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STATE OF CHARGE ESTIMATION OF LITHIUM-ION BATTERY BASED ON EXTENDED KALMAN FILTER AT DIFFERENT TEMPERATURES

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ABSTRACT

In this paper, a state of charge (SOC)estimation method for lithium battery based on extended Kalman filter is proposed, and the estimation accuracy of SOC for lithium battery at different temperatures is analyzed. Firstly, a Thevenin equivalent circuit model is adapted to describe the battery considering model complexity, model accuracy and robustness of the model. Secondly, battery capacity and dynamic working condition experiment are carried out based on the battery test bench. Then, battery model parameters are identified by Forgetting Factor Recursive Least Square Algorithms (FFLS) based on China City Bus Cycle (CCBC) experiment data at different temperatures. Last but not least, a state of charge estimation method based on Extended Kalman Filter is adapted and the estimation accuracy is analyzed base on Urban Dynamometer Driving Schedule (UDDS). The results show that the estimation error is less than 4% in different temperatures based on the proposed method.

Keywords: Lithium-ion battery, Extended Kalman Filter, Forgetting Factor Recursive Least Square Algorithms, State of Charge estimation

NONMENCLATURE

Abbreviations	
EKF	Extended Kalman Filter
SOC	State of Charge
RLS	Recursive Least Square Algorithms
FFLS	Forgetting Factor Recursive Least Square Algorithms
CCBC	China City Bus Cycle
UDDS	Urban Dynamometer Driving Schedule

1. INTRODUCTION

Lithium-ion batteries have been widely used in electric vehicles (EVs) because of their advantages of lightweight, fast charging, and high energy density, low self-discharge and long lifespan [1]. For safe operation of batteries and efficient energy management strategy, the accuracy estimation of the SOC is essential for battery management systems. However, it's difficult to accurately estimate the SOC of batteries due to the changeable working environment and operating temperature of batteries. In this paper, the SOC of lithium batteries under dynamic conditions at different temperatures is studied.

The SOC estimation methods can generally be divided into four categories: coulomb counting method (ampere-hour method), characteristic parameters based methods, data-driven methods and multi-method fusion based methods [2]. The SOC estimation based on extended Kalman filter shows a high accuracy with a fast convergence at erroneous initial values of SOC [3]. The battery models proposed mainly vary in terms of model structure, model complexity, required computing power and reliability of the obtained results [4]. In [4], Thevenin model is preferred for LiNMC cells by examining model complexity, model accuracy and robustness between twelve equivalent circuit models for Li-ion batteries.

In this paper, a Thevenin model along with the EKF algorithms is adapted to estimate the SOC at different temperatures. The outline of the paper is as follows: The introduction is presented in Section 1. Section 2 describes the Thevenin model, the FFLS algorithms and the Extended Kalman filter algorithms. Section 3 shows the battery test bench and the model parameters are identified at different temperatures based on CCBC experiment data. The SOC estimation results based on Extended Kalman filter algorithm are verified by UDDS experimental data in section 4. The conclusions are given in section 5.

2. METHODS

2.1 Thevenin model

Thevenin model (see Fig 1) consists of one RC networks to predict the battery response at a particular state of charge and open circuit voltage. Thevenin model is capable of forecasting the transient response of the battery voltage with a variation of current load, and thus it can be applied to different dynamic conditions.

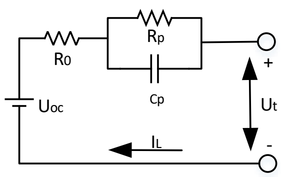


Fig 1 Structure of Thevenin model

The state space representation of Thevenin model can be obtained from Kirchhoff voltage laws and Kirchhoff's current law. The state equation and the observation equation are shown in the Eq. (1).

$$\begin{cases} \dot{U}_p = \dfrac{I_L}{C_p} - \dfrac{U_p}{R_p C_p} \\ U_t = U_{oc} - U_p - I_L R_0 \end{cases} \tag{1}$$

Where U_{OC} is the OCV, U_t is the terminal voltage; I_L is the load current; R_0 is the equivalent ohmic resistance; U_P is the voltage across the RC network; R_P is the resistance in the RC network; C_P is the capacitance in the RC network.

The state space representation is shown in Eq. (2) by discretizing the Eq. (1) and adding the state variable SOC.

$$\begin{cases} \begin{bmatrix} SOC(k+1) \\ U_p(k+1) \end{bmatrix} = [\begin{matrix} 1 & 0 \\ 0 & 1-\dfrac{T_s}{C_p R_p} \end{matrix}][\begin{matrix} SOC(k) \\ U_p(k) \end{matrix}] + [\begin{matrix} -\dfrac{T_s}{Q_0} \\ \dfrac{T}{C_p} \end{matrix}][I_L(k)] \\ [U_t(k)] = [\begin{matrix} \dfrac{\partial U_{oc}}{\partial SOC} & -1 \end{matrix}][\begin{matrix} SOC \\ U_p \end{matrix}] + [-R_0][I_L(k)] \end{cases} \tag{2}$$

The frequency domain of thevenin model can be expressed as Eq. (3).

$$U_L(s) = U_{oc}(s) - U_p(s) - I_L R_0(s) \tag{3}$$

Define E_L=U_L-U_{OC}, the transfer function of Eq. (3) can be written as Eq. (4).

$$s = \frac{2}{\triangle t}\ \frac{1-z^{-1}}{1+z^{-1}} \tag{4}$$

A bilinear transformation method shown in Eq. (5) is employed for the discretization calculation of Eq. (4) and the result is shown in Eq. (6).

$$U_L(s) = U_{oc}(s) - U_p(s) - I_L R_0(s) \tag{5}$$

Where z is the discretization operator.

$$G(z^{-1}) = \frac{a_2 + a_3 z^{-1}}{1 - a_1 z^{-1}} \tag{6}$$

Where:

$$\begin{cases} a_1 = -\dfrac{T - 2R_P C_P}{T + 2R_P C_P} \\ a_2 = -\dfrac{R_0 T + R_P T + 2R_0 R_P C_P}{T + 2R_P C_P} \\ a_3 = -\dfrac{R_0 T + R_P T - 2R_0 R_P C_P}{T + 2R_P C_P} \end{cases}$$

Eq. (3) is rewritten as Eq. (7) after discretization, where k =1,2,3,...

$$E_L(k) - a_1 E_L(k-1) = a_2 I_L(k) + a_3 I_L(k-1) \tag{7}$$

Where:

$$\begin{cases} E_L(k) = U_L(k) - U_{oc}(k) \\ E_L(k-1) = U_L(k-1) - U_{oc}(k-1) \end{cases}$$

The open-circuit voltage can be considered to be constant per unit sampling time. Eq. (7) is rewritten as Eq. (8).

$$\begin{aligned} U_L(k) = (1-a_1)U_{oc}(k) + a_1 U_L(k-1) \\ + a_2 I_L(k) + a_3 I_L(k-1) \end{aligned} \tag{8}$$

Define:

$$\begin{cases} \phi(k) = \left[1 \ \ \mathrm{U_L(k\text{-}1)} \ \ \mathrm{I_L(k)} \ \ \mathrm{I_L(k\text{-}1)}\right] \\ \theta(k) = \left[(1-a_1)U_{oc}(k) \ \ a_1 \ \ a_2 \ \ a_3\right]^T \\ y(k) = U_L(k) \end{cases}$$

Then Eq. (8) is rewritten as Eq. (9).

$$y_k = \phi(k)\theta(k) \tag{9}$$

2.2 *Forgetting Factor Recursive Least Square Algorithms*

The recursive least square (RLS) method is the recursive form of the LS method and it's Suitable for real-time update. In order to improve the reliability of system parameter identification and reduce the influence of historical data on the system, a forgetting factor is added to RLS method and Forgetting Factor Recursive Least Square Algorithms (FFLS) is employed to identify the model parameters [5]. The basic flowchart of FFLS can be seen from table (1) based on Eq. (9).

Table 1. The implementation flowchart of FFLS.

Step1:	Initialization parameters: $\hat{\theta}(0)\ \ P(0)\ \ \lambda$
Step2:	Calculate Measurement Vector $\phi(k)=\left[1\ \ \mathrm{U_L(k\text{-}1)}\ \ \mathrm{I_L(k)}\ \ \mathrm{I_L(k\text{-}1)}\right]$
Step3:	Calculation factor $\alpha=\lambda+\phi^{\mathrm{T}}(k\text{-}1)P(k\text{-}1)\phi(k\text{-}1)$
Step4:	Calculate algorithms gain $K(k)=P(k\text{-}1)\varphi(k\text{-}1)\alpha^{-1}$
Step5:	Update the parameter vector $\hat{\theta}(k)=\hat{\theta}(k\text{-}1)+K(k)[y(k)\text{-}\phi^{\mathrm{T}}(k\text{-}1)\hat{\theta}(k\text{-}1)]$
Step6:	Calculate covariance matrix $P(k)=[I\text{-}K(k)\phi^{\mathrm{T}}(k\text{-}1)]P(k\text{-}1)/\lambda$
Step7:	Calculate model parameters $U_{OC}\ \ R_0\ \ R_P\ \ C_P$

Where $\hat{\theta}(k)$ is the estimation of the parameter vector, *K*(k) is the algorithm gain, and *P*(k) is the covariance matrix.

2.3 Extended Kalman Filter

Extended Kalman filter (EKF) algorithm is based on Taylor expansion for nonlinear systems. After the battery model is approximately converted to linear system, the SOC estimation can be carried out using standard Kalman filter. Considering the state space equation as shown in Eq. 10, the basic implementation flowchart of FFLS can be seen from table (2).

$$\begin{cases} x(k)=A(k\text{-}1)x(k\text{-}1)+B(k\text{-}1)u(k\text{-}1)+q(k-1) \\ y(k)=C(k)x(k)+D(k)u(k)+r(k) \end{cases} \tag{9}$$

Where *x*(k) is the state vector at time k; *y*(k) is the measurement vector at time *k*; *q* and *r* are independent Gaussian white process noise and measurement noise with covariance *Q* and *R*, respectively.

Table 2. The implementation flowchart of FFLS.

Step1:	Initialization parameters: x_0,P_0,Q_0,R_0
Step2:	Estimate the predicted state $\hat{x}(k\mid k-1)=A(k)\hat{x}(k-1)+B(k)u(k)$
Step3:	Estimate the covariance matrix $P(k\mid k-1)=A(k)P(k-1)A(k)^T+Q_0$
Step4:	Calculate Kalman gain $K(k)=P(k\mid k-1)C(k)^T(C(k)P(k\mid k-1)C(k)^T+R_0)^{-1}$
Step5:	Update the state vector $\begin{cases} e(k)=y(k)-C(k)\hat{x}(k\mid k-1)-D(k)u(k) \\ \hat{x}(k)=\hat{x}(k\mid k-1)+K(k)e(k) \end{cases}$
Step6:	Calculate covariance matrix $P(k\mid k)=(I-K(k)C(k))P(k\mid k-1)$

Where P is covariance matrix and K is Kalman gain.

3. EXPERIMENTS

3.1 Battery test bench

The battery test bench (shown in Fig 1) consists of battery testing system (Arbin BT2000), CSZ thermal chamber, computer and the test battery. The battery testing system regulates battery charging and discharging with the established strategy and collects currents and voltages, which are then sent to the computer. The thermal chamber is used to control the environment during the test.

The 2P5S battery pack under test in this study uses a $LiMn_2O_4$ Lithium-ion battery cell with a rated capacity of 48Ah. The temperature is set as constant -5℃, 5℃ and 25℃.

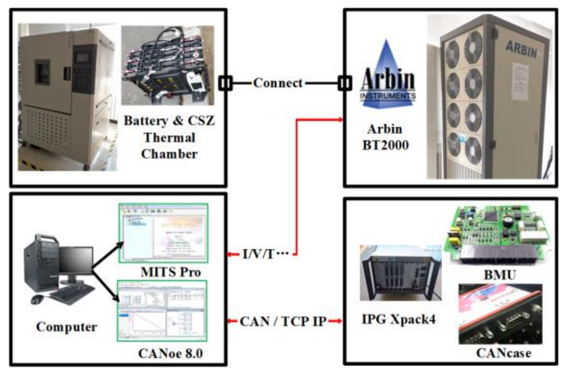
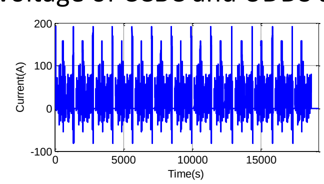
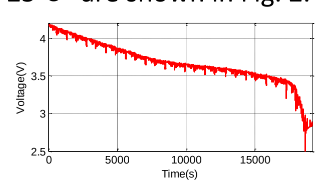


Fig 1 Structure of battery test bench

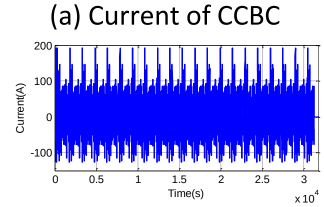
Based on the built test bench, the China City Bus Cycle (CCBC) and Urban Dynamometer Driving Schedule (UDDS) experiments at different temperatures are carried out.The dynamic current and the terminal voltage of CCBC and UDDS at 25℃ are shown in Fig. 2.



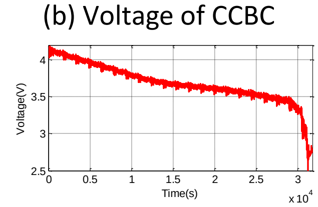
(a) Current of CCBC



(b) Voltage of CCBC



(c) Current of UDDS

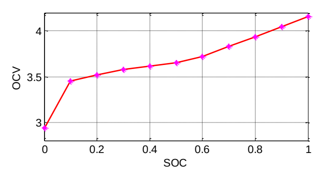


(d) Voltage of UDDS

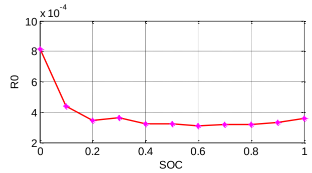
Fig 2 Dynamic current and Terminal voltage at 25℃

3.2 Parameters identification results

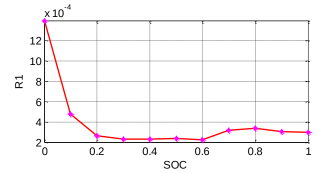
The battery model parameters are identified from CCBC test results based on FFLS method. The model parameters in function with SOC at different temperatures are shown in Fig 3.



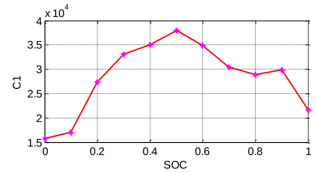
(a) SOC-OCV



(b) R0



(c) Rp

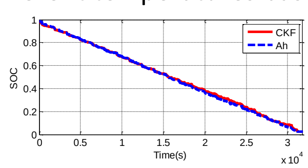


(d) Cp

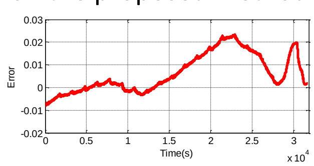
Fig 3 Thevenin model parameters at 25℃

4. RESULTS

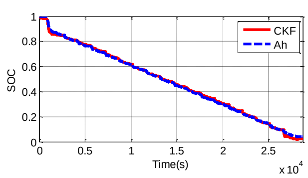
The initial values of EKF is setting as: x_0=*[1,0.04]; R=1; Q=diag (1,1)*1e-6;* P_0=*diag (1,1)*1e-6*. The SOC estimations results under UDDS are shown in Fig 4. The results show that the estimation error is less than 4% in different temperatures based on the proposed method.



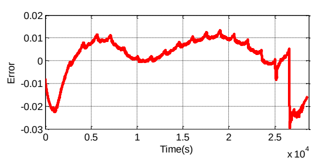
(a) SOC at 25℃



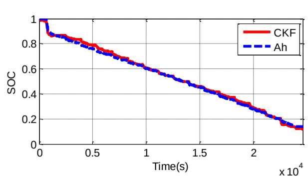
(b) Error at 25℃



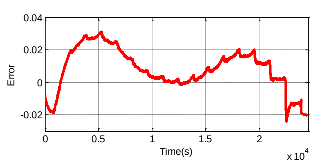
(c) SOC at 5℃



(d) Error at 5℃



(e) SOC at -5℃



(f) Error at -5℃

Fig 4 SOC estimation results at different temparature

5. CONCLUSION

This paper adapted Thevenin model for battery modeling. The model parameters are identified by FFLS method under CCBC experiments. The SOC estimations results under UDDS at different temperatures by EKF is analyzed. The results show that the estimation error is less than 4% in different temperatures based on the proposed method.

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