Comparative study of SOC estimation Technique, Coulomb Counting Method and Kalman Filter Method

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***Abstract*—A Battery Management System (BMS) manages and monitors the performance, safety, and health of a battery pack. One of its key function is estimating the State-of-Charge (SOC), which indicates the remaining energy in the battery. Monitoring the SOC of a battery is crucial for ensuring the efficient operation of energy storage systems. Since SOC cannot be directly measured, achieving accurate estimation plays a pivotal role in enhancing both system performance and operational flexibility. Furthermore, the information provided by SOC is instrumental in ensuring the safe functioning of the storage system and prolonging the battery's lifespan by avoiding overcharging or excessive discharging. Selecting a suitable SOC estimation algorithm often involves balancing the trade-off between the complexity of the algorithm and its accuracy. Among various available methods of SOC estimation, in this paper, emphasis is given on two basic methods i. e., the Kalman Filter Method and Coulomb Counting Method. Furthermore results from both these techniques are compared to give a better overview of efficient technique. These techniques are implemented on different battery models starting from the very basic single RC model to double RC model and compared on Matlab/Simulink.**

Keywords—Battery Management System, State of Charge, Coulomb Counting Method, Kalman Filter Method

I. Introduction

This Accurate estimation of the State of Charge (SOC) is crucial for ensuring the performance and longevity of batteries in renewable energy systems and electric vehicles. Lead-acid batteries, widely used in renewable energy applications, require precise SOC monitoring to avoid overcharging or over-discharging, which can result in performance degradation. The Coulomb Counting method, a commonly employed technique, estimates SOC by summing the charge flowing into and out of the battery. However, its reliance on the initial SOC value and sensor precision makes it prone to cumulative errors, limiting its effectiveness in dynamic conditions.[1]

To address these limitations, hybrid approaches combine traditional methods with corrections for real-time inaccuracies. For example, an Enhanced Coulomb Counting (ECC) method integrates the Coulomb Counting and Open Circuit Voltage (OCV) techniques. This method accounts for battery aging and dynamic parameter variations, improving the accuracy of SOC and State of Health (SOH) estimations. By compensating for drift errors and degradation effects, the ECC method provides a reliable framework for long-term battery management[2].

Battery modelling is another critical aspect of SOC estimation. Studies have evaluated various battery models, including Simple, Thevenin, and Modified Thevenin, to enhance estimation accuracy. Among the methods tested, the Kalman Filter has proven superior, outperforming Coulomb Counting and OCV techniques. Its ability to handle dynamic system changes makes it highly effective, as it provides accurate SOC estimates while quickly correcting errors caused by incorrect initial assumptions [3].

Lithium-ion batteries, commonly used in electric vehicles and portable devices, pose unique challenges for SOC estimation. Advanced models specifically designed for these batteries integrate the Kalman Filter to manage uncertainties and noise effectively. This approach enhances estimation precision, ensuring that the method is robust even in highly dynamic operating conditions. As a result, it is well-suited for applications requiring high accuracy and reliability, such as electric vehicles [4].

Comparative research highlights the effectiveness of Kalman-based filters, including the Extended Kalman Filter (EKF) and the Unscented Kalman Filter (UKF). Both filters perform well under various conditions, but the UKF demonstrates greater accuracy, particularly in nonlinear environments. This makes it a promising tool for advanced battery management systems.[5]

Additionally, adaptive battery models, building on traditional frameworks like Randles' model, have improved SOC estimation. These models dynamically adjust circuit parameters to account for aging and other changes, enhancing performance in lead-acid batteries and extending their operational lifespan.[6]

Finally, integrating Kalman Filters with MATLAB Simulink models has shown promise for Lithium-ion batteries. This combination leverages simulation tools to address challenges such as overcharging and discharging, thereby improving performance and extending battery life. These advancements demonstrate the value of combining theoretical approaches with practical simulations to optimize energy storage solutions.[7]

In summary, ongoing developments in SOC estimation techniques, particularly those leveraging the Kalman Filter and adaptive models, have significantly improved the reliability, accuracy, and efficiency of battery management systems. These advancements address critical challenges across diverse battery chemistry and applications.

In this paper, a comparison of basic two SOC estimation methods which are Columb counting method and Kalman Filter method is done on different battery models including the equivalent battery models and Matlab/Simulink in-built model. The rest of the paper as organized as: Section II discusses Coulomb Counting and Kalman Filter method.

II. METHODS OF STATE ESTIMATION

A. *Coulomb Counting Method*

This method measures the discharging current of a battery and integrates the discharging current over time in order to estimate SOC. Coulomb counting method [3] is done to estimate the SOC(t), which is estimated from the discharging current, I(t), and previously estimated SOC values, SOC(t-1). SOC is calculated by the following equation

$$\mathrm{SOC(t)} = \mathrm{SOC(t-1)} + \frac{\int_{t-1}^{t} \mathrm{i(t)dt}}{\mathrm{Q_n}} \tag{1}$$

where,

SOC(t) is SOC at time instant "t".

SOC(t-1) is Previous known SOC i.e. SOC at instant "t-1"

i(t) is Charging current

Q_n is Nominal capacity of battery

B. *Kalman Filter Method*

It is designed to strip unwanted noise out of a stream of data. It operates by predicting the new state and its uncertainty, then correcting this with a new measurement.It is suitable for systems subject to multiple inputs and is used extensively in predictive control loops.With the Kalman Filter [7] the accuracy of the battery SOC prediction model can be improved and thus battery performance is enhanced. SoC is calculated by:

Linear Kalman Filter Formulas:

Prediction Step:

1. State Prediction:

$$\hat{x}_k^- = A_k \hat{x}_{k-1} + B_k u_k \tag{2}$$

Where,

$\hat{x}_k^-$ is the predicted state at time k.

A_k is the state transition matrix.

$\hat{x}_{k-1}$ is the estimated state from the previous time step.

B_k is the control input matrix.

u_k is the control input.

2. Covariance Prediction:

$$P_k^- = A_k P_{k-1} A_k^T + Q_k \tag{3}$$

Where,

P_k^- is the predicted covariance matrix.

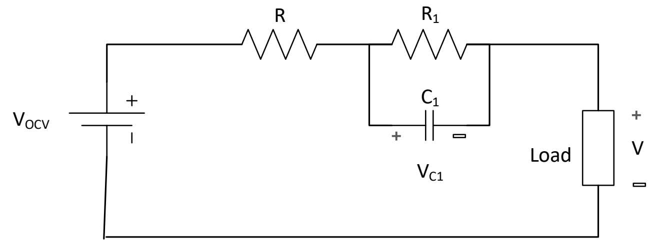

Fig. 1: Equivalent battery model (Single RC)

P_{k-1} is the state covariance matrix from the previous step.

A_k^T is the transpose of the state transition matrix A

Q_k is the process noise covariance matrix.

Update Step:

1. Kalman Gain:

$$K_k = P_k^- H_k^T ((H_k P_k^- H_k^T + R_k)^{-1} \tag{4}$$

Where,

K_k is the Kalman gain.

H is the observation matrix.

R is the measurement noise covariance matrix.

2. State Update:

$$\hat{x}_k = \hat{x}_k^- + K_k (Z_k - H_k \hat{x}_k^-) \tag{5}$$

Where,

Z_k is the measurement at time k.

$H_k \hat{x}_k^-$ is the predicted measurement

3. Covariance Update:

$$P_k = (I - K_k H_k) p_k^- \tag{6}$$

Where,

P_k is the updated covariance matrix.

I is the identity matrix.

III. EQUIVALENT MODELS OF BATTERY

The equivalent models of the battery are used to capture its electrical characteristics and to emulate the dynamic nature of the battery. Different equivalent models of the battery are available in the literature. The sophistication of an equivalent circuit is determined by the complexity of the model. There is always a trade-off between the accuracy of the result obtained from a model and the computational effort. Two most popularly used equivalent models of the battery are discussed here.

A. *Thevenin Battery Model with single RC*

The single RC equivalent model of battery is shown in Fig. 1 and it can be described by (7).

$$v(t) = V_{OCV} - Ri(t) - v_{c1}(t) \tag{7}$$

Where V_{ocv} characterizes the open circuit voltage.
'R' is the ohmic impedance of the contacts and electrolyte.

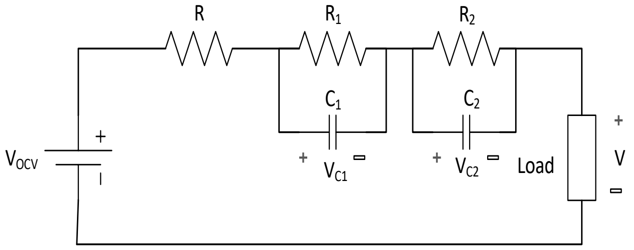

Fig. 2: Equivalent battery model (double RC)

R_1 and C_1 captures the slow transient of the battery.

Single RC model can be used as a substitute to real time battery as it models the internal resistance (R) and the slow transient behavior caused by the electrochemical reactions using the RC circuit. The single RC model can effectively describe the battery's behavior under steady-state and low-frequency conditions.

B. *Thevenin Battery Model with double RC*

Double RC Thevenin equivalent model of the battery is shown in Fig. 2 and can be represented as in (8)

$$v(t) = V_{OCV} - Ri(t) - v_{c1}(t) - v_{c2}(t) \tag{8}$$

In double RC model, two RC parallel branches are connected in series, one of them is to capture the slow dynamics and the second one to incorporate the fast transient condition. Double RC model has an edge over single RC since it represents both short-term (fast dynamics) and long-term (slow dynamics) responses, making it more accurate for dynamic conditions like rapid charging/discharging. It covers a broader range of frequencies, making it suitable for applications with rapidly changing load conditions.

IV. COMPARATIVE ANALYSIS AND RESULTS

In this section, the SoC estimation using techniques like Coulomb Counting Method and Kalman Filter Method are thoroughly discussed in a comparative manner. These comparisons are backed with different simulation results. To get a clear picture of which technique is more reliable and accurate, different battery models such as the in-built battery model itself, Equivalent battery models such as Single RC (Fig. 1) and Double RC model (Fig. 2) are used. All possible conditions are considered to estimate SoC such as with and without considering noise effects to simulate real time and ideal conditions respectively. In all above-mentioned conditions, SoC is calculated by both the methods i.e. Coulomb Counting as well as Kalman Filter Method and results are presented in comparative way.

A. *Simulation Result*

Fig. 3. presents the State of Charge (SoC) estimation using the Coulomb counting method under different scenarios. The comparison highlights the impact of noise and errors on the accuracy of SoC predictions. SoC by Coulomb Counting with all noises (shown with blue curve in Fig. 3) demonstrates the SoC estimation using the Coulomb counting method in a real-world setting, where various sources of noise and errors, such as sensor inaccuracies and environmental disturbances, are

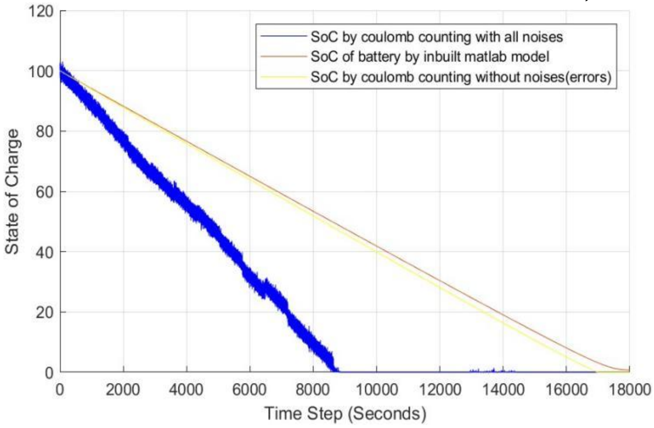

Fig. 3. SOC estimation using Coulomb Counting method with and without noises

present. The noticeable fluctuations in the curve illustrate the influence of these factors on the SoC estimation. The SoC shown with yellow curve in Fig. 3, represents the SoC estimation obtained from the MATLAB inbuilt battery model, which serves as a standard reference for comparison. The smooth nature of this curve suggests high reliability and accuracy.

SoC by Coulomb Counting Without Noises or Errors (green curve, Fig. 3) reflects an ideal case where Coulomb counting is performed without any external disturbances or errors. It provides a baseline to understand the maximum potential accuracy of the method.

The Coulomb counting method is prone to the accumulation of errors over time due to factors such as inaccuracies in current measurements, variations in temperature, sensor drift, and numerical integration errors. These errors progressively degrade the accuracy of State of Charge (SoC) estimation, as demonstrated by the fluctuating nature of the curve when noise and real-world disturbances are included. This makes the method less reliable for long-term applications unless error correction techniques are implemented.

The results reveal that the Coulomb counting method is highly sensitive to noise and errors, as seen in the fluctuating blue curve under real-world conditions (Fig. 3). While the method demonstrates ideal accuracy in noise-free scenarios (green curve), its reliance on precise current measurements and susceptibility to error accumulation make it less reliable for long-term applications. This highlights the necessity for implementing error-correction techniques to improve its practicality. The MATLAB inbuilt battery model provides a reliable benchmark for SoC estimation, exhibiting a smooth and accurate performance (yellow curve in Fig. 3). Its high reliability and alignment with advanced methods underscore its utility as a reference for validating other estimation techniques.

Fig.4. demonstrates a comparative analysis of using different models of the battery to State of Charge (SOC) estimation methods, including the single RC network model, Randles' lead-acid battery model, and Coulomb counting under different conditions using CCM. The focus of the analysis is on the accuracy and behavior of these methods over time, as represented by the curves. The Randles' lead-

acid battery model (double RC network) and the single RC network model showcase consistent and stable results,

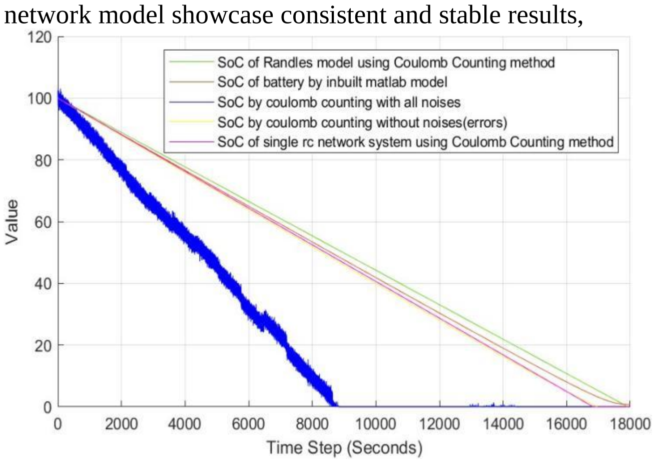

Fig. 4. SOC estimation Comparison by CCM between Single RC network developed,Equivalent battery nodel, and in-built battery method.

emphasizing their ability to capture dynamic battery characteristics effectively. The inbuilt MATLAB model serves as a benchmark, closely aligning with the more accurate methods, indicating its reliability for SoC estimation.

This comparative approach underscores the importance of balancing computational efficiency, modeling complexity, and practical accuracy in selecting an appropriate SoC estimation technique for various applications. Advanced models like the double RC network offer higher precision but may require more computational resources, while simpler models and error-compensated practical methods can provide a feasible alternative for real-time use. Advanced models such as the Randles' lead-acid battery model and the double RC network demonstrate superior accuracy in capturing battery dynamics (Fig. 4). These models, despite their higher computational demands, provide a stable and precise SoC estimation, making them suitable for complex and dynamic applications. Simpler models like the single RC network, while computationally efficient, show limitations in accurately modeling nonlinear battery characteristics.

Fig.5. presents a comparative analysis of using different battery models to State of Charge (SoC) estimation using Kalman filter method. Estimated SoC of Single RC Network using Kalman Filter, shown with green curve in Fig. 5, demonstrates the SoC estimation for a single RC network model enhanced by a Kalman filter. The Kalman filter effectively mitigates noise, resulting in smoother estimations, but it deviates slightly from the reference, particularly at lower SoC levels. This indicates the need for more precise parameter tuning or additional error-compensation techniques. Estimated SoC of Double RC Network Using Kalman Filter (shown with sky-blue curve, Fig. 5) shows improved alignment with the reference model compared to the single RC network. The double RC network captures the battery's dynamic behavior more accurately, especially at lower SoC levels, demonstrating its robustness and suitability for complex applications. The application of Kalman filtering significantly reduces noise in both RC network models, enhancing their reliability for real-world applications. The double RC network model provides better accuracy than the single RC network due to its ability to model the battery's dynamics more comprehensively. The single RC network is computationally simpler but may not

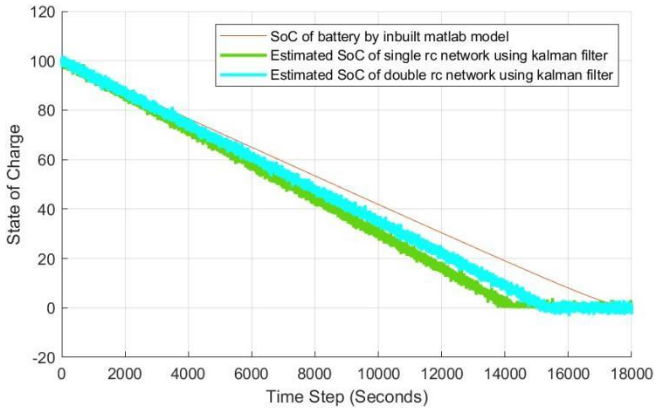

Fig. 5. SOC estimation Comparison by Kalman Filter Method between Single RC network developed,Equivalent battery nodel, and in-built battery method.

fully capture the nonlinear characteristics of the battery, leading to slight deviations from the reference.

Fig.6. compares the Coulomb Counting Method with Kalman Filter method of SoC estimation. The Kalman filter addresses the drawbacks of the Coulomb counting method by incorporating a dynamic system model and correcting errors through measurements. The curves labeled for Kalman filter-based SoC estimations (single RC network and double RC network) demonstrate better alignment with the true SoC. Kalman Filter method provides a more accurate and stable SoC estimation by minimizing the impact of noise and compensating for cumulative errors over time.

The integration of Kalman filtering with the single and double RC network models (Figs. 5 and 6) effectively mitigates noise and compensates for cumulative errors. The double RC network enhanced with Kalman filtering exhibits the best alignment with the true SoC, particularly at lower levels, showcasing its robustness and accuracy. The single RC network with Kalman filtering, though computationally simpler, shows slight deviations, emphasizing the trade-off between simplicity and precision.

In conclusion, while the Coulomb counting method suffers from cumulative error issues, the Kalman filter method significantly enhance SoC estimation accuracy by dynamically correcting errors, making them more suitable for real-world battery management applications. By continuously updating the state estimates based on observed data, Kalman filter methods effectively reduce the impact of noise and model inaccuracies. Additionally, their adaptability to varying operating conditions ensures higher reliability and precision over time. This makes them particularly valuable in applications where consistent performance and safety are critical. Despite their computational complexity, the benefits of Kalman filter methods far outweigh the drawbacks, offering a robust solution for modern energy storage systems.

B. Quantitative Comparison

The observations from the error analysis of various State of Charge (SoC) estimation methods reveal distinct performance characteristics under different conditions (refer table.1). The Coulomb counting method without considering

TABLE I. COMPARISON OF ERRORS OF DIFFERENT SOC ESTIMATION METHODS

Errors	**Method Name**					
	Coulomb Counting without considering errors	***Single RC Model using Coulomb Counting***	***Randles Model using Coulomb counting***	***Coulomb Counting with considering errors***	***Single RC Model Using Kalman Filter***	***Double RC Model Using Kalman Filter***
Average error(%)	0.03	0.11	0.017	0.5	0.19	0.15
Maximum error(%)	4	5	2	55	20	12

errors achieves a low average error of 0.03% and a maximum error of 4%, making it unreliable in extreme scenarios. The Single RC model using Coulomb counting shows maximum error of 5% and average error of 0.11%. The Randle's model exhibits an average error of 0.017%, and significantly reduced maximum error of 2%, demonstrating its robustness and suitability for practical applications. In contrast, Coulomb counting with noise leads to drastically degraded performance, with an average error of 0.5%, a maximum error of 55%, reflecting its poor reliability in real-world conditions.

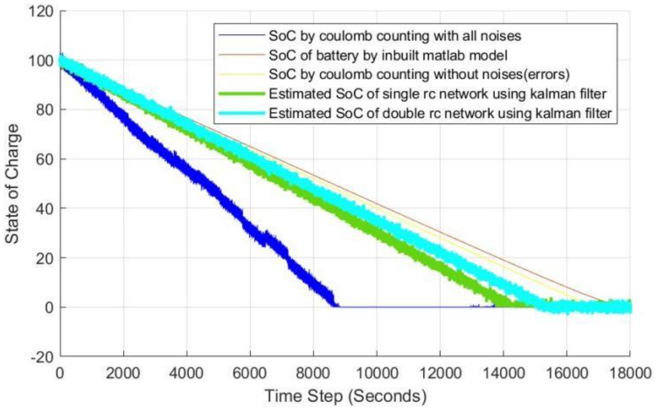

Fig. 6. Comparison of all models using Coulomb counting Method and Kalman Filter Method in consideration with noises.

The integration of Kalman filtering enhances the performance of both RC network models compared to the case using coulomb counting with noisy data. The Single RC model with the Kalman filter achieves an average error of 0.19%, a maximum error of 20%, significantly mitigating noise and improving robustness. However, the Double RC model with the Kalman filter emerges as the most accurate and reliable method, with an average error of 0.15%, a maximum error of 12%. This underscores the effectiveness of the Double RC model in capturing battery dynamics and the Kalman filter's capability to reduce noise and compensate for cumulative errors, making it a robust choice for real-world battery management applications. Furthermore, the Double RC model's enhanced accuracy allows for better prediction of battery performance, leading to improved energy efficiency and safety. Its adaptability under varying load and environmental conditions makes it highly suitable for applications like electric vehicles and renewable energy systems, where precise state estimation is critical.

V. CONCLUSION

The analysis of MATLAB results underscores the critical aspects of various State of Charge (SoC) estimation methods, highlighting their strengths and limitations in different scenarios. In summary, the results highlight the limitations of the Coulomb counting method due to error accumulation and the advantages of dynamic modeling and filtering techniques in addressing these challenges. While computational simplicity favors methods like the single RC network, the double RC network with Kalman filtering emerges as the most reliable approach for accurate and stable SoC estimation in real-world battery management applications.

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