# Accurate State of Charge Estimation for Electric Vertical Take-Off and Landing (eVTOL) Aircraft Batteries Using Coulomb Counting

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**Abstract.** Electric Vertical Take-Off and Landing (eVTOL) aircraft are emerging as a promising solution for urban air mobility, offering rapid and efficient transportation in congested areas. A critical challenge in these systems is the accurate estimation of the battery State of Charge (SoC), which directly impacts flight safety and operational reliability. This study evaluates the performance of the Coulomb Counting method for SoC estimation using a MATLAB-based simulation. The method demonstrated high accuracy across all flight phases, with estimation errors remaining below 0.01 specifically 0.0053 during take-off, 0.0050 during hover, 0.0080 during cruise, and 0.0077 during landing. These results confirm the suitability of Coulomb Counting for real-time SoC tracking in eVTOL applications, while emphasizing the importance of calibration and drift correction for long-term accuracy.
Key words : Battery Management System (BMS); State of Charge (SoC); Electric Vertical Take-Off and Landing (eVTOL);Aircraft; Coulomb Counting; Urban Air Mobility.

## 1 Introduction

Electric Vertical Take-Off and Landing (eVTOL) aircraft are emerging as a promising solution for urban air mobility, offering fast and flexible transportation in congested areas while reducing emissions. However, the performance and safety of these aircraft depend heavily on the reliability of their battery systems. Accurate estimation of the battery's State of Charge (SoC) is essential to prevent over-discharge or overcharge, both of which can reduce battery lifespan and compromise flight safety. Consequently, SoC estimation is a critical function of the Battery Management System (BMS). Among the various estimation techniques, the Coulomb Counting method remains one of the most widely used due to its simplicity and real-time capability. This approach estimates SoC by integrating the current flowing into and

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out of the battery over time and normalizing it by the nominal capacity. While effective, it is sensitive to sensor drift and cumulative errors, which can affect accuracy during long missions or under highly dynamic load conditions. In this study, a MATLAB/Simulink-based simulation was developed to evaluate SoC estimation across different eVTOL flight phases, including take-off, hover, cruise, and landing. The results demonstrate that the Coulomb Counting method achieves high accuracy under short-duration missions, with estimation errors remaining below 0.01 across all phases. These findings confirm the method's suitability for real-time monitoring in eVTOL systems, while also emphasizing the need for periodic recalibration or hybrid approaches to mitigate drift and ensure long-term reliability.

## 2 Literature Review

Accurate estimation of the State of Charge (SoC) in Battery Management Systems (BMS) is essential for the safe and efficient operation of electric Vertical Take-Off and Landing (eVTOL) aircraft. While recent research has explored advanced techniques such as machine learning and deep learning, traditional methods like Coulomb counting remain widely used due to their simplicity and real-time applicability.

Liu et al. [1] highlighted the economic and environmental benefits of battery-electric eVTOLs compared to fuel cell and internal combustion engine alternatives, reinforcing the importance of reliable battery management strategies. Kim et al. [2] emphasized the sustainability of Li-ion battery-powered eVTOLs and the critical role of accurate SoC estimation in preventing overcharge and over-discharge conditions. Similarly, An et al. [3] and Souidi et al. [4] demonstrated that precise SoC estimation is indispensable for hybrid VTOL systems and Electric Vehicles to balance energy flows between battery and fuel sources.

Labiri et al. [5] focused on the Coulomb counting method, which calculates SoC by integrating the current flowing in and out of the battery over time. This approach is widely adopted for its simplicity and ability to provide real-time data, making it highly relevant for eVTOL applications where flight planning and energy management depend on accurate SoC information. Despite its limitations such as sensitivity to sensor drift and initial calibration errors Coulomb counting offers a practical solution without requiring complex computational resources.

In contrast, Zhang et al. [6], Krishna et al. [7], and Yao and Kowal [8] explored AI-based methods for SoC estimation, including deep learning and hybrid models. While these approaches can improve accuracy under certain conditions, they require large datasets, high computational power, and extensive training, which may not be feasible for real-time onboard applications in eVTOL systems. Moreover, their performance can degrade when exposed to unseen operating conditions, raising concerns about robustness and reliability.

Mukherjee and Chowdhury [9], Shirguppikar et al. [10], and Das, K [11] provided comprehensive reviews of SoC estimation techniques, noting that AI-driven methods are promising but still face challenges in terms of scalability, interpretability, and integration into safety-critical systems.

In summary, while AI-based techniques offer potential improvements in accuracy, their complexity and resource requirements limit their practical application in real-time eVTOL operations. Coulomb counting, despite its known limitations, remains a robust and efficient choice for scenarios where simplicity, reliability, and real-time performance are paramount.

## 3 Method

To apply Coulomb counting in practice, the algorithm continuously integrates the current drawn from the battery over time to update the State of Charge (SoC). It accounts for the total current consumed by multiple motors and adjusts the SoC dynamically, ensuring it remains within safe operating limits. In addition to SoC estimation, the algorithm predicts the remaining flight time by considering the available battery capacity, the instantaneous current demand, and an efficiency factor to reflect real-world conditions. This dual estimation approach tracking SoC and forecasting endurance provides critical information for energy management and mission planning in electric VTOL systems, enabling safe operation across all flight phases.

The BMS typically uses Coulomb counting, which integrates the current over time to estimate SoC in equation (1):

$$\mathrm{SoC}(t) = \mathrm{SoC}(t_0) - \frac{1}{C_{\mathrm{nom}}} \int_{t_0}^{t} I(\tau)\, d\tau \tag{1}$$

where:

- $\mathrm{SoC}(t)$ is the estimated state of charge at time $t$
- $\mathrm{SoC}(t_0)$ is the initial state of charge
- $C_{\mathrm{nom}}$ is the nominal battery capacity (Ah)
- $I(\tau)$ is the discharge current at time $\tau$

***Overestimation**

If the estimated SoC is greater than the actual SoC:

$$\Delta\mathrm{SoC}_{\mathrm{error}} = \mathrm{SoC}_{\mathrm{est}} - \mathrm{SoC}_{\mathrm{actual}} > 0 \tag{2}$$

This may lead to unexpected power depletion mid-flight, risking thrust loss or emergency landing.

***Underestimation**

If the estimated SoC is less than the actual SoC:

$$\Delta\mathrm{SoC}_{\mathrm{error}} < 0 \tag{3}$$

This results in conservative flight planning, reduced payload capacity, and inefficient energy usage.

***Error Accumulation**

Coulomb counting is sensitive to sensor drift and integration error:

$$\epsilon_{\mathrm{SoC}}(t) = \frac{1}{C_{\mathrm{nom}}} \int_{t_0}^{t} \delta I(\tau)\, d\tau \tag{4}$$

where $\delta I(\tau)$ is the current measurement error. Over time, this leads to SoC drift, which can compromise thermal management, fault detection, and certification compliance. In safety-critical systems like eVTOLs, precise SoC estimation is essential for operational reliability, energy budgeting, and regulatory adherence. Even small errors can undermine redundancy strategies and flight safety.

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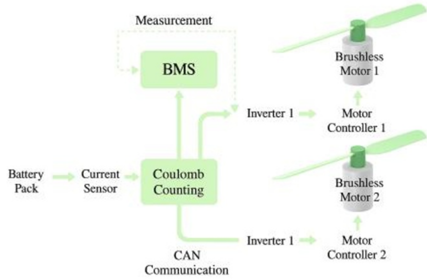


**Figure 1.** Battery Management System of an Electric Vertical Take-Off and Landing (eVTOL)

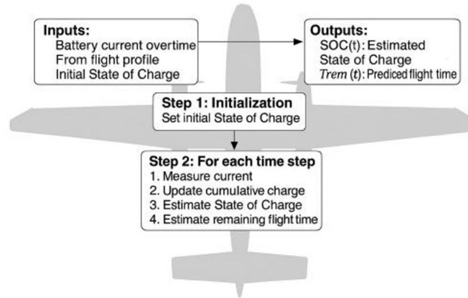


**Figure 2.** Algorithm Couloumb Counting Based SoC and Flight Time for eVTOL Missions

As shown in Figures (1) and (2), in an electric VTOL system, the energy flow begins at the battery pack, which stores and supplies the electrical power necessary for propulsion. The Battery Management System (BMS) is directly connected to the battery pack to monitor cell voltages, temperatures, and overall health. It performs critical functions such as Coulomb counting for State of Charge (SoC) estimation, State of Health (SoH) monitoring, and cell balancing to ensure safe and efficient operation. As current flows from the battery, it passes through a current sensor, and the measured data is communicated to the BMS for accurate energy tracking. The BMS then shares this information via CAN communication with other components for system control. The electrical power is subsequently directed to two inverters, which convert the direct current from the battery into alternating current suitable for driving the motors. Each inverter feeds its respective motor controller, which regulates the voltage, frequency, and phase of the AC power to precisely control the speed and torque of the motors. Finally, the controlled AC power reaches Brushless DC Motor 1 and 2, which convert the electrical energy into mechanical thrust, enabling the VTOL aircraft to fly.

## 4 Simulation and Results

In the eVTOL environment, accurate monitoring of the battery State of Charge (SoC) is critical due to the aircraft's full reliance on electric propulsion. As shown in Table I, the simulation was implemented in MATLAB/Simulink using the Coulomb Counting method, which estimates SoC by integrating the battery current over time and normalizing by the nominal capacity. A flight profile current signal was applied to represent realistic mission phases: take-off, hover, cruise, and landing. These phases exhibit distinct power demands, with higher currents during take-off and hover, moderate consumption during cruise, and near-zero current during landing.

**Table 1.** Simulation Setup for SoC Estimation

| **Component** | **Description** |
|---|---|
| Simulation | MATLAB Simulink |
| Estimation Method | Coulomb counting (current integration) |
| Sensor Input | Battery Current Flight Profile |
| Validation Data | Real SoC |
| Output | Estimated SoC trajectory |

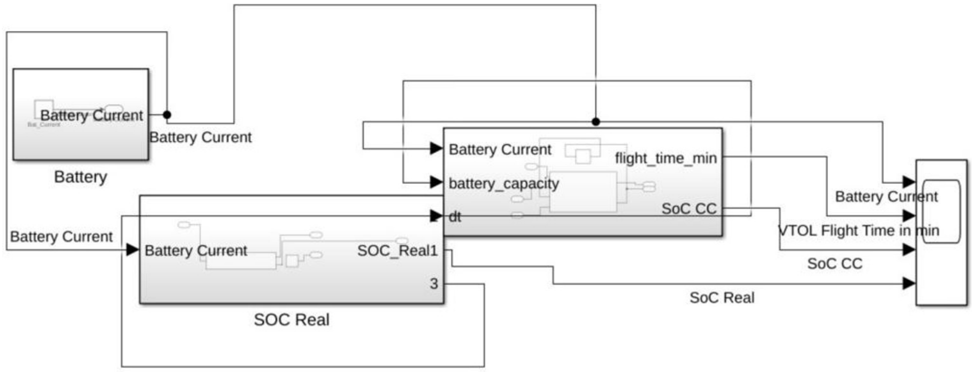


**Figure 3.** Simulation Setup

The simulation was developed in MATLAB/Simulink to evaluate the State of Charge (SoC) estimation for an eVTOL battery under near realistic flight mission conditions as shown in figure (3), it illustrates the model architecture, which includes three main components: a Battery Current block that generates the current profile for the flight phases (take-off, hover, cruise, and landing), a Coulomb Counting subsystem that computes SoC and predicts remaining flight time based on the integrated current and battery capacity, and a reference SoC block for validation. The outputs estimated SoC, real SoC, and flight time—are displayed for comparison. This configuration enables dynamic testing under varying load conditions and demonstrates the practical implementation of Coulomb Counting in a real-time simulation environment.

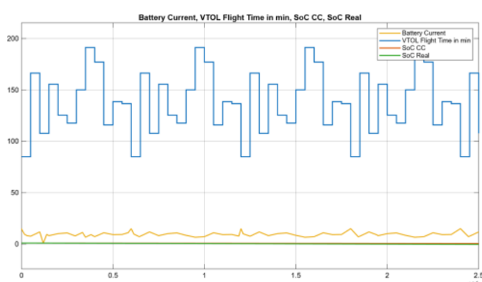


**Figure 4.** Simulation results showing dynamic eVTOL flight profile with Coulomb Counting SoC estimation and predicted flight time.

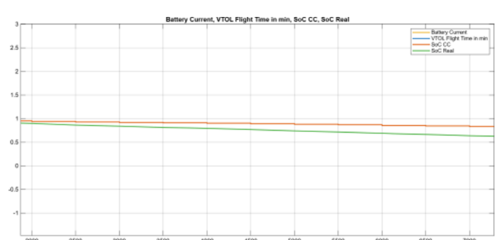


**Figure 5.** Simulation results under a smoother flight profile, illustrating gradual SoC decrease and improved Coulomb Counting accuracy.

Figure (4) illustrates the dynamic behavior of the eVTOL battery under a mission profile using the Coulomb Counting (CC) method for SoC estimation. The blue curve represents the battery current, which varies significantly across phases such as take-off, hover, cruise, and landing, reflecting the high-power demands of vertical flight. The orange curve shows the predicted remaining flight time, which fluctuates inversely with current magnitude—higher currents during take-off and hover reduce endurance, while lower currents during cruise extend it. The green curve corresponds to the reference SoC, whereas the CC-based estimate remains near zero throughout the simulation. This discrepancy highlights a critical limitation of Coulomb Counting: its sensitivity to initialization and integration drift over long durations. Despite these limitations, CC remains widely used in Battery Management Systems (BMS) because it is computationally simple, requires only current measurements, and can operate in real time without complex models or high-cost sensors. However, these results confirm that without periodic recalibration or correction strategies, CC alone cannot guarantee accurate SoC tracking in multi-cycle eVTOL missions, reinforcing the need for hybrid or model-based approaches.

Figure (5) shows the SoC estimation using Coulomb Counting (CC) under a smoother eVTOL flight profile compared to the previous scenario. The blue curve represents the battery current, which remains relatively stable with moderate variations, while the orange curve indicates the predicted remaining flight time. Both the CC-based SoC (red) and the reference SoC (green) start near 1 (100 percent) and decrease gradually over time, reflecting continuous energy consumption during take-off, hover, cruise, and landing phases. Unlike the previous case where CC drifted significantly, here the CC estimate closely follows the real SoC, demonstrating that Coulomb Counting performs well under controlled conditions and short-duration missions. This reinforces why CC is widely used in Battery Management Systems: it is simple, requires only current measurement, and operates in real time without complex models.

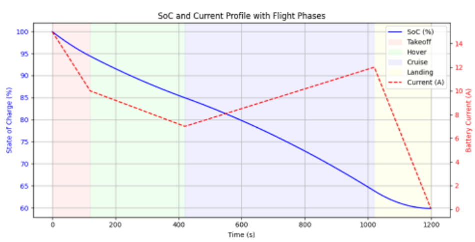


**Figure 6.** SoC vs. Current during Flight

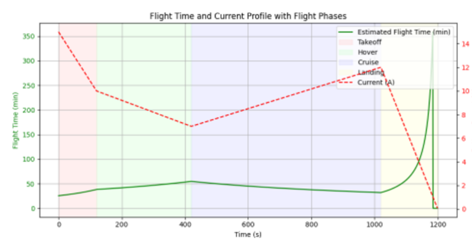


**Figure 7.** Flight Time per Phase

Figure (6) illustrates the SoC evolution and current profile across the four eVTOL flight phases: take-off, hover, cruise, and landing. The blue curve represents the State of Charge (SoC), which starts at 100 percent and decreases progressively as the mission advances. The red dashed curve shows the battery current, which varies according to the power demand of each phase highest during take-off, moderate during hover, lowest during cruise, and near zero during landing. The colored background segments highlight the distinct phases, making the correlation between current demand and SoC depletion clear. The results confirm that SoC declines faster during high-current phases (take-off and hover) and more slowly during cruise, validating the Coulomb Counting approach for short-term estimation under dynamic load conditions. This figure also emphasizes the importance of accurate current measurement and phase-aware energy management in eVTOL missions.

Figure (7) illustrates the estimated remaining flight time and current profile across the four eVTOL flight phases: take-off, hover, cruise, and landing. The green curve represents the predicted flight time in minutes, while the red dashed curve shows the battery current. As expected, the estimated flight time decreases sharply during high-current phases such as take-off and hover, reflecting increased power demand, and stabilizes during cruise when the current is lower. Near the landing phase, the flight time prediction rises sharply as the current approaches zero, indicating minimal energy consumption. This behavior demonstrates the responsiveness of the Coulomb Counting-based algorithm for endurance prediction under dynamic load conditions. However, it also highlights the need for caution when interpreting sudden increases in predicted flight time during low-current phases, as these do not account for operational constraints or reserve energy requirements.

## 5 Discussion

The presented study demonstrates a practical approach for estimating the State of Charge (SoC) in eVTOL battery systems using a current sensor-based Coulomb Counting method implemented in MATLAB/Simulink. This approach, which integrates current over time and normalizes it by the nominal battery capacity, is computationally efficient and suitable for real-time applications. The simulation framework, summarized in Table 1, provides a structured methodology, and the comparison with reference SoC values supports the validity of the results. As illustrated in Figures (3) and (4), the method performs well under steady-state conditions, where the estimated SoC closely follows the actual SoC trajectory. However, during dynamic flight phases such as take-off and hover, deviations become evident, reflecting the method's sensitivity to current measurement errors and integration drift. These discrepancies, although expected, highlight the limitations of Coulomb Counting when applied to highly variable load profiles typical of eVTOL missions. To improve robustness, future work could incorporate drift correction strategies, such as periodic recalibration using voltage-based estimation or adaptive filtering techniques. Additionally, integrating temperature and aging models would enhance the realism of the simulation and extend its applicability to long-duration missions. Finally, expanding the approach to multi-cell battery packs and hybrid estimation methods could provide a more comprehensive solution for advanced eVTOL Battery Management Systems.

## 6 Conclusion

This work presented a practical approach for estimating the State of Charge (SoC) in eVTOL battery systems using the Coulomb Counting method implemented in MATLAB/Simulink. The results confirm that this method is computationally efficient and suitable for real-time applications, particularly under stable operating conditions. However, its sensitivity to current measurement errors and integration drift during dynamic flight phases highlights the need for correction strategies to ensure long-term accuracy. Future research should focus on integrating hybrid estimation techniques, temperature and aging models, and multi-cell pack simulations to enhance reliability and applicability in full-scale eVTOL Battery Management Systems.

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