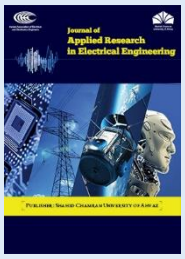
Shahid Chamran University of Ahvaz

Iranian Association of Electrical and Electronics Engineers

Journal of Applied Research in Electrical Engineering

E-ISSN: 2783-2864
P-ISSN: 2717-414X
Homepage: https://jaree.scu.ac.ir/



Research Article

Selecting an Optimal Single-Temperature Battery Model for Robust State-of-Charge Estimation across Thermal Conditions

Behnam Ersi Alambaz[1], Mohsen Ghalehnoie[1,*], and Hamid Reza Moazami [2]

[1] *Faculty of Electrical Engineering, Shahrood University of Technology, Shahrood, Iran.*

[2] *Nuclear Fuel Cycle Research School, Nuclear Science and Technology Research Institute (NSTRI), Tehran, Iran*

* *Corresponding Author: ghalehnoie@shahroodut.ac.ir*

Abstract: This paper investigates the effect of ambient temperature on the accuracy of state-of-charge (SoC) estimation in lithium-ion batteries using the Extended Kalman Filter (EKF). Experimental evaluations were conducted at three distinct temperatures—5°C, 25°C, and 45°C—representing low, nominal, and high thermal conditions. Results reveal that battery performance and SoC estimation accuracy significantly depend on temperature, with 25°C providing the most stable electrochemical behavior and lowest estimation error. A dual-cell equivalent circuit model is employed to simulate the battery dynamics, and EKF is utilized as a real-time estimator due to its robustness in handling non-linear systems. Additionally, a thermally stable SoC operating range between 70% and 30% is identified, where the battery exhibits a reliable and predictable response across all tested conditions. These findings underline the importance of incorporating temperature effects into battery modeling for improved performance and safety in practical applications.

Keywords: Lithium-ion battery, State-of-charge, Temperature dependence, Extended Kalman Filter, Dual-cell equivalent circuit model, Thermal behavior

Article history
Received 16 June 2025; Revised 23 December 2025; Accepted 25 February 2026; Published online 2 October 2026 .
© 2026 Published by Shahid Chamran University of Ahvaz & Iranian Association of Electrical and Electronics Engineers (IAEEE)
How to cite this article
B. Ersi Alambaz, M. Ghalehnoie, and H. R. Moazami, " Selecting an Optimal Single-Temperature Battery Model for Robust State-of-Charge Estimation across Thermal Conditions," *J. Appl. Res. Electr. Eng.*, vol. 4, no. 2, pp. 266-273, 2025. DOI: https://doi.org/10.22055/jaree.2026.49987.1243

Check for updates

1. INTRODUCTION

In the face of escalating climate change concerns and the global transition toward sustainable energy, lithium-ion batteries (LIBs) have become a foundational technology powering this transformation. From electric vehicles that redefine urban mobility to renewable energy systems that stabilize modern power grids and even the smartphones in our pockets—LIBs are silently but fundamentally shaping the future of energy use. Their success stems from a unique combination of high energy density, low self-discharge, and long operational lifespan. Beyond vehicle-level applications, lithium-ion batteries are increasingly deployed in integrated energy systems—such as electric vehicle charging infrastructures coupled with renewable generation and stationary storage—where reliable battery state estimation is essential for economic operation and system-level decision making [1]. However, the true potential of lithium-ion batteries is only unlocked when their internal state can be reliably monitored and controlled. Among the various internal variables, the state of-charge which represents the remaining usable energy in a battery stands out as the most essential yet the most elusive. Unlike current or voltage, SoC cannot be directly measured. It must be estimated using indirect methods, and this estimation lies at the heart of battery management systems. A misestimated SoC not only reduces system performance but may also lead to premature aging, thermal runaway [2], or even safety hazards. Therefore, achieving accurate, robust, and real-time SoC estimation is not just a technical challenge—it is a critical enabler of trust in battery-powered technologies that now support everything from daily life to large-scale energy infrastructure.

Over the past two decades, a wide range of modeling approaches have been proposed to estimate the state-of-charge (SoC) of lithium-ion batteries. These approaches can be broadly categorized into three main groups: electrochemical models [3], black-box models [4], and equivalent circuit models [5] (ECMs), each with distinct advantages and inherent limitations.

Electrochemical models aim to simulate the internal physical and chemical processes of the battery with high fidelity. These models capture phenomena such as lithium-ion diffusion, charge transfer kinetics, and solid electrolyte interphase (SEI) growth. Although they offer detailed physical insight and are valuable for understanding degradation mechanisms, their application in real-time SoC estimation is limited due to high computational demands, nonlinear partial differential equations, and the need for precise internal parameters, which are often difficult to obtain experimentally [6]. Black-box models, such as those based on artificial neural networks [7], support vector machines [8], or deep learning architectures, have gained popularity for their ability to learn complex nonlinear behaviors directly from data. These models require no explicit knowledge of the battery's internal structure and are generally fast to deploy once trained. However, they suffer from low interpretability, poor generalization to unseen conditions, and a heavy dependence on high-quality, labeled training datasets. Moreover, their performance can deteriorate significantly under dynamic or non-standard operating environments, such as varying temperature or load profiles.

Recent comprehensive review studies, most notably the work by Miao et al. [9], have systematically analyzed state-of-charge estimation methods across wide temperature ranges. That study provides a thorough comparison of model-based and data-driven approaches, highlighting how temperature variations affect estimation accuracy, stability, and computational requirements. While such reviews offer valuable insights into the relative strengths and weaknesses of existing SoC estimation techniques, they primarily focus on method-level comparisons rather than addressing practical modeling decisions faced in real-world BMS implementation. In particular, the question of how model identification temperature influences the robustness of a single SoC estimator across varying thermal conditions remains largely unexplored.

In contrast, equivalent circuit models (ECMs) provide a practical balance between physical interpretability and computational efficiency [10]. By representing the battery with lumped electrical elements—such as resistors and capacitors, ECMs can approximate key electrochemical dynamics while remaining simple enough for implementation in real-time systems. Among ECMs, the single-cell RC model has been widely adopted due to its minimal parameter requirements and straightforward structure [11]. However, single-cell models tend to oversimplify the internal behavior of lithium-ion batteries, often neglecting slower processes such as diffusion delays and interfacial polarization. To address these limitations, more advanced models, such as dual-cell or multi-time constant ECMs, have been introduced. These models separate fast and slow dynamic components, providing a more accurate and flexible representation of the battery's transient behavior without the complexity of full electrochemical formulations [12]. For example, in our previous work [13], a dual-cell ECM combined with a Kalman-filter-based observer was used to investigate the effect of excitation signal design on parameter identification and SoC estimation accuracy at a nominal temperature of 25°C. That study demonstrated that long-pulse excitation signals significantly improve parameter identifiability and estimation accuracy under isothermal conditions. While that study established an effective identification strategy under nominal thermal conditions, it did not address how the choice of identification temperature influences model fidelity and SoC estimation performance.

In addition, recent review studies have systematically compared various state estimation and optimization techniques used in battery management systems, emphasizing the trade-off between estimation accuracy, computational complexity, and suitability for real-time implementation, and highlighting model-based observers such as Kalman-filter-based methods as practical solutions for online SoC estimation [9] and [14].

However, many studies using ECMs still assume isothermal conditions and rarely account for the influence of ambient temperature on the estimation performance. This omission can significantly compromise accuracy in real-world applications, particularly when models identified at a nominal temperature are applied under varying thermal conditions. Despite advancements in model estimation techniques for lithium-ion batteries, temperature remains an often overlooked yet critical factor affecting both the internal dynamics of the battery and the reliability of state-of-charge (SoC) estimation [15]. Although temperature-dependent modeling can improve accuracy, it often comes at the cost of increased model complexity and computational burden, which limits its practicality for real-time and embedded battery management systems. Consequently, most existing models and observers still rely on a single battery model identified at a fixed temperature while in practical scenarios, batteries experience a wide range of thermal conditions that significantly influence their electrical and electrochemical behavior. From this perspective, an important yet insufficiently addressed question arises: *if only one battery model can be identified, at which ambient temperature should the identification be performed to achieve the most accurate and robust state-of-charge (SoC) estimation across operating conditions?*

To address this question, the present study systematically investigates the effect of identification temperature on SoC estimation performance using a dual-cell (2RC) equivalent circuit model and an Extended Kalman Filter (EKF) framework [13]. Controlled experiments are conducted at three representative ambient temperatures—5 °C, 25 °C, and 45 °C—to quantify estimation accuracy, robustness, and generalization. Unlike prior comparative reviews, this work focuses on identifying an optimal single identification temperature that maximizes SoC estimation robustness across thermal conditions without resorting to temperature-dependent modeling.

The novelty of this study lies in identifying an optimal single-temperature ECM for robust SoC estimation across varying thermal conditions, extending our previous long-pulse identification strategy [13]. Also, rather than comparing

estimation methods, as in [9], this work addresses a complementary and practically motivated problem: optimizing model identification strategy under single-model constraints. So, the main contributions of this paper can be summarized as follows:

- A systematic experimental evaluation of SoC estimation performance when a dual-cell ECM is identified at different ambient temperatures (5 °C, 25 °C, and 45 °C), from a practical, online BMS perspective.
- Identification of an optimal identification temperature that provides the best trade-off between estimation accuracy and model simplicity, avoiding the need for temperature-dependent parameterization.
- Quantitative analysis of the robustness of a single-temperature-identified model when applied across a wide thermal operating range.
- An experimentally validated framework suitable for real-time and resource-constrained battery management systems.

2. Equivalent Circuit Modeling of Lithium-ion Batteries

Accurate estimation of the state-of-charge (SoC) in lithium-ion batteries requires a battery model that can adequately capture the dominant internal dynamics while remaining computationally tractable for real-time implementation. Among the available modeling approaches, equivalent circuit models (ECMs) have been widely adopted due to their balance between physical interpretability, numerical efficiency, and suitability for embedded battery management systems (BMSs) [13].

In this study, a dual-cell equivalent circuit model (commonly referred to as a 2RC model) is employed. This model structure has been shown to effectively represent both fast and slow electrochemical dynamics associated with charge transfer and diffusion phenomena, without introducing the complexity of high-order electrochemical models. The same model topology was previously validated by the authors in [13] for state-of-charge estimation under nominal thermal conditions. Therefore, the present work adopts this established model structure and focuses on investigating how the temperature at which the model parameters are identified influences SoC estimation performance.

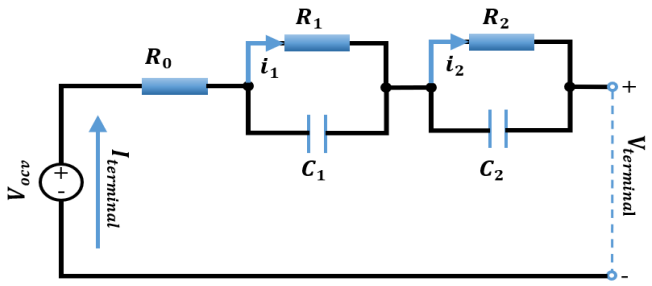


Fig. 1. Dual-cell (2RC) equivalent circuit model of a lithium-ion battery, consisting of an ohmic resistance R_0, two polarization resistances $R_1$and R_2, and their associated capacitances C_1 and C_2.

As illustrated in Fig. 1, the dual-cell ECM consists of an ohmic resistance R_0 representing instantaneous voltage losses, two parallel RC branches (R_1, C_1) and (R_2, C_2) that capture polarization effects occurring at different time scales, and a controlled voltage source representing the open-circuit voltage V_{OC}. The internal states of the model include the currents flowing through each RC branch and the state of charge of the battery. The open-circuit voltage V_{oc} is a nonlinear function of SOC and reflects the equilibrium voltage of the battery when no current is flowing [16].

The continuous-time state equations of the dual-cell ECM describe the dynamics of the RC branch currents and the SoC evolution based on charge balance principles. The detailed derivation of these equations, as well as their discretization procedure, have been thoroughly presented in the authors' previous work [13] and are therefore not repeated here for brevity.

For implementation within the Extended Kalman Filter (EKF) framework, the model is expressed in discrete-time state-space form. The resulting discrete-time state equation is given by

$$\mathrm{x}(k+1) = \mathrm{A}\mathrm{x}(k) + \mathrm{B}I_t(k), \tag{1}$$

where the state vector is defined as $\mathrm{x}(k) = [i_1(k), i_2(k), SOC(k)]^T$. Here, $i_1(k)$ and $i_2(k)$ denote the currents through the two RC branches, and $SOC(k)$ represents the state of charge at discrete time step k. The input $I_t(k)$ is the measured terminal current, defined as positive during discharge. Also, The system and input matrices are given by

$$\mathrm{A} = \begin{bmatrix} e^{-\frac{\Delta t}{R_1 C_1}} & 0 & 0 \\ 0 & e^{-\frac{\Delta t}{R_2 C_2}} & 0 \\ 0 & 0 & 1 \end{bmatrix}, \mathrm{B} = \begin{bmatrix} 1 - e^{-\frac{\Delta t}{R_1 C_1}} \\ 1 - e^{-\frac{\Delta t}{R_2 C_2}} \\ -\frac{\Delta t}{C_n} \end{bmatrix}, \tag{2}$$

where Δt is the sampling interval and C_n denotes the nominal capacity of the cell.

The discrete-time output equation relating the terminal voltage to the model states is expressed as,

$$V_t(k) = V_{OC}(SOC(k)) - R_0 I_t(k) - R_1 i_1(k) - R_2 i_2(k). \tag{3}$$

This discrete-time model is directly employed within the EKF for SoC estimation. Since the model structure remains unchanged across all experiments, variations in estimation performance can be attributed solely to the temperature-dependent identification of model parameters.

3. Experimental Setup and Temperature-Oriented Model Identification

Accurate state-of-charge estimation relies on precise identification of the model parameters under conditions that reflect real-world battery operation. Unlike our previous study [13], where the main objective was to compare short- and long-pulse excitation signals at a fixed nominal temperature, the present work adopts a long-pulse excitation strategy and focuses on investigating the influence of identification temperature on model fidelity and SoC estimation accuracy. Specifically, the goal is to determine an optimal identification temperature that provides the most

robust SoC estimation across a wide range of thermal operating conditions.

All experimental data used in this study were generated by the authors through controlled laboratory experiments specifically designed for model identification and state-of-charge estimation purposes. The dataset consists of synchronized measurements of terminal voltage, applied current, and ambient temperature, collected under repeatable and well-defined operating conditions. The same experimental platform and data acquisition procedure were used for all temperature settings to ensure consistency and comparability across tests.

3.1 Battery Specification and Thermal Conditioning

Experiments were conducted on commercially available Maxell ER3 14250 lithium-ion cells with the following characteristics: nominal capacity 500 mAh, nominal voltage 3.7 V, maximum voltage 4.2 V, and cut-off voltage 3.0 V. Each experiment was performed on a fresh cell of the same model to avoid performance degradation effects caused by aging or cycling history. Prior to testing, each cell was stabilized at the target ambient temperature to ensure thermal equilibrium. Temperature conditioning was achieved using a climate-controlled chamber, and cells were held at the desired temperature for a sufficient duration before data acquisition to guarantee uniform internal temperature distribution.

Three representative identification temperatures were selected to cover practical operating conditions: Low temperature (5°C), Nominal temperature (25°C), and High temperature (45°C). These temperatures were chosen to capture the influence of thermal variations on internal battery dynamics, such as ohmic and polarization resistances and capacitive effects, which are known to affect SoC estimation accuracy.

3.2 Excitation Signal and Measurement Protocol

Following the findings in [13], a long-pulse current profile was applied to all experiments to ensure reliable parameter identification. This approach captures both fast and slow electrochemical dynamics while maintaining a low computational burden suitable for real-time implementation. The applied current profile and measurement protocol were identical for all temperature cases, ensuring that observed differences in model parameters arise solely from temperature effects rather than excitation variability.

Terminal voltage and current were recorded throughout the discharge cycle. All signals were sampled at a fixed sampling interval and recorded using a calibrated data acquisition system to ensure measurement accuracy and repeatability. Rest periods were incorporated between pulses to allow the terminal voltage to relax toward the open-circuit voltage, which serves as a reference for model parameter identification. Fig. 2 presents a comparison of terminal voltage curves across these three temperature settings during a standard long-pulse discharge cycle.

As shown, both the initial response and relaxation behavior of the battery are noticeably influenced by temperature, revealing slower dynamics and voltage sag at lower temperatures, and increased instability at higher ones.

3.3 Discrete-Time Parameter Identification

The dual-cell ECM structure described in Section 2 was employed for all tests. Parameter identification followed a three-step procedure, consistent with the methodology in [13]:

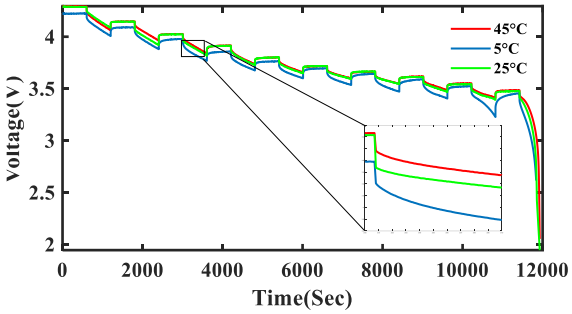


Fig. 2. Terminal voltage at 5°C, 25°C, and 45°C

1. Open-circuit voltage identification: The terminal voltage during rest intervals was used to construct the nonlinear $V_{OC} - SOC$ relationship, providing a reference for subsequent parameter estimation.
2. Ohmic resistance estimation (R_0): Voltage drops during current steps and rest periods were used to calculate R_0 according to:

$$R_0 = \frac{(V_A - V_B) + (V_D - V_C)}{2I_t} \quad (4)$$

where V_A, V_B, V_C, and V_D denote measured voltages at selected points in the discharge-rest cycles [17-18]. For the current experiments, the identified value of R_0 was $0.0749\ \Omega$. This indicates that the type of experiment has a negligible impact on the estimation of the battery's ohmic resistance.

3. ARX-based identification of polarization parameters (R_1, R_2, C_1, C_2): The remaining dynamic parameters were estimated by fitting a discrete-time Auto-Regressive with eXogenous input (ARX) model to the measured voltage and current data. The resulting coefficients were then mapped onto the dual-cell ECM parameters following the procedure described in [13].

The complete identification process was carried out independently using datasets obtained at 5°C, 25°C, and 45°C, resulting in three temperature-specific parameter sets derived from experimentally measured data rather than simulated or synthetic inputs. Table 1 summarizes the extracted ECM parameters at the three identification temperatures. The results demonstrate clear temperature dependence:

These observations highlight that the same ECM structure exhibits significant variation in parameters depending on the identification temperature, which directly affects SoC estimation performance.

Table 1. Dual-cell ECM parameters identified at three different temperatures.

	5°C	25°C	45°C
R_1 (Ω)	0.0777	0.0532	0.0901
R_2 (Ω)	0.2595	0.1373	0.36716
C_1 (F)	30.5007	72.7049	48.51382
C_2 (F)	701.2893	778.1462	3068.72

4. State Estimation with Extended Kalman Filter

SoC estimation in lithium-ion batteries constitutes a nonlinear state estimation problem, as the internal battery states are not directly measurable and the terminal voltage depends nonlinearly on SoC through the open-circuit voltage characteristic. In this work, an Extended Kalman Filter (EKF) is adopted to recursively estimate the internal states of the dual-cell equivalent circuit model, including the SoC and polarization dynamics, using measured terminal current and voltage [19].

The EKF framework combines a physics-based battery model with stochastic estimation theory. In the prediction step, the discrete-time state equations propagate the internal states forward using the measured current input, while accounting for model uncertainty through process noise. In the correction step, the predicted terminal voltage—computed from the estimated states and the nonlinear $V_{OC}(SOC)$ relationship—is compared with the measured voltage, and the resulting innovation is used to update the state estimates [20]. This recursive prediction–correction structure enables the EKF to compensate for modeling inaccuracies and measurement noise in real time.

4.1 Estimation Mechanism and Observability Analysis

Based on the discrete-time model introduced in Section 2, the state and measurement equations used in the EKF are expressed as:

$$\begin{aligned} \mathrm{x}_{k+1} &= \mathrm{A}\mathrm{x}_k + \mathrm{B}I_k + \mathrm{w}_k \\ V_{t,k} &= h(\mathrm{x}_k, I_k) + v_k \end{aligned} \tag{5}$$

where

$$h(\mathbf{x}_k, I_k) = V_{OC}(SOC_k) - R_0 I_k - R_1 i_{1,k} - R_2 i_{2,k} \tag{6}$$

and w_k and v_k represent zero-mean Gaussian process and measurement noise, respectively.

At each sampling instant, the EKF performs linearization of the nonlinear output equation around the current state estimate. The corresponding output Jacobian is given by:

$$\mathrm{H}_k = \left[-R_1 \quad -R_2 \quad \frac{dV_{OC}(SOC_k)}{dSOC}\right] \tag{7}$$

This expression explicitly shows that the SoC state enters the measurement equation through the slope of the open-circuit voltage curve. Consequently, local observability of SoC is ensured when:

$$\frac{dV_{OC}(SOC)}{dSOC} \neq 0 \tag{8}$$

Under dynamic current excitation, the polarization states i_1 and i_2 further enhance observability by introducing transient voltage responses that couple the internal dynamics to the measured terminal voltage. In contrast, during near-rest conditions or in flat regions of the $V_{OC} - SOC$ curve, the contribution of SoC to the measurement equation diminishes, leading to reduced observability[21-22]. In such cases, the EKF correction relies primarily on the state prediction governed by coulomb counting.

This behavior reflects a fundamental limitation of voltage-based SoC estimation rather than a shortcoming of the EKF itself.

4.2 Stability and Practical Convergence Properties

Due to the nonlinear nature of the battery model, the EKF does not provide global stability guarantees [21]. However, local stability and bounded estimation errors can be ensured under standard assumptions on noise statistics, model fidelity, and filter tuning.

The EKF covariance propagation and correction steps are governed by:

$$\begin{aligned} \mathrm{P}_{k|k-1} &= \mathrm{F}_k \mathrm{P}_{k-1|k-1} \mathrm{F}_k^T + \mathrm{Q} \\ \mathrm{K}_k &= \mathrm{P}_{k|k-1} \mathrm{H}_k^T (\mathrm{H}_k \mathrm{P}_{k|k-1} \mathrm{H}_k^T + R)^{-1} \\ \mathrm{P}_{k|k} &= (\mathrm{I} - \mathrm{K}_k \mathrm{H}_k) \mathrm{P}_{k|k-1} \end{aligned} \tag{9}$$

where $\mathrm{F}_k = \mathrm{A}$ for the linear state equation and H_k is the Jacobian defined in (7).

In this study, practical stability of the EKF is achieved by selecting physically meaningful covariance matrices. For example, the following diagonal structures were found to yield stable and well-convergent behavior across all experiments:

$$\mathrm{Q} = \mathrm{diag}\left(q_{i_1},\ q_{i_2},\ q_{SOC}\right), R = r_v \tag{10}$$

with representative values on the order of:

$$\begin{aligned} &q_{SOC} = \mathcal{O}(10^{-6}), \\ &q_{i_1}, q_{i_2} = \mathcal{O}(10^{-6}), \\ &r_v = \mathcal{O}(10^{-6}) \end{aligned} \tag{11}$$

With appropriate initialization and tuning, the EKF consistently exhibits bounded estimation errors and convergent behavior. Since the EKF structure, noise covariances, and initialization strategy are identical for all temperature cases considered in this work, any observed differences in convergence speed or estimation accuracy can be attributed to temperature-dependent model parameter variations rather than estimator instability.

4.3 Advantages and Limitations

The EKF offers an effective balance between estimation accuracy and computational efficiency, making it suitable for real-time implementation in battery management systems. Its ability to accommodate nonlinear battery characteristics and fuse model-based prediction with voltage measurements provides robustness against sensor noise and modeling uncertainties.

Nevertheless, EKF performance remains strongly dependent on model accuracy. Parameter mismatches—particularly those induced by temperature-dependent behavior—can degrade estimation accuracy and slow convergence. This limitation directly motivates the central objective of this paper, which is to assess how the temperature at which model parameters are identified influences SoC estimation performance when the same estimation framework is applied.

A detailed derivation of the EKF recursion equations and implementation details is provided in [13], and is therefore not repeated here.

5. Results and Discussion

To further evaluate the robustness and thermal sensitivity of the Extended Kalman Filter (EKF), a series of simulations were conducted to estimate the state of charge (SoC) of the lithium-ion battery at three key temperature levels: 5°C, 25°C, and 45°C. These temperature points were selected to represent typical low, nominal, and high operating conditions and to highlight the battery's electrochemical behavior across the thermal spectrum. As illustrated in Fig. 3, 4, and 5, the EKF-based SoC estimation demonstrates noticeably different performance characteristics under each thermal condition.

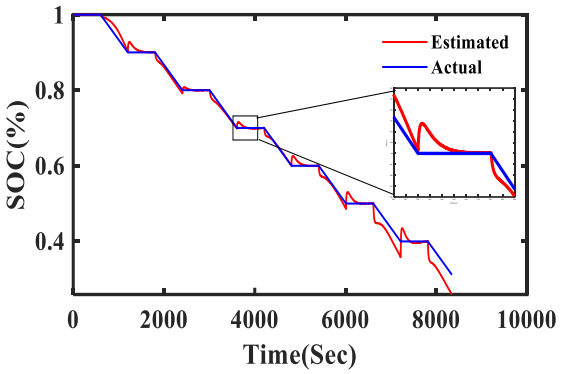


Fig. 3. Comparison of estimated and actual SoC in a lithium-ion battery at 5°C

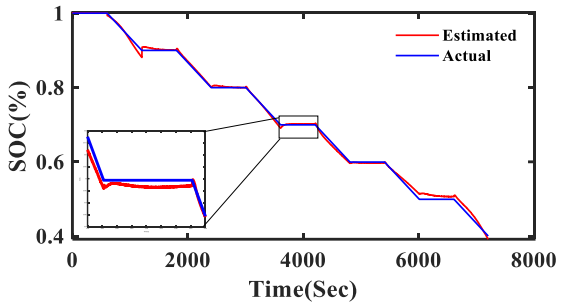


Fig. 4. Comparison of estimated and actual SoC in a lithium-ion battery at 25°C

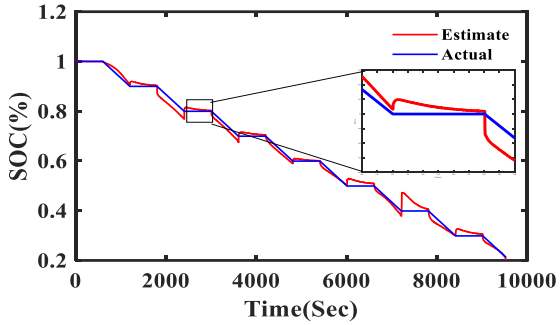


Fig. 5. Comparison of estimated and actual SoC in a lithium-ion battery at 45°C

At 5°C, the battery exhibits sluggish ion kinetics and increased internal resistance, which introduce delay and deviation in the voltage response. Consequently, the EKF struggles to accurately track the real-time SoC, resulting in visible over- or under-estimations throughout the cycle. In contrast, at 45°C, although the battery shows more dynamic voltage changes due to accelerated charge transfer, the system is also subject to increased instability stemming from side reactions, voltage noise, and self-discharge phenomena. This results in estimation drift and reduced prediction confidence in high-temperature environments. At 25°C, which corresponds to the manufacturer's nominal operating temperature, the battery maintains a balanced electrochemical environment. Ion diffusion, charge transport, and electrode kinetics are optimized, allowing the EKF to model the system dynamics with high precision. The estimated and actual SoC curves align closely, and minimal deviation is observed across the entire operating range.

Fig. 6 presents a direct comparison of the SoC estimation error at 5°C, 25°C, and 45°C. The lowest error consistently occurs at 25°C, where the EKF accurately tracks the actual SoC with minimal deviation. At 5°C, higher internal resistance slows down voltage dynamics, producing a noticeable transient error at the beginning of the cycle. In contrast, the 45°C curve exhibits larger fluctuations and drift due to thermal instability and increased measurement noise. Overall, this figure quantitatively demonstrates that the estimation accuracy and stability of the EKF are strongly affected by ambient temperature, confirming the necessity of selecting an optimal identification temperature for robust SoC estimation.

To further validate this behavior, Table. 2 presents the mean absolute error (MAE) and root mean square error (RMSE) of SoC estimation across the three temperature scenarios. The numerical results strongly support the visual trends observed in the figures. While SoC estimation at 5°C and 45°C suffers from higher variance and transient deviations, the performance at 25°C consistently yields the lowest errors, reinforcing the importance of thermal adaptation in battery modeling and observer design. These results collectively demonstrate that temperature is a dominant factor in the reliability of SoC estimation. Incorporating thermal characteristics into both the battery model and observer logic is thus crucial for ensuring accuracy and safety in real-world battery management systems.

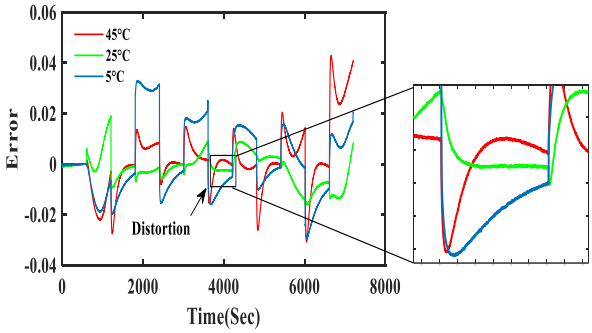


Fig. 6. Error comparison in state-of-charge estimation at 5°C, 25°C, and 45°C, highlighting distortion effects at higher temperatures.

Table 2. Error Analysis of SoC Estimation Using EKF Across Thermal Scenarios.

Temperature	RMSE	MAE
5°C	0.0165	0.0101
25°C	0.0073	0.0048
45°C	0.0185	0.0134

6. CONCLUSION

In this study, we investigated the impact of ambient temperature on the accuracy of state-of-charge (SoC) estimation in lithium-ion batteries using a dual-cell equivalent circuit model and the Extended Kalman Filter (EKF). Experiments were conducted at three critical thermal conditions 5°C, 25°C, and 45°C to reflect a wide operational range and reveal temperature-dependent estimation behavior.

The results of this study clearly demonstrate that ambient temperature has a decisive influence on both the electrochemical behavior of lithium-ion batteries and the accuracy of state-of-charge (SoC) estimation. Experimental evaluations conducted at 5°C, 25°C, and 45°C show that the battery model identified at the nominal temperature of 25°C consistently provides the highest estimation accuracy and stability compared to models extracted at low and high temperatures. At low temperature (5°C), reduced lithium-ion mobility and increased internal resistance lead to sluggish voltage dynamics and pronounced polarization effects, which degrade model fidelity and reduce estimation accuracy. Conversely, at high temperature (45°C), accelerated side reactions, increased self-discharge, and thermal-induced parameter drift introduce voltage noise and estimation drift, despite faster ion transport.

Beyond temperature effects, this work also emphasizes the importance of evaluating battery behavior within a realistic and practically relevant operating SoC range. To this end, the operational window between 70% and 30% SoC was systematically investigated, as this region represents normal usage conditions in many battery-powered applications and avoids extreme nonlinearities associated with fully charged or deeply discharged states. Within this interval, the battery exhibits reduced voltage hysteresis, more stable equivalent-circuit parameters, and smoother voltage dynamics. The experimental results confirm that the EKF-based estimation error remains significantly lower and more stable in this range compared to high- or low-SoC extremes, where internal resistance increases and electrochemical nonlinearities become more pronounced. By jointly considering temperature dependency and the practical operating SoC window, this study provides an explicit criterion for selecting the most reliable battery model.

The superior performance observed within the 70%–30% SoC range, combined with the lowest estimation error at 25°C, indicates that the model identified under nominal thermal conditions offers the most accurate and physically consistent representation of battery behavior. Overall, the proposed framework—based on a simple dual-RC model and the Extended Kalman Filter—achieves a favorable balance among modeling simplicity, computational efficiency, and estimation accuracy, making it well-suited for real-time implementation in battery management systems.

Future work should focus on integrating temperature-adaptive mechanisms into observer design and evaluating the performance of this framework under real-world load profiles, including those encountered in electric vehicle applications. Additionally, expanding this method to other battery chemistries could further validate its generalizability across modern battery management systems.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Behnam Ersi Alambaz: Conceptualization, Formal analysis, Methodology, Software, Roles/Writing - original draft, Writing - review & editing. **Mohsen Ghalehnoie**: Conceptualization, Formal analysis, Methodology, Supervision, Validation, Roles/Writing - original draft, Writing - review & editing. **Hamid Reza Moazami**: Formal analysis, Methodology, Supervision, Validation, Writing - review & editing.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The ethical issues; including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy has been completely observed by the authors.

REFRENCES

[1] M. Khosravi, S. Hasanvand, M. Abasi, and M. E. Hassanzadeh, "Economic Analysis of Photovoltaic Systems During Peak Load of the Electric Power Distribution System in the Presence of Electric Vehicles," *J. Appl. Res. Electr. Eng.*, vol. 3, no. 2, pp. 177–184, Jul. 2024.

[2] P. Wang, L. Yang, H. Wang, D. M. Tartakovsky, and S. Onori, "Temperature estimation from current and voltage measurements in lithium-ion battery systems," *J. Energy Storage*, vol. 34, no. September 2020, 2021.

[3] I. M. Monirul, L. Qiu, and R. Ruby, "Accurate SOC estimation of ternary lithium-ion batteries by HPPC test-based extended Kalman filter," *J. Energy Storage*, vol. 92, no. May, p. 112304, 2024.

[4] C. Jiang, S. Wang, B. Wu, C. Fernandez, X. Xiong, and J. Coffie-Ken, "A state-of-charge estimation method of the power lithium-ion battery in complex conditions based on adaptive square root extended Kalman filter," *Energy*, vol. 219, 2021.

[5] Y. Li, C. Wang, and J. Gong, "A multi-model probability SOC fusion estimation approach using an improved adaptive unscented Kalman filter technique," *Energy*, vol. 141, pp. 1402–1415, 2017.

[6] H. Fang, Y. Zhang, M. Liu, and W. Shen, "S WDWH RI C KDUJH Estimation of Lithium-ion Battery % ased on an , mproved Kalman Filter," pp. 515–520, 2017.

[7] J. Meng, D. I. Stroe, M. Ricco, G. Luo, and R. Teodorescu, "A simplified model-based state-of-charge estimation approach for lithium-ion battery with dynamic linear model," *IEEE Trans. Ind. Electron.*, vol. 66, no. 10, pp. 7717–7727, 2019.

[8] K. Propp, D. J. Auger, A. Fotouhi, S. Longo, and V. Knap, "Kalman-variant estimators for state of charge in lithium-sulfur batteries," *J. Power Sources*, vol. 343, pp. 254–267, 2017.

[9] Y. Miao, Y. Gao, X. Liu, Y. Liang, and L. Liu, "Analysis of State-of-Charge Estimation Methods for Li-Ion Batteries Considering Wide Temperature Range," Mar. 01, 2025.

[10] Y. Chen *et al.*, "A New State of Charge Estimation Algorithm for Lithium-Ion Batteries Based on the Fractional Unscented Kalman Filter," *Energies*, 2017.

[11] M. Zhu, K. Qian, and X. Liu, "A three-time-scale dual

extended Kalman filtering for parameter and state estimation of Li-ion battery," *Proc. Inst. Mech. Eng. Part D J. Automob. Eng.*, vol. 238, no. 6, pp. 1352–1367, 2024.
[12] R. Mahamud and C. Park, "Theory and Practices of Li-Ion Battery Thermal Management for Electric and Hybrid Electric Vehicles," *Energies*, vol. 15, no. 11, 2022.
[13] B. E. Alambaz, M. Ghalehnoie, and H. R. Moazami, "Comparative Analysis of Lithium-ion Battery for Long and Short Pulse Discharge Experiments in State-of-Charge Estimation with Extended Kalman Filter," *J. Appl. Res. Electr. Eng.*, vol. 3, no. 2, pp. 200–206, 2024.
[14] Khan, Mohammad Junaid, Ram Murat Singh, Md Naqui Akhtar, and Asyraf Afthanorhan. "Comparative Analysis of Various Optimization Techniques for Battery Management Systems in Electrical Vehicles." *Journal of Applied Research in Electrical Engineering* 2025.
[15] B. Yao *et al.*, "State-of-charge estimation for lithium-ion batteries based on modified unscented Kalman filter using improved parameter identification," *Int. J. Electrochem. Sci.*, vol. 19, no. 5, p. 100574, 2024.
[16] X. Zhang, L. Duan, Q. Gong, Y. Wang, and H. Song, "State of charge estimation for lithium-ion battery based on adaptive extended Kalman filter with improved residual covariance matrix estimator," *J. Power Sources*, vol. 589, pp. 1–39, 2024.
[17] C. Fang *et al.*, "Estimation of Lithium-Ion Battery SOC Model Based on AGA-FOUKF Algorithm," *Front. Energy Res.*, 2021.
[18] X. K. Chen and D. Sun, "Modeling and state of charge estimation of lithium-ion battery," *Adv. Manuf.*, vol. 3, no. 3, pp. 202–211, 2015.
[19] T. Ouyang *et al.*, "Co-estimation of State-of-Charge and State-of-Health for Power Batteries Based on Multi-thread Dynamic Optimization Method," *IEEE Trans. Ind. Electron.*, 2021.
[20] Y. Wang *et al.*, "A comprehensive review of battery modeling and state estimation approaches for advanced battery management systems," *Renew. Sustain. Energy Rev.*, vol. 131, no. June, p. 110015, 2020.
[21] X. Wei, M. Yimin, and Z. Feng, "Identification of Parameters in Li-Ion Battery Model by Least Squares Method with Variable Forgetting Factor," *Int. J. Comput. Methods*, vol. 17, no. 7, pp. 1–20, 2020.
[22] U. Yayan, A. T. Arslan, and H. Yucel, "A Novel Method for SoH Prediction of Batteries Based on Stacked LSTM with Quick Charge Data," *Appl. Artif. Intell.*, vol. 35, no. 6, pp. 421–439, 2021.

BIOGRAPHY



Behnam Ersi Alambaz was born in Mazandaran, Iran in 1994. He finished his M.Sc. in electrical control engineering at Shahrood University of Technology, Shahrood, Iran. His research interests are control and system identification.



Mohsen Ghalehnoie was born in Shahrood, Iran, in 1982, and holds Bachelor's, Master's, and Doctoral degrees in control engineering. He earned his B.Sc. and M.Sc. degrees from Iran University of Science and the University of Tehran in 2005 and 2008, respectively. Additionally, he received his Ph.D. from Ferdowsi University of Mashhad in 2018. Currently, he serves as an assistant professor of control engineering at Shahrood University of Technology, Shahrood, Iran. His work focuses on control systems theory, optimization, fuzzy control, data fusion, and expert systems, especially for hybrid switched systems and industrial processes.



Hamid Reza Moazami received his bachelor's degree in Applied Chemistry from Isfahan University of Technology in 2002, and his master's degree in Analytical Chemistry from Tehran University in 2005. He received his PhD in Analytical Chemistry from the Shahid Beheshti University in 2015. He is currently an assistant professor at Nuclear Science and Technology Research Institute. His research focuses on the development of novel electrochemical systems for energy and environmental applications.

Copyrights
© 2026 by the author(s). Licensee Shahid Chamran University of Ahvaz, Ahvaz, Iran. This article is an open-access article distributed under the terms and conditions of the Creative Commons Attribution –NonCommercial 4.0 International (CC BY-NC 4.0) License (http://creativecommons.org/licenses/by-nc/4.0/).