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SOC Estimation of Lithium-ion Battery Packs Based on Thevenin Model

Yuanqi Fang[1,a], Ximing Cheng[1,b,★] and Yilin Yin[1,c]

[1]National Engineering Laboratory for Electric Vehicle, Beijing Institute of Technology, Beijing, China

★Corresponding author

[a]E-mail: fangyuanqi1988@163.com, [b]E-mail: cxm2004@bit.edu.cn, [c]E-mail: yinyilin2008@126.com

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Abstract. Due to the immeasurability of SOC in battery and inevitability of error in current collection, SOC estimation of Lithium-ion battery has become a focus of EV research. With Thevenin equivalent circuit model, this paper employs EKF algorithm to estimate SOC, which takes into consideration both precision requirement of the estimation and amount of computation involved in online estimation. Based on above-mentioned objectives and principles, a test platform composed of Digatron battery test system and thermostat was built. Experimental result has confirmed that the combination of EKF algorithm with Thevenin model can improve precision and reduce amount of computation.

Introduction

As an important component of EVs, battery management system can achieve real time monitoring and manage the battery's working condition [1][2].One of the most fundamental and also the most important function of the management system is the estimation of SOC. However, due to the immeasurability of SOC [3], accurate estimation of SOC in power battery has long been a challenging task, and more and more methods are applied into this issue, for example, the Ampere-Hour integral [4], the open-circuit- voltage(OCV) measurement. The result of Ah approach is substantially influenced by the precision of current measurement and the initial value. OCV measurement requires long time of standing before operation [5]. The application of EKF into the estimation of SOC can by contrast effectively make up for the deficiencies of the above-mentioned approaches.

Establishment of Equivalent Circuit Model

It is important to establish a battery model of high precision for the application of EKF into the estimation of SOC. Thevenin model is adopted in this paper, which takes the polarization phenomena of battery into consideration, shown in Fig.1.

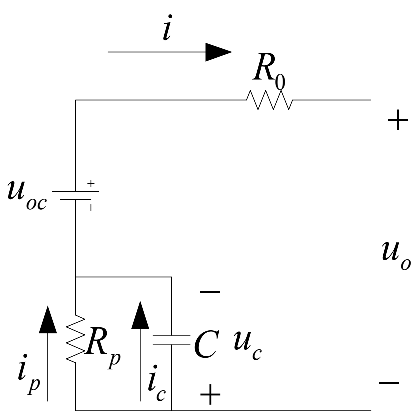

Fig.1: Thevenin equivalent circuit mode

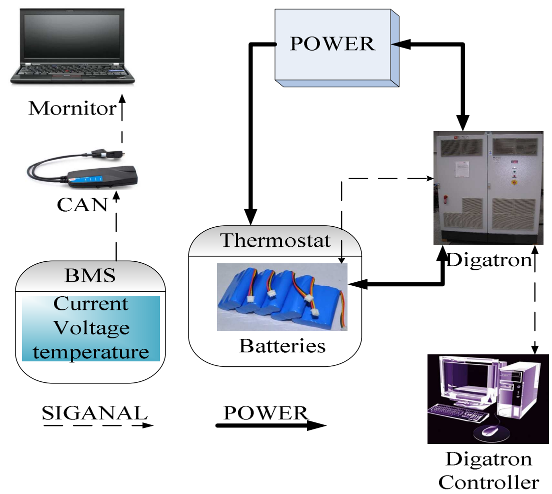

Fig.2: Battery test bench

In Fig.1, R_0 is used to describe ohmic polarization effect, u_0 represents the voltage of R_0, u_{oc} represents OCV, which is a function of SOC. u_o represents the load voltage, resistance Rp and capacity C represent polarization phenomena, u_c represents the voltage of Rp.

Parameter Determination of Thevenin Model

The determination of battery model parameters should consider the following two aspects, fitting of open OCV-SOC curve and determination of R_0, R_p, C, both of which must be conducted after HPPC test.

Battery Test Bench. To acquire experimental data, a battery test bench was established. Battery packs composed of 36 battery cells produced by China BAK Battery Inc. serves as experiment object. Information of the battery cell is shown in Table 1.

Table 1: Information of battery cell

Nominal capacity [mAh]	Nominal voltage [V]	Maximum charging/ discharging current [mA]	Maxmum charging/ discharging temperature [℃]
2000	3.6	2000/4000	60/75

Fig.2 is the schematic diagram of the battery test bench. The test system adopted Digatron EVT 500-500, which can collect data such as time, voltage, current, charge and discharge energy, charge and discharge capacity of the battery with its maximum sampling frequency being as high as 10 Hz.

Parameter Determination. The current excitation and voltage response in HPPC test are shown in Fig. 3. The cutoff condition of the experiment is set as SOC=0.2 to avoid over-discharge.

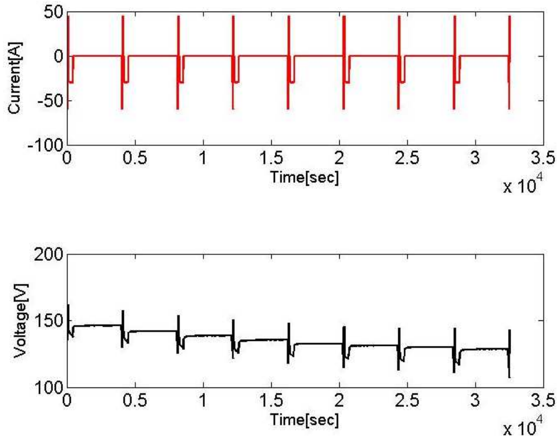

Fig. 3: HPPC test

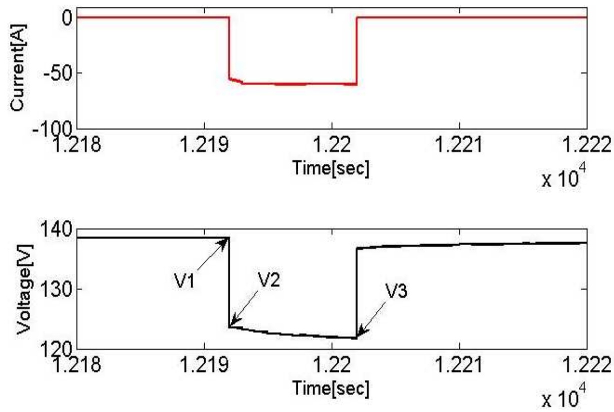

Fig. 4: Voltage responses at SOC=0.7

As is shown in Fig. 4, the value of OCV and R_0 can be worked out with Eq. (1) and Eq. (2). During V2~V3, load voltage is shown as Eq. (3). According to the least square method, the target function has been derivate shown in Eq. (4). R_p and C can be calculated with fminsearch function in Matlab. The discharging current has been set as I.

$$u_{oc} = V_1 \tag{1}$$

$$R_0 = (V_2 - V_1)/I \tag{2}$$

$$u_o = u_{oc} - iR_0 - iR_p(1 - e^{-t/\tau}) \tag{3}$$

$$J = \min(\sum (v_{m,i} - v_{e,i})^2) \tag{4}$$

where $\tau = R_p C$, $i = 1,2,3,\cdots n$, n represents the number of sampling point, $v_{m,i}$ and $v_{e,i}$ represent measured and calculated load voltage at i respectively.

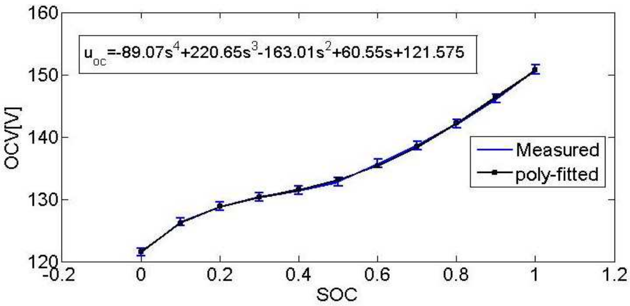

Fig. 5: OCV-SOC curves fitting

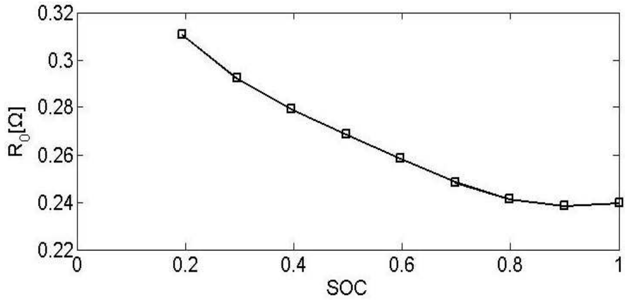

Fig. 6 R_0-SOC curve

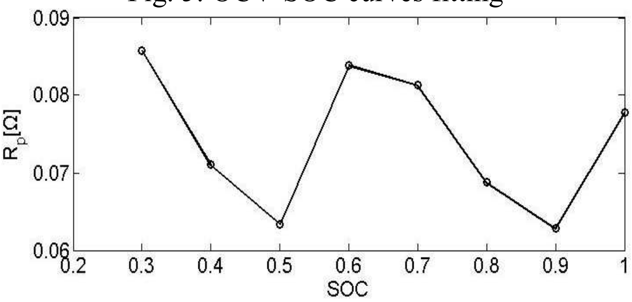

Fig. 7 R_p-SOC curve

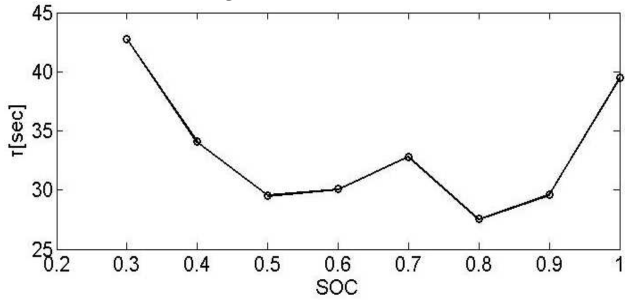

Fig. 8 τ -SOC curve

Fig. 5 shows the result of quartic-polynomial fitting of OCV and SOC curves. It is clear that polynomial fitting result meets the precision requirement, and error is just 5‰. R_0, R_p and C have been shown in Fig. 6~Fig. 8. R_0, R_p and τ have been defined as the average of all values at different SOC point respectively, shown in Table 2.

Table 2 Values of model parameters

R_0 [Ω]	R_p[Ω]	τ [sec]
0.2713	0.0694	29.67

Validation of Parameters. As is shown in Fig. 9, to validate the accuracy of the model parameters, the terminal voltage's simulation values and experimental values are compared in the excitation of the current values composed of ECE, FTP and J1015 cycle condition. Relative error is to evaluate the model precision, which is shown in Eq. (5).

$$relative\_error = | v_{m,i} - v_{e,i} | / v_{m,i} \tag{5}$$

Where $i = 1, 2, 3, \cdots n$, n represents the number of sampling point, $v_{m,i}$ and $v_{e,i}$ represent measured and calculated load voltage at i respectively.

Fig. 9 illustrates that the vast majority of relative error o is below 5%. Calculations have shown that the average relative error is only 0.64%. Therefore, quartic-polynomial fitting can be applied to SOC estimation.

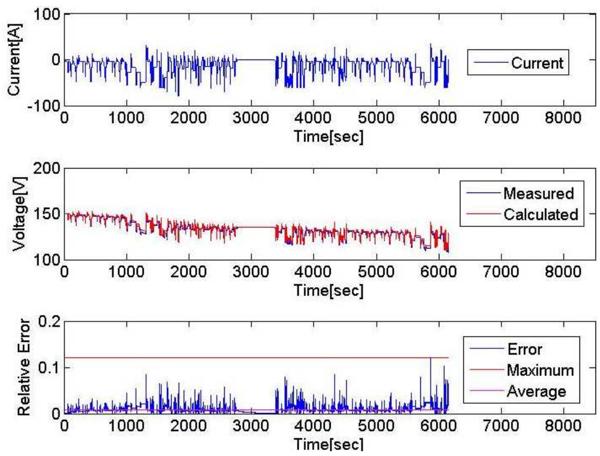

Fig. 9 Validation of model parameters

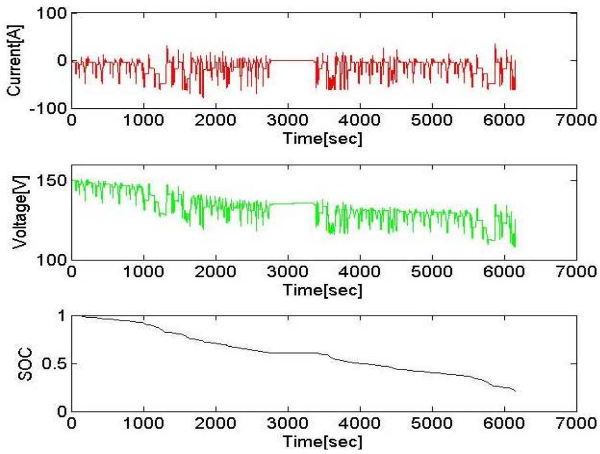

Fig. 10 The rusult of combined working condition test

SOC Estimation Using EKF Algorithm

EKF algorithm is a recursive approach to get the status value of nonlinear system utilizing Linear Minimum Square Error estimation method [6]. In Eq. (6) and (8), state and observation equation are formulated by combining Ampere-Hour integral model and Thevenin model.

$$x_{k+1} = A_k x_k + B_k i_k + w_k \tag{6}$$

$$u_{o,k} = G(i_k, x_k) + v_k \tag{7}$$

$$G(x_k, i_k) = u_{oc,k} - u_{c,k} - i_k R_0 \tag{8}$$

Where $x_k = \begin{bmatrix} s_k \\ u_{c,k} \end{bmatrix}$ $A_k = \begin{bmatrix} 1 & 0 \\ 0 & \alpha \end{bmatrix}$ $B_k = \begin{bmatrix} -\eta T_s / C_n \\ \beta \end{bmatrix}$ $\alpha = e^{-T_s/\tau}$ $\beta = R_p(1 - e^{-T_s/\tau})$. T_s is the sampling period. C_n is the nominal capacity. S_k is the SOC value and $u_{c,k}$ is the voltage value of R_p at sampling instant of kT_s. ω_k is the system's random disturbance. v_k is the measurement noise.

SOC estimation utilizing EKF algorithm can be formulated. The recursion is shown as follws:

a) $\hat{x}_{k,k-1} = A_{k-1}\hat{x}_{k-1} + B_{k-1} i_{k-1}$

b) $P_{k,k-1} = A_k P_{k-1} A_k^T + Q_{k-1}$

c) $K_k = P_{k,k-1} C_k^T [C_k P_{k,k-1} C_k^T + R_k]^{-1}$

d) $\hat{x}_k = \hat{x}_{k,k-1} + K_k [u_{L,k} - G(\hat{x}_{k,k-1}, i_{k-1}, t)]$

e) $P_k = [I - K_k C_k] P_{k/k-1}$

Where $C_k = \left.\dfrac{dG(x_k, i_k)}{dx_k}\right|_{x_k = \hat{x}_{k,k-1}}$, $\dfrac{dG(x_k, i_k)}{dx_k} = \dfrac{\partial G}{\partial x_k} + \dfrac{\partial G}{\partial R_{0,k}} \dfrac{dR_{0,k}}{dx_k}$,

$\dfrac{\partial G}{\partial x_k} = \left[k_{v,1} + 2k_{v,2}s_k + 3k_{v,3}s_k^{\ 2} + 4k_{v,4}s_k^{\ 3} \quad 1 \right]$, $\dfrac{\partial G}{\partial R_{0,k}} \dfrac{dR_{0,k}}{dx_k} = \left[0 \quad 0 \right]$.

Experiment Analysis

As is shown in Fig. 10, combined cycle working condition is taken as an example to evaluate EKF algorithm. SOC estimation precision is evaluated by absolute error, as is shown in Eq. (9).

$$absolute\_error = | s_{e,i} - s_{m,i} | / \left\{ \max(s_{m,i}) - \min(s_{m,i}) \right\} \tag{9}$$

Where $i = 1, 2, 3, \cdots n$, n represents the number of sampling point, $s_{m,i}$ and $s_{e,i}$ represent measured and calculated SOC at i respectively.

Initial values of EKF filtering is shown as follow:

$\hat{x}_0 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$ $P_0 = \begin{bmatrix} 11520 & 0 \\ 0 & 11520 \end{bmatrix}$ $Q = \begin{bmatrix} 0.0005 & 0 \\ 0 & 0.0005 \end{bmatrix}$, $R = 24036663.3984$.

R_0 is defined as 0.8 R_0,0.9 R_0, R_0,1.1 R_0,1.2 R_0, the influence of internal resistance has been shown in Fig.11, which manifests that the more the internal resistance deviates from the exact value R_0, the lower the estimation precision becomes.

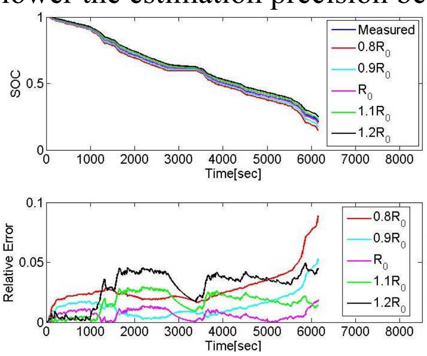

Fig.11: Influence of internal resistance

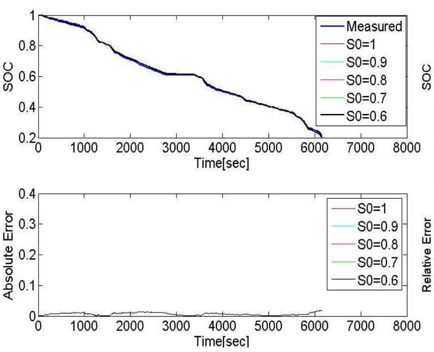

Fig. 12(a): Influence of initial value

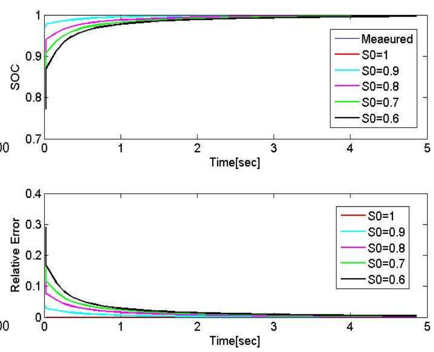

Fig. 12(b): Initial stage

It is clearly shown from Fig. 12 that the influence of initial value is only minimal. Estimated SOC can quickly follow the track of the measured SOC.

As is show in Fig. 13, the comparison between measured SOC and estimated SOC at the time R_0 is set as R_0, only exhibits the maximum absolute error of 1.42% and the mean absolute error of 0.52%.

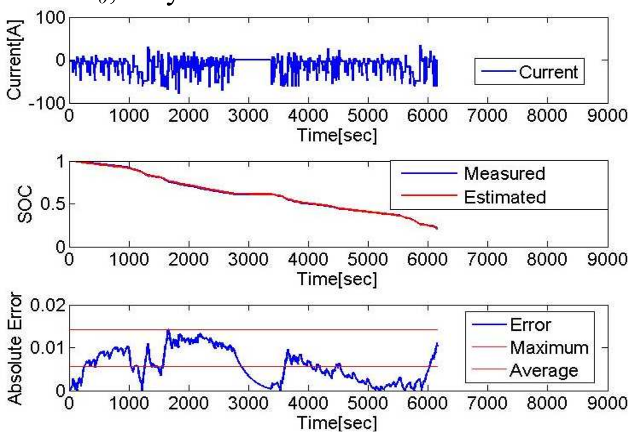

Fig. 13: Measured SOC and estimated SOC

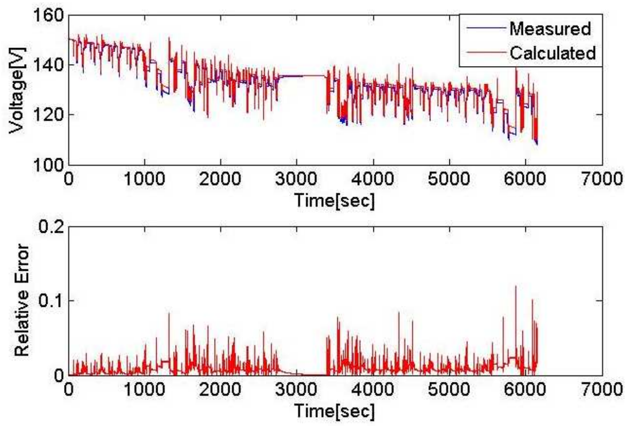

Fig.14: Measured voltage and calculated voltage

Fig.14 is the comparison between estimated and measured terminal voltage value, the former is calculated with estimated SOC value. For the most part the relative error is below 5% with a mean relative error of 0.72%. This has laid the foundation for subsequent online identification of battery parameters and will further facilitate the application of double Kalman filter into the simultaneous online estimation of battery parameter and SOC.

Conclusion

Experimental results have manifested that the application of EKF algorithm into Thevenin equivalent circuit model can realize relatively high SOC estimation precision. The method also achieves a balance between amount of computation and precision. In addition, this paper also confirms that the accurate estimation of internal resistance has a direct bearing on the improvement of SOC estimation precision, and initial values only exert influence at the initial stage, which effectively overcome the deficiencies facing Ampere-Hour integral.

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