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Selection of Suitable Optimization Algorithm for Equivalent Circuit Model Paramter Identification of 100Ah Prismatic Lithium-Ion Battery

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Abstract: Accurate estimation of the State of Charge (SoC) is essential for the reliable and safe operation of lithium-ion batteries in Electric Vehicles (EVs). Conventional SoC estimation methods such as open-circuit voltage method and Coulomb counting have limitations including the accumulation of arbitrary errors over time and susceptibility to dynamic operating conditions. Additionally, battery systems exhibit highly non-linear characteristics. To overcome these limitations and handle the non-linearity, model-based techniques have been increasingly adopted in recent years. Hence, identification of accurate battery model parameters is very essential. The main objective of this work is to select suitable optimization algorithm for identifing the equivalent circuit model (ECM) parameters of 100Ah lithium-ion battery. Initially, a Hybrid Pulse Power Characterization (HPPC) test is conducted to identify the initial parameters of a Two RC-network ECM for the 100Ah prismatic cell under discharging condition. The experiments are carried out on a fully charged battery. For HPPC test, discharging from 100% SoC to 0% SoC with step changes of 10%, 0.5C constant discharging and dynamic discharging with variable steps while recording the battery voltage. The ECM parameters are identified for all the 10 regions of battery voltages obtained through HPPC. Further,the ECM parameters, are optimized using Simplex, Nonlinear Least Squares (NLS), and Pattern Search (PS) algorithms. Finally, the performances of the optimization algorithms are compared by estimating battery voltage with optimized parameters against 0.5C constant discharging and dynamic discharging conditions.

Keywords: SoC, BMS, ECM, HPPC, Dynamic discharging, Local search optimization algorithms

1. INTRODUCTION

The determination of SoC is crucial for the safe and efficient operation of lithium-ion batteries in EVs.Accurate SoC estimation primarily depends on two critical aspects: (i) accuracy of the battery model, and (ii) appropriate selection of the estimation algorithm. Conventional SoC estimation algorithm namely Coulomb counting is simple to apply, however incur error over time (Bai *et al*. 2020). Advanced methods such as physics-based, data-driven, and hybrid that combines physics-based and data-driven techniques are widely used for SoC estimation (Wu et al., 2024; El-Sayed et al., 2024; Tao et al., 2024). Physics-based algorithm offers good interpretability, strong generalization capability, and high real-time performance. However, they highly depend on model accuracy, and is sensitive to noise. In contrast, data-driven approachs rely mainly on data rather than physical characteristics, requires long training times, and lack interpretability. To combine the advantages of both approaches, hybrid models have been proposed to achieve improved accuracy and reduced computation time. Hence, advanced estimation algorithms are strongly dependent on the accuracy of the battery model.

Equivalent Circuit Models (ECMs) are widely used in lithium-ion BMS because they have simple mathematical model to capture battery dynamics with low computational complexity. Among various ECM models, 1-RC ECM is simple and computationally efficient however it has limited dynamic accuracy, while the 3-RC ECM provides higher modelling accuracy with increased complexity. The 2-RC ECM compromises the trade-off between modelling performance and computational complexity(Mohamed et al.2025, Sun et al.2026).Accurate ECM parameter initialization is essential for reliable SoC and battery health estimation.ECM parameter extraction methods are broadly classified into frequency-domain and time-domain approaches (Peng et al. 2023). Among these, time-domain methods, commonly based on HPPC tests, are preferred for estimation of ECM parameters offline under controlled conditions. Several studies are performed for improved parameter reliability under fixed SoC and temperature conditions (He et al. 2020) and multi-stage identification methods to achieve enhanced dynamic accuracy (Li et al. 2022). Consequently, HPPC-based analytical methods remain a reliable foundation for ECM parameter initialization in real-time BMS applications (Liu et al. 2023).

Reliable prediction of lithium-ion battery performance using ECMs requires accurate parameter optimization. The Levenberg–Marquardt algorithm has been widely used for first-order ECM parameter estimation due to its balance between accuracy and computational speed (Du et al. 2023; Alshawabkeh et al. 2024). Nonlinear Least Squares (NLS)

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methods remain popular for parameter optimization because of their simplicity and efficiency. Derivative-free methods such as the Nelder–Mead Simplex algorithm are effective for estimating age-dependent parameters in non-convex optimization problems (Madeley et al. 2022). Particle swarm techniques are preferred for global optimization to avoid local minima, while hybrid Recursive Least Squares (RLS) and Recursive Total Least Squares (RTLS) methods improve robustness against sensor noise and initialization errors. Bayesian Optimization (BO) has recently emerged as an efficient alternative for ECM parameter tuning, particularly for computationally expensive battery models (Pi et al. 2024). Sensitivity analysis methods, including the Cramer–Rao lower bound and profile likelihood, are also used to evaluate parameter identifiability and robustness. In addition, neural networks and Gaussian Process Regression are increasingly applied for offline and online ECM parameter optimization, combining data-driven learning with physical modelling (Santoni et al. 2024).

These developments highlight the growing importance of hybrid AI-assisted optimization frameworks for robust battery modelling under varying operating conditions.ECM parameter identification commonly uses local search algorithms such as NLS, Simplex, and PS algorithms. NLS converges quickly however it is sensitive to initialization and local minima. Simplex is derivative-free however lacks global search capability.PS improves global exploration with higher computational cost, however, limited studies have combined these methods for ECM optimization. Their integration can improve parameter accuracy, convergence, and robustness under varying SoC conditions.

Major contributions of this research work are: (i) Design experiments and collect experimental data from a 100 Ah $LiFePO_4$ battery. (ii) Identification of ECM parameters using HPPC test, iii) Optimization of ECM parameters using various optimization algorithms such as Pattern Search (PS), Nonlinear Least Squares (NLS), and Simplex. (iv) Estimation battery voltage based on the identified parameters under constant and dynamic discharging conditions. (v) Performance analysis under constant and dynamic discharging conditions.

This research work has been organized as follows: Section 2 provides a description of the proposed methodology, which includes the experimental data collection and ECM parameter identification from HPPC test data. Parameter optimization using local search optimization techniques is discussed in Section3. Discussion of results is presented in Section 4. The conclusions of the work are reported in Section 5.

2. PROPOSED METHODOLOGY

This section presents the proposed methodology, starting with experimental data acquisition using a Neware power cell tester for a 100 Ah $LiFePO_4$ battery. The dataset includes current, voltage, and temperature, which capture the nonlinear behaviour of the cell.

A second-order Thevenin ECM is used to model the battery dynamics. Parameter identification is carried out in two stages: (i) initial estimation using Method-3 and (ii) refinement using standalone optimization techniques to improve accuracy. The overall methodology is shown in Fig 1.

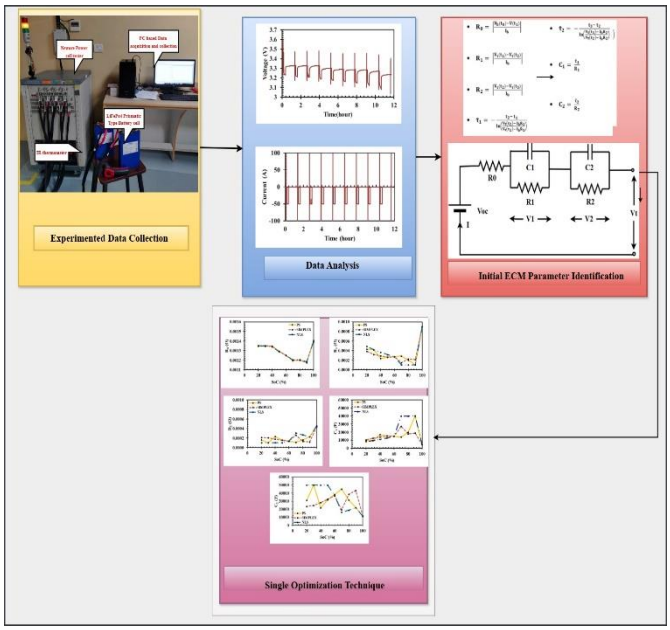


Fig. 1. Block diagram of proposed methodology for ECM parameter identification

2.1 Experimental Data collection and data description

The first step in the methodology involved the collection of experimental data necessary for model identification and validation. The data are collected under three conditions:- i) HPPC test condition, ii) 0.5C static discharging condition and iii) dynamic discharging condition.

A) HPPC Test

Fig. 2(a–b). illustrates the current and corresponding voltage response from a HPPC test, a standard protocol used for parameter identification in battery modelling and state estimation algorithms. In Fig. 2(a)., the current profile exhibits a sequence of high-amplitude charge and discharge pulses, symmetrically applied across the test duration. Each pulse typically lasts for a fixed period followed by rest intervals, allowing the cell to relax. Fig. 2(b). presents the battery's terminal voltage response to the pulsed current.

The initial voltage dip corresponds to the ohmic resistance (R_0), while the gradual voltage recovery (or sag) reflects the RC network dynamics (R_1C_1 and R_2C_2). As the test progresses, the voltage response also captures the SoC-dependent variation in impedance characteristics, which are later used to extract region-wise ECM parameters.

Fig. 3. illustrates the voltage response of the battery during the initial region of the HPPC test, specifically within a narrow SoC window referred to as region 1. At time $t_0 = 0$ seconds, the battery is at rest, and the terminal voltage is stable. Upon application of a step discharge current at $t_1 = 1$ second, the

voltage immediately drops due to the R_0, which is quantified by the instantaneous voltage drop ΔV_1.

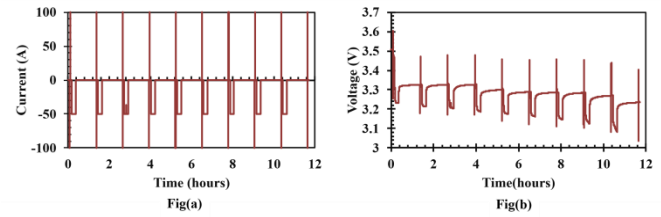


Fig. 2. HPPC test data for 100Ah Li-ion battery (a) current (b) voltage

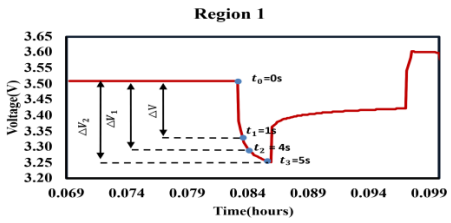


Fig. 3. Battery voltage for Region 1

Subsequent to this initial drop, the voltage continues to decrease gradually, which corresponds to the dynamic behaviour governed by the RC time constants of the ECM. The further drop ΔV_2, observed between $t_1 = 1$ and $t_2 = 4$ seconds, captures the slower polarization effect. The total voltage drops $\Delta V = \Delta V_1 + \Delta V_2$ can be used to characterize the combined influence of R_0, R_1, R_2, C_1 and C_2. By fitting the voltage relaxation curve using exponential functions, the time constants $\tau_1 = R_1 C_1$ and $\tau_2 = R_2 C_2$ are extracted.

The rest period after t_2 allows the battery to relax, and the recovery of voltage provides additional information for the fitting process. At $t_3 = 5$ seconds, the voltage is measured again to observe the relaxation behaviour, further supporting the estimation of RC parameters.

B) 0.5C Static discharge profile

Fig. 4. shows the variation of terminal voltage, current, and temperature of the lithium-ion battery during a 0.5 C steady-state discharge profile. The current profile remains constant at around –50 A, representing the required 0.5 C discharge rate applied throughout the experiment. The terminal voltage decreases gradually from approximately 3.35 V to 3.05 V over about 2.3 hours, indicating normal discharge behaviour under load. The temperature exhibits a stepwise increase from 30 °C to 34 °C, attributed to internal heat generation as the discharge progresses.

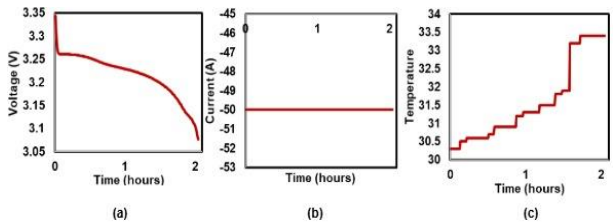


Fig. 4. 100Ah Li-ion battery 0.5 C static discharge profile (a) Voltage, (b) Current and (c) Temperature

C) Dynamic discharging

Fig. 5. presents the dynamic discharge characteristics of the 100 Ah lithium-ion battery. The applied current varies from 0.2 C to 1 C (-20 A to -100 A) in multiple steps lasting 10-20 minutes each. The terminal voltage exhibits stepwise drops with increasing discharge current and partial recovery during lower current levels, representing the effects of internal resistance and polarization. The cell temperature gradually rises from 30 °C to 34 °C, with higher C-rates contributing to increased heat generation.

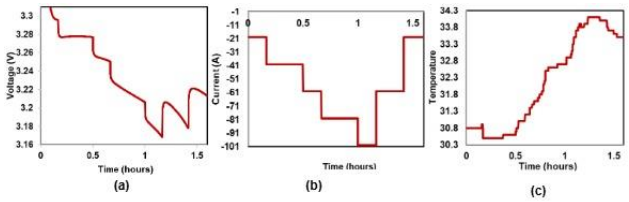


Fig. 5. 100Ah Li-ion battery dynamic discharge profile (a) Voltage, (b) Current and (c) Temperature

2.2 ECM parameter identification using offline

Using the data collected through HPPC testing, a second-order ECM (Fig.6.) was developed to replicate the dynamic behaviour of the battery. The ECM consists of an open-circuit voltage source that varies with SoC, a series resistance (R_0), and two RC branches (R_1C_1 and R_2C_2) that represent the short- and long-term transient responses. To ensure accuracy across the battery's operating range, the SoC range was divided into ten regions. For each region, values for R_0, R_1, R_2, C_1, and C_2 were identified using curve fitting and parameter optimization techniques.

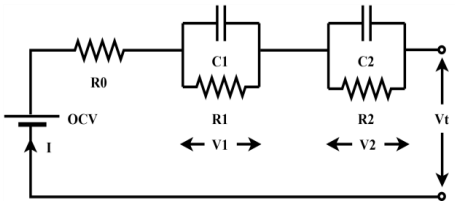


Fig. 6. ECM Model for 2-RC network

Calculation of initial parameters of ECM :
The initial parameters were calculated using method 3 (Pandian at 2025). The parameters of a two RC ECM using the pulse charge/discharge (PC/PD) period rather than the relaxation period. During the PC/PD period, we can segment the voltage response into three-time regions: a fast response (0–1 s); a mid-range dynamic (1–10 s); and a slow response (10–18 s), each arguably representing discrete electrochemical dynamics. The instantaneous voltage drop at the beginning of the application of a current pulse is used to derive the Ohmic resistance (R_0). Then, the short time constant ($\tau_1 = R_1C_1$) and long-time constant ($\tau_2 = R_2C_2$) are determined from the slopes of the voltage decay (time response) curves during the 1–10 s and 10s–18 s time regions, respectively. Using these time constants enables R_1 and R_2 to be determined given the detected current amplitude and the exponential decay curve.

Following this, C_1 and C_2 can be determined from the relation $C = \tau/R$.

ECM initial parameters are calculated using (1) – (7)

$$R_0 = \left|\frac{V_b(t_0) - V(t_1)}{I_b}\right| \quad (1)$$

$$R_1 = \left|\frac{V_\tau(t_1) - V_\tau(t_2)}{I_b}\right| \quad (2)$$

$$R_2 = \left|\frac{V_\tau(t_2) - V_\tau(t_3)}{I_b}\right| \quad (3)$$

$$\hat{\tau}_1 = -\frac{t_2 - t_1}{ln\left(\frac{V_\tau(t_2) - I_b R_1}{V_\tau(t_1) - I_b R_1}\right)} \quad (4)$$

$$\hat{\tau}_2 = -\frac{t_3 - t_2}{ln\left(\frac{V_\tau(t_3) - I_b R_2}{V_\tau(t_2) - I_b R_2}\right)} \quad (5)$$

$$C_1 = \frac{\hat{\tau}_1}{R_1} \quad (6)$$

$$C_2 = \frac{\hat{\tau}_2}{R_2} \quad (7)$$

Table 2. Parameters of ECM

Region	I_b (A)	R_0 (Ω)	R_1 (Ω)	R_2 (Ω)	C_1 (F)	C_2 (F)	SoC (%)	Tem (°C)
1	100	0.0015	0.0008	0.0002	5000	25000	100	29.5
2	100	0.0011	0.0001	0.0001	40000	50000	90	30.3
3	100	0.0011	0.0001	0.0001	40000	50000	80	30.8
4	100	0.0011	0.0002	0.0001	20000	50000	70	31
5	100	0.0014	0.0002	0.0001	20000	50000	60	31.4
6	100	0.0014	0.0001	0.0001	40000	50000	50	31.6
7	100	0.0014	0.0002	0.0002	20000	25000	40	31.4
8	100	0.0015	0.0002	0.0001	20000	50000	30	32.5
9	100	0.0016	0.0002	0.0002	20000	25000	20	32.5

3. PARAMETER IDENTIFICATION USING VARIOUS OPTIMIZATION TECHNIQUE

3.1 NLS

The NLS optimization method is powerful approaches that optimize the parameters for models with nonlinear relationships between inputs and the outputs. The goal of NLS is to minimize the sum of squared differences (residuals) between the observed data and model's predicted output using optimization as given in (8). The Gauss-Newton and Levenberg-Marquardt iterative methods are the common methods to solve the NLS problem. It is sensitive to initial parameter guesses, so useful guesses for starting parameter values will increase convergence rates.

The objective of NLS is to minimize the sum of squared errors:

$$\min_\theta J(\theta) = \sum_{k=1}^{N} [(y_k) - f(x_k, \theta))]^2 \quad (8)$$

where y_k= measured output

$f(x_k, \theta)$ = model output with parameters θ

θ = parameter vector = [R_0, R_1,C_1,R_2,C_2]

The residual vector $r(\theta) = y - f(x_k, \theta)$ and the Jacobian matrix $J(\theta) = \frac{\partial r(\theta)}{\partial \theta}$

Input: Data $\{x_k, y_k\}$, initial parameters θ_0, tolerance ε, max iterations

Output: Optimized parameters θ*

3.2 Simplex Method

The simplex optimization technique, also known as the Nelder-Mead method, is a derivative-free optimization algorithm used for the optimization of nonlinear functions. The Simplex establishes an evaluation of the objective function at varying points to create a simplex, unlikely a shape with (n + 1) edges in (n)-dimensional space. The simplex can repeatedly change by plasm movement using operations such as: reflection, expansion, contraction, and shrink to measure towards the direction of the optimum.

For ECM parameters (θ) are identified using simplex method with objective as given by (8), In n-dimensional space, a simplex has n+1 vertices $\theta_1, \theta_2, \ldots, \theta_{n+1}$ with corresponding function values: $J_i = J(\theta_i), i = 1, 2, \ldots, n+1$, centroid of best n vertices can be calculated as $\theta_c = \frac{1}{n}\sum_{i=1}^{n} \theta_i$.

Reflection :$\theta_r = \theta_c + \alpha\,(\theta_c - \theta_{n+1}), \alpha > 0$

Expansion:$\theta_e = \theta_c + \gamma(\theta_r - \theta_c), \gamma > 0$

Contraction:

Outside contraction $\theta_{oc} = \theta_c + \beta\,(\theta_r - \theta_c),\ 0 < \beta > 1$

Inside contraction $\theta_{ic} = \theta_c - \beta\,(\theta_c - \theta_{n+1}),\ 0 < \beta > 1$

Shrink: $\theta_i = \theta_1 + \delta\,(\theta_i - \theta_1)\ i = 2,3.n+1\ , 0 < \delta < 1$

Parameter update rule is given by

$$\theta_{n+1} \leftarrow \begin{cases} \theta_r \text{ if reflection improves J}(\theta) \\ \theta_e \text{if expansion better than reflection} \\ \theta_{oc} \text{ if outside contarction works} \\ \theta_{ic} \text{if outside contarction works} \\ \text{shrink all vertices toward } \theta_1 \text{ otherwise} \end{cases}$$

Convergence criteria:$max\ _i |J(\theta_i) - J(\theta_1)| < \in$

3.3 Pattern Search method

Pattern search is a derivative-free optimization method used to solve nonlinear optimization problems when gradient information is not available or trustworthy. PS uses a fixed set of directions called a pattern and explores the search space around a current solution point. Importantly, the method works without exploiting smoothness or continuity properties of the objective function, making it applicable to complicated, noisy, and/or discontinuous problems. In battery modeling, PS is applied to estimate ECM parameters by minimizing the discrepancy between measured and model-predicted terminal voltage as given in (8).

4. RESULTS AND DISCUSSION

4.1 ECM parameter calculation in offline

Accurate identification of the ECM parameters is critical for high-fidelity battery simulation and reliable SoC estimation. Five key parameters were derived through HPPC: R_0, R_1, R_2 and C_1, C_2. These parameters vary with SoC and reflect the underlying electrochemical dynamics. As depicted in Fig 10 (a–e), the internal resistance R_0 declines steadily until 70% SoC, beyond which it increases sharply toward full charge.

Polarization resistances R_1 and R_2 follow a similar trend, remaining low over most of the SoC range but increasing at high SoC, indicative of limited diffusion pathways. Capacitances C_1 and C_2, meanwhile, fluctuate with SoC and exhibit maxima at mid-range SoC, revealing enhanced charge storage and electrochemical stability in this region.

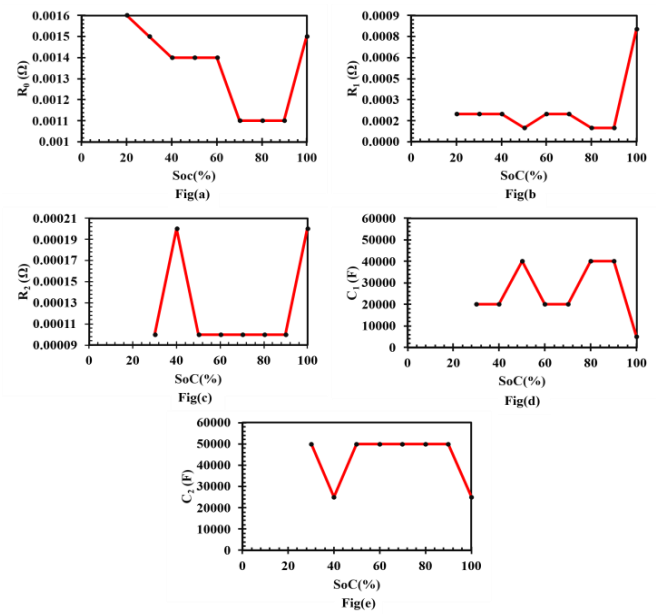


Fig. 10. Initial parameters of ECM a) R_0 b) R_1 c) R_2 d) C_1 and e) C_2

4.2 Optimization of ECM parameters using optimization algorithms

To improve the accuracy of ECM parameters, three optimization methods were employed: PS, Simplex, and NLS. These methods aim to minimize the deviation between simulated and actual terminal voltages by adjusting ECM parameters over various SoC ranges.

The outcomes of these optimization strategies are presented in Fig. 11(a–e). PS yields smooth, continuous curves across the SoC domain, ideal for hardware applications requiring consistency. NLS delivers marginally improved convergence accuracy, however with increased computational complexity.

4.3 Performance metric formula

The RMSE is used to evaluate the accuracy of model predictions using (9).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{i=n}(V_{measured,i} - V_{simulated,i})^2} \quad (9)$$

Quantitative evaluation of the three optimization methods are reported in Fig.12. PS recorded the lowest RMSE of 0.0010270, highlighting its superior accuracy.

Simplex, while slightly less accurate (0.0010566 RMSE), demonstrated the shortest computation time of 2.1s. Conversely, NLS offered moderate accuracy (0.0010450 RMSE) however required significantly longer computation time(8.56s). This analysis emphasizes that although NLS is capable of high accuracy, its computational overhead limits its suitability for embedded and real-time systems. PS, offering the best trade-off between speed and precision, is better suited for practical BMS integration.

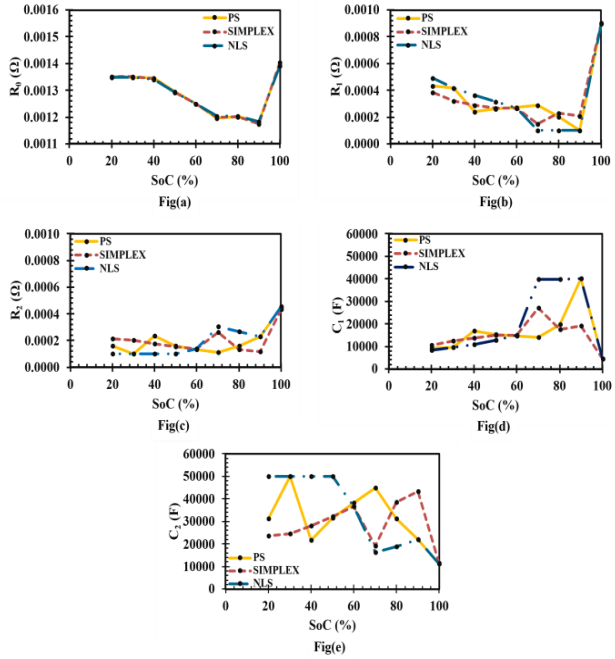


Fig. 11. ECM parameter optimization using PS,Simplex and NLS a) R_0 b) R_1 c) R_2 d) C_1 and e) C_2

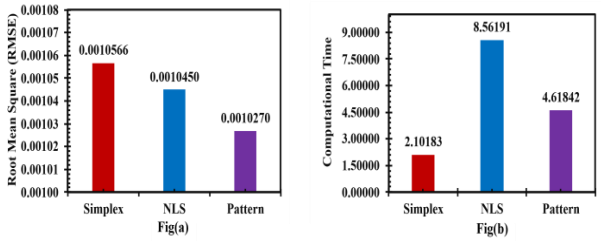


Fig. 12. Performance comparison using a) RMSE b) Computation time

4.4 Performance analysis of optimization algorithms against static and dynamic discharging conditions

Validation of the optimized ECM was carried out with the experimental voltage data for constant and dynamic discharge profile of 100Ah Li-ion battery.

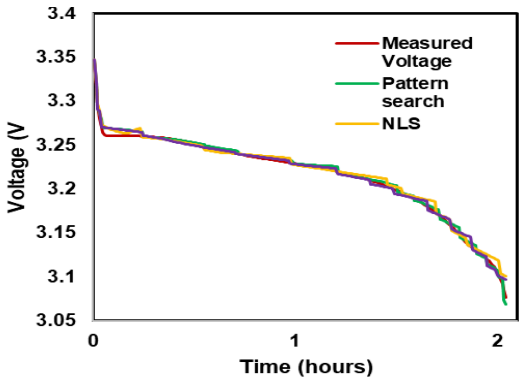


Fig.13. 0.5 C Static discharge for Simplex , NLS and Pattern search

Fig. 13. and Fig. 14. depicts these comparisons, revealing a high degree of agreement across all methods. PS-based simulation exhibits the closest match to the measured voltage profile, particularly during steep transients and relaxation periods. This superior performance is attributable to its accurate representation of the battery's internal dynamics. While all three models provide acceptable accuracy, PS consistently demonstrated the lowest deviation in both steady-state and transient phases.

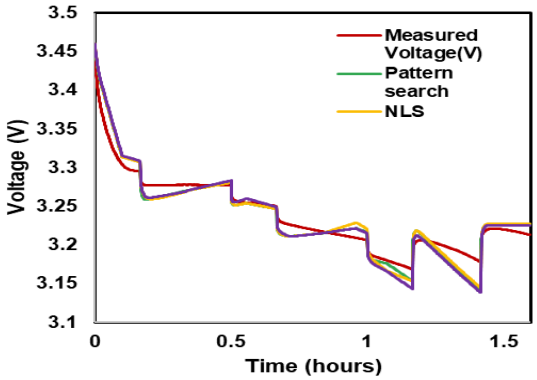


Fig.14. Dynamic discharge for Simplex , NLS and Pattern search

5. CONCLUSION

This study introduces a structured approach for identifying the parameters of a 2 RC ECM for lithium-ion batteries. The region-wise modelling based on experimental data captures the battery dynamic characteristics across different SoC levels with improved accuracy. A major contribution lies in the comparative assessment of optimization strategies, where the PS method emerged as a reliable and precise technique for parameter tuning. The results affirm that the proposed framework delivers a dependable battery model that can serve as a foundation for real-time estimation, control, and integration into embedded BMS. This work sets the stage for future developments in model-based SoC estimation,diagnostics and battery monitoring applications.

ACKNOWLEDGEMENT

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