BATTERY CAPACITY PREDICTION USING DEEP LEARNING

Estimating battery capacity using cycling data and deep learning methods

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ABSTRACT

The growing urgency of climate change has led to growth in the electrification technology field, where batteries have emerged as an essential role in the renewable energy transition, supporting the implementation of environmentally friendly technologies such as smart grids, energy storage systems, and electric vehicles. Battery cell degradation is a common occurrence indicating battery usage. Optimizing lithium-ion battery degradation during operation benefits the prediction of future degradation, minimizing the degradation mechanisms that result in power fade and capacity fade. This degree project aims to investigate battery degradation prediction based on capacity using deep learning methods. Through analysis of battery degradation and health prediction for lithium-ion cells using non-destructive techniques. Such as electrochemical impedance spectroscopy obtaining ECM and three different deep learning models using multi-channel data. Additionally, the AI models were designed and developed using multi-channel data and evaluated performance within MATLAB. The results reveal an increased resistance from EIS measurements as an indicator of ongoing battery aging processes such as loss o active materials, solid-electrolyte interphase thickening, and lithium plating. The AI models demonstrate accurate capacity estimation, with the LSTM model revealing exceptional performance based on the model evaluation with RMSE. These findings highlight the importance of carefully managing battery charging processes and considering factors contributing to degradation. Understanding degradation mechanisms enables the development of strategies to mitigate aging processes and extend battery lifespan, ultimately leading to improved performance.

Keywords: Lithium-ion batteries, battery degradation mechanisms, battery cycle life, Electrical impedance spectroscopy, Capacity estimation, Incremental capacity analysis, Deep learning models

PREFACE

I want to take this opportunity to express my heartfelt gratitude to all those who have contributed to the successful completion of my degree project. Firstly, I am immensely grateful to my supervisor, *Maher Azaza,* for his invaluable guidance and mentorship. His profound knowledge, expertise, and dedication have shaped my research and pushed me to strive for excellence. His unwavering support, insightful feedback, and inspiring discussions have enriched my academic experience. I also extend my most profound appreciation to Professor *Erik Dahlquist*, who served as the examiner for this research, along with insightful lectures and engaging discussions. I became deeply interested in this research object, which holds significant potential for advancement. I would like to express my sincere gratitude to the academic institution, *Mälardalens University*, where this degree project was conducted for providing the necessary resources and environment conducive to learning, experiments, and exploration.

This thesis is a culmination of dedication, perseverance, and collaborative efforts. I am grateful for the opportunity to contribute to advancing knowledge in this field. I hope this work contributes meaningfully to the field and serves as a stepping stone for future research endeavours and thriving for sustainability.

Lastly, I am deeply thankful to my family for their undeviating support and encouragement throughout my journey. Their belief in my abilities and constant motivation was pivotal in my academic pursuits. Mi familia Rojas Vazquez gracias por su apoyo y amor incondicional a lo largo de mis estudios.

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SCIENTIFIC SUMMARY IN SWEDISH

I samverkan med att minska växthusgasutsläpp har batterier spelat en viktig roll i övergången till förnybar energi, särskilt litiumjonbatterier. Dem anses vara en av de mest betydelsefulla energilagringssystemen för tekniska tillämpningar då dem besitter med en överlägsen energieffektivitet i jämförelse med andra batterityper. En av de utmaningar som uppstår vid användning av litiumjonbatterier är att förstå degraderingsprocesserna och deras påverkan på batteriets livslängd och prestanda. Oförutsägbar batteridegradering kan leda till minskad tillförlitlighet, säkerhet och funktionalitet i systemet, hos bland annat elektriska fordon. Därför är det av avgörande att kunna förutsäga och kvantifiera batteridegradering under olika degraderingsmekanismer. För att förstå hur batterier försämras över tiden är det viktigt att utforska batterihanteringssystemet, genom noggranna analyser av batteriets karaktärer under cykelscenarier. Studien kan bidra till en ökad förståelse för batteridegraderingens mekanismer och dess konsekvenser för batteriets prestanda och livslängd. Nedbrytningen av litiumjonbatterier under drift möjliggör förutsägelse av framtida batterinedbrytning och optimering av driftsstrategin genom att minimera de dominerande nedbrytningsmekanismerna som leder till effektförlust och kapacitetsförlust. Dessutom kan det bidra till utvecklingen av bättre prognosmodeller och strategier för att förutse och hantera batteridegradering, vilket är av stor betydelse för en säker och effektiv användning av litiumjonbatterier inom elektriska fordon och andra tekniska tillämpningar

I denna studie undersöktes batteriernas prestanda och karaktärer genom att identifiera de indikatorer som påverkar batteriåldringen och återstående användbar livslängd baserat på batterikapaciteten. Syftet med denna studie är att undersöka hur man kan förutsäga batteridegradering genom att använda batterikapaciteten och AI-metoder.

Metoden bestod av en litteraturstudie för att förstå funktionen och komplexiteten hos en battericell, samt analys av degraderingsmekanismer och indikatorer på batterinedbrytning. I fallstudien genomgick battericellerna flera cyklar under olika laddnings- och urladdningsförhållanden, battericyklarna utfördes i ett batteri testningssystem, Neware, och resistanskarakterisering genomfördes med elektrisk impedansspektroskopi (EIS). AI-metoderna utvecklades i Matlab med avancerade maskininlärningsalgoritmer och tränade modeller med noggrant utvalda träningsdata för att uppnå hög förutsägelsekapacitet. Genom att jämföra modellens förutsägelser med verkliga experimentella data.

Resultat från denna studie visar att inkrementell kapacitetsanalys (ICA) fungerar som distinkta markörer för den interna strukturen hos en battericell, där varje förskjutning och form ger värdefulla indikatorer för nedbrytningsmekanismer. Nedbrytningsprocessen är särskilt framträdande i snabbladdade battericeller på grund av den ökade belastning de utsätts för. De främsta observerade källorna till nedbrytning inkluderar litium plätering, förlust av litiuminnehåll (LLI) och förlust av aktivt material (LAM). Resistansen som erhölls från EIS-mätningarna används som en indikator för att bestämma battericellens hälsotillstånd. En ökad resistans under battericykling indikerar pågående batteriåldrande, där varje specifik resistans ger insikt i LLI. Vid förutsägelse av batteriets kapacitet användes batteriindikatorer som ström, spänning och inkrementell kapacitet. Funktionaliteten att kunna förutsäga batteriets kapacitet med hjälp av AI-modeller bekräftades med en utvärdering på modellprestanda genom

kalkyler, som medelvärdet av standardavvikelserna (RMSE). Efter en noggrann utvärdering visade det sig att modellen långtidsminnet (LSTM) presterade enastående resultat. Modellen lyckades generera förutsägelser som var i nära överensstämmelse med de experimentella datavärdena.

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NOMENCLATURE

Symbol	Description	Unit
C	Capacity (C-rate)	Ah
f	Frequency	Hz
I	Current	A
P	Power	W
R	Resistance	Ohm
T	Time	s
V	Voltage	V
Z’	Impedance real	-
Z”	Impedance imaginary	-

ABBREVIATIONS

Abbreviation	Description
AC	Alternating current
AI	Artificial intelligence
BTS	Battery Testing System
BMS	Battery management system
CC	Constant current
CC-CV	Constant current-constant voltage
CCCV Chg.	Constant current-constant voltage charge
CC DChg	Constant current-constant voltage discharge
CE	Columbic efficiency
CNN	Conventional neural network
CO_2	Carbon dioxide

Abbreviation	Description
C rates	Current rates
DC	Direct current
DoD	Depths of discharge
EBA	European Battery Alliance
ECM	Equivalent circuit model
EIS	Electrochemical impedance spectroscopy
EM	Electrochemical model
EV	Electrical vehicles
FNN	Feedforward neural network
GBR	Gradient Boosting Regression
IC	Incremental capacity
ICA	Incremental capacity analysis
K-NN	K-Nearest Neighbor Regression
LAM	Loss of active material
LiB	Lithium-ion batteries
Li-ion	Lithium-ion
LCA	Life-Cycle Assessment
LLI	Loss of lithium inventory
LFP	Lithium iron phosphate
LMO	Lithium-ion manganese oxide
LSTM	Long short-term memory
ML	Machine learning
MLR	Multiple Linear Regression
NCA	Nickel Cobalt Aluminium
NMC	Nickel Manganese Cobalt
OCV	Open circuit voltage
PNGV	Partnership for a new generation of vehicles models
RC	Resistance-capacitance
RNN	Recurrent neural network
RMSE	Root-mean-square error
RVM	Relevance Vector Machine
RUL	Remaining useful life
SEI	Solid-electrolyte interphase
SoC	State of charge
SoH	State of health

Abbreviation	Description
SVM	Support Vector Machine
SVR	Support Vector Regression

DEFINITIONS

Definition	Description
Capacity/ Nominal Capacity	The total Ah available when the battery is discharged at a certain discharge current before it is fully discharged (Team, 2008).
C-rate	Battery description on current discharge and measured at the battery discharge in relation to its max. capacity (Team, 2008).
Markov chain	Mathematical tool to identify the independence of the past and future variable, when the present is known (Myers et al., n.d).
Minkowski distance	Metric in normed vector space (Çolakoğlu, 2019).

1 INTRODUCTION

There are various pathways to achieve the Paris climate target indication of net zero carbon dioxide emissions by 2050. The leading transformation is to decrease greenhouse gas emissions by replacing fossil fuels with electricity from advancements in low-carbon technologies and renewable energy sources (IBM, 2022). Electrification is the fundament of energy technologies; meeting the criteria for a sustainable future is essential with the increased demand. That can be performed by implementing environmentally friendly technologies, for example, smart grids, microgrids, storage, and electric vehicles. With the concerned meeting, net zero emissions have led to growth in electrification transportation. In 2021, the global market for EV sales was 10% and was continuously increasing (IEA, 2022).

Batteries have become a part of an important role in the renewable energy transition. It is an essential component to thrive for the balance between supply and demand within the power system (Williard, 2011). Lithium-ion batteries are classified as one of the essential energy storage systems for technical applications, first and foremost for electric vehicles (D. Wang et al., 2022). The resilience of batteries against degradation varies depending on their usage and storage conditions. Battery degradation of lithium-ion batteries during operation benefits the prediction of future degradation and enables the optimization of operation strategy by minimizing the dominant degradation mechanisms that lead to power fade and capacity fade. Furthermore, causing a decreased system reliability, safety, and operation of battery systems (W. Li et al., 2022).

Moreover, the estimation of battery degradation informs the state of health of the batteries. It is essential for evaluating the lifespan, particularly in applications like EVs (W. Li et al., 2022), by prognosticating the properties of batteries with electrochemical impedance spectroscopy (S. Wang et al., 2021). Thus, EIS provides a valuable understanding of the power delivery capacity of lithium-ion battery systems. This technique allows to characterize and quantify the cell resistances, such as the interface layer and charge transfer reaction, without perturbing the cell (Yoon et al., 2020).

The indication has required acknowledging the information regarding the battery state, such as state of health, remaining useful life, and evaluation of the state of charge, and additionally, providing improved performance and reliable characterizations for the batteries (Williard, 2011). Therefore, this degree project will investigate the battery's degradation mechanisms by inspecting the characteristics of the batteries under different aging scenarios with deep learning methods combined with electrochemical impedance spectroscopy.

1.1 Background

The background section will include the fundamental science and theory behind batteries, providing crucial insights into their operation and underlying principles. This knowledge serves as a foundation for comprehending the subsequent chapters of this degree project. The initial section explains battery structure and the processes involved during charge and discharge. It is followed by battery terminologies, the battery lifecycle, and a subsequent emphasis on the design of lithium-ion batteries, specifically, the most commercialized battery cell. And further leads to the motivation and research objectives for this degree project.

1.1.1 Battery structure

The battery is an electrochemical mechanism that stores chemical energy from converted electricity. A battery cell consists of two electrodes, an anode and a cathode. Within the cell, there are electrolytes. The electrolyte formulation involves the preparation of non-aqueous solvents by dissolving lithium salts in a mixture of ethylene carbonate, diethyl carbonate, dimethyl carbonate, vinylene carbonate, and lithium hexafluorophosphate (D. Li et al., 2019).

The electrolyte facilitates the charge transfer and is also the source of Lithium-ion, the electrodes in Lithium-ion batteries are attributed to be either an anode or cathode. The active materials, cathode, and anodes are covered with metal foil on current collectors to ease the transportation of the electrons to the active materials (Edge et al., 2021). As D. Li et al. (2019) mention, the electrolyte and electrode material decide the battery's stability and energy density for Li-ion batteries.

During charging and discharging, the electrode is dependent on the electrode potential for the anode or cathode. An electrode with higher electrode potential indicates as the cathode, positive electrode. The structure of the cathode is with an oxide material such as lithium transition metal by letting the positive electrode undergo charging of lithium-ion, also termed as a reversible delithiation. The anode is constructed with layers of material as in series, such as graphite. The negative electrode undergoing discharging refers to as lithiation (Edge et al., 2021). However, other materials for the anode except graphite are silicon or silicon oxide; as for the cathode, the material must involve high-nickel materials (Grey & Hall, 2020).

D. Li et al. (2019) explain that electrons are extracted from the cathode into the anode when a battery undergoes charging in the outer circuit. The Li-ion is delithiated from the cathode through the electrolyte to the anode, and the produced electric energy converts into chemical energy. Edge et al. (2021) describes that during the discharge, the electrons generate a flow from the anode to the cathode, and the chemical energy from the charge converts to electrical energy. When a battery charges, the cathode is oxidized, letting the electrons release to the external circuit from the cathode structure.

Between the two electrodes, there is a separator. The purpose of the separator is to prevent short-circuiting charge ions from migrating through (Edge et al., 2021), meaning interdict the electrical contact (D. Li et al., 2019). When the ions migrate through the separator, the electrons flow externally to the anode, while reducing anodes and oxidizing cathodes creates electron release to an external circuit, letting the battery maintain charge neutrality. The process is reversible during discharge, reducing cathodes and oxidizing anodes, alternating the cycle for charging, and discharging the battery cell (Edge et al., 2021).

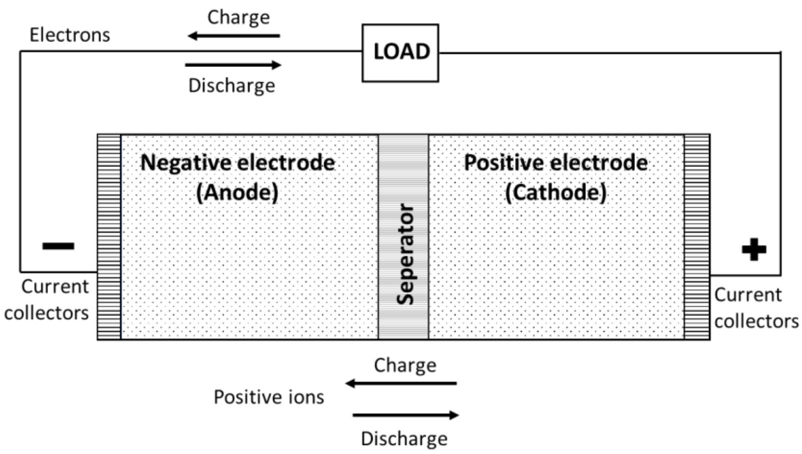


Figure 1: An illustration of battery cell. Adapted by (Plett, 2015)

In Figure 1, the electrons are extracted from the cathode, LFP (into the anode, graphite) during charging. Discharge of the battery is the reverse process. Lithium-ion batteries have low power consumption, a significant charge/discharge efficiency, and are very energy efficient compared to other battery types. LiBs operate with excellent reliability and a life prediction for 15 years or more. The battery characteristics for LiBs health degradation are acknowledged as an increase in impedance and energy decline (Nazari & Pistoia, 2009).

1.1.2 Battery terminologies

Battery voltage: A measurement between the voltage and voltage of the battery terminals *+vc* and *-vc* (Satpathy & Pamuru, 2021).

Nominal voltage: The Nominal voltage is a battery's average operating voltage range, typically between 3.5V and 3.7V. In contrast, the Maximum voltage of the cell refers to the upper limit voltage, which is typically around 4.2V (Söderhielm, 2021)

Cut-off voltage: indicated by Satpathy & Pamuru (2021), the lowest voltage a battery system can operate. Battery manufacturers indicate the cut-off or end-of-discharge voltage at a specific discharge rate.

Battery charge and discharge: The current rate of a charged or discharged battery is the ratio of the nominal battery capacity during a particular time to achieve a full charge/discharge. Moreover, various types of batteries have different capacities and charges/discharges with different currents (Satpathy & Pamuru, 2021).

Self-discharge: is the electrical capacity loss for a battery not in use by cause of an internal electrochemical process, explained by Satpathy & Pamuru.

Battery capacity: This is a measurement of the ability to store or deliver electrical energy; the SI units are in ampere-hours. That can specify a battery's charge/discharge rate or current rate. The battery capacity relies on the operational conditions, the load, discharge rate, depth of discharge, cut-off voltage, temperature, and battery cycle. With the following factors; quantity of active material, number and physical dimensions of plates, and specific gravity of the electrolyte. Capacity reduction in batteries can also attribute to low temperatures and rapid discharge rates. A battery that operates in low temperatures affects the rate of internal chemical reactions within a battery cell, leading to a decreased rate of active material reformation. Also, a fast-discharging battery generates water as a reaction by-product which interferes with the electrolyte, limiting the overall capacity (Satpathy & Pamuru, 2021).

Depth of discharge: The depth of discharge of a battery indicates the amount of charge removed from the battery in conjunction with the total amount of charge that can store in the battery. The DoD begins with a fully charged battery, and thus less chance of being influenced by external conditions, considering new batteries rather than empty ones (Waag & Sauer, 2009). As subsection 1.1.5 by Qadrdan et al. (2018) mentioned, the discharge depth decides the battery discharge. Therefore, when the DoD increases, the life cycle of the battery decreases (Figure 2).

DoD expressed by Waag & Sauer (2009) as the equation below:

$$DoD = \frac{removed\ amount\ of\ charge}{maximum\ available\ amount\ of\ charge} = \frac{Q_d}{C} * 100\ [\%]$$

1.1.3 Lifecycle of a battery

The cycle life of a battery indicates a number consisting of charge/ discharge the battery can imperforate before the battery performance falls. The discharge of a battery indicates the utilized storage capacity. Therefore, when a battery is discharged, depending on the depth of the discharge, it contributes to the battery cycle life (Qadrdan et al., 2018). Figure 2 shows how the cycle life decreases if the DoD increases.

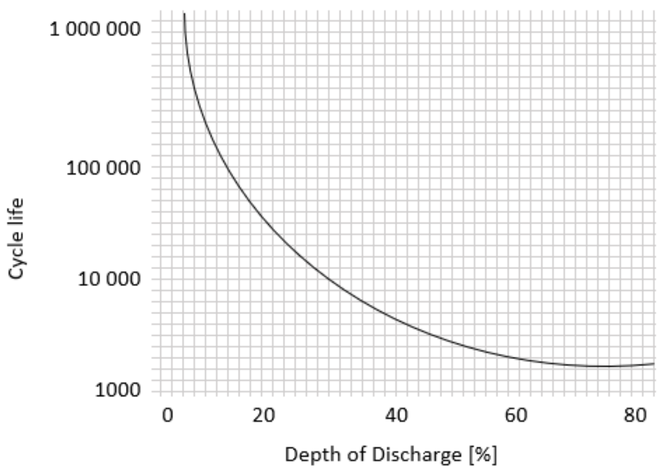


Figure 2: Cycle life of battery depending on DoD. Adapted by (Qadrdan et al., 2018)

1.1.4 Lithium-ion battery design

D. Li et al. (2019) describe that the cell design of a battery is fundamental and affects the performance and storage age, indicating the time a battery can be stored, cycle life, safety characteristics, energy, and power densities. There are several models for Li-ion batteries: cylindrical cell, prismatic cell, pouch cell, and coin cell. The focus design cell of Li-ion is the cylindrical batteries; three standard models in cylindrical batteries are 18 650, 21 700, and 26 650. The 18 650 cell is advanced and the uttermost commercialist cell used in Li-ion batteries. The 21 700 has an easier manufacturing and optimal capacity and has, over time, become increasingly common in batteries used by Samsung, Panasonic, and several others.

The most common battery used is the lithium-ion battery, although Nickel, Manganese Cobalt, and Lithium Nickel-Cobalt-Aluminium Oxide are considered the most optimal battery (Saldaña et al., 2019). LiBs have a high-power density in battery cells and commercial products, such as EVs. They have a low self-discharge rate and are designed to be lightweight. Besides, they have a longer life cycle than other rechargeable batteries (Brike & Karabelli, 2022). Although there are some disadvantages to the smaller battery cells, the number of connections inside one cell is significantly more and, therefore, more sensitive and complex, which sets the internal resistance at risk by increasing and a higher possibility for battery failure (Kopczyński et al., 2018).

A well-known company, Tesla, uses Li-ion batteries to a greater extent because of their design, lightweight, and compact size (Brike & Karabelli, 2022). The 21 700 cells are used for Li-ion batteries in Tesla Motors (D. Li et al., 2019). This has led to the necessity of battery-conforming packs into modules for the automotive field. Consequently, the efficiency of the batteries has degenerated in dangerous environments because of the high temperatures in the space of the battery cells (Brike & Karabelli, 2022). The production of EVs has increased worldwide; therefore, the consumption and fabrication of battery technologies have required significant investment and developments to decrease electric waste materials and incorporate technology recycling (Manzetti & Mariasiu, 2015). Tesla Motors encourages LiBs since they are inexpensive and have a longer lifespan (D. Li et al., 2019).

Saldaña et al. (2019) explain that batteries inside an EV need to fulfil the simulation of several EV processes, so selecting an appropriate battery model is therefore crucial for EV operation. There are several battery models; the electric equivalent circuit model performs a real-time simulation and is one of the models that investigate the details within the battery cell and the electrochemical reactions. The electrical model is similar to the previous model and can reproduce the factors affecting the battery under operation.

Lastly, the mathematical models are pertinent for experimental tests with calculations such as statistical cycle life. The European Union implemented regulations to decrease greenhouse gas emissions from material and chemical production from batteries by evaluating the life cycle of batteries (Manzetti & Mariasiu, 2015).

1.2 Problem statement

Battery degradation is a rather complex issue but crucial to indicate the entire life cycle of the battery. The battery management system needs to be explored by engineers to understand how a battery will degrade over time (Energsoft, 2021). The understanding the impact of unpredictable battery degradation, some indicators must be considered, including accurate characteristics of the State of Health, State of Charge, and remaining useful life (Y. Zhang et al., 2020).

Lithium-ion battery degradation affects performance, such as increased internal resistance, capacity degradation, Etc. (D. Wang et al., 2022). LiBs have a standard operation life cycle of 2-3 years, which can further complicate experimental research for battery application and usage in EVs. Today's batteries last around 15 years, compared to phone batteries that last around two years (Energsoft, 2021). It is essential to predict the characteristics of battery degradation under different aging mechanisms; its importance is highly dependent on the one using the battery. The prognosis of the battery might indicate if the battery needs replacement and the quality of the battery for recycling purposes in the recycling sector (Y. Zhang et al., 2020).

The indicators for predicting battery degradation for the one in use are establishing safe driving and state-of-health essential for electrical vehicle application (D. Wang et al., 2022). These results could lead to reduced environmental impact and improved sustainability, economic benefits, and thus, more accessibility for electrification transportation.

1.3 Purpose

The purpose of this degree project is to investigate how to predict battery degradation by the battery capacity with deep learning methods. Investigating the performance and characteristics of the batteries will further help identify indicators of battery aging and the remaining useful life of the battery from the battery capacity.

1.4 Research questions

- How could the different battery degradations be characterized, when using battery life cycle data and electrochemical impedance spectroscopy data?
- What health indicators for battery degradations could be used?
- How could the battery degradations be predicted by using AI models and what accuracy could be achieved?

1.5 Delimitation

This degree project was performed at Mälardalens University within the SITE project funded by the Swedish Energy Agency and in collaboration with ALSTOM. Concerning time management, some delimitations were considered. This degree project will focus on the cylindrical NMC cells under different cycling scenarios and the general active material occurring internally in the battery. The electrochemical impedance spectroscopy measurements will be tracked on the fully charged cells, whereas the EIS at different states of charge will not be included. Lastly, the temperature as an aging parameter is excluded.

2 METHOD

The method used for this degree project consisted of a theoretical framework, experiments on battery cells, and modeling methods—a general explanation of how this work proceeded and the chosen methodology's reason. The method section includes a literature study conducted parallel with the model development and accelerated battery aging. The model development consisted of a machine learning process with deep learning models to predict the health of a battery, and the accelerated battery aging was performed in a testing system for several battery cells and simulated in software tools for electrochemical impedance spectroscopy.

2.1 Literature study

The literature study is presented in a theoretical framework. It consists of the theory required to understand the function and complexity of a battery cell, the analysis of aging mechanisms, and indicators of battery degradation. The method was literature study methodology, where the literature collected was sorted and analysed. This method required logical analysis, judging, critical thinking, reasoning, and comparison to achieve relevant scientific knowledge in the research field.

The literature was obtained from the web portal Primo at Mälardalens University and databases such as Science Direct, DiVA, Nature, and MDPI. The key search words used for the systemic literature review were the following: *Battery degradation, Battery cell, Lithium-ion battery, Battery aging, Battery degradation, Battery models, Electrochemical impedance spectroscopy, SoH, Battery in EVs, Battery destructive and battery regulations*.

2.2 Data collection

The data collected from batteries must meet the requirements to predict factors of the battery characterizations during battery degradation, with the help of simulation tools and literature study. The data was collected using two software tools, a Battery testing system by Neware Battery and Ivium technologies. The experimental data for the battery life cycle was done on the Neware battery testing system. Accelerated battery aging is done through different operational profiles of the battery, such as charging, discharging, and rest, with different input parameters for battery performance. The experimental measurements for the EIS spectrum was performed in Ivium technology. The data collection was used for simulation in electrochemical impedance spectroscopy spectrum and calibration of deep learning models to validate the performance, comparing the results from the machine learning prediction of battery degradation with experimental data and validating the different machine learning approaches and the accuracy.

2.3 Simulation tools

The simulation tools used for battery health evaluation are the software tools BTS Client 8.0.0.471, Ivium technologies, Excel and MATLAB. The battery testing system allows battery cycling, an accelerated battery aging. Battery Testing System is a machine that is used for battery cells and has the possibility for battery tests during different aging mechanisms that is useful for the objective of this degree project and evaluating the battery characteristics. Including the capacity to simulate several battery cells under different parameters makes it possible to simulate several battery types under "fast" and "normal" cycling. Considering the battery type and software tool accessibility at MDU, BTS is the most optimal.

The Ivium technology endorses EIS scans, obtaining battery characteristics along with ECM. IviumSoft is one of many applications that Ivium technology has, and this application uses electrochemical method selection and composition for data display and analysis (Ivium, 2017b). The Ivium technologies were used for the battery cell simulation to generate the electrochemical research because EIS is an electrochemical technique that investigated the impedance of electrochemical processes and reactions, which is the ratio between the voltage and current. Since the impedance is a complex function and consists of a real variable and an imaginary variable, the system's frequency can diversify with an implemented trigger on the voltage and current for an expected response for the electrochemical system (Ivium, 2021c). Also, EIS exhibits exceptional sensitivity towards systems comprising multiple impedance elements, encompassing bulk components and interfaces. This characteristic is suitable for investigating complex devices like batteries, which consist of multiple components (Middlemiss et al., 2020). With the collected data from Ivium, a data set was retrieved to Excel and further implemented for machine learning.

The model development was used for the machine learning, deep learning method. Designed in a chosen software tool, MATLAB. Because the experimental measurements can be controlled in MATLAB with data acquisition and algorithm evaluation setup (NASA, 2023), the exported data set, excel facilitated the implementation with a calling function to MATLAB. There is also a machine learning method with a deep learning toolbox in MATLAB that can implement multi-channel profiles such as voltage and current. The deep learning models allow the model to understand how the value of the assumptions for a battery based on experimental measurements will indicate and predict the user about the battery's health if the battery is in its final stage of battery life or if it is a fresh battery. MATLAB can use other machine learning approaches to improve the accuracy of validating the model, such as long-short-term memory (MathWorks, 2020).

2.4 Data analysis

The data was analysed on different types of battery cells because they have different manufacturers, and internal chemistry structures, impacting battery performance during battery cycling. The collected data from the software tools underwent a meticulous examination to initiate the data analysis process. Non-usable parameters were identified and subsequently removed from the dataset to further ensure the accuracy and reliability of the analysis. This critical step helped streamline the dataset, narrowing the focus to relevant parameters for further analysis. Furthermore, Ivium technology, an electrochemical impedance spectroscopy analysis tool, was utilized to investigate battery aging characterization. This advanced technology enabled a thorough analysis of the electrochemical behaviour of the batteries, shedding light on their aging patterns and characteristics.

In addition to the above, the AI model data set was divided into separate datasets for training, testing, and validation. This division facilitated practical model training and evaluation, enhancing the accuracy and reliability of the analysis results.

2.4.1 Battery performance

Different battery performances will be considered for the experimental battery testing system, meaning fresh and aged battery cells. A new battery cell operates differently than an aged battery cell, which has undergone several charging and discharging processes (Che et al., 2022). Each battery cells have different inputs in current, C-rate, and voltage, which control the charge and discharge of the battery, depending on the input value for the battery cell will affect the speed of the charge/discharge for each battery, which further affects how fast a cycle goes off the battery and thus also indicates how the battery operates under different conditions. The battery testing system will have “fast” cycling cells and “normal” cycling cells.

2.5 Validation of models

The validation of the models used real-life experimental measurements from battery cycling data. As for the performance from EIS, an equivalent electrical model fitting will be used. The ECM fitting was adapted to the Nyquist plot with as little error as possible to produce fit parameters and a graph that indicates the errors, ensuring the battery degradation through characteristics. Furthermore, for validation from the performance of the AI model, the machine learning approaches: FNN, CNN, and LTSM are used for model calibration compared to the measured data from the battery cycling and validating the accuracy of the results, along with which machine learning approach is the most competent.

3 THEORETICAL FRAMEWORK

The following chapters will contain the required knowledge to understand the battery characteristics for battery failures during different aging mechanisms. Firstly, the chapter regarding battery health status prediction methods divided into different battery models will be mentioned. Thereafter, the battery degradation mechanisms, what it means, and influential factors. Continuing with factors known as battery characteristics, on the remaining battery usage, reduced battery lifespan from aging mechanisms and indicators on battery state of health, how they can contribute to the estimation of the battery health, how these characteristics are involved in the battery cell degradation.

Thereafter, theories on electrochemical techniques will be described as incremental capacity analysis and electrochemical impedance spectroscopy techniques that will be studied in this degree project, such as the machine learning approaches to understand the battery on a deeper level. Furthermore, machine learning approaches are employed to gain deeper insights into AI methods. Lastly, significant previous studies have been done within this degree project, what methods, approaches, investigations, and contributions the studies have made, and how their significant research is relevant to this degree project. In addition, the environmental and economic perspectives of batteries, along with battery regulations, are considered to address the entire lifecycle of batteries, from production to end-of-life.

3.1 Battery Models

Campagna et al. (2020) mention many different types of battery models. To understand the electrochemical model complexity of a battery, a more well-developed model provides better battery results, combined with a design and evaluation of battery management systems to have feasible solutions for experimental tests. The battery design phases are divided into three different models: electrochemical, mathematical, and electrical model.

The electrochemical model is categorized as one of the more complex models, describing a battery cell's thermodynamic and kinetic phenomena (Campagna et al., 2020). On a deeper level describing the electrochemical reaction within the battery cell (Saldaña et al., 2019). The system is built on time-variant spatial partial differential equations and includes parameters such as electrodes, the thickness of each component, cell chemistry, and production process (Campagna et al., 2020). As for the battery design phase, the Galerkin projection method is used for LFO and NMC batteries, a model designed to achieve maximum RMSE to measure the voltage with the electrochemical output for battery cells (Fan et al., 2018, as cited in Campagna et al., 2020).

Campagna et al. (2020) further explain that mathematical models consist of empirical and stochastic models. The empirical model uses simple equations to describe the usage behaviour of the battery, with a higher possibility of achieving real-time parameter identifications and a lowering complexity compared to the others. The error for this mathematical model is relatively low, between 5-20%. The stochastic model gives a low complexity with fast simulation while achieving highly accurate results using the discrete-time Markov chain. Saldaña et al. (2019) mention that the mathematical models are not based on physical analogy.

Lastly, the electrical model is designed to be data-driven and monitored with battery system behaviours and battery development for machine learning methods based on regression methods (Campagna et al., 2020). Multiple Linear Regression, Support Vector Regression, Gradient Boosting Regression, Decision tree, and K-Nearest Neighbor Regression are just some of the machine learning methods for the electrical model battery; these different methods are modelled to optimize the extensive amount of data for the time-dependent battery processes. MLR is used for SoC because, during the discharge of the battery, the behaviour is non-linear. SVR is also used for SoC on virtual battery models but approaches hyperparameters with a flat model function on one side and minor deviations on the other side, as for the K-NN, where k controls the complexity of the model, and p sets the metric power factor in a Minkowski distance, which are essential hyperparameters. The decision tree is a simplified white box model where nodes are adjusted to control the size (Heinrich et al., 2021). Electrical models suited for Li-ion batteries for EVs, based on ECMs, implying electrical models suitable for BMS, such as Thevenin models and partnership for a new generation of vehicles models, are used for steady-state analysis and impedance models for the AC conduction and runtime models, handling the DC conduction (Saldaña et al., 2019).

3.2 Mechanisms of battery degradation

Edge et al. (2021) explain that battery cell degradation is a common phenomenon of battery usage; one way to explain the degradation is with a sudden decrease in capacity while the number of cycles increase (Yu et al., 2023). The mechanisms of battery degradations occur on a deeper level, and the changes can be explained on a chemical and physical level. Besides this, it is worth investigating the mechanisms and in what order they degrade the battery; this can be done with empirical or semi-empirical models. As well as, investigating factors triggering the degradation mechanisms is crucial, either through calendar aging, during rest, in use, or charged. Because there is practical importance in understanding battery degradation (Edge et al., 2021), such as an improvement in energy grids, transport for more cost-effective decarbonization (Y. Zhang et al., 2020), designing batteries with high-quality performance and applicable in various technologies with an increase in an operational lifetime (Edge et al., 2021).

D. Li et al. (2019) explain the degradations mechanisms of LiBs, indicating that all LiBs deteriorate from capacity loss during cycling and storage. The capacity loss is divided into reversible capacity loss and irreversible capacity loss. The reversible capacity loss can be retrieved in the subsequent cycles under low current settings. The irreversible capacity loss is a combination of many processes and factors; there is a challenge to identify the impact factors of the individual processes on the total capacity loss. The main degradation mechanisms and processes are discussed in the following sections.

Edge et al. (2021) continue with degradations modes, a congregated grouped mechanism used to analyze the impacts on the battery cell; the degradations modes are applied between the description of degradation mechanisms and the analysis of mechanisms. The cell's thermodynamic and kinetic behavior impact is based on the battery cell's capacity and the open circuit voltage figure. The significant impacts vary depending on the construction and chemistry of the battery in use as well as the history of usage of the battery; some of these impact modes will be mentioned below:

- Impedance increase: described as resistance increase or impedance rise from loss of electrolyte caused by mechanisms mentioned before, such as SEI growth, high voltages, high temperatures, formation of hydrofluoric acid formation, Etc. The hydrofluoric acid formation is a reaction with moisturizing contamination. Additionally, electrolyte loss leads to active material loss because of a volume reduction of electrolytes.
- Loss of active material: A material reduction occurs in the electrodes, anode, and cathode where the particles lose contact between the electrode material and current collector, impacting the electrochemical activity.
- Loss of lithium inventory: lithium reduction during each cycle used for transport between the electrodes.
- Ohmic resistance increase: occurs when the current collector deteriorates through electronic conduction.
- Faradic rate degradation: The reaction rate of lithium ions is not the same as at the beginning of the battery's life, caused by SEI growth and pore blockage.

Edge et al. (2021) continue by describing the degradations mechanisms that are considered the most important during battery application, such as high temperature, load profile, solid electrolyte interphase format (Edge et al., 2021), high voltages, lithium plating, hydrofluoric acid formation, state of health, state of charge and the charging/discharging cycles (Y. Zhang et al., 2020), some of these mechanisms will be mentioned (Edge et al., 2021).

As Edge et al. (2021) mention, temperature leads to accelerated battery failure, even from the standard temperature of 25°C. The manufacturing defects can contribute to the significance of these influences, but as Edge et al. mention, this kind of statement can be argued. A fully charged battery undergoes a phenomenon of Lithium ions losses leading to degradation (Agubra & Fergus, 2013). In contrast, the solid-electrolyte interphase layer increases the rate of lithium plating caused by pore blockage, creating a drop-off in cell capacity (Edge et al., 2021). According to Xiong et al. (2020), a temperature above 25°C thickens the SEI film.

In lithium plating described by Edge et al. (2021), metallic Li-ion forms on the surface instead of Li-ion intercalating the cathode. One of the causes is fast charging since the high electrolyte potential increases the reaction rate: low temperatures, high SoC, high voltage, and high charge current impact lithium plating. A higher current imposes mechanical stress on the battery during cycling and the formation of lithium plating during charge. The cathode's unused capacity is set to 10-20% to prevent overcharge. Since there are, several variations on capacity fades for different cell types. A suggested method explained by Edge et al. (2021) is to use modified measurement using cyclic capacity fade by detecting the inverse stripping reaction from a single charge through informative plots in differential voltage (dv/dq) or incremental capacity analysis (dq/dv). However, these methods must be adjusted and modeled according to the reaction to predict the correct amount of lithium plating.

The SEI layers grow from the first cycle of the battery cell; from electrochemical reduction when the cathode is lithiated and evident to the electrolyte, the liquid electrolyte encounters the anode surface. The reactions lead to a thin film forming on the surface on top of the electrode material, letting Li-ions be interpolated, but the electrolyte solvent is consumed; hence the electrolyte flow is restricted and increases the impedance of cells. SEI forms from high temperatures and high currents caused by particle cracking, and as the SEI thickness increases, the molecule diffusion slows down (Edge et al., 2021). As Agubra & Fergus (2013) explain, the material lithium is consumed from an internal reaction. The layer grows and thicknesses, preventing the lithium-ion transfer between the cathode and anode. Since the SEI grows from the first cycle, the battery cell's capacity is reduced by 10%. A tested experimental method used the EIS method to track the impedance changes obtainable from SEI growth (Edge et al., 2021).

Regarding the SoC, a high SoC needs to be considered for the network between the rate of side reaction and the electrode potentials (Edge et al., 2021). Another phenomenon is the structural changes in the anodes (Agubra & Fergus, 2013), where the structured carbon electrode becomes less structured. Although analyzing the mechanisms during battery degradation is challenging, the data collection by measurements is accessible, but the observation needs to be more detailed and more problematic. Practical measurements such as capacity fade, and power fade is therefore complicated; the capacity fade is the capacity used in the cell, and the power fade is the power delivered to the cell after degradation (Edge et al., 2021).

According to Edge et al. (2021), when choosing the models for battery degradations, considering the inner structure's complexity is essential since it impacts performance and behavior. Various researchers have approached battery degradation by isolating other influencing factors by basing the model on input parameters that can be obtained directly from the battery; this includes voltage, current, and temperature. Empirical models, considered a black box imitates the behavior of the battery. Among many empirical models, there are equivalent circuit models that will be explained more in-depth in section 3.6. Mechanist models estimate the cell voltage and capacity occurring on significant degradation mechanisms, where the usage has increased in machine learning methods and BMS. Other models worth mentioning are physical-based models based on equations and physical chemistry, within the molecular scale to the structure of the whole cell and single-particle models.

3.3 Remaining useful life of a battery

As Gao et al. (2022) mention, predicting the remaining useful life of a battery can help extend battery life and avoid losses from battery failures. As crucial as predicting a battery's health and degradation, it is just as critical to predicting the remaining useful life. The RUL can be determined by defining the length of time from the current to the very end of the useful stage and life. Thus, improved and reliable techniques are crucial, and the predications method is divided into three sections: model-based, data-driven, and hybrids.

A model-based method consists of electrochemical methods, equivalent circuit models, and empirical degradations model that analyses the complex degradations inside LiBs. Continuing with data-driven models that use numerous data analyses excluding information from the internal mechanisms of LiBs, with signal processes such as empirical modal decomposition and wavelet transform, or machine learning approach using support vector machines, related vector machines, artificial neural networks and long–short-term memory network, or else time series methods with autoregression, autoregressive integrated moving average. Lastly, statistical analysis methods with Gauss process regression (Gao et al., 2022). Hybrid methods s assimilated methods, data-driven and model-based methods (Wu et al., 2019). Although as Pang et al. (2021) mention, there are some disadvantages to using these methods because they lack uncertainty and a non-reliable prediction. If these methods were to be applied to industrial applications, the obtained data could lead to poor prediction reliability, and these uncertainties need to be considered when predicting the RUL of LiBs.

3.4 Reduced lifespan on a battery from aging mechanisms

The aging mechanisms affect internally on the battery where different reactions occur (Xiong et al., 2020). An aging battery can lead to detrimental effects where the lifespan of a battery is reduced; this is caused by the battery components that experience a different extent of decay. That can decrease the energy and power efficiency while increasing the failure risks and further the EVs risk and cost investment (D. Li et al., 2019). In reducing the aging process of a battery, it is essential to understand the aging mechanisms and the advanced battery development challenges (Agubra & Fergus, 2013). Identifying the aging mechanisms can advise RUL, SoH, and safer driving operations for EVs., where the capacity of 80% is accepted and significates the end life of a LiB in EVs (Xiong et al., 2020).

According to Xiong et al. (2020), a battery's aging mechanisms depend on its type, the various electrochemical reaction stages, and the battery operating conditions. Significant aging features are obtained from data-driven models, such as EIS, incremental capacity curve, and temperature (Wang et al., 2022). The component in a battery depends on the material progress and therefore endure the aging mechanisms in different ways. The most common aging mechanisms are the binder and electrolyte decomposition, the cathode abides metal dissolution, the current collector deterioration, the separator melts and deteriorates, and performance degradation for the electrochemical part in the LiB (Agubra & Fergus, 2013). Other factors accelerating the aging of the batteries are extreme temperature, high DoD, and extensive charge-discharge rate (Xiong et al., 2020).

Capacity loss is an aging mechanism and can be used to diagnose the aging of batteries. The analysis method to approach the aging diagnosis mentioned by Xiong et al. (2020) is Disassembly- based post-mortem analysis, which uses cross-validation, which is a direct measurement of each component of the batteries through material analysis for the inside aging reactions. Although it is restricted to laboratory experiments, it has high experimental costs and is a complicated operation. The other two are Curve-base analysis, quantitative analysis, Model-base analysis, non-destructive methods using electrochemical impedance spectrum, open-circuit voltage curve, and battery model parameters. The advantages of these two analyses are good versatility and non-destructive diagnosis. The disadvantages of curve-bases analysis are restricted C rates to retrieve the curves and sensitivity to battery polarization; as for the model-bases analysis, it is challenging measuring EIS and irrelevant parameters in the EM. The aging diagnosis obstacle is performing quantitative aging diagnosis and implementing methods on onboard applications.

Moreover, with the capacity loss, the reactions on the material of the anode and cathode of Li-ion batteries decrease in power and capacity when the cycle number increases (Xiong et al., 2020). In contrast, the electrode degrades and affects the impact of capacity loss under different aging conditions such as SoC, temperatures, and cycling currents (Agubra & Fergus, 2013). By including data-driven methods as an aging model for capacity loss, it can contribute to a greater understanding of the aging mechanisms of the battery and thus develop new generations of batteries with higher battery cycling performance. In this way, manufacturers can also optimize the battery's manufacturing, design, and procedure. The same aging model can be used to predict battery cycle life, increasing battery efficiency and safety and contributing to more developed BMSs. Regarding battery storage, there are two types of capacity losses, reversible and irreversible. The reversible capacity loss decreases due to self-discharging; the irreversible capacity loss occurs because of changing conditions such as temperature and battery storage time in the battery storage process (Xiong et al., 2020).

Xiong et al. (2020) divide physical and chemical reactions into two categories, continuing with the internal aging mechanisms. Enduring the main aging conditions, the loss of lithium inventory, and the loss of active material. Inactive materials have less impact on battery aging than active materials in anode and cathode, as well as electrolytes. Therefore, a volume change in active materials leads to contact loss in inert materials, graphite particles, the current collector, and the binder, all related to the battery resistance. Another aging condition is the binders and current collectors that corrode when the batteries are in use, which increases the resistance and, therefore, further contact loss within the active materials. As for the separator, when its porosity changes, the ion rate, and battery capacity change.

The anode endures countless different types of aging mechanisms that induce, as mentioned, the electrochemical performance. The anode consists of materials such as lithium and carbon compounds and has been proven incredibly sensitive and affected by aging mechanisms. (Agubra & Fergus, 2013). Agubra & Fergus (2013) explain how lithium batteries' anode is very sensitive to the degradation mechanisms; the material directly influences its performance on the grounds of microstructure, texture, crystallinity, and morphology. The cathode in LFP batteries has a high stability property at a moderate temperature. It is a suitable battery type to investigate by applying all the focus on the graphite anode (D. Li et al., 2019). The LFP battery also has a well-functioning voltage, specific energy, and a long cycle life. Here a non-destructive approach is used for the aging mechanism, with graphite degradation based on electromotive force. The experimental and theoretical methods for analyzing the aging mechanisms during calendar and cycling conditions have been made on the capacity loss and graphite degradation, with the help of scanning electron microscopy, X-ray photoelectron spectroscopy, and Raman spectroscopy. In other cases, a simulation is added to investigate the irreversible capacity loss during various aging conditions with the help of an electrochemical model (Xiong et al., 2020).

Just as important, external factors impact temperature, charge-discharge rate, and DoD. The temperature is an aging mechanism by cause of different high and low temperatures; the aging rate increases when the temperature is above 25°C or below 25°C. A temperature above 25°C degrades the cathode and thickness of the SEI film. Whereas a temperature below 25°C, lithium plating at the anode causes intercalation dynamics to interfere with lithium ions, which interferes with battery safety negatively and, with the help of preheating method, can improve the battery performance. As for the Charge-discharge rate, different current rates influence the battery aging; a lower charge rate restrains lithium plating, and a more significant discharge rate reduces delithiation of the anode. The battery performance at high C rates is limited due to the capacity of the anode, and the cathode is less limited at high C rates. The aging mechanisms under different DoD differ because of different battery types. For instance, NCA batteries micro-cracks on the cathode, LFP battery loses the active Li-ions leading to cathode degradation, and NCM battery undergoes short circuits, formats lithium dendrites, and discards the resistive layers on the battery (Xiong et al., 2020).

Despite this, it is essential to know that the battery's aging is inevitable and will happen. The risks will thus increase simultaneously as the EV drive range and service life decrease (Xiong et al., 2020). Experiments have shown that the use of the battery can slow down the aging of the battery, according to Xiong et al. (2020), by increasing the kinetic velocity of the electrode, which helps Li-ions to pass more smoothly, which positively affects the graphite anode.

3.5 State of health of a battery

The state of health of a battery is a crucial indicator that points out battery aging and deterioration and can be worthwhile for battery replacements in systems (Yu et al., 2023). SoH designates the function between the current capacity and the initial capacity of the battery (Wen et al., 2022), and analysing the battery capacity can be difficult (Yu et al., 2023). Therefore, the SoH is predicted by measuring voltage and current, although the solution is to predict the remaining capacity of the battery that indicates the health status by diversified approaches (Yu et al., 2023). LiBs are implied to experience capacity decay during battery cycles, different temperatures and over time, and inactive batteries (Wen et al., 2022).

The development techniques and methodologies improve health prediction and are divided into data-driven and based prediction methods. The data-driven method can be used at home and abroad and is based on chemical processes within the battery (Yu et al., 2023).

Yu et al. (2023) mention three different methods of considering health indicators: Support Vector Machine, Gaussian Process Regression, and Relevance Vector Machine. X. Li., et al. (2019, as cited in Yu et al., 2023) explain by collecting parameters from capacity curves and modeling according to the Gaussian process regression technique. The algorithm complexity is high and can be challenging when modeling and limited training data sets. Y. Zhang et al. (2015, as cited in Yu et al., 2023) optimize the battery cycles during charge and discharge with an RVM prediction model for the SoH. However, the model is limited during short-time simulation. Tian et al. (2015, as cited in Yu et al., 2023) methods include the temperature difference on batteries during charging processes, with SVM algorithm, with limits of process data with the kernel function. Also, long- and short-term memory neural networks can examine a combined estimated analysis of both SoH and SoC (Yin et al., 2022, cited in Yu et al., 2023).

A further method used to detect the state of health of a battery is the IC method; the result visualization is accessible from the current charging or discharging test (D. Wang et al., 2022). The IC method uses the least square method and the SoH prediction model by analysing the IC curve's temperature and characteristics to project the interaction between the IC curve and SoH. A collection of the discharge curves of the battery at different temperatures are measured and analysed with the capacity effect by comparing the changes in the curves. The IC curve endures during charging and discharging on the voltage curve. Moreover, the least square method is used to fit the discharge curves between temperature and SoH to estimate the battery state of health further (Wen et al., 2022).

Wen et al. (2022) explain that such prediction operates more with data-driven models, either electrochemical models or equivalent circuits. Zhao & Qi (2014, as cited in Wen et al., 2022) uses both data-driven models to interpret battery internal resistance during different settings, improving the battery model and more over the SoH estimation.

3.6 Incremental capacity analysis: An Electrochemical Technique

The incremental capacity analysis explained by Anseán et al. (2019) is an electrochemical technique that identifies cell degradation at the electrode level by detecting and analysing the changes in cell behaviour during cycling yielding in IC curves. The mathematical methodology is applied to obtain IC curves with the capacity increments allied with the voltage step as the cell voltage advances. The IC is computed from the ratio between the capacity and voltage increment, shown in the equation below. The ICA results in IC peaks vary the intensities based on the cell voltage profile.

$$IC = \frac{\Delta Q}{\Delta V} = \frac{Different\ capacities}{Fixed - voltage\ step}$$

The raw IC curve cannot be used directly because of noises; by applying a filter, these noises can be filtered out (Xiong et al., 2020), for example, the Gaussian filter to smooth the curves (Xiong et al., 2020). The advantage of IC analysis is that the analysis enables a precis battery diagnostic in a time-resolved manner by identifying the cell aging modes. ICA is an extinguished technique to understand cell degradation while feasible in BMS applications (Anseán et al., 2019).

3.7 Electrochemical Impedance Spectroscopy: An Electrochemical Technique

This subheading captures the essence of the statement while indicating that the content will provide a guide to using EIS and offer a comparison with other electrochemical techniques. Various electrical techniques have been expanded and developed in recent decades, improving experimental tools and modeling. A few electrochemical techniques are cyclic voltammetry, scanning electrochemical microscopy, and electrochemical impedance spectroscopy (S. Wang et al., 2021).

Electrochemical impedance spectroscopy is a powerful technique; the purpose of EIS is to investigate and analyze the properties of the materials in a battery, the electrode reactions (S. Wang et al., 2021), and degradation caused by an increase in the battery's internal resistance (Xiong et al., 2020). Additionally, EIS is a non-destructive method according to Middlemiss et al. (2020), a non-destructive method refers to an approach that enables the examination and characterization of a system or material, extracting valuable data and insights while maintaining the value of the sample and avoiding alteration to its structure or properties. EIS also provides a better understanding of the electrochemical mechanisms operating in commercial batteries and occurring at an electrified interface in one single measurement (S. Wang et al., 2021). The benefits of EIS are that it can also provide a substantial amount of information within a relativity short time while maintaining the battery integrity (Middlemiss et al., 2020). Valid EIS data should be presented to the K-K relations, a comparison between the recent data to the measured data resulting in an analysis of the spectrum according to the K-K relations (Yang et al., 2022).

S. Wang et al. (2021) describe how using EIS becomes imperative from utilizing transient methodologies and the mechanisms impacting the electrochemical system. Each mechanism is time-dependent for each step within the system to analyze the electrochemical system response at specific frequencies. The system response includes a small amplitude of potential or current to simulate the electrochemical system.

Initially, in the process operation of EIS, a small amplitude sinusoidal potential signal of alternating current is applied to an electrochemical system. At the same time, it is under open-circuit conditions during direct current polarization (Xiong et al., 2020). The signal is employed over a broad spectrum of frequencies (Middlemiss et al., 2020), and the current response and potential input are used to calculate the electrochemical AC impedance in the frequency domain—the input from sinusoidal current results in a phase shift (Xiong et al., 2020).

Further, as S. Wang et al. (2019) explain the response measurement where a transfer function is calculated, which is the electrochemical impedance of the system within the electrochemical cell, the impedance (Z) is expressed with the equation below, f [Hz] is the frequency, ω is the angular frequency, from $\omega = 2\pi f$, ϕ is the phase angle 100 between the input/ output signal, and $j = \sqrt{-1}$ is the imaginary number.

$$Z(\omega) = \frac{\tilde{V}(\omega)}{\tilde{\imath}(\omega)} = \left|\frac{\tilde{V}(\omega)}{\tilde{\imath}(\omega)}\right| \left(\cos\phi(\omega) + j\sin\phi\,(\omega)\right) = Z_r + jZ_j$$

3.7.1 An Equivalent Circuit Model for modeling with EIS

The EIS can be modeled by an equivalent circuit model, as Xiong et al. (2020) explain, and with the data visualized in a Nyquist plot or a Bode plot. The ECM describes the electrical behavior of battery usage in combination with circuit elements such as resistors and capacitors and is used in BMS to predict the SoC and SoH of batteries for vehicle performance management control. ECM is an empirical model with restrictions on the experimental data that needs to provide deeper insight into the electrochemical interactions. Moreover, the most common ECM are the Thevenin model, Randle's model, and resistance-capacitance network, whereas there are first-order RC, second-order RC, and third-order RC models (Yu et al., 2023).

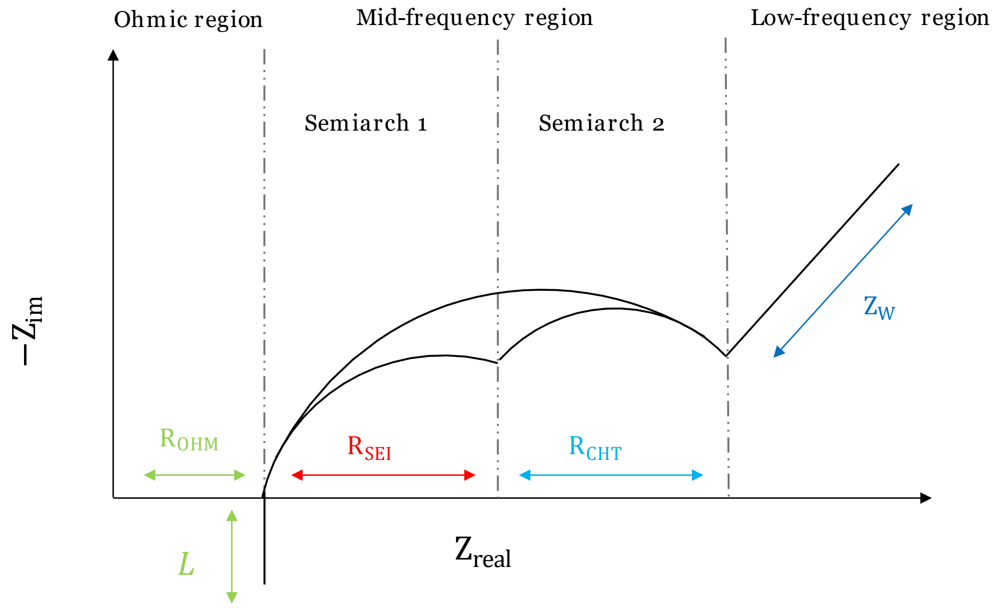


Figure 3: Analysis of EIS in a Nyquist plot. Adapted by (Xiong et al., 2020) & (Iurilli et al., 2021)

The ECM fitting to the experimental dataset can be uncertain since various configurations of circuit elements can yield comparable impedance curves. The circuit element can only be attained with sufficient knowledge of available electrochemical phenomena (Yu et al., 2023). As Yu et al. explain, the model predicts the battery voltage based on inputs in combination with different resistors and capacitors that demonstrate the time constant inherent in the battery cell.

Although the elements in the model may not directly correspond to the essential components of the device, they simulate its overall behavior due to the efficiency factors, for instance, speed, memory, and numerical convergence. A developed ECM does not have to apply to another model (Yu et al., 2023).

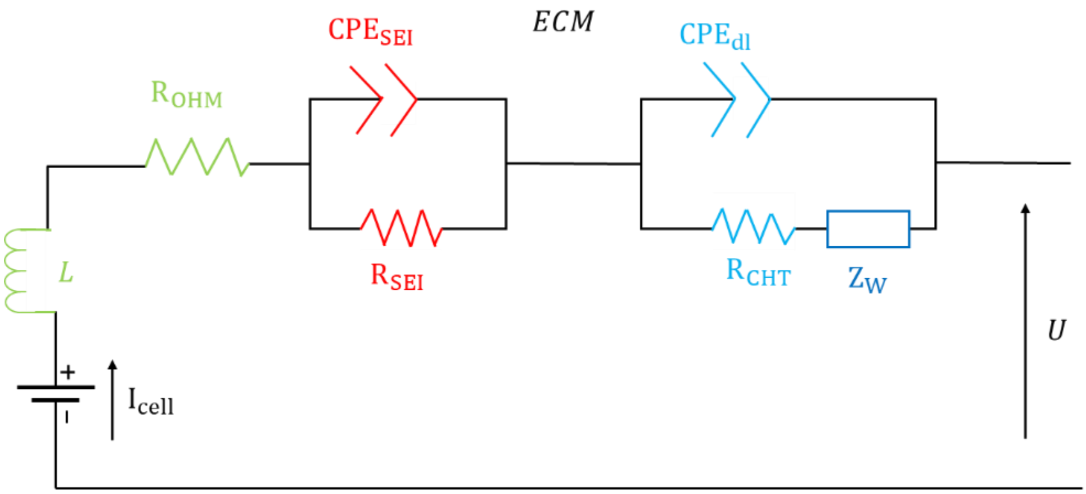


Figure 4: Common equivalent circuit model. Adapted by (Xiong et al., 2020)

According to Xiong et al. (2020) the model in figure 4 is the most common ECM, which is composed of three parts:

- Part 1: a series of R_{OHM} and L
- Part 2: a parallel of CPE_{SEI} and R_{SEI}
- Part 3: a parallel of CPE_{dl} and series of R_{CHT} and Z_W

Part 1 indicates the ohmic resistance increase, incorporating the ohmic resistance of electrolytes, electrodes, binder, and current collector. It can be acquired by resolving the intersection among the Nyquist plot's impedance spectrum and high-frequency region. The impedance positive imaginary part can acquire the inductance incorporated in the high-frequency phenomena occurring in the collector. Part 2 describes the SEI film's formation, decomposition, and growth, calculated from the first semi-arch span at mid-frequency. Part 3, the charge transfer resistance attained by a second semi-arch at low frequency, simulates the double-layer effect during battery discharge for electrode shape (Xiong et al., 2020).

3.8 Machine learning approaches

The volume of input data has increased in recent years. For this reason, machine learning has been developed at multiple length scales to help the researchers handle the data and new understandings at the microstructure level. For example, linear regressions on different neural network types can accurately predict the remaining useful life from the input voltage and resistance data (Edge et al., 2021).

According to Severson (2019, as cited in Edge et al., 2021), the same data can be developed into differentials, demonstrating that capacity is a strong indicator of RUL. Moreover, modifying these approaches with EIS is a good indication of the RUL. Zhang et al. (2020, as cited in Edge et al., 2021) implement EIS to measure the battery age by using Gaussian process regression followed by an indication approach to identify specific frequencies that are indicators sensitive to battery degradation. A few researchers have used ML in different ways to observe the battery cell. Wei et al. (2018, as cited in Edge et al., 2021) have used ML to analyse the effect of heterogeneous electrode particle degradation on a cell level on a larger dataset. Jiang et al. (2020, as cited in Edge et al., 2021) used an ML approach, a neural network, to analyse the effects on internal degradations between electrode particles and binders holding the active electrode material. ML approaches aid in automating analysis insight into battery cells and developing a more profound understanding (Edge et al., 2021).

Choi et al. (2019) mention machine-learning methods that will be further explained, such as recurrent neural network, long short-term memory, feedforward neural network, and convolutional neural network. A deep learning method estimating the battery capacity to predict the discharge voltage is called recurrent neural network, and was suggested by Guo et al. (28, as cited in Yu et al., 2023). A disadvantage with RNN is that their input data is restricted and endures persistent and unmanageable dependence over the long term (Yu et al., 2023). Feedforward neural network is a machine learning technique that uses collected voltage data to calculate the RUL. FNN consists of multiple layers, with each layer housing neurons that deliver nonlinear activation according to the weight connections to the previous layer (Choi et al., 2019).

The convolutional neural network uses a different layer, a deep learning architecture. The CNN structure consists of three layers; a convolutional layer, a pooling layer, and a fully connected layer. The convolutional operation process extracts feature and passes the output to the activation function. The pooling layer serves the objective of diminishing the spatial dimensions of the feature map, thereby facilitating robust learning outcomes for the input data. The output signal gets passed on to the next layer through multiple steps of convolutional and pooling layers. Lastly, classification or regression is accomplished with a fully connected layer (Choi et al., 2019).

Long Short-Term memory is based on an empirical parameter and therefore has a more significant prediction capability to store long-term information; it is also the most complex machine learning method. LSTM consists of an input gate, an output gate, and a forget gate. For each gate, the cell remembers the values across indefinite periods while the three layers control the movement of data in/out of the cell. The memory of the cell connects with the previous output and future input to determine the elements of the internal state vector that should be modified, preserved, or erased (Choi et al., 2019). Disadvantages with LSTM are the abundance of prediction parameters and the challenge of empirically selecting suitable parameters that burden predictive capabilities and effective utilization (Yu et al., 2023).

3.9 Previous research

There have been various research dedicated to investigating the various aspects of battery deterioration, one research regarding battery degradation diagnosis using impedance-based modeling conducted by (W. Li et al., 2022) will be further described since their analysis influenced the EIS measurements in this degree project. Collecting battery data and creating a digital twin in the cloud allows online monitoring of battery degradation on the electrode level. The authors use an impedance-based model and an open-circuit voltage to construct the capacity and power fade model. This combination captures changes in impedance across a wide frequency range and the evolution of the OCV during degradation. A data-driven method reconstructs the battery cell's electrochemical impedance spectra and OCV profiles while qualitatively identifying degradation modes. The data was collected with a sampling time of 0.1 seconds and a maximum frequency of 10 Hz. The EIS method resulted in low frequency data, due to limited settings. However, significant changes were observed in the identified EIS, an increase in the ohmic resistance, charge transfer impedance, and diffusion impedance, indicating battery, the aging process. Recording electrode-level degradation information in the battery health passport throughout the battery's lifespan adds value to both first- and second-life applications. A drawback of this research is that the optimal sampling time may vary in different applications depending on load profiles and hardware conditions. Therefore, a similar analysis needs to be performed considering the specific requirements of each application. Although, it holds the potential to be applied in cloud-based battery diagnostics for different battery materials and diverse application scenarios (W. Li et al., 2022).

Moreover, another research conducted by (Choi et al., 2019) will be presented. This degree project was influenced by machine learning capacity estimation on lithium-ion batteries with multi-channel charging profile. Choi et al (2019) explains that accurately modelling on the aging battery cells has a high cost, especially during irregular cycling operations, is crucial for energy storage planning and operations. Their research focuses on semi-empirical degradation model for lithium-ion batteries that evaluates the loss of battery cell life based on operating profiles. The model is developed by combining fundamental battery degradation theories with observations from aging test results. It is adaptable to various types of lithium-ion batteries, and the scientific article presents methods for adjusting the model coefficients using battery data sets by NASA. A cycle-counting technique is used to identify stress cycles resulting from irregular operations, enabling the degradation model to be applied in any battery energy storage application. The effectiveness of the model is demonstrated by assessing the degradation induced by a battery energy storage with frequency control. The research also proposes a capacity estimation for lithium-ion batteries using FNN, CNN, and LSTM machine learning models, based on single data, voltage and multi-channel data; voltage, current and temperature. While evaluating the estimation results using error indices and capacity difference per cycle. The numerical findings showcased the significance of diverse and feasible data for achieving highly accurate estimations. Notably, the proposed multi-channel data method outperformed on single voltage data, with improvements of up to 58% (FNN), 46% (CNN), and 25% (LSTM) in terms of MAPE. The developed model results in (Choi et al., 2019) predicting the battery health can be seen in Table 1. For future work, the authors suggest extending the proposed method by incorporating an online approach that dynamically updates the internal parameters of physics-based equations to reflect actual degradation in real-time practical operations.

Table 1: Estimation error based on the findings. Adapted by (Choi et al., 2019)

Model	RMSE	MAE	MAPE (%)
MC-FNN-1	0.0379	0.0329	1.9800
MC-FNN-2	0.0298	0.0242	1.7300
MC-CNN-1	0.0584	0.0443	2.8961
MC-CNN-2	0.0443	0.0364	2.3731
MC-LSTM	0.0246	0.0159	1.0320

3.10 Life-cycle assessment on Batteries

The Life-Cycle Assessment analyzes batteries' environmental and economic performance, using analysis tool to evaluate the environmental consequences over their entire life and the effect on human health. It contributes to precious information that industry and government can relate to when choosing batteries during their life cycle (Arshad et al., 2022). When doing an LCA on batteries, many factors must be considered because of the life cycle impacts from manufacturing, production, usage to recycling or disposal stage. There are various batteries with specific chemistries of battery, construction materials and production methods that have different efficiencies, which in their way, has low or high environmental impact. Although batteries are a rather complex mechanism, previous studies on the LCA of batteries differ since the chemistry has its environmental impact.

With material production, Arshad et al. has considered both LiBs and next-generation batteries. LFP and LMO do not contain toxic or hazardous metals and therefore have the most negligible environmental impact. Converting metal and components to materials in batteries involves mining, mineral processing, smelting, and refining. Metals such as lithium, cobalt, nickel, and manganese are the most common and the majority of the raw materials used in LiBs. Some metals are from the copper industry; others come from various parts of the world. The leading producer of cobalt is African countries. Lithium is mainly produced in Australia, Brazil, and Chile. Manganese is produced and supplied in South Africa, Ukraine, and Australia.

Moreover, during battery manufacturing the significant impacts are water pollution, air emissions, and hazardous wastes, specifically for LiB production. Hazardous wastes are also harmful to health. Greenhouse gas emissions are estimated at $12.5\, kg\ CO_2/kg$ of LiB, requiring 90 MJ per kg of energy, making greenhouse gas emissions one of the most severe environmental impacts. Evaluating the GHG of cathode materials for batteries are the following: LFP is 3061 $kgCO_{2eq}$, LMO is 2705 $kgCO_{2eq}$ and NMC is 2912 $kgCO_{2eq}$. Besides the production of the materials, the transportation of batteries is equally essential; the distribution of batteries including packaging storage and transport require safer packaging and appropriate materials to prevent e.g., fire incidents.

During the disposal stage there are essential impacts considered alarming according to Arshad et al., because of the packaging of batteries, fire incidents and short-circuit accidents. Strict requirements to prevent cell leakage are to separate the packaging cover the battery cells with heavy plastic or polypropylene to improve these dangerous hazards.

Recycling has been raised as it is beneficial for the environment by reducing the GHG emission, because the material is released, which restrains new raw materials to be formed. Recycling is not only beneficial for the environment, but it has also improved resource efficiency. Hence, the toxins released during recycling such as zinc, nickel, cadmium, cobalt, and manganese modifies the chemistries in the environment to be more accessible and induce a difficulty in recovering the materials. As well as the air pollution and toxic gaseous emissions are unfortunately released with recycling.

3.11 Battery regulations

The European Commission (n.d) describes that with an increasing application of batteries, in 2017 the European Commission launched a confederation exclusively for batteries. The European Battery Alliance targets the presumptions for building battery technology and increasing production capacity. The EBA's object is to cooperate in the vital clean and digital transition, making Europe a global leader in the sustainability of batteries by enabling a leading technology that will be essential for the developing automotive sector, with low emission mobility and necessary for energy storage.

According to the European Commission, the alliance develops a sustainable battery value chain in Europe, starting with retrieving raw materials, manufacturing components, cells, and battery packs, manufacturing the electric vehicle, and recycling. Improving conditions and handling batteries will make it easier to move towards a climate-neutral economy and contribute to minimizing carbon dioxide emissions. At the same time, companies receive support to invest and develop products and technologies. They are leaning toward a sustainable, safe, circular battery economy in the European market (European Commission, n.d).

4 CURRENT STUDY

The current study of this degree project consists of building deep learning models that can accurately predict the battery capacity while capturing the impact of different aging processes occurring inside the battery on the battery performance. Firstly, this degree project will investigate the degradation of the Li-cells by tracking the degradation behaviour during cycling and analysing different health indicators such as the capacity fade and the discharging characteristics. Then, non-destructive techniques such as electrochemical impedance spectroscopy and incremental capacity will be used to gain more insights into the responsible aging mechanisms behind the performance degradation of the Li-cells. Analysing the cell's behaviours under cycling will allow selecting the useful predictors feeding the deep learning prediction models to estimate the cell's capacity accurately. Finally, the performance evaluation of different deep learning models will be evaluated.

4.1 Investigation procedure

The whole investigation will be based on different methods:

- Experimental measurement of the cell's cycling data, such as the voltage, the current, the capacity
- Experimental measurement of electrochemical impedance spectroscopy using Ivium instrument:
- Experimental data analysis using embedded MATLAB toolboxes for data processing, such as data cleaning (noisy data removal, outlier data removal, data fitting, and more)
- Deep learning models will be developed using MATLAB's built-in toolbox for deep learning.

The flowchart of the different methods used in the current study is presented in Figure 5.

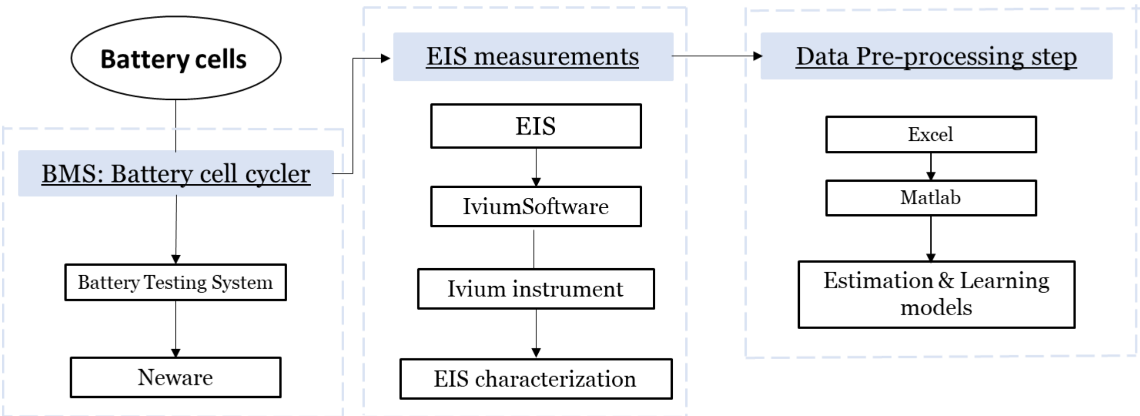


Figure 5: Flowchart describing the methods used in the current study

4.1.1 Neware battery system for cycling

For the data collection of the batteries using Panasonic and Biltema battery cells, as mentioned in the previous subtitle. BTS has several testing systems, as (Neware, n.d.b) mentions; one is the Cell Tester, with eight channels, enabling the possibility to test several batteries simultaneously, with configuration on each battery cell under different parameters. The simulation operates without affecting each other the simulation time runs when each battery cell has started its simulation. At the same time, the battery is allowed to undergo cycles during simulation time, which allows each battery to simulate under different cycles with input parameters such as voltage and current for the battery type. This testing system endorses battery cells to undergo aging through cycling by charging and discharging processes, which accelerates the battery aging (Che et al., 2022).

4.1.2 Ivium instrument for electrochemical impedance spectroscopy

The data collection for the battery data consisted of simulation in a software tool. The software tool is called Ivium technologies. Ivium technologies is an innovative solution for electrochemical research and excellent software for several applications. According to Ivium (2023a), the software is developed by engineers that suit more precise and advanced requirements depending on what applications. Ivium technologies can conduct graphs and numerical data (Ivium, 2017b).

The simulation proceeded for each cell, one at a time, due to the software set up at the laboratory in MDU. The battery cells were simulated for a certain number of cycles, and measured: the capacity, voltage, impedance, and current of the battery cells during these cycles while preserving the measured data in the software tool.

4.1.3 Excel for pre-processing and data export

This study's pre-processing and data export methodology involved utilizing Excel to clean and extract important parameters from a downloaded Excel file obtained from the Battery Management System. Where the raw data was downloaded in an Excel file from the BMS, this file contained various parameters related to battery performance and operation, where the data was cleaned out because irrelevant or unnecessary parameters were irrelevant to the identification process for the AI model. After the data cleaning process, these parameters were identified based on their relevance to the specific objectives and requirements for the prediction—the final step involved exporting the cleaned and organized data from Excel by exporting the data in a suitable format as function calling in MATLAB.

4.1.4 MATLAB toolboxes: for data processing and AI based model's development.

The methodology for data processing and model selection involved several steps. Initially, the battery dataset was pre-processed by removing outliers and ensuring data availability. Four sets of battery data resulted, each exhibiting degradation characteristics per cycle, carefully considering distinct changes over time and model complexity to determine the appropriate number of samples for analysis. The sampled dataset was configured according to capture the necessary information. Three different models were then applied to the pre-processed data: FNN, CNN, and LSTM, subsequently conducting the model selection using a validation set. The mean squared error was the loss function for evaluation and comparison purposes. The estimation results were presented based on the utilization of multi-channel data.

4.2 Advanced Software Solutions for Data Collection and Processing

4.2.1.1. Neware Battery cycler

BTS Client 8.0.0.471 by Neware is the software tool used to analyse the batteries in the Battery testing system. Neware is a leading global manufacturer of battery testing that has, over the years, developed to specialize in battery testing, for instance, LiB, Lithium-ion phosphate, and fuel cells (Neware, n.d.a). The battery cells are inserted in the battery testing system and simulated. The batteries undergo a charge, discharge, and rest on repeat. The results from the software tool were retrieved in Excel to visualize the capacity and the cycles of the battery, a method to construct graphs.

4.2.1.2. Battery type: Lithium-ion cell

The battery shape, size, and operation specifications were chosen to fit the Neware battery testing system and what MDU could offer for experimental tests. The battery cell chosen for the battery testing is lithium-ion batteries from Panasonic, NCR18650B Panasonic, and ICR18650 Li-ion battery (Biltema).

Foremost, because both hybrid and electric vehicles conduct with Li-ion batteries, the sizing of Panasonic batteries is the better type of cells to implement in Battery systems because they have a smaller current load. Table 2 shows the parameters for the battery cell (Kopczyński et al., 2018). Batteries from the manufacturer, Biltema, can have different performances and will give a more varied analysis of the battery (table 3).

Table 2: Parameters for Panasonic NCR18650B (Kopczyński et al., 2018)

Parameters:	**Panasonic NCR18650B**
Nominal voltage	3.7V
Voltage range	2.5-4.2V
Technology	Lithium-ion
Capacity minimal	3250mAh
Capacity typical	3350mAh
Charging current (max.)	1625mA
Discharging current (max.)	4.87A
Pick current (max.)	6.8A
Cell shape	Cylindrical
Dimension	18.5mm x 65.3mm
Weight	47.5g

Table 3: Parameters for battery cell Biltema (Biltema, n.d)

Parameters:	**Biltema ICR18650**
Nominal voltage	3.7V
Voltage range	2.5-4.2V (4.2V max)
Technology	Lithium-ion
Capacity	2950 mAh (±50 mAh)
Charging current (max.)	4A
Discharging current (max.)	5.9A
Cell shape	Cylindrical
Dimension	18.4mm x 65mm
Weight	47.5g

4.2.2 Cell cycling policy

The battery testing system was utilized to examine the behaviour of batteries through cycling, encompassing both charging and discharging operations. Charging was conducted using a constant current approach until the battery voltage reached a maximum limit of 4.2V and a minimum of 2.5V. Each battery underwent cycling under specific parameters to investigate the effects of different aging conditions. Battery cells s17 and s5 were subjected to higher current levels, resulting in a "fast" cycling rate. Conversely, battery cells s16 and Biltema were exposed to a lower current, representing a "normal" cycling rate. For detailed information on the specific input parameters employed during the cycling process, please refer to Table 4.

Table 4: Battery parameters during cycling in battery testing system

Cell	**Step Index**	**Step Name**	**Voltage(V)**	**C-rate (C)**	**Current(A)**	**Cutoff voltage (V)**	**Cut-off current (A)**
s16	1	CCCV Chg.	4.2		1.5		0.065
	2	Rest					
	3	CC DChg.			3.08	2.5	
s17	1	Rest					
	2	CCCV Chg.	4.2	2.069	6		0.065
	3	Rest					
	4	CC DChg.		2.069	6	2.5	
s5	1	CC DChg.			6	2.5	
	2	Rest					
	3	CCCV Chg.	4.2		6		0.065
	4	Rest					
Biltema	1	CC DChg.			6	2.5	
	2	Rest					
	3	CCCV Chg.	4.2		1.45		0.05

4.3 EIS measurements

This experimental measurement utilizes electrochemical impedance spectroscopy (EIS) to analyse battery aging characteristics. The EIS analysis method involves conducting experimental tests using a software tool called Ivium. During the cycling process in the Battery Testing System (BTS), EIS scans were collected at various cycles for each battery cell to monitor the ongoing degradation. Prior to each EIS scan, the cells were allowed to relax for a period ranging from 15 minutes to 1 hour. The EIS scans were performed with a scanning frequency range of 1 kHz to 10 mHz and a voltage amplitude of 10 mV. This procedure was repeated multiple times for each battery cell when the voltage was approximately 4V. Different equivalent circuit models were applied following the EIS scans to fit the Nyquist plot measurements. The model exhibiting the lowest error was selected, and its fitting parameters were recorded as characterization indicators for further analysis. The fitting is performed using the embedded Ivium Equivalent Circuit fitting tool to edit the circuit to fit the impedance data from the simulation (Ivium, 2017b).

4.4 Model development for machine-learning estimation

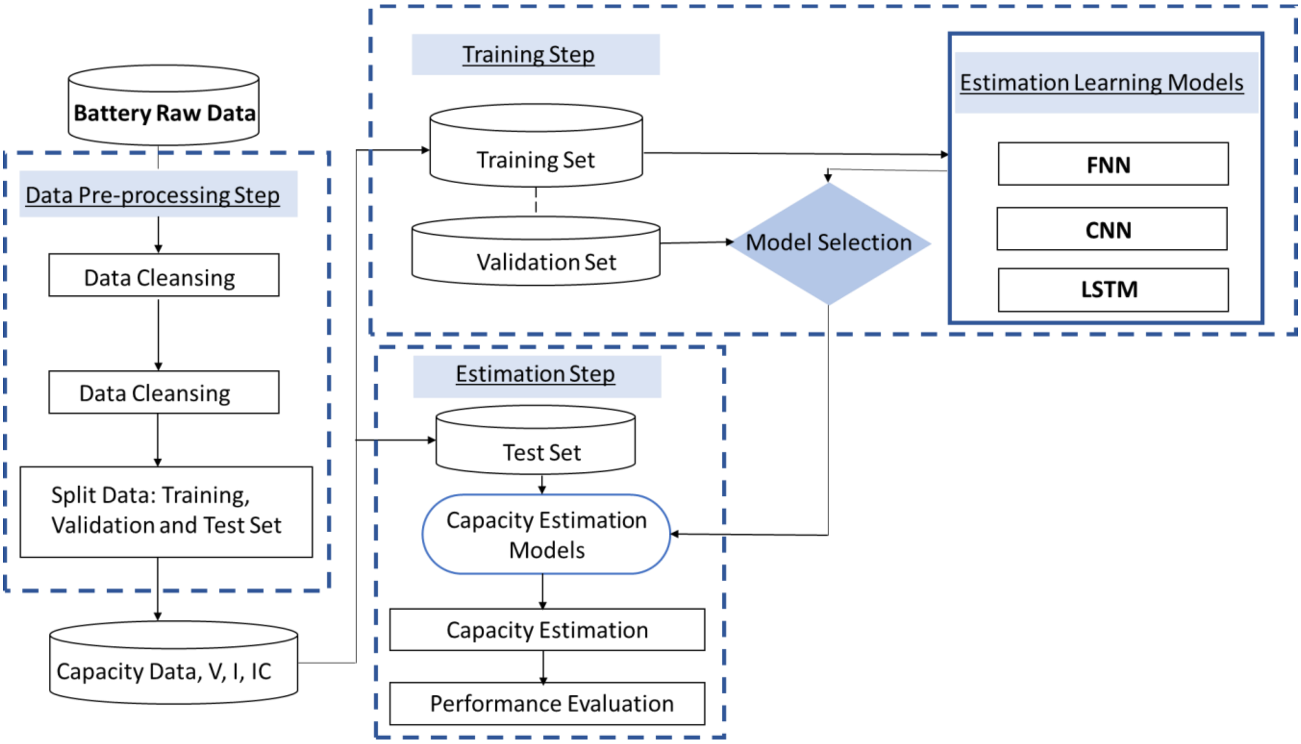


Figure 6: Flowchart for the deep learning methods, the capacity estimation of battery degradation

Battery capacity can be estimated by utilizing charging voltage, charging current, and IC data through the implementation of FNN, CNN, and LSTM. An overview of the proposed flowchart of the AI model development is presented in Figure 6. The flowchart involves three main steps: data pre-processing, training, and estimation. During the first step, the noisy data is cleaned and filtered using MATLAB, followed by normalization through the min-max normalization technique. Subsequently, the dataset was divided into training, validation, and test sets.

Subsequently, different models such as FNN, CNN, and LSTM are evaluated using the training and validation sets for the estimation learning model selection. Finally, the selected capacity estimation models from the previous step were employed in the third step to estimate battery capacity. The performance of the proposed methods is evaluated through thorough calculations using estimation errors, Root-mean-square errors. The development of the models was guided by a reference paper authored by Choi et al. (2019).

Table 5: The structure of deep learning models used in estimation step. Adapted by (Choi et al., 2019)

Model	**Models Structure/parameters**
FNN10	10 hidden layers Input
FNN40	40 hidden layers Input
CNN1	Convolution Layer with filter size [1, 2] and number of filters 10, 5. Learning rate: 0,001
CNN2	Convolution Layer with filter size [1, 2] and number of filters 100, 20. Learning rate: 0.001
LSTM	Sequence Length :60 Learning rate: 0.001

5 RESULTS

The results will be presented with the cell's behavior when cycled, with emphasis on the voltage curves, current, and capacity during charging and discharging. Further, the analysis of the incremental capacity is presented for two case studies of two commercial cells: the first, named "Biltema," cycled at a lower current of 1.5A compared to the second, named s16, cycled at a higher current of 6A to reveal the impact of fast charging on the cell performance. As mentioned earlier, EIS measurement has been performed for the cells during cycling to track the occurring electrochemical processes responsible for the cell's degradation. Lastly, the result of the deep learning models is presented with the model's performance evaluation for different cells cycled with different charging and discharging policy.

5.1 Cycling data analysis

This section will present the cycling data analysis during charge and discharge with voltage, current and capacity profiles for battery cell Biltema from the fresh cell cycle to the last cycle.

5.1.1 Charging and Discharging characteristics

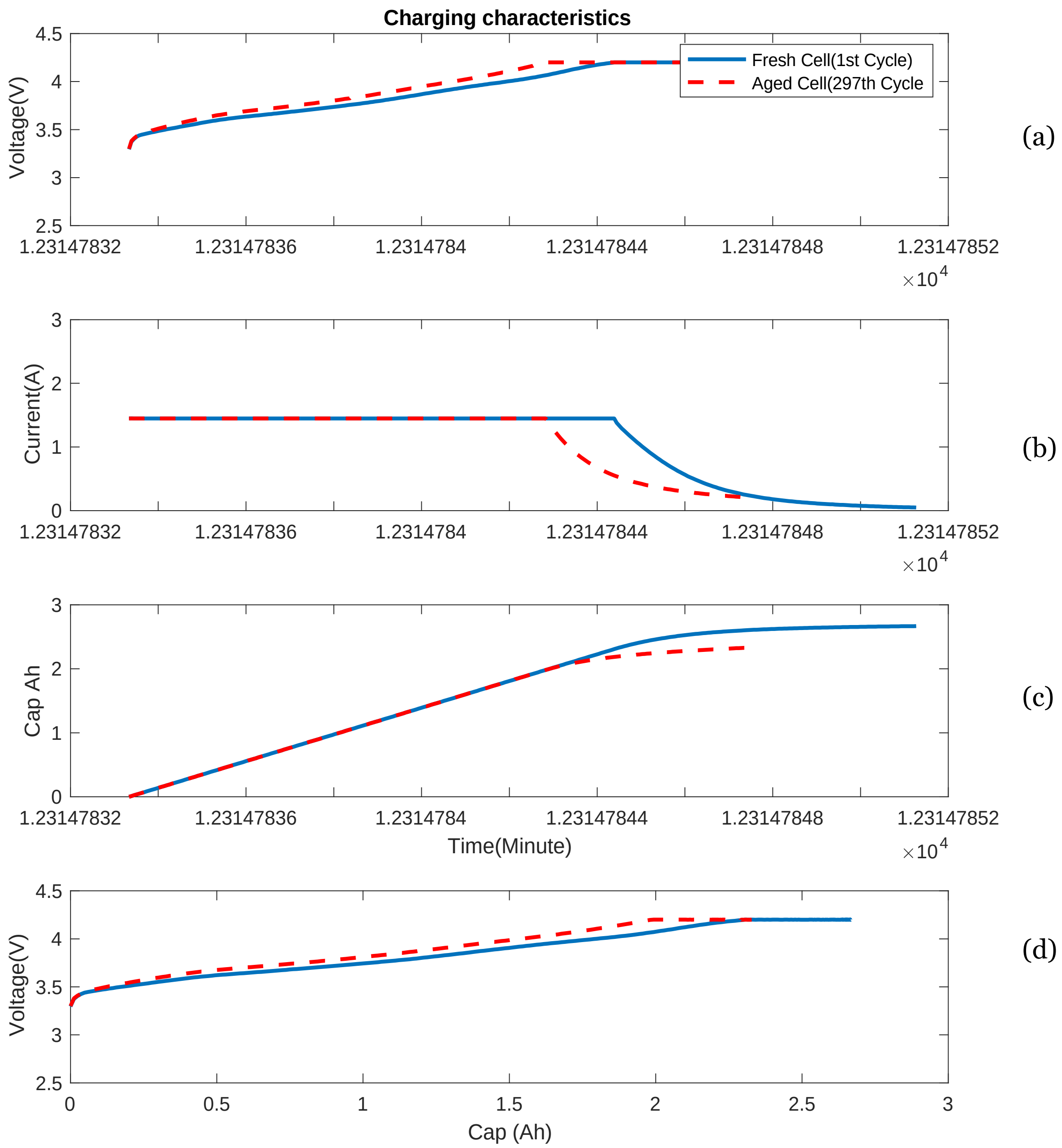


Figure 7: Charging profile for Biltema cell for the first cycle and last cycle (a) function of voltage over time, (b) function of current over time, (c) function of capacity over time and (d) voltage over capacity

Figure 7 (a) shows a comparison between the profile of the charging voltage when the cell is still fresh (cycle 1) and after the last cycle (297th cycle). As seen in Fig.7 (a), the beginning of the charging process at 2.5V was not captured, and that is due to the sharp increase of the voltage at the beginning of charging, which requires a higher sampling rate to be captured. Further, the time required to achieve the upper voltage limit of 4.2V slightly decreases over the cycling. The whole charging current, Fig.7 (b), is kept constant until the cell achieves the voltage upper limit of 4.2V and then starts to decrease to prevent the cell from being overcharged; therefore, at 4.2V, the cell is charged at a constant voltage while smoothly decreasing the current. Moreover, it can be seen in Fig.7 (c) that the capacity at the end of the charge decreases from cycle 1 to cycle 297, indicating that the cell's charging capacity is not maintained and decreases over the cycling. Lastly, Fig.7 (d) is a function between the voltage and capacity, where the fresh and aged cell increases at the same speed with minimal difference. The applied charging voltage varies between 2.5V and 4.2V, which correspond, respectively, to the end-of-discharge voltage at which the cell is fully discharged and the maximum voltage that the cell could support at which the cell is considered fully charged.

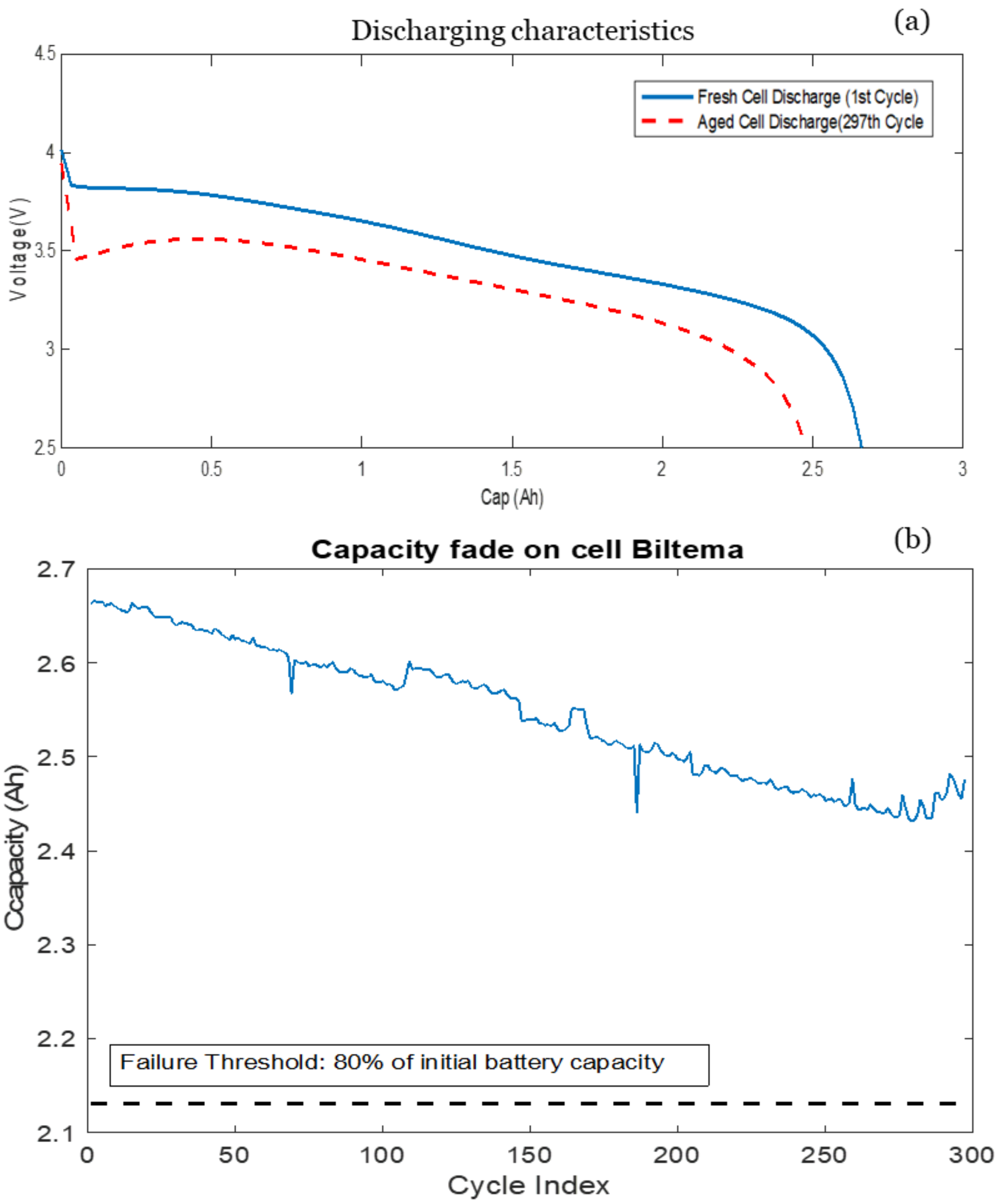


Figure 8: Discharging profile for cell Biltema (a) function of voltage over capacity for the first cycle and last cycle and (b) the discharge capacity fade

Fig.8 (a) depicts the discharge voltage profile as a function of the cell's discharge capacity of the fresh cell (cycle 1) and the aged cell after 297 cycles varying from 4.2V to 2.5V. At the beginning of discharge, the voltage drops rapidly from 4.2V to 3.9V for the fresh cell, where it drops below 3.5V for the aged cell. The rise of the cell's internal resistance over cycling mainly explains this drop. After this voltage drop, the cell is discharged at a slightly linearly decreasing voltage curve, called voltage plateau ([3.9-3.2V] for the fresh cell), where most of the cell capacity is used. Then, the cell capacity sharply decreases after the linear decreasing voltage plateau.

Moreover, the whole discharge voltage plateau is moving towards lower voltage over the cycling due to an increase in the cell's internal resistance. The discharge capacity fade was tracked over the cycling, as shown in Fig.8 (b), and it could be seen that the clear decreasing trend of the discharge capacity suggests that different aging electrochemical processes happening inside the cell are responsible for the cell's capacity fade. The capacity decreases from 2.68Ah to 2.46Ah after 297 cycles.

5.1.2 Differential capacity analysis

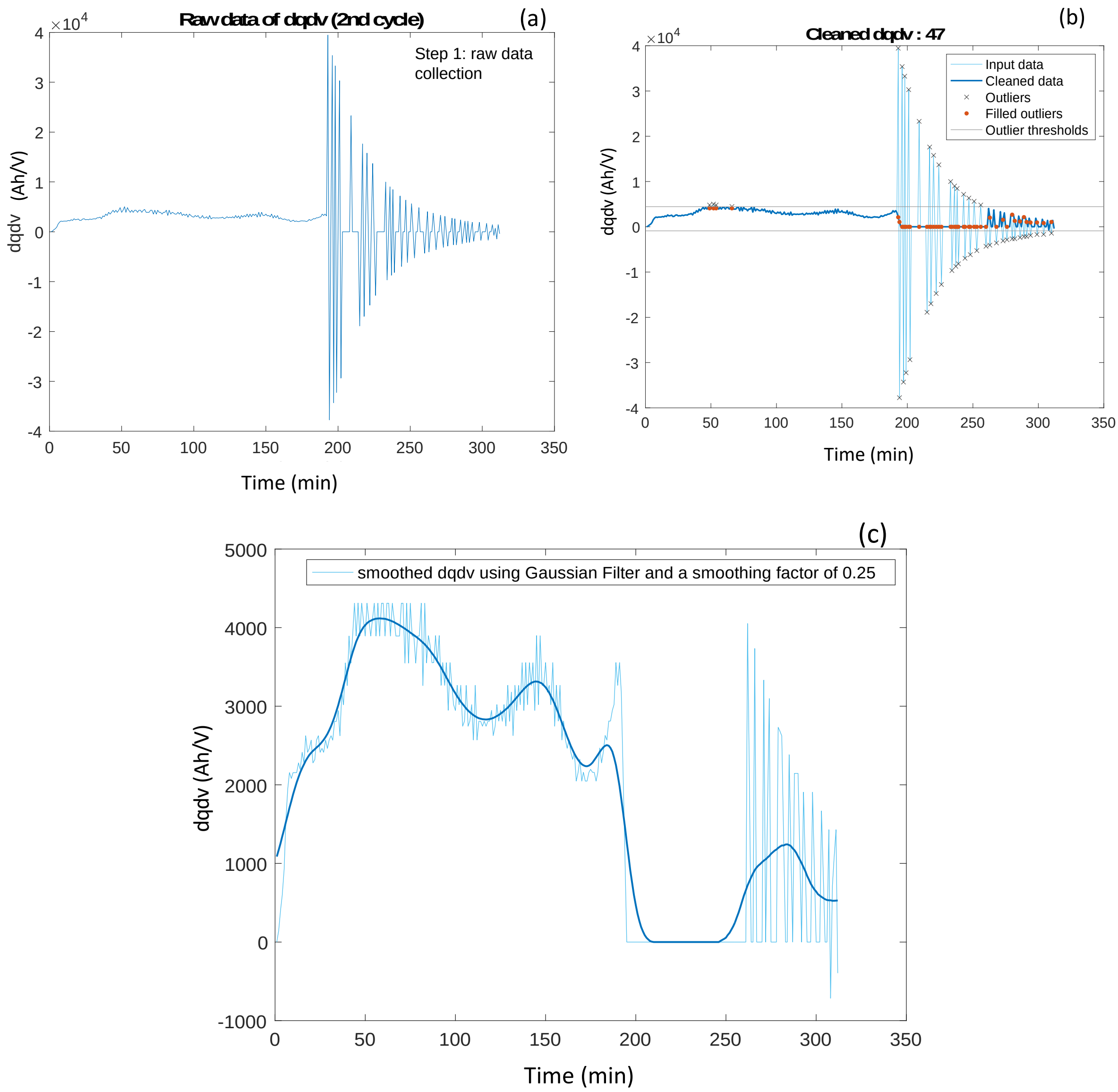


Figure 9: Differential capacity measurement for Biltema cell. (a) raw data, (b) cleaned data and (c) smoothed data

Fig.9 (a) shows the raw data of IC acquired from the Neware cycler during one charging step. It could be seen that the raw measurement data is highly noisy, containing several outliers' points leading to difficulties in identifying any typical behavior on the cells since the outlier's points are hiding the valuable part of the IC curve, time interval [0- 190] in Fig.9 (a), where most of the changes on the cell behavior could be identified. Therefore, the raw IC data were exported to MATLAB for further processing. First, all the outlier's point has been detected, see Fig.9 (b), by applying quartile filters of a threshold factor of 0,25. Then, a Gaussian filter with a smoothing factor of 0,25 was applied to smooth out the resulting IC-cleaned raw data. Fig.9 (c) depicts the IC curve after filtering out the outliers point, and the resulting Gaussian smoothed IC data. As seen in Fig.9 (c), the cleaned IC data shows clear peaks occurring at different times with different magnitudes.

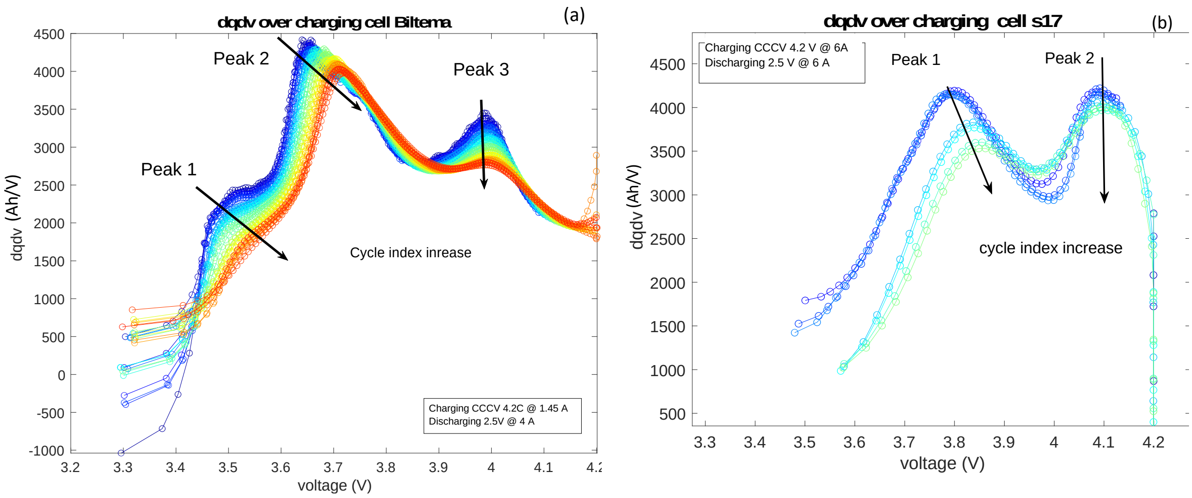


Figure 10: Results of the incremental capacity analysis over the cell's cycling (a) Biltema cell and (b) s17 cell

The overlay of all the resulting IC curves over the cycling for two cells is presented in Fig. 10 (a) and Fig.10 (b). the cells have been charged at different c-rate: Biltema at 0.5C and s17 at 2C. The IC curves in the first graph of the Biltema cell (Fig. 10a), three distinct peaks: Peak 1, Peak 2, and Peak 3, can be identified. The cycling index, ranging from blue to red, indicates the progression of cycles, with blue representing the initial cycles and red representing the final cycles. Further, it could be seen that each peak exhibits a distinctive shape and form:

- Peak 1, is shifting to the right while disappearing.
- Peak 2, is also shifting to the right while the magnitude is decreasing.
- Peak 3, magnitude is decreasing while keeping the same position (same voltage of 4V).

Compared to the Biltema cell, the second cell s17, where a high-charging current is applied, only two peaks have been identified, see Fig.10 (b). That could tell us that the number of peaks that could be identified in IC analysis is highly dependent on the c-rates used for charging and discharging. For instance, Peak 1 identified at 3,5V in the Biltema cell was not identified in the IC curves of s17. Moreover, Peak 1 and Peak 2 (for cell s17) exhibit the same behaviors as Peak 2 and Peak 3 in the Biltema cell, which can be explained by similar electrochemical processes in both cells. Furthermore, for s17, the magnitude of Peak 2 is rapidly decreasing over the cycling, which tells that the aging process is more pronounced in s17 when fast charging is employed. For instance, the magnitude of Peak 2 falls from 4200 Ah/V to 3500Ah/V after only 57 cycles, while the magnitude of the same peak in the Biltema cell falls from 4200 Ah/V to 3900Ah/V after only 297 cycles.

5.2 Electrochemical Impedance spectroscopy analysis

This section will show results from the EIS analysis showing the Nyquist plots, the equivalent circuit models fitting, and the characteristics of the model's components over the cycling.

5.2.1 *Results of the EIS analysis*

Two different cells have been analyzed through the EIS, where different c-rates for the charging are used. For, s16 is charged at 1.5 A while s5 is charged at a higher current of 6 A. It should be noticed that from the left to the right of the Nyquist plot, the frequency is decreasing where the left side of the Nyquist plot corresponds to the higher frequencies regions and the right side corresponds to the low-frequency region close to 10 mHz.

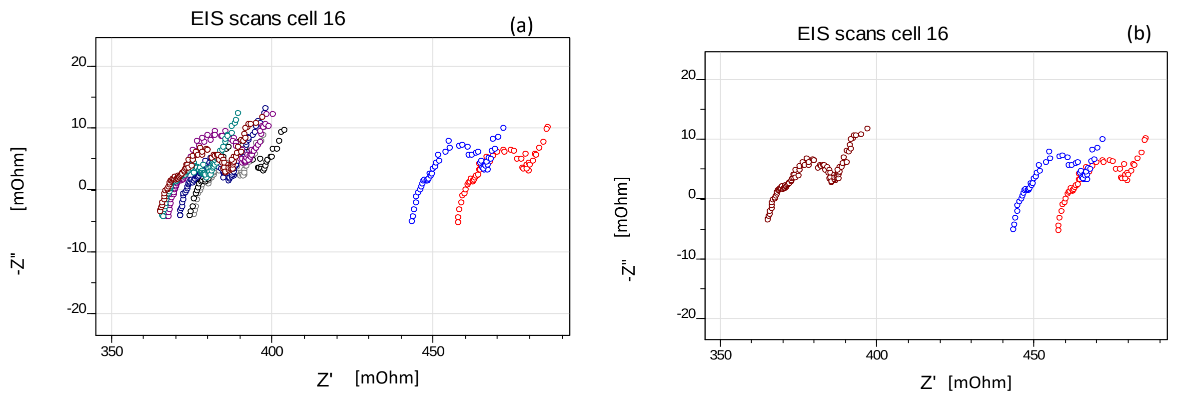


Figure 11: (a) Nyquist plot for battery cell s16, from fresh cell to last cycle, (b) Nyquist plot for battery cell s16, cycle 200, 207 and 300

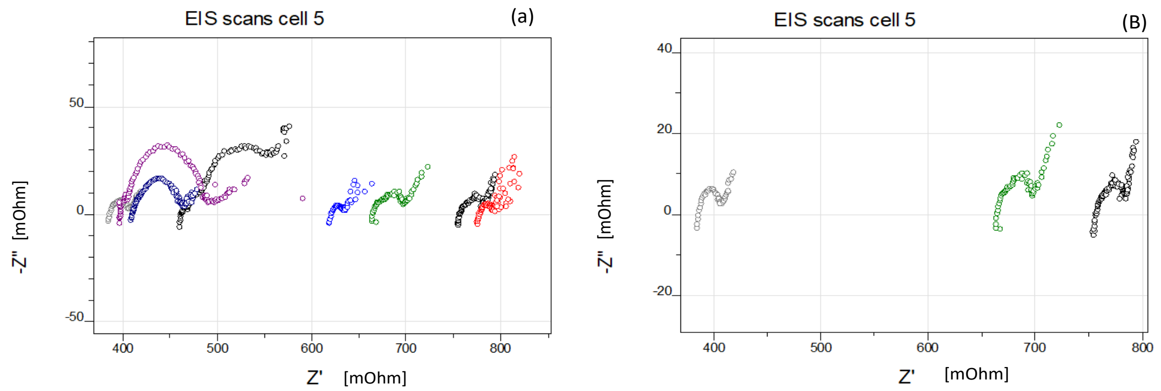


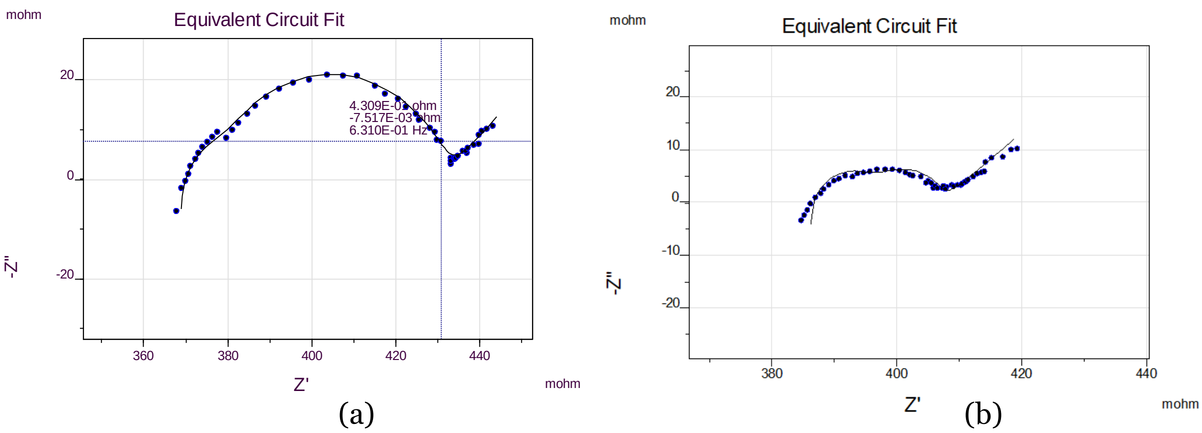
Figure 12: (a) Nyquist plot for cell s5, from fresh cell to cycle 69th, (b) Nyquist plot for cell s5, cycle; 13, 61 and 69

The Nyquist plots of the impedance measurement for the two cells at different cycles are depicted in Fig.11 (a) and Fig.12 (a). For clarity purposes and to track the changes on the plots over cycling, fewer selected scans are shown in Fig.11 (b) and Fig.12 (b).

For both cells, the plot shows an inductive tail at the beginning of the scans at the higher frequencies followed by a small loop, a larger loop, and a straight tail at the low frequency region (the right side of the Nyquist plot). The two loops may have partly overlapped, or one of the loops may become relatively too small to observe. Furthermore, over the cycling, both EIS plot shows a shift to the right side toward the higher impedance values. The x-axis offset increases continuously from the first to the last cycles for both cells. At the same time, it could be remarked that this offset is increasing rapidly towards the higher impedance values for the cell charged at a higher current. For s16, the offset shifts from 360 mW to 460 mW after more than 250 cycles, whereas it shifts from 380 mW to more than 750 mW for the fast-charged cell s5. Hence, high-current charging led to a more severe increase in x-axis offset which refer mainly to the rapid increase in the battery's internal resistance.

5.2.2 Equivalent circuit model of the EIS scans

The EIS results of the investigated cells s16 and s5 are fitted to their corresponding equivalent circuit models, as shown in Fig.13 (a), (b). The blue dots represent the Nyquist plot, and the straight graph is the equivalent circuit fit most suited for the Nyquist plot. The error of the fitting results is presented in Fig.14 (a), (b). The results indicate the accuracy of the fitting, an error plot between the Nyquist plot, and an equivalent circuit fit. The equivalents models of the two cells are shown in Fig.15 and represent the designed equivalent circuit model fitting according to the Nyquist plot for each battery cell. Fig.15 (a) is the ECM for cell s16 with a serial resistor in series connected with two serial-parallel resistors, and constant phase element, and a Warburg element; for Fig.15 (b), the ECM for cell s5 is modeled with a serial inductor, a serial resistor in series connected with two serial-parallel resistor and constant phase element and Warburg element.



(a) (b)

Figure 13: Equivalent circuit fit on battery (a) cell s16 cycle 1, (b) cell s5 cycle 13

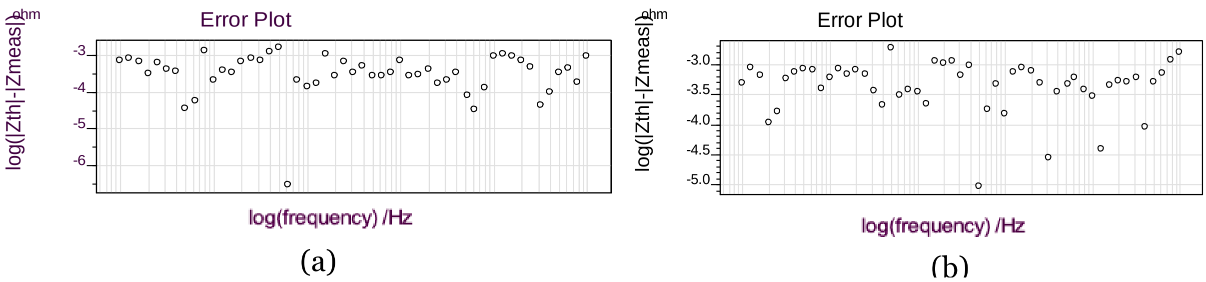


Figure 14: Error plot from ECM battery (a) cell s16 cycle 1, (b) cell s5 cycle 13

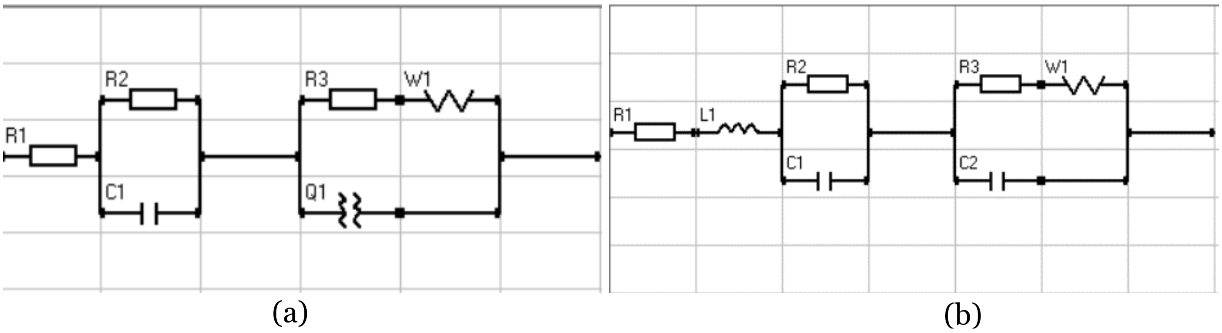


Figure 15: Equivalent circuit model for battery (a) cell s16 cycle 1, (b) cell s5 cycle 13

5.2.3 Characterization of resistance

Below are the results from the equivalent circuit model fitting parameters for cell s16 for "normal" cycling, cell s17, and s5 for "fast" cycling, with obtained internal resistance.

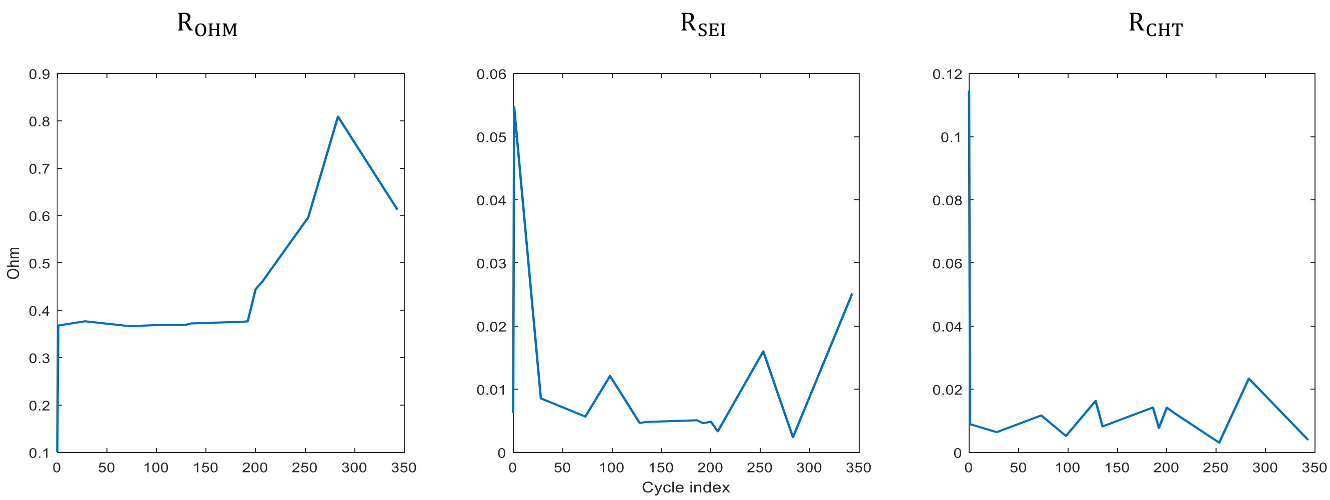


Figure 16: Resistances over the cycle index on cell s16

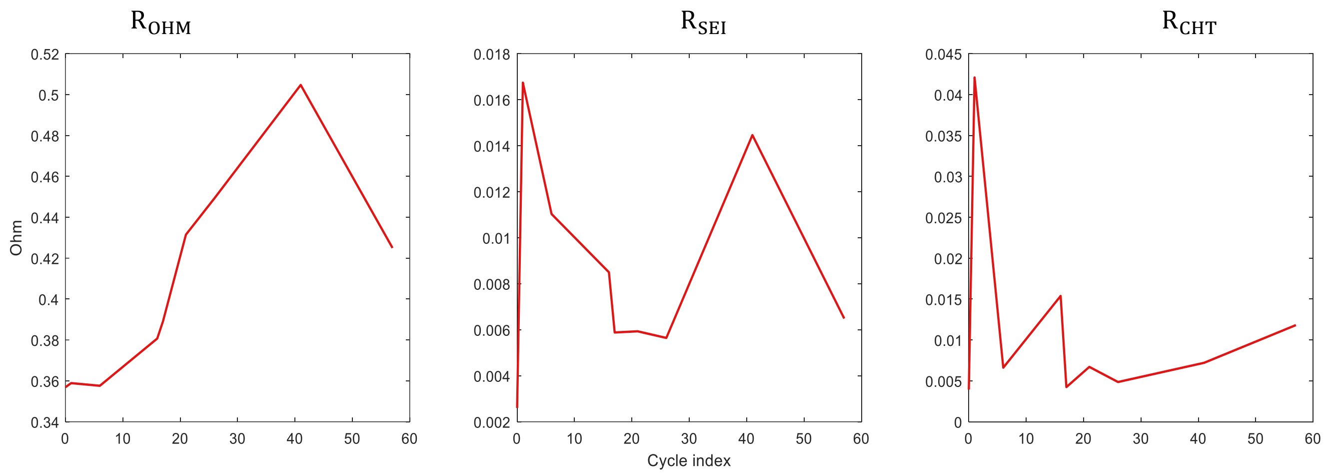


Figure 17: Resistances over the cycle index on cell s17

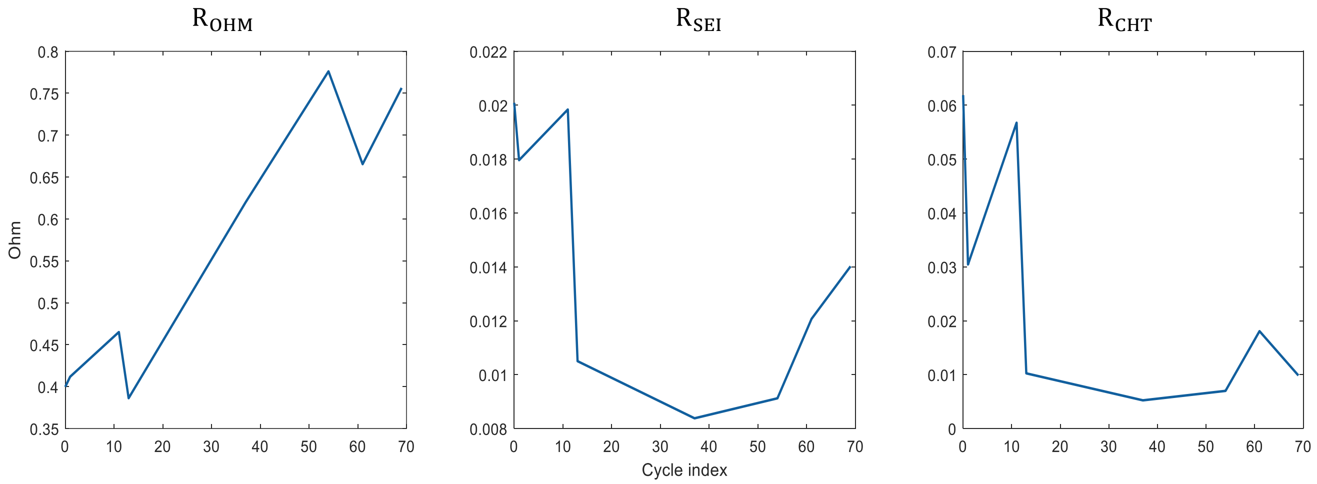


Figure 18: Resistances over the cycle index on cell s5

Figure 17 shows the resistances for cell s16 over the cycle index. It is increasing from cycle 200, R_{SEI} is increasing slowly, and R_{CHT} is increasing/ decreasing between the interval 0 Ohm and 0.04 Ohm. Figure 18 shows the resistance for cell s17 over the cycle index. R_{OHM} increases gradually from cycle 7 to cycle 40, where it reaches 0.51 Ohm, while, R_{SEI} decreases in the first 20 cycles, and increases from cycle 27 to cycle 40. R_{CHT} is decreasing, however, from cycle 27, the resistance increases linearly. In Figure 19, cell s5 is shown, where R_{OHM} increases from the first cycle and significantly linearly increases from cycle 12 to cycle 52, R_{SEI} decreases from cycle 10 to cycle 38, and from cycle 38, the resistance increases. R_{CHT} has a resistance drop at 10th cycle.

5.3 Capacity estimation using different deep learning models

This section estimates capacity using different deep-learning models such as FNN, CNN, and LSTM. These deep learning models are also compared to the actual value from experimental measurements from BMS. Two architectures, FNN and CNN, have been tested to check for any gain in the model accuracy; see Table 4 for model parameters.

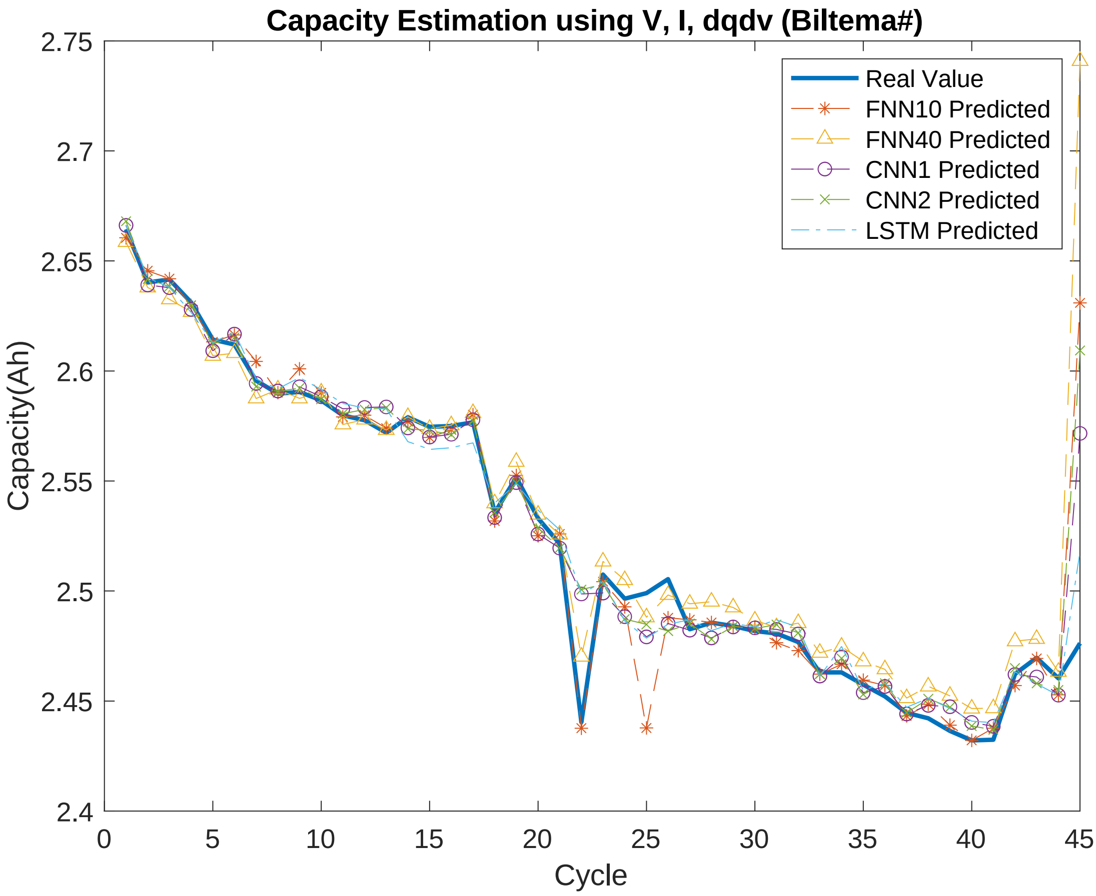


Figure 19: Capacity estimation using deep learning models on cell Biltema

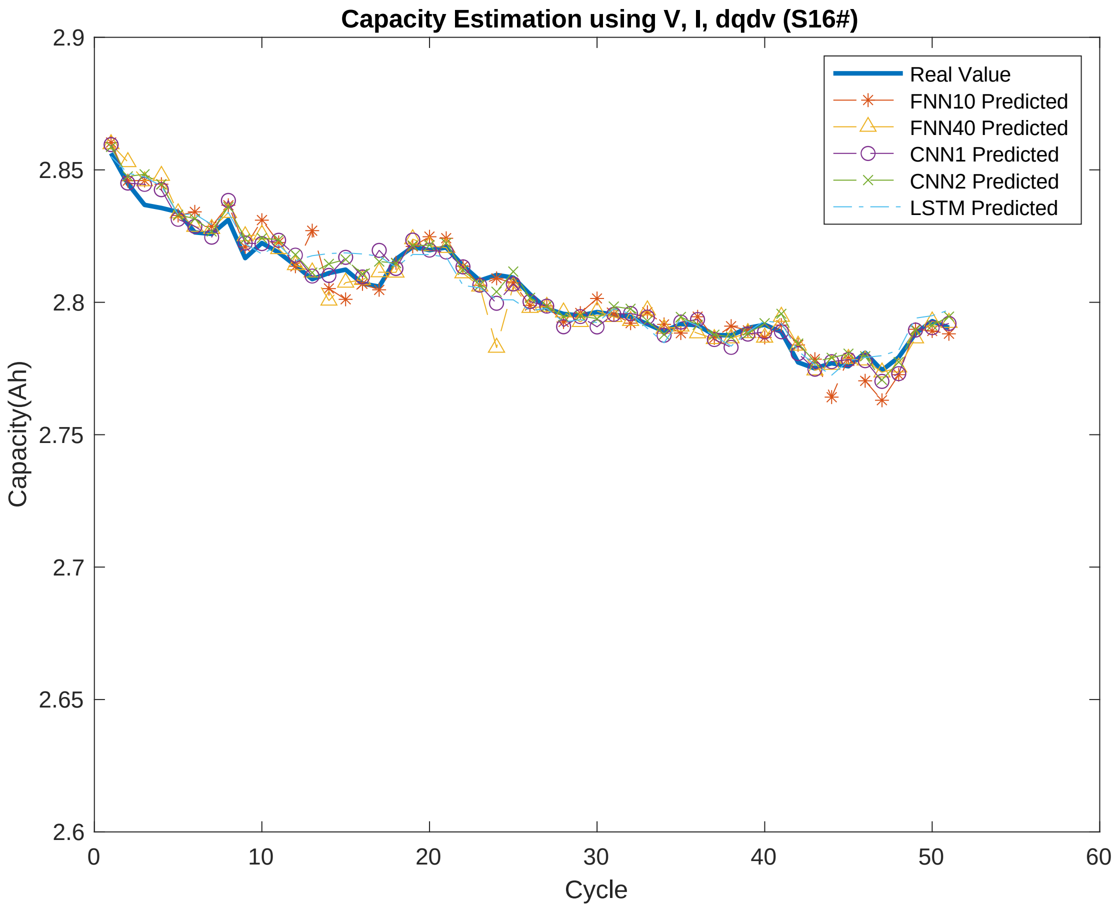


Figure 20: Capacity estimation using deep learning models on cell s16

In Figure 19 and Figure 20, the capacity is estimated for cell Biltema and cell s16 using deep cycling data of the corresponding cells: voltage, current, and differential capacity analysis. The capacity estimation is plotted per cycle and predicts the upcoming cycle's capacity for the battery cells. Figure 19 and Figure 20 show the test capacity estimation results of different models FNN10, FNN40, CNN1, CNN2, and LSTM.

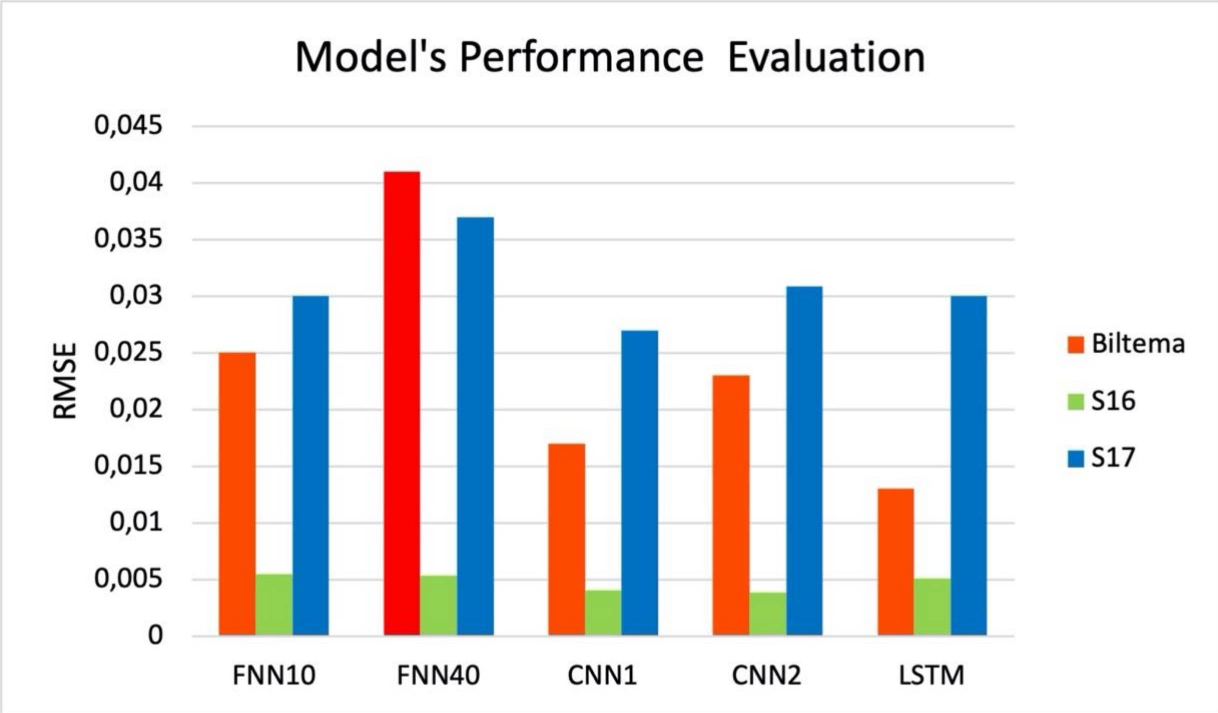


Figure 21: Summarized model performance evaluation for different deep learning models

In Figure 21, the results summarize the capacity estimation RMSE for each deep learning model; FNN10, FNN40, CNN1, CNN2, and LSTM for three cells; Biltema, s16, and s17. The model CNN1 and LSTM have the lowest RMSE, while FNN40 and FNN10 have the highest error.

6 DISCUSSION

This section will provide an in-depth exploration of the tools utilized to generate the results, presenting them in conjunction with the corresponding outcomes that address the research questions. Furthermore, the discussion will encompass the social, economic, and sustainability dimensions within the field of batteries.

6.1 Battery indicators reflecting the health status

From the cycling data analysis, the degradation of the cell capacity was demonstrated for cell Biltema. Fig.8 (a), (b) shows a linear capacity decline and a decreased discharge time. The capacity fade indicates insufficient support during cycling, charge, and discharge between the anode and cathode, where the lithium-ion stored in the cathode ends up in the anode (Yang et al., 2022). The decline cannot only be attributed to a single mechanism of degradation (Kemeny et al., 2023). Various factors lead to a decline of active anode material, causing battery capacity fade (Yang et al., 2022), such as electrolyte reduction, SEI thickening, and loss of active cathode material (Kemeny et al., 2023).

As discussed by Anseán et al. (2019), the results from IC peaks involve the electrochemical signatures of the electrodes, anode, and cathode and are illustrated with a unique shape and intensity; the tracked evolution of IC peaks as the cell ages inform the electrochemical phenomena on the cell and electrode degradation mechanism. The results of the incremental capacity analysis show mainly three peaks during the charging of the cell Biltema: Peak 1, Peak 2, and Peak 3, see Fig.10 (a). According to the results, Peak 1 distorts towards higher voltages over cycling. A prominent Peak 2 decreases and shifts slightly to higher voltages from 3.65V to 3.73V. Peak 3 is decreasing at the same voltage, 4V.

The ICA analysis of cell s17 has only two peaks: Peak 1 and Peak 2, that have been detected compared to the previous cell due to the high charging/discharging current rate, which impacts the number of detected peaks. In practice, lower charging and discharging rates are recommended to detect all the degradation processes. Furthermore, it could be seen that Peak 1 is decreasing rapidly over cycling when compared to the same peak detected at the same voltage, 3.7V, in the Biltema cell. For instance, Peak 2 in the Biltema cell decreased from 4200Ah/V to 3900 Ah/V after 297 cycles, whereas for the fast-charged cell s17, it decreased from 4200Ah/V to 3500 Ah/V after 57 cycles. That means that the degradation process is likely to be highly pronounced in the fast-charged cell, which is as expected since the cell is highly stressed when fast charging is used. The peaks represent footprints of the internal battery cell structure each shift, and the shape of the peaks indicates the degradation mechanisms responsible for the capacity degradation over the cycling (Kemeny et al., 2023). As Kemeny et al. suggests, the LAM mainly explains this footprint as the dominant source of degradation, while it is accompanied by LLI and Lithium plating.

It should be noted that the reconstruction of the IC curves from the raw data while including the informative peaks that reflects the different aging electrochemical process in the cell is vulnerable to several factors, such as the sampling rate of the data used for the data collection impacts the level of noisy data in terms of amounts and amplitudes and the charging and discharging c-rates that impact the number of peaks that could be identified, as well the shape and the magnitude of peaks. As reported in a study conducted by (Kemeny et al., 2023), seven peaks have been identified for a Panasonic cell NCR18650B. Similar results could be obtained in this degree project if the batteries had undergone several cycles, and the EIS scanning time would have had a lower frequency input, lower than 10mHz.

6.2 EIS degradation characteristics

The impedance presented in the Nyquist plots in Figures 11 and 12 is shifted gradually to higher real impedance values, as well as the shape of the semicircle indicates the battery cell aging process (Yoon et al., 2020). This can be seen significantly in Fig.11 (b) and Fig.12 (b) enhanced Nyquist plots, figure 11 cell s16, cycle 73 is 380Z', cycle 200 is 460Z', and cycle 207 is 480Z'. In Fig. 13, battery cell s5, cycle 13 is 400Z', cycle 61 is 760Z', and cycle 69 is 780Z'. Besides the semi-arch shapes, the mid-frequency region on the Nyquist plots for cells s16 and s5 results in one or two semi-arches and indicates an ongoing aging mechanism. The first or only semi-arch in the Nyquist plot expresses the loss of active anode material. As for the low-frequency region, the increase indicates the electrode diffusion process but could be investigated more if the battery cell was cycled for longer. The second semi-arches obtained from the Nyquist plot are formed from the behavior impacts of the temperature, which indicated the loss of active cathode material (Iurilli et al., 2021).

The electrochemical technique EIS can identify the change within the cell during battery aging, changes such as charge transfer impedance and diffusion impedance (W. Li et al., 2022). The resistance in a battery is increasing over time, meaning that an aged batteries internal resistance is increasing and indicates that there is a battery aging process as the cycling continues (Yoon et al., 2020). Moreover, R_{OHM} and R_{SEI} tend to increase during battery aging process (W. Li et al., 2022). According to Eddahech et al. (2014, as cited in Choi et al., 2020) different batteries with graphite electrode and different cathode materials have showed an increase in resistance values. From the EIS measurements observed in Fig.16, 17 and 18 the resistors are increasing with the increasing cycle index, based on the findings of a recent survey (Kemeny et al., 2023) implicates that the SEI layer is remained stable during the EIS scan and increase for R_{OHM} indicates the occurrence of conductivity losses, increase of R_{SEI} indicates change in active materials by decreased lithium-ion diffusion. These factors for R_{OHM} and R_{SEI} lead to SEI thickening and lithium-ion consumption that further leads to loss of lithium inventory degrading the battery cell for each cycling (Kemeny et al., 2023). The resistance obtained from EIS measurements and ECM is used as an indicator to determine the state of health of the battery cell (Yoon et al., 2020).

It is worth noting that Fig.13 illustrates the visual representation of an equivalent circuit fit, which varies depending on the battery type and the cycle. The utilized model, known as the equivalent circuit model, is tailored to accommodate the EIS scan, specific battery type and the cycle. Consequently, the model employed for battery cell s16 cycle 1 differs from model fitting for cycle 200. This discrepancy poses a disadvantage when considering fit parameters such as

R_{OHM} , R_{SEI} and inductance this can be seen in Fig.15. Therefore, it is preferable to solely focus on R_{OHM} that is the fundamental resistance used for all batteries regarding the battery cycle. Besides, during the EIS scan, it was observed that allowing the battery cell to rest for more than 1 hour after cycling, charge/discharge significantly improved the scan results. Failure to do so resulted in a scattered and noisy Nyquist graph, impeding the performance of an equivalent circuit fitting and ECM analysis. Additionally, with the various available electrochemical analysis techniques to study the internal process degradation of a battery, EIS distinguishes itself as a standout method. The EIS is an efficient analytical tool investigating the reaction and degradation mechanisms of a battery, it can also be applicable to batteries of various sizes and conditions. The EIS using non-destructive method does not damage the battery and can be performed quickly, since it provides accurate information in one experiment about each component in a battery cell (Yoon et al., 2020).

Moreover, a drawback is that an ECM formulated for a specific scenario may not be used for other models. The battery in EV assumes a standardized daily charging pattern obtained for the precise empirical model degradation. It requires conducting an aging experiment for each new application, which can take months and even several years (Yu et al., 2023). The electrochemical model defines the physical and chemical processes inside a battery cell, such as electrochemical reactions and lithium and ohmic action migration. By examining, contrasting, and evaluating the measurements from ECM, it becomes feasible to distinguish the distinct aging reactions occurring within the battery and gain insight into the corresponding aging modes (Xiong et al., 2020).

6.3 Battery degradation prediction

The capacity estimation results can be observed in Figures 20 and 21. The current, the voltage, and the IC curves have been used as indicators to feed in the AI models. The RMSE in Figure 22 summarizes the capacity estimation performance for the different deep learning models for battery cell Biltema, s16, and s17. The best model for Biltema was LSTM with RMSE 0.013; for cell s16, the model CNN2 resulted in RMSE 0.039, and CNN1 for cell s17 with an RMSE 0.027. The deep learning model's LSTM and CNN1 had the overall lowest RMSE on the three battery cells. LSTM for battery cells: Biltema RMSE 0.013, cell s16 RMSE 0.051, and cell s17 RMSE 0.03. What can be seen when comparing the different models, the LSTM model is exceptional and has the best performance because of the competent management of time series data regression. When comparing the achieved results in this degree project with a similar result from the literature results in Table 1 by (Choi et al., 2019), where the predictors used for feed in the models are the voltage, the current, and the temperature, we can see that with the deep learning models when using the IC instead of the temperature, the performance can be achieved with exceeding results for the indicators.

6.4 The intersection on Society, Economy, and Sustainability

Battery technology and its impact on society, economy, and sustainability are critical considerations today. The degradation of batteries poses significant challenges in these dimensions. From a social perspective, the widespread adoption of battery devices and electric vehicles can improve the quality of life by reducing reliance on fossil fuels, decreasing air pollution, and promoting energy independence. However, battery degradation affects the performance and reliability of these devices, which can lead to consumer dissatisfaction and hinder the transition to sustainable energy systems. The increasing demand for batteries has stimulated innovation and economic growth. Addressing battery degradation through improved materials, manufacturing processes, and predictive maintenance strategies can enhance the economic viability of batteries, encourage investment in research and development, and drive the growth of the battery industry. From a sustainability standpoint, battery degradation has environmental implications. The traditional recycling process has its obstacles for especially LiBs, which contributes to an environmental impact. Despite this, adapting recycling to the evolving technologies for LiBs is vital. With the increased usage and demand of recycle materials required in batteries the soaring prices, graphite component and electrolyte extraction process, especially in countries where the production is less primary, since it can lead to health hazards producing toxic, inflammable and volatile electrolyte components. Arshad et al. (2022) mention that it has been studied that LiBs has less impact on the environment than Nickel-cadmium and Nickel metal hydride batteries, due to containing less hazardous materials. Batteries with high energy-density and long-life expectancy have the lowest negative environmental impact, and a lighter battery with newer chemistry such as a lithium-nickel-cobalt-aluminum-oxide battery. The carbon dioxide, when manufacture the metal aluminum for LiBs for EVs, are estimated to be $2 - 3kgCO_2$ equivalent per kg of battery. Many variations and factors have been studied in the categories of GWP. The range for carbon dioxide emissions are between $12 - 313\ kgCO_2$ equivalent.

The production and disposal of batteries involve extracting raw materials and potentially hazardous waste. Reducing battery degradation can extend battery lifespan, reducing environmental footprint and lowering resource consumption. Additionally, advocating stricter battery regulations and developing sustainable and recyclable battery technologies can minimize environmental impact and contribute to a circular economy approach.

7 CONCLUSIONS

This degree project analysed the battery degradation, capacity prediction and battery health indicators on four battery cells: Biltema, Panasonic: s17, s16, and s5 under different aging conditions, via non-destructive method. Such as electrochemical impedance spectroscopy was employed to analyse the degradation, while deep learning models were utilized to predict capacity.

The Incremental capacity analysis reveals essential insights into the state of health of a battery. By utilizing the derivative equation and calculating the two-phase transition, we can identify voltage elevations that manifest as ICA peaks. These peaks serve as distinctive markers of the internal battery cell structure, with each shift and shape providing valuable indicators of degradation mechanisms. The degradation process is particularly pronounced in fast-charged cells due to the heightened stress they experience during rapid charging. The primary sources of degradation observed include lithium plating, lithium loss inventory, and loss of active material. Furthermore, battery capacity fade can be attributed to various factors, including decreased active anode material, electrolyte reduction, solid-electrolyte interphase thickening, and loss of active cathode material.

The resistance obtained from EIS measurements and ECM is used as an indicator to determine the state of health of the battery cell. Each element within the ECM corresponds to distinct aging reactions, and the integration of these reactions indicates the overall aging behaviour of the battery. Increased resistance during battery cycling indicates an aging process, where R_{OHM} and R_{CHT} provides insights into the LLI effects and Z_W, the LAM effects.

In battery prediction using AI models, indicators such as current, voltage, and IC are utilized to estimate the capacity. FNN, CNN, and LSTM models are employed, and their performance is evaluated. The models provide accurate capacity estimation per cycle for battery cells. Among these models, LSTM stands out with exceptional performance. Specifically, the LSTM model demonstrates the best performance, with RMSE values of 0.013 for Biltema, 0.051 for cell s16, and 0.03 for cell s17. Remarkably, using IC instead of temperature yields even better results, surpassing expectations.

These findings emphasize the need to carefully manage battery charging processes and consider factors contributing to degradation. By understanding these mechanisms, we can develop strategies to mitigate degradation and prolong battery lifespan, enhancing performance and reliability along with technological advancement in the full potential of batteries in driving social progress, fostering economic growth, and achieving sustainability goals.

8 SUGGESTIONS FOR FURTHER WORK

Several potential avenues are recommended for further exploration in this degree project to enhance contributions and broaden the scope of future investigations. The current design of aging prediction applications is limited and needs further exploration and research to address several specific challenges. One of the challenges that have gained prominence but need to be addressed is the application of effective data techniques in Battery Management Systems on online applications. A large volume of data processing with advanced algorithms may entail significant processing time. The focus of this challenge should be on developing innovative solutions to advance aging predictions to facilitate extensive data techniques in BMSs (R. Xiong et al., 2020). Another challenge that needs further investigation is the low-frequency region in the EIS that needs to be addressed, with an extended duration for impedance measurement at lower frequencies that can be attributed to an accurate representation of the diffusion process. However, this requires capturing and simulating additional cycles on various batteries (Iurilli et al., 2021).

However, another challenge that needs to be developed is the extraction of curves and plots from experimental measurements and charging data for curve-based analysis due to the need for complete charging data in onboard applications by investigating the impact of temperature, current rates, and several cycles. Further exploration to accomplish an optimal balance between the computation of diagnosis quantity and accuracy is paramount. The field development of diagnosis methods utilizing cloud computing has gained significant attention. This approach enables the data collection from BMSs to be transmitted to the cloud, where model training and parameter identification can be performed. The results can then be returned to the BMSs in electric vehicles for subsequent implementation (R. Xiong et al., 2020).

It is crucial to consider the environmental contributions for broadening investigation throughout the entire battery cell lifespan. Whereas developing analysis tools to gather further information regarding the opportunities associated with recycling has gained increasing attention due to its significant environmental benefits, particularly in reducing greenhouse gas emissions. Recycling not only contributes to environmental preservation but also enhances resource efficiency. The adverse environmental impact can be minimized while maximizing sustainability by focusing on batteries with high energy density and long-life expectancy (Arshad et al., 2022).

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