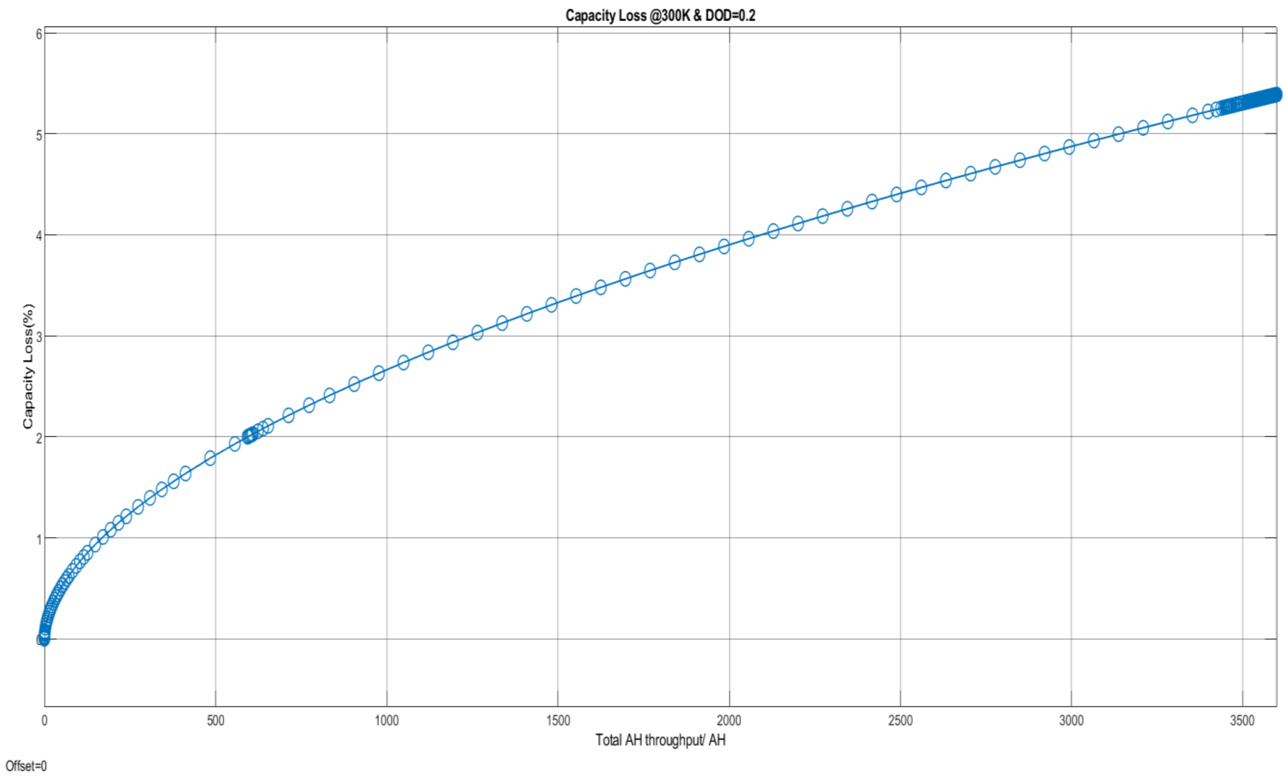

Fig. 4.19 Capacity fading @300 K and DOD=0.2

4.3 SOC Estimation:

4.3.1 Coulomb Counting:

Here a simple **coulomb counting** method is implemented in MATLAB simulink to estimate State of Charge of theLi-ion battery. The mathematical equation used to estimate SOC is:

$$SOC = SOC_o - [\ \acute{\eta} * \int i\_discharge(t)*dt\ ]/C_n$$

Initial value of SOC=100 %

The battery is discharged till it’s SOC reaches 50%.

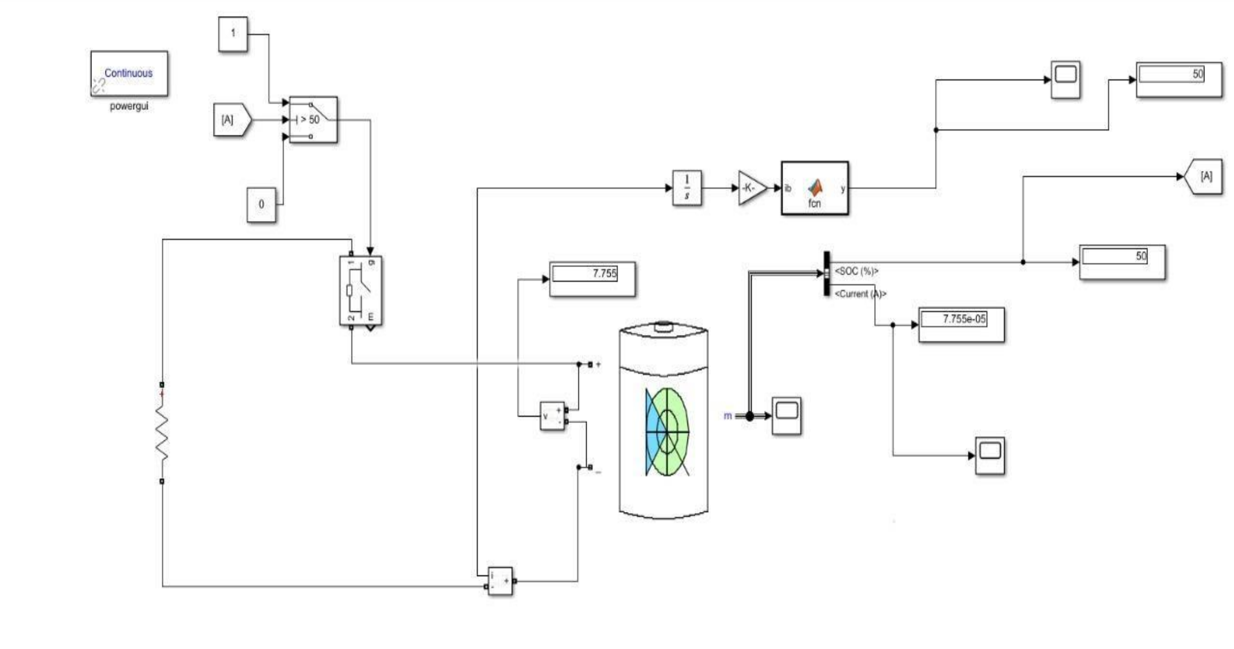

Fig. 4.20 Simulink Model for SOC estimation (Coulomb Counting)

As seen from the figure below that battery current is going to fall to zero from 7.55A after the battery reaches 50% SOC. Here the value of SOC has been accurately estimated as 50% as shown in display after the function block.

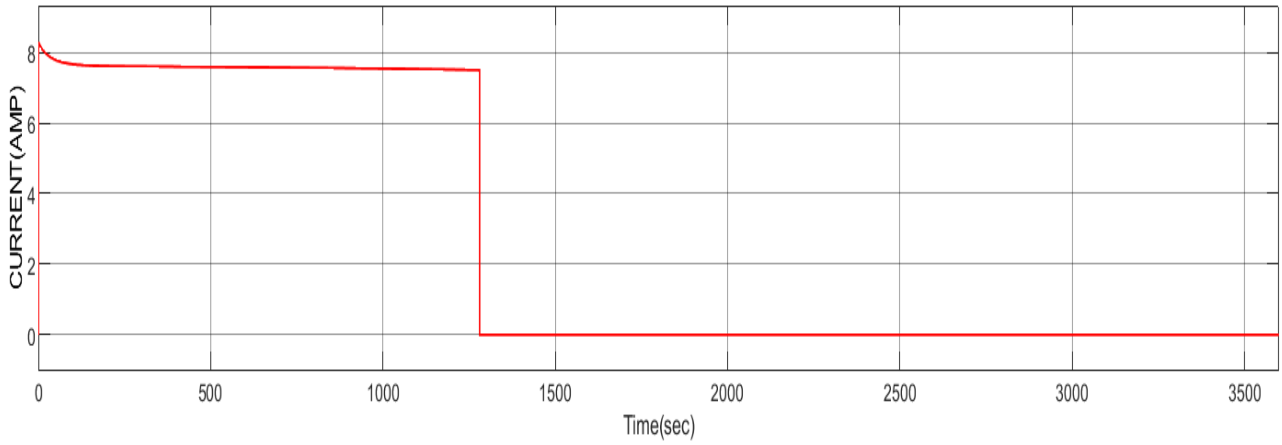

Fig. 4.21 Battery Current

In the figure below, the SOC falling because battery is getting discharged until 50%SOC is reached.

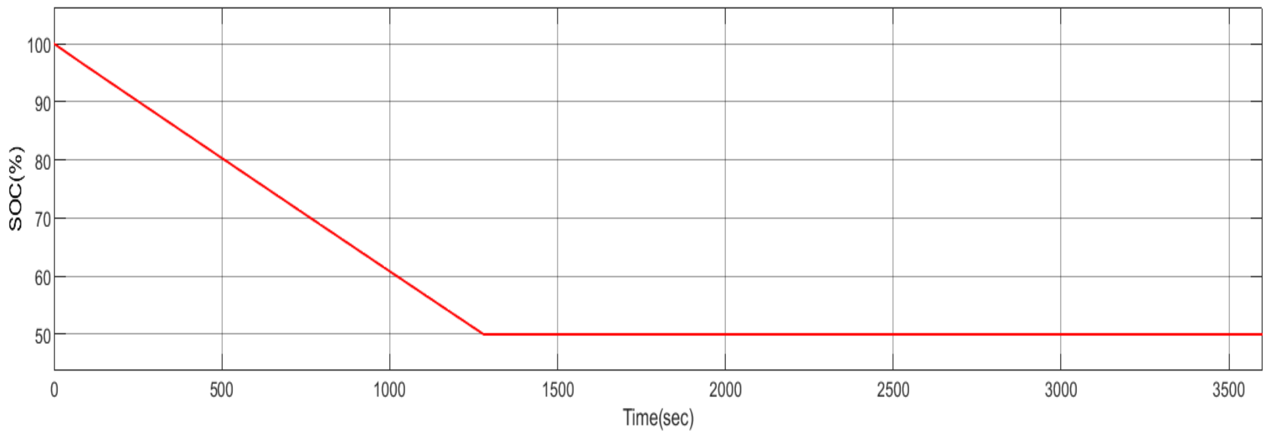

Fig. 4.22 SOC Estimation

4.3.2SOC estimation using PIO method:

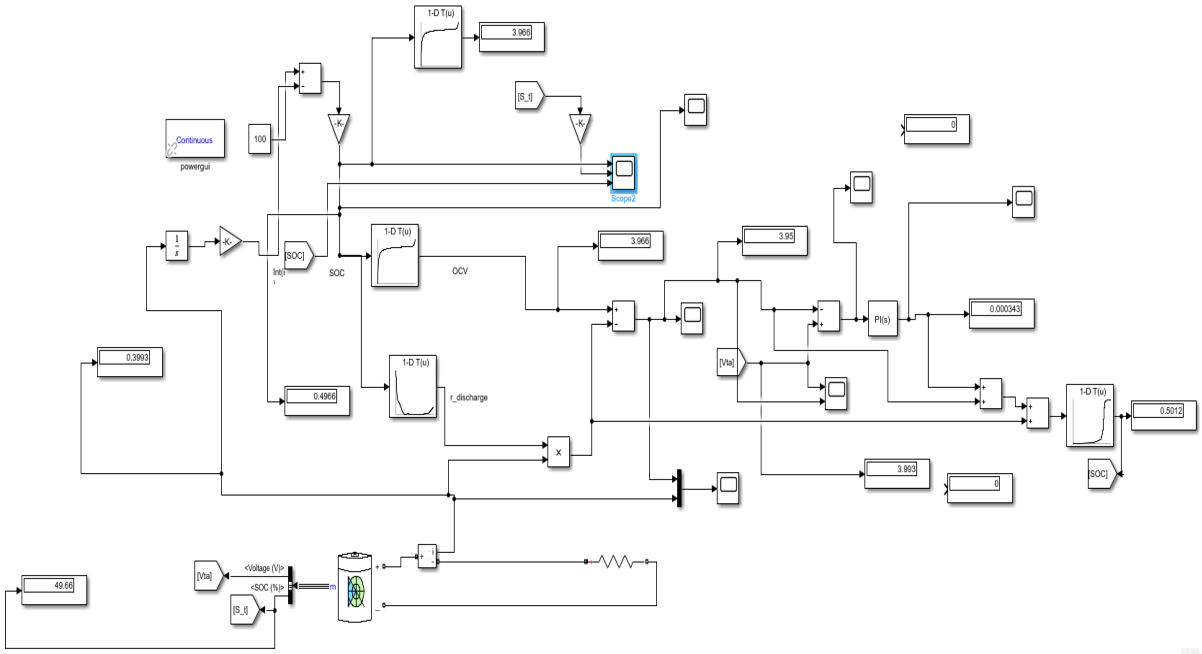

Fig. 4.23 MATLAB Simulink Model (PIO)

The block diagram of the PIO method is given below:

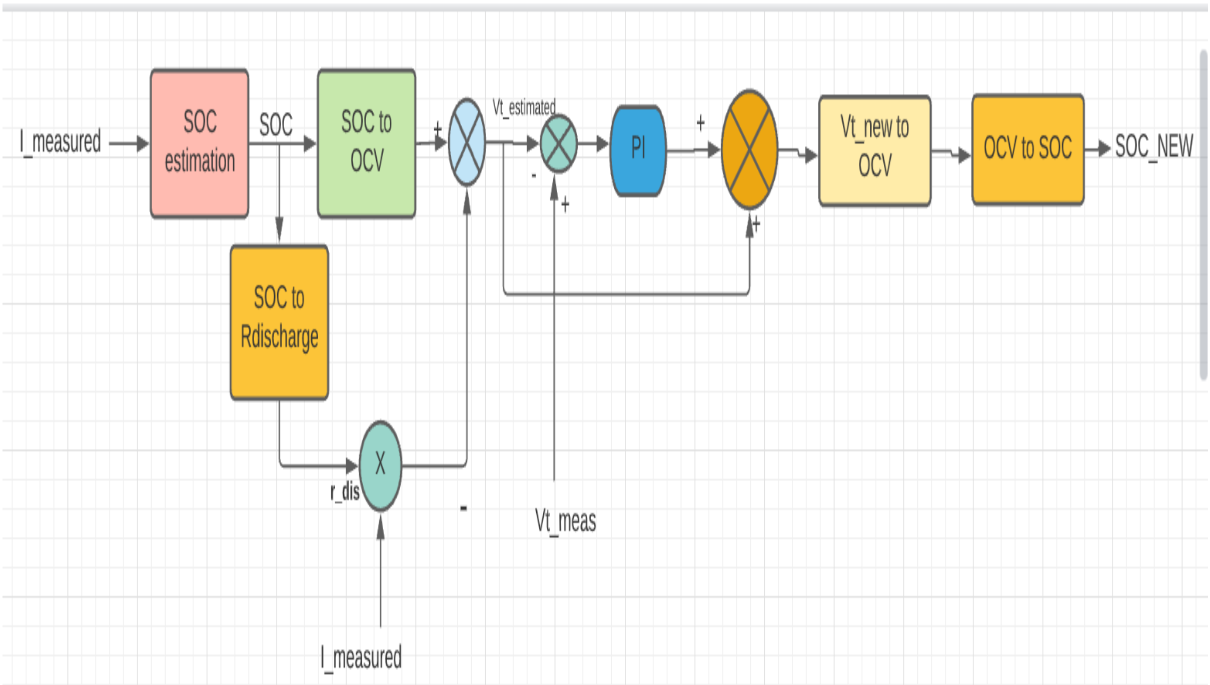

Fig. 4.24 Block Diagram of PIO based estimation of SOC

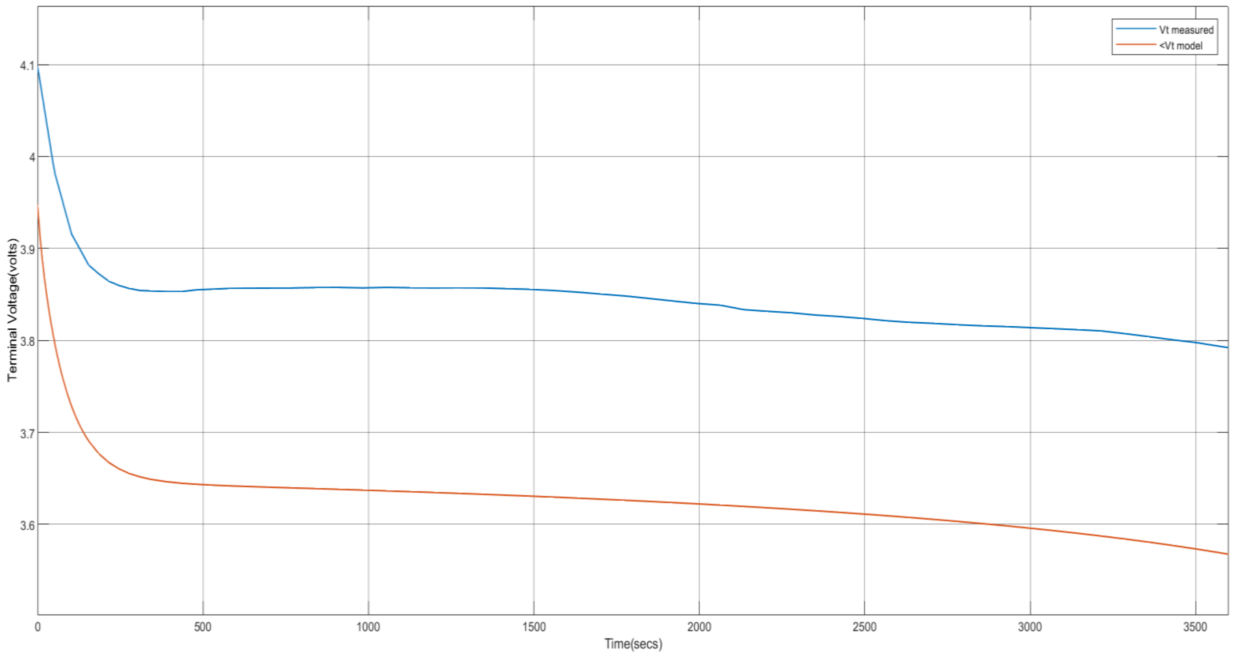

Fig. 4.25 Comparison of Terminal Voltages

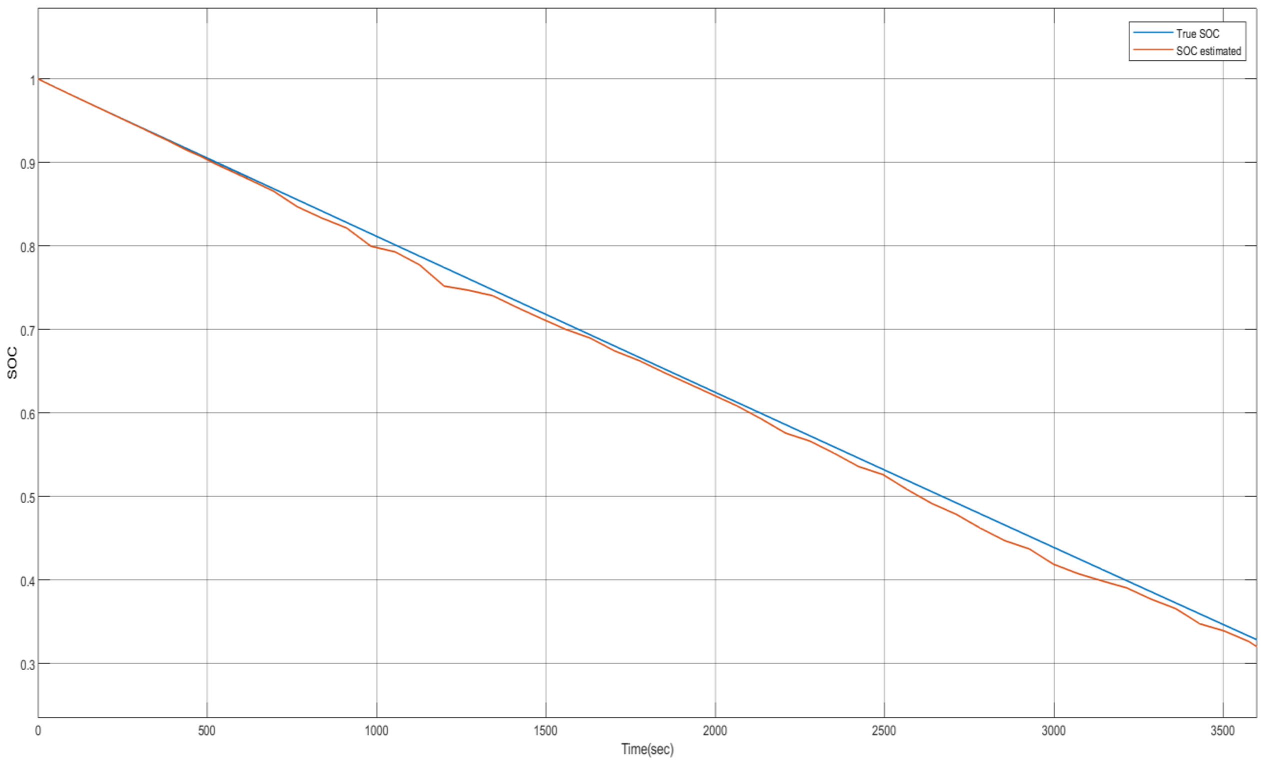

Fig. 4.26 Comparison of SOC

4.4 SOH Estimation:

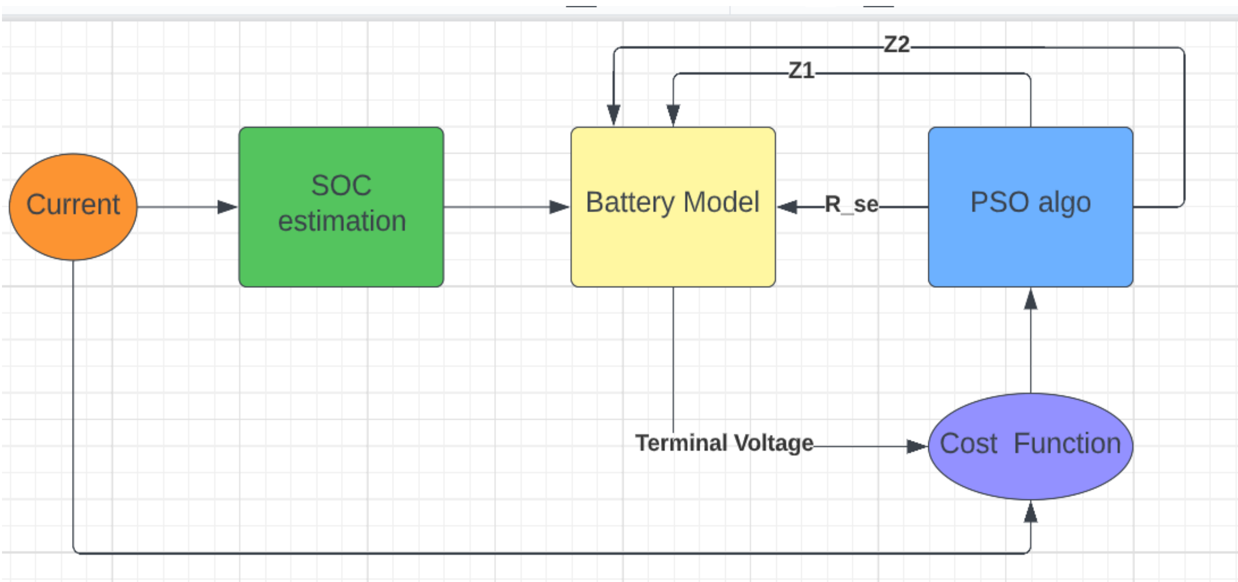

Fig. 4.27 Block diagram for SOH estimation using PSO algorithm

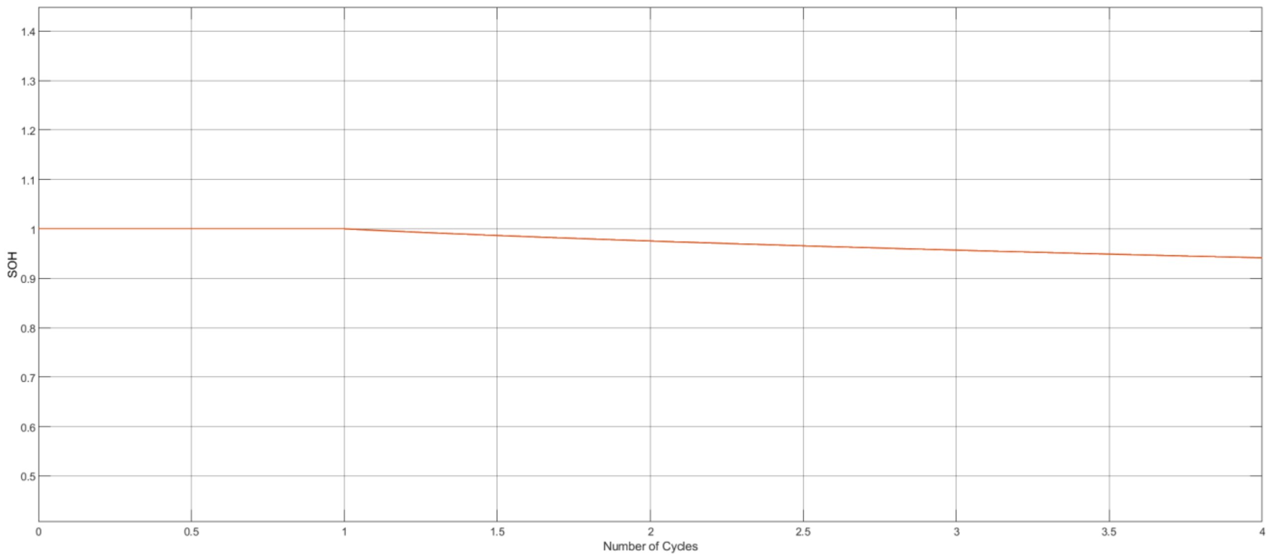

Fig. 4.28 SOH estimation Vs No. of cycles

Chapter 5: Conclusion

In this project the discussion started with the batteries, the battery parameters like SOC, DOD and Nominal Voltage etc are defined. Then some examples of rechargeable batteries like Li-ion batteries and their types are given. Brief Discussion on the modelling of the Li-ion battery was done. Later the battery is modelled using lookup table and Thevenin equivalent model of battery is modelled using empirical modelling.

From the above discussion the need of BMS has been established, and from there the report went on to define the basic of BMS for example functionality of the BMS and so on. Then discussion on methods of estimation of SOC, for example Coulomb Counting method took place, after that discussion about the disadvantages and advantages of the method along with other important methods such as PIO, KF and PSO based estimation, later on in the report discussion on the needs of balancing are briefly discussed active and passive biasing. Then SOH estimation using PSO algorithm is discussed.

Then in the report has been established our objectives has been established and that ends the chapter one. In chapter 2 these simulations are shown

1. Passive Balancing
2. Modelling of batteries for EVs using look up table
3. Modelling of batteries for EVs using empirical Model
4. SOC estimation using Coulomb Counting method
5. SOC estimation using PI observer
6. SOH estimation using PSO algorithm

At the end the MATLAB codes used for the simulation has been provided.

References

[1] Raszmann, E.; Baker, K.; Shi, Y.; Christensen, D. Modeling stationary lithium-ion batteries for optimization and predictive control. In Proceedings of the 2017 IEEE Power and Energy Conference at Illinois (PECI), Champaign, IL, USA, 23–24 February 2017.

[2] J. S. Lokhande, P. M. Daigavhane and M. Sarkar, "A Critical Approach Towards a Smarter Battery Management System for Electric Vehicle," 2020 4th International Conference on Trends in Electronics and Informatics (ICOEI)(48184), 2020, pp. 232-235, doi: 10.1109/ICOEI48184.2020.9142869.

[3] Linden D. and Reddy T.B., Handbook of Batteries, McGraw-Hill, 2001.

[4] D. N. T. How, M. A. Hannan, M. S. Hossain Lipu and P. J. Ker, "State of Charge Estimation for Lithium-Ion Batteries Using Model-Based and Data-Driven Methods: A Review," in IEEE Access, vol. 7, pp. 136116-136136, 2019, doi:10.1109/ACCESS.2019.2942213.

[5] M. S. H. Lipu, A. Hussain, M. H. M. Saad, A. Ayob and M. A. Hannan, "Improved recurrent NARX neural network model for state of charge estimation of lithium-ion battery using pso algorithm", *Proc. IEEE Symp. Comput. Appl. Ind. Electron. (ISCAIE)*, pp. 354-359, Apr. 2018.

[6] P. Shen, M. Ouyang, L. Lu, J. Li and X. Feng, "The co-estimation of state of charge state of health and state of function for lithium-ion batteries in electric vehicles", *IEEE Trans. Veh. Technol.*, vol. 67, no. 1, pp. 92-103, Jan. 2018.

[7]. Truchot, M. Dubarry and B. Y. Liaw, "State-of-charge estimation and uncertainty for lithium-ion battery strings", *Appl. Energy*, vol. 119, pp. 218-227, Apr. 2014.

[8.] K. S. Ng, C.-S. Moo, Y.-P. Chen and Y.-C. Hsieh, "Enhanced Coulomb counting method for estimating state-of-charge and state-of-health of lithium-ion batteries", *Appl. Energy*, vol. 86, no. 9, pp. 1506-1511, Sep. 2009.

[9] Y. Zheng, M. Ouyang, X. Han, L. Lu and J. Li, "Investigating the error sources of the online state of charge estimation methods for lithium-ion batteries in electric vehicles", *J. Power Sources*, vol. 377, pp. 161-188, Feb. 2018.

[10] M. Faisal, M. A. Hannan, P. J. Ker, A. Hussain, M. B. Mansor and F. Blaabjerg, "Review of energy storage system technologies in microgrid applications: Issues and challenges", *IEEE Access*, vol. 6, pp. 35143-35164, 2018.

[11] L. Gurjer, P. Chaudhary and H. K. Verma, "Detailed Modelling Procedure for Lithium-ion Battery Using Thevenin Equivalent," *2019 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT)*, 2019, pp. 1-6, doi: 10.1109/ICECCT.2019.8869224.

[12] B. Payyappilly and V. John, "Run-time simulation model for Li-ion battery using in-circuit extracted mass transport parameters," 2017 IEEE Transportation Electrification Conference (ITEC-India), 2017, pp. 1-6, doi: 10.1109/ITEC-India.2017.8333836.

[13] A. Manthopoulos and X. Wang, "A Review and Comparison of Lithium-Ion Battery SOC Estimation Methods for Electric Vehicles," IECON 2020 The 46th Annual Conference of the IEEE Industrial Electronics Society, 2020, pp. 2385-2392, doi: 10.1109/IECON43393.2020.9254918.

[14] J. Rivera-Barrera, N. Muñoz-Galeano, and H. Sarmiento-Maldonado, "SoC Estimation for Lithium-ion Batteries: Review and Future Challenges," *Electronics*, vol. 6, no. 4, p. 102, Nov. 2017.

[15] D. N. T. How, M. A. Hannan, M. S. Hossain Lipu and P. J. Ker, "State of Charge Estimation for Lithium-Ion Batteries Using Model-Based and Data-Driven Methods: A Review," in IEEE Access, vol. 7, pp. 136116-136136, 2019, doi: 10.1109/ACCESS.2019.2942213.

[16] R. Zhang, B. Xia, B. Li, L. Cao, Y. Lai, W. Zheng, H. Wang, and W. Wang, "State of the Art of Lithium-Ion Battery SOC Estimation for Electrical Vehicles," *Energies*, vol. 11, no. 7, p. 1820, Jul. 2018.

[17] H. Aung, K. Low and J. J. Soon, "State-of-charge estimation using particle swarm optimization with inverse barrier constraint in a nanosatellite," 2015 IEEE 10th Conference on Industrial Electronics and Applications (ICIEA), 2015, pp. 1-6, doi: 10.1109/ICIEA.2015.7334074.

[18] Z. B. Omariba, L. Zhang and D. Sun, "Review of Battery Cell Balancing Methodologies for Optimizing Battery Pack Performance in Electric Vehicles," in *IEEE Access*, vol. 7, pp. 129335-129352, 2019, doi: 10.1109/ACCESS.2019.2940090.

[19] D. Haifeng, W. Xuezhe and S. Zechang, "A new SOH prediction concept for the power lithium-ion battery used on HEVs," 2009 IEEE Vehicle Power and Propulsion Conference, 2009, pp. 1649-1653, doi: 10.1109/VPPC.2009.5289654.

[20] M. A. Rahman, S. Anwar, and A. Izadian, "Electrochemical model parameter identification of a lithium-ion battery using particle swarm optimization method," Journal of Power Sources, vol. 307, pp. 86–97, 2016.

[21] P. Liu, J. Wang, J. Hicks-Garner, E. Sherman, S. Soukiazian, M.W. Verbrugge, H. Tataria, J. Musser, P. Finamore, J. Electrochem. Soc. 157 (2010) A499.

[22] M. Kassem, J. Bernard, R. Revel, S. Pélissier, F. Duclaud, C. Delacourt, Calendar aging of a graphite/LiFePO4 cell,Journal of Power Sources, Volume 208, 2012, Pages 296-305,ISSN 0378-7753.

[23] Anthony Barré, Benjamin Deguilhem, Sébastien Grolleau, Mathias Gérard, Frédéric Suard, Delphine Riu, A review on lithium-ion battery ageing mechanisms and estimations for automotive

applications Journal of Power Sources,Volume 241,2013,Pages 680-689,ISSN 0378-7753.

[24] Z. Yu, L. Xiao, H. Li, X. Zhu and R. Huai, "Model Parameter Identification for Lithium Batteries Using the Coevolutionary Particle Swarm Optimization Method," in IEEE Transactions on Industrial Electronics, vol. 64, no. 7, pp. 5690-5700, July 2017, doi: 10.1109/TIE.2017.2677319.

[25] J. Li, Y. Wu and X. He, "Parameter Identification of Lithium Battery Model Based on Improved Fireworks Algorithm," *2021 40th Chinese Control Conference (CCC)*, 2021, pp. 1255-1260, doi: 10.23919/CCC52363.2021.9549571.

[26] M. Chen and G. A. Rincon-Mora, "Accurate electrical battery model capable of predicting runtime and I-V performance," in IEEE Transactions on Energy Conversion, vol. 21, no. 2, pp. 504-511, June 2006, doi: 10.1109/TEC.2006.874229.

[27] John Wang, Ping Liu, Jocelyn Hicks-Garner, Elena Sherman, Souren Soukiazian, Mark Verbrugge, Harshad Tataria, James Musser, Peter Finamore, Cycle-life model for graphite-LiFePO4 cells,Journal of Power Sources, Volume 196, Issue 8, 2011, Pages 3942-3948, ISSN 0378-7753,

[28] I. Bloom, B.W. Cole, J.J. Sohn, S.A. Jones, E.G. Polzin, V.S. Battaglia, G.L. Henriksen, C. Motloch, R. Richardson, T. Unkelhaeuser, D. Ingersoll, H.L. Case, J. Power Sources 101 (2001) 238.

Appendix

MATLAB codes:

*For Biasing Circuit

```
function [y1, y2,  y3] = fcn(s1, s2, s3)

 s1=int16(s1);
 s2=int16(s2);
 s3=int16(s3);



a=min([s1, s2 ,s3]);

if (s1 == a)
    if(s1 == a && s2==a)
        y1=0;
        y2=0;
        y3=0;
    elseif(s1 == a && s2==a)
        y1=0;
        y2=1;
        y3=0;
    elseif(s1 == a)
        y1=0;
        y2=1;
        y3=1;
    else
```

y1=0;

y2=0;

y3=0;

```
    end
elseif(s2 == a)
    if(s2 == a && s3 == a)
        y1=1;
        y2=0;
        y3=0;
    elseif(s2 ==a)
        y1=1;
        y2=0;
        y3=1;
         else
        y1=0;
        y2=0;
        y3=0;
    end
elseif(s3==a)
    y1=1;
    y2=1;
    y3=0;
     else
        y1=0;
        y2=0;
        y3=0;
end
end
```

MATLAB CODE:

For Battery modelling

```
clc
```

```
clear all
close all
data=xlsread('Battery_Parameters')
% Vr=OCV(SOC)-i*R(T,SOC)
%SOC=SOCo-(1/Cn)*integrate(i(t))dt
%% data reading

soc=data(:,1)
OCV=data(:,2)
r_charge=data(:,3)
r_discharge=data(:,4)

%% input data
i=2.3
Cn=(2.3*3600)
% sim_time=3600

%% simulate

sim('bat_mod')
%% plot
plot(soc,OCV)

figure

plot(soc,r_discharge)
```

MATLAB CODE:

PSO estimation of battery parameters

```
function out = fcn(Vt,I)


   %% problem defination
 CostFunction =@(x,I,Vt) Sphere(x,I,Vt); %cost function
nVar=4; %no of decision variables
Varsize=[1 nVar]; %matrix size of decsion variables
VarMin= 0; %lower bopund of decision Var
VarMax=4; %Upper bopund of decision Var




%% Parameters of PSO
MaxIt =100; % maximum no of iteration
nPop=50;  %Population size(swarm size)
w=0.8;  %inertia coffecient
c1=2; %personal acceleration coffecient
c2=2; %social acceleration coffecient



%% Intialisation
%particle template
empty_particle.Position=zeros([1 4]);
empty_particle.Velocity=zeros([1 4]);
empty_particle.Cost=zeros([1 1]);
empty_particle.Best.Position=zeros([1 4]);
empty_particle.Best.Cost=zeros([1 1]);

%to achieve 50 particles

particle=repmat(empty_particle, nPop ,1);
%initialise the global best
GlobalBest.Cost=inf;
GlobalBest.Position=zeros([1 4]);
%initialise population members
for i=1:nPop
   particle(i).Position(1,1)=unifrnd(VarMin, VarMax, 1);
   particle(i).Position(1,2)=unifrnd(0, 0.1, 1);
   particle(i).Position(1,3)=unifrnd(0, 1, 1);
   particle(i).Position(1,4)=unifrnd(0, 1, 1);
   particle(i).Velocity=zeros(Varsize); %intialise the velocity


particle(i).Cost= CostFunction( particle(i).Position,I,Vt); %evaluation
%particle(i).Cost= (Vm-Vt).^2
```

```
%update personal best
particle(i).Best.Position= particle(i).Position;
particle(i).Best.Cost= particle(i).Cost
%update global best
if particle(i).Best.Cost<GlobalBest.Cost
   GlobalBest.Cost=particle(i).Best.Cost;
end
end
%array to hold best cost value at each iteration
 BestCosts= zeros(MaxIt,1);

%% Main loop of PSO
for it=1:MaxIt
   for i=1:nPop
      particle(i).Velocity=w*particle(i).Velocity+c1*rand(Varsize).*(particle(i).Best.Position-
particle(i).Position)+c2*rand(Varsize).*(GlobalBest.Position-particle(i).Position);

      particle(i).Position=particle(i).Position+particle(i).Velocity;
      if (particle(i).Position(1,1) >=0) && (particle(i).Position(1,1) <=4 )
         particle(i).Position(1,1)=particle(i).Position(1,1)
      else
         particle(i).Position(1,1)=3.4
      end
      if (particle(i).Position(1,2) >0.0103) && (particle(i).Position(1,2) <0.025 )
         particle(i).Position(1,2)=particle(i).Position(1,2)
      else
         particle(i).Position(1,2)=0.0103
      end
      if (particle(i).Position(1,3) >0.001) && (particle(i).Position(1,3) <0.4)
         particle(i).Position(1,3)=particle(i).Position(1,3)
      else
         particle(i).Position(1,3)=0.001
      end
      if (particle(i).Position(1,4) >0.0003) && (particle(i).Position(1,4) <0.8)
         particle(i).Position(1,4)=particle(i).Position(1,4)
      else
         particle(i).Position(1,4)=0.0003
      end
     particle(i).Cost=CostFunction(particle(i).Position,I,Vt);
% particle(i).Cost=(Vm-Vt).^2
      if particle(i).Cost<particle(i).Best.Cost
         particle(i).Best.Position=particle(i).Position
         particle(i).Best.Cost=particle(i).Cost;

   %update global best
if particle(i).Best.Cost<GlobalBest.Cost
   GlobalBest.Cost=particle(i).Best.Cost;
%     if particle(i).Best.Position > 4
%         GlobalBest.Position=0
%     else if particle(i).Best.Position <= 4
   GlobalBest.Position=particle(i).Best.Position;
      end

end
      end
%     end
```

```
    BestCosts(it)=GlobalBest.Cost
%     disp(['Iteration' num2str(it) ': Best Cost= ' num2str(BestCosts(it))]);
out=GlobalBest.Position
end
%% Results
% figure;
% plot(BestCosts, 'LineWidth',2);
% xlabel('Iteration');
% ylabel('best Cost');


end
```