

Bridging Accuracy and Efficiency: A Hybrid Approach for SOC Estimation

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Abstract— This paper presents an analysis of State of Charge (SOC) estimation using two primary methods—Coulomb counting (CC) and adaptive Kalman filtering (AKF)—and explores a hybrid approach that combines CC with Kalman filter-based error correction. Accurate SOC and State of Health (SOH) estimation are crucial for ensuring the longevity, safety, and performance of batteries, particularly in critical applications such as electric vehicles.

Our MATLAB-based model simulates each method independently, illustrating the simplicity yet susceptibility to drift in Coulomb counting, and the high accuracy yet computational intensity of adaptive Kalman filtering. We then analyze the benefits of hybridization, showing how the combined approach leverages CC's efficiency and AKF's accuracy. Through a comparison of error-correction capabilities, it is evident that while the hybrid method may not reach the stability and precision of standalone AKF, it effectively balances accuracy and computational requirements, providing a viable solution for real-time battery management systems in resource-constrained settings. This research highlights the potential impact of advanced SOC estimation techniques in enhancing battery monitoring and prolonging battery life.

Index Terms— SOC Estimation, Battery Management, Coulomb Counting , Kalman Filtering and error-correction.

I. INTRODUCTION

Battery Management Systems (BMS) are critical for ensuring the safety, efficiency, and longevity of battery-powered devices by continuously monitoring key parameters, including voltage, temperature, and current, to prevent unsafe operating conditions [1]. For example, in lithium-ion batteries, maintaining operational limits—typically 0°C to 45°C for temperature and a maximum of 4.2V per cell—is essential to avoid accelerated degradation and severe safety risks, such as thermal runaway [2]. The BMS mitigates these risks through protective actions, such as disconnecting circuits, activating cell balancing [3], and managing temperature via passive cooling, air cooling, or liquid cooling. In high-power applications like electric vehicles (EVs), advanced cooling strategies, such as phase-change materials [4], are utilized to stabilize temperature, thereby enhancing safety and prolonging battery life.

In EVs, the BMS plays an indispensable role in managing the high energy densities and demanding performance requirements of the battery system. Accurate estimation of the State of Charge (SOC) and State of Health (SOH) is vital for optimizing battery capacity, range, and overall performance [5].

Traditional SOC estimation techniques, like Coulomb counting (CC), offer simplicity but suffer from drift errors over time [6], whereas Adaptive Kalman Filtering (AKF) provides higher accuracy at the cost of greater computational demand [7]. To address this trade-off, this study introduces a MATLAB model that compares SOC estimation methods: CC, AKF, and a hybrid method combining CC with Kalman filter-based error correction, to achieve an optimal balance between computational efficiency and accuracy for real-time BMS applications [8].

The paper is organized as follows: Section II outlines the methodology employed in developing the SOC estimation model, with a detailed description of the design and simulation parameters. Section III presents the results, providing a comparative analysis of each method's accuracy and computational efficiency. Finally, Section IV concludes with a summary of the key findings and their implications for enhancing SOC estimation in practical applications.

II. METHODOLOGY

The block diagram depicted in Fig. 1 illustrates the simulation framework used to estimate the State of Charge (SOC) of a 27 Ah battery, which is charged and discharged over a 10-hour period. Using two estimation methods—Coulomb counting and an Adaptive Kalman Filter (AKF)—the model analyses battery performance in real-time under realistic conditions, incorporating sensor noise and current fluctuations [9]. The results from these two methods are then compared with a hybrid method, enabling a deeper understanding of the accuracy and reliability of SOC estimation under varying operational scenarios. A battery block simulates the electrochemical behaviour of the cell with equivalent circuit elements, while voltage and current sensors feed data to the SOC estimation algorithms. To simulate real-world disturbances, noise blocks introduce random variations in sensor readings, allowing evaluation of each estimator's robustness. The model includes a dynamic current profile that replicates real operating conditions, such as discharge cycles and current spikes.

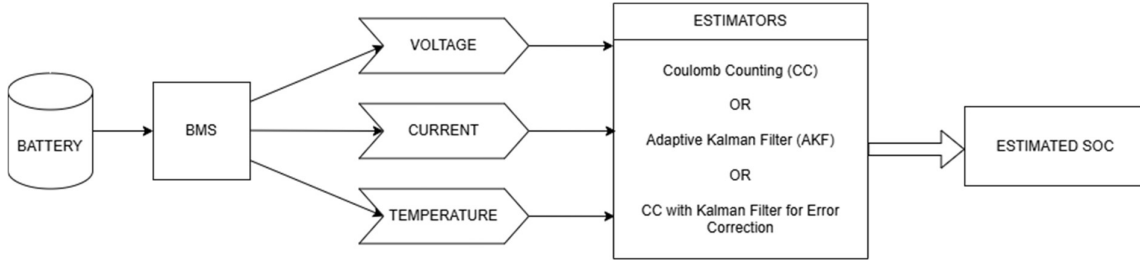


Figure 1. Block diagram for SOC estimation using different estimators

A. Types of SOC estimation methods

Coulomb Counting

Coulomb counting is a method that estimates the State of Charge (SOC) by integrating the current over time, tracking the net charge flow in and out of the battery. Although simple and widely used, it's prone to cumulative errors from sensor noise and inaccuracies in the initial SOC, as it lacks error-correction mechanisms, making it best suited for applications where precision is not critical [10]. The SOC at any time t , denoted as $SOC(t)$, can be expressed by the following equation [11]:

$$SOC(t) \approx SOC(t_0) - \frac{1}{C_{rated}} \int_{t_0}^t I_{batt} d\tau \quad (1)$$

Where $SOC(t_0)$ is the initial SOC at time t_0 , C_{rated} is the nominal capacity of the battery (Ah) and I_{batt} is the battery current (positive during discharge and negative during charge).

Adaptive Unscented Kalman Filter (AUKF)

The Kalman filter is a robust SOC estimation method, ideal for dynamic systems with noise and model uncertainties. It corrects the cumulative error in Coulomb counting by continuously refining SOC estimates [12]. Through prediction (using a system model) and correction (integrating real-time sensor data like voltage, current, and temperature), it reduces sensor noise impact and model errors, ensuring high accuracy under changing conditions [13]. The AUKF enhances precision by generating sigma points around the estimated mean, capturing nonlinear dynamics more accurately. This adaptability allows for dynamic adjustments of the process noise Q and measurement noise R matrices based on estimation errors, further improving the filter's ability to cope with

changing system dynamics [14]. By updating mean and covariance with these points, the AUKF improves estimation accuracy, especially during system fluctuations or unexpected changes. The flowchart in Fig. 2 depicts the steps of the filtering process.

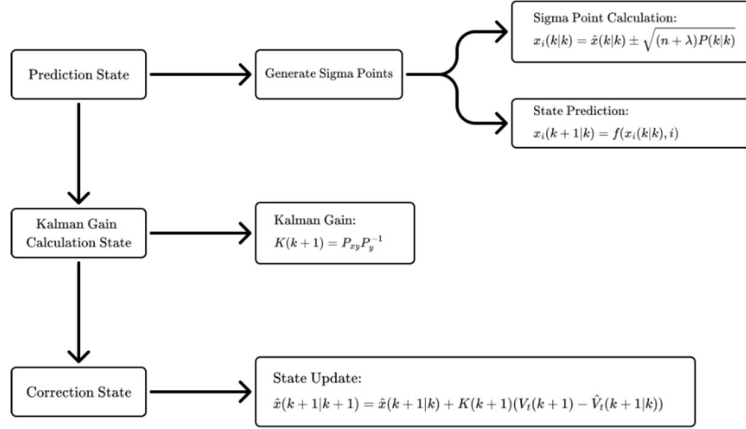


Figure 2. Adaptive Kalman Filtering steps

Coulomb Counting with Kalman Filter-Based Error Correction

In this method, Coulomb counting is used as the primary estimator for SOC. However, to address the limitations of Coulomb counting, especially its inability to correct for initial SOC errors and its sensitivity to current spikes, the Kalman filter periodically checks and corrects the SOC estimate [15],[16]. Fig. 3 shows the functioning of the hybrid method.

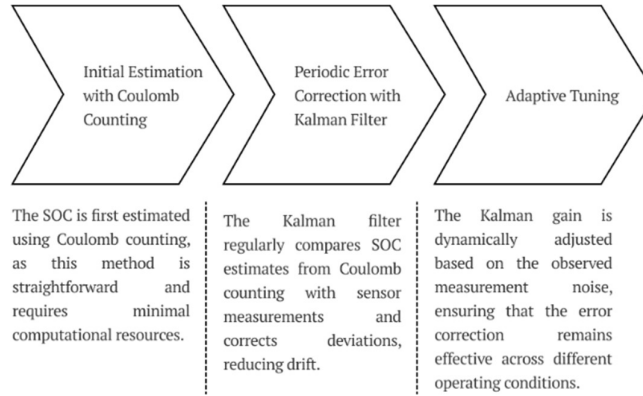


Figure 3. Process of Coulomb Counting with Kalman Filter-Based Error Correction technique

B. Tests to Compare the Methods of SOC Estimation

Initial SOC Mismatch Correction

For a 27Ah battery running for 10 hours, the initial SOC for the estimator was deliberately set at 0.65, while the actual SOC was 0.6. This setup was intentionally designed to evaluate the performances of the three methods - Coulomb counting (CC), Adaptive Kalman filter (AKF) and Coulomb Counting with Kalman Filter-Based Error Correction under conditions of initial SOC mismatch.

Response to Current Profile Spikes

For the current spike test, we incorporated a pulse generator to simulate sudden current spikes that can occur in real-world scenarios. The current profile graph, as seen in Fig. 4, illustrates the effect of this generator, producing a spike with an amplitude of 90 for a duration of just a few seconds. As a result, four distinct pulses are observed throughout the 10-hour simulation, with the first pulse occurring one hour into the simulation. This brief pulse duration is significant because the Coulomb counting method struggles to detect such small spikes, leading to cumulative errors and drift over time. In contrast, the Kalman filter effectively adapts to these abrupt changes, maintaining a more accurate SOC estimation.

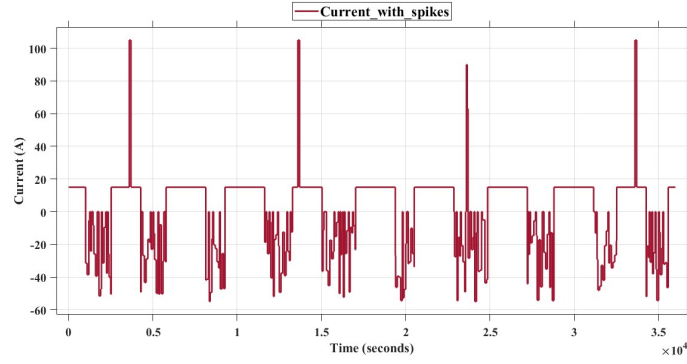


Figure 4. Input current profile with induced current spikes by adding a pulse generator for the current spike test

III. RESULTS

A. Mismatch in Initial SOC Test

Accurately determining the initial SOC is crucial in SOC estimation, posing a significant challenge for estimation methods. As observed in Fig. 5, for Coulomb Counting, inaccuracies in the initial SOC led to an immediate deviation in the estimated SOC, which compounds and amplifies over time, showing lack of an adaptive mechanism to adjust for initial errors. Unlike Coulomb counting, the Kalman filter quickly adjusts the SOC estimate [17], when the initial SOC is inaccurate, effectively "locking onto" the real SOC after a few iterations, compensating for the initial mismatch. This comparison highlights the Kalman filter's adaptability, making it more reliable for real-time applications where initial SOC errors are common.

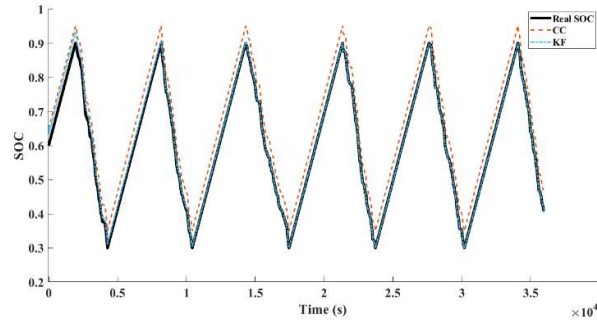


Figure 5. Initial SOC mismatch test in Coulomb Counting method and Adaptive Kalman Filter method

Based on the observations in Fig. 6, the SOC with error correction closely follows the real SOC while minimizing the drift observed in the standalone Coulomb counting method. This hybrid method achieves an improved balance by correcting for the cumulative errors inherent in Coulomb counting while reducing the computational complexity associated with a full Kalman filter implementation.

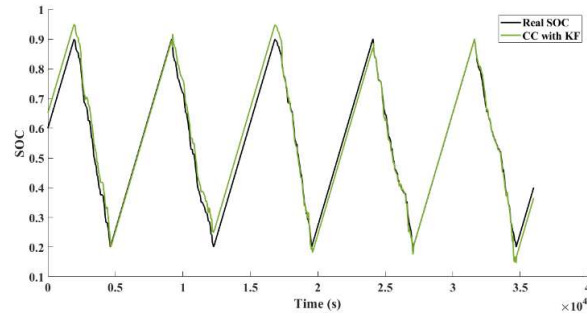


Figure 6. Initial SOC mismatch test in Coulomb Counting with Kalman Filter-Based Error Correction method

B. Inducing Current Spikes Test

In practical applications, sudden changes in the current profile—such as a spike in current due to high discharge or charging events—can cause inaccuracies in SOC estimation.

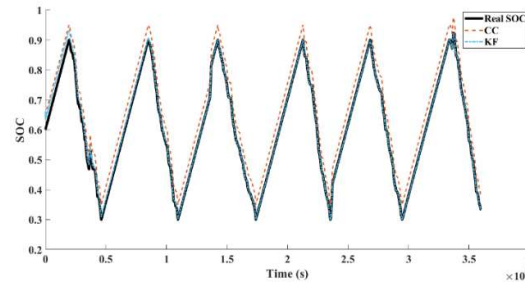


Figure 7. Resulting SOC graph after inducing current spikes in Coulomb Counting method and Adaptive Kalman Filter method

In Fig. 7, the SOC estimation using Coulomb counting briefly converges with the real SOC at a few points, especially around the peaks and troughs of each cycle. This occurs due to the induced current spikes at regular intervals, which temporarily align the estimated SOC with the actual values. However, this behavior highlights the limitations of Coulomb counting, as it cannot maintain alignment over time and begins to drift due to cumulative errors that it is unable to correct. Whereas, the stability highlights the AKF's effectiveness in dynamic conditions, providing a more accurate estimation compared to Coulomb counting [18]. This consistent alignment of the estimated SOC with the real SOC further emphasizes the effectiveness of the filter in dynamic environments where current fluctuations are common.

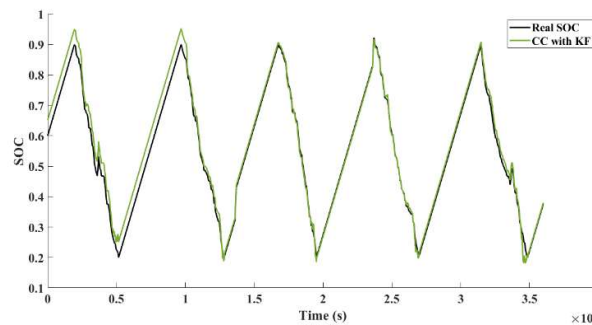


Figure 8. Resulting SOC graph after inducing current spikes in Coulomb Counting with Kalman Filter-Based Error Correction method

On the other hand in the hybrid method, as seen in Fig. 8, the Kalman filter corrects the cumulative error from Coulomb counting, reducing drift and compensating for current spikes more effectively than Coulomb counting alone. This method demonstrates improved accuracy by leveraging the Kalman filter's adaptive error correction, making it more reliable in fluctuating current conditions. Although this hybrid approach does not achieve the full accuracy of a standalone Kalman filter, it provides a more stable and accurate estimate compared to Coulomb counting alone, ensuring reliable battery management.

In Table I, we compare different methods based on various parameters to provide a clearer understanding of how these methods align with specific applications and their suitability for different operational conditions.

TABLE I. COMPARISON OF DIFFERENT METHODS OF SOC ESTIMATION USING DIFFERENT PARAMETERS

Reference	Method	Accuracy	Computational Efficiency	SOC Error Correction (in %)	Noise Sensitivity	Complexity
[6]	Enhanced Coulomb counting based on coulomb efficiency	Low-Moderate	High	3-4%	High	Low
[19]	Extended Kalman Filter	High	Moderate	2-3%	Moderate	High

[4]	Hybrid SoC Estimation (Coulomb Counting + AUKF)	Moderate	Moderate-High	3-5%	Moderate	Moderate
Proposed model	Hybrid Kalman Filtering Approach	Moderate-High	Moderate-High	~3%	Moderate-High	Moderate

IV. CONCLUSION

In conclusion, this study analyzed two SOC estimation methods—Coulomb counting and a standalone adaptive Kalman filter—and compared them with a hybrid approach that combines Coulomb counting with a Kalman filter for error correction. While Coulomb counting is simple and computationally efficient, it suffers from drift and inaccuracies over time. The adaptive Kalman filter offers high accuracy and resilience to disturbances but demands more computational power. The hybrid method balances these aspects, providing improved accuracy over Coulomb counting alone without the resource intensity of a full Kalman filter. This hybrid approach offers a practical, efficient solution for SOC estimation in battery systems where both accuracy and computational efficiency are essential.

The unique strengths of each method make them suitable for different applications. Coulomb counting, due to its simplicity and minimal computational needs, is advantageous in low-power applications such as portable devices or basic embedded systems where minor SOC drift is acceptable. The adaptive Kalman filter, with its high accuracy and adaptive error correction, suits applications needing precise, disturbance-resilient SOC tracking, like high-performance EVs and renewable energy storage systems [20]. A hybrid of Coulomb counting with Kalman filter-based error correction strikes an optimal balance, offering reliable SOC estimates with reduced computational load, making it ideal for a range of battery-dependent applications, especially in real-time embedded systems where both accuracy and efficiency are critical. Future work could optimize filtering algorithms to further lower computational load without sacrificing accuracy or develop adaptive mechanisms to dynamically switch between methods based on system demands, enhancing SOC and SOH estimation for extended battery life and improved performance across battery management applications.

REFERENCES

- [1] M. Murnane and A. Ghazel, "A closer look at state of charge (SOC) and state of health (SOH) estimation techniques for batteries," *Analog Devices*, vol. 2, pp. 426–436, 2017.
- [2] M. B. Lazreg, S. Jemmali, I. Baccouche, B. Manai, and M. Hamouda, "Lithium-ion battery pack modeling using accurate OCV model: Application for SoC and SoH estimation," in *2020 IEEE 4th International Conference on Intelligent Energy and Power Systems (IEPS)*, pp. 175–179, 2020.
- [3] H. Song and D. Shin, "Method for evaluating the accuracy of state-of-charge (SOC)/state-of-health (SOH) estimation of BMSs," *Energy Science & Engineering*, vol. 11, 2023.
- [4] G. S. Misyris, D. I. Doukas, T. A. Papadopoulos, D. P. Labridis and V. G. Agelidis, "State-of-Charge Estimation for Li-Ion Batteries: A More Accurate Hybrid Approach," in *IEEE Transactions on Energy Conversion*, vol. 34, no. 1, pp. 109–119, March 2019.
- [5] [K. I. Prashanth, D. Rao, and A. Sharma, "Estimation of SOC and SOH of Li-Ion Batteries," *International Journal of Computer Applications*, vol. 104, no. 4, pp. 45–49, 2014.
- [6] J. Lee and J. Won, "Enhanced Coulomb Counting Method for SoC and SoH Estimation Based on Coulombic Efficiency," *IEEE Access*, vol. 11, pp. 15449–15459, 2023.
- [7] M. Ye, H. Guo, and B. Cao, "A model-based adaptive state of charge estimator for a lithium-ion battery using an improved adaptive particle filter," *Applied Energy*, vol. 190, pp. 740–748, 2017.
- [8] H. M. Fahmy, R. A. Swief, H. M. Hasanien, M. Alharbi, J. L. Maldonado, and F. Jurado, "Hybrid state of charge estimation of lithium-ion battery using the Coulomb counting method and an adaptive unscented Kalman filter," *Energies*, vol. 16, no. 14, p. 5558, 2023.
- [9] C. Zhang, J. Jiang, L. Zhang, S. Liu, L. Wang, and P. C. Loh, "A generalized SOC-OCV model for lithium-ion batteries and the SOC estimation for LNMCO battery," *Energies*, vol. 9, no. 11, p. 900, 2016.
- [10] K. A. Gaikwad and V. Bhanuse, "State of charge estimation techniques," *International Journal of Engineering Research & Technology (IJERT)*, vol. 8, no. 7, 2019.
- [11] I. Baccouche, A. Mlayah, S. Jemmali, B. Manai, and N. E. B. Amara, "Implementation of a Coulomb counting algorithm for SOC estimation of Li-Ion battery for multimedia applications," in *2015 IEEE 12th International Multi-Conference on Systems, Signals & Devices (SSD15)*, pp. 1–6, 2015.
- [12] G. Erlangga, A. Perwira, and A. Widyotriatmo, "State of charge and state of health estimation of lithium battery using dual Kalman filter method," *2018 International Conference on Signals and Systems (ICSigSys)*, Bali, Indonesia, May 2018, pp. 243–248.

- [13] H. Li, S. Y. Liu, and Y. Yu, "State of charge estimation of lithium-ion battery using extended Kalman filter based on a comprehensive model," *Applied Mechanics and Materials*, vols. 496–500, pp. 999–1002, 2014.
- [14] A. M. Ramadan, A. F. Yousef, and M. K. Khalil, "Impact of the double sampling technique on reducing the mismatch risk of acceptance sampling plans," *International Journal of Quality & Reliability Management*, vol. 34, no. 9, pp. 1580–1597, 2017.
- [15] Z. Cui, J. Dai, J. Sun, D. Li, L. Wang, and K. Wang, "Hybrid methods using neural network and Kalman filter for the state of charge estimation of lithium-ion battery," *Mathematical Problems in Engineering*, vol. 2022, no. 1, p. 9616124, 2022.
- [16] Y. Ko, K. Cho, M. Kim, and W. Choi, "A Novel Capacity Estimation Method for Lithium Batteries Using the Enhanced Coulomb Counting Method with Kalman Filtering," *IEEE Access*, vol. 10, pp. 38793–38801, 2022.
- [17] Jokić, I., Z. Zecevic, and B. Krstajic, "State-of-charge estimation of lithium-ion batteries using extended Kalman filter and unscented Kalman filter," in *2018 IEEE Conference on Systems, Process, and Information Technology (SPIT)*, pp. 1–4, 2018.
- [18] Hyunsik Song and Donghyun Shin, "Method for evaluating the accuracy of state-of-charge (SOC)/state-of-health (SOH) estimation of BMSs," *Energy Science & Engineering*, vol. 11, pp. 4273–4286, 2023.
- [19] H.S. Ramadan, M. Becherif, and F. Claude, "Extended Kalman filter for accurate state of charge estimation of lithium-based batteries: a comparative analysis," *International Journal of Hydrogen Energy*, vol. xx, no. xx, pp. 1-14, 2017.
- [20] P. Dini, A. Colicelli, and S. Saponara, "Review on Modeling and SOC/SOH Estimation of Batteries for Automotive Applications," *Batteries*, vol. 10, p. 34, 2024.