RESEARCH ARTICLE

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Coulomb Counting Method based SOC Estimation of Lithium-Ion Batteries Considering Battery Temperature and Aging

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Abstract

The Coulomb counting method is simple and effective in terms of state of charge (SOC) estimation of lithium-ion batteries. However, if the current measurement is not accurate, it will cause a cumulative calculation error, which will gradually increase with the time. And if the ambient temperature changes, the available capacity and initial SOC of the battery will also change. In order to solve the shortcomings of the traditional Coulomb counting method of SOC estimation, an improved method was proposed in this paper by taking into account the influence of battery temperature and aging on SOC. It can correct the initial value of SOC and the maximum available capacity of the battery more accurately, thus it solves the cumulative error problem, and improves the SOC estimation accuracy. A simple, accurate, and easy-to-implement method of battery SOC estimation is provided for the battery management system, which has practical application value.

Keywords: SOC estimation, coulomb counting method, electric vehicles, battery management system.

Nomenclature	Meaning
$SOC(t)$	the SOC value at time t
Q_{rem}	the battery remaining capacity
Q_{max}	the maximum available capacity
$SOC(t_0)$	the initial value of SOC
ΔQ	the change in charge/discharge capacity from the initial state to the current state
$i(t)$	the battery charging and discharging current
η	the Coulomb efficiency,
SOC_k	the SOC in the present time step
SOC_{k-1}	the SOC in the previous time step
i_k	the battery current in the present time step
Δt	the duration of each time step
u	the correction coefficient that Q_{max} is affected by temperature and aging
γ	the correction coefficient that the SOC initial value is affected by the self-discharge and battery aging

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Abbreviations	Full Term
EV	electric vehicle
BMS	battery management system
SOC	state of charge
OCV	open circuit voltage
EKF	extended Kalman filter
AI	artificial intelligence
NN	neural network
GA	genetic algorithm,
CCCV	constant current constant voltage
CC	constant current
CV	constant voltage
HPPC	hybrid pulse power characteristic

1 Introduction

Different from traditional fuel vehicles, the energy of electric vehicles (EVs) comes from power batteries. Lithium-ion batteries have become one of the most attractive rechargeable batteries for EVs due to their high energy density, low self-discharge rate, no memory effect, and high cell voltage [1, 2]. Power battery and battery management system (BMS) are very important to the power, safe operation and economic performance of the vehicle, which are currently a key factor restricting the scale development of EVs [3, 4].

The state of charge (SOC) is a very important parameter in the operation of batteries and EVs, because it is an important index for judging the remaining capacity of battery, preventing the battery from overcharging and over-discharging, and whether it needs to be balanced, etc. Similar to the fuel gauge of a fuel vehicle, the battery SOC reflects the remaining power of the battery [5]. However, the difference between them is that the SOC cannot be directly measured by a sensor, which must be obtained indirectly with corresponding estimation algorithms through some other measurable physical quantities, such as battery terminal voltage, charging and discharging current, and battery temperature, etc. [6].

The research content and arrangement of this paper are as follows. The Section 2 analyzes and compares the advantages and disadvantages of existing SOC estimation methods, points out the position and problems of Coulomb counting method in SOC estimation, and introduces the research content and significance. The Section 3 provides the basic definition of Coulomb counting. Subsequently, it provides a refined method and process for implementing Coulomb counting method. The Section 4 describes how the method has been improved, and the Section 5 is experimental simulation and comparison. Finally, the summary and conclusion of this study are presented.

2 Analysis and Comparison of SOC Estimation Methods for Batteries

The SOC estimation methods mainly include direct estimation methods and indirect estimation methods. Direct estimation methods include the discharge method, the open circuit voltage (OCV) method, the Coulomb counting method, the electrochemical impedance method, etc., while indirect estimation methods mainly include the model-based filtering/observer methods, such as extended Kalman filter (EKF), particle filter, H_∞filter, etc. [7, 8], and the artificial intelligence (AI) method, such as neural network (NN), genetic algorithm (GA), etc. [9, 10]. The discharge method is simple, but it needs a lot of experimental data, so it is difficult to be applied in practice without meeting the requirements of online estimation in the driving of EVs. The OCV method is simple, and only need a small amount of calculation by using the look-up table method. However, the error is large during charging and discharging, and the battery must be left for a long time for OCV prediction, which contradicts the application of EVs. It is usually used in conjunction with the Coulomb counting method [11]. The Coulomb counting method, also known as ampere hour integration method or current integration method, is simple and effective. However, if the current measurement is not accurate, it will cause a SOC cumulative calculation error, which will gradually increase with the time. Once the ambient temperature changes, the available capacity and initial SOC of the battery will also change [12]. The electrochemical impedance method has a clear physical meaning, and it can give relevant electrochemical explanations [13]. However, it is inaccurate due to the small change in AC impedance when the capacity is in the middle section, and the impedance is difficult to be estimated due to greatly affected by the initial power, temperature, aging, etc. Thus, it is difficult to implement on the controller chip, and rarely used in practice. The model-based filter/observer method has a strong correction effect on the initial estimation error with various optimization algorithms [14], but the amount of calculation is large. Drift of internal working point and interference noise have a great influence

Table 1. Advantages and disadvantages of various SOC estimation methods.

Methods	Advantages	Precision
Discharge	Simple	Relatively high
OCV	Simple	High at the beginning/end of charging and discharging
Coulomb counting	Simple, effective	Medium
Electrochemical impedance	Clear physical meaning	Relatively high
Model-based filter/observer	Strong correction of the initial estimation error	High
AI algorithm	Data driven-based	High

on estimation accuracy. If there are uncertainties in the system model and noise statistics, its application will be limited. The AI method is mainly based on data driven without battery model, and it is good at handling nonlinearity [15]. However, a large amount of data is required for training, the process is complicated and easily affected by training data and training methods. When it is applied in BMS, it is difficult to set up the system, so the cost is high. The main advantages and precision of various methods are summarized in Table 1.

The Coulomb counting method calculates the SOC of the battery by integrating the current over time. The method is accurate for calculating the power discharged by the battery, and it is the most commonly used for EVs However, the internal chemical reaction process of batteries is very complicated when charging and discharging, and battery SOC is easily affected by many factors such as temperature, ageing [16], current, self-discharge, etc., which makes it difficult to accurately achieve thermal modeling and estimate the SOC [17]. Its traditional form suffers from cumulative errors, dependence on initial SOC, and inability to cope with dynamic operating conditions. By optimizing algorithms, compensating for multiple parameters, and integrating other technologies, the Coulomb counting method can be improved, significantly enhancing the accuracy and robustness of SOC estimation, which is of great significance for BMS. Nowadays, electric vehicle manufacturers have increasingly high requirements for SOC estimation accuracy, which is very challenging. The traditional Coulomb counting method does not consider the influence of temperature and ageing, so the estimation accuracy is limited. To solve the above problems, this paper proposes an improved SOC estimation method based on Coulomb counting considering temperature and battery ageing.

3 Definition of SOC and Coulomb Counting Method

The battery SOC refers to the percentage of the battery remaining capacity to the maximum available capacity, generally, the rated capacity is directly used, which can be expressed as [18, 19]:

$$SOC(t) = \frac{Q_{\text{rem}}(t)}{Q_{\text{max}}(t)} \times 100\% \tag{1}$$

where $SOC(t)$ is the SOC value at time t; Q_{rem} is the battery remaining capacity, which refers to the total electricity released from the current state to the fully discharged state; Q_{max} is the maximum available capacity, which refers to the total electricity released from the fully charged state to the discharged state with a sufficiently small current. Q_{max} is affected by the battery design capacity, temperature, and aging.

The Coulomb counting method is to calculate the SOC of the battery by integrating the battery current over time. The basic principle is shown as follows [20, 21]:

$$SOC(t) = SOC(t_0) - \frac{\Delta Q}{Q_{\text{max}}} = SOC(t_0) - \frac{\eta}{Q_{\text{max}}} \int_{t_0}^{t} i(t)\, dt \tag{2}$$

where $SOC(t_0)$ represents the initial value of SOC when the battery starts to charge and discharge; ΔQ is the change in charge/discharge capacity from the initial state to the current state; $i(t)$ represents the battery charging and discharging current, with a positive value when discharging. η is the Coulomb efficiency, which is utilized only during charge when $\eta < 1$, and $\eta = 1$ during discharge.

In order to simplify the expression, the initial time $t_0 = 0$.

$$SOC(t) = SOC_0 - \frac{\eta}{Q_{\text{max}}} \int_{0}^{t} i(t)\, dt \tag{3}$$

At the same time, according to the above definition of SOC, in theory, if we know the value of the battery

SOC at two moments and the total released capacity, then the maximum available capacity of the battery can be estimated by the following formula:

$$Q_{\max} = \frac{\Delta Q}{SOC(t_2) - SOC(t_1)} = \frac{\int_{t_1}^{t_2} i(t)\,dt}{SOC(t_2) - SOC(t_1)} \tag{4}$$

The Coulomb counting method is described in (2). However, a digital system works with discrete time, therefore the discrete-time version of the equation utilized is (4).

$$SOC_k = SOC_{k-1} - \frac{\eta}{Q_{\max}} i_k \Delta t \tag{5}$$

where SOC_k is the SOC in the present time step, and SOC_{k-1} is the SOC in the previous time step, i_k is the battery current in the present time step, Δt is the duration of each time step (such as 100 ms).

According to the basic definition of the Coulomb counting method, we can obtain the basic implementation steps of the method.

- Data collection: real time monitoring of battery charging and discharging current through high-precision current sensors;
- Discretization processing: divide continuous current into sampling values with fixed time intervals (such as 500ms);
- Integral calculation: the product of accumulated current and time, i.e. ΔQ;
- SOC update: combining the initial SOC and total battery capacity, output real-time SOC values.

4 Improved Coulomb Counting Method

As shown in Figure 1, the improved Coulomb counting method mainly includes the correction of the initial SOC and the maximum available capacity considering the temperature and aging.

- Correction of initial SOC: Inaccurate initial value $SOC(t0)$ can lead to subsequent estimation biases. Combining the OCV method, regularly use the OCV when the battery is idle to correct the initial SOC and reduce cumulative errors.
- Dynamic capacity calibration: Adjust the value of Q_{max} dynamically based on temperature and cycle times. The rated capacity of a battery is affected by the ambient temperature and the number of battery cycles. Therefore, the rated capacity of the battery can be corrected by introducing environmental temperature correction coefficient and cycle number correction coefficients, thereby improving the accuracy of SOC estimation.

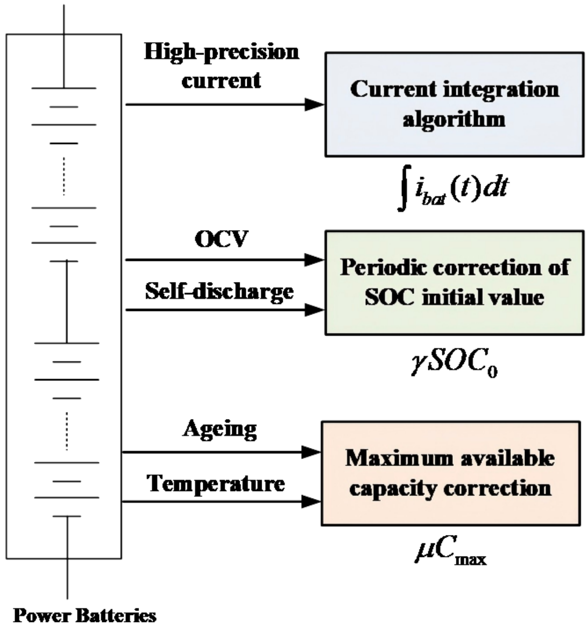

Figure 1. The improved Coulomb counting method for SOC estimation.

According to the obtained correction coefficient, the Coulomb counting algorithm can be implemented for the battery SOC estimation, which can be expressed as:

$$SOC(t) = \gamma SOC_0 - \frac{\eta}{\mu Q_{\max}} \int_0^t i(t)\,dt \tag{6}$$

where μ represents the correction coefficient that $Q_{\max}$ is affected by temperature and aging, and then $\mu Q_{\max}$ is the maximum available capacity of the battery under different temperature and aging degrees; γ is the correction coefficient that the initial value of the battery SOC is affected by the self-discharge and battery aging, and then γSOC_0 is the initial value of battery SOC under different aging.

The discrete-time version of equation (6) in a digital system is expressed as

$$SOC_k = \gamma SOC_{k-1} - \frac{\eta}{\mu Q_{\max}} i_k \Delta t \tag{7}$$

5 Simulation and Verification

Taking a lithium-iron battery pack with a rated capacity of 31 Ah as an example, constant current constant voltage (CCCV) charge tests and hybrid

Table 2. Basic parameters of battery.

Battery parameter	values
Rated capacity	31Ah
Discharge termination voltage	2.0 V
Nominal voltage	3.2 V
Charging termination voltage	3.65 V

pulse power characteristic (HPPC) discharge tests were conducted on the battery separately. The basic parameters of the battery are shown in Table 2.

The basic testing process is as follows: firstly, the lithium-ion battery module is fully charged using the CCCV charging strategy. In the CC stage, the charging current is set to 1/3 C; in the CV stage, the charging voltage is set to 3.65V, and the charging cut-off current is 1/50C, or the charging is stopped when the charging time has reached 1 hour. After charging is completed, the lithium-ion battery module is left to stand and then subjected to HPPC testing, applying a certain pulse signal and measuring the battery response. The mixed pulses in HPPC are decomposed into discharge pulses and charge pulses, therefore, battery charging and discharging are divided into two processes: pulse current discharge process and pulse current charging process. During the pulse current discharge process, a fully charged battery is discharged at a rate of 1C, with a discharge pulse stage of 5% SOC, until the battery is completely discharged. Here, 1C represents continuous discharge of the battery for 1 hour at a current equal to the nominal capacity.

The charging and discharging current of CCCV and HPPC is shown in Figures 2 and 3. And the tested current data is used to verify the estimation accuracy of battery SOC under charging and discharging conditions using different methods.

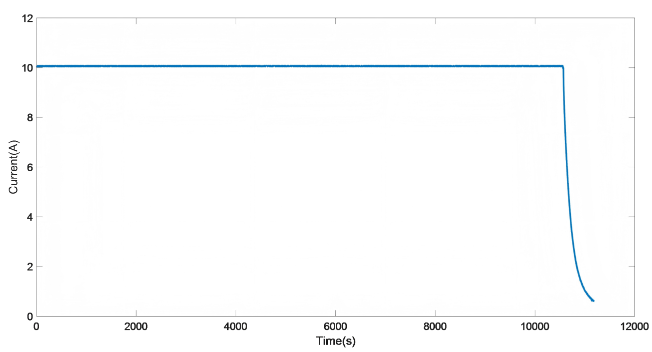

Figure 2. Charging current of CCCV.

The parameter settings of different Coulomb counting algorithms for SOC estimation are shown in Table 3.

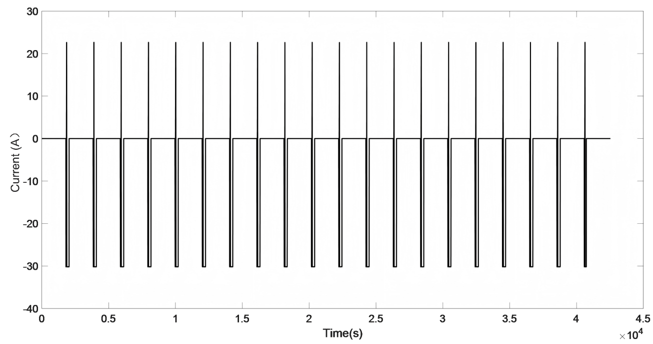

Figure 3. Charging and discharging current of HPPC.

Table 3. Parameter settings of different Coulomb counting algorithms for SOC estimation.

Methods	Description	Parameter Values
M1	Test value	/
M2	No correction	γ=1, u =1
M3	Improvement 1	γ=0.985, u=0.982
M4	Improvement 2	γ=0.998, u=0.996

M1 represents the test data, M2 represents the Coulomb counting algorithms without correction factors, M3 and M4 represent the Coulomb counting algorithms method with different correction factors, respectively.

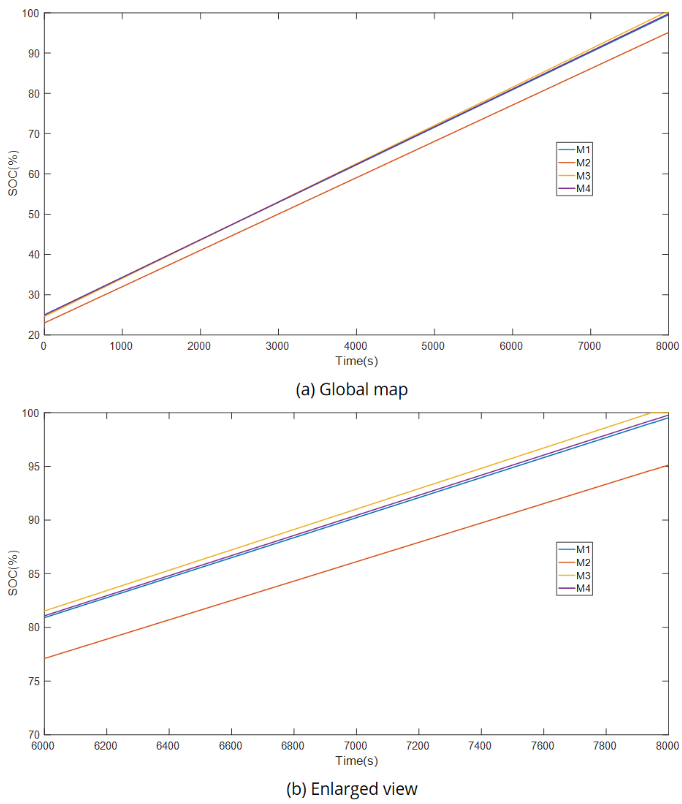

Figure 4. SOC estimation under constant current charging.

Different comparative experiments are modeled and

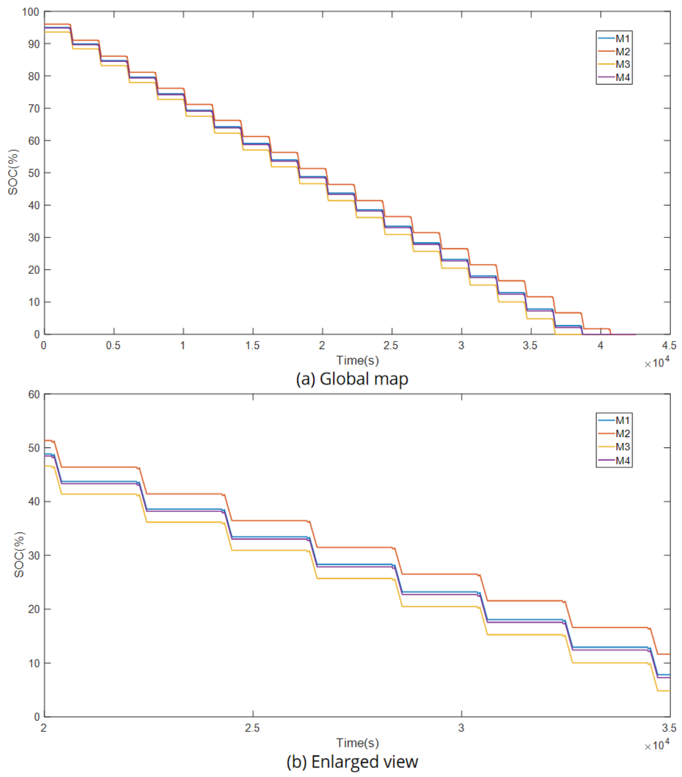

Figure 5. SOC estimation under HPPC discharging.

simulated in the MATLAB environment. The Matlab simulation model mainly includes input modules for charging and discharging current over time, standard and improved Coulomb counting methods with correction factors, battery capacity modules, and output oscilloscope modules.

Figures 4 and 5 show the estimation of SOC under CCCV charge and HPPC discharge, respectively. The M4 method estimates SOC with the highest accuracy, while the uncorrected M2 method estimates SOC with the lowest accuracy. It can be seen that the more accurate the identification of the correction coefficient, the higher the accuracy of SOC estimation.

The comparison of the maximum error (ME), mean absolute error (MAE), and root mean square error (RMSE) indicators of the three methods is shown in Table 4. Among them, MAE represents the average absolute error between the predicted value and the true value of the model, which is used to measure the degree of closeness between the prediction and the final result. The smaller the MAE, the better the prediction. Its definition is as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{8}$$

where n is the number of samples, y_i is the actual value,

Table 4. Comparison of regression evaluation indicators.

Tests	Methods	ME	MAE	RMSE
CCCV	M2	4.42	0.63	1.46
	M3	0.98	0.07	0.21
	M4	0.25	0.02	0.06
HPPC	M2	4.07	2.35	2.55
	M3	3.09	2.02	2.17
	M4	0.57	0.34	0.37

and $\hat{y}_i$ is the predicted value.

RMSE is used to evaluate the difference between observed values and model predictions, and to compare the prediction errors of different models on specific datasets. The smaller the RMSE value, the closer the predicted value is to the true value, and the higher the prediction accuracy of the model. Its definition is as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{9}$$

From the experimental results, it can be seen that initial SOC and aging have a significant impact on the accuracy of the entire SOC estimation process. As the battery is used for a period of time, it is necessary to correct parameters such as the initial SOC value and maximum available capacity to eliminate cumulative errors caused by current sensor errors and measurement noise.

6 Conclusion

Portable devices such as mobile phones and laptops require real-time monitoring of battery status, and the Coulomb counting method can meet the requirement by providing reliable SOC estimation. However, electric vehicles, energy storage systems, and others require higher accuracy in estimating battery SOC. Therefore, it is necessary to improve the Coulomb counting method to provide real-time SOC information, help manage the charging and discharging process of the battery, and optimize energy efficiency.

An improved Coulomb counting method is proposed by taking into account the influence of battery temperature and ageing on SOC, which can correct the initial value of SOC and the maximum available capacity of the battery more accurately, thus it solves the cumulative error of the Coulomb counting method, and improves the SOC estimation accuracy.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The authors declare no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

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