The State of Charge Estimation of Lithium-Ion Batteries Based on a Proportional-Integral Observer

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***Abstract*—With the development of electric drive vehicles (EDVs), the state-of-charge (SOC) estimation for lithium-ion (Li-ion) batteries has become increasingly more important. Based on the analysis of some of the most popular model-based SOC estimation methods, the proportional-integral (PI) observer is proposed to estimate the SOC of lithium-ion batteries in EDVs. The structure of the proposed PI observer is analyzed, and the convergence of the estimation method with model errors is verified. To demonstrate the superiority and compensation properties of the proposed PI observer, the simple-structure RC battery model is utilized to model the Li-ion battery. To validate the results of the proposed PI-based SOC estimation method, the experimental battery test bench is established. In the validation, the urban dynamometer driving schedule (UDDS) drive cycle is utilized, and the PI-based SOC estimation results are found to agree with the reference SOC, generally within the 2% error band for both the known and unknown initial SOC cases.**

***Index Terms*—Battery, electric vehicle, lithium-ion (Li-ion) battery, proportional-integral (PI) observer, sliding-mode observer, state of charge (SOC).**

I. Introduction

ELECTRIC drive vehicles (EDVs), including battery electric vehicles (BEVs), hybrid electric vehicles (HEVs), and plug-in hybrid electric vehicles (PHEVs), are playing increasingly more important roles worldwide. As one of the most essential parts in EDVs, the traction battery greatly impacts the performance of an EDV. Considered as the only viable solution for EDVs at the present time, lithium-ion (Li-ion) batteries have drawn increasingly more attention.

As an essential indicator for Li-ion batteries, state of charge (SOC) is a key state to estimate the drive distance of an EDV. If an accurate SOC can be obtained, the SOC range that can be used could be extended. Thus, a smaller battery pack will be able to satisfy the demand of an EDV that right now is equipped with a large battery pack. Thus, the price for the battery pack can be dramatically decreased to further help the market penetration of EDVs.

However, Li-ion batteries are electrochemical systems with strong nonlinearity; they should not be overcharged or overdischarged to avoid damaging the batteries, shortening the battery life, or even causing fire or explosion. To model such a strong nonlinear system is very difficult. To draw states that cannot be directly measured, such as the SOC and parameters of a battery, would be even more difficult.

A number of methods to estimate the SOC of Li-ion batteries have been reported in previous literature. The ampere-hour counting (Coulomb counting, or current integration) method for the calculation of battery SOC is simple and easy to implement; however, it needs prior knowledge of initial SOC and suffers from accumulated errors of noise and measurement error [1], [2]. The open-circuit voltage (OCV) method is very accurate; however, it needs a long rest time to estimate the SOC and, thus, cannot be used in real-time applications [1]. Intelligent algorithms, such as artificial neural networks, fuzzy logic, and so forth, have been studied to estimate the SOC by treating the battery as a black-box system [3], [4]. These methods can often produce a good estimation of SOC due to the powerful ability to approximate nonlinear functions. However, the learning process is quite computational and complex; thus, it can hardly be used in online applications.

SOC estimation methods based on battery models are the most popular solutions. The main methodology is to apply the measured input signals to the model and calculate the output using the present and/or past states and parameters of the model. The differences between the calculated and measured values or the so-called errors are applied to an algorithm to intelligently update the estimation of the model states. Such model-based SOC estimation methods could be the Luenberger observer [5]–[7], the Kalman filter [8]–[11], and the sliding-mode observer [12]–[14].

The Luenberger observer was first proposed by Luenberger [15] in 1966 and is now widely used in linear, nonlinear, and time-varying systems. It was also introduced to estimate the SOC of a battery and had good results [5]–[7]. The Kalman filter uses the entire observed input data and output data to find the minimum-mean-square-error estimation states of the true states of the Li-ion batteries [11]. Hence, essentially, the main idea of the Kalman filter is to use prior information, such as input current and output terminal voltage, to minimize the error to solve the best Kalman gain. This Kalman gain multiplying

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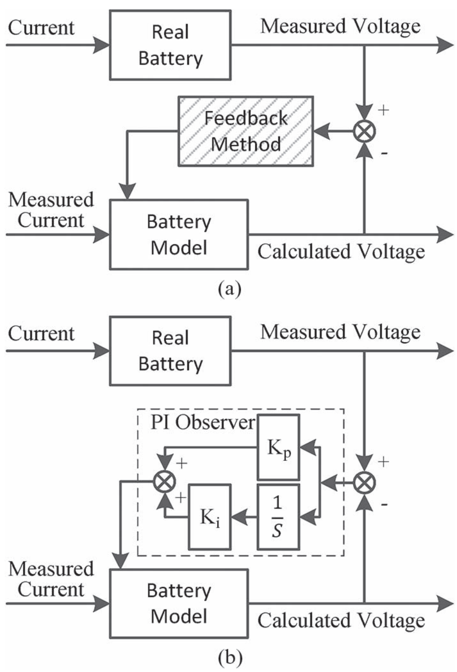

Fig. 1. Block diagram of different observer-based SOC estimation methods for Li-ion batteries. (a) Block diagram of the common structure. (b) Block diagram of a PI observer.

the error is feedback to correct the differences between the model calculated states and the true states of the Li-ion battery. From a certain perspective, the Kalman filter is an optimization method of the Luenberger observer.

However, an accurate battery model is required for both the Luenberger observer method and the Kalman filter method. Without an accurate battery model, neither of the two methods could perform well. However, an accurate battery model is hard to obtain, considering the inconsistency of cells, the operating temperature, different SOC, and aging of batteries. Meanwhile, even if there is such a battery model that is accurate enough for SOC estimation, the computation complexity would make it difficult to apply online.

The sliding-mode observer was introduced to estimate the states of a battery [12]. As indicated in the paper, the sliding-mode controller was robust in the presence of parameter uncertainties and disturbances, and the sliding-mode observers inherited such robust properties. In the sliding-mode observer, the error of the terminal voltage goes through the sliding-mode observer and feeds back to the battery model. It is robust under modeling uncertainties, but the chatter problem can not be ignored.

For the given three methods, feedback methods are the only differences, and the structure of the three methods is nearly the same, which is shown in Fig. 1(a). From the control theory point of view, Fig. 1(a) could be considered as a control system. The input signal is the voltage response of the real battery, and the output signal is the voltage response of the battery model. Thus, the feedback method could be considered as a controller. The goal of such a controller is to force the calculated terminal voltage to converge to the measured terminal voltage and eventually force the states of the battery model to converge to the true states of the battery.

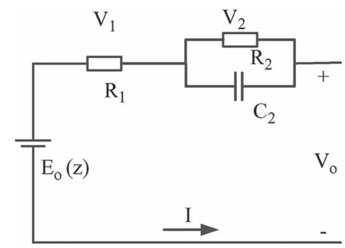

Fig. 2. Equivalent circuit of the RC model of Li-ion batteries.

As far as a controller is concerned, the proportional-integral (PI) controller, which is the most widely used control method, is introduced in this paper, as shown in Fig. 1(b). The feedback method is replaced by the PI controller, which could be referred to as the PI observer in the structure. The PI observer is proposed to estimate the SOC of Li-ion batteries in this paper.

It has been reported that the addition of the integrator of a PI observer confers to the observer more robustness with respect to modeling uncertainties [16]. Since there is always modeling uncertainties for a battery model, the PI observer improves the accuracy and speed of SOC estimation of Li-ion batteries.

II. Battery Modeling

It is difficult to obtain a battery model since Li-ion batteries are considered to be complex electrochemical and strong nonlinear systems. Attempts have been made to evaluate the models for the estimation of Li-ion batteries, such as the Rint Model [9], [17], [18], the first-order RC model [18]–[20], the second-order RC model [8], [18], and the impedance model [21]–[23]. Other models have also been researched based on those previously mentioned, such as the hysteresis model [9]. Normally, the estimation would be more accurate if the model can characterize the battery better, but it would also cause a more complex computation problem. Considering the properties and advantages of the proposed PI observer, the simple first-order RC model (referred to as the RC Model) is utilized in this paper. The RC model may cause large model errors and model uncertainties, but these are expected to be compensated by the PI observer. Therefore, it can avoid the complex computation and is robust to model errors and model uncertainties.

A. Introduction of RC Model

The RC model of Li-ion batteries is shown in Fig. 2. It consists of a voltage source $(E_o(z))$, a resistor (R_1), and a parallel capacitor (C_2) and resistor (R_2). The voltage source is a function of the SOC, which is denoted by z. The resistor represents the battery inner resistance. Capacitor C_2 and resistor R_2 are utilized to model the chemical diffusion of the electrolyte with the Li-ion batteries.

In Fig. 2, the relationship between V_2 and current I can be obtained by considering the parallel R_2 and C_2, i.e.,

$$\dot{V}_2 = -\frac{1}{R_2 C_2} V_2 + \frac{1}{C_2} I. \tag{1}$$

Meanwhile, according to circuit theory, the terminal voltage can be calculated as follows:

$$V_o = E_o(z) + V_1 + V_2. \tag{2}$$

In most studies, E_o is estimated using a model-based method, and SOC is inferred from E_o. In this paper, the SOC is chosen as the state instead of E_o. The definition of SOC of a battery is the ratio of the remaining capacity to the nominal capacity of the battery, which can be described as

$$\text{SOC} = \frac{\text{Remaining Capacity}}{\text{Nominal Capacity}}. \tag{3}$$

If the initial SOC and the current SOC are denoted by $z(0)$ and $z(t)$, respectively, the mathematical relationship can be written as

$$z(t) = z(0) + \Delta z = z(0) + \int_0^t \frac{\eta_i I(\tau)}{C_n} d\tau \tag{4}$$

where Δz is the variation of battery SOC during time period 0 to t, $I(\tau)$ is the instantaneous battery current, η_i is the battery Coulombic efficiency, and C_n is the nominal battery capacity. Since $z(0)$ is a constant for any given situation, (4) can be rewritten as

$$\dot{z} = \frac{\eta_i}{C_n} I. \tag{5}$$

If V_2 and z are chosen as the states of the battery model, the state function can be written as

$$\begin{cases} \dot{V}_2 = -\frac{1}{R_2 C_2} V_2 + \frac{1}{C_2} I \\ \dot{z} = \frac{\eta_i}{C_n} I. \end{cases} \tag{6}$$

However, output equation (2) is not expressed directly with these two states but with $E_o(z)$. The relationship between SOC and $E_o(z)$ is nonlinear, and it is not easy to draw a mathematical interpretation for it. To deal with this problem and simplify the computation, a gain scheduling method [24] is introduced, which typically employs an approach whereby the nonlinear system is decomposed into a number of linear subsystems. For a given nonlinear system, the relationship between SOC and $E_o(z)$ can be divided into several sections, and the subsystem in each section is considered to be linear, as shown in Fig. 3.

Hence, the relationship can be written in the short SOC interval as follows for the ith SOC interval $(i-1) \cdot \Delta_{\text{SOC}} \le \text{SOC}_i \le i \cdot \Delta_{\text{SOC}}$:

$$E_o = a_i \cdot \text{SOC}_i + b_i \tag{7}$$

where Δ_{SOC} is the SOC interval length ($\Delta_{\text{SOC}} = 10\%$ in this paper).

For the ith SOC interval $(i-1) \cdot \Delta_{\text{SOC}} \le \text{SOC}_i \le i \cdot \Delta_{\text{SOC}}$, the corresponding set (a_i, b_i) can be calculated from the curve and will be maintaned constant in the ith SOC interval. The parameters of the approximation of the relationship between SOC and OCV are listed in Table I. The measured and approximated curves of the relationship between SOC and OCV are shown in Fig. 3. The two curves are consistent, indicating that such an approximation is reasonable with sufficient accuracy.

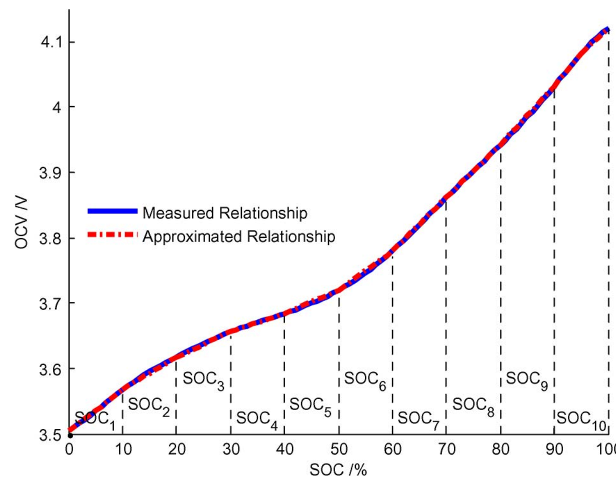

Fig. 3. Approximation of the relationship between SOC and OCV.

TABLE I
PARAMETERS OF THE APPROXIMATION OF THE RELATIONSHIP BETWEEN SOC AND OCV

i^{th}	1	2	3	4	5
SOC_i	0-10	10-20	20-30	30-40	40-50
a_i	0.0059	0.0049	0.0039	0.0028	0.0036
b_i	3.5052	3.5188	3.5397	3.5728	3.5416
i^{th}	6	7	8	9	10
SOC_i	50-60	60-70	70-80	80-90	90-100
a_i	0.006	0.0082	0.008	0.009	0.0099
b_i	3.4199	3.2864	3.3004	3.2232	3.1364

According to the given explanation, the output equation can be described as

$$V_o = V_2 + a_i \cdot z + b_i + R_1 \cdot I. \tag{8}$$

The state-space function with the additional state z can be rewritten as

$$\begin{cases} \dot{x} = Ax + Bu \\ y = Cx + Du \end{cases} \tag{9}$$

where

$$A = \begin{bmatrix} -\frac{1}{R_2C_2} & 0 \\ 0 & 0 \end{bmatrix}$$

$$B = \begin{bmatrix} \frac{1}{C_2} \\ \frac{\eta_i}{C_n} \end{bmatrix}$$

$$C = [1 \quad a_i], D = R_1$$

$$x = \begin{bmatrix} V_2 \\ z \end{bmatrix}, y = V_o - b_i, u = I.$$

B. Observability of the Battery Model

In control theory, observability measures how well the internal states of a system can be inferred by knowledge of its external outputs. A system is said to be observable if it is possible to determine the states from the observation of the output over a finite time interval. The concept of observability is useful in solving the problem of reconstructing immeasurable state variables from measurable variables [25].

To assure that the states of the Li-ion batteries could be estimated by the described battery model, the observability of the model needs to be analyzed. The observability matrix [25] of the battery model can be written as

$$O = \begin{bmatrix} C \\ CA \end{bmatrix} = \begin{bmatrix} 1 & a_i \\ -\frac{1}{R_2C_2} & 0 \end{bmatrix}. \tag{10}$$

In practical situations, under no circumstance would $-1/R_2C_2$ or a_i be zero; hence, the observability matrix would always be full rank. It means that the battery model is observable under any operation condition; thus, it is possible to estimate the internal states of the Li-ion batteries.

III. Proportional-Integral Observer Design

Based on the analysis previously stated, the design procedure of the SOC estimation method based on the PI observer is described in this section. To demonstrate the properties of the PI observer, such as robustness to model uncertainties and model errors, two systems are considered, namely, the linear system and the nonlinear system.

A linear system is given as follows, which could be used to describe a class of dynamical systems with acceptable accuracy (referred to as System 1):

$$\begin{cases} \dot{x} = Ax + Bu \\ y = Cx + Du. \end{cases} \tag{11}$$

Comparing (11) with (9), it is clear that these two systems are the same. Hence, if no modeling error or other nonlinearities are considered, the battery model could be fully regarded as a linear system. Thus, in this section, the PI observer is applied to such a linear system first, and the convergence of the designed PI observer is proved.

However, owing to nonlinear effects in battery systems, such as modeling errors, capacity variation, and so forth, System 1 could not be sufficient to model such a nonlinear system. The nonlinear part should be added to the system for a Li-ion battery model, and a nonlinear system could be described as follows (referred to as System 2) [26]–[28]:

$$\begin{cases} \dot{x} = Ax + Bu + Ev(t) \\ y = Cx + Du \end{cases} \tag{12}$$

where E is used to describe the influence by the nonlinearities to the different states, and such relationships could be obtained by experiments and some "try and error" approaches; $v(t)$ describes the nonlinearities of the plant and may be a nonlinear function of time. $v(t)$ is referred to as disturbance in this paper, as shown in Fig. 4.

Considering the special applications of the battery for EDVs, the disturbance could be caused by temperature, sensor noise, and so on. Taking temperature as an example, the variation rate

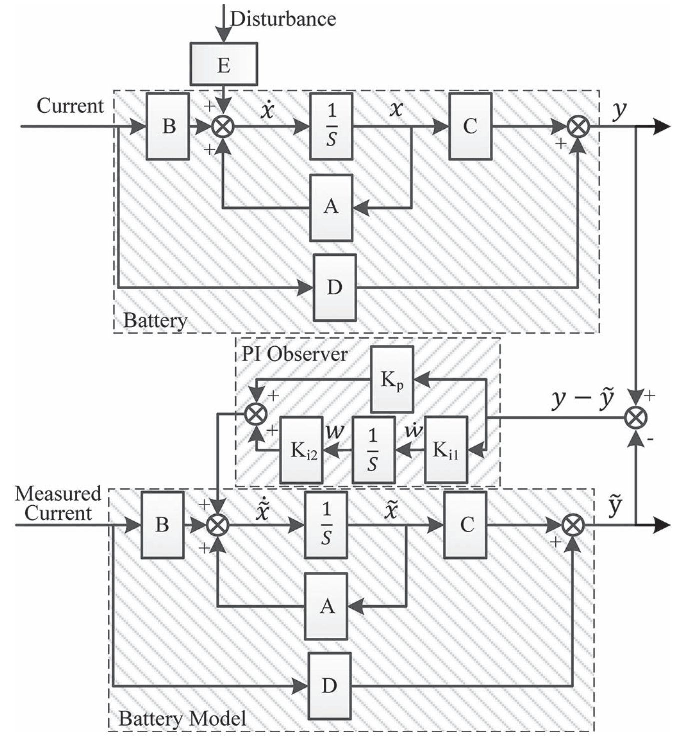

Fig. 4. Approximation of the relationship between SOC and OCV.

could be very slow, and thus, $\dot{v}(t) \approx 0$ when the temperature is considered. For sensor noise, it is considered to be Gaussian noise with a zero-mean value. Even some sensor failure occurs (take the current sensor drift for example), it could also be considered to be slow changing, and thus, $\dot{v}(t) \approx 0$ could also be assumed. Hence, in this paper, the simplest case $\dot{v}(t) = 0$ is assumed, and the following statements are based on this assumption. Besides, for practical applications, it is assumed that $\lim_{t\to\infty} v(t)$ would always exist but not necessarily equal to zero.

According to the definition of the PI observer, the PI observer is designed as follows:

$$\begin{cases} \dot{\tilde{x}} = A\tilde{x} + Bu + K_p(y - \tilde{y}) + K_{i2}w \\ \dot{w} = K_{i1}(y - \tilde{y}). \end{cases} \tag{13}$$

Note that variable w is defined as the integral of the difference $(y - \tilde{y})$. Vectors $K_p \in \mathbb{R}^{2\times 1}$ and $K_{i1} \in \mathbb{R}^{1\times 1}$ $K_{i2} \in \mathbb{R}^{2\times 1}$ are the proportional and integral gains, respectively. The design block of the PI observer is given in Fig. 4.

The ideal Li-ion battery model is considered first. The PI observer is applied to System 1, and according to $e = \tilde{x} - x$, the following equations could be obtained:

$$\begin{cases} \dot{e} = Ae - K_pCe + K_{i2}w \\ \dot{w} = -K_{i1}Ce. \end{cases} \tag{14}$$

These equations could be rewritten as follows:

$$\begin{pmatrix} \dot{e} \\ \dot{w} \end{pmatrix} = A_e \begin{pmatrix} e \\ w \end{pmatrix} \tag{15}$$

where $A_e = \begin{bmatrix} A - K_pC & K_{i2} \\ -K_{i1}C & 0 \end{bmatrix}$.

Substituting parameters $K_p = \begin{bmatrix} K_{p_1} \\ K_{p_2} \end{bmatrix}$ and $K_{i2} = \begin{bmatrix} K_{i2_1} \\ K_{i2_2} \end{bmatrix}$ with matrix A_e, we have

$$A_e = \begin{bmatrix} A - K_p C & K_{i2} \\ -K_{i1} C & 0 \end{bmatrix} = \begin{bmatrix} -\frac{1}{R_2 C_2} - K_{p_1} & -K_{p_1} a_i & K_{i2_1} \\ -K_{p_2} & -K_{p_2} a_i & K_{i2_2} \\ -K_{i1} & -K_{i1} a_i & 0 \end{bmatrix}. \quad (16)$$

A_e could be arbitrarily assigned if and only if the system without disturbance is observable. Since observability is proved in Section II, parameters K_p, K_{i1}, and K_{i2} can be selected using the LQ method or the pole place method to assure A_e is Hurwitz, indicating that the system would converge. Hence, we can conclude that $e \to 0$ and $w \to 0$ as $t \to \infty$, which means that the estimation states would converge to the true states.

Second, the unknown disturbance is considered, which would lead to modeling a more accurate battery characteristics. The PI observer is applied to System 2; when $e_x = \tilde{x} - x$, $e_v = w - v$, and $K_{i2} = E$ are assumed, the error equations could be obtained as follows:

$$\begin{cases} \dot{e}_x = Ae_x - K_p C e_x + K_{i2} e_v \\ \dot{w} = -K_{i1} C e_x. \end{cases} \quad (17)$$

These equations could be rewritten as

$$\begin{pmatrix} \dot{e}_x \\ \dot{w} \end{pmatrix} = \begin{bmatrix} A - K_p C & K_{i2} \\ -K_{i1} C & 0 \end{bmatrix} \begin{pmatrix} e_x \\ e_v \end{pmatrix}. \quad (18)$$

Hence

$$\begin{pmatrix} \dot{e}_x \\ \dot{e}_v \end{pmatrix} = A_e \begin{pmatrix} e_x \\ e_v \end{pmatrix} - \begin{bmatrix} 0 \\ I \end{bmatrix} \dot{v}. \quad (19)$$

Since $\dot{v} = 0$ for the certain application in this paper, as previously stated, this equation could be rewritten as follows:

$$\begin{pmatrix} \dot{e}_x \\ \dot{e}_v \end{pmatrix} = A_e \begin{pmatrix} e_x \\ e_v \end{pmatrix}. \quad (20)$$

A_e could be arbitrarily assigned if and only if the following matrix pair is observable:

$$\left(\begin{bmatrix} A & E \\ 0 & 0 \end{bmatrix}, [C \quad 0] \right) \quad (21)$$

which is equivalent to the following equation:

$$\text{rank} \left\{ \begin{bmatrix} A & K_{i2} \\ C & 0 \end{bmatrix} \right\} = n + r \quad (22)$$

where r is the dimension of disturbance v, and it is assumed to be 1 in this paper. Since $n = 2$ in this paper, the rank of the matrix should be 3.

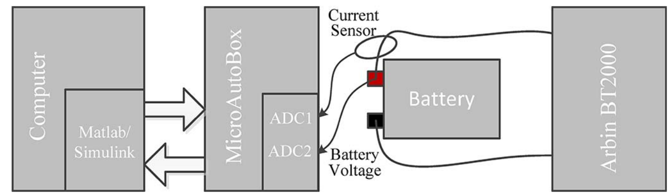

Fig. 5. Configuration of battery test workbench.

Substitute the parameters of the battery model into the matrix, we get

$$\text{rank} \left\{ \begin{bmatrix} A & K_{i2} \\ C & 0 \end{bmatrix} \right\} = \text{rank} \left\{ \begin{bmatrix} -\frac{1}{R_2 C_2} & 0 & K_{i2_1} \\ 0 & 0 & K_{i2_2} \\ 1 & a_i & 0 \end{bmatrix} \right\} = 3 \quad (23)$$

which is full rank, and the rank is 3. The conditions are satisfied; hence, A_e could be arbitrarily assigned.

K_p and K_{i1} could be selected by utilizing the LQ method or the pole place method, such that A_e is Hurwitz, as previously stated. If A_e is Hurwitz, the system would converge. Hence, from the given analysis, we can conclude that $e_x \to 0$ and $e_v \to 0$ as $t \to \infty$, which means that when $t \to \infty$, $\tilde{x}$ would converge to x. Take Li-ion battery model in this paper for example, the estimated SOC would converge to the true SOC.

IV. Experimental Verification

A. Experiment Equipment and the Configuration

To identify the battery model and verify the proposed PI-based SOC estimation method, an experimental battery test bench is established.

As shown in Fig. 5, the battery test workbench consists of a battery cycler Arbin BT2000, a computer, and a MicroAutoBox. The battery test equipment is responsible for charging and discharging the Li-ion batteries according to the required current profiles. The current sensor measures the current of the battery. The MicroAutoBox is controlled by a computer through MATLAB/Simulink to acquire the data of the battery. The PI observer algorithm is programmed in MATLAB/Simulink, and the algorithm is downloaded; it could run in the MicroAutoBox to calculate the SOC of the battery based on the PI observer. The experimental battery test workbench is also established according to the configuration previously stated, as shown in Fig. 6.

B. Identification Method and the Results

For convenience, the data to obtain the relationship between SOC and OCV are used to identify the battery model. The least squares method is introduced to calculate the best set of R_1, R_2, and C_2. The identification results are listed in Table II.

The identification results, compared with the original measured data, are depicted in Fig. 7. The figure shows that the terminal voltage calculated by the model generally fits the measured terminal voltage well. However, in the lower part of

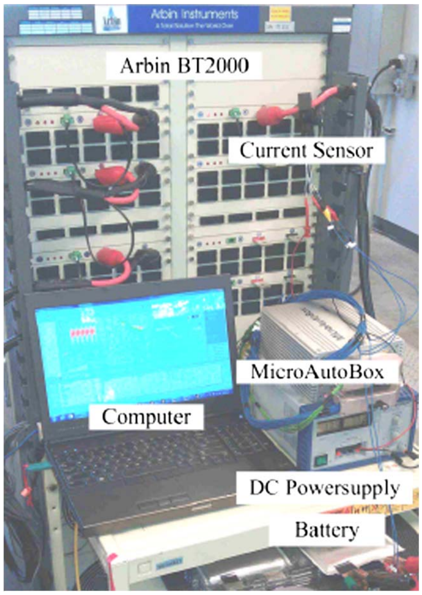

Fig. 6. Experimental battery test workbench.

TABLE II
PARAMETERS OF THE IDENTIFICATION RESULTS

Items	R_1/Ω	R_2/Ω	C_2/F
Identification Results	0.0027	0.0042	25000

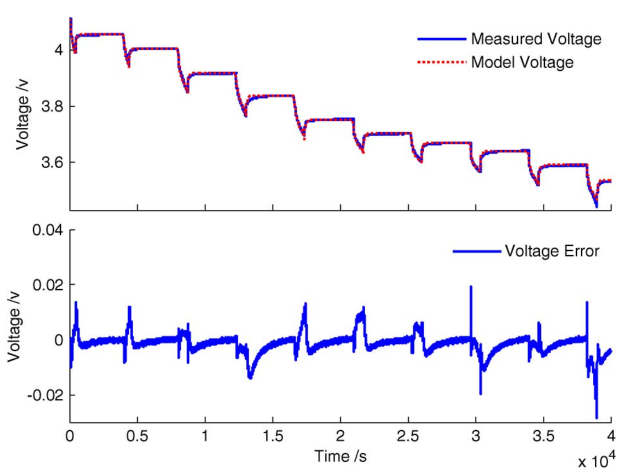

Fig. 7. Identification results.

Fig. 7, large errors exist, particularly when the current quickly varies. These can be considered to be caused by the modeling error and model uncertainties. From the given discussion, it is clear that the RC model could generally model the characteristics of the Li-ion battery but with large model errors.

To verify the proposed PI-based SOC estimation method for Li-ion batteries, the urban dynamometer driving schedule (UDDS) drive cycle is utilized. The UDDS drive cycle is widely used to test vehicle performance, while it is also introduced to verify the performance of EDVs in recent days. The UDDS drive cycle used in this paper is the current demand of the battery pack while the EDV is applied by the speed profile of the traditional UDDS drive cycle. Since only a battery cell is tested in this paper, the UDDS drive cycle is scaled down according to the voltage and the capacity. Fig. 8 shows the UDDS current profile that is scaled down and used in this paper.

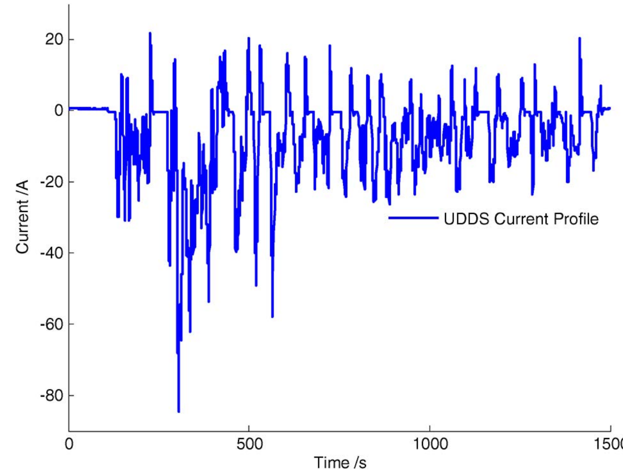

Fig. 8. UDDS current profile.

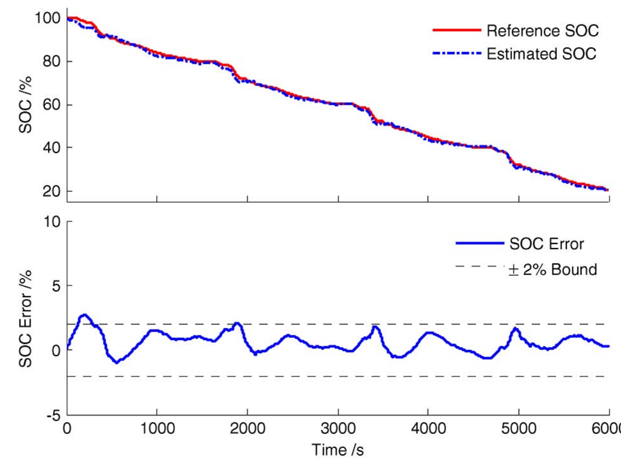

Fig. 9. SOC estimation results when the initial SOC is given.

To demonstrate the validation results, the reference SOC should first be defined. The ampere-hour (Ah) counting method is simple and has good accuracy when the initial SOC is given and the current sensor is accurate enough, particularly when the test is in a short time in a confined laboratory environment. Hence, the Ah-counting method is chosen as the reference SOC in this paper. Before the validation starts, the battery is charged to full according to the battery specifications. The initial SOC of the reference SOC is identical, and thus, the reference SOC could be known during the whole experiment.

The validation procedure is divided into two cases. In the first case, the initial SOC is assumed to be given for the PI observer. Hence, when the experiment starts, the estimated SOC is the same as the reference SOC. The estimation results in such a situation are given in Fig. 9. In the beginning, the SOC diverges a little since the model is not so accurate. Then, the estimated SOC quickly converges to the reference SOC and keeps on tracing it with small errors. It indicates that the proposed method could estimate the SOC of the Li-ion batteries with small errors when the initial SOC is given, even if there are large model errors in the simple battery model.

In the second case, the initial SOC is assumed to be unknown for the PI observer. In this case, the initial SOC of the PI

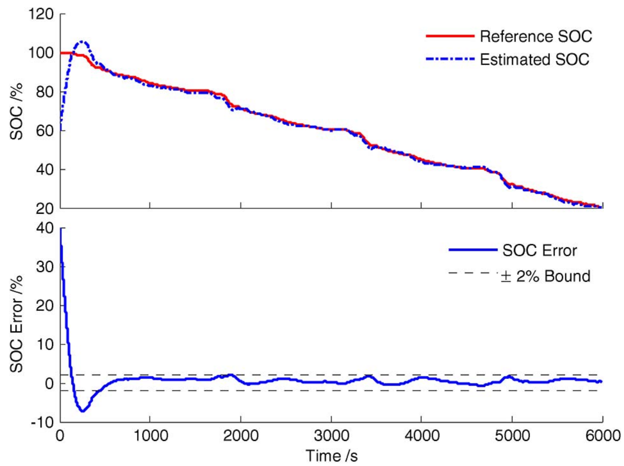

Fig. 10. SOC estimation results when the initial SOC is unknown.

observer is set to be 60%, while the reference SOC is actually 100%. The results of this experiment are shown in Fig. 10. In the figure, the estimated SOC is different at the beginning, with 40% error. Then, the estimated SOC quickly increases, converging to the reference SOC. Even with some overshoots, it comes to the steady state quickly. Then, the estimated SOC stays with the reference SOC, overlapping with small errors, most of which are confined to $\pm 2\%$ error band. It indicates that the proposed PI-based SOC estimation method can compensate the initial SOC error and make the estimated SOC converge to the reference SOC quickly. Meanwhile, when it comes to the steady state, the SOC estimation errors are maintained small thereafter.

From the previous discussions, it can be concluded that the PI observer works well in the SOC estimation of Li-ion batteries. The PI observer estimates the SOC with a small error, even with a simple battery model, compensating for the modeling errors and modeling uncertainties.

V. Conclusion

A battery SOC estimation algorithm based on a PI observer has been proposed for Li-ion batteries. Acceptable accuracy has been verified by experiments on battery bench testing for both known and unknown initial SOC. The PI-based SOC estimation has a simple structure and is easy to implement. The compensation properties of the PI observer demonstrate that a simple RC model can be utilized to model the Li-ion battery. The estimated SOC with the PI observer converges to the reference SOC quickly, and the SOC estimation errors are maintained in a small band. Most of the errors of the PI-based SOC estimation method are confined to $\pm 2\%$ when compared with the reference SOC that is based on Coulomb counting with known initial SOC.

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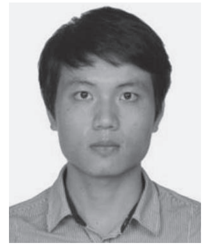

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