

Article

Low-Cost Experimental Validation of Lithium-Ion Battery Models and SOC Estimators Under Dynamic Current Profiles

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Abstract

Reliable experimental platforms are essential for lithium-ion (Li-Ion) battery characterization, equivalent circuit model (ECM) identification, and state-of-charge (SOC) estimator validation. However, access to commercial battery cyclers and high-end instrumentation can be limited in academic and applied research environments, which motivates the development of low-cost and reproducible test benches. This work presents the development and validation of a low-cost experimental platform for Li-Ion battery characterization, SOC-dependent ECM identification, voltage model validation, and SOC estimator assessment. The proposed platform integrates constant-current–constant-voltage (CC-CV) charging, a controlled-current electronic load implemented on a printed circuit board (PCB), ESP32-based embedded acquisition, and MATLAB-based data processing. A Samsung INR18650-35E cell was characterized through full-discharge tests at different C-rates, pulse discharge tests (PDTs), and dynamic current profiles. The measured capacity at 0.2C was 3345.1 mAh, showing close agreement with the manufacturer-reported minimum nominal capacity of 3350 mAh. First- and second-order Thévenin ECMs were identified from PDT data, parameterized as SOC-dependent models, and validated under Scaled Dynamic Stress Test (DST) and Modified Pulsed Dynamic Stress Test (P-DST) profiles. The second-order ECM identified from the most complete PDT dataset achieved voltage RMSE values of 23.24 mV and 12.14 mV under the DST and P-DST profiles, respectively. The platform was further used to evaluate SOC estimators based on extended Kalman filters (EKF) and a hybrid Extended Kalman Filter-Artificial Neural Network (EKF-ANN) residual correction method. The EKF based on the second-order ECM achieved SOC RMSE values of 0.5088% and 1.0890% under the complete dynamic profiles, while the hybrid EKF-ANN reduced the RMSE to 0.2276% and 0.2788% over the dynamic test blocks. These results show that the proposed platform provides an accessible experimental framework for connecting battery testing, ECM identification, voltage validation, and BMS-oriented SOC estimator evaluation within a single reproducible workflow.

Keywords: Li-Ion battery characterization; SOC estimation; Thévenin model; EKF-ANN; low-cost experimental platform; dynamic validation; ECM parameter identification.



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1. Introduction

The increasing integration of renewable energy sources has strengthened the role of energy storage systems (ESSs) in modern power systems. ESSs help mitigate the intermittency of wind and solar generation and improve grid flexibility, reliability, and power quality [1–4]. Among the available technologies, lithium-ion (Li-Ion) batteries are widely used because of their high energy density, low self-discharge rate, long cycle life, and high efficiency [5,6]. Other storage technologies, such as redox flow batteries [7], are also relevant for stationary applications because of their scalability and independent power and energy sizing; however, Li-Ion batteries remain particularly attractive for applications requiring compactness, high efficiency, and fast dynamic response. Recent studies report Li-Ion battery energy densities in the range of 200–500 Wh/kg and efficiencies typically between 85% and 95%, making them suitable for both stationary and mobility-related applications [8]. Despite these advantages, their performance, safety, and lifetime are strongly affected by operating conditions such as depth of discharge, temperature, current rate, and charge/discharge history [5,6].

Safe and efficient operation of Li-Ion batteries requires continuous monitoring and control through battery management systems (BMSs). A BMS integrates several functions, including charge/discharge control, protection, thermal management, cell balancing, and state estimation [9]. Among these functions, state-of-charge (SOC) estimation is particularly important because it provides information about the remaining available capacity and supports the estimation of other internal states, such as State of Energy (SOE), State of Health (SOH), and State of Power (SOP) [10]. Nevertheless, SOC cannot be measured directly and must be inferred from external variables such as terminal voltage, current, and, in some cases, temperature [11]. This estimation process is affected by nonlinear electrochemical behavior, parameter variability, aging, measurement noise, temperature, and dynamic operating conditions, making accurate real-time SOC estimation a challenging task [12–14].

Several SOC estimation strategies have been reported in the literature and are commonly classified into conventional, model-based, data-driven, and hybrid methods [3,13,15]. Conventional techniques, such as coulomb counting and voltage-based methods, are simple and computationally efficient, but they are sensitive to current sensor offsets, initial SOC uncertainty, available capacity, and voltage hysteresis [13,16]. Model-based approaches use mathematical or electrical representations of the battery, including electrochemical models and Equivalent Circuit Models (ECMs). In particular, Thévenin-type ECMs combined with Kalman filter variants are widely used because they provide a suitable balance between dynamic accuracy, interpretability, and computational feasibility for BMS applications [11,17].

In parallel, data-driven methods based on machine learning, neural networks, and deep learning have gained attention due to their ability to capture nonlinear relationships from experimental data [18,19]. However, these methods require representative datasets and careful validation to avoid overfitting and limited generalization under operating conditions not included during training [20,21]. Hybrid approaches have therefore emerged as a practical alternative, combining the interpretability of model-based estimators with the correction capability of data-driven algorithms [22–24]. This combination is particularly relevant when the objective is to improve SOC estimation accuracy while preserving a feasible level of model complexity for BMS-oriented implementation.

Beyond estimator design, reliable experimental platforms are required to generate consistent data for battery characterization, ECM parameter identification, voltage-model validation, and SOC estimator assessment under controlled and dynamic operating conditions. Commercial battery cyclers and high-end test systems provide accurate and automated operation, but their cost may limit their use in academic laboratories, educational

environments, and early-stage applied research. For this reason, low-cost programmable test benches have become relevant tools for BMS-oriented research, especially when they can reproduce different charge/discharge modes, pulse tests, dynamic current profiles, and synchronized data acquisition [25–27]. Nevertheless, many low-cost implementations focus on isolated functions, such as charge/discharge testing or data acquisition, while fewer studies present an integrated workflow that connects hardware implementation, battery characterization, ECM identification, independent voltage-model validation, and SOC estimator evaluation using the same experimental platform.

In this context, this work presents a low-cost experimental platform designed to support the complete workflow required for Li-Ion battery characterization, SOC-dependent ECM identification, voltage-model validation, and SOC estimator assessment. The platform integrates CC-CV charging, a PCB-based controlled-current electronic load, ESP32-based acquisition and control, and a MATLAB-based interface for test configuration, data logging, calibration processing, model identification, and estimator evaluation. Unlike a commercial cycler-oriented approach, the proposed platform emphasizes accessibility, modular implementation, and reproducible experimental procedures for laboratory-scale Li-Ion cell studies.

The proposed test bench was validated using a Samsung INR18650-35E cell (SAMSUNG SDI Co., Ltd., Yongin, South Korea).

Full-discharge tests at different C-rates were used to evaluate the capacity response of the cell, while pulse discharge tests were used to identify SOC-dependent first- and second-order Thévenin ECMs, denoted as 1RC and 2RC models. The identified models were then validated under independent dynamic current profiles, including a scaled Dynamic Stress Test (DST) and a modified Pulsed Dynamic Stress Test (P-DST). Finally, the experimentally identified ECMs were used as the basis for extended Kalman filter (EKF)-based SOC estimation and for a hybrid extended Kalman filter–artificial neural network (EKF-ANN) residual correction strategy. The main contribution of this work is the experimental integration of a low-cost platform that connects Li-ion battery testing, SOC-dependent ECM identification, independent voltage model validation, and BMS-oriented SOC estimator evaluation within a single reproducible workflow. The work does not aim to introduce a new SOC estimation algorithm; instead, it demonstrates how accessible hardware can be used to support the experimental chain required to evaluate conventional and hybrid SOC estimators under controlled and dynamic operating conditions. The main contributions of this paper are summarized as follows:

1. A low-cost experimental platform for Li-Ion battery characterization was developed by integrating CC-CV charging, a PCB-based controlled-current electronic load, ESP32-based acquisition and control, and MATLAB-based test configuration, data logging, and post-processing.
2. The platform was experimentally validated using a Samsung INR18650-35E cell through full-discharge tests at different C-rates and pulse discharge tests, enabling capacity characterization and SOC-dependent identification of first- and second-order Thévenin ECMs.
3. A complete model-validation and SOC-estimation workflow was demonstrated by evaluating the identified ECMs under independent dynamic current profiles and using them as the basis for EKF and hybrid EKF-ANN SOC estimation, showing the capability of the platform to support BMS-oriented Li-Ion battery modeling studies.

2. Experimental Platform and Battery Characterization

2.1. General Architecture of the Experimental Platform

Dynamic characterization of Li-Ion batteries requires experimental platforms that can reproduce controlled charge/discharge conditions while synchronously acquiring voltage, current, and time data [28,29]. This capability is essential not only for capacity testing, but also for pulse discharge test (PDT) execution, equivalent circuit model (ECM) parameter identification, dynamic voltage model validation, and battery management system (BMS) algorithm development [30–32]. Based on these requirements, this work implements a low-cost experimental test bench capable of performing CC-CV charging, controlled-current discharge, PDT sequences, dynamic current profile generation, Thévenin ECM identification, and SOC estimator validation within the same experimental workflow. Figure 1 shows the general architecture of the implemented platform. The system integrates a programmable laboratory power supply for charging tests, a controlled-current electronic load designed on a dedicated PCB, an ESP32-based embedded controller, analog and digital instrumentation for signal acquisition, and a MATLAB interface for test configuration, real-time visualization, and automatic data storage. The platform supports CC-CV charging, constant-current discharge, pulse discharge tests, dynamic current profiles, and automated experimental characterization. The experimental validation was performed using a Samsung INR18650-35E Li-Ion cell based on nickel–cobalt metal oxide chemistry and a graphite anode. The main manufacturer specifications are summarized in Table 1. Before the main experimental tests, the cell was preconditioned through four preliminary charge-discharge cycles using the same CC-CV charging procedure and discharge cut-off voltage adopted in the characterization tests, following common procedures for Li-Ion battery ECM parameter identification [33].

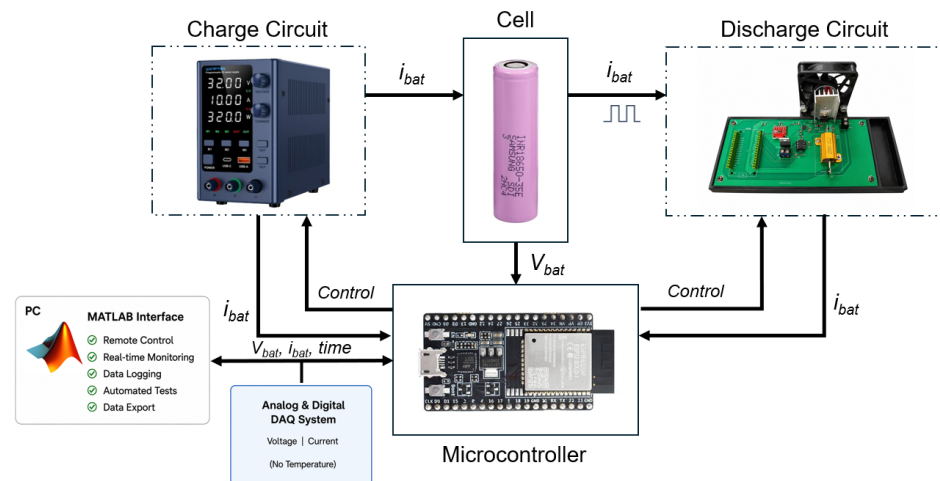


Figure 1. Implemented experimental test bench architecture.

Table 1. Li-Ion battery cell specifications [34].

Parameter	Value
Cell model	Samsung INR18650-35E
Nominal voltage	3.6 V
1C current	3.4 A
Minimum nominal capacity	3350 mAh
Standard charge current	1.7 A
Maximum charge voltage	4.2 V
Maximum continuous discharge current	8 A
Discharge cut-off voltage	2.65 V

The main hardware components and approximate costs of the implemented single-cell charge–discharge experimental platform are summarized in Table 2. The table distinguishes between the controlled-current discharge module and the charging/source-current module to clarify the cost contribution of each subsystem.

Table 2. Main Components, Function, and Approximate Cost of the Single-Cell Charge–Discharge Experimental Platform.

Component	Description	Function in the Experimental Module	Approx. Cost [USD]
Controlled-current discharge module			
Microcontroller	ESP32 DevKit V1	Embedded control, protection logic, data acquisition, and serial communication.	6–10
DAC	MCP4725	Generates the analog current reference for the electronic load.	2–5
ADC	MCP3202	Measures battery terminal voltage and shunt voltage.	2–5
Operational amplifier	MCP6002	Conditions the control signal for MOSFET gate regulation.	1–3
MOSFET	IRLZ44N	Dissipative power element for controlled-current discharge.	1–4
Shunt resistor	0.1 Ω /25 W	Current-sensing element and feedback variable for current regulation.	2–6
Voltage regulator	LM7805	Provides regulated auxiliary supply for the analog stage.	1–2
Cooling system	Techman VN2350 fan with aluminum heat sink	Provides forced-air cooling for the MOSFET during discharge operation.	5–12
Fabricated PCB and passive components	PCB, resistors, capacitors, connectors, and terminals	Electrical integration, filtering, scaling, and signal conditioning.	15–30
Communication interface	UART serial	Bidirectional communication between ESP32 and the processing interface.	Included
Discharge module subtotal	—	Controlled-current electronic-load prototype.	35–77
Charging/source-current module			
DC power supply	Wanptek EPS3210	External DC source used for CC-CV charging and charge-current segments in dynamic profiles.	60–90
Current sensor	WCS1800 adjustable 35 A current sensor	Measures source/charging current during CC-CV operation and charge-current profile segments.	8–15
ADC module	ADS1115	Digitizes the source-current sensor output.	2–6
Relay module	SRD-05VDC-SL-C with opto-coupler	Provides auxiliary switching and isolation for the source-current stage.	1–3
Charging/source-current module subtotal	—	External DC source, source-current measurement chain, and auxiliary switching.	71–114
Estimated hardware total	—	Single-cell charge–discharge experimental platform, excluding computer, battery cell, and reference calibration instruments.	106–191

Note: Approximate prices correspond to typical market values for low-volume purchases and may vary depending on supplier, country, and purchase date. The discharge module subtotal supports the low-cost nature of the implemented electronic-load stage, whereas the total platform estimate includes the external DC source, the source-current measurement chain, and auxiliary switching used during charging and charge-current profile segments. These estimates distinguish the proposed single-cell experimental platform from general-purpose laboratory equipment and commercial battery cyclers.

In related Li-Ion battery test benches, the conventional charge–discharge architecture typically combines a programmable DC power supply for charging, a programmable DC electronic load for discharge, and an external data-acquisition/control system [26,35,36]. These configurations provide robust laboratory-grade operation but rely on higher-cost instrumentation. To contextualize the cost of the proposed platform, Table 3 summarizes representative laboratory-grade charge–discharge equipment reported in these related studies and their approximate market prices.

Table 3. Representative Laboratory-Grade Charge–Discharge Equipment Reported in Related Battery Test Benches.

Reference	Charging/Source Equipment	Discharge/Load Equipment	Approx. Total Cost [USD]
Vergori et al. [26]	Aim-TTi QPX600DP programmable DC power supply <i>Cost: 2948 USD</i>	EA-EL 9080-400 programmable DC electronic load <i>Cost: 4653 USD</i>	7600
Poopanya et al. [35]	DP811/DP811A programmable DC power supply <i>Cost: 739–975 USD</i>	DL3021/DL3021A programmable DC electronic load <i>Cost: 725–923 USD</i>	1464–1898
Sungur and Kaleli [36]	Aim-TTi QPX1200SP programmable DC power supply <i>Cost: 2392 USD</i>	PRODIGIT 3117 programmable DC electronic load <i>Cost: 1400–1500 USD</i>	3792–3892

Note: Prices are included as representative market references for the equipment models reported in the cited studies and may vary depending on supplier, country, taxes, availability, calibration options, accessories, exchange rate, and purchase date. Values converted from other currencies were rounded to the nearest USD. The comparison is intended to contextualize the cost scale of conventional laboratory-grade charge–discharge equipment, not to imply functional equivalence between the proposed platform and commercial battery cyclers or high-power test systems.

Although the proposed platform reduces hardware cost for single-cell characterization, ECM identification, and SOC-estimator validation, it is not intended to replace commercial battery cyclers or high-power multichannel systems. Its noise floor and accuracy are mainly affected by ADC resolution, current-sensor offset and drift, shunt tolerance, PCB voltage drops, and electromagnetic interference. Scaling to multicell packs would require isolated or differential voltage sensing, channel synchronization, higher-power charge–discharge stages, enhanced thermal management, and additional protection circuitry.

2.2. CC-CV Charging System

Battery charging tests were performed using a Wanptek EPS3210 programmable DC power supply configured in Constant Current–Constant Voltage (CC-CV) mode. This method remains the conventional charging strategy for Li-Ion batteries because it maintains the cell within its Safe Operating Area (SOA), reducing the risk of overvoltage, thermal runaway, and accelerated degradation [26,32]. CC-CV charging is also widely used in experimental characterization due to its stability, repeatability, and straightforward implementation in BMS-oriented test platforms [37,38].

During the constant-current stage, the cell is charged at a fixed current until the terminal voltage reaches the maximum value specified by the manufacturer. Then, the power supply enters the constant-voltage stage, maintaining the battery terminal voltage while the current progressively decreases toward the charge termination condition [39]. Figure 2 shows the experimental CC-CV charging behavior. The current remains approximately constant during the CC stage, while the battery voltage increases gradually. Once the 4.2 V threshold is reached, the system operates in CV mode and the current decreases toward zero. The manufacturer-reported charge termination current for this cell is 68 mA [34].

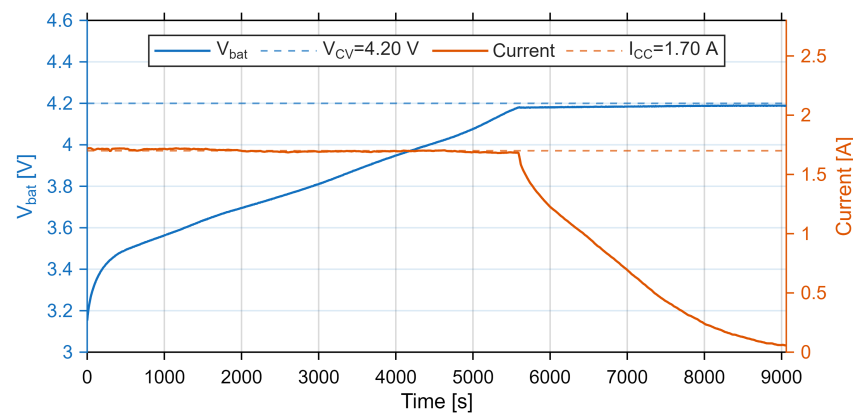


Figure 2. Experimental CC–CV behavior during battery charging.

To reduce the influence of transient polarization between consecutive tests, rest periods of at least 60 min were implemented after charging and discharge procedures. This protocol allows the cell to approach a quasi-equilibrium condition near the stationary Open-Circuit Voltage (OCV), improving the consistency of subsequent characterization and identification tests [40,41].

2.3. Controlled-Current Electronic Load

For the discharge processes, a low-cost controlled-current electronic load was designed and implemented on a dedicated PCB. The module was developed for Li-Ion battery characterization, PDT execution, and dynamic current profile generation. Similar low-cost programmable discharge systems have been reported as useful tools for battery model identification and experimental validation when flexible current control and synchronized data acquisition are required [42,43]. However, these systems mainly focus on current-profile generation, pulsed discharge or cycling tests, voltage/current acquisition, and ECM parameter identification [27,43]. Therefore, the contribution of the proposed platform lies in connecting Li-Ion cell characterization, PDT-based Thévenin ECM identification, DST/P-DST voltage validation, and BMS-oriented SOC estimator assessment using the same experimental architecture.

The system is based on an ESP32 microcontroller, responsible for current reference generation, signal acquisition, experimental control, and serial communication with MATLAB [27,44]. The current regulation stage uses an MCP4725 digital-to-analog converter, an MCP6002 operational amplifier, and an IRLZ44N MOSFET operating in the linear region as the controlled dissipative element. The MOSFET was mounted on a fan-assisted aluminum heat sink, and active cooling was maintained whenever the discharge bench was operating. This topology is commonly used in electronic loads for battery discharge applications [27,45]. The battery terminal voltage and shunt voltage are acquired using an MCP3202 12-bit analog-to-digital converter. The discharge current is calculated in the firmware from the measured voltage drop across a $0.1\ \Omega$ shunt resistor using Ohm's law. The electronic-load components and their approximate cost contribution are included in Table 2 as part of the overall single-cell charge–discharge platform.

The present implementation was validated as a low-cost single-cell electronic-load stage; operation beyond the reported current and power range would require a dedicated redesign of the dissipative hardware stage and was not evaluated in this work.

Figure 3 shows the general schematic of the controlled-current electronic load. The system acquires the battery terminal voltage, shunt voltage, and test time. From the shunt voltage, the firmware computes the discharge current and updates the control signal applied to the MOSFET gate through the DAC and operational amplifier stage.

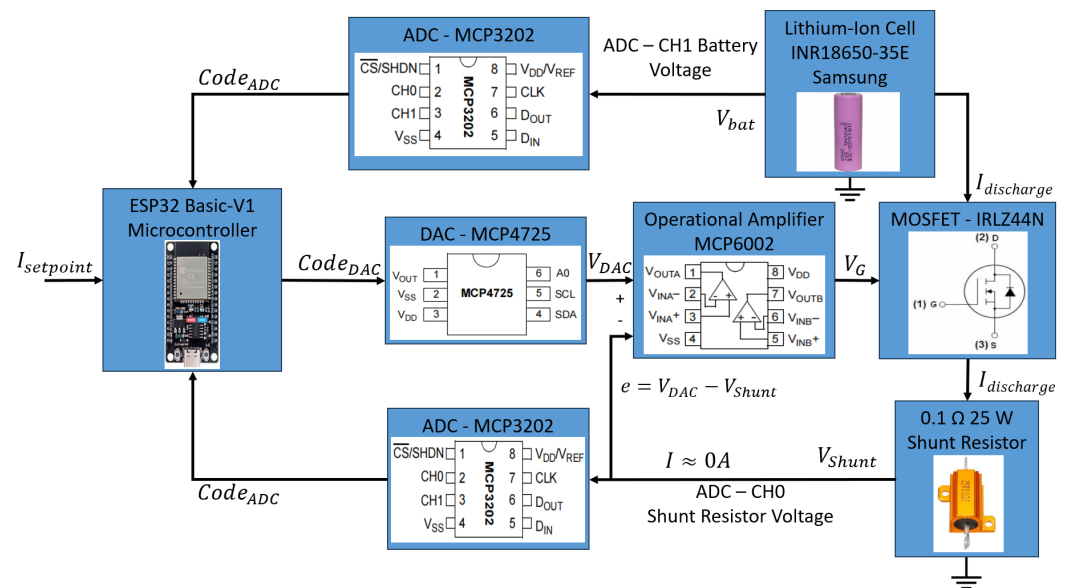


Figure 3. General schematic of the Programmable Electronic Load Experimental Module.

Unlike test systems limited to stationary discharge conditions, the implemented firmware includes programmable modes for dynamic characterization and SOC algorithm validation [28]. These modes include full constant-current discharge, limited-duration discharge, PDT, dynamic current profiles, no-load voltage measurement, manual current control, automatic event logging, and configurable experimental parameters [42]. This flexibility allows the platform to reproduce controlled current profiles, relaxation intervals, and synchronized electrical measurements required for ECM parameter identification and subsequent SOC estimation [27,42].

2.4. Calibration and Experimental Instrumentation

Measurement accuracy is critical for parameter identification and SOC estimation, since small deviations in current or voltage can propagate into significant errors during coulomb counting, ECM fitting, and model-based estimation [46,47]. Therefore, current and voltage calibration procedures were implemented before using the experimental data for model identification and SOC validation.

The shunt resistor used for discharge current estimation was experimentally characterized using a HIOKI IM3570 impedance analyzer (Hioki E.E. Corporation, Ueda, Japan), as shown in Figure 4. The frequency response was evaluated in terms of the series resistance (R_s) and reactance (X). In the figure, R_s is plotted on the left vertical axis in mΩ, while X is plotted on the right vertical axis in mΩ; the horizontal axis represents the excitation frequency in Hz. R_s remained close to the nominal value of 0.1 Ω over the evaluated frequency range, with a relative error below 1.04% and an RMSE of 1.79 mΩ. X remained comparatively small at low and medium frequencies, indicating that the shunt behaves predominantly as a resistive element in the operating range used for discharge current measurement. This validation supports the use of the shunt resistor as the reference element for current estimation in the dynamic discharge tests.

In addition, an automatic zero-offset calibration procedure was implemented in the ESP32 firmware to compensate for electronic noise and acquisition offsets under zero-current conditions. This procedure is executed before each test with the MOSFET disabled and the battery at rest.

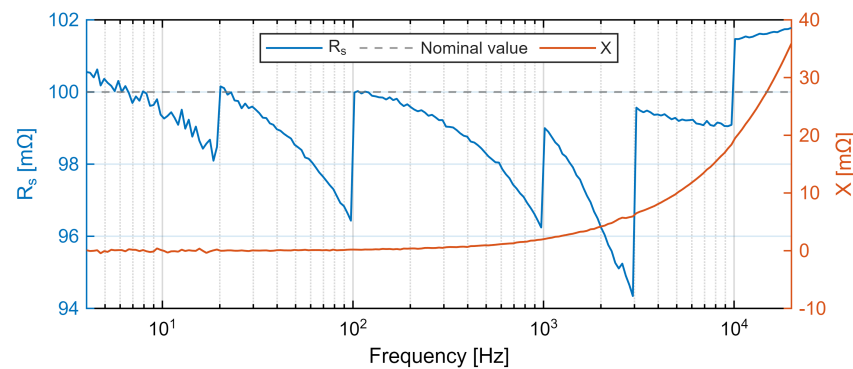


Figure 4. Experimental impedance characterization of the 0.1 Ω shunt resistor using a HIOKI IM3570 impedance analyzer. The left vertical axis shows the measured series resistance R_s in m Ω , the right vertical axis shows the reactance X in m Ω , and the horizontal axis shows the excitation frequency in Hz. The dashed horizontal line indicates the nominal resistance value.

For battery voltage measurement, an experimental correction was applied to account for the current-dependent deviation observed in the measured terminal voltage. The voltage correction, ΔV_{bat} , was defined as the difference between the reference voltage and the voltage measured by the acquisition system. The resulting linear fit is shown in (1):

$$\Delta V_{\text{bat}} = 0.0251 I_{\text{dis}} + 0.0028 \quad (1)$$

where I_{dis} is the discharge current in amperes. Therefore, the corrected battery voltage was calculated as Equation (2):

$$V_{\text{bat,corr}} = V_{\text{bat,raw}} + \Delta V_{\text{bat}} \quad (2)$$

Substituting (1) into (2), the corrected voltage is obtained as (3):

$$V_{\text{bat,corr}} = V_{\text{bat,raw}} + 0.0251 I_{\text{dis}} + 0.0028 \quad (3)$$

The fit presented a coefficient of determination $R^2 = 0.9989$, indicating a suitable linear relationship between voltage correction and discharge current. Figure 5 shows the experimental calibration fit and the corresponding residual analysis.

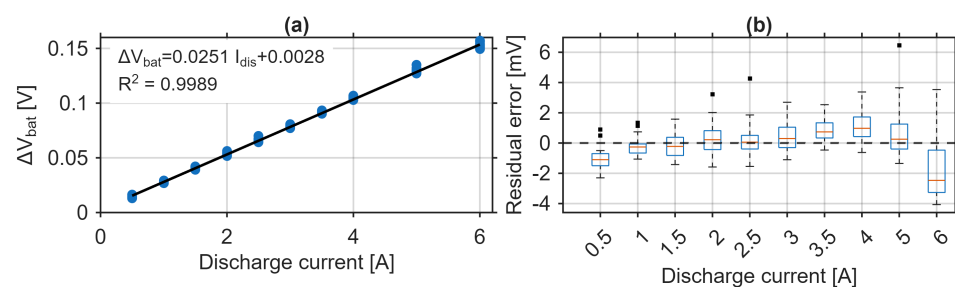


Figure 5. Current-Dependent Battery Voltage Correction: (a) Linear Calibration Fit, where blue markers denote calibration data and the black line denotes the linear fit; (b) Residual Error Boxplots by Reference Discharge Current Level, with the dashed line indicating zero residual error.

For the charging current measurement, the WCS1800 Hall-effect current sensor and ADS1115 converter were calibrated using the DC power supply current reading as reference. The current initially calculated by the measurement system was denoted as $I_{\text{ch,raw}}$, while the reference current was denoted as $I_{\text{ch,ref}}$. The experimental relationship was expressed in (4):

$$I_{\text{ch,raw}} = 1.0169I_{\text{ch,ref}} - 0.0450 \quad (4)$$

with a coefficient of determination $R^2 = 0.9999$. The corrected charging current was obtained by inverting the calibration model (5):

$$I_{\text{ch,corr}} = \frac{I_{\text{ch,raw}} + 0.0450}{1.0169} \quad (5)$$

This correction compensates for both gain error and offset in the WCS1800/ADS1115 measurement system. Figure 6 presents the calibration fit and residual distribution by reference current level.

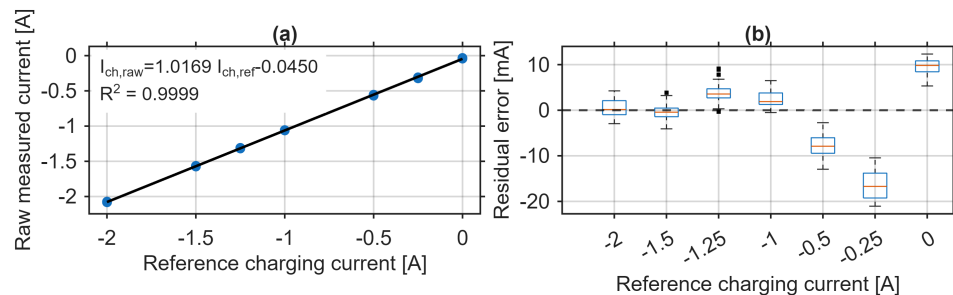


Figure 6. Charging Current Measurement Calibration Using the WCS1800/ADS1115 System: (a) Linear Calibration Fit, where blue markers denote calibration data and the black line denotes the linear fit; (b) Residual Error Boxplots by Reference Charging Current Level, with the dashed line indicating zero residual error.

The temporal stability of the WCS1800/ADS1115 charging-current measurement was also evaluated during the constant-current stage of a 0.3C CC-CV charge test. From 60 s to 8800 s, the corrected current presented a standard deviation of 5.82 mA, an RMSE of 7.56 mA with respect to the 1.02 A reference. A linear trend fitted to the corrected-current signal indicated an estimated variation of -16.6 mA over the analyzed interval, suggesting acceptable temporal stability for the charging-current measurement during the CC stage.

Together with the shunt characterization and the voltage and charging-current calibration results, this analysis provides reference-based support for the charge–discharge measurement chains used in the prototype.

2.5. Data Acquisition and Processing

Experimental data acquisition was performed through a MATLAB (R2025b) interface connected to the ESP32 via UART serial communication at 115,200 bps. The interface was used to configure the tests, visualize the measured variables in real time, store the experimental data, and support subsequent calibration, model identification, and SOC estimator evaluation. Although MATLAB was used in this implementation as a research-oriented environment, the platform is not intrinsically dependent on it, since the serial communication and post-processing routines can be migrated to open-source environments such as Python or GNU Octave. Previous studies have used MATLAB/Simulink interfaces, Arduino-based microcontrollers, automated DC-DC converters, and electronic loads for battery characterization, mainly to generate current-demand profiles, execute pulsed discharge or cycling protocols, acquire voltage and current data, and identify ECM parameters using methods such as PEM or Levenberg–Marquardt nonlinear regression [27,43]. In contrast, the proposed platform integrates test configuration, real-time acquisition, automatic data logging, calibration processing, PDT execution, dynamic current profile generation, Thévenin ECM identification, voltage model validation, and SOC estimator evaluation within a single low-cost experimental workflow. Thus, its contribution lies in connecting

battery testing, model identification, and BMS-oriented SOC estimator validation using the same experimental architecture.

The interface allows configuration of the discharge current, cut-off voltage, sampling period, PDT parameters, operating mode, and experimental metadata. The ESP32 firmware implements several operating modes for battery characterization and SOC estimation, including no-load voltage measurement (VONLY), CC-CV full-charge test (CHARGE), full discharge (FULL), short-duration discharge (SHORT), Pulse Discharge Test (PDT), dynamic SOC-oriented profiles, and manual current control (MANUAL). During each test, voltage, current, time, control events, and experimental parameters are stored automatically in Excel files for subsequent processing in MATLAB. The data-recording period was configured from the MATLAB interface through the T_s parameter, which can be modified for any test mode. In the reported experiments, $T_s = 1000$ ms was used, corresponding to a data-recording frequency of 1 Hz. The ESP32 current-control loop was updated every 50 ms. This integration between embedded control, experimental instrumentation, and numerical processing enabled the implementation of a flexible platform for Thévenin ECM parameter identification and SOC estimation algorithm validation.

2.6. Experimental Characterization Under Constant-Current Discharge Tests

Figures 7 and 8 show the experimental full-discharge voltage curves at 0.2C, 0.5C, 1C, and 1.5C, plotted as a function of time and Depth of Discharge (DoD), respectively. Table 4 summarizes the extracted capacity values for each discharge test, obtained by calibrated current integration using the recorded time vector of each dataset. Between tests, the cell was restored using the CC-CV charging protocol, with charging currents within the manufacturer-specified standard charge condition. Although the measured capacity varied with C-rate, the 0.2C result was retained as the nominal capacity baseline because it closely matched the manufacturer-specified standard capacity.

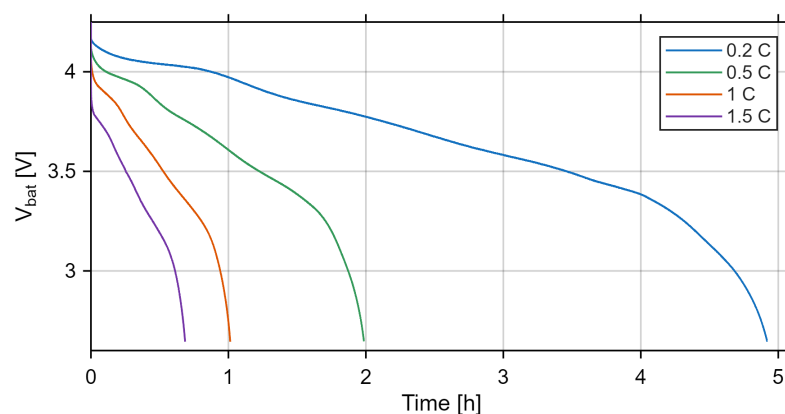


Figure 7. Experimental Full-Discharge Voltage Curves at Different C-Rates.

The results show a gradual increase in usable capacity as the discharge rate increases. This behavior differs from the classical capacity reduction expected at high currents due to the Peukert effect [30]. During the 1C and 1.5C tests, perceptible cell heating was qualitatively observed. Since these tests were performed without active thermal control or direct temperature measurement, the observed capacity increase may be associated with self-heating effects caused by the higher discharge current; however, this interpretation should be considered a plausible hypothesis and a limitation of the current platform.

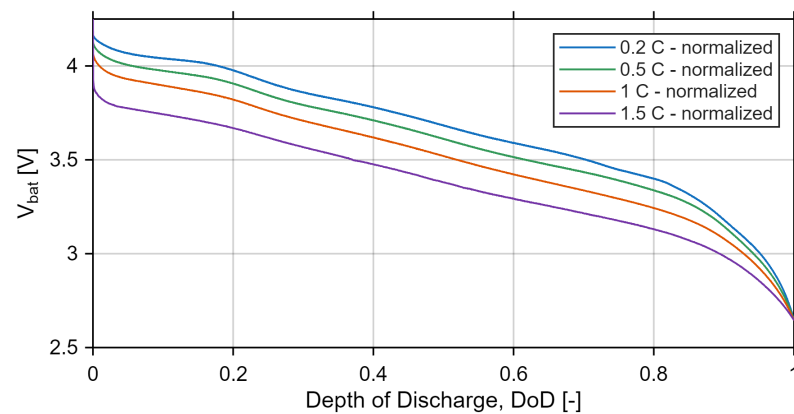


Figure 8. Experimental Normalized Discharge Curves at Different C-Rates.

Table 4. Discharge Capacity Summary at Different C-Rates.

Test	Capacity [mAh]
0.2C	3345.1
0.5C	3376.4
1C	3444.9
1.5C	3491.8

Several studies have reported that temperature strongly affects the dynamic behavior of Li-Ion batteries. As the cell temperature increases, electrochemical diffusion is favored and internal resistance or impedance can decrease significantly, modifying the apparent voltage response and available capacity during discharge [48,49]. In addition, the coupled interaction between temperature and discharge rate can produce nonlinear variations in internal parameters, temporarily counteracting polarization losses and allowing higher energy extraction under specific test conditions [50].

Consequently, the higher measured capacity at 1C and 1.5C should not be interpreted as an improvement in nominal cell performance. Because cell temperature was not directly measured or actively controlled, this result was interpreted as a C-rate-dependent experimental response under uncontrolled thermal conditions. Thus, self-heating is discussed only as a plausible contributing mechanism and not as a quantified effect. Future work will incorporate direct temperature measurement and thermal control to evaluate this effect and its influence on ECM parameter identification and SOC estimation.

3. Thévenin ECM Modeling and Parameter Identification

ECMs are widely used for Li-Ion battery modeling because they provide a suitable compromise between dynamic accuracy, low computational cost, and implementation simplicity in BMS applications [30,35]. Compared with electrochemical models, ECMs require fewer parameters and are more suitable for real-time estimation algorithms, while still capturing the main transient electrical phenomena observed during charge and discharge processes [51,52].

In this work, first-order and second-order Thévenin ECMs, denoted as 1RC and 2RC, were identified offline using experimental Pulse Discharge Test (PDT) data. The resulting SOC-dependent models were subsequently validated under dynamic current profiles before being used as the model basis for SOC estimation.

3.1. Thévenin Equivalent Circuit Models

Thévenin ECMs represent the battery terminal behavior using an SOC-dependent voltage source coupled with resistive and capacitive elements that emulate ohmic losses

and polarization dynamics. Figure 9 shows the equivalent circuit structures considered in this work: a first-order Thévenin model with one RC branch and a second-order Thévenin model with two RC branches. Although the proposed workflow can be extended to higher-order ECMs, this study focused on 1RC and 2RC Thévenin models for PDT-based parameter identification and SOC estimation.

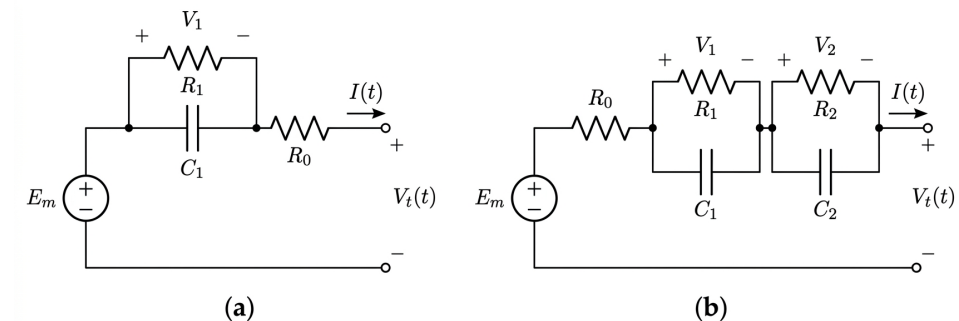


Figure 9. Schematic diagram of the ECMs: (a) first-order Thévenin model (1RC), (b) second-order Thévenin model (2RC).

In both models, E_m represents the OCV, which depends nonlinearly on SOC and temperature. The ohmic resistance R_0 accounts for the instantaneous voltage drop associated with lumped ohmic contributions, including electrolyte resistance, electronic conduction through current collectors, and contact resistances [53,54]. The RC branches describe transient polarization phenomena. In the 1RC model, a single branch represented by R_1 and C_1 approximates the combined effect of charge-transfer and diffusion-related dynamics. In the 2RC model, the additional branch R_2C_2 allows the model to represent two different time scales, improving the reproduction of transient behavior under variable current profiles [55,56].

For the 1RC model, the terminal voltage V_t is given by (6)

$$V_t(t) = E_m(t) - I(t)R_0(t) - V_1(t) \quad (6)$$

where $V_1(t)$ is the polarization voltage and I_t is the battery current, defined as positive during discharge. The polarization voltage dynamics are described by (7):

$$\frac{dV_1(t)}{dt} = -\frac{1}{R_1C_1}V_1(t) + \frac{1}{C_1}I(t) \quad (7)$$

with the dominant time constant $\tau_1 = R_1C_1$. For the 2RC model, the terminal voltage is expressed as (8):

$$V_t(t) = E_m(t) - I(t)R_0(t) - V_1(t) - V_2(t) \quad (8)$$

where $V_1(t)$ and $V_2(t)$ are the transient voltages associated with the fast and slow polarization branches, respectively. Their dynamics are given in (9) and (10), that is,

$$\frac{dV_1(t)}{dt} = -\frac{1}{R_1C_1}V_1(t) + \frac{1}{C_1}I(t) \quad (9)$$

$$\frac{dV_2(t)}{dt} = -\frac{1}{R_2C_2}V_2(t) + \frac{1}{C_2}I(t) \quad (10)$$

with the corresponding time constants $\tau_1 = R_1C_1$ and $\tau_2 = R_2C_2$. Since the electrical parameters of Li-Ion batteries vary nonlinearly with SOC and temperature, the cell behavior should be represented using parameters that depend on the operating conditions rather

than assuming constant values throughout the discharge process [35,57]. In this work, temperature was not actively controlled or directly measured during the full-discharge and PDT tests; therefore, the parameter identification was formulated mainly as a function of SOC, while recognizing that thermal variations may influence the estimated parameters.

3.2. PDT-Based Parameter Identification

Offline parameter identification was performed using Pulse Discharge Tests. The PDT profile consisted of constant-current discharge pulses with $I_{\text{set}} = 3.35$ A and a duration of 6 min, followed by 24 min open-circuit relaxation periods. This sequence was repeated for ten pulses, allowing the battery voltage response to be evaluated at different SOC levels while separating the instantaneous ohmic drop from the slower relaxation dynamics [57,58].

Figure 10 illustrates the voltage response during a single discharge pulse. At the beginning of the pulse, the instantaneous voltage drop is mainly associated with R_0 . The value of ΔV_0 was determined from the voltage immediately before the current step and the first voltage sample after the discharge current reaches I_p , so that only the initial ohmic drop is considered and the following RC polarization decay is excluded [35]. During the pulse, the voltage evolves according to the polarization dynamics represented by the RC branch. After current interruption, the cell enters a relaxation period and the terminal voltage gradually recovers toward a quasi-equilibrium condition. This graphical identification principle is commonly used to obtain physically meaningful initial values for Thévenin ECM parameters before numerical optimization [30].

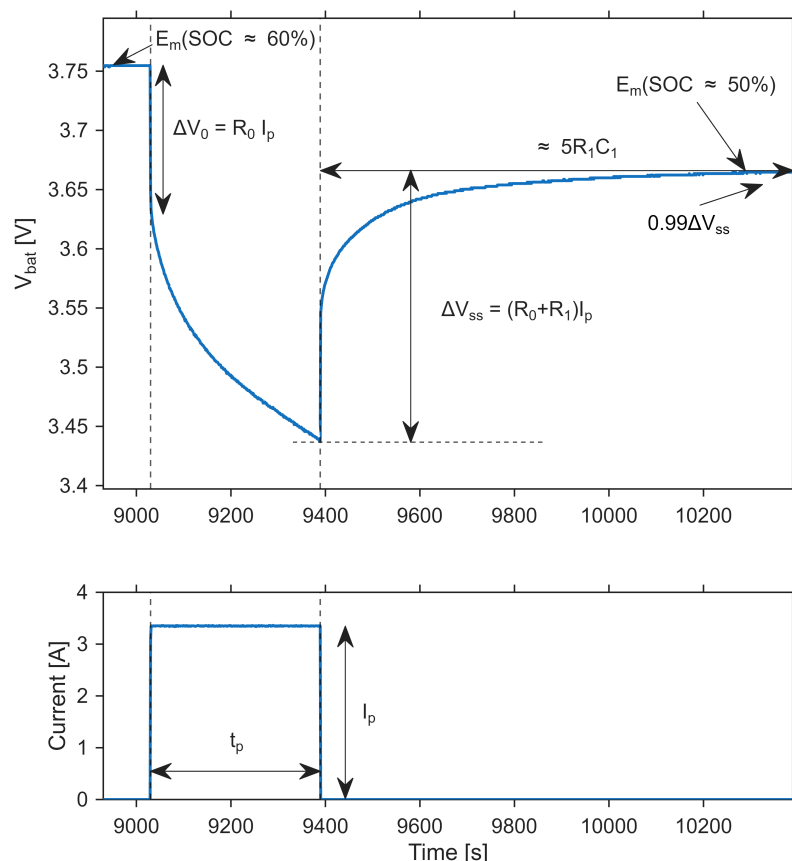


Figure 10. Dynamic voltage response during a single pulse discharge test (PDT) current pulse for the 1RC Thévenin model parameter identification.

For each pulse, the ohmic resistance was initially inferred from the instantaneous voltage drop, while the polarization resistance and capacitance were estimated from the total voltage variation and the relaxation time. For the 2RC model, the total polarization

resistance was distributed between a fast and a slow branch to initialize two transient time scales. This analytical initialization was not used as the final parameter set; instead, it provided physically consistent starting points for the subsequent nonlinear optimization.

3.3. Initial Parameter Estimation

For the Samsung INR18650-35E cell, a nominal capacity of 3350 mAh was adopted, corresponding to the minimum capacity specified by the manufacturer under standard 0.2C discharge conditions. For the PDT sequences, E_m was initialized from the terminal voltage measured after the CC-CV charging stage and a relaxation period longer than the 60 min minimum described in Section 2.2. This value was used as a quasi-equilibrium approximation of the OCV before starting the pulse sequence. From the experimental pulse shown in Figure 10, the baseline values summarized in Table 5 were extracted.

Table 5. Baseline Values Extracted from the Experimental Discharge Pulse.

Variable	E_m (SOC $\approx$ 60%)	E_m (SOC $\approx$ 50%)	ΔV_0	ΔV_{ss}	Δt_{ss}
Measured value	3.7547 V	3.6647 V	0.1213 V	0.2275 V	$\approx$ 990 s

Using the graphical estimation procedure reported for Thévenin ECM initialization [30], the initial parameter vector for the 1RC model was defined. For the 2RC structure, this criterion was extended by preserving the total polarization resistance obtained from the 1RC initialization and distributing it into two branches associated with fast and slow transient dynamics. Thus, the condition $R_1 + R_2 = 0.0317 \Omega$ was imposed, with initial values $R_1 = 0.0127 \Omega$ and $R_2 = 0.0190 \Omega$. Approximate time constants of $\tau_1 \approx 50$ s and $\tau_2 \approx 198$ s were then assigned to initialize the corresponding capacitances, yielding $C_1 \approx 3937$ F and $C_2 \approx 10421$ F. The initial parameter vectors used in the optimization are summarized in Table 6.

Table 6. Estimated Initial Parameter Vectors θ_0 for the 1RC and 2RC Models.

ECM Model	Structure of the θ_0 Vector	Estimated Initial Parameters
1RC Thévenin	$[R_0, R_1, C_1, E_m]$	$[0.0362 \Omega, 0.0317 \Omega, 6247 \text{ F}, 3.7547 \text{ V}]$
2RC Thévenin	$[R_0, R_1, C_1, R_2, C_2, E_m]$	$[0.0362 \Omega, 0.0127 \Omega, 3937 \text{ F}, 0.0190 \Omega, 10421 \text{ F}, 3.7547 \text{ V}]$

These initial vectors provided a physically consistent basis for the nonlinear fitting stage, reducing the risk of convergence toward nonphysical local minima.

3.4. Nonlinear Least-Squares Optimization

Starting from the initial parameter vectors θ_0 , nonlinear least-squares optimization was performed in MATLAB using the lsqnonlin function. This approach is commonly applied for ECM parameter identification because it minimizes the residual error between the measured terminal voltage and the simulated model response [59–61].

The objective function was defined by (11),

$$J(\theta) = \sum_{k=1}^N (V_{\text{exp}}(k) - V_{\text{model}}(k, \theta))^2 \quad (11)$$

where $V_{\text{exp}}(k)$ is the experimentally measured terminal voltage, $V_{\text{model}}(k, \theta)$ is the simulated ECM voltage, and θ is the parameter vector to be optimized. To evaluate the behavior of the identified ECMs under different initial charge conditions, three PDT tests were

performed with different initial battery voltages: $V_{\text{bat},0} \approx 4.2239$ V, $V_{\text{bat},0} \approx 4.1987$ V, and $V_{\text{bat},0} \approx 4.1819$ V. The third test completed the full pulse-discharge sequence down to a terminal voltage close to the manufacturer-specified cut-off voltage, whereas the two tests with higher initial voltages ended slightly above this condition. These three experimental datasets provided multiple dynamic profiles for model identification and subsequent SOC estimation analysis.

Figure 11 presents the multi-test identification results for the 1RC ECM. Figure 11a compares the measured and estimated terminal voltage, Figure 11b shows the PDT current profile, and Figure 11c presents the voltage residual. Figure 12 shows the corresponding identified 1RC parameters as a function of SOC.

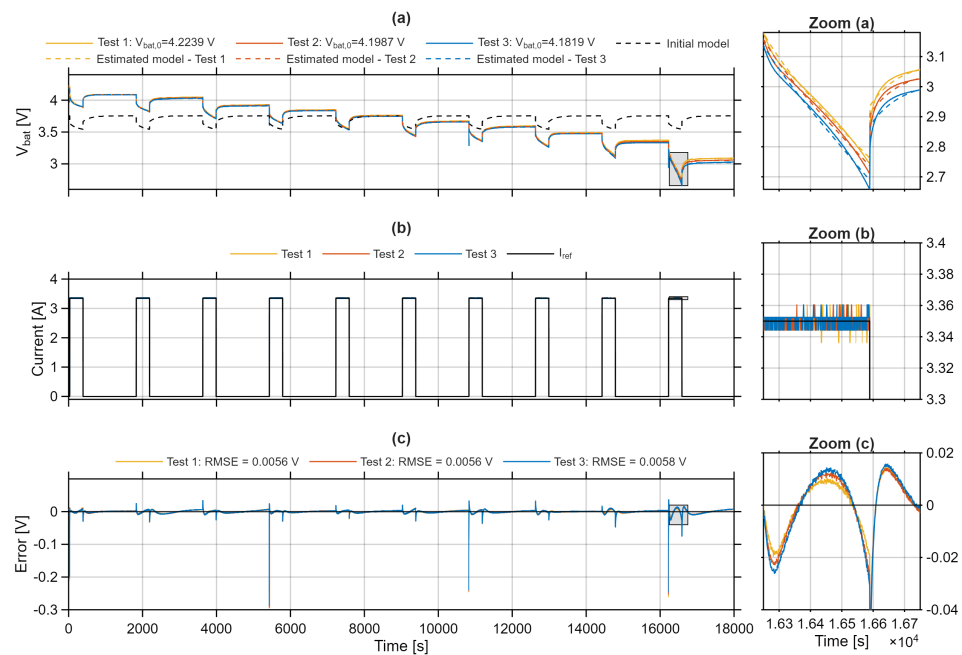


Figure 11. Multi-Test Identification Results for the 1RC ECM: (a) Experimental and Estimated Voltage Response, (b) PDT Current Profile, and (c) Voltage Error.

The 1RC model reproduced the global voltage dynamics of the PDT profiles with RMSE values below 6 mV. The identified E_m curve presented a smooth and monotonic trend with SOC, while R_0 increased at low SOC, consistent with the expected rise in internal resistance in highly nonlinear operating regions [57]. The variations observed in C_1 can be associated with the numerical sensitivity of time-constant estimation during polarization fitting [35,55]. The same optimization procedure was applied to the 2RC ECM. The voltage identification results are shown in Figure 13, while the SOC-dependent parameters are presented in Figure 14.

Compared with the 1RC model, the 2RC structure provided a better approximation of the transient voltage response, particularly during relaxation periods after each current pulse. This improvement is attributed to the second RC branch, which enables the model to represent polarization and diffusion phenomena occurring at different time scales [55,62].

Table 7 summarizes the optimization results for both ECMs. The 2RC model reduced the RMSE by approximately 22–24% compared with the 1RC model. However, this improvement was obtained at the expense of higher computational cost, reflected in longer optimization times and a larger number of iterations. This behavior confirms the trade-off between dynamic accuracy and computational complexity in ECMs of different order, which is particularly relevant for embedded BMS applications and real-time SOC estimation [55,56,63].

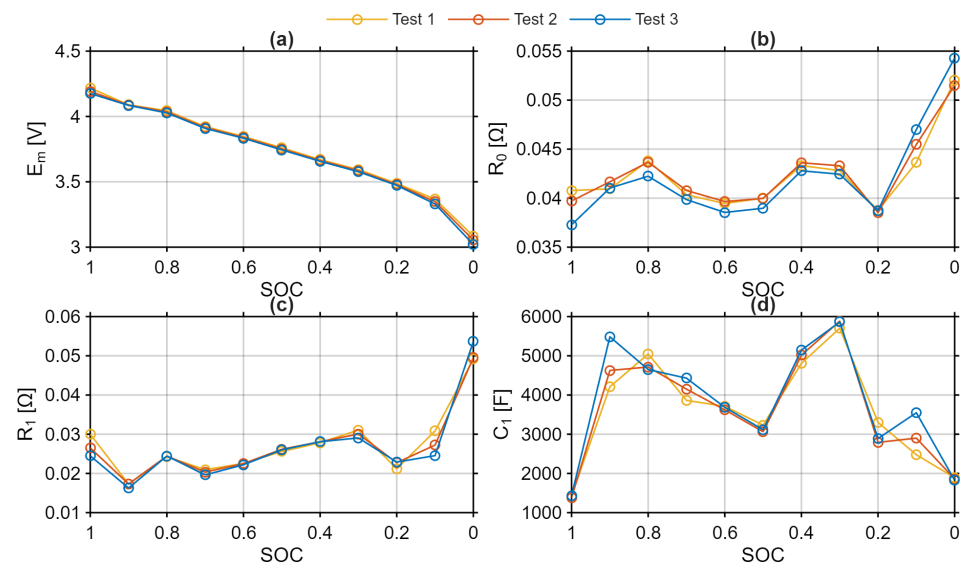


Figure 12. Identified 1RC ECM Parameters as a Function of SOC: (a) E_m , (b) R_0 , (c) R_1 , (d) C_1 .

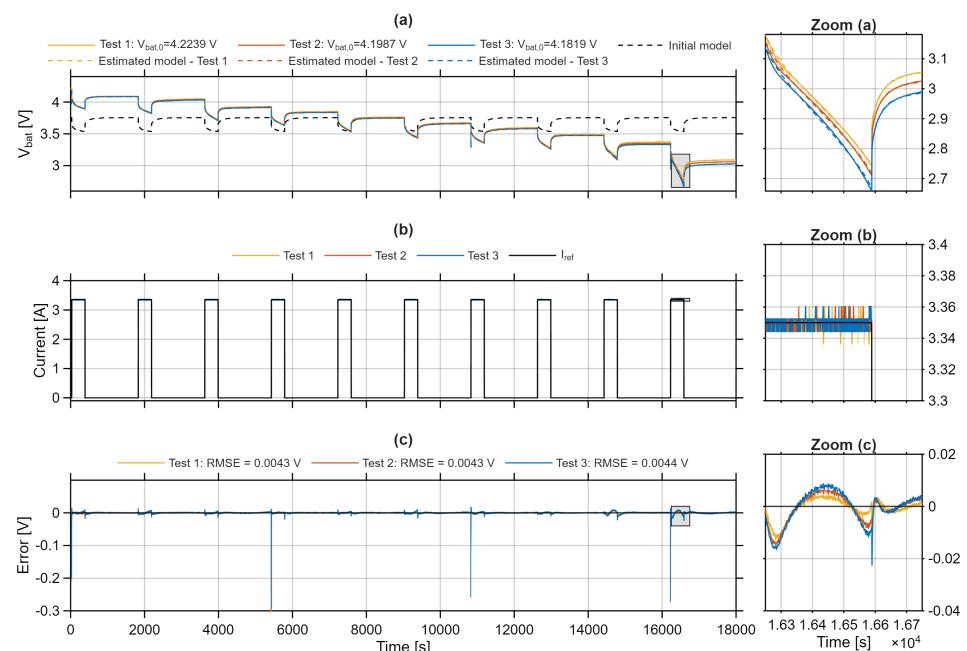


Figure 13. Multi-Test Identification Results for the 2RC ECM: (a) Experimental and Estimated Voltage Response, (b) PDT Current Profile, and (c) Voltage Error.

Table 7. Optimization results summary for the 1RC and 2RC ECMs.

Model	Test	$V_{bat,0}$ [V]	Estimated RMSE [V]	Optimization Time [s]	Iterations
1RC	Test 1	4.2239	0.005551	1.48	25
1RC	Test 2	4.1987	0.005615	1.20	25
1RC	Test 3	4.1819	0.005753	1.06	22
2RC	Test 1	4.2239	0.004303	30.23	343
2RC	Test 2	4.1987	0.004325	9.43	110
2RC	Test 3	4.1819	0.004364	9.52	102

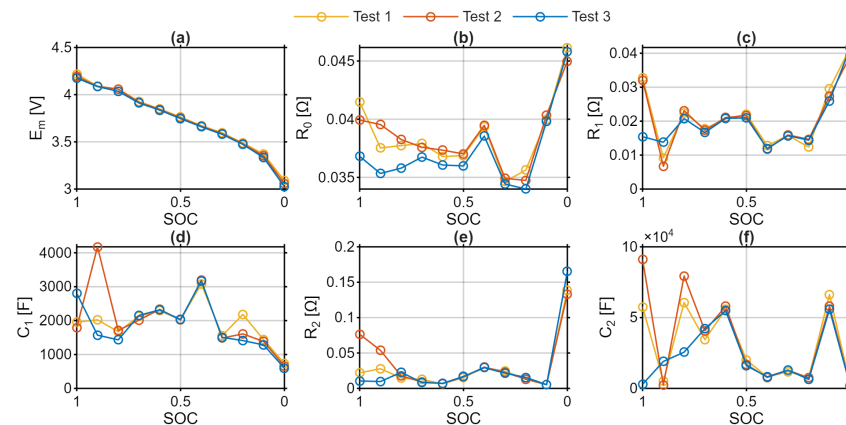


Figure 14. Identified 2RC ECM Parameters as a Function of SOC: (a) E_m , (b) R_0 , (c) R_1 , (d) C_1 , (e) R_2 , (f) C_2 .

The higher computational demand observed for the 2RC model in Test 1 may be related to the high initial SOC region near the beginning of the test. Near full charge, residual voltage relaxation after the CC-CV stage and SOC-dependent parameter variations can make the pulse response more sensitive to small changes in the initial electrical state. This effect becomes more relevant for the 2RC model because the additional RC branch increases the parameter search space and may amplify dispersion in highly dynamic parameters such as C_2 [35]. Therefore, although the 2RC model improves transient voltage representation, its selection for embedded BMS-oriented implementation must consider whether the accuracy gain justifies the additional states, parameter-identification demands, and computational cost.

3.5. SOC-Dependent Parameterization

The optimization results confirm that ECM parameters cannot be assumed constant throughout the discharge process. In particular, the equivalent resistances and capacitances vary nonlinearly with SOC, with more pronounced changes at low SOC and near the operating limits of the cell. Similar behavior has been reported in ECM identification studies, where R_0 , R_1 , R_2 , C_1 , C_2 , and the OCV–SOC relationship show significant variation along the discharge range [35,57].

Based on the optimized parameters at different SOC levels, Lookup Tables (LUTs) were constructed for each ECM parameter. The parameter vector of the 1RC ECM was defined as $\theta_{1RC}(SOC) = [R_0(SOC), R_1(SOC), C_1(SOC), E_m(SOC)]$, whereas the parameter vector of the 2RC ECM was defined as $\theta_{2RC}(SOC) = [R_0(SOC), R_1(SOC), C_1(SOC), R_2(SOC), C_2(SOC), E_m(SOC)]$.

To enable continuous dynamic simulation, the discrete LUT values were interpolated using the Piecewise Cubic Hermite Interpolating Polynomial (PCHIP) method in MATLAB. This interpolation preserves the local shape of the identified data and avoids overshoot or nonphysical values that may appear with conventional cubic splines, particularly in sensitive parameters such as equivalent capacitances. From a numerical perspective, this approach also avoids the artificial oscillations associated with high-order global polynomial fitting near the interval boundaries [64,65].

For each identified parameter p_i , the continuous function used in simulation was defined by (12), where SOC_j represents the discrete SOC points used during identification, and $p_{i,j}$ is the optimized value of parameter p_i at each experimental point. This formulation was applied to $R_0(SOC)$, $R_1(SOC)$, $C_1(SOC)$, $R_2(SOC)$, $C_2(SOC)$ and $E_m(SOC)$, allowing the ECMs to update their parameters as SOC evolves during simulation.

$$p_i(\text{SOC}) = \text{pchip}(\text{SOC}_j, p_{i,j}) \quad (12)$$

Figure 15 shows the interpolated 1RC parameters $E_m(\text{SOC})$, $R_0(\text{SOC})$, $R_1(\text{SOC})$ and $C_1(\text{SOC})$. Figure 16 presents the corresponding 2RC interpolation, including $R_2(\text{SOC})$ and $C_2(\text{SOC})$. In both cases, the interpolated curves preserved the general trends of the experimental data and provided continuous parameter maps for dynamic simulation and SOC estimation.

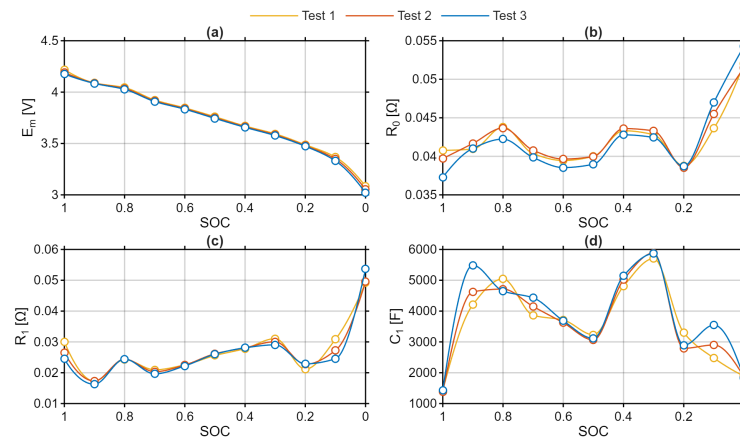


Figure 15. PCHIP interpolation of the identified 1RC ECM parameters as a function of SOC: (a) E_m , (b) R_0 , (c) R_1 , (d) C_1 . Solid lines represent the PCHIP interpolation, and open-circle markers denote the discrete identified parameter values.

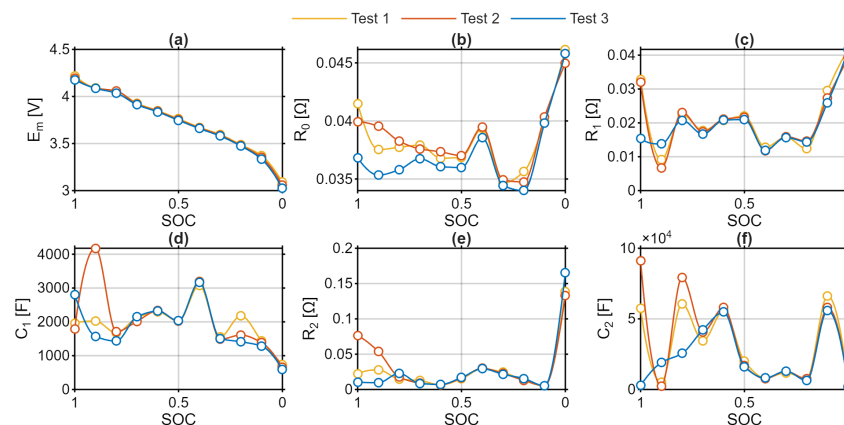


Figure 16. PCHIP interpolation of the identified 2RC ECM parameters as a function of SOC: (a) E_m , (b) R_0 , (c) R_1 , (d) C_1 , (e) R_2 , (f) C_2 . Solid lines represent the PCHIP interpolation, and open-circle markers denote the discrete identified parameter values.

3.6. Voltage-Based Dynamic Validation of the Identified ECMs

Before using the identified ECMs as the model basis for SOC estimation, their ability to reproduce the battery terminal voltage was evaluated under dynamic profiles not directly used during parameter identification. This validation was performed using two experimental profiles: a scaled Dynamic Stress Test (DST) profile and a modified Pulsed Dynamic Stress Test (P-DST) profile with high dynamics. The Scaled DST profile consists of a 360 s dynamic sequence with different current levels and rest periods [66]. The Modified P-DST profile consists of a 180 s highly dynamic sequence without rest periods, including abrupt transitions between 1 A charging periods and different discharge current levels. Dynamic profiles are widely used to assess battery models and SOC estimation algorithms under variable operating conditions [59,67].

The voltage error was defined as $e_V(k) = V_{\text{exp}}(k) - V_{\text{model}}(k)$, where $V_{\text{exp}}(k)$ is the measured terminal voltage and $V_{\text{model}}(k)$ is the simulated voltage obtained from the 1RC or 2RC ECM. The error metrics were calculated as (13)–(15), that is,

$$\text{RMSE}_V = \sqrt{\frac{1}{N} \sum_{k=1}^N e_V^2(k)} \quad (13)$$

$$\text{MAE}_V = \frac{1}{N} \sum_{k=1}^N |e_V(k)| \quad (14)$$

$$\text{MaxAE}_V = \max_k |e_V(k)| \quad (15)$$

Figures 17 and 18 show the dynamic voltage validation for the Test 3 parameter set, which provided the best overall performance in both profiles. The complete error metrics for the six evaluated models are summarized in Table 8.

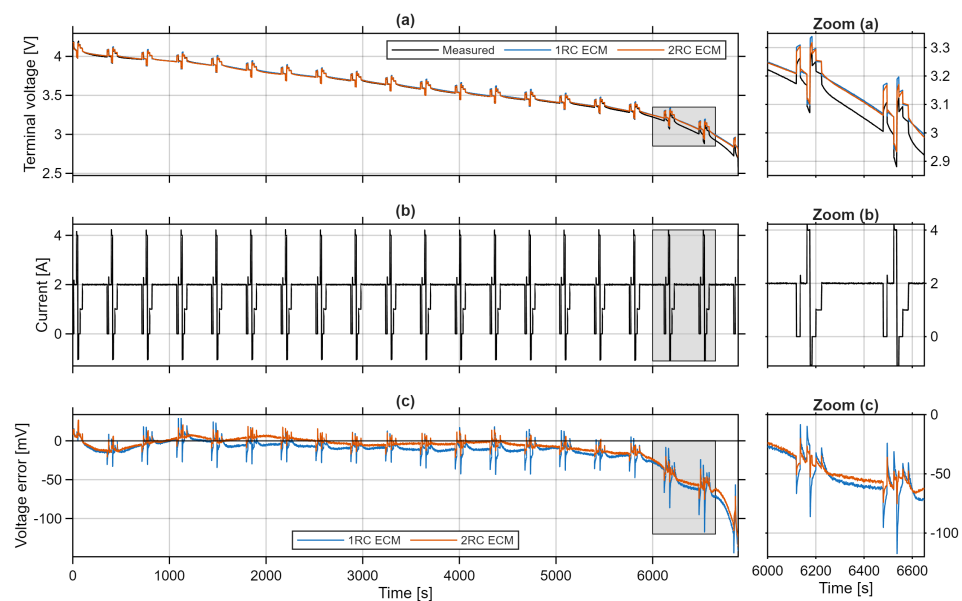


Figure 17. Voltage-based Dynamic Validation of the 1RC and 2RC ECMs—Test 3: (a) Measured and Simulated Terminal Voltage under the Scaled DST Profile, (b) Scaled DST Current Profile, (c) Voltage Error.

Table 8. Voltage-based dynamic validation of the 1RC and 2RC ECMs under Scaled DST and Modified P-DST profiles.

Test	ECM Model	Scaled DST			Modified P-DST		
		RMSE _V [mV]	MAE _V [mV]	MaxAE _V [mV]	RMSE _V [mV]	MAE _V [mV]	MaxAE _V [mV]
Test 1	1RC	46.0348	32.7603	217.2496	33.8480	25.4147	164.3979
Test 1	2RC	42.5525	27.4366	209.7050	30.1008	20.9672	143.6708
Test 2	1RC	36.3904	23.4054	190.8971	24.4637	16.8447	137.9596
Test 2	2RC	36.3348	24.0937	182.4824	25.0861	17.5295	116.7136
Test 3	1RC	26.3893	16.6328	144.2246	15.8642	11.0733	107.3323
Test 3	2RC	23.2425	12.8570	137.1429	12.1399	8.3502	101.0652

The results show that the voltage prediction error decreases from Test 1 to Test 3 for both dynamic profiles. The best performance was obtained with the 2RC model identified from Test 3, reaching RMSE_V values of 23.24 mV for the Scaled DST profile and 12.14 mV for the Modified P-DST profile. In general, the 2RC model provided better dynamic representation than the 1RC model, although the difference between both models

was reduced in some intermediate cases. The largest MaxAE_v values occurred mainly during abrupt current transitions and near the end-of-discharge region, where the voltage response becomes more nonlinear. The remaining deviations are associated with combined measurement and modeling factors, including ADC resolution, sensor offset and noise, shunt and voltage-scaling tolerances, PCB voltage drops, initial SOC/OCV uncertainty, SOC-dependent parameter interpolation, unmeasured temperature variations, and the limited-order 1RC/2RC ECM structure. This validation closes the ECM modeling and identification stage and confirms that the identified SOC-dependent models provide a suitable basis for the SOC estimation methods evaluated in the following section.

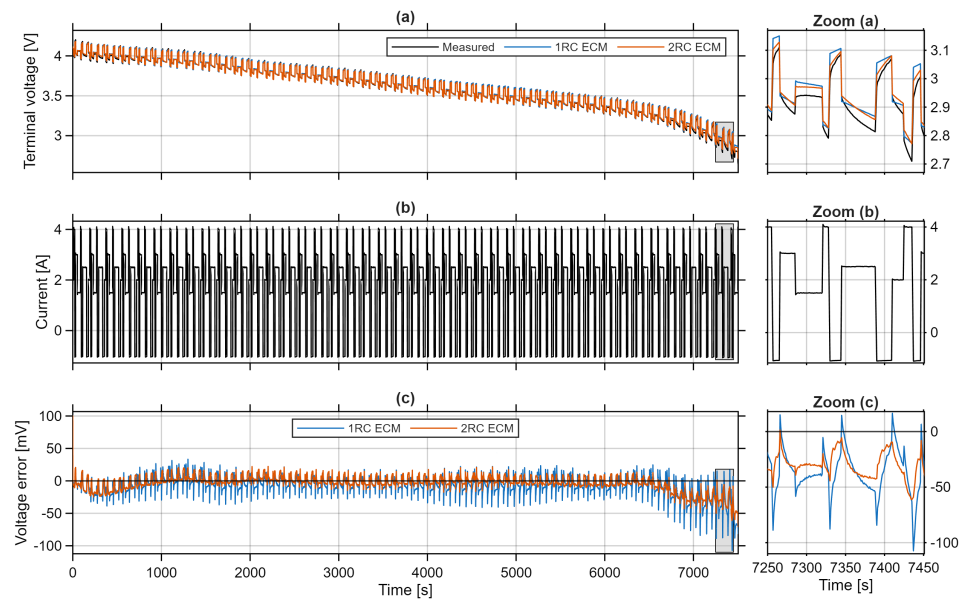


Figure 18. Voltage-based High-Dynamic Validation of the 1RC and 2RC ECMs—Test 3: (a) Measured and Simulated Terminal Voltage under the Modified P-DST Profile, (b) Modified P-DST Current Profile, (c) Voltage Error.

4. SOC Estimation and Performance Evaluation

SOC estimation is one of the core functions of a BMS, since it provides information about the available capacity of the cell and helps prevent unsafe operation under overcharge or overdischarge conditions. However, SOC cannot be measured directly and must be inferred from external variables such as current, terminal voltage, and, in some cases, temperature. This task becomes more challenging in Li-Ion batteries due to their nonlinear electrochemical behavior, SOC-dependent parameters, and sensitivity to dynamic operating conditions [14,59].

In this section, three SOC estimation strategies are evaluated using the SOC-dependent ECMs identified and validated in Section 3: coulomb counting as an operational reference, EKF estimators based on the 1RC and 2RC ECMs, and a hybrid EKF-ANN method for residual SOC correction. This structure allows a progressive comparison from conventional current integration to model-based estimation and data-assisted correction, while maintaining a compact methodology consistent with recent reviews on SOC estimation, Kalman filtering, and hybrid approaches [3,11].

4.1. Estimation by Coulomb Counting

Coulomb counting was used as the operational SOC reference due to its computational simplicity, low parameter requirement, and widespread use in BMS applications. The method estimates SOC through time integration of the measured current; therefore, its accuracy depends on the initial SOC, the available cell capacity, current sensor offset

compensation, and coulombic efficiency [3,59]. Although it provides a practical reference, coulomb counting can accumulate drift during long cycles or dynamic profiles if no correction mechanism is included [11,14,68]. The SOC estimation by coulomb counting was computed as follows,

$$SOC(k) = SOC(k-1) - \frac{\eta I(k)\Delta t}{Q_n} \quad (16)$$

where Q_n is the assumed nominal capacity, η is the coulombic efficiency, $I(k)$ is the measured current, and Δt is the sampling period. In this work, current is considered positive during discharge; therefore, SOC decreases when $I(k) > 0$. For comparison purposes, the operational reference SOC was also obtained by current integration using the adopted reference capacity and calibrated current measurements, that is,

$$SOC_{\text{ref}}(k) = SOC_0 - \frac{1}{Q_{\text{ref}}} \sum_{i=1}^k I(i)\Delta t \quad (17)$$

This approach allows coulomb counting to be used as the experimental SOC reference, provided that Q_{ref} , current offset, and initial SOC are properly defined. Accordingly, $Q_{\text{ref}} = 3.35 \text{ Ah}$ was fixed for all SOC calculations, rather than being recalculated from the capacity obtained at each C-rate condition.

4.2. EKF-Based SOC Estimation Using 1RC and 2RC ECMs

To reduce the cumulative drift associated with coulomb counting, Extended Kalman Filter (EKF) estimators were implemented using the SOC-dependent 1RC and 2RC ECMs. Kalman filters and their variants are widely used for SOC estimation because they combine dynamic model prediction with voltage-based correction, partially compensating for integration errors, measurement noise, and model uncertainty [11,59,69]. In addition, the use of SOC-dependent ECM parameters, as implemented in this work through LUTs, has been reported as an effective strategy to improve EKF-based SOC estimation under dynamic operating conditions [11,70]. The general discrete-time state-space representation was expressed as:

$$x_k = f(x_{k-1}, I_{k-1}, \theta(SOC_{k-1})) + w_k \quad (18)$$

$$V_{t,k} = h(x_k, I_k, \theta(SOC_k)) + v_k \quad (19)$$

where x_k is the state vector, w_k is the process noise, v_k is the measurement noise, and $\theta(SOC)$ is the SOC-dependent parameter set obtained from the LUTs and PCHIP interpolation described in Section 3.5. For the 1RC ECM, the state vector consisted of the battery SOC and the polarization voltage state, $x_{1RC,k} = [SOC_k, V_{1,k}]^T$. For the 2RC ECM, an additional polarization state was included, resulting in $x_{2RC,k} = [SOC_k, V_{1,k}, V_{2,k}]^T$. The EKF prediction stage was performed using the nonlinear state-transition function and the previous state estimate, according to the model represented by (18).

The state update was performed from the difference between the measured terminal voltage and the model-estimated voltage:

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k [V_{\text{exp}}(k) - V_{\text{model}}(k)] \quad (20)$$

where K_k is the Kalman gain. In both EKF implementations, the covariance matrices Q , R , and P_0 were experimentally tuned, while the electrical parameters were directly obtained from the corresponding 1RC and 2RC LUTs.

Figures 19 and 20 show the SOC estimation results obtained with the Test 3 parameter set, selected for graphical representation because it provided the best overall performance in the dynamic voltage validation of Section 3.6. Under the Scaled DST profile, EKF-2RC achieved the lowest estimation error in Test 3, with $RMSE_{SOC} = 0.5088\%$, $MAE_{SOC} = 0.4532\%$, and $MaxAE_{SOC} = 1.0560\%$. In comparison, EKF-1RC yielded $RMSE_{SOC} = 0.8715\%$, $MAE_{SOC} = 0.7971\%$, and $MaxAE_{SOC} = 1.6750\%$. Consequently, the inclusion of the second RC branch reduced the RMSE by approximately 41.6%, the MAE by 43.1%, and the maximum absolute error by 37.0%. These results indicate that the additional polarization branch improves the representation of battery transient dynamics, leading to more accurate voltage prediction and, consequently, enhanced EKF-based SOC estimation. This behavior is consistent with previous studies reporting a direct relationship between ECM voltage model accuracy and the performance of Kalman-filter-based SOC estimators [17,71].

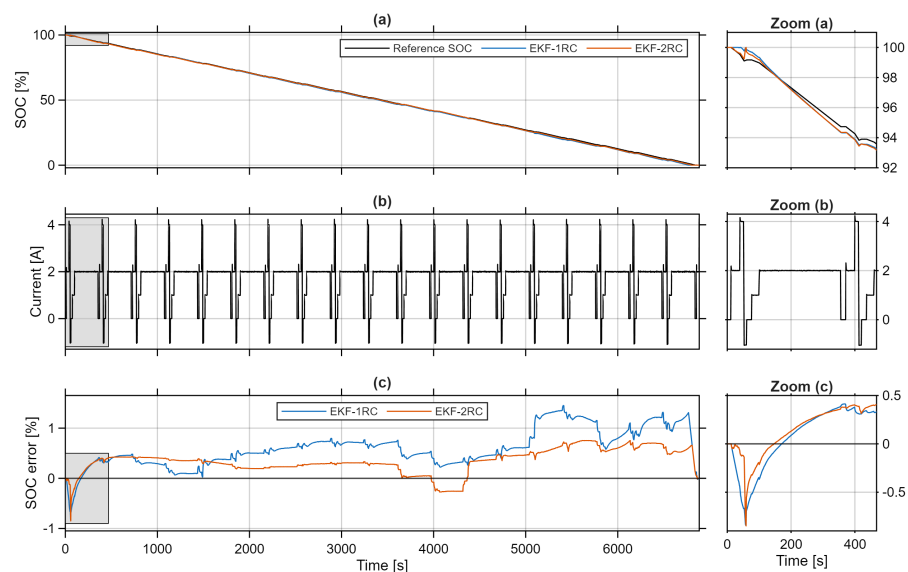


Figure 19. SOC Estimation Results under the Scaled DST Profile—Test 3: (a) Reference and Estimated SOC using EKF-1RC and EKF-2RC, (b) Scaled DST Current Profile, (c) SOC Estimation Error.

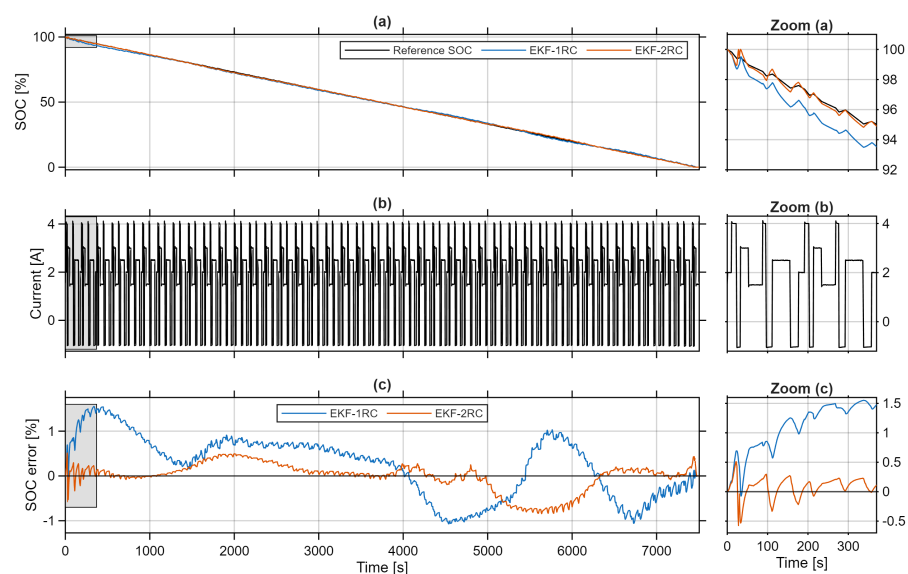


Figure 20. SOC Estimation Results under the highly dynamic Modified P-DST Profile—Test 3: (a) Reference and Estimated SOC using EKF-1RC and EKF-2RC, (b) Modified P-DST Current Profile, (c) SOC Estimation Error.

Under the Modified P-DST profile, characterized by abrupt current transitions and absence of rest periods, both EKF estimators remained within adequate error ranges. For Test 3, EKF-2RC achieved $RMSE_{SOC} = 1.0890\%$ and $MAE_{SOC} = 0.9466\%$, whereas EKF-1RC obtained 1.2282% and 1.0717% , respectively. Although the $MaxAE_{SOC}$ of EKF-2RC was slightly higher in this profile, its lower RMSE and MAE indicate better average tracking during most of the cycle. This behavior suggests that abrupt current transitions may produce localized peak errors without significantly affecting the overall SOC trajectory.

Table 9 summarizes the SOC estimation error metrics for the EKF-1RC and EKF-2RC estimators under DST and P-DST profiles. The results show a progressive improvement from the Test 1 to the Test 3 parameter sets. The EKF-2RC estimator provided the best average performance in most cases, with all $RMSE_{SOC}$ values below 1.64% and values below 1.1% for Test 3 in both profiles. This trend also suggests that the initial conditions of the PDT used for parameter identification influence the subsequent SOC estimation performance. In particular, parameter sets obtained from tests starting at ultra-high SOC levels may be more sensitive to nonlinear polarization behavior in the upper voltage region, affecting the robustness of the resulting ECM during dynamic SOC estimation.

Overall, the EKF-2RC estimator offered the best trade-off among the conventional ECM-based methods, improving SOC tracking while preserving the interpretability of the equivalent circuit structure. Although the 2RC model is more complex than the 1RC model, the observed error reduction supports its use when higher dynamic accuracy is required in BMS-oriented applications [71,72].

Table 9. SOC Estimation Error Metrics for the EKF-1RC and EKF-2RC Estimators under the Scaled DST and Modified P-DST Profiles.

Test	Estimator	Scaled DST			Modified P-DST		
		$RMSE_{SOC} [\%]$	$MAE_{SOC} [\%]$	$MaxAE_{SOC} [\%]$	$RMSE_{SOC} [\%]$	$MAE_{SOC} [\%]$	$MaxAE_{SOC} [\%]$
Test 1	EKF-1RC	2.2098	2.1280	3.3310	2.5007	2.3214	4.2290
Test 1	EKF-2RC	1.3543	1.2120	2.3477	1.3988	0.9940	3.4947
Test 2	EKF-1RC	1.3917	1.2966	2.3348	1.7216	1.4968	3.3244
Test 2	EKF-2RC	1.0730	0.9335	2.0804	1.6382	1.4375	3.0861
Test 3	EKF-1RC	0.8715	0.7971	1.6750	1.2282	1.0717	2.5819
Test 3	EKF-2RC	0.5088	0.4532	1.0560	1.0890	0.9466	2.8343

4.3. Hybrid EKF-ANN Method for SOC Residual Correction

A hybrid EKF-ANN structure was implemented to improve the SOC estimation obtained from the best model-based estimator. In this approach, the EKF provides an initial SOC estimate based on the ECM, while an Artificial Neural Network (ANN) corrects residual errors associated with nonlinearities not fully captured by the model, parameter uncertainty, and unmodeled dynamic effects. This strategy preserves the interpretability of the ECM-based estimator while adding a data-driven correction stage.

The selection of this architecture is supported by previous studies combining Kalman filters and neural networks for Li-Ion battery SOC estimation. Dao et al. [73] implemented an EKF-ANN scheme based on a Thévenin model and reported maximum errors of approximately 2.6% for ANN, 2.8% for EKF, and below 1% for the hybrid EKF-ANN structure. This result highlights the potential of combining model-based estimation with residual correction learned from experimental data. Recent studies on data-driven SOC estimation also emphasize that model selection must balance accuracy, computational complexity, and generalization capability, particularly in BMS applications with implementation constraints [74].

In this work, the hybrid structure was formulated as a residual correction applied to the EKF-2RC estimator identified from Test 3, which showed the best overall performance in the dynamic profiles. The corrected SOC was defined by (21),

$$\text{SOC}_{\text{hyb}}(k) = \text{SOC}_{\text{EKF-2RC}}(k) + \Delta\text{SOC}_{\text{ANN}}(k) \quad (21)$$

where $\Delta\text{SOC}_{\text{ANN}}(k)$ is the correction estimated by the neural network. The correction target was defined as the residual error between the reference SOC and the EKF-2RC estimate (see Equation (22))

$$\Delta\text{SOC}(k) = \text{SOC}_{\text{ref}}(k) - \text{SOC}_{\text{EKF-2RC}}(k) \quad (22)$$

The ANN input vector was composed of experimental signals and low-complexity derived variables. In data-driven SOC estimation, the inclusion of local dynamic information has been identified as a relevant strategy to improve accuracy and generalization [74]. In particular, local voltage variation has been used in recent SOC estimation approaches to adapt the estimator response to regions with different dynamic sensitivity [75]. Therefore, the ANN input vector was defined in terms of the measured terminal voltage $V_t(k)$, the battery current $I(k)$, the SOC estimate provided by the EKF-2RC estimator $\text{SOC}_{\text{EKF-2RC}}(k)$, the instantaneous voltage model error $e_V(k)$, and the discrete derivatives $\Delta I(k)/\Delta t$ and $\Delta V_t(k)/\Delta t$.

The derived variables $\Delta I(k)/\Delta t$ and $\Delta V_t(k)/\Delta t$, computed as first-order finite differences between consecutive samples, provide local dynamic information related to current transients and voltage response variations.

To maintain a simple and reproducible implementation, a low-complexity feedforward ANN was trained in MATLAB using the Levenberg–Marquardt algorithm. This choice is consistent with studies using multilayer perceptron (MLP)-type networks for SOC estimation while seeking a balance between accuracy, computational cost, and BMS implementation feasibility [76,77]. The ANN was configured with two hidden layers of 10 and 5 neurons, resulting in 131 trainable parameters, and was trained to estimate the residual correction $\Delta\text{SOC}(k)$. This compact topology was retained after preliminary trials with nearby low-complexity configurations, while a full hyperparameter search was outside the scope because the ANN was used only as a bounded residual correction stage for the EKF-2RC estimator, not as a standalone SOC estimator.

To reduce overfitting and data leakage, the ANN dataset was partitioned by profile or by contiguous temporal blocks rather than by random point-wise sampling. PDT Tests 1–3, full-discharge tests at 0.2C and 1C, and one complete charge test were used for training, whereas the DST and P-DST profiles were divided into temporal blocks assigned exclusively to training, internal validation, and testing using a 60/20/20 ratio. The full-discharge tests at 0.5C and 1.5C were kept unseen during training and used as external validation profiles. The resulting performance under the Scaled DST and Modified P-DST profiles is presented in Figures 21 and 22, respectively, while the external validation results at 0.5C and 1.5C are shown in Figures 23 and 24.

4.4. Performance Comparison and Error Analysis

The performance of the SOC estimators was evaluated by comparing the estimated SOC trajectory with the operational reference SOC obtained by calibrated current integration. For each method, the following metrics were calculated:

$$\text{RMSE}_{\text{SOC}} = \sqrt{\frac{1}{N} \sum_{k=1}^N (\text{SOC}_{\text{ref}}(k) - \text{SOC}_{\text{est}}(k))^2} \quad (23)$$

$$\text{MAE}_{\text{SOC}} = \frac{1}{N} \sum_{k=1}^N |\text{SOC}_{\text{ref}}(k) - \text{SOC}_{\text{est}}(k)| \quad (24)$$

$$\text{MaxAE}_{\text{SOC}} = \max_k |\text{SOC}_{\text{ref}}(k) - \text{SOC}_{\text{est}}(k)| \quad (25)$$

Table 10 summarizes the results obtained under the Scaled DST and Modified P-DST profiles. For these profiles, the metrics were computed only over the test blocks not used during ANN training. Figures 21 and 22 show the complete temporal response, while the quantitative comparison is performed over the block-based test partition.

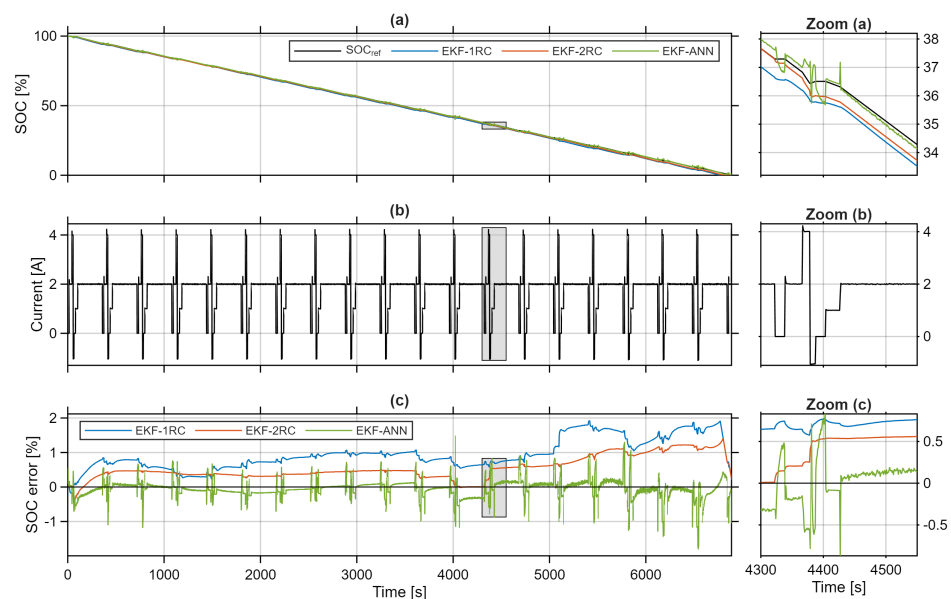


Figure 21. Hybrid SOC Estimation Results under the Scaled DST Profile using the Test 3 ECM Parameter Set: (a) Reference and Estimated SOC using EKF-1RC, EKF-2RC, and EKF-ANN, (b) Scaled DST Current Profile, (c) SOC Estimation Error.

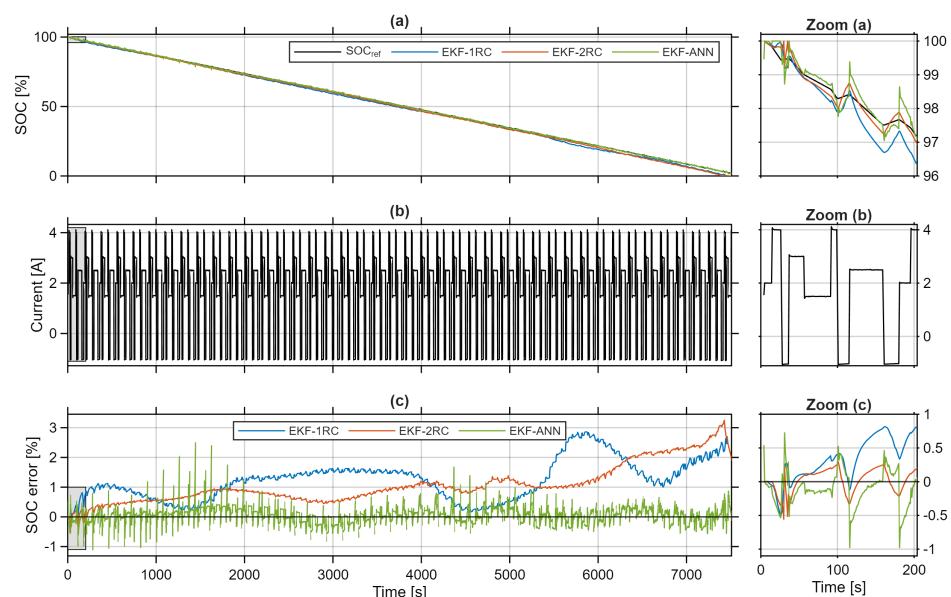


Figure 22. Hybrid SOC Estimation Results under the highly dynamic Modified P-DST Profile using the Test 3 ECM Parameter Set: (a) Reference and Estimated SOC using EKF-1RC, EKF-2RC, and EKF-ANN, (b) Modified P-DST Current Profile, (c) SOC Estimation Error.

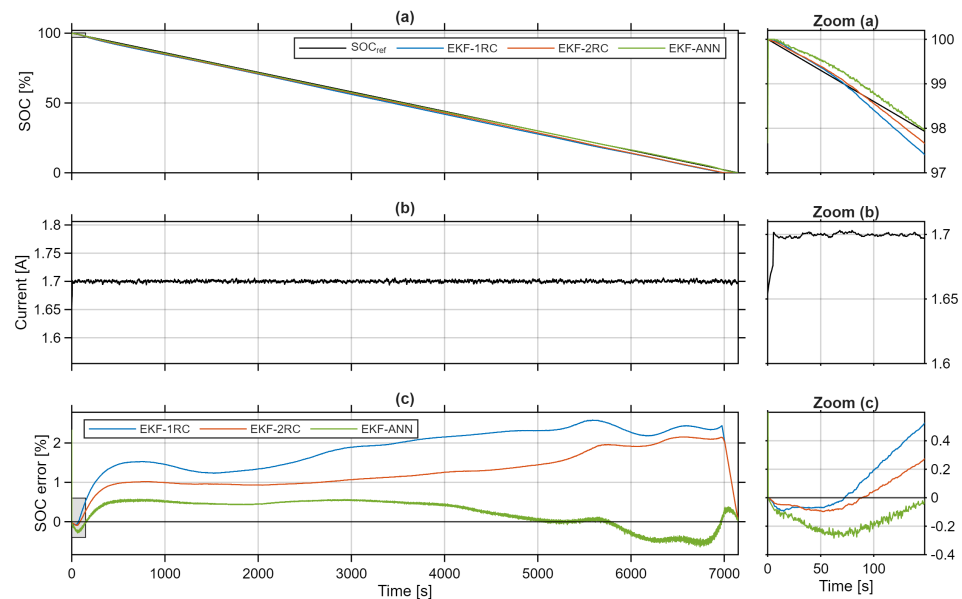


Figure 23. Hybrid SOC Estimation Results under the Full 0.5C Discharge Profile using the Test 3 ECM Parameter Set: (a) Reference and Estimated SOC using EKF-1RC, EKF-2RC, and EKF-ANN, (b) Full 0.5C Current Profile, (c) SOC Estimation Error.

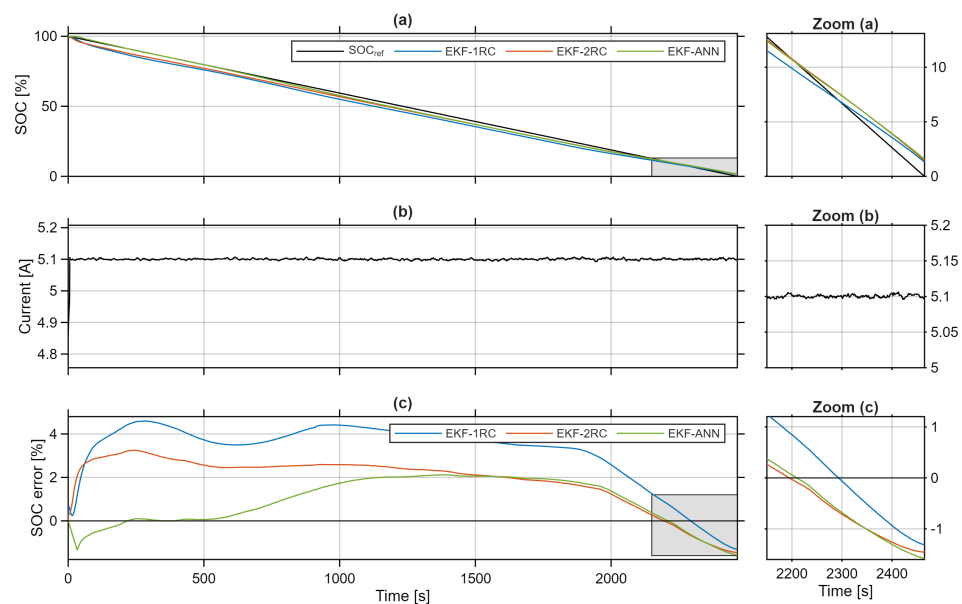


Figure 24. Hybrid SOC Estimation Results under the Full 1.5C Discharge Profile using the Test 3 ECM Parameter Set: (a) Reference and Estimated SOC using EKF-1RC, EKF-2RC, and EKF-ANN, (b) Full 1.5C Current Profile, (c) SOC Estimation Error.

The results show that EKF-2RC improved the performance of EKF-1RC in both dynamic profiles, confirming the advantage of including a second polarization branch to represent transient behavior with different time scales. In the Scaled DST profile, EKF-2RC reduced $RMSE_{SOC}$ from 1.1321% to 0.5473%, while in the Modified P-DST profile the error decreased from 1.3778% to 1.2508%. This trend is consistent with the dependence of Kalman-filter-based SOC estimation on the voltage prediction capability of the underlying ECM [71].

The hybrid EKF-ANN method achieved the best average accuracy in both dynamic profiles. In the Scaled DST case, $RMSE_{SOC}$ was reduced to 0.2276%, whereas in the Modified P-DST profile $RMSE_{SOC}$ reached 0.2788%. This result indicates that the residual correction learned by the ANN compensated part of the remaining EKF-2RC errors, particularly those

associated with dynamic transitions and local model deviations. However, $\text{MaxAE}_{\text{SOC}}$ was not uniformly reduced in all cases. For the Scaled DST profile, EKF-ANN showed a slightly higher maximum error than EKF-2RC, indicating that the ANN improved the average behavior but may introduce localized deviations during transient events.

Table 10. SOC Estimation Error Metrics for EKF-1RC, EKF-2RC, and EKF-ANN under the Dynamic Validation Profiles.

SOC Estimator	Scaled DST			Modified P-DST		
	RMSE_{SOC} [%]	MAE_{SOC} [%]	$\text{MaxAE}_{\text{SOC}}$ [%]	RMSE_{SOC} [%]	MAE_{SOC} [%]	$\text{MaxAE}_{\text{SOC}}$ [%]
EKF-1RC	1.1321	1.0270	1.8430	1.3778	1.2507	2.4630
EKF-2RC	0.5473	0.5230	0.9140	1.2508	1.1065	2.4650
EKF-ANN	0.2276	0.1626	1.0699	0.2788	0.2079	2.3952

Table 11 presents the external validation performed with full-discharge tests at 0.5C and 1.5C, which were not used during ANN training. This comparison evaluates the estimator performance under unseen constant-current conditions, including an intermediate discharge rate and a more demanding current level.

Table 11. SOC Estimation Error Metrics for EKF-1RC, EKF-2RC, and EKF-ANN under External Full-Discharge Validation Profiles.

SOC Estimator	Full-Discharge 0.5C			Full-Discharge 1.5C		
	RMSE_{SOC} [%]	MAE_{SOC} [%]	$\text{MaxAE}_{\text{SOC}}$ [%]	RMSE_{SOC} [%]	MAE_{SOC} [%]	$\text{MaxAE}_{\text{SOC}}$ [%]
EKF-1RC	1.9273	1.8530	2.5803	3.4698	3.2460	4.5960
EKF-2RC	1.3607	1.2807	2.1540	2.2106	2.0649	3.2517
EKF-ANN	0.4099	0.3687	2.3391	1.3872	1.1532	2.1173

In the external full-discharge profiles, EKF-2RC again achieved lower error than EKF-1RC, confirming that the second-order ECM maintained better performance outside the dynamic profiles used for model validation. EKF-ANN also reduced the average errors substantially, reaching $\text{RMSE}_{\text{SOC}} = 0.4099\%$ in the 0.5C discharge and $\text{RMSE}_{\text{SOC}} = 1.3872\%$ in the 1.5C discharge. The latter case is particularly relevant because it represents a more demanding current condition than the full-discharge profiles used during ANN training. However, in the 0.5C discharge, the $\text{MaxAE}_{\text{SOC}}$ of EKF-ANN was slightly higher than that of EKF-2RC, reinforcing that the improvement of the hybrid method is mainly observed in average metrics such as RMSE_{SOC} and MAE_{SOC} , rather than in all localized maximum errors.

Overall, the results indicate that EKF-2RC is the most robust conventional estimator among the ECM-based methods, while EKF-ANN provides an additional improvement through data-driven residual correction. This improvement was achieved without modifying the identified ECM or increasing its order, which is consistent with the scope of this work: the development and validation of a low-cost experimental platform for Li-Ion battery characterization, modeling, and SOC estimation. Nevertheless, because the ANN depends on representative training data, its performance should be interpreted within the experimental domain covered by the training, validation, and external test profiles.

5. Discussion

The results demonstrate that the proposed test bench provides a functional experimental platform for Li-Ion cell characterization, SOC-dependent ECM parameter identification, voltage model validation, and SOC estimator assessment. The system integrates CC-CV

charging, controlled-current discharge through a PCB-based electronic load, ESP32-based acquisition, and MATLAB-based processing. This integration allowed the implementation of a complete experimental workflow, including capacity tests, PDT experiments, dynamic current profiles, voltage-based ECM validation, and SOC estimation using both conventional and hybrid methods.

From an experimental perspective, the main contribution of the platform lies in its accessibility and reproducibility rather than in high-power operation. In contrast with test systems based on commercial cyclers or high-current laboratory equipment [26,27], the proposed architecture demonstrates that a low-cost hardware configuration can generate consistent experimental data for battery modeling and BMS-oriented estimator validation. The platform should therefore be understood as a research-oriented baseline that can be extended in future versions through higher-power electronic-load stages, thermal instrumentation, multicell configurations, and embedded estimator implementation.

The capacity characterization provided an initial verification of the experimental procedure. The measured capacity at 0.2C was 3345.1 mAh, which is close to the minimum nominal capacity of 3350 mAh reported for the Samsung INR18650-35E cell. The tests performed at 0.5C, 1C, and 1.5C extended the analysis to more demanding discharge conditions. The observed increase in usable capacity at higher C-rates may be associated with self-heating effects; however, because temperature was not directly measured or controlled, this interpretation should be considered a plausible explanation rather than a direct experimental conclusion. This limitation reinforces the need to include thermal measurement and control in future versions of the platform.

The PDT-based identification showed that both 1RC and 2RC Thévenin ECMs reproduced the measured voltage response with low error. The 2RC model achieved RMSE values close to 4.3 mV during identification, outperforming the 1RC structure and confirming the advantage of representing polarization phenomena through two time constants. This behavior agrees with ECM studies where higher order structures improve dynamic fidelity at the expense of additional parameters and computational effort [30,55]. In particular, Campagna et al. [30] showed that Thévenin-type models provide better performance than simpler structures under dynamic tests, while [55] highlight the suitability of 2RC models for BMS-oriented applications due to their balance between accuracy, interpretability, and computational feasibility.

The dynamic validation confirmed that the identified parameters were not limited to fitting the PDT data. For the Test 3 parameter set, the 2RC model achieved $RMSE_V$ values of 23.24 mV under Scaled DST and 12.14 mV under Modified P-DST, outperforming the 1RC model in both profiles. These values are in a competitive range when compared methodologically with [30], who reported RMSE values of 14.8 mV for PDT and 43.6 mV for a Dynamic Discharge Test using a Thévenin model. Although the cells, profiles, and model structures are not identical, the comparison supports the validity of the proposed low-cost platform for dynamic model validation, particularly considering the absence of active thermal control.

The link between ECM voltage accuracy and SOC estimation performance was also observed. Aher et al. [71] reported a direct correlation between battery model voltage error and Kalman-filter-based SOC estimation error, with Pearson coefficients close to 0.91 and R^2 values above 0.82. In this work, the EKF-2RC estimator, based on the model with better voltage reproduction, generally outperformed EKF-1RC. This confirms that voltage-based ECM validation is not only a modeling step, but a necessary condition for reliable model-based SOC estimation.

A relevant finding is the influence of the initial conditions of the PDT tests on the subsequent SOC estimation performance. The parameter sets obtained from Test 1 and

Test 2, which started at higher initial voltages and ultra-high SOC conditions, produced larger SOC estimation errors than the Test 3 parameter set. This suggests that PDT design affects not only the voltage fitting quality, but also the robustness of the identified ECM when used inside an estimator. In the upper SOC region, voltage relaxation and polarization effects may provide less informative or more nonlinear responses, making parameter identification more sensitive. Therefore, the selection of initial SOC conditions in PDT experiments should be considered an important practical factor for ECM-based SOC estimator development.

Among the conventional ECM-based estimators, EKF-2RC showed the best overall behavior. Using the Test 3 parameter set, EKF-2RC reached $RMSE_{SOC}$ values of 0.5088% for Scaled DST and 1.0890% for Modified P-DST in the complete-profile evaluation. In the block-based dynamic validation, the corresponding $RMSE_{SOC}$ values were 0.5473% and 1.2508%, while in the external full-discharge tests EKF-2RC obtained 1.3607% at 0.5C and 2.2106% at 1.5C. These results indicate that the second RC branch improves SOC tracking under both dynamic and constant-current profiles, while preserving a model structure suitable for BMS-oriented implementation.

The hybrid EKF-ANN method further improved the average SOC estimation metrics by applying a residual correction to the EKF-2RC output. In the dynamic test blocks, EKF-ANN reduced $RMSE_{SOC}$ to 0.2276% for Scaled DST and 0.2788% for Modified P-DST, while in the external full-discharge tests it achieved 0.4099% at 0.5C and 1.3872% at 1.5C. The corresponding $MaxAE_{SOC}$ values were 1.0699% and 2.3952% for Scaled DST and Modified P-DST, respectively, and 2.3391% and 2.1173% for the 0.5C and 1.5C external full-discharge profiles. For context, an EKF+ANN approach using the same Samsung INR18650-35E cell reference reduced the maximum SOC error below 1%, compared with approximately 2.8% for EKF and 2.6% for ANN [73]. In addition, a comparative online SOC-estimation study based on experimental dynamic-load data reported $RMSE_{SOC}$ values of 0.5368% for EKF, 0.3176% for adaptive EKF, and 0.8172% for a backpropagation neural network [78]. Although the experimental conditions, metrics, instrumentation, and validation protocols are not directly equivalent, these comparisons indicate that the data generated by the proposed low-cost platform yield SOC-estimation errors of comparable order and support the use of neural networks as a residual correction stage without replacing the physical ECM structure.

Nevertheless, the ANN results must be interpreted within the experimental domain covered by the available data. The network was trained using PDT tests, selected full-discharge profiles, one complete charge test, and block-based partitions of the DST and P-DST profiles. The 0.5C and 1.5C full-discharge tests were reserved as external validation profiles. This strategy reduces the risk of evaluating the hybrid estimator only on data already used during training and provides a more consistent assessment of its generalization capability. However, as with any data-driven method, its performance remains dependent on the representativeness of the training dataset.

The main limitations of the platform are the absence of active thermal control, validation with a single cell, and current capability constrained by the electronic load power stage. These limitations define the scope of the study and indicate the main directions for future development. The results show that an accessible experimental platform can generate useful and consistent data for capacity characterization, ECM identification, voltage validation, and SOC estimator comparison. Overall, these limitations define the scope of the present single-cell validation and motivate future extensions of the platform.

6. Conclusions

This work developed and validated a low-cost experimental platform for Li-Ion battery characterization, SOC-dependent ECM parameter identification, and SOC estimator evaluation. The platform integrates CC-CV charging, a PCB-based controlled-current electronic load, ESP32-based acquisition, and MATLAB-based processing. The resulting architecture enables a complete experimental workflow that includes full-discharge tests, pulse discharge tests, dynamic current profiles, ECM identification, voltage model validation, and SOC estimation. The experimental characterization of a Samsung INR18650-35E cell showed that the measured capacity at 0.2C was 3345.1 mAh, in close agreement with the manufacturer-reported minimum nominal capacity of 3350 mAh. The higher C-rate tests revealed behavior that may be associated with self-heating effects, although the absence of direct temperature measurement limits the interpretation of these results. This finding highlights the importance of incorporating thermal instrumentation in future versions of the platform. The PDT-based identification allowed SOC-dependent 1RC and 2RC Thévenin ECMs to be obtained. The 2RC model provided better voltage reproduction than the 1RC model, achieving identification RMSE values close to 4.3 mV. Under independent dynamic validation profiles, the Test 3 2RC model achieved voltage RMSE values of 23.24 mV under the Scaled DST profile and 12.14mV under the Modified P-DST profile, confirming its ability to reproduce the terminal voltage under operating conditions not directly used during identification. For SOC estimation, the EKF-2RC estimator outperformed the EKF-1RC estimator in most evaluated cases, confirming the benefit of including a second polarization branch when higher dynamic accuracy is required. The hybrid EKF-ANN residual correction method further improved the average SOC estimation accuracy, especially over the dynamic test blocks. However, its performance should be interpreted within the experimental domain represented by the training and validation data. Although the platform was validated using a single cell and without active thermal control, the results demonstrate its usefulness as an accessible experimental tool for Li-ion battery characterization, ECM validation, and SOC estimator assessment. Future work should include thermal measurement and control, validation with multiple cells and different states of health, aging tests, multicell configurations, and embedded implementation of the estimators.

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Abbreviations

The following abbreviations are used in this manuscript:

1RC	First-order Thévenin equivalent circuit model
2RC	Second-order Thévenin equivalent circuit model

ANN	Artificial Neural Network
BMS	Battery Management System
CC-CV	Constant-Current–Constant-Voltage
DST	Dynamic Stress Test
ECM	Equivalent Circuit Model
EKF	Extended Kalman Filter
EKF-ANN	Hybrid Extended Kalman Filter–Artificial Neural Network method
Li-Ion	Lithium-Ion
MAE	Mean Absolute Error
MaxAE	Maximum Absolute Error
OCV	Open-Circuit Voltage
PCB	Printed Circuit Board
PCHIP	Piecewise Cubic Hermite Interpolating Polynomial
P-DST	Pulse Dynamic Stress Test
PDT	Pulse Discharge Test
RMSE	Root Mean Square Error
SOC	State of Charge

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