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Combined state of charge estimator for electric vehicle battery pack

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Abstract

Ah counting is not a satisfactory method for the estimation of the state of charge (SOC) of a battery, as the initial SOC and coulomb efficiency are difficult to measure. To address this issue, an equivalent coulomb efficiency is defined and a new SOC estimation method, denoted as ''KalmanAh'', is proposed. This method uses the Kalman filtering method to correct for the initial value used in the Ah counting method. A Ni/MH battery test, consisting of 8.08 continuous federal urban driving schedule (FUDS) cycles, is carried out to verify the method. The SOC estimation error is 2.5% when compared with the real SOC obtained from a discharge test. This compares favorably with an estimation error of 11.4% when using Ah counting.

Keywords: Electric vehicle; Battery management system; State of charge; Extended Kalman filter

1. Introduction

In electric vehicles (EV), the state of charge (SOC) of a battery is an important quantity, as it is a measure of the amount of electrical energy stored in the battery. It is analogous to the fuel gauge for the conventional internal combustion (IC) engine (John & Baskar, 2005). The voltage, as the judgment criterion, is used to avoid overcharge and overdischarge to maintain the battery within safe operating limits. However, this method does not satisfy the requirement as the battery's current changes dramatically in EV. Thus, the accurate estimation of the SOC of the battery pack is the key factor for managing batteries efficiently. In addition, the accurate estimating battery SOC is also the basis of the power distribution strategy for hybrid electric vehicles (HEV). Estimating the battery's SOC is complicated by the fact that the SOC depends on many factors such as temperature, battery capacitance and internal resistance. Some SOC estimation approaches are presented with the development of EV technology. The main SOC estimation approaches including the discharge test approach, the Ah counting approach, the open-circuit voltage approach, the load voltage approach, the inherent resistance approach, the neural networks approach and the Kalman filtering (KF) approach, have been studied in Alzieu, Smimite, and Glaize (1997), Gregory (2004a, 2004b, 2004c), Ma, Chen, and Qi (2001), Osvaldo, Francesco, and Luigi (2006), Piller, Perrin, and Jossen (2001), Qi, Li, Jia, and Xu (1997), and Wang, Chen, and Lin (2005), respectively. Researchers have realized that integration of several individual approaches may give rise to better performance. In John and Baskar's (2005) paper, an extended Kalman filter (EKF) is used to estimate the open-circuit voltage and then the open-circuit voltage method is used to estimate the SOC.

The SOC is a relative quantity that describes the ratio of the remaining capacity to the nominal capacity of the battery. It is given by

$$S(t) = S(0) - \int_0^t \frac{\eta I(t)}{C_n} \, dt, \tag{1}$$

where $S(t)$ is the SOC at time instant t, $S(0)$ is the initial value, C_n is the nominal capacity, and $I(t)$ is the current at time t. The current is positive while discharging and negative while charging. η is the coulombic efficiency. Usually, $\eta = 1$ for discharge and $\eta < 1$ for charge under standard conditions with a constant $C/3$ rate. However, the

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current rate changes drastically in real situations. Thus, the equivalent coulomb efficiency is introduced in Section 2 to measure the energy loss in the general situation.

The Ah counting approach is the straightforward application of Eq. (1). The current entering and leaving the battery is measured periodically. Then, the SOC of the battery is updated by adding or subtracting the last period's net cumulative charge. If a sufficiently accurate current sensor is used, this method is reasonably accurate and inexpensive to implement. However, it suffers several drawbacks (Hansen & Wang, 2005). Firstly, it is difficulty to estimate coulombic efficiency η accurately. Secondly, this approach itself is not able to determine the initial SOC denoted as SOC_0 and solve the variation of SOC_0 resulting from self-discharge and other factors. Thirdly, the error is larger when the battery works at high and low temperature or when the current fluctuates dramatically. Finally, the method is an open loop SOC estimator and errors in the current detector are accumulated by the estimator. The longer the estimator is operated, the larger the cumulative error becomes. In order to solve these problems, the Ah counting approach is always combined with other approaches. For example, the Ah counting approach is combined with the Peukert equation, which is used to calculate the coulombic efficiency. However, the coulombic efficiency is not only a function of current but also affected by SOC and temperature, so that the combination of the two methods are not satisfied. The Kalman filter approach provides not only the estimated SOC but also the estimation error, making this approach especially suitable for the SOC estimation in the HEV application. Due to the large number of matrix calculations involved, the drawbacks of this method lie in the higher requirement on the accuracy of the battery model and the calculation ability of the battery management systems (BMS). Gregory (2004a, 2004b, 2004c) studied the SOC estimation method of an LiPB cell based on the Kalman filter, but the research into the battery pack is suitable to the requirement of the vehicle.

In order to precisely estimate the SOC, the equivalent coulomb efficiency is tested and used in the Ah counting method. A new SOC estimation method is proposed, denoted as "KalmanAh", that uses the KF method to correct for the initial value used in the Ah counting method. In this method, the KF method is used to make the approximate initial value converge to its real value. Then the Ah counting method, considering the equivalent coulombic efficiency and self-discharge, is applied to estimate the SOC for the long working time. A Ni/MH battery with a nominal voltage 384 V and the nominal capacity of 80 Ah is used to implement the experiments concerning efficiency, self-discharge and to verify the SOC estimation method.

2. Equivalent coulombic efficiency

The battery's coulombic efficiency is defined in USABC (1996) as the ratio of the discharged capacity to the capacity needed to be charged to the initial state before discharge. The coulombic efficiency is shown as

$$\eta = \int_0^{t_d} I_d \,\mathrm{d}t \Big/ \int_0^{t_c} I_c \,\mathrm{d}t, \tag{2}$$

where I_d is the discharge current, I_c is the charge current, t_d is the discharge time and t_c is the charge time.

Under laboratory conditions, the efficiency test is performed by this method. The batteries are charged at a certain constant current, while the battery is in the balance state. It is discharged at the same current until the initial state is reached. The coulombic efficiency, shown as Eq. (2), is the ratio of the discharge capacity to the charge capacity. The experiment indicates that the coulombic efficiency is different with respect to different current rates. The energy loss is inevitable in the operating process due to internal resistance, and only the average coulombic efficiency in the whole charge and discharge process is obtained from Eq. (2). So far, no effective methods and equipment have been found to accurately calculate the charged coulombic efficiency by means of just a single charging process. The charge and discharge process alternates and the current in the EV changes continuously. Thus, calculating the charge and discharge coulombic efficiency, respectively, has the major significance in accurate estimation of the SOC.

2.1. Calculation of equivalent coulombic efficiency

In order to calculate the charge and discharge coulombic efficiency, respectively, the measurement method of equivalent coulombic efficiency is presented (Lin et al., 2006). As the coulombic efficiency is different at different currents, the $C/3$ rate (C is nominal capacity) is used as the base current to define the base coulombic efficiency and the equivalent coulombic efficiency when batteries are charged or discharged.

The base coulombic efficiency is measured by Eq. (3) according to the following test procedures: (a) the battery is discharged at the $C/3$ rate until terminal voltage is reached; (b) the battery is charged at the $C/3$ rate until SOC = 1, the charged capacity is Q_{cb}; (c) the battery is rested for 5 min until it is in the balanced state; (d) the battery is discharged at the $C/3$ rate until terminal voltage is reached, the discharged capacity is Q_{db}; and (e) the base coulombic efficiency is calculated from

$$\eta_{C/3} = Q_{db}/Q_{cb}. \tag{3}$$

The equivalent charge coulombic efficiency is measured by Eq. (4) according to the following test procedures: (a) the battery is discharged at the C/3 rate until terminal voltage is reached; (b) the battery is charged at the certain currents I_n ($C/3$, $C/2$, $1C$, $1.5C$, $2C$, etc) until SOC = 1, the charged capacity is $Q_{cc} = I_n t_{cc}$, t_{cc} is the charge time; (c) the battery is rested for 5 min until it is in the balanced state; (d) the battery is discharged at the $C/3$ rate until terminal voltage reached, the discharged capacity is

$Q_{dc}=(C/3)\,t_{dc}$, t_{dc} is the discharge time; and (e) the charge equivalent coulombic efficiency is calculated from

$$\eta_c = Q_{dc}/Q_{cc} = (\tfrac{C}{3}\,t_{dc})/(I_n\,t_{cc}). \tag{4}$$

The equivalent discharge coulombic efficiency is measured by Eq. (5) according to the following test procedures: (a) the battery is discharged at a specific current until terminal voltage reached; (b) the battery is charged at the $C/3$ rate until SOC $=1$, the charged capacity is $Q_{cd}=(C/3)t_{cd}$, t_{cd} is the charge time; (c) the battery is rested for 5 min until it is in the balanced state; (d) the battery is discharged at the specific currents I_n ($C/3$, $C/2$, $1C$, $1.5C$, $2C$, etc) until terminal voltage reached, the discharged capacity is $Q_{dd}=I_n\,t_{dd}$, t_{dd} is the discharge time; and (e) the equivalent discharge coulombic efficiency is calculated from

$$\eta_d = Q_{dd}/Q_{cd} = (I_n\,t_{dd})/(\tfrac{C}{3}\,t_{cd}). \tag{5}$$

A graph of the equivalent coulombic efficiency is shown in Fig. 1, and the base coulombic efficiency $\eta_{c/3}=0.971$. In order to calculate these results conveniently, a linear fitting method is used to fit the equivalent coulombic efficiency.

The charge and discharge process for variable current can be converted to the one for constant current. For example, if Q_0 is the initial capacity, Q_{n1} is the charged capacity at current I_{n1} where $Q_{n1}=I_{n1}t_{n1}$ and t_{n1} is the charge time, Q_{n2} is the discharged capacity at the current I_{n2} where $Q_{n2}=I_{n2}t_{n2}$ and t_{n2} is the discharge time. The equivalent charge capacity Q_1 and its discharged one Q_2 are calculated by Eqs. (6) and (7), respectively,

$$Q_1 = \frac{Q_{n1}}{\eta_{C/3}}\,\eta_c = \frac{I_{n1}t_{n1}}{\eta_{C/3}}\,\eta_c, \tag{6}$$

$$Q_2 = \frac{Q_{n2}}{\eta_d}\,\eta_{C/3} = \frac{I_{n2}t_{n2}}{\eta_d}\,\eta_{C/3}. \tag{7}$$

In the entire working process of the batteries, the surplus capacity Q_t defined by the base current, is calculated by Eq. (8). Where Q_c is the equivalent charge capacity, Q_d is the equivalent discharge capacity:

$$Q_t = Q_0 + \sum Q_c\,\eta_{C/3} - \sum Q_d = Q_0 + \sum I_{cn}t_{cn}\,\eta_c - \sum \frac{I_{dn}t_{dn}}{\eta_d}\,\eta_{C/3}. \tag{8}$$

2.2. Influence of temperature and SOC on the coulombic efficiency

The coulombic efficiency is affected not only by current but also by the SOC and the temperature.

2.2.1. Influence of SOC on the coulombic efficiency

Fig. 2 shows the influence of the available capacity related to the SOC on the coulombic efficiency. The coulombic efficiency in the low SOC range (the capacity <12 Ah) and the high SOC range (the capacity >76 Ah) is smaller than that in the normal SOC range (SOC $=$ 0.2–0.8). For EV, the coulombic efficiency is kept in the range of 0.94–0.98 in the normal SOC range. In this paper, the coefficient K_S is defined to modify the influence of the SOC on the coulombic efficiency. In the normal SOC range, the difference of base coulombic efficiency is considerably small, so a constant value $K_S=0.96$ is used in the normal SOC range.

2.2.2. Influence of temperature on the coulombic efficiency

Fig. 3 shows the influence of temperature on the coulombic efficiency. The battery pack is charged and discharged at the $C/3$ rate under different temperatures (25, 0 and $-10\,^{\circ}$C), respectively. The test indicates that temperature influences the coulombic efficiency. The relationship between efficiency and temperature is linear. A coefficient K_T is defined to modify the influence of the temperature on the coulombic efficiency. Suppose the influence coefficient at room temperature K_T (25 °C) $=1$, then K_T (0 °C) $=0.872/0.97=0.898$, and K_T (-10 °C) $=$ $0.828/0.97=0.853$.

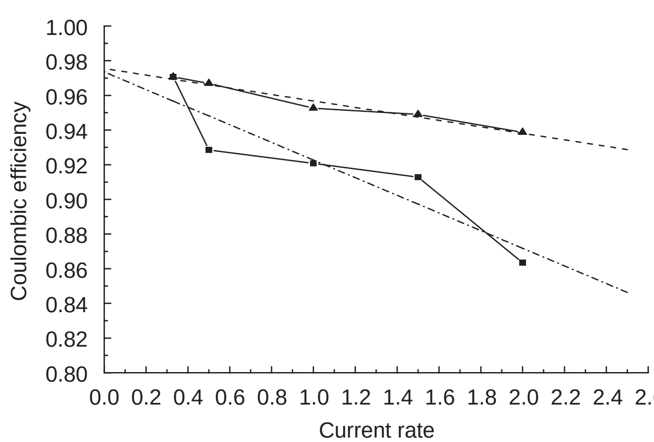

Fig. 1. The equivalent coulombic efficiency; ▲, equivalent discharge efficiency; - - - -, linear fitted discharge efficiency; ■; equivalent charge efficiency; - · - · -, linear fitted charge efficiency.

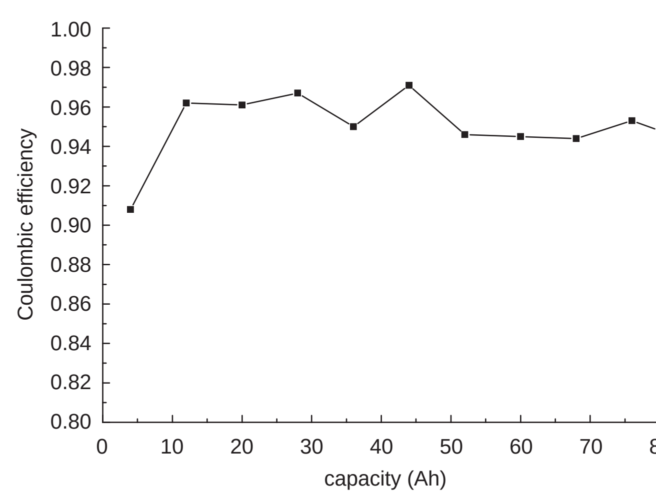

Fig. 2. The influence of capacity on coulombic efficiency.

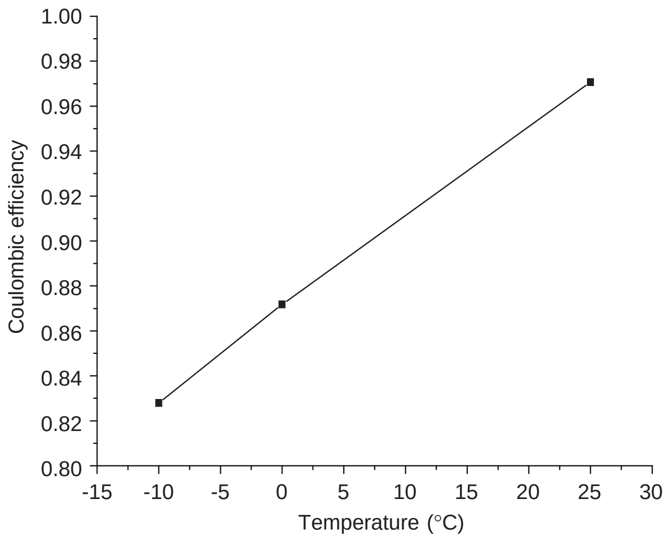

Fig. 3. The influence of temperature on coulombic efficiency.

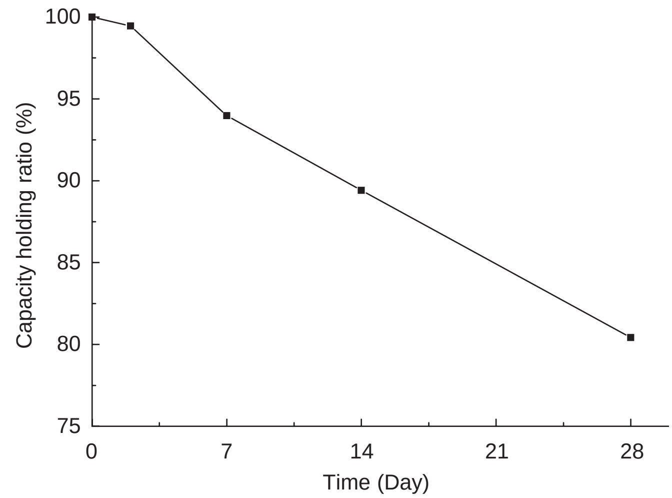

Fig. 4. Self-discharge rule of Ni/MH batteries at room temperature.

3. Estimation of energy loss caused by self-discharge

Self-discharge is a phenomenon where the available capacity is reduced after the battery has been rested for a long time. It affects the SOC estimation accuracy significantly. The higher the environmental temperature is, the larger the self-discharge becomes. Fig. 4 shows the self-discharge rule of Ni/MH batteries at room temperature. The whole self-discharge process is linear. K_{qs} is defined as the self-discharge coefficient of Ni/MH batteries at room temperature. For example, if batteries had been rested for 4 weeks, then $K_{qs} = 1-0.8042 = 0.1958$. Supposing the self-discharge quantity of battery pack is Q_s, Eq. (8) can be converted into the following equation:

$$Q_t = Q_0 - Q_s + \sum Q_c\, \eta_{C/3} - \sum Q_d = Q_0 - K_{qs}\, C + \sum I_{cn} t_{cn}\, \eta_c - \sum \frac{I_{dn} t_{dn}}{\eta_d}\, \eta_{C/3}. \tag{9}$$

4. An extended Kalman filter approach for initial SOC estimation

4.1. The extended Kalman filter

KF is an established technology which provides a theoretically elegant and time-proven method to filter measurements of system input and output to produce an intelligent estimation of a dynamic system's state. It is in common use in many fields including target tracking, navigation and communication, but is not widely used in the battery field. The Kalman filter problem uses the observed input data and output data to find the minimum mean squared error estimate $\hat{x}_k$ of the true state x_k. The solution to this problem is standard KF. The KF is the optimum state estimator for a linear system with the assumptions that the process noise and sensor noise are independent, zero-mean, Gaussian noise processes. If the system is nonlinear, then a linearization process at every time step is used to approximate the nonlinear system with a linear time varying system. The linear time varying system is then used in the KF, resulting in an EKF on the true nonlinear system. Although EKF is not necessarily optimal, it often works very well.

The nonlinear system model is:

$$\boldsymbol{x}_{k+1} = f(\boldsymbol{x}_k, \boldsymbol{u}_k) + \boldsymbol{w}_k, \tag{10}$$

$$y_k = g(\boldsymbol{x}_k, \boldsymbol{u}_k) + v_k, \tag{11}$$

where x_k is the system state vector at time index k, and Eq. (10) is called the state equation. The known and measurable input to the system is u_k and the measurable output is y_k computed by the output equation (11). $f(\boldsymbol{x}_k, \boldsymbol{u}_k)$ and $g(\boldsymbol{x}_k, \boldsymbol{u}_k)$ are the nonlinear state transition function and measurement function, respectively. w_k and v_k are independent, zero-mean, Gaussian noise processes with covariance matrices R_w and $Q_{v,}$ respectively. If $f(\boldsymbol{x}_k, \boldsymbol{u}_k)$ and $g(\boldsymbol{x}_k, \boldsymbol{u}_k)$ are linearized by a first-order Taylor-series expansion, the linearized model as Eqs. (12) and (13) describes the true nonlinear system:

$$\boldsymbol{x}_{k+1} = \hat{A}_k \boldsymbol{x}_k + f(\hat{\boldsymbol{x}}_k, \boldsymbol{u}_k) - \hat{A}_k \hat{\boldsymbol{x}}_k + \boldsymbol{w}_k, \tag{12}$$

$$y_k = \hat{C}_k \boldsymbol{x}_k + g(\hat{\boldsymbol{x}}_k, \boldsymbol{u}_k) - \hat{C}_k \hat{\boldsymbol{x}}_k + v_k, \tag{13}$$

where

$$\hat{A}_k = \left.\frac{\partial f(\boldsymbol{x}_k, \boldsymbol{u}_k)}{\partial \boldsymbol{x}_k}\right|_{x_k=\hat{x}_k} \quad \text{and} \quad \hat{C}_k = \left.\frac{\partial g(\boldsymbol{x}_k, \boldsymbol{u}_k)}{\partial \boldsymbol{x}_k}\right|_{x_k=\hat{x}_k}.$$

The algorithm of the EKF is summarized as following:

- *Initialization*: For $k = 0$, given the initial state value of $\hat{x}_0$, covariance matrix p_0, noise variance R_w and Q_v. Following initialization, the algorithm repeatedly performs two steps at each measurement interval. First, it predicts the value of the present state, output and error covariance. Second, using a measurement of the physical system output, it corrects the state estimate and error covariance. These two steps are performed according to the following equations:

- *Computation*: For $k = 1,2,\ldots$ compute

State estimate time update

$$\hat{\mathbf{x}}_{k/k-1} = f(\hat{\mathbf{x}}_{k-1/k-1}, u_{k-1}). \tag{14}$$

Error covariance time update

$$P_{k/k-1} = \hat{A}_{k-1} P_{k-1/k-1} \hat{A}_{k-1}^{\mathrm{T}} + R_w. \tag{15}$$

Kalman gain matrix

$$L_k = P_{k/k-1} \hat{C}_k^{\mathrm{T}} [\hat{C}_k P_{k/k-1} \hat{C}_k^{\mathrm{T}} + Q_v]^{-1}. \tag{16}$$

State estimate measurement update

$$\hat{x}_{k/k} = \hat{x}_{k/k-1} + L_k \left[y_k - g(I_k, \hat{x}_{k/k-1}) \right]. \tag{17}$$

Error covariance measurement update

$$P_{k/k} = (I - L_k \hat{C}_k) P_{k/k-1}. \tag{18}$$

By modeling the battery system as Eqs. (12) and (13) to include the wanted unknown quantities in its state description, the EKF is applied to estimate their values. An additional benefit of the EKF is that it automatically provides dynamic estimation error bounds on these estimates as well. Suppose that the SOC of the batteries is one of the system states x_k, the SOC at time index k can be estimated using the EKF method mentioned above. Unlike the Ah counting method, which is an open loop SOC estimator, the EKF method is a close loop SOC estimator.

4.2. The EKF based SOC estimation algorithm

In order to use Kalman-based methods for a BMS, a battery model in a discrete-time state-space form (Hansen & Wang, 2005; Wang, Chen, & Cao, 2006; Wang et al., 2006, 2005; Wang, Chen, & Chen, 2006) is needed. After setting the SOC as the single model state, terminal voltage may be predicted by the combined model presented in Gregory (2004a, 2004b, 2004c).

The discrete function of Eq. (1) can be written as

$$S_{k+1} = S_k - \frac{\eta I_k \Delta t}{C_n}. \tag{19}$$

Supposing that $x_k = S_k$ and considering the equivalent coulombic efficiency and self-discharge described in Eq. (9), the state function is given by

$$x_{k+1} = \begin{cases} x_k - K_{qs} - I_k \Delta t K_S K_T \eta_c / C_n, & I_k < 0, \\ x_k - K_{qs} - I_k \Delta t K_S K_T \frac{\eta_{C/3}}{\eta_d} \Big/ C_n, & I_k > 0. \end{cases} \tag{20}$$

The combined model based measurement function can be written as

$$\begin{aligned} y_k = g(I_k, x_k) + v_k = K_0 - R I_k - K_1/x_k - K_2 x_k \\ + K_3 \ln(x_k) + K_4 \ln(1 - x_k) + v_k, \end{aligned} \tag{21}$$

where R is the internal resistance, K_0, K_1, K_2, K_3, K_4 are the fitting coefficients, and v_k is the measurement noise with variance Q.

Eqs. (20) and (21) constitute the nonlinear discrete-time state-space battery model. Thus, the EKF can be applied to estimate the SOC. The algorithm is described as follows:

- *Initialization*: Given an initial SOC estimate $\hat{x}_0$, initial covariance matrix p_0 and measurement noise variance Q.
- For sampling time $k = 1, 2, 3\ldots$, sampling battery load voltage y_k, current I_k, the calculation process is iterated as follows.

State (SOC) estimate time update:

$$\hat{x}_{k/k-1} = \begin{cases} \hat{x}_{k-1/k-1} - K_{qs} - I_k \Delta t\, K_S K_T \eta_c / C_n, & I_k < 0, \\ \hat{x}_{k-1/k-1} - K_{qs} - I_k \Delta t\, K_S K_T \frac{\eta_{C/3}}{\eta_d} \Big/ C_n, & I_k > 0. \end{cases} \tag{22}$$

Error covariance time update

$$P_{k/k-1} = P_{k-1/k-1}. \tag{23}$$

Kalman gain matrix

$$\begin{aligned} \hat{C}_k = \left. \frac{\partial g(I_k, x_k)}{\partial x_k} \right|_{x_k = \hat{x}_{k/k-1}} &= K_1/(\hat{x}_{k/k-1})^2 - K_2 + K_3/\hat{x}_{k/k-1} \\ &- K_4/(1 - \hat{x}_{k/k-1}), \end{aligned} \tag{24}$$

$$L_k = P_{k/k-1} \hat{C}_k^{\mathrm{T}} [\hat{C}_k P_{k/k-1} \hat{C}_k^{\mathrm{T}} + Q]^{-1}. \tag{25}$$

State estimate measurement update

$$\hat{x}_{k/k} = \hat{x}_{k/k-1} + L_k \left[y_k - g(I_k, \hat{x}_{k/k-1}) \right]. \tag{26}$$

Error covariance measurement update

$$P_{k/k} = (I - L_k \hat{C}_k) P_{k/k-1}. \tag{27}$$

4.3. Parameter identification of battery model

Battery pack tests are performed to identify the model parameters. It comprises a sequence of constant-current discharge pulses and followed by a sequence of constant-current charge pulses. The AV-900 test equipment is the power processing system which has the flexibility to implement virtually any electrical driving cycle, and can offer and regenerate power up to 250 kW, with a voltage range of 8–900 VDC and a current range of $\pm$1000 ADC. During the experiment, the current, the voltage and the temperature data are collected by the AV-900. The current and voltage profiles for this test are shown in Fig. 5(a) and (b) respectively, and the SOC calculated by the AV-900 is shown in Fig. 5(c).

Given a set of N samples including the current, the voltage and the SOC of the battery pack, the parameter vector $\boldsymbol{\theta}$ in Eq. (21) may be solved using the least squares estimation method:

$$\boldsymbol{\theta} = [K_0, R^+, R^-, K_1, K_2, K_3, K_4]^{\mathrm{T}} = (H^{\mathrm{T}} H)^{-1} H^{\mathrm{T}} Y, \tag{28}$$

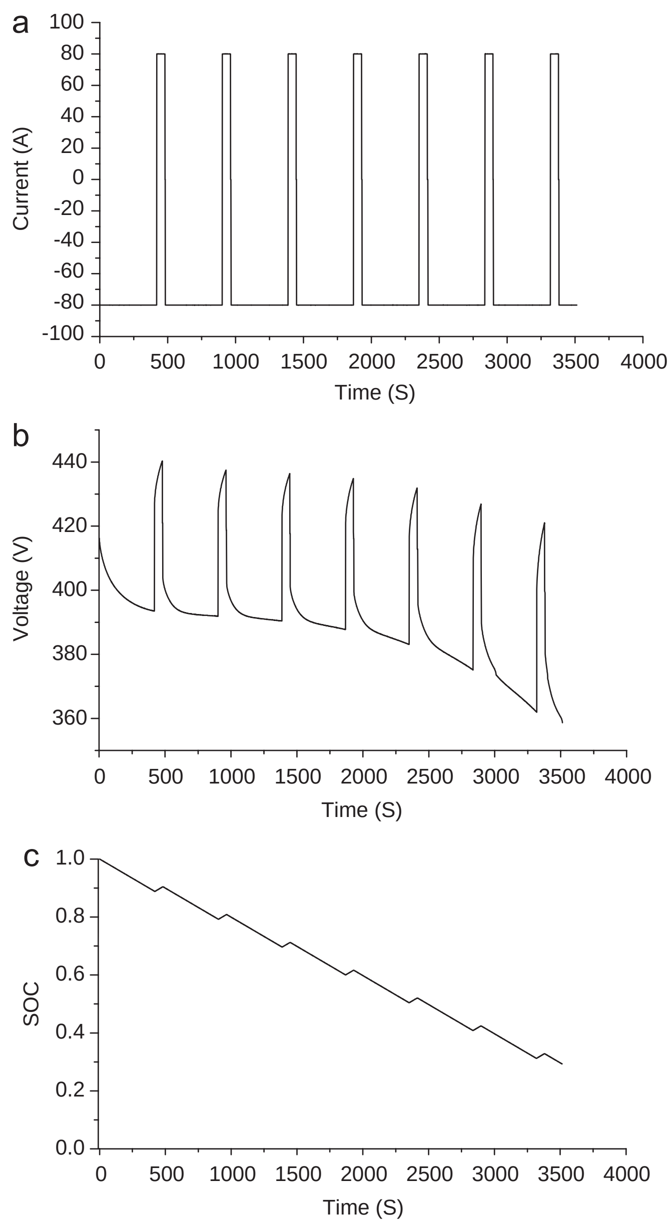

Fig. 5. Current, voltage and SOC profiles of the identification test.

where $Y = [y_1, y_2, \ldots, y_N]$ is the voltage sequence, $H = [h_1, h_2, \ldots, h_N]^{\mathrm{T}}$, $h_j = [1, I_j^+, I_j^-, 1/x_j, x_j, \ln(x_j), \ln(1-x_j)]$, I_j^+ is equal to I_j if $I_j > 0$, I_j^- is equal to I_j if $I_j < 0$, else I_j^+ and I_j^- are zero. The subscript N denotes the sampling numbers of data, R^+ is the battery internal resistance when discharged, R^- is the battery internal resistance when charged.

The identified model parameters of the Ni/MH battery pack are $\boldsymbol{\theta} = [534.002, 0.346, 0.1799, 2.6273, -131.704, 95.453, -6.26]^{\mathrm{T}}$.

5. The combined SOC estimation algorithm

As mentioned above, the Kalman filter approach is a closed loop estimation algorithm which is especially suitable for the SOC estimation for HEV applications. The drawback of this method lies in the high computation cost. The Ah counting approach can provide accurate estimation with low computation cost when given an accurate initial SOC value. The combined SOC estimation algorithm, denoted as "KalmanAh", is a method that uses KF to correct for the initial value used in the Ah counting method. This method possesses advantages of both methods. The calculation process used in this method is described as follows.

In the first step, the approximate initial SOC of the battery pack (namely SOC_0) is given by the BMS according to the value saved in the BMS.

In the second step, the EKF algorithm, shown in Eqs. (22)–(27), is applied to find the initial value SOC_0 to converge to its real value.

In the third step, the Ah counting approach, shown as Eq. (22), which considered the equivalent coulombic efficiency and self-discharge, is applied to predict the SOC for the long working time.

6. Experiment

6.1. Battery experiment

The federal urban driving schedules (FUDS) cycle is a typical working cycle that lasts for 1372 s. The FUDS test for Ni/MH battery is applied to certify and evaluate the KalmanAh method presented in this paper. The AV-900 test equipment is also used. 8.08 work cycles are performed with a sampling time of 1 s and a working time of 11,085 s. Thus, the test cycle can simulate the operation of the battery pack in EV. The maximum discharge current is 129.2 A and the maximum charge current is 63.8 A. The average temperature is 25.91 °C when the test begins and 27.52 °C when the test ends. The batteries are charged to 53.47 Ah at the $C/3$ rate before test and discharged to 12.79 Ah at the $C/3$ rate after test. The net discharged capacity recorded by the AV-900 is 36.79 Ah, while the coulombic efficiency is neglected by the AV-900. The voltage and current profiles of Ni/MH batteries sampled during the FUDS cycles are shown in Fig. 6(a) and (b) respectively.

6.2. Analysis and comparison

Four different SOC estimation methods including Accurate-Ah, KalmanAh, AhEquip and OcvAh are used on the same battery pack for comparison. The estimation results are shown in Fig. 7(a) and (b). The Accurate-Ah is an Ah counting method where accurate initial SOC is given and the coulombic efficiency is considered. KalmanAh is the method proposed in this paper. AhEquip is an Ah counting method estimated by the AV-900 equipment which does not consider the coulombic efficiency. OcvAh is an Ah counting method where the initial SOC is estimated by the open-circuit voltage approach and the coulombic

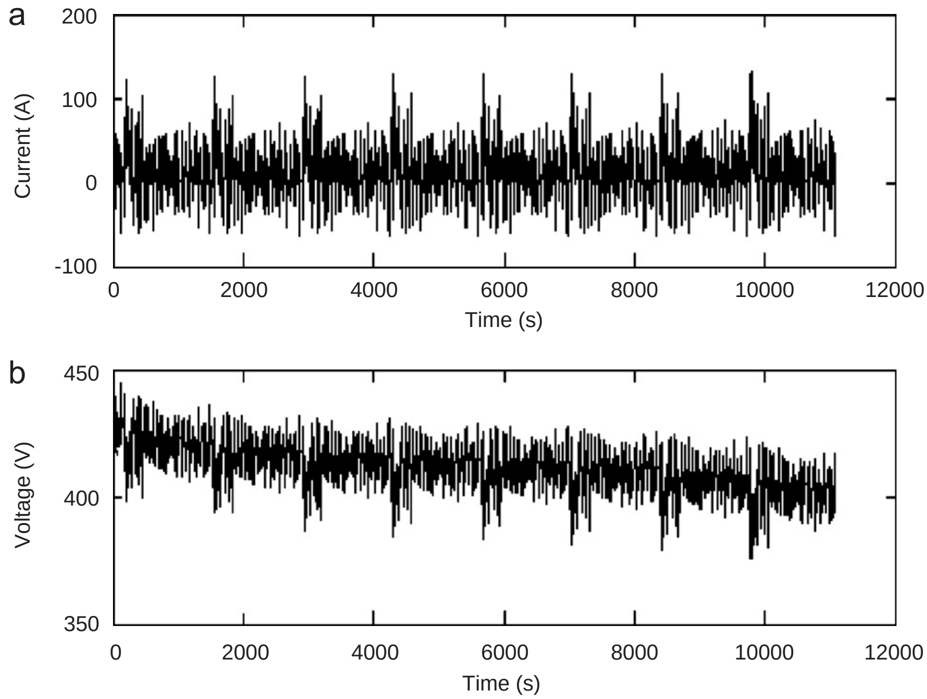

Fig. 6. Current and voltage profiles of the FUDS test cycles.

efficiency is not considered. In the KalmanAh approach, given an initial SOC $x_0 = 0.69$, the EKF approach is used within the time interval of the 1st to the 100th second. The initial value $p_0 = 0.05$ and the measurement noise variance is 0.2. From Fig. 7, the SOC value estimated by the KalmanAh approach is very close to the real SOC at 30 s. Then the Ah counting approach shown in Eq. (22) is used.

Table 1 shows a comparison of the different SOC estimation methods. It is assumed that the SOC obtained from the discharge test at the $C/3$ rate is the real value. The SOC estimation value from the Accurate-Ah approach is closest to that from the discharge test approach. Compared with the Accurate-Ah approach, the estimation error from the AhEquip approach is apparently large since the coulombic efficiency is not considered. This indicates that the equivalent coulombic efficiency is very important for accurate SOC estimation. The error contained in the starting estimate will be carried forward, so that the OcvAh approach is not able to satisfy the EV requirement due to larger estimation error. The Accurate-Ah approach is slightly better than the KalmanAh approach, but only implemented in the laboratory because it is not easy to get an accuracy initial SOC. The KalmanAh approach uses a single-variable battery model to estimate the SOC, which has less computation burden and is easily applied to BMS.

7. Conclusions

The Ah counting method is the simplest technique to estimate the battery pack SOC in EV. However, the lack of knowledge about the initial SOC and the coulomb

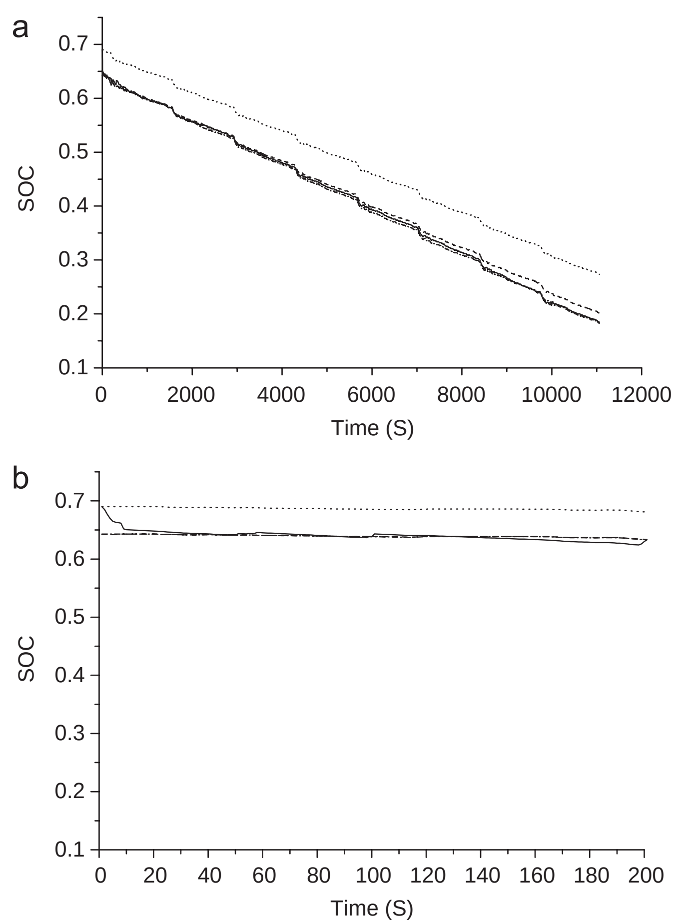

Fig. 7. SOC estimation results using four methods, Panel (b) is the enlarged part of Panel (a); ...., OcvAh method; - - - -, AhEquip method; —, KalmanAh method; - · - · -, accurate-Ah method.

Table 1
SOC estimation error

Method	Dicharge test	AhEquip	Accurate-Ah	OcvAh	KalmanAh
Initial SOC	0.643	0.651	0.643	0.690	0.690
Terminal SOC	0.160	0.201	0.183	0.274	0.185
Estimation error	0	0.041	0.023	0.114	0.025

efficiency limit the improvement of the accuracy. The KF is especially suitable for SOC estimation. Due to the large number of matrix calculation involved, the drawback of this method lies in the higher requirement on the accuracy of the battery model and calculation ability of the BMS.

A new SOC estimation method, denoted as "KalmanAh", is proposed. It uses the KF method to correct for the initial value used in the Ah counting method. The measurement methods of equivalent coulombic efficiency are presented to solve the problems of coulombic efficiency measurement and applied to variant current. The approximate initial SOC of the battery pack is given, and the EKF approach based on the single-variable battery model is used to make the initial SOC converge to its real value. Then, the improved Ah approach, considering the coulombic efficiency and self-discharge, is used to estimate the SOC for a long working time. The experiment shows that this method is simple and has been effectively applied to the real BMS in EV.

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