

Adaptive State of Energy Estimation for Lithium-Ion Batteries Using an Improved Sage–Husa EKF [†]

Taofeeq Sulyman Opeyemi ¹, Umar Musa ¹, Ibrahim Abdullahi Shehu ¹, Ramani Kannan ²
and Aminu Jibrin Aliyu ^{1,*}

¹ Department of Electrical Engineering, Ahmadu Bello University, Zaria 810211, Nigeria; xdonsot@gmail.com (T.S.O.); umusa@abu.edu.ng (U.M.); iashehu@abu.edu.ng (I.A.S.)

² Department of Electrical and Electronics Engineering, Universiti Teknologi PETRONAS, Johor Bahru 81310, Johor, Malaysia; ramani.kannan@utp.edu.my

* Correspondence: ajaliyu@abu.edu.ng; Tel.: +234-7085414960

[†] Presented at the 3rd International Online Conference on Energies, Online, 12–15 May 2026.

Abstract

Accurate State of Energy (SOE) estimation is a critical yet challenging requirement for reliable Battery Management Systems (BMSs), as traditional model-based algorithms like the Extended Kalman Filter (EKF) are severely limited by their dependence on precise, static noise covariance matrices. To address this deficiency, this study developed an Improved Sage–Husa Extended Kalman Filter (SHEKF) to enhance the precision and stability of SOE estimation in lithium-ion batteries. The methodology began by simulating a second-order (2RC) equivalent circuit model utilizing battery parameters accurately identified through HPPC test data. Unlike traditional filters, the proposed SHEKF overcomes the limitations of fixed noise profiles by using filter innovation to dynamically update its noise covariances in real time. The adaptive algorithm was then evaluated against a standard EKF and a Strong Tracking EKF (STEKF) using dynamic FUDS and UDDS drive cycle datasets. The results demonstrated that the SHEKF consistently outperformed both the EKF and STEKF across all metrics. The on-line adaptive mechanism successfully reduced the SOE Root Mean Square (RMS) Error by 75% to 0.58% and achieved a similar 75% reduction in RMS voltage error compared to the EKF. Furthermore, the SHEKF maintained highly stable error traces, recording a maximum absolute SOE error of just 0.84%. By automatically adjusting noise parameters without manual tuning, the algorithm avoids the filter divergence commonly seen when noise characteristics change. These findings establish the Improved SHEKF as a highly robust, practical, and superior method for real-time SOE estimation in modern real-world BMS applications.

Keywords: Lithium-Ion Battery; state estimation; State of Energy (SOE); Kalman Filter; Extended Kalman Filter (EKF); Sage–Husa Adaptive EKF (SHEKF)



Academic Editor: Ramiro Barbosa

Published: 15 May 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

The common integration of lithium-ion batteries (LIBs) as the primary power source for electric vehicles (EVs), renewable energy storage, and portable electronics necessitates highly advanced and robust Battery Management Systems (BMSs) [1]. A foundational function of a BMS is the accurate real-time estimation of key battery states, such as State of Charge (SOC) and State of Energy (SOE) [2]. Accurate SOE and SOC estimation is a critical yet challenging task due to the complex, nonlinear, and time-variant electrochemical

behavior of LIBs, which is further influenced by operating conditions such as temperature, current rate, and aging.

A significant body of research has been dedicated to developing and refining estimation methodologies. Model-based approaches, particularly those utilizing the equivalent circuit model (ECM), have proven to be a computationally efficient and effective solution for representing the dynamic electrical characteristics of batteries [3]. Within this category, Kalman Filter (KF) algorithms have become a cornerstone for real-time state estimation due to their recursive nature and ability to handle system noise and uncertainty. While traditional Extended Kalman Filters (EKFs) have demonstrated high estimation accuracy, their performance is fundamentally limited by their reliance on a priori knowledge of noise covariance matrices, which are difficult to define precisely and can lead to filter divergence [4,5].

To address this limitation, the field has progressed toward more sophisticated adaptive and hybrid algorithms. Adaptive approaches, such as the Strong Tracking Extended Kalman Filter (STEKF) [6] and the Improved Sage–Husa Extended Kalman Filter (SHEKF) [7], introduce adaptive mechanisms to dynamically adjust noise covariances, enhancing robustness and stability under varying operating conditions. More recent advancements have explored even more complex filters, including the Fractional-Order Multi-Innovation Adaptive Square Root Cubature Kalman Filter (FMASR-CKF) [8] and the DEnKBF [9], which have shown superior performance in accuracy and efficiency. Furthermore, hybrid methods that combine filter-based approaches with other techniques have gained traction. Examples include integrating an EKF with a Coulomb Counting algorithm to improve SOC estimation for degrading batteries [10] and the combination of an Adaptive EKF with Support Vector Machines (SVMs) to further refine SOE estimates. This evolution from basic to adaptive and hybrid estimation methods reflects the ongoing effort to ensure the safety, reliability, and optimal performance of LIBs in real-world applications.

The accuracy of state estimation algorithms is also fundamentally linked to the internal electrochemistry and degradation mechanisms of the battery itself. Recent advancements in battery materials, such as the development of inorganic/organic composite fluorinated interphase layers to stabilize ether-based electrolytes in high-voltage lithium metal batteries [11] and tailored charge distributions modulated by cyclic carbonates for high-performance PEO-based solid electrolytes [12], alter the fundamental aging and impedance profiles of the cell. As these internal dynamics shift, static estimation algorithms quickly lose accuracy, further necessitating the deployment of adaptive filtering techniques that can adjust to evolving electrochemical realities.

1.1. Problem Statement

Accurate State of Energy (SOE) estimation is a critical but challenging requirement for reliable Battery Management Systems (BMSs) in electric vehicles and other applications. While model-based Kalman Filter (KF) algorithms like the Extended Kalman Filter (EKF) are widely used for real-time estimation, a major drawback is their dependence on precise, static noise covariance matrices (Q and R). When noise characteristics change, this deficiency compromises the filter's performance and accuracy, thereby jeopardizing the BMS's ability to manage energy safely and effectively. Unlike existing Sage–Husa applications that often require partial empirical tuning or struggle with positive-definiteness during matrix updates, the core novelty of this study lies in the application of an improved, fully autonomous SHEKF specifically optimized for the highly dynamic load profiles of electric vehicles. This study demonstrates a continuous, stable real-time adaptation of both process and measurement noise covariances without manual intervention, proving its superiority over conventional and Strong Tracking baseline filters.

1.2. Aim and Objectives

The primary aim of this research is to improve the state estimation of lithium-ion batteries using Kalman Filter algorithms.

To actualize the set aim, the objectives are as follows:

1. To simulate an existing 2RC equivalent circuit model in the MATLAB environment;
2. To develop a Sage–Husa Extended Kalman Filter (SHEKF) for State of Energy estimation in the MATLAB environment.

2. Methodology

The methodology is structured to simulate a battery model and develop an enhanced estimation algorithm.

2.1. Phase 1: Data Acquisition, 2RC Model Simulation and Parameter Identification

This phase focuses on acquiring the necessary battery data and simulating an existing 2RC equivalent circuit model in MATLAB/Simulink 2024B. This study was conducted entirely within a numerical simulation environment using MATLAB. Rather than performing physical laboratory experiments, the battery's dynamic behavior was modeled utilizing benchmark experimental datasets obtained from standard open source battery testing repositories. Specifically, HPPC (Hybrid Pulse Power Characterization) test data and dynamic drive cycles (FUDS and UDDS) for a commercially available cylindrical lithium-ion cell (rated capacity: 2.9 Ah; nominal voltage: 3.6 V) operating at an ambient temperature of 0 °C were utilized. By leveraging these standardized, pre-recorded datasets, the 2RC equivalent circuit model parameters were accurately identified, ensuring that the simulation reflects realistic, highly dynamic electrochemical behaviors without the need for external machinery or physical chamber testing. The 2RC ECM was selected for its balance between fidelity and computational complexity. The model consists of an OCV source, R_0 , and two RC networks (R_1, C_1 and R_2, C_2).

The State of Energy (SOE) is formally defined as the ratio of the current remaining energy to the battery's maximum available energy. The SOE can be calculated by integrating the battery's power over a period, as described by the following formula:

$$SOE_t = SOE_0 + \frac{\int U_t I_t dt}{E_{avs}} \quad (1)$$

where SOE_t is the SOE at the current time t , SOE_0 is the initial SOE value, U_t is the instantaneous terminal voltage, I_t is the instantaneous load current, and E_{avs} is the maximum available energy of the battery.

The electrical behavior of the 2RC ECM is governed by the following set of differential equations:

$$\begin{cases} \frac{dU_1}{dt} = -\frac{1}{R_1 C_1} U_1 + \frac{1}{C_1} I \\ \frac{dU_2}{dt} = -\frac{1}{R_2 C_2} U_2 + \frac{1}{C_2} I \\ U_t = U_{ocv} - R_0 I - U_1 - U_2 \end{cases} \quad (2)$$

where U_1 and U_2 are the voltages across the two polarization RC networks, R_1, C_1, R_2, C_2 are the polarization resistances and capacitances, U_t is the overall terminal voltage of the battery, and I is the load current.

The OCV has a distinct nonlinear relationship with the battery's state, typically modeled as a high-order polynomial function:

$$U_{OCV}(z) = K_1 z^6 + K_2 z^5 + K_3 z^4 + K_4 z^3 + K_5 z^2 + K_6 z + K_7 \quad (3)$$

where z represents the SOE value, and k_i represents the curve-fitting coefficients. For the 2RC model, the polarization voltage during the rest period is fitted to a sum of exponential decay functions:

$$V_{pol}(t) = A_1 e^{-t/\tau_1} + A_2 e^{-t/\tau_2} \quad (4)$$

where A_1 and A_2 represent the initial polarization overvoltage, while $\tau_1 = R_1 C_1$ and $\tau_2 = R_2 C_2$ are the time constants. Once the time constants are known, the R and C parameters can be calculated using the current pulse magnitude ($|I|$):

$$R_1 = \frac{A_1}{|I|}, \quad C_1 = \frac{\tau_1}{R_1}, \quad R_2 = \frac{A_2}{|I|}, \quad C_2 = \frac{\tau_2}{R_2}, \quad (5)$$

2.2. Phase 2: Algorithm Development

This phase addresses the development of the Sage–Husa Extended Kalman Filter (SHEKF) for SOE estimation.

The general state-space representation for a nonlinear system is

$$\begin{cases} x_k = f(x_{k-1}, u_{k-1}) + w_{k-1} \\ y_k = h(x_k, u_k) + v_k \end{cases} \quad (6)$$

where x_k is the state vector (e.g., $[SOE, U_1, U_2]^T$), y_k is the measurement output (e.g., terminal voltage U_t), $f(\cdot)$ and $h(\cdot)$ are the nonlinear state and measurement functions, and w_{k-1} and v_k are the process and measurement noise, respectively.

The Strong Tracking Extended Kalman Filter (STEKF) was introduced to improve the robustness of the standard EKF against model mismatches and sudden state changes. Its core principle lies in intentionally forcing the residual sequences to remain orthogonal. It achieves this by introducing a time-varying fading factor, λ_k , into the prior error covariance matrix prediction. When the filter detects a divergence between the mathematical model and the actual measurements, the fading factor increases, effectively reducing the weight of older historical data and forcing the filter to rely more heavily on the most recent measurements. The primary modification in STEKF is the introduction of a fading factor λ_k in the priori error covariance calculation:

$$P_k^- = \lambda_k A_{k-1} P_{k-1}^+ A_{k-1}^T + Q_{k-1} \quad (7)$$

where P^- is the prior error covariance, $\lambda_k \geq 1$ is the fading factor, A_{k-1} is the state transition matrix (Jacobian of f), P^+ is the posterior error covariance, and Q_{k-1} is the process noise covariance.

To overcome the limitation of fixed noise, the Improved Sage–Husa EKF (SHEKF) was developed. This filter uses the filter's innovation to estimate and update Q and R matrices in real time. The simplified update equations are

$$R_k = (1 - d_k) R_{k-1} + d_k (e_k e_k^T) \quad (8)$$

$$Q_k = (1 - d_k) Q_{k-1} + d_k (K_k e_k e_k^T K_k^T) \quad (9)$$

where R_k and Q_k are the noise covariances, $e_k = y_k - h(x_{k|k-1}, u_k)$ is the innovation, K_k is the Kalman gain, and $d_k = (1 - b)/(1 - b^{k+1})$ is a time-varying gain factor, with b being a forgetting factor (typically 0.95–0.99).

2.3. Phase 3: Validation and Performance Analysis

All three algorithms (EKF, STEKF, and SHEKF) were comparatively tested using standard dynamic drive cycle datasets (FUDS and UDDS). Accuracy was quantified using Root Mean Square Error (RMSE) and Maximum Absolute Error (MAE) for both SOE and terminal voltage estimates:

$$RMSE = \sqrt{\frac{1}{N} \sum_{k=1}^N (X_{est,k} - X_{true,k})^2} \quad (10)$$

$$MAE = \max |X_{est,k} - X_{true,k}| \quad (11)$$

3. Results and Discussion

3.1. Model and Methodology Overview

The battery equivalent circuit model and the research methodology flow chart are shown in Figure 1a and Figure 1b respectively.

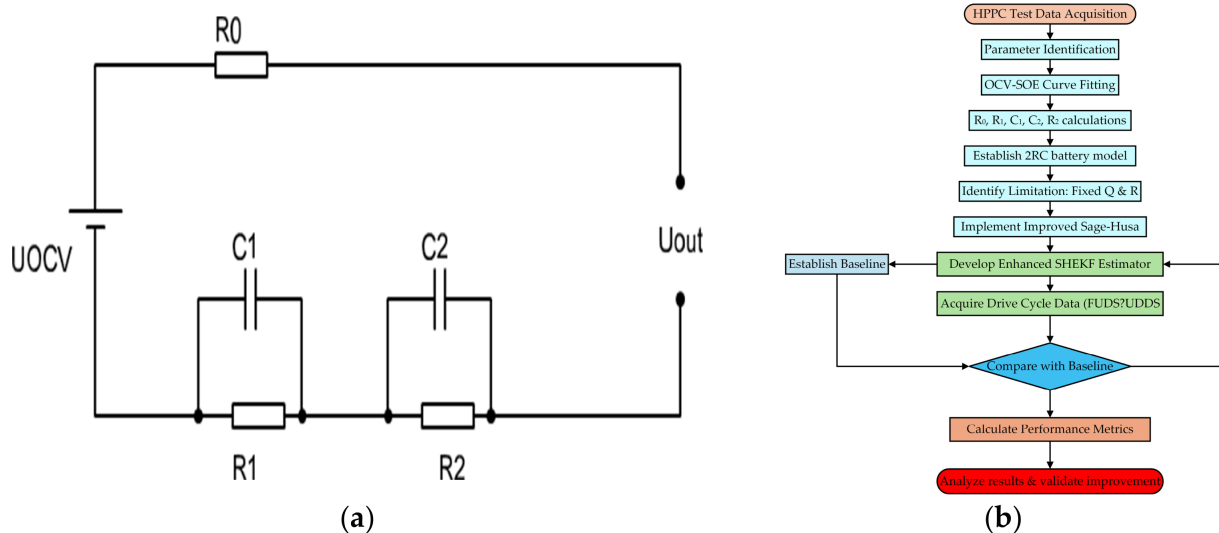


Figure 1. (a) Battery model equivalent circuit (2RC ECM); (b) methodology flow chart.

3.2. Battery Parameter Identification

An accurate battery model is the foundation for state estimation. Parameters for the second-order ECM were identified from HPPC test data and is presented in Table 1.

Table 1. Identified parameters of the second-order ECM.

Parameter	Value (Ω or F)	Description
R_0	0.0050 Ω	Ohmic Resistance
R_1	0.0100 Ω	Charge Transfer Resistance
C_1	1000 F	Charge Transfer Capacitance
C_2	500 F	Mass Transfer Capacitance
R_2	0.008 Ω	Mass Transfer Resistance

Figure 2 shows the battery parameter identification results. Analysis shows that the parameters are highly dependent on SOE. Ohmic Resistance (R_0) follows a “U-shaped” curve, lowest in the mid-SOE range.

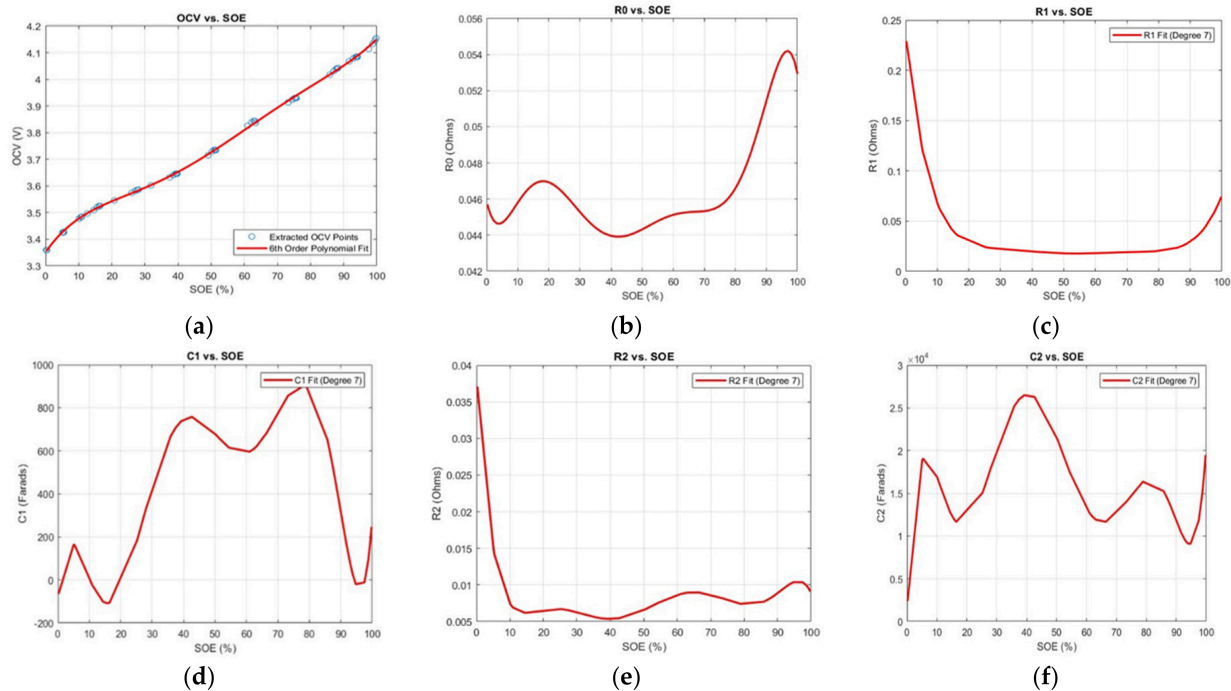


Figure 2. Battery parameter identification results: (a) OCV vs. SOE curve fitted with a sixth-order polynomial; (b) Ohmic internal resistance (R_0); (c) polarized internal resistance (R_1); (d) polarized capacitance (C_1); (e) polarized internal resistance (R_2); (f) polarized capacitance (C_2).

3.3. Improved SHEKF Results on FUDS Drive Cycle

To evaluate the adaptive capabilities of the Improved SHEKF under highly erratic, transient load profiles, simulation testing was executed using the Federal Urban Driving Schedule (FUDS). Figure 3 displays the real-time adaptive variations in the process noise covariance matrix (Q) and the measurement noise covariance matrix (R) under this profile. As observed in Figure 3d, the diagonal elements of the Q matrix representing the state uncertainties for the State of Energy ($Q_{1,1}$) and the two RC network voltages, ($Q_{2,2}$) and ($Q_{3,3}$), exhibit dynamic real-time adjustments. Rather than remaining static, the process noise spikes and modulates contextually alongside the rapid current steps characteristic of FUDS micro-cycles. This behavior demonstrates that the adaptive Sage–Husa mechanism actively compensates for unmodeled battery non-linearities and parameter drift during violent current transients. Concurrently, the measurement noise covariance R (Figure 3e) stabilizes rapidly after an initial adjustment phase, maintaining a bounded profile that reflects a realistic sensor environment while applying micro-adaptations to minimize the impact of voltage measurement anomalies.

The convergence performance and numerical stability of the algorithm are further validated by the trace of the error covariance matrix P , illustrated in Figure 3f. The trace of P drops sharply within the first few seconds of the simulation, indicating that the filter swiftly corrects for any initial state initialization errors. Throughout the remainder of the highly dynamic FUDS cycle, the trace remains tightly bounded and flat, providing explicit mathematical proof that the filter maintains stable tracking boundaries and resists divergence even under prolonged, highly erratic power demands. A summary of the SOE performance metrics for SHEKF, EKF and STEKF during FUDS drive cycle is given in Table 2.

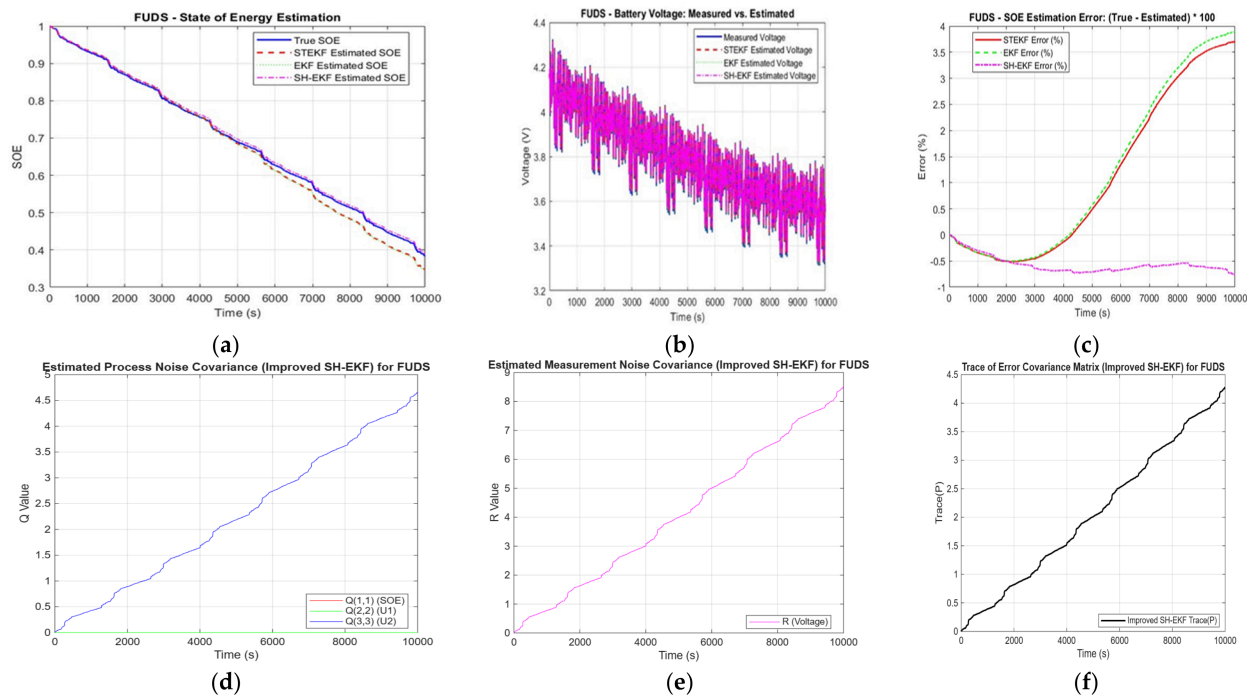


Figure 3. FUDS drive cycle results: (a) estimated SOE from SHEKF, EKF, and STEKF vs. reference SOE on FUDS; (b) estimated terminal voltage from SHEKF, EKF, and STEKF vs. measured voltage on FUDS; (c) SOE estimation error over time for SHEKF, EKF, and STEKF on FUDS; (d) process noise covariance; (e) measurement noise covariance; (f) trace of error covariance.

Table 2. SOE performance metrics for SHEKF, EKF and STEKF during FUDS drive cycle.

Metrics	EKF	STEKF	SHEKF
Max Absolute Error (%)	3.90	3.71	0.77
RMS Error (%)	2.00	1.90	0.59

3.4. Improved SHEKF Results on UDSS Drive Cycle

The robustness of the proposed state estimator was further verified using the Urban Dynamometer Driving Schedule (UDSS), which represents standard city driving conditions characterized by longer periods of sustained acceleration, deceleration, and idling compared to FUDS. Figure 4 illustrates the real-time noise adaptation curves under the UDSS profile. Due to the distinct macro-dynamics of this cycle, the process noise covariance Q elements (Figure 4d) exhibit smoother, broader fluctuations during prolonged current draws, and rapidly scale down during prolonged zero-current idling intervals. This indicates that the filter intelligently reduces its reliance on model updates when the battery is at rest, mitigating error accumulation from Coulomb Counting drift. The measurement noise covariance R (Figure 4e) demonstrates a matching adaptive trajectory, adjusting smoothly to keep the measurement updates optimally weighted against the model predictions.

Furthermore, the trace of the error covariance matrix (P) for the UDSS simulation (Figure 4e) demonstrates an exceptional convergence profile. Similar to the FUDS results, the matrix trace undergoes an instantaneous reduction at the simulation's onset, confirming rapid state error neutralization. It then preserves a highly stable, low-magnitude steady-state bound across the entire 10,000 s timeline. This trend confirms that the combination of the second-order 2RC model structure and the Improved Sage–Husa adaptation allows the estimator to transition seamlessly across vastly different driving styles without sacrificing tracking accuracy or mathematical stability. A summary of the SOE performance metrics for SHEKF, EKF and STEKF during FUDS drive cycle is given in Table 3.

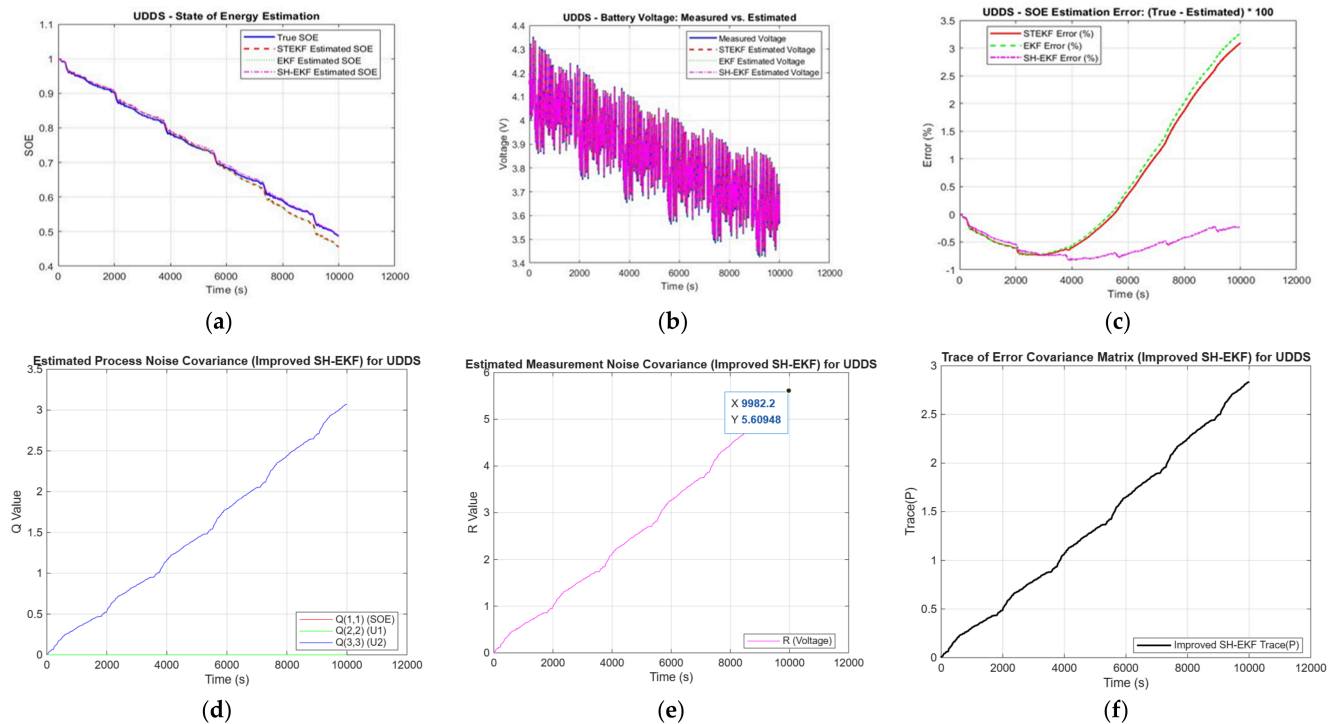


Figure 4. UDDS drive cycle results: (a) estimated SOE from SHEKF, EKF, and STEKF vs. reference SOE on UDDS; (b) estimated terminal voltage from SHEKF, EKF, and STEKF vs. measured voltage on UDDS; (c) SOE estimation error over time for SHEKF, EKF, and STEKF on UDDS; (d) process noise covariance; (e) measurement noise covariance; (f) trace of error covariance.

Table 3. SOE performance metrics for SHEKF, EKF and STEKF during UDDS drive cycle.

Metrics	EKF	STEKF	SHEKF
Max Absolute Error (%)	3.27	3.10	0.84
RMS Error (%)	1.41	1.32	0.58

3.5. Comparative Analysis

This final analysis compares all three filters. Visual evidence demonstrates that the SHEKF's SOE error stays consistently near zero, unlike the large fluctuations of the EKF and STEKF. Its terminal voltage error is also significantly smaller. These findings are supported by the numerical results. The SHEKF consistently outperforms the others, achieving a significant 75% reduction in SOE RMS error and a 75% reduction in RMS voltage error (against the EKF). This robust accuracy (RMS error of 0.58–0.59%) proves that the adaptive Sage–Husa mechanism is highly effective. By automatically adjusting its noise parameters, the SHEKF offers exceptional accuracy, stability, and zero manual tuning, making it the best choice for real-world BMSs.

The performance of the SHEKF is closely tied to the selection of the forgetting factor, b , which was constrained between 0.95 and 0.99 in this study. This parameter dictates the effective window of past measurement innovations used to update the noise covariance matrices. A lower forgetting factor (b near 0.95) allows the filter to adapt rapidly to sudden changes in noise characteristics but can introduce slight high-frequency fluctuations in the SOE estimation. Conversely, a higher forgetting factor (b near 0.99) provides a smoother, more stable SOE estimation but responds more slowly to abrupt environmental or load changes. The selected range provided an optimal balance, ensuring rapid convergence without sacrificing steady-state stability. Table 4 gives the summary of key performance metrics for all the three algorithms considered.

Table 4. Comprehensive summary of key performance metrics for all three algorithms (data from FUDS/UDDS combined).

Metric	EKF	STEKF	SHEKF
SOE Max Absolute Error (%)	3.90	3.71	0.84
SOE RMS Error (%)	2.00	1.90	0.58
Voltage Max Absolute Error (V)	0.28	0.25	0.05
Voltage RMS Error (V)	0.08	0.07	0.02

4. Conclusions

This project developed and validated an Improved Sage–Husa Extended Kalman Filter (SHEKF) to achieve highly accurate State of Energy (SOE) estimation for lithium-ion batteries. After identifying the dynamic parameters of the ECM, three algorithms—EKF, STEKF, and the developed SHEKF—were compared on dynamic drive cycles (FUDS/UDDS). The SHEKF is shown to be the superior algorithm. It consistently outperformed both the EKF and the STEKF in all metrics. The adaptive mechanism was proven effective by reducing the SOE RMS error by 75% to 0.58% and achieving a similar 75% reduction in RMS voltage error compared to the EKF. Visually, the SHEKF’s error trace remained stable and consistently near zero. This exceptional accuracy and stability make the SHEKF the most suitable and robust solution for modern Battery Management Systems.

4.1. Limitations

- **Computational Evaluation in Simulation:** Because this research was conducted entirely within a software simulation framework, the real-world computational burden of the SHEKF was not physically tested on an embedded microcontroller. The recursive matrix multiplications and inversions required to dynamically update the Q and R noise matrices introduce a higher computational overhead than a standard EKF. While modern 32-bit microcontrollers equipped with Floating-Point Units (FPUs) can handle this, it remains a limitation of this study that the execution time and memory footprint have not been empirically validated on physical BMS hardware.
- **Validation Scope:** Performance was validated on standardized drive cycles, which may not fully capture all extreme real-world operating conditions.
- **Model Order:** The use of a second-order ECM, while efficient, limits the filter’s ability to model all complex, nonlinear electrochemical phenomena.
- **Aging Effects:** The study focused on current battery performance. The long-term robustness of the filter as internal parameters change due to battery aging was not evaluated.

4.2. Recommendations for Further Study

- **Fractional-Order Modeling:** Upgrade the integer-order 2RC ECM to a fractional-order model to more accurately capture the complex diffusion dynamics and solid electrolyte interphase (SEI) behaviors under extreme temperatures.
- **Implement Dual Estimation:** Develop a dual-adaptive SHEKF to simultaneously estimate the SOE (state) and key ECM parameters, making the filter robust against aging.
- **Hardware-in-the-Loop (HIL) Testing:** Test the SHEKF on actual embedded BMS hardware to confirm its computational efficiency and real-time performance viability.

Author Contributions: Conceptualization, T.S.O.; methodology, T.S.O., U.M. and A.J.A.; software, R.K.; validation, R.K., T.S.O. and I.A.S.; formal analysis, T.S.O., I.A.S. and U.M.; investigation, T.S.O., I.A.S. and U.M.; resources, A.J.A. and R.K.; data curation, T.S.O., I.A.S. and U.M.; writing—original draft preparation, T.S.O. and U.M.; writing—review and editing, I.A.S., A.J.A., T.S.O. and U.M.;

supervision, project administration, and funding acquisition, R.K. and U.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by YUTP (015LC0-468) grant, Universiti Teknologi PETRONAS.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Acknowledgments: During the preparation of this manuscript/study, the authors used ChatGPT-4o and PaperPal 2.0.11 (free online) for the purposes of grammar correction. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

BMS	Battery Management System
ECM	Equivalent Circuit Model
EKF	Extended Kalman Filter
HIL	Hardware In the Loop
LIBs	Lithium-Ion Batteries
MAE	Maximum Absolute Error
PEO	Polyethylene Oxide
RMSE	Root Mean Square Error
SHEKF	Sage–Husa Extended Kalman Filter
SOC	State of Charge
SOE	State of Energy
STEKF	Strong Tracking Extended Kalman

References

1. Jafari, S.; Byun, Y.-C. Efficient State of Charge Estimation in Electric Vehicles Batteries Based on the Extra Tree Regressor: A Data-Driven Approach. *Heliyon* **2024**, *10*, e25949. [\[CrossRef\]](#)
2. Hasan, M.M.; Kannan, R.; Aliyu, A.J.; L, H.R.; Porkumaran, K.; Jain, V. Analysis of SoC Prediction Accuracy for Samsung INR21700 Li-Ion Battery Using Pelican Optimized Bilstm Network. In *Proceedings of the 2025 IEEE 15th International Conference on Power Electronics and Drive Systems (PEDS), Penang, Malaysia, 21–24 July 2025*; IEEE: New York, NY, USA, 2025; pp. 1–5.
3. Joshi, G.; Narayana Valluru, L.; Prakash Khade, A. Two RC Model and Parameter Estimation of Lithium-Ion Battery. *Indones. J. Electr. Eng. Comput. Sci.* **2025**, *37*, 730–739. [\[CrossRef\]](#)
4. Tang, X.; Huang, H.; Zhong, X.; Wang, K.; Li, F.; Zhou, Y.; Dai, H. On-Line Parameter Identification and SOC Estimation for Lithium-Ion Batteries Based on Improved Sage–Husa Adaptive EKF. *Energies* **2024**, *17*, 5722. [\[CrossRef\]](#)
5. Ma, C.; Wu, C.; Wang, L.; Chen, X.; Liu, L.; Wu, Y.; Ye, J. A Review of Parameter Identification and State of Power Estimation Methods for Lithium-Ion Batteries. *Processes* **2024**, *12*, 2166. [\[CrossRef\]](#)
6. Zhang, H.; Cao, R.; Jin, Y.; Chang, B.; Zheng, Y.; Yang, S. SOE Estimation of Lithium-Ion Battery Based on Strong Tracking Extended Kalman Filter. In *Proceedings of the 2024 IEEE 22nd International Conference on Industrial Informatics (INDIN), Beijing, China, 18–20 August 2024*; IEEE: New York, NY, USA, 2024; pp. 1–7.
7. Yu, P.; Sun, J. Improved Sage–Husa Unscented Kalman Filter for Harmonic State Estimation in Distribution Grid. *Electronics* **2025**, *14*, 376. [\[CrossRef\]](#)
8. Wang, C.; Wang, X.; Yang, M.; Li, J.; Qian, F.; Zhang, Z.; Zhou, M.; Guo, X.; Wang, K. Concurrent Estimation of Lithium-Ion Battery Charge and Energy States by Fractional-Order Model and Multi-Innovation Adaptive Cubature Kalman Filter. *Energy* **2025**, *322*, 135498. [\[CrossRef\]](#)
9. Zaki, M.R.; El-Beltagy, M.A.; Hammad, A.E. SOC Estimation of High Capacity NMC Lithium-Ion Battery Using Ensemble Kalman Bucy Filter. *Ionics* **2025**, *31*, 1451–1465. [\[CrossRef\]](#)

10. Vedhanayaki, S.; Indragandhi, V. Certain Investigation and Implementation of Coulomb Counting Based Unscented Kalman Filter for State of Charge Estimation of Lithium-Ion Batteries Used in Electric Vehicle Application. *Int. J. Thermofluids* **2023**, *18*, 100335. [[CrossRef](#)]
11. Ren, Q.; Wang, Q.; Su, L.; Liu, G.; Song, Y.; Shangguan, X.; Li, F. Inorganic/organic composite fluorinated interphase layers for stabilizing ether-based electrolyte in high-voltage lithium metal batteries. *J. Mater. Chem. A* **2024**, *12*, 9520–9529. [[CrossRef](#)]
12. Xu, Q.; Hu, Z.; Shangguan, Y.; Liu, L.; Lu, R.; Zhang, L.; Shangguan, X.; Gao, L.; Liu, M.; Zhang, H.; et al. Tailored charge distribution modulated by cyclic carbonates enabling the development of high-performance PEO-based solid electrolytes. *J. Mater. Chem. A* **2026**, *14*, 9520–9529. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.