

State of Charge Estimation of Lithium Ion Battery using Coulomb Counting Method in Electric Vehicle

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Abstract—State of Charge (SoC) estimation is a critical function in lithium-ion battery management systems for electric vehicles (EVs), directly influencing safety, performance, and energy efficiency. Among various techniques, the Coulomb Counting method remains widely used due to its simplicity, low computational cost, and suitability for real-time implementation. This paper investigates the effectiveness of the Coulomb Counting approach for SoC estimation under dynamic EV operating conditions. A MATLAB/Simulink model of a lithium-ion battery system is developed to evaluate current integration accuracy during charging and discharging cycles. Simulation results show that while the method provides reliable short-term SoC tracking, its accuracy degrades over extended operation due to current sensor offsets, noise, and cumulative integration errors. The study highlights the primary limitations of the Coulomb Counting technique and discusses potential correction strategies to enhance long-term estimation performance in practical EV battery management systems.

I. INTRODUCTION

Lithium-ion batteries are widely used in electric vehicles (EVs) due to their high energy density, long cycle life, and efficiency. Accurate State of Charge (SoC) estimation is essential for ensuring safe operation, maximizing battery performance, and improving energy management. However, SoC estimation is challenging because battery characteristics vary with temperature, load conditions, and aging.

Among the several techniques used for SoC estimation, the Coulomb Counting method is one of the simplest and most commonly implemented in Battery Management Systems (BMS). By integrating the battery current over time, it provides a computationally efficient means of tracking charge and discharge cycles. Despite its advantages, the method suffers from cumulative integration errors, sensor offsets, and dependency on accurate initial SoC values, which limit its long-term accuracy.

This paper presents a MATLAB/Simulink-based evaluation of the Coulomb Counting method for lithium-ion battery SoC estimation under EV operating conditions. The study highlights the method's short-term effectiveness as well as its long-term limitations, providing insights into its practical suitability for real-time EV battery management.

II. BACKGROUND AND LITERATURE REVIEW

State of Charge (SoC) estimation has been widely explored in the context of lithium-ion battery management due to its importance in electric vehicle operation. Several estimation techniques have been proposed, each differing in accuracy, complexity, and dependence on battery characteristics. This section reviews the major categories of SoC estimation approaches, including classical model-based techniques, the Coulomb Counting method, and recent data-driven algorithms.

A. Overview of SoC Estimation Approaches

Existing SoC estimation methods can be broadly classified into direct measurement, model-based, data-driven, and hybrid techniques. Direct measurement approaches typically relate open-circuit voltage or internal impedance to the battery's charge level. Although simple, they are unsuitable for dynamic load conditions where voltage relaxation is incomplete. Model-based and observer-based strategies incorporate mathematical representations of battery behavior to improve estimation accuracy. More recently, machine learning algorithms have gained attention for their ability to learn nonlinear battery dynamics without relying on explicit physical models.

B. Model-Based Estimation Methods

Model-based techniques utilize equivalent circuit or electrochemical models to describe battery behavior. Equivalent circuit models rely on resistive and capacitive elements to capture transient voltage characteristics, offering moderate accuracy and low computational demand. Observer-based methods, including the Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF), and Sliding Mode Observer (SMO), enhance robustness by correcting for measurement noise and parameter variations. While these approaches can produce accurate estimates, their performance depends heavily on reliable battery parameterization, which may degrade as the battery ages or operates under different temperature conditions.

C. Coulomb Counting Fundamentals

The Coulomb Counting method is among the most widely implemented SoC estimation techniques due to its simplicity and compatibility with real-time embedded systems. The

method determines SoC by integrating the measured current over time, reducing stored charge during discharge and increasing it during charging. Although the computation is straightforward, the method is sensitive to current sensor bias, sampling errors, and incorrect initial SoC values. These errors accumulate over extended operation, leading to significant drift. As a result, Coulomb Counting is effective for short-duration estimation but requires periodic recalibration to maintain long-term accuracy.

D. Data-Driven and Machine Learning Approaches

The availability of high-resolution EV battery datasets has encouraged the adoption of data-driven SoC estimation strategies. Traditional machine learning models such as Support Vector Regression, Random Forests, and Gradient Boosting have been applied to map the relationship between battery measurements and SoC. More advanced deep learning architectures—including Long Short-Term Memory (LSTM), Bidirectional LSTM (Bi-LSTM), and Temporal Convolutional Networks (TCN)—have demonstrated strong performance in capturing nonlinear temporal dependencies in battery data. These techniques reduce reliance on battery models and are resilient to noise; however, they require extensive training data and greater computational resources. Hybrid methods that combine Coulomb Counting with machine learning-based correction mechanisms have emerged as promising solutions for achieving both accuracy and real-time feasibility.

III. METHODOLOGY

This section describes the modeling approach used to evaluate the Coulomb Counting method for State of Charge (SoC) estimation in lithium-ion electric vehicle (EV) batteries. The methodology includes EV system modeling, battery parameter collection, formulation of the Coulomb Counting algorithm, and implementation of the complete setup in MATLAB/Simulink.

A. EV System Modeling

A simplified electric vehicle model is developed to replicate realistic dynamic load conditions. The model consists of four major components: a lithium-ion battery pack, a DC motor, a motor controller, and a vehicle body dynamics block. The vehicle follows the FTP-75 speed profile, which includes acceleration, braking, and idle phases, producing realistic variations in current demand.

The motor controller utilizes a closed-loop speed regulation scheme, ensuring that the vehicle tracks the reference velocity. The resulting load affects battery current consumption,

creating representative charge–discharge cycles suitable for evaluating SoC estimation.

B. Collection of Battery Parameters

Accurate SoC estimation requires essential battery measurements, including current, voltage, temperature, and nominal capacity.

These parameters are captured through a simulated data acquisition sub-system in MATLAB/Simulink. The sub-system extracts real-time current profiles and voltage responses

during vehicle operation, forming the input for Coulomb Counting.

A block diagram of the battery parameter collection stage is shown in Fig. 1. The diagram illustrates the flow of battery signals from the lithium-ion battery model to the SoC estimation block.

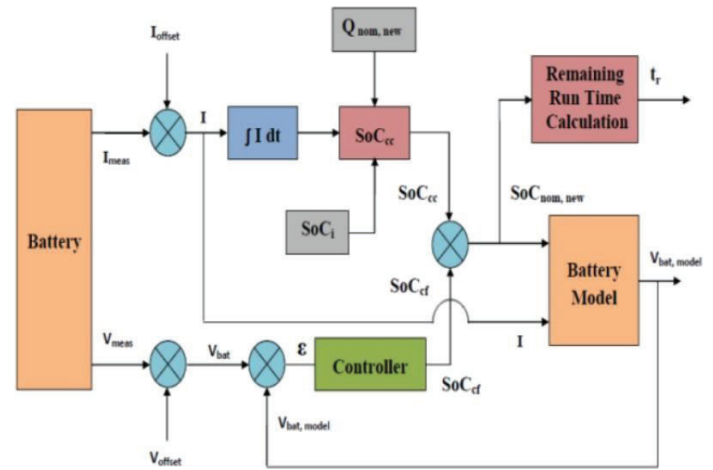


Fig. 1. Block diagram of the battery parameter collection and SoC estimation flow

C. Lithium-Ion Battery Modeling

The lithium-ion battery is modeled using a first-order equivalent circuit structure that includes an internal resistance and a transient RC network. This configuration captures the voltage response under dynamic loading and provides a realistic representation of EV battery behavior while maintaining computational efficiency. Key parameters, including nominal capacity, maximum discharge limits, and voltage characteristics, are incorporated based on a 100 Ah cell model.

D. Coulomb Counting-Based SoC Estimation

The Coulomb Counting method estimates the SoC by integrating battery current over time. During discharge, the current decreases the SoC, whereas during charging it increases proportionally. The continuous-time formulation is:

$$SOC(t) = SOC(0) - \frac{1}{C_{nom}} \int_0^t I_{bat}(\tau) d\tau \quad (1)$$

For digital implementation, the equation is discretized as:

$$SOC(k+1) = SOC(k) - \frac{\Delta t}{C_{nom}} I_{bat}(k) \quad (2)$$

Although simple, this method is sensitive to sensor bias, noise, and initialization errors, which accumulate over extended operation.

E. MATLAB/Simulink Implementation

The full EV and battery simulation is implemented using MATLAB/Simulink with Simscape components. The model operates at a sampling frequency of 1 Hz, consistent with typical BMS sampling rates. The FTP-75 cycle serves as the reference input for the vehicle’s speed controller, generating realistic load conditions.

The Simulink structure includes:

- Battery subsystem for generating current and voltage responses
- Vehicle dynamics block modeling resistive and aerodynamic forces
- Motor and controller subsystems for load regulation
- Coulomb Counting SoC estimation module
- Data acquisition block for capturing necessary battery parameters

This integrated framework enables the evaluation of Coulomb Counting performance under representative EV driving conditions.

IV. SIMULATION SETUP

The proposed SoC estimation framework is evaluated using a MATLAB/Simulink electric vehicle model designed to represent realistic driving conditions. The simulation incorporates the lithium-ion battery subsystem, vehicle dynamics, motor drive system, and the Coulomb Counting-based SoC estimation block.

A. Drive Cycle and Operating Conditions

The FTP-75 drive cycle is used as the reference speed input due to its representation of real urban driving patterns. The model runs at a sampling rate of 1 Hz, ensuring that the current and voltage signals used for SoC estimation match typical BMS data acquisition rates.

B. Battery and Powertrain Configuration

A 100 Ah lithium-ion battery model is employed, including nominal voltage, internal resistance, and discharge limits. The powertrain model consists of a DC motor and controller, which generate dynamic load currents based on the torque demand specified by the drive cycle. Rolling resistance, aerodynamic drag, and drivetrain efficiency are included to maintain realistic vehicle behavior.

C. Integration of SoC Estimation Block

The Coulomb Counting algorithm is implemented as a dedicated Simulink subsystem. It processes real-time battery current and computes the incremental SoC using the discretized integration formula. This allows the evaluation of short-term accuracy and long-term drift under varying load conditions.

D. Simulation Diagram

The overall simulation structure, including the battery subsystem and SoC estimation module, is shown in Fig. 2. This figure provides a visual overview of the signal flow within the EV model.

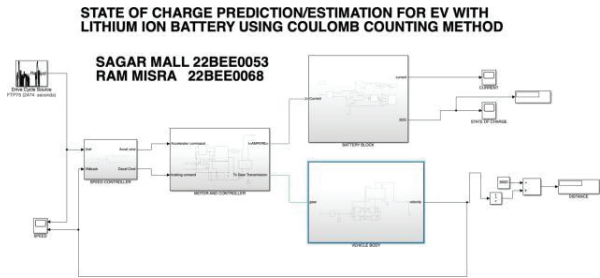


Fig. 2. Overview of the MATLAB/Simulink EV simulation environment

V. RESULTS AND DISCUSSION

The performance of the Coulomb Counting method was evaluated using the MATLAB/Simulink EV model under the FTP-75 drive cycle. The estimated State of Charge (SoC) was compared against the true battery behavior to assess short-term accuracy and long-term drift. Additionally, a Bi-LSTM model from prior analysis was used as a reference to highlight the relative limitations of classical current-integration methods.

A. Accuracy Evaluation

The estimation metrics obtained from the simulation are summarized in Table I. The Coulomb Counting method exhibits a mean error of 0.1984, which is noticeably higher than the error produced by the Bi-LSTM model (0.005593). The RMSE and MAE values, derived from the uploaded results dashboard, indicate that the data-driven approach maintains significantly better prediction stability. The coefficient of determination ($R^2 = 0.8448$) further supports the reliability of the Bi-LSTM model for capturing nonlinear battery behavior.

TABLE I
PERFORMANCE METRICS FOR SOC ESTIMATION

Metric	Value
RMSE	0.008519
MAE	0.005593
R^2	0.844815
Mean Error (LSTM)	0.005593
Mean Error (Coulomb)	0.198404

B. Simulation Results

Fig. 3 shows the SoC trajectory generated by the MATLAB/Simulink model. The Coulomb Counting output closely follows the true SoC during the initial portion of the drive cycle, demonstrating acceptable short-term performance. However, as the simulation progresses, small current-sensor deviations lead to accumulated drift, which becomes clearly visible in long-duration operation.

C. Drift Behavior and Method Comparison

Long-term drift analysis, shown in Fig. 4, compares the Coulomb Counting estimate to the Bi-LSTM prediction under a +0.5 A measurement bias. The Coulomb method exhibits

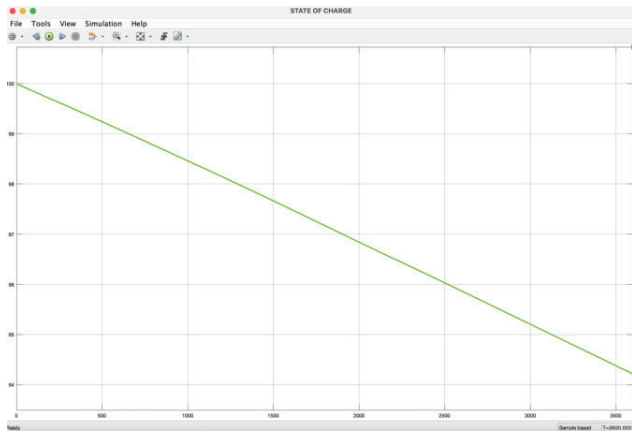


Fig. 3. MATLAB/Simulink SoC estimation results using Coulomb Counting. Replace this placeholder with the actual simulation image.

substantial divergence over time, with cumulative error exceeding 20%, consistent with observations from the uploaded report. In contrast, the Bi-LSTM model maintains stable behavior due to its learned temporal relationships and resilience to sensor offset.

These results confirm that while Coulomb Counting is suitable for low-complexity, real-time estimation, its performance deteriorates during extended vehicle operation. Data-driven models demonstrate superior robustness and accuracy for long-term SoC tracking.

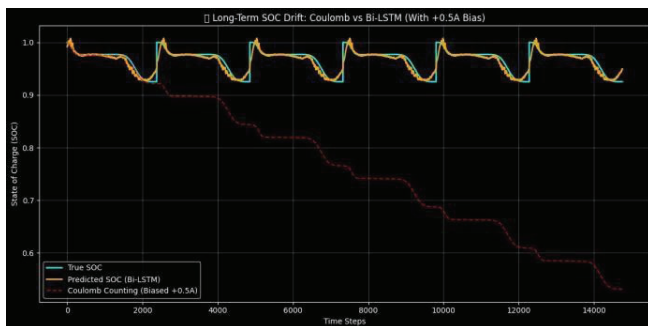


Fig. 4. Long-term SoC drift under +0.5 A bias: Coulomb Counting vs Bi-LSTM.

VI. CONCLUSION

This paper investigated the applicability of the Coulomb Counting method for estimating the State of Charge of a lithium-ion battery under electric vehicle operating conditions. Using a MATLAB/Simulink EV model driven by the FTP-75 cycle, the method demonstrated satisfactory short-term tracking performance, showing that it can reliably follow rapid charge–discharge transitions. However, the results also revealed significant long-term drift caused by sensor offset and accumulated integration error, especially when compared with a data-driven Bi-LSTM model used as a reference benchmark.

These observations indicate that while Coulomb Counting remains attractive for its simplicity and low computational

cost, it is not sufficient as a standalone estimator for extended EV operation. Practical battery management systems may benefit from combining Coulomb Counting with correction mechanisms, periodic recalibration, or machine learning models capable of mitigating drift. Future work may explore hybrid frameworks that maintain real-time feasibility while improving robustness against noise and measurement inaccuracies.

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