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Characterization and Modelling of Second-Life 18650 Lithium-Ion Batteries

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ABSTRACT :

The potential to shift from heavily reliant on fossil fuels for traditional energy systems to more sustainable ones depends on energy storage technology developments. One of the main contributors to this transformation nowadays is Lithium-ion (Li-ion) batteries, which offer the best energy density, longevity, and dependability. These batteries are commonly served in electric vehicles (EVs) as their primary purpose but can be served in stationary Energy Storage Systems (ESS) because of their vast capacity.

This master's thesis explores the complex area of second life for lithium-ion batteries, primarily focusing on the 18650-cell format. By combining the theoretical framework, experimental studies, and optimization approaches, this work enriches the advancements in the fast-growing area of battery science. The first part of the study focuses on reviewing the literature on lithium-ion batteries to demonstrate their background, chronology, chemistry, and degradation mechanism. Based on that, the research further involves modeling and characterizing essential parameters of 18650 Li-ion cells utilized in Tesla EVs. Therefore, the study performs a real-world valid model using experimental data and equivalent circuit modeling and optimization tools for these cells and their performance under different operating conditions.

Each critical performance factor, like internal resistance, open circuit voltage, and polarization resistance, is highly elucidated. Optimization of capacity involves compromise decisions concerning capacity factors, load of internal stimulants, deterioration, thermal factors, and costs at a particular phase of time. Some practical solutions prove the efficiency of the introduced optimization methods and illustrate how second-life batteries can be incorporated into grid storage systems and portable devices. The thesis also considers the cost-benefit analysis of second-life batteries, thus offering recommendations in terms of applicability for people in industries and scholars globally. Some of the subjects addressed are the next cell sorting infrastructure issues, thermal control systems, batteries' control systems, and integration issues. Moreover, it also investigates the trends for the future, such as the need for a more integrative approach and advancements in technologies on battery research.

KEYWORDS: 18650 lithium-ion batteries; second-life applications; battery modeling; equivalent circuit models; design of experiments

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Abbreviations

EV	Electric Vehicle
Li-ion	Lithium-Ion
EIS	Electrochemical Impedance Spectroscopy
CV	Cyclic Voltammetry
FEM	Finite Element Methods
CFD	Computational fluid dynamics
ECM	Equivalent Circuit Model
DOE	Design of Experiments
ESS	Energy Storage Systems
NMC	Nickel Manganese Cobalt Oxide
LFP	Lithium Iron Phosphate
NCA	Nickel Cobalt Aluminum Oxide
SSB	Solid-State Battery
BMS	Battery Management System
SOC	State of Charge
CCCV	Constant Current Constant Voltage
CC	Constant Charge
OCV	Open Circuit Voltage
HPPC	Hybrid Pulse Power Characterization
SEI	Solid-Electrolyte Interphase
ANN	Artificial Neural Network
ERBM	Equivalent R_{int} Battery Model
EGTBM	Equivalent Generalized Thevenin Battery Model
PNGV	Partnership for a New Generation of Vehicle
IoT	Internet of Things

1 Introduction

The transition from conventional fossil fuel-based energy to clean or green energy is proceeding rapidly through the revolution of newer energy technology, especially the development of energy storage and consumption technology. Both battery and electric vehicles (EVs) are two focused areas where proper technological improvement can impact this whole transition (Zimm, 2021). Counting this development and popularity of electric vehicles (EVs), lithium-ion (Li-ion) batteries—especially the 18650-cell format—are frequently used in the most popular EV series because of their improved energy density, longevity, and dependability (Yang et al., 2023). However, the life cycle of these battery cells is not linear, nor does it end with their usage in electric vehicles (Koroma et al., 2022). The EV needs an exceptional level of performance from these cell modules. After a while, this battery module is not capable of delivering the expected requirement of the second-life application in stationary energy storage systems of these modules; hence, the battery cell can utilize these energy storage resources effectively (Roschier et al., 2020). It is evident that this dual application facilitates the integration of renewable energy sources into the power utility grid while also reducing the environmental effects of battery disposal (Razif et al., 2024). As the battery cells are not brand new and have some limitations in delivering at full potential, hence, proper modeling and characterization can help to provide appropriate figures for reusing the batteries for optimum performance while guaranteeing their longevity. This work is directed towards the background of this procedure, developing the advanced structural models, and distinguishing important aspects of attributes of 18650 Li-ion cells for both principal and secondary use.

1.1 Background and Motivation

Energy storage devices are becoming more and more necessary as the focus shifts to higher environmental management through sustainable energy systems. Figure 1 shows the market condition of energy storage installation globally. The rate of installation is increasing exponentially because of the focus on establishing sustainable energy systems.

The 18650-battery cell module is one of the popular modules in EVs for its higher performance in smaller dimensions and better thermal stability than stacked thin pouch cells without coolant pipes (Zhao et al., 2022).

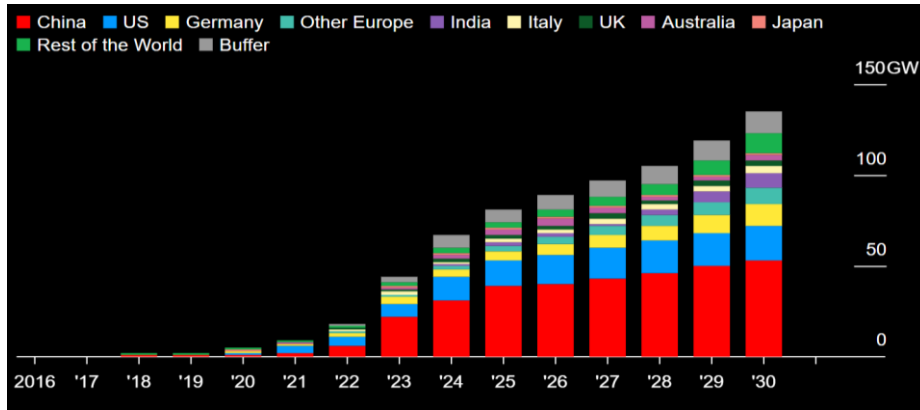


Figure 1. Global gross energy storage additions by market (“Global Energy Storage Market Records Biggest Jump Yet,” 2024)

Nevertheless, once their lifecycle in EVs comes to an end, they possess a considerable capacity to remain viable in the secondary application of ESS. Figure 2 depicts the amount of battery modules returned from EV servicing, and the forecasting also shows exponential growth.

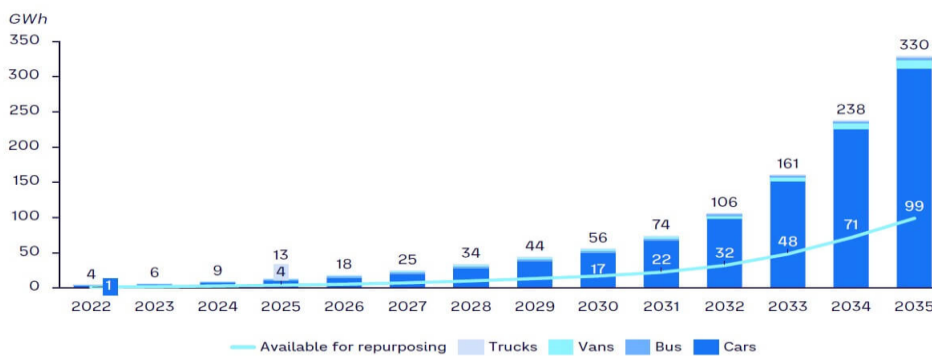


Figure 2. Global returning EV batteries forecast (*Second Life*, 2024)

Hence, this creates a massive market for recyclable potential battery modules. From that perspective, Lithium-ion (Li-ion) batteries in the 18650 types are readily available in the

secondary battery market, and they have high energy density and long cycle life in this battery format.

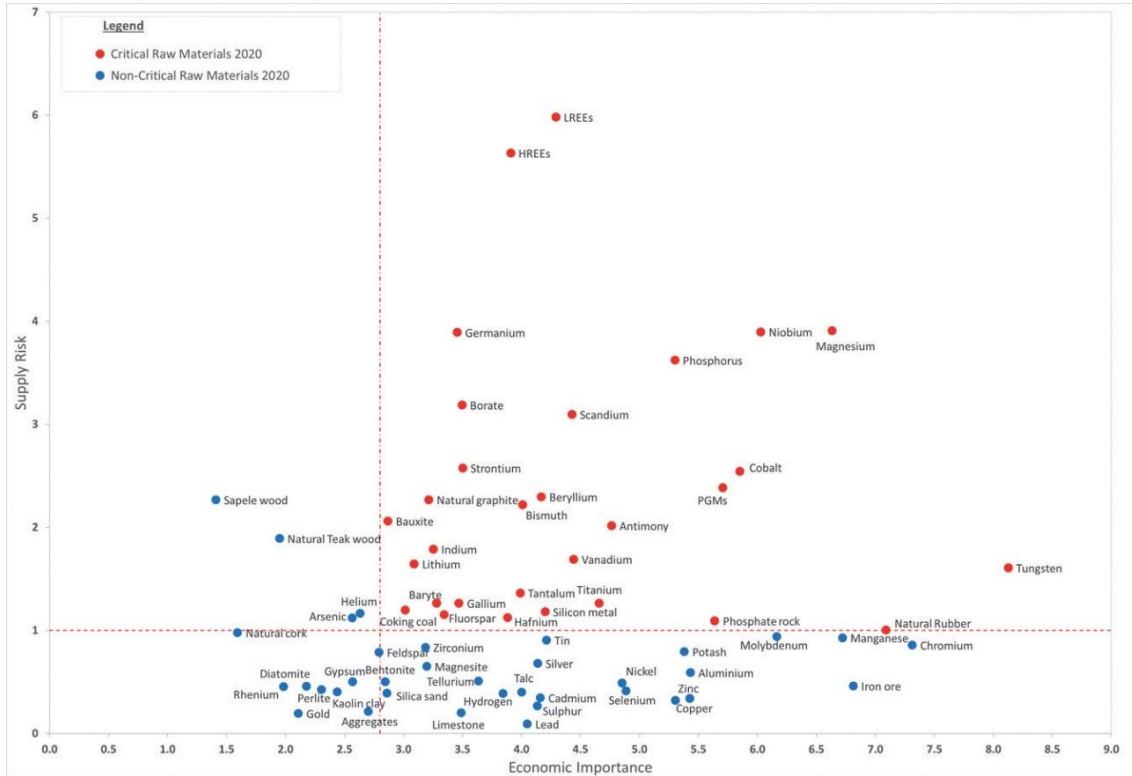


Figure 3. List of critical raw materials established by the EU according to their economic importance and supply risk (Commission et al., 2020)

Besides the availability, there are some environmental impacts as well to recycling those batteries without reusing them. The consequences of disposal of used batteries from electric vehicles (EVs) have numerous adverse effects, particularly on the environment and human health. Heavy solid metals and other toxic chemical substances contamination of the soil and water is one such concern (Guzek et al., 2024). Also, it contributes significantly to the economic cost of battery disposal and the cost at which raw materials for these batteries are extracted. Figure 3 shows that some of the necessary raw materials, including lithium, are considered critical raw materials defined by the EU from both economic and availability perspectives. These motives accelerate the use of second-life batteries by EVs in potential application sectors. Figure 4 shows the EV battery lifecycle, including the possibility of a second-life battery application. Second-life batteries offer a

favorable application in stationary ESS for operating and fine-tuning electricity generation from infrastructures such as solar power plants, windmills, or other renewable sources.

As for renewable energies on their own, they fluctuate by nature, meaning storage solutions and balancing of supply and demand need to be in place (Gan et al., 2020). ESS is essential in renewable energy systems for solving technical issues with voltage fluctuations, system inertia, and frequency stability.

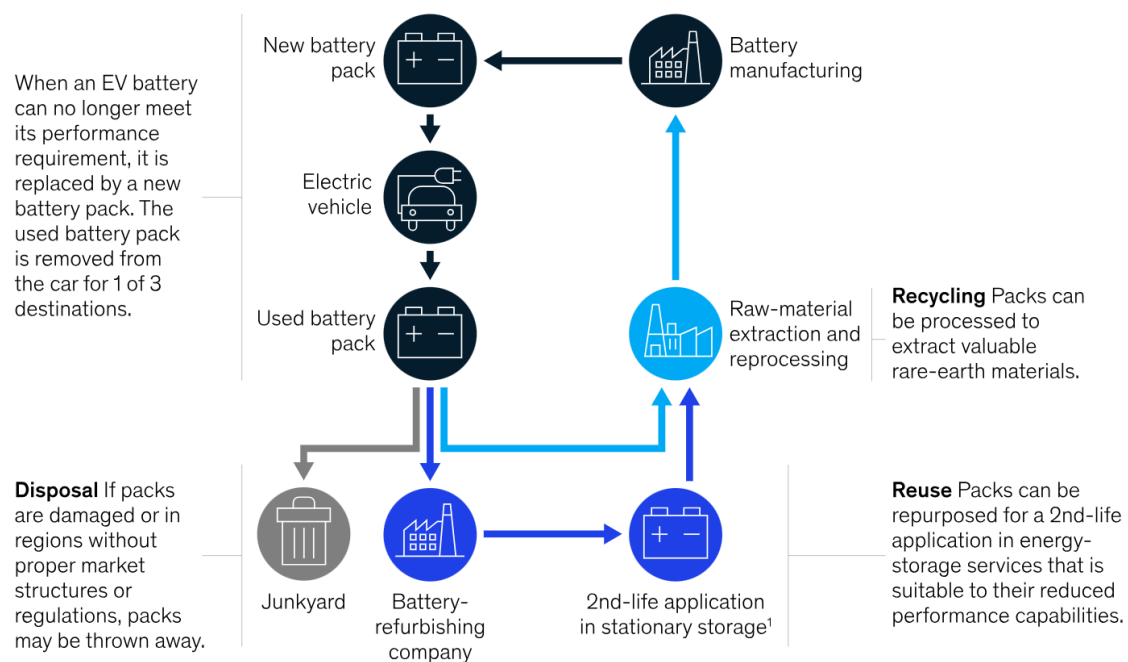


Figure 4. EV battery lifecycle (including second-life application) (*Electric Vehicles, Second Life Batteries, and Their Effect on the Power Sector | McKinsey, 2019*)

These systems can swiftly react to grid disruptions by supplying or absorbing power as needed to preserve frequency regulation and guarantee the integrity of the energy system. Second-life batteries can help store renewable energy produced during the day when the sun is shining or during windy times and discharge during the evening or during windless times, hence stabilizing the grid and improving the reliability of renewable energy systems.

Since second-life batteries require trade-offs between cost and battery degradation, the second-life strategy should be informed by accurate modeling of battery performance and degradation over the battery's lifetime and for any proposed use (Ahmadi et al., 2014). Electrochemical models, which simulate the internal working procedure of batteries and how they behave under different vehicle settings, are another type of diagnostic that may be useful in assessing battery health and level of discharge. These models incorporate several variables that impact a battery's life cycle, temperature, cycles of charge and discharge, and battery aging (Smith et al., 2010). Methods for characterizing electrode materials are also essential in evaluating the microstructural evolutions during the cycling process. Metrics like internal resistance, energy capacity loss over the battery's usage, as well as general and degradation modes, give a detailed perspective of a battery's health status in an electrical format (Ibraheem et al., 2023). These include details that are highly useful in determining the efficiency of second-life batteries and how best they could be utilized or disposed of. Another factor that holds an input towards the dependency aspect is known as the capacity fade, which refers to energy losses that accumulate over the regular use of the battery (Q. Zhang & White, 2008). Several age-related processes, like the deterioration of the battery's electrolyte and the development of solid electrolyte interface layers, are further described to be active parameters that influence the capacity and overall durability of the battery. Several parameterization techniques or procedures are available, and the calculation of internal resistance and capacitance depends on different types of test responses. The most crucial factor that needs to be found is the capacity of the battery cells, which eventually represents the state of health of the batteries.

Newer innovations need to be combined to characterize batteries with faster, safer, and more effective strategies to ensure the efficiency of second-life batteries in ESS applications. Methods such as Electrochemical Impedance Spectroscopy (EIS) and Cyclic Voltammetry (CV) can give detailed insights into the internal migration and storage in a battery in terms of the internal resistance as well as the capacity (Azizighalehsari et al., 2024). Furthermore, for enhanced simulation possibilities, other methodologies can be

incorporated, for example, finite element methods (FEM) and computational fluid dynamics (CFD), for concluding the inside phenomena of the battery and its behaviors under operative control. In addition, SOC estimation plays a critical role in BMS technology and, hence, should be optimized. These estimates assist in making recommendations of the right time for battery refurbishment or replacement, as well as in control of the ESS's operation performance. Sophisticated techniques in modeling and characterization can improve the prediction of SOC in batteries and, consequently, the effective coordination of second-life batteries. Hence, the advanced level of modeling like EIS, CV or FEM, and CFD are more feasible or practical in modeling when the battery is installed in any application concerning desired load demand and different constraints. Apart from that, the equivalent circuit model analysis with SOC optimization is more vital since it represents the current capacity conditions of the module or cell and the state of charge of the batteries, establishing whether those batteries are efficient enough to be installed in any desired secondary applications.

From an electrical engineering standpoint, the fundamental analysis of second-life EV battery cells requires an initial focus on Equivalent Circuit Modeling (ECM). Eventually, this intuition motivates me to focus on defining the objective and scope of this research work and proceed further.

1.2 Objectives of the Study

The main aim of this study is to develop the procedure and justify comprehensive equivalent circuit models for second-life 18650 Li-ion cells and to characterize critical parameters influencing their performance, primarily related to battery health and capacity. The detailed objectives include the following –

- (1) **Design of Experiments (DOE):** Proper planning and the design of experiments are essential for obtaining valid and reproducible results. A detailed methodology for the design of experiments will be developed to include different operating

conditions, such as temperature variations, charge/discharge rates, and aging cycles, to capture the performance characteristics of the battery over its designed life.

- (2) **Experimental Data Analysis:** The experimental data has several key phases that need proper data sorting and analysis. The analysis of this experimental data using advanced statistical tools and machine learning methods for meaningful inferences and to establish quantitative relationships between key parameters such as internal resistance, capacity fade, and degradation mechanisms and the battery performance indicators.
- (3) **Equivalent Circuit Modeling:** Based on the principles of electrical circuit theory and using experimental data, equivalent circuit models will be developed to capture the dynamic behavior of the 18650 lithium-ion cells appropriately. This should include the SOC estimation and temperature dependency on the model parameters for appropriate performance prediction under different operating schemes.
- (4) **Parameterization and Modeling Methods:** Development of modern data-driven techniques that will enable the accurate parameterization of the equivalent circuit models concerning the experimental setup. Such methods will involve the use of advanced optimization tools at an extended level to extract and match model parameters with experimental data.
- (5) **Characterization Techniques:** Temperature dependency on the characterization technique is essential as all electrical parameters, like resistors and capacitors, are dependent on temperature fluctuation. Hence, focusing on temperature variation has been prioritized over other application-based characterization techniques. Such insights will inform the modeling efforts and improve the understanding of degradation mechanisms.

- (6) **Second-Life Applications:** The performance of second-life 18650 cells will be assessed within stationary energy storage systems, particularly for integrating renewable energy. For this, modeling techniques will be developed, considering aging and degradation, as well as the influence of thermal management on the performance of the batteries, thereby enabling the optimization of energy storage systems and maximization of the lifespan of second-life cells.

Through the fulfillment of these objectives, this research will contribute to the realization of models for the efficient use of second-life lithium-ion batteries in many applications and to the development of energy storage technology.

1.3 Scope and Limitations

The prospects of battery modeling are wide enough at the application level. However, the scope of extending to an advanced, sophisticated level of design includes chemical degradation, thermal runaway, 3D thermal and resistive loss calculation, etc., needs a more advanced level of research procedure and knowledge. Hence, the scope of this research work can be described as –

1.3.1 Scope

The scope of this work is limited to modeling and characterizing the 18650 lithium-ion cells, focusing on their principal application in electric vehicles (EVs) and their subsequent usage in stationary backup storage systems (ESS). Development of detailed equivalent circuit models able to simulate the dynamic behavior of 18650 lithium-ion cells with high accuracy at various operating conditions, such as temperature changes, charge and discharge cycles, and the aging process. Besides that, robust characterization methodologies of internal resistance, capacitance, and open-circuit voltage as a function of SOC and second-life battery modeling optimization with equivalent circuit models to fit

experimental data and reliable predictions for second-life battery performance during stationary ESS use.

1.3.2 Limitations

In all comprehensiveness, there are some limitations in this scope area, which can be defined as:

- (1) **Data Limitations:** The dependence on the available experimental data may not cover all the possible degradation cases and operational conditions that exist in real applications; this could limit the generalizability of the results. However, variations in test profiles with charging-discharging duration, number of cycles, and timing replicate most of the degradation behaviors.
- (2) **Operational Assumptions:** Standard conditions for battery operations are considered in this study, which may tend to drift from realistic situations, as such practical scenarios deviate from ideal conditions on account of several environmental and operational factors relevant to the real world. Additionally, this analysis focuses on the cell level, where various power electronics equipment integrates at the module level to achieve desired performance outcomes. In particular, the BMS assists in maintaining control over some difficult parameters that can only be reached at the module or management level through complex control strategies.
- (3) **Model Complexity:** The equivalent circuit models developed might not capture all the intricate electrochemical processes and interactivity within the battery, and hence, their predictive and accurate capabilities could be restrained in some respects.

- (4) **Sensitivity of Testing Module:** The sensitivity of the testing module used in this work might not be so sensitive or capable of hosting all types of testing with accurate precision. As the cell dimension is a factor related to the sensitivity, the obtained results might be uncertain or limited up to the testing capabilities.

When extrapolating findings to different contexts or applications, it is essential to carefully consider these constraints. Future studies should also focus on overcoming these obstacles and improving modeling and characterization techniques for lithium-ion batteries.

1.4 Structure of the Thesis

In an effort to do so, this master's thesis is divided into six distinctive chapters that systematically analyze the background, modeling, parameterization, and optimization of an 18650 lithium-ion cell specifically for the usage of secondary stationary energy storage systems.

- Chapter 1 presents a brief background to the study as well as the importance or reasons why this research work is significant, and it outlines the goals, extent, and constraints of the research work on which the rest of this dissertation will be built.
- Chapter 2 focuses on the related literature of this scientific development on this model, to be precise on lithium-ion battery technology. It includes the past and evolution of the 18650 cells, second life utilization, cost and effects on economy and environment, and the major degradation processes. This chapter also explained the cell specifications, construction, initial background, and technological development of specific Tesla 18650 lithium-ion cells, e.g., energy density, cycle life, and thermal stability over time from an industrial point of view.

- Chapter 3 emphasizes an outline of the methods used in the study of the presented subject: the experimental data acquisition and theoretical parameter estimations, the development of the equivalent circuit model for a battery on the MATLAB platform, the optimization process, and other methods relevant to battery behavioral prediction.
- In Chapter 4, the key aspects are to give the reader an understanding of what battery modeling encompasses and can be divided into three categories which are Electrochemical Models, Data-driven Models, and Equivalent Circuit Models. The strategies in developing, verifying, and simulating ECMs and second-life applications for 18650 cells are demonstrated and analyzed. This chapter also describes the techniques for the identification of the parameters, estimation of SOC, model development, optimization, and validation.
- Chapter 5, "Applications and Future Work," illustrates the current use of the concept in grid storage solutions and portable electronics. Therefore, it outlines the future intentions and modern development of battery chemistry and the battery's integration into renewable systems and presents potential research areas, new technologies, and a multidisciplinary focus.
- Chapter 6 also summarizes the thesis's overall outcomes, research contributions, and future recommendations for industry and academia regarding energy transition and the realization of second-life batteries.

To provide a thorough understanding of this topic and the possibilities for future developments in the field of energy storage systems (ESS) with this second-life lithium-ion 18650 cell, this research work delivers a step-by-step through the structured set of information regarding the cell modeling, parameter characterization, and optimization.

2 Literature Review

As the demand for lithium-ion battery technology is growing significantly, technological development is massively achieved at the research level. In this chapter, the focus is to discuss these findings and their limitations, which eventually help to improve this research work and contribute further.

2.1 Overview of Li-ion Battery Technology

Lithium-ion battery technology is an addition to the already established different battery technologies with more efficient chemical substances. The historical development in lithium-ion batteries helps to minimize the gap between commercial use in energy storage systems with batteries.

2.1.1 History and Development of Li-ion Batteries

Consequently, it may be traced back to the foundational ideas established by M. Stanley Whittingham at the dawn of technology in the early 1970s. Whittingham was a member of the breakthrough Stanford University team that developed titanium disulfide (TiS_2) as a host for lithium intercalation (*The Nobel Prize in Chemistry 2019*, n.d.). Figure 5 shows the Structure of TiS_2 with different lithium filling techniques. The development of lithium-ion batteries proceeded further, and in 1980, John B. Goodenough from the University of Oxford revealed lithium cobalt oxide ($LiCoO_2$) as a potential cathode material (O'Neill, 2020). This was a major achievement in the development of lithium technology. The energy density and electrochemical properties of lithium-based battery systems rapidly improved because of this finding.

However, the major advancement was demonstrated in 1985 when Akira Yoshino of Asahi Kasei Corporation and his research team demonstrated that forming a composite of a carbonaceous anode material (carbon-based material), namely petroleum coke with Goodenough's ($LiCoO_2$) cathode would indeed deliver batteries which are performing

on an expected scale (*The Nobel Prize in Chemistry 2019*, n.d.). This addressed the fundamental step in countering the safety challenges that were attributed to the highly reactive lithium metal anodes, hence providing the much-needed pathway toward the future availability of Li-ion batteries with enhanced safety margins. The first commercial Li-ion battery was produced in 1991 by Sony Corporation, although the first experimental models were previously produced by NEI and Sony in 1985 (Yoshino, 2012).

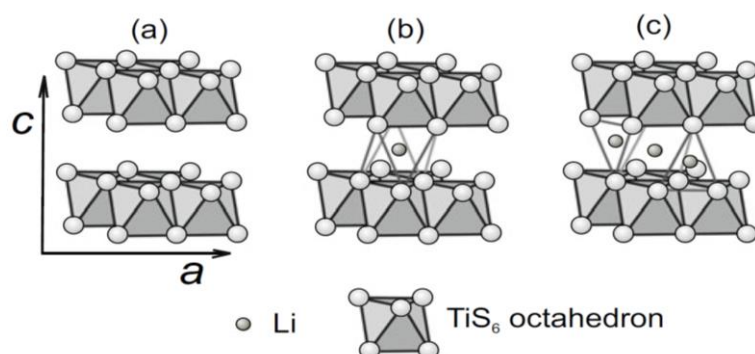


Figure 5. Structure of TiS_2 in three different filling techniques of Lithium (Suslov et al., 2016)

The lithium cobalt oxide cathode and the carbon anode are two components of this part. This brought in a completely new era of energy storage technology, which, when received massive adoption, can further enhance the ongoing research and development. Subsequent extensive research focuses on the cathode materials for battery application to fine-tune the four vital factors such as energy density, power density, safety, and cost. Through these efforts, three dominant cathode chemistries evolved. Lithium Nickel Manganese Cobalt Oxide (NMC), in which nickel, manganese, and cobalt oxides in a solution of varying ratios, provides high energy density, power, and thermal characteristics (Yoshizawa & Ohzuku, 2007). More Nickel content gives high energy density with the disadvantage of low stability, while Manganese improves thermal stability and decreases cost (Li et al., 2024). Current Generation NMC cathodes are employed in electric vehicles (EVs) and large-scale energy storage solutions because of their density and thermal behavior. Lithium iron phosphate, or (LFP), is made up of Lithium, Iron, and phosphate, which has a natural or inherent edge in safety features, thermal issues, and cost influence (Song et

al., 2024). Despite possessing lower energy compared to NMC and NCA, LFP cathodes offer high power density, longevity, and safety due to their high thermal and chemical stability, which make them ideal in sectors that require many long and powerful cycles as well as safety in powering tools, energy storages, and some EV models. Lithium Nickel Cobalt Aluminum Oxide (NCA) with high nickel concentration is supposed to provide energy density on the level of or even higher compared to NMC cathodes as well as good power delivery ability; however, it has poor thermal stability and is sensitive to abuse conditions (Seong et al., 2020).

2.1.2 Chemistry and Structure of 18650 Li-ion Cells

Currently, the 18650 cylindrical Li-ion cell is widely used in various aspects of life, including in consumer electronics, EVs, and Stand-alone ESSs. The term "18650" refers to its dimensions:

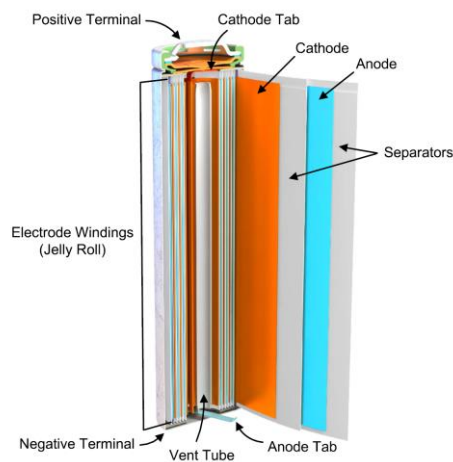


Figure 6. Rendered cross-sectional diagram of a typical 18650 Li-ion (Nagourney et al., 2021)

The subsequent set of pipes had a diameter of 18 mm and a length of 65 mm. When it comes to the construction of an 18650 Li-ion cell, one holds the anode, cathode, electrolyte, and separator as critical building blocks. The anode is generally made of graphite, a carbon-based material that can periodically handle the process of intercalation and deintercalation of lithium ions (Hausbrand et al., 2015). The cathode is a lithium-based

oxide material like LiCoO_2 , NMC, or NCA offers the structure where lithium ions reside when charging and discharging. Figure 6 shows the cross-sectional diagram of a typical 18650 Li-ion.

The principle of lithium-ion transport throughout the cell is by the assistance of the electrolyte which is located between the electrodes. It is generally a solution of lithium salt in an organic fluid, which may be a composite of ethylene carbonate/ dimethyl carbonate or other linear carbonates (Berhaut et al., 2015). The salt is a microporous polymer membrane that separates the anode and cathode and allows lithium ions to pass through, which minimizes the risk of internal short circuits and makes the battery safe.

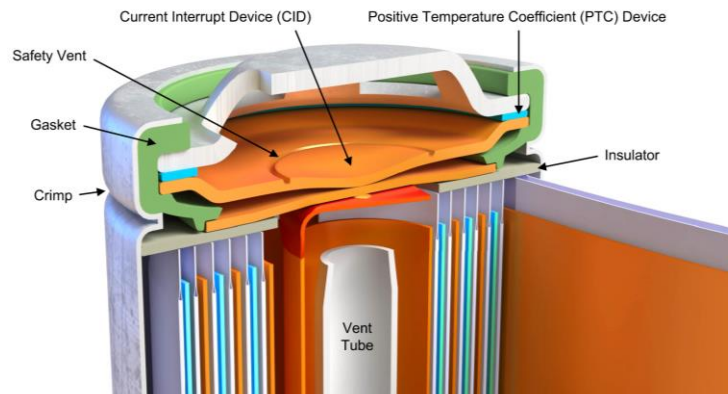


Figure 7. Rendered cross-sectional view of an 18650-cell positive terminal cap assembly

This is most often tightly coiled or wound with the multiple layers of these components enveloped in a metallic casing which can be made of aluminum or steel. The casing also creates structural support, and it is the negative electrode while the positive electrode is coupled to the cathode material (Zafirakis, 2010).

The working principles of an 18650 Li-ion cell are based on electrochemical mechanisms that allow for charge and discharge cycles by shuttling lithium ions between the anode and cathode. Lithium-ion movement: In other words, during charging, negative ions move to the positive electrode and take up intercalation sites while the electrons move through the external loop. During discharge, the process is reversed, and the lithium ions

move from the anode right to the cathode settling electrical energy to the connected load.

Indeed, the 18650 Li-ion cell's energy density, power density, cycle life, and safety performance characteristics are intrinsic to structural design coupled with the chemistry of the cell. Figure 7 shows the 18650-cell positive terminal cap assembly with safety vent and insulator detailing to replicate its structural safety factor. Further improvements of these internal parameters are in progress to enhance the energy density, power density, efficiency, cost, and safety by technology progresses in material science, electrochemistry, and design engineering to develop better energy storage devices for various uses.

2.2 Overview of Tesla 18650 Li-ion Cells

Specific Tesla 18650 Li-ion cell is different in performance and safety aspects as Tesla started to implement their 18650 in commercial EVs with refined materials that have higher safety capacity and efficiency (Uitz et al., 2017). Generally, the Model S battery module consists of 444 pieces of 18650 cells, and each cell weighs around 47 gm (Tesla 18650, 2170 and 4680 Battery Cell Comparison Basics | Torque News, 2024). In this research work, the specific variation of the Tesla 18650 cell was collected from the 2014 Model S series. The dismantling process was done at Technobothnia under VAMK supervision.

2.2.1 History and Development

The commercial use of 18650 cells is traceable to 1991 when Sony Corporation, a company rooted in the manufacture of batteries and energy devices, first developed the cell for use in computers and portable consumer electronics. After the early cells using lithium cobalt oxide (LiCoO_2) cathode material, there has been a very considerable enhancement in energy density and weight in contrast to the earlier nickel-cadmium (NiCd) and nickel metal hydride (NiMH) batteries (Khan et al., 2023).

Over the years, new cathode chemicals like Lithium Nickel Manganese Cobalt Oxide (NMC) and Lithium Iron Phosphate (LFP) increased in Material Science and Manufacturing emerging processes with improved performance and safety of 18650 cells (Houache et al., 2022). Tesla identified the capability of these cells in the middle of this decade and collaborated with Panasonic, the battery makers, to adapt and enhance 18650 cells for EV purposes. Tesla and Panasonic system cooperation has played a key role in the progress of 18650 cells for automotive use. Panasonic's years of experience and Tesla's relentless push for optimization have resulted in near-constant enhancements in cell form factor, chemistries, and production process. As a result, it has led to the creation of advanced high-energy 18650 cells that are specifically well-suited for usage in electric vehicles because they enable more energy density, a long cycle, safety, and thermal stability.

2.2.2 Design and Construction

The Tesla 18650 cell is a cylindrical lithium-ion battery cell consisting of typical key components like a cathode, anode, separator, electrolyte, current collectors, casing, etc. The cathode is generally constructed from lithium-metal oxide materials such as LiCoO_2 , NMC, or LFP, where the lithium ions are blocked and freed during the charging process of the battery (Chen et al., 2021).



Figure 8. Single cell after dismantling from the 2014 Tesla module

Tesla's 18650 cells are predominantly manufactured from either NCA (lithium nickel cobalt aluminum oxide) or NMC cathode materials, which are effective in providing optimum energy density, a high rate of energy density, and thermal stability (Saaid et al., 2024). This research work doesn't focus on cross-sectional examination. It's not possible to examine the internal chemistry details. However, some documentation mentioned that the cathode material is nickel cobalt aluminum (NCA), but it is not mentioned in any reliable or official documentation. The anode is composed of graphite, which is a carbon-based material, and it is the negatively charged electrode as well as media for lithium ions during discharge. Cells in Tesla's designs incorporate highly purified and uniformly shaped graphite anodes to boost current collector performance and cycle life (Olona & Castejón, 2024). A thin, flexible layer of polymer embedded with iron phosphate covers the cathode and anode layers, but it only allows lithium ions to pass through; it also cannot allow the electrodes to touch each other directly, which could spark and cause a short circuit. The goal of using laser technology in Tesla's cell construction is to prevent thermal runaway at high temperatures or physical pressure while maintaining the separator's structural stability. The electrolyte is a lithium salt dissolved in an organic solvent or an elastic gel that allows the lithium ions to migrate between electrodes on charge and discharge (Swiderska-Mocek & Rudnicka, 2014). Tesla cells utilize high-performance electrolyte compositions that are designed for high-voltage applications as well as for maintaining their stability under thermal or low-temperature conditions. The electron is gathered and conducted with the help of metal foils or grids, which are applied to accommodate the cathode and anode when electrochemical reactions occur. In the cells, Tesla incorporates highly conductive materials in the cathode, such as aluminum and copper, for the anode current collectors (Yang et al., 2020). The whole design and all the components are housed in a casing, generally made of aluminum, thus offering a solid casing to safeguard the interior parts from physical harm. Tesla's cells include durable shells which are specially intended for preserving cells from mechanical shock and vibrations that are characteristic of automobile sector commercial use (Ank et al., 2023). Figure 8 shows the dismantling Tesla 18650 cell that was used in this research work.

2.2.3 Performance Characteristics

As the cell has refined raw materials and a solid mechanical structure, its performance tested at the lab was different from that of similar 18650 cells. The nominal voltage of this Tesla battery cell is around 3.7 V per cell, or 4.2 V when fully charged.

2.2.3.1 Energy Density

The impact of energy density on the driving range and the overall weight of a car makes it extremely important. Nevertheless, one of the key benefits that Tesla has in the design of their 18650 cells is the level of energy density, which is achieved and fine-tuned by reducing and changing all possible aspects of cell chemistry, as well as the formation of the electrodes used and manufacturing processes. According to the information provided by Tesla's Lithium-ion supplier – Panasonic, about the 18650 cells, the capacity of cells ranged nominally around 3,500 milliampere-hours (mAh). The measurement of the energy density of the pack can be 156 Wh/kg and the pack volumetric energy density can go up to about 700 Wh/L. These values are believed to be among the best by means of the present-day cylindrical Li-ion cells existing in the industry, as the current solid-state battery (SSB) pouch cell has an energy density of 240 Wh/kg (Schmaltz, 2022). The cathode materials used in Tesla 18650 batteries have a higher energy density because the cathode contains nickel-rich lithium nickel cobalt aluminum oxide. By offering better specific capacity and operating voltage than Lithium Cobalt Oxide (LCO) cathodes, all these cathode chemistries created an increased energy density. Furthermore, the schemed electrode structure and high electrode loading density of Tesla's cells demonstrate the possibility of maximizing the amount of active pointed material and minimizing the amount of inactive material. Thirdly, it also helps to further raise the specific energy density of the cells.

2.2.3.2 Cycle Life

Since EV batteries must withstand several electrical charges and discharge cycles and are expensive, cycle life is a critical factor in defining performance. The Tesla 18650 cells

ensure that the cell cycle life is provided to improve the car's reliability and increase the longevity of the vehicles, thus eliminating the likelihood of experiencing more EV recurrence expenses. The general anticipations of cycle strength of lithium-ion batteries are the number of charging-discharging cycles that can be done on any battery and the charging-discharging cycle accomplished before its strength falls to less than the 80 % efficient level. For Tesla 18650 cells, which are used in Model S, the cells are capable of over 1,000 at a depth of discharge of 80 % per cycle, and as tested, some cells appear to have even better cycle life. These are cell chemistry and other incremental improvements to the electrodes as well as the thermal system. The materials used are even utilized in the cathode collectors, such as nickel, cobalt, aluminum alloy, and high-quality graphite anodes prior to cycle balance and improved lifetime decay (Mahmud et al., 2022). Moreover, the effective battery management system (BMS) of Tesla contributes the largest portion by improving the cycle life of the cells. Such features include voltage currents, temperatures, and other important parameters that are used in charging or discharging the cells with the aim of shortening or prolonging the life span of the BMS.

2.2.3.3 Thermal Stability

It is a safety factor to look at thermal stability since the battery can easily catch fire at higher temperatures, and its performance and life expectancy at the cell level are also affected. Due to the adoption of an appropriate strategy for thermal solutions and their thermal properties, Tesla's 18650 cells are safe and dependable. The ability of Tesla to experience thermal stability in its cells is mainly realized through the choice of cell formation and better material. Because of this, it is feasible to use cathode materials with a high nickel concentration, such as NCA, which does not include any LCO elements that may lead to high rates of thermal runaway processes (R. Wang et al., 2022). Further other cells of Tesla contain superior separators and electrolyte materials that can perform consistently at high temperatures. These components serve important functions in various applications, particularly to de-energize cells and prevent internal short circuits, as well as reduce the possibility of thermal runaway conditions. Many of the features

seen in Tesla battery packs are influenced by aircraft design, including temperature sensors and integrated liquid cooling channels to monitor the battery cells' performance (Saw et al., 2015). This thermal management system makes sure that the cells run at the right temperature range to prevent degradations but with the right optimality for the cells' performance as well as safety. Although the cell by itself is a part of battery packs under the thermal stability scheme, the individual cell, after dismantling, doesn't contain any thermal stability scheme other than material efficiency. All in all, the thermal stability of Tesla's 18650 packs speaks volumes of the safety and reliability of Tesla's battery and efforts towards delivering electric vehicles that are designed to operate under various operating conditions safely and efficiently.

2.3 Applications of Second-Life Batteries

The availability and production costs of lithium-ion batteries are one of the key challenges in the frequent usage of energy storage systems. The sector in which second-life batteries may be utilized efficiently was initially quite limited since second-life batteries are not commonly available. Li-ion batteries were originally developed and created for higher performance and instant or sensitive response applications, like operating electric cars (EV), power electronic-based applications, or being a primary energy storage solution in renewable energy integrations. However, these batteries, as the aged ones and those that have deteriorated to below their minimal allowable capacity, which ranges between 70-80% of their initial capacity, are deemed unsuitable for their projected application and, in most cases, are retired or programmed for recycling (Jennifer, 2024). However, such retired batteries still have comparative capacity and energy they can be used again in other applications known as second-life applications. These secondary applications usually have lesser energy density requirements and power demands than the primary uses, making it possible to use comparatively poor batteries. The market for second-hand batteries has grown significantly over time, opening the possibility of using these batteries in a variety of applications. The goal is to utilize those batteries in energy storage systems, although backup energy storage stations, usage in light commercial

buildings, low-speed transportation, and use in residential structures are some of the typical applications for second-life batteries right now (Nina, 2023).

Second-life batteries provide substantial economic and environmental advantages compared to new products and conditional energy management. From an economic standpoint, there is the potential of using retired batteries as energy storage systems in what is known as a second-life application, significantly decreasing the cost of energy storage systems. These batteries can be attained at a very cheap price as compared to the new ones, yet they can provide enough power for their intended second life. Lowering expenses may also increase the economics of renewable energy systems and facilitate the adoption of sustainable energy solutions.

From the environmental aspect, second-life batteries reduce the dependency on mining and refining raw materials to manufacture new batteries, including lithium, cobalt, and nickel. It's critical to recognize that many of these materials have negative environmental implications, including environmental pollution, water pollution during extraction and refinement, and energy consumption in processing. Effective use of second-life batteries in less intensive applications will reduce the demand for new batteries, which eventually reduces the production of new batteries and improves those environmental aspects.

Additionally, repurposed batteries lessen the amount of electronic trash produced and the hazards associated with improper recycling. Li-ion batteries have preceding materials that can be risky and unearthing them in landfills or through burning makes the surroundings and human health very vulnerable. If these batteries are used again, the disposal problem is postponed for a longer period, and resources are used in recycling to cut down on waste when the battery's prolonged useful life comes to an end.

2.4 Degradation Mechanisms in Li-ion Batteries

As lithium-ion batteries' performance is not linear based on their capacity or sizes hence, their degradation mechanism is also not linearly dependent on a single aspect but rather depends on various factors and impacts on their performance, safety, and life cycle. The most important factors that need to be counted for battery degradation are electrochemical degradation, mechanical degradation, and thermal degradation, where adaptive strategies are needed to minimize the degradational effect on batteries and enhance overall efficiency.

2.4.1 Electrochemical Degradation

Electrochemical degradation mechanisms are closely related to electrochemical reaction procedures as well as reciprocal interactions among cell components during the charging and discharging processes. Among the well-known electrochemical degradation processes, the creation of the solid-electrolyte interphase (SEI) layer on the anode is especially important. Studying the phenomenon, pioneering research by (Peled & Menkin, 2017) clarified the functions of an SEI layer, including the suppression of additional electrolyte decomposition and the preservation of anode surface integrity. (A. Wang et al., 2018) In their study of SEI layer growth on commercial Li-ion cells, they analyzed the growth characteristics of the SEI layer from impedance rise and capacity fading using EIS techniques.

Another prominent degradative electrochemical process is lithium plating, which informs lithium dendrites and can finally cause internal short circuits. (Waldmann et al., 2015) studied the effects of temperatures and charging rates on the formation of lithium on the surface of graphite anodes, while (Steiger et al., 2014) looked into the relationship between lithium plating and dendrite growth. In addition, active electrode materials are always easily perilous for electrochemical degradation. In their study, (Bang et al., 2006) explore the phase changes and material breakdown of $\text{LiNi}_{0.8}\text{Co}_{0.15}\text{Al}_{0.05}$. The NCA cathode material was introduced in this study to give information on the capacity fade

and impedance rise. Overall, this mechanism is quite frequent and impactful in the degradation of lithium battery cells.

2.4.2 Mechanical and Thermal Degradation

Electrochemical degradation is supplemented by the mechanical and thermal degradation processes that are expected to be common in Li-ion batteries and that may have important consequences affecting the overall performance and safety of these elements. The major factor which contributes to the mechanical degradation is the changes in the volume that take place during the intercalation/deintercalation process of lithium. Like silicon, (Deshpande et al., 2010) reported stress evolution and fracture behavior in silicon anodes using coupled electrochemical and mechanical models that silicon undergoes large volume change during lithiation. Another study conducted (Renganathan et al., 2010) focused on the mechanical degradation of (LiCoO_2) cathode particles; the influences of the particle size and known cycling conditions on particle breakage and capability loss were considered.

Temperature deterioration has a substantial influence on total battery performance, and it is not just determined by the temperature condition of the batteries; other degradation processes, such as electrochemical and mechanical degradation, are also linked to thermal degradation. Temperature increases have a direct effect on electrolyte decomposition because, at high temperatures, organic solvents break down the electrolyte and form gaseous products that are complex insoluble compounds (Kurzweil & Chwistek, 2008). This gradually reduces ion movement via the electrolyte and increases internal pressure inside the cell, thus deforming the mechanical structure of the battery. Besides the electrolyte decomposition, an increase in temperature can break down or grow the SEI layer, which eventually increases the impedance and decreases ion diffusion (Bloom et al., 2002). This phenomenon is mainly responsible for capacity fading and power loss of the battery cell over time. Continuous temperature rising can also cause metal dissolution in the cathode (Gallus et al., 2014). This dissolution migrates to the anode and

makes a layer on its surface. As the anode is made with graphite, exfoliation of the graphene layer can also form because of thermal degradation. These exfoliation Processes increase the anode surface area, which eventually promotes the electrolyte decomposition and SEI growth.

There has been a lot of effort towards overcoming mechanical and thermal degradation by developing new electrodes and cell structures. For instance, (Liu et al., 2023) examined a silicon-based nanostructured anode to facilitate volume change during lithiation. These degradations are not entirely preventable, but they may be reduced by optimizing approaches in chemical reactions inside the cell and battery thermal management against degradation, which eventually increases the reliability and stability of battery performance by slowing the deterioration process.

2.5 Current Research on Second-Life Battery Use

In today's world, optimizing second-life batteries for various applications is not the sole subject for researchers; discovering successful sectors is another challenge. Second-life battery research and applications include case studies and real-world field testing, with the goal of investigating the viability of second-life battery applications and estimating their efficiency under specified situations. Not only have these studies demonstrated the effects and benefits of employing repurposed batteries from old EVs, but they have also raised public awareness of the need to recycle EV batteries and reuse them in new applications.

2.5.1 Case Studies and Implementations

(Neubauer et al., 2015) from NREL studied in one notable work, the potential of EV batteries meant for a second life as stationary storage systems. The researchers evaluated several performance tests on Nissan Leaf batteries and built models to forecast the capacity and lifetime of retired packs. This paper highlighted the opportunity for second-life batteries in utility-scale energy storage systems by showing results of the variety of

cost savings and environmental advantages. In another study done by (Colarullo & Thakur, 2022) where researchers examined the feasibility of second-life batteries for the community including portable and off-grid applications.

2.5.2 Challenges and Opportunities

On one hand, the possibility of using a battery's second life in various applications is obvious and attractive, on the other hand, there are several points to consider to adequately manage them and complement the operating life.

One of the major difficulties is that it is often difficult to predict and evaluate the current potential of converted EV batteries to store and provide energy afterward. Such differences may be manifested in different usage profiles, different environmental conditions, and various depredation modes that directly cause differences in the health and performance of battery packs at the cellular level. Techniques like EIS and incremental capacity analysis are still under research to determine a more effective testing protocol for second-life batteries (Dubarry & Anseán, 2022).

Another difficulty is related to the design of proper BMS suitable for second-life operation, not necessarily aimed at electric vehicle use. They must take into consideration the various states of health and capacity in a battery pack and provide the right algorithms for performance, thermal, and safety control at the application level. Scholars are therefore exploring more complex functions and control techniques in BMS to realize potential second-life battery systems. Other than that, the effective use of second-life batteries does not fulfill the expectation.

From an economic standpoint, one of the most predictive issues is the development of efficient chains for supply and logistics dealing with collecting, transporting, and reusing old EV batteries. Additional factors that are critical for maximizing the return on investment of second-life batteries are the efficiency and cost of the processes involved. In

addition, improvement of working norms and legal prerequisites is also an urgent prerequisite for the safe and sensible use of batteries in further service life (New EU Battery Regulation, 2023).

Nevertheless, the opportunities of the second-life battery business are diverse the following are some opportunities of the second-life batteries business. However, beyond the post-usage economic and environmental impact, the application of recycled batteries to support other infrastructural domains can further capacitate the advancement of a progressive energy sector. Second-life batteries allow for the implementation and dissemination of several energy storage solutions at a more reasonable price point, which benefits the further inclusion of renewable energy into existing grids, making the path to a more sustainable energy paradigm smoother (Why Are Second-Life Battery Storage Solutions so Important?, 2022).

Thus, the additional benefits of second-life batteries can promote innovation and new technologies in areas such as BMS, diagnostics, or recycling. These developments must mean that the entire scope of the battery industry can be further enabled and hence take forward more developments on the aspects that affect battery performance, safety, and sustainability across several applications. The demands call for better and sustainable energy storage solutions making the second-life battery application a great topic that has the potential to significantly define the energy storage future while at the same time contributing to a circular economy.

3 Methodology

In this research work, the hybrid methodology is being followed to relate all the resources that are implied in this modeling. This approach entails an integration of theoretical work and computational methods, experiments and simulations, and the use of models as well as testing results to develop a method for the effective analysis and enhancement of lithium-ion battery performance. Figure 9 shows the whole process flow from experimental data collection to object-oriented optimization.

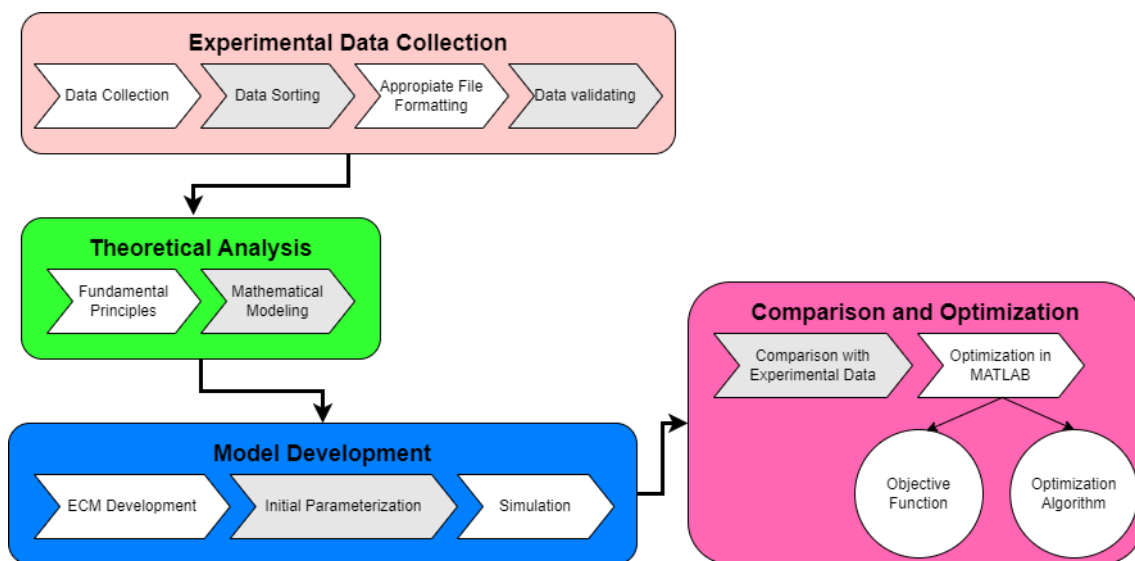


Figure 9. Process flow of the working procedure

The reasons for the applicability of the hybrid approach are the complex features of lithium-ion batteries, which require an individual approach to the choice of statistical methods. These energy storage devices are based on complex electrochemical mechanisms that cannot be easily addressed through any one of the mentioned research methodologies. This way, combining several methods allows to mitigate the issues arising when analyzing a complicated system as limitations of one method can be compensated for by the advantages offered by the other.

The basic advantage of an experimental part of this hybrid approach is realism with the collected experimental data. It enables the accurate electrical behavior of the 18650 Li-ion batteries under various testing circumstances, therefore supporting the theoretical analysis and numerical simulation. The empirical basis is critical for ensuring that subsequent analyses or optimizations apply to applications. The theoretical part of the methodology deals with the fundamental principle of the working mechanisms and predicts the behavior of batteries by creating mathematical models of the batteries. This theoretical framework offers a point of reference where the nature and dynamics of battery performance can be understood and where characteristics of cell behavior may be determined easily. Generally, in research work, the theoretical approach of hybrid methodology has a computational component that accounts for the differences between theoretical and experimental outcomes (Krupa & Hajek, 2022). However, using electrical circuit equivalents and algorithms in MATLAB allows to model battery behaviors, analyze and improve theoretical models using optimization techniques, and make predictions about how it will perform. The integration of these different methodological approaches is crucial for several reasons:

- (1) **Complexity Management:** Lithium-ion batteries have many factors involved in one and multiple interacting effects, and their nature is non-linear. Due to the hybrid methodology, this complexity can be subdivided into more comprehensible segments.
- (2) **Validation and Refinement:** With the outcomes obtained from experimental setup, theoretical analysis, and computational simulations, the models could be constantly updated and improved.
- (3) **Cost and Time Efficiency:** Even though the usage of experiments often results in high costs and is considerably time-consuming for battery testing profiles, the hybrid approach can significantly reduce the extent of the experimental testing by adopting the computational models as predictive and design tools.

- (4) **Insight Generation:** The use of multiple methodologies helps to get multiple viewpoints when it comes to battery behavior, and this is mostly very insightful when one technique can overshadow what the other is going to reveal.
- (5) **Practical Applicability:** This approach enables the theoretical and computational models to interact closely with the actual performance, making research results practically relevant for battery design and improvement.

In this context, the comparison of the 18650 Li-ion cells, the described approach is not only useful but also crucial. These cells involve the chemistry, electrical, and thermal properties, which may demand comprehensive methods to achieve comprehensive characterization and optimization. Other methods that are strictly based on either one of the groups would most likely fail to provide the necessary information on the occurrence of all types of Battery behavior and, hence, would prevent effective optimization. In this chapter, the research methodology is explained in more detail in the following section.

3.1 Experimental Data Collection

The need for comprehensive and precise battery data to improve models and serve as performance benchmarks for these models remains unfulfilled. Consequently, in the present work, a well-structured methodology was followed to gather information from a statistically different testing profile of commercially available Tesla 18650 lithium-ion cells. This led to the following procedure of data collection: The experimental aspect of this study entailed performing different test profiles and thermal monitoring experiments. The capacity, power, and energy fading tests were conducted at SOC, temperature, and cycling conditions to account for the behavior of the cell dependent on these working parameters. The performance of the battery capacities was evaluated by performing discharge and charge tests which were implemented by a programmable battery cycler, for instance, Neware BTS8000. To ascertain the capacity loss and the cell loss over

time, the intended technique involved cycling the cells at various C rates, i.e., low rates like 0.2C and higher rates like 3C in a charge-discharge cycle. However, it's not achievable for such a small-sized battery cell to test at a low C rate like 0.2C in this testing setup. Tests for Open Circuit Voltage (OCV) were carried out appropriately following the cells' establishment of a steady-state SOC, as documented in the experiment. After the cell was maintained at a specific SOC level, the OCV was monitored to determine the correlation between OCV and SOC once the voltage value stabilized. Also, the Hybrid Pulse Power Characterization (HPPC) test plays an important role in calculating internal initial parameters, which need some defined C-rates testing profile.

Furthermore, all the described tests were associated with thermal analysis aimed at the identification of temperature changes within the cells. The thermal sensor and ambient temperature chamber help to trace and control the thermal behavior of testing cells. The experimental setup section has a more detailed explanation of the testing setup and its working capability.

3.2 Initial Theoretical Parameter Calculation

As a preliminary step in the model development phase, first, calculations were carried out using theoretical principles. These calculations were the first step in determining the model initialization. This parameter is vital in deciding on theoretical cell capacity and energy density and measuring the experimental capacities against them. Some parameters were ignored as these parameters are mostly related to chemical reaction procedures, however, has a very negligible impact on cell electric behavior. Such types of parameters as effective diffusion coefficients for the lithium-ion transport within the electrode materials. All the electrical parameters of a 2RC equivalent circuit model can be initialized from the theoretical framework, where every parameter has a mathematical equation concerning internal resistance and capacitance, open circuit voltage, and current.

3.3 Equivalent Circuit Model Development in MATLAB

To get a true representation of the electrochemical/thermal behavior of the Tesla 18650 lithium-ion cells, an ECM was created using MATLAB software. This model was used to obtain a framework for simulating cell behavior under different operating conditions and for parameter tuning.

3.3.1 Model Development

The equivalent circuit model was derived based on the established approach for equivalent circuit modeling for lithium-ion batteries, which represents electrical behavior properly. The equivalent circuit used resistors, capacitors, and voltage sources of the cell and assessed voltage response and impedance. The ECM has two parallel RC branches operating in series, where both RC networks represent slow-acting diffusion. Capturing this diffusion is not possible with a simple internal resistance-based model or 1RC modeling procedure.

3.3.2 Initial Parameterization

The theoretical parameter estimations were used to help estimate the simplified equivalent circuit model's parameters in the first step. After examining the HPPC response, iterative parameter estimations can be performed by defining the response's time constants. This process involved fine-tuning the initial model parameters.

3.3.3 Simulation

The parameterized equivalent circuit model was then used to predict the cell's behaviors depending on the charging/discharging rates, temperatures, and cycling profiles. The linear and nonlinear simulations of the models presented in this paper were solved in MATLAB using the ordinary differential equations solvers and numerical integration tools

available in the software. These simulations entailed finding a set of differential equations that combined the electrochemical and thermal phenomena taking place in the cell.

3.3.4 Comparison with Experimental Data

The simulation results, such as voltage response, impedance, and temperature, were compared with responses derived from the characterization tests. For a similar current response, there will be a distinct difference between experimental and simulated values. This voltage response is also used for validation purposes after optimization.

3.4 Optimization in MATLAB

Further, to improve the power flow and achieve a more accurate equivalent circuit model, an optimization process was used with the help of the MATLAB optimization toolbox. This optimization is performed based on two factors.

3.4.1 Objective Function

An objective function was thus formulated for evaluating the error between the simulated and experimental data. This objective function considered not only voltage curves, impedance characteristics, or thermal effects of the cell but also incorporated performance parameters as a function of the operating conditions well, e.g., C-rates, temperatures, and SOC levels. For most of the objective functions employed, we noticed that the objective was normally expressed in a weighted least squared sense where the residuals were defined as the differences between the observed and simulated data points.

3.4.2 Optimization Algorithm

Due to the nature of the objective function and the restrictions given by the model parameters, an appropriate optimizer was chosen. In this optimization process, the method

of optimization is nonlinear least square, and the algorithm is named trust-region reflective. The parallel computing toolbox is also implied by using the `matlabpool` command to speed up the processing time. This selected optimization algorithm allowed tweaking the model parameters in iterations to minimize the objective function and lessen the differences with the experimental data. Through this method, they determined the maximum distance that can be taken from selected reference points for input variables within the physical restrictions of a problem while maintaining certainty that the solution they ultimately arrived at is the best possible overall. Flows visualization after the optimization resulted in the verification of the model parameters with another dataset that was not used in the optimization process. This step helped the model develop generic features and make it more capable of providing the necessary prediction of the cell's behavior under different operating conditions.

4 Modeling of Second-Life Tesla 18650 Li-ion Cell

For modeling second-life 18650 lithium-ion cells like those powering Tesla automobiles, precise and correct modeling methodologies are significant to achieve the highest efficiency, reliability, and durability. During the first cycle life of electric vehicles, they experience substantial degradation and wearing from the cycling cells, which affects the electrochemical properties and performance parameters. Therefore, the modeling methods must be correctly chosen to portray all the useful features of second-life cells adequately. In this chapter, the focus is on detailing the modeling fundamentals and effective procedures for modeling including experimental procedure and model development.

4.1 Fundamentals of Battery Modeling

The battery modeling is a required step to integrate any battery module in any application from a technical point of view. However, one battery cell or module can be modeled in different aspects, prioritizing different parameters or levels of complexity. It is essential to have correct approaches to modeling the battery to enhance its integration and safety features and to maximize its lifetime. In this section, a few effective, prominent, and fundamental modeling approaches are discussed to understand the importance and justify the effectiveness of the approach followed in this research work.

4.1.1 Electrochemical Models

Improvements in integrating electrochemical models are thought to offer data on various electrochemical processes that take place in lithium-ion batteries over repeated cycles of charging and discharging. These models are the most useful for explaining the mechanisms underlying some concentrations of Li-ion batteries, the gradient in Li-ion concentration, and some over-potential and side reactions that are detrimental to the safety and efficiency of batteries to varying degrees.

This model is referred to as the DFN model, where the DFN stands for Doyle, Fuller, and Newman, the authors of this model, and this model has been applied in battery research as a model. This is predicated on the DFN model's initial assumptions on electrochemistry, transport phenomena, and kinetics, as well as the part that represents the primary battery response as reaction kinetics, migration, and lithium-ion diffusion. Electrochemical models can be further classified into two main categories known as pseudo-2D models and single-particle models. Figure 10 shows the electrochemical working procedure for both the charging and discharging cycle from a material perspective.

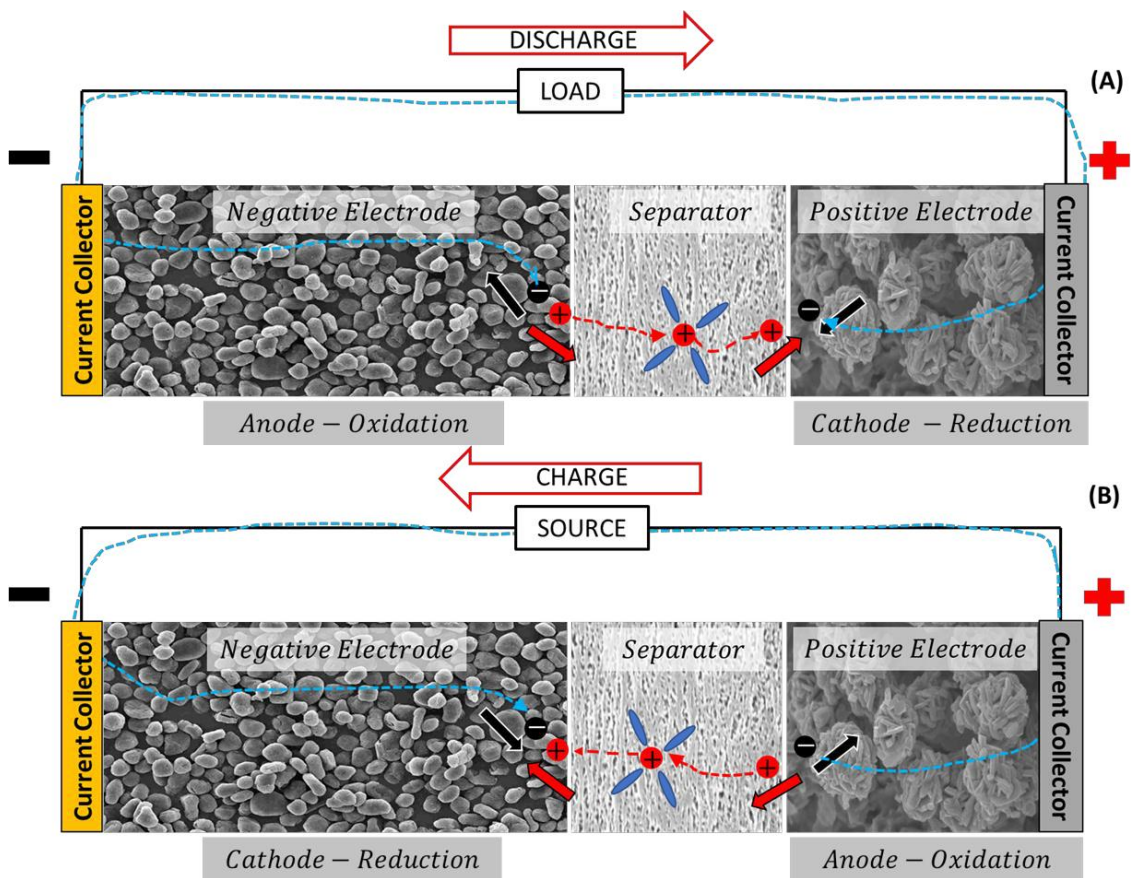


Figure 10. The electrochemical working principle of a lithium-ion cell (Falconi, 2018)

4.1.1.1 Pseudo-2D Model

According to the definition, the pseudo-2D models are particularly useful for second-life cell chemical analysis because they can qualitatively characterize the electrochemical

processes. These models can very well describe the degradation effects on some of the electron system components, such as electrodes and electrolytes of the cell. Nevertheless, there are certain difficulties with such approaches because P2D models are usually of a higher dimension and can describe multiple properties of a cell simultaneously; these difficulties include computational limitations and the identification of all the different parameters, where the cell may be old or exhausted (Subramanian et al., 2009). The P2D modeling has some key strengths like –

- The spatial distribution on a layer and the corresponding electrochemical processes are also reconstructed in the computer model.
- The function is to capture the level of influence held by degradation on the cell components
- Helper for the evaluation of the role of aging on the ability of the layer to allow the movement of lithium-ions as well as the speed of the entire reaction.

Although the P2D models effectively portray the electrochemical process in a computational environment with detail degradation and ion movement, this model still has some limitations that also need to be counted. These are –

- The widely used Two-equation instability modeling also entails computations with partial differential equations hence slightly time-consuming.
- Their measurement is also quite complicated most of the time, especially when working with old or deteriorated cells.
- Can be resource-intensive for experimentation or model calibration or tuning which may need large data.

4.1.1.2 Single-Particle Model

Second-life cell modeling can also be approached through single-particle models (SPM). This modeling process is computationally friendly and good for real-time simulations.

Some of these models can qualitatively capture the bipolar behavior of aging or deteriorated cells, but they do not consider the impact of electrolyte transport and instead examine circular processes on active material particles (Brown et al., 2008). Some key strengths of this model are –

- Its low complexity, ideal for real-time processing, makes this model computationally efficient and ideal for use in real-time applications.
- Possibilities include being able to model and replicate the key electrochemical paths of degraded or aged cells.
- The reduced complication also entails easier parameterization as opposed to other difficult models.

As this model has a low computational effort or processing time, it has some common limitations as well. For instance –

- Over-simplification could, therefore, result in the making of some wrong assumptions that are not as accurate as they should be on some occasions.
- Inability to capture the increases or decreases within the cell at certain spatial frequencies
- May need refinement or fix-up for cells that are much more distorted.

For the case of second-life 18650 lithium-ion cells, it could be helpful to use more than one mode of electrochemical modeling to capture the true nature of 18650 lithium-ion cells' behavior and degradation like complex descriptive models such as the pseudo-2D models can be used for the degradation analysis and characterization while simplified ones like the single particle models can be applied in real-time battery management systems or in those applications that require limited computational resources.

4.1.1.3 Nernst Equation

In other words, the Nernst equation is one of the central ideas in electrochemistry, which links the equilibrium electrode potential with the transport numbers and activities or concentrations of the electroactive species undergoing the electrochemical reactions. Regarding lithium-ion batteries, the equilibrium potential of the system depends on the position of the electrode or electrolyte interface. The equations of the Nernst equation can be mathematically expressed in this way (Flowers et al., 2015) –

$$E_{cell} = E^0_{cell} - \frac{RT}{nF} \ln Q \quad (1)$$

Where,

E_{cell} = Cell potential

E^0_{cell} = Standard cell potential

R = Universal gas constant

T = Temperature in kelvin

n = Ion charge (moles of electrons)

F = Faraday constant

Q = Reaction quotient

At standard temperature (298.15 K), for most applications, the Nernst equation can be conveniently rewritten with R and F basic values and a factor that converts normal to base-10 logarithms as –

$$E_{cell} = E^0_{cell} - \frac{0.0592 V}{n} \log Q \quad (2)$$

In the case of lithium-ion batteries, the concentration of the electrode layer is denoted by c_s , and the concentration of the electrolyte layer is denoted by c_e , hence, the Nernst equation can be derived by involving these parameters –

$$E_{cell} = E^0_{cell} - \frac{0.0592 V}{n} \log\left(\frac{c_s}{c_e}\right) \quad (3)$$

As previously stated, this equation is extremely valuable to electrochemists since it allows one to determine the electrode's open circuit potential (OCP), like open circuit voltage, from the chemical perspective, which concerns the difference in Lithium-ion concentration between the electrode and the electrolyte. This knowledge is essential to charge and discharge the electrochemical system and the cell's conditions during such intensive and repeated operations. By including this equation in the electrochemical models, researchers can obtain enormous information on lithium-ion batteries' activity and performance, which can be used for further progression in battery technologies.

4.1.2 Empirical Model

With empirical models, one can facilitate the definition of the terminal voltage behavior of lithium-ion batteries. These models are based on algebraic or functional relations connecting parameters such as SOC, current, etc., with the actual physical and electrochemical processes involved (Gu et al., 2022). Among these models, the empirical models are less precise than the above models, but since these last ones are complex from the computational point of view, this kind of model can yield a somewhat fair estimation of batteries' non-linear features. Empirical models are typically categorized into five main types –

- (1) **Shepherd model:** The OCV and the voltage drop due to polarization phenomena increase exponentially and are described by the hyperbolic sine function of coulombs, respectively.
- (2) **Unnewehr universal model:** The model also includes the determination of the opening-circuit voltage as a polynomial function of SOC plus terms, including the dynamics of the model.

- (3) **Nernst model:** The Nernst model relies on the Nernst equation, which was discussed in the previous section, and has some correlation with the open circuit voltage, state of charge as well as several other thermodynamic quantities.
- (4) **Enhanced self-correcting model:** This model also incorporates a self-adjustment factor to give a better estimation of OCV, especially for lithium-ion batteries.
- (5) **Zero-hysteresis model:** This model does not incorporate any of the hysteresis effects that may be present in the way OCV changes with SOC as a way of eliminating hysteresis in the model.

Empirical models have the benefit of being simple to design and capable of performing basic arithmetic operations. Nevertheless, in most situations, the procedure estimates a large error margin if the batteries are running below optimal conditions. They can fail to accurately capture the details of the electrochemical processes while trying to explain battery performances or even distinguish the effect of degradation processes.

4.1.3 Data-Driven Model

An important research area with increasing interest over the last few years is forecasting, which utilizes advanced machine-learning strategies and data mining. In batteries, these models use past and current values of the battery and other factors like SOC estimation, temperature, voltage, and current while it can depict their inter-relations without integrating the electrochemical or physical aspects of the battery into the general model. There are two different procedures to build this type of model, which are discussed below –

4.1.3.1 Machine Learning Approaches

Machine learning techniques are effective because the time-based behavior and interaction of battery systems may be adequately captured by non-linear mathematical models. Several commonly used data-driven models in battery modeling are

- (1) **Neural Network Model:** Advanced machine learning techniques such as artificial neural networks (ANNs) can be applied to find non-linear dependence patterns in data sets. These models consist of neighboring neurons layered in between with every connection possessing its weight. These weights are then adjusted during the training phase as a method of capturing the true and corresponding relationship between the data sets. Thus, ANNs can be effective when applied to battery modeling because they can capture physical non-linear relationships and work with a large number of variables (Olabi et al., 2024). This process's ability to generate extremely detailed patterns and handle multiple dependency conditions between battery variables—such as temperature, current, voltage, and state of charge—makes it suitable for tasks like state estimation, estimating the remaining useful life of a battery, and performance optimization from the standpoint of future performance.

- (2) **Support Vector Machine (SVM) Model:** When the data needs to be classified or needs to use regression method in modeling, this supervised learning classification method can be used which is also known as Support Vector Machines (SVM). SVMs work by building hyperplanes which is a fundamental geometric concept in a space of high dimensionality that can act as a decision boundary for classifying points or for a regression function. SVMs are, however, very good at dealing with non-linearity and high dimensional data, which makes this ideal for use in battery modeling (Junping et al., 2006). The functions of the SVM include tasks such as state-of-charge estimation, remaining useful life prediction, and fault diagnosis.

(3) **Extreme Learning Machine (ELM) Model:** In ELMs, the output weights are computed mathematically using the least squares method. This preliminary evaluation shows that the present approach drastically brings down the computational load and training time compared to conventional neural networks. ELMs are more useful in tasks related to battery modeling, for instance, in state-of-charge estimation, capacity forecasting, and residual/remaining useful life prediction (Yao et al., 2022). ELMs can differentiate nonlinear relationships and update quickly through training, so they can effectively estimate battery performance and degradation.

4.1.3.2 Statistical Analysis Approach

Besides using machine learning methodologies, mathematical calculations in statistical analysis also have a significant role in battery modeling. These enable one to obtain meaningful information, establish patterns, or even quantify the interdependency of battery variables (Amiri et al., 2024). Regression analysis is a well-known statistical analysis technique that looks at one or more independent variables (like temperature, current, voltage, etc.) and one or more dependent variables (like battery capacity, SOC, etc.). Several methods of analysis are currently used on battery data, and these include but are not limited to Linear regression, polynomial regression, and logistic regression. The other statistical analysis method is time-series analysis, which is usually applied when dealing with time series, that is, time-varying data. In addition, hypothesis testing, analysis of variance test, and correlation test may be employed to determine the signification of the relationships between the battery variables and to select influential factors for assessing the strength of the relationships.

4.1.4 Equivalent Circuit Models (ECMs)

Lithium-ion battery models have been developed over the years, and the Equivalent Circuit Model (ECM) has proven to be popular in modeling lithium-ion battery cells, including Tesla's 18650 cells. These are simplified representations of the battery's electrical

behavior employing necessary electrical circuit components such as voltage sources, resistors as well as capacitors. ECMs are relatively accurate compared to their less computationally intensive counterparts, and they are applied to handling battery control systems, and SOC calculations (Shi et al., 2023). The basis of the ECMs is in the perception that the battery system can be modeled by an equivalent electric circuit, where every element corresponds to one of the battery characteristics. The most known models are the R_{int} model, Thevenin model, and PNGV model.

4.1.4.1 R_{int} Model

The Equivalent R_{int} Battery Model (ERBM) offers several advantages that contribute to its widespread adoption in battery modeling. The most obvious advantage is its simplicity and capability to be easily implemented.

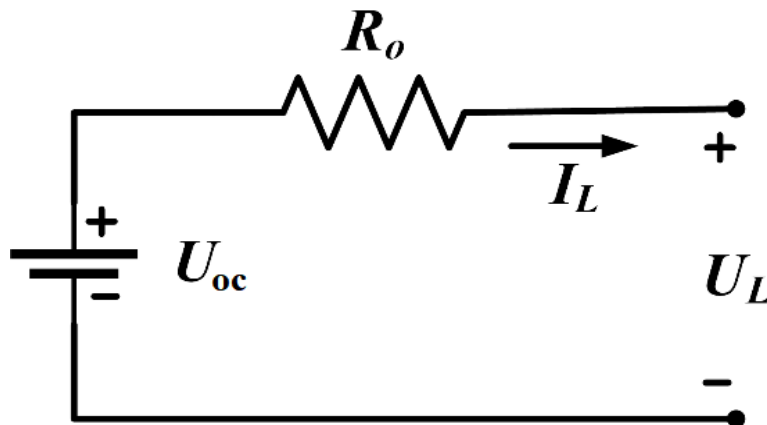


Figure 11. Equivalent R_{int} battery model

ERBM lacks the need to have so many parameters; hence, it does not take so much computer power and thus can be implemented for real-time use (Aurilio et al., 2015). Moreover, the introduced concept of ERBM offers satisfactory accuracy and simplicity, which will help make quite reasonable expectations of the battery behavior without the need for computational overloading. However, it is important to recognize the limitations of the ERBM. A major drawback is that it is a non-dynamic model, so the battery's behavior

has not been contemplated under various conditions of work. ERBM assumes the internal resistance of the battery as pure resistance, which remains constant over a long period without regard to temperature effects, aging, or other effects that might change the internal resistance (Mat Razi et al., 2021). Also, the ERBM might fail to capture intricate electrochemical processes and events that are present in specific electrode chemistries or at extreme operating conditions. The equivalent circuit of the R_{int} Battery Model is illustrated in Figure 11. Nonetheless, it can be stated that the shortcomings described above do not deprive the ERBM of its significance in the modeling and simulation of battery systems, as it allows for reasonably accurate prediction of the battery behavior in many real-life cases.

4.1.4.2 Thevenin Model

The Equivalent generalized Thevenin battery model (EGTBM) is another significant tool widely used in battery modeling and simulation. Its roots are based on the Thevenin equivalent circuit that simplifies and renders a given complex battery system manageable. This one assumes a battery as a voltage source in series with a resistance load, and it captures the essential features of a battery's characteristics. The EGTBM is useful for determining how batteries behave at different conditions of operation because it provides a correct dynamic response. Since the EGTBM contains the equivalent voltage source V and internal resistance R_o , appropriate changes in the values of the components allow the circuit to emulate other battery chemistries or arrangements. This flexibility allows researchers to investigate and compare the characteristics of various battery systems at the macro level without the knowledge of complex microscale electrochemistry. There are various benefits of the EGTBM, one of which is its inherent capability to model battery characteristics' nonlinearity. Due to the generalized form of model parameters, it is possible to achieve a good fit of nonlinearities of a specific battery, and thus, the EGTBM allows for precise simulation of voltage and current characteristics at various operating points. Because of this capability, it is widely used in battery monitoring, system control, and the development of control algorithms.

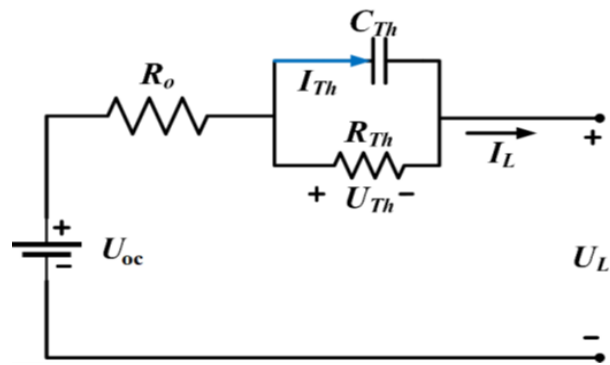


Figure 12. Equivalent 1RC battery Thevenin model

There are two prominent types of Thevenin models widely used in battery analysis. One is the Thevenin model with an RC parallel circuit, which defines the relaxation behavior and transient behavior of the battery (He et al., 2011). Figure 12 illustrates the electrical equivalent circuit of 1RC modeling. This 1RC branch is especially critical in analyzing the battery's behavior during charging and discharging operations.

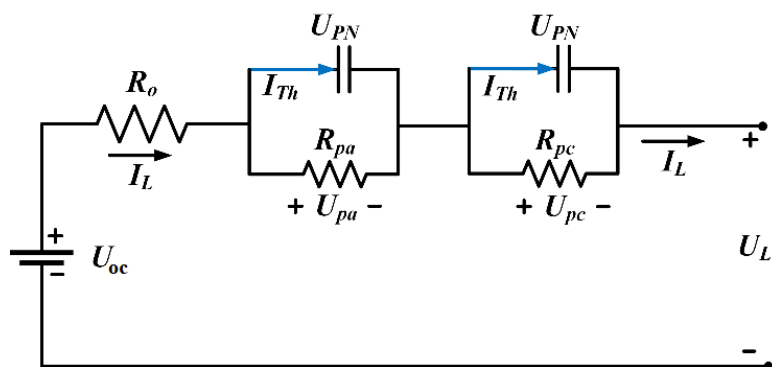


Figure 13. Equivalent 2RC battery Thevenin model

On the other hand, modeling with the Thevenin equivalent and the 2RC parallel branch would be used more widely and efficiently in the case of the electrochemical modeling represented in Figure 13. The surface capacitance and correlated resistance are represented by the first RC circuit, while the diffusion capacitance and correlated resistance are represented by the second RC circuit (Thakkar, 2021). These two, in parallel with each other, model the internal impedance of a battery, which causes the voltage drop and

energy dissipation during the charging and discharging operations. This is the primary target to search for these impedances of the battery. This model can be easily used to predict the behavior of the battery at any certain temperature or when is under load. It also helps in the assessment of the SOC of the battery, which is an essential parameter for any efficient functioning of a battery. The primary aim of this testing is to realize the model parameter and further estimate the SOC for the 2nd life Tesla cell, which can be achieved by this modeling and subsequent estimation.

4.1.4.3 PNGV Model

The Partnership for a New Generation of Vehicle (PNGV) model installs one more capacitor in series connection with the established Thevenin model depicted in Figure 14. The open circuit voltage variations that occur when the load current builds up are explained by the additional capacitor (Daowd et al., 2011). The new RC networks included in the PNGV model are more applicable than all the R_{int} and Thevenin models, which allows a more accurate description of the terminal voltage if the applications are related to EV integration.

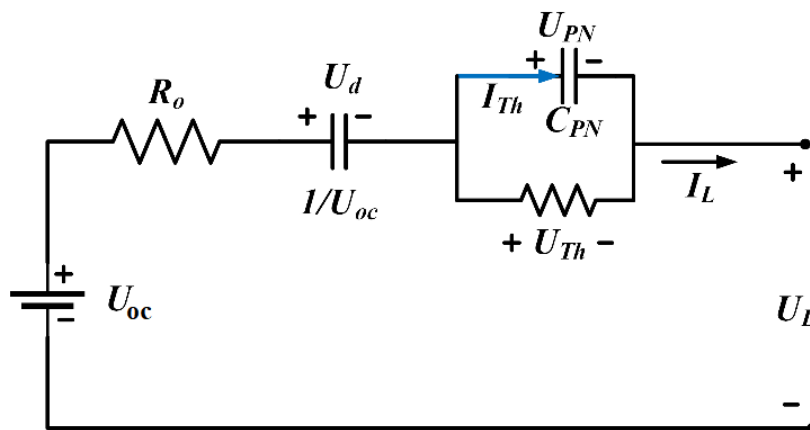


Figure 14. Equivalent PNGV model

4.1.4.4 Key Advantages of ECM

This procedure of modeling provides a less complex representation of the battery's electrical characteristics, offering ECMs that are computationally lightweight and ideal for implementation in real-time controllers. Besides that, the ECMs can be modified depending on the battery chemistry and geometry by selecting appropriate component values. Thus, the circuit models can simulate various battery systems. The usage of the RC networks helps the ECM to simulate the response of the batteries when subjected to transient conditions, mostly used in charge and discharge cycles.

4.1.4.5 Limitations of ECM

From the assessment through ECM, certain limitations can be identified like the errors in the calculation of the ECM parameters, including resistances and capacitances, which may affect the overall result. This can be difficult, particularly if the battery is old or, in any way, deteriorated, where the parameters of the battery response are likely to have shifted due to the changes in the physical properties and chemical constitution of the battery (Apribowo et al., 2022). In some cases, it would also imply that the system non-linearity, which might be present in charging and or discharging the battery, could not be precisely captured in ECMs due to certain nonlinear behaviors inherent in certain battery chemistries or at certain extreme operating conditions. Particularly under high currents, low states of charge, or high temperatures, lithium-ion batteries exhibit more complicated second-order nonlinear behaviors. As a result, these ECMs may increase the mathematical complexity required to incorporate the nonlinear portion or may need the consideration of additional nonlinear elements as a new ECM (Shen et al., 2024). While using ECMs, one may get a very slow and even very poor result regarding how a battery is aging and degrading over a long time. Depending on the time of operation, several degradation phenomena can occur like SEI layer growth, electromechanical or thermal breakdowns, electrode corrosion, or active mass dissolution that alters the electrical properties of the battery. These effects present a challenge for the simulation of the aging effects. Self-discharge of Li-ion batteries greatly depends on the temperature; the

batteries and their capabilities degrade under high and low temperatures. Some of the current ECMs have assumed attempts to account for temperature impact through varying parameters using empirical studies without considering the nonlinear parameter modification of the thermal behavior of electrochemical processes and degradations within the battery.

4.1.5 Hybrid Modelling Approach

Researchers consistently recommend using techniques like adaptive parameter estimation (APE), a variety of modeling schemes, and the integration of machine learning techniques to overcome these issues and raise the accuracy of ECMs. These hybrid models should try to integrate the physical insight from the electrochemical models, the mathematical methods developed for nonlinear modeling from the ECM, and the data-driven methods for capturing the dynamic behavior. It could also enhance the precision and completeness of the representation of battery behavior by the interaction of the two kinds of models which are analytic and semi-empirical.

In conclusion, the selection of the modeling approach depends on the requirement of a specific task, the required accuracy, the computational abilities of the software, and the quality and quantity of data available for analysis. For instance, models based on data may be more resilient to noise and fluctuations than models based on empirical data, although the empirical one may be computationally simpler and faster. In contrast, electrochemical models represent the base model that describes the battery electrochemistry and helps enhance cells' performance for second-life or old batteries. Using these approaches in integrated form by utilizing hybrid modeling seems to have the potential for higher accuracy and reliability in battery modeling.

4.2 Experimental Procedure and Difficulties/limitations

The experimental setup or equipment at VEBIC laboratories is quite reliable and accurate for battery testing. However, that is more effective with a bigger-size battery cell or battery pack. In the case of small-size battery cells like the Tesla 18650 lithium-ion battery cell, the main challenge is to connect the test setup with the battery cell inside of the WEISS ambient temperature chamber and consider the sensitivity or accuracy of the testing kit. Some testing profiles, for instance, constant current constant voltage (CCCV) at low C-rates is difficult to achieve through this testing setup at that time. In this section, the discussion will be enclosed in the experimental procedure, available testing equipment specification, and the challenges observed at the time of testing the battery cell.

4.2.1 Testing Equipment Specifications

The testing was carried out using the BTS 8000 series testing kit, which is mainly suitable for densely built and large modules' batteries.



Figure 15. Battery testing facilities at VEBIC (WEISS thermal chamber, Neware BTS8000 and BTS4000 cycler and connector, data server)

Figure 15 shows the test setup at VEBIC, mentioning from left is the WEISS ambient temperature control chamber; in the middle is the Neware BTS8000 series testing module; and on the right is the computational server containing related BTS 7 software as an interface data server. The BTS8000 testing module specification and sensitivity are given in Table 1. There are 4 independent channels available per unit, and all of them are independent. All the channel cables are aux-type heavy cable which has a higher internal resistance and, hence, is not suitable for small-size cell connections. Generally, for small cylindrical or coin-type cells, there is another more sensitive testing kit available which has better accuracy in short range.

Table 1. The Neware BTS8000 Series 5V 200A Battery Cyclers key specification

Subject	Index
Input AC	AC 380V±10%/50 Hz
Input Power	7089 W
Input Impedance	≥100 kΩ
Voltage	Per Channel Range = 0.025-5 V Accuracy = ±0.05% of FS
Current	Per Channel Range = (10, 20, 30, 40) A Accuracy = ±0.05% of FS
Power	Output Per Channel = 1000 W
Charging	Charge Modes: Constant current charging, constant voltage charging, constant current constant voltage charging, constant power charging Cut-off condition: Voltage, Current, Time, Capacity, -ΔV
Discharging	Discharge Modes: Constant current discharging, constant power discharging, constant resistance discharging Cut-off condition: Voltage, Current, Time, Capacity
DCIR Test	Supported
Cycle	Range: 1-65535 times Maximum steps per 254
Operating temperature	0°C~40°C
Storage temperature	-10°C~50°C

4.2.2 Testing Procedure and Challenges

In the Neware battery testing system, the user needs to define the testing profile with multiple steps. The maximum number of steps per cycle can be 254 stated on the spec sheet of Neware BTS8000. In this characterization procedure having different types of testing profiles helps to increase the accuracy of the data set. Some common testing procedures need to be followed, for instance, capacity testing, and open-circuit voltage testing. HPPC testing, etc. for better accuracy in basic modeling. However, it was challenging to complete this HPPC testing profile in this machine for such a small-capacity battery cell like the Tesla 18650. The CCCV cycle is one of the primary steps for HPPC testing profile which is not achievable at different C-rates, especially below 1C-rates. This cycle is responsible for calculating the initial time constant T_1 and T_2 , which eventually calculate the theoretical parameter of the modeling. Besides that, another issue encountered during testing was the need to prepare the 18650 batteries for proper connection. However, unlike larger battery modules, small cells do not include connectors or terminal points, making it difficult to establish strong and stable connections for testing and other purposes.



Figure 16. Cable connector technique to extend the positive pole from the negative pole

First, efforts were made to solder connectors or long wires to the cells' terminals by direct joining, as seen in Figure 16. However, this approach created additional resistance which caused a scope of errors in the testing procedures, especially during charging-discharging and temperature measurements. Since the cell must be separated to define the positive and negative polarization throughout the testing period, for a stable connection, several other approaches must be used instead of this additional wire. Hence, raising the positive pole a little bit by soldering so that the cell can be connected with the probe properly, and then the use of electrical tape helps to isolate the positive terminal from the rest of the body. This ensures that the cell now has a distinguished connection pole. However, achieving stability in testing is still unsolved with all these big connector and sensor probes. The extended and isolated positive pole is shown in Figure 17.



Figure 17. Two different steps to extend and isolate the positive pole from the negative pole

To minimize the instability issue during the experiment, a classical clamp technique can be used, demonstrated in Figure 18; this involves the existing soldering and isolating of the positive terminal of the cell into a clamp setup so that all the connectors and thermal sensors stay in a stable connection and don't come out accidentally or in contact with the outer body of the cell. This stable setup ensured safety against short-circuiting during conductivity tests.

The test was performed inside the WEISS thermal test chamber so that the operating temperature maintained a defined boundary for the testing of the equipment at various operational conditions. Despite the measures taken to ensure accurate testing. Still, certain limitations and challenges persisted in this testing procedure:

- (1) **Constant Current Constant Voltage (CCCV) Testing:** These 18650 cells could not be allowed to lower than 1C-rates of the rated current, and this stalled the CCCV test profiles at the HPPC test which is one critical testing for observing detailed characterization of the battery cell.
- (2) **Data Fluctuations:** The cells tested in this research work are comparatively small, which is required to increase the measurement sensitivity for an accurate response. As the testing facilities were not feasible enough to ensure that sensitivity, there were noticeable changes in the data which could pose accuracy issues as well as the precision of the measurements.

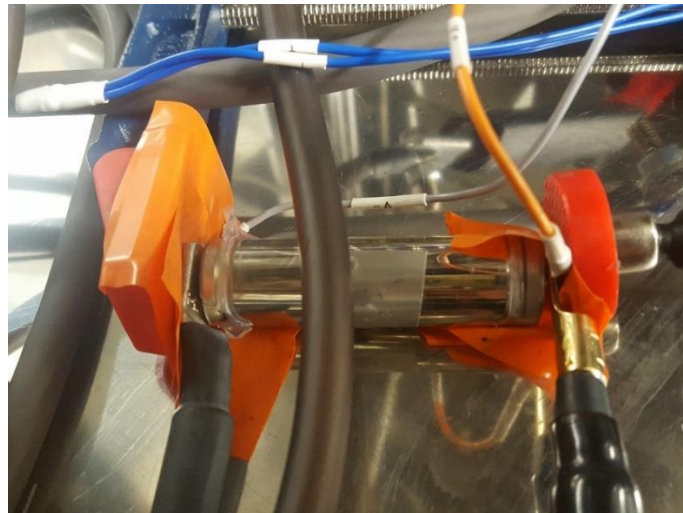


Figure 18. Clamp housing process with different sensor connection

- (3) **Aging and Degradation Analysis:** To capture aging and degradation mechanisms that affect second-life 18650 cells, it may be necessary to conduct more tests

which might be more time-consuming, and test equipment might also be more versatile since the degradation process is not always observable and can take different forms.

- (4) **Temperature Dependence:** Although it was possible to regulate the temperature through the controlled thermal chamber, it might prove difficult to capture the detailed dependence of temperature on the electrochemical experiments and degradation of reactions within the cells utilizing the employed testing setup. That means the operating temperature can be defined by the user, which gives a realistic data set from testing. However, in real life, the variation of temperature is different from the defined testing temperature and depends on applications, which is not capturable in testing facilities.

Therefore, to eliminate these obstacles and enhance the testing metrics for used 18650 lithium-ion batteries, the authorities have taken a few initiatives. For example, the University of Vaasa has received funding for a brand-new testing cyclers from Neware called the BTS4000 5V20A battery cycler, which can test this type of smaller cell, such as coin cells or cylindrical 18650 cells, with the appropriate connectors and adapters at an advanced level. Furthermore, due to their unique characteristics, behavioral patterns, and potential in a variety of second-life applications, current research investigations have switched to developing evaluation protocols and standards for second-life battery cells. Understanding those limitations helped to build proper procedures for testing the second-life 18650 lithium-ion cells and capture the behavior, allowing for changes in the battery management systems, life span, and repeatability of use within the applications for these cells.

4.2.3 Experimental Results

There are different types of testing profiles used. Figure 19 shows a testing profile with 100 cycles, and each cycle has a period of a minimum of 6 hours and 20 minutes. Each cycle proceeds with a specific charging-discharging time with some rest period. This

helped to reach a steady state and repeat the process. This 100-cycle testing profile helped to understand the second-life battery capacity fluctuations as well as the performance consistency.

Figure 20 shows the voltage and current response from the experimental setup. Both current and voltage responses show a fluctuation in the charging-discharging state as the battery is charging and discharging at constant current (CC) mode; hence, the current response is constant when the battery is charging or discharging.

Channel Info							
Property	Value	Property	Value	Property	Value		
Dev_Unit_Ch1	#1_1_1	Volt Upper	4.2000 V	Aux Volt Upper	--		
Start Time	2023-05-17 12:30:51	Volt Lower	2.5000 V	Aux Volt Lower	--		
Start StepID	1	Cur Upper	1.1000 A	Aux Temp Upper	45.0 °C		
Time in Step	00:09:18:600	Cur Lower	--	Aux Temp Lower	10.0 °C		
Capacity	0.0000 Ah	Cap Upper	--	Aux Volt Range	5 V		
Cycle	66	Barcode		Aux Temp Range	400 °C		
Record Condition	0.1 sec 0.0 mV 0.000 mA	P/N	2023-05-17 12:30:50	Aux Curr Range	--		
Volt Range	5 V	Creator		Aux Record Con...	0.1 sec 0 mV 0 °C		
Curr Range	±300A	Remarks		Aux Diff Volt	--		
Step File		Plat Volt1	--				
NA		Plat Volt2	--				
Formation Name		Plat Volt3	--				
Rate change ab...	0.0s 0.0mv						
delay time	1 sec						
Material	--						
Step delay	--						
Continue delay	--						
Main Aux delay	--						
ZwJ and XwJ inf...	Wright click to get more info...						
Service version	BTSServer(R3)-7.6.0.166 (2...						
Client version	BTS 7.6.0.1114(2017.01.22...						
ZwJ version	4S_1.1.5.2_20170405_174...						
ZwJ SN							
XwJ main chann...	M01000106_160811_0847...						
ID	Step name	StepTime(hh:mm:ss:ms)	GoTo	Volt(V)	Curr(A)	Cap(Ah)	Pressur
1	Rest	00:10:00:000					
2	CC_Chg	02:30:00:000		4.1000	1.0000		
3	Rest	00:10:00:000					
4	CC_DChg	02:30:00:000		2.6000	1.0000		
5	Rest	01:00:00:000					
6	Cycle	Begin ID: 1	Times: 100				
7	End						

Figure 19. CC charging-discharging testing profile for 100 cycles in BTS 7 software

However, there is a big margin of fluctuations in current, and this fluctuation happened as the accuracy is achievable with this type of smaller cell and test setup (The cell was tested earlier with the BTS8000 testing module).

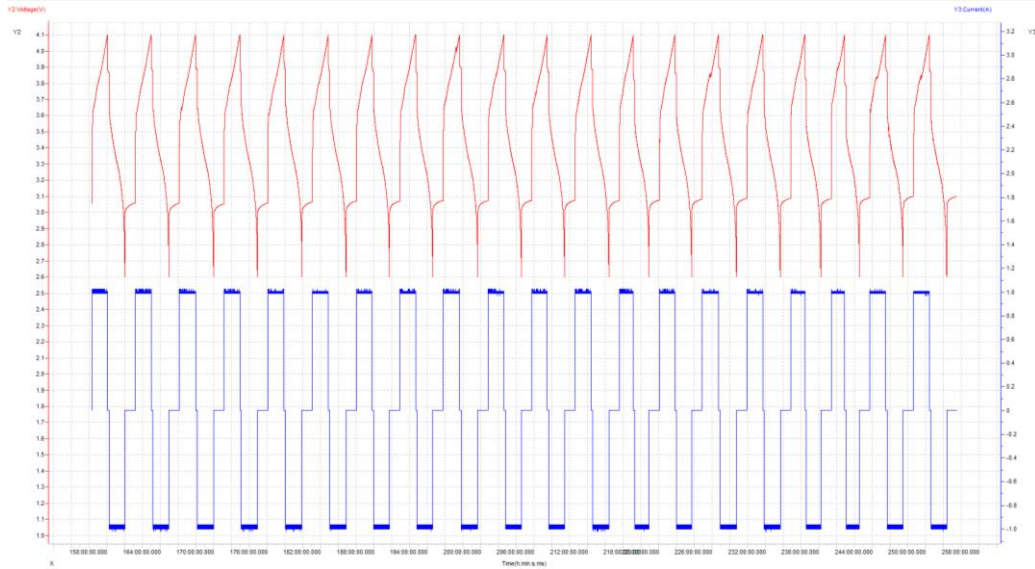


Figure 20. Voltage and current response at constant current mode, 1C

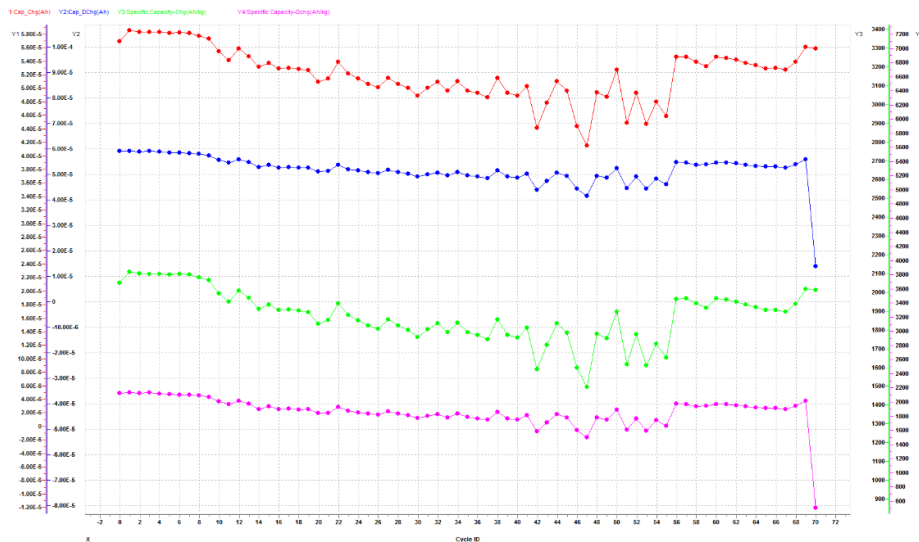


Figure 21. Capacity and specific capacity plotting of cell (up to 70 cycles)

Figure 21 shows the capacity each cycle provides in the charging-discharging procedure for the whole test profile. In this case, the test profile was run for 100 cycles. Here, the capacity was traced up to 70 cycles, which shows a good number of fluctuations between 40-56 cycles.

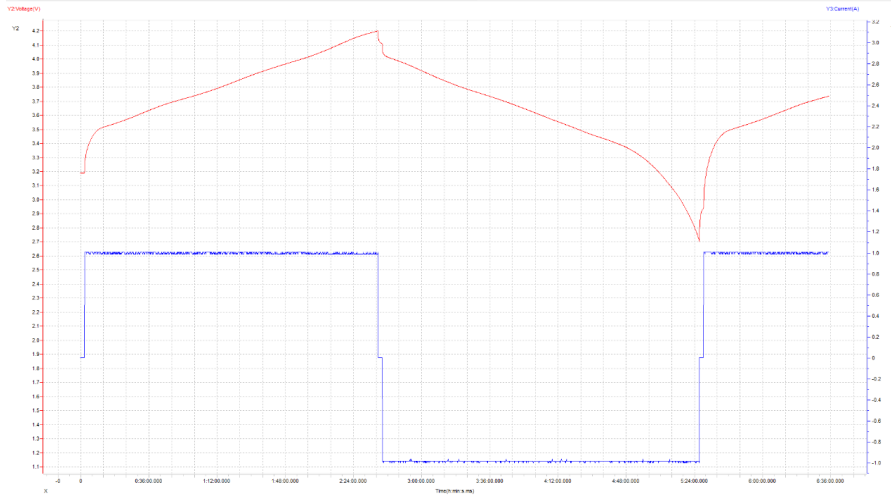


Figure 22. Voltage and current response at constant current mode, 1C

Initially, the charging-discharging process has some consistent capacity. However, discharging is more consistent in maintaining the capacity and has some noticeable fluctuation after 40 cycles. Again, the ripple settles after 56 cycles, showing some inconsistency through the cycling process. The second life is one of the reasons that the cell doesn't perform consistently in the long run.

However, in single-cycle charging-discharging at 1C or less than 1C rates, the peak voltage is higher than the continuous charging-discharging shown in Figure 22. This shows the importance of the relaxation period of battery cells in operation, as the battery is in its second life, and it is difficult to achieve full capacity at a continuous charge-discharge process. Also, continuous charging and discharging at full capacity may reduce the battery's performance, and this can easily be compared to the capacity response of 100 and 2 cycles.

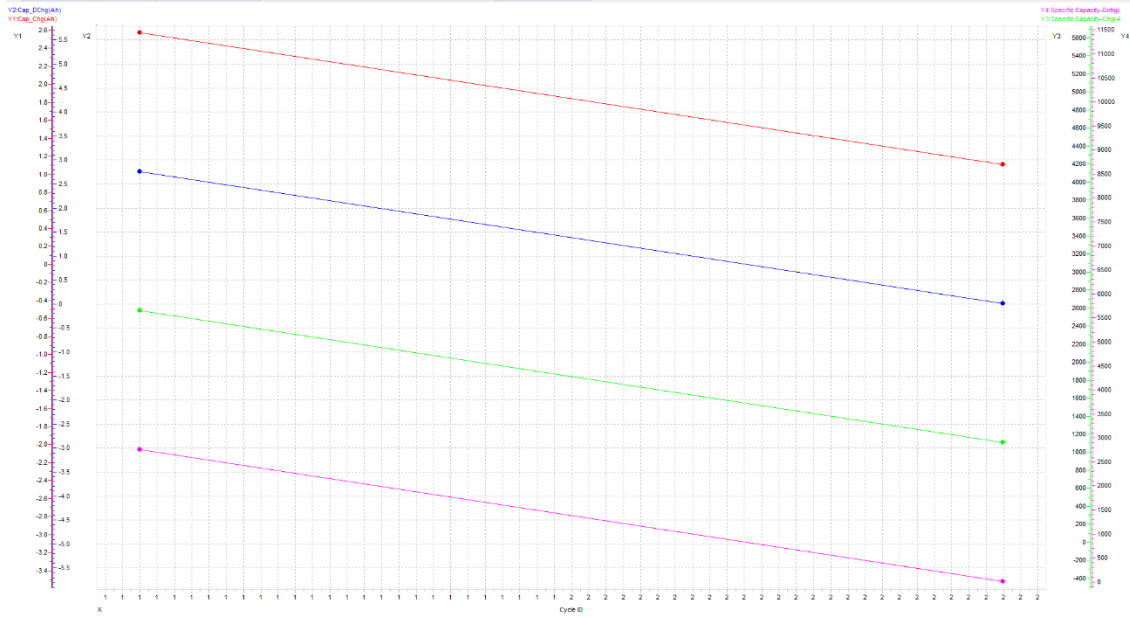


Figure 23. Capacity and specific capacity plotting of cell each cycle (up to 2 cycles)

The consistency of charging-discharging slowly decreases shown in Figure 23 when the cycle number is lower. This experimental data is important to characterize this battery cell and its dynamic behavior. To first predict the initial values of parameters, the HPPC parameterization process will be run for each temperature step. These initial values are then standardized using the methodology of least square fittings to get better parameter values at different temperatures.

4.3 Model Development

In this section, a second-order Equivalent circuit model for second-life Tesla 18650 lithium-ion cells will be proposed, and initial model parameters will be defined. The version of the ECM used in the study is simplified in terms of electrical behavior but capable of capturing the important dynamic and nonlinear effects of the battery.

4.3.1 Assumptions and Criteria

To develop an effective ECM, several criteria need to be defined. Those are –

- (1) This type of battery is assumed to be a uniformly reacting energy storage device, and the electrochemical processes are presumed to be evenly distributed within the system.
- (2) The electrolyte is a dissolved salt, and the only ions that move in the system are those of the salt; this allows for short-distance diffusion, which enables higher-frequency operations.
- (3) The model is helpful when frequencies are within the range of the impacts of electrochemical kinetics and diffusion.
- (4) The aging factor has some influence on the characteristics but is not measured through this parameterization process as it needs more detailed testing facilities and time for a particular battery cell.
- (5) All the sample battery cells are performed similarly as the capacity and voltage of all the sample cells are quite similar.
- (6) The Tesla 18650 cell has a comparable performance graph to other branded 18650 batteries when looking at the acquired testing data resemblance point of view, despite the fact that the Tesla 18650 is more effective and reliable in terms of usage in application.

These approximations allow for creating a model that uses parameters derived from the linear circuit theory, which makes the calculations efficient and applicable in real-time environments.

4.3.2 Parameter Identification

In this research work, the parameters are identified initially from different test data. The most important or crucial test profiles are the open circuit voltage (OCV) testing and HPPC testing.

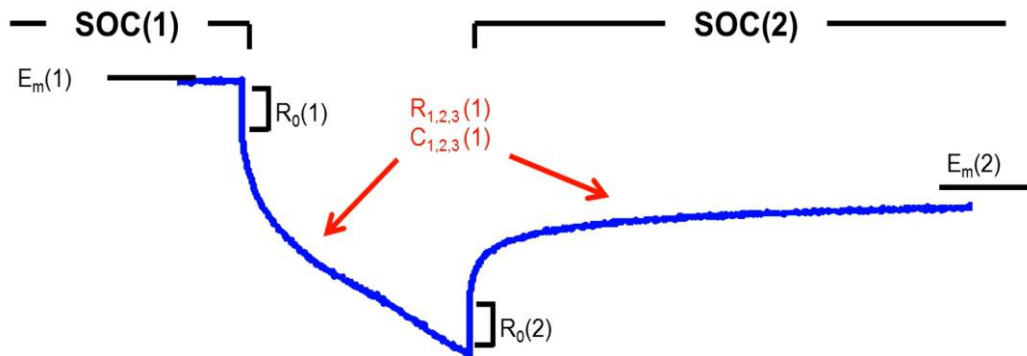


Figure 24. Parameter identification procedure from HPPC test

Most of the parameters are calculated from the HPPC testing plot by calculating different time constants from the transient response. Although it's not possible to do any HPPC testing profile here, hence, the HPPC testing data was collected from the Battery Archive (BatteryArchive.Org, n.d.), Mendeley open data source, and DATTES by Université Gustave Eiffel (DATTES, n.d.). Data from comparable 18650 models from other manufacturers with similar capacities was collected instead of directly testing the specific Tesla 18650 cell from the 2014 model. The data similarity should be 90 to 95%. Figure 24 shows how the time constant will be calculated from the transient response and which parameter is dependent on a specific time constant. Further detailing of HPPC response can be illustrated in Figure 25 –

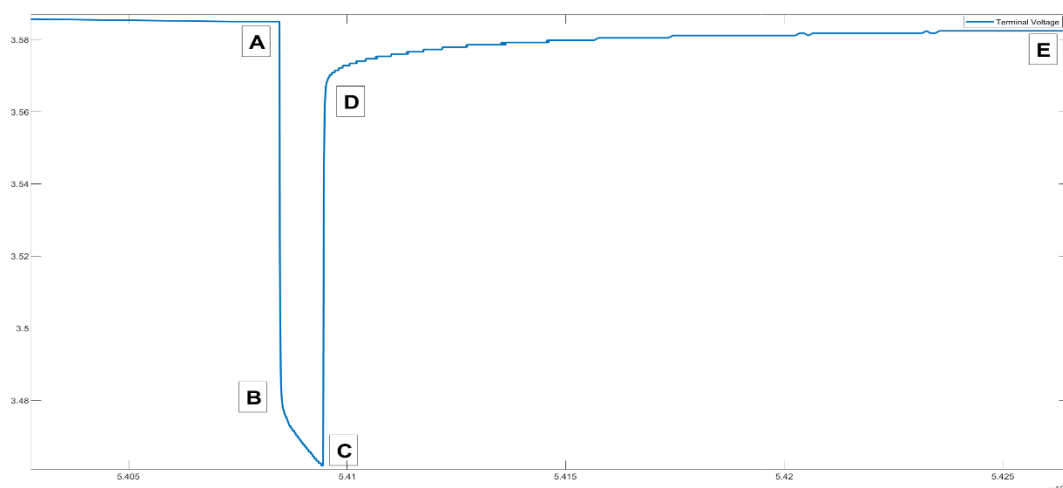


Figure 25. One pulse of the HPPC profile

From the figure, the battery state changes from a discharge state to a static stage, where five different voltage differences can be traceable. In segment AB, the terminal voltage abruptly declines when the battery transitions from its initial static no-load condition to one of loading and discharging. As the voltage drop across the capacitor cannot change suddenly, this variation in voltage happens because of the ohmic internal resistance. In segment BC, the transient properties show that the voltage decreases gradually until it reaches the minimum level, and that portion is affected by two or more RC branches. In the CD segment of the plot, the pulse stimulation stops, the battery is no longer depleted, and the device becomes inactive without load. The capacitor's internal resistance prevents rapid voltage changes. In the DE section, the voltage increases gradually and exponentially until it reaches its peak. This whole voltage shift case is known as the battery's voltage recovery process. When the battery is loaded, it will experience a particular voltage drop due to factors such as electrode composition, electrolyte, and battery polarization. These elements are used to calculate the battery's equivalent impedance. Different elements of the equivalent impedance contribute to the recovery voltage characteristic. In this research work the equivalent impedance is also calculated from this procedure. All the internal ohmic resistance, polarization resistance, and polarization capacitance will be calculated from this method.

4.3.3 Mathematical Illustration

Internal ohmic resistance is characterized by the response of both AB and CD sections. Hence, the average of these two responses represents the internal ohmic resistance. Hence,

$$R_0 = \frac{1}{2} \left(\frac{U_A - U_B}{I_L} + \frac{U_D - U_C}{I_L} \right) \quad (4)$$

The other two branches of RC can be determined from the slow changes as the capacitance cannot change instantly, hence, the slow changes at BC and DE segment represent the characteristics of both RC branches. As this is a 2nd-order Thevenin equivalent model, the mathematical formula of a second-order RC circuit would be –

$$\begin{aligned} \frac{dU_1}{dt} &= \frac{I_L}{C_1} - \frac{U_1}{R_1 C_1} \\ \frac{dU_2}{dt} &= \frac{I_L}{C_2} - \frac{U_2}{R_2 C_2} \end{aligned}$$

After solving both differential equations,

$$\begin{aligned} U_1(t) &= U_1(0)e^{-t/\tau_1} + I_L R_1 (1 - e^{-t/\tau_1}) \\ U_2(t) &= U_2(0)e^{-t/\tau_2} + I_L R_2 (1 - e^{-t/\tau_2}) \end{aligned}$$

Here, time constant $\tau_1 = R_1 C_1$, $\tau_2 = R_2 C_2$ and $\tau_1 < \tau_2$

Before the AB segment, if the battery stands by for a long time, the BC segment rewrites as a zero-state response. From that perspective, both RC loops can be written as

$$\begin{aligned} U_1(t) &= I_L R_1 (1 - e^{-t/\tau_1}) \\ U_2(t) &= I_L R_2 (1 - e^{-t/\tau_2}) \end{aligned}$$

Hence, the output equation should be –

$$U_L(t) = OCV - I_L R_0 - I_L R_1 (1 - e^{-t/\tau_1}) - I_L R_2 (1 - e^{-t/\tau_2}) \quad (5)$$

An exponential function can be used to fit these four SOC parameters from 2RC branches.

Hence, the equation for exponential fitting looks like this –

$$U_L(t) = k_0 - k_1 (1 - e^{-t/\tau_1}) - k_2 (1 - e^{-t/\tau_2}) \quad (6)$$

With the comparison of equation (5) and (6), It can be derived that –

$$R_1 = \frac{k_1}{I_L}$$

$$R_2 = \frac{k_2}{I_L}$$

And

$$C_1 = \frac{\tau_1}{R_1}$$

$$C_2 = \frac{\tau_2}{R_2}$$

Considering these parameters' mathematical format, the initial parameter was calculated from the experimental data for three different temperatures, as mentioned in the procedure in sections 4.2.3 and 4.3.2.

4.3.4 Simulation of Battery Behavior

An equivalent circuit is a common model structure used to approximate the performance of a chemical battery. The objective is to use this model to measure data for a Tesla

18650 battery cell at extremely high accuracy while operating settings, which is required for creating battery controllers for various applications.

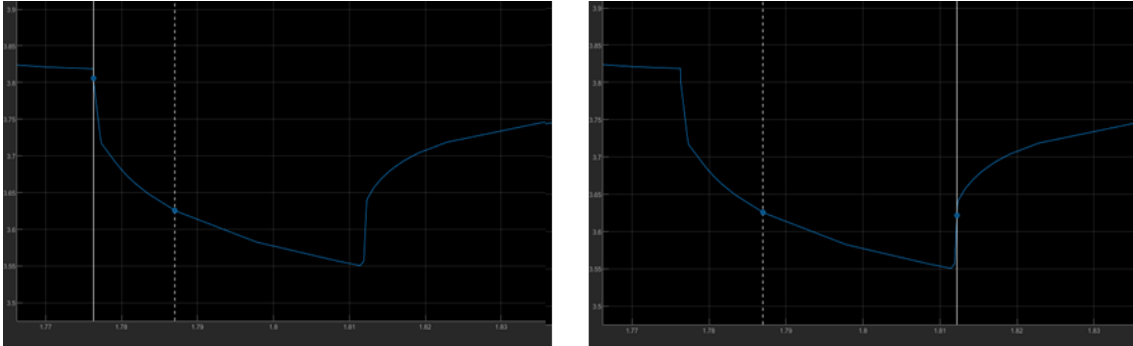


Figure 26. Sample time constant τ_1, τ_2 measurements procedure

For choosing the equivalent circuit model, the first attempt was to use the systematic approach and try to work out a complex model with sufficient accuracy.

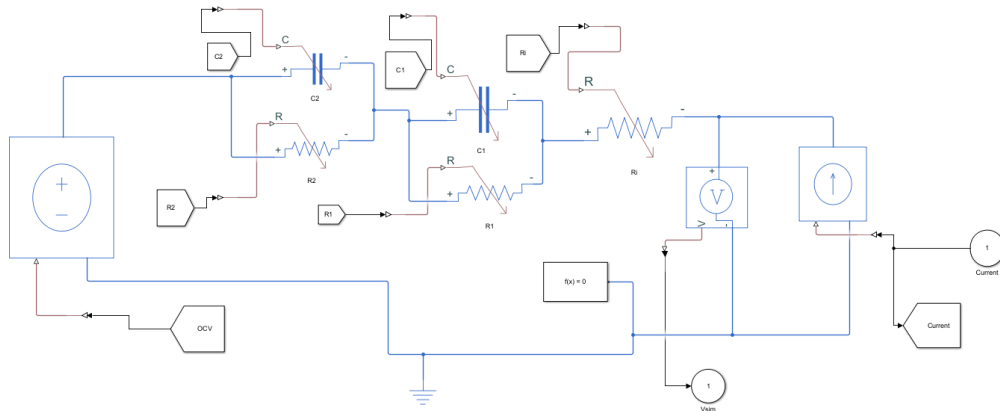


Figure 27. Equivalent circuit model in MATLAB

It could be seen that although a single RC branch within a model's circuit appeared to be sufficient at first glance, a more detailed look at the system's transient response indicated the potential value of further RC branches. The 2nd order equivalent circuit transient response is shown in Figure 26. This detailed response analysis emphasizes second-order RC circuit modeling. The schematic equivalent circuit model is shown in Figure 27.

This circuit has several components, typically including an open circuit voltage (OCV), series resistance R_0 and two parallel RC branches.

This structure captures both the instantaneous voltage response and the dynamic behavior of the battery at different time scales, and depending on the battery speeds and operating conditions, some of them exhibit quite dramatic behavior. Sorting those values in lookup tables is effective even though the open circuit voltage concerning the SOC and temperature is one method to deal with this behavior. The output of this circuit shows the ideal response of terminal voltage for a specified input current data set that was collected from the test. With this basic second-order ECM model, the SOC estimation technique is incorporated.

4.3.5 State of Charge (SOC) Estimation Technique

While the SOC has one relationship with OCV, hence, look-up table procedure is a common practice to estimate SOC at different experimental levels in the simulation where the coulomb counting method is used for cell SOC estimation. Coulomb counting, or the ampere-hour method, is one of the most widely applied strategies for SOC evaluation. In this technique, the SOC can be determined using the battery current and accumulate the result. The algorithm begins with initialization where SOC at a certain time, $t = t_0$, is denoted as SOC_0 is known. This initial value can be established through the calibration or initialization phase of the system. During the operation of the battery, the current that is either flowing into or out of the battery is described as $I(batt)$ for which the corresponding current is either measured or sampled periodically. This current measurement can be done using current sensors or any appropriate method. When integrated with the measured current over time, the accumulated charge or discharge, apparently denoted as $Q(t)$, can be determined.

$$SOC(t) = SOC(t_0) + \frac{1}{C_{rated}} \int_{t_0}^{t_0+\tau} I(batt) \quad (7)$$

SOC at a given time is denoted by $SOC(t)$ and is determined by dividing the accumulated charge by the battery's rated capacity C_{rated} . The coulomb counting method has a higher accuracy as compared to other methods of SOC estimation and is useful for tracking fast dynamics of the SOC level; this method does not require much computational work.

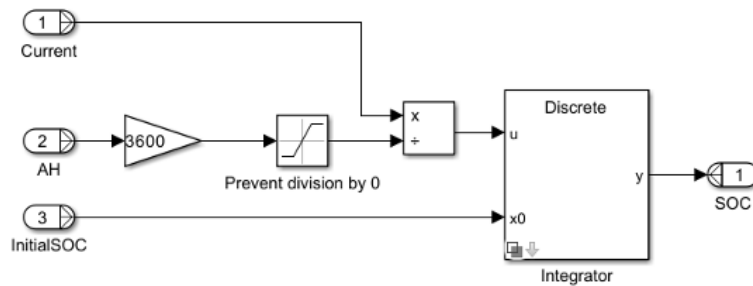


Figure 28. Coulomb counting SOC estimator

However, the error arising from the current measurement accuracy, system calibration, and the differences in battery characteristics must be taken into consideration to make the SOC estimation accurate when using this method.

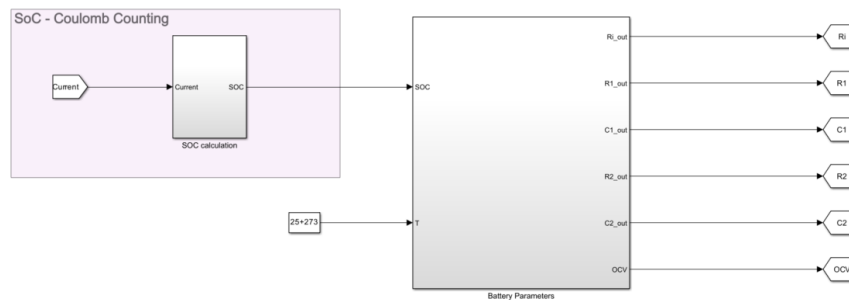


Figure 29. SOC estimation circuit incorporating to estimate parameters

Figure 28 depicts the internal block of the Coulomb-counting SOC estimator. Parameter estimation is carried out using SOC and temperature for evolution. Figure 29 shows the use of Coulomb-counting SOC estimation incorporated into the battery parameter estimation process, which will be used for parameter optimization.

4.4 Optimization of 18650 Li-ion Cell

The performance and cycle life of these second-life 18650 lithium-ion cells, once they get utilized in the initial application, needs to be fine-tuned for reuse in other applications. These cells have differed in terms of how much has been degraded and what remaining capacity, internal resistance, and a healthy portion is left. Optimization strategies are designed to fully realize this potential, to get the most out of these cells, and to delay their decrement curve. Hence, testing the battery cell in a controlled profile with the expected SOC level and capacity level and optimized parameters based on that experimental output will eventually optimize the cell behavior.

4.4.1 Optimization Criteria

The optimization of second-life 18650 cells has a few factors that can be improved further. Remaining capacity utilization is a way of establishing the optimal operating current range as well as safe charge/discharge rates to enhance output. Considering and limiting the internal resistance fluctuation over the SOC changing is another criterion. However, need to consider the dependency on temperature as the electrochemical reaction generates heat, which eventually fluctuates the internal resistivity of the cell. It is not practical to fully optimize or be independent regarding temperature dependency, as mentioned, although it is possible to balance cell function even at higher temperatures, such as 45°C. Hence, parameter optimization should support the operation of the cell at extreme thermal conditions. For that purpose, the operating temperature at testing was considered 15°C, 25°C, and 45°C. Safety considerations are another point that has a greater impact though at the cell level without a management system, it is not feasible to optimize.

4.4.2 Optimization Techniques

To address all the related criteria of the second-life 18650 cells, there are several optimization techniques available that can be used. It is also possible to group these techniques into cell selection level and simulation level. At the cell selection level, there are a few factors like capacity sorting, internal resistance screening, and electrochemical characterization that have a greater impact. There is a possibility to sort cells by remaining capacity that allows to selection of cells with the same type of performance. Some of these advantages include this can enhance the uniformity of the packs to eliminate imbalances during functioning.

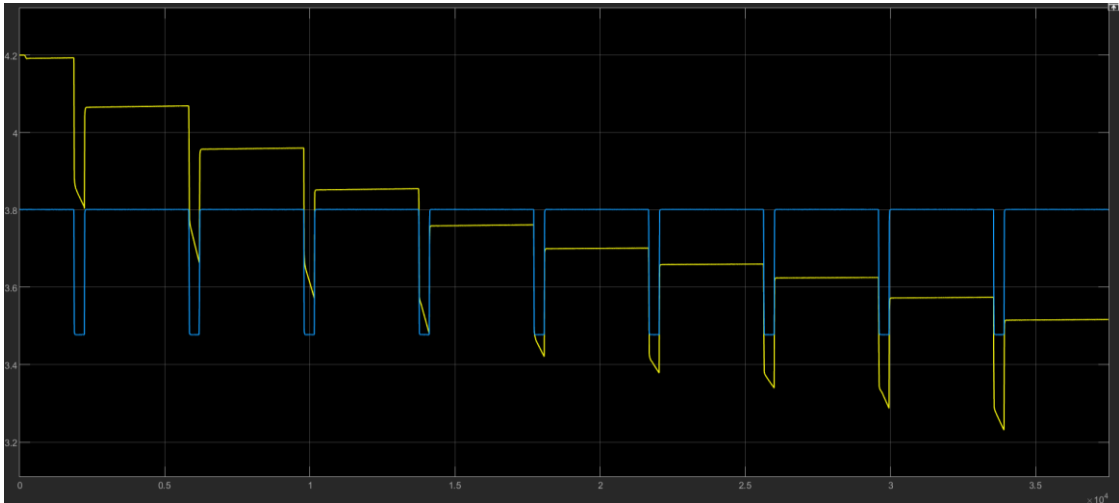


Figure 30. Simulated and experimental voltage response comparison (before optimization)

In this experimental testing, there are a total of 8 cells where the first step was to sort based on their capacity remaining, and 5 different cells are tested with similar capacity. In terms of performance, all the cells produce similar output, which justifies this sorting procedure. On the other hand, poor-quality cells with high inner resistance can be sorted out from selected packs, hence lowering the overall pack resistance with the resultant decrease in losses. This process doesn't have any impact on cell level rather pack level, however, for testing a single cell, the priority was to pick the lesser internal resistance one. Regarding the determination of the cells' electrochemical characteristics, methods such as OCV, HPPC, and DCIR can offer valuable information for accurate selection and

matching processes. In Figure 30, the plot shows the experimental voltage response and the simulated voltage response.

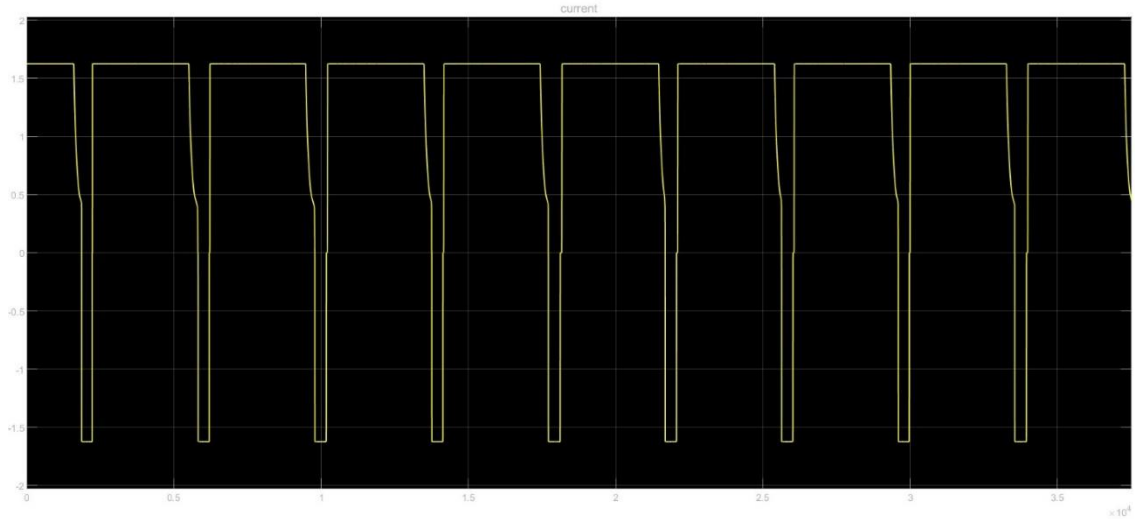


Figure 31. Current profile

The experimental value is collected in a controlled way so that it fulfills all the optimization criteria considered in the experimental phase, although the simulated result is an ideal condition for a specific stage.

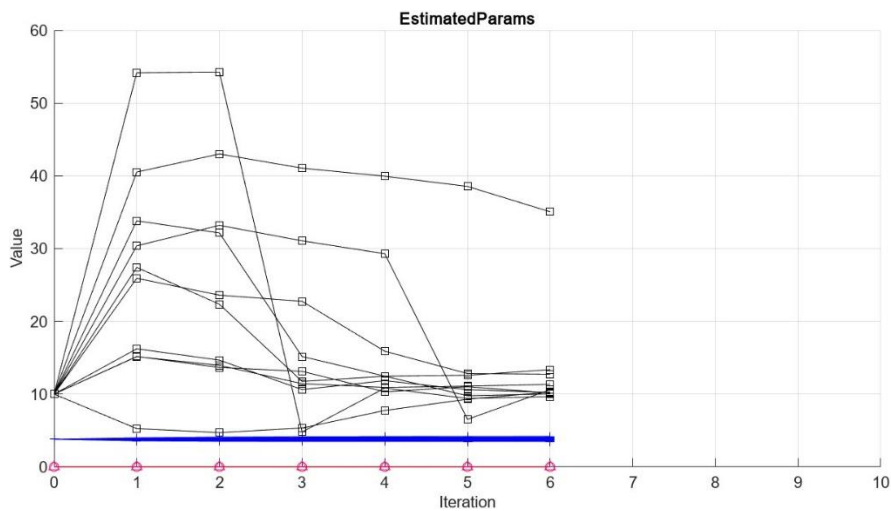


Figure 32. Parameter optimization iteration

From optimization at the simulation level, optimization methods may also be employed with the use of experimental approaches and electrochemical evaluation in addition to computational analysis.

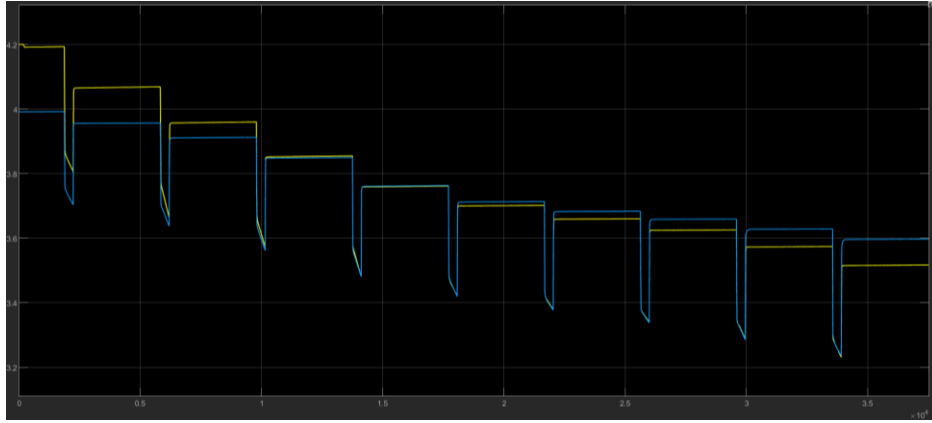


Figure 33. Parameter optimization process ongoing (voltage response)

Considering that procedure, Simulink Design Optimization (SDO) can be used to calculate the optimized value for the parameters and update these lookup tables. The input constant current response from experimental data is plotted in Figure 31. It begins with importing experimental test data which are usually current profiles and corresponding voltages at the experimental optimization level. Data is then split to isolate specific operating circumstances for focused parameter assessment.

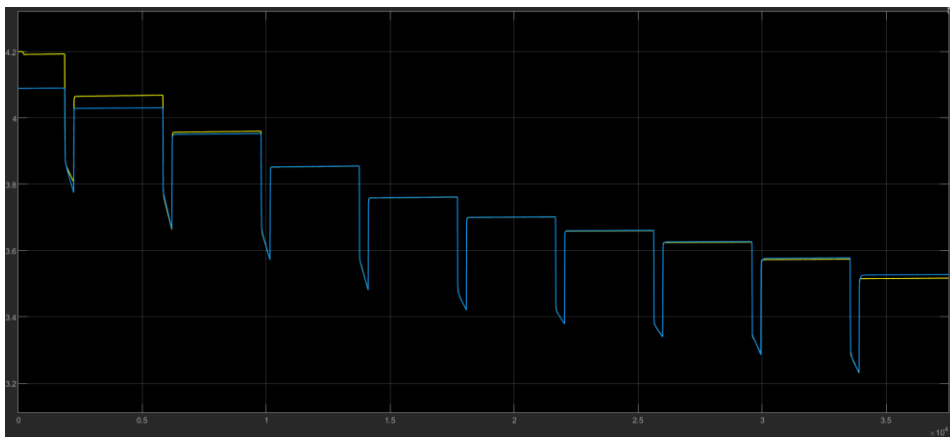


Figure 34. Parameter optimization process ongoing (voltage response after 3rd iteration)

There are limits for each circuit element parameter's range to narrow down the optimization area by setting its minimum and maximum values.

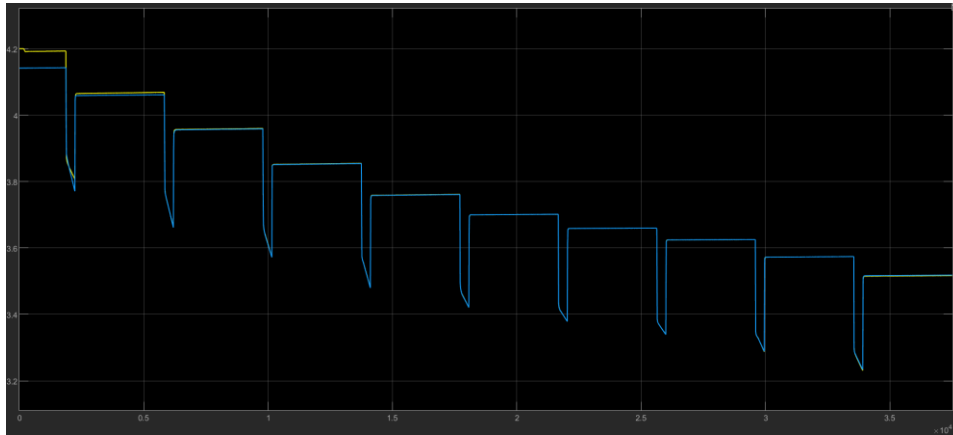


Figure 35. Parameter optimization process ongoing (voltage response)

Initial values are chosen based on the order of magnitude for the given battery chemistry and size. The optimization algorithm, usually nonlinear least squares, finds the parameters that reduce the error between the voltage response and the model's predicted output. Figure 32 shows the iteration process based on defined optimization criteria.

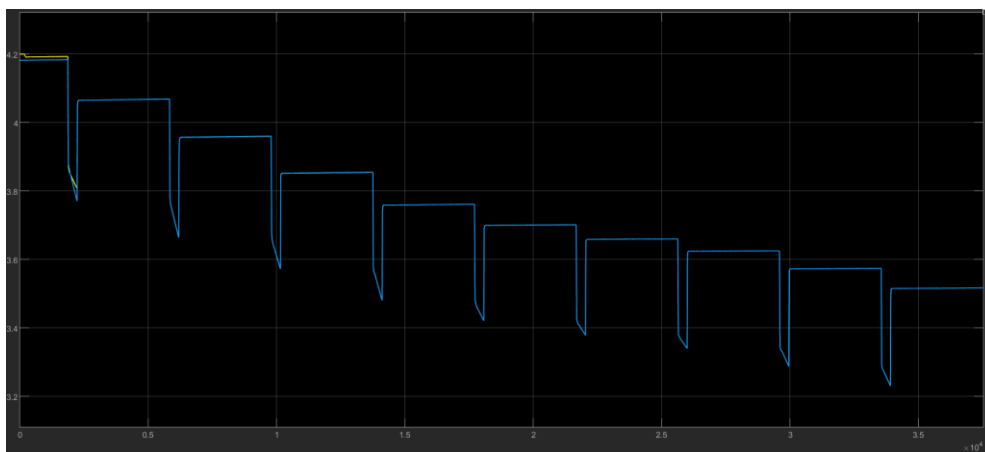


Figure 36. Parameter optimization process ongoing (voltage response)

It is the process of optimizing within the given ranges for each parameter, that is performed in a step-by-step manner by moving to the closest optimal solution. To decrease

the inaccuracy, the SOC breakpoints in the look-up tables coincide with the resolution of the measured data. For example, if test pulses at a certain percentage of SOC were conducted, their respective percentage figure would be employed in setting the breakpoints of the lookup table. The estimation is done successively for different operating conditions, particularly in terms of temperature. This implies that it is also possible to specify how each layer of the multi-dimensional look-up table structure is filled.

Intense computer processes save time while doing optimization iterations. In this case, parallelism is a possibility that can help to enrich this process using several cores or distribute the computing process. Generally, the `matlabpool` command uses all the processing power of the computer to speed up the process and several iteration steps are taking place to compute the optimized value.

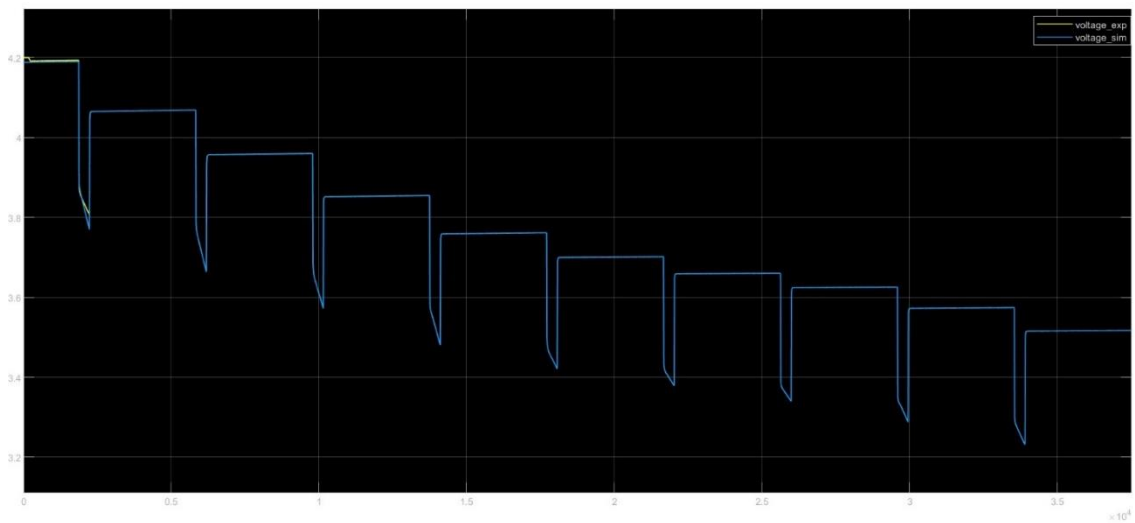


Figure 37. Parameter optimization process ongoing (voltage response after 6 iterations)

In optimization, the parameters' values are adjusted, and the new values are assessed as optimal to produce the model response. The synchronization is checked using the errors and the values of the parameters that should become stable. It stops when it has found the best match or when the number does not exceed the maximum number of attempts.

Iteration	F-count	synthData (Minimize)
0	81	9.2260
1	162	1.0874
2	243	0.1815
3	324	0.0315
4	405	0.0064
5	486	0.0011
6	567	0.0001

Configuring parallel workers for optimization.
Parallel workers configured for optimization.

Figure 38. Estimation validation progress report

After six levels of iteration, the parameter estimation process is shown in Figure 33-37. By using the optimizing tool, a re-estimation of 6 parameters is done. The estimating process is depicted in Figure 38, where the minimization during optimization and the F-counts are shown from each iteration step. After optimization, each defined parameter is re-evaluated and created a new look-up table. Figure 39 shows the mesh plotting of the parameter R_0 . The plot observation defined that the increase in State of Charge (SOC) with aging in the coulomb counting or ampere-hour method can be attributed to the gradual loss of active materials within the battery.

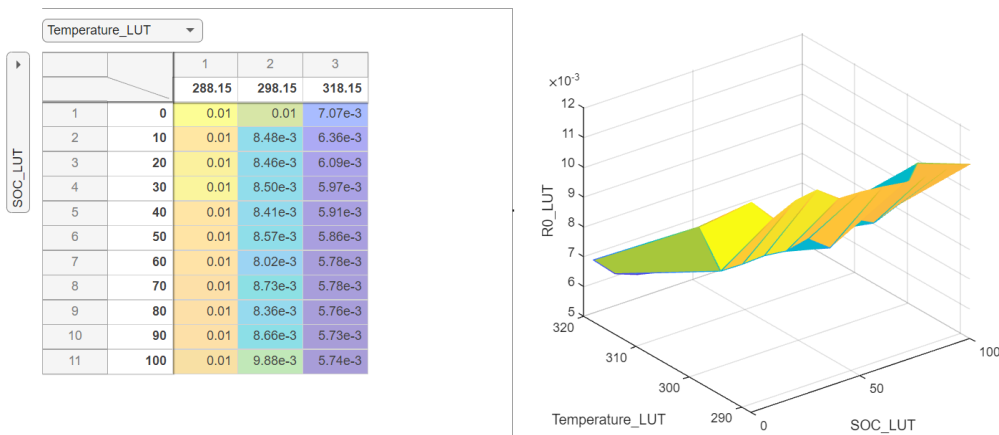


Figure 39. Parameter R_0 mesh plotting

The parameters associated with the short transients of the RC branch, derived from the time-varying voltage (ΔV_1), are assumed to highlight the dynamics during the charge transfer process of cell operations.

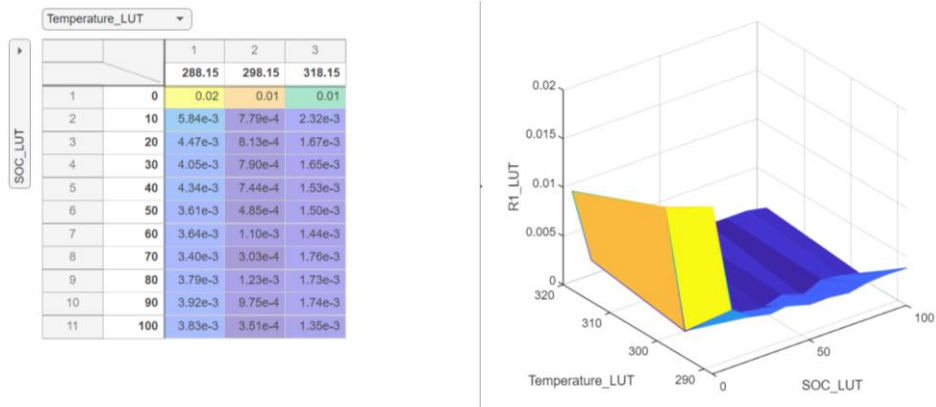


Figure 40. Parameter R_1 mesh plotting

Significant changes obtained from the analysis show that the efficiency of the charge transfer process deteriorates with aging, mainly due to the increase in R_1 and C_1 . The mesh plot of R_1 and C_1 is depicted in Figure 40 and Figure 41 respectively. The components of R_1 can grow due to many reasons depending on the conditions of battery use as well as due to the aging processes such as electrode degradation, the increase of the internal resistance, and the changes in electrolyte characteristics.

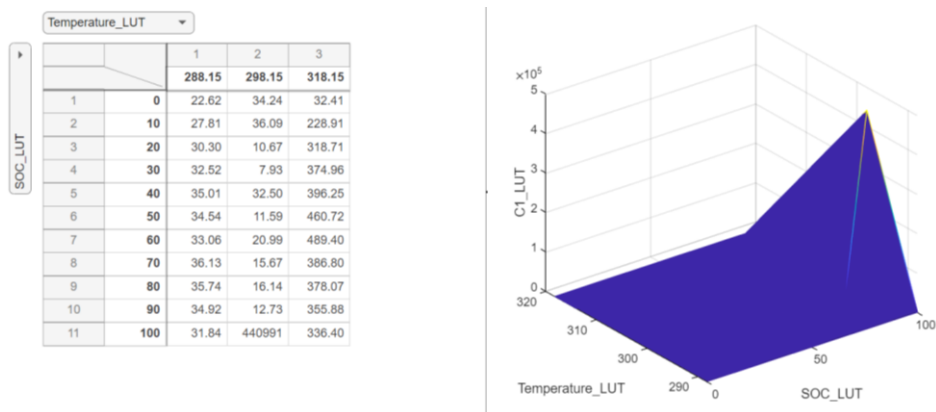


Figure 41. Parameter C_1 mesh plotting

Higher resistance values mean higher-end voltages as the charge transfer processes are accompanied by higher voltage drops. At low battery temperatures C_1 values may vary due to changes in electrode surface morphology, electrode/electrolyte interface, and electrolyte. Thus, the rise of C_1 implies a deterioration in the system's ability to efficiently store and release charge.

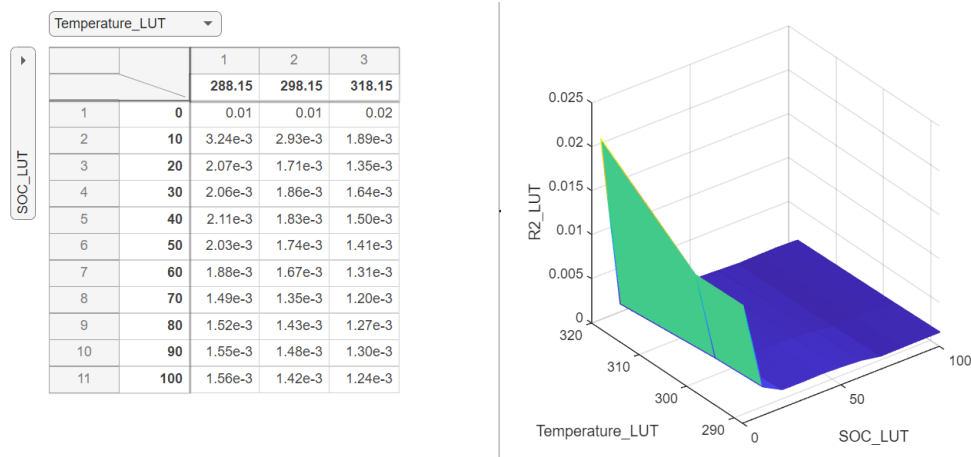


Figure 42. Parameter R_2 mesh plotting

The parameters related to the long transients of the RC branch are obtained using the time-varying voltage ΔV_2 , are supposed to give an insight into the dynamics at the time of diffusion of the cell operations. The mesh plots of these two parameters of RC branches as R_2 and C_2 are illustrated correspondingly in Figure 42 and Figure 43. These parameters give information relative to the diffusion process of ions through the battery during charging as well as during the discharging process. The R_2 is used to capture the degeneration in the ability of the battery's electrodes as well as the electrolyte to prevent the migration of specific ions. R_2 can, therefore, be variable over time because of different processes that occur within the system, for example, degradation of the electrodes, alteration of the electrolyte composition, and creation of SEI layers. Lower values of SOC are related to greater resistance to the ion diffusion, and therefore, charge/discharge rates are slower, while the overall system efficiency decreases with the increasing of R_2 .

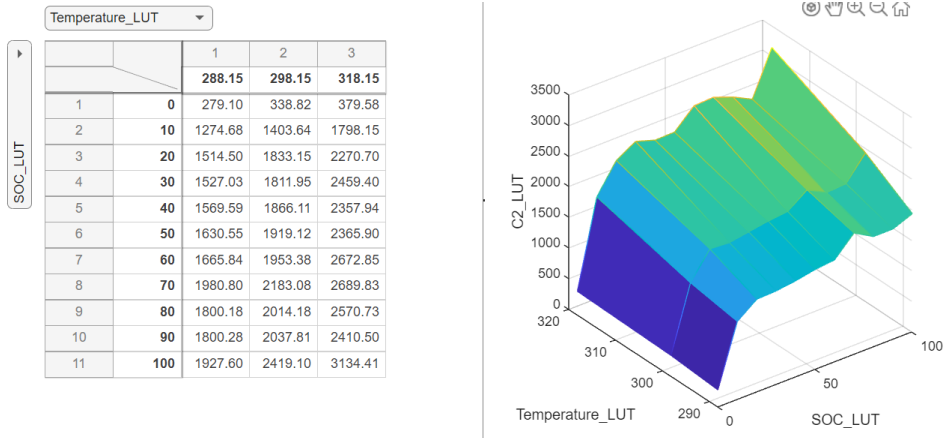


Figure 43. Parameter C_2 mesh plotting

C_2 stands for the capacity which is allocated in the system because of diffusion effects. Both activation energy and transmission coefficient are found to depend on the properties of the electrodes, electrolyte, and the interface, as represented by the parameter C_2 . It can now be seen that C_2 may change due to aging, changes in the interface of electrode and electrolyte, the composition of the electrolyte, and the morphology of the electrode. A lowering of C_2 indicates that the ability to store charge through the mechanisms of diffusion is lowered, and it is heavily dependent on changes in SOC and temperature alterations.

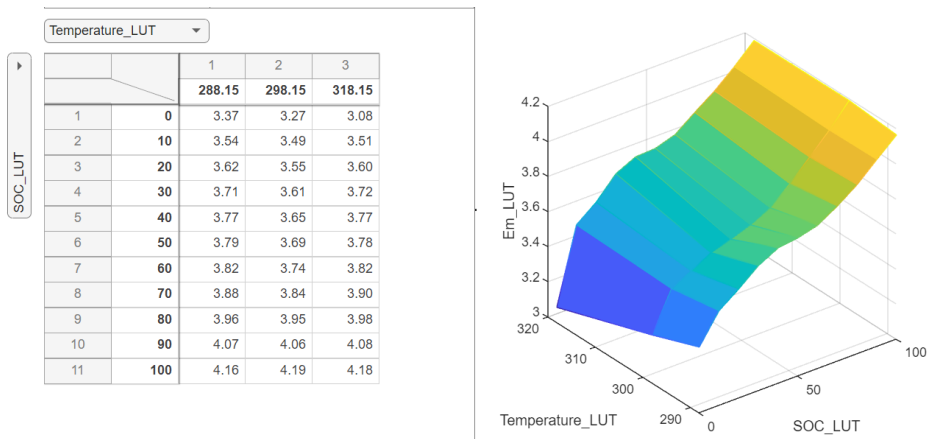


Figure 44. Parameter OCV mesh plotting

Figure 44 illustrates the OCV mesh plotting through which the changes in open circuit voltage (OCV) are noticed at the later stage of the respective cycles. This is because OCV values are highly dependent on the loss of the cyclable amount of lithium ions within the battery. Lithium ions are incorporated and released to/from the active materials of the electrodes during the charge and discharge of lithium-ion batteries. This process is crucial for the battery to function, and it dictates the behaviors and capacity of the battery. However, as the cycles go through each cycle, additional possibilities, such as structural alterations, electrolyte breakdown, and side reactions can cause catastrophic performance degradation.

4.5 Model Validation

The second-order equivalent circuit model (ECM) for Second-life Tesla 18650 lithium-ion cells needs to be validated to verify the accuracy of the developed second-order ECM. Model validation includes comparing the model output with the experimental measurements of a system and assessing the behavior of the model due to variations in parameters and operating environment.

4.5.1 Experimental Setup and Protocols

To confirm the ECM, a detailed experimental architecture and precise testing procedures are required. The experiment modification should reflect operating conditions as close to the real application as possible while sufficiently capturing the behaviors of the battery under study. The design of experiments (DOE) should have this modification from the components and testing procedure point of view. From the testing equipment involvement in an experimental protocol typically involves –

- (1) **Battery test station:** A precise and automated battery test system that can apply predefined charging and discharging currents, voltage and current signals, and have thermal conditioning. In the case of the University of Vaasa, there are two battery cyclers available right now, and both are from Neware cyclers. One is for

higher-rated battery testing classified as the BTS 8000 series model, and another one is the newly installed BTS 4000 series for sensitive small-size battery cells like 18650 and coin cells with proper connecting probes and thermal sensors. Figure 45 shows the battery cyclers with appropriate connectors.

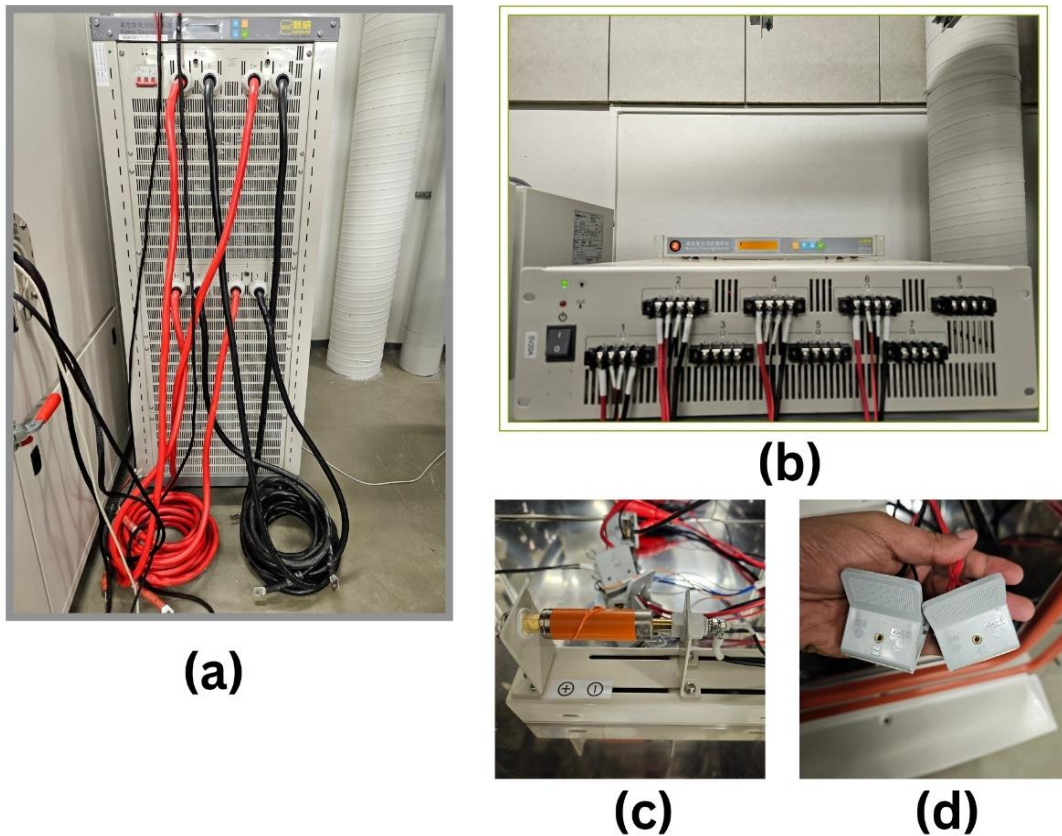


Figure 45. Battery test station at the VEBIC lab, University of Vaasa (a) Neware BTS 8000 series cycler, (b) BTS 4000 series cycler, (c) connecting probes for 18650, and (d) connecting probes for coin cell

(2) **Environmental chamber:** A thermal enclosure or thermal control system that helps in maintaining the actual/test operating temperature during the test. In VEBIC the WEISS is used for this purpose. Figure 46 shows the WEISS thermal test chamber.



Figure 46. WEISS test chamber

- (3) **Data acquisition system:** Accurate measurement data acquisition system for capturing voltage, current, temperature, and other required signals with appropriate accuracy and speed. The computer station used in battery testing facilities has 3 different software from equipment provider Neware for synchronizing the testing machine and processing all the data. The data server is in the same computer to access and convert into an appropriate file format.

- (4) **Safety measures:** Accurate protective measures which include overcharge/over-discharge protection and other measures like thermal and ventilation systems to facilitate safe test operations. The software BTS7.0 has these overcharge/over-discharge limiting features. Besides that, the thermal sensor is used to sense the operating temperature and act based on the limit provided in every test profile. For the external ventilation system, there are two big exhaust systems which connect to the test chamber and help to circulate air for proper ventilation.

The testing protocols should be carefully designed to capture the battery's behavior under various operating conditions, including –

- (1) **Pulse discharge tests:** To analyze the battery's dynamic properties and figure out the ECM coefficients, these experiments assume that a variety of discharge pulses are applied to the battery at different SOC levels.
- (2) **Constant current (CC) discharge tests:** CC discharge tests at different C-rates (e.g., 1C, 2C, 3C) can give information about how much capacity, energy density, and rate capability of the battery.
- (3) **Cycle life tests:** Cycle-life tests, which may include several consecutive charge/discharge cycles, can provide insights into the degradation characteristics of the battery.
- (4) **Temperature variation tests:** The model could also be validated by testing at different temperatures, for instance, in this research work, the testing temperatures were 15°C, 25°C, and 45°C.

4.5.2 Simulation Validation and Error Calculation

The validation from the simulation side is an essential part of supporting the modeling after obtaining the precise experimental data from the established experimental methods. Like simulation design optimization, there is an option to validate the optimization process. From there, the sensitivity can also be calculated to find the error between the experimental and simulation models or the real and estimated optimized parameters. Figure 47 shows the output of the validator tool, which analyzes both the experimental and optimized simulated output to validate the design principle.

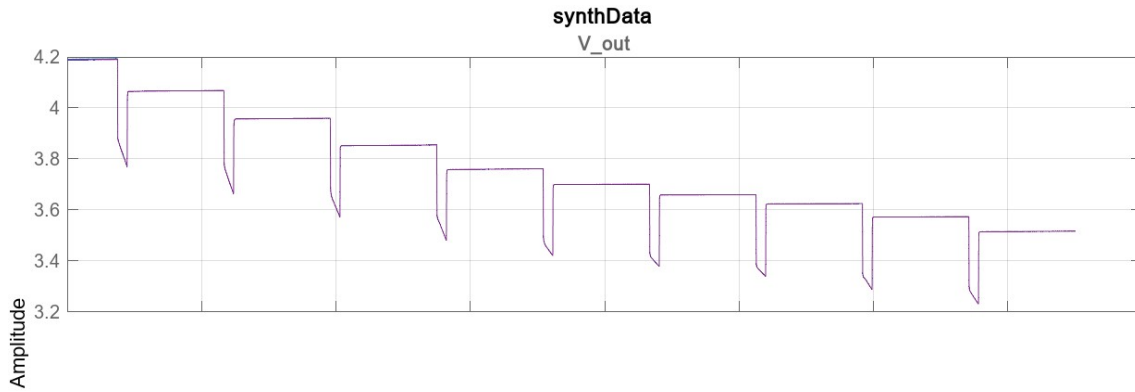


Figure 47. The validation is done by the validated tool in MATLAB

The optimization perfectly replicates the original response from experimental test data, however, there is some mismatch when the short and long transients change their states, which eventually leads to some errors between experimental and simulated data.

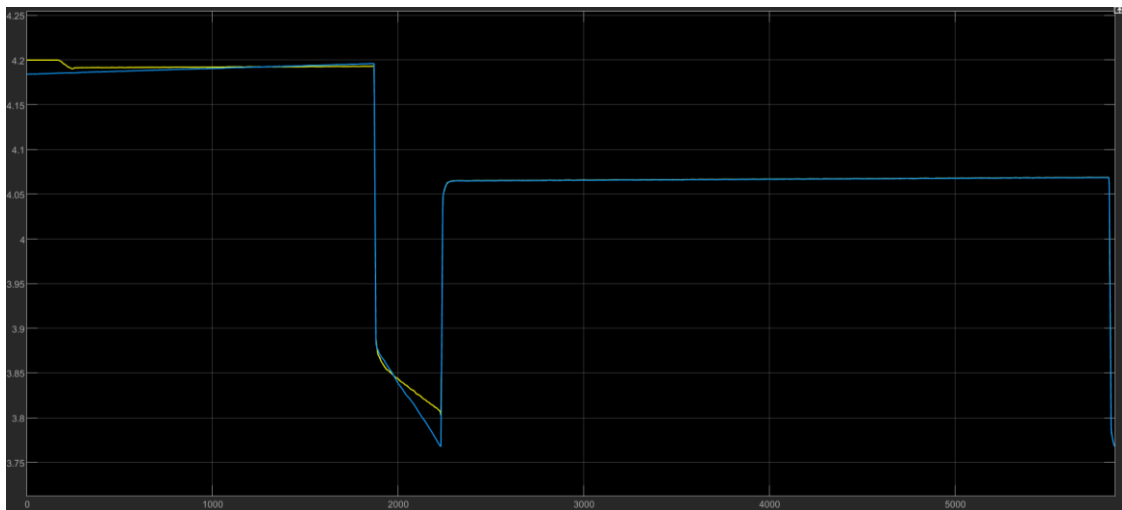


Figure 48. After optimization, the mismatch between experimental & simulated data

Figure 48 shows the mismatch between the experimental and optimized response from the simulation, and Figure 49 shows the percentage error between experimental and simulated data.

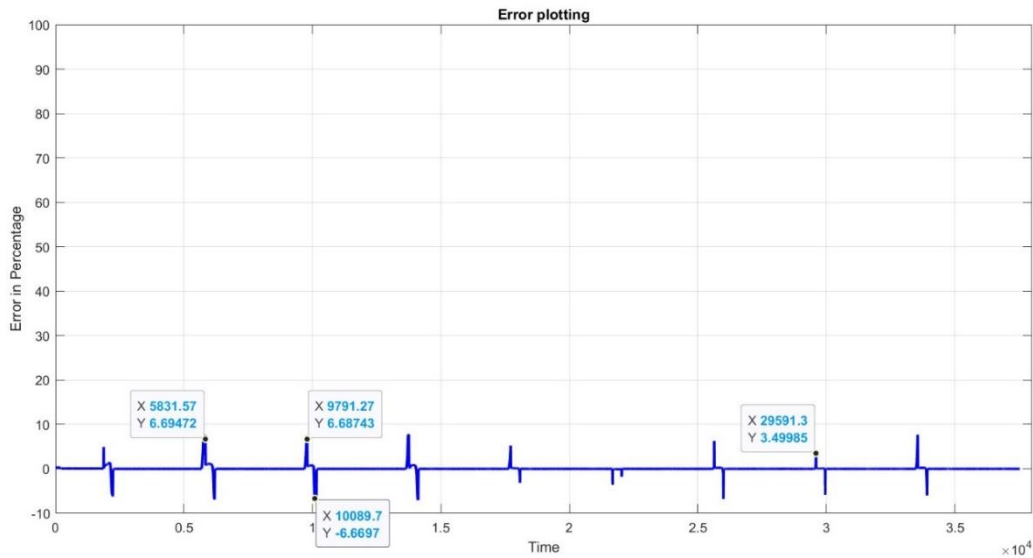


Figure 49. Error in Percentages

4.6 Implementation of Optimization Strategies

From a practical and economical point of view, the integration of optimization factors in second-life battery applications is crucial, and hence, there is a need to adopt a holistic view of second-life battery management, which must confront and overcome a series of technical and organizational issues. Battery module integration includes coherence testing and validation of each integrated battery module at the application level; it presupposes the availability of an optimum battery model. Battery modeling and optimization is always time-consuming because of the cyclic procedures of battery testing. It is essential to maintain a high level of strictness in experimental processes to obtain the best test results in the shortest amount of time. These practical approaches to optimization must be integrated into the development and execution of Battery Management Systems (BMS) because advanced experimentations increase the efficiency of the Energy Storage Management Systems. From a technical standpoint, the optimization process encompasses several critical aspects: comprehensive electrochemical characterization that includes tests like Hybrid Pulse Power Characterization (HPPC tests) and Electrochemical Impedance Spectroscopy (EIS); elaborate cell sorting and screening to improve

pack's performance and coherency; efficient thermal management systems to minimize degradation and maintain the high-performance level.

Nonetheless, from an economical point of view, optimization measures can help in cutting down on the overall cost of integrating second-life batteries significantly and at the same time enhance the efficiency as well as longevity of the power system. The fact that second-life 18650 cells are acquired from various segments such as ex-automotive, ex-power tool, and other electric batteries introduces variations in the acquisition costs, hence the need for an effective supplier evaluation technique to reduce costs given the volatile market. The primary cost in terms of full electrochemical characterization, cell sorting, and performance testing is high and involves the use of sophisticated instruments, experienced staff, and overhead costs. Still, these costs are recoverable with concrete benefits like improved efficiency, better power flow, improved reliability with low maintenance need, and longer service lifespan of systems. Another component of the overall economic evaluation includes the end-of-second-life disassembly or proper disposal and recycling costs of the cells. Thus, it is crucially important to perform detailed calculations of costs and benefits by implementing certain optimization strategies in the provided applications based on the specific requirements of the target market and improved performance scales. These assessments should be mainly in terms of sensitivity, scenario modeling, and life cycle costs, including risks and future market conditions. Naturally, it must be recognized that second-life business models are subjected to rather dynamic economics due to changing optimization strategies and procedures, ongoing advancements in battery production, and constant progress in the field of recycling processes. Thus, the subsequent economic assessments are needed for the researcher, the industry's specialists, and the policymakers. An analytical integration of both technical and non-technical aspects along with appropriate economical balancing enables the stakeholders to come up with some practical measures for the utilization of optimization techniques in second-life 18650 lithium-ion cell applications.

5 Applications and Future Work

Second-life 18650 lithium-ion cells have a lot of potential, which has made their use practical in different applications, hence promoting the creation of a circular economy. Soon after serving the primary application, e.g., EVs or consumer electronics, such optimization approaches can still be reused and hence add as much value as possible to any system. This section discusses current uses of Optimized second-life batteries and seeks to identify other probable advancements in research and development.

5.1 Current Applications of Optimized Second-Life Batteries

The worthwhile further utilization of these second-life 18650 lithium-ion cells opens a multitude of opportunities for their application in diverse real-world scenarios, effectively promoting the cyclic use of these battery cells and, hence, the circular economy. Before these cells reach the final stage of their first-cycle useful life in uses such as electric automobiles or electronics, recycling often offers attempts to further prolong their usefulness through optimization. This section discusses the state-of-the-art of the second-life batteries optimized, and relevant information on the performance, reliability, and robustness in its deployment is also presented.

5.1.1 Grid Storage Solutions

There is a high potential for a second-life 18650 cell as an optimized solution for large-scale batteries at the grid level. Being that the present and future world is shifting towards more sustainable and renewable energy, there is a need to ensure that the systems that are used to store energy are efficient, affordable, and reliable. Some key scopes where the second-life battery can effectively sustain. For instance,

- (1) **Frequency Regulation:** Due to appropriate and fast response to the variations within the power grid, optimal battery systems assist in achieving consistent

power supplies and maintaining the stability and reliability of the grid. This can be manageable by using intelligent Battery Management Systems (BMS).

- (2) **Peak Shaving and Load Shifting:** At moments of raised-up consumer utilization, well-coordinated battery systems can release their accumulated energy instead of creating extra generating capacity to address the issue of imminent peak loads. On the other hand, they can be charged during periods of low demand, allowing shift loads and optimal use of renewable resources.
- (3) **Renewable Energy Integration:** Renewable energy integration causes tremendous fluctuations in load, and often, these renewable energy sources are not consistent, thereby proving to be unstable at times. By employing second-life battery systems, capacity can be optimized to store energy that would have been lost during periods of high renewable generation and release it as needed for grid integration.
- (4) **Backup Power and Microgrid Support:** In case of voltage surge or shedding, second-life battery systems that have been optimized for efficiency can supply backup power for the continuity of essential operations as well as contribute to microgrid stability. This is because these elements possess the ability to release stored energy quickly and smoothly.

The integration of optimized second-life batteries into grid storage solutions raises some considerations about the technical characteristics consisting of energy density, power density, cycle life, and safety. Second-life cells may be prepared for grid-scale applications by analyzing the related metrics, which are complicated by cell characterization and optimization techniques such cell sorting, ideal operational settings, and thermal management techniques. In addition, it is worth mentioning that the economic feasibility of these solutions is even higher added to the fact that the second-life batteries are significantly cheaper than newly acquired battery systems. Furthermore, making use of

these batteries' lifespan and not producing new ones is environmentally friendly and cost-effective.

5.1.2 Portable Electronics and Other Applications

Aside from the grid storage solutions, the second-life 18650 cell has made its way into several portable electronics and many other sectors. Indeed, this fact does not imply that grid-scale systems have significantly higher energy and power requirements than the other applications outlined above, but there are numerous synergies in the utilization of second-life batteries that can be valuable and cost-effective. A common example is mobile power banks and backups in consumer electronics. The second life of cells, if optimized, can offer cheap, effective mobile power for charging common portable gadgets such as smartphones, tablets, laptops, and other gadgets whenever conventional power sources are not available. Their sizes are relatively small and thus highly portable, and their energy density is high to support this role. Also, in the transportation sector, there are potential applications for the integration of second-life batteries optimized for each model. For example, it is possible to employ graphite as inserts in various types of light electric vehicles, such as electric bicycles, scooters, etc., thus replacing lead-acid batteries, which are more expensive and environmentally unfriendly. The utilization of those optimization methods can also assist in the development of longer-range, longer-lasting electric vehicles and contribute to ecological automotive technology. Moreover, it is possible to use second-life batteries in various types of industrial and commercial domains as backup power sources for important equipment, uninterrupted power supplies (UPS), and energy storage systems for monitoring and controlling devices and systems installed in remote areas. The capability of delivering dependable and reasonably priced energy storage strengthens the robustness of these systems so that they continue to function effectively even in the context of adverse power supply conditions. Although second-life cells may have lower energy and power densities than fresh cells, these optimization techniques can successfully increase the residual capacity and performance potential of second-life cells. In this way, by accurately addressing the limitation of the optimized cell characteristics that correspond to certain concrete application tasks, the

researchers and engineers can guarantee reliable and effective work, as well as the use of the valuable energy storage lifespan.

5.2 Future Trends and Innovations

In an era of increasing sustainable energy storage demands that enhance the efficiency of power storage administrations, second-life 18650 lithium-ion cell improvement and transformation services will inevitably be central. Nonetheless, the advancement of this field provides a greater outlook for the future due to additional investment and developments on multiple fronts.

5.2.1 Advances in Battery Chemistry

Another promising field is the improvements in the development of new chemistry, which can increase the efficiency and the lifetime of the second-life battery. Researchers are studying the development of new electrode materials, firstly, as well as improvements to the electrolyte compositions of the cell by which the battery is constructed and advanced designs of the electrochemical cell itself that resulted in better energy density, capacity, and certain safety features.

For instance, higher capacity cathode material such as lithium-rich layered material or lithium manganese-rich material can bring higher energy density values in second-life cells and store more energy in the same volume/capacity. Moreover, if more research is done on solid-state electrolytes and new advanced separators that could enhance safety and thermal stability, second-life cells can withstand exploitation conditions. Other research areas that hold the potential for the next step are associated with improving the cell design, like lithium-metal batteries or lithium-sulfur batteries. Though these technologies are still in their early development phase, it should be highlighted that they have a huge potential to significantly increase energy density, which raises the efficiency of second-life batteries.

5.2.2 Integration with Renewable Energy Systems

The use of second-life batteries integrated with renewable energy systems is projected to be a significant aspect of the future energy supply infrastructure. With a major focus on EU countries and organizations to ensure green and decarbonized energy systems, the importance of efficient energy storage systems will only increase in the future. Potential focus areas will include how the second-life battery system will work with solar and wind power plants. These battery systems also address the variability of renewable energy sources to charge their batteries during periods of high renewable production and discharge them during high demand periods to maintain a constant electricity supply to the grid. Furthermore, the enhancement of the smart grid technologies and the EMS will also help in the application of second-life batteries. These systems have the functions of charge and discharge control of second-life batteries, with the application of complex algorithms and real-time analysis, to ensure that batteries perform at an optimum level for as long as possible while at the same time maintaining the stability of the grid.

5.2.3 Recycling and Circular Economy Initiatives

After the second life of batteries is over, recycling and circular economy concepts will play a more vital role. Many researchers and industry players are already looking for practical and low-impact ways to recycle and reclaim usable materials from spent batteries. Using efficient technologies, including direct recycling methods, some raw materials, including lithium, cobalt, and nickel, could be recycled, hence cutting down the potential raw material supply from the mines and encouraging the circular economy (J. Zhang & Azimi, 2022). Moreover, the adaptation of protocols and regulations regarding second-life application and battery recycling will be significant in achieving safe second-life application use. Close cooperation between battery makers and manufacturers, recyclers, and federal and local authorities will be needed to create a solid and efficient infrastructure for second-life batteries' utilization. By incorporating these future trends

and innovations, the optimization and the use of second-life 18650 lithium-ion cells could be placed at the core of a green energy storage transition.

5.3 Potential Research Directions

As for prospects for further studies, several points consider new opportunities based on optimization and using second-life 18650 lithium-ion cells, which are growing. The area of this research concerns the technologies of the future, the intensification of interdisciplinary work, and the preliminary outlines of new business models and markets.

5.3.1 Emerging Technologies

A high growth rate has been observed in the original field that is, battery technology, and for utilizing second-life cells, plenty of new advanced technologies are available for enhancing performance and their life cycle. There was the probability for improved SOC and SOH estimates through the application of advanced AI and ML advancements in the BMS, which determined charge/discharge cycling for preserved battery life. Integrated with these systems were methods of conditioning the energy that is fed into batteries and the means to periodically or instantly check on the batteries and usage for adjustments of parameters as per existing conditions. IoT and edge computing is another such fresh tech that may come in handy when it comes to second-life battery effectiveness. Likewise, secondary battery systems could be launched into the market with an effective power system for IoT sensors and edge computations the similar method researchers could add to the signifies of monitoring, predicated maintenance, and intuitive energy management. IoT sensors could capture data about battery state or load, climate, and real application and usage, and this information could then be processed to determine the probability of future issues and alert corresponding predictive algorithms to avoid such issue occurrences. Perhaps, these devices might be able to perform this type of data analysis on the edge with minimum time delay, and therefore use minimum battery power. Nonetheless, the second-life batteries may integrate with smart energy management systems plus microgrids in the contemporary power system. This means that

through the integration of second-life battery systems in renewable energy systems, energy storage, and better load management, researchers are able to develop sophisticated, efficient microgrid designs in order to avoid some of the existing issues with energy insecurity, unreliability, and unsustainability.

5.3.2 Interdisciplinary Approaches

The use of second-life 18650 lithium-ion cells for recycling also involves the collaboration of many professionals, and experts in different fields like electrochemistry, material science, electrical engineering, computer engineering, and data analysis professionals among others. Ideas and solutions would flow freely when researchers from such various fields strategically join to work on the second-life battery integration process. For instance, materials scientists could work on using novel compositions and structures for electrodes and cells, and electrochemists could study complex electrolytes and degradation phenomena. Pacifying the automotive industry, electrical engineers could submit their insights on power electronic integration, battery systems, and how they correlate with renewable systems. Computer scientists and data analysts could design and accelerate other complex progressive algorithms and predictive models for maintenance, energy, and battery usage.

5.3.3 Business Models and Market Opportunities

The market for efficient and environmentally friendly energy storage solutions is still growing. A specific topic for future studies could cover the search for new appropriate business models that would help to gather, sort, and transport second-life batteries. Such models may consist of collaboration with battery makers, automobile producers employing electric vehicles, as well as recycling and secondary use of the battery firms which make a chain among all the key stakeholders. Furthermore, innovative studies might be pursued to show how these systems might be put up for resale in second-life form and in a more optimized manner since recycling is currently not a common practice. It is noteworthy that these markets could target applications ranging from home energy

storage solutions or backup power provision to portable power solutions in off-grid or hard-to-reach locations. In addition, there are opportunities for second-life battery systems to be interconnected with new technological devices, such as IoT and edge computing, pursuing new pure-play or service-based revenue streams. For instance, subscription services for energy management could be addressed wherein optimized second-life batteries and real-time monitoring could be provided by the companies. For one to fully exploit these market opportunities, there is a need for the researchers to consult with industry players, policymakers, and regulatory agencies on the possibility of formulating standard and certification procedures for second-life battery systems. These measures could increase consumer confidence and safety, as well as promote the growth of a market that enables the practical and efficient secondary use of batteries.

6 Conclusion

Altogether, this master's thesis contributions improve the knowledge and real-world utilization of second-life lithium-ion battery effectiveness, especially in the context of Tesla 18650 cells, and provide the groundwork for further research and development in this area. The use of a multilevel framework approach to fill the gap between theoretical modeling, having a standard experimental procedure, and the real-world application of sustainable energy storage, which is essential for future advancements in the field. In this section, the summary of this master's thesis and expected future contributions are discussed to confirm that the expected objectives are achieved.

6.1 Summary of Findings

This master's thesis titled "Characterization and Modelling of Second-Life 18650 Lithium-Ion Batteries" has explored the complex world of second-life lithium-ion batteries with more focus on the 18650-cell form factor. Pursuing the comprehensive theoretical and experimental analysis as well as the applied optimization techniques and methodologies in the framework of this research, the investigation has provided significant findings and value to the rapidly evolving area of battery science.

The thesis began with a literature review where the historical development of lithium-ion batteries, the detailed description of the chemistry, and the elaboration of the degradation processes that define the performance tendency of these batteries over time were described. This knowledge laid the groundwork for a reinterpretation of the complex activities bound up in reusing and enhancing second-life lithium-ion cells. On this theoretical base, the scope of the research venture extended to the modeling and characterization of parameters in the context of 18650 Li-ion cells that are used in Tesla electric cars. Using the data obtained together with experimental data and equivalent circuit modeling coupled with optimization algorithms this study presents a real-world valid model of these cells and their behavior under different operating conditions. Under well-defined experimental procedures and data processing, critical cell performance factors

such as internal resistance, open circuit voltage, polarization resistance, and others have been carefully unraveled. Other considerations during the optimization of the trade-off factors include capacity utilization, deterioration avoidance, thermal control, and the costs involved. Real-life examples that showcased how current second-life batteries can be implemented in grid storage solutions, portable electronics, and elsewhere confirmed the effectiveness and the advantages of the described optimized approaches and tactics. In addition, the thesis provided information on the possibilities and cost-benefit balance relating to the use of second-life batteries and optimization strategies for this technology. Cell sorting and screening infrastructure, thermal management systems, battery management systems, and challenges involved in system integration were discussed and analyzed admitting useful information to the intended users of information – the industry practitioners and researchers across the globe and in the society. To guide the study, the research utilized insights on current trends and best practices that may exist or are likely to develop in the areas of second-life batteries in the future. A lot of progress can be made in this area of specialization, as evidenced by the discussions on new developments in battery chemistry, how to incorporate batteries into renewable energy-storage systems, and how cutting-edge brands and systems can complement batteries in the power sector. Future research topics that were pointed out include the use of relevant new technologies like artificial intelligence, machine learning, and the Internet of Things (IoT) interdisciplinary developments whereby collaboration between different fields. These directions contain the seeds for opening new paths in batteries and storage and energy solutions.

6.2 Contributions to the Field

Altogether, the thorough approach to the conducted research was based on three key areas of consideration: technological, environmental, and economic opportunities based on the second-life battery optimization. This thesis's findings and existing knowledge can be used to contribute to this change and establish a sustainable and circular economy where resources such as energy storage and its footprints are optimized.

In terms of technical contributions, this research effort has reported noteworthy results on the modeling, simulation, and optimization of new 18650 lithium-ion cells for second-life applications. By using proper experimental approaches and related mathematical analysis, the research has been able to define the equivalent parameter of complex electrochemical processes that control the energy-storage capacity and reliability of batteries, as well as the reactions that cause battery degradation. This model is also as effective at modeling battery behavior, while it provides the approach of calibration of such significant parameters as SOC as well as internal resistance that contribute to the effective utilization of the cell's resources and its longevity. Besides that, the design of the experiment helps to standardize the experimental procedure for this type of battery cell and define which factors need to be considered.

Furthermore, the thesis has explained the issues of practical implementation of the strategies for second-life batteries as well as the economic evaluation of optimization solutions. By analyzing topics like cell sorting and screening solutions, thermal management solutions, battery control solutions, and system integration issues, the work offers a great transaction of practical significance for various professionals of the industry, as well as academic specialists, so that the best of theory can be carried to reality.

Apart from reviewing the approaches that have been employed in the optimization of second-life batteries, the research has also analyzed the environmental and economic impacts of such batteries. In this sense, the conclusions of this thesis are perceived with an affinity to circular economy, as the results of the investigations prolong the life span of these essential energy storage products and contribute to the decreased use of new resources in the respective manufacturing processes.

In conclusion, this thesis boarded on presenting significant research findings in the area of battery technology, especially second-life Li-ion cell optimization. In terms of theoretical enhancement as a theoretical model based on 18650 lithium-ion cells, with characterization techniques, optimization methods, and practical application of those cells, it

has contributed to the knowledge base and offered practical prediction and optimization methods for lithium-ion cells. The knowledge generated by the results of this work can further advance the understanding of critical issues and help to engender worthy progress for a better energy future.

6.3 Recommendations for Industry and Academia

As for recommendations for the industrial and academic sceneries to contribute to the advancement of second-life LI Battery optimization in all industries and fields, it is possible to present several proposals.

- (1) **Establish standardized protocols and guidelines:** The findings that have been produced from the primary research focusing on second-life battery systems and other related areas also imply the need for standard research methods and guidelines for the stakeholders about such issues to enhance the effectiveness of the utilized battery units as much as possible consistently. As for the above standards, it is suggested what kind of item should it covered, test of performance, integration, and compatibility. These standards will be met to advance reuse by achieving more technological synchronization across battery types and making consumers more comfortable with second-life battery materials.

- (2) **Invest in advanced characterization and testing infrastructure:** Optimization schemes involve proper characterization and testing of second-life cells, and this could be done optimally if only we characterize and test the cells in that manner. Market participants need state-of-the-art characterization facilities and equipment, such as automated sorting equipment, thermal characterization capabilities testing kit, HPPC and EIS compatible cyclers, and other tools, in order to achieve this with high precision. These tools will enable the evaluation of cell performance, degradation, or optimization possibilities which in turn will turn second-life battery systems into economic successes.

- (3) **Develop robust Battery Management Systems (BMS):** Optimized battery systems requirement in second-life scenarios is to get specific BMS solutions for the recognition of the profile and requirements of the repurposed cell. Another important area where the industry should direct its attention is BMS, to improve algorithms and hardware needed for accurate SOC calculation, proper techniques in thermal regulation, and cell balancing.
- (4) **Explore innovative business models and partnerships:** Therefore, for optimized second-life battery solutions to be commercialized, it is imperative to consider new and various business and partnership models. Market actors should think about models that would enable the collection, sorting, and distribution of second-life cells, and some of the service-based models may imply the use of IoT and edge computing capabilities. Stakeholders, including the manufacturers of batteries, EV producers, recycling firms, and customers are valuable players in developing a closed-loop efficient system of reusing second-life batteries.
- (5) **Engage in collaborations and knowledge sharing:** It can, therefore, be seen that the management of second-life lithium-ion cells is a complex phenomenon that possibly needs inputs from the fields of electrochemistry, material science, electrical engineering, data science, and even business management. Industry should play an active role in partnerships with academia, research institutes, and other industries so that new knowledge and ideas can be introduced and full hypotheses of solutions can be achieved.
- (6) **Prioritize research on advanced battery materials and chemistries:** Further studies and developments of high energy density materials and chemistries are vital for both improving the performance of Li-ion cells in their primary and future second-life cycles. More research needs to be directed toward higher-capacity electrode materials, solid electrolytes, enhanced separators, and innovative

cell structures (e.g., solid-state batteries) to gain enhanced energy density, cycle life, and safety features.

- (7) **Develop innovative modeling and simulation tools:** Valid modeling and numerical tools are crucial in the prediction of the battery characteristic and achievement of high performance and the assessment of the influence of different optimization techniques. The involvement of machine learning, artificial intelligence, and physical model prototyping helps to build a deeper understanding of intricate electrochemical phenomena, allowing experimental investigations and improvements in simulation at a detailed level and thus promoting the creation of efficient second-life batteries faster and more effectively.
- (8) **Explore interdisciplinary collaborations:** Another important aspect is the fact that the optimization of second-life lithium-ion cells common knowledge that necessitates knowledge in electrochemistry, materials science, electrical engineering, computer science, data analytics, and economics is needed. Researchers must encourage and enable interdisciplinarity sharing which eventually fosters the synthesis of multiple views and facilitation of new opportunities for enhancing second-life battery applications.
- (9) **Foster industry-academia partnerships:** The dissemination of research results implicates the work of both academic science and business circles. Academia should be more proactive in seeking collaborations with industry counterparts, and this should entail sharing knowledge, as well as engaging in collaborative research activities and tech transfer activities. These partnerships can help in the process of significant developments, proving that academic findings are still valuable to solve present problems where the industry can demonstrate the solution in a complete commercial package suitable for end users.

Thus, it will be essential to pursue a cooperative approach to the subject, share relevant information, and adhere to the practices of sustainability and circular economy to ensure that lithium-ion cells' second life will reach its full potential in the context of making energy storage more efficient and friendly to the environment. Industry and academia joint efforts will foster innovation, help to address technological challenges, and define new development trends with a focus on a safer, smarter, and more sustainable energy future.

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Appendices

Appendix 1. Defining Parameter Function, Current, and Voltage of the HPPC Test and Coulomb Counting Calculation

Defining Parameter Function

```

%%R0 at 15C%%
for idx_cell = 1:size(parameter,1) out.(parameter{idx_cell})={};
i = length(parameter)
parameter{1:i}
parameter{4:15,2}
x=1
for x=1:i;
RO{x}=parameter{x,2};
end;

```

```

%%R0 at 25C%%
for idx_cell = 1:size(parameter,2) out.(parameter{idx_cell})={};
i = length(parameter)
parameter{1:i}
parameter{4:15,3}
x=1
for x=1:i;
RO{x}=parameter{x,3};
end;

```

```

%%R0 at 45C%%
for idx_cell = 1:size(parameter,3) out.(parameter{idx_cell})={};
i = length(parameter)
parameter{1:i}
parameter{4:15,4}
x=1
for x=1:i;
RO{x}=parameter{x,4};
end;

```

```

%%R1 at 15C%%
for idx_cell = 1:size(parameter,4) out.(parameter{idx_cell})={};
i = length(parameter)
parameter{1:i}
parameter{4:15,6}
x=1

```

```

for x=1:i;
R1{x}=parameter{x,6};
end;

%%R1 at 25C%%
for idx_cell = 1:size(parameter,5) out.(parameter{idx_cell})={};
i = length(parameter)
parameter{1:i}
parameter{4:15,7}
x=1
for x=1:i;
R1{x}=parameter{x,7};
end;

%%R1 at 45C%%
for idx_cell = 1:size(parameter,6) out.(parameter{idx_cell})={};
i = length(parameter)
parameter{1:i}
parameter{4:15,8}
x=1
for x=1:i;
R1{x}=parameter{x,8};
end;

%%R2 at 15C%%
for idx_cell = 1:size(parameter,7) out.(parameter{idx_cell})={};
i = length(parameter)
parameter{1:i}
parameter{4:15,10}
x=1
for x=1:i;
R2{x}=parameter{x,10};
end;

%%R2 at 25C%%
for idx_cell = 1:size(parameter,8) out.(parameter{idx_cell})={};
i = length(parameter)
parameter{1:i}
parameter{4:15,11}
x=1
for x=1:i;
R2{x}=parameter{x,11};
end;

%%R2 at 45C%%
for idx_cell = 1:size(parameter,9) out.(parameter{idx_cell})={};
i = length(parameter)
parameter{1:i}

```

```
parameter{4:15,12}
x=1
for x=1:i;
R2{x}=parameter{x,12};
end;

%%C1 at 15C%%
for idx_cell = 1:size(parameter,10) out.(parameter{idx_cell})={};
i = length(parameter)
parameter{1:i}
parameter{4:15,14}
x=1
for x=1:i;
C1{x}=parameter{x,14};
end;

%%C1 at 25C%%
for idx_cell = 1:size(parameter,11) out.(parameter{idx_cell})={};
i = length(parameter)
parameter{1:i}
parameter{4:15,15}
x=1
for x=1:i;
C1{x}=parameter{x,15};
end;

%%C1 at 45C%%
for idx_cell = 1:size(parameter,12) out.(parameter{idx_cell})={};
i = length(parameter)
parameter{1:i}
parameter{4:15,16}
x=1
for x=1:i;
C1{x}=parameter{x,16};
end;

%%C2 at 15C%%
for idx_cell = 1:size(parameter,13) out.(parameter{idx_cell})={};
i = length(parameter)
parameter{1:i}
parameter{4:15,18}
x=1
for x=1:i;
C2{x}=parameter{x,18};
end;

%%C2 at 25C%%
```

```

for idx_cell = 1:size(parameter,14) out.(parameter{idx_cell})={};
i = length(parameter)
parameter{1:i}
parameter{4:15,19}
x=1
for x=1:i;
C2{x}=parameter{x,19};
end;

%%C2 at 45C%%
for idx_cell = 1:size(parameter,15) out.(parameter{idx_cell})={};
i = length(parameter)
parameter{1:i}
parameter{4:15,20}
x=1
for x=1:i;
C2{x}=parameter{x,20};
end;

%%Em at 15C%%
for idx_cell = 1:size(parameter,16) out.(parameter{idx_cell})={};
i = length(parameter)
parameter{1:i}
parameter{4:15,22}
x=1
for x=1:i;
Em{x}=parameter{x,22};
end;

%%Em at 25C%%
for idx_cell = 1:size(parameter,17) out.(parameter{idx_cell})={};
i = length(parameter)
parameter{1:i}
parameter{4:15,23}
x=1
for x=1:i;
Em{x}=parameter{x,23};
end;

%%Em at 45C%%
for idx_cell = 1:size(parameter,18) out.(parameter{idx_cell})={};
i = length(parameter)
parameter{1:i}
parameter{4:15,24}
x=1
for x=1:i;
Em{x}=parameter{x,24};
end;

```

Defining the Current and Voltage of the HPPC Test

```

%%Current%%
for idx_cell = 1:size(parameter,19) out.(parameter{idx_cell})={};
i = length(parameter)
parameter{1:i}
parameter{4:56521,26}
x=1
for x=1:i;
Current{x}=parameter{x,26};
end;

%%Voltage%%
for idx_cell = 1:size(parameter,20) out.(parameter{idx_cell})={};
i = length(parameter)
parameter{1:i}
parameter{4:56521,27}
x=1
for x=1:i;
Voltage{x}=parameter{x,27};
end;

%%Time%%
for idx_cell = 1:size(parameter,21) out.(parameter{idx_cell})={};
i = length(parameter)
parameter{1:i}
parameter{4:56521,28}
x=1
for x=1:i;
Time{x}=parameter{x,28};
end;

%%SOC%%
for idx_cell = 1:size(parameter,22) out.(parameter{idx_cell})={};
i = length(parameter)
parameter{1:i}
parameter{4:15,29}
x=1
for x=1:i;
SOC{x}=parameter{x,29};
end;

Temperature_LUT(1,:) = [288.15 298.15 318.15];
Temperature_LUT = Temperature_LUT';

Qe_init = 0
Clearvars

```

Coulomb Counting Calculation

```
%%Calculate cumulative charge%%  
charge = cumsum(Current)*sampleTime/3600; % Cumulative charge  
in Ah
```

```
%%Calculate SOC%%  
soc=(charge/capacity)*100; % SOC in percentage
```