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Online SOC and SOH Estimation for Multicell Lithium-ion Batteries Based on an Adaptive Hybrid Battery Model and Sliding-Mode Observer

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***Abstract*—This paper proposes an adaptive hybrid battery model-based high-fidelity state of charge (SOC) and state of health (SOH) estimation method for rechargeable multicell batteries. The hybrid battery model consists of an enhanced Coulomb counting algorithm for SOC estimation and an electrical circuit battery model. A variable-length sliding window least squares (VSWLS)-based online parameter identification algorithm is designed to estimate the electrical parameters of the electrical battery model, which are then used as the parameters of an adaptive discrete-time sliding-mode observer (ADSMO) for terminal and open-circuit voltage estimation of a battery cell. The error of the SOC estimated from the enhanced Coulomb counting algorithm is then corrected by using the SOC obtained from the ADSMO-estimated open-circuit voltage. This leads to an accurate, robust real-time SOC estimation. In addition, the maximum capacity of the cell is estimated to determine the SOH of the cell. The proposed method is validated by simulation and experimental results for a four-cell cylindrical lithium-ion battery pack.**

I. INTRODUCTION

Multicell lithium-ion batteries have been pervasively used in various electrical systems, such as renewable power systems, electric vehicles (EVs), plug-in hybrid electric vehicles (PHEVs), etc. In order to ensure optimal performance, availability, and reliability of a battery system, it is crucial to precisely estimate the cell-level state of charge (SOC) and state of health (SOH) of the multicell batteries. Therefore, SOC and SOH are the main parameters of a battery management system (BMS) during battery operation [1].

A variety of battery SOC estimation methods have been developed, which, in general, can be classified into four categories: Coulomb counting-based methods, computational intelligence-based methods, model-based methods, and mixed methods. The Coulomb counting-based methods are simple and easy to implement in real-time systems [2]. However, they have unrecoverable problems that might be caused by factors such as a wrong initial SOC value, a wrong maximum capacity, the accumulation of estimation errors, and neglecting the self-discharge effect. Moreover, the Coulomb counting-based methods cannot keep track of battery nonlinear capacity variation effects, such as the rate capacity effect and recovery effect [3].

The computational intelligence-based methods describe the nonlinear relationship between the SOC and the factors influencing the SOC, such as battery voltage, current and temperature [4]-[6]. Artificial neural network (ANN)-based methods [4], fuzzy logic methods [5], and support vector regression methods [6] have been used to estimate the SOC of a battery. Although a precise estimation of the SOC can be obtained by the computational intelligence-based methods, the learning process required by these methods has a quite high computational burden, and is difficult to implement in real-time SOC tracking.

Model-based SOC estimation methods basically utilize state-space electrochemical-based mathematical models or electrical circuit battery models to design an observer for real-time SOC estimation. For example, Kalman filter [7], extended Kalman filter (EKF) [8], and sigma-point Kalman filter (SPKF) [9] have been used to estimate the SOC of a battery for PHEV and EV applications. In general, the EKF and SPKF methods provide an accurate solution for long-term SOC estimation. However, these methods require an accurate battery model, whose parameters, e.g., resistances and capacitances, typically vary with the SOC, temperature, current, aging, etc., of the battery cell. Therefore, additional online parameter estimation is usually needed to provide an accurate battery model [9]. Furthermore, even with an accurate battery model, the estimation error can be large when unexpected noise is present [10]. Moreover, the model-based SOC estimation methods have a higher

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computational complexity than the nonmodel-based Coulomb counting methods. To overcome model parameter uncertainties and computational burden, a sliding-mode observer (SMO) was designed for battery SOC estimation [11]. However, the accuracy of the SMO-based method will degrade due to the chattering problem when model uncertainties are significant [12]. The mixed SOC estimation methods combine the advantages of the aforementioned three methods [13].

The SOH is an indicator of battery aging, which results in capacity and power degradation. In general, capacity, internal resistance, and SOC are the commonly used battery parameters to quantify SOH [14]-[16]. Therefore, an accurate SOC estimation will facilitate the estimation of the SOH. Similar or the same techniques used for SOC estimation mentioned above can be applied to SOH estimation. For example, an ANN-based method [14], EKF [15], and SMO [16] have been applied to estimate the SOH of a battery. A main difference between SOC and SOH estimation is that the calculation time of SOH is much larger than that of SOC because the dynamics associated with SOH are much slower than SOC [16].

This paper proposes an adaptive hybrid battery model-based real-time SOC and SOH estimation method for multicell lithium-ion batteries used in EVs and PHEVs. The hybrid battery model consists of an enhanced Coulomb counting algorithm and an electrical circuit battery model [3]. The former is used to estimate the SOC of each battery cell, while the latter is used as a system model for designing an adaptive discrete-time (ADSMO), which is executed in real time to estimate the terminal voltages and open-circuit voltages of the cells in a battery pack sequentially. The errors of the Coulomb counting-based SOC estimation is corrected by an SOC compensator for the cells in the battery pack sequentially. The SOC compensator estimates the SOC of each cell from the ADSMO. The internal impedances of the battery cell required to implement the ADSMO are updated by a variable-length sliding window least squares (VSWLS)-based online parameter identification algorithm [18]. Therefore, the proposed method is capable of capturing nonlinear capacity effects of a battery and ensuring the robustness of the SOC estimation to unknown initial SOC, wrong maximum capacity, and error accumulation. In addition, the SOH is determined by comparing the rated capacity and the estimated maximum capacity of a cell. Furthermore, the estimated electrical parameters such as a series resistance [9] and [11], a diffusion resistance [19] and a diffusion capacitance [20] can be used for an additional indicator for SOH estimation. The proposed method is validated by using simulation and experimental results for a four-cell cylindrical lithium-ion battery pack.

II. The Proposed Method

The proposed SOC and SOH estimation method consists of four parts as shown in Fig. 1: (1) a hybrid battery model including an enhanced Coulomb counting algorithm and an electrical circuit battery model; (2) a VSWLS-based parameter identification algorithm; (3) an SOC compensator consisting of an ADSMO SOC estimator and a closed-loop weighting SOC compensation algorithm (i.e., the WF) for correcting the error of the enhanced Coulomb counting-based SOC estimation; and (4) an SOH estimator. The proposed SOC compensator method is executed sequentially for each cell of a series-connected m-cell battery pack.

A. The Hybrid Battery Model

The enhanced Coulomb counting algorithm is designed to estimate the SOC of a battery cell based on a Kinetic Battery Model (KiBaM) [3]. It can capture the nonlinear capacity effects, such as the recovery effect and rate

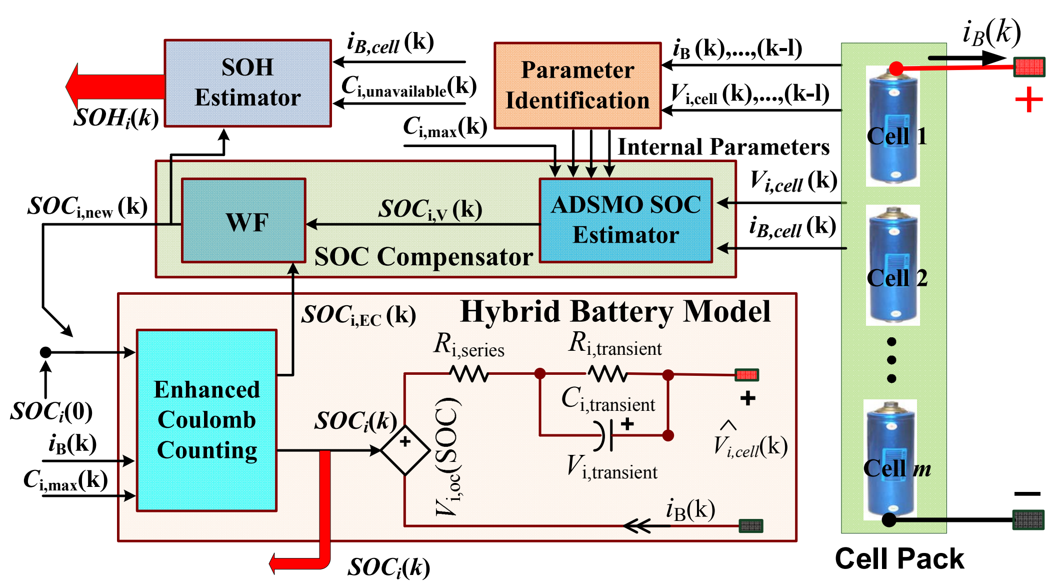


Fig. 1. The proposed SOC and SOH estimation method for a series-connected m-cell battery pack.

capacity effect, of the battery cell with a low computational cost, thereby is feasible for real-time applications [3]. A voltage-controlled voltage source, $V_{i,oc}(SOC)$, is used to bridge the SOC to the cell open-circuit voltage, where i = 1, ···. m, and m is the total number of cells in the pack. The resistor-capacitor circuit (i.e., the electrical circuit battery model) models the I-V characteristics and transient response of the battery cell, where the series resistance, $R_{i,series}$, is used to characterize the charge/discharge energy losses of Cell i; other resistance and capacitance are used to characterize the transient responses of Cell i; and $V_{i,cell}$ and $\hat{V}_{i,cell}$ represent the actual terminal voltage and electrical circuit terminal voltage of Cell i, respectively. Assuming that $V_{i,oc}(SOC)$ is $b_1 \cdot SOC+b_0$ [17], a discrete-time version of the hybrid battery model can be expressed as follows:

$$\begin{bmatrix} SOC_i(k+1) \\ V_{i,transient}(k+1) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & e^{\left(\frac{-T}{\tau_i}\right)} \end{bmatrix} \cdot \begin{bmatrix} SOC_i(k) \\ V_{i,transient}(k) \end{bmatrix} + \begin{bmatrix} \dfrac{-T}{C_{i,\max}} \\ R_{i,transient}\left(1-e^{\left(\frac{-T}{\tau_i}\right)}\right) \end{bmatrix} \cdot i_B(k) - \begin{bmatrix} \dfrac{\Delta C_{i,unavailable}(k)}{C_{i,\max}} \\ 0 \end{bmatrix} \quad (1)$$

$$\hat{V}_{i,cell}(k) = \begin{bmatrix} b_{i,1} & 0 \\ 0 & -1 \end{bmatrix} \begin{bmatrix} SOC_i(k) \\ V_{i,transient}(k) \end{bmatrix} - R_{i,series} \cdot i_B(k) + b_{i,0} \quad (2)$$

$$\begin{aligned} C_{i,unavailable}(k) &= C_{i,unavailable}(k-1) \cdot e^{-k'T} \\ &+ (1-c)\frac{(1-e^{-k'T})}{c \cdot k'} \times i_B(k-1) \end{aligned} \quad (3)$$

where T is the sampling period; $\tau_i = R_{i,transient} \cdot C_{i,transient}$, is the time constant of Cell i; $i_B(k)$ is the instantaneous current of the battery pack at the time index k; k' and c are the parameters of the KiBaM; $C_{i,max}$, $C_{i,unavailable}$, and $\Delta C_{i,unavailable}$ are the maximum and unavailable capacities and the derivative of the unavailable capacity of Cell i during T, respectively. The initial SOC of Cell i, i.e., $SOC_i(0)$, is the estimated SOC at the end of the last operating period (i.e., k = 0).

B. Parameter Identification by VSWLS

The VSWLS method is employed to identify the internal parameters of the electrical circuit model of each battery cell, which include the electrical impedances $R_{i,series}$, $R_{i,transient}$, and $C_{i,transient}$, of Cell i. Assuming that T is short (e.g., $T \le 1$ second) such that $\Delta C_{i,unavailable}$ is negligible, the z-transfer function of (2) is given in (4) and the corresponding difference equation is given in (5).

$$\begin{aligned} \frac{\hat{V}_{i,cell}(z) - b_{i,0}}{i_B(z)} &= C_i(zI_{2\times 2} - A_i)^{-1}B_i - D_i \\ &= \frac{x_{i,3} + x_{i,4}z^{-1} + x_{i,5}z^{-2}}{1 + x_{i,1}z^{-1} + x_{i,2}z^{-2}} \end{aligned} \quad (4)$$

$$\begin{aligned} \hat{V}_{i,cell}(k) = &-x_{i,1} \cdot V_{i,cell}(k-1) - x_{i,2} \cdot V_{i,cell}(k-2) + x_{i,3} \cdot i_B(k) \\ &+ x_{i,4} \cdot i_B(k-1) + x_{i,5} \cdot i_B(k-2) + b_0(1 + x_{i,1} + x_{i,2}) \end{aligned} \quad (5)$$

where

$$\begin{cases} x_{i,1} = -e^{\left(\frac{-T}{\tau_i}\right)} - 1 \\ x_{i,2} = e^{\left(\frac{-T}{\tau_i}\right)} \\ x_{i,3} = -R_{i,series} \\ x_{i,4} = \dfrac{-b_{i,1}T}{C_{i,\max}} + 2R_{i,transient}\left(e^{\left(\frac{-T}{\tau_i}\right)} + 1\right) \\ x_{i,5} = R_{i,transient}\left(1 - e^{\left(\frac{-T}{\tau_i}\right)}\right) - e^{\left(\frac{-T}{\tau_i}\right)}\left(\dfrac{b_{i,1}T}{C_{i,\max}} - R_{i,series}\right) \end{cases} \quad (6)$$

Because $(1+x_{i,1}+x_{i,2})$ is zero, (5) can be reformulated into the regression form of the input/output relationship.

$$\begin{aligned} \hat{V}_{i,cell}(k) = &-x_{i,1} \cdot V_{i,cell}(k-1) - x_{i,2} \cdot V_{i,cell}(k-2) + x_{i,3} \cdot i_B(k) \\ &+ x_{i,4} \cdot i_B(k-1) + x_{i,5} \cdot i_B(k-2) = \phi_i^T(k) \cdot \theta_i \end{aligned} \quad (7)$$

where the regressor is $\phi_i^T(k) = [-V_{i,cell}(k\text{-}1), -V_{i,cell}(k\text{-}2), i_B(k), i_B(k\text{-}1), i_B(k\text{-}2)]$ and the vector of the parameters to be estimated is $\theta_i = [x_{i,1}, x_{i,2}, x_{i,3}, x_{i,4}, x_{i,5}]^T$. Then, the VSWLS algorism is designed to estimate the vector θ_i. The VSWLS is an advanced least squares estimation algorithm with a forgetting factor [18]. It uses the block data captured by a variable sliding window to keep track of the nonlinear time-variant parameters. The internal parameters of the electrical circuit battery cell model can then be calculated by (6) after θ_i is identified. This leads to an adaptive battery model.

The length of the sliding window can be variable depending on the estimation error of the terminal voltage [18]. Due to the nonlinear time-variant parameters of battery cells, a long sliding window will include more information on the nonlinearity, but may degrade the accuracy of parameter estimation, resulting in a large estimation error of the terminal voltage. Furthermore, the excitation level of the input signal is also an important factor in choosing the length of the sliding window [21]. For example, if long discharge pulses are applied to the battery, the sliding window should have at least one of the pulse edges. On the other hand, the length of the window can be set to be short (e.g., the allowed minimum value), if the input signals are fully exited within a short window. The abnormal values of the estimated internal parameters due to low perturbation or

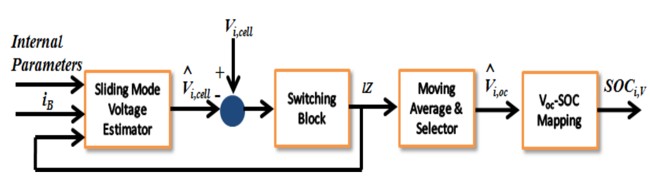


Fig. 2. The block diagram of the ADSMO-based SOC estimator.

quality of the input signals will be discarded.

C. SOC Estimation by ADSMO

The ADSMO is proposed to estimate $V_{i,oc}$ of Cell i (i = 1, ···, m). Fig. 2 shows the block diagram of the ADSMO. Using the first-order forward Euler method and the actual terminal voltage $V_{i,cell}$, (2) can be written as follows [16]:

$$V_{i,cell}(k+1)=\left(1-\frac{T_S}{\tau_i}\right)V_{i,cell}(k)+\frac{T_S}{\tau_i}V_{i,OC}(k) -\left(\frac{T_S}{C_{i,\max}}+\frac{T_S}{C_{i,transient}}+\frac{T_S\cdot R_{i,series}}{\tau_i}\right)i_B(k) \tag{8}$$

The ADSMO is designed as:

$$\hat{V}_{i,cell}(k+1)=\left(1-\frac{T_S}{\tau_i}\right)\hat{V}_{i,cell}(k)+\frac{T_S}{\tau_i}lZ -\left(\frac{T_S}{C_{i,\max}}+\frac{T_S}{C_{i,transient}}+\frac{T_S\cdot R_{i,series}}{\tau_i}\right)i_B(k) \tag{9}$$

where l is the SMO gain of the switching control vector Z; T_s is the sampling period of the ADSMO. In (9), the internal parameters $R_{i,series}$, $R_{i,transient}$ and $C_{i,transient}$ are used, which are obtained from the parameter identification process. Define the voltage estimation error $\varepsilon(k)$ = $V_{i,cell}(k)$ − $\hat{V}_{i,cell}(k)$, (10) can be obtained by subtracting (9) from (8):

$$\varepsilon(k+1)=\left(1-\frac{T_S}{\tau_s}\right)\varepsilon(k)+\frac{T_S}{\tau_s}V_{i,OC}(k)-\frac{T_S}{\tau_s}lZ \tag{10}$$

The sliding surface is designed as $s(k)$ = $\varepsilon(k)$ = 0. The dynamic of the ADSMO can be written as:

$$\frac{s(k+1)-s(k)}{T_S}=-\frac{1}{\tau_s}s(k)+\frac{1}{\tau_s}V_{i,OC}(k)-\frac{1}{\tau_s}lZ \tag{11}$$

A variable switching function is defined as follows for the ADSMO.

$$Z=\begin{cases} Z_0 & \varepsilon(k)>Z_0 \\ \varepsilon(k) & -Z_0>\varepsilon(k)>Z_0 \\ -Z_0 & \varepsilon(k)>Z_0 \end{cases} \tag{12}$$

where Z_0 is the width of the boundary layer. Due to the switching function, S is bounded. According to (11), the

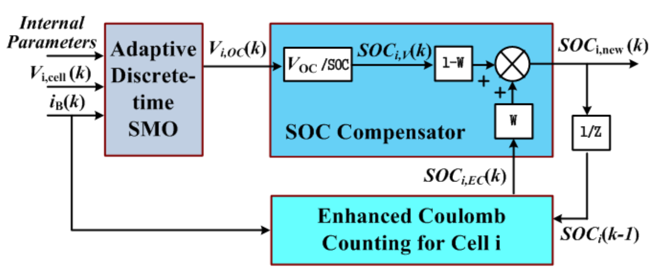


Fig. 3. The proposed closed-loop weighting SOC estimation algorithm.

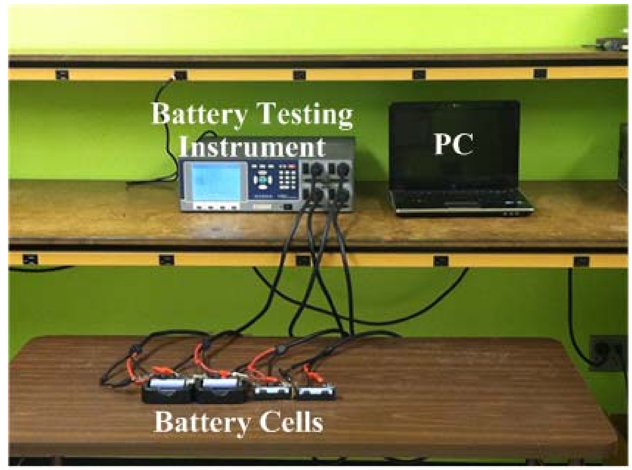


Fig. 4. The experimental setup.

Lyapunov stability condition (i.e., $\dot{S}\cdot S<0$) will be satisfied if $l > V_{i,oc.max}/Z_0$, where $V_{i,oc.max}$ is the maximum open-circuit voltage of Cell i. Finally, the state trajectory will approach the sliding surface defined by $\dot{S}=S=0$. When the tracking error is zero, the output of the designed switching function, lZ, will be equal to $V_{i,oc}$. If there is an abrupt change in the cell current (such as pulse charge or discharge current), the ADSMO will not be able to catch up with the change of the terminal voltage quickly when T_s is large (e.g., T_s = one second). As a result, the output of the switching function will oscillate until ε becomes small. The moving average (or low-pass filter) and selector module in Fig. 2 will smooth lZ and discard the highly oscillated values, respectively.

The estimated open-circuit voltage $V_{i,oc}$ is then used to calculate the SOC ($SOC_{i,V}$) of Cell i according to the a SOC–V_{oc} look-up table. Assuming that the hysteresis effect is negligible in the lithium-ion battery cells, the relationship between SOC and V_{oc} is dependent on temperature and aging, but their influence will be negligible if the SOC is expressed using the relative capacity [17]. In practice, the SOC–V_{oc} relationship can be obtained from laboratory experiments.

D. SOC Estimation

The enhanced Coulomb counting method based on (1) and (3) is an open-loop SOC estimation method. It may be subject to problems of a wrong initial SOC, wrong C_{max}, and accumulating estimation errors, leading to a wrong SOC estimation. To solve these problems, this paper uses a closed-loop weighting SOC estimation method [22] and [23] with the ADSMO-based SOC estimator together to form an SOC compensator to correct the error of the SOC (i.e., $SOC_{i,EC}$) obtained from the enhanced Coulomb counting algorithm for the cells sequentially, as shown in Fig. 3. The equations are given by the following:

$$SOC_{i,new}(k)=W\cdot SOC_{i,EC}(k)+(1-W)\cdot SOC_{i,V}(k) \tag{13}$$

$$SOC_{i,EC}(k) = SOC_i(k-1) - \frac{1}{C_{i,\max}}[i_B(k-1)\cdot T + \Delta C_{unavaiable}(k-1)] \quad (14)$$

where W is a variable weighting factor ($0<W<1$); $C_{i,max}$ is estimated maximum capacity of Cell i and will be updated by the capacity estimation in the SOH estimator; $SOC_{i,V}$ is the SOC estimated from the ADSMO-based SOC estimator shown in Fig. 2. The SOC compensator uses $SOC_{i,V}$ to correct the $SOC_{i,EC}$. In this paper, $C_{i,max}$ is updated by estimating the cell capacity, which will be discussed in (15) in the next subsection E; and the SOC–V_{oc} look-up table is obtained under the ambient temperature. The $SOC_{i,V}$ and $SOC_{i,EC}$ are multiplied by their weighting factors and then added together to generate a compensated SOC (i.e., SOC_{new}). The SOC_{new} is then used as the initial SOC (SOC_i) of the enhanced Coulomb counting algorithm to estimate the SOC in the next time step.

The SOC compensator is executed periodically with a certain interval during operation or during a long relaxation period of the battery cell. The performance of the SOC compensator highly depends on the accuracy of the internal electrical parameters of the battery cell and the weighting factor W. The default value of W is one when only the enhanced Coulomb counting is used for SOC estimation. The value of W will be changed when the SOC compensator is used. In this paper, W is set to be 0.5 once the SOC compensator is activated. In practice, W will be set to be a value larger than 0.5 for a smooth transition of the SOC values. Moreover, when the battery cell is operated in a long-time relaxation mode, the $SOC_{i,V}$ will be close to the real SOC. In this case, the weighting factor W will be set to be zero. When W is zero and the battery cell is operated in the charge/discharge mode again, the execution of the SOC compensator will be over, and W will be reset to be one.

E. SOH Estimation

Due to cell state variations, the maximum capacities of the battery cells in a pack will be unequal to the nominal capacity that the manufacturer offers. Such variations depend on manufacturing environment and temperature conditions. Moreover, the maximum capacity of a cell will reduce due to aging. Therefore, the value of $C_{i,max}$ is a good indicator of the SOH of a battery cell C_i, and can be updated from (1) using the compensated SOC_i as follows:

$$C_{i,\max}(k) = \frac{T\sum_{k=k_1}^{k_2} i_B(k) + C_{i,unavailable}(k)}{SOC_i(k_1) - SOC_i(k_2)} \quad (15)$$

where k_1 and k_2 are the beginning time and end time of the SOH estimation period, respectively.

The SOH represents the capacity and power capability of a battery cell to deliver the specified performance compared with a new battery. The SOH can be indicated by a single measurement of the conductance or impedance of the cell, which is easy but imprecise. Other battery parameters, such as the maximum capacity, internal resistance, self-discharge rate, charge acceptance, discharge capability can be used to estimate the SOH. In this paper, the SOH is estimated as the ratio of the maximum capacity of a battery cell (i.e., $C_{i,max}$) to that of the cell when it is new (i.e., C_{i,max_new}). Such an SOH represents the capacity degradation of the cell.

$$SOH_i(k) = \frac{C_{i,\max}(k)}{C_{i,\max\_new}} \quad (16)$$

In addition, the impedance estimated by using the VSWLS can be utilized for SOH estimation from the perspective of power degradation.

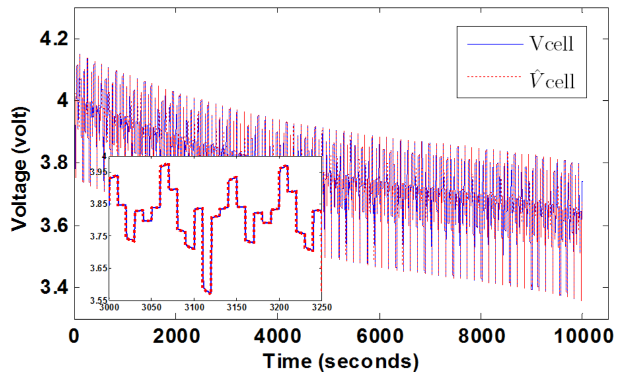
III. RESULTS

The proposed SOC and SOH estimation method is validated by simulation and experimental data for a four-cell cylindrical lithium-ion battery pack (see Appendix). The experimental data of the cell voltage and current are collected from a CADEX battery tester C8000 (shown in Fig. 4) under the ambient temperature. The proposed method shown in Fig. 1 is implemented in MATLAB/Simulink.

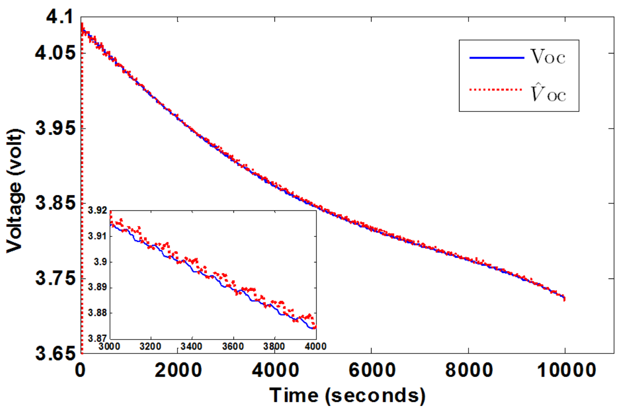
The cell voltage and current measured from the battery tester are used by the proposed method for real-time SOC and SOH estimation of each battery cell. The values of $V_{oc}(SOC)$ and C_{max} are first extracted offline for each battery cell [3] . They are then used as the true values for comparison with the values obtained from the proposed method in real time. In order to set initial SOCs for the test battery cells, they are first fully charged and rest for one hour. Then the cells are discharged using a small current to the desired initial SOC values. Finally, the cells rest (or may need further charge or discharge using very small currents) until their open-circuit voltages equal to the true values corresponding to the initial SOCs.

First, the identification of V_{oc} and C_{max} is investigated. Fig. 5(a)-(c) compare the true and estimated V_{cell}, V_{oc}, and C_{max} for a dynamic current cycle shown in Fig. 5(d). The parameter identification algorithm is executed by using the data sampled with a 1 Hz rate and a 20-second moving window. Then, the ADSMO is executed with a sampling rate of 100 Hz to estimate the V_{oc}. The results show that the values of V_{cell}, V_{oc} and $C_{\max}$ are estimated accurately in real time. Then, the SOH of the cell can be estimated using the estimated $C_{\max}$. However, it takes a relatively long time to get $C_{\max}$ close to its true value.

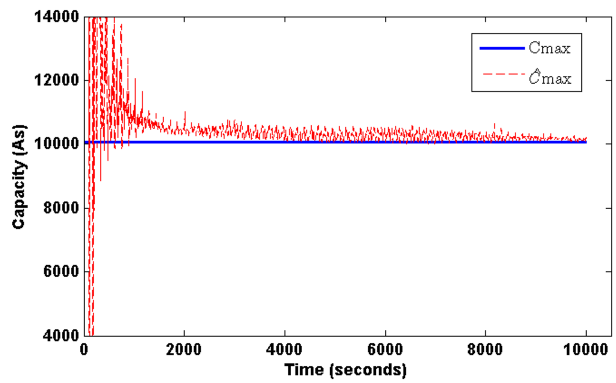
Next, the SOC estimation algorithm for multicell batteries is investigated using the measured data of the four-cell battery pack. All cells are initially set with a wrong initial SOC of 50%; while the real initial SOCs of Cells 1, 2, 3 and 4 are 100, 90, 80 and 70%, respectively. The battery pack is operated with a dynamic current cycle as shown in Fig. 5(d). The SOC compensator is executed sequentially with an interval of 100 seconds for each cell to compensate



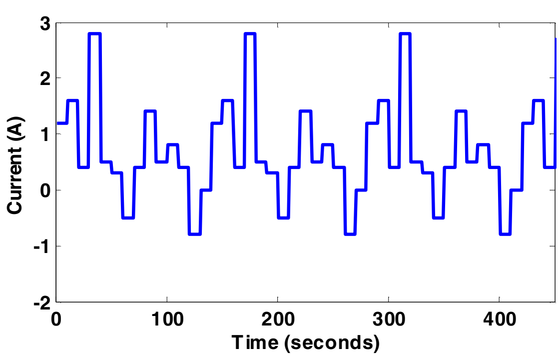
(a)



(b)



(c)



(d)

Fig. 5. Comparision of true and estimated parameters of a battery cell: (a) V_{cell}, (b) V_{oc}, (c) C_{max}, and (f) a dynamic current cycle.

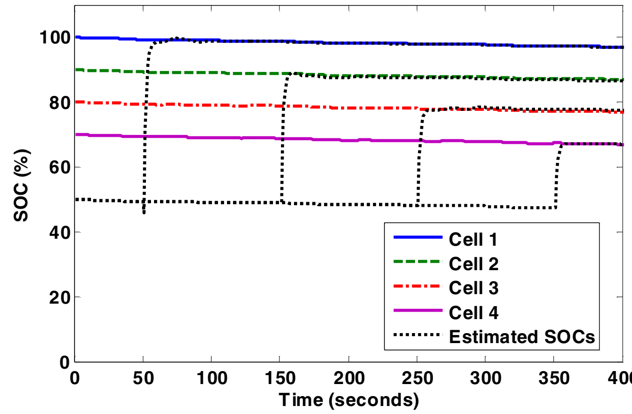


Fig. 6. Comparison of the estimated and measured SOCs for the four cells.

its SOC. Fig. 6 compares the SOCs estimated by the proposed method with those measured from the battery tester. The estimated SOC of each cell matches the measured value although the initial SOC is set wrong in the proposed method. This result clearly shows that the proposed algorithm is robust to the error of the initial SOC, which however is important to the accuracy of the traditional Coulomb counting methods.

IV. CONCULUSIONS AND FUTURE WORK

This paper has proposed a novel adaptive hybrid model-based real-time SOC and SOH estimation method for multicell lithium-ion batteries. The proposed method has been implemented in MATLAB/Simulink and validated by simulation and experimental results for a four-cell cylindrical lithium-ion battery pack. The proposed method can be used for power management, condition monitoring and diagnostics of batteries in various applications, such as EVs and PHEVs. In the future work, the analysis of the parameter changes in the enhanced battery model due to temperature and aging and hardware-in-the-loop tests for the proposed method will be conducted to validate it for real-time applications.

APPENDIX

Battery cell: Samsung ICR18650-28A; nominal voltage: 3.75 V; nominal capacity: 2800 mAh; discharge cutoff voltage (V_{cutoff}): 3 V; charge cutoff voltage (V_{over}): 4.3 V; maximum discharge current: 2C (5.6 A).

REFERENCES

[1] A. Eddahech, O. Briat, and J. Vinassa, "Real-time SOC and SOH estimation for EV Li-ion cell using online parameters identification," in *Proc. IEEE Energy Conversion Congress and Exposition*, Sept. 15-20, 2012, pp. 4501-4505.

[2] Y. Çadırcı and Y. Özkazanç. "Microcontroller-based on-line state-of-charge estimator for sealed lead-acid batteries," *J. Power Sources*, vol. 129, pp. 330–342, 2004.

[3] T. Kim and W. Qiao, "A hybrid battery model capable of capturing dynamic circuit characteristics and nonlinear capacity effects," *IEEE Trans. Energy Conversion*, vol. 26, no. 4, pp. 1172-1180, Dec. 2011.

[4] W.X. Shen, K.T. Chau, and C.C. Chan, "Neural network-based residual capacity indicator for nickel-metal hydride batteries in

electric vehicles," *IEEE Trans. Veh. Tech*., vol. 54, no. 5, pp. 1705–1712, Sept. 2005.

[5] S. Malkhandi, "Fuzzy logic-based learning system and estimation of state of charge of lead-acid battery," *Eng. Appl. Artif. Intel*., vol. 19, pp. 479–485, 2006.

[6] T. Hansen and C. Wang, "Support vector based battery state of charge estimator," *J. Power Sources*, vol. 141, pp. 351–358, 2005.

[7] B.S Bhangu, P. Bentley, D.A. Stone, and C.M. Bingham, "Nonlinear observers for predicting state-of-charge and state-of-health of lead-acid batteries for hybrid-electric vehicles," *IEEE Trans. Veh. Tech*., vol. 54, pp. 783–794, 2005.

[8] A. Vasebi, S. M. T. Bathaee, and M. Partovibakhsh, "Predicting state of charge of lead-acid batteries for hybrid electric vehicles by extended Kalman filter," *Energy Convers. Manage*. vol. 49, pp. 75–82, 2008.

[9] G. L. Plett, "Sigma-point Kalman filtering for battery management system of LiPB-based HEV battery pack: Part 2: Simulatneous state and parameter estimation," *J. Power Sources*, vol. 161, pp. 1369–1384, 2006.

[10] S. Jang, M. Shin, C. Yoon, and R. Campbell, "A study on adaptive autoreclosure scheme with real-time transient stability," *J. Elect. Eng. & Technol.*, vol. 1, no. 1, pp. 8–15, 2006.

[11] I. Kim, "The novel state of charge estimation method for lithium battery using sliding mode obserber," *J. Power Sources*, vol. 163, pp. 584-590, 2006.

[12] M. Li, W. Chen, H. Wu, and D. Gorski, "Robust state of charge estimation of lithium-ion batteries via an iterative learning observer," SAE Technical Paper 2012-01-0659, 2012.

[13] M. Charkhgard and M. Farrokhi, "State of charge estimation for Lithium-ion batteries using neural networks and EKF," *IEEE Trans. Industrial Electronics*, vol. 57, no. 12, pp. 4178 - 4187, Dec. 2010.

[14] C. C. Can, E. W. C. Lo, and S. Weixiang, "The available capacity computation model based on artificial neural network for lead-acid batteries in electric vehicles," *J. Power Sources*, vol. 87, pp. 201-204, 2000.

[15] B. S. Bhangu, P. Stone, and D. A. Bingham, "Nonlinear observers for predicting state-of-charge and state-of-health of lead-acid batteries for hybrid-electric vehicles," *IEEE Trans. Veh. Tech*., vol. 54, pp. 783-794, 2005.

[16] I. Kim, "A technique for estimating the state of health of lithium batteries through a dual-sliding-mode observer," *IEEE Trans. Power Electronics*, vol. 25, pp. 1013-1022, 2010.

[17] S. Lee, J. Kim, J. Lee, and B. H. Cho, "State-of-cahrge and capacity estimation of lithium-ion battery using a new open-cirucit voltage versus state-of-charge," *J. Power Sources*, vol. 185, pp. 1367-1373, 2008.

[18] J. Jiang and Y. Zhang, "A revisit to block and recursive least squares for parameter estimation," *Comput. Electr. Eng.*, vol. 30, no. 5, pp. 403 -416, 2004.

[19] J. Kim and B. H. Cho, "State-of-charge estimation and state-of-health prediction of a Li-Ion degraded battery based on an EKF combined with a per-unit system," *IEEE Trans. Veh. Tech.*, vol. 60, no. 9, pp. 4249-4260, 2011.

[20] Z. Cheng, C. C. Mi, Y. Fu, J. Xu, and X. Gong, "Online battery state of health estimation based on genetic algorithm for electric and hybrid vehicle applications," *J. Power Sources*, vol. 240, pp. 184-192, 2013.

[21] H. R. Eichi and M. Chow, "Adaptive Parameter Identificaiton and state-of-charge estimation of lithium-ion batteries," in *Proc. 38th Annual Conference of the IEEE industrial Electronics Society,* Oct. 2012, pp. 3012-4017.

[22] T. Kim, W. Qiao, and L. Qu, "Real-time state of charge and electrical impedance estimation for lithium-ion batteries based on a hybrid battery model," in *Proc. 28th Annual IEEE Applied Power Electronics Conference and Exposition*, Mar. 2013, pp. 563-568.

[23] T. Kim, W. Qiao, and L. Qu, "Online state of charge and electrial impedance estimation for multicell lithium-ion batteries," in *Proc. IEEE Transportation Electrification Conference and Expo*, Jun. 16-19, 2013, pp. 1-6.