Project title:

Battery Modeling

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Group 1A Battery modeling

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PREFACE

The Battery modelling project is part of the master System Engineering at Han university of applied sciences. It is focused on allowing students to practice with finding the equation of a physical system and then design a model for it. The project taught us to simulate a model of a physical system.

During lectures we were taught to define different systems and find their equations, and we discovered that designing a physical and real system comes with a whole new set of challenges. For most of us this project is the first time we tried design a model of a physical system based on its equations. With the help of our supervisor Siddharth Ajaykumar the project got off to a great start. We would like to thank Siddharth for providing us with useful directions during the project. We would also like to thank HAN university and Hyster yale company for providing us necessary information.

The project group consists of Vahid Vejdaniroshan, Jim Damman, Mohammad Reza Pirzade, Anurag Shinde and Caique Souza Pedroso. We are grateful for the cooperation and dedication of all the group members.

SUMMARY

To manufacture zero-emission trucks and forklifts, the Hyster Yale Group uses fuel cells and batteries in their trucks. Batteries wear by time and use. Therefore, (EV) batteries require monitoring to keep track of the current capacity of the battery as well as the degradation of the maximum capacity of the battery. The state of charge (SoC) and the state of health (SoH) cannot be measured directly. A battery management system (BMS) will need to do various measurements to estimate the SoC and SoH. To estimate the SOC and SOH of a battery, battery models are used. These models will be implemented in Simulink software to evaluate the results.

The project focused on developing a model to predict the optimal time for battery replacement by analyzing key parameters such as voltage, capacity, current, State of Charge (SOC), and temperature changes during usage. The goal was to provide timely alerts to customers about the need for battery replacement, preventing potential failures or damage to the battery and the vehicle, ultimately determining the State of Health (SOH) of the battery.

The approach involved creating a battery model in MATLAB Simulink using an equivalent circuit. This model estimated SOC and SOH, considering factors like C-rate and temperature. The Coulomb counting method was used for SOC estimation, providing an effective measure of the battery's charge level. Additionally, the capacity degradation method was employed to estimate SOH, offering a comprehensive evaluation of the battery's health over time. This method uses a constant value that is subtracted from the current capacity every cycle. The value of the degredation constant is dependent on the current and is based on low current and high current input.

By successfully implementing these methods, the project not only achieved its objectives but also contributed valuable insights to the field of battery health monitoring and replacement forecasting.

The secondary objective of the project involved gathering practical information on cell balancing and its impact on the state of health (SOH) without the implementation of a cell balancing mechanism. The primary focus was on extracting relevant insights from real-world scenarios and practical considerations associated with cell balancing, aligning with the project's broader goal of battery health monitoring and replacement forecasting.

NOMENCLATURE

SoC or SOC	State of charge
SoH or SOH	State of health
BMS	Battery management system
EV	Electric vehicle
ECM / EECM	(Electrical) Equivalent circuit model
FET	Field effect transistor
EOL	End of Life of the battery
OCV	Open circuit voltage: voltage of a battery when no load is connected.
DoD	Depth of Discharge: how far the battery is discharged.
NMC	Nickel Manganese Cobalt
LC	Low current
HC	High current

Parameters	**Description**
R0 (Rint)	*Internal resistor*
Voc	*Open circuit voltage*
Ibat	*Battery current*
SoC	*State of charge*
SoH	*State of health*

CONTENTS

1 INTRODUCTION

1.1 Background

Electric vehicles (EVs) have become increasingly popular in the world, as the need for low emission energy sources for transport increases and solutions to global warming. Central to the success of these eco-friendly vehicles is their battery technology, which stores and provides the energy required to power EVs. Battery powered equipment solutions are required and engineered in several companies to achieve better performance with low emissions, such as Hyster Yale group. [1] Hyster Yale Group is a group of companies that manufactures forklifts of all sizes. Some of their brands are focused on manufacturing parts of forklifts such as handler attachments and fuel cells. To manufacture zero-emission trucks and forklifts, the Hyster Yale Group uses fuel cells and batteries in their trucks. Batteries wear by time and use. Therefore, (EV) batteries require monitoring to keep track of the current capacity of the battery. For EV batteries, multiple cells are combined in a pack to create a bigger capacity and higher power output. However, combining these cells comes with challenges such as heat generation and unbalanced cells. Cell balancing is a maintenance technique that rebalances the cells of a battery pack. The monitoring and maintenance of the battery pack is done by a battery management system (BMS). The Hyster Yale Group has the desire to make the battery management system themselves. This requires knowledge of battery behaviour. In this project, the focus will be on modelling and simulating a battery model for the batteries used by the Hyster Yale Group. Next to that, a literature study on cell balancing will be performed.

A battery cell is the basic building block of a battery. It is a self-contained electrochemical device that can store and release electrical energy through chemical reactions.

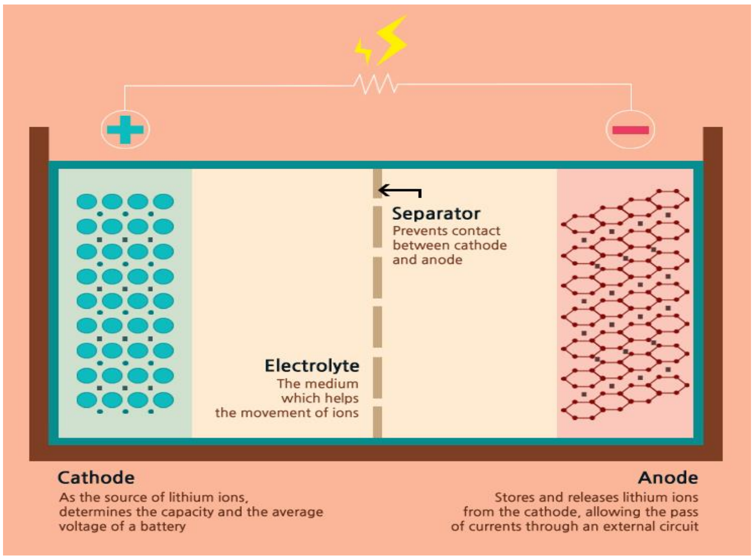


Figure 1 : Schematic overview of the components of a battery cell. [2]

Battery cells consist of several key components which are shown in Figure 1 .

- Electrodes: Battery cells have two electrodes, a positive electrode (cathode) and a negative electrode (anode). These electrodes are typically made of materials that can undergo reversible chemical reactions when the battery is charged and discharged.
- Electrolyte: The electrodes are separated by an electrolyte, which is an ion-conductive material. The electrolyte allows ions to move between the electrodes, facilitating the flow of electrical current during charge and discharge cycles.

- Separator: A separator is a porous membrane that physically separates the positive and negative electrodes while allowing the passage of ions. It prevents short circuits by keeping the electrodes from coming into direct contact.
- Casing: The battery cell is enclosed in a protective casing, which is often made of metal or plastic. The casing provides structural integrity and safety to the cell.

When a battery is connected to a circuit, chemical reactions occur at the electrodes, leading to the movement of ions between them through the electrolyte. This flow of ions generates an electric current that can be used to power electronic devices or perform other electrical work. The voltage, capacity, and overall performance of a battery depend on the specific materials and design of its battery cells. [3]
Multiple battery cells are often combined into a single battery pack to provide the desired voltage and capacity for a particular application. In the context of electric vehicles, a battery pack is engineered to deliver sufficient voltage for driving the electric motor and supporting other essential systems.
The lifespan of a battery pack depends on several factors, including the physicochemical characteristics of the battery (material compositions on components will define electrical parameters, such as voltage, insulation, maximum current, etc.), as well as the operating conditions it encounters, such as temperature, current, and the number of charging cycles, among others [3].
Each of these variables exerts an influence on the battery's overall capacity—the measure of how much charge it can store consequently, how long it can sustain a device or supply electricity. Battery capacity is conventionally quantified in units such as ampere-hours (Ah). The term ‘State of Health’ (SoH) is used to quantify the health of the battery. It gives a measure to determine when a battery should be replaced. Batteries are often declared as end-of-life when the SOH has reached 80% [3].

Additionally, the capacity of a battery is important to determine the State of Charge (SOC), which is a measure of how much electrical energy is currently stored in the battery compared to its maximum capacity. It is typically expressed as a percentage, where 0% represents a completely discharged battery, and 100% represents a fully charged battery.
One method to estimate the SOC and energy consumption is measuring the voltage and current of the battery to calculate the amount of energy stored. By measuring the voltage behavior while a certain amount of current is used on time, it is possible to determine the energy delivered and available. To estimate the SOC and SOH of a battery, battery models are used. There are various ways to implement a battery model. Three main routes to achieve a battery model exist:

1. Electrochemical models
2. Equivalent circuit models (ECM)
3. Black box models

Black box models use data to establish a model and do not need any physical knowledge about the battery. Electrochemical models on the other hand use physical laws to describe the behaviour of the battery. [3] They require a great understanding of the electrochemical processes in a battery. The equivalent circuit models use components like capacitors, resistors and, voltage sources to model the battery. The complexity of these models varies with their order. The higher the order of the model, the better the accuracy of the model.

1.2 Problem definition

As previously mentioned, the behaviour of electric vehicle batteries is influenced by several key parameters, and this has a direct impact on the maintenance process of these batteries. To establish an effective maintenance strategy for electric batteries, the essential component is a battery management system. This system plays a critical role in monitoring and managing various parameters related to the battery's performance.

To execute its functions effectively, this monitoring system must possess a high level of precision. It needs to be capable of measuring the battery voltages, currents, and temperatures accurately. Additionally, it must be proficient in calculating the State of Charge (SoC) and State of Health (SoH).

The calculation of the battery's State of Health poses its own set of challenges. One of the foremost challenges is to design a mathematical model that can faithfully represent the battery's behaviour in a realistic manner. This mathematical model should not only account for the electrical aspects of the motor and accessories but also incorporate the mechanical behaviour of the vehicle.

Once this mathematical model is developed, it needs to be translated into a software implementation through MATLAB. This system is responsible for gathering data from a network of sensors and actuators. With this wealth of information at its disposal, the system can comprehensively assess the status of the vehicle and predict the optimal timing for battery maintenance.

The objective of this project is to provide an analysis of the issue at hand and propose the creation of a predictive model for assessing the health of electric vehicle batteries. Its primary function is to offer real-time and precise insights into the condition of the battery. By accomplishing this, it will facilitate the early detection of degradation, refine maintenance strategies, extend the lifespan of batteries, enhance the overall performance of electric vehicles, and ultimately reduce the total cost of ownership for electric vehicle users.

1.3 Project Objectives

Instead of relying on reactive measures or fixed schedules for replacing batteries in a vehicle, the goal is to use the advantages of predictive analysis to determine the time for battery replacement. This will not only improve the efficiency and lifespan of the batteries but also help reduce the cost and potential downtimes related to unexpected battery failures in a vehicle.

Primary objective:

To model a battery system which can help us predict the time for maintenance:

- Develop a model that can predict when a battery needs to be replaced based on analysis of various parameters and usage patterns such as battery voltage, current, SOC (State of Charge) and change in battery temperature from both the environment and the heat generated by the battery usage.
- The model should provide timely indication to the customer indicating the need for battery replacement before any potential failure or damage to the battery or the vehicle. In other words, determine the State of Health.

The secondary objective is to find information on cell balancing and its effects on the state of health.

1.4 Research question

Predictive Accuracy: What degree of accuracy and reliability can be achieved in predicting battery replacements, and how does this impact vehicle performance and maintenance strategies?

Parameter Analysis: Which parameters (e.g., voltage, current, SOC, temperature) are most pivotal in determining the optimal time for battery replacement, and how do they interrelate?
What is cell balancing? When to do cell balancing? How does cell balance impact the degradation of the battery (SoH)?

1.5 Approach

As the focus of this projects lays on the state of charge and state of health of the battery, the modelling of the battery cell was also focused on modelling these aspects. Especially the effects of temperature and C-rate were of particular interest. With the limited time and experience of the group, a simple ECM with a voltage source and one internal resistor was chosen. The provided data of the battery allowed to model the effects of temperature and current on the state of charge and the internal resistor. For the state of health there was no such data available. Through literature research, a way of calculating the degradation of the battery health was found. Unfortunately, there was insufficient time to combine the battery model and the state of health calculation.
Therefore, the battery is modelled as simple as possible with a voltage source and one internal resistor in series. With the provided battery data, the state of charge was modelled. Simulink was used as software.

1.6 Outline of the minor project report

Chapter 1 is the introduction that handles the background of the problem and its definition. Furthermore, it describes the objective and approach of the project. In chapter 2, the literature survey elaborates the techniques that are used to tackle the problem. Other techniques and their (dis)advantages are explained. Although it has not been implemented in the resulting model, the literature survey also describes what cell balancing is and how it affects state of health. In chapter 3 the methods, handles the choices made in the project and why those choices were made. In chapter 4, the results of the model are shown. Those results are discussed in chapter 5. Finally, the project is concluded.

2 LITERATURE SURVEY

2.1 Battery modelling methods

There are different ways to model batteries, including mechanism modelling, experimental modelling, and hybrid modelling. The mathematical model comes from theoretical formulas, like physical and chemical reaction principles. Treating the battery like a black box; the model is built by observing changes in certain features of the battery through experiments. To create a complete model, both mechanism modelling and experimental modelling are combined. Batteries are complex devices that store energy, and it's hard to precisely describe what happens inside using formulas. That's why hybrid modelling, combining mechanism and experimental approaches, is more common. This is because using experimental data, like with neural networks, requires a lot of information and learning. To obtain the battery state conveniently and accurately, it is necessary to select the appropriate battery model to get the appropriate scheme. In general, 3 different methods are used in battery modelling: Black box modelling, Electrochemical modelling, and Equivalent circuit modelling. Figure 2 represents an overview of common battery modelling methods.

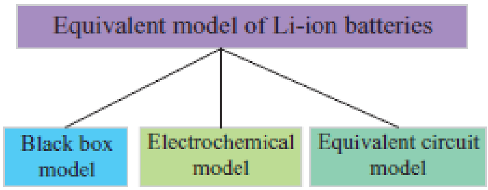


Figure 2: Common battery models

2.1.1 Black box model

The black box model serves as either a linear or nonlinear function depicting how a battery's voltage responds. It directs attention to the internal workings of the battery data, influencing its ability to create a flexible model structure and parameterization. However, it falls short in providing a deep understanding of the physical essence. The challenge with black-box modelling lies in its sensitivity to the amount of training data, affecting its performance. Typically, it requires support from data-driven algorithms like neural networks and support vector regression to enhance accuracy and reliability.

2.1.2 Electrochemical model

The original intention of the electrochemical model was to design the battery structure. To obtain the internal state of the battery and combine it with its energy generating mechanism, the analysis of macroscopic data is conducted onto the battery together with the internal microscopic particle activity. The model mainly reflects the internal battery chemical reaction status. Electrochemical models can analyse the internal characteristics from a microscopic perspective. To express these characteristics of the battery, electrochemical models usually need to establish multiple sets of complex time-varying partial differential equations. It usually takes a long time to solve these equations.

2.1.3 Equivalent Electric circuit

The equivalent circuit model is employed in engineering applications to construct a specific circuit network, utilizing circuit components to characterize the operational traits of a circuit. This model establishes a correlation between the external characteristics exhibited during a battery's operation and the battery's internal state. Notably, the equivalent circuit model is recognized for its intuitive nature, ease of processing, and moderate computational demands. The model's parameters are easily identifiable, rendering it suitable for conducting simulation experiments within circuit applications. Consequently, the widespread utilization of the equivalent circuit model is observed in practical engineering scenarios.

The development of a battery equivalent model encompasses two primary approaches: theoretical and experimental analysis. Theoretical analysis relies on a comprehensive understanding of the internal laws governing the research objective, leading to the deduction of dynamic equations representing the changing patterns of the object. Conversely, experimental analysis involves the collection of input and output signals from the object. While the equivalent circuit model derived from experimental analysis exhibits high precision and offers a profound understanding of the evolution of battery characteristics, it is associated with the drawback of increased complexity, which poses challenges to its practical application in engineering contexts. The equivalent model uses circuit components such as capacitors, resistors, and constant voltage sources to form a circuit network to simulate the dynamic voltage response characteristics of the battery. The relationship between the parameters in this model is direct and obvious, and it generally contains relatively few components. This equivalent model is quantified as some electronic components, which makes the mathematical state-space description easier, so it has been widely used in system simulation and management. The battery electrical circuit models contain a variety of structural frameworks. The following is a brief description of several related concepts.

2.1.4 Simple linear model

A simplistic yet foundational representation, referred to as the ideal model, features solely a constant voltage source while omitting consideration of other internal parameters. The terminal voltage consistently aligns with the open-circuit voltage at every juncture. Consequently, this model does not account for voltage variations amidst load fluctuations, alterations in State of Charge (SoC), or any other transient phenomena. The generic specifications for an ideal battery encompass capacity (Ah) and voltage (V). The quantified stored energy is a product of these parameters, expressed as watt-hours (Wh). This model sustains a steadfast voltage independent of external factors until complete discharge, at which juncture the voltage descends to zero. However, in real-world battery systems, voltage dynamics are influenced by the State of Charge (SoC), as the capacity diminishes with heightened loads. The following figure illustrates this model.

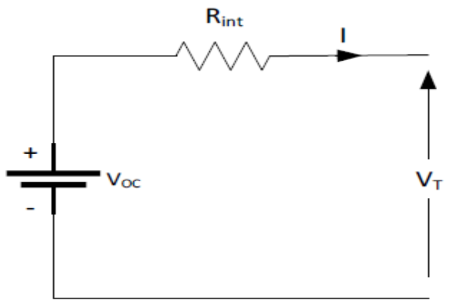


Figure 3: Simple or linear model

Resistance from Figure 3, R_{int}, differs in charging or discharging mode. Therefore, different resistances can be considered for better accuracy, R_c for charging and R_d for discharging, as shown in Figure 4.

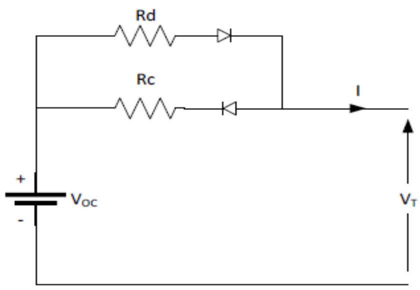


Figure 4: Simple battery model considering charging and discharging resistance

When charging, the diode associated with R_c is directly polarized and will conduct, but the diode associated with R_d is reversely polarized, avoiding current circulation. When discharging, R_d will be activated and R_c blocked, so that only one resistance will be activated in each process.

2.1.5 Enhanced simple battery model

Figure 5 shows the enhanced simple battery model, which considers the effect of the SoC in the resistance.

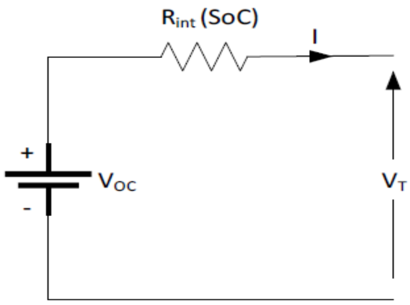


Figure 5: Simple battery model considering charging and discharging resistance

In this model, the terminal voltage is given by:

$$V_T = V_{OC} R_{int} \times I \tag{1}$$

where R_{int} and SoC are initial internal resistance, current SoC.

Among drawbacks, it does not reduce capacity when load increases, so it is not valid for dynamic systems or transient states. Although resistance varies, it does not vary as a function of the temperature. It is noteworthy that the V_{OC} should be dynamic.

2.1.6 Resistor-capacitor (RC) or dynamic model

The RC or dynamic model is visually represented in the ensuing Figure 6. This model comprises several elements, namely a capacitor C_B symbolizing stored capacity, a series resistance R_b indicative of propagation effects, a capacitor ,C_p and a current-dependent resistance R_p denoting polarization and diffusion effects. Additionally, an internal resistance R_{int} is part of this model. It is noteworthy that CP typically has a negligible value, whereas C_b tends to assume significantly larger values. In the context of Li-Ion batteries, the self-discharge resistance is commonly disregarded. The State of Charge is delineated by the voltage variation across the capacitor C_b. The operational dynamics of this model are governed by the following equations:

$$V_T = V_{OC} - I_B \times R_B - R_{int} \times I \tag{2}$$

$$V_T = V_{CP} - I_P \times R_P - R_{int} \times I \tag{3}$$

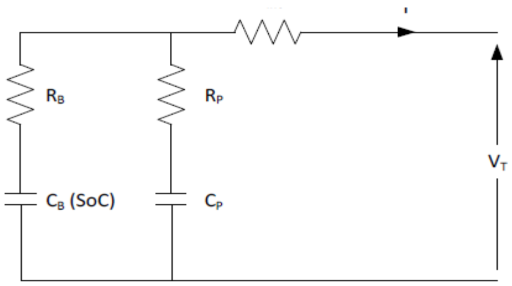


Figure 6: Resistor-capacitor (RC) or dynamic model

2.1.7 Thevenin based Battery Models

None of the models presented above are valid for transient state simulations. To simulate transients, some phenomena as polarization must be considered. In this subsection, some of the most used models for transient state simulation are explained.

2.1.8 (First-order) Thevenin model

The simplest Thevenin model, commonly called first order or one time constant is composed by a voltage source V_{OC}, an internal resistance R_{int}, and a RC pair (R_1 and C_1) representing the capacitance effect between two parallel plates and the contact resistance. This model is shown in Figure 7.

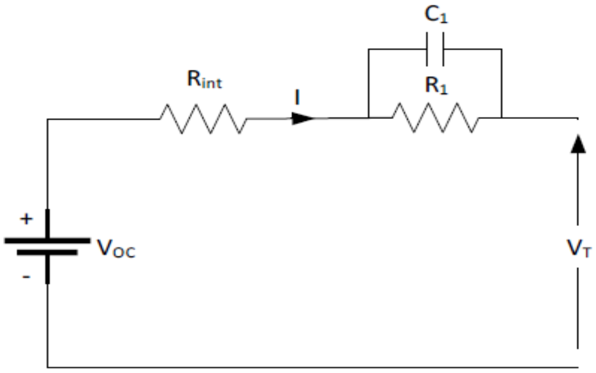


Figure 7: First order Thevenin model

The aim of adding a RC pair to the simple linear model is to represent transient phenomena. The main drawback of the Thevenin model is that all the parameters are considered to be constant. However, it is known that parameters are dependent on SoC, C-Rate, temperature, SoH, etc.

2.1.9 (Second-order) Thevenin model

The second-order model (Figure 8), two-time constants, or dual polarization model adds a second RC pair (R_2 and C_2) with a larger time constant to the previous model. Thus, it is possible to accurately represent the terminal voltage when the current is zero.

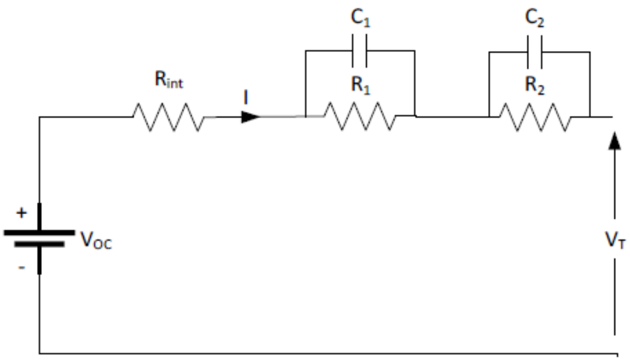


Figure 8: Second order Thevenin model

Therefore, the first RC pair has a low time constant for describing short-term transient effects, while the second RC pair has a larger time constant for describing long-term transient effects. These transient effects are related to electrochemical and concentration polarization effects, including charge transfer effect, diffusion, and other factors.

2.1.10 Runtime Models

The models introduced above can represent the voltage and current evolution. However, runtime data are not provided. Figure 9 shows a runtime model, which is commonly used for runtime simulation of a battery under a fixed average current.

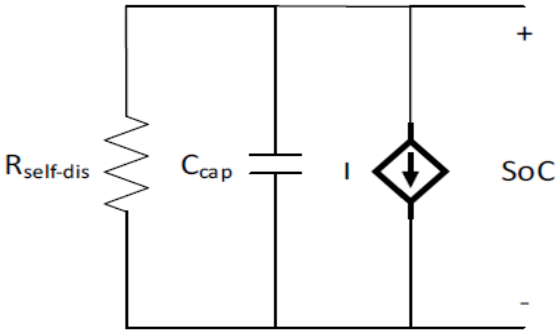


Figure 9 : Runtime model

In these models, State of charge of the battery has also been considered and hence, it is able to provide the dynamics of the battery.

2.2 Modelling and calculating state of charge (SoC)

Modelling the state of charge is crucial in various applications, especially in systems that use rechargeable batteries. SoC represents the remaining capacity of a battery relative to its fully charged state. The SoC cannot be measured directly and therefore must be estimated. There are several ways to model the SoC, and the choice depends on factors such as accuracy requirements, computational complexity, and available data. Here are some common methods:

2.2.1 Coulomb Counting:

Coulomb counting is a technique to estimate the state of charge by keeping track of the amount of energy that went in and out of the battery. This is done by integrating the current of the battery over time. The advantage of this technique is that it is simple and only requires a current sensor. However, it also comes with a few drawbacks.

- To measure and integrate the used current, the current will be sampled. In between the samples, the current is considered linear. Which, especially under dynamic conditions, is not true and introduces differences between the calculated and actual state of charge. [4]
- As the coulomb counting method only calculates the changes of SoC over time, it requires a very accurate estimation of the initial SoC. [5]
- Every battery has a certain amount of self-discharging. This energy loss cannot be measured by the current sensor at the terminals of the battery. Therefore, the loss of self-discharging is not considered.

In this work, the coulomb counting is used to calculate the SoC. Based on the SoC and the temperature the OCV is calculated.

2.2.2 Open-Circuit Voltage (OCV) Method:

The SoC and the open circuit voltage of a battery are closely correlated and have a typical curve. Using the curve and measuring the open circuit voltage, one can determine the current SoC of the battery cell. One should take care though, that the relationship might vary slightly from battery to battery. [6] Furthermore, to measure the OCV of, a sufficient rest time before measuring the voltage is required, as the battery must return to a steady state after charging or discharging. This limits the possibilities of this method to estimate the SoC while the electric vehicle is actively used.

The OCV curve is also relatively flat for lithium-ion batteries. Which results in large variations of SoC for small variations of the OCV. The ambient temperature is another factor that affects the OCV, making OCV measurements less accurate if the temperature effect is not accounted for. [7] Xing et al. [7] used a temperature based internal resistance to improve the SOC estimation under dynamic loads. The OCV is determined dynamically by measuring the current and the terminal voltage.

$$U_{OC} = U_{term} + I \times R_{int} \tag{4}$$

The calculated OCV is then converted to the SoC using lookup tables that also consider the current temperature.

In this project, something similar has been done. The SoC is calculated through coulomb counting. The initial value of the SoC can be set at the start. Based on the SoC and the temperature the OCV is determined. Using the current and an internal resistor that varies with the temperature, the terminal voltage is calculated.

2.2.3 Kalman Filtering and variants:

A Kalman filter is an optimal estimation algorithm. It helps to estimate some value, in this case SoC, using other measurements such as the current, OCV and temperature. The fundamental principle of Kalman filter algorithms is to recursively estimate the current state with help of the previously estimated state and the current measurement signals. This feature makes it very suitable for online SoC estimation. Various variants of Kalman filters have their own properties. Therefore, they do require a sufficient understanding to properly implement them. [8] [9]

2.2.4 Neural Network Models:

To estimate the SoC (and often SoH as well), artificial intelligence is used. The artificial neural network of Fragmental.[11] is such an example. Although the techniques can reach very accurate results, it also has various disadvantages such as that it requires a lot of data and computation power. [10] For this work neither the data nor the expertise to implement such a model is present.

2.2.5 Impedance-Based Models:

Batteries can be modelled as an electrical equivalent circuit model (EECM or ECM). The values of the components of the circuit model change with SoC of SoH. These values can be subtracted from the battery using electrochemical impedance spectroscopy (EIS). The resulting spectra has different outcomes for different levels of SoC. Therefore, the components of the circuit model also vary in value for different levels of SoC. Applying EIS in stationary conditions with the right equipment is not a problem. However, when the battery is employed in a vehicle, these tests are tough to implement. The varying component values provide a solution though, as they can also be subtracted from a voltage/current graph. This allows to interpret the component values and link them to the SoC as shown by Xu et al. [11]

2.3 Modelling and calculating state of health (SOH)

2.3.1 Definition and Importance:

SoH is a measure of the condition of a battery compared to its ideal conditions. It's often expressed as a percentage, where 100% SoH means the battery is in its original condition. It is a critical metric used to evaluate the health and efficiency of a battery. It helps determine the level of degradation of a battery in use with time. Understanding SoH is crucial for predicting battery life, ensuring reliability, and maintaining performance standards. It helps in scheduling maintenance, replacements, and understanding the end-of-life of a battery.

2.3.2 Factors Affecting SoH:

SoH can be determined through various methods, including measurement of battery parameters (like voltage, current, and temperature) and using this data with complex algorithms that estimate SoH based on usage patterns. Several factors impact the SoH of a battery which include:

- Cycling: Every charge and discharge cycle slightly degrades the battery's capacity.
- Temperature: Extreme temperatures (both hot and cold) can negatively affect the battery and cause degradation.
- Age: Over time, even with minimal use, batteries degrade.
- Usage: High loads and high discharging rates can accelerate degradation.

2.3.3 Capacity fade models:

SoH is particularly significant in sectors where battery reliability and performance are critical, like electric vehicles, renewable energy storage systems, and portable electronics. Continuous monitoring of SoH is important for proactive maintenance. It's often integrated into battery management systems (BMS) that provides real-time data and warnings about battery health. Now, below given are the models considering capacity fade as an indicator of SoH. [12]

2.3.4 Palmgren Miner Rule:

The rule states that the life of a component under a variable load is reduced each time by a finite fraction. This fraction corresponds to the ratio between the time the component spent under a given constant load and the lifetime of the component if it would be subjected to the same load.

$$\frac{\sum_{i=1}^{E} Ah_{ef,i}}{Ah_{total}} = \frac{\sum_{i=1}^{E} n_i \sigma_i Ah_i}{Ah_{total}} = 1 \qquad (5)$$

Here n_i is the number of events under event *I*, $Ah_{ef,i}$ is the effective Ah discharged under reference conditions and Ah_{total} is the total Ah discharged to reach the EoL under reference conditions. Using this equation only the EoL Ah-throughput for reference conditions has to be determined. The stress factor σ_i consists of multiple stress factors that have effect on the capacity fading of a cell, which must be determined experimentally.

2.3.5 Damage Accumulation model:

The amount of capacity fading of a battery cell is modelled as damage in the damage accumulation model. The rate at which the damage develops can be described by the equation below:

$$\frac{d\xi(t)}{dt} = \varphi(\xi, \sigma) \qquad (6)$$

where ξ is the amount of damage and ϕ is a function of ξ and stress factor σ. This means that the variation of the damage is a function of the current amount of damage and the stress factor σ. The damage rate can be modelled with an Ah or Wh dependency instead of time. The total damage can be calculated by the below equation:

$$\xi = \sum_{i=1}^{E}\left(\int_{t_{i-1}}^{t_i} d\,\xi_i\,(\mathrm{t})\right) = \sum_{i=1}^{E}\left(\int_{t_{i-1}}^{t_i} \varphi(\xi_i\,(t), \sigma_i)dt\right) \tag{7}$$

Where, t_{i-1} is the starting time of an event, t_i the end time of the event, E the total number of events and ξ_i is the damage development with time at a constant stress factor σ_i.

2.3.6 SoH model with cycling loss rate:

Capacity fading with charge-discharge cycles can be described with:

$$\xi = k_1 n + k_2\sqrt{n} + \xi_0 \tag{8}$$

where ξ is the amount of capacity fading, *k1* and *k2* the stress factor dependent parameters, *n* the number of cycles and ξ_0 the damage on the cell at the start of the measurement. For a fresh cell ξ_0 is zero.

2.3.7 Capacity of the cell

In this method SoH is dependent on Temperature, recharge C-rate, Average SoC and Ah processed. The below given formulas can be used:

$$C_{use}(T,\xi) = (Q_{nom} - \xi)\cdot e^{k_1\left(\frac{1}{T-k_2} - \frac{1}{T_{ref}-k_2}\right)} \tag{9}$$

$$\xi(T, SoC_{avg}, SoC_{dev}, Ah) = \sum_{i}^{E}\left(\left(k_{s1}SoC_{dev,i}\cdot e^{(k_{s2}SoC_{avg,i})} + k_{s3}e^{k_{s4}SoC_{dev,i}}\right)e^{\left(-\frac{E_a}{R}\left(\frac{1}{T_i}-\frac{1}{T_{ref}}\right)\right)}\right)Ah_i \tag{10}$$

where, ξ is the amount of capacity fading and:

$$SoC_{avg} = \frac{1}{\Delta Ah_m}\int_{Ah_{m-1}}^{Ah_m} SoC(Ah)dAh \tag{11}$$

$$SoC_{dev} = \sqrt{\frac{3}{\Delta Ah_m}\int_{Ah_{m-1}}^{Ah_m}\left(SoC(Ah) - SoC_{avg}\right)^2 dAh} \tag{12}$$

2.4 Cell balancing

To provide enough energy for a specific electric vehicle, it is necessary to set a group of individual cells, in parallel (to increase the pack capacity) and series (to increase the operating voltage), in a battery pack. Although, due to small variations of capacity on each battery cell, the battery pack can have imbalance between them, causing reduced charge capacity, low energy efficiency and thus less vehicle range [13].

Those variations in the voltages tend to increase during the usage of the battery pack and can be caused by several factors. These factors include variations in the manufacturing process, material composition, charge/discharge current and heat distribution/dissipation. An example of an unbalanced battery pack is shown in Figure 10.

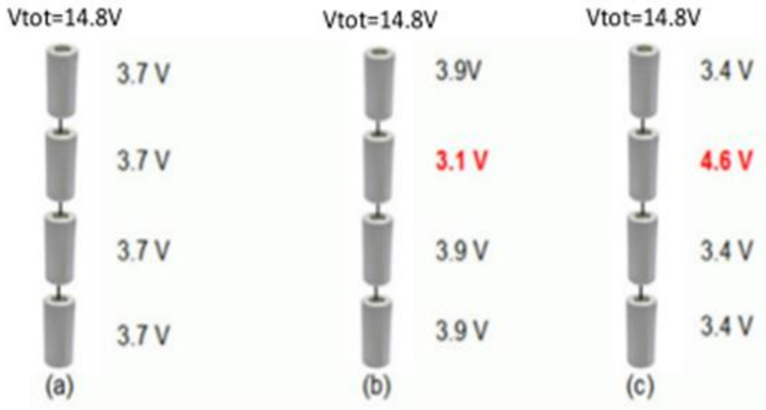


Figure 10: Example of different battery balance conditions. (a) All cells have the same SOC, (b) Imbalanced battery with one having low SOC, (c) Imbalanced battery with one cell with high SOC. [14]

To equalize the voltage levels of the cells, it is necessary to balance the battery pack. This process can be executed by the battery management systems automatically, or by service providers during the maintenance process. The process consists of charging or discharging battery cells and modules individually, to achieve the same level of SOC for all cells present in the pack. Examples of a battery balancer is shown in Figure 11 and Figure 12.

The balancing process executed externally to the vehicle is performed using balancer machines connected to the battery terminals. The device is going to discharge or charge a battery, under controlled conditions.

Figure 12: Example of battery balancer device [14]

Figure 11: Battery balancer connected to a battery module [14]

Other balancing methods, which are components and strategies added to the battery management systems in the vehicle, are discussed in the following topics.

2.4.1 Other balancing methods

The cell balancing methods employs either capacitive or inductive charge shifting to move charge from cells with higher charge to those with lower charge or for dissipation. This approach aims to equalize differences among series-connected cells by transferring energy from cells with higher State of Charge (SOC) to those with lower SOC, with minimal loss. When a cell holds a charge higher than the average charge of the balancing module, it must release the excess charge, which can be redirected to a resistor or then redirected to cells with lower charges. [13]

One method is the Current Bypass approach. The straightforward application of cell balancing involves incorporating a Field-Effect Transistor (FET) in parallel with individual cells as shown in Figure 13. These FETs are governed by a comparator for basic voltage-based algorithms, activating the bypass FETs when voltage discrepancies emerge. Alternatively, a microcontroller can be employed for more intricate and efficient algorithms, enabling continuous operation irrespective of voltage variations. [13]

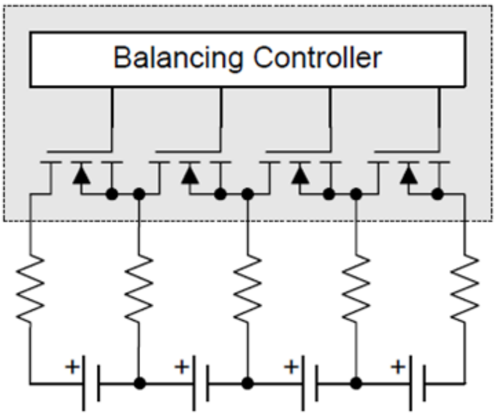


Figure 13: Bypass FET method schematic. [13]

The downside of the current bypass method is that the energy from the bypassed charge ends up wasted. Although this might not be a big concern when the system charges while connected to a power grid, it becomes crucial in portable applications where every small amount of energy matters. This calls for a cell-balancing approach that efficiently drains excess charge from high cells to low cells.

Other solutions include circuits designed to transfer energy from high cells to low cells rather than wasting it through a bypass resistor. One simple technique involves redistributing energy between cells using a capacitor, initially connecting it to the higher voltage cell and then to the lower voltage cell. [13] This technique is shown in Figure 14.

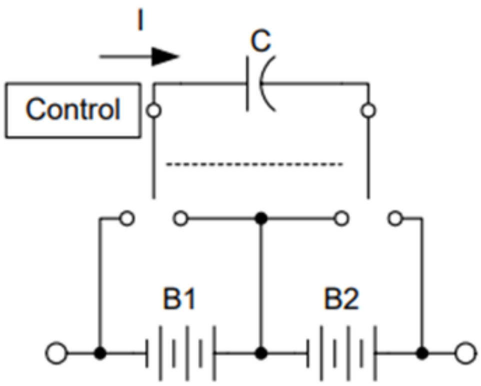


Figure 14: Basic shuttle cell balancing circuit. [13]

Those are the main strategies for cell balancing in battery packs. Although, other methods for balancing exists and are still subject for research, which the principles are always going to be like the previous ones: redirect energy from unbalanced cell to other locations when needed.

2.4.2 How does unbalanced cell impact the degradation of the battery

A batterypack is balanced if all batterycells of the pack have the same SoC. Due to cycling an imbalance occurs between the cells. A batterypack can only be charged to the point where one of the cells has reached it highest SoC (100%). At that point the charging is stopped, to prevent overcharging. This may leave other cells at a lower SoC, eventhough some energy can still be supplied there. This means that the pack as a whole has not reached 100% SoC. As the imbalance grows over time, you could say that the state of health of the battery decreases.

In situations where there's an imbalance in either the State of Charge (SoC) or the total capacity, the cell with the higher resulting SoC is subject to increased voltages. For instance, if a cell with lower capacity is part of a series connection within the pack, it will exhibit a much higher voltage than the other cells after charging, while the cells with normal capacity will have lower voltages compared to their usual charging levels. This difference can accelerate degradation or pose safety concerns for the low-capacity cell.

Furthermore, the degradation caused by imbalance tends to worsen itself. Once a cell's capacity diminishes, it faces progressively higher voltages during charging, leading to faster degradation and a further reduction in capacity. This sets off a cycle of degradation that perpetuates itself.

Li-ion batteries contain a substantial amount of electrical energy within a small space. While mechanisms exist to prevent the release of this energy through a short circuit via appropriate mechanical safeguards, the presence of highly reactive chemicals in proximity inherently poses a risk with these batteries. Overcharging or overheating can trigger reactions between active components and the electrolyte, potentially leading to explosions and fires. [15]

If one cell is compromised, the other cells in the battery pack may become part of the explosive chain reaction. To mitigate these risks, cell balancing techniques are essential to prevent any cells from reaching hazardous voltage levels. Additionally, safety protection circuits are crucial as they should terminate the charging process if cells still approach these dangerous voltage thresholds. [15]

3 METHODS

The primary objective of this project is to develop and validate a model for a Lithium battery under varying conditions. The study aims to explore the relationships between key battery parameters and factors to enhance the accuracy of the model in predicting battery behaviour.

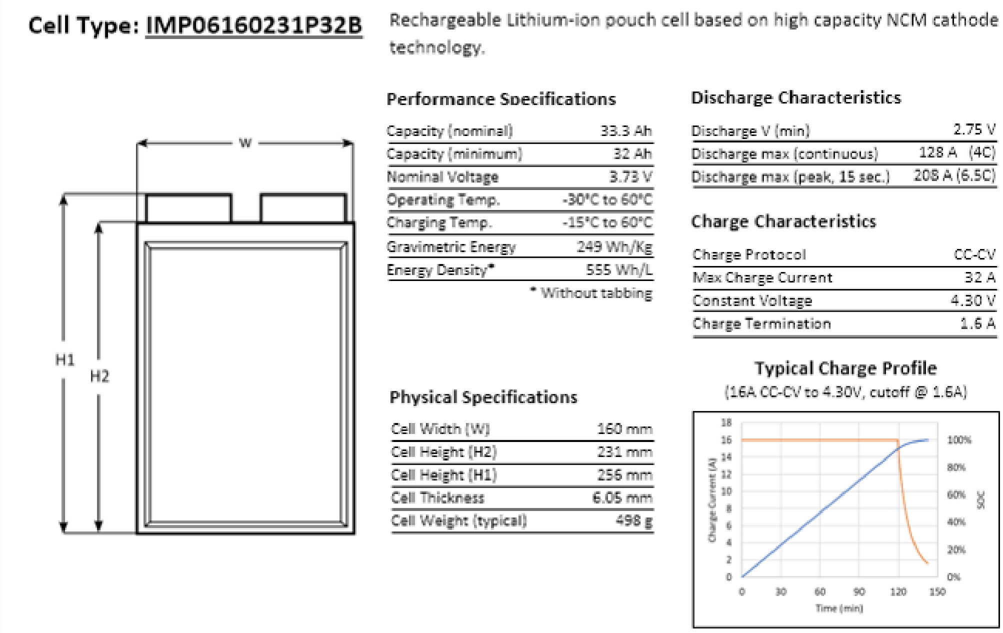
To achieve these results, literature research was performed to better understand all the basic concepts of an electric vehicle power battery, focusing on the Lithium batteries implementation on a Hyster Yale Product.

After this, a comprehensive battery characterization was conducted, encompassing an analysis of battery classification, capacity, charging and discharging patterns across various conditions, voltage responses, and impedances. Through the assimilation of this extensive dataset, it became feasible to establish correlations between the outcomes derived from the Simulink model, thereby facilitating subsequent validation.

3.1 Battery Characterization

The battery information was provided by the electric vehicle supplier Hyster Yale. The datasheet included with the main parameters, such as the open circuit voltages (OCV) for different state of charge (SOC), behaviour under several temperatures, impedances, and cycle life performance.

The battery type used for the study as reference was Farasis P32 Lithium with NCM cathode (nickel cobalt manganese), with nominal capacity of 33.3Ah and nominal voltage 3.73V. [16] All main characteristics from datasheet are shown below in Figure 15:


Cell Type: IMP06160231P32B

Rechargeable Lithium-ion pouch cell based on high capacity NCM cathode technology.

Performance Specifications

Capacity (nominal)	33.3 Ah
Capacity (minimum)	32 Ah
Nominal Voltage	3.73 V
Operating Temp.	-30°C to 60°C
Charging Temp.	-15°C to 60°C
Gravimetric Energy	249 Wh/Kg
Energy Density*	555 Wh/L

* Without tabbing

Discharge Characteristics

Discharge V (min)	2.75 V
Discharge max (continuous)	128 A (4C)
Discharge max (peak, 15 sec.)	208 A (6.5C)

Charge Characteristics

Charge Protocol	CC-CV
Max Charge Current	32 A
Constant Voltage	4.30 V
Charge Termination	1.6 A

Physical Specifications

Cell Width (W)	160 mm
Cell Height (H2)	231 mm
Cell Height (H1)	256 mm
Cell Thickness	6.05 mm
Cell Weight (typical)	498 g

Figure 15: Farasis P32 Battery cell parameters sheet [16]

The battery discharge behaviour under several different rates, as well as the capacity degradation according to cycles are also specified (Figure 16). This information was used as the main reference to model the discharge and charge behaviour under different currents, as well as to model the cell degradation.

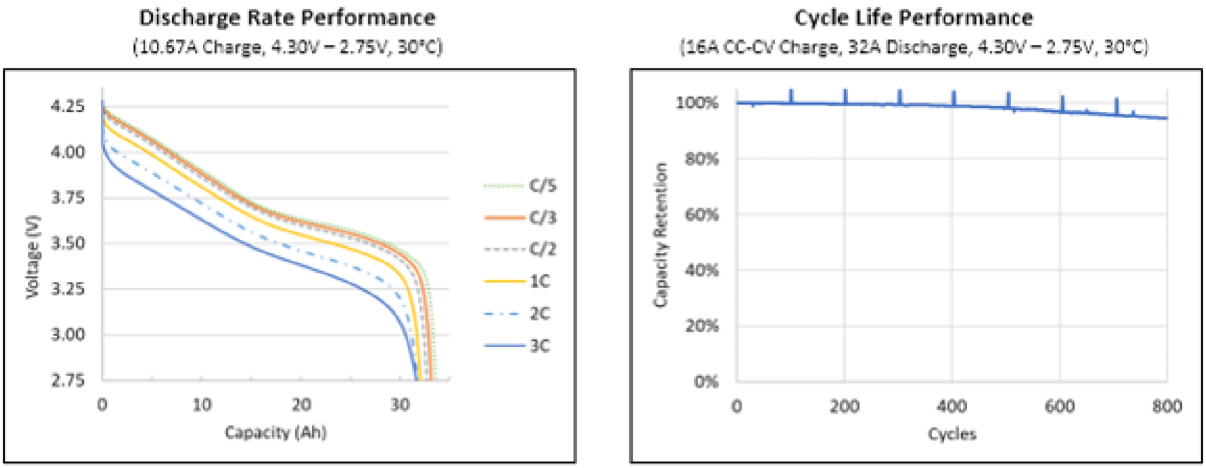


Figure 16: Farasis P32 battery cell discharge performance and capacity retention

Another important behavior present in the Farasis datasheet is the OCV variation for different temperatures (Figure 17). This is crucial to the battery modelling for reference, as it is needed to represent the battery for a wide range of temperatures. The capacity varies according to the operating temperature, as well as the OCV.

	-30°C		-20°C		-10°C		0°C		10°C		25°C		45°C		55°C	
SOC	OCV	Ah	OCV	Ah	OCV	Ah	OCV	Ah	OCV	Ah	OCV	Ah	OCV	Ah	OCV	Ah
100%	4,266	19,39	4,268	22,85	4,266	26,65	4,272	28,95	4,272	31,23	4,278	33,33	4,278	35,03	4,261	35,48
90%	4,133	17,45	4,154	20,56	4,158	23,99	4,165	26,06	4,164	28,10	4,161	30,00	4,161	31,53	4,149	31,94
80%	4,048	15,51	4,071	18,28	4,069	21,32	4,070	23,16	4,063	24,98	4,050	26,66	4,050	28,03	4,033	28,39
70%	3,971	13,57	3,984	15,99	3,973	18,66	3,968	20,27	3,957	21,86	3,938	23,33	3,938	24,52	3,917	24,84
60%	3,898	11,64	3,901	13,71	3,878	15,99	3,862	17,37	3,850	18,74	3,831	20,00	3,831	21,02	3,806	21,29
50%	3,831	9,70	3,821	11,42	3,788	13,33	3,764	14,48	3,743	15,61	3,720	16,66	3,720	17,52	3,702	17,74
40%	3,768	7,76	3,749	9,14	3,715	10,66	3,694	11,58	3,678	12,49	3,665	13,33	3,665	14,01	3,655	14,19
30%	3,713	5,82	3,690	6,85	3,663	8,00	3,651	8,69	3,641	9,37	3,632	10,00	3,632	10,51	3,619	10,65
20%	3,669	3,88	3,647	4,57	3,625	5,33	3,617	5,79	3,608	6,25	3,589	6,67	3,589	7,01	3,547	7,10
10%	3,635	1,94	3,610	2,28	3,588	2,67	3,581	2,90	3,558	3,12	3,516	3,33	3,516	3,50	3,462	3,55
5%	3,631	0,97	3,597	1,14	3,574	1,33	3,559	1,45	3,523	1,56	3,473	1,67	3,473	1,75	3,425	1,77
0%		0		0		0		0		0		0		0		0

Figure 17: OCV (in Volts) vs Capacity (in Ah) for different temperatures

The impedance of the battery cell, or the direct current internal resistance (DCIR), is the resistance to charge/discharge of a certain battery across the terminals. This parameter under several temperatures is very important to the battery modelling for SOC correlations and terminal voltages.

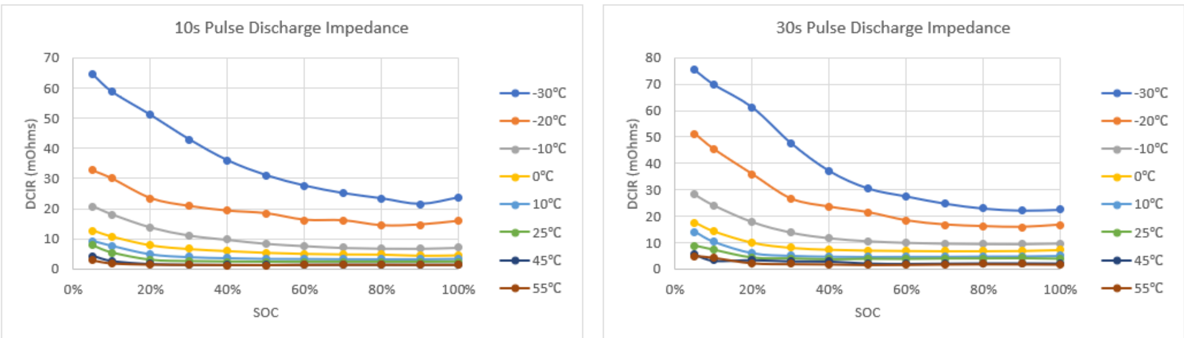


Figure 18: Direct current internal resistance (DCIR) for 300A pulse current

3.2 Battery Modelling

The battery was modelled in Simulink. Simulink offers a visual modelling interface, which was more intuitive for the project. Rather than writing the code, the model was created models using visual blocks and connections, expediting development for certain types of dynamic systems. This includes factors like state of charge, state of health, voltage response under temperature effects, etc.

First, as the datasheet from Farasis references the battery behavior in several tables, all the correlations were adapted into 2D lookup tables (Figure 19). This means that the values of OCV, capacity, temperature, impedances were included, and using linear interpolation for in-between values.

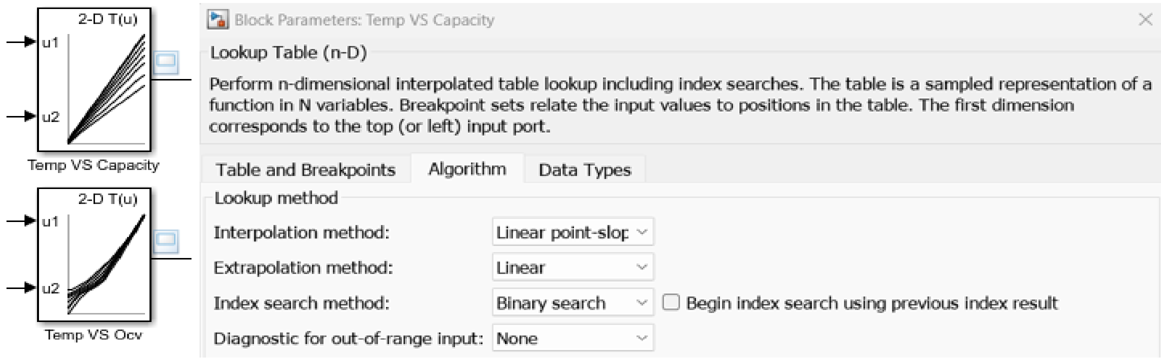


Figure 19: Lookup table block and parameters used for Temperature vs Capacity and Temperature vs OCV tables.

As the battery can be simulated for different temperatures and currents, to the correct correlation it was necessary to include a selector to modify the variables to be used in the simulation interface. In this project, radio button blocks (Figure 20) were used for temperature and current. This way the model can be modular and changeable during live simulation and get the best result to simulate the battery behavior.

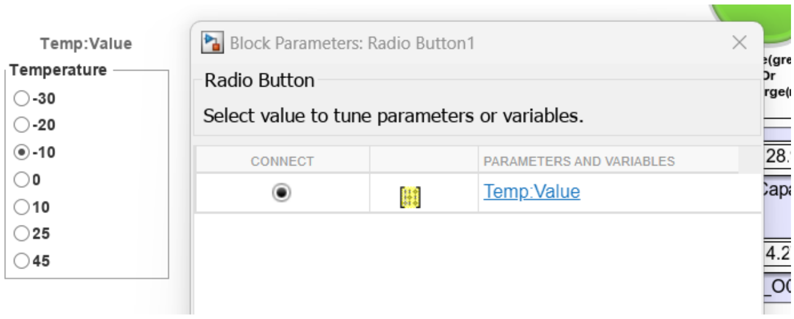


Figure 20: Temperature selector used to define variable "Temp" in the Simulink model. Same strategy was used to select the discharge and charge current.

In the context of State of Charge calculations, it was necessary to include the internal resistance effect into the battery model. This integration served to ascertain the precise voltage drop associated with a given current consumption, with the radio button block facilitating the selection of different C-rates. The implementation of internal resistance was executed as an elaborate subsystem, integrating temperature dynamics and impedance fluctuations.

Finally, the State of Health calculation was predicated on a linear estimation, as elucidated in the subsequent section. This subsystem featured a cycle counter intricately linked with the SOC subsystem, thereby enabling the continuous assessment of degradation throughout the entirety of the simulation.

4 RESULTS

4.1 Battery model

The complete battery model in Simulink calculates SOC and SOH and shows the results in percentage and graph. The effect of internal resistance on terminal voltage has been considered. Subsystems were created to facilitate navigation and comprehension, as shown in Figure 21:

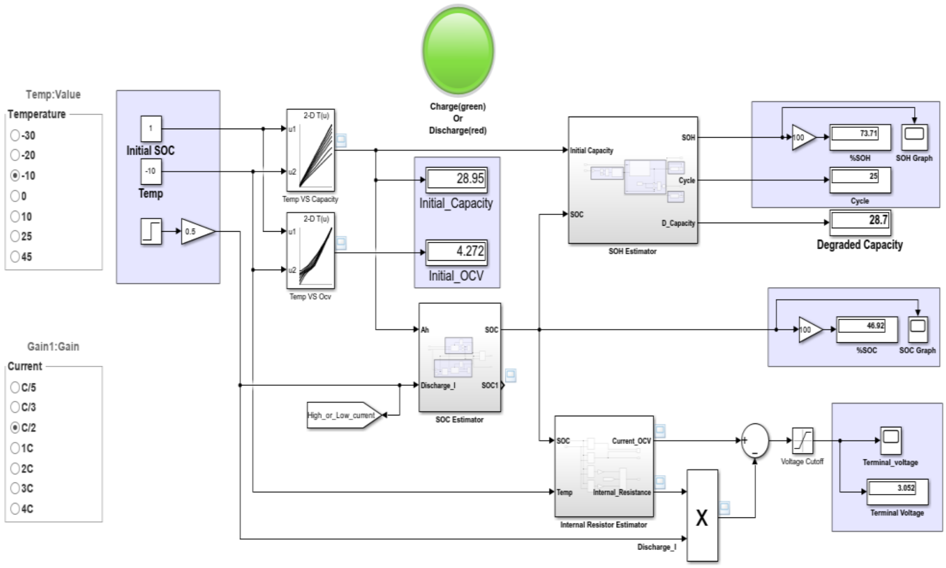


Figure 21: Final Simulink model for the Farasis Lithium battery

Inputs are the temperature and current. All estimations in the model are calculated based on these two parameters. The first lookup tables are used to find the corelated capacity and OCV based on input temperature and initial SOC. The SOC estimation block then uses this information to calculate the battery SOC and then feed the SOH and internal resistance subsystems.

There is a lamp in interface of the simulation to indicate charging and discharging cycles. Different C-rates are also considered in the model to observe different effects of it on the battery. SOC estimator block, SOH estimator block and Internal resistor block will elaborate more in next sections.

The company did not provide us with some parameters such as DOD. So, the DOD of 65% assumed and applied to the model. However, this number applied modular in simulation and it is changeable.

4.2 State of Charge

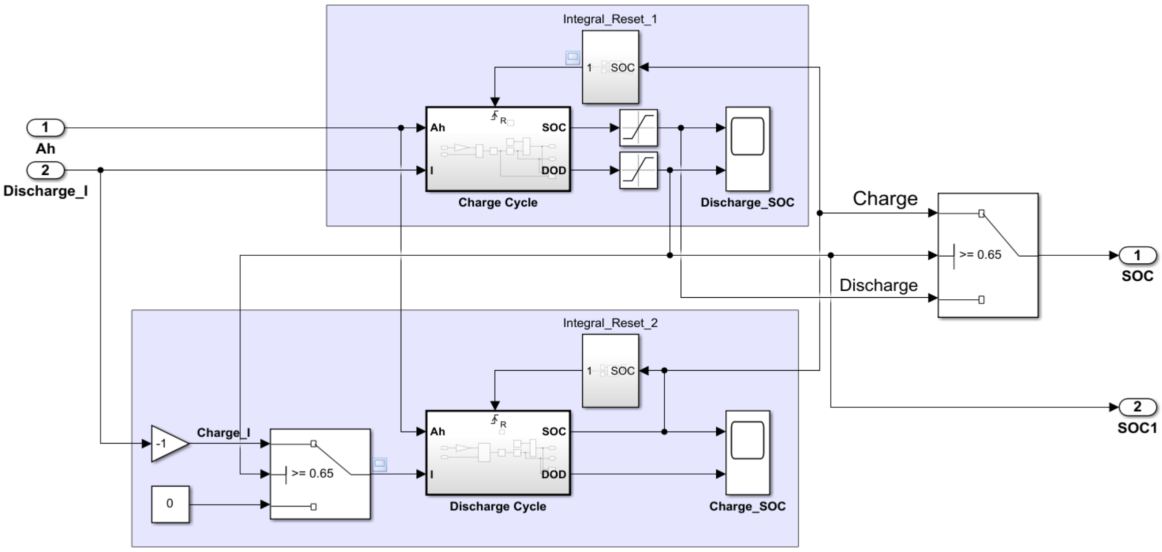


Figure 22: State of Charge (SOC) subsystem

The SoC subsystem, as shown in Figure 22, takes in consideration the capacity from the initial lookup table and the C-rate as the inputs, depending on the chosen temperature. In the SoC estimator block, there are two charging and discharging block. The SoC estimation block is based on coulomb counting method which is shown in Figure 23.

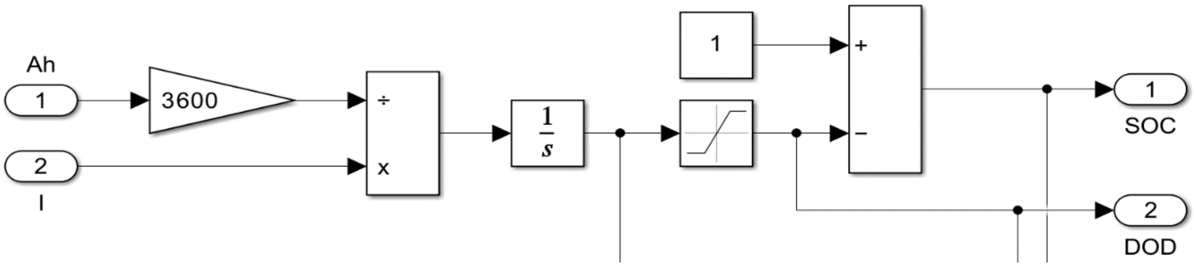


Figure 23: Coulomb counting implementation

According to what was said in the methods sections, the SoC and DoD can extracted from this formula. But the DoD is set to 65%; so, in discharge cycle the SoC would decrease from 100% to 35% and then in charging cycle it increases from 35% to 100% and this shown in Figure 24 and Figure 25.

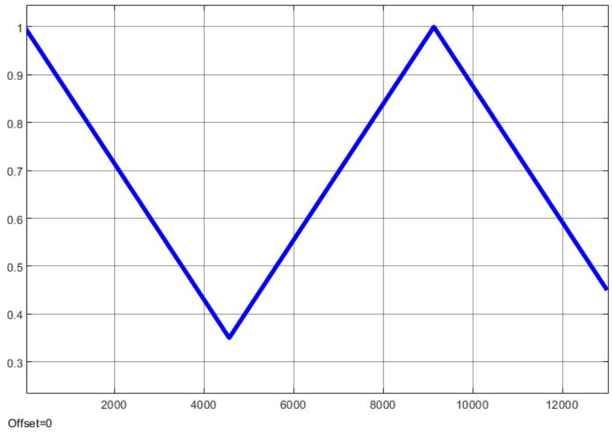


Figure 24: SOC at 1/2C (Xaxis:Time[s] - Yaxis:SOC[100%])

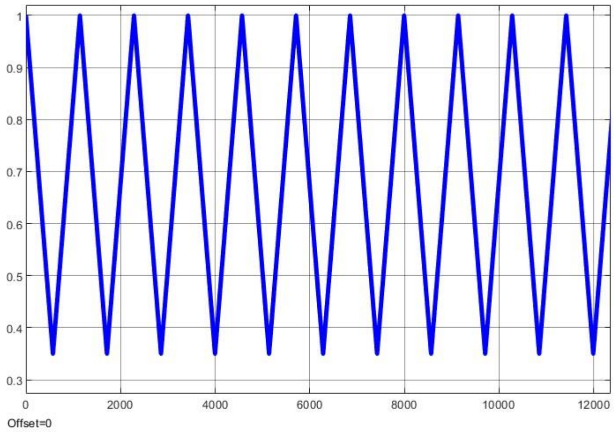


Figure 25: SOC at 4C (Xaxis:Time[s] - Yaxis:SOC[%])

The SoC-trend does not change in different C-rates and temperatures, only the time duration will change. At high C-rates, charge/discharge SoC patterns would happen faster than low C-rates.

4.3 Variable internal resistance

The internal resistance was calculated using the battery tables provided by Hyster Yale and associating the impedance to the charge or discharge current. The high current and low current impedances were considered to determine the internal resistance. If the chosen current for the circuit is more than 1C (32Amps), then it is considered a high current and all the direct current discharge impedance (DCIR) from high current DC resistance of Farasis datasheet it is used as reference. Otherwise, it is considered low current. To choose the proper current characteristic, a switch block was implemented. The implementation is displayed in Figure 26.

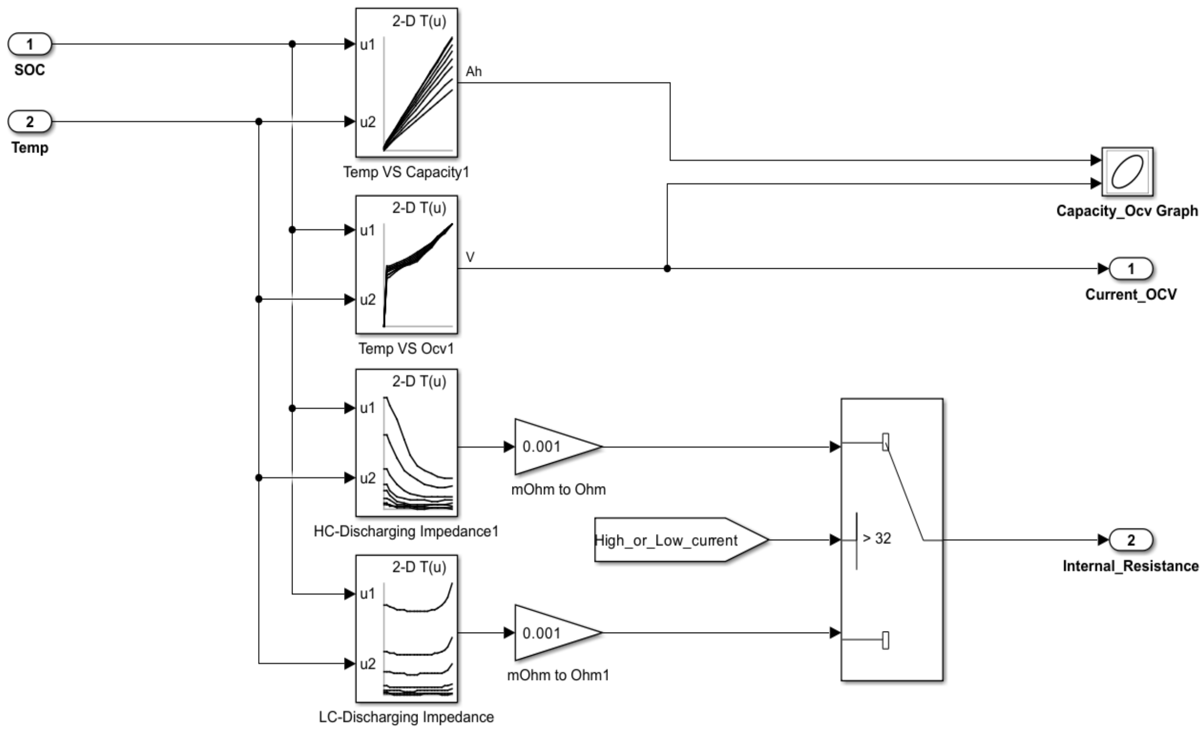


Figure 26: Internal resistance lookup tables implementation based on the DCIR information from Farasis

The internal resistances can be obtained from the model using a scope block. Different temperature and different C-rates change the trend of internal resistance at different states of charge. These differences are shown in Figure 27, Figure 28, Figure 29 and Figure 30.

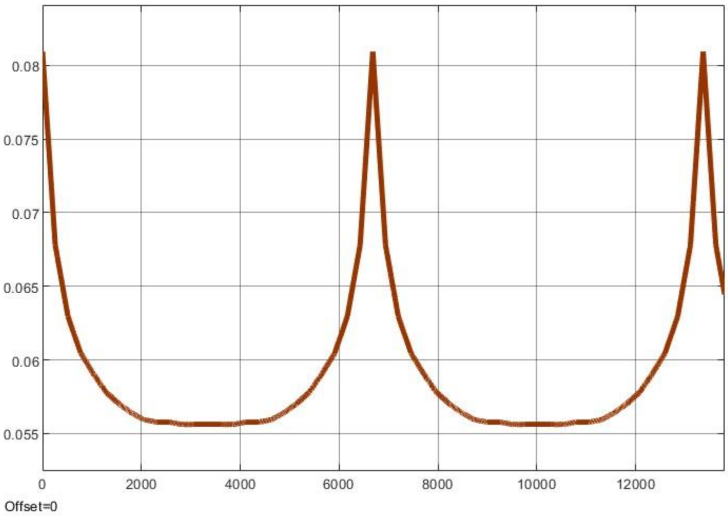


Figure 27: Internal resistance changes based on soc at LC and -20C (Xaxis:Time[s] - Yaxis:Restistance [Ω])

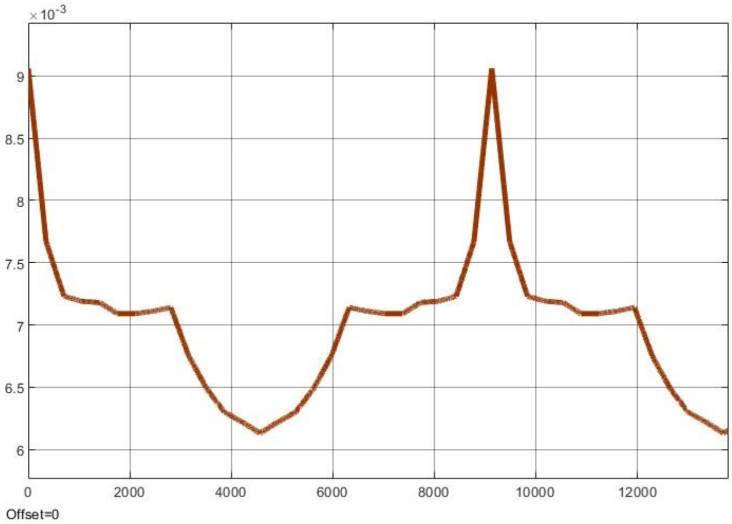


Figure 28: Internal resistance changes based on soc at LC and +10C (Xaxis:Time[s] - Yaxis:Restistance [Ω])

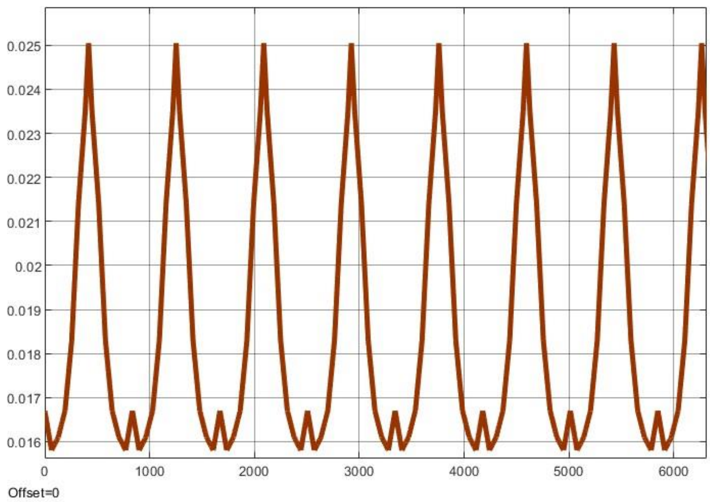


Figure 29: Internal resistance changes based on soc at HC and -20C (Xaxis:Time[s] - Yaxis:Restistance [Ω])

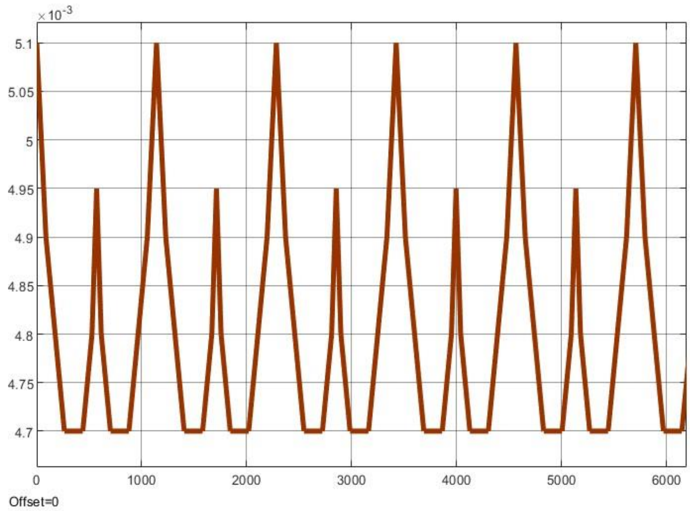


Figure 30: Internal resistance changes based on soc at LC and -20C (Xaxis:Time[s] - Yaxis:Restistance [Ω])

4.4 Terminal Voltage

The terminal voltage ($V_{terminal}$) can be calculated after the internal resistance (R_{int}) calculation, as by Ohm's law (using the charge/discharge current) it is possible to determine the voltage drop due to this impedance. The difference between the OCV and the voltage drop from internal resistance it is going to be the terminal voltage:

$$V_{terminal} = V_{OC} - (I \times R_{Int}) \tag{13}$$

This formula has been implemented in Simulink as shown in Figure 31.

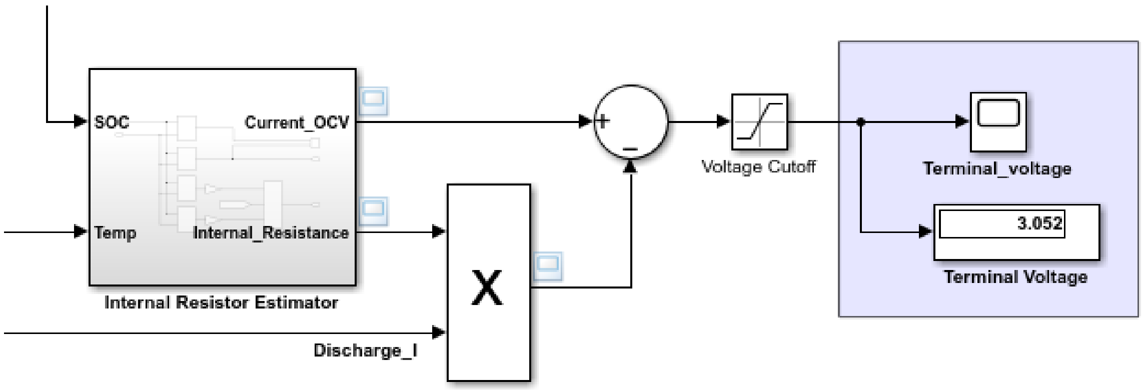


Figure 31: Terminal voltage calculation and display, after the internal resistance subsystem. OCV is based on the table using the temperature as input

The results from terminal voltages can be monitored by a scope block in the model. As the simulation keeps repeating charging and discharging cycles, the terminal voltage presents a variation from low SOC to high SOC as expected. Different C-rates and temperatures affect internal resistor and internal resistor changes have a direct effect on OCV. By changing C-rates from LC to HC, a sharp drop of OCV is observed in Figure 32. Also, OCV drop is observable when the temperature goes down as shown in Figure 33.

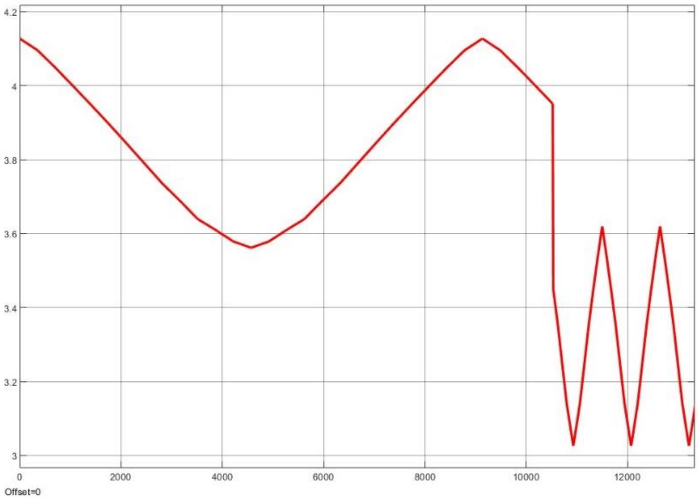


Figure 32: Ocv changes based on LC to HC at +10C (Xaxis:Time[s] - Yaxis:Voltage[V])

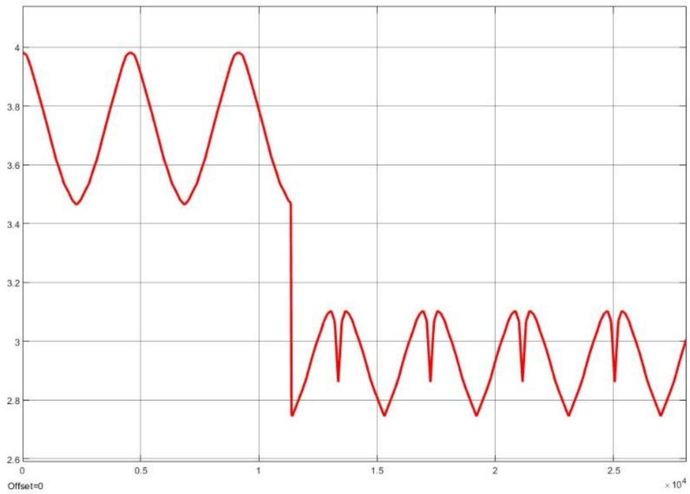


Figure 33: Ocv changes based on decreasing the temperature (Xaxis:Time[s] - Yaxis:Voltage[V])

4.5 State of Health

To model the State of Health of the battery we have used the capacity fading model with linear degradation which uses a degradation factor for every charge-discharge cycle decreasing the maximum capacity of the battery and determines the state of health of the battery.

Two different degradation rates were used in this algorithm, one for high current and one for low current to simulate the increase in degradation when the load is high.

0.01 and 0.001 were used as degradation rate values for high and low current respectively, these were values for testing the algorithm and the actual values need to be provided by the company based on experimental data of the battery system and can be inserted in this function to model the actual degradation of the maximum capacity of the battery.

The constants for degradation rate are used to calculate the degraded capacity after every cycle using the formula below:

$$Degraded\ capacity = Initial\ capacity - Degredation\ rate\ \times Cycle \quad 14$$

The values of degraded capacity after every cycle are then inserted in the main formula for calculating the SoH. The formula used for this in the Simulink model is as follows:

$$SoH\% = \frac{Degraded\ capacity - EOL\ capacity}{Initial\ capacity - EOL\ capacity} \cdot 100 \quad 15$$

Where, 'EOL_capacity' is the end-of-life capacity of the cell.

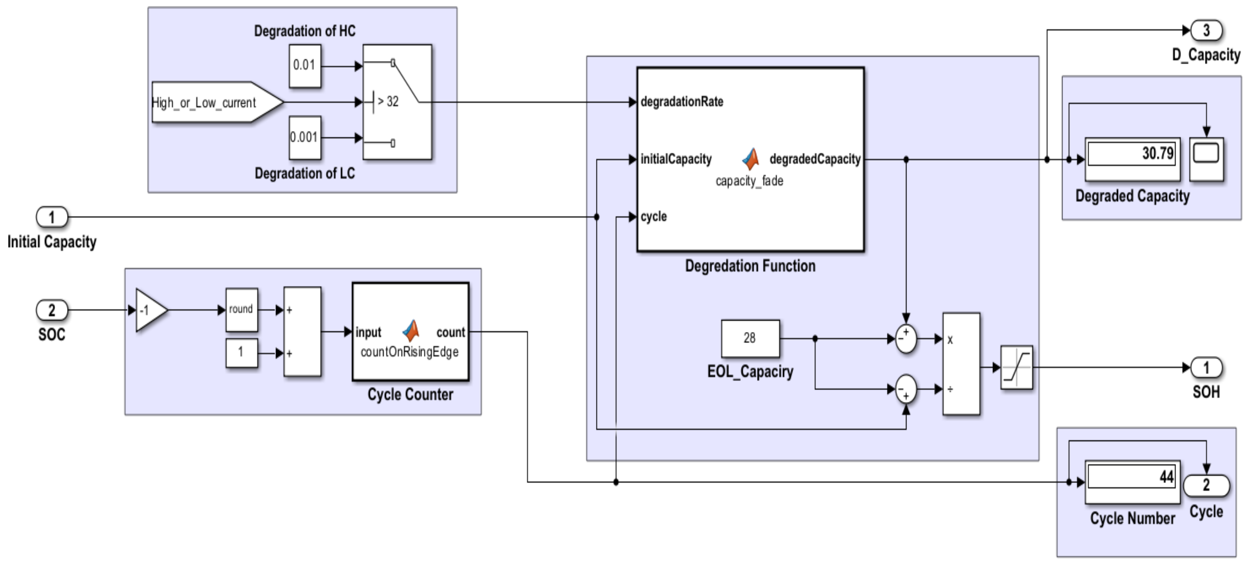


Figure 34: State of Health Estimation implementation

There was also used a 'MATLAB function' block for counting the number of charge-discharge cycles. This function uses the output from the SoC block and counts the number of times the battery is fully charged and discharged and outputs this value for use in the calculation for degraded capacity. Figure 35 shows the plot for capacity degradation and the effect of low current and high current c_rates on it:

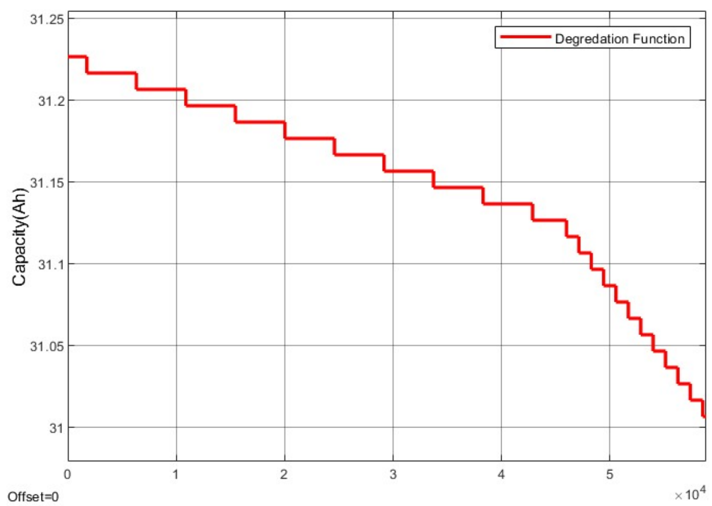


Figure 35: Effect of LC to HC changes on capacity degradation

As it is obvious, by changing the c_rate, the damage factor would change and it's number will increase in the model based on real battery models. The battery life would be in danger if it used in high current discharge cycles.

SOH will be affected by changing C-rate and temperature. This effect is justified by the different damage factor of different C-rates on battery health. Based on testing damage factor assumptions, the results shown below:

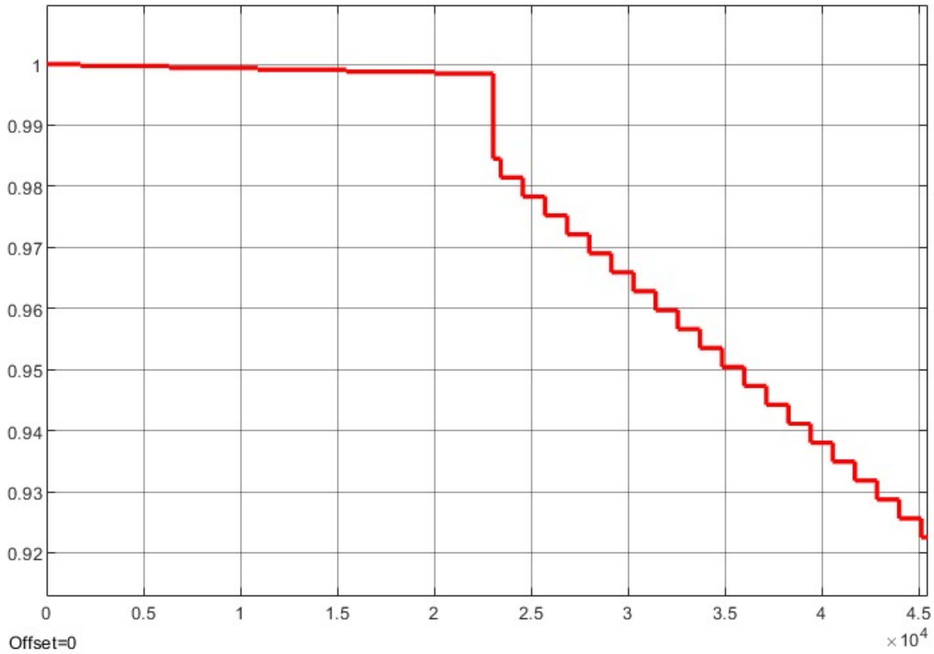


Figure 36: Effect of LC to HC changes on SOH (Xaxis:Time[s] - Yaxis:SOH[%])

By comparing the SoH plot with Figure 37, it can be seen how the SoH of the battery decreases with the number of charge-discharge cycles. The result can be validated by comparing the SoH plot to the plot of capacity retention given in the Farasis datasheet provided by Hyster Yale.

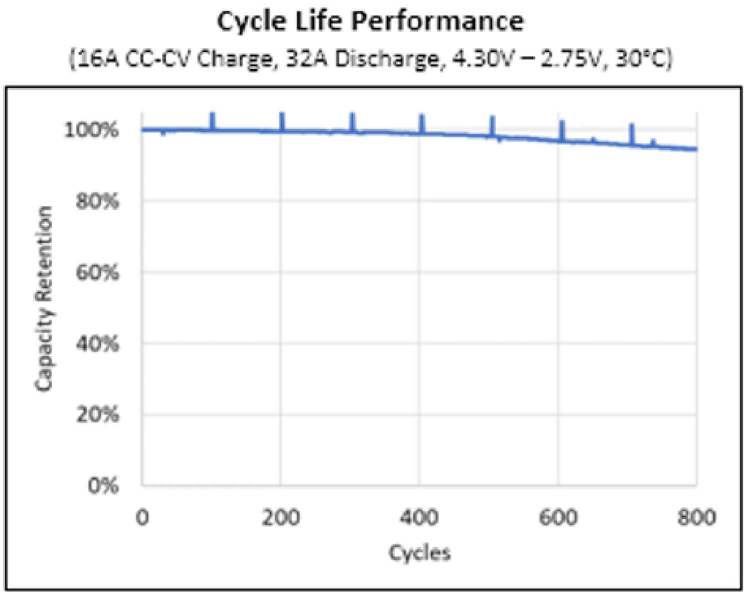


Figure 37 Farasis P32 battery cell capacity retention

5 DISCUSSION

As explored in preceding sections, the model demonstrates a commendable ability to forecast the behaviour of the actual value with acceptable precision. Nonetheless, there is room for enhancement. Initially, the model operates within specific C-rates, and while this limitation does not result in a substantial deviation from the actual battery's behaviour, introducing additional C-rates would bolster the model's reliability. From the literature review, it is learned that the self-discharge and accumulative erros of coulomb counting can be significant. In the current model, these effects are not implemented.

Furthermore, the degradation function employed in the battery is currently a linear function. While this function proves reliable and accurate in terms of performance, it lacks inclusion of the battery's chemical characteristics. This deficiency arises from the absence of crucial parameters pertaining to the internal chemistry of the battery. It is important to highlight that the data supplied by the company solely depicts the model's behaviour in anticipated scenarios, with no mention of unexpected situations, such as instances of high current consumption. Consequently, the battery is modelled based on expected situations, with special cases left unaccounted for. Another critical issue is the absence of information from the company regarding the state-of-health of the battery. Consequently, validating the model's behaviour in this regard is not feasible due to the lack of pertinent data.

Overall, judging from the graphs supplied by the company, the implemented battery model exhibits a remarkably similar functioning, leading to the conclusion that the implementation has been successful.

6 CONCLUSIONS (AND RECOMMENDATIONS)

In conclusion, our project successfully implemented a comprehensive approach to understanding and predicting battery performance and longevity. Using Coulomb counting, we modelled the State of Charge (SOC) of the cell with succes, as the SoC goes through more cycles is in the same amount of time when the current is increases. Coulomb counting however, has as drawback that it does not consider self-discharging and it can accumulate an error when the current-measurement is not accurate enough.

The State of Health (SOH) was meticulously modelled, incorporating a degradation constant to simulate a linear decline in the battery’s capacity after every charge-discharge cycle, also taking into account the degradation at both higher and lower loads. This aspect of the model is particularly crucial, as it offers a predictive look at the battery's lifespan and helps in planning maintenance and replacement schedules. But the chosen algorithm in this project results in a linear degradation in the State of Health after every cycle and does not accurately represent the real behaviour of a battery. Therefore, in the future it is recommended to use the method no. 4 given in the literature research part of State of Health estimation which takes into account the effect of damage accumulation on the degradation of the battery.

When batteries are assembled into a pack, charging and discharging leads to imbalances of current capacities in some cells. This causes different voltages and SoC’s of the individual cells. Since the batteries can't be charged beyond the capacity of the highest-capacity cell, some cells in the pack won't be fully charged. Consequently, the overall capacity and the State of Health of the pack are diminished. Therefore, the importance and methods of cell balancing were also mentioned.

Our model incorporated a range of parameters and variables, reflecting the complex nature of battery behaviour under various conditions. The findings from this project have significant implications for the design and management of battery systems in various applications. As battery technology continues to evolve and play a crucial role in numerous industries, the insights gained from this project will be invaluable in driving innovation and efficiency in battery usage and management.

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8 LIST OF FIGURES