



# An Active Balancing Method Based on SOC and Capacitance for Lithium-Ion Batteries in Electric Vehicles

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An active balancing method based on the state of charge (SOC) and capacitance is presented in this article to solve the inconsistency problem of lithium-ion batteries in electric vehicles. The terminal voltage of each battery is collected first. Then, each battery SOC is accurately estimated by an extended Kalman filter (EKF) algorithm. In the experiment, the maximum absolute error of SOC evaluation is only 0.0061, and the mean absolute error is 0.0013 when the initial battery SOC is clear. Meanwhile, the maximum absolute error of SOC evaluation is 0.5 and the average absolute error of SOC is 0.0015 when the initial battery SOC is not clear. Afterward, an active balancing circuit based on the estimated battery SOC and capacitance is designed. The energy of capacitance is charged by the battery whose SOC is higher than the other batteries through the circuit to avoid the battery being overcharged. Then, the SOC of batteries gradually turn consistent. In the simulation experiment, the SOC difference of batteries is 7% before the balancing. Meanwhile, the SOC difference of batteries reduces to 0.02% after the balancing and the consuming time is merely 272s, which manifests that the proposed balancing method has a fast balancing speed and better balancing efficiency.

**Keywords:** lithium-ion batteries, active balancing, SOC, EKF algorithm, capacitance

## INTRODUCTION

Power system is one of the key components of electric vehicles, and it is usually composed of a large number of lithium-ion batteries in series and parallels (Yuan et al., 2015; Li et al., 2020). Owing to the differences in manufacturing processes and working conditions, voltage, capacity, internal resistance, self-discharge rate, and other parameters of batteries turn inconsistent gradually (Zhang et al., 2017; Zheng et al., 2018). With the elapse of battery cycle, the inconsistency of batteries increases dramatically, which increases the risk of runaway heat. Meanwhile, the battery balancing methods can effectively reduce the inconsistency (Baughman and Ferdowsi, 2008; Zhang et al., 2011; Gong and Tang, 2012; Phung et al., 2012; Hua et al., 2015; Lee et al., 2016; Morstyn et al., 2017; Ouyang et al., 2017; Shang et al., 2017; Wang et al., 2019; Moral et al., 2020).

According to circuit topology, battery balancing methods can be divided into passive balancing (Zhang et al., 2011; Hua et al., 2015) and active balancing methods (Baughman and Ferdowsi, 2008; Gong and Tang, 2012; Lee et al., 2016; Shang et al., 2017). The passive balancing method is an energy dissipation balancing. The excess power in the battery is converted into heat energy by energy dissipation elements to refine inconsistency of batteries. Resistance balancing is a typical passive balancing method (Zhang et al., 2011; Hua et al., 2015). The disadvantage of this balancing method is that it is impossible to replenish energy for low-capacity batteries. The active balancing method is an

on-dispersive balancing method. Through different circuit topology and control strategy, energy transfers from battery to other batteries. Typical active balancing methods include transformer balancing method (Lee et al., 2016; Shang et al., 2017), inductance balancing method (Gong and Tang, 2012), capacitance balancing method (Baughman and Ferdowsi, 2008; Moral et al., 2020), and so on. However, it is difficult to develop topology with small size, easy integration, low cost, fast balancing speed, and high reliability for the balancing circuits. In recent years, the design of the active balancing circuit based on capacitance becomes feasible due to the emergence of various capacitances with large capacity and small volume. Meanwhile, it has advantages that include the following: the wasted energy is very low in the balancing process, the balancing process does not produce heat, and the balancing can be started in the case of charging, discharging, and preserving.

Based on the different control variables, the battery balancing methods can be divided into voltage balancing method (Phung et al., 2012; Wang et al., 2019) and state of charge (SOC) balancing method (Morstyn et al., 2017; Ouyang et al., 2017; Tang et al., 2020). The voltage balancing cannot represent the real state of electricity in each battery, so it cannot be promised in the application. Meanwhile, the SOC balancing method can overcome this shortcoming. The primary difficulty of applying SOC balancing is that the battery SOC cannot be measured directly, and it needs to be estimated. Therefore, the SOC estimation accuracy is critically related to the balancing effect.

Presently, the commonly used SOC estimation methods include open circuit voltage (OCV) method (Weng et al., 2014), current integration method (Okoshi et al., 2006), neural network (Yang et al., 2019), and Kalman filter algorithm (Kim and Cho, 2011; Xiong et al., 2012; Wang et al., 2018; Shrivastava et al., 2019). The OCV method needs to measure the battery OCV after the battery preserving for a long time and then estimate the corresponding SOC by searching the table. The current integration method can accurately estimate the battery SOC, but this method needs an accurate initial SOC value. Neural network needs a large number of historical test data to train and test the algorithm. The calculation of this method is very large and it is difficult to be applied in hardware with poor computing power. Extended Kalman filter (EKF) algorithm is an extended form of standard Kalman filter in the nonlinear case, and it is an efficient recursive filter. By using Taylor series expansion, the nonlinear system is linearized and then the signal is filtered by the Kalman filter framework, which shows excellent performance in battery SOC estimation (Kim and Cho, 2011; Xiong et al., 2012; Wang et al., 2018).

To prolong the cycle life of the batteries and protect their safety, an active balancing method based on SOC and capacitance is presented in this article. The terminal voltage of each battery is collected first, and then each battery SOC is estimated by using the EKF algorithm accurately. Afterward, an active balancing circuit based on the estimated SOC and capacitance is designed. During the working process of the balancing circuit, the energy of capacitance is charged by the battery whose SOC is higher than the other batteries to avoid the battery being overcharged. The

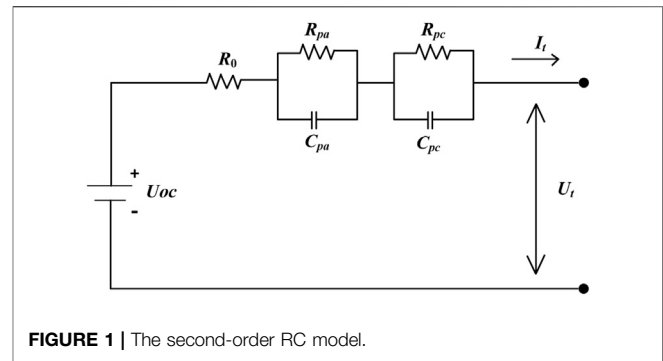


FIGURE 1 | The second-order RC model.

balancing method improves the overall battery pack inconsistency fast and greatly in the experiment.

The rest of the article is arranged as follows. *Battery Equivalent Circuit Model* presents the battery equivalent circuit model. *Extended Kalman Filter Algorithm Based Battery State of Charge Estimate Method* illustrates the EKF algorithm-based battery SOC estimate method. *Experiment Procedure and Results* implements the experiment and gives the discussion. Finally, conclusion is drawn in *Conclusion*.

## BATTERY EQUIVALENT CIRCUIT MODEL

The battery equivalent circuit models mainly include Rint model, Thevenin model, the second-order RC model, and the n-order RC model (Wang et al., 2020). In general, the model is more accurate when the number of RC increases. Meanwhile, the more model parameters need to be recognized and the corresponding amount of computation rises. In the work, the second-order RC model is selected, which is shown in **Figure 1**.

The battery SOC defined by United States Advanced Battery Consortium (USABC) is the remaining battery capacity divided by the rated capacity under the same conditions of constant discharging current and constant temperature, which is as

$$SOC(t) = SOC(t_0) - \int_{t_0}^t \frac{\eta I}{Q_n} dt, \quad (1)$$

where  $SOC(t)$  is the SOC at the time  $t$ ;  $SOC(t_0)$  is the SOC at the time  $t_0$ ;  $\eta = 1$  is a Coulomb efficiency;  $I$  is the input current;  $Q_n$  is the rated capacity of the battery. According to Kirchhoff's law of the circuit, the second-order RC model can be expressed by **Eqs 2–4** as

$$\dot{U}_1 = -\frac{1}{R_{pa}C_{pa}}U_1 + \frac{1}{C_{pa}}I_t, \quad (2)$$

$$\dot{U}_2 = -\frac{1}{R_{pc}C_{pc}}U_2 + \frac{1}{C_{pc}}I_t, \quad (3)$$

$$U_t = U_{OCV} - U_1 - U_2 - R_0I_t, \quad (4)$$

where  $R_0$  is the internal resistance of the battery;  $R_{pa}$  and  $R_{pc}$  are respectively the polarization resistance and concentration

**TABLE 1** | Detailed parameters of the used 18650 battery.

Brand	Tianjin Lishen
Battery model	LR1865SZ
Nominal capacity	2.5 Ah
Minimum capacity	2.4 Ah
Charging voltage	4.2 V
Nominal voltage	3.6 V
Maximum charging current	1 C (2.4 A)
Maximum discharging current	3 C (7.2 A)

resistance;  $C_{pa}$  and  $C_{pc}$  are respectively the polarization capacitance and concentration capacitance;  $U_1$  and  $U_2$  are respectively the terminal voltages of  $R_{pa}$  and  $R_{pc}$ ;  $U_t$  is the terminal voltage of the battery;  $U_{OCV}$  is the battery OCV; and  $I_t$  is the current of  $R_0$ .

## EXTENDED KALMAN FILTER ALGORITHM-BASED BATTERY STATE OF CHARGE ESTIMATE METHOD

The constructed battery model in *Battery Equivalent Circuit Model* reflects the relationship between the battery inputs, inner states, and battery outputs. The EKF algorithm estimates the battery system states after obtaining the battery model's inputs and outputs for the battery in a typically dynamic nonlinear system (Kim and Cho, 2011; Xiong et al., 2012; Wang et al., 2018). A partly highlighted specific of the EKF algorithm is introduced.

First, the battery SOC is estimated by the Kalman observer through the following state space and measurement equations for the battery state model in the discrete time

$$x_{k+1} = f(x_k, u_k) + q_k^x, \quad (5)$$

$$y_k = g(x_k, u_k) + r_k^x, \quad (6)$$

where  $x_k$  and  $y_k$  are the state vector and the system output at step  $k$ , respectively;  $f$  and  $g$  are continuously differentiable nonlinear functions;  $q_k^x$  and  $r_k^x$  are the additional stochastic noises (zero-mean white Gaussian), which is applicative for the filter to modify the states in the estimation, and this is an adjustment of the measurement and the prediction.

The nonlinear system is linearized by the EKF algorithm at every data point, which is as follows:

$$\hat{A}_k = \frac{\delta f(\cdot)}{\delta \hat{x}_k^+} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & e^{-\frac{dt}{R_{pa}C_{pa}}} & 0 \\ 0 & 0 & e^{-\frac{dt}{R_{pc}C_{pc}}} \end{bmatrix}, \quad (7)$$

$$\hat{C}_k = \frac{\delta g(\cdot)}{\delta \hat{x}_{k+1}^-} = \begin{bmatrix} \frac{\delta U_{OCV}}{\delta SOC} \Big|_{\hat{x}_{k+1}^-} & 1 & 1 \end{bmatrix}. \quad (8)$$

Mostly, the EKF algorithm can estimate the battery state space model accurately, as well as its parameters. The EKF algorithm based battery SOC estimation is reliable, high-precision, rapidly

**FIGURE 2** | The HPPC test installations.

convergent, and robust even if starting values are erroneous. As a result, the EKF algorithm is adopted in the work to estimate the battery SOC for balancing strategy.

## EXPERIMENT PROCEDURE AND RESULTS

### The Identification of Battery Equivalent Circuit Model Parameter

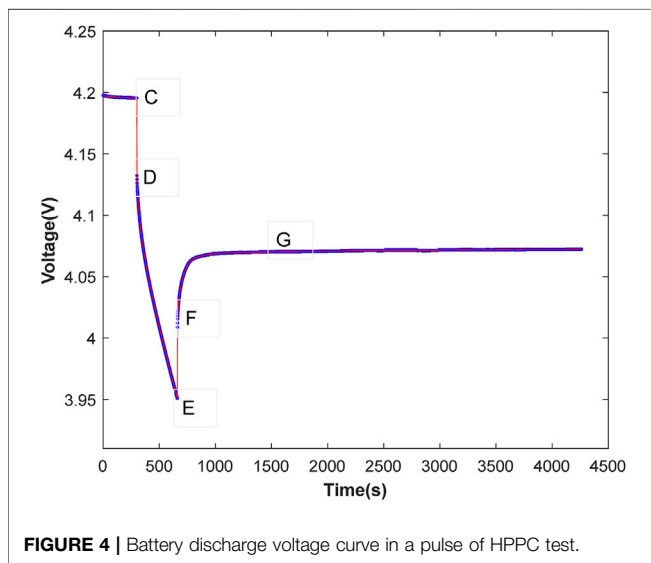
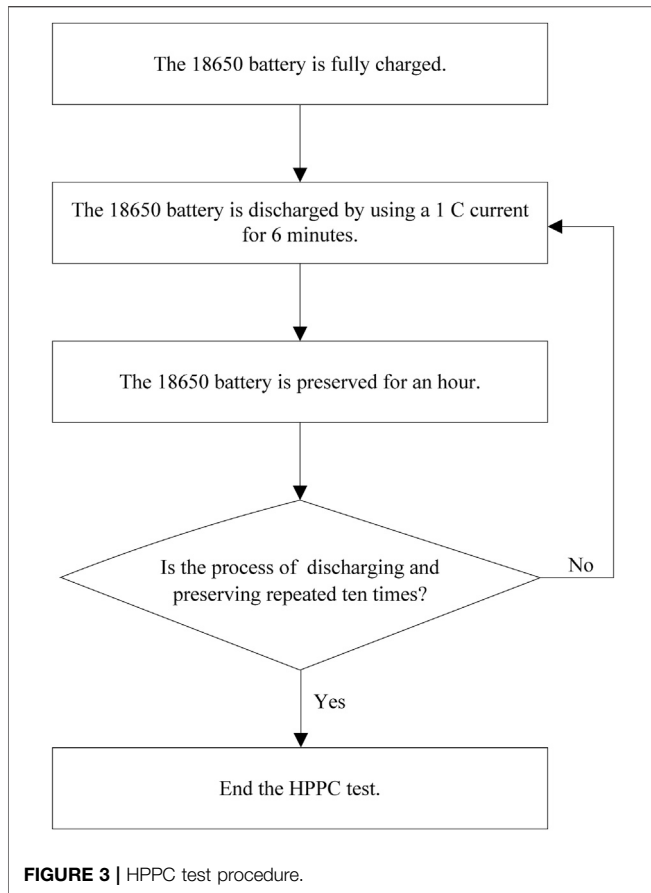
In the work, a hybrid pulse power characteristic (HPPC) test of the battery is performed to obtain the discharge data. 18650 lithium-ion battery with a rated capacity of 2.5 Ah is used in the experiment, and its detailed parameters are shown in **Table 1**. The HPPC test is conducted with 5 V 20 A NEWARE battery testing system (BTS 4000 type) and a calorstat at 25°C, which is shown in **Figure 2**.

**Figure 3** gives the HPPC test procedure. First, the 18650 battery is fully charged by using 0.5 C current, and the terminal voltage of the battery is 4.2 V. Then, the HPPC test is started. In the HPPC test process, the 18650 battery is discharged by using a 1 C current for 6 min at 25°C. Then, the battery is preserved for an hour, and the measured voltage variation curve of the 18650 battery in the 66 min is shown in **Figure 4**. The above process of discharging and preserving is repeated ten times. At last, the battery SOC is reduced to 0, and the battery voltage in the whole HPPC test process is shown in **Figure 5**.

In **Figure 4**, time  $C$  is the starting time of discharging and time  $E$  is the end time of discharging. From the figure, it can be observed that the voltage drops at time  $C$  and increases at time  $E$ . Therefore, the voltage variation can be used to calculate the internal resistance  $R_0$  as

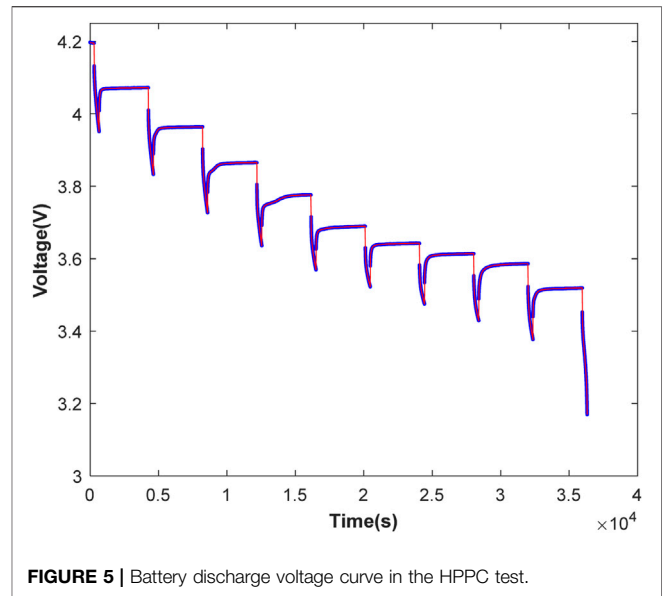
$$R_0 = \frac{(U_C - U_D) + (U_F - U_E)}{2I}, \quad (9)$$

where  $U_C$ ,  $U_D$ ,  $U_E$ , and  $U_F$  represent the voltage of times  $C$ ,  $D$ ,  $E$ , and  $F$ , respectively.



The dynamic characteristics include polarization characteristics and concentration effects of battery. The time constant and initial voltages can be calculated as follows:

$$\tau = RC, \tag{10}$$



$$U_1(t) = U_1(0)e^{-t/\tau_1} + IR_{pa}(1 - e^{-t/\tau_1}), \tag{11}$$

$$U_2(t) = U_2(0)e^{-t/\tau_2} + IR_{pc}(1 - e^{-t/\tau_2}), \tag{12}$$

where  $U_1(0)$  and  $U_2(0)$  are the initial voltages of the two RC networks, respectively.  $\tau_1$  is the polarization time constant;  $\tau_2$  is the concentration time constant; time  $F$  to time  $G$  is battery-preserving time after discharging; and the input current is 0. Therefore, it can be considered as RC network zero input state response. Terminal voltage can be calculated by substituting Eq. 11 and Eq. 12 into Eq. 10 as

$$U(t) = U_{OCV} - U_1(0)e^{-t/\tau_1} + U_2(0)e^{-t/\tau_2}. \tag{13}$$

The variation of polarization and concentration voltage can be obtained by subtracting the terminal voltage that is preserved 15 min from the open circuit voltage at time  $F$ . The curve fitting tool was used to perform exponential fitting of polarization voltage according to

$$f(t) = ae^{-\lambda_1 t} + be^{-\lambda_2 t}. \tag{14}$$

Referencing Eq. 13 and Eq. 14, the following parameters are generated:

$$a = U_1(0), b = U_2(0), \tau_1 = \frac{1}{\lambda_1}, \text{ and } \tau_2 = \frac{1}{\lambda_2}. \tag{15}$$

The battery has been preserved for enough time before time  $D$  and the polarization and concentration effect can be regarded as 0. Referencing Eq. 11 and Eq. 12, the following equations can be obtained:

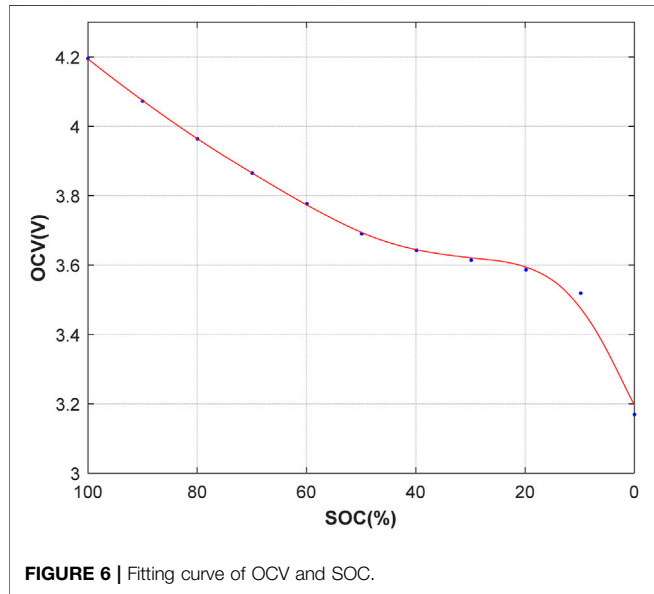
$$U_1(t) = IR_{pa}(1 - e^{-t/\tau_1}), \tag{16}$$

$$U_2(t) = IR_{pc}(1 - e^{-t/\tau_2}). \tag{17}$$

A very short variation from time  $E$  to time  $F$  can be regarded as 0, and the polarization and concentration voltage is unchanged. Eq. 16 and Eq. 17 are substituted as

**TABLE 2** | Model parameters obtained in the HPPC test.

Model Parameter	Value
$R_0$	0.025 $\Omega$
$R_{pa}$	0.019 $\Omega$
$R_{pc}$	0.026 $\Omega$
$C_{pa}$	2380.940 n F
$C_{pc}$	35630.410 n F



**FIGURE 6** | Fitting curve of OCV and SOC.

$$U_1(0) = IR_{pa}, \tag{18}$$

$$U_2(0) = IR_{pc}. \tag{19}$$

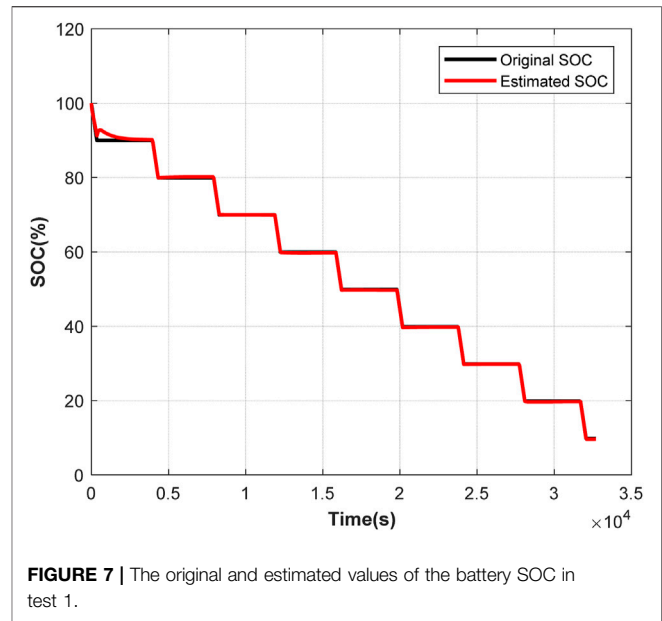
Therefore, the model parameters can be obtained from the above equations, and recorded in **Table 2**.

The measured battery discharge voltage curve in the HPPC test is shown in **Figure 5**. Meanwhile, the relationship of  $U_{OCV}$  and SOC is obtained by using the curve fitting tool, which is shown in **Figure 6** and its fitting polynomial is as

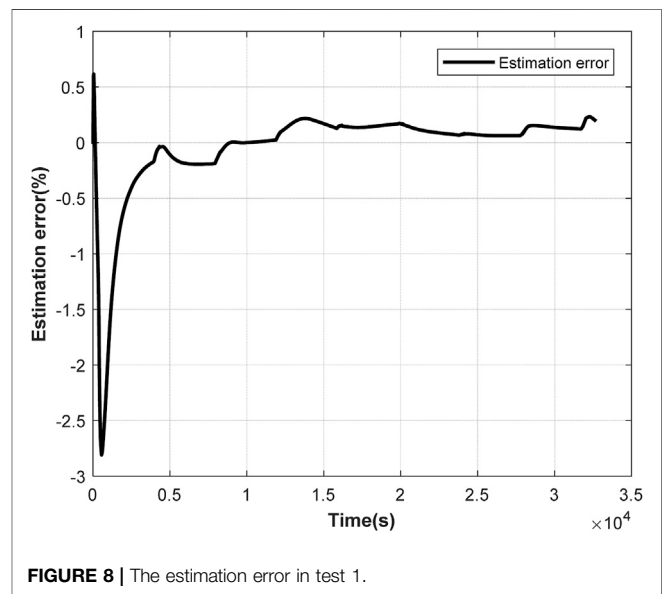
$$\begin{aligned}
 U_{OCV} = & -36.9035 \times SOC^8 + 112.1698 \times SOC^7 - 106.0058 \\
 & \times SOC^6 + 5.7740 \times SOC^5 + 44.7613 \times SOC^4 - 21.7232 \\
 & \times SOC^3 + 1.6606 \times SOC^2 + 1.0452 \times SOC + 3.4171.
 \end{aligned} \tag{20}$$

### Battery State of Charge Estimation Experiment

After the second-order RC equivalent circuit model of each battery is established and the parameters are identified. Battery SOC estimation experiment based on the EKF algorithm is performed then. The estimation includes two tests. In test 1, the initial battery SOC is clear. Meanwhile, the initial battery SOC is not clear in test 2.



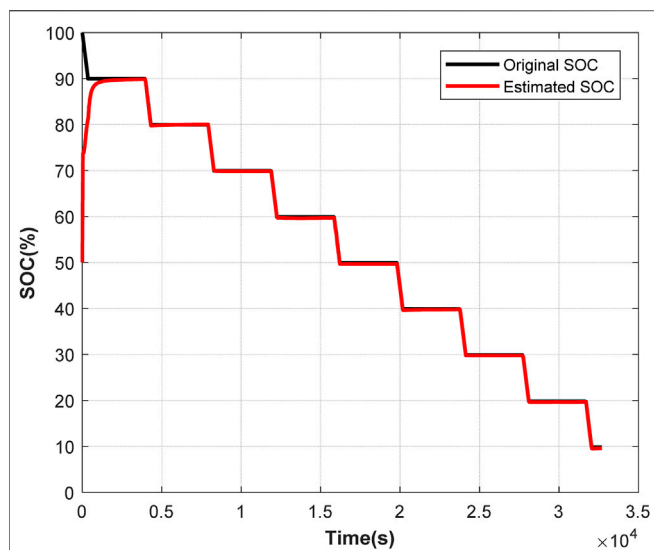
**FIGURE 7** | The original and estimated values of the battery SOC in test 1.



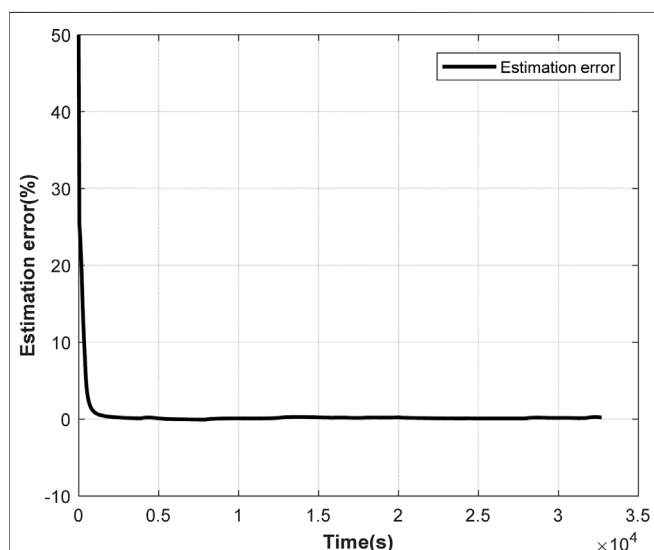
**FIGURE 8** | The estimation error in test 1.

In test 1, the EKF algorithm is used to estimate battery SOC based on the voltage. **Figure 7** shows the original battery SOC and the estimated battery SOC. **Figure 8** shows the estimation error. In test 1, the maximum absolute error is 0.0061 and the mean absolute error is 0.0013.

In test 2, the initial battery SOC is unknown, and it is assumed to be 0.5. The estimated SOC value converges to the true value while the initial SOC differs greatly from the true value. Original battery SOC and estimated battery SOC are shown in **Figure 9**. The estimation error is shown in **Figure 10**. As shown in **Figure 9** and **Figure 10**, the battery SOC estimated by the EKF algorithm has little error with the original battery SOC. In test 2, the maximum absolute error of SOC is 0.5 and the average absolute error of SOC is 0.0015.



**FIGURE 9** | The original and estimated values of the battery SOC in test 2.

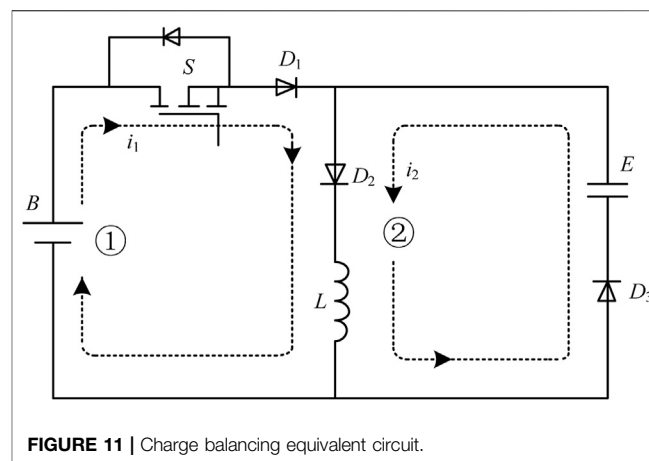


**FIGURE 10** | The estimation error in test 2.

From **Figures 7–10**, it can be concluded that the estimated SOC can rapidly converge to the original SOC even if the initial SOC value is uncertain, which indicates that the EKF algorithm has the advantages of high accuracy, fast convergence, and strong practicability in battery SOC estimation. The estimation method is applied to the balancing of batteries to improve the accuracy of estimating SOC.

## The Simulation Design of Battery Pack Active Balancing Circuit

In the working process of batteries, its active balancing equivalent circuit based on the capacitance is shown in **Figure 11**. Pulse width



**FIGURE 11** | Charge balancing equivalent circuit.

modulation (PWM) signal controlling is carried out on switch tube S. Meanwhile, the battery B charges the supercapacitor E through the inductance L. First, the switching tube S is on. The battery B supplies power to the inductance L through circuit 1 to store energy, and  $i_1$  is the balancing current. Then the switch is off, the energy stored in the inductance L is released to the supercapacitor E through circuit 2. The supercapacitor E is charged by current  $i_2$ . The balancing equivalent circuit is a chopper circuit, so the balancing current  $i_1$  can be controlled by adjusting the PWM wave duty ratio of the switching tube S.

The Simulink module is used to simulate the battery balancing circuit that is analyzed. **Figure 12** shows the active balancing circuit in the work. Battery 1 to Battery 8 are eight batteries in series. The battery's nominal voltage is set to 3.6 V and the rated capacity is set to 2.4 Ah. Rated capacity initial SOC of each battery is respectively set to 50%, 51%, 52%, 53%, 54%, 55%, 56%, and 57%. The batteries are charged by a 2.4 A current with 5 kHz switching frequency and 20% duty ratio.

The procedure of the active balancing method is shown in **Figure 13**, and the balancing control method adopts the extreme difference method. When the deviation of maximum SOC and minimum SOC of batteries is greater than 0.02, the balancing circuit is working. Otherwise, the balancing circuit is out of work. The program is written in the Matlab-Function module, and each battery SOC is the input of the module. When the battery is charged, the module outputs the difference between the maximum and minimum SOC of batteries, as well as the number of the battery with the maximum SOC. The output of the Matlab-Function module is used as the input of the IF-Action module in the Simulink, and it controls the balancing circuit by setting the judgment conditions.

**Figure 14** shows the SOC variations of eight batteries. When the time is 272s, all battery SOC's turn consistent, and the balancing process is completed. The inductance current variation is shown in **Figure 15**. In the figure, the balancing current reduces to 0 as the time is 272s.

Seven-phase steady-state inductor current of charge balancing is shown in **Figure 16**, which is a clear presentation of **Figure 15**.

After the batteries are charged, the inconsistency of the batteries is improved. The SOC difference of batteries is 7%

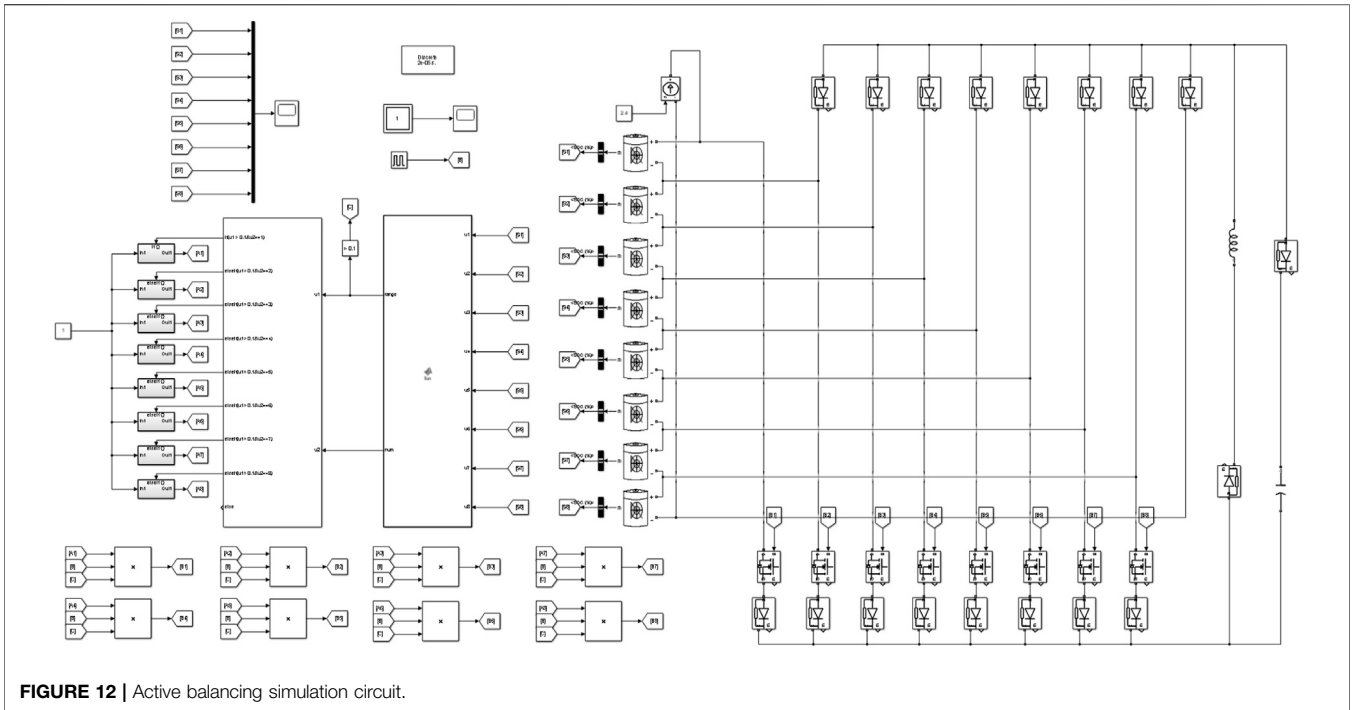


FIGURE 12 | Active balancing simulation circuit.

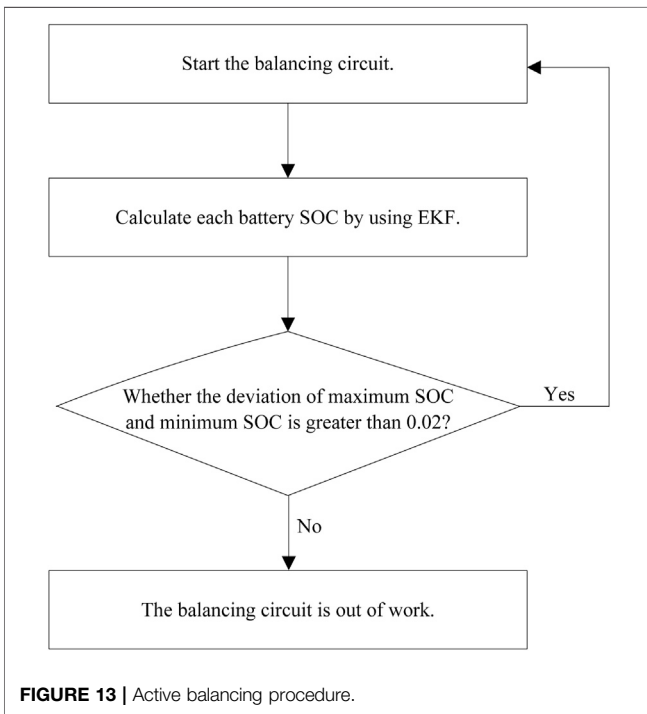


FIGURE 13 | Active balancing procedure.

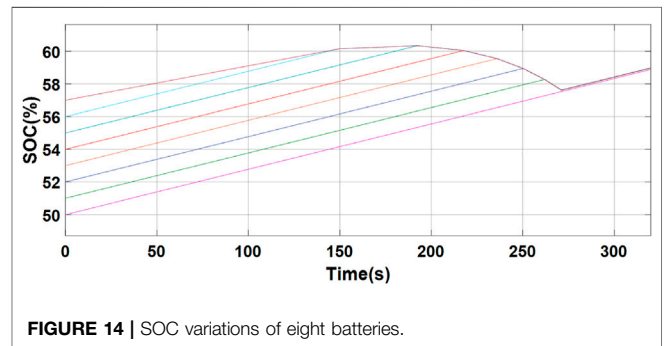


FIGURE 14 | SOC variations of eight batteries.

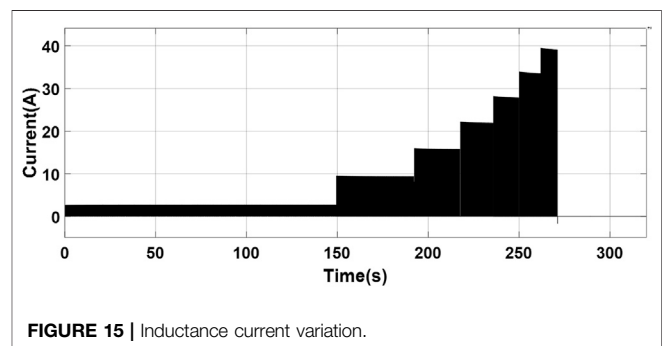


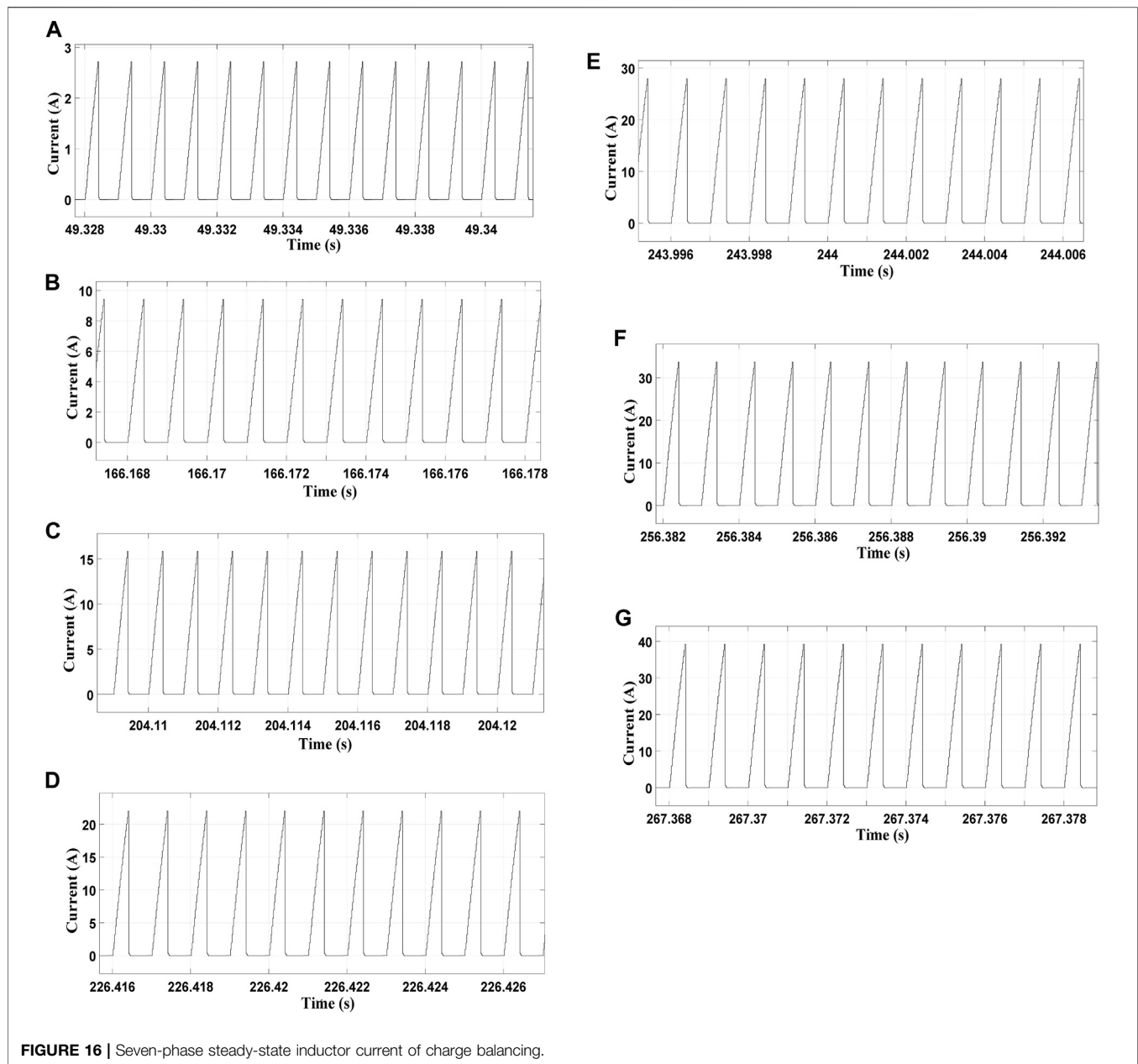
FIGURE 15 | Inductance current variation.

before charging. After balancing, the SOC difference of batteries drops to 0.02%. Meanwhile, the balancing time is merely 272s.

Therefore, this balancing scheme not only improves the inconsistency of the batteries but also increases the performance of the batteries. The balancing circuit current is controllable, and the balancing method is effective.

## CONCLUSION

An active balancing method based on SOC and capacitance has been presented to solve the inconsistency problem of lithium-ion batteries



in the battery packs of electric vehicles. The battery SOC has been estimated by the EKF algorithm accurately. The maximum absolute error of SOC evaluation is 0.0061, and the mean absolute error is 0.0013 when the initial battery SOC is clear. Meanwhile, the maximum absolute error of SOC evaluation is 0.5 and the average absolute error of SOC is 0.0015 when the initial battery SOC is not clear. An active balancing circuit based on the estimated battery SOC and capacitance balancing has been designed, and the balancing procedure only costs 272s, which is controllable and effective.

## DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

## AUTHOR CONTRIBUTIONS

RL wrote the manuscript. CZ implemented the experiment.

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