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# Online full-parameter identification and SOC estimation of lithium-ion battery pack based on composite electrochemical - dual circuit polarization modeling

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**Abstract.** A new composite electrochemistry-dual circuit polarization model (E-DCP) is proposed by combining the advantages of various electrochemical empirical models in this paper. Then, the multi-innovation least squares (MILS) algorithm is used to perform online full parameter identification for the E-DCP model in order to improve data usage efficiency and parameter identification accuracy. In addition, on the basis of the E-DCP model, the MILS and the extended Kalman filter (EKF) are combined to enhance the state estimation accuracy of the battery management system (BMS). Finally, the model and the algorithm are both verified through urban dynamometer driving schedule (UDDS) and the complex charge-discharge loop test. The results indicate that the accuracy of E-DCP is relatively high under different working conditions, and the errors of state of charge (SOC) estimation after the combination of MILS and EKF are all within 2.2%. This lays a concrete foundation for practical use of the BMS in the future.

## 1. Introduction

The Battery Management System (BMS) monitoring and regulating the core parameter of SOC will affect the effect and security of the battery power supply system output in the entire life cycle of the lithium-ion battery pack. Therefore, it is absolutely necessary to monitor SOC change in real time to ensure secure and reliable operation of the lithium-ion battery pack [1-3].

As the most widely used estimation method in recent years, the accuracy of the Kalman filter has been constantly improved. Wang et al. proposed a compound equivalent circuit model and used an improved Kalman filter algorithm to estimate the state of lithium-ion batteries [4]. In the literature [5], the SOC estimation method of the lithium-ion battery based on tomographic images is studied. Wang et al. studied a new SOC estimation method based on parameter estimation open circuit voltage (OCV) [6]. In the literature [7], a new battery state estimation method based on multi-model switching strategy is proposed. In the literature [8], an energy management strategy for ternary lithium batteries based on dynamic equivalent circuit modeling and differential Kalman filter under time varying conditions is proposed. Jin et al. compared the SOC estimation effects of the integer order model and the fractional order model under different working conditions [9]. Wang et al. built a fractional order equivalent circuit model for super capacitors and estimated SOC based on this model [10-12]. In the



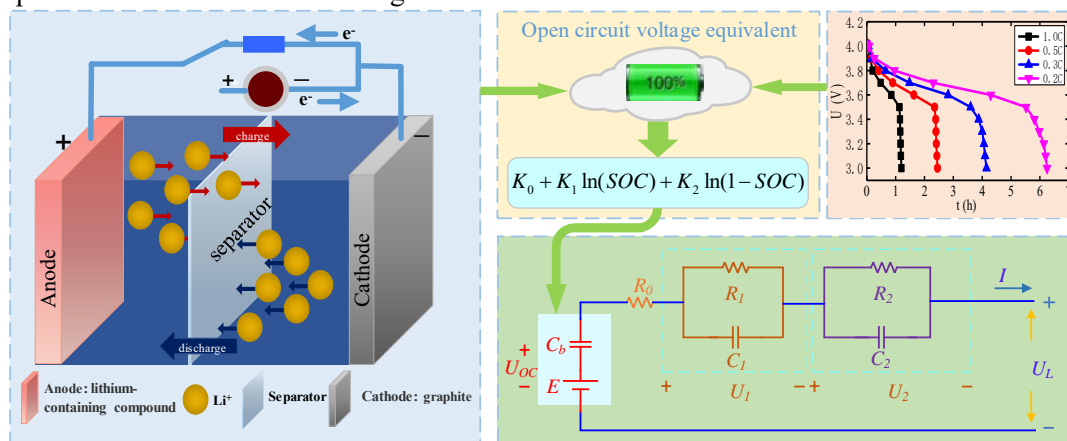
literature [13], an equivalent circuit modeling method considering the inconsistencies of battery cells is proposed

A new composite E-DCP model is proposed by combining the advantages of various electrochemical empirical models in this paper, and the MILS algorithm is used to perform online full parameter identification for the E-DCP model, in order to better present the dynamic performance of power lithium-ion batteries. Besides, EKF is used for system state estimation to achieve adaptive tracking adjustment of the state variable. This lays a concrete foundation for accurate BMS SOC estimation.

## 2. Theoretical analysis

### 2.1. Electrical equivalent modeling

A new E-DCP model is proposed by analyzing commonly used electrochemical models, and combining the advantages of various empirical models under the premise that the requirement of secure and reliable energy supply is met, in order to reveal the internal oxidation-reduction mechanism of lithium-ion batteries and achieve accurate modelling of the battery model. The equivalent structure of each part of the model is shown in Figure 1.



**Figure 1.** Electrical equivalent modelling.

In Figure 1,  $R_0$  is the battery ohmic resistance, which is the instantaneous voltage drop caused by battery current;  $R_1$  and  $R_2$  the polarization resistance of the battery;  $C_1$  and  $C_2$  are the polarization capacitance of the battery. The parallel circuit composed of  $R_1$  and  $C_1$  has a large time constant; the parallel circuit composed of  $R_2$  and  $C_2$  has a small time constant;  $I$  is the loop current of the battery;  $U_L$  is the battery terminal voltage.  $E$  is the ideal voltage source.  $E$  is used together with  $C_b$  as a whole to represent the change of open circuit voltage  $U_{oc}$ . The open circuit voltage in the E-DCP model is represented by the optimized electrochemical empirical equation.

### 2.2. State space description

Based on the voltage and current reference directions in Figure 1, the continuous state space equation can be obtained based on the E-DCP model by combining the KCL and KVL law, as shown in Equation (1).

$$\begin{cases} dU_1/dt = I_1/C_1 - U_1/R_1C_1 \\ dU_2/dt = I_2/C_2 - U_2/R_2C_2 \\ U_L = U_{oc}(SOC_t) - I_tR_0 - U_1 - U_2 \end{cases} \quad (1)$$

Discretization processing is performed for the continuous state space expression is equation 1 to meet the requirement of parameter identification. The obtained differential equation is shown in Equation (2).

$$\begin{cases} [U_1(k) - U_1(k-1)]/T = -U_1(k)/R_1C_1 + I(k)/C_1 \\ [U_1(k-1) - U_1(k-2)]/T = -U_1(k-1)/R_1C_1 + I(k-1)/C_1 \\ [U_2(k) - U_2(k-1)]/T = -U_2(k)/R_2C_2 + I(k)/C_2 \\ [U_2(k-1) - U_2(k-2)]/T = -U_2(k-1)/R_2C_2 + I(k-1)/C_2 \end{cases} \quad (2)$$

where T is the sampling time.

With the simultaneous equations of equation 1 and equation 2, the differential equation for the full parameter identification system can be obtained, as shown in Equation (3).

$$U_L(k) = c_0 + c_1U_L(k-1) + c_2U_L(k-2) + c_3I(k) + c_4I(k-1) + c_5I(k-2) \quad (3)$$

where  $c_0$  is the constant term and  $c_1$  to  $c_5$  are the coefficients of the differential equation.

### 2.3. Full-parameter online identification

The recursive least squares (RLS) algorithm is the online form of the minimal least algorithm. This algorithm is easy to realize and has high accuracy, but tends to have problems, such as data saturation, with the increase of the data volume. To avoid the above-mentioned problems, the MILS algorithm is used for online parameter identification for the lithium-ion battery.

As a dynamic system, its least squares form is expressed as:

$$y(k) = \boldsymbol{\varphi}^T(k)\boldsymbol{\theta} \leftarrow \begin{cases} y(k) = U_L(k), \boldsymbol{\theta} = [c_0, c_1, c_2, c_3, c_4, c_5]^T \\ \boldsymbol{\varphi}(k) = [1, U(k-1), U(k-2), I(k), I(k-1), I(k-2)]^T \end{cases} \quad (4)$$

where  $y(k)$  represents the output vector,  $\boldsymbol{\varphi}(k)$  represents the data vector,  $\boldsymbol{\theta}$  represents the parameter vector.

The calculated  $\boldsymbol{\theta}$  is shown in Equation (5).

$$\begin{cases} c_0 = (1 - c_1 - c_2)U_{oc}(k), c_1 = 2\tau_1\tau_2 + (\tau_1 + \tau_2)T / [\tau_1\tau_2 + (\tau_1 + \tau_2)T + T^2] \\ c_2 = -\tau_1\tau_2 / [\tau_1\tau_2 + (\tau_1 + \tau_2)T + T^2], c_5 = -R_0\tau_1\tau_2 / [\tau_1\tau_2 + (\tau_1 + \tau_2)T + T^2] \\ c_3 = -[R_0\tau_1\tau_2 + R_0(\tau_1 + \tau_2)T + R_1\tau_2T + R_2\tau_1T + (R_0 + R_1 + R_2)T^2] / [\tau_1\tau_2 + (\tau_1 + \tau_2)T + T^2] \\ c_4 = [2R_0\tau_1\tau_2 + R_0(\tau_1 + \tau_2)T + R_1\tau_2T + R_2\tau_1T] / [\tau_1\tau_2 + (\tau_1 + \tau_2)T + T^2] \end{cases} \quad (5)$$

where  $\tau_1$  and  $\tau_2$  are the time constants of the two RC parallel circuits, and their values are shown in Equation (6).

$$\begin{cases} \tau_1 = \max\left(\frac{1}{2}\left[\frac{c_1 + 2c_2}{1 - c_1 - c_2} + \sqrt{\left(\frac{c_1 + 2c_2}{1 - c_1 - c_2}\right)^2 + \frac{4c_2T^2}{1 - c_1 - c_2}}\right], \frac{1}{2}\left[\frac{c_1 + 2c_2}{1 - c_1 - c_2} - \sqrt{\left(\frac{c_1 + 2c_2}{1 - c_1 - c_2}\right)^2 + \frac{4c_2T^2}{1 - c_1 - c_2}}\right]\right) \\ \tau_2 = \min\left(\frac{1}{2}\left[\frac{c_1 + 2c_2}{1 - c_1 - c_2} + \sqrt{\left(\frac{c_1 + 2c_2}{1 - c_1 - c_2}\right)^2 + \frac{4c_2T^2}{1 - c_1 - c_2}}\right], \frac{1}{2}\left[\frac{c_1 + 2c_2}{1 - c_1 - c_2} - \sqrt{\left(\frac{c_1 + 2c_2}{1 - c_1 - c_2}\right)^2 + \frac{4c_2T^2}{1 - c_1 - c_2}}\right]\right) \end{cases} \quad (6)$$

Through combination of equation (5-6), the parameter separation result is shown in Equation (7).

$$\begin{cases} R_0 = c_5/c_2, R_2 = -\frac{c_3 + c_4 + c_5}{1 - c_1 - c_2} - R_0 - R_1, C_1 = \tau_1/R_1, C_2 = \tau_2/R_2 \\ R_1 = \left[-\tau_1 \frac{c_3 + c_4 + c_5}{1 - c_1 - c_2} + R_0 \frac{c_1 + 2c_2}{1 - c_1 - c_2} T - R_0\tau_1 - \frac{c_4 + 2c_5}{1 - c_1 - c_2} T\right] / (\tau_1 - \tau_2) \end{cases} \quad (7)$$

The matrix innovation in the MILS algorithm can correct the parameter identification result of the previous moment in the iteration process to improve the parameter identification accuracy. By using the matrix innovation to correct the parameter identification result of the previous moment, the system MILS algorithm model can be obtained as:

$$\mathbf{V}(p, k) = \begin{bmatrix} y(k) - \boldsymbol{\varphi}^T(k)\hat{\boldsymbol{\theta}}(k-1) \\ y(k-1) - \boldsymbol{\varphi}^T(k-1)\hat{\boldsymbol{\theta}}(k-2) \\ \vdots \\ y(k-p+1) - \boldsymbol{\varphi}^T(k-p+1)\hat{\boldsymbol{\theta}}(k-p) \end{bmatrix} \Leftarrow \mathbf{Y}(k) = \boldsymbol{\varphi}^T(k)\boldsymbol{\theta}(k-1) + \mathbf{V}(p, k) \quad (8)$$

where  $p$  is the matrix innovation length.

After calculation and separation of the parameters to be identified in the E-DCP model through equation (7), equation (9) is used to perform iterative updating for the parameter values.

$$\begin{cases} G(k) = P(k-1)\boldsymbol{\varphi}(k)[\mathbf{I}_{n_p} + \boldsymbol{\varphi}^T(n_p, k)P(k-1)\boldsymbol{\varphi}(n_p, k)]^{-1} \\ P(k) = P(k-1) - G(k)\boldsymbol{\varphi}^T(k)P(k-1) \\ \hat{\boldsymbol{\theta}}(k) = \hat{\boldsymbol{\theta}}(k-1) + G(k)[\mathbf{Y}(k) - \boldsymbol{\varphi}^T(k)\hat{\boldsymbol{\theta}}(k-1)] \end{cases} \quad (9)$$

where  $G(k)$  is the correction factor in the MILS algorithm. The parameter values of the E-DCP model is accurately estimated based on the above-mentioned theoretical deduction and algorithm iteration.

#### 2.4. SOC estimation strategy

The EKF algorithm is one of the most common SOC estimation algorithms. State estimation for the BMS is achieved by combining MILS and EKF on the basis of the E-DCP model in this paper. To use the EKF algorithm, the expression of the state equation and the observation equation is constructed, as shown in Equation (10).

$$\begin{cases} x_k = A_{k-1}x_{k-1} + B_{k-1}u_{k-1} + w_{k-1} \\ y_k = C_k x_k + D_{k-1}u_k + v_k \end{cases} \Leftarrow \begin{cases} A_k = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \exp(-T/\tau_1) & 0 \\ 0 & 0 & \exp(-T/\tau_2) \end{bmatrix}, C_k = \begin{bmatrix} dU_{oc}(SOC) \\ d(SOC) \end{bmatrix} \\ B_k = [-\eta T/Q_N, R_1[1 - \exp(-T/\tau_1)], R_2[1 - \exp(-T/\tau_2)]]^T, I \end{cases} \quad (10)$$

where  $x = [SOC, U_1, U_2]$  is the system state variable,  $u = I$  and  $y = U$  are the system input and output respectively,  $w_k$  and  $v_k$  are the system process noise and measurement noise, with the covariance matrices being  $Q$  and  $R$  respectively.

The open circuit voltage equation's first-order Taylor expansion is shown in Equation (11).

$$dU_{oc}(SOC)/d(SOC) = K_1/SOC - K_2/(1 - SOC) \quad (11)$$

Iteration calculation for the SOC value of each moment is performed by using the EKF algorithm based on the above-mentioned state space expression under the discrete state. The state estimation equation is shown in Equation (12).

$$\begin{cases} \hat{x}_{k+1/k} = A_k \hat{x}_k + B_k u_k + w_k \\ P_{k+1/k} = A_k P_k A_k^T + Q_k \end{cases} \quad (12)$$

The algorithm estimation equation includes both state estimation and state covariance estimation. The estimation value of the system in the next moment and the covariance matrix value of the state variable can be obtained through the above-mentioned equation, but the values of the two are not optimal. Therefore, time updating is required. The updating equation is shown in Equation (13).

$$\begin{cases} K_{k+1} = P_{k+1/k} C_{k+1}^T (C_{k+1} P_{k+1/k} C_{k+1}^T + R_{k+1})^{-1} \\ x_{k+1} = \hat{x}_{k+1/k} + K_{k+1} (y_{k+1} - \hat{y}_{k+1}) \\ P_{k+1} = (I_k - K_{k+1} C_{k+1}) P_{k+1/k} \end{cases} \quad (13)$$

The system's optimal filter gains matrix  $K_{k+1}$ , optimal state matrix  $x_{k+1}$  and optimal covariance matrix value  $P_{k+1}$  can be obtained through equation 16. The entire iteration process is calculated

through the "estimation-correction-updating" method, making the state estimation value of each moment of the algorithm optimal.

### 3. Experimental analysis

#### 3.1. Experimental sample

To verify the accuracy of the E-DCP model and the precision after combination of the MILS and EKF algorithms, the lithium-ion battery pack is used as the sample for research in this paper. The sample mainly consists of seven battery pack units in series connection. The parameters of this lithium-ion battery pack samples are shown in Table 1. XX in this table represents the battery capacity.

**Table 1.** The basic performance parameters of the Lib pack samples.

No.	Parameter Name	Parameter Value	No.	Parameter Name	Parameter Value
[1]	Battery model	7-ICP XX	[4]	Unit nominal voltage	3.70V
[2]	Rated capacity	4.00 Ah	[5]	Discharge cut-off voltage	3.00V
[3]	Pack nominal voltage	25.90V	[6]	Charge cut-off voltage	4.15V

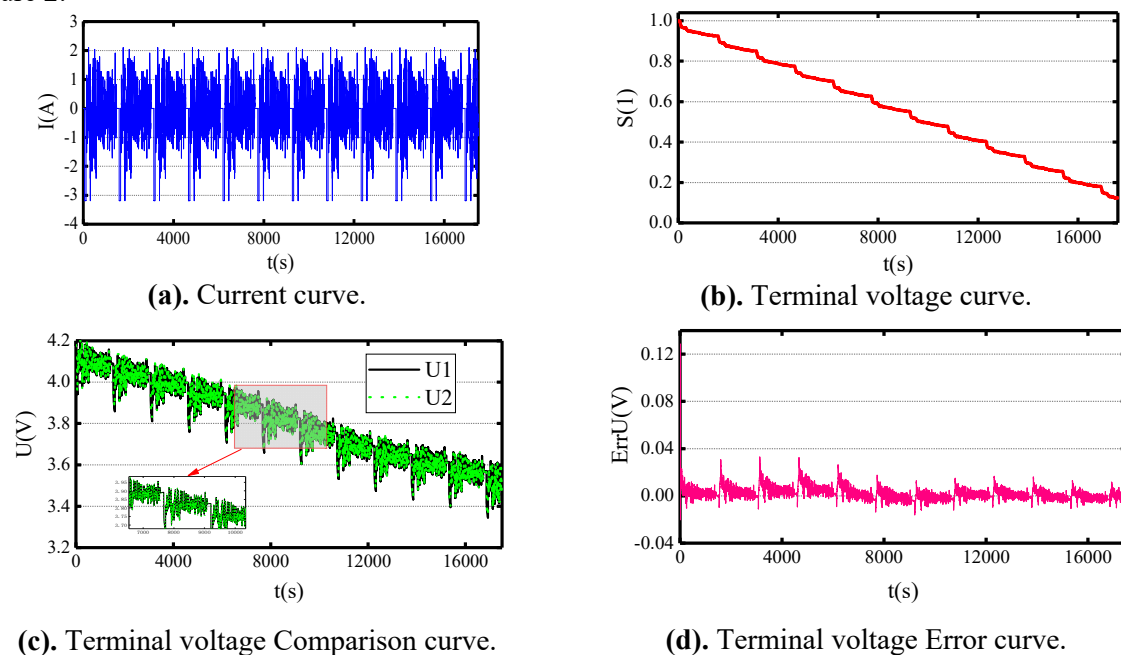
#### 3.2. Open circuit voltage identification

Discharge of 0.05 is performed for the fully charged lithium-ion battery packs each time, and then the packs sit for one hour for battery activation, which is repeated for 20 times to obtain 20 OCV-SOC values. The optimized electrochemical equation is used for dataset fitting to obtain a good dynamic function relationship of OCV-SOC. The obtained OCV-SOV change relationship is shown in Equation (14).

$$U_{oc}(k) = 25.9846 + 0.4441 * \ln[SOC(k)] - 0.8883 * \ln[1 - SOC(k)] \quad (14)$$

#### 3.3. Model validation

To verify the convergence of the MILS algorithm under highly complex working conditions, the UDDS working conditions are selected for model full-parameter identification. The related experimental curves and the model error result under the UDDS working conditions are shown in Figure 2.

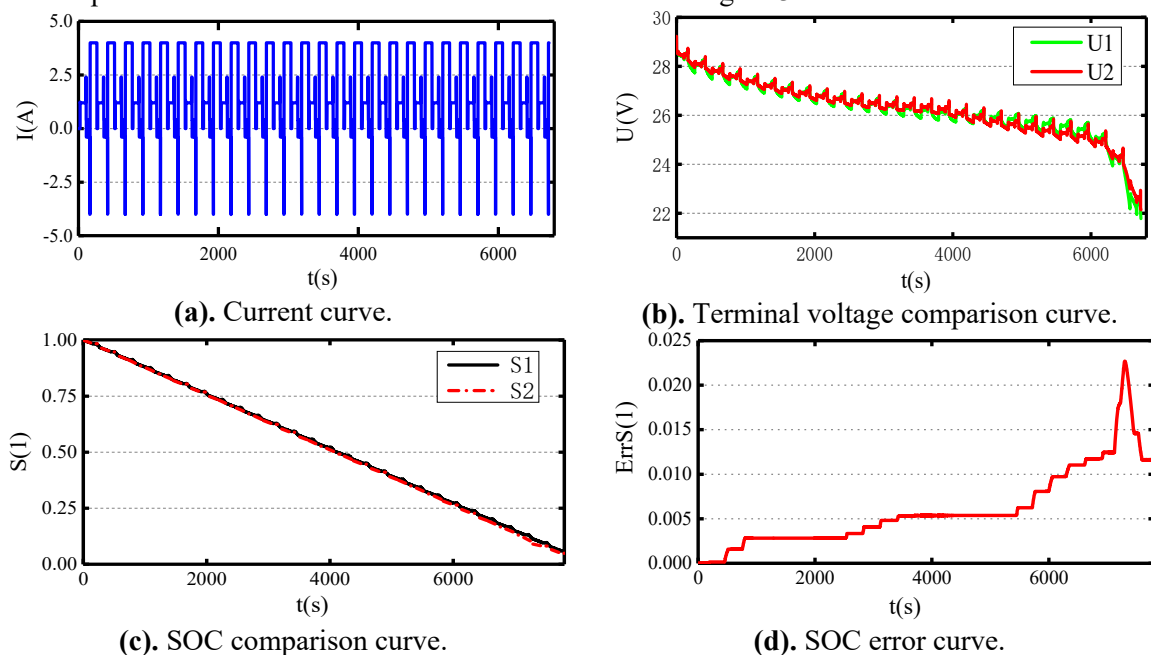


**Figure 2.** Related experimental curves and model error curve under the UDDS working conditions.

In Figure 2,  $U_1$  is the actual terminal voltage value under the UDDS working conditions,  $U_2$  is the estimated terminal voltage value based on the MILS algorithm. It can be seen from Figure 2(c-d) that with the relative big terminal voltage error caused by the system at the beginning of the identification ignored, under the highly complex UDDS working conditions, the maximal terminal voltage error obtained from the combination of the E-DCP model and the MILS algorithm is 0.96%, and the tracking effect is extremely good.

### 3.4. Algorithm verification

The EKF is used for SOC estimation of the lithium-ion battery packs and a complex charge-discharge cyclic test is performed for the lithium-ion battery packs to further verify the feasibility of using the MILS algorithm for online parameter identification and EKF algorithm for state estimation. The related experimental curves and the error result are shown in Figure 3.



**Figure 3.** Related experimental curves under complex charge-discharge cyclic test.

In Figure 3,  $U_1$  is the actual terminal voltage value in the complex charge-discharge loop test,  $U_2$  is the estimated terminal voltage value in the complex charge-discharge loop test. It can be seen from Figure 3(c-d) that the error during the early stage of the experiment is relatively small and within 0.5%, the error slightly increases during the middle stage of the experiment but still within 0.5%, the error fluctuates during the late stage of the experiment, with the maximal error rising to 2.2%, but the error quickly reduces to within 1.3% under the correction of the EKF algorithm.

## 4. Conclusions

A new composite E-DCP model is proposed by analyzing commonly used electrochemical models. The MILS algorithm is used for online parameter identification of the lithium-ion battery to improve data usage efficiency and parameter identification accuracy. Then, EKF is used to estimate the system state to achieve adaptive tracking adjustment of the state variable. The test results indicate that the accuracy of the E-DCP model is relatively high under different working conditions, and this lays a concrete foundation for practical use of the BMS in the future.



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