THESIS

BATTERY IDENTIFICATION, PREDICTION AND MODELLING

Submitted by

Syed Mahdi Azam

Department of Electrical and Computer Engineering

In partial fulfillment of the requirements

For the Degree of Master of Science

Colorado State University

Fort Collins, Colorado

Summer 2018

Master's Committee:

Advisor: Peter M Young

George Collins
Dan Zimmerle

ABSTRACT

BATTERY IDENTIFICATION, PREDICTION AND MODELLING

In this paper a process of modelling batteries for energy management systems has been discussed. With the increase demand of energy management modelling, it is crucial that modelling of the components in an energy management model be done properly, effectively, and with least amount of time. The process introduced in this paper requires only one discharge data to model a battery. The internal parameters identified focuses on the electrical behaviour rather than on electrochemical aspects of the battery. The battery model presented here helps to predict the discharge behaviour of the battery in multiple discharging scenarios. In this modelling process, Online Parameter Identification technique has been used to identify the parameters of the battery. The parameters of the battery identified in this paper to predict the discharge behaviour of a battery are internal resistance, polarization constant, nominal voltage and actual capacity of a battery. Shepherd's equation and MATLAB's optimization toolbox was used to identify the parameters

ACKNOWLEDGEMENTS

I am grateful to Dr. Young for his support, guidance and compassion. I would like to thank Dan Zimmerle for allowing me to be a part of his Small-Village Micro-grid project and helping me all the way. As a part of Dan's group I got to learn a lot about practical executions of the micro-grid. I would like to thank Jerry Duggan for being an awesome supervisor at the Powerhouse Energy Campus and providing me the resources to execute my experiments. Last but not the least I would like to thank Arthur, Avipreet Singh and Fathalla for their unconditional support.

DEDICATION

I would like to dedicate this thesis to my Parents, Dr.Young, Dan and Dr. Lamia Iftekhar.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1

Introduction

1.1 Problem Description

With the increase of micro-grid installations and use, the increase in modelling the components of a micro-grid from a control's point of view has become very vital [3]. A micro-grid should have a reliable and flexible control model which can replicate a real-time scenario [7]. Scenarios such as when to power up the back-up generators when there is a possible deficiency of energy from renewable or storage sources or when should a storage system supply the energy requirements. Batteries play a huge role in micro-grid models, hence it is very important to model a battery in a way which will allow the users to know the state of the battery [1]. The battery models should be able to adjust to different discharging and charging currents.

In addition to micro-grids, electric vehicles (EVs) and hybrid electric vehicles (HEVs) are also rapidly gaining popularity worldwide in decarbonizing the whole energy cycle, from energy supply to energy utilization. Due to their advantages, such as high energy density, high power density, low self-discharge rate, and no memory effect, Li-ion cells are now widely used in EV/HEV applications. To ensure safe and efficient operation, a proper battery model is essential in predicting battery behaviour under various operating conditions to avoid improper operations, such as overcharging, over-discharging and high temperature [11].

There has been numerous work done to model a battery, both electrochemically and electrically. Matlab's Simscape Power Systems for example have their own battery models where they have included electrochemical, electrical, ageing and temperature factors. However, because of it's detailed designing issues, it becomes cumbersome to simulate an energy model as it deals with transient responses in a detailed manner which from an energy management's point of view is not necessary. From an energy management or control's perspective, a detailed but fast approach of modelling a battery is needed. In this paper, a simple experimental method to model any battery has been introduced. This method uses Shepherd's Model [6] as a base, and requires minimal amount of experimented data to model a battery. To model a battery in this process will require:

- A battery's nominal capacity
- A single complete discharge data of the battery
- Starting voltages of different current discharges. These discharge currents should range from the minimum to the maximum current the battery will be used for discharging.

Once these requirements are met, the proposed methodology will be able to predict the discharge characteristics of a battery. Some of the techniques that were used before to model a battery required a number of discharge data; however, for this methodology a single complete discharge data would be sufficient. The starting voltages data that is required will not need a lot of time, as the batteries need not be fully discharged. To record the starting voltage of a battery, the battery needs to discharge for only 5-10 seconds. The battery model that has been generated here, has been verified with Lithium-ion batteries of different capacities and a Lead-acid battery.

1.2 Different Battery Modelling Strategies

Some of the most common battery modelling strategies are:

- Equivalent Circuit Models
  1. Linear Model
  2. RC Model
- Mathematical Models
  1. Shepherd's Model
  2. Unnewehr Universal Model
  3. Nernst Model

1.2.1 The Equivalent Circuit Models

The equivalent circuit models are structured based on the Thevenin Circuit Model. Thevenin model consists of a network of resistors and capacitors. The equivalent circuit models can predict the time-dependent effects of charge depletion and recovery. Charge depletion is an effect seen when one first begins to discharge a battery. Due to an initially high concentration of chemical products near the cathode and anode, the initial battery voltage drop is subdued and gradually decreases as chemical products are consumed. Charge recovery has the opposite effect, where the battery seems to recharge itself after discharging has stopped, due to chemical products diffusing from within the body of the battery to the anode and cathode. These behaviours can be seen when pulse discharging a battery. [5].

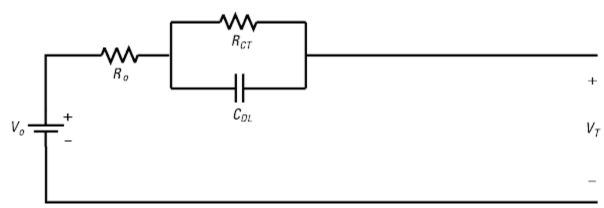

Figure 1.1: Basic Equivalent Circuit Model

Figure - 1.1, shows a typical representation of an equivalent circuit model. In equivalent circuit model the resistor R_{CT}, is considered as the charge transfer resistance and, the capacitor C_{DL} represents double layer capacitance. The arrangement shown in Figure - 1.1 is just a model, there are no real resistors or capacitors present inside a battery. The equivalent circuit model is a lumped circuit approximation of the internal resistance and capacitance of the battery. To achieve accuracy, the number of RC elements in the circuit may be introduced. The R and C parameters will certainly vary based upon temperature, state of charge and state of health of the battery. Because equivalent circuit models are only based on electronic components, it does not give an efficient approximation of the battery's internal parameters, hence mathematical modelling is chosen to serve the purpose of this paper. However, depending on the battery type either modelling methods could be used.

1.2.2 The Mathematical Models

Unlike equivalent circuit modelling approaches, mathematical models explicitly represent the internal parameters of the battery. These models describe the battery processes in great detail, making them the most accurate of battery models. In [9] the Unnewehr Universal Model:

$$y_k = E_o - Ri_k - \mu(SOC_k) \tag{1.1}$$

In Equation - 1.1,

- y_k is the model voltage
- k is a time index
- E_o is a DC gain
- R is the cell internal resistance
- i_k is the cell current
- μ is a constant for curve fitting

And the Nernst Model is given as:

$$y_k = E_o - Ri_k + \mu_1 ln(SOC_k) + \mu_2 ln(1 - SOC_k) \tag{1.2}$$

In Equation - 1.2,

- y_k is the model voltage
- k is a time index
- E_o is a DC gain
- R is the cell internal resistance

- i_k is the cell current
- μ_1 and μ_2 are constants for curve fitting

The two mathematical models presented in Equations 1.1 and 1.2 do not present a comprehensive account of the internal parameters of the battery. However, to use the Nernst and Unnewehr's models one needs to include the electrochemical properties to the equation, which will eventually lead to considerable computational complexities. Hence, in this paper, Shepherd's Model has been used where internal parameters and polarization constant has been taken into consideration. Just as Nernst and Unnewehr's models, Shepherd's model can also be modified to accommodate factors like temperature and ageing factor to provide more accurate predictions of the internal parameters of the battery. Because the intent of the paper is to model a battery with the least complex computation, the original form of the Shepherd's model has been chosen.

1.2.3 Shepherd's Model and it's Modification

In [6], the discharge model of a battery has been presented in the following form:

$$E(t) = E_s - K(\frac{Q}{Q - it})i - ri + Ae^{(-BQ^{-1}it)} \tag{1.3}$$

where,

$E(t)$ is the Terminal Voltage of the battery with respect to time in Volts

E_s is the Nominal Voltage of the Battery in Volts

K is the Polarization constant of the battery in ohms

Q is the Nominal Capacity of the battery in Amps-hour

i is the Discharged Current in Amps

t is the Time Elapsed after the discharge process has started in seconds

r is the Internal Resistance of the Battery in ohms

A and B are the Empirical Constants, which estimates the initial discharge drop.

In [6] Shepherd discharged the batteries at a constant current using a variable resistance control method. For the experiments here various constant discharge currents have been selected and the corresponding voltages have been recorded to examine discharge behaviours of different battery models. For the experiments i was controlled as constant, however in an active discharge :

$$i = i(t)$$

Therefore, the terms "it" in Equation - 1.3 become integrals that represent the total discharge from the battery. Hence, the discharged capacitance (Q_d) can be represented as:

$$Q_d(t) = \int_0^t i(\tau) d\tau \tag{1.4}$$

For the experiments in this paper, state of charge (SOC) has been calculated as:

$$SOC = \frac{Q - Q_d}{Q} = 1 - \frac{Q_d}{Q} \tag{1.5}$$

and so SOC can be represented as:

$$1 - SOC = \frac{Q_d}{Q} \tag{1.6}$$

And this enables Equation - 1.3 to be explained in terms of SOC:

$$E(t) = E_s - ri(t) - K(\frac{1}{SOC(t)})i(t) + Ae^{-B(1-SOC(t))} \tag{1.7}$$

In Equation - 1.7 there are few aspects which needs to be noticed:

- The sign of the current $i(t)$ is positive during discharge
- This is an explicit equation that maps current, including current integrated over time, to voltage. There is no dynamic component. The independent variable for the equation can be

expressed as either $i(t)$ or $SOC(t)$; which shows that:

$$i(t) = \frac{dQ_d}{dt}$$

and

$$\frac{dSOC}{dt} = \frac{\frac{-dQ_d}{dt}}{Q_d} = \frac{-i}{Q_d}$$

For the experiments voltages and currents readings were taken and then state of charge with respect to the voltages were calculated. The following equation was used in calculating the state of charge:

$$SOC = 1 - \frac{Q_d}{Q} \tag{1.8}$$

1.3 Battery Identification and Modelling Procedure

The steps followed to model a battery are as follows:

1. Discharged a fully charged battery with known nominal capacity and the known type of battery (Lithium-ion and Lead-Acid batteries, details of these batteries will be presented later) at a constant current. The discharge current was chosen based on the capacitance of the battery.

2. Discharged data (Current and Voltage values with respect to time) were extracted. These data were collected at an interval of 1 second.

3. With the discharge data State of Charge (SOC) of the battery was calculated using Equation - 1.8.

4. A discharge curve of Voltage against SOC of the battery was plotted

5. Matlab's Optimization Toolbox was used to generate a best fit graph using Equation - 1.7

(details of fitting routine to be presented later). The best fit model gave out the battery parameters such as:

- Internal resistance, r
- Polarisation Constant, K
- Nominal Voltage, E_s
- Empirical Constants, A and B

6. Formed a table of starting voltages from different discharging currents of the battery (details of the constant discharging currents to be presented later)

7. Then Equation - 1.7 and the starting voltage table was used to predict a discharge curve at current x

To validate the predicted discharge, the battery was then discharged at x current and then compared with the prediction. For comparison, a relative root-mean square calculation was done between the original and predicted data. In this paper, experiments were done with three Lithium-ion batteries of different capacities and a Lead-Acid battery.

1.3.1 The Physical Components for Battery Discharge and Data Collection

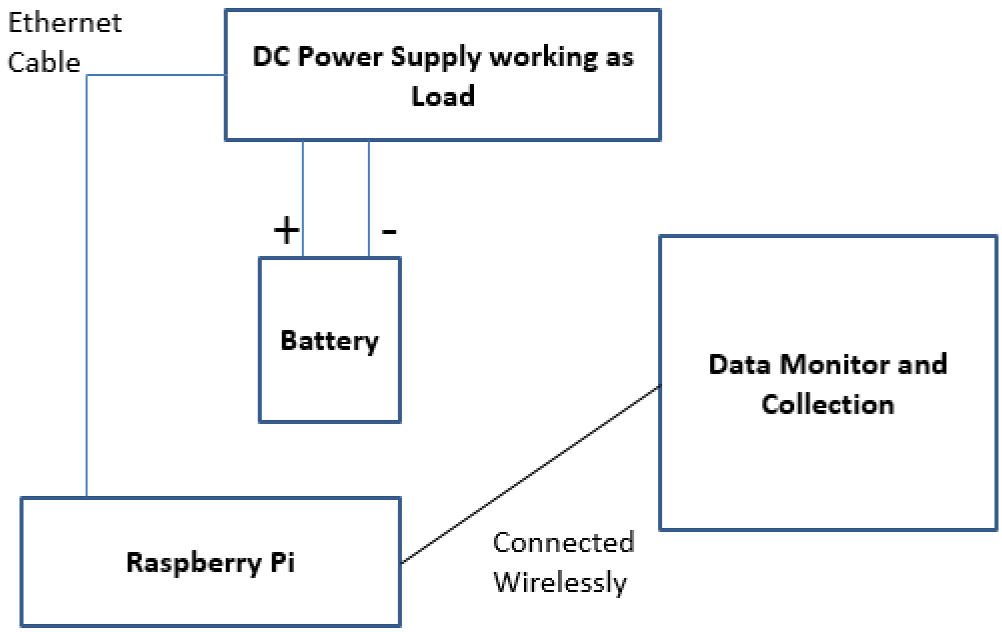

Figure 1.2: The Discharging Block Diagram

Figure-1.2 shows the block diagram of the discharging process. The entire data collection was done with the help of the following components:

- Lithium-ion batteries of different nominal capacities

Figure 1.3: 400mAh Battery with Nominal Voltage 3.7 V

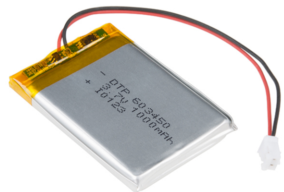

Figure 1.4: 1000 mAh Lithium-ion Battery with Nominal Voltage 3.7 V

Figure 1.5: 6000 mAh Lithium-ion Battery with Nominal Voltage 3.7 V

- Lead Acid Battery

Figure 1.6: Lead Acid Battery with Nominal Voltage 12 V

- DC Power Supply

Figure 1.7: DC Power Supply from Keysight Technologies

The DC Power Supply used here acts as a load and is also capable of charging the batteries. The charging and discharging parameters are programmable, either through the web interface or by the Raspberry Pi. The highest voltage used to charge the batteries was 12 V, and the maximum discharging current was 10 A. However, the N7973A Model (this model was used in all the experiments in this paper) has the ability to charge up to 60 V, and can have a maximum discharging current of 33 A. While operating the DC Power Supply, certain attention needs to be given to the Voltage and Current Settings. These settings may not match the measured output voltage or current. For example, in constant voltage operation, the output current setting (limit) may be set to 1 A, but the actual (measured) output current must be less than 1 A for the output to remain in constant voltage mode. If the Current limit is reached, the output will no longer be operating in constant voltage mode, but will be in current limit mode. In this case, the actual output voltage will now be less than the output voltage setting [4].

- Babysitter

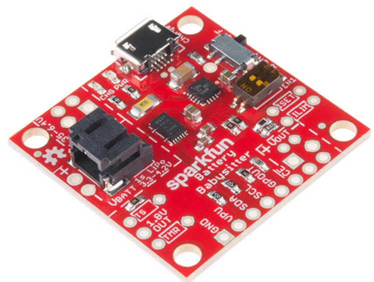

Figure 1.8: The babysitter

The batteries before getting discharged were fully charged. The Li-ion batteries while getting charged were connected to the babysitter. The babysitter controlled the charging, it stopped charging once the battery reached 100% SOC. The charger supports adjustable charge rates of up to 1.5A, as well as USB-compliant 100mA and 500mA options. It is also connected to a current-sensing resistor, which allows it to measure current and power.

- A Raspberry Pi was used to acquire discharging data. Raspberry Pi used here like any other micro-controller was contained on a single circuit board with featured ports for Ethernet Cable, HDMI, Analog Audio, USB 2.0, Power and SD Card.

A similar method was followed while accumulating the starting voltages. For the starting voltages, the batteries were not discharged fully, they were discharged for the first 10 seconds. The discharging currents ranged from 0.01 C to 1 C depending on the capacity of the battery. If the battery is discharged with higher C rates, there is a higher chance of introducing unwanted noises and also degrade the battery faster. In this paper prediction results without the starting voltages were shown and then starting voltages were included in Equation - 1.7 to improve the predictions. Knowing the starting voltages in the prediction process improves the prediction, and thus establishes the actual effectiveness of the battery modelling process presented in this paper.

1.3.2 Battery Discharging Rates

The battery's capacity is usually denoted by C. C is the amount of charge obtained from the battery; the unit is Ah or mAh. In fact, C has another layer of meaning that is used to describe the relationship of capacity of battery and the discharge capacity. For example, for a 5Ah battery, 1C means 5A continuous current discharge capacity and 10C means 50A, 30C means 150A, and so on. Therefore, in the battery specifications C also denotes the maximum output current that battery can withstand [2].

For analysis, different discharging currents were used on the batteries.

- Discharging currents of 0.2 A, 0.3 A and 0.4 A were used for the 400mAh lithium-ion battery
- Discharging currents of 0.5 A, 0.75 A and 1 A were used for the 1000mAh lithium-ion battery
- Discharging currents of 0.9 A, 1.2 A and 1.5 A were used for the 6000mAh lithium-ion battery
- Discharging currents of 5.0 A, 7.5 A and 10.0 A were used for the Lead Acid battery

For proper validation of the experiments three sets of each of the discharges were collected and the identification process were performed on all the sets.

1.3.3 Identification and Prediction via Matlab's Optimization Toolbox

The discharge data were converted to a .mat file format and then MATLAB's lsqcurvefit function was used to identify the unknown parameters: r, K, A, B and E_s. The parameters found and the starting voltages were used to predict the discharge behaviour of some other X Amp discharge current. The predicted curve was then compared to experimented X Amp discharge curve to verify the strength of the model using relative root-mean square method. The process described above is called Online Parameter Identification method.

Online Parameter Identification using Recursive Least Square Method

As defined in [10] while using the Online Parameter Identification method the model parameters are determined from the observation of voltages and currents of the battery discharge. First the discharge data (voltages and currents) were collected and then the voltage curve from the data was used to generate a best fit model with respect to Equation - 1.7 using Recursive Least Square Method. In a recursive least square fit routine, the discharge data can be presented as a function of time [10]. After doing the best fit, an approximation of the unknown parameters of the battery such as r,K,A,B and Es is known. Using these parameters in Equation - 1.7, predictions on different current discharges can be made. The magnitude of the error between the predicted voltage and measured voltage is a measure of the quality of the predicted model. It is desirable to find a set of parameters that minimizes the value of the error between the predicted and measured values of the system states for all points in time. Which also signifies the fact that the recursive least square method during the curve fitting will give values that best fit the model, and will not in general, provide values that represent battery's internal parameters. In MATLAB's lsqcurvefit function there is a provision for constrained optimization and it has been used for the experiments here, so that reasonable values can be obtained for the battery's internal parameters.

The Non-linear least-squares solver generally finds the coefficient x that solves the equation:

$$min_x \|F(x, xdata) - ydata\|_2^2 = min_x \sum_i (F(x, xdata_i) - ydata_i)^2 \tag{1.9}$$

in which $xdata$ is the input, and the observed output is $ydata$; $xdata$ and $ydata$ can be either matrices or vectors. To perform constrained optimization the components of x can have lower and upper bounds denoted by lb and ub.

For this experiment equation (1.9) has been changed to:

$$min_x \|F(x, E) - V\|_2^2 = min_x \sum_i (F(x, E_i) - V_i)^2 \tag{1.10}$$

Here in Equation - 1.10,

x represents the unknown parameters, r, K, A, B and E_s

E represents the predicted terminal voltage

V represents the actual terminal voltage

F represents the function of the parameters x and E

Error Calculation Using RMSE

The error between the Predicted Discharge Voltages (V_i) and the Experimental Discharge Voltages (E_i) were calculated using relative Root Mean Square Error (RMSE) method, and then those RMSE values were presented as percentages. The relative Root Mean Square Error method uses the following formulation to calculate the error between two data sets, in this case between V_i and E_i, where V_i is the observed voltage and E_i is the predicted voltage:

$$RMSE = \frac{\sqrt[2]{\frac{\sum_i^N (V(i)-E(i))^2}{V}}}{N} * 100 \tag{1.11}$$

In Equation - 1.11, N represents the time in seconds for the battery to get completely discharged. For example, if a battery took 2000 seconds to discharge, the value of N will be 2000. V_i is the observed voltage and E_i is the predicted voltage at i second. After the RMSE value is known, it is then converted to percentage, so that the error observations can be made more clearer. For the experiments carried out here, the minimum number of data points that has been observed over a single discharge is 3038 data points and the maximum was 21,052 data points.

Chapter 2

The Results of Identification and Prediction Process

2.1 The Identification Process using constrained optimization

In this section, results of the identification process of the battery models are presented. The identification process was based on the Shepherd's model and Online Parameter Identification Method. Constrained optimization was used to select parameters so as to minimize error between the predicted model and experimental data.

2.1.1 The 400 mAh Lithium-Ion Battery Parameters Identification

The battery was discharged at three different currents of 0.2 A, 0.3 A and 0.4 A. And then for each of the discharges, a best fit was done to obtain the unknown parameters of the battery under constrained optimization. The unknown parameters were constrained as follows:

- r = [0.0001,1]
- K = [0.0001,1]
- A = [0.1,20]
- B = [0.1,20]
- E_s = [3.50,3.80]

The parameters have been constrained based on the battery manufacturer's data-sheet. However, the parameters do change with varying currents. An example of parameter changing is the varying internal resistance (r) of a battery; with high current discharges the internal resistance decreases and with lower current discharge the internal resistance increases. The rate at which the internal resistance changes depends upon the manufacturing of the battery.

The empirical constants on [6] will also change based on the discharging current. And these empirical constants are presented at the first place to give a mathematical explanation to the initial drop of voltage once the discharging starts.

The following values for the parameters were obtained from the 0.2 A discharge:

- r = 0.5482
- K = 0.2935
- A = 0.3589
- B = 5.7455
- E_s = 3.8000

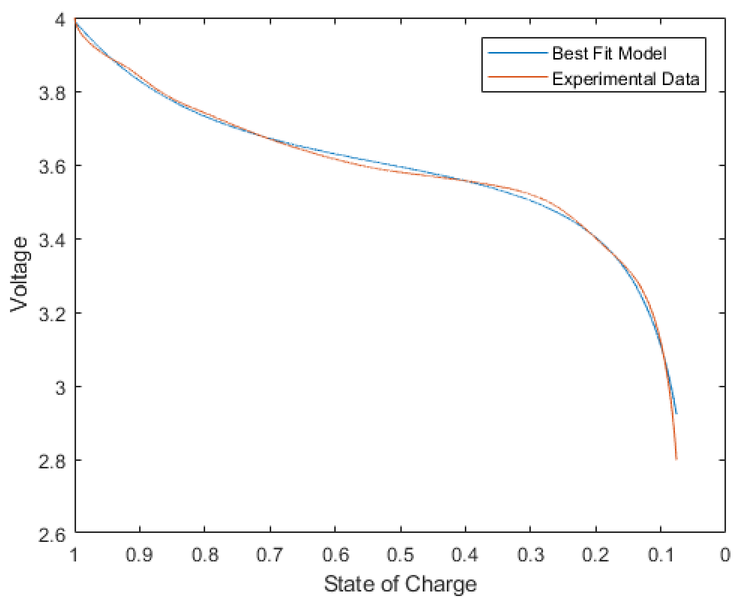

Figure 2.1: Identification of 400mAh Lithium-ion battery at 0.2 A discharge - Data Set 1

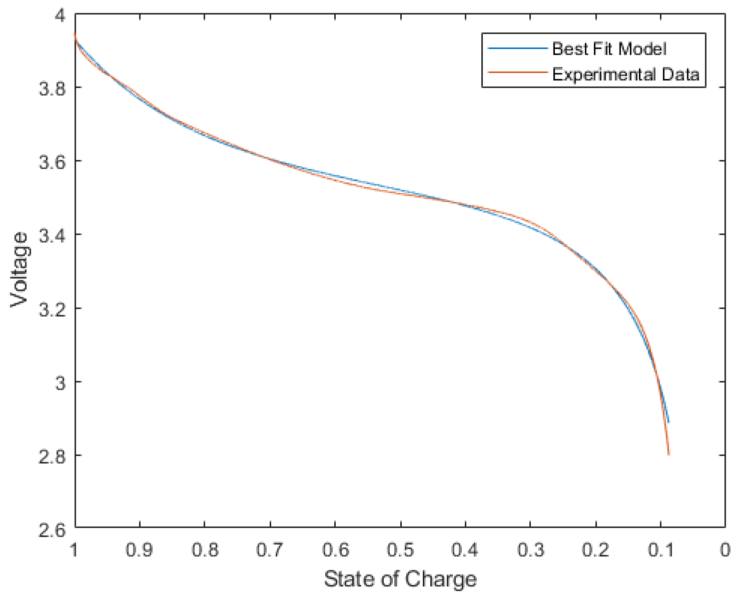

Figure 2.2: Identification of 400mAh Lithium-ion battery at 0.3 A discharge - Data Set 1

The following values for the parameters were obtained from the 0.3 A discharge:

- r = 0.5862
- K = 0.2162
- A = 0.3691
- B = 5.4740
- E_s = 3.8000

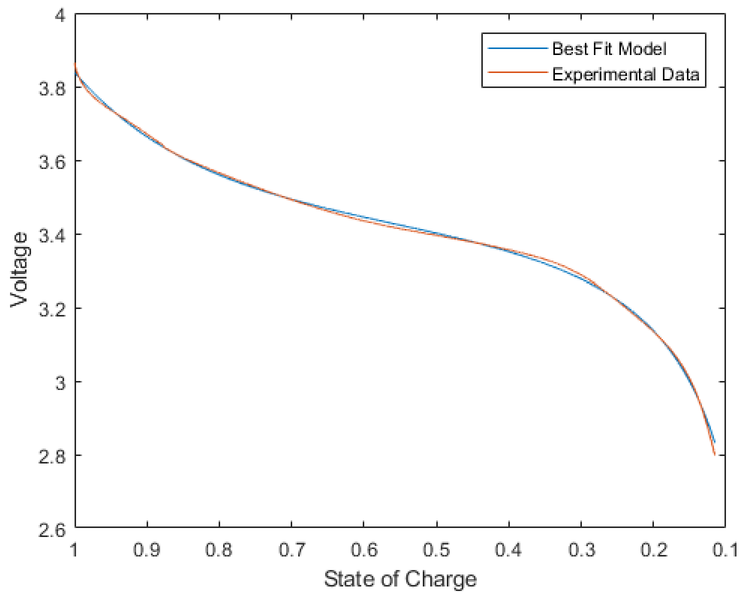

Figure 2.3: Identification of 400mAh Lithium-ion battery at 0.4 A discharge - Data Set 1

The following values for the parameters were obtained from the 0.4 A discharge:

- r = 0.1000
- K = 0.2067
- A = 0.3752
- B = 5.8172
- E_s = 3.5459

Similar discharges were done for Data Set 2 and 3, and the following parameters were obtained:

Table 2.1: Data Set-1 Parameters

Parameters	**0.2 A**	**0.3 A**	**0.4 A**
r	0.5482	0.5862	0.1
K	0.2935	0.2162	0.2067
A	0.3589	0.3691	0.3752
B	5.7455	5.474	5.8172
Es	3.8	3.8	3.5459

Table 2.2: Data Set-2 Parameters

Parameters	**0.2 A**	**0.3 A**	**0.4 A**
r	0.5741	0.5741	0.1
K	0.3061	0.2191	0.1996
A	0.3762	0.3783	0.3222
B	5.4463	5.4461	5.8027
Es	3.8	3.8	3.6098

Table 2.3: Data Set-3 Parameters

Parameters	**0.2 A**	**0.3 A**	**0.4 A**
r	0.5748	0.5761	0.1
K	0.3742	0.2198	0.1816
A	0.3762	0.3793	0.3356
B	5.4461	5.5461	5.9072
Es	3.8	3.8	3.6102

Looking at Table 2.1,2.2 and 2.3 it can be seen that the best-fit provided different parameter values for the 400 mAh battery which shows that with different discharge currents the internal parameters of a battery changes. In addition to that it can also be seen that with 0.4 A discharge the nominal voltage differs and gives a nominal voltage below the manufacturing voltage. One reason behind that is the discharge rate is 1C which is higher than the other discharging rates. Which shows with a higher discharging current the initial voltage drops faster than expected, which results in a lower nominal voltage, and different parameter values.

The internal resistance of the battery also shows a large variation from 0.2 A and 0.3 A discharge to 0.4 A discharge. With a 1 C discharge, the internal resistance decreases drastically. However, it is also interesting to see that the internal resistance of the battery did not change a large amount between the discharge of 0.2 A and 0.3 A.

The slight discrepancies in the parameter identification process has low impact on the prediction, as it will be shown in the next section. On a different note the parameter values obtained from using Online Parametrization cannot be assumed as the real parameter values, as it is the product of a mathematical optimization routine based on the equation (2.1).

$$E(t) = E_s - ri(t) - K(\frac{1}{SOC(t)})i(t) + Ae^{-B(1-SOC(t))} \tag{2.1}$$

Also, looking at the Figures 2.1,2.5 and 2.6, the nominal voltages based on the definition presented in [8] are 3.62 V, 3.58 V and 3.42 V respectively, which are different from what Matlab's bestfit routine presented.

2.1.2 The 1000 mAh Lithium-Ion Battery Parameters Identification

The 1000 mAh battery was discharged at three different currents of 0.5 A, 0.75 A and 1.0 A. And then for each of the discharges, a best fit was done to obtain the unknown parameters of the battery under constrained optimization. The unknown parameters were constrained as follows:

- r = [0.0001,2]

- K = [0.0001,1]

- A = [0.1,20]

- B = [0.1,20]

- E_s = [3.50,3.80]

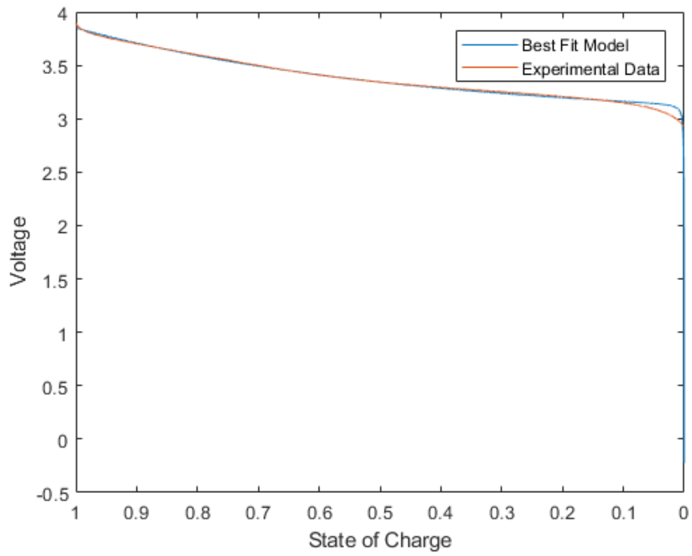

Figure 2.4: Identification of 1000mAh Lithium-ion battery at 0.5 A discharge - Data Set 1

The following values for the parameters were obtained from the 0.5 A discharge:

- r = 1.1370

- K = 0.0010

- A = 0.8284

- B = 2.0195

- E_s = 3.6049

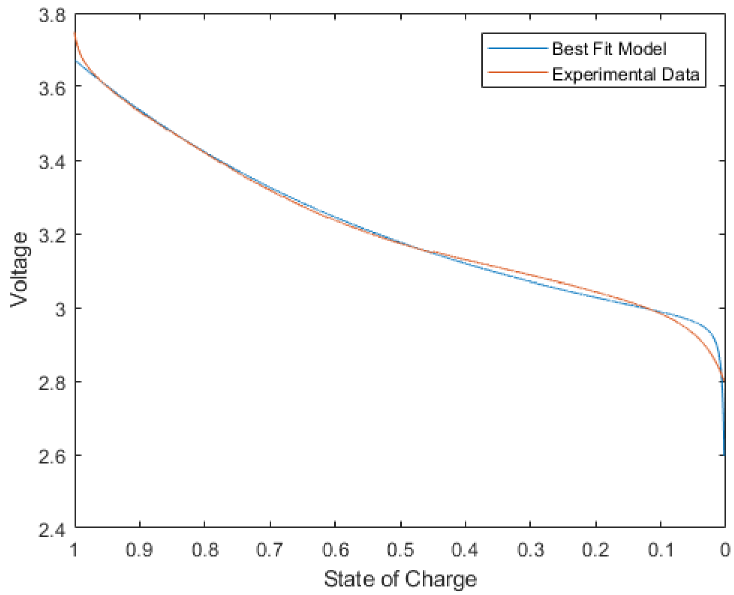

Figure 2.5: Identification of 1000mAh Lithium-ion battery at 0.75 A discharge - Data Set 1

The following values for the parameters were obtained from the 0.75 A discharge:

- r = 1.3075
- K = 0.0015
- A = 0.8537
- B = 1.7354
- E_s = 3.8000

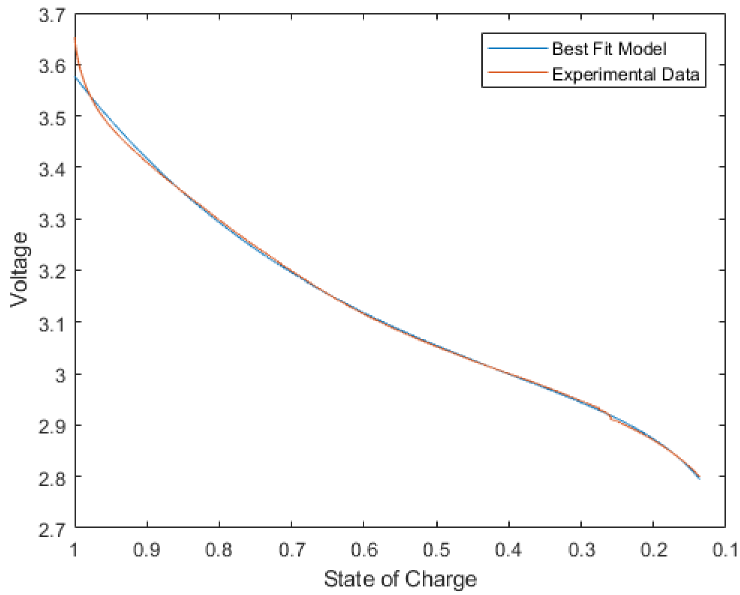

Figure 2.6: Identification of 1000mAh Lithium-ion battery at 1.0 A discharge - Data Set 1

The following values for the parameters were obtained from the 1.0 A discharge:

- r = 0.5667
- K = 0.0281
- A = 0.6718
- B = 2.6639
- E_s = 3.5000

Similar discharges were done for Data Set 2 and 3, and the following parameters were obtained:

Table 2.4: Parameters from Data Set-1

Parameters	**0.5 A**	**0.75 A**	**1.0 A**
r	1.137	1.3075	0.5667
K	0.001	0.0015	0.0281
A	0.8284	0.8537	0.6718
B	2.0195	1.7354	2.6639
Es	3.6049	3.8	3.5

Table 2.5: Parameters from Data Set-2

Parameters	**0.5 A**	**0.75 A**	**1.0 A**
r	1.018	0.8688	0.751
K	0.001	0.0065	0.0055
A	0.8358	0.8198	0.7521
B	1.7535	2.3077	1.8909
Es	3.5	3.5	3.5

Table 2.6: Parameters from Data Set-3

Parameters	**0.5 A**	**0.75 A**	**1.0 A**
r	1.134	0.9688	0.8512
K	0.002	0.0165	0.006
A	0.9289	0.8298	0.8521
B	1.7942	2.4187	1.8909
Es	3.5	3.5	3.5

Similar to the 400 mAh battery, the 1000 mAh battery's parameters differed for the three discharging currents. The highest difference was observed between the currents of 0.5 A and 1.0 A. And in 2.4 and 2.6, the difference between the starting voltages also indicates there would be differences in parameter identification. Another significant change was noticed in the internal resistance, and how it decreases with increase in discharge current. A similar pattern of internal resistance decreasing with increased current was also observed with the 400 mAh battery.

2.1.3 The 6000 mAh Lithium-Ion Battery Parameters Identification

The 6000 mAh battery was discharged at three different currents of 0.9 A, 1.20 A and 1.50 A. The unknown parameters for the best-fit were constrained as follows:

- r = [0.0001,1]
- K = [0.0001,1]
- A = [0.1,20]
- B = [0.1,20]
- E_s = [3.50,3.80]

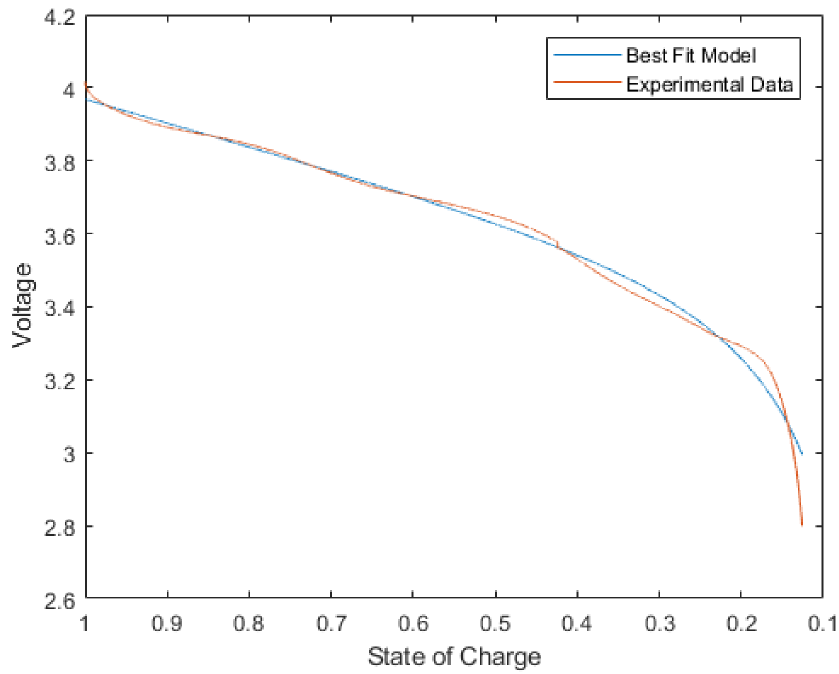

Figure 2.7: Identification of 6000mAh Lithium-ion battery at 0.9 A discharge - Data Set 1

The following values for the parameters were obtained from the 0.9 A discharge:

- r = 0.9988
- K = 0.0871
- A = 1.4464
- B = 0.4018
- E_s = 3.5000

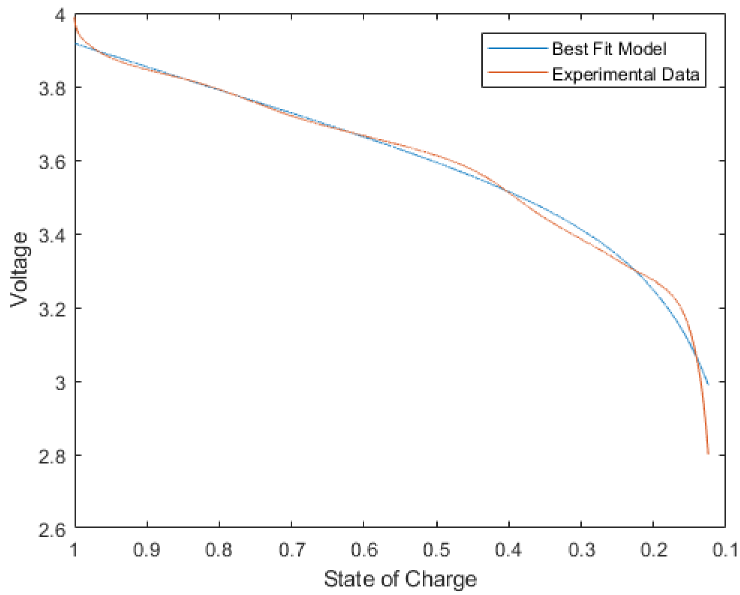

Figure 2.8: Identification of 6000mAh Lithium-ion battery at 1.20 A discharge - Data Set 1

The following values for the parameters were obtained from the 1.20 A discharge:

- r = 0.4142
- K = 0.0636
- A = 0.9904
- B = 0.5756
- E_s = 3.5000

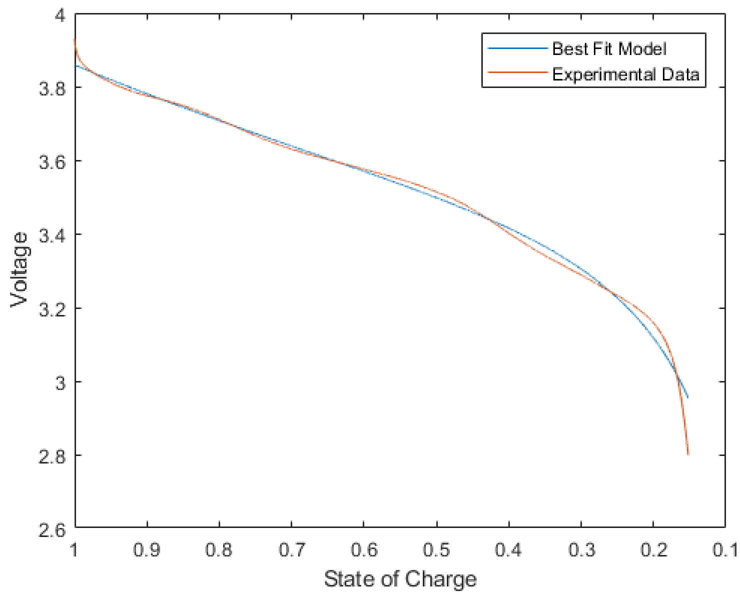

Figure 2.9: Identification of 6000mAh Lithium-ion battery at 1.50 A discharge - Data Set 1

The following values for the parameters were obtained from the 1.50 A discharge:

- r = 0.2640
- K = 0.0639
- A = 0.5505
- B = 1.3173
- E_s = 3.8000

Similar discharges were done for Data Set 2 and 3, and the following parameter tables were generated:

Table 2.7: Parameter Table for Data Set-1

Parameters	**0.9 A**	**1.2 A**	**1.5 A**
r	0.9988	0.4142	0.264
K	0.0871	0.0636	0.0639
A	1.4464	0.9904	0.5505
B	0.4018	0.5756	1.3173
Es	3.5	3.5	3.8

Table 2.8: Parameter Table for Data Set-2

Parameters	**0.9 A**	**1.2 A**	**1.5 A**
r	0.9999	0.4248	0.2989
K	0.083	0.0614	0.0469
A	1.4507	1.7164	1.9686
B	0.393	0.3709	0.2811
Es	3.5	3.5	3.5

Table 2.9: Parameter Table for Data Set-3

Parameters	**0.9 A**	**1.2 A**	**1.5 A**
r	0.9999	0.4172	0.2842
K	0.083	0.0636	0.0639
A	1.4507	0.9904	0.5505
B	0.393	0.5756	1.3173
Es	3.5	3.5	3.8

2.1.4 The Lead-Acid Battery Parameters Identification

The Lead-Acid battery was discharged at three different currents of 5.0 A, 7.50 A and 10.0 A. The unknown parameters for the best-fit were constrained as follows:

- r = [0.0001,0.1]
- K = [0.00001,1]
- A = [0.001,20]
- B = [1,20]
- E_s = 11.0,12.4]

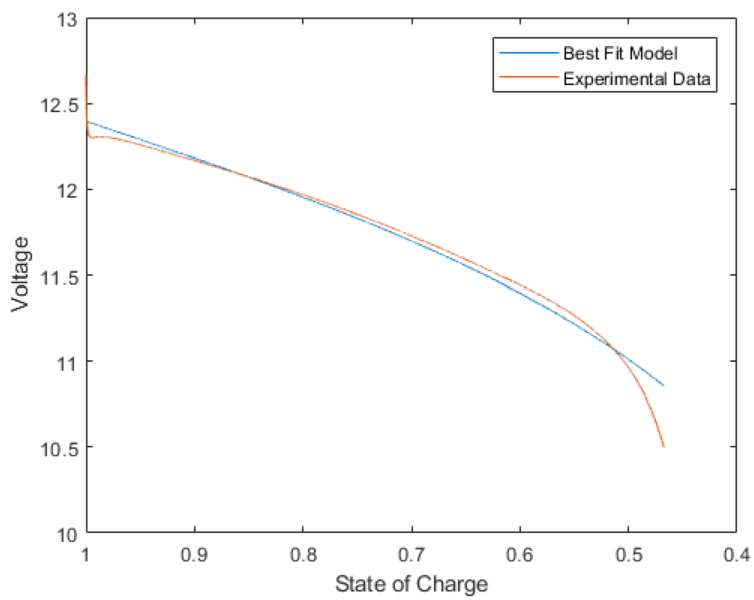

Figure 2.10: Identification of Lead battery at 5.0 A discharge - Data Set 1

The following values for the parameters were obtained from the 5.0 A discharge:

- r = 0.0992

- K = 0.0001
- A = 1.8505
- B = 1.2198
- E_s = 11.1982

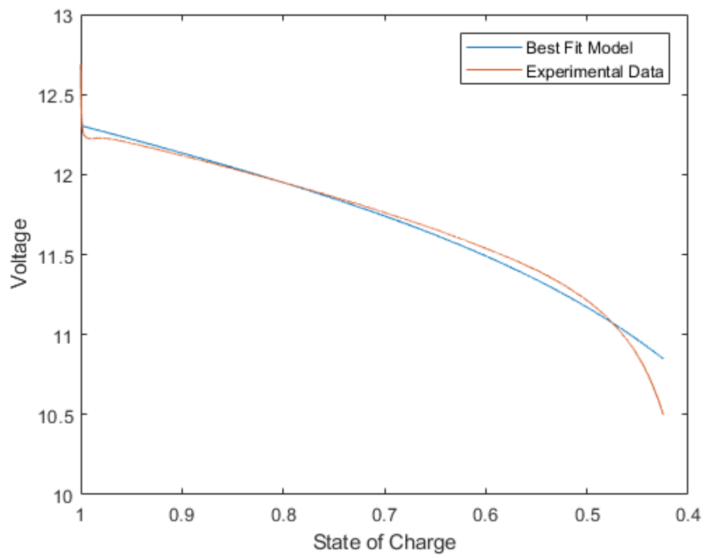

Figure 2.11: Identification of Lead battery at 7.5 A discharge - Data Set 1

The following values for the parameters were obtained from the 7.5 A discharge:

- r = 0.0999
- K = 0.0001
- A = 1.5792
- B = 1.2389
- E_s = 11.6239

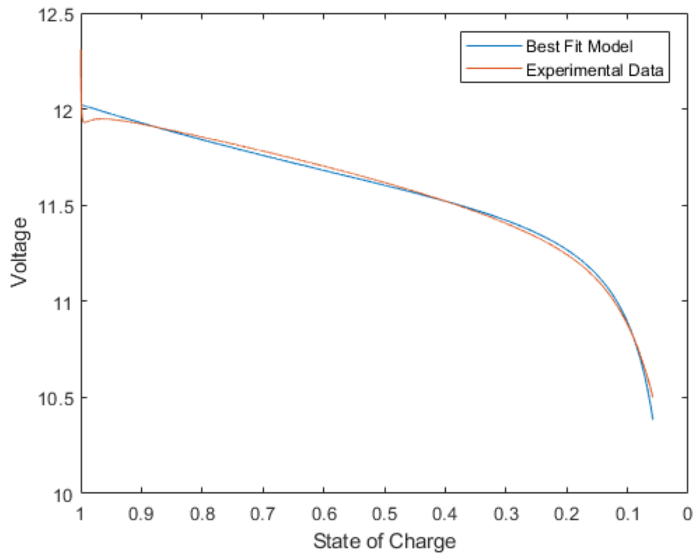

Figure 2.12: Identification of Lead battery at 10.0 A discharge - Data Set 1

The following values for the parameters were obtained from the 10.0 A discharge:

- r = 0.0675
- K = 0.0069
- A = 0.7779
- B = 1.2421
- E_s = 11.9896

Similar discharges were done for Data Set 2 and 3, and the following parameter tables were generated:

Table 2.10: Lead-Acid Battery Parameter Table for Data Set-1

Parameters	**5.0 A**	**7.5 A**	**10.0 A**
r	0.0992	0.0999	0.0675
K	0.0001	0.0001	0.0069
A	1.8505	1.5792	0.7779
B	1.2198	1.2389	1.2421
Es	11.1982	11.6239	11.9896

Table 2.11: Lead-Acid Battery Parameter Table for Data Set-2

Parameters	**5.0 A**	**7.5 A**	**10.0 A**
r	0.0872	0.0989	0.0698
K	0.0001	0.0001	0.0084
A	1.9516	1.8724	0.8873
B	1.2254	1.2411	1.2409
Es	11.4376	11.7682	11.9

Table 2.12: Lead-Acid Battery Parameter Table for Data Set-3

Parameters	**5.0 A**	**7.5 A**	**10.0 A**
r	0.0972	0.0899	0.0798
K	0.0001	0.0001	0.0064
A	1.9852	1.9727	0.8469
B	1.2132	1.2339	1.24
Es	11.4761	11.7688	11.8962

From Tables 2.10,2.11 and 2.12, it can be seen that with increasing discharging currents the internal resistance of the Lead-Acid Battery decreased, and the polarization constant increased. From Figures- 2.10, 2.11 and 2.12, it is seen that with higher discharging currents, a higher initial C-rate is observed. The identification process presented was successful in identifying the parameters of all the experimented batteries. As stated earlier, the parameters identified by this method were only mathematical approximations. It was observed that the internal resistance of the batteries increased with increased discharged current. The polarisation constant of the batteries also changed with increased current.

2.2 Prediction Using the Identified Parameters

In this section the prediction results of the identified parameters of the four types of batteries will be observed. Relative root-mean square method was used to calculate the errors of the prediction.

2.2.1 Prediction using the 400mAh Lithium-Ion battery

- Using the identified parameters from the discharge of 0.2 A to predict discharge behaviour of 0.3 A and 0.4 A discharges

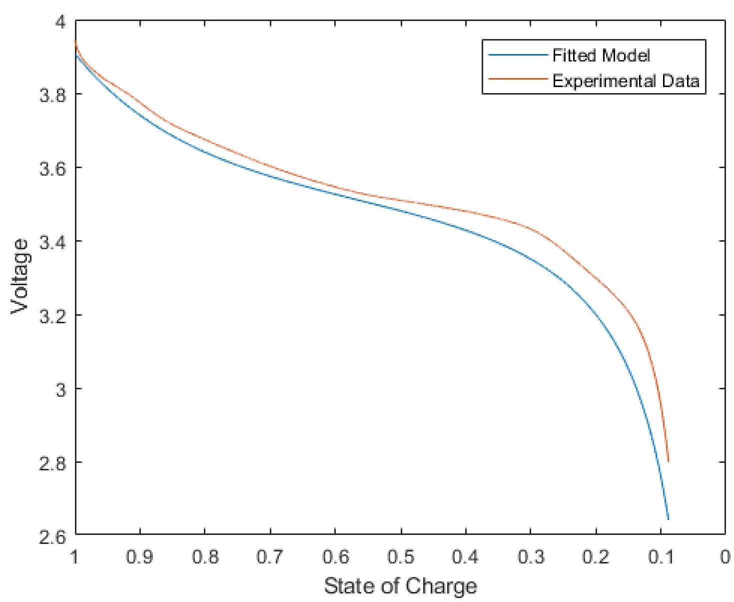

Figure 2.13: Prediction of 0.3 A discharge with parameters of 0.2 A

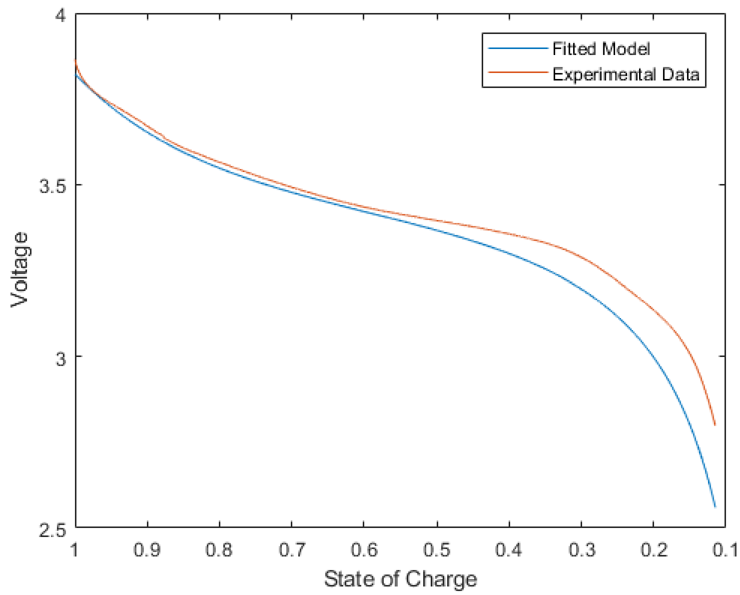

Figure 2.14: Prediction of 0.4 A discharge with parameters of 0.2 A

- Using the identified parameters from the discharge of 0.3 A to predict discharge behaviour of 0.2 A and 0.4 A discharges

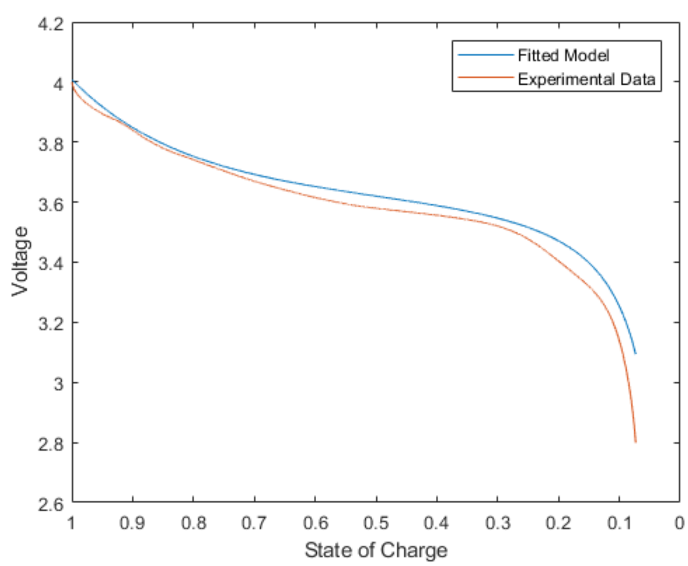

Figure 2.15: Prediction of 0.2 A discharge with parameters of 0.3 A

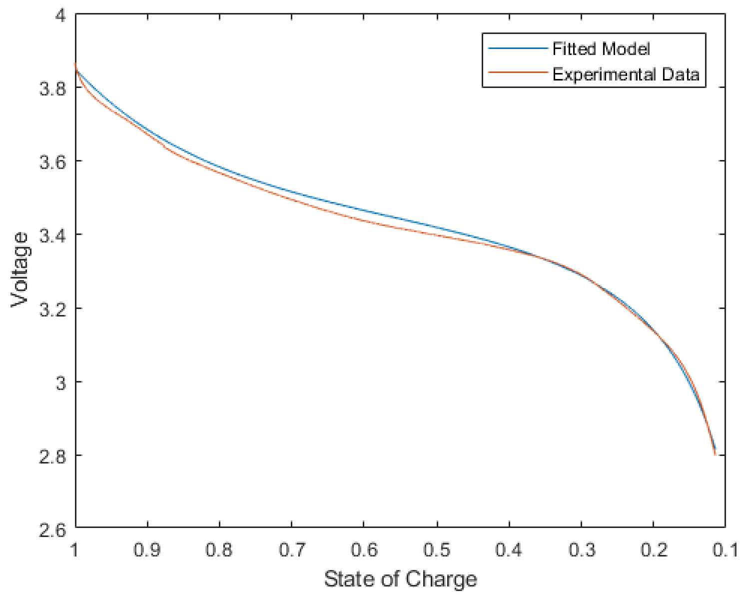

Figure 2.16: Prediction of 0.4 A discharge with parameters of 0.3 A

- Using the identified parameters from the discharge of 0.4 A to predict discharge behaviour of 0.2 A and 0.3 A discharges

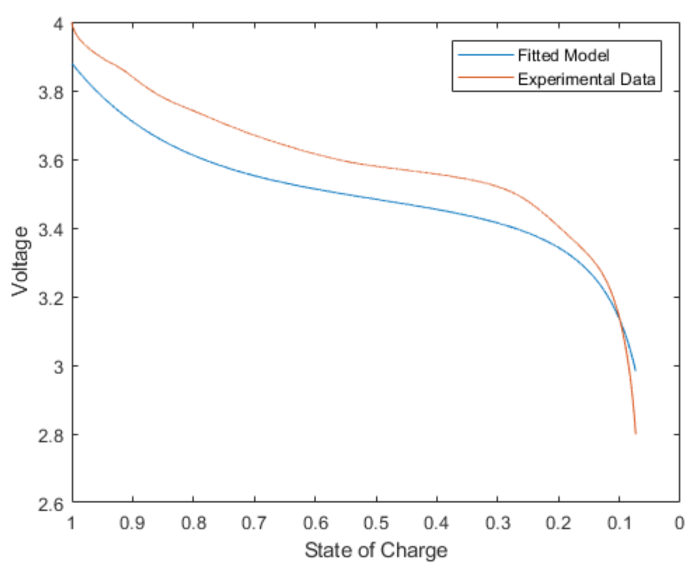

Figure 2.17: Prediction of 0.2 A discharge with parameters of 0.4 A

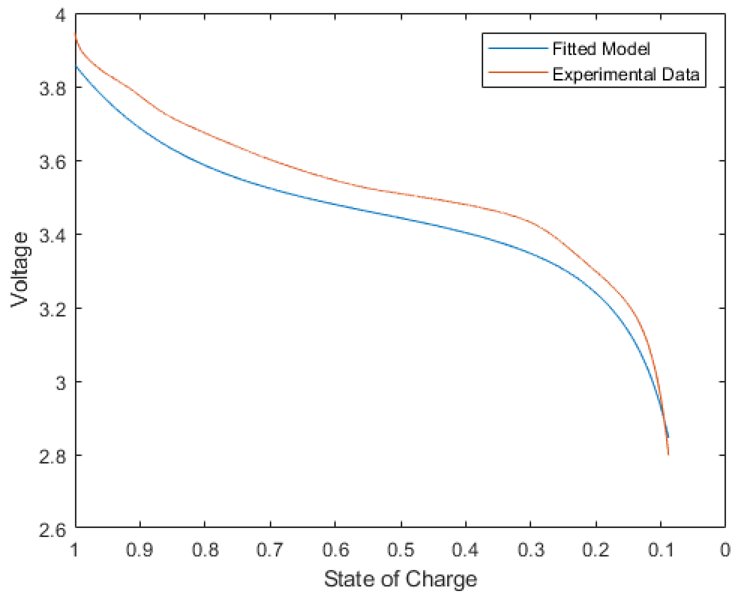

Figure 2.18: Prediction of 0.3 A discharge with parameters of 0.4 A

Similar predictions were done for Data Set 2 and 3 and the following error table in predictions were obtained:

Table 2.13: Error Table for Data Set-1 of 400 mAh Battery

Error (%) in Prediction	**0.2 A**	**0.3 A**	**0.4 A**
0.2 A	NA	3.61	3.94
0.3 A	2.53	NA	0.93
0.4 A	5.5709	4.01	NA

Table 2.14: Error Table for Data Set-2 of 400 mAh Battery

Error (%) in Prediction	0.2 A	0.3 A	0.4 A
0.2 A	NA	4.52	6.28
0.3 A	3.06	NA	1.51
0.4 A	4.15	2.93	NA

Table 2.15: Error Table for Data Set-3 of 400 mAh Battery

Error (%) in Prediction	0.2 A	0.3 A	0.4 A
0.2 A	NA	3.61	3.94
0.3 A	2.53	NA	1.37
0.4 A	4.01	2.67	NA

2.2.2 Prediction using the 1000mAh Lithium-Ion battery

- Using the identified parameters from the discharge of 0.5 A to predict discharge behaviour of 0.75 A and 1.0 A discharges

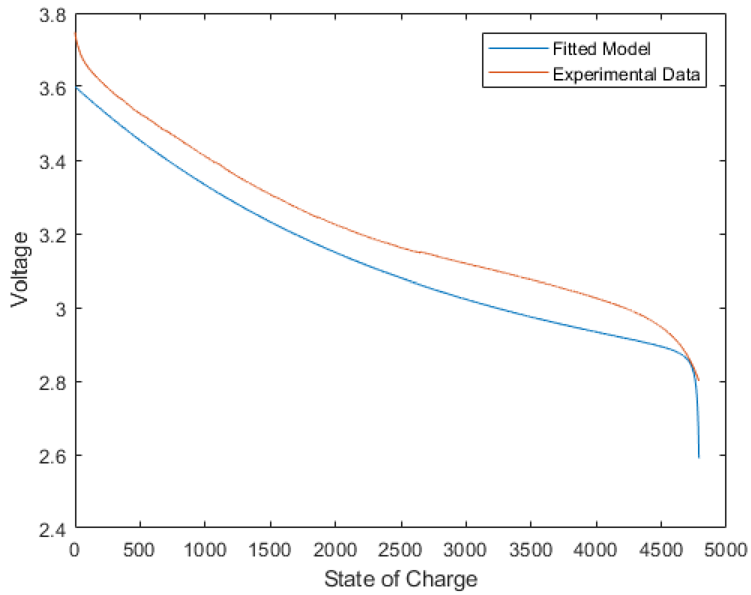

Figure 2.19: Prediction of 0.75 A discharge with parameters of 0.5 A

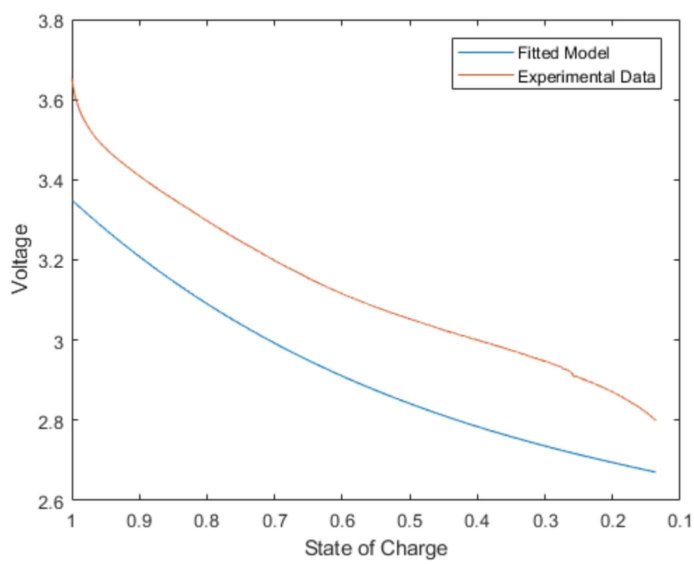

Figure 2.20: Prediction of 1.0 A discharge with parameters of 0.5 A

- Using the identified parameters from the discharge of 0.75 A to predict discharge behaviour of 0.5 A and 1.0 A discharges

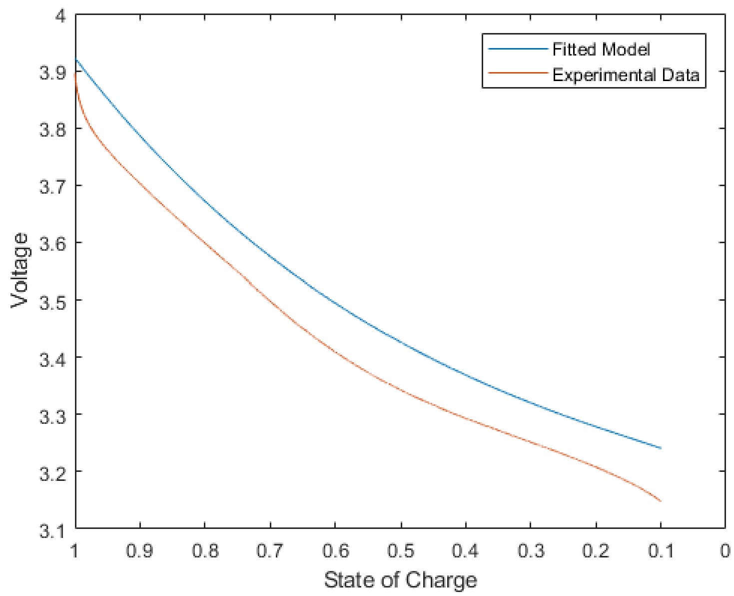

Figure 2.21: Prediction of 0.5 A discharge with parameters of 0.75 A

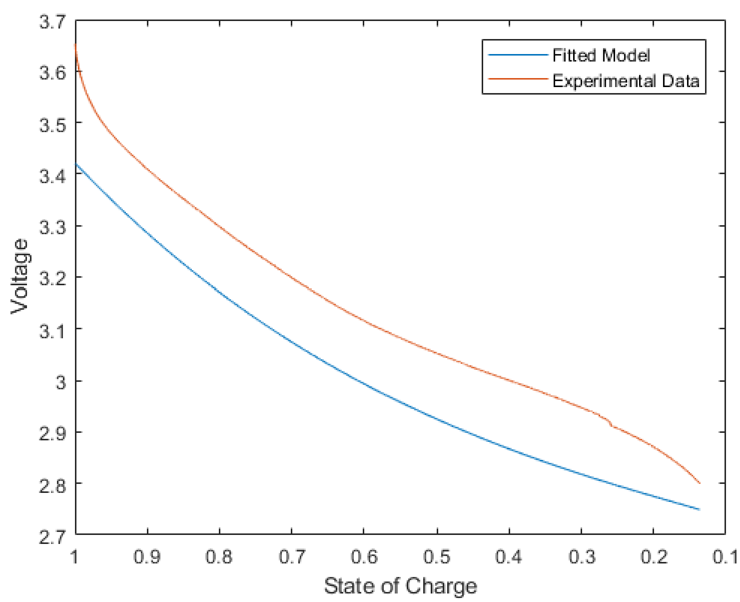

Figure 2.22: Prediction of 1.0 A discharge with parameters of 0.75 A

• Using the identified parameters from the discharge of 1.0 A to predict discharge behaviour of 0.5 A and 0.75 A discharges

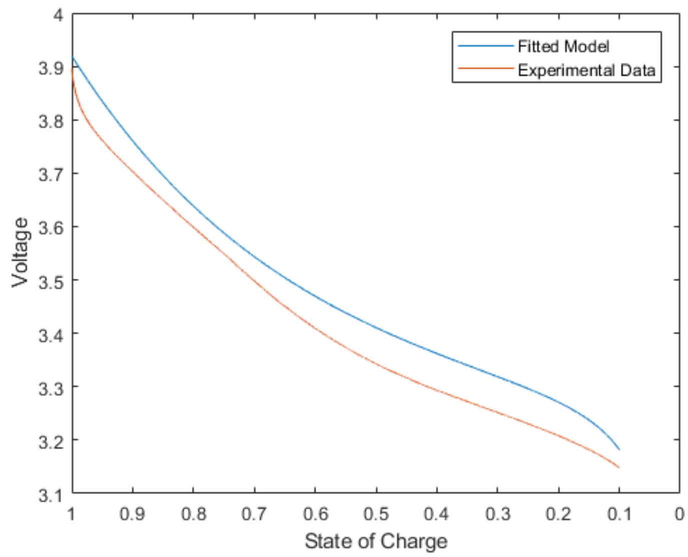

Figure 2.23: Prediction of 0.5 A discharge with parameters of 1 A

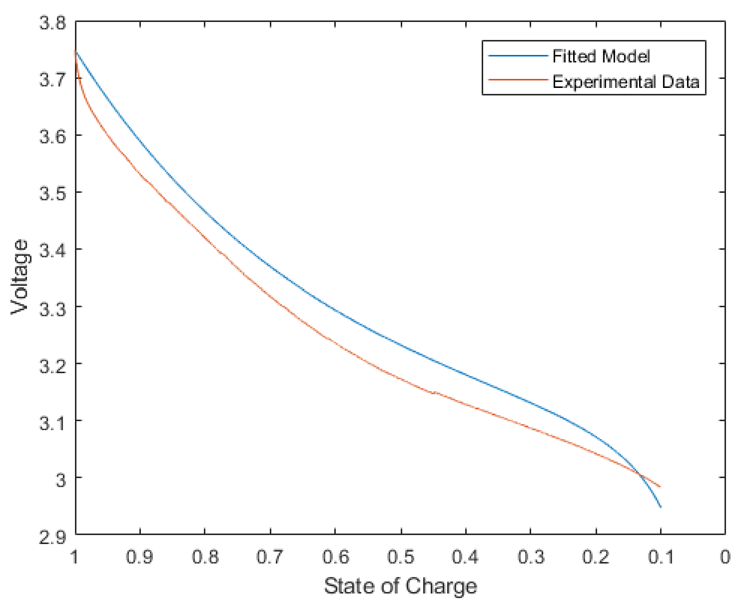

Figure 2.24: Prediction of 0.75 A discharge with parameters of 1.0 A

Similar predictions were done for Data Set 2 and 3 and the following error table in predictions were obtained:

Table 2.16: Error Table for Data Set-1 of 1000 mAh Battery

RMSE in Prediction	**0.5 A**	**0.75 A**	**1.0 A**
0.5 A	NA	4.6	10.21
0.75 A	8.18	NA	10.73
1.0 A	0.95	1.63	NA

Table 2.17: Error Table for Data Set-2 of 1000 mAh Battery

Error (%) in Prediction	**0.5 A**	**0.75 A**	**1.0 A**
0.5 A	NA	2.06	10.51
0.75 A	5.17	NA	8.03
1.0 A	1.62	3.04	NA

Table 2.18: Error Table for Data Set-3 of 1000 mAh Battery

Error (%) in Prediction	**0.5 A**	**0.75 A**	**1.0 A**
0.5 A	NA	10.94	3.04
0.75 A	10.06	NA	10.43
1.0 A	3.12	2.61	NA

2.2.3 Prediction using the 6000mAh Lithium-Ion battery

- Using the identified parameters from the discharge of 0.9 A to predict discharge behaviour of 1.2 A and 1.5 A discharges.

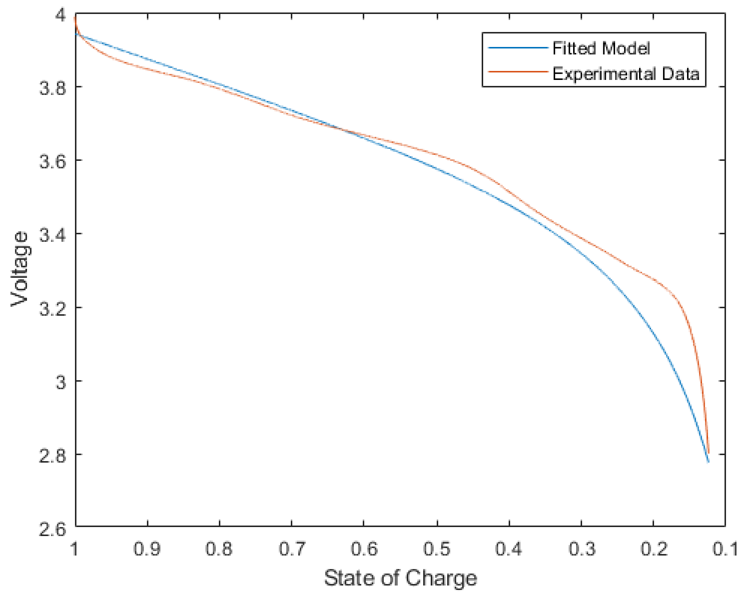

Figure 2.25: Prediction of 1.2 A discharge with parameters of 0.9 A

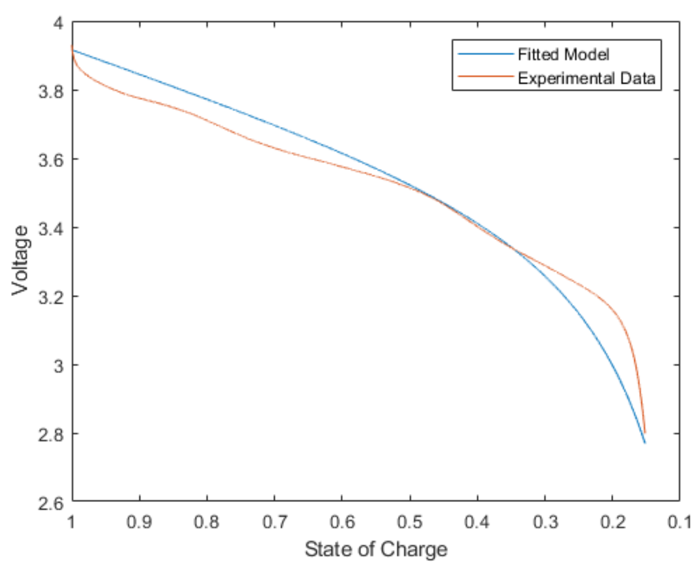

Figure 2.26: Prediction of 1.50 A discharge with parameters of 0.9 A

- Using the identified parameters from the discharge of 1.2 A to predict discharge behaviour of 0.9 A and 1.5 A discharges

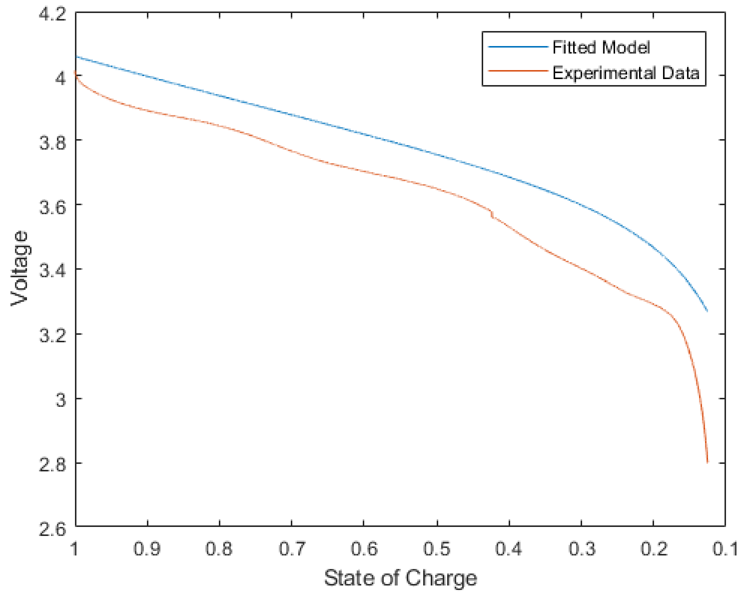

Figure 2.27: Prediction of 0.9 A discharge with parameters of 1.20 A

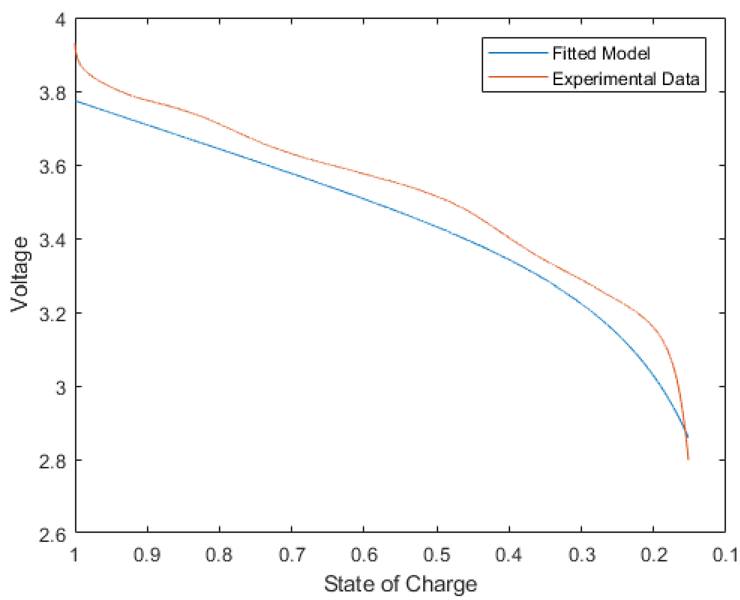

Figure 2.28: Prediction of 1.50 A discharge with parameters of 1.20 A

- Using the identified parameters from the discharge of 1.5 A to predict discharge behaviour of 0.9 A and 1.2 A discharges

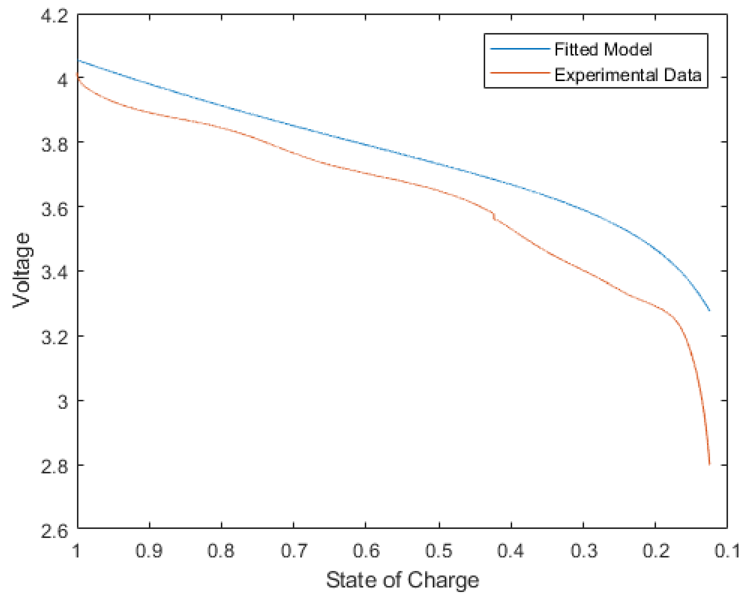

Figure 2.29: Prediction of 0.9 A discharge with parameters of 1.50 A

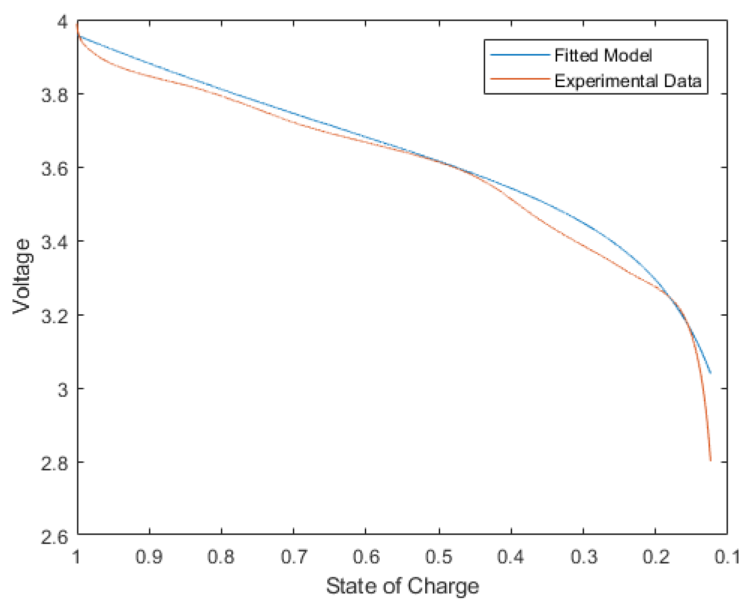

Figure 2.30: Prediction of 1.20 A discharge with parameters of 1.50 A

Similar predictions were done for Data Set 2 and 3 and the following error table in predictions were obtained:

Table 2.19: Error Table for Table Set-1 of 6000 mAh Battery

Error (%) in Prediction	**0.9 A**	**1.2 A**	**1.5 A**
0.9 A	NA	8.13	9.98
1.2 A	7.26	NA	3.99
1.5 A	5.62	1.84	NA

Table 2.20: Error Table for Table Set-2 of 6000 mAh Battery

Error (%) in Prediction	**0.9 A**	**1.2 A**	**1.5 A**
0.9 A	NA	8.44	9.32
1.2 A	6.78	NA	4.24
1.5 A	5.86	2.34	NA

Table 2.21: Error Table for Table Set-3 of 6000 mAh Battery

Error (%) in Prediction	**0.9 A**	**1.2 A**	**1.5 A**
0.9 A	NA	9.14	10.17
1.2 A	6.4	NA	3.99
1.5 A	5.76	1.84	NA

2.2.4 Prediction using the Lead-Acid Battery

- Using the identified parameters from the discharge of 10 A to predict discharge behaviour of 5.0 A and 7.5 A discharges.

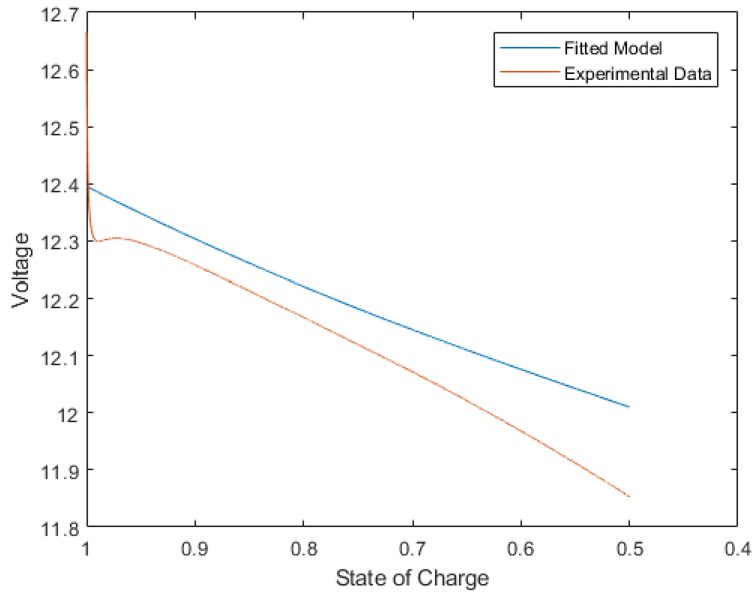

Figure 2.31: Prediction of 5.0 A discharge with parameters of 10.0 A

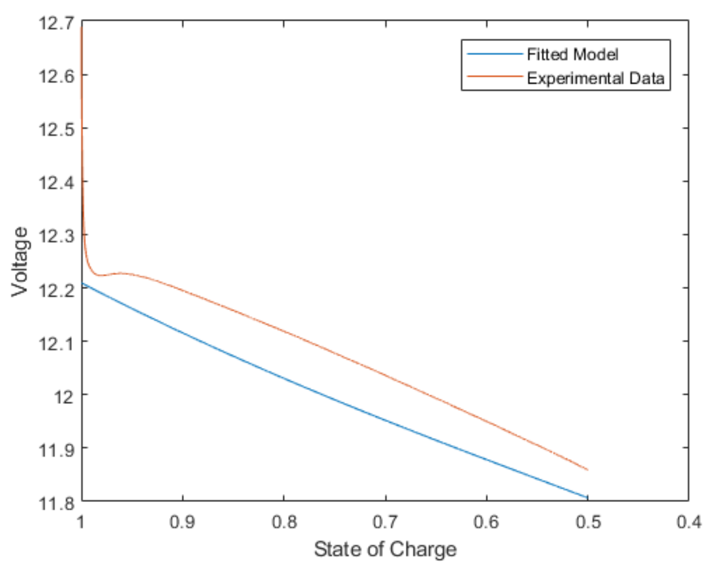

Figure 2.32: Prediction of 7.50 A discharge with parameters of 10.0 A

It can be seen from Figure 2.31 and 2.32, it can be seen that the parameters were not able to predict the initial discharge of the lead-acid battery. Similar trends were also seen with other discharging currents. However, despite of the difference in the exponential region, the prediction errors were reasonable as it will be shown later in this section.

- Using the identified parameters from the discharge of 7.5 A to predict discharge behaviour of 5.0 A and 10.0 A discharges.

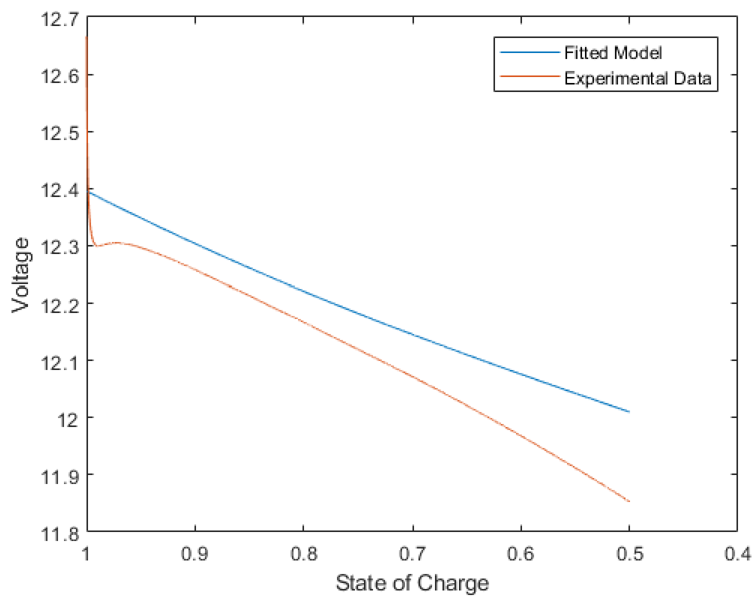

Figure 2.33: Prediction of 5.0 A discharge with parameters of 7.5 A

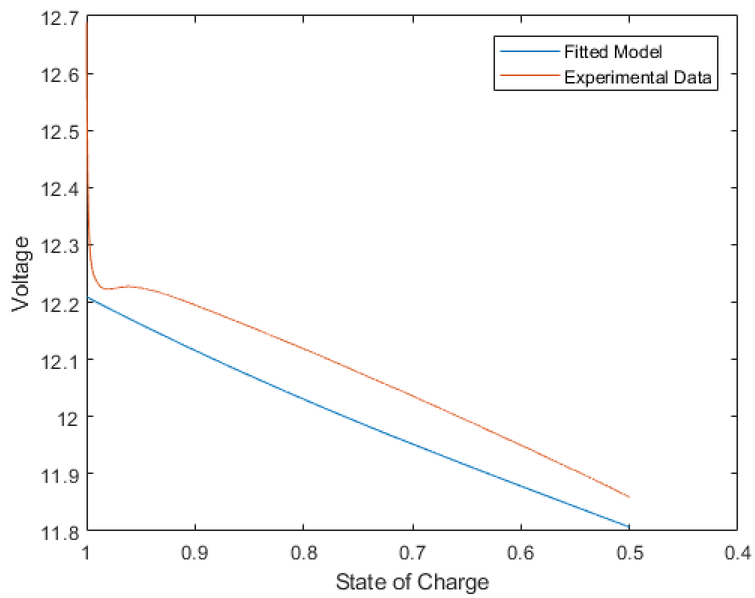

Figure 2.34: Prediction of 10.0 A discharge with parameters of 7.5 A

- Using the identified parameters from the discharge of 5.0 A to predict discharge behaviour of 7.5 A and 10.0 A discharges.

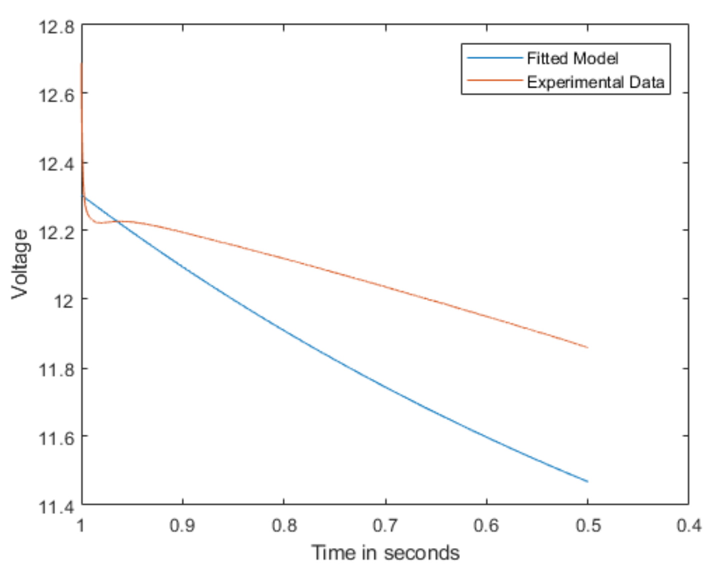

Figure 2.35: Prediction of 7.5 A discharge with parameters of 5.0 A

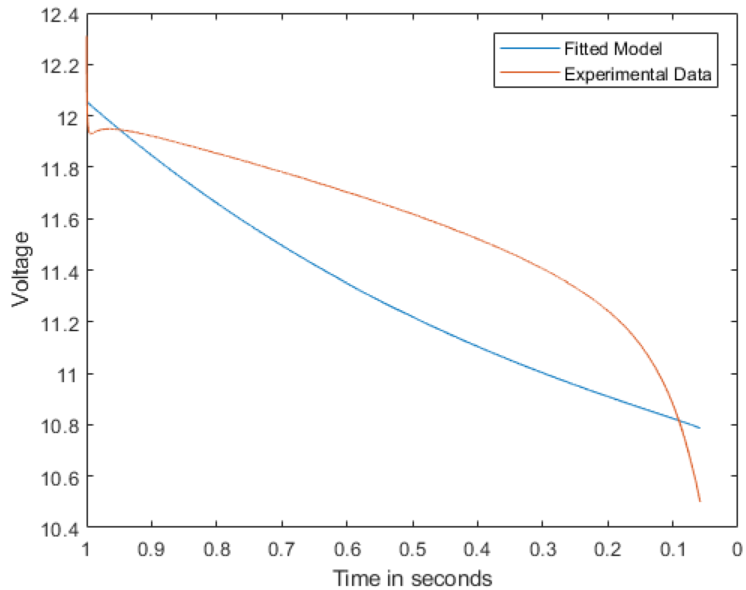

Figure 2.36: Prediction of 10.0 A discharge with parameters of 5.0 A

Similar predictions were done for Data Set 2 and 3 and the following error table in predictions were obtained:

Table 2.22: Lead-Acid Battery Battery Prediction Error for Data Set-1

Error (%) in Prediction	**5.0 A**	**7.5 A**	**10.0 A**
5.0 A	NA	7.5058	9.0074
7.5 A	5.3241	NA	6.9246
10.0 A	2.4045	2.2466	NA

Table 2.23: Lead-Acid Battery Battery Prediction Error for Data Set-2

Error (%) in Prediction	5.0 A	7.5 A	10.0 A
5.0 A	NA	6.7018	10.1062
7.5 A	4.3348	NA	4.1244
10.0 A	2.3215	2.9926	NA

Table 2.24: Lead-Acid Battery Battery Prediction Error for Data Set-3

Error (%) in Prediction	5.0 A	7.5 A	10.0 A
5.0 A	NA	7.0051	9.1072
7.5 A	5.0249	NA	5.1246
10.0 A	2.9088	1.9466	NA

Most of the predictions shown in this section were not precise, as there were differences between the starting voltages of the experimented and predicted data. In the next chapter process of improving the prediction will be shown.

2.3 Prediction of Pulse Current Discharges

In a real-time scenario of a micro-grid it is of great importance to see how a battery recovers after the discharging is stopped. In this section the three Lithium-ion batteries were discharged at intervals; which is they were discharged at a certain current for 2 minutes and were given 2 minutes rest (current of 0 A) to observe their recovery voltage. This way of experimentation gives a picture of how well the battery model replicate the recovery voltage.

The first variating current experiment was done for the 400 mAh battery. Figure 2.37 shows the experimented response, when the 400 mAh battery was discharged using variating current of 0.4 A. Figure 2.38 shows the predicted response using the identified parameters of the 400 mAh battery with the discharge of 0.4 A. There was an error of 4.55 % in the prediction. Similar experiments were done with the 1000 mAh and 6000 Lithium-ion batteries with variating current of 1 A and 1.5 A respectively. The 1000 mAh and 6000 mAh Lithium-ion batteries had an prediction error of 4.76 % and 4.28 % respectively.

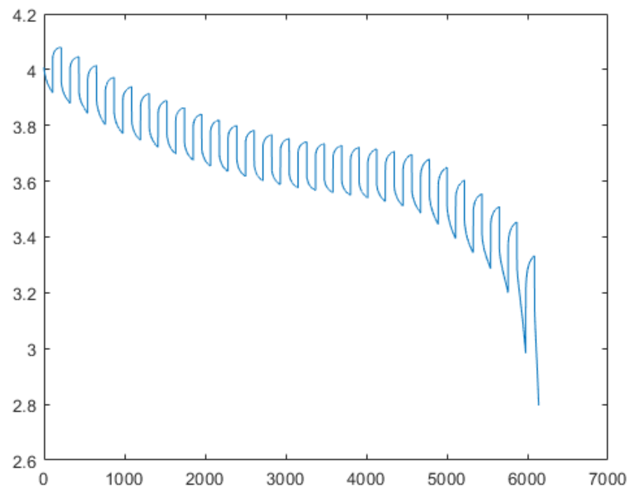

Figure 2.37: 400 mAh Battery with variating current of 0.4 A

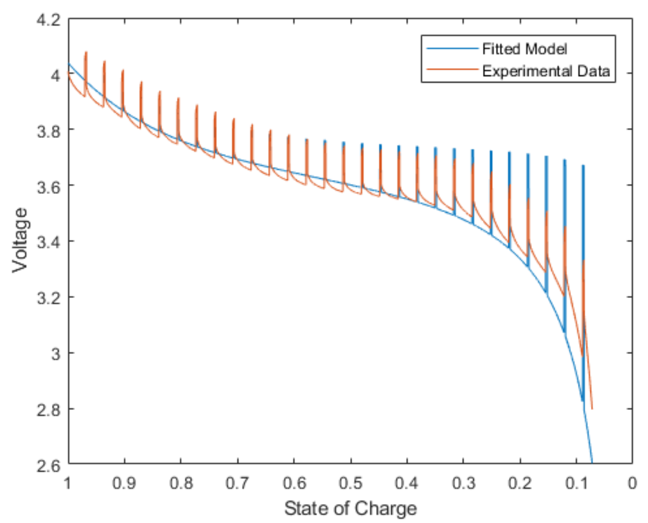

Figure 2.38: Predicting 400 mAh Battery with variating current of 0.4 A

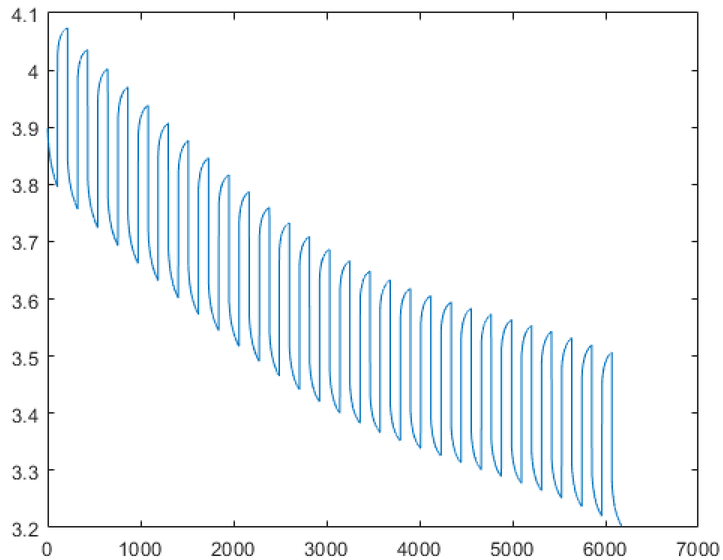

Figure 2.39: 1000 mAh Battery with variating current of 1.0 A

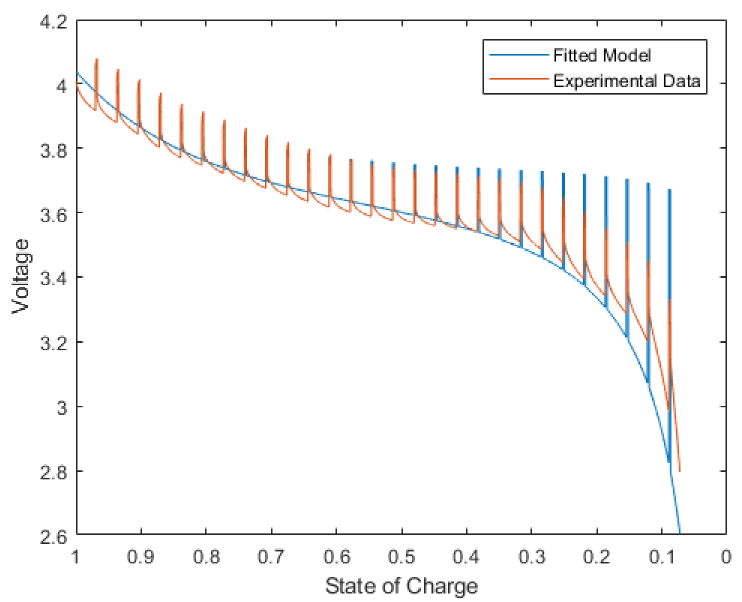

Figure 2.40: Predicting 1000 mAh Battery with variating current of 1.0 A

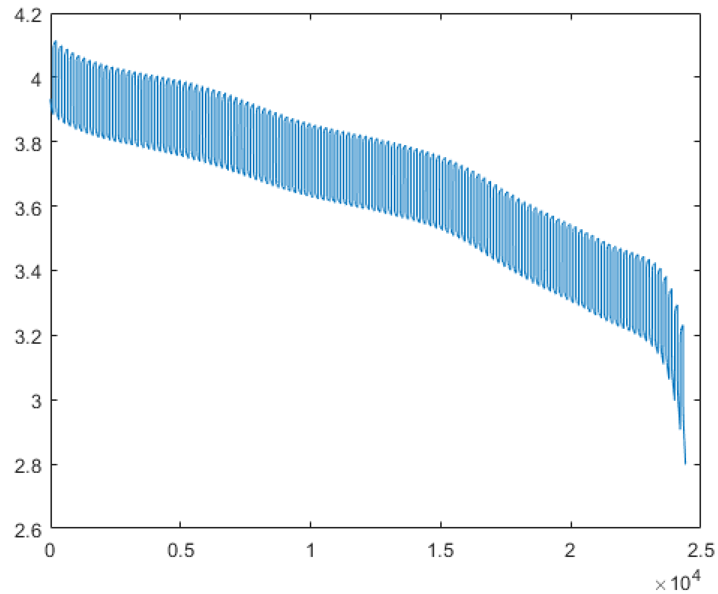

Figure 2.41: 6000 mAh Battery with variating current of 1.5 A

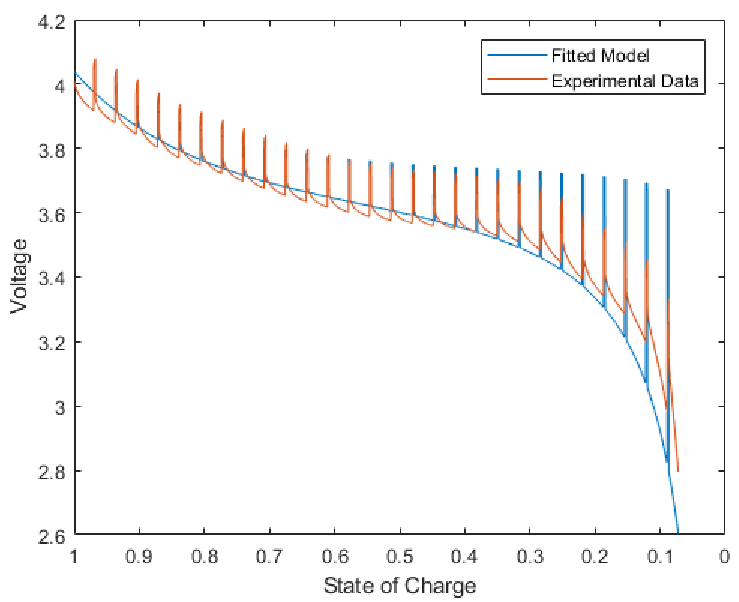

Figure 2.42: Predicting 6000 mAh Battery with variating current of 1.5 A

The predictions with pulse discharging current shows that the identified parameters were not able to predict the recovery voltage of the batteries. The recovery voltage has an exponential behaviour which the identified parameters were not able to replicate the discharge behaviour precisely.

Chapter 3

Starting Voltages and Error Reduction

In this chapter the errors occurred during the prediction process are analysed and possible causes and solution are discussed.

$$E(t) = E_s - ri(t) - K(\frac{1}{SOC(t)})i(t) + Ae^{-B(1-SOC(t))} \tag{3.1}$$

Equation -3.1 represents the modified version of the Shepherd's equation (as derived in Chapter 1), and this is the equation that is used for identifying the battery parameters E_s, r, K, A and B as shown in the last chapter.

As shown in the last chapter E_s the nominal voltage in the identification process is decided by MATLAB's best-fit routine. That means the routine gives solutions which best fits the experimental curve. So, whatever number comes as a solution for Nominal Voltage may not qualify for the actual nominal voltage of the battery. In [8] Nominal Voltage is defined as the voltage at 50% of SOC; that is the voltage at which half of the capacity of the battery has been drained. In the last chapter results did not support the definition of Nominal Voltage in [8]. Similar arguments can be made about the other identified parameters as they are all obtained by the process of a mathematical model. However, as it was shown in the last chapter, these identified parameters were successfully able to model and predict the batteries, but with errors. One major cause of this error is difference between the predicted starting voltage and experimented starting voltage.

If the start of the discharge is considered, that is when t = 0 sec and SOC is 100%, the starting voltage depends upon:

$$E(0) = E_s - ri(0) - Ki(0) + A \tag{3.2}$$

where,

E_s = Identified Nominal Voltage in Volts

A = Empirical Constant

r = Identified internal resistance

K = Identified Polarisation constant

$i(0)$ = Current at time 0 sec or at SOC 100%

In this chapter, correction of the errors with modified Shepherd's equation will be discussed. But, first two important scenarios will be presented where the importance of the starting voltages in the prediction process are presented.

3.1 Predicting High Current discharge using Low Current discharge Parameters

An example of predicting high current discharge characteristics using low current discharge parameters is when the parameters of 0.5 A discharge of the 1000 mAh was used to predict the discharge characteristic of 1 A discharge of the 1000 mAh battery.

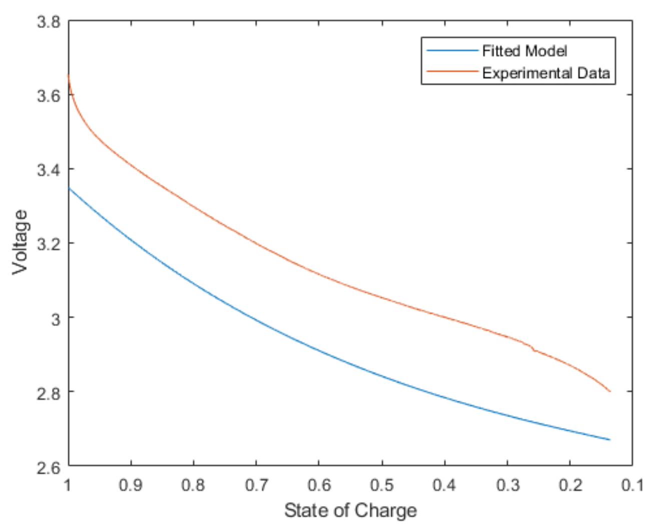

Figure 3.1: Prediction of 1.0 A discharge with parameters of 0.50 A

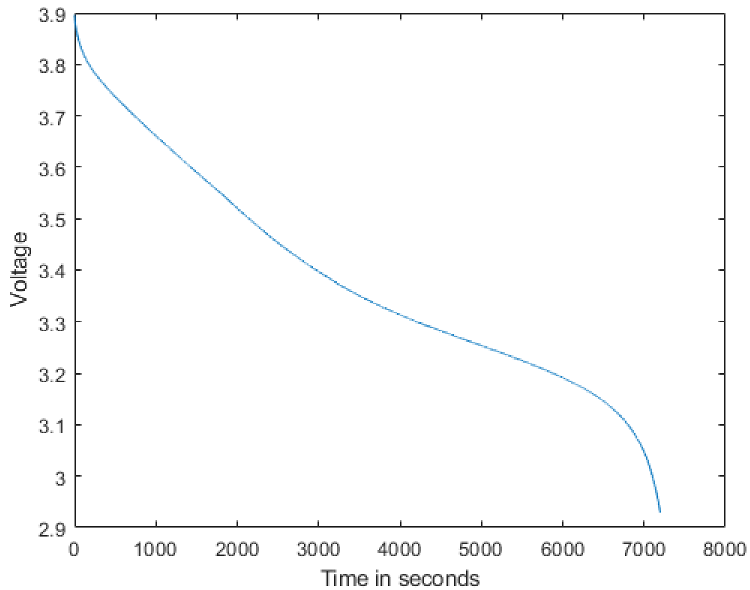

Figure 3.2: 0.50 A discharge of the 1000 mAh battery

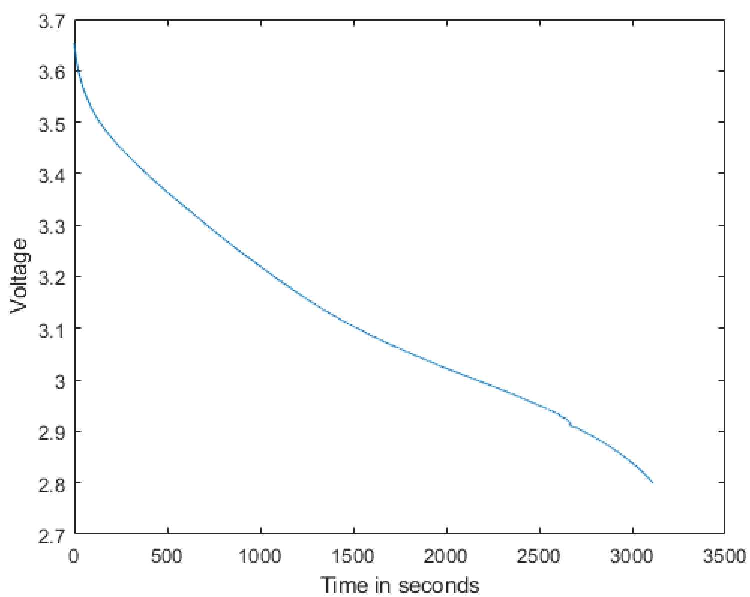

Figure 3.3: 1.0 A discharge of the 1000 mAh battery

There is an error of 10.21 % in the prediction. From Figure -3.2 it can be seen that the starting voltage is 3.8989 V. The original 1.0 A discharge of the 1000 mAh is shown in Figure - 3.3, where it can be seen that the starting voltage is 3.65 V. And, using the parameters identified by the 0.5 A discharge will give out a starting voltage of 3.3491 V. So, clearly there will be a huge error located at the beginning of the discharge. When parameters of the 1.0 A discharge was calculated using experimental data, it was seen that empirical constant values were higher than it was predicted as shown in Table 3.1.

Table 3.1: Parameters of 1000 mAh Battery from Date Set-1

Parameters	**0.5 A**	**0.75 A**	**1.0 A**
r	1.137	1.3075	0.5667
K	0.001	0.0015	0.0281
A	0.8284	0.8537	0.6718
B	2.0195	1.7354	2.6639
Es	3.6049	3.8	3.5

However, if the starting voltages of the prediction curve were brought close to the original graph which in this case is 3.65 V, the error would have been reduced 1.1437 % as shown in Figure - 3.4. How the starting voltage was adjusted will be discussed later in this chapter.

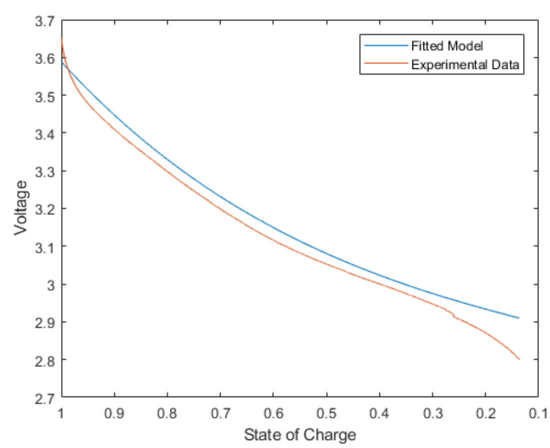

Figure 3.4: Reduced error after adjustment of the starting voltage

A similar case was observed with prediction of 1.0 A discharge using the parameters of 0.75 A discharge, which had an error of 4.0923% as shown in Figure - 3.5.

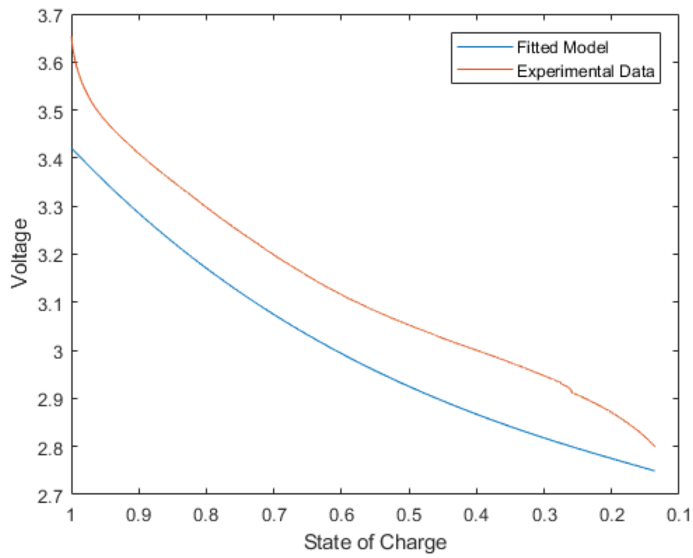

Figure 3.5: Prediction of 1.0 A using parameters of 0.75 A discharge

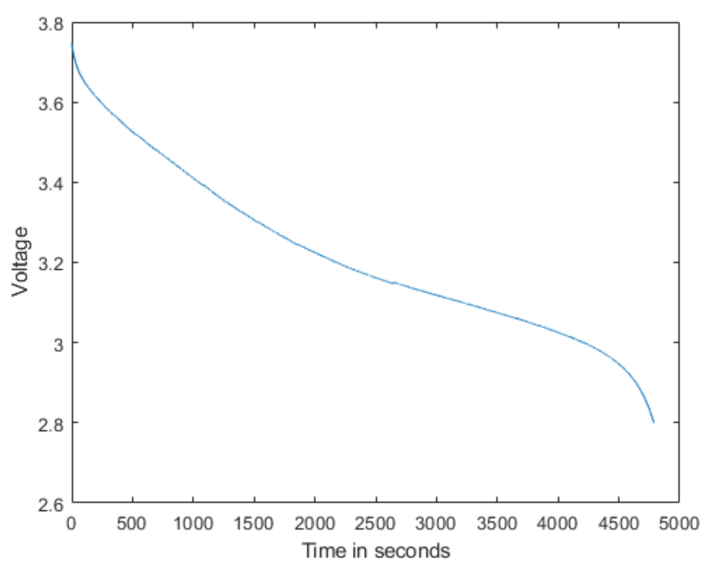

Figure 3.6: Discharge of 1000 mAh battery with 0.75 A

The 0.75 A discharge is shown in Figure - 3.6, where the starting voltage is 3.7480 V. And based on the parameters identified by the 0.75 A discharge, the starting voltage of the 1.0 A discharge was found to be 3.4211 V; whereas the experimental starting voltage is 3.65 V. And then when the starting voltage of the predicted curve was adjusted the error got reduced to 1.91 % as shown in Figure - 3.7.

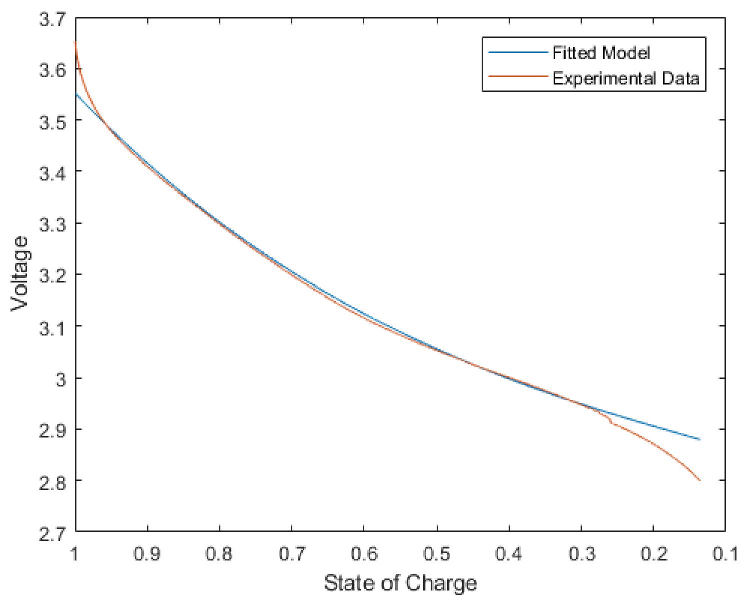

Figure 3.7: Error Reduction

For 400 mAh the error was minimal without the adjustments, as it is a low capacity battery and the initial C-rate did not impose a major difference. The 6000 mAh battery had a similar pattern of large starting voltage differences as the 1000 mAh.

3.2 Predicting Low Current discharge using High Current discharge Parameters

With a higher current discharge, the value of the empirical constants (A and B) had a higher value as the initial voltage drop was larger. Hence, when these parameters was used to predict a low current discharge characteristics, it showed a high starting voltage than the experimental value. So, to reduce the error, the starting voltages needed to be adjusted.

An example of this is shown in Figure - 3.8, where the prediction error is 5.62 %.

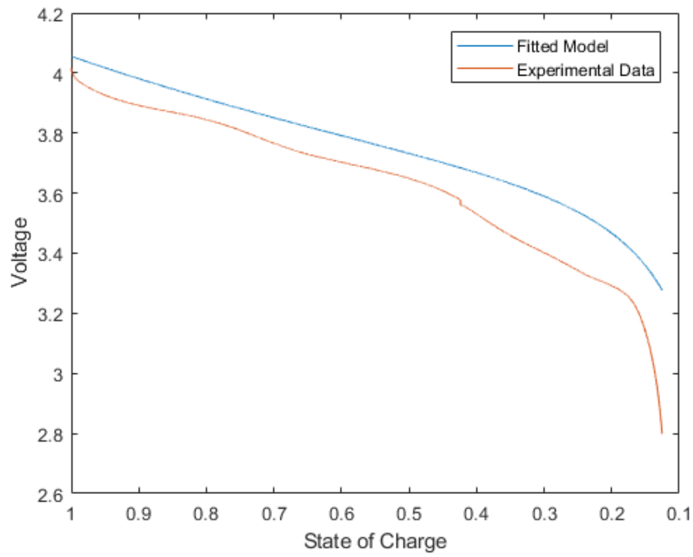

Figure 3.8: Prediction of 0.9 A discharge using 1.5 A discharge parameters

And when the starting voltage was adjusted, the error gets reduced to 1.1537% as shown in Figure - 3.9.

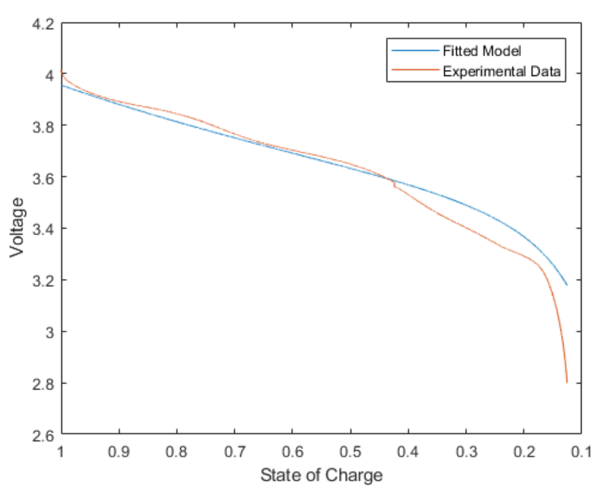

Figure 3.9: Error Reduction

3.3 Modified Shepherd's Equation for Prediction

To adjust the starting voltage one needs to know the experimental starting voltage, so that the predicted parameters can start the prediction as the same voltage as the experimental values.

For the 0.5 A discharge of the 1000 mAh battery, the following parameters were obtained:

- r = 1.1370
- K = 0.0010
- A = 0.8284
- B = 2.0195
- E_s = 3.6049

While predicting the discharge behaviour of 0.75 A with the above parameters, the starting voltage was found to be 3.5795 V. However, when the experiment was done for a 0.75 A discharge, the starting voltage was 3.7480 V. Because the predicted curve started from a lower voltage, it showed a RMSE of 6.60 % as shown in Figure -3.10.

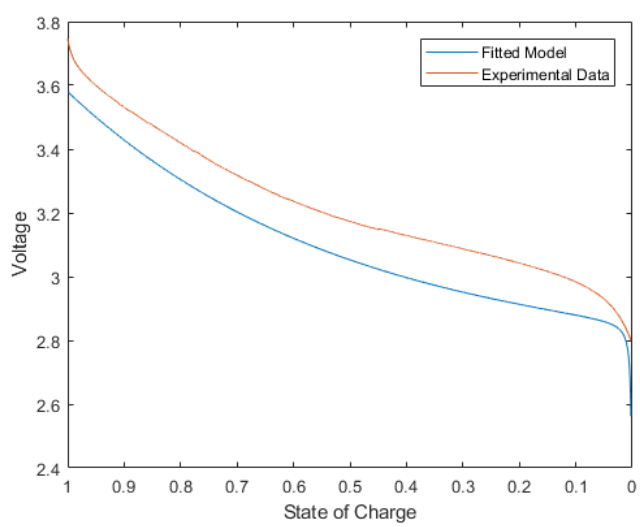

Figure 3.10: 0.5 A discharge parameters used to predict the discharge behaviour of 0.75 A discharge

Now, to reduce the error, the starting voltage of the predicted curve needs to be adjusted. Therefore, a variable named E_a can be added to the Shepherd's equation and E_a is defined as the difference between the Experimental Starting Voltage (E_{start}) and the Predicted Starting Voltage (V_{start}).

$$E_a = E_{start} - V_{start} \tag{3.3}$$

So, now the Shepherd's equation for the prediction process can be defined as:

$$E(t) = E_s + E_a - ri(t) - K(\frac{1}{SOC(t)})i(t) + Ae^{-B(1-SOC(t))} \tag{3.4}$$

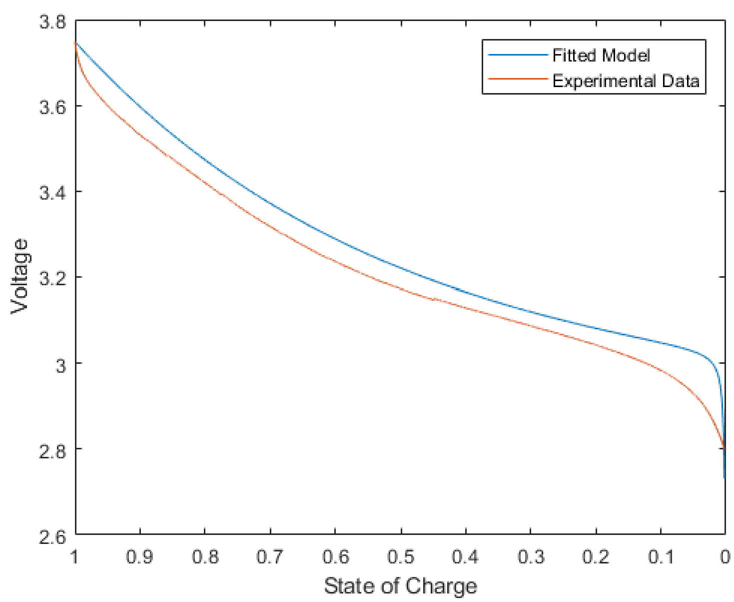

Figure 3.11: 0.5 A discharge parameters used to predict the discharge behaviour of 0.75 A discharge with E_a factor

After the E_a was added to the prediction, the RMSE went down to 1.79 % as shown in Figure - 3.11.

For predicting a low current discharge with high current parameters, E_a will be negative. An example of this scenario is when 0.75 A current discharge parameters of the 1000 mAh Li-ion battery is used to predict the discharge behaviour of a 0.5 A current discharge. The 0.75 A discharge parameters are as follows:

- r = 1.3075
- K = 0.0015
- A = 0.8537
- B = 1.7354
- E_s = 3.8

Using the 0.75 A parameters the predicted starting voltage came out to be 3.9990 V, while the experimental value was 3.8959 V; hence a PMSE of 8.18 % was observed, as shown in Figure - 3.12

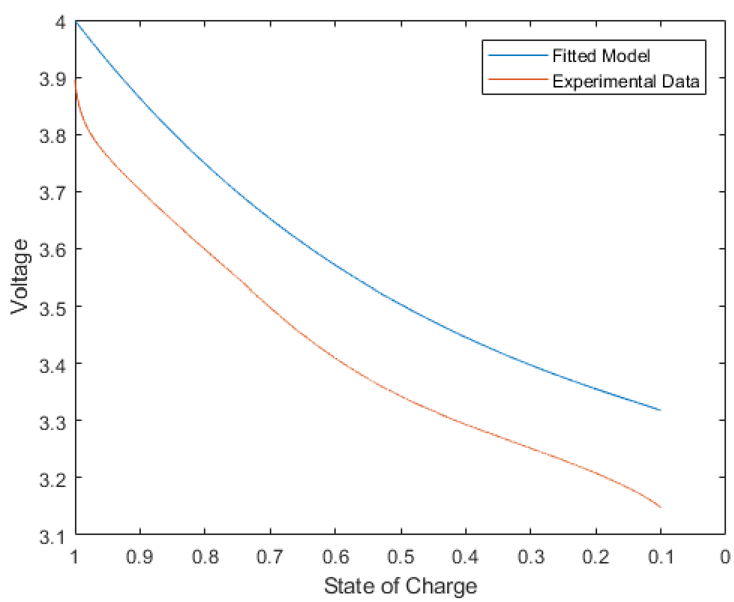

Figure 3.12: 0.75 A discharge parameters used to predict the discharge behaviour of 0.5 A discharge

Based on Equation - 3.3 E_a has a negative value of -0.1031. And using the E_a value, the RMSE is brought down to 0.45 %, as shown in Figure - 3.13.

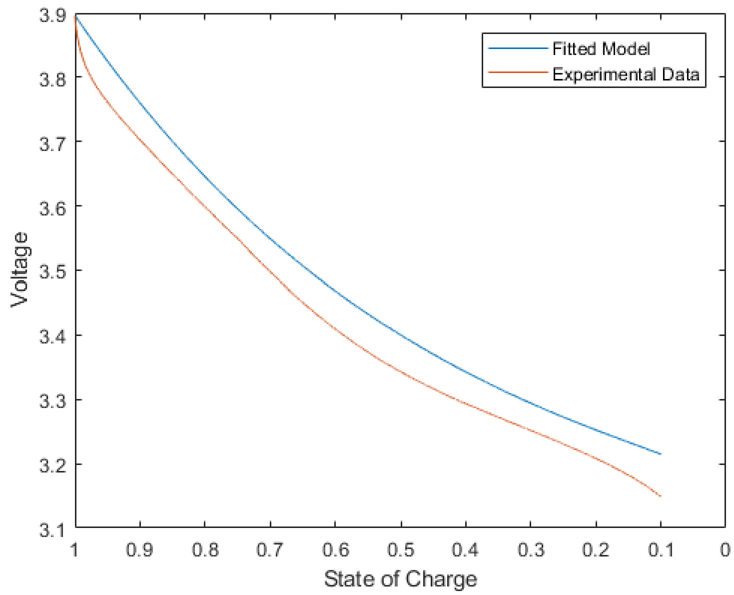

Figure 3.13: 0.75 A discharge parameters used to predict the discharge behaviour of 0.5 A discharge with E_a factor

3.4 The E_a Table for Reducing Prediction Errors

As shown in the previous section how including the E_a factor improved the prediction, in this section E_a values are generated using experimented starting voltages. Starting voltages for different discharging currents of the three Lithium-ion batteries were recorded, and then their respective E_a values were recorded. And finally, the prediction error table for the batteries were calculated.

Table 3.2: 400 mAh Lithium-ion Battery Starting Voltages

Discharging Currents in Amp	**Starting Voltages in V**
0.05	4.1
0.1	4.09
0.15	4.09
0.2	4.07
0.25	4.06
0.3	4.04
0.35	4.02
4	3.98

Table 3.3: 1000 mAh Lithium-ion Battery Starting Voltages

Discharging Currents in Amp	Starting Voltages in V
0.1	4.08
0.2	4.07
0.3	4.05
0.4	4.02
0.5	3.98
0.6	3.97
0.75	3.95
0.8	3.91
0.9	3.9
1	3.88

Table 3.4: 6000 mAh Lithium-ion Battery Starting Voltages

Discharging Currents in Amp	Starting Voltages in V
0.3	4.1
0.45	4.09
0.6	4.06
0.75	4.04
0.9	4.01
1.05	3.99
1.2	3.97
1.5	3.94
2.5	3.83
3	3.72

The starting voltages in Table 3.2,3.3 and 3.4 also indicates the initial C-rate of the batteries, with increasing discharging current, a large drop at the beginning of the discharge is noticed. Using these starting voltages, E_a values for prediction can be calculated once the predicted starting voltages is known. Table 3.2,3.3 and 3.4 is also presented graphically in Figures - 3.14,3.15 and 3.16.

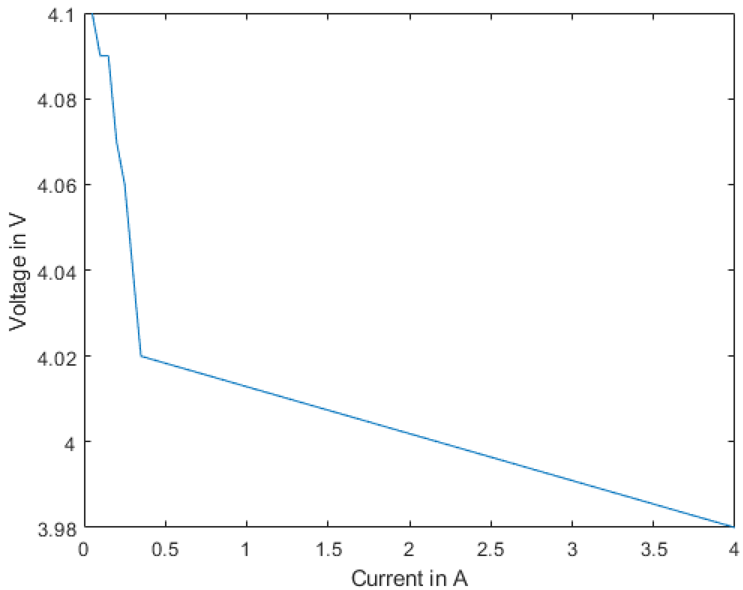

Figure 3.14: 400 mAh Lithium-ion Battery Starting Voltages

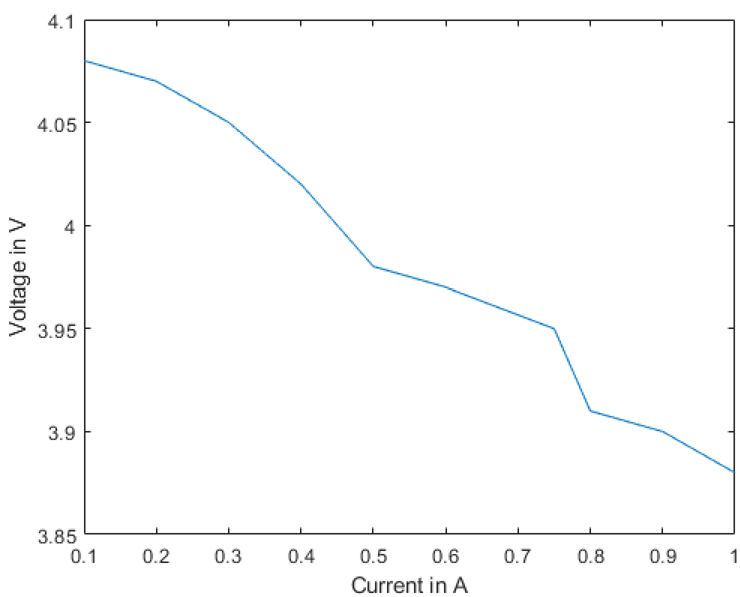

Figure 3.15: 1000 mAh Lithium-ion Battery Starting Voltages

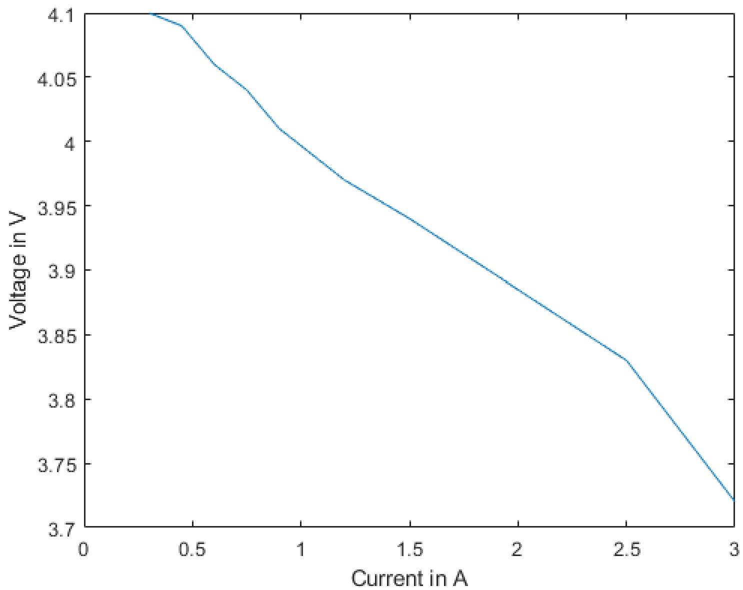

Figure 3.16: 6000 mAh Lithium-ion Battery Starting Voltages

From the Starting Voltages of the batteries, the E_a values are computed and is shown in Tables - 3.5,3.6 and 3.7.

Table 3.5: 400 mAh Battery E_a chart

Ea Values Relative to Starting Voltages in V	**0.2**	**0.3**	**0.4**
0.2	NA	0.08	0.04
0.3	-0.01	NA	0.01
0.4	-0.1	-0.09	NA

Table 3.6: 1000 mAh Battery E_a chart

Ea Values Relative to Starting Voltages in V	**0.5**	**0.75**	**1**
0.5	NA	0.15	0.25
0.75	-0.15	NA	0.23
1	-0.01	-0.001	NA

Table 3.7: 6000 mAh Battery E_a chart

Ea Values Relative to Starting Voltages in V	**0.9**	**1.2**	**1.5**
0.9	NA	0.31	0.29
1.2	-0.1	NA	0.1
1.5	-0.12	-0.09	NA

The E_a values were used in Equation - 3.4, and the predictions error were computed for Data Set-1 as shown in Tables - 3.8,3.9 and 3.10. The error tables show that all the predictions made after the inclusion of E_a got improved.

Table 3.8: 400 mAh Prediction Error Table

RMSE in Prediction	**0.2 A**	**0.3 A**	**0.4 A**
0.2 A	NA	2.72	2.94
0.3 A	2.15	NA	0.83
0.4 A	1.91	1.11	NA

Table 3.9: 1000 mAh Prediction Error Table

RMSE in Prediction	0.5 A	0.75 A	1.0 A
0.5 A	NA	1.79	1.7
0.75 A	0.45	NA	1.91
1.0 A	0.65	1.59	NA

Table 3.10: 6000 mAh Prediction Error Table

Error (%) in Prediction	0.9 A	1.2 A	1.5 A
0.9 A	NA	2.85	3.31
1.2 A	3.1	NA	1.8
1.5 A	2.97	1.62	NA

Chapter 4

Results and Future Directions

This paper presents a process of modelling Batteries. The process required fully discharged data of a battery, a set of starting voltages of the battery and value of the manufactured nominal capacity of the battery. With this given information, the modelling process was able to predict the discharging behaviour of Lithium-ion and Lead-acid batteries. For the identification process Online Parameter Identification method has been used. The Online Parameter Identification method used the best fit procedure (lsqcurvefit) from MATLAB's constrained optimization toolbox to identify the internal parameters of the batteries. The constrained optimization was based upon the Shepherd's Model from [6]. Mathematical modelling was chosen over Equivalent Circuit modelling for this paper, as Mathematical models had the capacity of identifying internal parameters such as Polarization constant, internal resistance and curve fitting empirical constants of a battery. In addition to that Mathematical models such as Shepherd, Unnewehr and Nernst's models can be modified to include temperature, ageing and other electrochemical factors.

For the prediction, relative RMSE was used to calculate the difference between the predicted discharge data and experimental discharge data. Overall, the method described in this paper to model batteries and identify their parameters was successful, as the average RMSE for predictions was less than 5.67%. After the starting voltages of the predicted curves were adjusted, the average error was brought down to 2.45%. In this a paper, for validating prediction the starting voltages were adjusted, so that an actual prediction of the model was observed. The starting voltages were used so that the predicted and actual voltages started close to each other, as that would indicate the efficiency of the identified parameters. The maximum error which was recorded here was 10.17%, and this was recorded while predicting the discharge behaviour of the 6000 mAh Lithium-ion battery without adjustment of the starting voltage. From control's point of view it was required to have fast computation rather than precision.

While predicting the pulse discharges, the modelling procedure described in this paper was unable to predict recovery voltage. During the recovery period the original graphs showed an exponential increase, which was not efficiently shown by the predicted model. Equivalent Circuit modelling can be a solution to this issue, however this will not allow one to know the other internal parameters.

Another important issue to be noticed here was the prediction of the Lead-acid battery. During the identification process, the best fit optimization was not able to predict the initial exponential discharge. This behaviour might indicate the fact that one might tweak the exponential part of the Shepherd's equation in [6] to get the desired initial exponential prediction.

To improve the prediction process and better identify the parameters of the battery, the internal resistance of a battery can be modelled first. As it was seen in the paper, the internal resistance changes it's behaviour as the battery discharges. If one wants to model a particular battery, modelling the internal resistance can be done using the Equivalent Circuit model with pulse discharging. After the internal resistance change is modelled, the Online Parameter Identification Method can be used to better identify the other internal parameters.

Bibliography

[1] Claudia Battistelli, Yashodhan P Agalgaonkar, and Bikash C Pal. Probabilistic dispatch of remote hybrid microgrids including battery storage and load management. *IEEE Transactions on Smart Grid*, 8(3):1305–1317, 2017.

[2] Huai Chuangfeng, Liu Pingan, and Jia Xueyan. Measurement and analysis for lithium battery of high-rate discharge performance. *Procedia Engineering*, 15:2619–2623, 2011.

[3] Adel Merabet, Khandker Tawfique Ahmed, Hussein Ibrahim, Rachid Beguenane, and Amer MYM Ghias. Energy management and control system for laboratory scale microgrid based wind-pv-battery. *IEEE transactions on sustainable energy*, 8(1):145–154, 2017.

[4] Rick Nelson. Instruments and systems measure thermal and electrical parameters. *EE-Evaluation Engineering*, 53(8):14–18, 2014.

[5] Aden Seaman, Thanh-Son Dao, and John McPhee. A survey of mathematics-based equivalent-circuit and electrochemical battery models for hybrid and electric vehicle simulation. *Journal of Power Sources*, 256:410–423, 2014.

[6] Clarence M Shepherd. Design of primary and secondary cells ii. an equation describing battery discharge. *Journal of the Electrochemical Society*, 112(7):657–664, 1965.

[7] Wenbo Shi, Na Li, Chi-Cheng Chu, and Rajit Gadh. Real-time energy management in microgrids. *IEEE Transactions on Smart Grid*, 8(1):228–238, 2017.

[8] Chester Simpson. Characteristics of rechargeable batteries. *National Semiconductor*, pages 1–12, 2011.

[9] Olivier Tremblay, Louis-A Dessaint, and Abdel-Illah Dekkiche. A generic battery model for the dynamic simulation of hybrid electric vehicles. In *Vehicle Power and Propulsion Conference, 2007. VPPC 2007. IEEE*, pages 284–289. Ieee, 2007.

[10] Phil Weicker. *A systems approach to lithium-ion battery management*. Artech house, 2013.

[11] Cheng Zhang, Kang Li, Sean Mcloone, and Zhile Yang. Battery modelling methods for electric vehicles-a review. In *Control Conference (ECC), 2014 European*, pages 2673–2678. IEEE, 2014.