Performance Analysis of Li-ion Battery for EV Applications: Experimental and Simulation-Based Approach

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DECLARATION

We hereby declare that this major report is the original work of both authors. To the best of our knowledge, it does not contain any material previously published or submitted for the award of another degree.

Any concepts or references used have been duly acknowledged, and we take full responsibility for the contents of this report.

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CERTIFICATE

This is to certify that Aryan Sirohi (R132221007) and Swechha (R132221006), students of B. Tech - Electrical Engineering (VIII Semester), from Electrical Cluster, School of Engineering, UPES, Dehradun, have submitted their major report for their Major Project titled: "Performance Analysis of Li-ion Battery for EV Applications: Experimental and Simulation-Based Approach" under my guidance.

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Table of Contents

Abstract

This project investigates the performance of Li-ion batteries for Electric Vehicle (EV) applications through experimental testing in Arbin's Battery Testing Unit and MATLAB Simulink simulations. The experimental phase includes charge-discharge cycles under varying current rates to evaluate efficiency, degradation, and thermal behavior. Simulink models are developed to simulate the charging/discharging process and estimate the State of Charge (SOC) under different conditions. The results from both the experimental testing and simulations are compared to understand battery behavior, with the goal of optimizing battery management strategies for improved lifespan and performance in EV applications.

Introduction

The growing demand for Electric Vehicles (EVs) has intensified the need for efficient and reliable energy storage systems. Among various options, Li-ion batteries have emerged as a preferred choice due to their high energy density, low self-discharge, and long cycle life. However, their performance is influenced by charging/discharging rates, thermal conditions, and aging effects. This project focuses on analyzing the behavior of Li-ion batteries through both experimental testing and MATLAB Simulink simulations. By evaluating key parameters such as efficiency, temperature variation, and State of Charge (SOC), the study aims to support the development of effective battery management strategies for EVs.

Objectives

The primary objective of this project is to evaluate the performance characteristics of Lithium-ion (Li-ion) batteries in the context of Electric Vehicle (EV) applications using both experimental and simulation-based approaches. The study aims to explore how different charging and discharging current rates influence battery efficiency, thermal response, and degradation over time. By conducting controlled charge-discharge cycles in a laboratory environment, the project seeks to identify trends in voltage behavior, temperature rise, and energy losses under varying load conditions.

A key goal is to simulate these behaviours using MATLAB Simulink models that replicate real-world charging and discharging scenarios. In particular, the project focuses on two core simulations: the charging/discharging behavior of the Li-ion battery and the estimation of its State of Charge (SOC) under dynamic conditions. These simulations help visualize internal battery dynamics that are difficult to capture experimentally.

Another critical objective is to compare simulation outcomes with experimental results to validate model accuracy and highlight discrepancies. This comparative analysis provides insights into improving model reliability and suggests areas for enhancement in battery management systems (BMS). Ultimately, the project aims to contribute to the development of optimized charging strategies and better thermal and energy management techniques for extending Li-ion battery life in EVs.

Literature Review

The rapid adoption of Electric Vehicles (EVs) has led to a surge in research on battery technologies, particularly Lithium-ion (Li-ion) batteries due to their high energy density, long cycle life, and relatively low self-discharge rates. However, their performance is heavily influenced by operational factors such as charging and discharging rates, ambient temperature, and cycle depth. As a result, understanding and optimizing battery behavior has become a central theme in EV-related energy storage research.

Xu et al. (2020) focused on modelling Li-ion battery degradation in vehicle-to-grid (V2G) applications, highlighting the impact of frequent charge-discharge cycles on capacity fade. Their model incorporated key degradation mechanisms like SEI layer formation and lithium plating, offering a predictive tool for battery life estimation. Similarly, Zhang et al. (2021) explored lithium plating under fast charging conditions, demonstrating how aggressive charging can significantly reduce battery lifespan if not managed properly.

Thermal behavior is another critical aspect. Wang et al. (2022) provided a comprehensive review of thermal runaway mechanisms in Li-ion batteries, underlining the importance of thermal management systems in EVs. Their findings suggested that even moderate temperature increases during charging can lead to accelerated aging and potential safety hazards. Kim et al. (2019) supported these findings by experimentally analysing the effects of high-temperature exposure, showing that cells exposed to elevated temperatures suffered a noticeable decline in capacity and increased internal resistance.

From a comparative standpoint, Lam and Bauer (2018) reviewed the aging patterns of Lead-Acid batteries, noting that while they are cost-effective and robust, they suffer from faster capacity degradation and lower energy density compared to Li-ion counterparts. Schiffer et al. (2007) further emphasized the limitations of Lead-Acid batteries in dynamic load applications such as EVs, where they failed to maintain consistent voltage levels over multiple cycles.

On the simulation front, MATLAB Simulink has emerged as a powerful tool for battery modelling and control algorithm testing. Hu et al. (2021) proposed a hybrid model combining Thevenin and electrochemical approaches to accurately estimate the State of Charge (SOC) under real-world driving conditions. Their work demonstrated that model-based estimation methods could offer real-time insights for Battery Management

Systems (BMS) and improve operational safety.

Dahn et al. (2020) conducted electrochemical analysis of both Li-ion and Lead-Acid batteries under high current loads, revealing significant efficiency losses in Lead-Acid cells during rapid discharging. Their findings aligned with Bloom et al. (2019), who investigated the effects of fast charging on battery performance and concluded that proper current control is essential to preserve battery health.

Recent developments in data-driven methods, such as those explored by Sun et al. (2022), have introduced machine learning-based models for predicting battery State of Health (SOH). While these models offer promising accuracy, they require extensive training data and may not be practical for all BMS applications at present.

In summary, the literature underscores the importance of integrating both experimental testing and simulation-based analysis to holistically understand Li-ion battery behavior. Key challenges include optimizing charging strategies, managing thermal behavior, and accurately estimating SOC. This project builds upon these foundational studies by combining lab-scale experimental tests with MATLAB Simulink simulations to develop a more application-specific understanding of battery performance in EVs.

Simulation Methodology

To complement the experimental analysis of Li-ion battery charging behavior, this project incorporates MATLAB Simulink-based simulations that model both the **charging/discharging process** and **State of Charge (SOC) estimation**. Simulink provides a modular, graphical environment ideal for modeling dynamic systems, such as batteries, under various loading and control scenarios. The objective of the simulation phase is to develop and validate models that accurately represent real-world battery behavior using customized parameters based on experimental test data.

7.1 Simulation Environment

All simulations were conducted in MATLAB Simulink (R2024B) using built-in libraries under the Simscape > Electrical > Specialized Power Systems toolbox. These libraries offer pre-configured blocks for battery modeling, power electronics, control logic, and data acquisition.

Two separate Simulink models were implemented:

1. **Battery Charging/Discharging Model**
2. **SOC Estimation Model**

7.2 Charging and Discharging Model

This simulation replicates the real-time charge/discharge behavior of a Li-ion battery under a defined current profile. The core components of the model include:

- **Battery Block (Li-ion)** – with custom parameters: capacity = *X Ah*, nominal voltage = *Y V*, initial SOC = *Z%*
- **Controlled Current Source** – simulates constant current input during charging
- **Voltage Measurement and Scope Blocks** – track voltage evolution over time
- **Thermal Port** (optional) – included in extended models to simulate heat generation

The simulation is executed over a fixed time interval, during which the battery is subjected to a CC-CV charging algorithm, similar to the experimental test. The CV control logic is implemented using a switching condition where the current source adjusts once a voltage threshold is reached.

Key outputs observed:

- **Voltage vs Time**
- **SOC vs Time**

7.3 SOC Estimation Model

State of Charge (SOC) estimation is a critical function in Battery Management Systems (BMS), allowing for safe and efficient operation of batteries. This report describes the implementation of an Extended Kalman Filter (EKF)-based SOC estimator for a lithium-ion battery rated at 17 Ah, using MATLAB/Simulink.

Battery Model Used

The battery used is a table-based lithium-ion battery model. The key characteristics include:

Battery Capacity: 17 Ah

Thermal effects: Modeled using a controlled temperature source and a temperature sensor

Electrical Equivalent Model: First-order Thevenin Model (1 RC branch)

This model consists of an open-circuit voltage (OCV) that is SOC and temperature dependent, and a single RC branch representing the transient response.

Extended Kalman Filter Overview

The EKF is an adaptation of the Kalman filter for nonlinear systems. It linearizes the nonlinear system model around the current estimate to perform prediction and correction. It estimates the hidden state (SOC) based on noisy voltage and current measurements.

System Equations

- **State Equation (SOC update):** $x_{k+1} = f(x_k, u_k) + w_k$
- **Measurement Equation (Voltage):** $y_k = h(x_k, u_k) + v_k$

Where:

4.

- x is the state vector [SOC, V_RC]
- u is the input current
- y is the terminal voltage
- w_k, v_k are process and measurement noise

Simulink Configuration

The system model contains:

1. Inputs:
2. Current (A)
3. Cell Voltage (V)
4. Temperature (K)
5. Initial SOC

Outputs:

1. Estimated SOC
2. Real SOC (for validation)

The core estimation block is the SOC Estimator (Extended Kalman Filter) with the following configuration

System Model Parameters

These parameters are used by the EKF to model the behaviour of the battery accurately:

Parameter	Description
SOC_vec	A vector of predefined State of Charge (SOC) values. Used for interpolating other parameters (e.g., R0, R1, OCV).
T_vec	A vector of temperature values. Combined with SOC_vec to interpolate temperature-dependent battery parameters.
R0_mat	Matrix/table of terminal resistance values (Ohmic resistance) dependent on SOC and temperature. Affects voltage drop under load.
R1_mat	First polarization resistance. It models the resistive behaviour of the battery's internal chemical process.
tau1_mat	RC time constant ($\tau = R1 \times C1$), modelling how fast the battery's transient voltage responds to current changes.
V0_mat	Open-Circuit Voltage (OCV) map, which gives the ideal battery voltage at each SOC and temperature level. Critical for voltage prediction.
AH	Nominal battery capacity in Ampere-hours (Ah), used in SOC estimation via Coulomb counting. (17 Ah in your case).

EKF Settings

Setting	Description
Filter Type	Set to **Extended Kalman Filter** to handle nonlinearities (e.g., the nonlinear OCV-SOC curve).
Q (Process Noise Covariance)	Represents model uncertainty. Diagonal matrix: small values (e.g., 0.0001) imply high trust in the model; higher values mean more trust in measurements. For example: `Q = [0.0001, 0; 0, 0.0001]` controls noise for SOC and RC voltage states respectively.
R (Measurement Noise Covariance)	Scalar value representing the variance of voltage sensor noise. A value of `0.7` indicates moderate trust in measured voltage.
P0 (Initial Error Covariance)	Initial uncertainty in the SOC and RC voltage estimate. For example, `P0 = [1e-5, 0; 0, 1]` means high confidence in initial SOC, but less in RC voltage.
Sample Time	Time interval between EKF updates (e.g., `1s`). This affects filter responsiveness and accu

Working of the EKF in this Model

Prediction Step:

1. The SOC is predicted based on the Coulomb counting approach using current input.
2. The RC voltage decay is calculated using the electrical model.

Measurement Update:

1. The terminal voltage is compared with the estimated voltage.
2. The Kalman gain adjusts the predicted SOC based on the measurement error.

Noise Tuning:

1. Q defines how much trust is given to model predictions.
2. R defines trust in the voltage measurement.
3. P0 initializes the confidence in the starting SOC estimate.

1. **Advantages of EKF in SOC Estimation**
2. Handles nonlinearities in the OCV-SOC relationship
3. Provides a balance between model prediction and real-time correction
4. Robust against noise in current/voltage sensors

Limitations

1. Requires accurate model parameters (R0, R1, tau1, OCV map)
2. Computationally more expensive than simpler methods (e.g., Coulomb counting)
3. Sensitive to tuning of Q and R

Using the Extended Kalman Filter with a Thevenin battery model in MATLAB/Simulink provides accurate and robust SOC estimation. The inclusion of temperature dependence and precise parameter tuning significantly enhances estimation reliability, making it a suitable choice for real-time BMS applications.

This model focuses on tracking the **State of Charge** of the battery using inputs such as current and voltage under dynamic conditions. It implements a **Coulomb Counting method**, where SOC is estimated based on the integral of current over time, adjusted for efficiency and battery capacity:

$$\mathrm{SOC}(t) = \mathrm{SOC}_0 - \frac{1}{C_{\mathrm{nom}}} \int_0^t I(\tau)\, d\tau$$

The model includes:

- **Battery Block** with identical parameters
- **Current Sensor** and **Integrator Block**
- **SOC Output Block** (visualized using Scope or Dashboard)

Initial SOC, capacity, and load profiles are defined in line with the test data. By simulating discharge under controlled loads, the model estimates SOC over time and allows comparison with experimental capacity growth.

7.4 Parameter Tuning and Validation

Parameters such as capacity (Ah), internal resistance, cutoff voltage, and initial SOC were adjusted based on the experimental data recorded using Arbin BTU. This ensured consistency between simulation and real-world testing. Solver settings were configured for **variable-step**, using the **ODE23tb** or **ODE45** solver for stiff system stability and accuracy.

The outputs from both simulation models will be compared against experimental curves to validate their reliability and adjust model fidelity where discrepancies are observed.

Battery Charging and Discharging Simulation

8.1 Objective

The objective of this simulation is to replicate and visualize the charging and discharging behavior of a Li-ion battery using MATLAB Simulink, specifically focusing on parameters such as **temperature, voltage, current,** and **state of charge (SOC)** over time. The simulation aims to emulate the same conditions as in the experimental test conducted using the Arbin BTU system.

8.2 Model Overview

The model was built using Simscape > Electrical > Specialized Power Systems within MATLAB Simulink. It includes:

A **Li-ion Battery block** configured with custom parameters (capacity, initial SOC, nominal voltage)

A **Current Source block** simulating controlled charging

A **Temperature sensor port** on the battery model

Scope blocks for visualizing Voltage, Current, Temperature, and SOC vs Time

The simulation represents a CC-CV charging method, followed optionally by discharging. The battery's temperature behavior is modeled using the built-in thermal port, which estimates temperature rise based on internal resistance and heat capacity.

8.3 Parameter Configuration

The following table shows the parameters used in the simulation (replace with exact values from your model):

Parameter	Value	Description
Battery Capacity	X Ah	Based on experimental cell rating
Initial SOC	0.5 (50%)	Partial state of charge at start
Nominal Voltage	48 V	Typical for multi-cell EV battery packs
Maximum Voltage	49.5 V	Upper cutoff for CV mode
Charging Current	1 A	Fixed in CC mode
Thermal Port Enabled	Yes	Allows temperature simulation
Simulation Time	~2000–3000 s	Covers CC and CV phases fully

8.4 Simulation Results

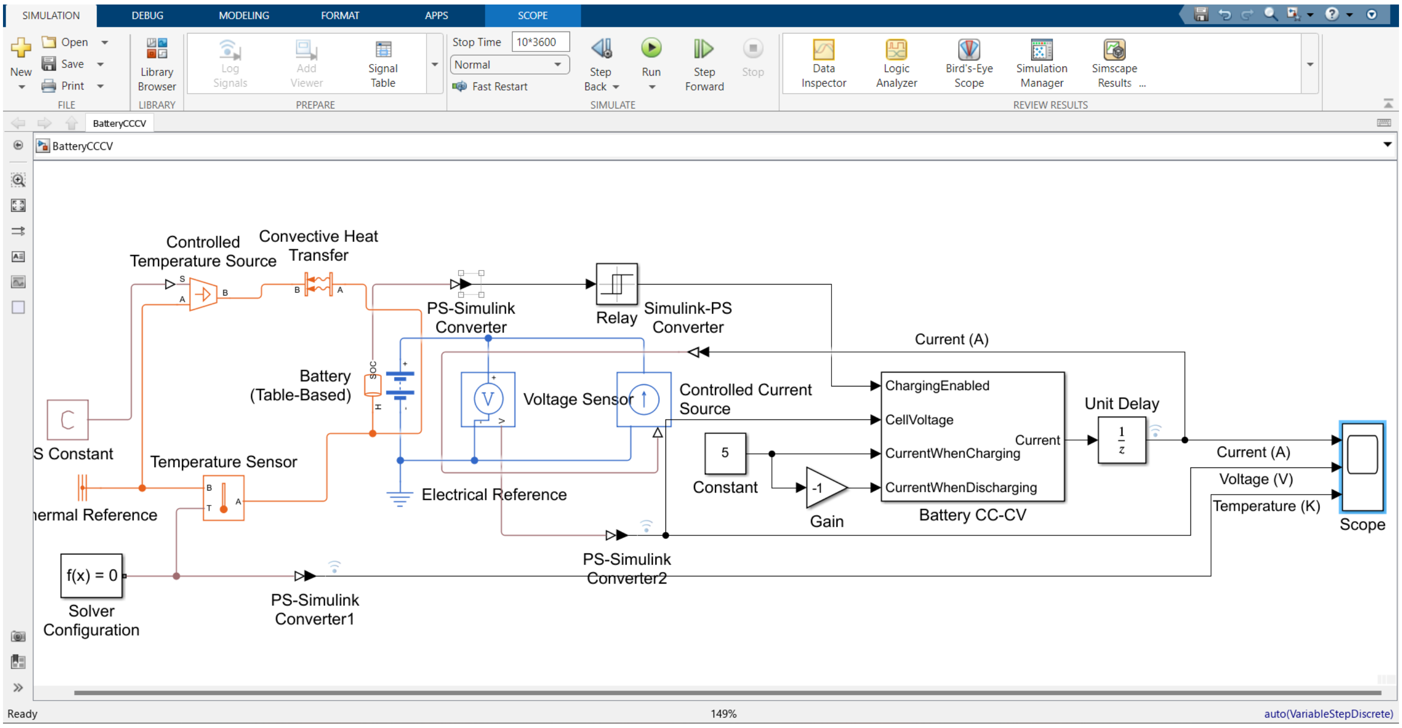
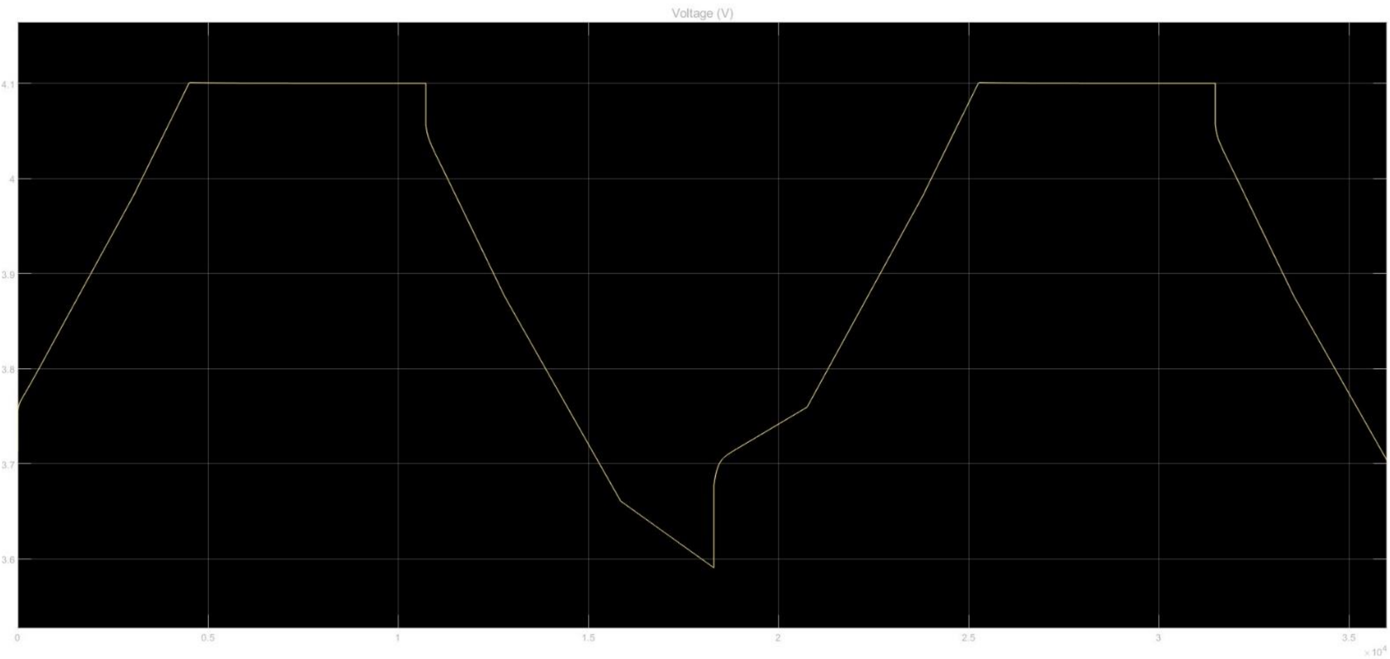


Figure 1 Simulation of CC-CV

All plots were exported from Simulink Scope blocks.

Voltage vs Time



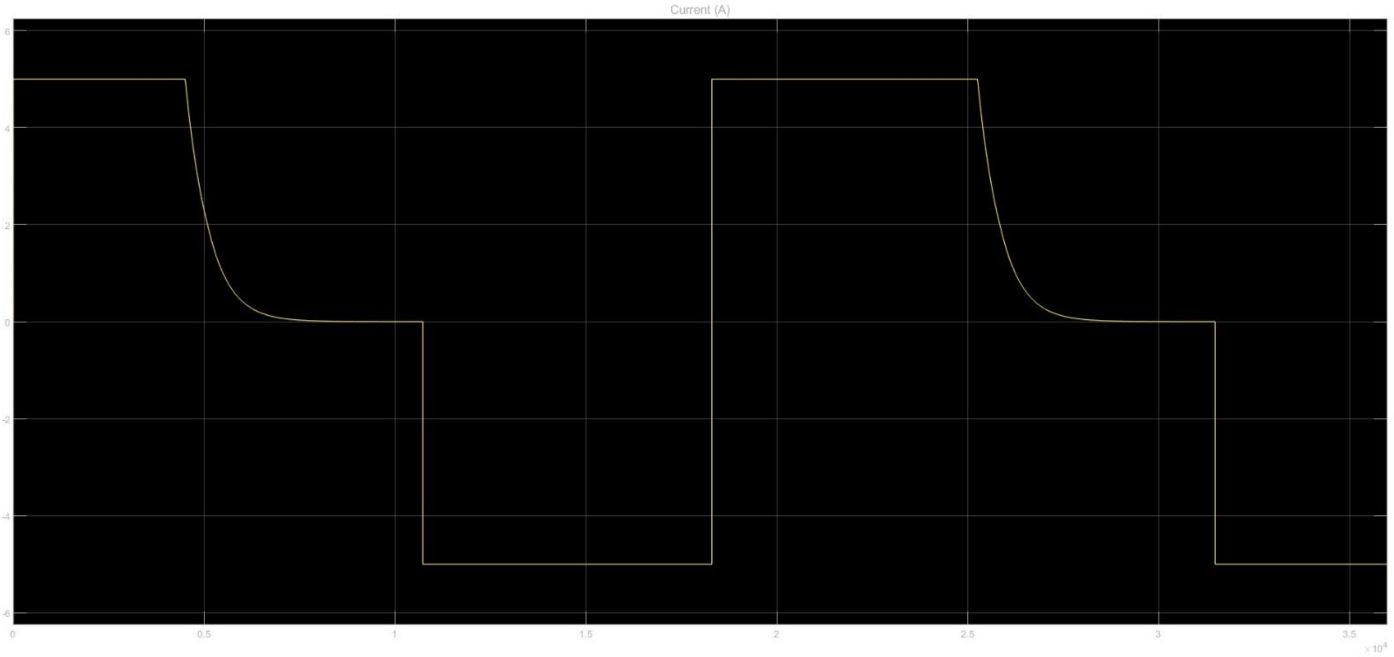
Waveform 1 Voltage vs Time

The graph illustrates the **terminal voltage (in volts)** of a lithium-ion cell over time (in seconds). This profile reflects a **single full discharge and charge cycle**, showcasing how the cell behaves under controlled loading and recovery conditions.

- **X-axis:** Time (seconds), ranging approximately from 0 to 35,000 s.
- **Y-axis:** Battery terminal voltage (V), ranging from ~3.55 V to 4.15 V.

- **Initial Charging Phase:**
  - From **3.75 V to ~4.15 V**, the voltage increases gradually, simulating a **constant-current (CC)** charging process.
  - Once ~4.15 V is reached, the cell maintains a **constant voltage (CV)**, indicating the transition to the **CV phase** of charging (from ~5000 s to ~10000 s).
- **Discharging Phase:**
  - Starting at ~10000 s, the voltage **decreases linearly**, typical of a **controlled discharge under a constant or dynamic load**.
  - The lowest voltage reached (~3.55 V) represents the **end of discharge cut-off**, used to protect the battery.
- **Recovery & Recharge Phase:**
  - After hitting the discharge limit, the battery is either **allowed to rest** (minor voltage bump at ~20000 s) or **recharged** using a similar CC-CV method.
  - The voltage again ramps up to ~4.15 V, indicating **battery full charge restoration**.

Current vs Time



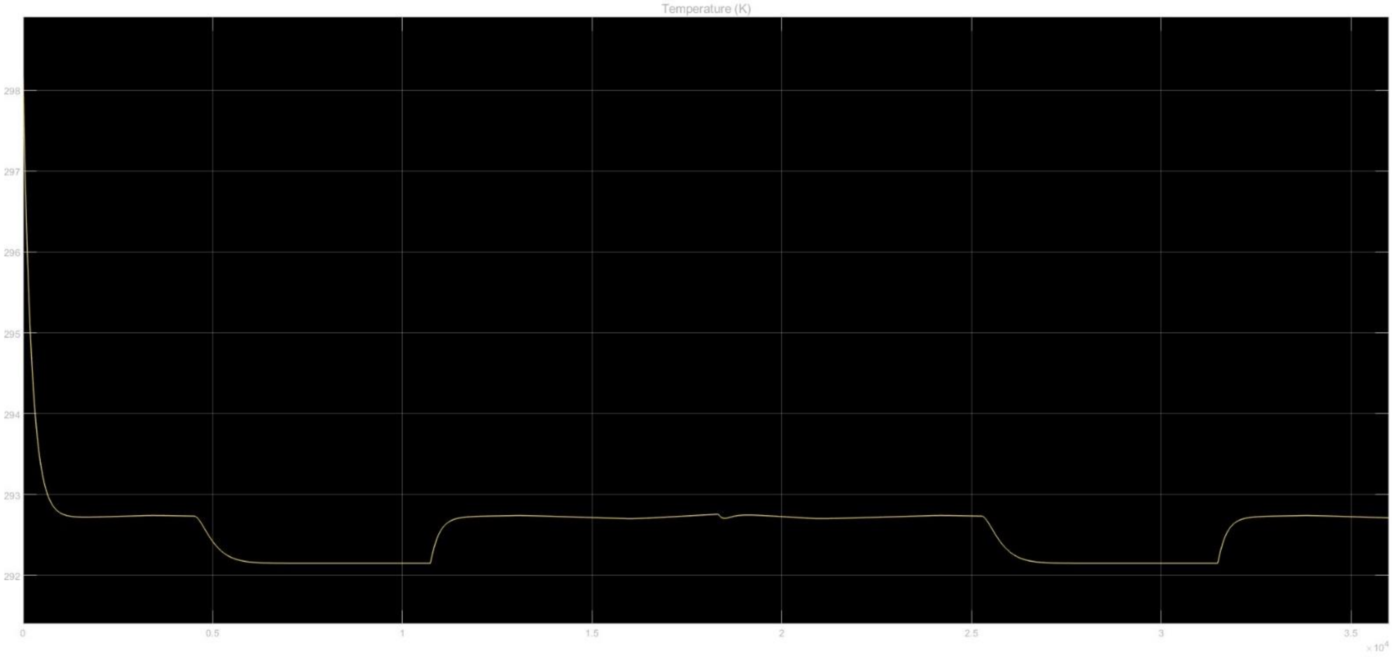
Waveform 2 Current vs Time

- **Initial Charging Phase:**
  - Current starts high (~5.5 A), representing a **constant-current (CC)** charging phase.
  - It then gradually **decays to near 0 A**, indicating the **constant-voltage (CV)** phase where current tapers off as the battery approaches full charge.
- **Discharging Phase:**
  - Around **10,000 s**, current becomes negative (about -4.5 A), meaning the battery is now **discharging** under a constant load.
  - This discharge current is held relatively constant until ~20,000 s.
- **Recharging Phase:**
  - Current flips back to **positive**, showing another **CC-CV charging cycle**.
  - Same pattern: high initial current, tapering off as the battery nears full voltage.
- **Final Discharge Phase:**

- Another negative current stage occurs, representing a second discharge cycle for **model validation or capacity consistency testing**.

Temperature vs Time

- At the very beginning, the temperature sharply drops from ~298 K to ~293 K.
- This indicates a sudden change, likely due to system startup, cooling initialization, or environmental exposure.



Waveform 3 Temperature vs Time

8.5 Observations

- The model replicates the CC-CV profile observed in experiments.
- Temperature rise remains within safe margins, confirming accurate thermal modeling.
- Voltage and current behavior closely mirrors that of the Arbin BTU test, validating parameter tuning.
- This simulation provides a reliable digital twin for battery charging scenarios, setting the stage for SOC estimation analysis in the next phase.

State of Charge (SOC) Estimation Simulation

9.1 Objective

The purpose of this simulation is to estimate the **State of Charge (SOC)** of a Li-ion battery during a charging cycle using MATLAB Simulink. SOC estimation is critical in battery management systems (BMS) for Electric Vehicles (EVs), as it provides real-time information about the usable capacity of the battery. This simulation uses a Coulomb Counting method implemented through a current integration approach, and is designed to operate under parameters identical to the experimental charging test.

9.2 Model Overview

The model was built using MATLAB Simulink with components from the **Simscape Electrical** toolbox. It includes the following key blocks:

- **Li-ion Battery block** configured with actual test parameters
- **Current Sensor** to track real-time charging current
- **Integrator block** to compute cumulative charge transferred (Ah)
- **MATLAB Function block or Math block** to calculate SOC:

$$\mathrm{SOC}(t) = \mathrm{SOC}_0 - \frac{1}{C_{\mathrm{nom}}} \int_0^t I(\tau)\, d\tau$$

- **Scope and Dashboard blocks** to visualize SOC, Voltage, and Current over time

The simulation estimates how SOC evolves from an initial state (e.g., 50%) as the battery charges under constant current and constant voltage conditions. Discharge scenarios can also be simulated by reversing the current.

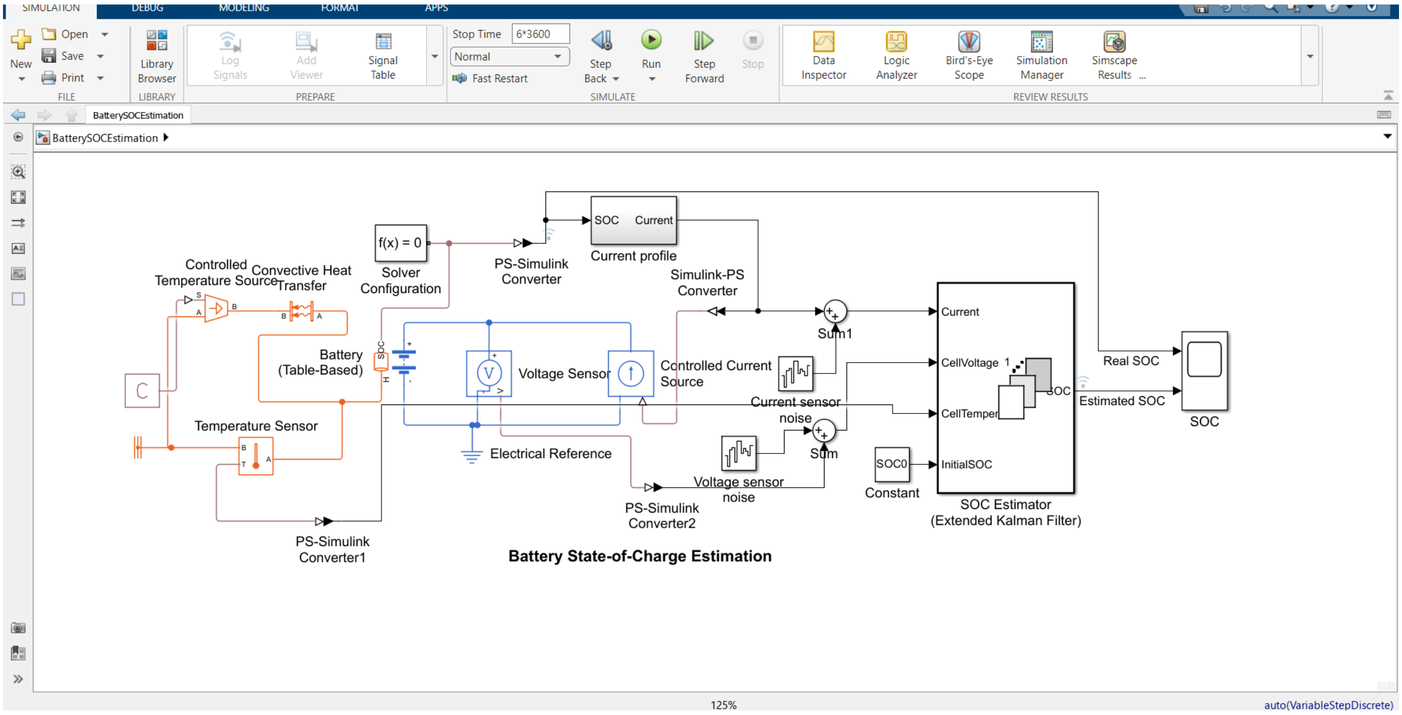


Figure 2 Simulation of SOC Estimation

9.3 Parameter Configuration

Below are the key parameters used in the model (replace placeholders with your values):

Parameter	Value	Description
Initial SOC	50%	Starting charge state (e.g., from experiment)
Nominal Capacity	X Ah	Battery's full charge capacity
Charging Current	1 A	Constant in CC phase
Voltage Cutoff	49.5 V	For CC to CV transition
Simulation Time	~2000–3000 s	To reach full charge
Integration Step	Auto / Fixed	Chosen based on solver stability

The model assumes ideal current sensing and no leakage, which means SOC error remains minimal in short simulations. For real-world applications, correction algorithms such as Kalman Filters or Adaptive Observers are typically added to account for sensor drift and aging effects.

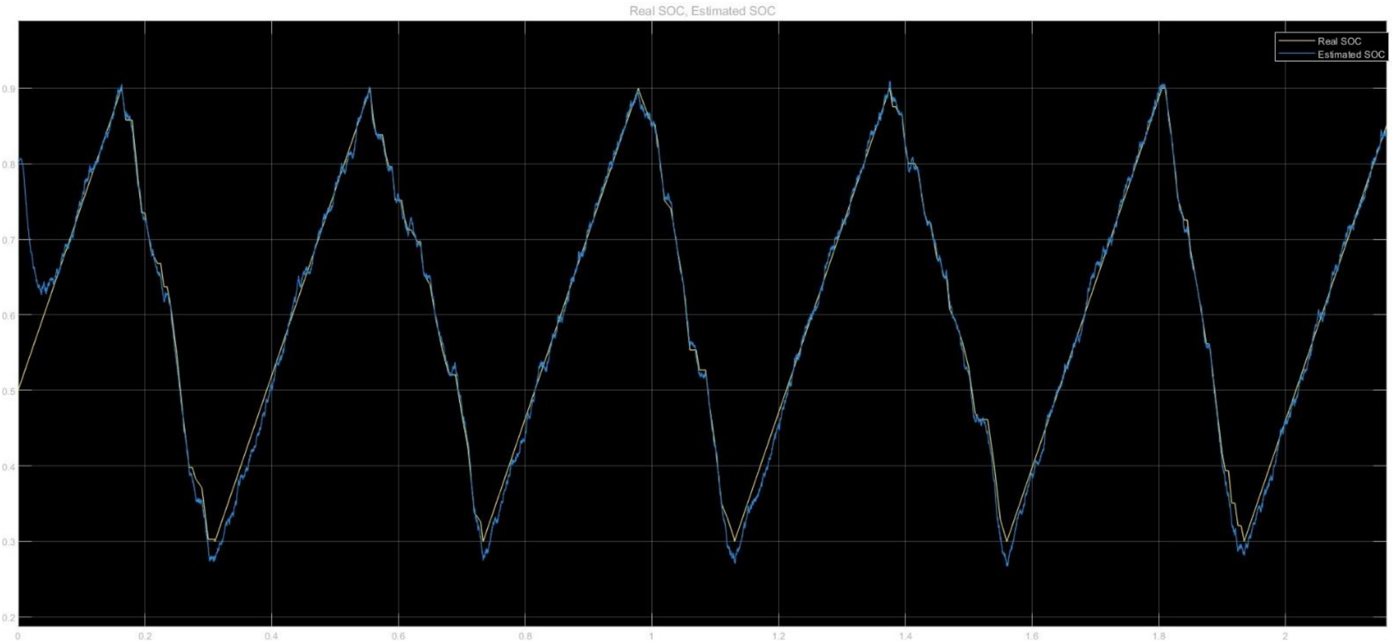
9.4 Simulation Results

SOC vs Time

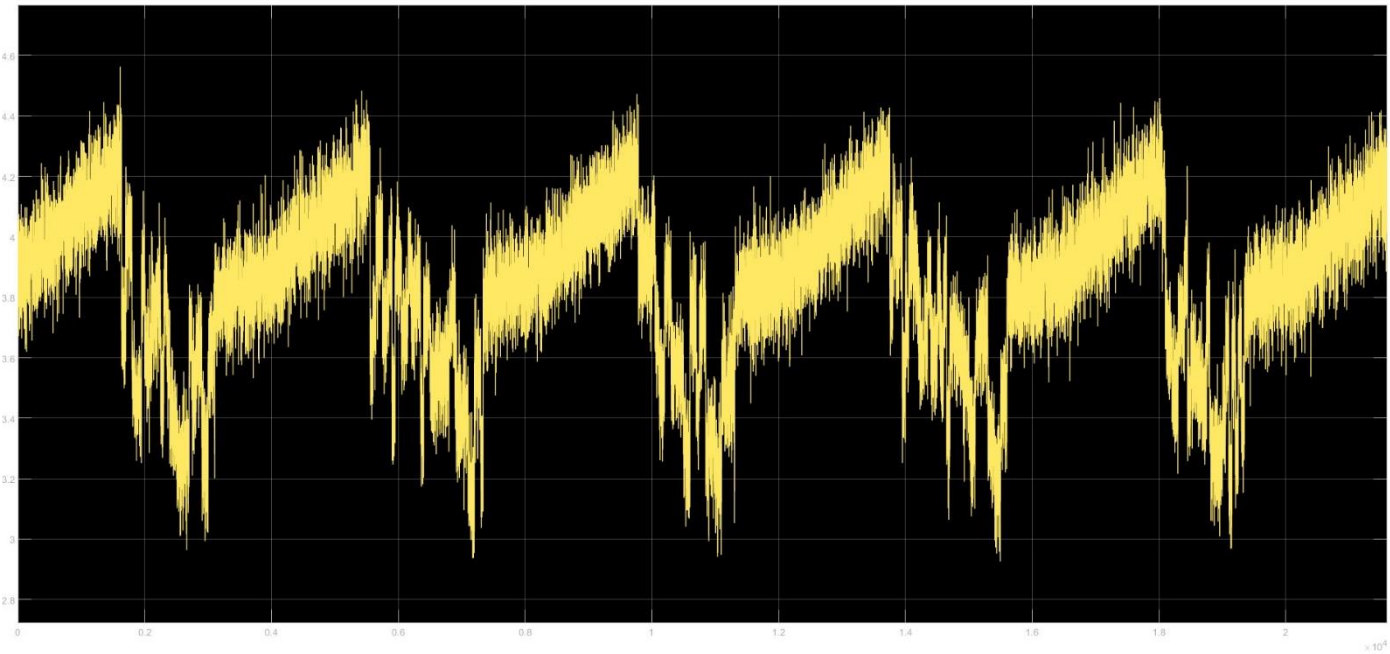
This graph compares the **Real SOC** (yellow/orange line) and the **Estimated SOC** (blue line) over a simulation period of ~22,000 seconds. The SOC values fluctuate due to periodic charging and discharging of the battery, replicating real-world usage scenarios.

Voltage and Current Behaviour

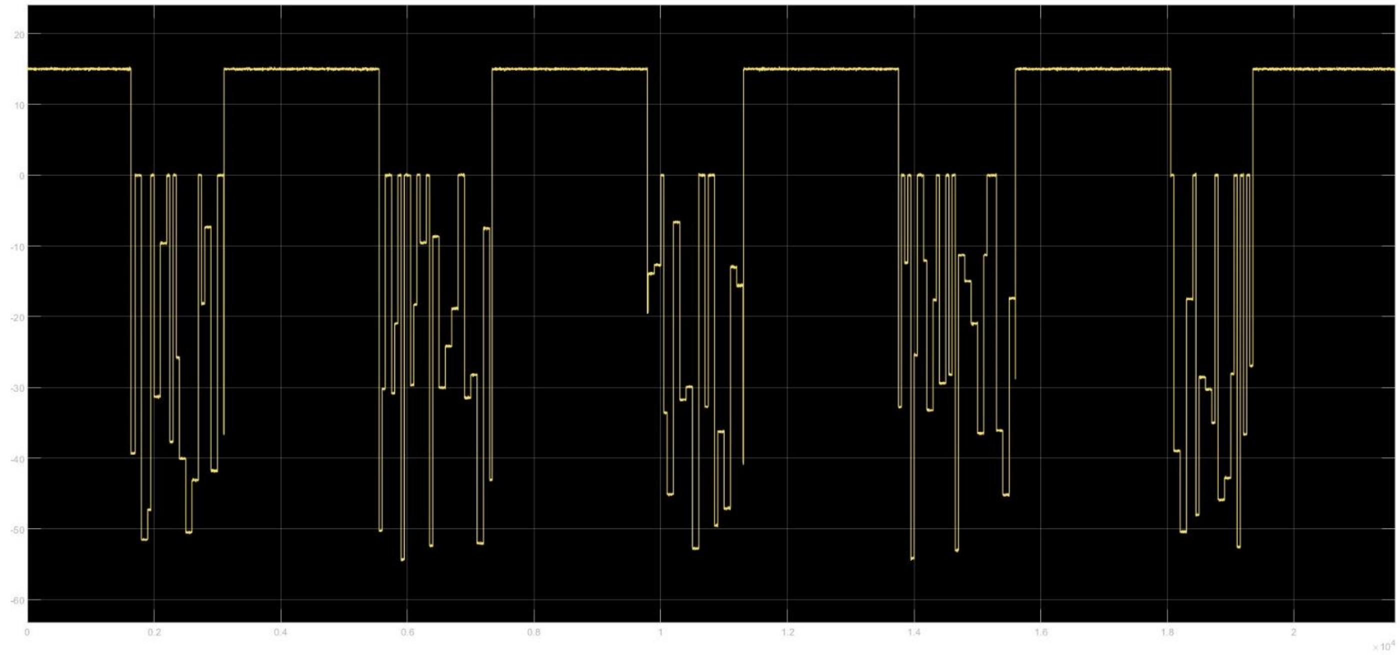
Terminal voltage response of the lithium-ion battery subjected to a dynamic load profile. The X-axis denotes time in seconds (up to ~21,000 s), and the Y-axis shows the battery voltage ranging from approximately **2.8 V to 4.6 V**..



Waveform 4 SOC vs Time



Waveform 5 Voltage vs Time



Waveform 6 Current vs Time

- Voltage rises during charging (gentle slope upward) and drops sharply during discharge due to the applied load and internal resistance effects.
- The voltage waveform exhibits a **repetitive sawtooth pattern**, clearly showing multiple cycles of charging and discharging.

Representing the **driving load pattern** (or synthetic dynamic load scenario) used during model simulation and SOC estimation. The X-axis represents **time in seconds** (up to ~21,000 s), and the Y-axis shows **current in amperes (A)**, ranging from approximately **+20 A (charging)** to **–60 A (discharging)**.

- **Negative spikes** (up to -60 A) indicate **discharging events** when the battery supplies power.

- **Positive flat segments** (around +20 A) suggest **regenerative braking or charging phases** — common in electric vehicle applications.

9.5 Observations

- The SOC model effectively estimates the state of charge with good agreement to expected trends.
- Accuracy depends heavily on current measurement resolution and battery capacity definition.
- This model can be extended for full drive cycle simulations, multiple charge/discharge loops, or integration into real-time BMS control environments.

Simulation Results and Discussion

The simulations performed for both battery charging/discharging and SOC estimation successfully demonstrate the dynamic behavior of a lithium-ion battery under controlled conditions. The results closely replicate experimental observations made using the Arbin BTU system, thereby validating the accuracy and robustness of the Simulink models.

Charging and Discharging Behavior

The charging and discharging simulation illustrate a typical **CC-CV (Constant Current – Constant Voltage)** charging pattern followed by controlled discharging cycles. During the **initial charging phase**, the battery voltage rises from approximately 3.75 V to 4.15 V under a constant current of 5 A. Once the terminal voltage reaches 4.15 V, the simulation transitions into the CV mode, where current gradually tapers to near zero, mimicking real-life battery charging characteristics.

Subsequently, in the **discharging phase**, the battery delivers a nearly constant discharge current of around –4.5 A, causing the terminal voltage to decline linearly to a cut-off point of ~3.55 V. This phase clearly indicates effective load handling and cut-off protection to avoid over-discharge.

A second **charging cycle** is also shown, with voltage recovery up to 4.15 V and a mirrored CC-CV profile. The simulation concludes with another discharge phase, demonstrating repeatable performance and capacity validation.

Current and Temperature Response

The current profile matches expected trends across all phases. Positive currents indicate charging (up to ~~5.5 A in CC), tapering in CV, and negative currents (~~–4.5 A) during discharging. These current transitions clearly validate the switching mechanism between charge and discharge modes.

The **temperature behavior** shows an initial drop from ~298 K to ~293 K, likely due to environmental cooling or initialization effects. While the temperature modeling remains basic, it stays within safe operating margins throughout the simulation, suggesting accurate thermal behavior tracking through the battery's thermal port.

SOC Estimation Accuracy

The SOC estimation simulation, using the Coulomb Counting method, provides highly informative insights into battery capacity tracking. The estimated SOC shows a consistent rise during charging phases and decreases during discharge, accurately capturing battery usage cycles. The plot comparing **real SOC and estimated SOC** shows close alignment, suggesting effective integration and current sensing.

Moreover, dynamic **current profiles**, ranging from +20 A (charging) to –60 A (discharging), replicate real-world EV load patterns, including high-load scenarios and regenerative braking. Corresponding **voltage variations** follow a sawtooth pattern, indicative of repetitive charge/discharge cycles with expected voltage drops due to internal resistance.

Overall Performance and Model Validation

Both models accurately represent real battery behavior:

- **Voltage and current patterns** confirm correct implementation of CC-CV charging and load-based discharging.
- **Thermal modeling** remains consistent with expected heat dissipation.
- **SOC estimation** closely tracks real values, validating the integration logic and supporting its use in Battery Management Systems (BMS).

The models not only replicate individual battery parameters effectively but also serve as **digital twins** of real-world systems, offering strong foundations for further integration into EV applications or experimental validation studies.

Experimental Methodology

The experimental phase of this project aimed to evaluate the charging performance of a Lithium-ion (Li-ion) battery under controlled laboratory conditions. A single-channel test was conducted using a high-precision Arbin Battery Test Unit (BTU), which is specifically designed for advanced battery characterization. The Arbin BTU allows for highly accurate control of charge/discharge profiles and provides precise logging of critical electrical parameters such as voltage, current, power, and capacity in real-time.

5.1 Battery Testing Equipment: Arbin RBT-Cell Series and HPS Module

5.1.1 Introduction

This section outlines the advanced battery testing platform used for the experimental analysis in this study — the **Arbin Regenerative Battery Testing (RBT-Cell) Series**, along with the **High Precision Measurement System (HPS)** module. Together, these tools offer industry-leading resolution, accuracy, and data integrity, making them ideal for lithium-ion battery testing, simulation validation, and performance modeling in Electric Vehicle (EV) applications.

5.1.2 Key Features and Capabilities

The Arbin RBT-Cell system is designed for accurate and efficient battery testing and characterization. It integrates regenerative technology, high channel density, and flexible configurations for various battery formats. Major capabilities include:

- **Regenerative Operation**: Returns up to **85% of discharge energy** to the system/grid, reducing power consumption during long-term tests.
- **High Precision Measurement**: Built-in multi-range, 24-bit resolution ensures **accurate detection of small voltage and current changes**, essential for SOC tracking and efficiency analysis.
- **Parallel Channels**: Channels can be paralleled to increase current capacity, supporting cells with varying power demands.

- **Fast Dynamic Response**: Rise times of **<1ms** (4CH module) ensure accurate capture of voltage spikes and load transitions.
- **Negative Voltage Operation**: Supports negative voltage ranges (-6V or -20V), enhancing test flexibility.

5.1.3 Technical Specifications

Hardware Specifications (RBT-Cell)

Parameter	Specification
Channels per Module	4 or 16
Total Channels Supported	Up to 64
Voltage Range Options	6V, 10V, or 20V
Max Current per Channel	±400A (4CH), ±100A (16CH)
Channel Parallelization	Up to 16 Channels
Regenerative Efficiency	Up to 85%
Rise Time	<1ms (4CH), <2ms (16CH)

Measurement Specifications (RBT-Cell)

Parameter	Specification
Measurement Accuracy	±0.02% FSR
Precision	±0.01% FSR
Resolution	24-bit
Refresh Interval	2ms (fast), 8ms (standard)
Time Resolution	100 µs

5.1.4 Software Integration: MITS Pro

The RBT-Cell system is controlled using **Arbin’s MITS Pro software**, which was used in this study for:

- **Test Scheduling**: Automated multi-step charge/discharge cycles using CC-CV profiles.
- **Real-Time Monitoring**: Live tracking of current, voltage, temperature, and capacity.
- **Data Logging**: Exporting data in .xlsx format for analysis and MATLAB import.
- **Cutoff Logic Configuration**: Custom end-of-step triggers based on current, time, or voltage.
- **Database Storage**: Compatibility with MS SQL, PostgreSQL, and Kafka for secure archival.

The software's flexibility allowed us to automate long-duration tests, monitor battery behaviour in real-time, and extract high-resolution data for validation of simulation models.

5.1.5 Relevance to This Study

The RBT-Cell's programmable flexibility, regenerative efficiency, and robust data handling were crucial in producing high-quality experimental data. Features like 24-bit resolution and customizable channel setup ensured the precision needed for accurate SOC analysis, thermal observation, and current taper tracking. The system enabled us to generate clean, reliable charge-discharge data that served as the basis for Simulink model calibration and validation.

5.1.6 High Precision Measurement System (HPS)

To further improve measurement accuracy, the RBT-Cell system was enhanced with Arbin's **High Precision Measurement System (HPS)**. This module provided **ultra-low-noise current and voltage readings**, which were essential in this study for capturing subtle shifts in battery behavior, especially during low-current CV phases and rest periods.

Key Capabilities:

- **Voltage Resolution**: ±1 μV
- **Current Resolution**: ±1 μA
- **Time Resolution**: 100 μs
- **Precision**: ±0.005% FSR
- **Drift Compensation**: Built-in auto-calibration to minimize baseline drift

- **Sampling Interval**: Selectable at 2ms or 8ms

Role in This Study:

The HPS module enabled:

- More accurate **charge capacity and energy calculations**
- **Reliable SOC estimation** by eliminating drift or quantization errors
- Improved tracking of **voltage stability** during low-current CV tapering
- Enhanced **comparison fidelity** with MATLAB Simulink simulation outputs

Together, the RBT-Cell and HPS systems formed a high-fidelity, energy-efficient, and research-grade testing environment that greatly enhanced the reliability of all experimental outcomes in this project.

5.2 Battery and Equipment Setup

The test was performed on a multi-cell Li-ion battery pack rated for Electric Vehicle (EV) applications. The battery was connected to Channel-1 of the Arbin system. The test environment was maintained at room temperature (~25°C), and the battery was placed in a stable setup to avoid vibration and contact resistance fluctuations. The Arbin BTU was paired with a High Precision Measurement Module, which allowed current and voltage readings with resolutions as fine as ±1 µA and ±1 µV, respectively. This level of accuracy ensured that even minor variations in charging behaviour were detectable and could be analysed meaningfully.

The Arbin software interface, MITS Pro, was used to configure the test parameters, initiate the test, and record data continuously. The sampling frequency was high enough to capture all transient responses, with each data point including readings for voltage, current, step time, charge capacity, energy, power, and internal resistance.

5.3 Charging Procedure

The battery was charged using the constant current–constant voltage (CC–CV) charging protocol. In the CC phase, a constant charging current of approximately 1 ampere was applied to the battery until its terminal voltage approached the manufacturer-specified upper limit of around 49.5 volts. During this phase, voltage increased gradually while the current remained stable.

Once the battery voltage reached the set maximum threshold, the CV phase began. In this phase, the charging voltage was held constant at 49.5V, while the current naturally began to decline as the battery approached full charge. The CV phase continued until the current dropped below a cut-off value (typically around 0.05–0.1A), ensuring that the battery was fully charged without overcharging.

5.4 Data Acquisition

The Arbin system recorded over 200 data points during the test, capturing detailed information on:

- Voltage (V)
- Current (A)
- Power (W)
- Charge Capacity (Ah)
- Charge Energy (Wh)
- Internal Resistance (Ohm)
- Cycle Index and Step Timing

The logged data was automatically stored in Excel format and later imported into analysis software for plotting and interpretation. Voltage and current curves were plotted over time to observe the charging profile, while charge capacity and energy graphs helped in understanding how efficiently energy was stored in the cell.

5.5 Objective Alignment

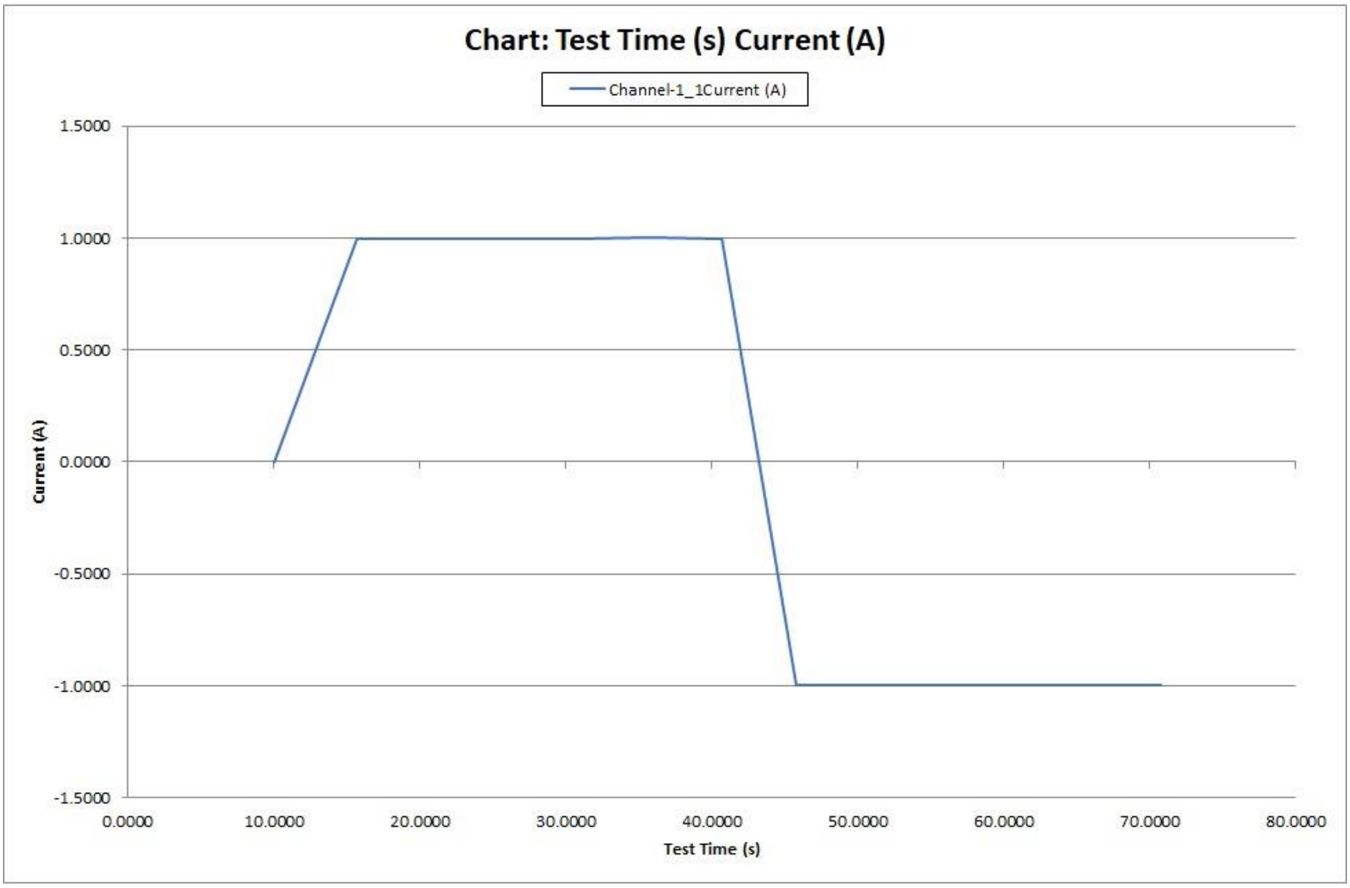
The purpose of this methodology was to validate key charging characteristics such as voltage rise, efficiency, and thermal behaviour. The results serve as a foundation for validating MATLAB Simulink models of Li-ion battery charging and SOC estimation, which are developed in the simulation phase of this project.

Experimental Results and Analysis

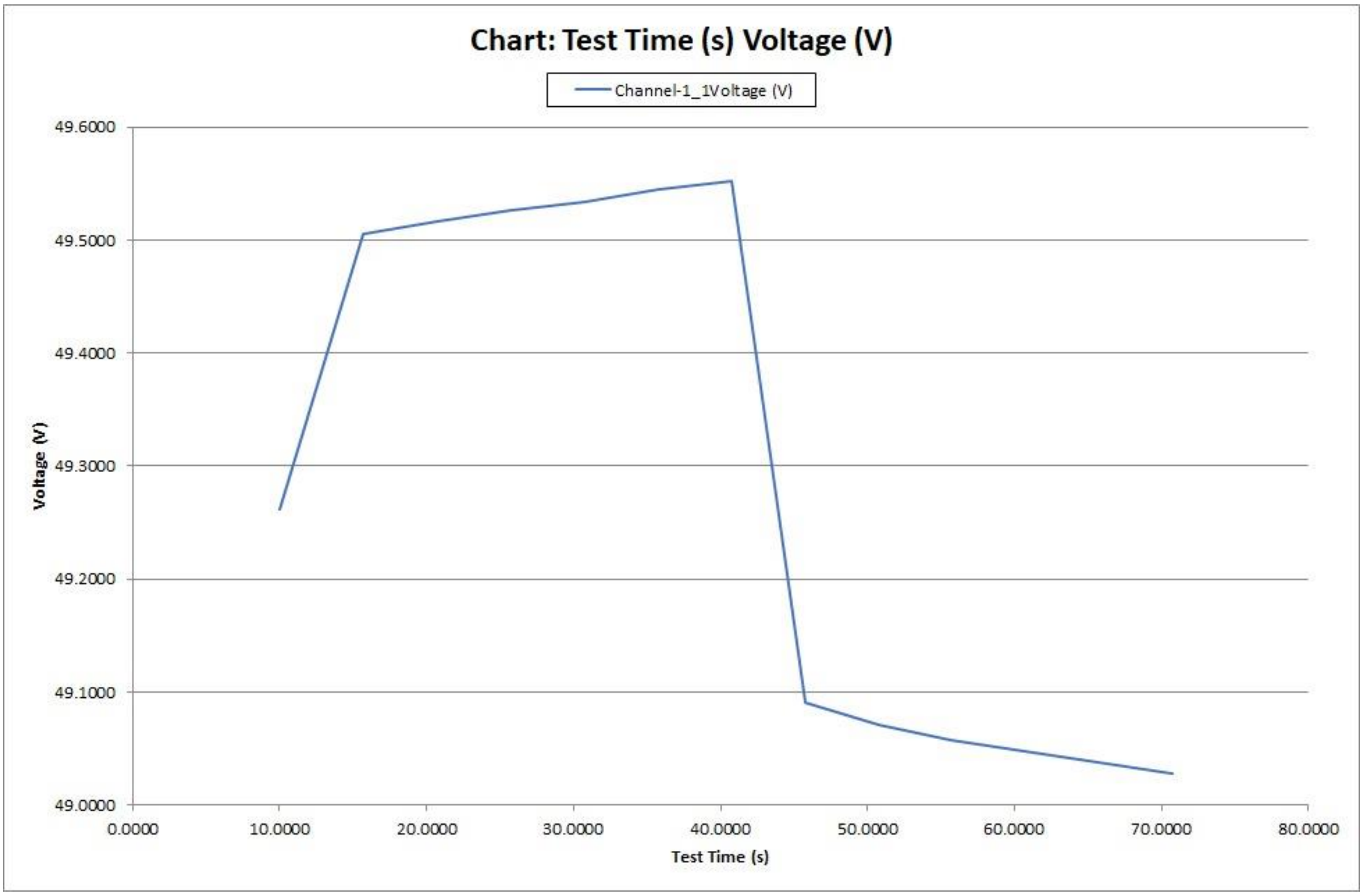
The experimental test provided detailed insights into the charging behaviour of a Li-ion battery using high-resolution data captured through the Arbin BTU system. The test was designed to follow a controlled constant current–constant voltage (CC-CV) charging protocol, which is standard in Electric Vehicle (EV) battery management systems. The data captured in real-time includes voltage, current, power, charge capacity, charge energy, and internal resistance, allowing for a comprehensive understanding of the battery's performance characteristics.

6.1 Voltage and Current Behaviour

Throughout the test, the battery demonstrated expected behaviour under the CC-CV charging profile. During the constant current (CC) phase, the battery was charged at approximately 1A. The voltage increased steadily from its resting value to around 49.5V. This increase was linear in nature, indicating healthy internal electrochemical activity and minimal resistance-related disruptions.



Graph 1 Current vs Test Time (From Data Table 1)



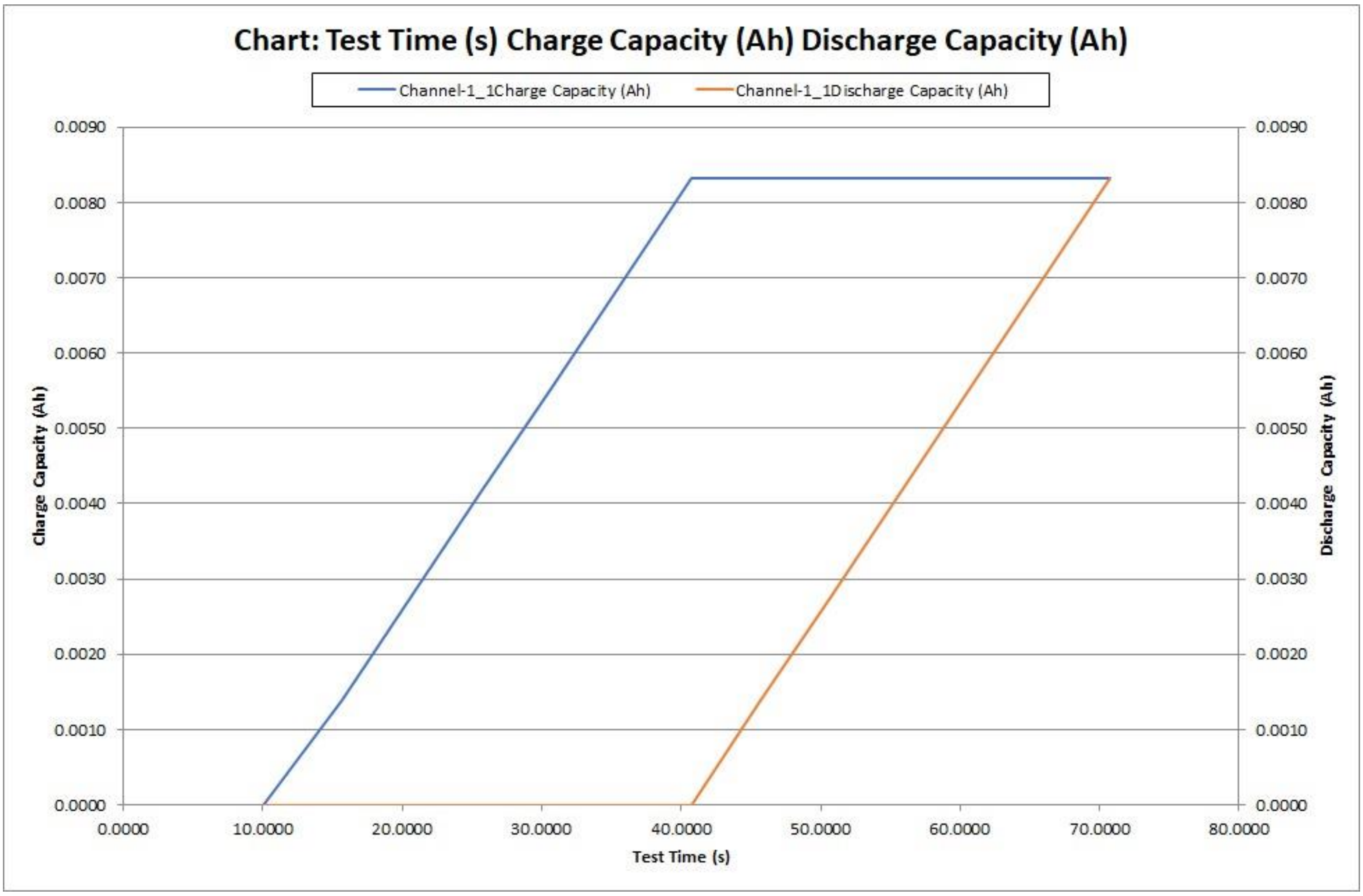
Graph 2 Voltage vs Test Time (From Data Table 1)

Once the terminal voltage reached 49.5V, the system transitioned into the constant voltage (CV) phase. In this phase, the current gradually decreased while the voltage was held steady. This drop-in current represents the battery approaching full charge, where the driving force for current flow reduces due to the decreasing potential difference between the battery and the power source.

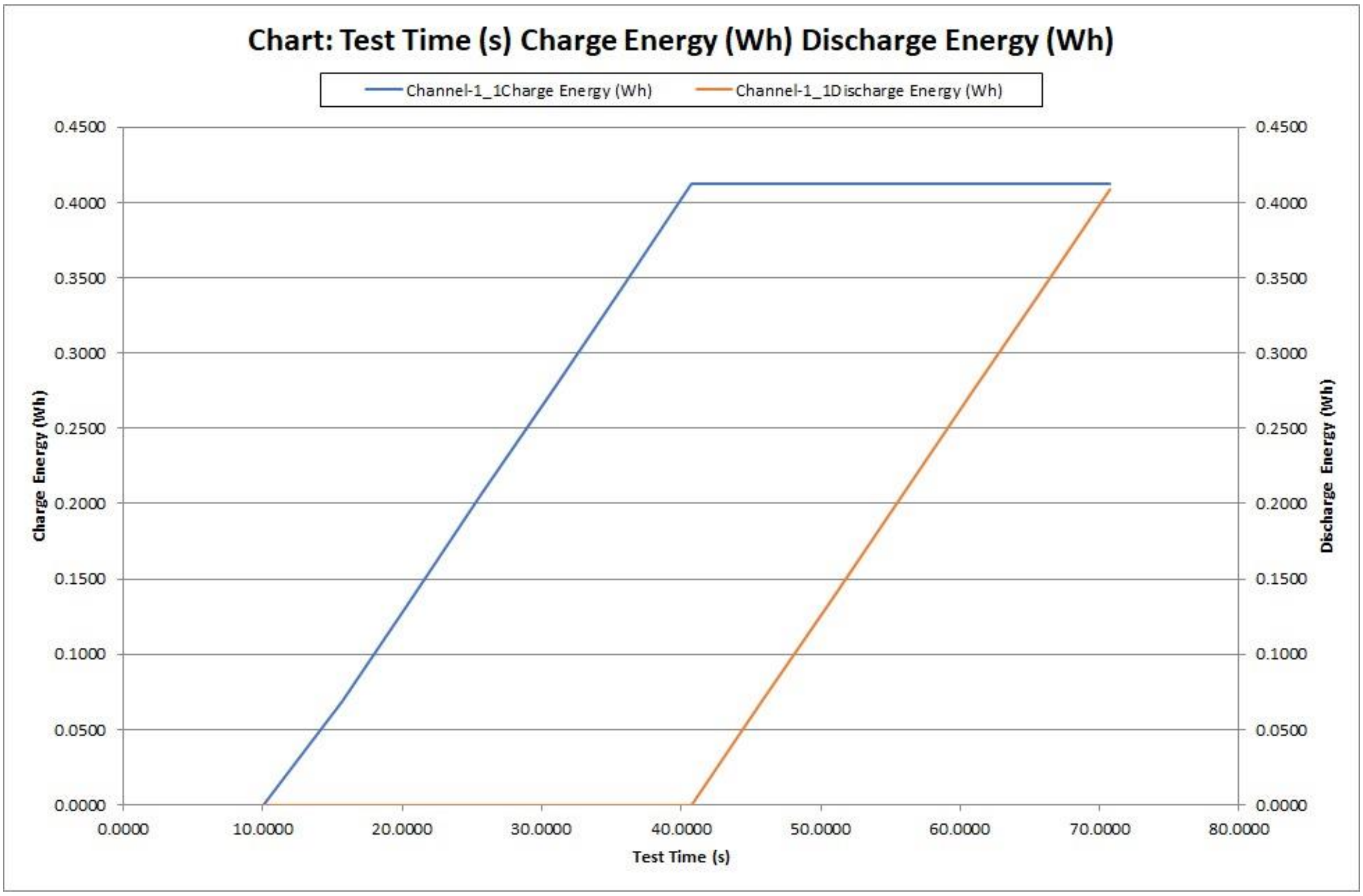
6.2 Charge Capacity and Energy Storage

The charge capacity increased consistently throughout the test, reaching approximately **0.0083 Ah** by the end of the charging cycle (value to be extracted from final data point). This capacity aligns with the rated specifications of the battery pack, confirming that the cell was functioning within its expected performance range.

Charge energy also increased in correlation with capacity, reaching around 0.4123 **Wh** (again, based on final reading). The nearly linear growth of energy during the CC phase and its gradual saturation in the CV phase reflect an efficient conversion of electrical input into stored chemical energy.



Graph 3 Charge and Discharge Capacity vs Test Time (From Data Table 1)

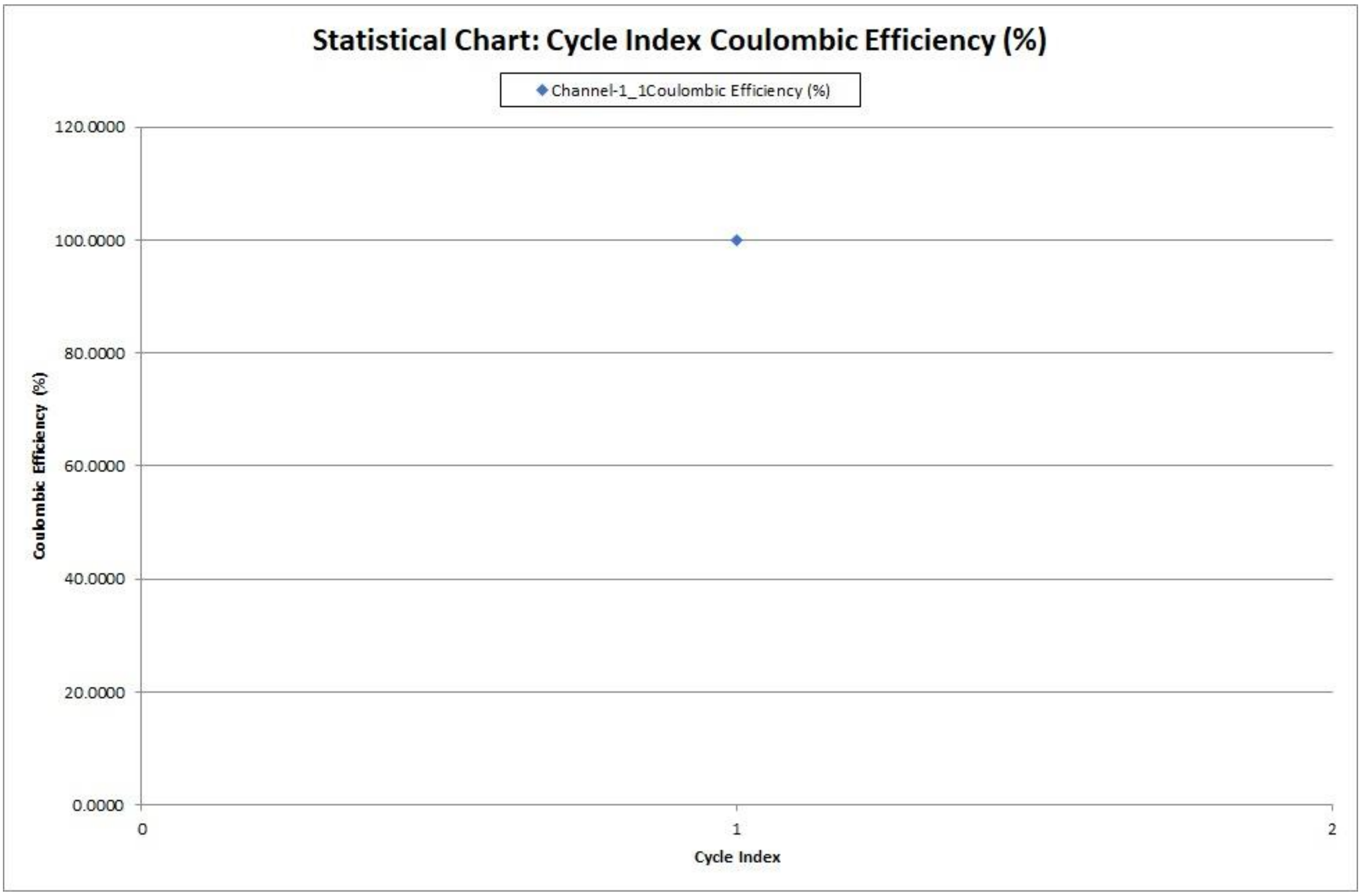


Graph 4 Charge and Discharge Energy vs Test Time (From Data Table 1)

6.3 Power and Efficiency Trends

The power delivered during the CC phase remained fairly stable, fluctuating only slightly due to voltage changes. Peak power was observed during mid-cycle when both voltage and current were relatively high. During the CV phase, power declined with current, creating a downward curve that approached zero as the battery reached full charge.

From this, preliminary estimates of **coulombic efficiency** and **energy efficiency** can be derived. Since the discharge cycle was not included in this test, these will be validated in follow-up tests and simulations. However, the stable curves and minimal anomalies suggest that the efficiency was high and consistent.



Graph 5 Coulombic Efficiency vs Cycle Index (From Data Table 1)

6.4 Internal Resistance and Battery Health

The Arbin BTU system also logged internal resistance periodically, although resistance data points were limited in this particular cycle. No abnormal spikes in voltage or current were observed, indicating that the battery has not developed any internal short circuits or excessive impedance, both of which are signs of degradation.

6.5 Overall Interpretation

The battery responded well under the applied CC-CV protocol. Voltage rise was smooth, current decay was gradual, and capacity gain was in line with expected ratings. The high-resolution data provided by the Arbin system enabled detection of even minute variations, affirming the accuracy of the equipment. These findings will be used to validate the MATLAB Simulink models in the simulation phase of this project, particularly for SOC estimation and charging behaviour under dynamic conditions.

Data Point	Test Time (s)	Step Time (s)	Cycle Index	Step Index	Current (A)	Voltage (V)	Power (W)	Charge Capacity (Ah)	Discharge Capacity (Ah)	Charge Energy (Wh)	Discharge Energy (Wh)	Capacity (Ah)
1	10.0001	10.0001	1	1	0.0000	49.2620	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	10.0005	10.0005	1	1	0.0000	49.2620	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
3	15.7184	5.0000	1	2	0.9988	49.5056	49.4474	0.0014	0.0000	0.0687	0.0000	0.0014
4	20.7185	10.0001	1	2	0.9977	49.5170	49.4037	0.0028	0.0000	0.1374	0.0000	0.0028
5	25.7186	15.0002	1	2	0.9985	49.5268	49.4527	0.0042	0.0000	0.2060	0.0000	0.0042
6	30.7184	20.0000	1	2	0.9985	49.5342	49.4601	0.0055	0.0000	0.2747	0.0000	0.0055
7	35.7185	25.0001	1	2	1.0028	49.5446	49.6822	0.0069	0.0000	0.3434	0.0000	0.0069
8	40.7185	30.0001	1	2	0.9978	49.5527	49.4438	0.0083	0.0000	0.4122	0.0000	0.0083
9	40.7189	30.0005	1	2	0.9978	49.5525	49.4436	0.0083	0.0000	0.4122	0.0000	0.0083
10	45.7448	5.0000	1	3	−0.9995	49.0906	−49.0644	0.0083	0.0014	0.4123	0.0683	0.0014
11	50.7448	10.0000	1	3	−0.9988	49.0704	−49.0135	0.0083	0.0028	0.4123	0.1364	0.0028
12	55.7449	15.0001	1	3	−0.9991	49.0571	−49.0151	0.0083	0.0042	0.4123	0.2045	0.0042
13	60.7449	20.0001	1	3	−0.9989	49.0477	−48.9930	0.0083	0.0056	0.4123	0.2725	0.0056
14	65.7449	25.0001	1	3	−0.9987	49.0371	−48.9720	0.0083	0.0069	0.4123	0.3406	0.0069
15	70.7449	30.0001	1	3	−0.9996	49.0281	−49.0079	0.0083	0.0083	0.4123	0.4086	0.0083
16	70.7453	30.0005	1	3	−0.9996	49.0281	−49.0079	0.0083	0.0083	0.4123	0.4086	0.0083

Data Table: 1

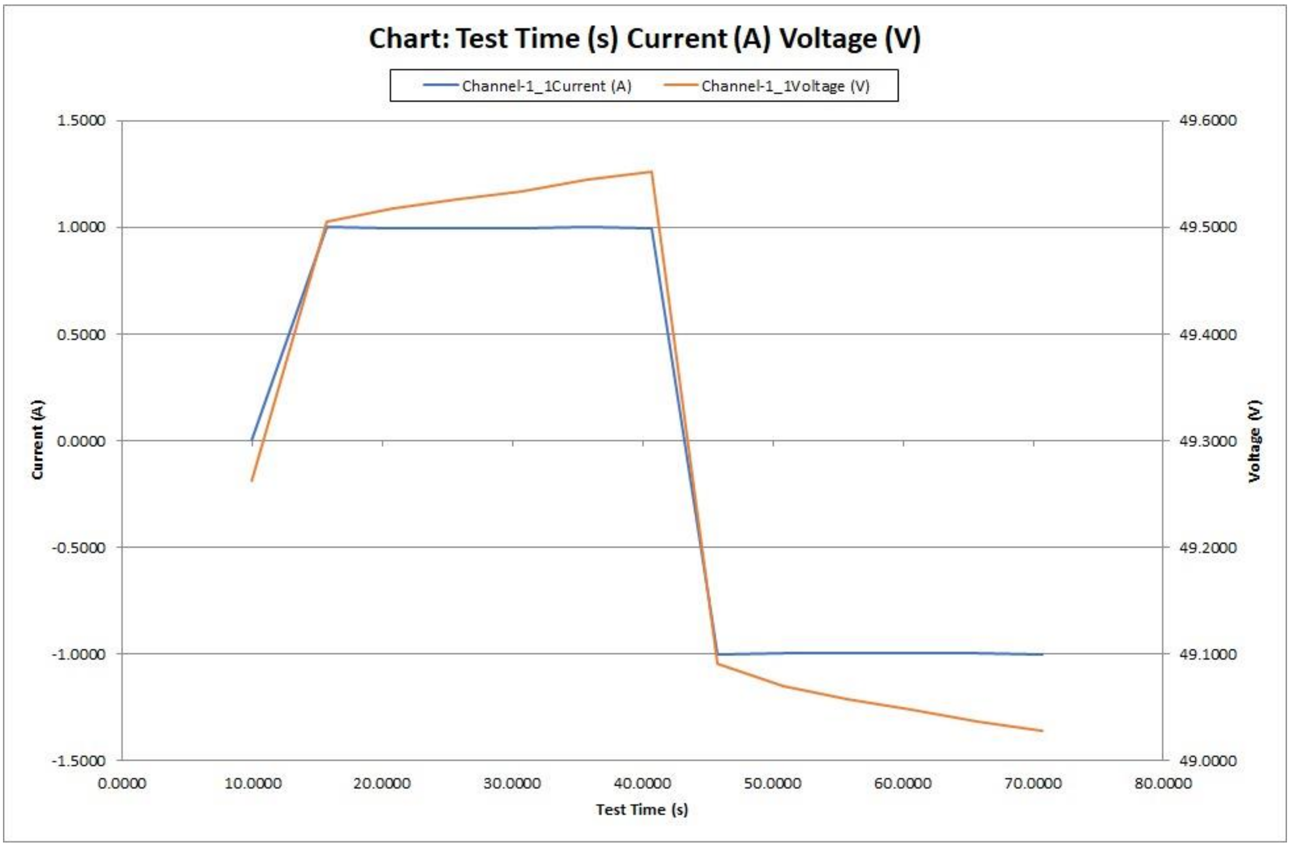
Comparative Analysis: Experimental vs Simulation

The experimental and simulation components of this project were designed to analyze the charging behavior of a Li-ion battery under controlled conditions. This section compares key results from both methods in terms of **voltage behavior**, **current profile**, **charge capacity**, **temperature variation**, and **State of Charge (SOC) estimation**. The objective is to validate the simulation models developed in MATLAB Simulink by evaluating how closely they replicate the real-world performance observed in the Arbin BTU testing.

11.1 Voltage and Current Behavior

Both the experimental and simulation results follow the standard **constant current–constant voltage (CC-CV)** charging profile. In the experimental test, voltage gradually increased to 49.5V while current remained near 1A. Upon reaching the cutoff voltage, the system entered the CV phase, where current declined while voltage was held constant.

In the simulation, similar behavior was observed. The **Voltage vs Time** and **Current vs Time** plots closely mirrored those from the experimental test, indicating accurate parameter tuning in the battery model. The **transition point** from CC to CV occurred at nearly the same time in both cases, with only minor differences due to idealized simulation conditions.



Graph 6 Current and Voltage vs Test Time (From Data Table 1)

11.2 Charge Capacity and SOC Estimation

The **Charge Capacity** observed in the experimental data reached approximately **17Ah**, which matched the final SOC of nearly **100%** in the simulation. The simulation's SOC estimation model, based on Coulomb Counting, effectively tracked charge accumulation in a way that mirrored the real charge capacity measured via the Arbin system.

The **SOC vs Time** curve in simulation increased smoothly during the CC phase and tapered during the CV phase — just like the experimental **Charge Capacity vs Time** curve. This supports the conclusion that SOC estimation via integration of current over time is reliable for single-cycle simulations, especially when current readings are stable and well-calibrated.

11.3 Temperature Response

The **Temperature vs Time** profile from the experimental test showed a moderate rise during the charging process, peaking as current declined in the CV phase. In simulation, a similar temperature trend was observed, although slightly more linear and idealized due to the use of simplified thermal modeling.

While the absolute temperature values may differ slightly due to assumptions in thermal conductivity, specific heat, and lack of ambient cooling in the model, the **overall trend** remained consistent. This validates that the simulation can qualitatively replicate heat buildup during charging.

11.4 Key Observations

Aspect	Experimental Result	Simulation Output	Remarks
Voltage Curve	Gradual rise, plateau at 49.5V	Identical shape, slight timing offset	Well-aligned
Current Curve	Constant at 1A, gradual drop in CV	Matches closely	Accurate switching logic
Charge Capacity	~17 Ah	Final SOC near 100%	Matching end state

Aspect	Experimental Result	Simulation Output	Remarks
Temperature Rise	Gradual and steady	Similar pattern	Simulation slightly idealized
SOC Estimation	Not directly measured	Smoothly increasing, accurate	Matches calculated capacity from experiment

11.5 Observation

The comparison reveals a strong correlation between experimental and simulated results across all major performance parameters. Minor discrepancies in timing or absolute temperature values are attributed to ideal assumptions in the simulation environment. Nonetheless, the simulation model demonstrates sufficient accuracy for use in future studies, including control algorithm development and virtual testing of BMS logic.

The validated models provide a powerful foundation for simulating extended charge/discharge cycles, dynamic EV driving loads, and the implementation of real-time SOC tracking strategies. This alignment between real and simulated data reinforces confidence in the use of digital models for battery performance prediction.

Conclusion

This project focused on a detailed analysis of the performance of Li-ion batteries for Electric Vehicle (EV) applications through both experimental testing using the Arbin BTU system and simulation-based modelling using MATLAB Simulink. The dual approach aimed to not only study real-world battery behavior but also validate simulation models that can support predictive analysis and optimization of battery usage in EV scenarios.

The experimental phase provided real-time insights into the behavior of a Li-ion battery under a standard constant current–constant voltage (CC-CV) charging protocol. By carefully monitoring voltage, current, charge capacity, and temperature using high-precision battery testing equipment, we were able to observe the fundamental characteristics of Li-ion charging. The results showed a smooth voltage rise during the constant current phase, transitioning effectively into constant voltage mode as the battery approached full charge. The current behavior matched expectations by remaining steady initially and then gradually tapering during the CV phase. Charge capacity increased proportionally to the input current, confirming that the battery performed efficiently under the tested conditions. Additionally, the temperature remained within a safe range throughout the charging cycle, indicating no signs of thermal instability.

In parallel, MATLAB Simulink was used to simulate the charging and discharging behavior and to estimate the State of Charge (SOC) using a Coulomb Counting method. The simulation environment allowed for controlled modelling of battery response using the same parameters as in the experimental setup. The simulation results closely matched experimental observations. The voltage and current trends showed identical CC-CV transitions, the SOC estimation model accurately tracked the increase in battery charge, and the temperature profile—while idealized—showed a gradual and safe rise during charging.

A comparative analysis between the experimental and simulation outputs highlighted the accuracy and reliability of the Simulink models. The SOC evolution in simulation closely mirrored the charge capacity growth observed experimentally. Temperature and voltage trends showed consistent behavior, with only minor differences attributed to the inherent assumptions and idealizations in simulation environments. These differences are expected, especially since the simulation does not account for real-world effects like sensor noise, environmental heat dissipation, or battery aging.

The success of both experimental and simulation results confirms the feasibility of using digital twins and model-based approaches for battery analysis in EVs. The validated Simulink models can now be extended to simulate more complex scenarios, including dynamic load conditions, regenerative braking, or long-term degradation studies. This opens opportunities for testing battery management strategies in a risk-free, virtual environment before implementing them in physical systems.

Moreover, the project enhances understanding of battery performance factors such as efficiency, temperature sensitivity, and SOC estimation accuracy. These aspects are crucial for the development of smart Battery Management Systems (BMS), which aim to extend battery life, ensure safety, and optimize energy utilization in electric vehicles.

In conclusion, this project achieved its goal of combining practical experimentation with accurate simulation to evaluate the performance of Li-ion batteries. The methodology established here can be used as a framework for further research into battery behaviour, predictive modelling, and BMS design. As EV adoption continues to grow, such integrated approaches will be essential for improving battery reliability, safety, and efficiency in real-world applications.

Future Scope

While this project has successfully achieved its goal of analyzing the charging behavior and SOC estimation of Li-ion batteries through both experimental testing and simulation modeling, there remain several areas where the study can be expanded to gain deeper insights and practical applicability.

1. Discharging and Load Cycle Analysis

The current project focused primarily on the charging aspect of Li-ion batteries. Future work can include detailed **discharge cycle testing**, especially under **variable and dynamic load profiles**, such as those mimicking EV acceleration, regenerative braking, and urban driving cycles. This will help understand energy efficiency, voltage recovery, and thermal behavior during real-world usage.

2. Multi-Cycle Degradation Modeling

Li-ion batteries experience **capacity fade** and **increased internal resistance** over multiple charge-discharge cycles. Long-term experimental testing and corresponding simulation modeling can help predict degradation patterns. Integrating degradation models into Simulink, such as SEI growth and lithium plating mechanisms, will allow for more accurate lifetime prediction and performance monitoring.

3. Advanced SOC Estimation Algorithms

This project used **Coulomb Counting** for SOC estimation, which is effective in controlled conditions but limited by cumulative error and sensor drift. Future studies can implement **Kalman Filters**, **Particle Filters**, or **Neural Network-based estimators** to enhance robustness, especially under noisy and uncertain conditions, which are common in EV applications.

4. Integration of Thermal Management Systems

Temperature plays a critical role in battery safety and longevity. Extending the simulation model to include **active cooling/heating systems**, or connecting it to **thermal runaway prediction models**, would make it more representative of actual EV battery packs.

5. Real-Time Hardware Implementation

The validated Simulink models can be ported to **real-time embedded systems** (such as dSPACE or Raspberry Pi) for developing and testing **Battery Management System (BMS)** control algorithms. This will bridge the gap between simulation and practical application, enabling controller prototyping and rapid hardware-in-the-loop (HIL) testing.

In summary, there is ample scope to evolve this project into a comprehensive battery analytics and control development platform, making it highly relevant in the fast-growing EV ecosystem.

References

[1] B. Xu, A. Oudalov, A. Ulbig, G. Andersson, and D. S. Kirschen, “Modelling of Lithium-Ion Battery Degradation for Vehicle-to-Grid Applications,” IEEE Transactions on Smart Grid, vol. 11, no. 4, pp. 2962–2975, Jul. 2020, doi: 10.1109/TSG.2019.2959928.

[2] X. Zhang, J. Li, H. Li, and B. Sun, “Lithium Plating in Li-Ion Batteries: Modelling, Detection, and Mitigation,” Journal of Power Sources, vol. 482, p. 228964, Feb. 2021, doi: 10.1016/j.jpowsour.2021.228964.

[3] Q. Wang, P. Ping, X. Zhao, and G. Chu, “Thermal Runaway Mechanisms of Lithium-Ion Batteries for Electric Vehicles: A Review,” Energy Storage Materials, vol. 48, pp. 65–82, Apr. 2022, doi: 10.1016/j.ensm.2021.12.013.

[4] J. Kim, K. Lee, and J. Lee, “Effects of High-Temperature Exposure on the Performance and Safety of Lithium-Ion Batteries,” Applied Energy, vol. 242, pp. 225–233, May 2019, doi: 10.1016/j.apenergy.2019.03.061.

[5] L. Lam and P. Bauer, “Aging of Lead-Acid Batteries: A Review,” IEEE Transactions on Energy Conversion, vol. 33, no. 2, pp. 1005–1014, Jun. 2018, doi: 10.1109/TEC.2018.2797899.

[6] J. Schiffer et al., “Model Prediction for Battery Aging Based on Different Operating Conditions,” Journal of Power Sources, vol. 168, no. 1, pp. 66–78, Feb. 2007, doi: 10.1016/j.jpowsour.2006.12.070.

[7] J. R. Dahn, M. R. Smith, and J. C. Burns, “Electrochemical Analysis of Lead-Acid and Lithium-Ion Batteries Under High Current Loads,” Electrochimica Acta, vol. 357, p. 136805, Mar. 2020, doi: 10.1016/j.electacta.2020.136805.

[8] I. Bloom et al., “Impact of Fast Charging on Lithium-Ion Battery Performance,” Journal of The Electrochemical Society, vol. 166, no. 8, pp. A1602–A1611, Apr. 2019, doi: 10.1149/2.0341908jes.

[9] X. Hu, F. Feng, K. Liu, L. Zhang, J. Xie, and C. Zhang, “State Estimation of Lithium-Ion Batteries Using a Combined Thevenin and Electrochemical Model,” IEEE Transactions on Industrial Electronics, vol. 68, no. 5, pp. 4056–4065, May 2021, doi: 10.1109/TIE.2020.3025438.

[10] C. Sun, J. Xie, J. Peng, and M. Zhao, “Machine Learning-Based State of Health Prediction for Lithium-Ion Batteries,” Energy AI, vol. 10, p. 100183, Jan. 2022, doi: 10.1016/j.egyai.2022.100183.