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Online State of Charge and Electrical Impedance Estimation for Multicell Lithium-ion Batteries

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***Abstract*—This paper proposes a hybrid battery model-based high-fidelity state of charge (SOC) and electrical impedance estimation method for multicell lithium-ion batteries. The hybrid battery model consists of an enhanced Coulomb counting algorithm for SOC estimation and an electrical circuit battery model. A particle swarm optimization (PSO)-based online parameter identification algorithm is designed to estimate the electrical parameters of the cells sequentially. An SOC compensator is designed to correct the errors of the enhanced Coulomb counting SOC estimations for the cells sequentially. This leads to an accurate, robust online SOC estimation for individual cells of a battery pack. The proposed method is validated by simulation and experimental data collected from a battery tester for a four-cell polymer lithium-ion battery pack. The proposed method is applicable to other types of electrochemical batteries.**

I. Introduction

Multicell lithium-ion batteries consisting of a large number of cells are commonly used in electric vehicles (EVs) and plug-in hybrid electric vehicles (PHEVs). A battery is a complex system in which different cells may have different states, such as SOC, state of health (SOH), impedance, and capacity, etc., during operation. A significant problem of the traditional battery management system (BMS) is that it lacks internal cell-level monitoring capabilities. In order to ensure optimal performance and reliability of a battery system, the BMS should precisely monitor the SOC and electrical impedance of each battery cell. Moreover, the SOC and impedances offer not only the information of the power capability and available energy [1], but also the condition monitoring and diagnostic capability (e.g., SOH) for the battery system [2]. Therefore, cell-level SOC and electrical impedances are the parameters of main interest for management of multicell batteries [3].

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 by integrating the battery current over time [4]. However, they have unrecoverable problems that might be caused by factors such as a wrong initial SOC value, accumulation of estimation errors, and neglecting the self-discharge effect. Moreover, the Coulomb counting methods cannot keep track of battery nonlinear capacity variation effects, such as the rate capacity effect and recovery effect [5]. A simple analytical model called Peukert's law [6] has been added to the Coulomb counting method [7] to capture the nonlinear relationship between the runtime of the battery and the rate of discharge; however, the recovery effect was not taken into account.

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. Artificial neural network (ANN)-based models [8], fuzzy logic models [9], and support vector regression models [10] have been used to estimate the SOC of a battery. Although accurate estimation of SOC can be obtained by the computational intelligence-based methods, the learning process required by these methods has a quite high computational cost, and is difficult to implement in real-time SOC tracking.

Model-based SOC estimation methods basically utilize a state-space battery model to design an observer for real-time SOC estimation. For example, the extended Kalman filter (EKF) has been widely used to estimate the SOC of a battery based on the electrical circuit model of the battery for PHEV and EV applications [11]. In general, the EKF methods provide an accurate solution for long-term SOC estimation. However, these methods require an accurate electrical circuit battery model, whose parameters, e.g., resistances and capacitances, typically vary with the SOC, temperature, current, aging, etc., of the battery cell. Therefore, online parameter estimation is usually needed to provide an accurate battery model in the EKF methods [12]. Furthermore, even with an accurate electrical circuit battery model, the estimation error can be large when unexpected noise is present [13]. Moreover, the model-based SOC estimation methods, especially the EKF methods, have a higher computational cost than the nonmodel-based Coulomb counting methods.

The mixed SOC estimation methods combine the advantages of the aforementioned three methods, such as the combination of an ANN and an EKF [14], or the combination of the Coulomb counting method with an EKF [15]. In [16], the authors proposed a hybrid battery model [5]-based real-time SOC and electrical impedance estimation method for a single polymer lithium-ion battery cell [17]. The hybrid battery model consists of an enhanced Coulomb counting algorithm and an electrical circuit battery model. The former was used to estimate the SOC of the battery cell, while the latter was used to estimate the internal parameters of the battery cell.

This paper extends the work of [16] by proposing a real-time cell-level SOC and electrical impedance estimation method for multicell lithium-ion batteries used in EVs and PHEVs. An enhanced Coulomb counting algorithm is applied for each cell. A SOC compensator is designed to correct the errors of the Coulomb counting-based SOC estimation for the cells sequentially by using the estimated cell open-circuit voltage V_{oc}. The values of V_{oc} and impedances of the cells are determined sequentially in real time by using a PSO-based online parameter identification algorithm. 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, error accumulation, and the error due to neglecting the self-discharge effect. The proposed method is validated by using simulation and experimental results for a four-cell polymer lithium-ion battery pack.

II. The Proposed Method

The proposed SOC and electrical impedance estimation method for multicell batteries consists of three parts as shown in Fig. 1: (1) a hybrid battery model, (2) a PSO-based parameter identification algorithm, and (3) an SOC compensator correcting the error of the enhanced Coulomb counting-based SOC estimation. The proposed method is executed to estimate the SOC and electrical impedances for each cell sequentially of a series-connected m-cell 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) [5]. It can capture the nonlinear capacity effects, such as the recovery effect and rate capacity effect, of the battery cell with a low computational cost, thereby is feasible for real-time applications [5]. The enhanced Coulomb counting algorithm for Cell i, (where $i = 1, \cdots, m$) is shown below:

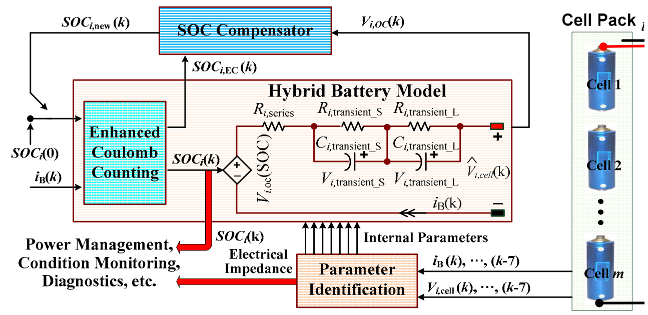


Fig. 1. The proposed SOC and electrical impedance estimation method for a series-connected m-cell pack.

$$SOC_i(k) = \frac{C_{i,available}(k)}{C_{i,\max}} = SOC_i(k-1) - \frac{1}{C_{i,\max}}[i_B(k-1)\cdot T + \Delta C_{i,unavailable}(k-1)] \tag{1}$$

$$C_{i,unavailable}(k) = C_{i,unavailable}(k-1)\cdot e^{-k'T} + (1-c)\frac{(1-e^{-k'T})}{c\cdot k'}\times i_B(k) \tag{2}$$

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

The electrical circuit battery model describes the I-V characteristics and transient response of the battery cell, where a voltage-controlled voltage source, $V_{i,oc}(SOC)$, is used to bridge the SOC to the cell open-circuit voltage; the series resistance, $R_{i,series}$, is used to characterize the charge/discharge energy losses of Cell i due to the resistances of electrode, electrolyte, separator, and contact; other resistances and capacitances are used to characterize the short-term (transient_S) transient response due to the double-layer capacitance and charge transfer as well as the long-term (transient_L) transient response due to the diffusion process of Cell i; and $V_{i.cell}$ represents the terminal voltage of Cell i. To facilitate real-system applications, a discrete-time version of the electrical circuit battery model is expressed as follows:

$$\begin{bmatrix} V_{i,transient\_S}(k) \\ V_{i,transient\_L}(k) \end{bmatrix} = \begin{bmatrix} x_1 & 0 \\ 0 & x_3 \end{bmatrix} \cdot \begin{bmatrix} V_{i,trasnsient}(k-1) \\ V_{i,trasnsient}(k-1) \end{bmatrix} + \begin{bmatrix} x_2 \\ x_4 \end{bmatrix} \cdot i_B(k-1) \tag{3}$$

where,

$$x_1 = \exp(-T/\tau_S),\ \ x_2 = R_{i,transient\_S}\cdot[1-\exp(-T/\tau_S)]$$
$$x_3 = \exp(-T/\tau_l),\ \ x_4 = R_{i,transient\_L}\cdot[1-\exp(-T/\tau_l)] \tag{4}$$

$$V_{i,cell}(k) = V_{i,OC}(k) - R_{i,series}\cdot i_B(k) - \begin{bmatrix} V_{i,transinent\_S}(k) \\ V_{i,transinent\_L}(k) \end{bmatrix} \tag{5}$$

where $\tau_S = R_{i,transient\_S}\cdot C_{i,transient\_S}$ and $\tau_l = R_{i,transient\_L}\cdot C_{i,transient\_L}$. Assuming that $V_{i,OC}$ is a constant, the z-transfer function of (5) is given in (6) and the corresponding difference equation is given in (7). The battery electrical parameters can be derived from (4), (7) and (8) if $V_{i,cell}$ and i_B are known.

$$\frac{V_{i,OC} - V_{i,cell}(z^{-1})}{i_B(z^{-1})} = \frac{b_0 - b_1 z^{-1} + b_2 z^{-2}}{1 - a_1 z^{-1} + a_2 z^{-2}} \tag{6}$$

$$V_{i,cell}(k) = a_1\cdot V_{i,cell}(k-1) - a_2\cdot V_{i,cell}(k-2) - b_0\cdot i_B(k)$$
$$+ b_1\cdot i_B(k-1) - b_2\cdot i_B(k-2) + [1-a_1+a_2]\cdot V_{i,OC} \tag{7}$$

where,

$$a_1 = (x_1+x_3),\ \ a_2 = x_1x_3,\ \ b_1 = R_{i,series}(x_1+x_3) - (x_2+x_4)$$
$$b_0 = R_{i,series},\ \text{and}\ \ \ b_2 = R_{i,series}x_1x_3 - (x_1x_4 + x_2x_3) \tag{8}$$

B. Electrical Parameter Identification by PSO

The PSO method is employed to identify the internal parameters of the battery model. This optimization algorithm is able to find the global optimal solution with a high computational efficiency and a low implementation cost. The battery internal parameters that need to be identified include the open-circuit voltage, V_{oc}, and electrical impedances, R_{series}, $R_{transient\_s}$, $C_{transient\_s}$, $R_{transient\_l}$, and $C_{transient\_l}$, which are unknown variables of (7). At least six independent equations are needed to solve for the six unknown parameters. The six equations can be obtained from (7) by using measured battery cell voltage and current at eight sequential operating points as follows.

$$\begin{aligned} F_j(X) &= V_{i,cell}(k-j) - (x_1+x_3)V_{i,cell}(k-1-j) \\ &\quad + x_1\cdot x_3\cdot V_{i,cell}(k-2-j) + i_B(k-j)\cdot R_{i,series} \\ &\quad - [R_{i,series}(x_1+x_3) - (x_2+x_4)]\cdot i_B(k-1-j) \\ &\quad + [R_{i,series}(x_1\cdot x_3) - (x_1\cdot x_4 + x_2\cdot x_3)]\cdot i_B(k-2-j) \\ &\quad - [1-(x_1+x_3) + x_1\cdot x_3]\cdot V_{i,OC} \end{aligned} \tag{9}$$

where $j = 0, \cdots, n$, $n \geq 5$; and $X = [x_1, x_2, x_3, x_4, R_{series}, V_{oc}]$ is a vector of the unknown parameters. The PSO algorithm is then designed to search for the optimal X to minimize the value of the following fitness function.

$$P(X) = \sum_{j=0}^{n} \left| F_j(X) \right| \tag{10}$$

Theoretically, the optimal X should make the fitness function value to be zero. In practice, once the value of $P(X)$ is below a predefined small threshold, e.g., 10^{-6}, the corresponding X can be treated as the optimal solution. From the optimal solution of X, the electrical impedances can be calculated from (8).

The PSO algorithm searches for the optimal solution using a population of moving particles. Each particle has a position represented by a position vector (X_i) and a moving velocity represented by a velocity vector (V_i) in the problem space. The position of each particle represents a potential solution. Each particle keeps track of its coordinates in the problem space, which are associated with the individual best position ($X_{i,pbest}$) achieved by the particle so far. Furthermore, the best position among all the particles obtained so far in the population is kept track of by all particles as the global best position (X_{gbest}). The PSO algorithm is implemented in the following iterative step for internal parameter estimation of a battery:

(i) Define the problem space with its boundaries extracted from off-line battery tests under various operating conditions.
(ii) Initialize a population of particles with random positions and velocities in the problem space.
(iii) Evaluate the fitness function.
(iv) Compare each particle's current position X_i with its $X_{i,pbest}$ based on the fitness evaluation. If X_i is better than $X_{i,pbest}$, then replace $X_{i,pbest}$ with X_i.
(v) If $X_{i,pbest}$ is updated, then compare the particle's $X_{i,pbest}$ with X_{gbest} based on the evaluation of the fitness function. If $X_{i,pbest}$ is better than X_{gbest}, then replace X_{gbest} with $X_{i,pbest}$.
(vi) Compute each particle's new velocity (V) and position at iteration k as follows:

$$V_i(k+1) = wV_i(k) + c_1r_1(X_{i,pbest}(k) - X_i(k))$$
$$+ c_2r_2(X_{gbest}(k) - X_i(k)),\quad i = 1,2,\cdots,N \tag{11}$$

$$X_i(k+1) = X_i(k) + V_i(k+1),\quad i = 1,2,\cdots,N \tag{12}$$

(vii) Repeat steps (iii)-(vi) until the stopping criterion is satisfied, e.g., an error threshold is reached or the maximum number of iterations is accomplished. The final value of X_{gbest} is the optimal solution of the problem.

In (11), c_1 and c_2 are the cognition learning rate and social learning rate of particles, respectively; w is the inertial weight which decreases as the number of iteration increases; r_1 and r_2 are uniformly distributed random numbers between 0 and 1; N is the number of particles in the swarm. The set of parameters for the PSO implementation of this paper are listed in TABLE I.

Due to slow changes in the internal parameters, the final solution X in each execution of the PSO algorithm, instead of random numbers, will be used as the initial positions for the population of particles in the next execution of the PSO algorithm. This reduces the number of iterations to identify the optimal solution. Moreover, it is important to choose appropriate boundary conditions for position X and velocity V in the PSO algorithm. The internal electrical parameters extracted from off-line battery tests under various operating conditions will be used to set the boundary conditions for X and V. Especially, the adaptive boundary condition, shown in

TABLE I
PSO PARAMETERS

Swarm Size (N)	20	**c_1**	2	***w* (start)**	0.7
Iteration	1000	**c_2**	2	***w* (end)**	0.1
α_1	0.198	**α_2**	0.118	**β_1**	0.188
β_2	0.104	**ϕ**	0.001		

TABLE II, is proposed for V_{oc} to improve the accuracy of parameter estimation, where V_{oc_max} and V_{oc_min} are the maximum and minimum V_{oc}, respectively; ϕ, α and β are the rest, discharge and charge constants, respectively; i_{rated} is the rated current. The inverse hyperbolic sine function is used to express the transient voltage in terms of the current rate during charge and discharge [18].

C. SOC Estimation and Compensation

The enhanced Coulomb counting method based on (1) and (2) is an open-loop SOC estimation method. It may be subject to problems of a wrong initial SOC and accumulating estimation errors, leading to a wrong SOC estimation. To solve these problems, this paper proposes a closed-loop weighting SOC estimation method, which uses a SOC compensator to correct the error of the SOC (i.e., $SOC_{i,EC}$) obtained from the enhanced Coulomb counting algorithm for each cell in the pack sequentially, as shown in Fig. 2. The corresponding equations are given by the following:

$$SOC_{i,new}(k) = W \cdot SOC_{i,EC}(k) + (1-W) \cdot SOC_{i,V}(k) \quad (14)$$

$$SOC_i(k-1) = SOC_{i,new}(k-1) \quad (15)$$

where W is a variable weighting factor ($0<W<1$); $SOC_{i,V}$ is the SOC estimated from the open-circuit voltage ($V_{i,oc}$) of Cell i, which in turn is estimated from the electrical battery model by using the PSO algorithm and the measured cell current and terminal voltage. The SOC compensator uses the estimated $V_{i,oc}$ and the $SOC_{i,EC}$ as the inputs. The $V_{i,oc}$ is converted to the $SOC_{i,V}$ by using a SOC–V_{oc} look-up table because V_{oc} is highly related to the SOC. In practice, the

TABLE II
BOUNDARY CONDITION OF V_{OC}

$i_B(k)>0$ (Discharge)	$V_{oc\_max}(k)$	$V_{cell}(k)+\alpha_1 \cdot \sinh^{-1}(i_{cell}(k)/i_{rated})$
	$V_{oc\_min}(k)$	$V_{cell}(k)+\alpha_2 \cdot \sinh^{-1}(i_{cell}(k)/i_{rated})$
$i_B(k)<0$ (Charge)	$V_{oc\_max}(k)$	$V_{cell}(k)+\beta_1 \cdot \sinh^{-1}(i_{cell}(k)/i_{rated})$
	$V_{oc\_min}(k)$	$V_{cell}(k)+\beta_2 \cdot \sinh^{-1}(i_{cell}(k)/i_{rated})$
$i_B(k)=0$ (Rest)	$V_{oc\_max}(k)$	$V_{oc\_max}(k-1)$
	$V_{oc\_min}(k)$	$V_{oc\_max}(k-1)$
	$V_{oc\_max}(k)$, $V_{oc\_min}(k)$	$V_{cell}(k)$, if $\Delta V_{cell}(k) < \phi$

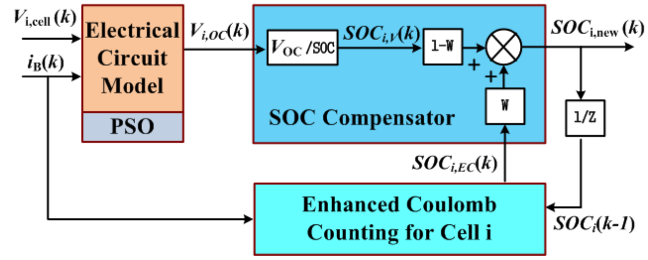


Fig. 2. The proposed closed-loop weighting SOC estimation algorithm.

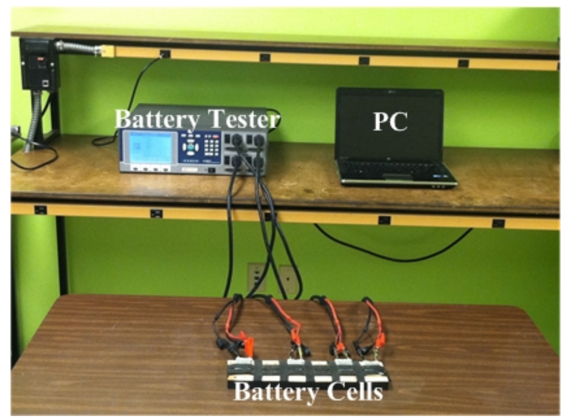


Fig. 3. The experimental setup.

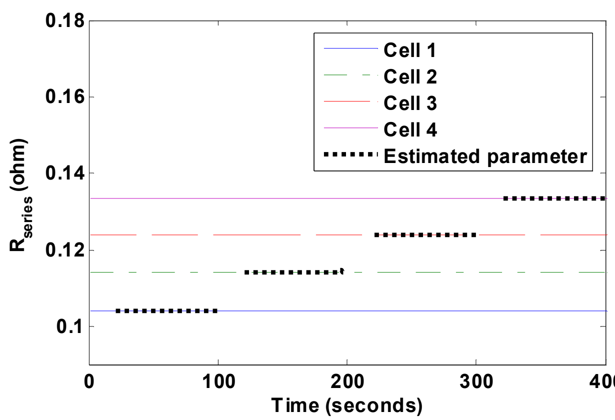
SOC–V_{oc} relationship can be obtained from laboratory experiments. The $SOC_{i,V}$ and $SOC_{i,EC}$ are multiplied by their weighting factors and then added together to generate a compensated SOC (i.e., $SOC_{i,new}$). The $SOC_{i,new}$ is then used as the initial SOC (i.e., SOC_i) of the enhanced 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 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. Moreover, when the battery 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 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.

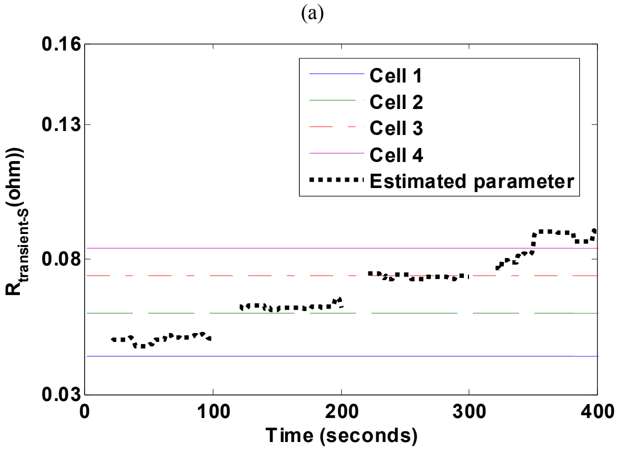
III. RESULTS

The proposed electrical impedance and SOC estimation method is validated by simulation and experimental data for a four-cell polymer lithium-ion pack. The nominal capacity, nominal voltage, and cutoff voltage of a single cell are 860 mAh, 3.7 V, and 3 V, respectively. The experimental data of the cell voltage and current are collected from a CADEX battery tester C8000 (shown in Fig. 3) under the ambient temperature. The proposed method shown in Fig. 1 is implemented in MATLAB/Simulink on a laptop computer (see Fig. 3). The measured cell voltage and current from the battery tester are used by the proposed method for real-time SOC and electrical impedance estimation for each individual battery cell. The electrical impedances of the electrical circuit battery model are first extracted offline for each battery cell by using the method described in [5]. These impedances are then used as the true values for comparison with those obtained from the proposed method in real time.

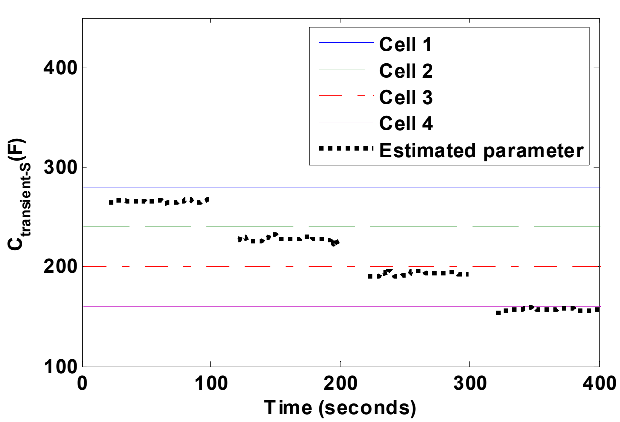
Fig. 4(a)-(e) compare the impedances of the hybrid battery cell model estimated by using the proposed online parameter identification algorithm with the true impedances extracted offline for the four battery cells for a dynamic current cycle shown in Fig. 4(f). The parameter identification algorithm is executed 100 seconds sequentially for each cell. The results show that the parameter identification algorithm estimates



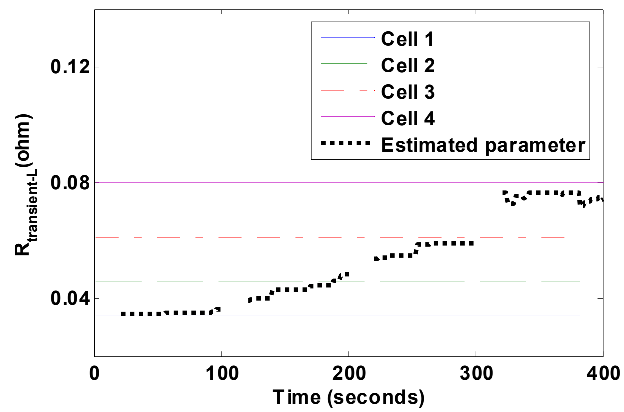
(a)



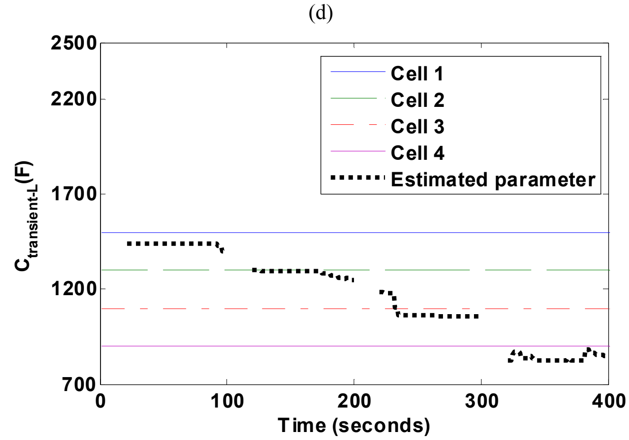
(b)



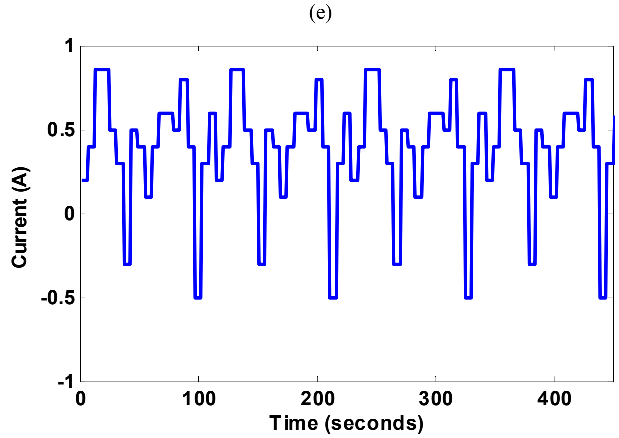
(c)



(d)



(e)



(f)

Fig. 4. Comparison of true and estimated impedances of the hybrid battery cell model for the four cells: (a) R_{series}, (b) $R_{transient\_S}$, (c) $C_{transient\_S}$, (d) $R_{transient\_L}$, (e) $C_{transient\_L}$, and (f) the dynamic current cycle applied to the battery pack.

the cell parameters fast and accurately.

Next, the SOC estimation algorithm is investigated with a wrong initial SOC of 50% for all the cells in the proposed method; while the real initial SOCs of Cells 1, 2, 3 and 4 are 90, 80, 70 and 60%, respectively. The multicell battery pack is operated with a dynamic current cycle as shown in Fig 4(f). The SOC compensator is executed 100 seconds sequentially for each cell to correct its SOC. Fig. 5 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 well 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 initial SOC, which however is important to the accuracy of the traditional Coulomb counting method.

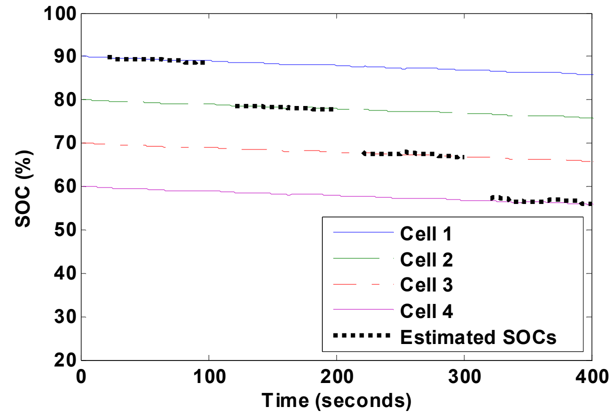


Fig. 5. Comparison of the estimated and measured SOCs for the four cells.

IV. Conclusion

This paper has proposed a novel hybrid model-based online SOC and electrical impedance 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 polymer lithium-ion battery pack. The proposed method can be used for power management, condition monitoring and diagnostics of batteries used in EVs and PHEVs. In addition to lithium-ion batteries, the proposed method is applicable to other types of batteries. In the future work, hardware-in-the-loop tests for the proposed method will be conducted to validate it for real-time EV and PHEV applications.

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Appendix

Battery cell: pl-383562 2C; nominal voltage: 3.7 V; nominal capacity: 860 mAh; discharge cutoff voltage (V_{cutoff}): 3 V; charge cutoff voltage (V_{over}): 4.2 V; maximum discharge current: 2C (1.72 A).

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