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Evaluation on State of Charge Estimation of Batteries With Adaptive Extended Kalman Filter by Experiment Approach

Rui Xiong, Student Member, IEEE, Hongwen He, Fengchun Sun, and Kai Zhao

Abstract—An accurate State-of-Charge (SoC) estimation plays a significant role in battery systems used in electric vehicles due to the arduous operation environments and the requirement of ensuring safe and reliable operations of batteries. Among the conventional methods to estimate SoC, the Coulomb counting method is widely used, but its accuracy is limited due to the accumulated error. Another commonly used method is model-based online iterative estimation with the Kalman filters, which improves the estimation accuracy in some extent. To improve the performance of Kalman filters in SoC estimation, the adaptive extended Kalman filter (AEKF), which employs the covariance matching approach, is applied in this paper. First, we built an implementation flowchart of the AEKF for a general system. Second, we built an online open-circuit voltage (OCV) estimation approach with the AEKF algorithm so that we can get the SoC estimate by looking up the OCV-SoC table. Third, we proposed a robust online model-based SoC estimation approach with the AEKF algorithm. Finally, an evaluation on the SoC estimation approaches is performed by the experiment approach from the aspects of SoC estimation accuracy and robustness. The results indicate that the proposed online SoC estimation with the AEKF algorithm performs optimally, and for different initial values, the maximum SoC estimation error is less than 2% with close-loop state estimation characteristics.

Index Terms—Adaptive extended Kalman filter (AEKF), battery management system, electric vehicles (EVs), lithium-ion battery, state of charge (SoC).

I. INTRODUCTION

Due to environmental issues, battery applications in the energy saving and energy efficiency areas have become widespread over the past few years, particularly in electric vehicles (EVs) [1]–[3]. To safeguard the good performance of the battery pack and extend its life, it is necessary to make good control and management for the batteries [4]. State of Charge (SoC) is used to determine the remaining capacity of the battery, and the battery performance has a big relationship with its SoC. In energy management systems, SoC monitoring is used to prevent the battery from possible overcharging or overdischarging, since these conditions may damage the battery. In addition, the accurate estimation of the battery’s SoC is also a key factor to manage batteries efficiently and to provide the basis for the determination of its power distribution strategy in EVs [5]–[9].

However, because the battery is a strong nonlinear and time-variable system, it is hard to measure the SoC directly for its complicated electrochemical process and various influence factors from practice applications [10]. Some SoC estimation approaches are presented with the development of EVs; the widely used method is the Coulomb counting method, which can be easily realized, but it has such problems as initial value and accumulated error [11], [12]. To reduce the initial SoC error, the SoC estimation based on an open-circuit voltage (OCV) versus SoC table is taken to an effective way to recalibrate the accumulated error [13]. Unfortunately, due to the uncertain driving cycles, complex application environments, etc., it is hard to measure the OCV real timely. Numerical methods, such as the neural and fuzzy methods, define the battery as a black-box system and can successfully deal with these problems [6], [14]–[16]. However, the estimated value may fluctuate widely because these methods are very sensitive to model error and disturbance.

The method of utilizing the advantages of the Coulomb counting method and the black-box system is the extended Kalman filter (EKF). It is doubtless that EKF provides the best solution for long-term SoC estimation [17]–[19]. However, the EKF-based algorithm strongly depends on the accuracy of the battery model as well as the predetermined variables of the system noise, such as mean value, pertinence, and covariance matrix. An improper setting of the predetermined variables of the system noise may result in remarkable errors and divergence [20]. For the SoC estimation, the error would be large or even diverge if inappropriate values of the noise covariance were used. Therefore, adaptive EKFs (AEKF) have been applied to implement online SoC estimation in [6], [13], and [21] to improve the accuracy of the EKF-based SoC estimation by adaptively updating the process and measurement noise covariance.

In this paper, based on the Thevenin battery model [10], an AEKF is applied to estimate the OCV and SoC of a 3.7-V/35-Ah LiMn$_2$O$_4$ cell in EVs. A description of the structure and parameterization of the Thevenin battery model is given in Section II. The three types of SoC estimation approach are

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II. Battery Model

To predict the battery SoC, we must build the battery model first. The battery is treated as a nonlinear dynamic system, which can be represented by a state-space form to be calculated in the computer as follows:

\[
\begin{align*}
\dot{x} &= f(x, u) + w \\
y &= g(x, u) + v
\end{align*}
\]

(1) (2)

where \(x\) is the system state vector, which represents the total effect of system inputs \(u\) on the current system operation, such as SoC, and \(y\) is the measurable system output. \(w\) is the unmeasured “process noise” that affects the system state, and \(v\) is the measurement noise that does not affect the system state but can be reflected in the system output. Moreover, \(w\) is assumed to be Gaussian white noise with zero mean and covariance \(Q\), and \(v\) is assumed to be Gaussian white noise with zero mean and covariance \(R\). \(f(x, u)\) and \(g(x, u)\) are functions specified by the particular used cell model.

All of the system dynamics are represented in state equation (1), and the output equation (2) is a static relationship.

A. SoC Definition

The SoC is a relative quantity that describes the ratio of the remaining capacity to the present maximum available capacity of a battery [20]; it is given by

\[
\text{SoC}_t = \text{SoC}_0 - \frac{1}{C_a} \int_0^t \eta_I L, \tau \, d\tau
\]

(3)

where \(\text{SoC}_t\) is the present SoC; \(\text{SoC}_0\) is the SoC initial value; \(I_{L, \tau}\) is the instantaneous load current (assumed positive for discharge, negative for charge); \(\eta_I\) is the Coulomb efficiency, which is the function of the current and the temperature; and \(C_a\) is the present maximum available capacity, which may be different from the rated capacity for the age effect.

Describing (3) with a discrete-time style

\[
\text{SoC}_k = \text{SoC}_{k-1} - \frac{\eta_I L, k \Delta t}{C_a}
\]

(4)

where \(\Delta t\) is the sampling period (in hours).

Equation (4) provides a basis to calculate the SoC with \(\text{SoC}_{k-1}\) and current \(I_{L, k}\) at the \(k\)th sample time in a state equation format. The battery model will then be differentiated by the additional components in the state vector and the functional form of \(f(x, u)\) and \(g(x, u)\).

B. Discrete State Space-Based Battery Model

Various battery models, such as the equivalent circuit models and the electrochemical models, are now widely used in EV studies. In [22], seven different forms are introduced. Due to the remarkable relaxation effect of the lithium-ion battery and the model requirements, including enough precision and suitable complexity, we select the Thevenin battery model shown in Fig. 1 as the battery model. The electrical behavior of the Thevenin model can be expressed as follows:

\[
\begin{align*}
\dot{U}_p &= -\frac{1}{C_p} R_p U_p + \frac{1}{C_p} I_L \\
U_t &= U_{oc} - U_p - I_L R_o
\end{align*}
\]

(5)

where \(U_t\) is the battery terminal voltage, \(U_{oc}\) is the battery OCV, \(I_L\) is the load current, \(R_o\) is the ohmic resistance, and \(R_p\) is the polarization resistance. The polarization capacitance \(C_p\) is used to describe the transient dynamic voltage response during charging and discharging. \(U_p\) is the polarization voltage across \(C_p\).

III. STATE-OF-CHARGE ESTIMATION APPROACH

To evaluate the SoC estimation approaches for a battery management system application, this section mainly describes the SoC estimation approaches.

A. AEKF Approach

The Kalman filter is a mathematical technique that provides an efficient recursive means for estimating the states of a process in such a way as to minimize the mean of the squared error. The filter has been applied extensively in the field of state estimation, parameter estimation, and dual estimation [6]. The system of interest is a continuous-time dynamics with discrete-time measurements given by (1) and (2).

A discrete form of state vector \(x\) and its covariance matrix \(P\) are calculated as

\[
\begin{align*}
x_k &= x_{k-1} + \dot{x}_k \Delta t \\
P_k &= (I + A_k \Delta t)P_{k-1}(I + A_k \Delta t)^T + Q_k \\
A_k &= \frac{\partial f}{\partial x} |_{x=x_{k-1}, u=u_{k-1}} \\
B_k &= \frac{\partial f}{\partial u} |_{u=u_{k-1}} \\
C_k &= \frac{\partial g}{\partial x} |_{x=x_{k-1}, u=u_k} \\
D_k &= \frac{\partial g}{\partial u} |_{u=u_k}
\end{align*}
\]

(6) (7) (8)

where \(I\) is a unit matrix, and \(A\) and \(C\) are the derivation matrices of \(f(x, u)\) and \(g(x, u)\) with respect to system state vector \(x\), respectively. \(B\) and \(D\) are the derivation matrices of \(f(x, u)\) and \(g(x, u)\) with respect to system input \(u\), respectively.

A drawback of the Kalman filter is the dependence on a good estimation of \(Q\) and \(R\). A Kalman filter basically assumes that the covariance of both the process and the measurement noise is known. Thus, in practice, inappropriate initial noise information will make the approach fail to ensure its performance. Otherwise, the covariance values can be estimated to improve the performance of the Kalman filter by employing an
adaptive Kalman filter. Mehra [23] classified adaptive Kalman filter methods into four categories: 1) Bayesian, 2) maximum likelihood, 3) correlation, and 4) covariance matching. These adaptive Kalman filter methods have been applied to other applications, including an inertial navigation system and a global positioning system. In this section, an AEKF employing the covariance matching approach was applied to realize a robust SoC estimation.

The AEKF provides further innovation in the algorithm using the filter’s innovation sequence. The innovation allows the parameters $Q_k$ and $R_k$ to be estimated and updated iteratively from the following equations [24]:

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

$$ Q_k = K_k H_k K_k^T $$

$$ R_k = H_k - C_k P_k C_k^T $$

where $H_k$ is the innovation covariance matrix based on the innovation sequence $e_i$ inside a moving estimation window of size $M$.

An implementation flowchart of the AEKF algorithm is listed in Fig. 2 for parameter identification or state estimation, where $K_k$ is the Kalman gain matrix, $e_i$ is defined as the difference between the observation $y_k$ and the predicted observation $g(x_k, u_k)$, $x_k$ is the priori estimate of $x_k$ before the measurement $y_k$ is taken into account, and $x_k^+$ is the estimate of $x_k$ after the measurement $y_k$ is taken into account, which is called the posteriori estimate.

B. SoC Estimation

1) Coulomb Counting Method: We use the SoC estimation based on the Coulomb counting method to provide a true SoC profile with some modifications for comparison purposes, and the recursive calculation equation of SoC is shown in (4).

To get the true SoC by experimental approach, first, the battery is fully charged to make sure that the initial SoC is 1.0, and then it is discharged by nominal current with 10% of its present maximum available capacity. After several consecutive urban dynamometer driving schedule (UDDS) tests are finished, the battery module is rested for at least 5 h, and a further discharge experiment with nominal current is conducted until the battery is fully discharged; then, the true value of the terminal SoC can be calculated according to the definition of the SoC. Since the true values of the initial SoC and the terminal SoC are determined, the Coulomb counting method is used to calculate the experimental SoC based on the load current profile, and the Coulomb efficiency map, which is also a proper adjustment coefficient that is calculated based on the true values of the initial and terminal SoCs, is applied during the calculation.

The Coulomb counting method with an adjustment approach based on a further discharging experiment can only be used in the laboratory since it is difficult to keep the battery as standing state frequently in practical EV application.

2) Method by Looking Up Table of the OCV Versus SoC: By this method, a reliable OCV estimate is the key to safeguard the SoC estimation accuracy. To get an accurate OCV value, the AEKF-based online parameter identification method for the Thevenin battery model is built and described as follows.

The derivation of $U_t$ in (5) is as follows:

$$ \dot{U}_t = U_{oc} - \dot{U}_p - \dot{I}_L R_o - \dot{I}_L \dot{R}_o. $$

It is well known that the battery’s load performance has a big relationship with the state parameters as SoC, working environment, particularly the operating temperature $T$, and usage history $h$. The model parameters can be described as a function of $T$, SoC, and $h$. Equation (11) can be simplified to (12) after considering the following assumptions [12], [13]:

$$ \frac{\partial \text{SoC}}{\partial t} \approx 0 $$

holds for battery energy, which is consumed or regained in a sample interval that is relatively small to
the total capacity available. Relying on the proper design of a cooling system/heater for the battery management system, the temperature rise/decrease of batteries should be slow, and the $\partial T/\partial t \approx 0$ holds for normal operating conditions. The $\partial h/\partial t \approx 0$ definitely holds since $h$ represents a long-term usage history

$$\dot{U}_t = -\dot{U}_p - \dot{I}_L R_o = \frac{I_L}{C_p} - \frac{U_{oc} - U_t - I_L R_o}{C_p R_p} - \dot{I}_L R_o. \quad (12)$$

The system state vector $x$ and the system input $u$ are defined as follows:

$$x = [U_{oc} \quad U_t \quad U_p \quad 1/C_p \quad 1/R_p \quad R_o]^T \quad (13)$$

$$u = [I_L]. \quad (14)$$

Considering the assumptions in [13], it can be concluded that the model parameters in a sample time can be viewed as a constant value and $U_{oc} \approx 0$, $(1/C_p) \approx 0$, $(1/R_p) \approx 0$, and $\dot{R}_o \approx 0$. Then, the $(x, u)$ can be built as follows:

$$f(x, u) = [f_1 \quad f_2 \quad f_3 \quad f_4 \quad f_5 \quad f_6]^T \quad (15)$$

where

$$\begin{aligned}
  f_1 &= 0 \\
  f_2 &= x_1 x_4 x_5 - x_2 x_4 x_5 - (x_4 x_5 x_6 + x_4) u - x_6 \dot{u} \\
  f_3 &= x_4 u - x_3 x_4 x_5 \\
  f_4 &= 0 \\
  f_5 &= 0 \\
  f_6 &= 0
\end{aligned} \quad (16)$$

and $x_i (i = 1, 2, \ldots, 6)$ is the $i$th element of $x$.

The terminal voltage $U_t$ is selected as the measured value, and then the observer vector can be deduced as

$$H = [0 \quad 1 \quad 0 \quad 0 \quad 0 \quad 0]^T. \quad (17)$$

According to the implementation flowchart of the AEKF algorithm shown in Fig. 2, the online estimation of $x$ can be conducted with the preset initials of $x_0$ and noise matrix.

3) Online SoC Estimation With Predefined Model Parameters: To conduct the online model-based SoC estimation, the parameters of the Thévenin model should be determined first. Offline parameter identification: To get a more accurate relaxation effect of the model, the traditional offline identification of the model parameters can be improved by a genetic algorithm [25].

The regress equation for (5) is shown in (18). The appropriate time constant of polarization ($\tau = R_p C_p$) needs to be given in advance based on the battery characteristics, where $I_p$ is the outflow current of $C_p$, and $U_{t,k}$, $I_{L,k}$, $I_{p,k}$ are the values of $U_t$, $I_L$, and $I_p$ at the $k$th sample time. In this paper, a genetic algorithm is used to find the optimal $\tau$ with the objective function [13]

$$\begin{aligned}
  &\min \left\{ f(\chi_j^{(g)}) \right\} \\
  &f(\chi_j^{(g)}) = \frac{1}{N} \sum_{i=1}^{N} (U_{i,j} - \hat{U}_{i,k} (\chi_j^{(g)}))^2
\end{aligned} \quad (19)$$

where $\chi_j^{(g)}$ is the estimation value of the current population $X_j$ at generation $g$, and $\chi_j$ is the current individual $j$ of the population $\chi$, where $\chi = [\tau]$, and $U_{i,j}$ is the estimation value of the terminal voltage $U_t$ at the individual $j$. Moreover, $N$ is the estimation length; here, we take $N = 100$.

Online SoC estimation: Transform (5) to a discrete form

$$\begin{aligned}
  &U_{p,k} = U_{p,k-1} \exp(-\Delta t/(\tau)) \\
  &+ R_{L,k-1} P_{p} \left(1 - \exp(-\Delta t/(\tau))\right) \\
  &U_{t,k} = U_{oc}(SoC_k) - I_{L,k} R_o - U_{p,k}
\end{aligned} \quad (20)$$

The state equation and the observation equation of the discrete system are as follows:

$$\begin{aligned}
  &x_k = \left( \begin{array}{c} U_{p,k} \\
  \text{SoC}_k \end{array} \right) \\
  &A_k = \left( \begin{array}{cc} \exp(-\Delta t/(R_p C_p)) & 0 \\
  0 & 1 \end{array} \right) \\
  &B_k = \left( \begin{array}{c} \frac{R_p \left(1 - \exp(-\Delta t/(R_p C_p))\right)}{\eta I / C_a} \\
 \eta_1 \Delta t / C_a \end{array} \right) \\
  &C_k = \frac{\partial U_t}{\partial x} \bigg|_{x=x_k} = \left[ \begin{array}{c} -1 \\
 \frac{dU_{oc}(SoC)/dSoC}{dSoC} \bigg|_{SoC_k} \end{array} \right] \\
  &D = [R_0]
\end{aligned} \quad (21)$$

where the calculation for $dU_{oc}(SoC)/dSoC$ will be discussed in Section IV.

The charging/discharging current is loaded on the lithium-ion cell and the battery model simultaneously. The voltage error between the estimation and the experimental data is reduced by adaptively updating the AEKF observer gain. Then, the observer with the updated gain is used to compensate for the state estimation error. The estimation of SoC is then fed back to update the parameters of the battery model for the next SoC estimation. In addition, the SoC estimation method based on AEKF is shown in Fig. 3.

IV. COMPARISON BETWEEN THE STATE-OF-CHARGE ESTIMATION APPROACHES

A. Experiments and Data Sampling

The test bench is shown in Fig. 4, which consists of an Arbin battery test system BT2000, a thermal chamber for
environment control, a host computer, and a MITS Pro soft for programming the BT2000. The BT2000 can charge/discharge a battery according to the designed program with maximum voltage of 60 V and maximum charge/discharge current of 300 A, and its recorded data include current, voltage, temperature, charge-discharge Amp-hours (Ah), Watt-hours (Wh), etc. The measured data are transmitted to the host computer through TCP/IP ports. The host computer has a low-pass filtering function to implement large noise cancellation [13]. Furthermore, to improve the sampling precision of the cell voltage, the Fluke 8846A multimeter, whose measurement accuracy of dc voltage is up to 0.0024% with a 6.5-digit resolution, has been applied for cell voltage measurement. The battery is kept in a thermal chamber, and the temperature is controlled within 20 ± 2 °C.

1) Static Capacity Test and Coulombic Efficiency Test: The available capacity test is based on the standard of [26] to measure the maximum available capacity. Usually, the available capacity test is repeated three times. If the error of the experiment results between the maximum and the average is within 2%, the available capacity test is effective, and the average value is taken as the actual maximum available capacity; however, if the error is more than 2%, the available capacity test should be repeated. For the LiMn$_2$O$_4$ lithium-ion cell, the available capacity test shows that its present maximum available capacity $C_a$ is 36.4 Ah, slightly higher than 35 Ah of the nominal capacity.

The Coulombic efficiency test is used to get the cell’s charge–discharge Coulombic efficiency; the test step is as follows:

Discharge Coulombic efficiency: Charging the battery fully at the nominal current with constant current and constant voltage (the charging cutoff voltage is 4.2 V) mode until the current reduces to the cutoff value of 1.2 A and then keeping the battery at rest for at least 2 hr and next discharging the battery at the 1-C current until the discharge cutoff voltage (3.0 V) is reached, the discharged capacity is calculated as $C_1$; then, keeping the battery at rest for at least 2 hr, and afterward discharging the battery at the nominal current until the discharge cutoff voltage is reached again, the capacity discharged is calculated as $C_2$; herein, the discharge Coulombic efficiency at 1-C current is calculated as the percent of $(C_a - C_2)/C_1$. Then, the discharge Coulombic efficiency for the other current is the same as this process.

### Table 1

<table>
<thead>
<tr>
<th>Current/A</th>
<th>12</th>
<th>35</th>
<th>70</th>
<th>105</th>
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<tbody>
<tr>
<td>Discharge Coulombic efficiency</td>
<td>1.000</td>
<td>0.995</td>
<td>0.990</td>
<td>0.989</td>
<td>0.989</td>
</tr>
<tr>
<td>Charge Coulombic efficiency</td>
<td>1.000</td>
<td>0.997</td>
<td>0.990</td>
<td>0.985</td>
<td>0.975</td>
</tr>
</tbody>
</table>

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**Fig. 3.** Adaptive observer-based robust SoC estimation.

**Fig. 4.** Schematic of the battery test bench.

**Fig. 5.** Test data of the OCV profile with SoC.
Fig. 6. Measured cell response in the hybrid pulse test. (a) Current profile of one hybrid pulse. (b) Voltage profile at SoC = 0.9. (c) Current profiles. (d) Voltage profiles.

Charge Coulombic efficiency: Charging the battery fully at the 1-C current with constant current and constant voltage (4.2 V) method until the current reduces to the cutoff values of 1.2 A; then, keeping the battery at rest for at least 2 hr and next discharging the battery at the nominal current until the discharge cutoff voltage is reached, the capacity discharged is calculated as C3. Then, the charge Coulombic efficiency at 1-C current is calculated as the percentage of C3/Ca. The charge Coulombic efficiency for the other current is the same as this process.

The experimental data of the Coulombic efficiency under different charge–discharge currents for the lithium-ion battery are listed in Table I, which shows that the Coulombic efficiency decreases with the increase of the current, and it is necessary to limit the current operation range for a higher efficiency.

2) OCV-SoC Test: To acquire data to calibrate the OCV, a test was performed on the LiMn2O4 cell. The test procedure is shown in [6]. In this paper, the hysteresis is ignored, and the OCV shown in Fig. 5 is defined as the average of the equilibrium potentials of charging and discharging to simplify the battery model. The OCV data can be fitted by (22) as follows:

\[
U_{oc}(\text{SoC}) = -3 \times \text{SoC}^4 + 7.2 \times \text{SoC}^3 - 6.1 \times \text{SoC}^2 + 2.8 \times \text{SoC} + 3.2. \tag{22}
\]

Then, we can get (23) for SoC estimation

\[
\frac{dU_{oc}(\text{SoC})}{d\text{SoC}} = -12 \times \text{SoC}^3 + 21.6 \times \text{SoC}^2 - 12.2 \times \text{SoC} + 2.8. \tag{23}
\]

3) Hybrid Pulse Power Characteristic (HPPC) Test: The HPPC test is from the battery test manual [27] and is the foundation of the power battery characteristic evaluation and model parameter identification, which achieves good results in offline parameter identification and is used widely.

A hybrid pulse test comprising a sequence of HPPC profiles, constant current discharge pulses, and rests was conducted. The HPPC test results are shown in Fig. 6, including a sample HPPC current curve, a sample HPPC voltage curve under SoC = 0.9, the current profiles, and the voltage profiles. Herein, the sample frequency is set to 10 Hz for each hybrid pulse within 1 min to improve the dynamic voltage identification accuracy, and for other rest moments, the sample frequency is set to 1 Hz.

The offline identification results of the model parameters within the SoC ranges of 0.6–0.9 are listed in Table II.
Fig. 8. Online estimation results with AEKF. (a) Terminal voltage profiles of the experiment and the online estimation. (b) Voltage error between the experiment and the online estimates. (c) OCV. (d) Ro.

4) UDDS Test: The UDDS test is a typical dynamic driving cycle that is often used to evaluate the performance of a vehicle, the effect of control strategies, the SoC estimation algorithms, etc. [13]. In this paper, several consecutive UDDS cycles are employed to verify the online estimation approach. The UDDS test is performed with the current profiles shown in Fig. 7 and terminated by a certain amount of Ah removed from the batteries or reaching a certain voltage level. The experimental current, voltage, and calculated SoC profiles are shown in Fig. 7.

B. SoC Estimation

1) Online SoC Estimation by Looking Up OCV-SoC Table: The online estimation of model parameters with the AEKF algorithm is conducted, and the results are shown in Fig. 8 with the initial parameters as follows:

\[
\begin{align*}
x_0 &= [4.1, 4.1, 0, 0, 10E6, 0]^T, \\
P_0 &= \begin{bmatrix} 0.01 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.01 & 0 & 0 & 0 & 0 \\ 0 & 0 & 30E-5 & 0 & 0 & 0 \\ 0 & 0 & 0 & 20 & 0 & 0 \\ 0 & 0 & 0 & 0 & 10E4 & 0 \\ 0 & 0 & 0 & 0 & 0 & 10E-5 \end{bmatrix}, \\
Q_0 &= \begin{bmatrix} 0.1 & 0 & 0 & 0 & 0 \\ 0 & 10 & 0 & 0 & 0 \\ 0 & 0 & 20 & 0 & 0 \\ 0 & 0 & 0 & 20 & 0 \\ 0 & 0 & 0 & 0 & 10E-6 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}, \\
R_0 &= 1.
\end{align*}
\] (24)

Fig. 8(a) shows the comparison profiles of the experiment and the online estimation terminal voltage profiles, which show that the AEKF-based online parameter identification method has good performance for the terminal voltage estimation, and the error profile of terminal voltages shown in Fig. 8(b) has verified its reliability. The maximum voltage error is less than 37 mV (1% of its nominal voltage), which suggests that the Thevenin model-based online parameter estimation algorithm has good accuracy. More importantly, the AEKF-based method can adjust the noise matrix quickly and reliably, and the voltage error gets less and less as the calculation goes on. Fig. 8(c) shows the online estimation results for the OCV, which can be used for SoC indication by looking up the OCV-SoC table.

Fig. 9 shows the SoC estimation profiles and the estimation error profiles. Fig. 9(a) and (b) shows that the maximum SoC error is 0.022, and the minimum error is $-0.035$. To evaluate the SoC accuracy in detail, we use the mean error and the root mean square error (RMSE) to describe the error performance, and the RMSE can show the dispersion degree and convergence performance of the SoC estimation error. Fig. 9(c) and (d) shows that the mean of absolute error and the RMSE of the SoC estimation result are all less than 0.02 and converge to 0.01 quickly.

2) Robust Online Model-Based SoC Estimation: The robust online SoC estimation with the AEKF algorithm is conducted, and the results are shown in Fig. 10 with the initial noise information $(P_0, Q_0, R_0)$ shown in (24) and $x_0 = [4.1 \ 0.9]^T$.

Fig. 10(a) shows the comparison profiles between the experiment and the online estimation terminal voltage profiles, which shows that there is little difference between the experiment data and the online estimation values. The error voltage profile shown in Fig. 10(b) has verified its accuracy, and its maximum terminal voltage error is around 0.04 V, which is higher than Fig. 8(b); however, this accuracy is enough for SoC estimation. Fig. 10(c) and (d) shows that the maximum SoC estimation error is within 0.02, and its absolute mean error and RMSE all are less than 0.02 and converge to 0.01 quickly.

C. Discussions and Analysis

The foregoing two AEKF-based SoC estimation approaches both perform well; the maximum absolute error is less than 0.04. In fact, the SoC estimation accuracy of the two foregoing approaches is influenced by the reliability of the OCV-SoC table. The OCV-based SoC estimation method uses the table after the OCV is estimated, whereas the latter uses the table in its recursive calculation process.
To evaluate the robustness of the SoC estimation methods, we assume that the OCV-SoC table is completely accurate. The accuracy of the OCV-based SoC estimation method is up to the real-time estimation of its OCV; however, we hardly can give feedback or directly correct for the OCV based on the measured values. The measures only affect the prediction of the terminal voltage, which can seldom give an accurate adjustment for SoC estimation results; therefore, this method estimates the SoC in an open-loop way. The SoC estimation accuracy with this method is limited, particularly for the battery with very flat OCV-SoC table such as LiFePO$_4$ battery; the SoC estimation will become worse. While the AEKF-based robust online SoC estimation approach with predefined model parameters uses the terminal voltage as feedback, because the model parameters have direct relevance with the SoC and the inappropriate SoC estimations will create an inaccurate OCV and other parameters, the terminal voltage error will, therefore, be bigger. This is different with the former method, whose incorrect OCV will hardly bring the model’s terminal voltage error because the error could be reduced by adjusting the model parameters. In fact, the latter approach takes the advantages of the information including model parameters and OCV to get a more reliable estimation by information fusing and decision-making method and provides a substantial probability for more accurate SoC estimation compared with the former method using only one table. If the accuracy of the model parameter and the model has been improved, the accuracy of the SoC estimation with the latter approach will be significantly improved.

An accurate SoC estimation depends on two aspects according to the definition of the SoC given by (4): One is the initial SoC, and the other is the calculation of SoC consumption. To investigate whether the SoC estimation with the AEKF approach

![Fig. 9. SoC estimation profiles and estimation error profiles. (a) SoC estimation results and true SoC profiles. (b) SoC estimation error profiles. (c) Mean absolute error of the SoC. (d) RMSE of the SoC.](image)

![Fig. 10. Online estimation results. (a) Terminal voltage profiles of the experiment (true value) and the online estimation (observer). (b) Terminal voltage error profiles. (c) SoC observer results and true SoC profiles. (d) SoC estimation error profiles. (e) Mean absolute error of the SoC. (f) RMSE of the SoC.](image)
can effectively solve the initial estimation inaccuracy of SoC, a further simulation analysis on the AEKF approaches is conducted. Two different SoC initial values, 0.90 and 0.50, are preset, and the corresponding SoC estimations are performed based on the UDDS cycles. The SoC estimation results are shown in Fig. 11.

It can be found that the robust online SoC estimation algorithms can quickly compensate the initial SoC errors and accurately track the experimental SoC values from Fig. 11(a) and its local enlarge figures. The difference among the different initial SoC values after correcting the initial errors except for the initial 10 samples is virtually indiscernible. Fig. 11(b) indicates that the SoC estimation error with inaccurate initial values shows the same tendency as that with accurate initial value in Fig. 10(d).

V. CONCLUSION

Based on the foregoing analysis, the main concluding remarks can be made as follows.

1) The Thevenin equivalent circuit model is selected for modeling the LiMn$_2$O$_4$ battery, and the offline identification method of the model parameters is improved by a genetic algorithm to get a more accurate relaxation time constant.

2) The battery test bench is built and the experiment schedule is designed, which includes static capacity, Coulombic efficiency, OCV-SoC, HPPC, and UDDS tests, and the offline model parameters are identified with the HPPC test.

3) The proposed AEKF-based online parameter estimation approach shows good performance in the accurate prediction of the terminal voltage and model parameters. The maximum voltage estimation error is within 1%, and there may be less error because of its favorable adjustment performance.

4) A systematic evaluation and analysis on the SoC estimation approach with online OCV estimation and with online model-based direct estimation show that the latter approach has superior performance with a close-loop characteristic and better robustness, the maximum SoC estimation error is within 2%, and the SoC estimation error can converge to 2% under different initial error SoCs.

Future work could be focused on how to improve the model accuracy and parameter identification method and finally get a more accurate SoC estimation.

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Rui Xiong (S’12) received the M.E. degree in vehicle engineering in 2010 from the Beijing Institute of Technology, Beijing, China, where he is currently working toward the Ph.D. degree in vehicle engineering. He is currently a joint Ph.D. student with the DTE Power Electronics Laboratory, University of Michigan-Dearborn.

His research mainly focuses on modeling and simulation, power batteries, and vehicular hybrid power systems.

Hongwen He received the M.E. degree from the Jilin University of Technology, Changchun, China, in 2000 and the Ph.D. degree from the Beijing Institute of Technology, Beijing, China, in 2003, both in vehicle engineering.

He is currently a Professor with the National Engineering Laboratory for Electric Vehicles, School of Mechanical Engineering, Beijing Institute of Technology. He has published 112 papers and holds six patents. His research interests include power battery modeling and simulation on electric vehicles, design, and control theory of the hybrid power train.

Dr. He received the first prize for Scientific or Technical Awards from the Beijing Institute of Technology in 2007.

Fengchun Sun received the M.E. and Ph.D. degrees in vehicle engineering from the Beijing Institute of Technology, Beijing, China, in 1984 and 1989, respectively. He studied at the Technical University of Berlin, Berlin, Germany, from 1987 to 1989 as a joint Ph.D. degree student.

He is currently a Professor and the Vice President of the Beijing Institute of Technology and the Director of the National Engineering Laboratory for Electric Vehicles. He has been conferred the title of "Cheung Kong Scholar" by the Ministry of Education, China. He has published more than 150 papers and is the holder of 19 patents. His research interests include electric vehicles, electric drive systems, electric vehicle demonstration, and infrastructure.

Dr. Sun received the second prize from the National Science and Technology Progress Awards in 2008, the second prize from the National Technological Innovation Awards in 2004 and 2009, and the award for industrial innovation from the Ho Leung Ho Lee Foundation in 2007.

Kai Zhao received the B.E. degree in physical electronics from the Ocean University of China, Qingdao, China, in 2009. He is currently working toward the M.E. degree in electric engineering with the Beijing Institute of Technology, Beijing, China.

His research mainly focuses on the battery management system in electric vehicles.