

## RESEARCH ARTICLE

# Fast Open Circuit Voltage Estimation of Lithium-Ion Batteries Using a Relaxation Model and Genetic Algorithm

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**ABSTRACT** Battery Open Circuit Voltage (OCV) is of fundamental characteristic for enabling battery modeling and states estimation. However, the traditional OCV measurement method takes a very long time to make the battery reaches its equilibrium, which is rather inconvenient and cannot be performed online for battery energy storage application. Motivated by this, this paper proposes an effective method for fast OCV estimation in the relaxation process. In this work, a novel relaxation model is designed for capturing the voltage response of a battery during relaxation time and the Genetic Algorithm (GA) is further applied for optimizing the model parameters and acquiring accurate OCV estimation results. Experimental results confirm the validity of the proposed method under different State of Charges (SOCs), current rates, ambient temperatures, and aging conditions. The results suggest that the proposed method can accurately and quickly estimate battery OCV, which only takes 10 minutes of measurement data (more than 2 hours for the traditional method) and the maximum estimation error is limited to merely 1.8 mV.

**INDEX TERMS** Lithium-ion battery, open circuit voltage, relaxation model.

## I. INTRODUCTION

With the continuously increasing concerns over fossil fuel consumption and the resulting environmental pollution crises, transportation electrification has become an inevitable trend for cutting carbon emissions and protecting the environment [1]. The eco-friendly and energy-efficient Electric Vehicles (EVs) have the chance to replace a great deal of internal combustion engine vehicles. However, a fundamental challenge is to find a suitable Energy Storage System (ESS) that can displace fossil fuel and support the high-mileage driving of EVs [2], [3], [4]. Among others, Lithium-ion (Li-ion) Batteries have recently been regarded as one of the most promising energy storage components because of their high energy and power density, high charge and discharge efficiency, no memory effect, and polluting-free characteristics [5], [6], [7], [8].

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However, the performance of the Li-ion battery is constantly influenced by various factors. A well-designed Battery Management System (BMS) is essential to guarantee the cells work within a proper and safe operating area [9], [10], [11], [12], [13]. As the basic indicators, battery State of Charge (SOC), State of Health (SOH), and State of Power (SOP) should be accurately monitored in real-time for the decision-marking of a BMS [14]. In practice, the strong nonlinear characteristics and the measurement noise interference often contaminate the accuracy of the battery status, which leaves the battery states estimation a remaining challenge [15], [16], [17].

Advanced model-based and data-driven methods use algorithms such as Kalman Filters [18], [19], [20], [21], H-infinity filters [22], [23], Particle filters [17], [24], [25], support vector machine [18], and deep neural networks [26], [27] to estimate the batteries' states. It is easy to understand that the model-based methods cannot perform well without a good battery model. In this thread, the Open Circuit Voltage (OCV)

is one of the fundamental characteristics of battery modeling. Generally, OCV represents the potential of the charge movements between the electrodes and is the intrinsic property of a battery.

As an indicator of the essential property of the Li-ion battery, the OCV of the Li-ion battery can be also used for state estimation besides modeling. For example, OCV is commonly applied for establishing an OCV-SOC function to estimate the battery SOC in BMS. It's obvious that the SOC estimation accuracy is highly related to a precise OCV measurement [28]. In order to reach the equilibrium state inside, the battery has to be fully relaxed usually requiring several hours or even days [29]. The lengthy relaxation time limits the usage of OCV for battery-based applications.

In this context, fast OCV measurement is an urgent demand to mitigate the long-time requirement. Dubarry *et al.* [30] and Cui *et al.* [31] use  $1/25$  C charging and discharging current aiming at obtaining the close-to-equilibrium OCV by calculating the average potential between the charging and discharging voltages. Chen *et al.* [32] choose  $C/2$  current to charge or discharge the battery with a 10% SOC interval, and OCV can be measured after 45 min rest period to reach an equilibrium condition. The average OCV between charging and discharging is used to model the battery. Knap and Stroe [33] evaluate four OCV test methods for battery SOC estimation including  $iOCV$ ,  $qOCV$ ,  $pOCV$ , and  $eOCV$ . The longest test procedure  $iOCV$  needs 680 hours to obtain the OCV curve. Some works [34] also use a high-order polynomial function to represent the OCV-SOC curve by measuring the OCV with 5% SOC resolution. From the above descriptions, we realize that the aforementioned OCV tests are still quite time-consuming and inconvenient for battery applications, especially, for the cases when OCV is expected to be obtained within a short time.

It is noted that EVs are often stopped during a traffic jam or traffic light, and the battery current is close to zero when the EV stops. There leaves a chance that the OCV could be estimated during a short interruption period, which facilitates onboard battery OCV acquisition. A straightforward way for battery OCV estimation is to utilize the characteristic of the voltage responses during relaxation time. Meng *et al.* [28] propose a novel multiple correction approach for battery OCV estimation, which has been proven to be feasible on a LiFePO<sub>4</sub> battery with different SOCs. However, the method suffers from a trouble tuning procedure of the parameters, which is not convenient for practical usage. Pei *et al.* [35] also develop a voltage relaxation model to estimate the terminal voltage of a battery. However, the relaxation voltage has a very strong nonlinear characteristic, which complicates the curving fitting process.

As an alternative choice, many researchers focus on estimating battery OCV using the Equivalent Circuit Models (ECMs). The reason is that the ECMs have a simple structure, while they can capture the main voltage dynamics of a battery. Duong *et al.* [36] propose a Multiple Adaptive Forgetting Factors based RLS (MAFF-RLS) method for identifying the

parameters of an ECM, which obtains the OCV from a 40 Ah LiFePO<sub>4</sub> battery. Yang [37] first estimates the OCV and the RC circuits of an ECM simultaneously using an evolutionary algorithm. Zhou *et al.* [38] proposed a weighted voltage relaxation model consisting of two parallel resistor-capacitor (RC) components for fast OCV estimation. By taking a short rest period (less than 30 minutes), the maximum OCV estimation error is limited to 4 mV through all the tests. It can be seen that the estimation accuracy is low due to the limited ECM modeling ability.

In this work, a novel voltage relaxation model is proposed for describing the dynamic response of a battery during the rest process. In comparison with the traditional Thevenin model, the proposed relaxation model is more accurate for simulating battery terminal voltage in relaxation time. For obtaining the best results, the Genetic Algorithm (GA) is further carried out for optimizing the model parameters, which shows an excellent performance in dealing with the nonlinear effects. The validity of the proposed method is verified experimentally in terms of accuracy and robustness with two batteries, which also considers both the temperature variations and the battery aging effect. The main contributions of this work are listed as follows:

- (1). The Li-ion battery OCV can be accurately estimated within 10 minutes by using the proposed voltage relaxation model, whose parameters are adjusted in a GA framework.
- (2). The validation of the proposed method is proved not only on different SOCs but also with the variation of temperatures and battery aging status.

The remainder of this paper is organized as follows. Section II introduces the proposed relaxation model. Section III elaborates the procedures of parameter optimization with the GA. Experimental results are carried out in Section IV. The main conclusions are given in Section V.

## II. BATTERY MODELING IN RELAXATION TIME

In this section, the experimental setup for measuring the OCVs of the batteries is introduced first. The voltage relaxation behavior of a battery is investigated afterward. A novel relaxation model is further carried out to describe the dynamic characteristics of the battery in relaxation time.

### A. EXPERIMENTAL SETUP

The experimental tests are carried out on two LiFePO<sub>4</sub> batteries with a 3.2 V nominal voltage to validate the performance of the proposed fast battery OCV estimation method. The upper and lower cut-off voltages of the batteries are 3.6 V and 2 V, respectively. The specifications of the batteries are listed in Tab. 1. As shown in Fig. 1, the battery test platform includes a thermal chamber to control the ambient temperature, a Chroma 17011 test station to charge and discharge the battery, a host computer to generate the control signal and store the measurement data. In this study, the sampling frequency is set to 1 Hz.

In this section, we have tested Cell A to measure the OCV with different SOCs and current rates. The voltage and current

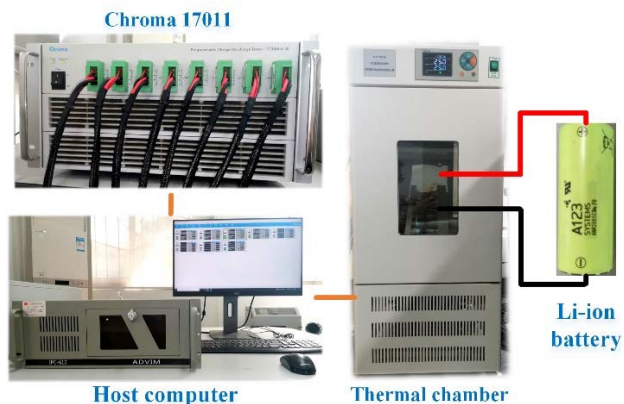


FIGURE 1. Experimental test platform for Li-ion batteries.

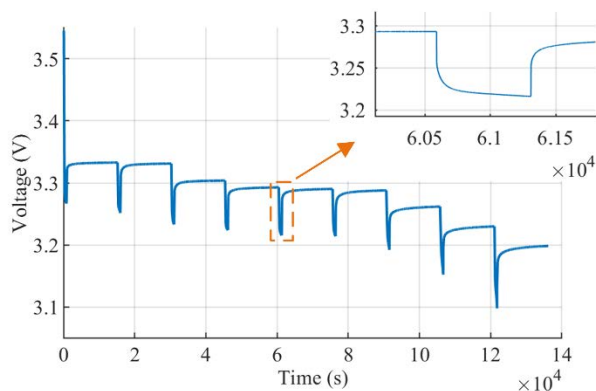


FIGURE 2. Voltage profile of battery OCV measurements with 0.5 C discharging rate under 25 °C.

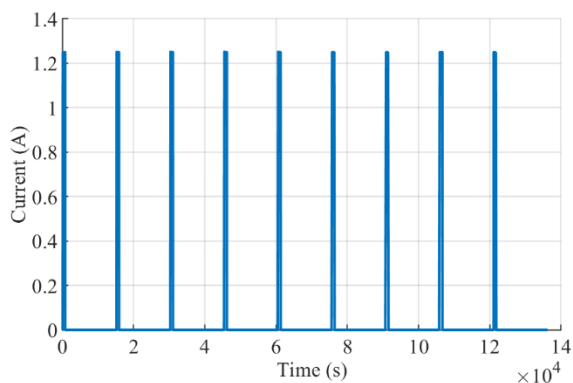


FIGURE 3. Current profile of battery OCV measurements with 0.5 C discharging rate under 25 °C.

profiles of the OCV measurements are shown in Figs. 2 and 3, where the ambient temperature is set to 25 °C. It can be seen that the battery is discharged with a 0.5 C rate with a 10% SOC resolution, the terminal voltages in 4 hour’s rest period are measured as OCVs.

**B. ANALYSIS OF BATTERY VOLTAGE RELAXATION BEHAVIOR**

Battery voltage is characterized by the potential difference between the two electrodes. Generally, the voltage response

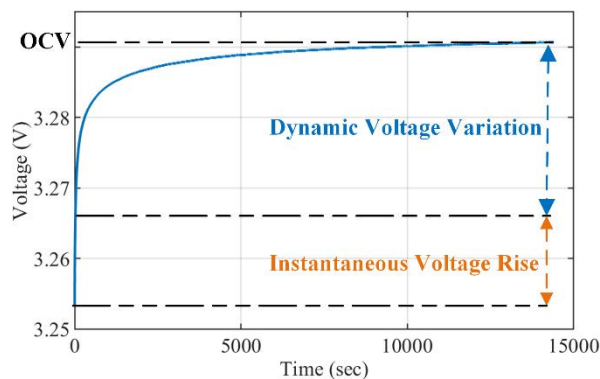


FIGURE 4. Post-discharging voltage relaxation profile.

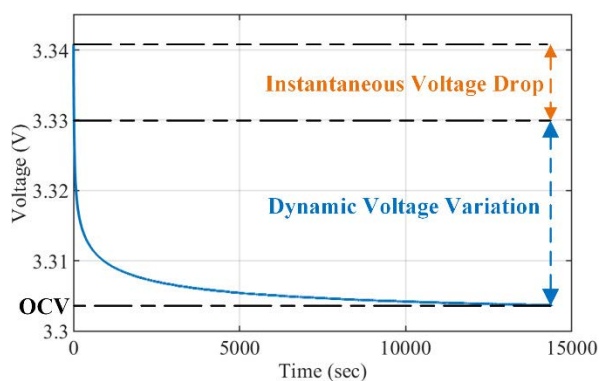


FIGURE 5. Post-charging voltage relaxation profile.

consists of instantaneous voltage variation, which is caused by the Ohmic resistance, and the dynamic variation, which is caused by the kinetic effect and ion transfer, etc. For obtaining the OCV of a battery, it has to take a long time (several hours or even days) for reaching the equilibrium state due to the slow process of the internal chemical and physical reaction. Consequently, the cut-off voltage of a battery cannot immediately meet the OCV without a long relaxation time.

As shown in Figs. 4 and 5, the relaxation voltage of a battery takes 4 hours for reaching an equilibrium, while the voltage trajectory has a quite strong nonlinear characteristic, where the voltage variation rate significantly decreases with time. Consequently, there remain difficulties in predicting battery OCV within a short relaxation time.

**C. RELAXATION MODEL**

In this subsection, a relaxation model is proposed to simulate the terminal voltage variation of a battery during the relaxation process.

The Thevenin model is the most used battery model as it has a simple structure and provides acceptable modeling accuracy under various operating conditions. As shown in Fig. 6,  $R_0$  is the Ohmic resistance, which consists of the electrolyte resistance and electrode material resistance, etc.  $R_p$  and  $C_p$  are the electrochemical polarization capacitance

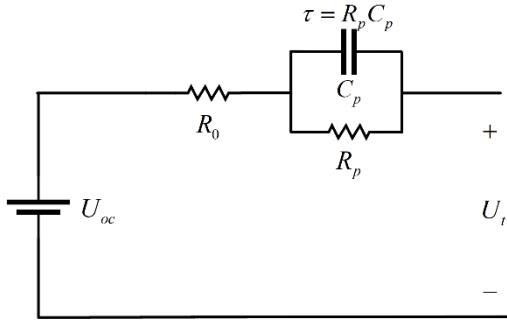


FIGURE 6. Conventional Thevenin model.

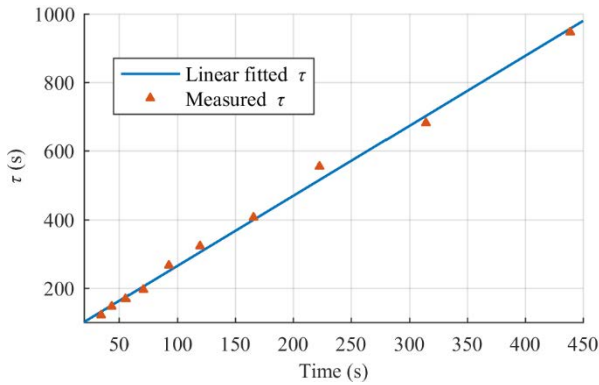


FIGURE 7. Post-discharging time constant profile.

and resistance, respectively.  $\tau$  is known as the time constant of a battery, which equals  $R_p C_p$  in the Thevenin model.

Despite the simplicity, the conventional Thevenin model with fixed parameter values is incompetent for describing the dynamic voltage variation through the relaxation process. During the relaxation period, the dynamical response of the battery transfers from the charge-transfer region with a minor time constant to the diffusion region with the slowest time constant. Consequently, the time constant  $\tau$  gradually increases with the increment of the relaxation time.

Here we define  $\tau_t$  as the time constant at the time of  $t$ , which is determined by,

$$\tau_t = 1 / \left( \ln \frac{U_{OC} - U_{t-1}}{U_{OC} - U_t} \right) \quad (1)$$

where  $U_{oc}$  is battery OCV,  $U_t$  and  $U_{t-1}$  are the terminal voltages at the time of  $t$  and  $t-1$  respectively. Assuming the  $U_{oc}$  is known, the time constant profiles at different times can be obtained, which are shown in Fig. 7 and Fig. 8.

It is observed that the  $\tau_t$  has an obvious linear relationship with the relaxation time. Besides,  $\tau_t$  is closely related to battery OCV and the terminal voltage in the relaxation process. Therefore, instead of using a fixed parameter to describe the time constant, a time-varying  $\tau_t$  is applied in this work for establishing a relaxation model.

As shown in Fig. 9, the Ohmic resistance is omitted since there is no current excitation during the relaxation process.

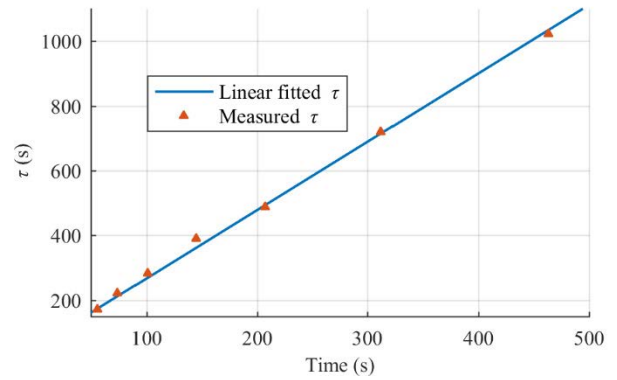


FIGURE 8. Post-charging time constant profile.

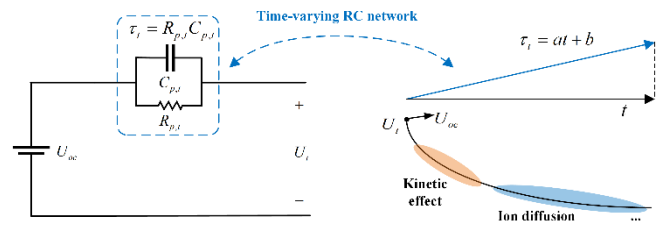


FIGURE 9. The proposed relaxation battery model.

The proposed relaxation battery model contains an RC network. Both the polarization capacitance  $C_{p,t}$  and the polarization resistance  $R_{p,t}$  are designed as time-varying parameters. The governing equation of the proposed relaxation battery model is expressed as,

$$\begin{cases} \hat{U}_t = U_{OC} - (U_{OC} - \hat{U}_{t-1}) e^{(-1/\tau_t)} \\ \tau_t = at + b \end{cases} \quad (2)$$

where  $U_t$  and  $U_{t-1}$  are the simulated voltages from the relaxation battery model at the time of  $t$  and  $t-1$ .  $\tau_t$  is subjected to a linear function, where  $a$  and  $b$  are the polynomial coefficients of the linear function.

It can be seen that  $a$ ,  $b$ , and  $U_{oc}$  are the parameters to be identified. The method for identifying the parameters is discussed in the following section.

### III. THE PROPOSED OCV ESTIMATION METHOD

#### A. PARAMETER IDENTIFICATION

The model parameters can be obtained by fitting the terminal voltage measurements with the output voltages from the relaxation battery model. Here we define a parameter vector, which is expressed as  $\theta = [a \ b \ U_{oc}]^T$ . A least-square based estimator is designed for estimating the model parameters, which is expressed as,

$$\hat{\theta} = \arg \min_{\theta} \sum_{t=t_i}^{t_u} (U_t - \hat{U}_t)^2 \quad (3)$$

where  $\hat{\theta}$  is the estimated parameter vector,  $U_t$  is the measured battery terminal voltage,  $\hat{U}_t$  is the model simulated voltage,

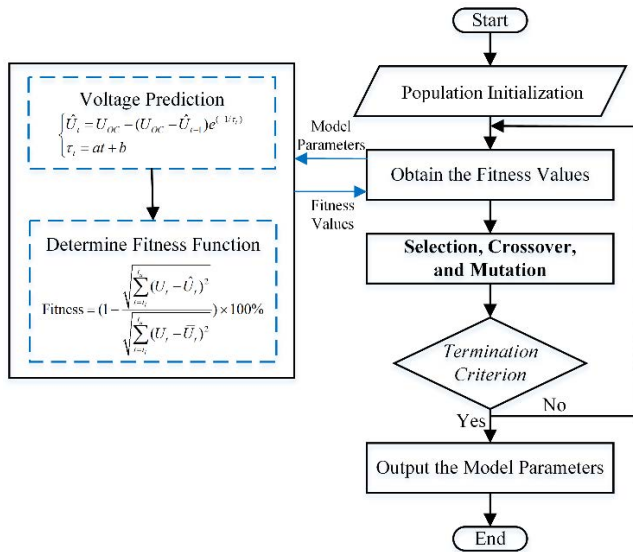


FIGURE 10. Flowchart of the optimization of model parameters with GA.

which is obtained from (2).  $t_l$  and  $t_h$  are the upper and lower limits of the investigated battery relaxation time.

The fitness function is further presented to compare the model output  $\hat{U}_t$  and the measured  $U_t$ , which is expressed as,

$$\text{Fitness} = \left( 1 - \frac{\sqrt{\sum_{t=t_l}^{t_u} (U_t - \hat{U}_t)^2}}{\sqrt{\sum_{t=t_l}^{t_u} (U_t - \bar{U}_t)^2}} \right) \times 100\% \quad (4)$$

where  $\bar{U}_t$  is the average value of  $U_t$  over the relaxation time period.

To obtain a reasonable parameter identification result, the GA is presented for optimizing the model parameters, which is further discussed in the following subsection.

### B. GENETIC ALGORITHM

In comparison with the conventional least square-based methods that are very sensitive to the initial values of the parameters, the GA is capable of finding the global optimal solution without any initial guesses. Based on Darwin’s theory of evolution, various species compete with each other in the environment and only the fittest can survive [1], [39], [40].

The evolutionary process of a population is introduced in this work for explaining the GA. The genetic information of the population is contained in the chromosomes, while the evolution process includes selection, crossover, and mutation. The selection refers to some of the existing population is selected to generate the offspring. During the crossover process, the chromosomes of the offspring are hybridized from the parents. The mutation process makes random changes to the chromosomes, which brings new genes into the population.

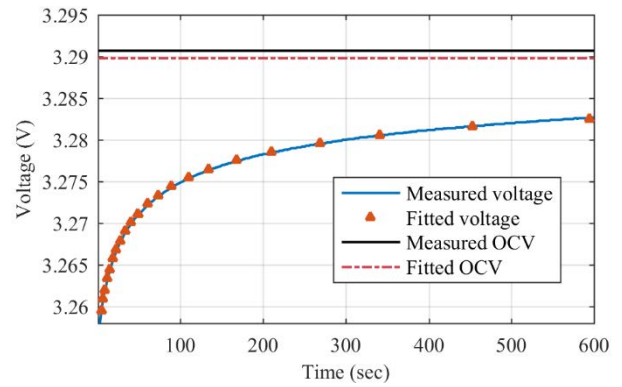


FIGURE 11. The experimental results of OCV estimation and the model fitted voltage in comparison with the measurements (50% SOC).

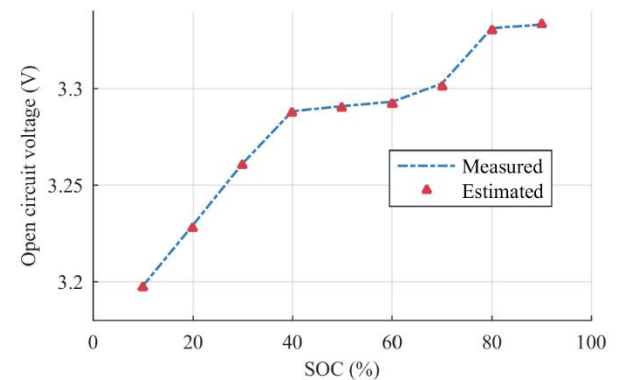


FIGURE 12. OCV estimation results with 0.5 C current rate.

The flowchart of the GA for optimizing the model parameters is shown in Fig. 10. The calculation is executed according to the fitness function. If the fitness value is not satisfied, GA takes the selection, crossover, and mutation for updating the parameters. The repetition terminates when the fitness value is larger than the boundary value and the output values are regarded as the final identified model parameters.

### IV. EXPERIMENTAL STUDIES

Considering a balance between practicability and modeling accuracy, we only take 600 s relaxation voltage measurements to establish the relaxation model and optimize the model parameters in this work. The experimental results concerning battery OCV estimation and the fitted terminal voltages are shown in Fig. 11. It can be seen that the simulated voltage plots almost identical curves in comparison with the voltage measurements, which confirms the modeling accuracy of the proposed relaxation model. Meanwhile, the estimated battery OCV is very close to the reference, which proves the accuracy of the proposed method for OCV estimation.

To further investigate the proposed fast OCV estimation method under different operating conditions, additional tests concerning different SOCs and current rates are carried out in this work. The experimental results with 0.5 C, 1 C, and 2 C current rates are shown in Figs. 12, 14, and 16. It can be seen

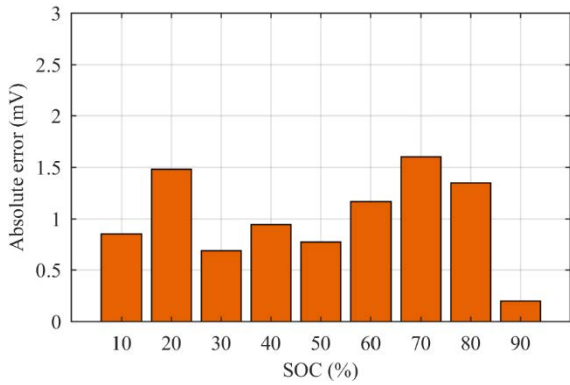


FIGURE 13. Absolute errors of OCV estimation with 0.5 C current rate.

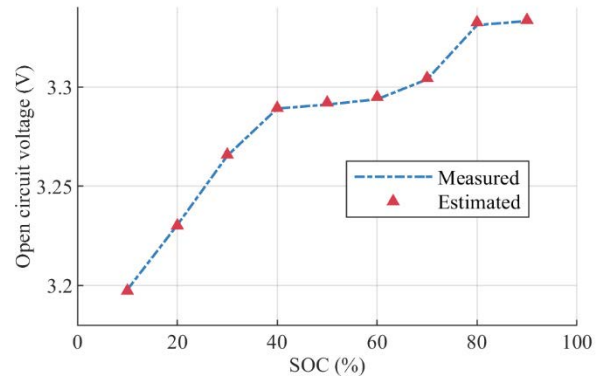


FIGURE 16. OCV estimation results with 2 C current rate.

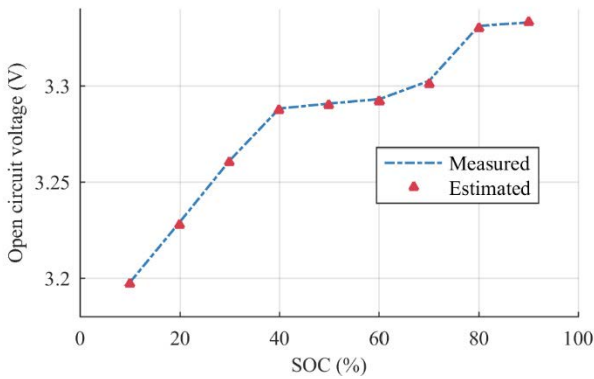


FIGURE 14. OCV estimation results with 1 C current rate.

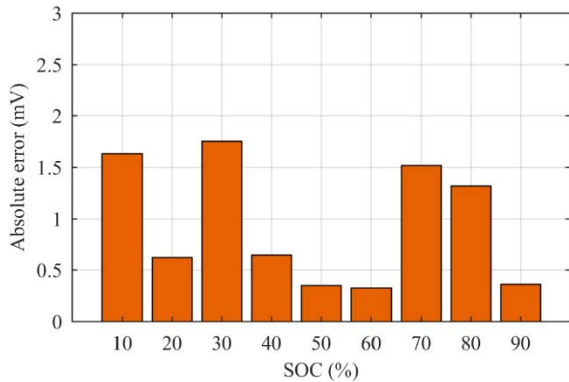


FIGURE 15. Absolute errors of OCV estimation with 1 C current rate.

that battery OCV is rather dependent on battery SOC instead of the current rates. The experimental results suggest that the proposed method can accurately estimate battery OCV, where the estimated OCV values can well track the references all the time. The absolute errors of the OCV estimation are shown in Figs. 13, 15, and 17, where the maximum error is limited to 1.8 mV. The validity of the proposed method with different SOC and current rates is proved accordingly.

**A. VALIDATION UNDER DIFFERENT AGING STATUSES AND AMBIENT TEMPERATURES**

To investigate the effectiveness of the proposed method under different circumstances, we have further verified the pro-

TABLE 1. Specifications of the LiFePO4 batteries.

	MODEL	Initial Capacity	Present Capacity
Cell A	ANR26650	2.55 Ah	2.55 Ah
Cell B	ANR26650	2.55 Ah	2.34 Ah

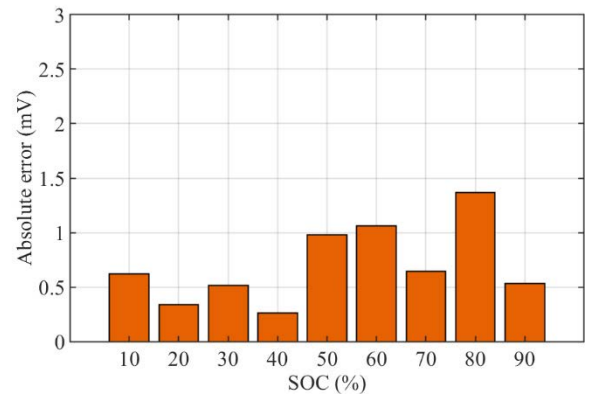


FIGURE 17. Absolute errors of OCV estimation with 2 C current rate.

posed method with different aging statuses and ambient temperatures in this work.

Batteries’ aging effects are commonly described as capacity losses. As shown in Table 1, Cell B has the same specifications as Cell A, while the capacity of Cell B is lower than the initial ones. Meanwhile, the thermal effects are investigated by testing Cell A under the ambient temperature of 40 °C. For controlling variables, the current rate is selected as 0.5 C in this subsection.

The experimental results concerning battery OCV estimation are shown in Figs. 18-21. It can be seen that both the aging and thermal effects only exert a slight influence on battery OCV. Likewise, the proposed method shows superb performance in terms of accuracy and robustness for estimating battery OCV, where the estimated values always track the reference. The feasibility and adaptability of the proposed method with different aging statuses and ambient temperatures are proved accordingly.

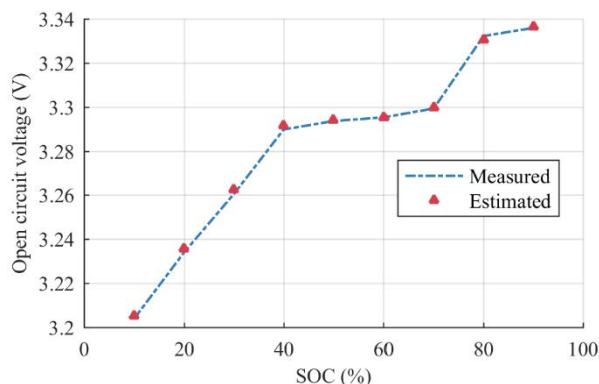


FIGURE 18. OCV estimation results of Cell B under 25 °C.

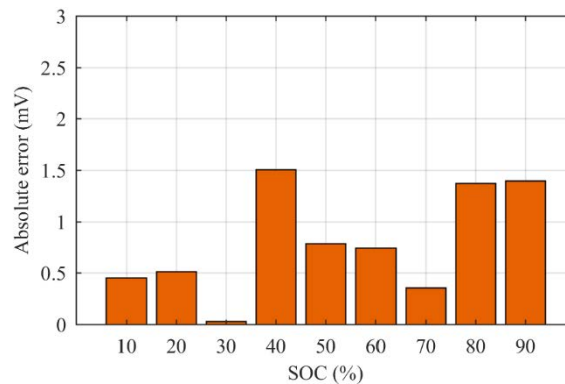


FIGURE 21. OCV estimation results of Cell A under 40 °C.

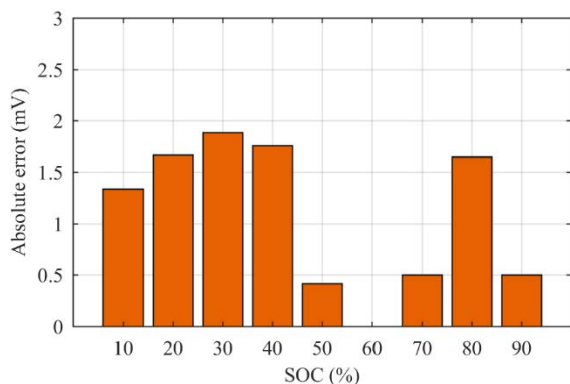


FIGURE 19. Absolute OCV estimation errors of Cell B under 25 °C.

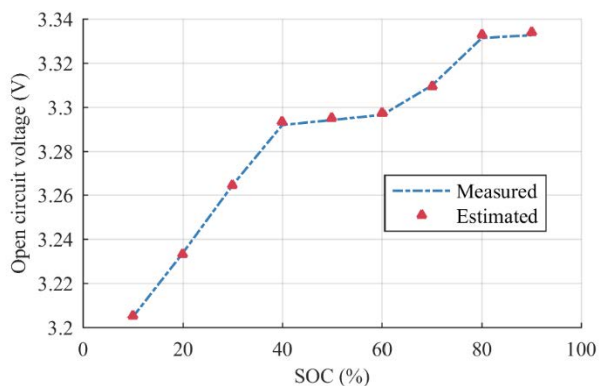


FIGURE 20. OCV estimation results of Cell A under 40 °C.

TABLE 2. Comparison of the relaxation time and the maximum errors using different methods.

Method	Relaxation time	Maximum error
Ref. [28]	15 minutes	3.97 mV
Ref. [35]	20 minutes	3.00 mV
Ref. [38]	30 minutes	4.00 mV
Proposed	10 minutes	1.80 mV

The required relaxation time and the maximum OCV estimation errors using different methods are compared in Table. 2. It can be seen that the maximum errors in [28], [35], and [38] are all higher than 3 mV. In contrast, the method

proposed in this work only takes 10 minutes of the relaxation time, and the maximum estimation error is limited to 1.8 mV. The above results confirm the superiority and practicability of the proposed method.

V. CONCLUSION

This study proposes an effective method for estimating battery OCV within a short relaxation time period. A novel relaxation model is designed for characterizing the voltage response of a battery during the relaxation process. The proposed relaxation model can correctly simulate the terminal voltage in relaxation time, which significantly outperforms the traditional Thevenin model in terms of accuracy. The GA can effectively deal with the nonlinear effect, which is applied for optimizing the model parameters and obtaining the best OCV estimation results.

Experimental tests have verified the effectiveness of the proposed method under different SOC's, current rates, aging status, and ambient temperatures. The proposed method shows excellent performance for estimating battery OCV, which takes only 10 minutes of measurement data, and the maximum estimation error is limited to 1.8 mV.

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