Implementation of The State of Charge Estimation with Adaptive Extended Kalman Filter for Lithium-ion Batteries by Arduino

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***Abstract*—This study considers the use of Arduino to achieve state of charge (SOC) estimation of lithium-ion batteries by adaptive extended Kalman filter (AEKF). To implement a SOC estimator for the lithium-ion battery, we adopt a first-order RC equivalent circuit as the equivalent circuit model (ECM) of the battery. The parameters of the ECM will be identified through the designed experiments, and they will be approximated by the piecewise linear functions and then will be built into Arduino. The AEKF algorithm will also be programed into Arduino to estimate the SOC. To verify the accuracy of the SOC estimation, some lithium-ion batteries are tested at room temperature. Experimental results show that the absolute value of the steady-state SOC estimation error is small.**

I. Introduction

Lithium-ion batteries have high energy, long cycle life and low self-discharge rate. Hence, they are widely used in energy storage power systems and electric vehicles [1]. The battery management system (BMS) is used to guarantee reliable and safe operation. In general, SOC is an important factor for the BMS since the SOC is considered as the energy of the battery [2]. However, the SOC cannot be directly measured. Hence, some SOC estimation methods have been proposed. Coulomb counting method is an SOC estimation method based on the current measurements [2-3]. This method has high accuracy due to the charge conservation. However, it may suffer from the problem of unknown initial SOC value of the battery. In addition, the accuracy of the current sensor also affects the performance. The model-based SOC estimation methods, such as the extended Kalman filter (EKF) [4-8] and the adaptive EKF (AEKF) [9-14], have been widely used.

In recent years, Arduino, a kind of microcontrollers has been applied to protect the battery from overcharge and over-discharge, and also has been used to measure the voltage and the current when the battery is operating [15-18]. In [15], a charge controller for solar battery has been proposed. In [16-17], Coulomb counting method is adopted to estimate the SOC of the battery. Although the Coulomb counting method is widely used in real application based on calculating the charge of the battery, it is seen that Coulomb counting is not a reliable SOC estimation method if the initial SOC is unknown. In [18], battery monitoring system based on LabVIEW and Arduino is proposed. It can provide the voltage and current measurements of the batteries in real-time. For SOC estimation, a hybrid filter-based SOC and SOH estimator for lithium-ion batteries has been proposed in [19] to implement an Arduino-based real-time embedded BMS.

In this study, we will implement a real-time embedded SOC estimator for lithium-ion battery cell by Arduino. Due to the low price and reliability of the Arduino MEGA 2560, we select it as the develop platform. A first-order RC equivalent circuit is adopted as the ECM of the battery. To identify the parameters of the ECM, the open-circuit voltage (OCV) test [20] and direct current internal resistance (DCIR) test [21-22] are applied. The relations between SOC and the parameters of the ECM are described by the piecewise linear functions. The parameters of the ECM and the AEKF algorithm will be programed into Arduino. Three lithium-ion battery cells will be tested at room temperature (25 °C). One of the batteries with certain initial SOC value is used to verify the accuracy of the SOC estimation. And the others with the uncertain initial SOC value are used to verify the reliability of the proposed real-time embedded SOC estimator. According to the verification results, it is seen that the proposed real-time embedded SOC estimator is reliable and has good performance.

The rest of this paper is organized as follows: Section II gives a brief discussion of the lithium-ion battery. Section III presents the process of SOC estimation based on Arduino. In Section IV, the verification results are shown in detail. Section V presents the conclusions.

II. Lithium-Ion Battery

The SOC of lithium-ion battery is defined as follows:

$$SOC(t) = \frac{\text{remaining capacity } (t)}{\text{nominal capacity}} \tag{1}$$

where the nominal capacity is the rated capacity of the battery which is usually provided by the manufacturer and the remaining capacity (t) is the charge of the battery at time t [23]. Rewriting (1), the Coulomb counting equation can be written as

$$SOC(t) = SOC(0) + \int_0^t \frac{1}{C_n} I(\tau)\, d\tau \tag{2}$$

where $SOC(t)$ is the state of charge of the battery at time t, $SOC(0)$ is the initial SOC, $I(\tau)$ is the load current flowing through the battery and C_n is the nominal capacity. Differentiating (2) with respect to the time t, we obtain

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$$\dot{SOC}(t) = \frac{1}{C_n} I(t) \tag{3}$$

A. ECM Establishment

A first-order RC circuit model as shown in Fig. 1 is adopted as the ECM of the lithium-ion battery [8-10], where V_{oc} denotes the OCV, R_t denotes the ohmic resistance, R_p denotes the diffusion resistance, C_p denotes the diffusion capacitance, $V_t(t)$ denotes the circuit terminal voltage and $I(t)$ denotes the load current. It is known that all the numerical values of the R_t, C_p, R_p and V_{oc} depend on SOC. The $V_{oc}(SOC)$ can be obtained by the OCV test [20], and the $R_t(SOC)$, $R_p(SOC)$, $C_p(SOC)$ can be obtained by the DCIR test [21-22]. According to the Kirchhoff's laws, we obtain

$$\dot{V}_p(t) = -\frac{1}{R_p C_p} V_p(t) + \frac{1}{C_p} I(t) \tag{4}$$

$$V_t(t) = V_{oc}(SOC) + R_t \cdot I(t) + V_p(t) \tag{5}$$

To identify the ECM of the lithium-ion battery, the battery cycler Chroma 17011 is utilized and a type ICR 18650J lithium-ion battery is tested. This battery has a rated capacity of 2.37 Ah and a standard voltage of 3.7 V. Other specifications of the battery provided by this manufacturer are listed in TABLE I. The battery is firstly fully charged by constant current constant voltage (CC-CV) charge method [20] before rest of 1 hour is applied to obtain the OCV of the battery at 100% SOC. Next, the following steps are repeated until the terminal voltage of the tested battery reaches 3 V. By the DCIR test, a pulse-type charge and discharge current of 2.4 A for 10 seconds is applied. Then, a discontinuous constant current of 0.25C is applied for the necessary time to discharge 5% SOC followed by the rest of 1 hour. The detail of the designed DCIR test can be seen in [24-25]. The whole experiments are conducted under room temperature condition (25 °C). According to the experimental data, we can obtain the $V_{oc}(SOC)$ and the parameters at each 5% SOC interval. In order to fit the experimental data, the experimental data are described by the following piecewise linear functions

$$V_{oc}\left(SOC_i\right) = a_i \cdot SOC_i + b_i \tag{6}$$

$$R_t\left(SOC_i\right) = c_i \cdot SOC_i + d_i \tag{7}$$

$$R_p\left(SOC_i\right) = e_i \cdot SOC_i + f_i \tag{8}$$

$$C_p\left(SOC_i\right) = g_i \cdot SOC_i + h_i \tag{9}$$

where the coefficients a_i, b_i, …, g_i, h_i are constants at ith SOC region, SOC_i denotes the 5% SOC interval of [5i%, 5(i+1)%]. Fig. 2 shows the experimental data and the resulting curve-fitting.

B. SOC Estimation Based on AEKF

According to (3)-(6), the discrete-time state-space model of the ECM can be obtained as

$$\begin{cases} \mathbf{x}[k+1] = \mathbf{A}[k]\mathbf{x}[k] + \mathbf{B}[k]u[k] + \mathbf{w}[k] \\ y[k] = \mathbf{C}[k]\mathbf{x}[k] + \mathbf{D}[k]u[k] + b_i + \mathbf{v}[k] \end{cases} \tag{10}$$

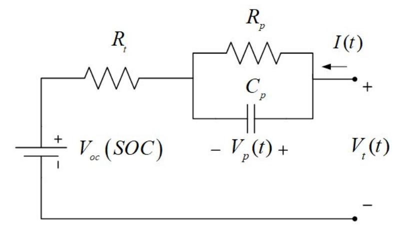

Figure 1. First-order RC equivalent circuit.

TABLE I. SPECIFICATIONS OF ICR 18650J

Standard Charge Time	Maximum Discharge Current	Upper Cut-Off Voltage	Lower Cut-Off Voltage
3 hrs	4 A at 60 °C 5 A at 60 °C	4.2 V	3 V

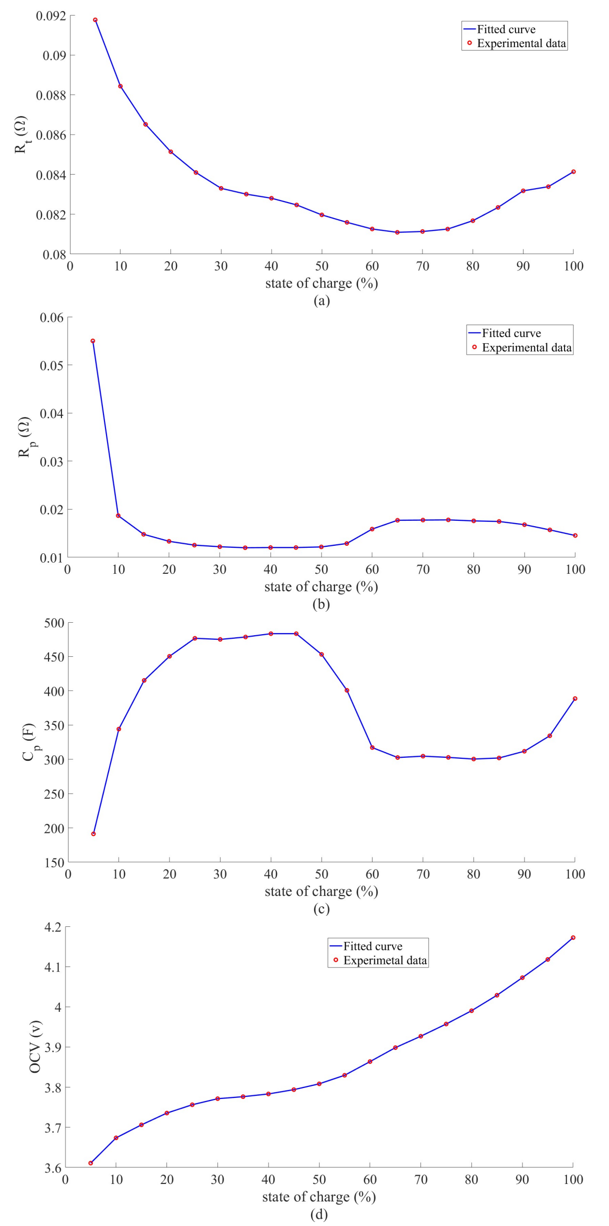

Figure 2. Piecewise linearization functions (a) R_t-SOC, (b) R_p-SOC, (c) C_p-SOC, (d) V_{oc}-SOC.

where $\mathbf{x}[k]=\left[SOC[k] \quad V_p[k]\right]^{\mathrm{T}}$, $y[k]=V_t[k]$, $u[k]=I[k]$, $\mathbf{w}[k]$ and $\mathbf{v}[k]$ are uncorrelated, zero-mean, Gaussian processes with covariance matrices $\mathbf{Q}[k]$ and $\mathbf{R}[k]$, respectively,

$$\mathbf{A}[k]=\begin{bmatrix}1 & 0\\ 0 & 1-\dfrac{\Delta \mathrm{T}}{R_p[k]\cdot C_p[k]}\end{bmatrix},\mathbf{B}[k]=\begin{bmatrix}\dfrac{\Delta \mathrm{T}}{C_n} & \dfrac{\Delta \mathrm{T}}{C_p[k]}\end{bmatrix}^{\mathrm{T}},$$

$\mathbf{C}[k]=\begin{bmatrix}a_i & 1\end{bmatrix}$, $\mathbf{D}[k]=R_t[k]$, $\Delta\mathrm{T}$ is sampling period.

Based on (10), the AEKF algorithm [13] is presented in TABLE II.

III. SOC Estimator Using Arduino

We choose the microcontroller board Arduino MEGA 2560 to implement a real-time embedded SOC estimator for lithium-ion battery. To measure the terminal voltage of the battery $V_t[k]$, the analog pin of the Arduino is used. In order to measure the inflow or outflow current of the battery $I[k]$, the voltage across a 1.15 Ω precision resistor in series with the battery can be used to calculate the current. The detail of the voltage and current measurement method are based on [15]. To avoid overcharge and over-discharge, a charge-discharge protection board is utilized. A LCD is used to display the data. Fig. 3 shows the wiring diagram of the SOC estimator. In Fig. 3, pin A0 is used to measure the terminal voltage of the battery. The voltage difference between pin A5 and pin A0 is the across voltage of the precision resistor. The proposed real-time embedded SOC estimator is shown in Fig. 4.

TABLE II. AEKF Algorithm

Step 1: Initialization, $k = 0$
$\hat{\mathbf{x}}^{+}[0]$, $\mathbf{P}^{+}[0]$, $\mathbf{Q}[0]$, $\mathbf{R}[0]$ Then, $k = 1$
Step 2: The priori process
$\hat{\mathbf{x}}^{-}[k]=\mathbf{A}[k-1]\hat{\mathbf{x}}^{+}[k-1]+\mathbf{B}[k-1]\,u[k-1]$ $\mathbf{P}^{-}[k]=\mathbf{A}[k-1]\mathbf{P}^{+}[k-1]\mathbf{A}^{\mathrm{T}}[k-1]+\mathbf{Q}[k-1]$
Step 3: Compute the innovation matrix and the Kalman gain
$e[k]=y[k]-(\mathbf{C}[k]\hat{\mathbf{x}}^{-}[k]+\mathbf{D}[k]u[k]+\hat{b}_i^{-})$ $\mathbf{K}[k]=\mathbf{P}^{-}[k]\mathbf{C}^{\mathrm{T}}[k]\left(\mathbf{C}[k]\mathbf{P}^{-}[k]\mathbf{C}^{\mathrm{T}}[k]+\mathbf{R}[k-1]\right)^{-1}$
Step 4: Adaptive covariance matching
$\mathbf{H}[k]=\dfrac{1}{k+1}\sum_{i=1}^{k}e[i]e[i]$ $\mathbf{R}[k]=\mathbf{H}[k]-\mathbf{C}[k]\mathbf{P}^{-}[k]\mathbf{C}^{\mathrm{T}}[k]$ $\mathbf{Q}[k]=\mathbf{K}[k]\mathbf{H}[k]\mathbf{K}^{\mathrm{T}}[k]$
Step 5: The posteriori process
$\hat{\mathbf{x}}^{+}[k]=\hat{\mathbf{x}}^{-}[k]+\mathbf{K}[k]e[k]$ $\mathbf{P}^{+}[k]=(\mathbf{I}-\mathbf{K}[k]\mathbf{C}[k])\mathbf{P}^{-}[k]$
Step 6: Let $k = k + 1$, go to Step 2

A. Programming

According to Fig. 2, the relations between the SOC_i and the coefficients a_i, b_i, …, g_i, h_i of (6)-(9) is established into Arduino. Next, the AEKF algorithm listed in Table II is programed into Arduino for SOC estimation. As shown in Fig. 5, the measurements of the terminal voltage V_t and the load current I are used as the output and input for (10), respectively. According to the SOC estimate $\widehat{SOC}[k]$ obtained by AEKF, the a_i, b_i, …, g_i, h_i can be determined by the look-up table method. And consequently, the parameters R_t, R_p, C_p can be calculated by (7)-(9). Finally, the matrices $\mathbf{A}[k]$, $\mathbf{B}[k]$, $\mathbf{C}[k]$, $\mathbf{D}[k]$ can be obtained.

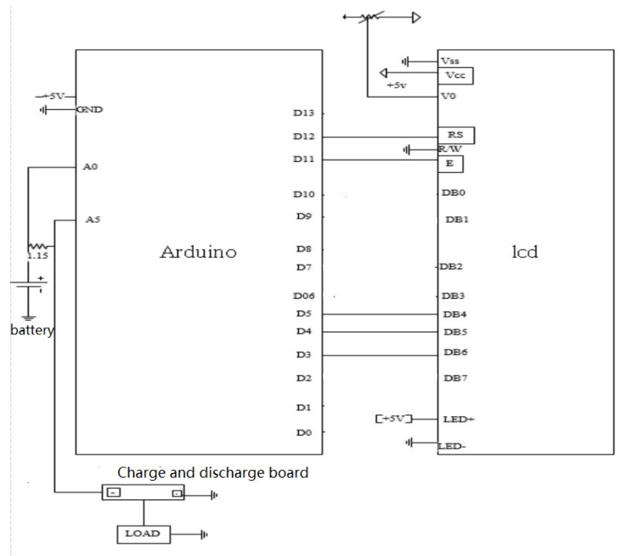

Figure 3. Wiring diagram.

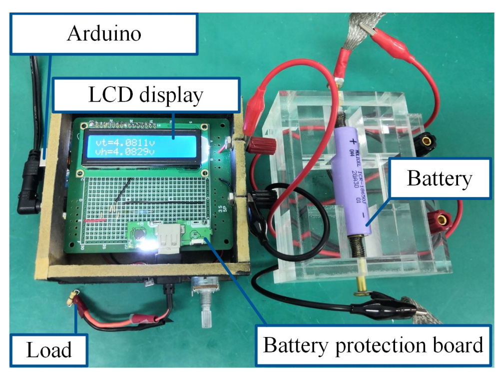

Figure 4. The real-time embedded SOC estimator.

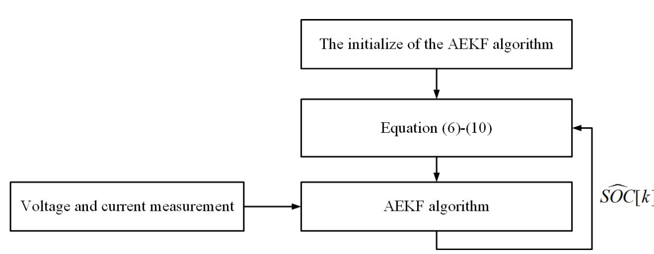

Figure 5. Flowchart of the SOC estimator.

Figure 6. First page of LCD display.

Figure 7. Second page of LCD display.

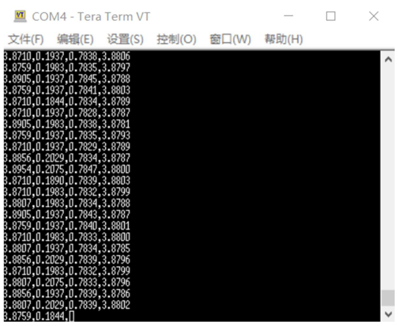

Figure 8. The logging results by Tera Term application.

B. LCD Display

The main screen shows the estimated data including the SOC estimates, load current, terminal voltage and terminal voltage estimates. There are two pages to show the data, and the page will flip over every 5 seconds. In the first page (see Fig. 6), the first row shows the SOC estimates of the battery which is denoted by soc. The second row shows the load current (in ampere) which is denoted by i. In the second page (see Fig. 7), the first row shows the terminal voltage (in volt) which is denoted by vt. The second row shows the terminal voltage estimates (in volt) which is denoted by vh.

IV. VERIFICATION RESULTS

In other to verify the performance of the proposed real-time embedded SOC estimator, three ICR 18650J lithium-ion batteries named Battery 1, Battery 2 and Battery 3 are tested, respectively. All the tests are conducted under room temperature condition (25 ℃). Battery 1 with initial SOC value 1 (100%) is tested for verifying the accuracy of the SOC estimation, and Battery 2 and Battery 3 with unknown initial SOC values are tested for verifying the reliability of the proposed real-time embedded SOC estimator. To log the data of the proposed real-time embedded SOC estimator, the Tera Term application which can log the data of the microcontroller to the computer is applied in this paper and its interface is shown in Fig. 8. The logged data are terminal voltage, load current and SOC. To demonstrate the SOC estimates, the Matlab is used to analyze the logged data.

To apply the proposed estimation method. The matrices $\hat{\mathbf{x}}^{+}[0]$, $\mathbf{P}^{+}[0]$, $\mathbf{Q}[0]$, $\mathbf{R}[0]$ of the AEKF algorithm are set as

$$\hat{\mathbf{x}}^{+}[0]=\begin{bmatrix}\widehat{SOC}[0]\\ 0.04\end{bmatrix},\ \hat{\mathbf{P}}^{+}[0]=\begin{bmatrix}0.01 & 0\\ 0 & 0.01\end{bmatrix},$$

$$\mathbf{Q}[0]=\begin{bmatrix}1 & 0\\ 0 & 1\end{bmatrix},\ \mathbf{R}[0]=1.$$

To verify the accuracy of the SOC estimation, the Coulomb counting method is applied to calculate the SOC of the Battery 1 as the reference SOC. The current profile of Battery 1 is shown in Fig. 9, and the average current value is –0.2233 A. The SOC estimates from the proposed real-time embedded SOC estimator and the reference SOC based on Coulomb counting method are shown in Fig. 10. According to Fig. 11, the absolute value of SOC estimation error of Battery 1 is less than 1%.

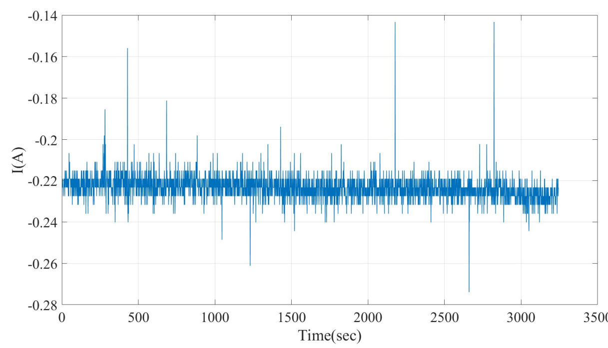

Figure 9. The current profile of Battery 1

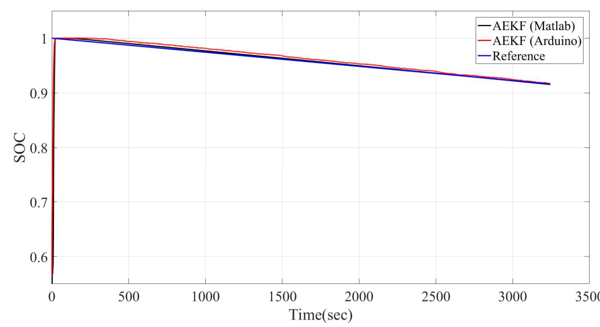

Figure 10. The SOC estimation of Battery 1 ($\widehat{SOC}[0]$ = 0.57).

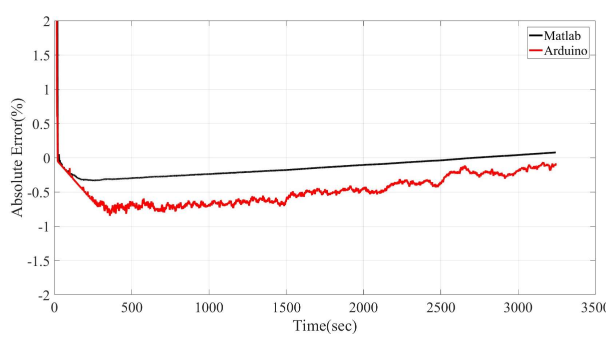

Figure 11. The absolute value of SOC estimation error of Battery 1.

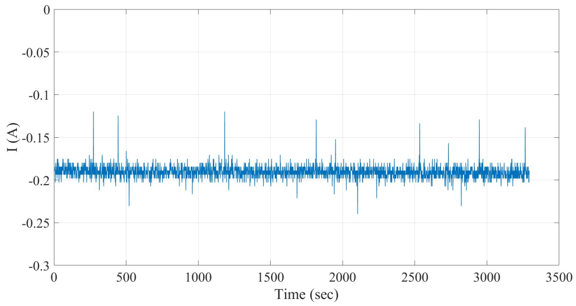

Figure 12. The current profile of Battery 2.

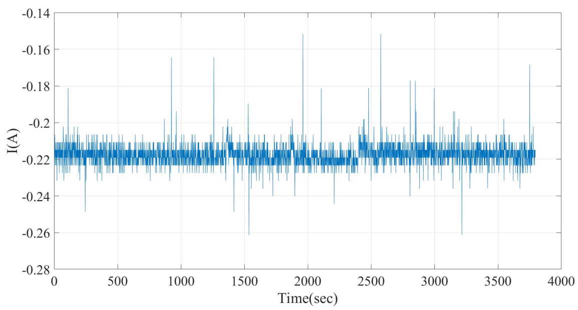

Figure 13. The current profile of Battery 3.

To verify the reliability of the real-time embedded SOC estimator, we directly compare the SOC estimates from the real-time embedded SOC estimator with the SOC estimates from Matlab. The current profile of Battery 2 and Battery 3 are shown in Fig. 12 and Fig. 13, respectively. The average current values of Battery 2 and Battery 3 are -0.1907 A and -0.2176 A, respectively. The SOC estimates from real-time embedded SOC estimator and Matlab of Battery 2 and Battery 3 are shown in Fig. 14 and Fig. 15, respectively. According to the Fig. 14 and Fig. 15, one can observe that the difference of the SOC estimates from the Matlab and the real-time embedded SOC estimator is small. Thus, the proposed real-time embedded SOC estimator performs well. Compared with the cost of the Matlab with PC, the cost of the proposed real-time embedded SOC estimator with Arduino is much lower.

V. Conclusion

The verification results indicate that the goal of developing an efficient and low cost real-time embedded SOC estimator for lithium-ion battery has been achieved. It is seen that the absolute value of the steady-state SOC estimation error is small. According to the experimental results, the AEKF algorithm which is implemented by Arduino works well. Hence, the proposed real-time embedded SOC estimator has good performance in the SOC estimation of lithium-ion battery.

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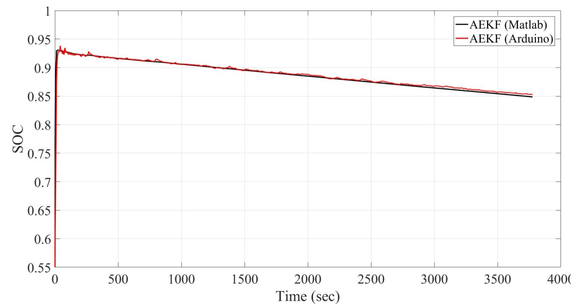

Figure 14. The SOC estimation of Battery 2 ($\widehat{SOC}[0] = 0.55$).

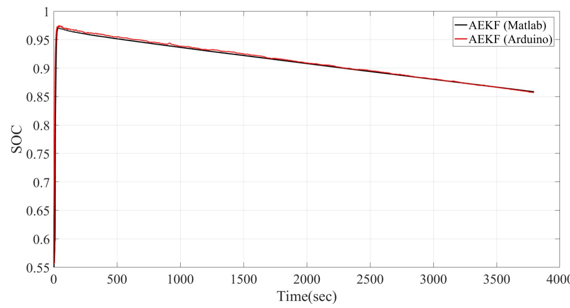

Figure 15. The SOC estimation of Battery 3 ($\widehat{SOC}[0] = 0.55$).

References

[1] T. B. Reddy, *Linden's handbook of batteries*, Mcgraw-Hill, 2011.

[2] R. Xiong, J. Cao, Q. Yu, H. He and F. Sun, "Critical Review on the Battery State of Charge Estimation Methods for Electric Vehicles," in *IEEE Access*, vol. 6, pp. 1832-1843, 2017.

[3] S. Piller, M. Perrin, A. Jossen, "Methods for state-of-charge determination and their applications," *J. Power Sources*, vol. 96, pp. 113-120, 2001.

[4] K. T. Lee, M. J. Dai and C. C. Chuang, "Temperature-Compensated Model for Lithium-Ion Polymer Batteries With Extended Kalman Filter State-of-Charge Estimation for an Implantable Charger," in *IEEE Trans. on Ind. Electron.*, vol. 65, no. 1, pp. 589-596, Jan. 2018.

[5] F. Yang, Y. Xing, D. Wang, and K. L. Tsui, "A comparative study of three model-based algorithms for estimating state-of-charge of lithium-ion batteries under a new combined dynamic loading profile," *Appl. Energy*, vol. 164, pp. 387–399, Feb. 2016.

[6] V. Sangwan, R. Kumar and A. K. Rathore, "State-of-charge estimation for li-ion battery using extended Kalman filter (EKF) and central difference Kalman filter (CDKF)," in *Proc. 2017 IEEE Industry Applications Society Annual Meeting*, Cincinnati, OH, pp. 1-6, 2017.

[7] S. Yang, C. Deng, Y. Zhang and Y. He, "State of Charge Estimation for Lithium-Ion Battery with a Temperature-Compensated Model," *Energies*, Oct. 2017.

[8] X. Li, J. Jiang, C. Zhang, L.Y. Wang, L. Zheng, "Robustness of SOC estimation algorithms for EV lithium-ion batteries against modeling errors and measurement noise," *Math. Probl. Eng.*, vol. 2015 (2015), pp. 1–14, Oct. 2015.

[9] F. Sun, R. Xiong, H. He, "Estimation of state-of-charge and state-of-power capability of lithium-ion battery considering varying health conditions," *J. Power Sources*, vol. 259, pp. 166 – 176, 2014.

[10] F. Sun and R. Xiong, "A novel dual-scale cell state-of-charge estimation approach for series-connected battery pack used in electric vehicles," *J. Power Source.*, vol. 274, pp. 582 – 594, 2015.

[11] C. C. Kung, S. C. Chang, S. M. Yeh, and P. H. Chen, "State of Charge Estimation of Lithium-Ion Battery with Aging Effect Using Adaptive Extended Kalman Filter," in *Proc. of the 2017 International Conference on Machine Learning and Cybernetics*, pp. 611-617, Jul. 2017.

[12] C. C. Kung, C. C. Weng, and T. H. Chen, “Fuzzy c-regression Model Based State of Charge Estimation for Lithium Battery Using Adaptive Extended Kalman Filter.” in *Proc. 2016 International Conference on Machine Learning and Cybernetics*, pp.958-963, Jul. 2016.

[13] J. Yang, B. Xia, Y. Shang, W. Huang and C. C. Mi, “Adaptive State-of-Charge Estimation Based on a Split Battery Model for Electric Vehicle Applications,” in *IEEE Trans. on Veh. Technol.*, vol. 66, no. 12, pp. 10889-10898, Dec. 2017.

[14] R. Xiong, H. He, F. Sun, and K. Zhao, “Evaluation on state of charge estimation of batteries with adaptive extended Kalman filter by experiment approach,” in *IEEE Trans. Veh. Technol.*, vol. 62, no. 1, pp. 108–117, Jan. 2013.

[15] W. Makni, N. Ben Hadj, H. Samet and R. Neji, “Design simulation and realization of solar battery charge controller using Arduino Uno,” in *Proc. 2016 17th International Conference on Sciences and Techniques of Automatic Control and Computer Engineering (STA)*, Sousse, pp. 635-639, 2016.

[16] N. Scharich, B. Schniter, A. Herbert and M. S. Islam, “Battery management system using Arduino,” in *Proc. 2017 IEEE Technology & Engineering Management Conference (TEMSCON)*, Santa Clara, CA, pp. 384-387, 2017.

[17] K. S. R. Kumar, V. V. Sastry, O. C. Sekhar, D. K. Mohanta, D. Rajesh and M. P. C. Varma, “Design and fabrication of coulomb counter for estimation of SOC of battery,” in *Proc. 2016 IEEE International Conference on Power Electronics, Drives and Energy Systems (PEDES)*, Trivandrum, pp. 1-6, 2016.

[18] A. Jamaluddin, L. Sihombing, A. Supriyanto, A. Purwanto and M. Nizam, “Design real time Battery Monitoring System using LabVIEW Interface for Arduino (LIFA),” in *Proc. 2013 Joint International Conference on Rural Information & Communication Technology and Electric-Vehicle Technology (rICT & ICeV-T)*, Bandung, pp. 1-4, 2013.

[19] T. Kim, A. Adhikaree, R. Pandey, D. Kang, M. Kim, and J. Baek, “A real-time condition monitoring for lithium-ion batteries using a lowpriced microcontroller,” in *Proc. 2017 IEEE Energy Conversion Congress and Exposition (ECCE)*, Cincinnati, OH, pp. 5248-5253, 2017.

[20] A. E. Mejdoubi, A. Oukaour, H. Chaoui, and H. Gualous, “State-of charge and state-of-health lithium-ion batteries’ diagnosis according to surface temperature variation,” in *IEEE Trans. Ind. Electron.*, vol. 63, no. 4, pp. 2391–2402, Apr. 2016.

[21] Jong Hoon Kim, Seong Jun Lee, Jae Moon Lee and Bo Hyung Cho, “A new direct current internal resistance and state of charge relationship for the Li-ion battery pulse power estimation,” in *Proc.* 2007 7th *International Conference on Power Electronics*, Daegu, pp. 1173-1178, Oct. 2007.

[22] J. Kim, J. Shin, C. Chun, and B. H. Cho, “Stable configuration of a Li-ion series battery pack based on a screening process for improved voltage/SOC balancing,” in *IEEE Trans. Power Electron.*, vol. 27, no. 1, pp. 411-424, Jan. 2012.

[23] J. Xu, C. C. Mi, B. G. Cao, and J. J. Deng, “The state of charge estimation of lithium-ion batteries based on a proportional-integral observer,” in *IEEE Trans. Veh. Technol.*, vol. 63, no. 4, pp. 1614-1621, May 2014.

[24] C. C. Kung, S. C. Chang, “The fuzzy c-regression model of the lithium battery and its application to the estimation of the state of charge,” in *Proc. of 2012 IEEE International Conference on Fuzzy Systems*, pp. 1-6, Jun. 2012.

[25] C. C. Kung, S. C. Chang and T. H. Chen, “The fuzzy c-regression model for lithium battery,” in *Proc. 2012 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, Seoul, pp. 1675-1680, Oct. 2012.