Available online at www.sciencedirect.com

ScienceDirect

Energy Procedia 152 (2018) 520–525

Energy Procedia

www.elsevier.com/locate/procedia

CUE2018-Applied Energy Symposium and Forum 2018: Low carbon cities and urban energy systems, 5–7 June 2018, Shanghai, China

Evaluation of SOC Estimation Method Based on EKF/AEKF under Noise Interference

Dong Xile*[,1,2], Zhang Caiping[1,2], Jiang Jiuchun[1,2]

1. National Active Distribution Network Technology Research Center, Beijing Jiaotong University, Beijing 100044, China
2. Collaborative Innovation Center of Electric Vehicles in Beijing, Haidian District, Beijing 100044, China

Abstract

In this paper, the error of data acquisition in battery management system is considered. Combined with the online parameter identification method based on recursive least squares (RLS), the state of charge (SOC) estimation method based on extended Kalman filter (EKF) and adaptive extended Kalman filter (AEKF) is established and tested under the federal urban driving schedule. Then in the presence of noise interference on the input signal, the anti-interference of three methods is compared. Finally, it is concluded that the AEKF method with innovation-based adaptive estimator has the strongest suppression of noise with less than 2% SOC estimation error. It provides the research foundation for the application of EKF/AEKF in the actual battery management system.

Keywords: Noise interference; EKF; AEKF; SOC estimation

1. Introduction

The EKF and AEKF methods have been proposed for several decades and these methods have been successfully applied in many fields, such as aerospace, communications, and control [1]. The research of EKF in state estimation of electric vehicle has also been carried out for more than one decade [2][3]. SOC estimation based on EKF and its various derivative methods have achieved high accuracy in simulation [4]. Many problems, however, caused it to be still rarely applied to the SOC estimation on real electric vehicles. Compared with the ampere-hour integral, EKF is apt to divergence due to the randomness of current and the large noise of data acquisition. In this paper, the online

* Corresponding author. Tel.: +86 13522099685
E-mail address: 16121433@bjtu.edu.cn

10.1016/j.egypro.2018.09.204

parameter identification method based on RLS and the SOC estimation method based on EKF or AEKF are used to construct a combined SOC estimation method. Then, the adaptability of several methods is discussed under the noise.

2. Online model parameter identification

The Thevenin model, shown in Fig. 1, can reflect the static and dynamic characteristic of the battery with high accuracy [5]. In the figure, U_{oc} is the open circuit voltage, which represents the electromotive force, R_o is the ohmic resistance, R_p is the polarization resistance, C_p is the polarization capacitance, U_L is the terminal voltage, I_L is the current, assuming charging is positive.

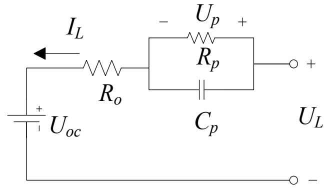

Fig. 1. Thevenin Circuit Model

According to the equivalent circuit model, the relationship between U_L and I_L in the s domain can be written as:

$$U_L(s) - U_{oc}(s) = \left(\frac{R_p}{\tau s + 1} + R_o\right) I_L(s) \tag{1}$$

Where $\tau = R_p C_p$ is the polarization time constant, s is the Laplace domain operator.

The equation (1) can be discretized into equation (2) using the bilinear transformation formula,

$$U_{L,k} - U_{oc,k} = \theta_1 (U_{L,k-1} - U_{oc,k-1}) + \theta_2 I_{L,k} + \theta_3 I_{L,k-1} \tag{2}$$

Where $\theta_1 = \dfrac{2\tau - T_s}{2\tau + T_s}$, $\theta_2 = \dfrac{R_p T_s + 2R_o \tau + R_o T_s}{2\tau + T_s}$, $\theta_3 = \dfrac{R_p T_s - 2R_o \tau + R_o T_s}{2\tau + T_s}$, and k is time index. Supposing that the sampling time T_s is a small interval, U_{oc} can be considered as a constant value during one sample interval [6], then equation (2) can be derived as follows:

$$U_{L,k} = \theta_1 U_{L,k-1} + \theta_2 I_{L,k} + \theta_3 I_{L,k-1} + (1 - \theta_1) U_{oc,k-1} \tag{3}$$

Assuming $\theta_4 = (1 - \theta_1) U_{oc,k-1}$ as a parameter to be identified, the above equation can be written as:

$$U_{L,k} = \theta_1 U_{L,k-1} + \theta_2 I_{L,k} + \theta_3 I_{L,k-1} + \theta_4 \tag{4}$$

Define $\hat{\boldsymbol{\theta}} = [\theta_1, \theta_2, \theta_3, \theta_4]^T$ as the parameter matrix to be identified. Use the RLS method (equation (5)) to obtain the $\hat{\boldsymbol{\theta}}$, and then the R_o, R_p, C_p can be acquired according to equation (6).

$$\begin{cases} y_k = U_{L,k} \\ \boldsymbol{\Phi}_k = [U_{L,k-1}, I_{L,k}, I_{L,k-1}, 1]^T \\ \boldsymbol{K}_k = \dfrac{\boldsymbol{P}_{k-1} \boldsymbol{\Phi}_k}{\lambda + \boldsymbol{\Phi}_k^T \boldsymbol{P}_{k-1} \boldsymbol{\Phi}_k} \\ \hat{\boldsymbol{\theta}}_k = \hat{\boldsymbol{\theta}}_{k-1} + \boldsymbol{K}_k (y_k - \boldsymbol{\Phi}_k^T \hat{\boldsymbol{\theta}}_{k-1}) \\ \boldsymbol{P}_k = \dfrac{1}{\lambda} (\boldsymbol{P}_{k-1} - \boldsymbol{K}_k \boldsymbol{\Phi}_k^T \boldsymbol{P}_{k-1}) \end{cases} \tag{5}$$

Where λ is the forgetting factor, $\boldsymbol{K}_k$ is the gain vector, and $\boldsymbol{P}_k$ is the covariance matrix.

$$R_o = \frac{\theta_2 - \theta_3}{1+\theta_1},\ R_p = \frac{2(\theta_1\theta_2 + \theta_3)}{1-\theta_1^2},\ C_p = \frac{T_s(1+\theta_1)^2}{4(\theta_1\theta_2+\theta_3)} \tag{6}$$

Hence, the parameters of the battery model can be identified with time, and systematic errors caused by making ($U_{L,k}$−$U_{oc,k}$) as the input [7] could be avoided.

3. SOC estimation methods

3.1. Extended Kalman filter (EKF)

Kalman filter (KF) is an optimal recursive data processing algorithm, but only applicable to the linear system. For a nonlinear dynamic system, like lithium ion battery, the EKF algorithm uses Taylor formula to linearize the state space equation of the system. The state space equation of a nonlinear discrete system is generally written as follows:

$$\begin{cases} x_{k+1} = f(x_k, u_k) + \omega_k \\ y_k = h(x_k, u_k) + \upsilon_k \end{cases} \quad \begin{cases} \omega_k \sim (0, Q_k) \\ \upsilon_k \sim (0, R_k) \end{cases} \tag{7}$$

Where x_k is state variable at time k, u_k is input variable, process noise ω and measured noise υ are independent. $f(x_k, u_k)$ and $h(x_k, u_k)$ are expanded at each moment with Taylor formula. The state transition matrix and observation matrix of nonlinear systems are obtained:

$$\hat{\boldsymbol{A}}_k = \left.\frac{\partial f(x_k, u_k)}{\partial \boldsymbol{x}_k}\right|_{\boldsymbol{x}_k = \hat{\boldsymbol{x}}_k^+},\ \hat{\boldsymbol{C}}_k = \left.\frac{\partial h(x_k, u_k)}{\partial \boldsymbol{x}_k}\right|_{\boldsymbol{x}_k = \hat{\boldsymbol{x}}_k^-} \tag{8}$$

SOC, as an intermediate state of the battery, cannot be measured directly. A widely used discretized state space equation describing the battery is shown in equation (9). The observability of this equation has been demonstrated [8].

$$\begin{cases} \begin{bmatrix} U_{p,k+1} \\ s_{k+1} \end{bmatrix} = \begin{bmatrix} \exp(-1/(R_pC_p)) & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} U_{p,k} \\ s_k \end{bmatrix} + \begin{bmatrix} R_p(1-\exp(-1/(R_pC_p))) \\ \eta / 3600 \cdot Q \end{bmatrix} I_{L,k} + \boldsymbol{\omega}_k \\ U_{L,k} = U_{OC}(s_k) + U_{p,k} + R_o I_{L,k} + \upsilon_k \end{cases} \tag{9}$$

Where s represents SOC, η is the Coulombic efficiency, noise $\boldsymbol{\omega}_k \sim (0, \boldsymbol{Q}_k)$ and $\upsilon_k \sim (0, R_k)$ are independent, and $U_{oc}(s_k)$ is a function of SOC, which is fitted by a nine-order polynomial in this paper.

That is $\boldsymbol{x}_k = [U_{p,k}, s_k]^T$, $y_k = U_{L,k}$, $\hat{\boldsymbol{A}}_k = \begin{bmatrix} \exp(-1/(R_pC_p)) & 0 \\ 0 & 1 \end{bmatrix}$, $\hat{\boldsymbol{C}}_k = \left[1, \left.\frac{\partial U_{oc}(s)}{\partial s}\right|_{s=\hat{s}_k^-} \right]$.

The process of SOC estimation using the EKF algorithm is as follows:

$$\begin{cases} \text{for } k = 0, \\ \text{Set } \hat{\boldsymbol{x}}_0^+ = E[\boldsymbol{x}_0], \boldsymbol{P}_0^+ = E[(\boldsymbol{x}_0 - \hat{\boldsymbol{x}}_0^+)(\boldsymbol{x}_0 - \hat{\boldsymbol{x}}_0^+)^T] \\ \text{for } k = 1, 2, 3, \ldots \\ \text{State estimate time update: } \hat{\boldsymbol{x}}_k^- = f(\hat{\boldsymbol{x}}_{k-1}^+, u_{k-1}) \\ \text{Error innovation: } e_k = y_k - h(\hat{\boldsymbol{x}}_k^-, u_k) \\ \text{Error covariance time update: } \boldsymbol{P}_k^- = \hat{\boldsymbol{A}}_{k-1}\boldsymbol{P}_{k-1}^+\hat{\boldsymbol{A}}_{k-1}^T + \boldsymbol{Q}_k \\ \text{Kalman gain matrix: } \boldsymbol{K}_k = \boldsymbol{P}_k^-\hat{\boldsymbol{C}}_k^T(\hat{\boldsymbol{C}}_k\boldsymbol{P}_k^-\hat{\boldsymbol{C}}_k^T + R_k)^{-1} \\ \text{State estimate measurement update: } \hat{\boldsymbol{x}}_k^+ = \hat{\boldsymbol{x}}_k^- + \boldsymbol{K}_k e_k \\ \text{Error covariance measurement update: } \boldsymbol{P}_k^+ = (\boldsymbol{I} - \boldsymbol{K}_k\hat{\boldsymbol{C}}_k)\boldsymbol{P}_k^- \end{cases} \tag{10}$$

The SOC estimation value, as an element of matrix $\boldsymbol{x}$, can be calculated by the equation (10) at each time k.

3.2. AEKF with Sage-Husa adaptive filter (SHAF)

The noise statistics, however, are often unknown in practice. To reduce the effect of unknown noise on state estimation, some adaptive filtering methods are added on EKF. While estimating states, the statistical characteristics of the system's process noise and measurement noise are estimated and corrected simultaneously according to the change of measurement data at each step. The two adaptive approaches mentioned in the paper are Sage-Husa adaptive filter and innovation-based adaptive estimator.

Define the noise $\boldsymbol{\omega}_k \sim (\boldsymbol{q}_k, \boldsymbol{Q}_k)$ and $\upsilon_k \sim (r_k, R_k)$ independent. Since the noise mean is no longer zero, the *State estimate time update* in EKF equation (10) changes to $\hat{\boldsymbol{x}}_k^- = f(\hat{\boldsymbol{x}}_{k-1}^+, u_{k-1}) + \hat{\boldsymbol{q}}_{k-1}$, the *Error innovation* changes to $e_k = y_k - h(\hat{\boldsymbol{x}}_k^-, u_k) - \hat{r}_{k-1}$. In each recursive cycle, the SHAF algorithm (equation (11)) is applied, in order to estimate the mean $\boldsymbol{q}_k$, r_k and the variance $\boldsymbol{Q}_k$, R_k online. The current state estimation value can be continuously modified according to the estimation results of noise mean and variance of each step [9].

$$\begin{cases} \boldsymbol{q}_k = (1-d_k)\boldsymbol{q}_{k-1} + d_k(\hat{\boldsymbol{x}}_k^+ - f(\hat{\boldsymbol{x}}_{k-1}^+, u_{k-1})) \\ \boldsymbol{Q}_k = (1-d_k)\boldsymbol{Q}_{k-1} + d_k(\boldsymbol{K}_k e_k e_k^T \boldsymbol{K}_k^T + \boldsymbol{P}_k^+ - \hat{\boldsymbol{A}}_{k-1}\boldsymbol{P}_{k-1}^+\hat{\boldsymbol{A}}_{k-1}^T) \\ r_k = (1-d_k)r_{k-1} + d_k(y_k - h(\hat{\boldsymbol{x}}_k^-, u_k)) \\ R_k = (1-d_k)R_{k-1} + d_k(e_k e_k^T - \hat{\boldsymbol{C}}_k \boldsymbol{P}_k^- \hat{\boldsymbol{C}}_k^T) \end{cases} \tag{11}$$

Where $d_k = (1-b)/(1-b^{k+1})$, b is forgetting factor and $0<b<1$.

3.3. AEKF with innovation-based adaptive estimator (IAE)

The IAE emphasizes the role of innovation in recent cycles, which makes use of the covariance matching approach. It estimates covariance matrices $\boldsymbol{Q}_k$ and R_k using the following equations [10]:

$$H_k = \frac{1}{M}\sum_{i=k-M+1}^{k} e_i e_i^T \tag{12}$$

$$\begin{cases} \boldsymbol{Q}_k = \boldsymbol{K}_k H_k \boldsymbol{K}_k^T \\ R_k = H_k - \hat{\boldsymbol{C}}_k \boldsymbol{P}_k^- \hat{\boldsymbol{C}}_k^T \end{cases} \tag{13}$$

Where H_k is the innovation covariance matrix based on the innovation sequence and M is the moving window size.

3.4. The combined SOC estimation method

The combined SOC estimation method contains following steps:

Step I: Taking $U_{L,k}$, $U_{L,k-1}$, $I_{L,k}$, $I_{L,k-1}$ as input, use RLS method to identify parameters of the battery model online, and get $R_{o,k}$, $R_{p,k}$, $C_{p,k}$ at time k;

Step II: Get $U_{oc,k}=f(s_{k-1})$[1] according to SOC obtained at time k-1;

Step III: Use the parameters $R_{o,k}$, $R_{p,k}$, $C_{p,k}$, $U_{oc,k}$ obtained in the previous two steps to perform SOC estimation by EKF/AEKF method;

Step IV: $k=k+1$, and go to Step I.

The above four steps are recursively executed, and with the increase of k, the SOC estimate value will converge to the real SOC.

[1] In section 2, the U_{oc} can be identified online, but it cannot be directly applied to EKF/AEKF. Because the observation equation needs to be an equation about two variables of SOC and U_p. If the identified U_{oc} is used directly, the SOC estimation will become open-loop control, resulting in divergence.

4. Experiment and discussion

4.1. Experiment and simulation

The experimental platform is composed of five parts: an Arbin BTS2000 battery test equipment with voltage and current acquisition accuracy within 0.05%, a host computer, a thermostat and cells. The cell is placed in the thermostat with a constant temperature of 25℃. The Arbin is used to carry out charging or discharging tests and record data at a sampling frequency of 1 Hz. The cell used in this study is graphite||NCM lithium-ion battery with a nominal capacity of 25Ah and the Coulombic efficiency is neglected.

In order to simulate the driving conditions of electric vehicles, the federal urban driving schedule (FUDS) is performed repeatedly to discharge the fully charged cell to 0% SOC. The combined SOC estimation method is modeled in Matlab/Simulink and the SOC value obtained by ampere-hour integral in Arbin is regarded as the true value. Add a normally distributed noise signal to the voltage and current data and input it to the model, then verify the applicability and anti-interference of the combined SOC estimation method under noise interference.

The parameters set in the experiment and simulation are given in Table 1.

Table 1. Parameter settings.

Parameters	Values	Parameters	Values
$\boldsymbol{P}_0$ (RLS)	$1000^2\mathbf{I}_4$	$\boldsymbol{q}_0$	$[0, 0]^T$
$\boldsymbol{\theta}_0$	$[0.97, 0.0014, -0.0013, 0.11]^T$	r_0	0
λ	0.985	b	0.975
$\boldsymbol{P}_0$ (EKF/SHAF/IAE)	[0.01, 0; 0, 0.01]	M	50
$\boldsymbol{x}_0$	$[0.5, 0]^T$	$U_{oc}(s)$	$368.93s^9-1860.73s^8+4042.42s^7-4940.51s^6+3714.82s^5-1763.32s^4+522.63s^3-92.49s^2+9.34s+3.09$
$\boldsymbol{Q}_0$ (EKF/SHAF/IAE)	$[10^{-4}, 0; 0, 2\times10^{-4}]$	Voltage noise	$N_U \sim (5\times10^{-3}, 5\times10^{-5})$
R_0 (EKF/SHAF/IAE)	10^{-4}	Current noise	$N_I \sim (0.1, 0.001)$

4.2. Results and analysis

The results are shown in Fig. 2, where Fig. a shows the error of three SOC estimation methods when conducting FUDS from 100% SOC to 0% SOC. This figure illustrates that the EKF method has the worst estimation accuracy, whose error is -3.0443%~4.0189%; the estimation accuracy of AEKF method with SHAF is superior to EKF, in the range of -1.9813%~2.3190%, and the error of AEKF method with IAE is smallest, between -0.9402%~ 1.2117%. Fig. b magnifies the first 80 seconds of the beginning of the test, i.e. the first gray square from the left in Fig. a. It can be seen that the convergence time of the three methods is almost the same (within 30 seconds). Fig. c is the enlargement of the second gray square from the left in Fig. a. EKF method has serious jitter under noise interference in the figure. The jitter of AEKF method with SHAF is slightly smaller, which indicates that this method has a certain inhibitory effect on noise, but it is still inferior to the AEKF method with IAE, which has the strongest noise suppression performance. Removing the initial convergence period, the error statistics are shown in Table 2. The IAE method has significant advantages over the other two methods, in terms of the mean, the standard deviation and the error band bandwidth. This is because the IAE method can make full use of the new innovation sequence in the sliding window and correct the filter gain matrix in time according to the newly measured information, which enhances its effect on noise filtering.

Table 2. Statistical information of SOC error.

	Mean	Standard Deviation	Minimum	Maximum
EKF	0.2158	0.8083	-3.0443	4.0189
SHAF	0.2130	0.5379	-1.9813	2.3190
IAE	0.1880	0.3467	-0.9402	1.2117

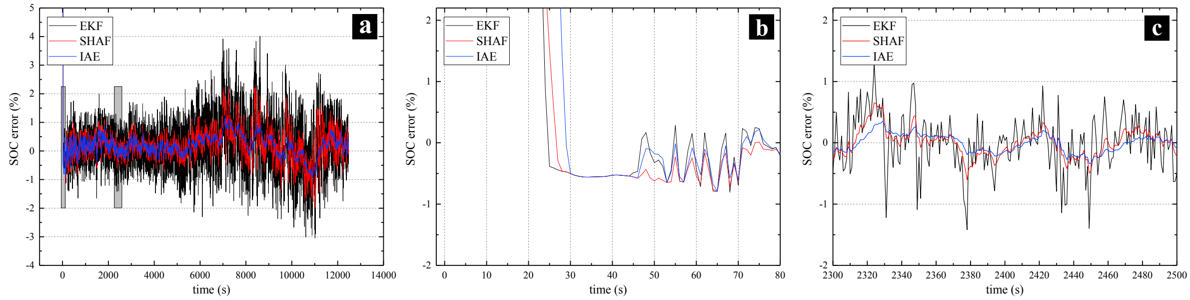

Fig. 2. SOC estimation error using three methods.

In addition, there is a problem that cannot be ignored. The online parameter identification of RLS is also affected by the noise, because it employs the voltage and current signals as well. The signals with noise will give rise to inaccurate parameters, resulting in poor accuracy of the SOC estimation. Therefore, to supply accurate data sources for parameter identification and SOC estimation, it should be start with the improvement of the equipment accuracy. Secondly, AEKF with IAE, with a strong ability to suppress noises, has great application value on SOC estimation. Its complex algorithm, however, puts higher requirements on the arithmetic chip.

5. Conclusion

In this paper, online parameter identification based on RLS is used to obtain the resistance and capacitance parameters of the battery model in real time, which avoids the problem of constructing complex parameter tables based on experiments and avoids errors caused by table interpolation. Then, a combined SOC estimation method is constructed to compare the estimation errors of EKF, AEKF with SHAF and AEKF with IAE. The results show that IAE method has obvious advantages over the other two methods. The error of SOC estimation under certain noise interference is within ±2%.

Acknowledgements

The work was supported by National Natural Science Foundation of China under Grant no. 51477009.

References

[1] Bugallo M, Nica F, Xu S, Djuri, Petar M. Performance comparison of EKF and particle filtering methods for maneuvering targets. Digital Signal Processing. 2007;17:774-86.
[2] Plett GL. Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs - Part 2. Modeling and identification. Journal of Power Sources. 2004;134:262-76.
[3] Plett GL. Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs. Part 3. State and parameter estimation. Journal of Power Sources. 2004;134:277-92.
[4] Ouyang M, Liu G, Lu L, Li J, Han X. Enhancing the estimation accuracy in low state-of-charge area: A novel onboard battery model through surface state of charge determination. Journal of Power Sources. 2014;270:221-37.
[5] Liaw BY, Nagasubramanian G, Jungst RG, Doughty DH. Modeling of lithium ion cells—A simple equivalent-circuit model approach. Solid State Ionics. 2004;175:835-9.
[6] Xiong R, He H, Sun F, Zhao K. Online Estimation of Peak Power Capability of Li-Ion Batteries in Electric Vehicles by a Hardware-in-Loop Approach. Energies. 2012;5:1455-69.
[7] Zhao T, Jiang J, Zhang C, Zheng L, Wen F. Error analysis of SOC estimation based on PI observer. Transportation Electrification Asia-Pacific2014. p. 1-5.
[8] Zheng L, Research on capacity estimation of traction battery pack for electric vehicle, Beijing Jiaotong University, 2014.
[9] Wang J, Guo J, Lei D. An adaptive Kalman filtering based State of Charge combined estimator for electric vehicle battery pack. Energy Conversion & Management. 2009;50:3182-6.
[10] Mohamed AH, Schwarz KP. Adaptive Kalman Filtering for INS/GPS. Journal of Geodesy. 1999;73:193-203.