Modelling the Degradation of Electric Vehicle Batteries Based on Initial State of Health and Charging Conditions in Kenya

By

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Declaration and Approval

Declaration

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

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Approval

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Abstract

The lifespan of electric vehicle (EV) batteries is a critical determinant of performance, safety, and consumer confidence, particularly in Kenya, where over 80% of EVs are second-hand imports. This study investigated the degradation patterns of lithium - ion EV batteries based on initial State of Health (SoH), charging voltage, charging current, and operational temperature—factors that influence the usable life of imported EVs.

An experimental approach was adopted, involving the cycling of 26650.format lithium - ion battery cells under controlled laboratory conditions to simulate real-world usage patterns. The test matrix included batteries with initial SoH levels of 60%, 80%, 90%, and 100%, subjected to charging currents of 0.5C, 1.0C, and 1.5C, voltages of 3.4V, 3.65V, and 4.02V, and ambient temperatures of 15°C, 27°C, and 35°C. Battery capacity fade was monitored over successive charge.discharge cycles, and regression models were developed to quantify degradation trends.

The findings indicate that battery degradation is significantly affected by the initial SoH. Batteries starting at 60% and 80% SoH exhibited a slight capacity gain of 0.0029 Ah per cycle, likely due to initial electrochemical stabilization. In contrast, new batteries with 100% SoH showed a consistent degradation rate of 0.0005 Ah per cycle. Charging current had a notable impact: batteries charged at 1.5C degraded at a rate of 0.0008 Ah per cycle—50% faster than those charged at 0.5C, which degraded at 0.0004 Ah per cycle. Charging voltage also played a critical role. Overvoltage conditions at 4.02V resulted in a degradation rate of 0.0008 Ah per cycle, while undervoltage charging at 3.4V preserved battery health but reduced usable capacity by approximately 10%, yielding 2.98 Ah compared to the nominal 3.3 Ah. Temperature effects were equally significant. Low temperatures (15°C) accelerated degradation, with a fade rate of 0.0019 Ah per cycle and corresponding capacity loss, while moderate temperatures between 27°C and 35°C yielded the most stable performance at a degradation rate of 0.0005 Ah per cycle.

The study highlights the urgent need for the regulation of public charging infrastructure to mitigate degradation risks. It recommends that national policies incorporate measures to ensure optimal thermal management, standardized charging protocols, and increased consumer awareness to enhance battery lifespan. These insights are crucial for policymakers, regulators, and EV buyers, as they help align Kenya's e-mobility transition with sustainability goals while minimizing the environmental and economic consequences of premature battery failure.

Table of Contents

List of Figures

List of Tables

List of Equations

List of Abbreviations

AC	.	Alternating Current
BEV	.	Battery electric vehicle
BMS	.	Battery management system
CO2	.	Carbon dioxide
CO2.eq	.	Carbon dioxide equivalents
CRA	.	Chemical risk assessment
DC	.	Direct Current
EPD	.	Environmental product declaration
ERV	.	Energy reduction value
EV	.	Electric vehicle
HEV	.	Hybrid electric vehicle
ICV	.	Internal combustion vehicle
ILCD	.	International reference life cycle data system
ISO	.	International organization for standardization
Kg	.	Kilogram
KWh	.	Kilowatt-hour, 1 kWh = 3.6 MJ
LCIA	.	Life cycle impact assessment
LCA	.	Life cycle assessment
LFP	.	Lithium-iron-phosphate (LiFePO4) battery cell
LiFePO4	.	Lithium-iron-phosphate (LFP) battery cell
LIB	.	Lithium - ion battery
LMB	.	Lithium-metal batteries
MJ	.	Mega joule
MSDS	.	Material safety data sheets
MWh	.	Megawatt-hour

NCA . Lithium-nickel-cobalt-aluminium-oxide battery cell

NMC . Lithium-nickel-manganese-cobalt-oxide battery cell

Definition of Terms

Battery capacity (Ah) is the total Amp. hours available when a battery is discharged by a load at a certain C-rate from 100% SOC to the cut-off voltage. Can be arrived at as product of the discharge current and the time in hours.(Peng et al., 2022)

Charge current (A) This is the current applied across the terminals of a battery to increase its charge capacity.(Weiss et al., 2021)

Charge retention is the remaining battery capacity available after a battery has been stored or used for a given period of time. (Weiss et al., 2021)

Charge voltage (V) is the voltage the battery is charged to when full capacity is reached. Charge voltage is achieved when the battery is charged to about 70% SOC. (Weiss et al., 2021)

C-rate. A C-rate defines the rate at which a battery is discharged with reference to its maximum capacity. (Sun et al., 2022)

Cut-off voltage (V) is the voltage at which a battery is considered fully discharged. It prevents the battery from going to the deep discharge. The battery stops running the load when the cut-off voltage is reached.(Sun et al., 2022)

Cycle life represents the total number of charge –discharge cycles that a battery can handle before it is unable to meet a specified performance criterion. It is defined based on specific charge and discharge conditions. (Haram et al., 2021) It is often dependent on the rate and depth of cycles and ambient conditions including as temperature and humidity.

Depth of discharge (DOD) This parameter is closely related to the SOC. It is the percentage of battery capacity that has been discharged with reference to the maximum battery capacity. (Liu et al., 2022).

Energy density/volumetric energy density (Wh/L) is the nominal battery energy per unit volume. A high volumetric energy density helps achieve smaller sized batteries within a specific energy output**.** (Son et al., 2021)

Internal resistance (IR) (Ω) is the impedance inherent to the battery. It varies when charging and discharging, and is dependent on the battery SOC. A high internal resistance, lowers the battery efficiency.(Moral et al., 2020)

Open-circuit voltage (V_{oc}) is the voltage measured between the battery positive and negative terminals when connected to no-load. It changes with State of Charge**.** (Liu et al., 2022).

Specific energy/gravimetric density (Wh/kg) is the nominal battery energy per unit mass. A higher gravimetric density is desired in order to lower overall battery weight for a specified energy output.(Son et al., 2021)

State of charge (SOC) This is the measure of the capacity of a battery in comparison to the maximum battery capacity expressed as a percentage. It shows remaining available power of the battery and is used to estimate the remaining mileage of the electric vehicle(Liu et al., 2022).

State of Health (SOH) This parameter characterizes the condition of a battery with reference to its initial condition. It measures the level of degradation and the remaining capacity of a battery. It is the ratio of the remaining capacity, when fully charged to the capacity of a new battery measured under ideal conditions and is often represented as a percentage.(Yao et al., 2021)

Terminal voltage (V) is the voltage measured between the battery positive and negative terminals when connected to a load. Terminal voltage changes with battery SOC and charge/discharge current.

Acknowledgment

I would like to thank Professor. Ismail Ateya for his dedication to ensuring that I understood Scientific Research Methodology properly and dedicating many weekends to improving this work.

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My special gratitude also goes to Kenya Bureau of Standards and for their assistance in conducting this research. It would not have been possible to complete this research without their assistance.

Dedication

I dedicate this research to my son, Karl. Always remember that you can do anything you set your mind to. Thank you for always giving me the motivation to move to the next level.

Chapter 1: Introduction

1.1 Background

The transport sector contributes to 25% of greenhouse gas emissions, and in about 45% of countries, transport is the highest contributor to GHGs. (UNEP, 2021) Electric vehicles are considered the key technology in decarbonizing road transport. According to the International Energy Agency, in order to limit the global temperature increase to below 2°C, at least 20% of all road transport vehicles must be electrically driven by 2030 (UNEP, 2018).

In support of the need to transition to clean transport systems, governments and other organizations have ramped up support for electric vehicles through funding and favourable policies. This has resulted in an exponential increase in Electric Vehicle uptake in recent years. The share of electric vehicle sales has more than tripled between 2020 and 2023, moving from 4% market share to over 15% market share. IEA (2023). This trend is replicated in many parts of the world, including Kenya.

Kenya's vehicle market (specifically 4-wheelers) is largely a second-hand market (Bommet & Wambua, 2020). The National Energy Efficiency and Conservation Strategy (2020) forecasts that 5 per cent of all registered vehicles in Kenya will be electric by 2030 (KNEEC, 2020). Of the total registered 4.4 million vehicles as reported by Lore & Baragu (2023), this would be about 220,000 electric vehicles, 80% of which would be second-hand, going by the current rates.

Data collated on the online platform Geotab (Geotab- EV Battery Degradation, 2023) shows that in the sixth year of use, EV battery residual capacities range from 80.1% to 87%. The official End of Life (EOL) capacity for a battery is considered to be 80%, which is due to the fact that after the battery health drops below 80% SoH, the capacity fades rapidly (Eider & Berl, 2018). In February 2024, Kenya, through Kenya Bureau of Standards introduced a new requirement that all Electric Vehicles imported into the country have a traction battery State of Health of not less than 80% (Nzomo, 2024). There is a concern that used vehicles imported in to the country would have a shortened lifespan associated with the already degraded state of health at the point of importation.

Short lifespans of EV batteries have far reaching impacts; Socio-economic, financial, environmental and even health risks. Research has linked poor e-waste disposal to water pollution and human toxicity and eco-toxicity (Kang et al., 2013). It is therefore imperative that Kenya takes a cautionary model to assuring the quality of imported used electric vehicles into the country.

This study investigated the impact of the initial state of health of second-hand EV batteries and charging conditions i.e. temperature, charging current and voltage on the lifespan of Electric Vehicles. By analysing data on battery degradation and battery capacity, the research has provided insights into the expected life expectancy of second hand EV batteries under different charging conditions. Overall, this Dissertation seeks to bridge the gap in understanding the impact of the initial state of health and charging conditions on the life expectancy of second-hand EV batteries in Kenya. This research is therefore vital for consumers and policymakers alike, as it offers practical guidance for EV buyers and shall inform sustainable EV adoption and management in Kenya.

1.2 Problem Statement

One of the biggest challenges facing electric vehicle uptake rates is range anxiety, a fear of running out of charge before reaching one's destination (Pevec et al., 2019). The range of an electric vehicle is directly correlated to the traction battery state of charge and state of health. State of charge can be easily fixed by charging the vehicle, but the state of health would require an overhaul of the battery, which is both cost intensive and time consuming. Therefore, the state of health has a significant impact on the range of electric vehicles, and consequently greatly impacts the uptake rates of electric vehicles.

The link between electric vehicle uptake and the state of health means that there is need to safeguard the battery life in order to ensure successful uptake of electric Vehicles. Kenya, has committed to increase its share of electric vehicle to 5% of all newly imported vehicles by the year 2025 (Dioha et al., 2022) as a strategy to decarbonize the transport sector. Mitigating factors that hamper the achievement of this goal is therefore a priority for the government. The country's used vehicle guidelines are based on Kenya Standard Code of practice for inspection of road vehicles of 2019. The code caps the age of used vehicles at a maximum of eight years from the year of first registration. This code is however silent on the quality of the batteries in electric vehicles. As a way to protect importers against importation of vehicles whose batteries are already at their end of life, Kenya Bureau of standards issued a directive in 2024 that all electric vehicles imported into the country have a traction battery State of Health of not less than 80%. While this cap provides an initial step towards the assurance of quality, there is insufficient data to advice on the lifespan of batteries imported at different states of health. Although prior research has explored battery degradation in new EVs, scant attention has been given to the impact of the initial state of health on the lifespan of second-hand EV batteries.

Eider and Berl (2018) concur that battery performance is impaired by battery degradation through chronological and utilization causes. Further, research has proven that the battery health state dictates current EV performance and hence EV batteries need to be observed and monitored so that the degradation can be limited and reliability can be guaranteed. (Bouchhima et al., 2018).

1.3 Research Objectives

1.3.1 General Objective

The general objective of this research was to assess the impact of initial state of health and charging conditions on electric vehicle battery lifespan.

1.3.2 Specific Objectives

The main objective was arrived at through conducting the following specific objectives.

i) To investigate the impact of the initial state of health on the degradation of EV batteries.
ii) To evaluate the effects of charging current on the degradation of EV batteries
iii) To analyse the effects of temperature on the degradation of EV batteries
iv) To examine the impact of Charging Voltages on EV Batteries
v) To generate degradation models in EV batteries based on the initial state of health and charging conditions.

1.4 Research Questions.

The study answered the following questions.

i) How does the initial state of health impact the degradation of an electric vehicle battery?
ii) How does ambient temperature impact the degradation of an electric vehicle battery?
iii) How does charging current impact the life expectancy of an electric vehicle battery?

iv) How does charging voltage impact the life expectancy of an electric vehicle battery?

v) What are the degradation models in Electric Vehicle Batteries based on the initial state of health and charging conditions?

1.5 Justification of The Study

The transport sector is responsible for approximately 25% of greenhouse gas emissions and in about 45% of countries transport is the highest contributor to GHGs. (UNEP, 2021) Electric vehicles are the key technology to decarbonize road transport. In support of the need to transition to clean transport systems, governments and other organizations have ramped up support for electric vehicles through funding and favourable policies. This has resulted in an exponential increase in Electric Vehicle uptake in the recent years. The share of electric vehicle sales has more than tripled between 2020 and 2023, moving from 4% market share to over 15% market share. IEA (2023). This trend is replicated in many parts of the world, including Kenya.

Kenya aims to increase the share of electric/hybrid vehicles in total vehicles imported into Kenya to 5% by 2025 (MOE, 2020.) This would translate to almost 20,000 units per year. (KNBS, 2022). For such a significant investment by the country, there is need to safeguard buyers by offering guidelines on good quality EVs that assure safety and reliability. This research shall assess the impacts of the current quality model for electric vehicles; where factors such as the state of health of batteries are not considered and the charging stations are not regulated.

The research also conducted a detailed study into the impacts of initial state of the vehicle battery at the point of importation on the subsequent degradation. Eider & Berl (2018) explain that degradation of EV batteries is not a linear process and beyond 80% SoH, the capacity fades rapidly. Therefore, the State of Health is a critical parameter in making the decision on the importation quality criteria for used Electric vehicles. The research aims to addressed a critical issue surrounding the adoption and management of second-hand Electric Vehicles (EVs) in Kenya, particularly focusing on the degradation of EV batteries.

As the global shift towards sustainable transportation gains momentum, understanding the performance and longevity of second-hand EVs becomes pivotal. With a specific focus on EV batteries, which serve as the heart of electric mobility, investigating the factors that influence their degradation is of paramount importance.

While Kenya's guidelines for used vehicle inspection exist (Kenya Standard Code of Practice for Inspection of Road Vehicles, 2019), they fail to address the quality and performance of batteries in EVs. As battery health directly impacts vehicle performance, safety, and environmental concerns (Mrozik et al., 2021), the lack of battery-specific regulations poses significant risks. This research seeks to bridge this gap in performance standards by investigating the state of health of second-hand EV batteries and its implications on their overall lifespan.

The study is grounded in the fact that despite growing global data trends (Geotab, 2023), there is a scarcity of information on second-hand EV battery performance within the unique context of Kenyan conditions. This information gap underpins the need for localized research that considers the specific challenges and environmental factors present in Kenya. The study aims to provide insights that are directly applicable to the Kenyan EV market and its consumers.

Sustainable transportation policies and practices are pivotal for addressing climate change and promoting environmental well-being. Kenya's transition to EVs aligns with these goals (Lore & Baragu, 2022). However, the success of such an adoption hinges on the reliability and longevity of EV batteries. Developing a model that factors in various parameters, such as the initial state of health, temperature, and charging conditions, can guide consumers, policymakers, and stakeholders in making informed decisions that support sustainable EV adoption.

The research objectives and questions align with practical implications for both consumers and policymakers. EV buyers will benefit from practical recommendations derived from the research, aiding them in selecting second-hand EVs based on battery health and expected longevity. For policymakers, this research can serve as a foundational resource for informed decision-making regarding regulations, incentives, and support mechanisms to promote sustainable EV adoption and management in Kenya.

In conclusion, the research addresses a critical need in the field of sustainable transportation by investigating the degradation of second-hand EV batteries within the unique context of Kenya.

1.6 Scope and Limitations of the Study

The limitations of this research are discussed as follows.;

i) The impact of relative humidity on battery degradation was not considered in this study
ii) The study was performed at the cell level; therefore, the study cannot guarantee that results will be replicated exactly at the battery pack level.
iii) The study did not factor in degradation due to calendar ageing.
iv) The study only used one battery chemistry, further studies need to be carried out on other battery chemistries.
v) Study was carried out over a period of three months. A longer period might provide more comprehensive results

Chapter 2: Literature Review

2.1 Introduction

Electric Vehicles are a vital component in the transition to sustainable transportation. The adoption of these Electric Vehicles is anchored on the performance of their batteries. It is critical to understand and to correctly model the performance and degradation of electric vehicle batteries. Battery degradation has a significant impact on the performance, safety and lifespan of Electric Vehicles. Therefore, developing accurate battery degradation models can provide insight into optimizing battery use, enhancing EV efficiency and can aid decision making during purchase.

This chapter looks at the operating principles of electric vehicles and analyses previous studies that are aligned to the research topic. The chapter is organized in to two sections; theoretical review and empirical review. Theoretical review delves into the history of electric vehicles, adoption and innovation trends. It also discusses the parts of an electric vehicle and their uses. In the empirical review section, we look at various works presented by other authors that are relevant to the study and analyse the gaps in these works that this study proposes to tackle.

2.2 Theoretical Review

2.2.1 History of Electric Vehicles from Early Innovations to Global Adoption.

The first electric vehicles were invented in the early 19th century as an alternative to steam and combustion engines. Thomas Davenport and Robert Anderson were among the first inventors of Electric Vehicles and carriages (Gilles, 2018). These electric vehicles offered a quiet operation, ease of use and lack of emissions as their key competitive advantages. They were mostly used by the affluent who could afford their relatively higher costs. These early vehicles laid a foundation for the new electric vehicles of today.

For a brief period in the early 19th century, electric vehicles outsold combustion vehicles. Over time however, electric vehicles were outperformed by combustion vehicles for a number of reasons; first, they suffered a relatively limited ranged, second, they required long charging periods and were more expensive as they did not enjoy economies of scale that came with mass production of combustion vehicles. The availability of affordable fuel for combustion vehicles further widened the market lead of ICE vehicles, leaving electric vehicles to serve niche markets. (Bansal & Kockelman, 2017).

Concerns over climate change due to carbon emissions caused by factors such as fossil fuels in ICE vehicles have created renewed interest in electric vehicles in the recent past. A study by the UN in 2018 showed that the transportation sector is one the biggest contributors to Green House Gases to the atmosphere, which adversely affect air quality, public health, and the environment (United Nations, 2018).

Electric vehicles are considered zero emission vehicles, significantly reducing the transport sector's contribution to climate change. There have also been significant improvements to electric vehicle which have improved its uptake. Innovations in battery technology has greatly enhanced EV range and this has played an essential part in alleviating range anxiety for EV users. The Charging infrastructure for EVs is rapidly growing around the world, making EVs a more reliable option. Charging period have also significantly been shortened with the rise of fast chargers. The cost of Electric vehicles is also gradually reducing, making them more accessible to a larger population thanks to advancements in technology and the emergence of healthy competition among EV manufacturers.

2.2.2 Components of an Electric Vehicle

Electric vehicles (EVs) are comprised of various interconnected components that work together to achieve efficient vehicles. In this sub section, the study looks at the key components of electric vehicle systems, including power electronics, charging systems, thermal management, regenerative braking, electric vehicle control units (EVCUs), electric motors, and traction batteries. These components play an important role in propelling, powering, and managing the energy flow within an EV. Figure 2.1 shows a typical schematic diagram of a Pure Electric vehicle (PEV), while Figure 2.2 is a diagrammatic representation of a typical PEV (Talukdar & Deka, 2021).

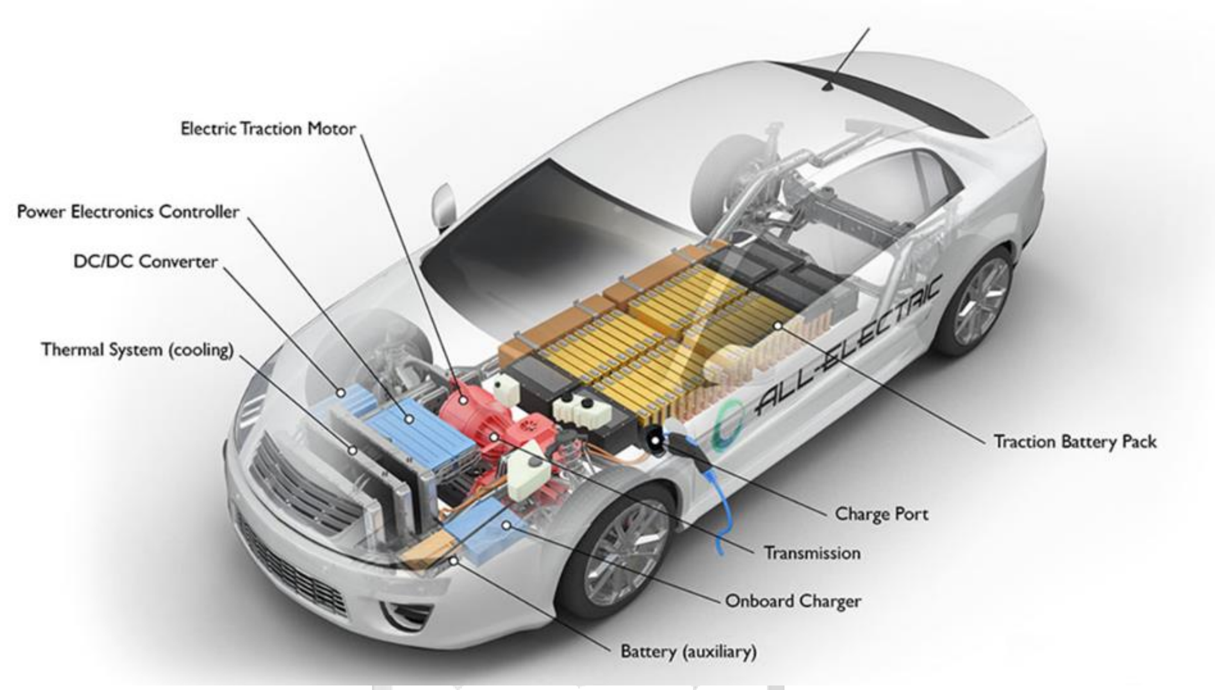

Figure 2.1: Components of a Pure Electric Vehicle

(Talukdar & Deka, 2021)

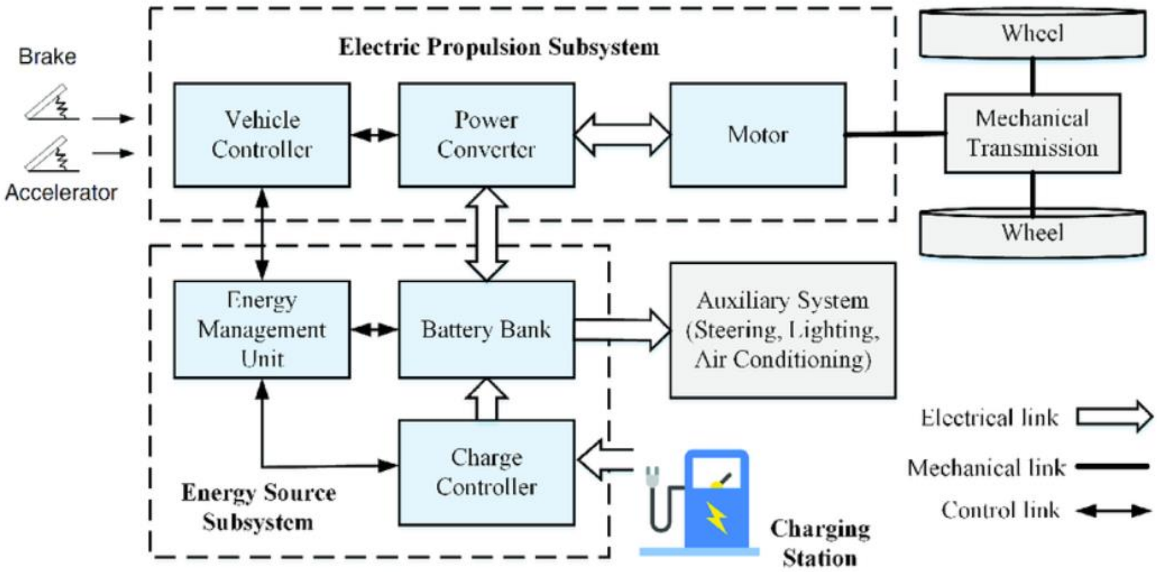

Figure 2.2: Schematic Diagram of a Pure Electric vehicle

(AFDC,2024)

2.2.3 Power Electronics

Power electronics are a critical part in an Electric Vehicle. They provide an efficient means to easily control and convert electrical power needed in various components of the vehicle. Power in electric vehicles is stored in traction batteries in the form of high. voltage Direct current source. This power must be converted into Alternating current to be supplied to the electric propulsion motor through the power electronics. Auxiliary systems, such as heating and cooling systems, lighting, and sound, also require direct current at a much lower voltage; therefore, conversion is required. The charging system and battery monitoring systems also utilize power electronics to achieve safe and efficient operation. Power electronics is therefore a central part of an electric vehicle, essentially the glue that holds the whole system together.

2.2.4 Charging System

The viability of electric vehicles lies in their ability to replenish battery capacity easily and conveniently whenever required. This is done through charging the batteries. Electric vehicles (EVs) are equipped with specialized charging systems to facilitate the charging of their batteries. Different types of charging systems are available, depending on the available power sources. To date, there are three main types of charging systems, namely on.board chargers, off.board chargers and wireless charging Stations. (California State University, 2024).

An on.board charger converts alternating current from an AC source to direct current in order to charge the traction battery. They are located inside the vehicle and normally operate at relatively low power levels. They are often used for home charging. (Penn State University, 2024). The on.board charger is an intelligent device that provides a conditioned power supply to the battery and communicates with the Electric Vehicle Control unit regarding power and safety needs.

Off.board chargers are external and can handle higher levels of charging power, allowing them to charge within a shorter period than on.board chargers. For this reason, these are the chargers used for public charging. Wireless charging is a relatively new concept that uses induction to transfer power. While this might be convenient, they suffer higher losses than contact chargers (California State University, 2024).

The chargers can also be categorised into four modes based on their power ratings. Mode 1 chargers use standard home socket outlets and can handle power up to 2.3 kW, mode 2 uses a control panel and allows AC power up to 7.4 kW. Mode 3 chargers are the commonly used public chargers, utilizing AC power from 3.7 kW to 43 Kw. Mode 4 chargers are fast chargers.

They supply DC power directly to the battery. They do not use the on board charger and can deliver hundreds of Kilo Watts of power.

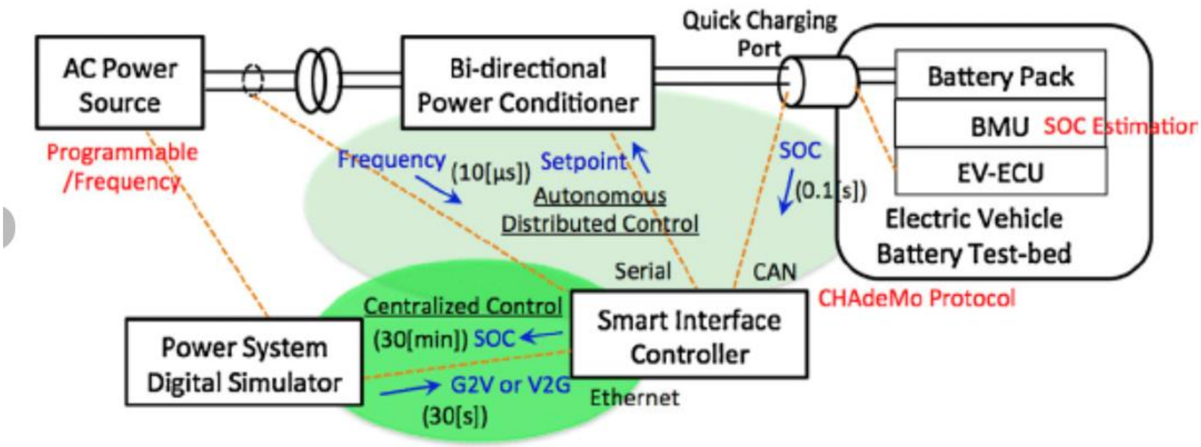

Figure 2.3: Schematic diagram of EV and charging system

(Ota et.al, 2014)

2.2.5 Thermal Management System

Most electric vehicles today use lithium ion traction batteries whose optimal operational temperature range is between 20 °C and 35 °C. Therefore, a robust cooling and heating system is required for efficient use of these vehicles (Hwang et al., 2024). Separately, there have been a number of reported cases of lithium ion batteries suffering thermal runaway, resulting in disastrous fires. This necessitates a reliable method for monitoring battery temperatures and cooling system whenever needed. This system consists of dedicated coolant loops with pumps that act as heat sinks while the vehicle is running.

Thermal management is also required for user comfort. Vehicles are equipped with heating and cooling systems that make the inside of an EV comfortable for passengers in spite of the external ambient extreme conditions. Efficient thermal management therefore ensures safety, and optimal performance of the traction battery. This can also be related to the lifespan of the traction battery too.

2.2.6 Regenerative Braking

Regenerative braking in electric vehicles (EVs) is one of its most interesting aspects. In traditional ICE vehicles, in order to reduce motion, mechanical brakes are applied resulting in to heat dissipation due to friction. In EVs however, regenerative braking allows the system to regain electrical energy back into the system when braking. This is possible because the electrical motor turns in to a generator during braking, converting kinetic energy of the vehicle into electrical energy. (Husain, 2011).

This energy is then stored in the traction battery. This not only reduces the reliance on external charging but also increases the overall range of the EV. Additionally, regenerative braking minimizes wear on the mechanical braking system, as it handles a significant portion of the braking force, leading to reduced maintenance costs and longer lifespan of brake components (Boulanger et al., 2011). It also enhances energy conservation and reduces GHG emissions that occur during heating of brake pads in traditional braking. In case of an urgent need for aggressive braking, the vehicles are also equipped with supporting hydraulic brakes. (MG Motor UK, 2024)

2.2.7 Electronic Vehicle Control Unit (EVCU)

The Electric Vehicle Control Unit is the brain of an electric vehicle. It coordinates all the functions of the vehicle, similarly to how the human brain controls all bodily functions. Its main functions are; torque control, battery management, thermal management, energy recovery and communication. The EVCU collects data from various integrated sensors and based on existing algorithms issues instructions to various systems to achieve efficient functions of an EV. Being a critical component of the EV, a lot of research and innovation has gone into improving its flexibility and adaptability while reducing its cost (Exro,2024).

2.2.8 Electric Motors

Electric motors are central to the functionality of electric vehicles by transforming electrical energy into mechanical energy. This process is vital for propelling the vehicle forward. The efficiency and performance of electric motors significantly affect an EV's range, acceleration, and overall energy consumption. Among the variety of electric motors employed in EVs, AC induction motors, permanent magnet synchronous motors (PMSMs), and switched reluctance motors (SRMs) are the most prevalent, each offering distinct advantages and drawbacks in terms of efficiency, cost, and complexity.

Efficiency is paramount in electric vehicle design, as it directly influences the vehicle's range and operational costs. Rajagopal et al. (2019) provided a comprehensive comparison of motor types, emphasizing that while PMSMs generally offer the highest efficiency, the selection of a motor type should consider the specific application, including the desired performance characteristics and cost constraints. Optimization of electric motor efficiency extends beyond the choice of motor type. Liu et al. (2020) explored advanced control strategies and material innovations as means to enhance the efficiency of electric motors. Techniques such as field-oriented control and the utilization of high-efficiency magnetic materials can lead to significant improvements in motor performance, reducing energy consumption and increasing the driving range of EVs.

Park et al. (2018) further illustrated the critical impact of motor efficiency on the overall energy efficiency of electric vehicles. Their simulations demonstrated that even slight improvements in motor efficiency could result in significant reductions in battery energy consumption across various driving cycles. This underscores the importance of optimizing motor efficiency to extend the range of EVs, particularly as drivers' demand vehicles capable of longer distances on a single charge.

In addition to efficiency considerations, the choice of electric motor technology impacts the vehicle's cost, weight, and design complexity. For instance, while PMSMs offer high efficiency and performance, their reliance on rare earth magnets can increase costs and raise sustainability concerns (Feng et al., 2019). Conversely, AC induction motors and SRMs, which do not require rare earth materials, present more cost-effective and environmentally friendly alternatives but may require more sophisticated control strategies to achieve comparable levels of efficiency and performance.

2.2.9 Traction Battery

The traction battery is a critical component of an electric vehicle (EV), serving as the primary energy storage system for powering the vehicle's electric motor. The selection of traction battery technology significantly influences the vehicle's range, performance, and overall efficiency. Figure 4 shows a typical disassembled Electric Vehicle traction battery. The two most common types of traction batteries used in EVs are Nickel-Metal Hydride (NiMH) and Lithium - ion (Li-ion) Batteries.

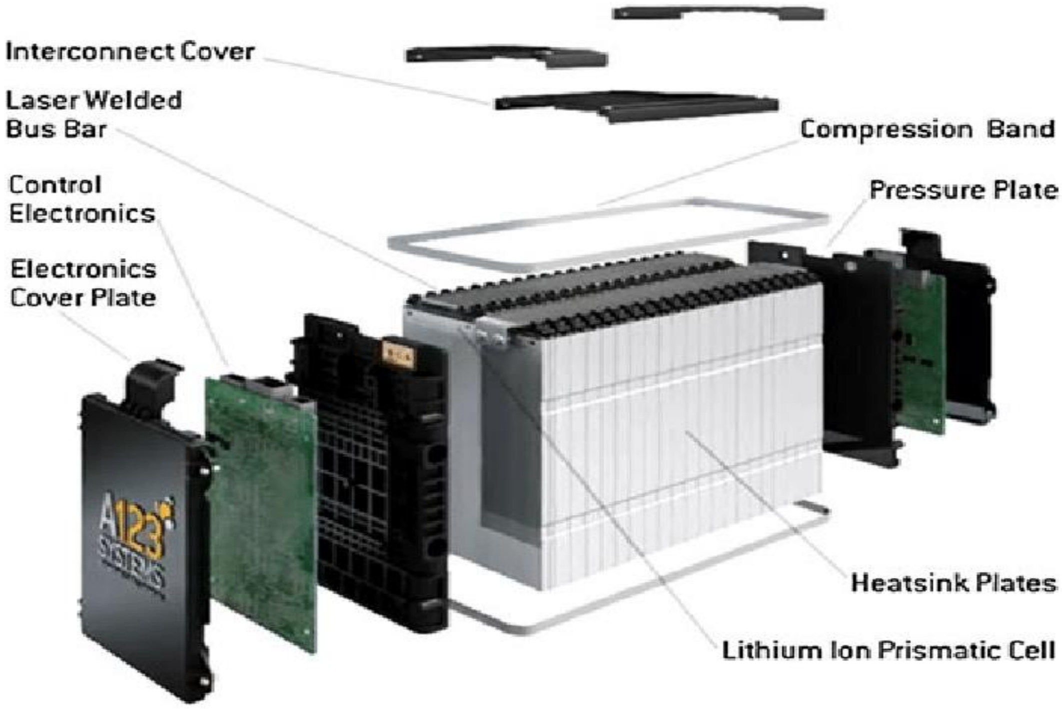

Figure 2.4: Typical Disassembled EV Traction Battery

(Ramont & Zhang, 2023)

2.2.9.1 Nickel-Metal Hydride (NiMH) Batteries

Nickel-Metal hydride (NiMH) batteries have historically been utilized in electric vehicles (EVs) and hybrid electric vehicles (HEVs) as an alternative to lithium - ion batteries, particularly in earlier generations of electrified vehicles. While they have been largely replaced by lithium - ion technology in modern EVs, NiMH batteries still offer certain advantages and continue to be used in specific applications (Scrosati & Garche, 2010). NiMH batteries are composed of a nickel oxy-hydroxide cathode, a hydrogen-absorbing alloy anode (often based on rare earth elements), and an alkaline electrolyte solution. The cathode typically consists of nickel hydroxide (Ni(OH)2) mixed with other metals like cobalt or manganese to enhance performance, while the anode comprises a metal alloy capable of absorbing and desorbing hydrogen during charge and discharge cycles (Lu et al., 2018).

NiMH batteries have moderate energy density compared to lithium - ion batteries, making them suitable for applications where space and weight constraints are less critical. They exhibit good power density and can deliver high discharge currents, rendering them suitable for use in HEVs and other high-power applications (Delacourt et al., 2017). However, NiMH batteries generally have lower specific energy and power compared to lithium - ion batteries, resulting in reduced driving range and performance in EVs. NiMH batteries typically demonstrate good cycle life and durability, capable of enduring thousands of charge and discharge cycles without significant degradation. They are less prone to capacity fade and thermal runaway compared to some other battery chemistries, contributing to their reliability and safety (Gulino et al., 2017). However, NiMH batteries may experience memory effects if not properly managed, leading to reduced usable capacity over time.

One of the notable advantages of NiMH batteries is their relatively low cost compared to lithium - ion batteries, making them appealing for certain applications, particularly in cost.sensitive markets (Ushikoshi et al., 2017). Additionally, NiMH batteries do not rely on rare or expensive materials, enhancing their availability and accessibility. However, advancements in lithium - ion technology have led to significant cost reductions, narrowing the cost gap between the two technologies. NiMH batteries are considered more environmentally friendly than some other battery chemistries due to their lower reliance on toxic or hazardous materials. They do not contain heavy metals such as cadmium or lead, reducing the environmental impact of battery disposal and recycling (Jin et al., 2020). NiMH batteries are also less prone to thermal runaway or fire hazards compared to lithium - ion batteries, enhancing their safety and environmental suitability.

2.2.9.2 Lithium - ion (Li.on) Batteries

Lithium - ion (Li.ion) batteries stand as the predominant choice for traction batteries in modern electric vehicles (EVs) due to their remarkable energy density, exceptional power.to.weight ratio, and extended cycle life (Tarascon & Armand, 2001). They have fundamentally transformed the electric vehicle industry by offering unparalleled performance and reliability compared to traditional battery chemistries. These batteries employ lithium compounds as the active material in both the cathode and anode. Common cathode materials include lithium cobalt oxide ($LiCoO_2$), lithium iron phosphate ($LiFePO_4$), lithium manganese oxide ($LiMn_2O_4$), and lithium nickel cobalt manganese oxide (NCM) (Manthiram et al., 2017). The anode typically comprises graphite, which intercalates lithium ions during charging and releases them during discharging. The electrolyte, consisting of a lithium salt dissolved in a solvent such as ethylene carbonate (EC) and dimethyl carbonate (DMC), facilitates the transport of lithium ions between the cathode and anode (Goodenough & Park, 2013).

Li-ion batteries boast one of the highest energy densities among rechargeable battery chemistries, providing substantial energy storage per unit weight and volume (Scrosati et al., 2011). This superior energy density translates to extended driving ranges and enhanced vehicle performance in EVs. Additionally, Li-ion batteries exhibit impressive power output capabilities, enabling rapid acceleration and efficient regenerative braking. Renowned for their long cycle life and durability, Li-ion batteries can endure thousands of charge and discharge cycles with minimal capacity degradation (Dunn et al., 2011). They demonstrate exceptional calendar life compared to other battery chemistries, making them highly suitable for prolonged use in EVs. Advances in electrode materials and cell design have further bolstered the cycle life and reliability of Li-ion batteries, contributing to their widespread adoption in automotive applications (Etacheri et al., 2011).

Despite their numerous advantages, the safe operation of Li-ion batteries necessitates careful management of charging and discharging conditions (Zheng et al., 2019). Thermal management systems play a crucial role in maintaining optimal operating temperatures within the battery pack and mitigating the risk of thermal runaway events. Various safety features, including thermal sensors, pressure relief valves, and battery management systems (BMS), monitor and regulate the battery's temperature, voltage, and state of charge to prevent overheating, overcharging, and short circuits (Santhanagopalan et al., 2008).

While Li-ion batteries are generally considered more environmentally friendly than traditional lead.acid batteries due to their lower environmental impact and higher energy efficiency (Peters et al., 2017), concerns regarding the extraction and processing of raw materials such as lithium and cobalt have raised environmental and ethical considerations. Efforts to improve recycling technologies and develop sustainable battery materials are underway to minimize the environmental footprint of Li-ion batteries throughout their lifecycle (Zheng et al., 2021).

2.2.10 Types of Aging Electric Vehicles Batteries

Electric vehicle (EV) batteries undergo various forms of ageing over time, impacting their performance, capacity, and overall longevity. Understanding these ageing mechanisms is crucial for developing strategies to mitigate degradation and enhance the sustainability of electric mobility. In this literature review, we delve into the key types of ageing in EV batteries.

2.2.10.1 Charging Cycles

Charging cycles refer to the process of discharging and recharging an electric vehicle battery. The repeated cycling of the battery, from a fully charged state to a discharged state and back, is a primary cause of ageing. As EVs are driven and charged, the electrochemical processes within the battery cells lead to gradual degradation. According to a study by Zhang et al. (2017), cycling-induced degradation is a complex process involving electrode morphology changes, solid-electrolyte interphase (SEI) formation, and lithium - ion concentration gradients. The study emphasizes the importance of advanced battery management systems (BMS) in optimizing charging algorithms to minimize cycling-induced ageing.

In the research conducted by Piller et al. (2019), the authors highlight the role of high charging currents in accelerating ageing effects. They propose strategies such as intelligent charging profiles and temperature management to mitigate the impact of charging cycles on battery health.

2.2.10.2 Calendar Ageing

Calendar ageing is associated with the passage of time, regardless of the number of charging cycles. Even when an EV is not in use, the battery undergoes chemical reactions that contribute to ageing. Factors such as temperature, state of charge, and storage conditions influence calendar ageing. A study by Wang et al. (2018) investigates the influence of calendar ageing on the capacity fade of lithium - ion batteries. The research emphasizes the significance of temperature control during both operation and storage to minimize calendar ageing effects. Huang et al. (2020) explore the impact of different charging states of charge (SOC) on calendar ageing. Their findings underscore the importance of maintaining the battery within optimal SOC ranges to mitigate ageing-related capacity losses.

2.2.10.3 Combined Effects

In real-world scenarios, electric vehicle batteries experience a combination of charging cycles and calendar ageing. Understanding the interplay between these ageing mechanisms is essential for developing comprehensive strategies to extend battery life and enhance overall performance. Research by Eddahech et al. (2021) focuses on the combined effects of cycling and calendar ageing on lithium - ion batteries. The study employs advanced modelling techniques to predict battery ageing under different usage patterns and environmental conditions. The findings emphasize the need for holistic approaches to battery management that consider both cycling and calendar ageing factors.

An investigation by Zheng et al. (2019) explores the impact of varying temperatures and charging regimes on the combined ageing effects in electric vehicle batteries. The study recommends adaptive thermal management systems and smart charging strategies to mitigate ageing.related risks.

2.2.11 Factors Affecting Battery Degradation in Electric Vehicles

Battery degradation is a critical concern in electric vehicles (EVs), impacting performance, range, and overall battery lifespan. Several factors contribute to battery degradation, including charging voltage, charging current, temperature, and the initial state of health (SoH). In this literature review, we explore the influence of these factors on battery degradation.

2.2.11.1 Charging Voltage

Charging voltage refers to the electrical potential applied to the battery during the charging process. High charging voltages can accelerate degradation by promoting side reactions, electrolyte decomposition, and electrode instability. A study by Wang et al. (2019) investigates the effects of charging voltage on lithium - ion battery degradation. The research demonstrates that elevated charging voltages lead to increased capacity fade and impedance rise due to the formation of detrimental electrolyte decomposition products. Zhang et al. (2020) propose voltage.limiting charging strategies to mitigate degradation in lithium - ion batteries. Their findings suggest that restricting charging voltage within optimal ranges can reduce the risk of capacity loss and enhance battery longevity.

2.2.11.2 Charging Current

Charging current refers to the rate at which electrical charge is delivered to the battery during charging. High charging currents can induce mechanical stress, heat generation, and electrode degradation, contributing to accelerated ageing. Research by Ouyang et al. (2018) examines the impact of charging current on lithium - ion battery degradation. The study reveals that excessive charging currents lead to elevated temperature gradients, electrolyte depletion, and lithium plating, compromising battery performance and safety. Liu et al. (2021) propose current-regulated charging schemes to mitigate degradation effects in lithium - ion batteries. Their results demonstrate that controlling charging currents within optimal limits can reduce electrode degradation and improve battery cycle life.

2.2.11.3 Temperature

Temperature plays a critical role in battery degradation, influencing reaction kinetics, electrolyte behaviour, and material stability. High temperatures accelerate degradation by promoting side reactions and accelerating chemical degradation processes. Huang et al. (2017) investigate the effects of temperature on lithium - ion battery ageing under different operating conditions. The study highlights the significance of thermal management systems in maintaining optimal temperature ranges to mitigate degradation and extend battery life. Wang et al. (2022) analyse the impact of temperature gradients on battery degradation in electric vehicles. Their research emphasizes the importance of temperature uniformity and heat dissipation strategies to minimize thermal stress and enhance battery reliability.

2.2.12 Charging Process of Li.On Batteries

Charging and discharging batteries is a chemical reaction that results in energy flowing in and out of the battery as part of ion movement between anode and cathode (BU, 2010). Figure 2.5 and Figure 2.6 below shows the charging stages of a lithium ion battery.

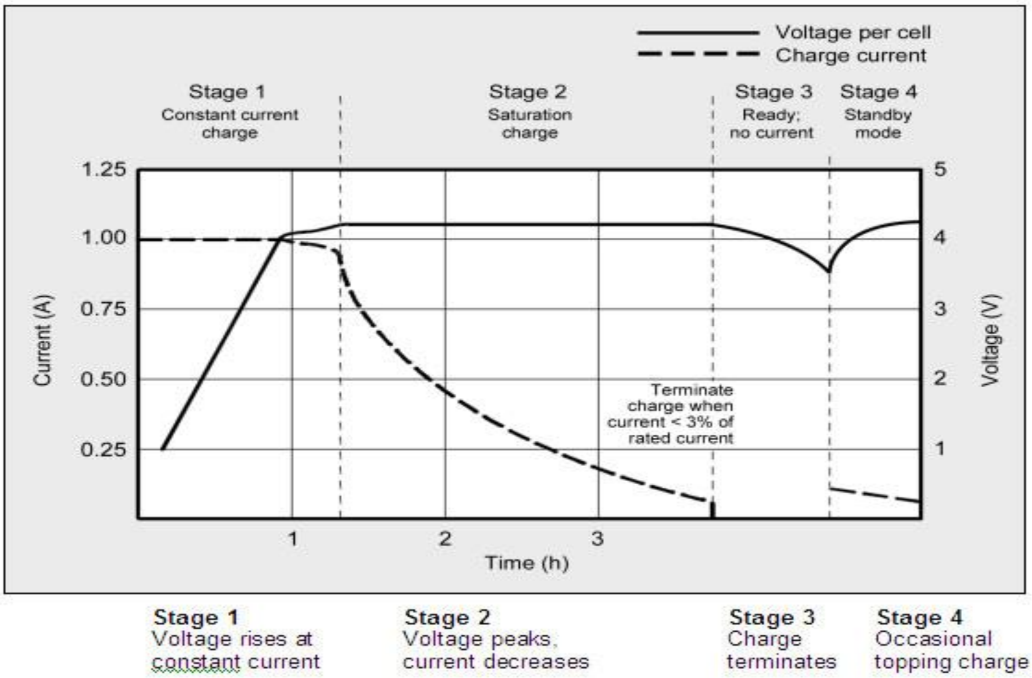

Figure 2.5: Lithium - ion battery charging stages

(BU, 2022)

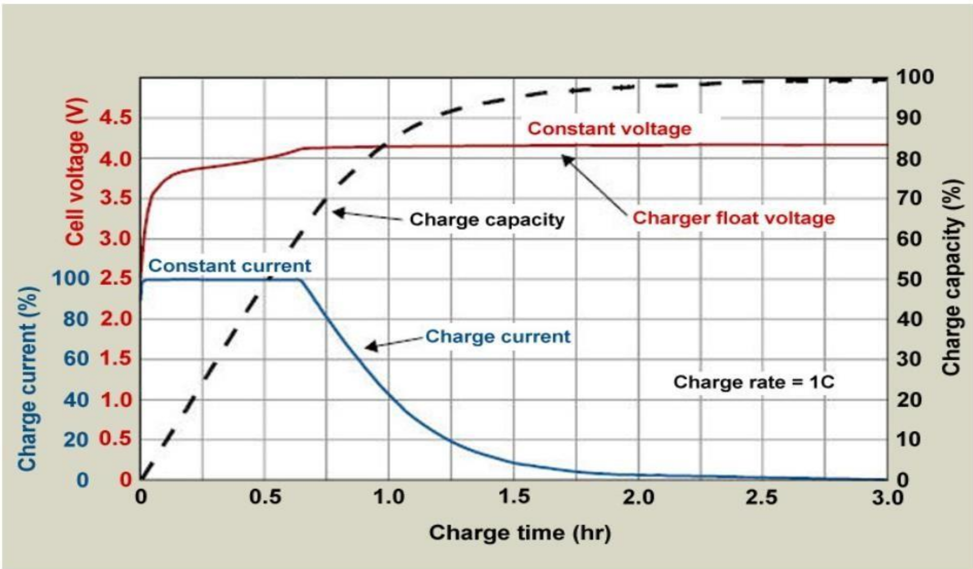

Figure 2.6: Volt/capacity vs Time during Li-ion battery charging

(BU, 2010)

At stage 1, with a constant charging current at 1C, voltage rises steadily. When the voltage peaks, the charging moves on to stage 2, where charging current declines. This is also called the saturation charge stage. The Li-ion battery is considered fully charged and stops charging when the charging current drops to a set point. It is advisable to charge at a rate between 0.5C and 1C. The charging rate affects the charge efficiency. A high charge efficiency results cool cell temperatures during charge. Some batteries experience a temperature rise of around Some Li-ion packs may experience a temperature rise of about 5ºC (9ºF) when they are fully charged.

A battery is fully charged when it reaches the voltage threshold and the current drops to 3 percent of the rated current, or if the current levels off and cannot drop further. This might be due to elevated self-discharge. It interesting to note that a higher charging current does not affect the full charging cycle time by much. A higher charge current shortens stage 1, but lengthens stage 2 (the charge saturation stage).

Table 2.1: Typical Charge Characteristics of Li-ion Batteries

CHARGE V/CELL	CAPACITY AT CUT-OFF VOLTAGE*	CHARGE TIME	CAPACITY WITH FULL SATURATION
3.80	~40%	120 min	~65%
3.90	~60%	135 min	~75%
4.00	~70%	150 min	~80%
4.10	~80%	165 min	~90%
4.20	~85%	180 min	100%

(BU, 2017)

To estimate the State of Charge, it is recommended that one measures the open circuit voltage (OCV) a few hours after the battery has rested. Li-ion batteries do not absorb overcharge. When placed under continuous trickle charge, plating of metallic lithium occurs, this has been linked to thermal runaway, in batteries a dangerous state. Therefore, it is imperative that when full charge state is achieved, charging current be cut off. After charging and battery rest it is observed that the battery voltage begins to drop which eases the voltage stress. The open circuit voltage settles between 3.70V and 3.90V/cell.

2.3 Empirical Review

Empirical review will look at other works that have been performed in relation to the four parameters of interest; temperature, voltage, current and initial state of health in respect to the degradation rate of EV batteries.

2.3.1 Empirical Review of Factors Affecting Battery Degradation

Keil and Jossen (2016) conducted a study that examined how various charging protocols affect the lifespan of lithium - ion batteries. Using an experimental method with different 18650 high-power cells, they observed that the influence of charging currents and voltages on cycle life significantly differs across various lithium - ion batteries. Their findings indicated that high charging currents had a more substantial impact on cycle life compared to high discharging currents. Additionally, the study explored the effects of charging currents and voltages on factors such as capacity utilization, charging time, and efficiency. While this research provides a solid foundation for analysing different charging protocols and their effectiveness in terms of battery lifespan, it did not fully address the degradation effects of charging currents and voltages on lithium - ion batteries, which this study aims to explore further.

Buchmann (2016) noted that lithium - ion batteries become unstable when charged beyond their specified voltage limits. A sustained voltage increase of just 0.1V above the recommended level can lead to lithium metal plating on the anode, causing the cathode material to act as an oxidizer and lose stability. This instability results in carbon dioxide emissions and increased cell pressure. If the current interrupt device (CID) fails to engage at pressures between 1,000 and 1,380 kPa, further pressure buildup may cause the safety membrane of some lithium - ion batteries to rupture at approximately 3,450 kPa (500 psi), potentially resulting in the battery venting with flames. However, this study did not establish a clear connection between variations in charging conditions and the life expectancy of electric vehicle (EV) batteries.

Kong et al. (2018) proposed two models for predicting the State of Health (SoH) of batteries: the decreasing battery V0+ model and the increasing CV charge capacity model. They also developed a simplified thermal model for the battery, based on temperature variation data. The decreasing V0+ model operates on the premise that a battery's charge-holding capacity diminishes over time, allowing SoH predictions to be made based on the V_0+ value. A regression line was fitted to obtain the function;

$$V_0 + (\gamma) = \beta_0 + \beta_1 . \gamma \quad (2.1)$$

Equation 2.1: Kong’s Battery Degradation Model

With the experimental data collected, the values of the constants were found to be

β_0	3.7831
β_1	.0.0006

Here, β_0 represents the V0+ (V) of a new battery which has not gone through any discharge/charge cycles, while β1 represents the rate of V0+ decrease with respect to cycle number (V/ γ). While this provides a useful approach to predicting the SoH of a battery, it does not include a model where the battery has already degraded at the start of the prediction model. The proposed research aims to address this gap by using batteries at different levels of degradation at the start of the experiment.

Recent studies have extensively examined the impact of temperature on the degradation of various components within lithium - ion batteries. Leng et al. (2015) explored how elevated temperatures influence the aging rate of lithium - ion batteries operating above room temperature. Using an electrochemistry-based model (ECBE), they analysed the aging trends in batteries cycled within a temperature range of 25 °C to 55 °C. The study identified the degradation rate of each battery component and linked it to cycling-induced aging. Their findings revealed that increased operating temperatures accelerated the deterioration of all battery components. This included a reduction in the battery's maximum charge capacity, the efficiency of the graphite electrode in releasing stored Lithium-ions, the charge transfer rate constant, the maximum capacity of the LCO electrode, as well as an increase in both electrode and electrode/electrolyte resistance, Warburg element capacitance, resistance, and RC time constant. Notably, the Warburg element and cell impedance degradation rates showed heightened sensitivity to temperature variations. The study also connected the permanent loss of capacity (SoH) to the formation and evolution of surface films on the electrodes and structural or phase changes in the LCO electrode as temperature changes. However, the research did not consider temperatures below room temperature, a gap that this study seeks to address.

Another significant factor impacting battery lifespan is the charging current, as demonstrated by Du et al. (2019). Their research introduced a testing procedure to analyse the capacity fading and thermal tolerance characteristics of lithium - ion batteries under high-power charging. The study also investigated how the temperature threshold for thermal runaway shifts during high-power charging. Their results showed that high-power charging greatly affects both the durability and thermal safety of high-capacity lithium - ion batteries, with capacity fading reaching as high as 30% after 100 charge cycles depending on the battery type. Additionally, thermal tolerance was found to decrease by up to 40%, with self-heating temperature changes serving as a key indicator. The authors emphasized the need for careful design of thermal management systems to meet high-power charging requirements. While the study provided valuable insights into capacity fading, thermal tolerance, and the migration characteristics of lithium - ion batteries, it did not explicitly address the relationship between operational temperature and battery degradation rates, which will be explored further in this research.

2.3.2 Electric Vehicle Battery Ageing Model Empirical Review

Canals Casals et al. (2022) highlight that, in addition to battery capacity and the year of EV registration, assessing the aging of electric vehicles over time is also crucial. Battery aging is typically estimated using various models, which range from simple electrical equivalent models to more complex physics-based ones. However, a significant challenge with these models is their specificity to particular battery types and usage patterns. This specificity means that a unique model would be needed for each type of battery on the market, requiring an impractical number of models. Moreover, since every driver has a unique driving profile, simulating battery aging for each individual use case would necessitate as many profiles as there are drivers, making the approach unfeasible.

As a more practical alternative, using empirical State of Health (SoH) data from different EVs can bypass the need to account for external aging factors such as temperature or driving habits, as these factors are inherently reflected in real-world data. This is the method utilized by the online tool Geotab, an EV Battery Degradation Comparison Tool that leverages data from real driving experiences of various vehicles across the globe.

The data gathered is used to derive degradation profiles for vehicles based on their age. These degradation curves provide forecasts for the SoH of vehicles currently in use. The findings to date suggest that the degradation trend is generally linear, with R^2 values of 0.83 or 0.85 when grouping all EV models, depending on battery size. The regression model is represented in Equation (2.2), where the parameter α quantifies the relationship between battery aging and time. It was observed that the value of α varies significantly depending on the battery's capacity, as shown in Table 2.2.

$$\mathrm{SoH_y} = 100 - \alpha \, . \, \mathrm{age} \qquad (2.2)$$

Equation 2.2: Casals Battery Degradation Model

Table 2.2: Casals's Value of α depending on model capacity

Battery Capacity	α
16 to 40 kWh	3.64
41 to 90 kWh	2.24

(Canals Casals et al., 2022)

While high capacity batteries might have a much better performance than low capacity ones in terms of mileage or lifetime, it is not the case when looking at the number of cycles. That is because ageing in different capacities of EVs does not seem to depend on battery technology.

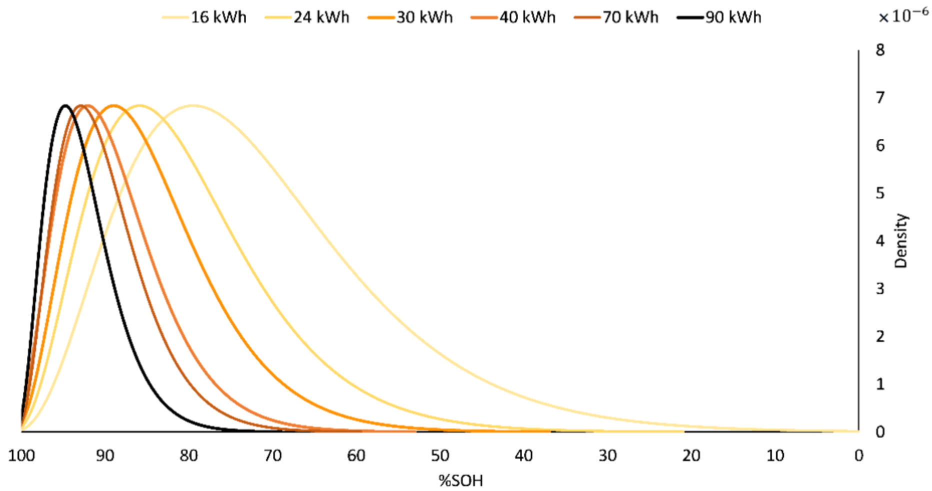

Figure 2.7: Example probability density function of the SOH per capacity for 5.year old Electric

(Canals Casals. et.al, 2022)

Figure 2.7 shows a snapshot of the Nissan Leaf ageing model in comparison to the all vehicle average and the Audi A3 Sportback e-Tron. From the figure we see significant differences in battery performances over the years. Nissan Leaf is one of the most popular brands in the Kenyan e-mobility sector. It is noted that the overall performance of the Nissan Leaf Model is well below the industry standard from the data below.

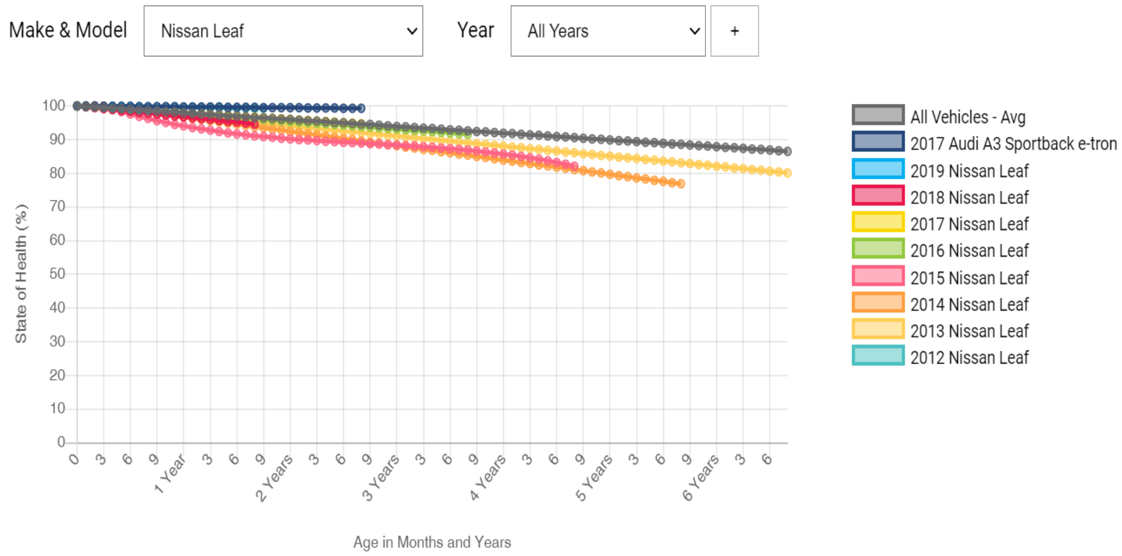

Figure 2.8: State of Health over time by Vehicle Make

(Geotab,2023)

While this study draws the most comprehensive picture of the degradation of electric vehicle degradation over time and with real life usage, it fails to show the actual effect of each of the contributing factors on the actual degradation of the Lithium Ion Battery. This research will address this gap by analysing each of the factors individually and relating it to the degradation of the battery.

2.3.3 Research Gaps

A lot of research has been conducted into the EV batteries over the past few years, leading to significant strides in making the electric vehicle a more viable option for transportation. For example, increased driving range per single charge and a reduction in overall charging period have contributed significantly to reduced range anxiety (Pevec et al., 2019). Despite this progress, there are some gaps that need to be addressed in order to further improve the uptake of Electric Vehicles across the globe. The degradation of the EV battery is a key factor in determining how long the EV will be of service and this is a dominant aspect considered by prospective buyers. From the studies evaluated, there is insufficient data to predict the lifespan of the EV battery during use under different conditions.

This research has identified the following as the study gaps;

a.) While studies reviewed in this research provided an analysis of how high-power charging impacts the capacity fading and thermal tolerance of lithium - ion batteries (Du et al,. 2019) they did not provide a contextual view of the specific Kenyan tropical ambient temperatures in which these vehicles shall be operating. This research proposes to carry out tests under the average temperatures of specified Kenyan regions which shall provide key insight to the consumers.

b.) The evaluated studies also indicated insufficient empirical data on degradation patterns where a vehicle battery is already partially degraded at the point of purchase, this is a key factor considering reports that a majority of imported vehicles are used (KEBS, 2023).

c.) Buchmann (2016) explored the consequences of overcharging lithium - ion batteries, particularly the instability that arises when these batteries are charged beyond their specified voltage limits. The study highlighted the risks associated with overcharging, such as lithium metal plating and the potential for thermal runaway, which can lead to severe safety hazards. However, Buchmann's research did not establish a clear relationship between these variations in charging conditions and the long-term life expectancy of EV batteries. Addressing this gap is crucial for developing charging practices that not only ensure safety but also maximize battery longevity.

2.4 Conceptual Framework

This study's conceptual framework is on the degradation of Electric vehicle batteries based on different factors. This lies under the e-mobility quality infrastructure, which encompasses the electrical grid, e-mobility policies and regulations, standards and conformity assessment. The specific concepts that will be covered are;

a.) EV charging infrastructure: A description of the systems and factors that are combined to provide a safe, secure and charging experience of electric Vehicles

b.) EV Battery Degradation: This will delve in to the specific factors affecting the capacity in EV Batteries and model the relationship between the factors and the rate of capacity fading.

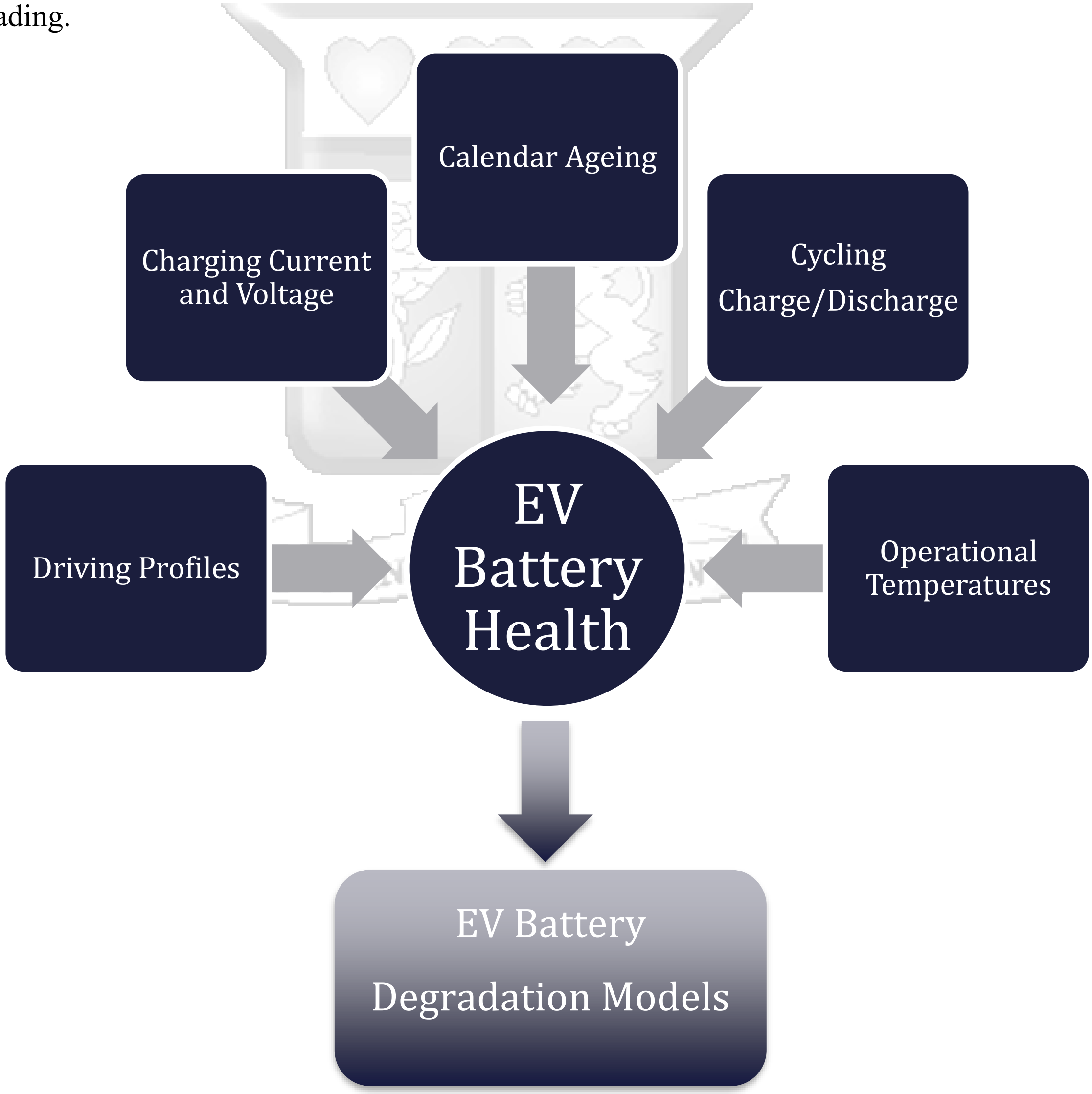

Figure 2.9: Conceptual Framework EV battery Degradation

2.5 Operationalization of Variables

This research modelled the degradation of EV batteries based on the various factors during cycling. The research measured degradation based on the varying levels of the battery state of health, which will depend on the measured capacity after a specified number of cycles.

The other variables that will be factored into the study are charging currents and voltages and the expected ambient temperatures. Table 2.3 shows the operationalization of the study variables.

Table 2.3: Operationalization of variables

	Acronym	**Measurement**	**Units**	**Data Source**
Battery Capacity	Q	Measure the amount of charge that a battery can store. Measured in Ampere hours current	Ampere – Hour (Ah)	Laboratory tests
State of Health	SoH	Measure of the battery capacity in reference to the nominal capacity. A ratio measurement	_	Laboratory tests, Battery specification
Charging Current	I	Measure of the electron flow during the charging process of a battery	Ampere (A)	Laboratory tests
Charging Voltage	V	Measure of specific voltage applied to a battery during the charging process to restore its energy capacity	Volts (V)	Laboratory tests.
Operational Temperature	T	Range of ambient temperatures within which battery tests are conducted battery	Degree Celsius (°C)	Laboratory tests

Chapter 3: Methodology

3.1 Introduction

Modelling the degradation of Electric Vehicle Batteries requires a well-structured and robust methodological approach. The main objective of this study was to model the degradation of EV batteries based on their initial SoH, the charging parameters and the environmental conditions. The research was tailored to mimic the environmental conditions prevalent in Kenya and use typical Battery SoH of vehicles imported into the country to make its output relevant and practical in the Kenyan context.

This section of the research will outline the experimental approach used to answer the research questions. The chapter is organized into three main sections. The first section of the chapter discusses the acquisition and preparation of the batteries that were used as the test specimens. The second section dwells on the preparation of the equipment that were used to test the effects of initial State of Health, temperature and charging conditions. The final section outlines the approach used in presenting the experimental results.

3.2 Research Methods

This study shall use the empirical research method. This is research that is based on observation and measurement of phenomena, as directly experienced by the researcher (Emerald, 2024). In this study, the variables of interest under the experiment were: State of Health, Temperature, charging current, charging voltage and battery capacity. The battery capacity will be the dependent variable, while the rest will be independent variables.

3.3 Methodological Approach

To investigate the effects of initial State of Health, Temperature, charging current, charging voltage on battery capacity, this work undertook two procedures: Setting up the experiment and analysing the results. These two procedures were applied separately for each variable under examination. For instance, there was a separate test and analysis on the effect of temperature on battery capacity. Such tests were carried out separately on other variables too.

3.3.1 Experimental Setup

The following equipment and material was used for the study:

i. Lithium Ion Cells

This study utilized 26650 lithium - ion batteries, chosen due to their availability and compatibility with existing testing equipment. The 26650 lithium - ion cell is a standard battery type, characterized by its dimensions: 26mm in diameter, 65mm in length, and its cylindrical shape, as indicated by the "0". These batteries are commonly used in electric vehicles and have a nominal voltage of 3.2V or 3.7V per cell, with a minimum discharge voltage ranging between 2.5V and 2.75V. Their capacities typically range from 1200mAh to 3300mAh (Lin, 2024). This research used 26650 Lithium ion battery cells, with varying states of health, preferably from 100% to 60%.

Figure 3.1: Lithium Ion Cells

ii. Lithium Ion Cell Battery Tester

This is an eight-channel battery analyser used to analyse polymer battery and cylindrical batteries from 0.5mA to 6A, up to 5V.

Figure 3.2: Lithium Ion Battery Tester

iii. Thermal chamber

A thermal chamber was used to achieve the required ambient conditions which will be based on average ambient conditions in different parts of Kenya. It provided a steady, regulated heat environment needed to precisely evaluate the performance, safety, and deterioration patterns of the batteries.

The air oven is built with sturdy steel outer casing to provides both insulation and protection for internal components. To avoid chemical reactions with battery samples, the inside chamber walled with stainless steel. High-efficiency fans are inbuilt to force air circulation, which results in uniform temperature distribution. Removal of temperature differentials and hotspots creates continuous airflow, which guarantees that the thermal conditions of all battery samples are the same.

Figure 3.3: Thermal Chamber

3.3.2 Testing Procedure

The purpose of this test is to evaluate the longevity of lithium - ion EV Battery cells by determining how their capacity and performance degrade over a specified number of charge-discharge cycles.

The test preparation took place in two stages; cell conditioning and environmental conditioning.

i. Cell Conditioning: This entailed fully charging the cell based on the manufacturers specified charging procedure and then allowing the cell to rest for a set period to stabilize.
ii. Environmental Conditioning: The thermal chamber was set to the desired temperature and allowed to stabilize over a period of one hour.

The cycle life testing procedure was based on ISO 62660.1:2018. "Secondary lithium - ion cells for the propulsion of electric road vehicles — Part 1: Performance testing." This standard contains test procedures for evaluating the performance of lithium - ion cells used in the propulsion of electric road vehicles.

The figure below a summary of the steps undertaken.

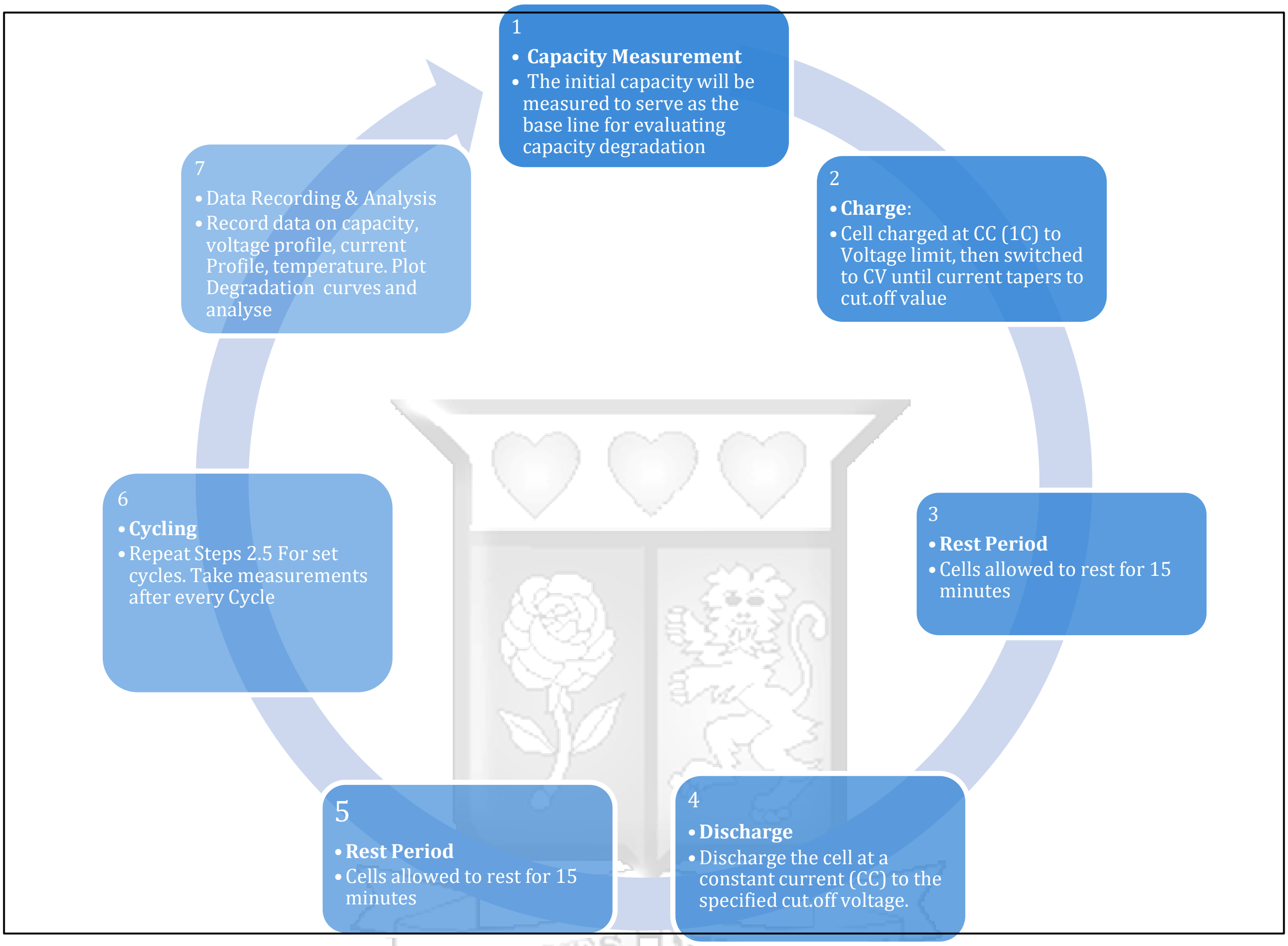

Figure 3.4: Cycle Life Testing Procedure

Capacity Measurement were made and recorded at every cycle.

Capacity was determined as Ampere Hours (Ah) as presented in Equation 3.1;

$$\text{Initial Capacity (Ah)} = \text{Avg Discharge Current x Avg Discharge Period} \quad (3.1)$$

Equation 3.1: Battery Capacity Determination

Where:

Average Discharge Period is in (Hours)

Average Discharge Current is in (Amps)

The end of life for these tests was considered 50% of the nominal cell capacity.

3.3.3 Experimental Variables:

For each of the steps listed in the diagram, tests will be carried out for temperature, current, and Voltage as presented in table

Table 3.1: Experimental Variables

	Experimental Variables	Criteria
1.	Temperature Variation	Cycle life testing performed at 15°C, 27°C, and 35°C,
2.	Charging Voltage	Done at 3.4 V, 3.65V and 4.02 V
3.	Charging Current	The tests were carried out at 0.5C, 1C and 1.5 C
4.	Initial State of Health	Performed for cells at 100% SoH, ~90% SoH, ~80% SoH and ~60% SoH.

(i) Temperature Variation:

Cycle life testing was performed at 15°C, 27°C, and 35°C, to cover the different climatic zones in Kenya. This helps to assess how the temperature affects the cell cycle life.

(ii) Charging Voltage:

A different set of tests was performed to analyse the impact of charging voltage on the battery degradation. The tests were done at 3.4 V, 3.65 V and 4.02 V using the Constant Charging Voltage method.

(iii) Charging Current

Tests were carried out to test the impact of charging currents on the cell degradation. The tests were carried out at 0.5C, 1C and 1.5C. The Constant Charging Current method was used for this test variable.

(iv) Initial State of Health

Cells were selected based on their initial state of health. Cells were chosen with 100% SoH, ~90% SoH, ~80% SoH and ~60% SoH. State of health was determined by following the initial capacity determination procedure and calculated using Equation 3.2;

$$SoH = \frac{Q1(Ah)}{QN\ (Ah)} * 100\% \qquad (3.2)$$

Equation 3.2 : State of Health Determination

Where:

SoH: Is the measured state of Health as a percentage of the nominal capacity
Q1: Is the Measured initial Cell Capacity
QN: Is the Nominal initial Cell Capacity based on Manufacturer's specifications

Initial capacity testing was carried out the following steps;

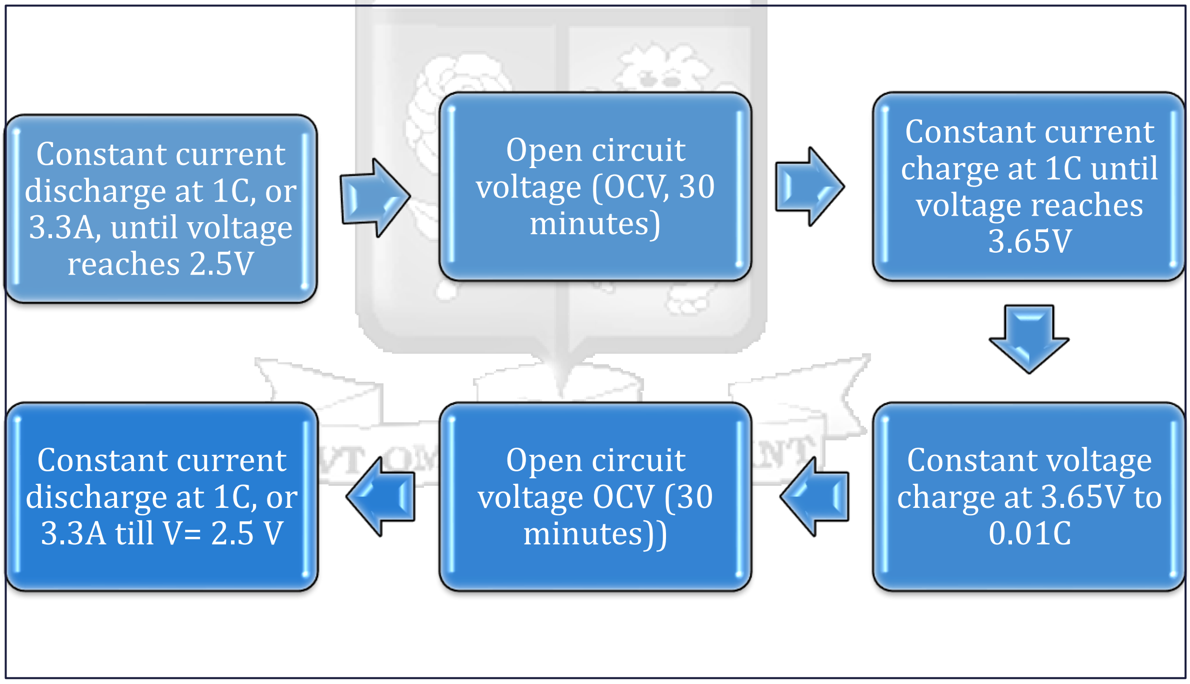

Figure 3.5: Initial Capacity Determination Procedure

The discharge period in hours and discharge current in Amps were recorded. At least 3 cycles were done for each cell, with data recorded at the end of each cycle.

Averages for of the measurements were calculated using equations 3.3 and 3.4;

Average time:

$$T = \left(\sum_{i=1}^{n} (T_i)\right)/n \tag{3.3}$$

Equation 3.3: Average time Calculation

Average Discharge Current

$$A = \left(\sum_{i=1}^{n} (A_i)\right)/n \tag{3.4}$$

Equation 3.4: Average Discharge Current Calculation

Therefore, the initial capacity shall be determined as:

$$\text{Initial Capacity (Ah)} = \text{Avg Discharge Current (Amps)} * \text{Avg Discharge Period (Hrs)}$$

$$Q1 = A * T \tag{3.5}$$

Equation 3.5: Initial Capacity Calculation

Where:

T:	Is the Average Discharge Period in Hours
T_i	Is the Cycle Discharge Period in Hours
A	Is the Average Discharge Current in Amperes
Ai	Is the Cycle Discharge Current in Amperes
n	Is the Total Number of cycles done for a specific Cell

3.3.4 Safety Management:

Owing to the risky nature of the experiment, the following safety precautions were observed;

i) Battery temperature and performance during cycling were continuously monitored to detect any abnormalities or safety hazards.

ii) To prevent risks associated with overcharging, over discharging, or thermal runaway events the entire process was done under authorized personnel supervision. Appropriate firefighting equipment were available at all times to intervene and implement emergency procedures if necessary.

iii) Personnel conducting experiments wore personal protective equipment at all times during the tests.

3.4 Population/ Sampling

This study used purposive sampling method which allowed the researcher to collect samples from specific groups or areas for analysis. This was deemed to be the most suitable sampling approach because the research topic is specific to lithium ion batteries used for e-mobility in the country. Cylindrical cells were selected as they are the most commonly found in the e-mobility sector in Kenya. Batteries were sampled from companies in Machakos and Nairobi. An equal number of samples was drawn from the 2 companies. The drawn samples were distributed as shown in Table 3.3.

Table 3.2: Sample Distribution

	Experimental Variables	**Criteria**	**Sample size**
1.	Temperature Variation	15°C	3
		25°C	3
		35°C	3
2.	Charging Voltage	3.4 V	3
		3.65 V	3
		4.02 V	3
3.	Charging Current	0.5C	3
		1C	3
		2C	3
4.	Initial State of Health	~60% SoH.	3
		~80% SoH	3
		~90% SoH	3
		100% SoH	3
		Total Sample Size	**39**

3.5 Data Collection/Instrumentation

These are the instruments or tools for gathering data in research used as basis for drawing conclusions or making inferences. Primary data was collected through laboratory equipment such as calibrated thermo-hygrometers and thermometers and data loggers. This data was recorded on to the battery performance data sheet shown appendix A.3. The battery analyser collected data on the charging voltage, charging current, battery capacity and charge / discharge cycles. This data is collected through the battery analyser software NEWARE.

3.6 Data Analysis Methods

This section describes the approach that was used to analyse and reduce the data. Data from the NEWARE software and the A.3 datasheets was uploaded to a spreadsheet, Microsoft Excel which was the statistical analysis tool for primary quantitative analysis. Inferential statistical methods such as regression analysis were employed to analyse the results.

3.7 Data Validation

Ensuring data accuracy and reliability is crucial for any study. In this research, several approaches were employed to ensure the fidelity of data collected and analysis of this data. At the data collection stage, the study ensured that equipment used were calibrated and that standard methods are used to conduct the tests. Consistency of data was confirmed by taking several data sets at each measurement points. The models were also compared against existing research models.

3.8 Ethical Considerations

This research adhered to the ethical standards set forth by Strathmore University's research guidelines. All requisite documentation was submitted to the Strathmore University Institutional Scientific and Ethics Review Committee (SU-IERC) for thorough evaluation and approval. The study was conducted in full compliance with the ethical research provisions of the University, ensuring transparency in the use of data throughout the process. Respondents were fully informed that the data collected will be used exclusively for research purposes and may be shared with examiners, classmates, and presented during academic seminars. By rigorously adhering to these ethical principles, the study seeks to contribute responsibly to the academic knowledge base and uphold the integrity of research within the field.

3.9 Dissemination of results

The dissemination of the research findings was carried out through several key channels to ensure both academic rigor and practical application of the results. First, the research was formally presented during a proposal defence session, where it underwent evaluation by a panel of academic experts. Upon successful completion, the Dissertation will be published in accordance with Strathmore University's requirements, making it available in the university's repository for wider academic access. In addition to the Dissertation publication, select findings will be compiled into research papers for submission to peer.reviewed journals. The selection of these journals will be based on their relevance to the field of study, their impact within the academic community, and their ability to reach a broad audience of scholars and practitioners.

Furthermore, considering that this research has been funded by the Kenya Bureau of Standards (KEBS), a detailed presentation of the results will be made to the KEBS management. This step will ensure that the insights derived from the research contribute to the strategic objectives and operational efficiency of KEBS. By engaging both academic and professional communities, the research aims to maximize its contribution to both theoretical knowledge and practical application in industry.

3.10 Utilization of results

The results of this research have practical applications for several key stakeholders in the electric vehicle (EV) ecosystem, including buyers, policymakers, and regulatory bodies. For EV buyers, the findings offer valuable insights on vehicle performance, safety, and sustainability, aiding informed purchasing decisions. Policymakers will utilize the data to craft standards and policies that promote the safe and sustainable adoption of EVs, supporting infrastructure development and consumer protection. Regulatory bodies like the Kenya Bureau of Standards (KEBS) can use the outcomes to improve certification processes, ensuring vehicles meet safety and environmental standards. Ultimately, the research has contributed to both the academic field and the practical advancement of EV adoption in Kenya.

Chapter 4: Results and Discussion

4.1 Introduction

This section presents results of battery cycling conducted at different conditions as presented in chapter three of this report. The results shall be presented separately for each of the research parameters and discussed within each separate subsection.

a) Battery degradation based on charging current
b) Battery degradation based on initial state of health
c) Battery degradation based on charging voltage
d) Battery degradation based on operational temperature

The results will be presented and discussed in the same section.

4.2 Experimental Set up

The experimental setup is shown in figure 4.1.

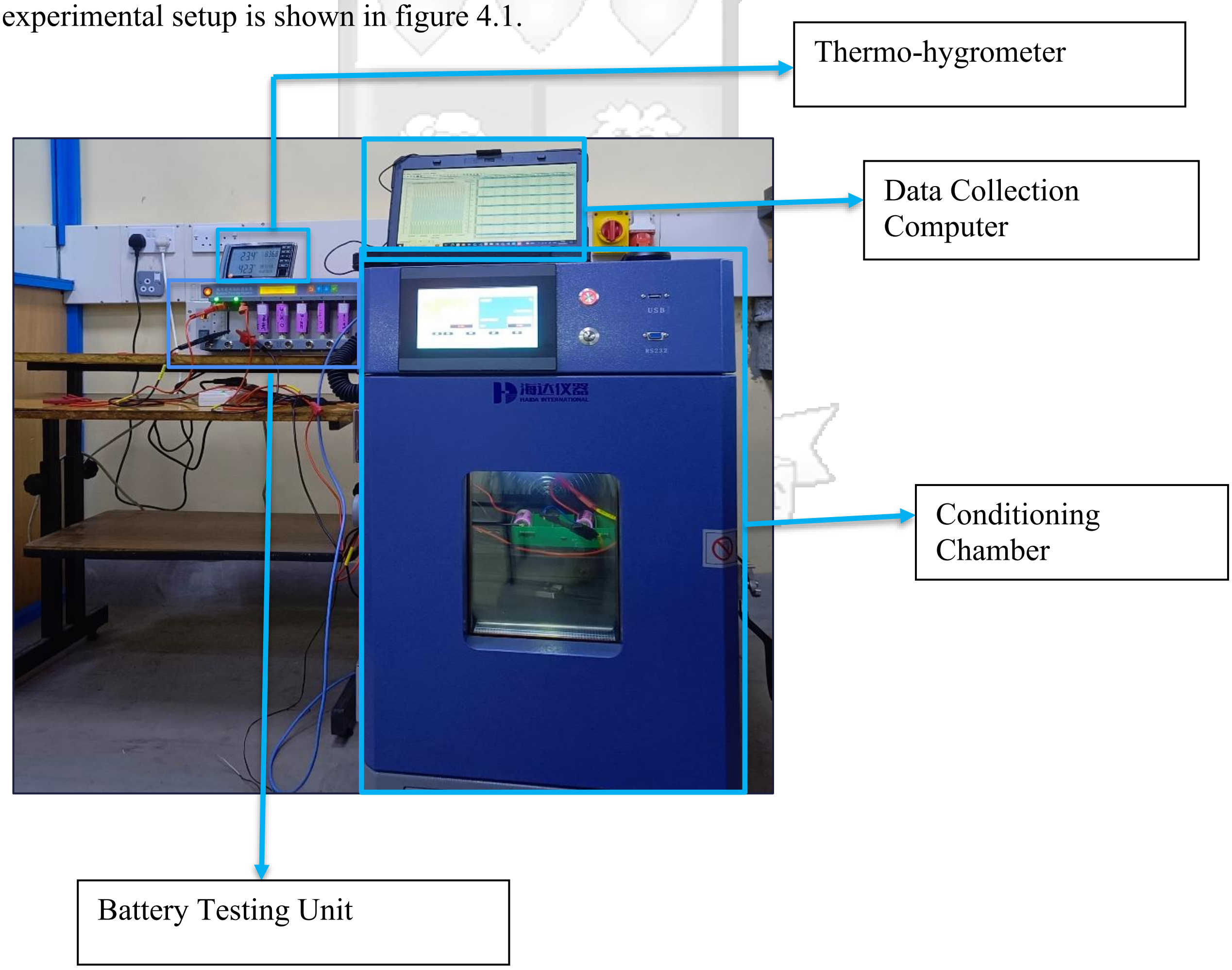

Figure 4.1: Experimental Setup

The experiments were carried out at the Kenya Bureau of Standards, Metrology Laboratory in Nairobi, Kenya. The sample Lithium Ion Battery Cells were cycled using Neware CT 800 Battery Tester. A calibrated conditioned chamber was used to achieve the desired temperatures. Battery cycling data was recorded on the Neware battery Tester and could be accessed through its software BTS 8.0.0 and BTSDA. The data was downloaded in Excel format through an Ethernet connection between the Tester and the computer. Testing profiles were built using the tester software called Build Test. The following sections shall discuss the testing profile for each of the four objectives.

4.2.1 Battery Cycling with varying Initial states of Health and Temperature

To test the impact of initial states of health and temperature, all sets of batteries were subjected to the same testing profile and were allowed to run for a specific number of cycles. The testing profile was based on the manufacturer specifications. Figure 4.2 shows the testing profile for the impact of SOH, 1C, and Temperature on battery degradation.

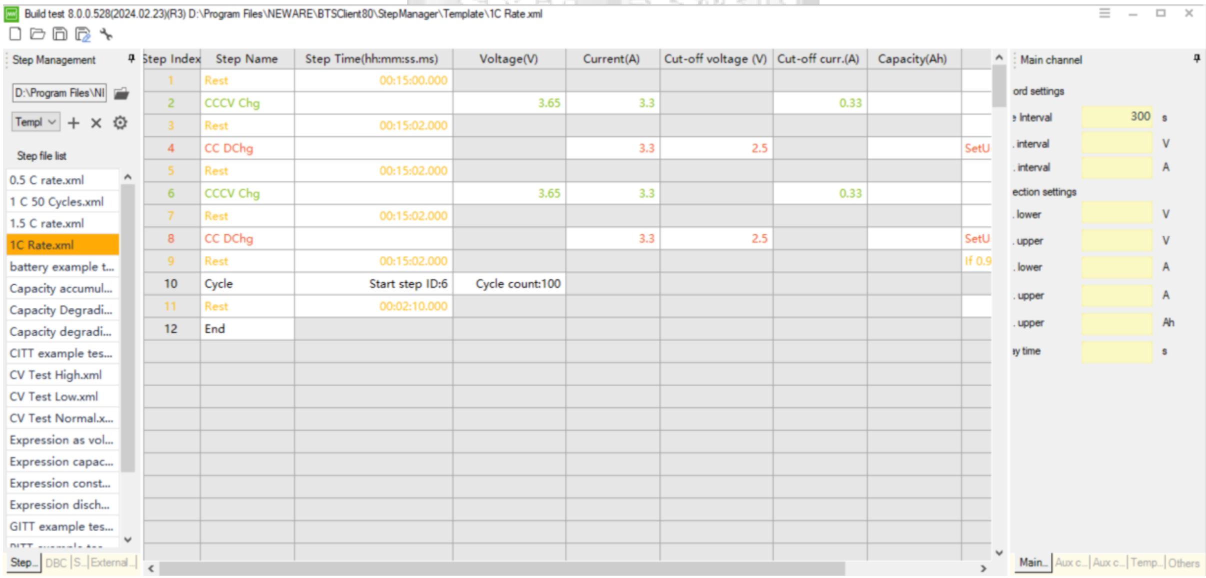

Figure 4.2: Battery Cycling with varying Initial states of Health and Temperature Test Profile

4.2.2 Battery Cycling with varying Charging Currents

To test the impact of charging currents, different sets of batteries were subjected to the 1C as in figures 4.2, 0.5 C in figure 4.3 and 1.5 C in figure 4.4. They were allowed to run for a specific number of cycles.

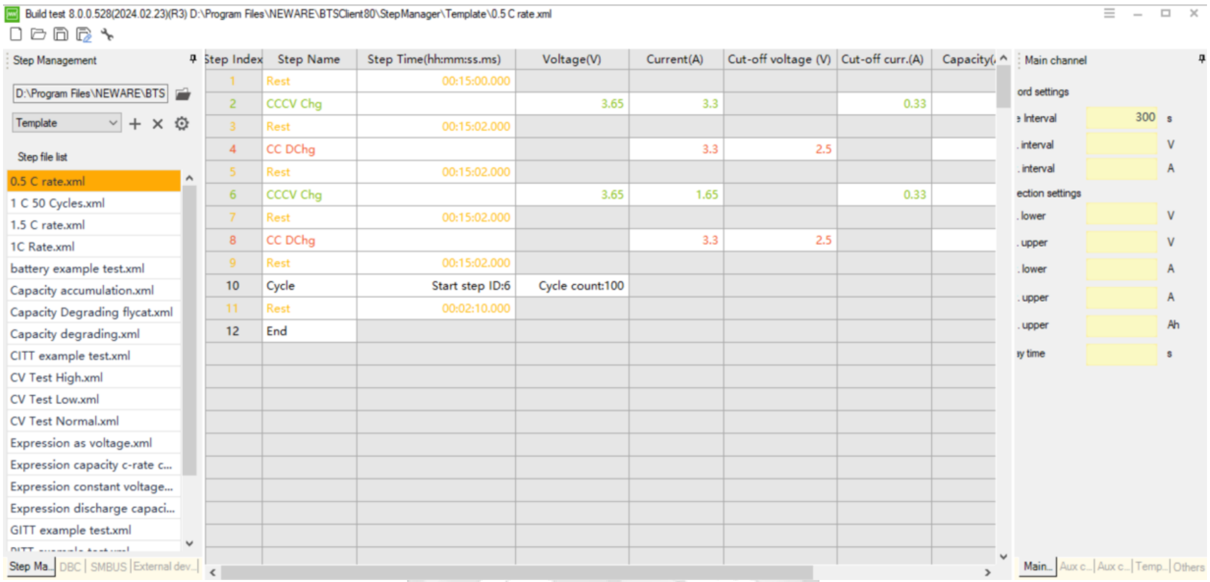

Figure 4.3: Battery Cycling with 0.5 C Test Profile

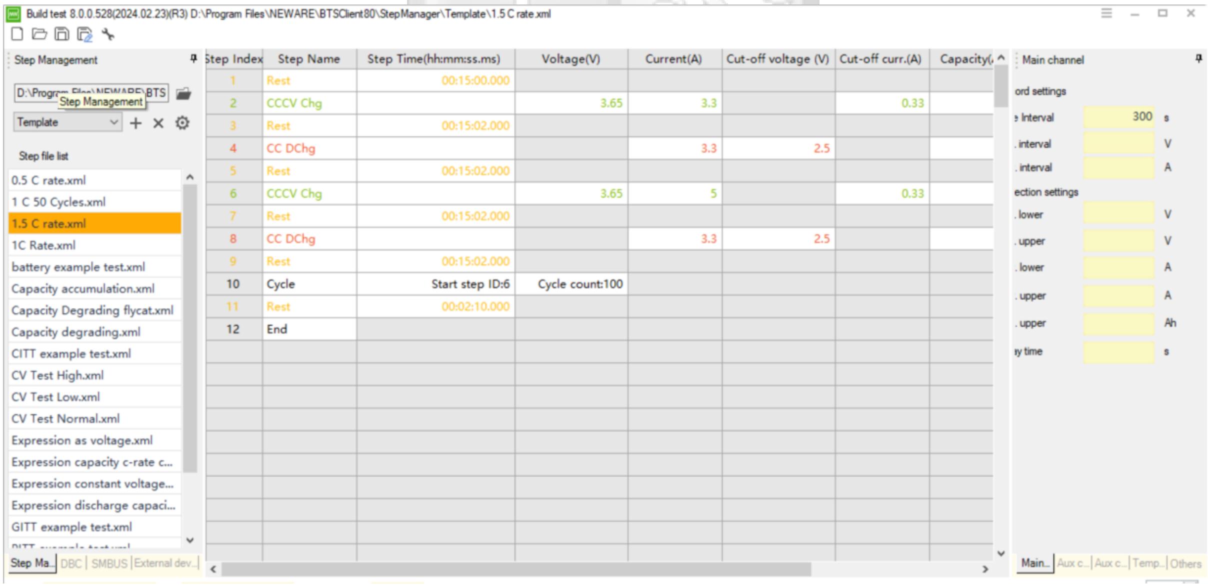

Figure 4.4: Battery Cycling with 1.5 C Test Profile

4.2.3 Battery Cycling with varying Charging Voltages

Figures 4.5 and 4.6 show the charging profiles employed to simulate high and low charging voltages.

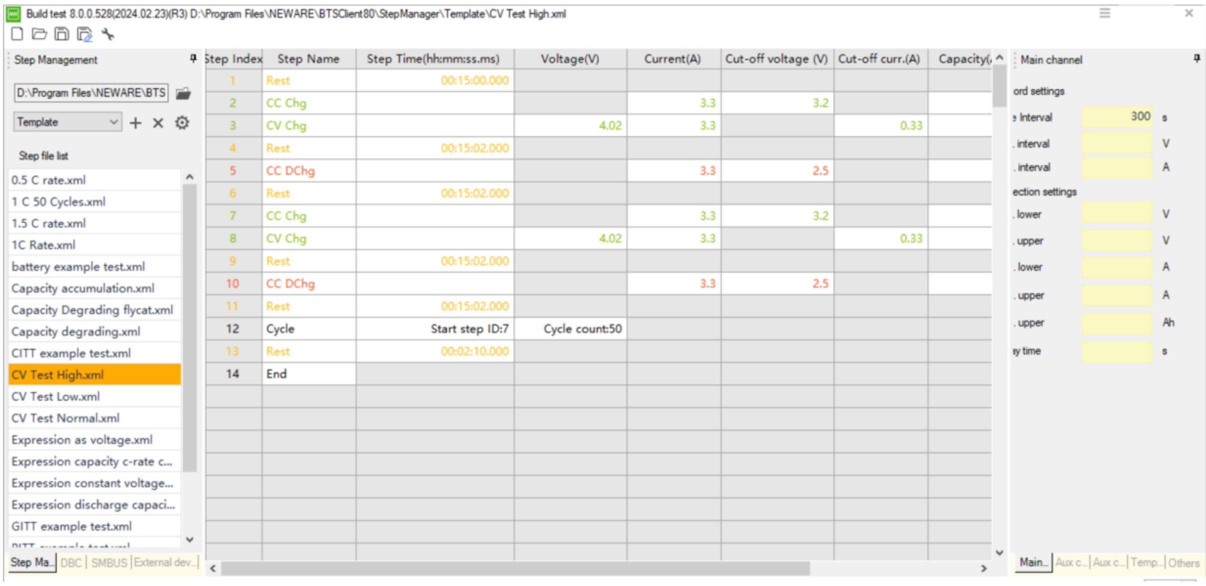

Figure 4.5: High Voltage Test Profile

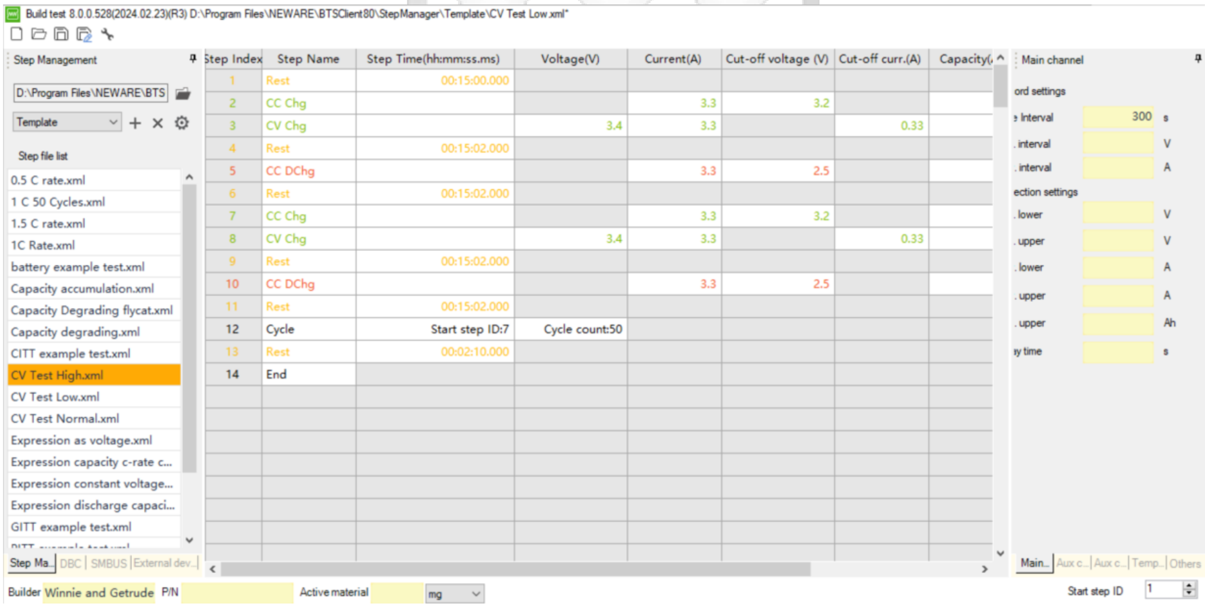

Figure 4.6: Low Voltage Test Profile

4.3 Battery Degradation Based on Initial State of Health Results and Discussion

To investigate the effects of initial State of Health on the degradation patterns of lithium ion batteries, battery cells sets at approximate state of health rates of 60%, 80%, 90% and 100% were cycled at standard conditions. The battery capacity and discharge efficiency were recorded at each cycle and the results are presented in the charts in figures 4.7, 4.8, 4.9 and 4.10. Figure 4.11 shows a comparative analysis of all batteries tested in this section.

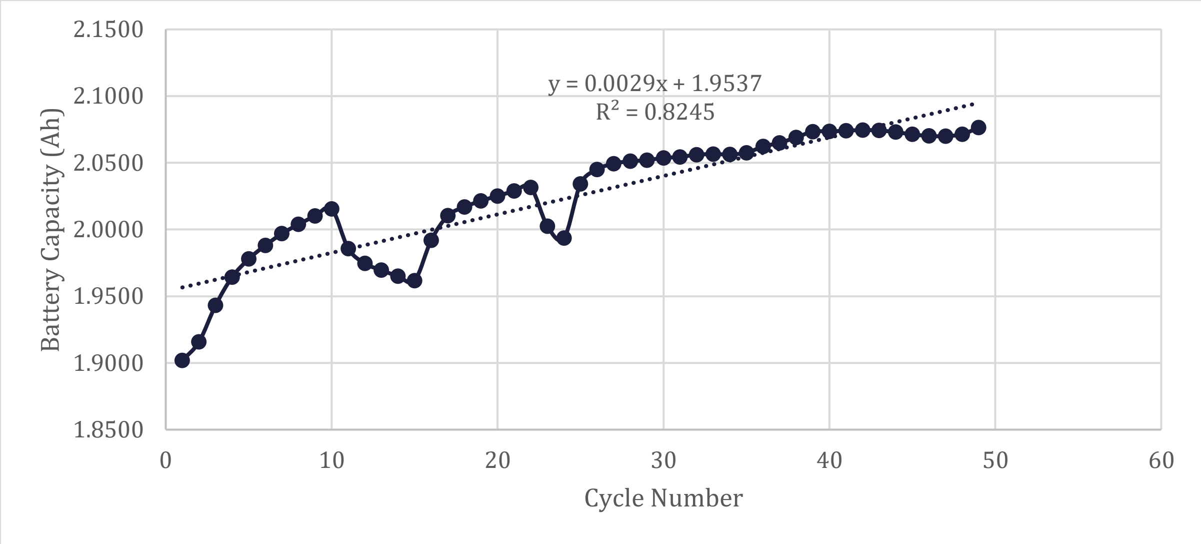

Figure 4.7: Degradation Curve for 60% initial state of health battery cells

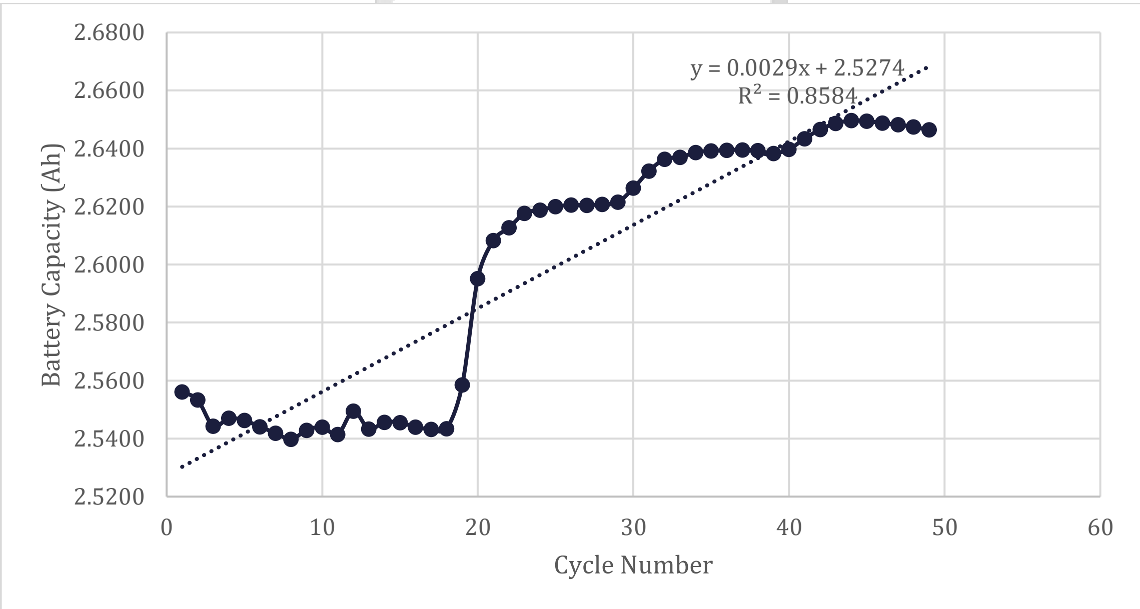

Figure 4.8: Degradation Curve for 80% initial state of health battery cells

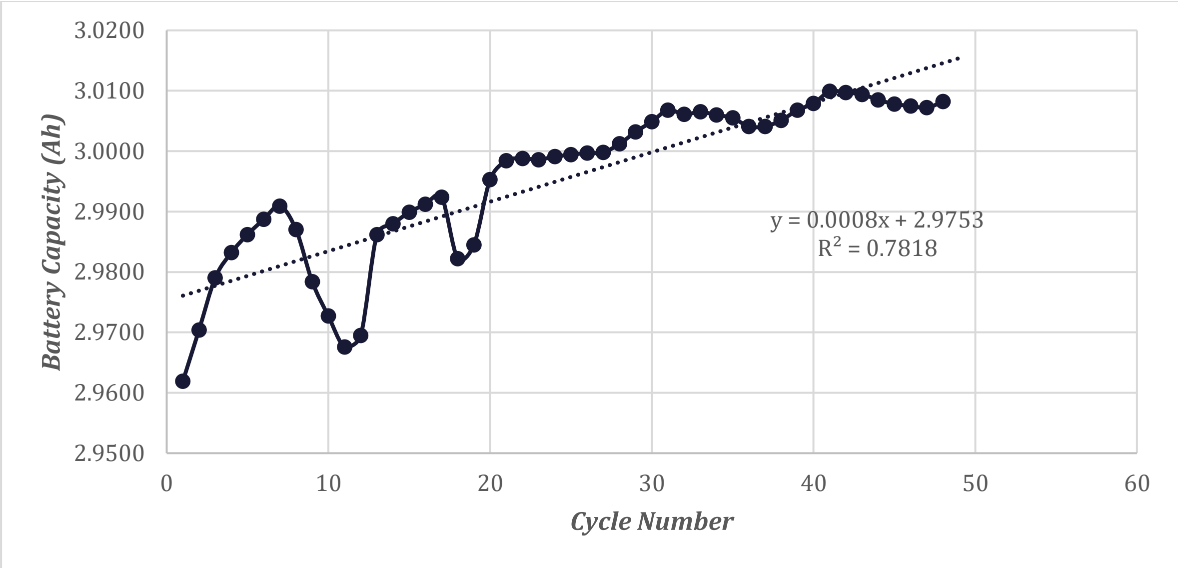

Figure 4.9: Degradation Curve for 90% initial state of health battery cells

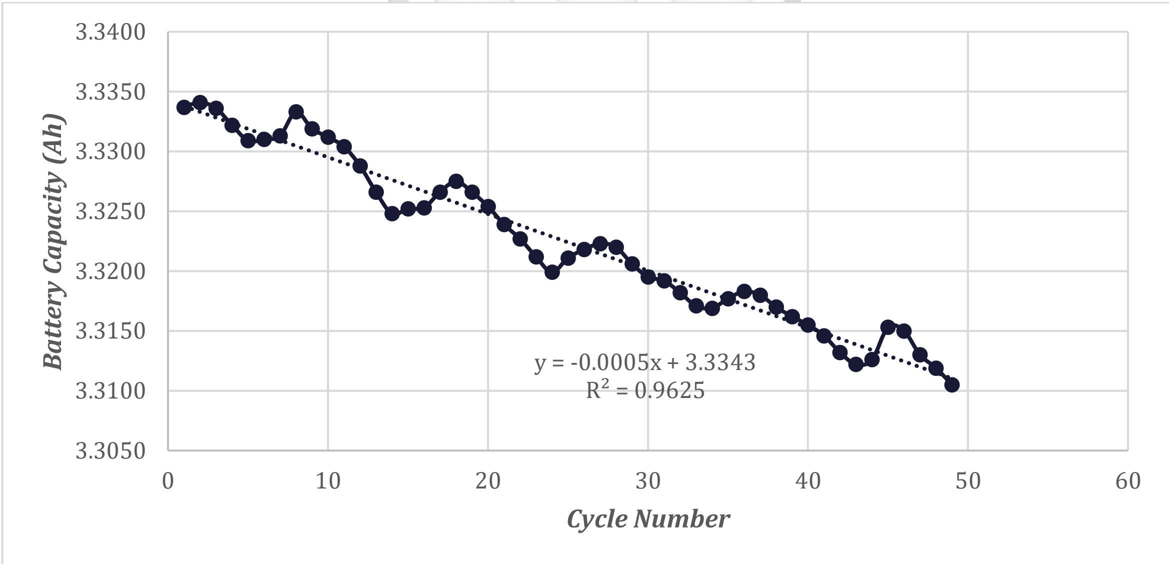

Figure 4.10: Degradation Curve for 100% initial state of health battery cells

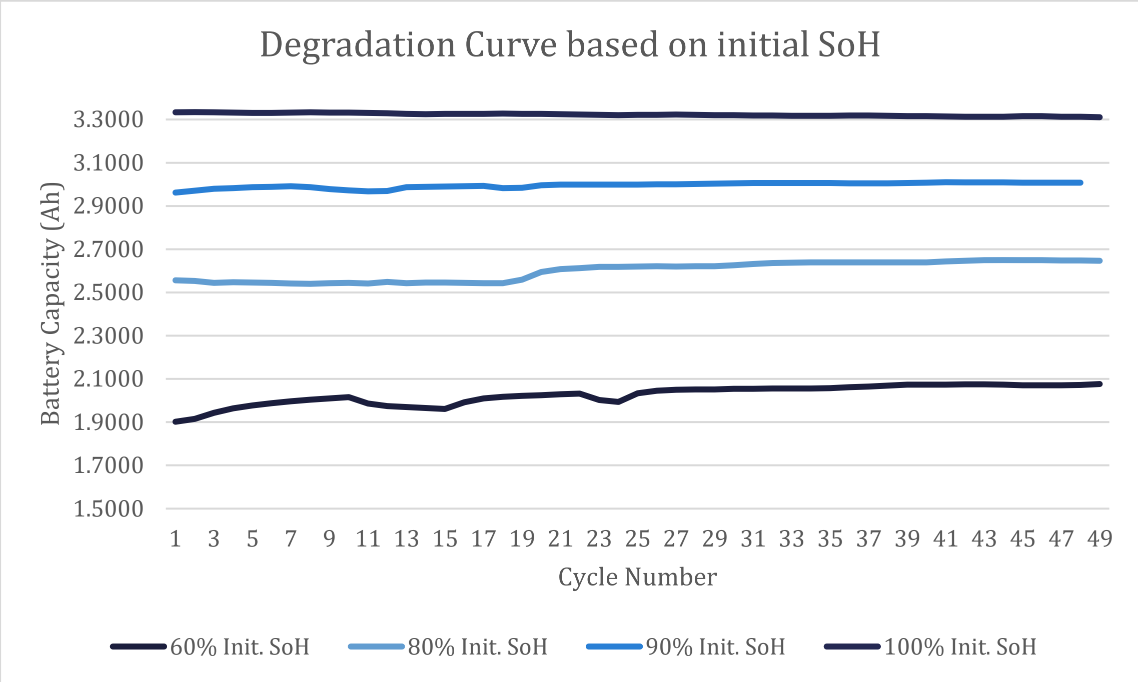

Figure 4.11: Comparative Analysis of battery degradation based on initial state of health

The results show an interesting gain of capacity in the used batteries as opposed to the observed degradation in the new cell batteries. Batteries at 60% SoH and 80% SoH were found to appreciate at a marginal rate of 0.0029 Ah after every cycle, while the appreciation rate in 90% SoH was much lower at 0.0008 Ah after every cycle. This data is consistent with previous research as documented by Guo et al., (2022) and Kobayashi et al., (2020) in their research studies. The initial gain of capacity has been attributed to a change in the electrochemical structure of the cell, that facilitates the Lithium ion diffusion, hence leading to an increase in the battery capacity. In their study, the incremental phenomenon was found to be correlated to deep discharge cycles as employed in this study. The increment was observed to persist for the first hundred cycles or so. The new battery cells were observed to degrade at a rate of 0.0005 Ah per cycle. The results therefore imply that for one to authoritatively determine the degradation rates based on the initial state-of-health, they should conduct well above a hundred cycles for the samples.

Table 4.1: Regression Analysis of Degradation Models Based on Initial SoH

Metric	Model 1 (60% SoH)	Model 2 (80% SoH)	Model 3 (90% SoH)	Model 4 (100% SoH)
Multiple R	0.908	0.926	0.884	0.981
R Square	0.824	0.858	0.782	0.962
Adjusted R Square	0.821	0.855	0.777	0.962
Standard Error	0.0192	0.0169	0.0061	0.0014
Observations	49	49	48	49
F-statistic	220.81	284.95	164.84	1204.87
Significance F	2.21E.19	1.39E.21	8.16E.17	3.74E.35
Coefficient (Intercept)	1.954	2.527	2.975	3.334
Standard Error (Intercept)	0.0056	0.0049	0.0018	0.0004
Coefficient (Cycle Number)	0.00288	0.00288	0.00082	.0.00047
Standard Error (Cycle Number)	0.00019	0.00017	0.00006	0.00001
t-Statistic	14.86	16.88	12.84	.34.71
P-Value	2.21E.19	1.39E.21	8.16E.17	3.74E.35

The regression model for 60% SoH demonstrated a strong correlation, R = 0.908, with an R^2 value of 0.824, indicating that 82.4% of the variance in battery capacity was explained by cycle number. The model was statistically significant, $F(1,47) = 220.81$, $p < .001$. The predictor variable had a significant positive coefficient ($B = 0.00288$, $t = 14.86$, $p < .001$), suggesting a direct relationship between cycle number and battery capacity.

The regression model for 80% SoH exhibited an even stronger correlation, R = 0.926, with an R^2 value of 0.858, meaning that 85.8% of the variance in battery capacity was explained by cycle number. The model was highly significant, $F(1,47) = 284.95$, $p < .001$. The predictor variable displayed a similar positive coefficient ($B = 0.00288$, $t = 16.88$, $p < .001$), reinforcing the direct relationship.

The regression model for 90% SoH yielded a slightly lower correlation, R = 0.884, with an R^2 value of 0.782, indicating that 78.2% of the variance in battery capacity was accounted for by cycle number. The model was statistically significant, $F(1,46) = 164.84$, $p < .001$. The predictor variable had a smaller positive coefficient ($B = 0.00082$, $t = 12.84$, $p < .001$), showing a weaker but still direct relationship.

In contrast, the regression model for 100% SoH revealed the highest correlation, R = 0.981, with an R^2 value of 0.962, meaning that 96.2% of the variance in battery capacity was explained by the predictor. The model was statistically significant, $F(1,47) = 1204.87$, $p < .001$. However, unlike the previous models, the predictor variable had a significant negative coefficient (B = .0.00047, t = .34.71, $p < .001$), indicating an inverse relationship between cycle number and battery capacity.

4.4 Battery Degradation Based on Charging Current Results and Discussion

To investigate the effects of charging current on the degradation patterns of lithium ion batteries, battery cells sets were cycled at different charging rates. The first set was cycled at 0.5 c.rate, the second set was cycled at 1.0 C-rate and the last set 1.5 C-rate. The graph in figures 4.12, 4.13, 4.14 and 4.15 illustrate the results obtained.

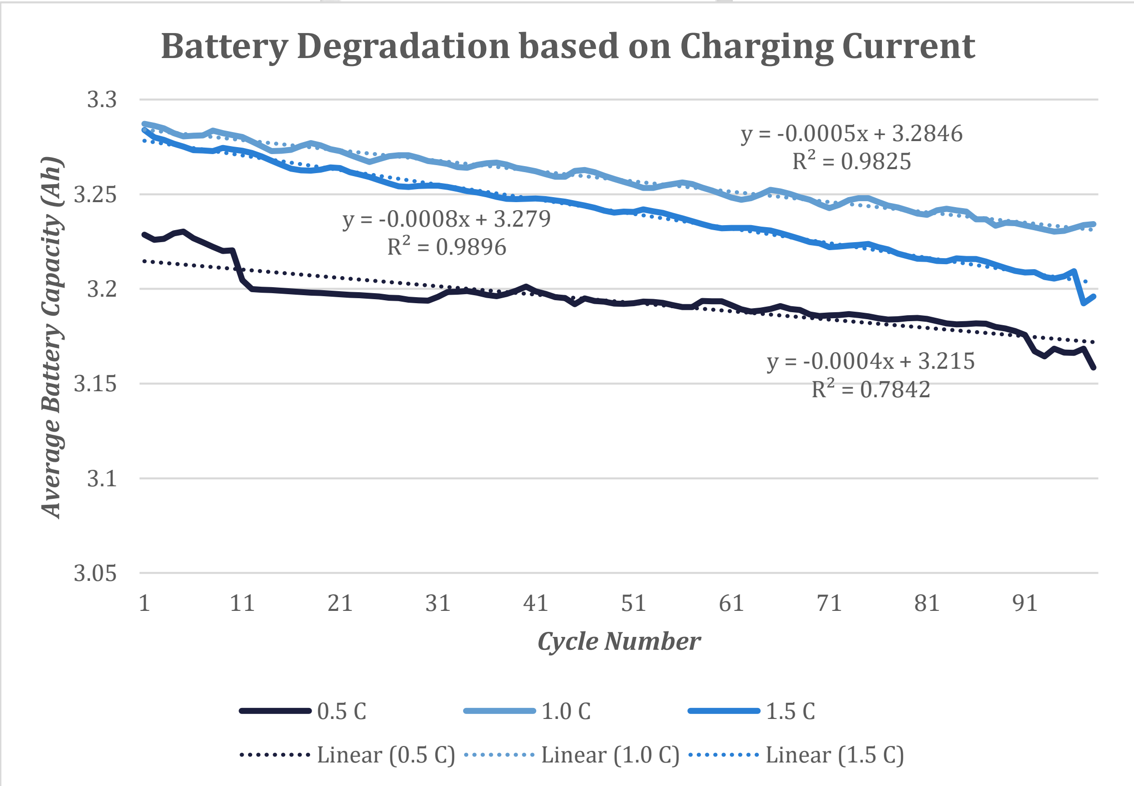

Figure 4.12: Battery degradation based on charging current comparative analysis

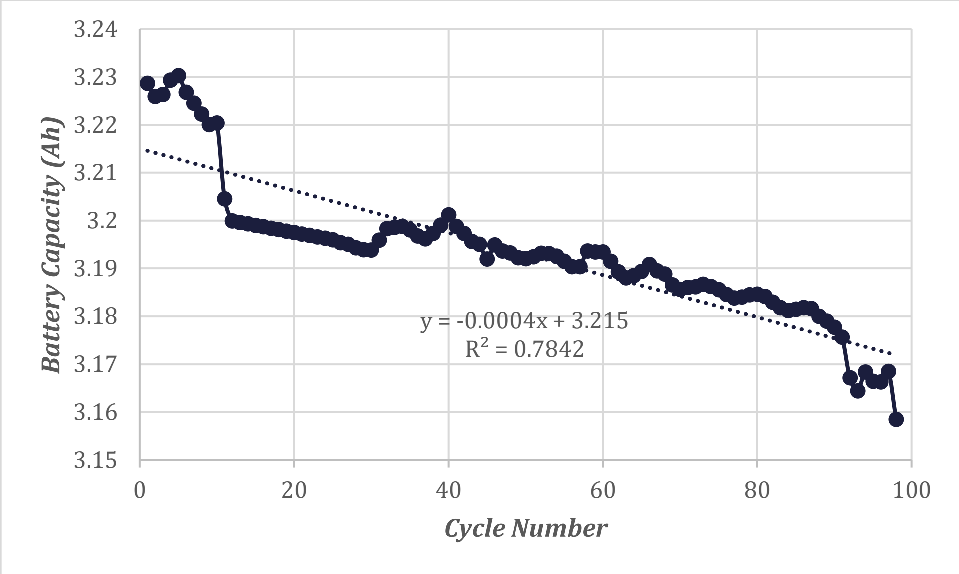

Figure 4.13: Battery Degradation at 0.5 C Charging Current

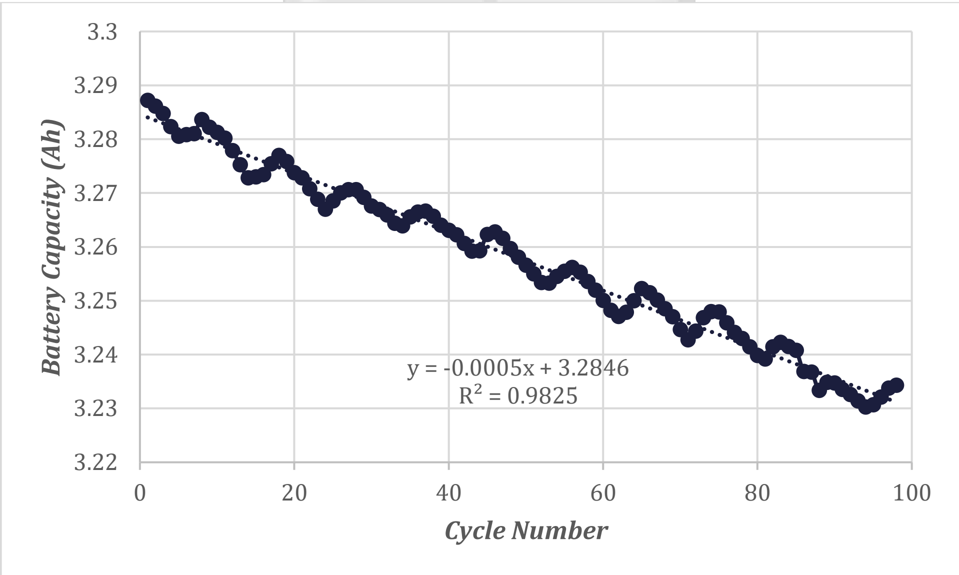

Figure 4.14: Battery Degradation at 1.0 C Charging Current

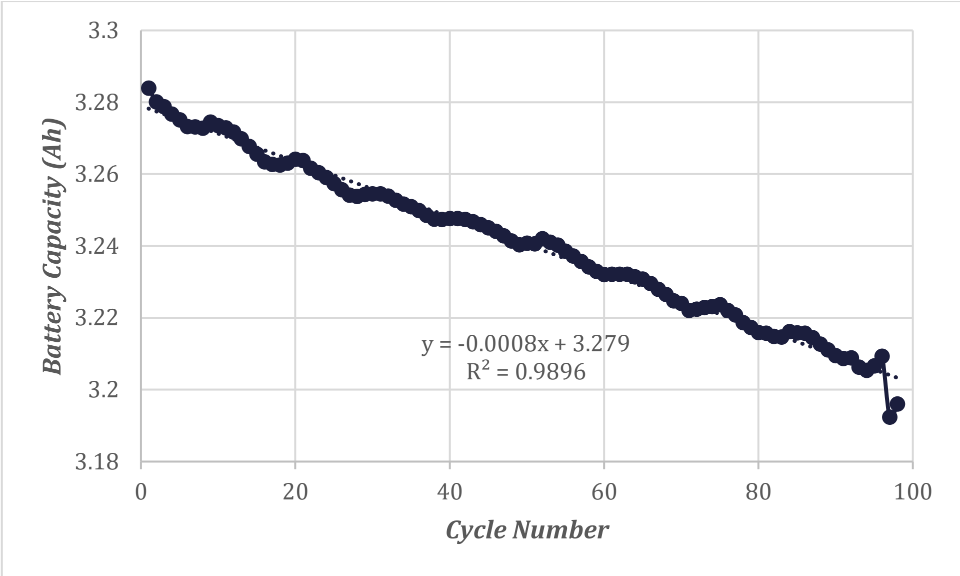

Figure 4.15: Battery Degradation at 1.5 C Charging Current

The results reveal that a charging rate of 1.5 C results in the highest degradation rate, at 0.0008 Ah per cycle. The 1C rate gives a capacity fade rate of 0.0005 Ah which is 37.5% lower than the 1.5 C-rate. The 0.5C rate resulted in the slowest capacity fade, with 0.0004 Ah lost per cycle, and this was 50 % slower than the fast charging rate of 1.5 C. These results are consistent with studies conducted by Gao et al.,(2017) and Weiss et al., (2021). Their studies concluded that higher C-rates. are associated with faster degradation of lithium ion batteries. Qu et al., (2022) explains that the high rates of degradation at high C-rates. are caused by macroscopic detachment of electrode material, the microscopic cracking of electrode particle, the lithium plating, and the structural change of layered material crystal. These results imply that within the Kenyan context, battery-swapping models that allow for slower charging rates would be recommended especially for three and two-wheelers.

Table 4.2: Regression Analysis of Degradation Models Based on Charging Current

	Model 1 (0.5 C Rate)	**Model 2 (1.0 C Rate)**	**Model 3 (1.5 C Rate)**
Multiple R	0.886	0.991	0.995
R Square	0.784	0.983	0.99
Adjusted R Square	0.782	0.982	0.989
Standard Error	0.0066	0.0021	0.0023
Observations	98	98	98
F-statistic	348.83	5401.27	9098.45
Significance F	9.93E.34	3.43E.86	6.48E.97

Coefficient (Intercept)	3.215	3.285	3.279
Standard Error (Intercept)	0.0013	0.0004	0.0005
Coefficient (Cycle Number)	.0.00044	.0.00055	.0.00077
Standard Error (Cycle Number)	2.36E.05	7.42E.06	8.10E.06
t-Statistic	.18.68	.73.49	.95.39
P-Value	9.93E.34	3.43E.86	6.48E.97
F-statistic	1320.85	12.04	214.57

The regression model for the first dataset (0.5 C Rate) yielded a strong correlation, R = 0.886, with an R^2 value of 0.784, indicating that approximately 78.4% of the variance in battery capacity was explained by the cycle number. The model was statistically significant, $F(1,96) = 348.83$, $p < .001$. The predictor variable had a significant negative coefficient ($B = -0.00044$, $t = -18.68$, $p < .001$), suggesting an inverse relationship between cycle number and battery capacity.

The regression model for the second dataset (1.0 C Rate) demonstrated an even stronger correlation, R = 0.991, and an R^2 value of 0.983, meaning that 98.3% of the variance in battery capacity was explained. The model was highly significant, $F(1,96) = 5401.27$, $p < .001$. The predictor variable exhibited a more pronounced negative relationship ($B = -0.00055$, $t = -73.49$, $p < .001$), indicating a stronger inverse relationship than Model 1.

The regression model for the third dataset (1.5 C Rate) revealed the highest correlation, R = 0.995, with an R^2 value of 0.990, suggesting that 99.0% of the variance in battery capacity was accounted for by cycle number. The model was statistically significant, $F(1,96) = 9098.45$, $p < .001$. The predictor variable had the most substantial negative coefficient ($B = -0.00077$, $t = -95.39$, $p < .001$), indicating the strongest inverse relationship between cycle number and battery capacity among the three models.

The increasing R^2 values and the progressively stronger negative coefficients across models suggest that battery capacity consistently declines with an increasing cycle number.

4.5 Battery Degradation Based on Charging Voltage Results and Discussion

To investigate the effects of charging voltage on the degradation patterns of lithium ion batteries, battery cells sets were cycled at different voltages at the constant Voltage stage. The batteries were subjected to Constant Current charging model and the switched to a constant Voltage as detailed in the methodology section. The first set was cycled at 3.4 V during the constant voltage charging stage, the second set was cycled at 3.65 V and the last set 4.02 V. The graph figures 4.16, 4.17, 4.18 and 4.19 illustrate the results obtained.

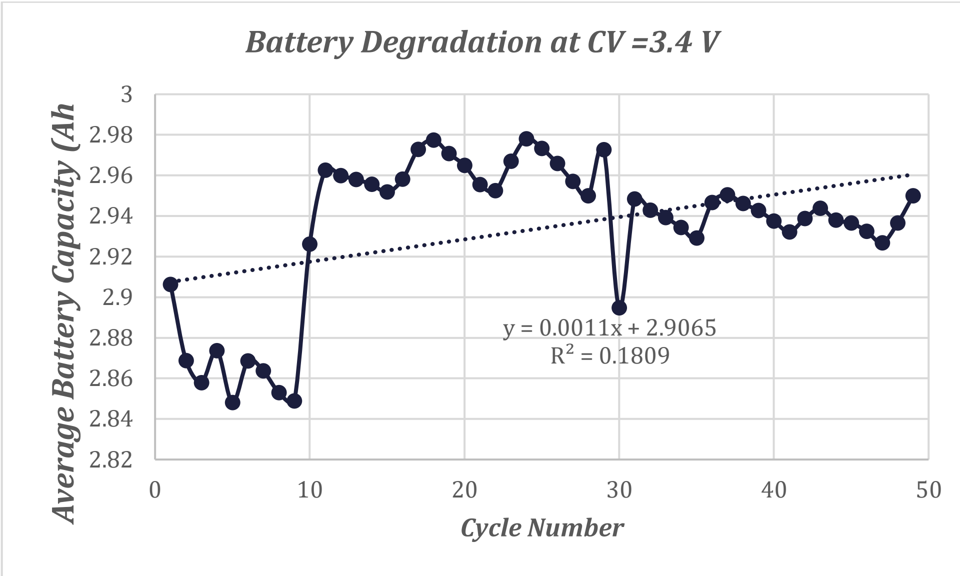

Figure 4.16: Battery Degradation at CV lower than recommended (3.4V)

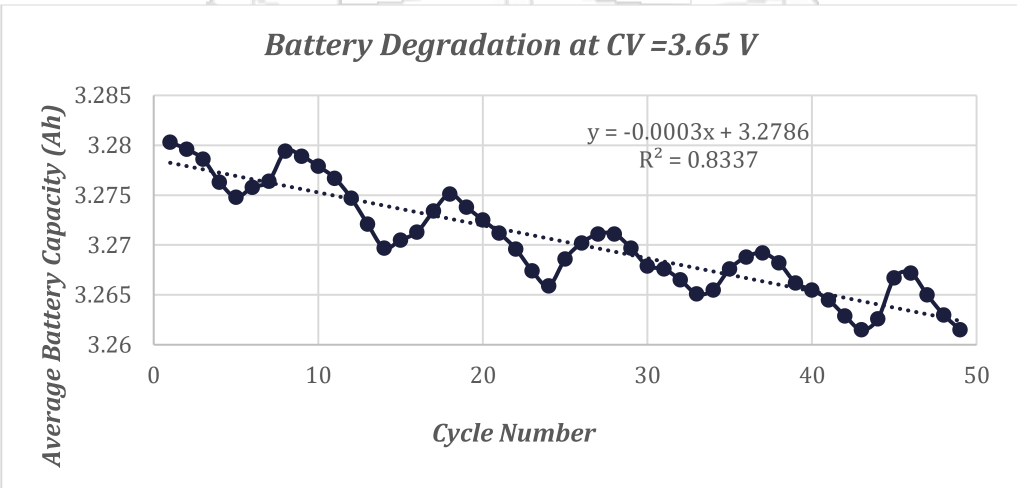

Figure 4.17: Battery Degradation at recommended Voltage (3.65V)

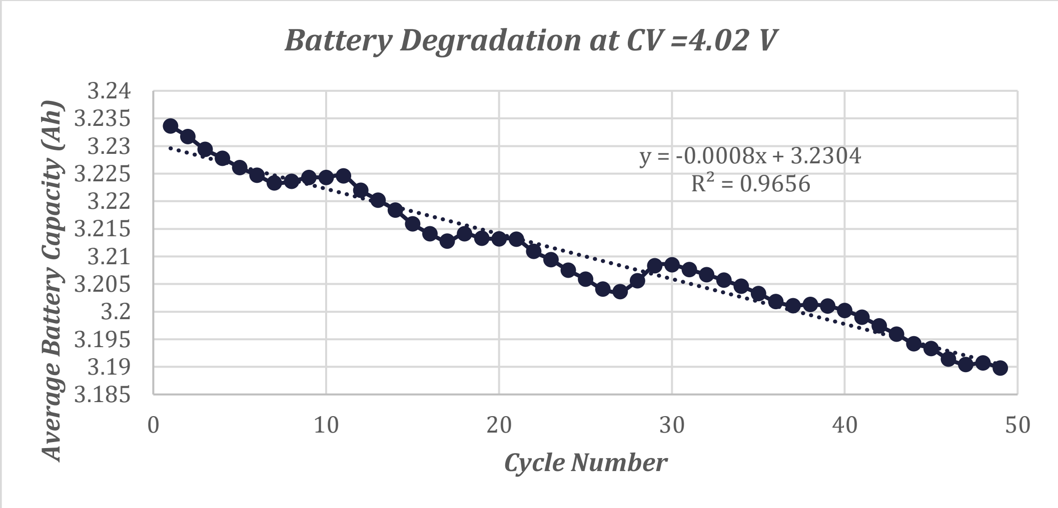

Figure 4.18: Battery Degradation at recommended at higher than recommended (4.02V)

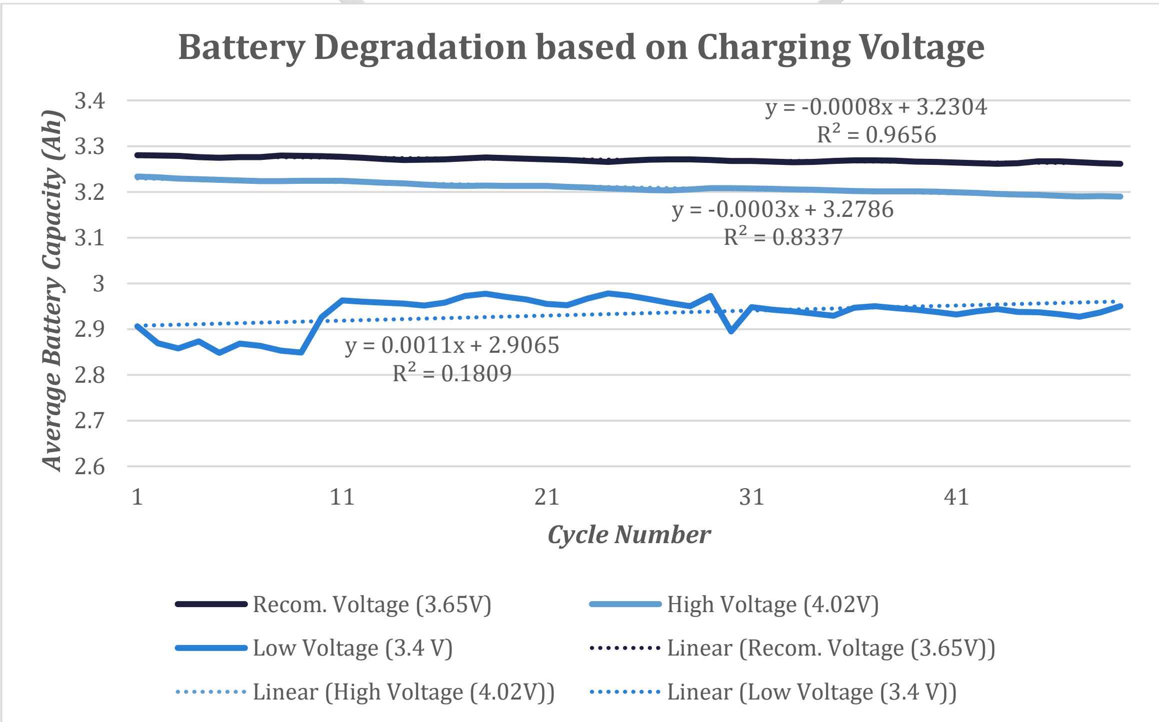

Figure 4.19: Comparative Analysis of Battery Degradation based on Charging Voltage

The results showed than when batteries are charged at lower than the recommended voltage, they are unable to attain their full capacity. In this case, the batteries were only able to achieve a maximum capacity of 2.98 Ah from a possible 3.3Ah while being charged at 3.4 V, which is 0.25V than the manufacturer's recommended Constant Charging Voltage. It was also observed that the degradation model was rather erratic and yielded a weak correlation factor at 0.1809 meaning that we could not easily predict the capacity of the battery with increasing usage. The reduction of the charging voltage by 0.25V was observed to double the charging time per cycle.

It is also important to note that overall, this charging profile resulted in the slowest degradation rate, with less than 0.01% capacity lost over 50 cycles. These results are supported by Isidor (2022) on his work on how to prolong battery Life.

On the other hand, with the battery charged at higher than recommended voltages, in this case 0.55V we observed a very predictable capacity degradation model. The battery degradation rate was observed to be 0.0008Ah per cycle with a correlation factor of 0.9656. This charging profile demonstrated that high charging voltage significantly increases the capacity fade rate of batteries. Based on research by Rikka et al., (2022) and Chen & Chung (2023) the charging voltage significantly impacts lithium - ion battery cycling performance by influencing capacity retention, degradation mechanisms, and overall lifespan. Higher voltages increase energy density but accelerate degradation, while lower voltages preserve cycle life at the cost of reduced capacity. These results imply that there is need for regulation of charging infrastructure to be regularly inspected to ensure that the voltage performance is accurate. It poses the responsibility to the regulatory authorities in Kenya.

A series of linear regression analyses were conducted to evaluate the relationship between cycling and battery capacities, at different voltage levels.

The regression model for CV = 4.02 V yielded a strong correlation, $R=0.98$ with an R^2 value of 0.9656, indicating that approximately 96.56% of the variance in the dependent variable was explained by the predictor. The model was statistically significant, $F(1,47) = 1320.85$, $p<.001$. The predictor variable had a significant negative coefficient ($B=-0.00082$, $t=-36.34$, $p<.001$), suggesting a strong inverse relationship.

The regression analysis CV = 3.65 V demonstrated a strong correlation, $R=0.9074$, and an R^2 value of 0.8235, meaning that 82.35% of the variance in the dependent variable was explained. The model was highly significant, $F(1,46) = 214.57$, $p<.001$ The predictor variable exhibited a significant negative relationship ($B = -0.00033$, $t=-14.65$, $p<.001$)

The regression analysis for CV = 3.4 V revealed a weaker correlation, $R=0.452$ with an R^2 value of 0.204, indicating that only 20.4% of the variance in the dependent variable was explained. The model remained statistically significant, $F(1,48) = 12.04$, $p=.001$. The predictor variable had a small but significant positive effect ($B=0.00015$, $t=3.51$, $p=.0.001$), suggesting a weaker but meaningful relationship.

The statistical significance across all models reinforces the reliability of these relationships.

Table 4.3: Regression Analysis of Degradation Models Based on Charging Voltage

	Model 1 (4.02V)	Model 2 (3.4V)	Model 3 (3.65V)
Multiple R	0.983	0.452	0.907
R.Squared (R^2)	0.966	0.204	0.824
Adjusted R^2	0.965	0.185	0.82
Standard Error	0.00222	0.03384	0.00215
Observations	48	49	48
Intercept (B_0)	3.2789	2.9065	3.2789
Slope (B_1)	.0.00082	0.00015	.0.00033
P-Value	<0.001	0.001	<0.001
F-statistic	1320.85	12.04	214.57

4.6 Battery Degradation Based on Operational Temperature Results and Discussion

The impact of operational temperature on the degradation of lithium ion batteries was studied by cycling a set of batteries under manufacturer-recommended profiles at different temperatures in a conditioned chamber. The first cycle set was cycled at 15 degrees Celsius, the second set at 27 degrees Celsius while the third set was cycled at 35 degrees Celsius. The results are displayed in figures 4.20, 4.21, 4.22 and 4.23.

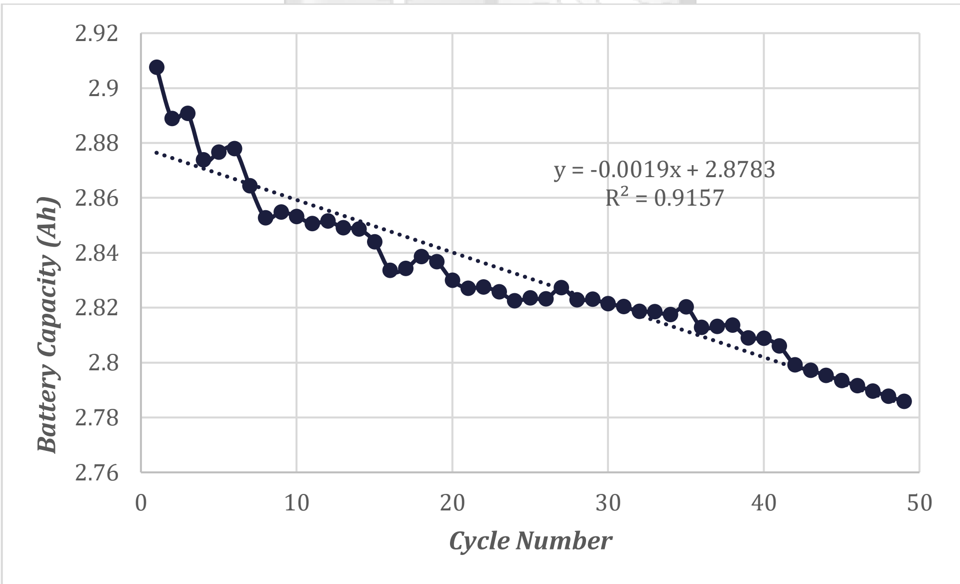

Figure 4.20: Lithium ion Battery Degradation at 15 degrees Celsius

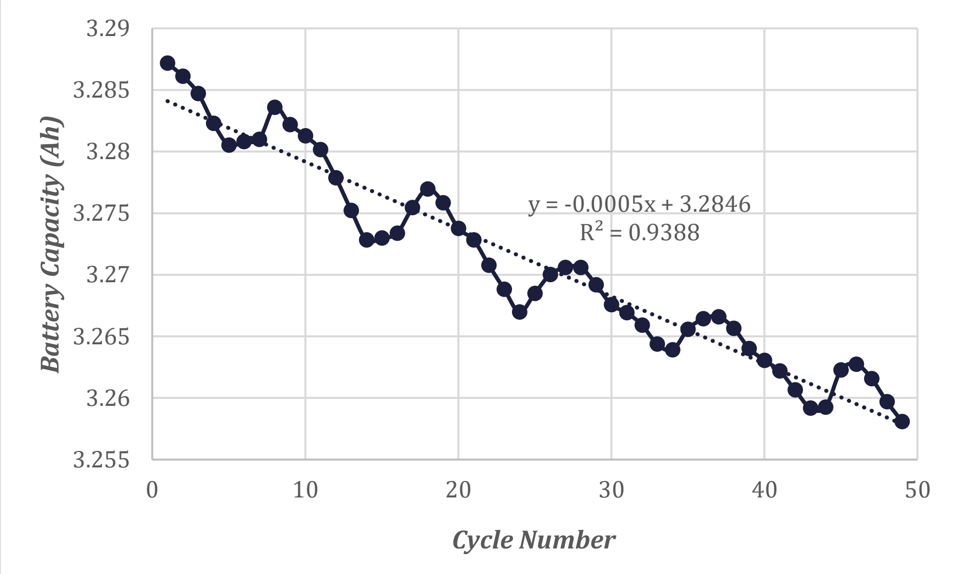

Figure 4.21: Lithium ion Battery Degradation at 27 degrees Celsius

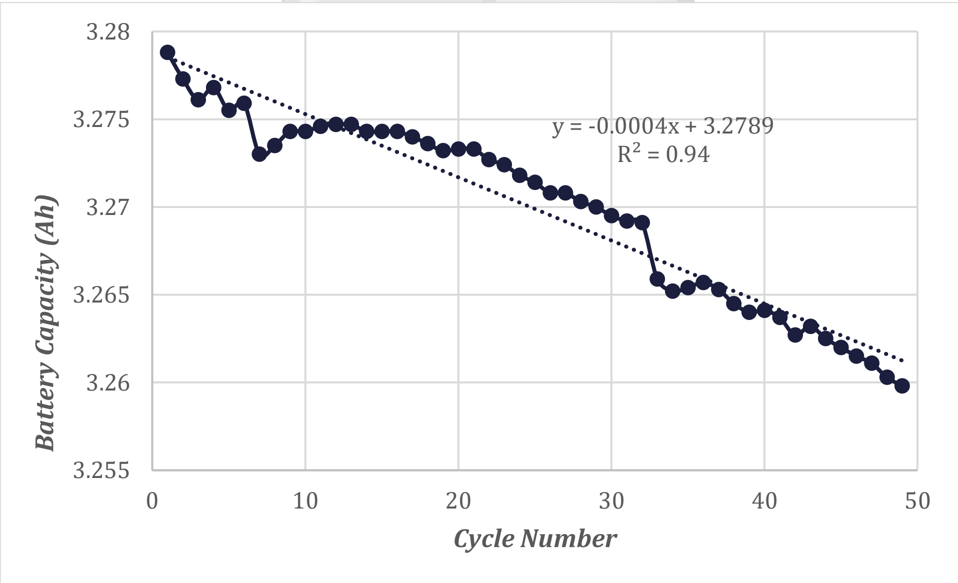

Figure 4.22: Lithium ion Battery Degradation at 35 degrees Celsius

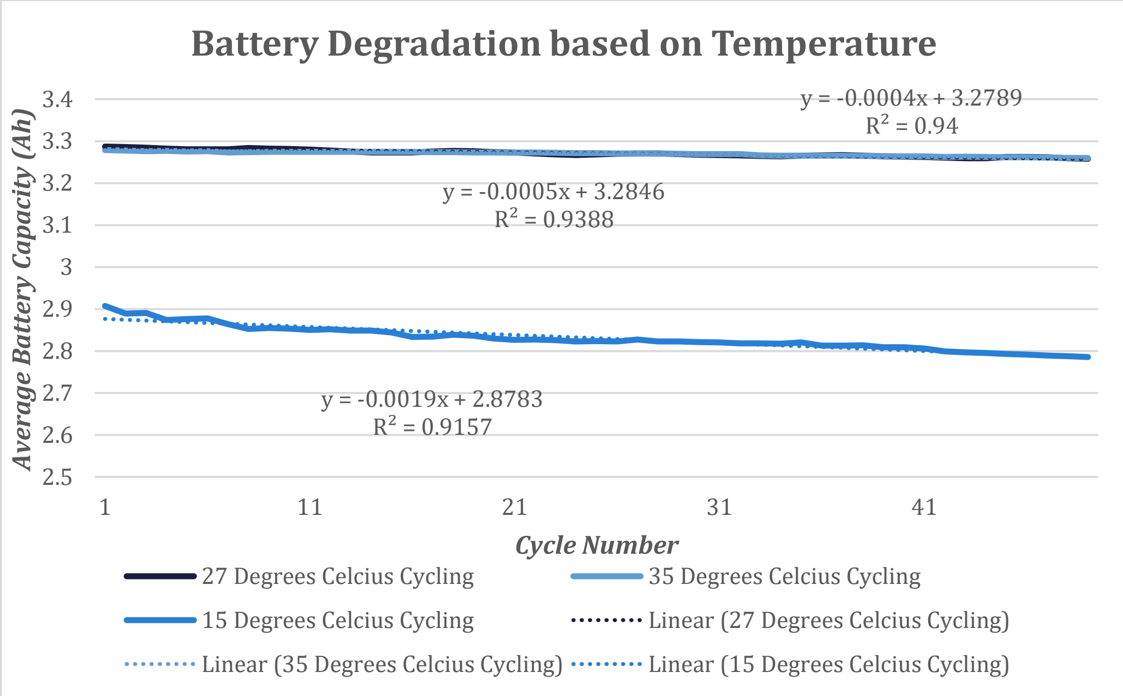

Figure 4.23: Comparative Analysis of Battery Degradation based on Temperature.

The study showed that for a battery cycled at 15 degrees Celsius, the battery was unable to achieve its full capacity. It further revealed an accelerated capacity fade rate, with about 0.0019 Ah lost in every full cycle. These results mimic a similar research conducted by Luo et al. (2022) . In their work they explain that low temperatures pose specific challenges for lithium ion batteries such as capacity reduction, security problems, and a sharp decline in cycle life. These problems are ascribed to the decrease in Lithium ion diffusion coefficient in both electrodes and electrolyte, poor transfer kinetics on the interphase, high Lithium ion dissolve barrier in the electrolyte, and severe Lithium plating.

For the batteries cycled at 27 degrees, the study revealed a moderate capacity fade rate at 0.0005 Ah per cycle and the ability of the batteries to achieve full capacity at each full charge cycle. Batteries cycled at 35 degrees Celsius performed very closely to the 27degree Celsius cycling rate. A one-way analysis of variance (ANOVA) was conducted to compare the mean battery capacity at the two different cycling temperatures: 27°C and 35°C. The analysis showed no statistically significant difference in battery capacity between the two conditions, $F(1, 96) = 0.63$, $p = .43$. Given that the p-value was greater than .05, we fail to reject the null hypothesis, suggesting that temperature variations between 27°C and 35°C do not significantly impact battery capacity. This data is consistent with the assertion by Lv et al. (2022) that lithium ion batteries perform optimally between 20 and 50 degrees Celsius. The results suggest that batteries in Kenya are likely not to be greatly impacted by the ambient temperatures as they tend to fall within the optimal range for the greater part of the year.

Table 4.4: Regression Analysis of Degradation Models Based on Operational Temperature

	Model 1 (27 ° C)	**Model 2 (35 ° C)**	**Model 3 (15 ° C)**
Multiple R	0.9689	0.9695	0.9569
R Square	0.9388	0.9399	0.9157
Adjusted R Square	0.9375	0.9387	0.9139
Standard Error	0.0020	0.0013	0.0084
Observations	49	49	49
Regression SS	0.0029	0.0013	0.0357
Residual SS	0.00019	0.00008	0.0033
Total SS	0.0031	0.0014	0.0390
F-statistic	721.08	736.05	510.77
Significance F	3.66E.30	2.33E.30	6.83E.27
Intercept	3.2846	3.2789	2.8783
Intercept Std. Err.	0.0006	0.0004	0.0024
Cycle Coefficient	.0.000546	.0.000360	.0.001910
Cycle Std. Err.	2.03E.05	1.33E.05	8.45E.05
Cycle t-Statistic	.26.85	.27.13	.22.60
Cycle P-Value	3.66E.30	2.33E.30	6.83E.27

The objective of this analysis is to compare three regression models examining battery degradation at different temperatures: 27°C (Model 1), 35°C (Model 2), and 15°C (Model 3). Each model explores the relationship between cycle count and battery capacity, with cycle number serving as the independent variable and battery capacity as the dependent variable. Among the three models, Model 2 (35°C) exhibits the highest coefficient of determination (R Square = 0.9399) and adjusted R Square (0.9387), indicating that it explains the most variance in battery capacity. Model 1 (27°C) follows closely with an R Square of 0.9388, whereas Model 3 (15°C) has the lowest R Square (0.9157), suggesting a relatively weaker predictive performance. The standard error of the estimate is lowest for Model 2 (0.0013), indicating higher precision in predictions, whereas Model 3 has the highest standard error (0.0084), implying greater variability in residuals.

All three models report highly significant p -values (< 0.0001) for the cycle variable, confirming the robustness of the relationship between cycle count and battery degradation. The absolute value of the cycle coefficient is largest in Model 3 (.0.001910), indicating the most rapid battery degradation at 15°C. In contrast, Model 2 has the smallest absolute coefficient (.0.000360), implying the slowest degradation rate at 35°C. Model 1 (.0.000546) falls in between these extremes. The F-statistics further reinforce the superior fit of Model 2 (F = 736.05), followed by Model 1 (F = 721.08), while Model 3 has the lowest F-statistic (510.77), aligning with its lower R Square value.

Chapter 5: Conclusion and Recommendations

5.1 Conclusion

This study quantified the impact of initial State of Health (SoH) and charging conditions on the degradation of lithium - ion EV batteries, providing critical insights for Kenya's growing e-mobility sector. The key findings, supported by experimental data, are summarized as follows:

i. Initial State of Health (SoH):

Batteries with 60% and 80% initial SoH showed a temporary capacity increase of 0.0029 Ah per cycle in the first 50 cycles, likely due to electrode restructuring. On the other hand, new batteries (100% SoH) degraded at a steady rate of 0.0005 Ah per cycle, this indicated that degradation is more predictable in new cells.

ii. Charging Current Impact:

Fast charging at 1.5C led to the highest degradation rate (0.0008 Ah/cycle), 100% faster than slow charging at 0.5C (0.0004 Ah/cycle). Standard 1.0C charging resulted in a moderate degradation rate of 0.00055 Ah/cycle, reinforcing the need for regulated charging speeds.

iii. Charging Voltage Effects:

Overcharging at 4.02V caused rapid capacity fade (0.0008 Ah/cycle), while optimal voltage (3.65V) resulted in a slower decline (0.00033 Ah/cycle). Undercharging at 3.4V prevented batteries from reaching full capacity (maximum capacity observed2.98 Ah vs. 3.3 Ah nominal), which resulted in the loss of 9.7%. of the usable capacity.

iv. Temperature Influence:

Low temperatures (15°C) accelerated degradation (0.0019 Ah/cycle) and reduced capacity by 12.8% compared to nominal conditions. Moderate temperatures (27°C–35°C) showed minimal degradation differences (0.0005 Ah/cycle vs. 0.00036 Ah/cycle), this confirms that Kenya's ambient climate is generally safe for EV batteries.

v. The study provided comparative degradation models for all study parameters as intended.

Overall, this study provides valuable insights into the challenges associated with second-hand EV battery imports in Kenya and offers actionable recommendations for stakeholders.

5.2 Recommendations

Based on the findings, this study recommends the following to enhance usability and scalability to the real-world application:

i. For Policymakers and Regulatory Bodies:

Policy makers should implement policies to regulate charging infrastructure to ensure optimal charging rates and voltages, thereby reducing the risk of premature battery degradation. They should also implement regulations to regularly check and calibrate thermal management systems in Electric vehicles to reduce degradation risks and thermal runaway.

ii. For Consumers and EV Buyers:

When purchasing used EVs, consumers should request comprehensive battery health documentation, including State of Health (SOH), charging history, and thermal exposure details. Consumers should also follow optimal charging practices and adhere strictly to the manufacturer's recommended charging protocols. Whenever possible, they should avoid fast charging and store vehicles in moderate temperatures to extend battery longevity.

iii. For Industry Stakeholders:

There is a need to improve consumer awareness in the Electric Vehicle sector, specifically on battery maintenance, charging best practices, and proper disposal methods. There is also a need to establish battery recycling programs in Kenya, owing to the current limitations in recycling infrastructure. It is essential to invest in facilities for the safe and sustainable management of end.of.life EV batteries.

5.3 Future work

While this study formed a basis for Electric Vehicle Battery research, it did not exhaust all the possible areas of interest and proposes the following areas for further research:

i. The use of a variety of battery chemistries. This study focused purely on LiFePO4 Batteries due to their availability in the market. It is however important to extend the research area to more chemistries as they emerge in the market

ii. Increase in the study cycling period. In order to conclusively determine the degradation process based on all factors, it is recommended that studies be conducted on the full lifecycle of batteries. This would require much more time but would provide better insights on the degradation rates.
iii. Study on battery packs. While this study provides critical information on the operation on the battery cells, it cannot guarantee that this results will be replicated accurately in battery packs that represent the real life application of EV batteries. It is therefore recommended that similar studies be carried out on battery packs rather than independent cells.

The transition to e-mobility in Kenya presents immense opportunities for reducing greenhouse gas emissions and advancing sustainable energy goals. However, challenges related to second-hand EV battery degradation must be addressed proactively. By implementing the recommendations outlined above, policymakers, consumers, and researchers can collectively contribute to a robust framework for sustainable EV adoption in Kenya.

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Appendix

A: Similarity Report

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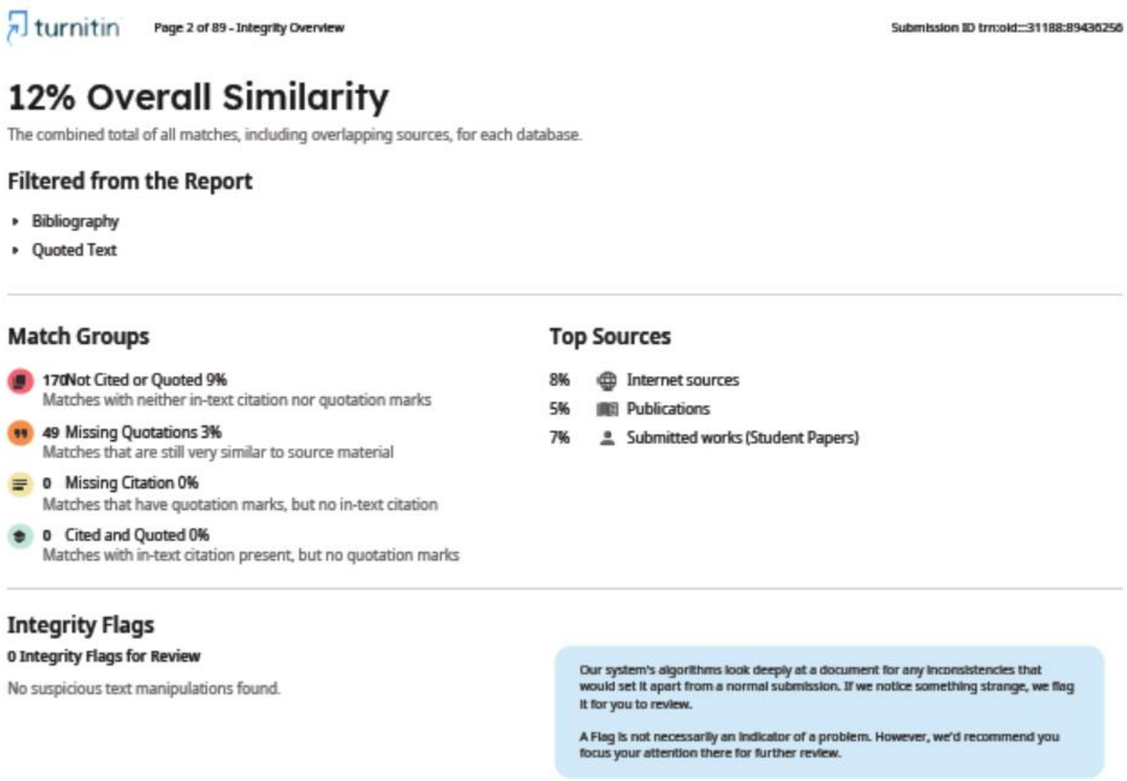

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Figure 6.1: Plagiarism Report

B: Ethical Review Authorization

This work was reviewed and approved by Strathmore University Institutional Scientific and Ethical Review Committee as shown in figure 6.2

Strathmore
UNIVERSITY

22nd October 2024

Ms Kimuya Winfred,
wmwende@gmail.com

Dear Ms Kimuya,

RE: Modelling the Degradation of Electric Vehicle Batteries Based on Initial State of Health and Charging Conditions in Kenya

This is to inform you that SU-ISERC has reviewed and **approved** your above **SU-masters** proposal. Your application reference number is **SU-ISERC2408/24**. The approval period is from **22nd October 2024 to 21st October 2025.**

This approval is subject to compliance with the following requirements:

i. Only approved documents including (informed consents, study instruments, MTA) will be used.
ii. All changes including (amendments, deviations, and violations) are submitted for review and approval by SU-ISERC.
iii. Death and life-threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to SU-ISERC within 72 hours of notification.
iv. Any changes anticipated or otherwise that may increase the risks or affected safety or welfare of study participants and others or affect the integrity of the research must be reported to SU-ISERC within 72 hours.
v. Clearance for the export of biological specimens must be obtained from relevant institutions.
vi. Submission of a request for renewal of approval at least 60 days prior to the expiry of the approval period. Attach a comprehensive progress report to support the renewal.
vii. Submission of an executive summary report within 90 days of completion of the study to SU-ISERC.

Before commencing your study, you will be expected to obtain a research license from National Commission for Science, Technology, and Innovation (NACOSTI) https://research-portal.nacosti.go.ke/ and obtain other clearances needed.

Yours sincerely,

Mr Ambrose Rachier,
Chairperson; SU-ISERC

Figure 6.2: Ethical Review Approval Letter

C: Sample Cycling Chart Results

Figure 7.2 shows an example of one of the charts obtained from cycling the batteries. This particular chart was for a 1C cycling rate over a hundred cycles.

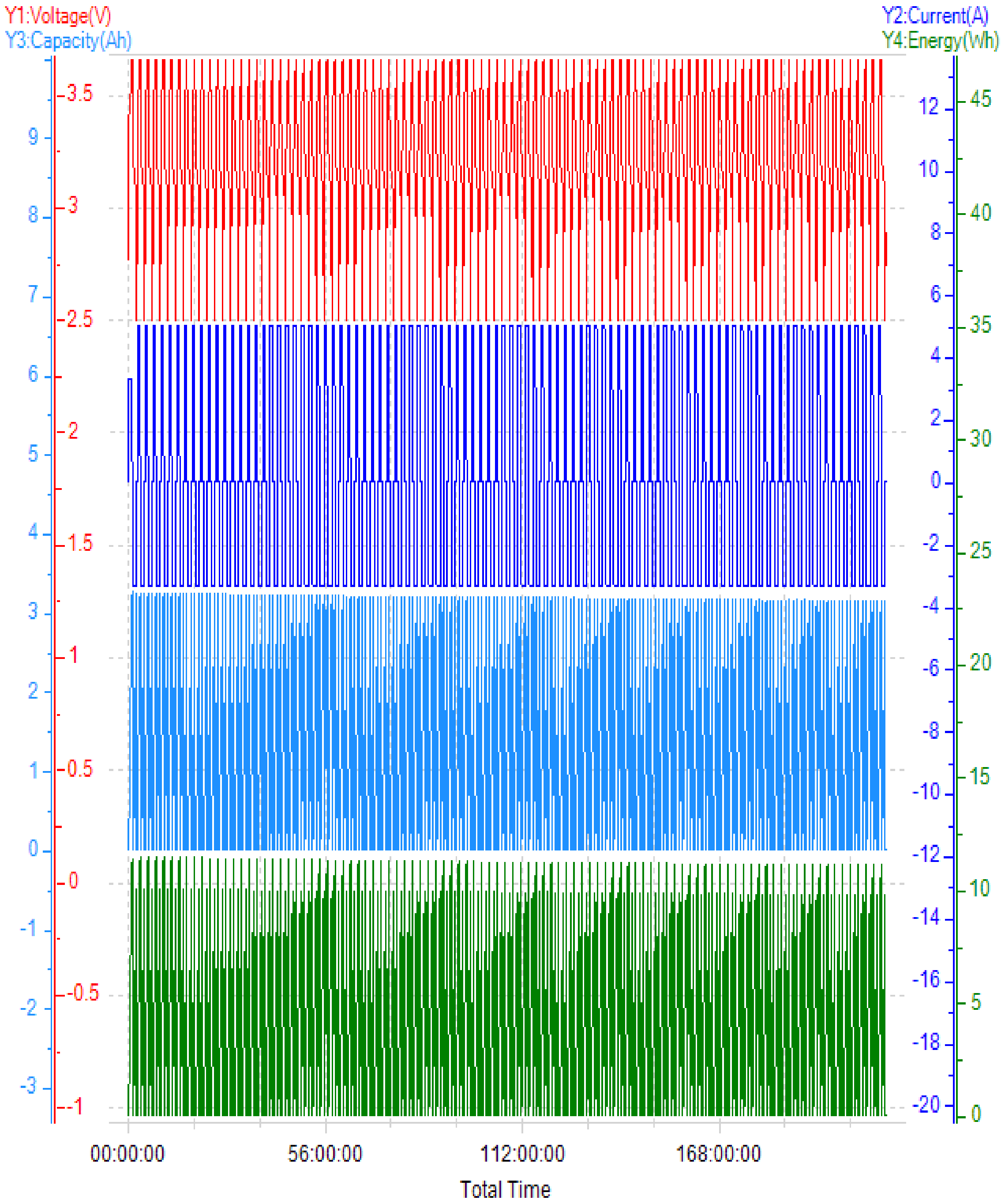

Figure 6.3: Sample Cycling Chart

D: Current Comparison Test Results

Table 7.1 gives the results cycling the batteries with different charging current rates, i.e. 1.0 C, 0.5 C and 1.5 C. The graphs and models presented in section 4.4 are derived from this data.

Table 6.1: Current Comparison Test Results

Current Comparison Test Results			
Cycle	**0.5 C Rate**	**1.0 C Rate**	**1.5 C Rate**
1	3.22867	3.28718	3.28390
2	3.22593	3.28613	3.28007
3	3.22637	3.28473	3.27873
4	3.22937	3.28230	3.27673
5	3.23027	3.28053	3.27510
6	3.22680	3.28083	3.27320
7	3.22453	3.28100	3.27310
8	3.22227	3.28360	3.27280
9	3.22007	3.28220	3.27447
10	3.22037	3.28128	3.27353
11	3.20453	3.28015	3.27290
12	3.19990	3.27788	3.27173
13	3.19960	3.27523	3.26987
14	3.19930	3.27283	3.26770
15	3.19900	3.27298	3.26557
16	3.19870	3.27338	3.26340
17	3.19840	3.27545	3.26270
18	3.19810	3.27698	3.26253
19	3.19780	3.27585	3.26303
20	3.19750	3.27378	3.26417
21	3.19720	3.27283	3.26373
22	3.19690	3.27078	3.26163
23	3.19660	3.26883	3.26043
24	3.19630	3.26698	3.25903
25	3.19600	3.26850	3.25737
26	3.19537	3.27003	3.25570
27	3.19507	3.27060	3.25413
28	3.19433	3.27060	3.25383
29	3.19390	3.26920	3.25437
30	3.19383	3.26758	3.25450
31	3.19590	3.26693	3.25447
32	3.19830	3.26593	3.25387
33	3.19857	3.26438	3.25277
34	3.19880	3.26390	3.25167
35	3.19803	3.26558	3.25090
36	3.19680	3.26643	3.24990
37	3.19620	3.26660	3.24853

38	3.19733	3.26565	3.24750
39	3.19907	3.26403	3.24737
40	3.20117	3.26305	3.24763
41	3.19877	3.26220	3.24767
42	3.19733	3.26065	3.24733
43	3.19563	3.25918	3.24677
44	3.19507	3.25925	3.24597
45	3.19200	3.26228	3.24503
46	3.19493	3.26275	3.24403
47	3.19367	3.26158	3.24280
48	3.19323	3.25970	3.24137
49	3.19223	3.25808	3.24033
50	3.19203	3.25660	3.24077
51	3.19243	3.25500	3.24057
52	3.19320	3.25340	3.24203
53	3.19310	3.25328	3.24100
54	3.19257	3.25453	3.24020
55	3.19150	3.25543	3.23853
56	3.19037	3.25618	3.23723
57	3.19037	3.25528	3.23570
58	3.19363	3.25358	3.23417
59	3.19343	3.25195	3.23290
60	3.19347	3.25008	3.23203
61	3.19150	3.24818	3.23210
62	3.18930	3.24710	3.23213
63	3.18803	3.24785	3.23213
64	3.18847	3.24998	3.23140
65	3.18937	3.25225	3.23080
66	3.19083	3.25145	3.22950
67	3.18947	3.25010	3.22797
68	3.18880	3.24848	3.22650
69	3.18657	3.24703	3.22473
70	3.18563	3.24463	3.22400
71	3.18603	3.24275	3.22207
72	3.18613	3.24433	3.22243
73	3.18670	3.24685	3.22283
74	3.18620	3.24795	3.22317
75	3.18557	3.24790	3.22370
76	3.18453	3.24590	3.22203
77	3.18380	3.24408	3.22083
78	3.18403	3.24300	3.21863
79	3.18447	3.24145	3.21730
80	3.18460	3.23980	3.21587
81	3.18417	3.23915	3.21573
82	3.18297	3.24143	3.21483
83	3.18183	3.24225	3.21463

84	3.18123	3.24148	3.21613
85	3.18147	3.24080	3.21583
86	3.18183	3.23683	3.21573
87	3.18160	3.23673	3.21447
88	3.18000	3.23335	3.21267
89	3.17903	3.23485	3.21107
90	3.17773	3.23473	3.20947
91	3.17567	3.23355	3.20870
92	3.16713	3.23258	3.20883
93	3.16440	3.23140	3.20623
94	3.16840	3.23025	3.20540
95	3.16640	3.23070	3.20667
96	3.16627	3.23213	3.20933
97	3.16850	3.23378	3.19237
98	3.15847	3.23428	3.19603

E: SoH Comparison Test Results

Table 7.2 gives the results cycling the batteries with different initial states of health, i.e. 60%, 80%, 90% and 100%. The graphs and models presented in section 4.3 are derived from this data.

Table 6.2: SoH Comparison Test Results

SoH Comparison Test Results				
Cycle	**60% Init. SoH**	**80% Init. SoH**	**90% Init. SoH**	**100% Init. SoH**
1	1.9019	2.5561	2.9619	3.3337
2	1.9157	2.5533	2.9704	3.3341
3	1.9431	2.5443	2.9790	3.3336
4	1.9643	2.5470	2.9832	3.3322
5	1.9779	2.5463	2.9862	3.3309
6	1.9881	2.5441	2.9887	3.3310
7	1.9969	2.5419	2.9909	3.3313
8	2.0039	2.5398	2.9870	3.3333
9	2.0101	2.5429	2.9784	3.3319
10	2.0155	2.5440	2.9727	3.3312
11	1.9858	2.5414	2.9676	3.3304
12	1.9746	2.5495	2.9695	3.3288
13	1.9695	2.5433	2.9862	3.3266
14	1.9650	2.5457	2.9880	3.3248
15	1.9617	2.5455	2.9899	3.3252
16	1.9920	2.5440	2.9912	3.3253
17	2.0103	2.5432	2.9924	3.3266

18	2.0169	2.5435	2.9822	3.3275
19	2.0215	2.5585	2.9845	3.3266
20	2.0251	2.5952	2.9953	3.3254
21	2.0288	2.6083	2.9984	3.3239
22	2.0316	2.6127	2.9988	3.3227
23	2.0026	2.6177	2.9986	3.3212
24	1.9935	2.6188	2.9991	3.3199
25	2.0343	2.6200	2.9994	3.3211
26	2.0451	2.6205	2.9997	3.3218
27	2.0494	2.6204	2.9998	3.3223
28	2.0512	2.6208	3.0012	3.322
29	2.0520	2.6215	3.0032	3.3206
30	2.0537	2.6263	3.0049	3.3195
31	2.0544	2.6323	3.0068	3.3192
32	2.0561	2.6363	3.0061	3.3182
33	2.0565	2.6370	3.0065	3.3171
34	2.0563	2.6386	3.0060	3.3169
35	2.0575	2.6392	3.0055	3.3177
36	2.0622	2.6394	3.0041	3.3183
37	2.0650	2.6395	3.0041	3.318
38	2.0690	2.6393	3.0051	3.317
39	2.0734	2.6383	3.0068	3.3162
40	2.0735	2.6398	3.0079	3.3155
41	2.0741	2.6434	3.0099	3.3146
42	2.0745	2.6466	3.0097	3.3132
43	2.0743	2.6487	3.0094	3.3122
44	2.0730	2.6496	3.0085	3.3126
45	2.0713	2.6495	3.0078	3.3153
46	2.0701	2.6487	3.0075	3.315
47	2.0700	2.6482	3.0072	3.313
48	2.0714	2.6474	3.0082	3.3119
49	2.0764	2.6465		3.3105

F: Voltage Comparison Test Results

Table 7.3 gives the results cycling the batteries with different charging voltages, i.e. 3.65V, 4.02V and 3.4 V. The graphs and models presented in section 4.5 are derived from this data.

Table 6.3: Voltage Comparison Test Results

Voltage Comparison Test Results			
Cycle	**Recom. Voltage (3.65V)**	**High Voltage (4.02V)**	**Low Voltage (3.4 V)**
1	3.2803	3.2336	2.9063
2	3.2796	3.2317	2.8688
3	3.2786	3.2294	2.8579
4	3.2763	3.2278	2.8736

5	3.2748	3.2261	2.8481
6	3.2758	3.2247	2.8686
7	3.2764	3.2233	2.8636
8	3.2794	3.2236	2.853
9	3.2789	3.2243	2.8489
10	3.2779	3.2243	2.9261
11	3.2767	3.2246	2.9626
12	3.2747	3.222	2.9599
13	3.2721	3.2202	2.958
14	3.2697	3.2184	2.9556
15	3.2705	3.2159	2.9518
16	3.2713	3.2141	2.9581
17	3.2734	3.2128	2.9729
18	3.2751	3.2141	2.9774
19	3.2738	3.2133	2.9707
20	3.2725	3.2132	2.9649
21	3.2712	3.2131	2.9554
22	3.2696	3.2109	2.9525
23	3.2674	3.2094	2.967
24	3.2659	3.2075	2.9781
25	3.2686	3.2059	2.9733
26	3.2702	3.2041	2.9659
27	3.2711	3.2036	2.957
28	3.2711	3.2056	2.9499
29	3.2697	3.2083	2.9726
30	3.2679	3.2085	2.8948
31	3.2676	3.2076	2.9483
32	3.2665	3.2067	2.9428
33	3.2651	3.2057	2.9393
34	3.2655	3.2046	2.9343
35	3.2676	3.2033	2.9292
36	3.2688	3.2018	2.9466
37	3.2692	3.2011	2.9504
38	3.2682	3.2013	2.9461
39	3.2662	3.201	2.9427
40	3.2655	3.2002	2.9375
41	3.2645	3.199	2.9322
42	3.2629	3.1974	2.9387
43	3.2615	3.1959	2.9438
44	3.2626	3.1942	2.9379
45	3.2667	3.1933	2.9366
46	3.2672	3.1914	2.9325
47	3.265	3.1904	2.9268
48	3.263	3.1907	2.9365
49	3.2615	3.1898	2.95

G: Temperature Comparison Test Results

Table 7.4 gives the results cycling the batteries under different operational temperatures, i.e. 35 °C, 15 °C and 27 °C. The graphs and models presented in section 4.6 are derived from this data.

Table 6.4: Temperature Comparison Test Results

Temperature Comparison Test Results			
Cycle	**27 Degrees Celsius Cycling**	**35 Degrees Celsius Cycling**	**15 Degrees Celsius Cycling**
1	3.287175	3.2788	2.9075
2	3.286125	3.2773	2.8889
3	3.284725	3.2761	2.8907
4	3.2823	3.2768	2.8738
5	3.280525	3.2755	2.8766
6	3.280825	3.2759	2.8779
7	3.281	3.273	2.8644
8	3.2836	3.2735	2.8527
9	3.2822	3.2743	2.8548
10	3.281275	3.2743	2.8532
11	3.28015	3.2746	2.8506
12	3.277875	3.2747	2.8515
13	3.275225	3.2747	2.8491
14	3.272825	3.2743	2.8486
15	3.272975	3.2743	2.8439
16	3.273375	3.2743	2.8335
17	3.27545	3.274	2.8342
18	3.276975	3.2736	2.8386
19	3.27585	3.2732	2.8367
20	3.273775	3.2733	2.8299
21	3.272825	3.2733	2.827
22	3.270775	3.2727	2.8275
23	3.268825	3.2724	2.8257
24	3.266975	3.2718	2.8225
25	3.2685	3.2714	2.8235
26	3.270025	3.2708	2.8232
27	3.2706	3.2708	2.8272
28	3.2706	3.2703	2.8228
29	3.2692	3.27	2.823
30	3.267575	3.2695	2.8214
31	3.266925	3.2692	2.8204
32	3.265925	3.2691	2.8186
33	3.264375	3.2659	2.8185
34	3.2639	3.2652	2.8175
35	3.265575	3.2654	2.8202

36	3.266425	3.2657	2.8128
37	3.2666	3.2653	2.8131
38	3.26565	3.2645	2.8136
39	3.264025	3.264	2.8089
40	3.26305	3.2641	2.8088
41	3.2622	3.2637	2.806
42	3.26065	3.2627	2.7991
43	3.259175	3.2632	2.7972
44	3.25925	3.2625	2.7953
45	3.262275	3.262	2.7934
46	3.26275	3.2615	2.7915
47	3.261575	3.2611	2.7896
48	3.2597	3.2603	2.7877
49	3.258075	3.2598	2.7858

H: Battery Tester Specifications

Table 7.5 shows the technical specifications of the battery tester used in this experiments.

Table 6.5: Battery Tester Specifications

Parameter		Parameter index
Input Power		AC 220V ±10% / 50Hz
Channel Features		Constant Current Source and Constant Voltage Source with Independent pairs of Closed-loop Structure
Channel Control Mode		Independent Control
Voltage	Constant voltage range	25mV~5V
	Discharge Min Voltage	The end of clamps can discharge to 1V, and the wire length of 2m can discharge to 1.5V
	Accuracy	± 0.05% of FS
	Stability	± 0.05% of FS
Current	Per Channel Current Range	Range 1: 0.5mA-0.1A Range 2: 0.1A-3A Range3: 3A-6A
	Accuracy	± 0.05% of FS
	Constant voltage cutoff current	Range 1: 0.2mA Range : 6mA Range 3: 12mA
	Stability	± 0.05% of FS
Power	Per Channel Output Power	30W
	Stability	± 0.1% of FS
Charge	Charge Mode	Constant Current Charge Constant Voltage Charge、Constant Current and Constant Voltage Charge、CPC
	End Condition	Voltage、Current、Relative Time、Capacity、-ΔV
Discharge	Discharge Mode	CCD、CVD, CPD, CRD, Constant Current and Constant Voltage Discharge
	End Condition	Voltage、Current、Relative Time、Capacity、
Cycle	Loop Measure Range	1~65535 times
	Max Steps Per Loop	254
	Nested Loop	Nested loop Function, Max Support 3 Layers

I: NACOSTI Permit

Figure 6.4 shows the permit by National Commission for Science, Technology and Innovation (NACOSTI) authorized that the study.

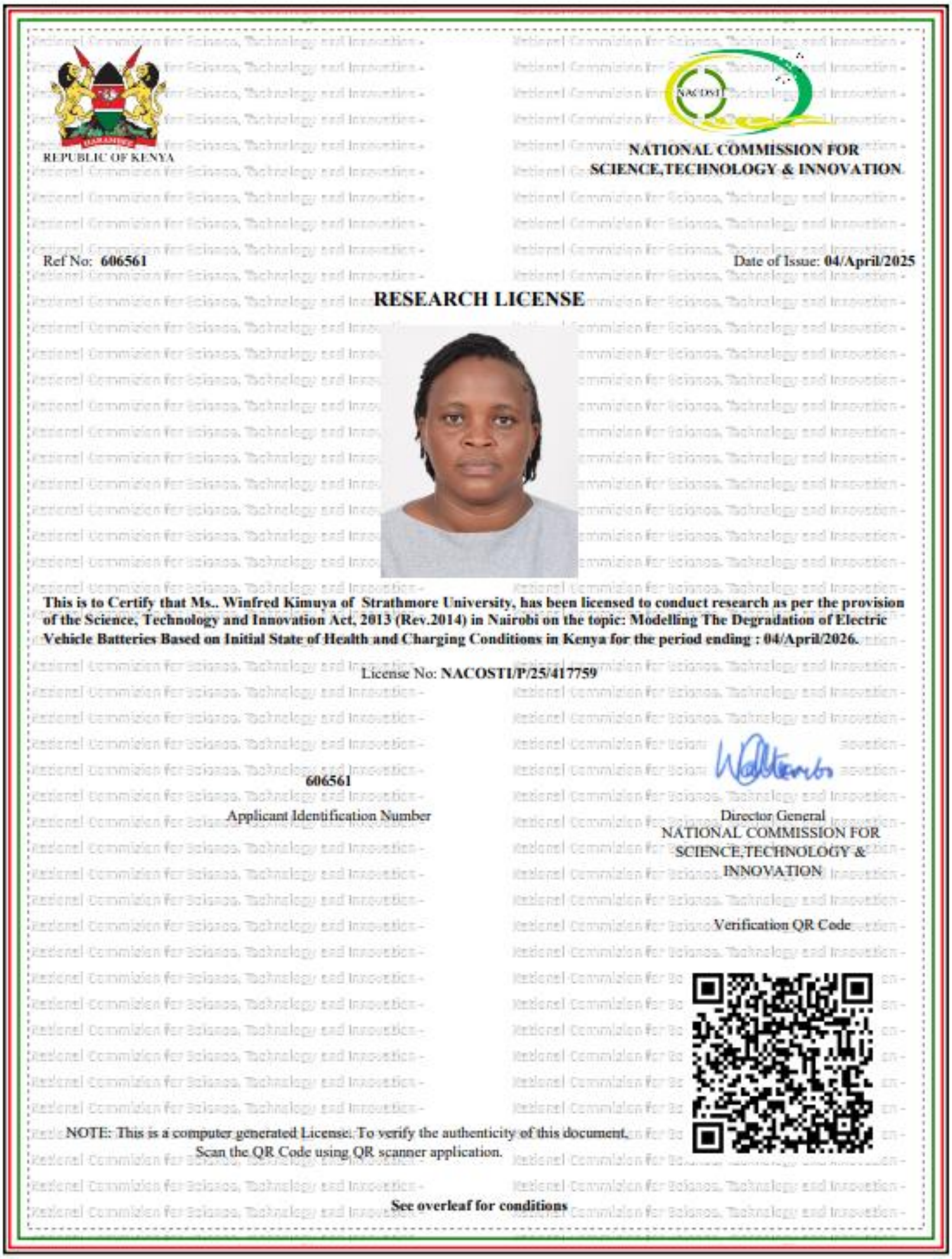

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Figure 6.4: NACOSTI Permit