Abstract
Lithium-Ion batteries are being popularly used in hybrid electric vehicles (HEVs), plug in electric vehicles (PEVs) and electric vehicles (EVs) due to its advantages such as high energy density, long cycle life and low self-discharge. Since the battery module is composed of many cells connected in series and parallel, it is important to get the accurate state information of each cell. In this paper a model-based approach to estimate the State-of-Charge (SOC) of multiple battery cells in a module by using a nonlinear state observer and online parameter identification is proposed. The battery impedance is calculated from the dynamic fraction of the battery voltage and it is used for the SOC estimation by a nonlinear state observer. A simple method to estimate the impedance and SOC of each cell in a module by employing a ratio vector with respect to the reference value is also presented. The variation in the battery parameters is considered by using an online parameter identification with Auto Regressive with eXogenous input (ARX) to guarantee the reliable estimation results under the various operating condition. The validity and feasibility of the proposed algorithm is verified by the experimental results.

Keywords: State of Charge Estimation, Lithium Ion Battery, Nonlinear State Observer, Online Parameter Identification, Ratio Vector

1 Introduction
Currently, Lithium-ion batteries are considered as a highly prospective technology for automotive applications such as Electric Vehicles (EVs) and Hybrid Electric Vehicles (HEVs) due to its long life cycle, high energy density and low self-discharge rate. SOC is a critical factor to guarantee the safety and reliable operation of the battery. Typically, the battery module used for vehicular application is comprised of several hundreds of cells connected in serial and in parallel in order to meet the required voltage and power level for the application. In this case, the state information of each cell is very important because any one battery cell in a string becomes faulty then the batteries may fail to supply the power to the vehicle. Some approaches such as Coulomb counting, Fuzzy Logic (FL), Artificial Neural Networks (ANNs) and Kalman filter have been applied for online SOC estimation of the battery [1-5]. The Coulomb counting or current integration method which measures the amount of charge taken out or put into the battery in terms of ampere hours is simple and requires low computing power. However, the initial SOC of the battery must be known for the start-up of the SOC estimation. Furthermore, accumulated measurement errors can be a source of significant inaccuracy of the SOC estimation, thus an additional recalibration is required when the ampere hours counting is performed over a long period of time. The ANNs and FL approaches can
estimate the SOC of a battery with an arbitrary initial SOC value [6], [7]. The robustness of this model strongly relies on the quantity and the quality of the training data set. A limited training data set may result in limited model robustness, hence reducing the applicability of the method [3], [8-10]. EKF approach is a computationally efficient recursive digital processing technique used to estimate the state of a nonlinear dynamic system from a series of incomplete and noisy measurements by way of minimizing the mean squared error [11], [12]. However, the limitations caused by the complexity of those algorithms make it difficult to be used for commercial applications, especially such as vehicular application with a battery pack consisting of hundreds of cells. Since a complex estimation algorithm for individual cell would lead to a computation overkill and would not be suitable for implementing it on a commercially available microcontroller [13]. In addition, the accurate information of the battery impedance based on the equivalent circuit model is essential for the high accuracy SOC estimation [13], [14]. Hence the parameter variation depending on the current rate, SOC, temperature and aging effect has to be investigated through the pre-tests in order to guarantee the reliable performance of the estimation under the various operating conditions and over the lifetime of the battery. However, the pre-tests for the parameter variation are not only time-consuming and labour intensive works but also require many kinds of instruments.

On the other hand, since the battery module for vehicular application is composed of up to hundreds of cells connected in serial and in parallel as mentioned above, the SOC imbalance occurs due to the characteristic differences of the cells. Thus, the battery management system is often adopted for managing the SOC of the battery cells in a module because any imbalance among the battery cells contributes to a capacity reduction of the battery module and may eventually cause an early failure of it. The imbalance among the cells in a battery pack can be caused by several factors, either extrinsic or intrinsic to the cell properties [15]. Extrinsic factors include current variations in parallel strings or voltage variations in a series string, which lead to unevenness in the extent of cell reaction. Intrinsic factors include variations in cell quality which result in variations in the content of active material, composition, and physical property among the cells. The side-effects of the cell imbalance can be addressed as three main points [16]. Firstly, premature cells will be degraded due to the overvoltage exposure. The cell degradation caused by the imbalance is accelerated automatically. Once a cell has a lower capacity, it is exposed to an increasingly higher voltage during charge, what makes it degrade faster, and so its capacity becomes even less, closing the runaway circle. Secondly, overcharging and overheating of the cell lead to a reaction of the active components with electrolyte and with each other ultimately, including explosion and fire [16]. Other cells of the module will also join the explosive chain reaction if one cell is compromised. Finally, charge and discharge period will be finished early, thereby reducing the capacity of the battery pack. The charging process is terminated if one of the cells exceeds the charge cut-off cell voltage for safety reasons. Similarly, the discharge process is terminated if any of the cells reaches the low voltage threshold. Therefore the individual cell SOC in a battery module needs to be estimated accurately in order to keep the energy of the cells balanced and to extend their lifetime.

In this paper, a simple SOC estimation method by using a nonlinear state observer with online parameter identification of the multiple Lithium-ion batteries which can be implemented by a low cost microcontroller is presented. The battery parameters are estimated by the Auto Regressive with eXogenous input (ARX) method which considers exogenous input effect and additive noise and the SOC of the battery is estimated by a nonlinear state observer which can be simply and easily implemented [17], [18]. Furthermore, the complex cell impedances are simplified to an ohmic resistance by using a ratio vector to reflect the relative impedance variation with respect to a certain cell in a module. This simplified algorithm is introduced to apply for the SOC estimation of the multiple cells in a battery module. The algorithm of the proposed method will be detailed in the following section and the performance of the proposed method will be verified by the experimental results.

2 Online parameter identification by using ARX model

Figure 1 shows an equivalent circuit of the battery contains an OCV connected in series with an internal resistance $R_i$ and a RC parallel branch composed of a charge transfer resistance $R_{ct}$ and a double layer capacitance $C_{dl}$. The electrical
behaviour of the equivalent circuit model can be expressed as (1) in the s-domain.

\[ U(s) = OCV(s) + U_{RRC}(s) \]  

(1)

The OCV-SOC relationship shown in Figure 2 is modelled by seventh order polynomial function of SOC and expressed as (2).

\[ OCV(SOC) = \sum_{i=0}^{7} a_{i,k} SOC_i \]  

(2)

![Figure 1: Equivalent circuit model of the Lithium-Ion battery](image1)

Figure 1: Equivalent circuit model of the Lithium-Ion battery

The dynamic fraction of the battery voltage \( U_{HPF} \) and battery current \( I_{HPF} \) are extracted by high-pass filtering the measured voltage and current of the cell. The dynamic voltage \( U_{HPF} \) which drops on the \( R_i \) and \( R_{ct}-C_{dl} \) network can be expressed as (3).

\[ U_{HPF}(s) = I_{HPF}(s)R_i + I_{HPF}(s) \frac{R_{ct}}{(R_{ct}C_{dl})s + 1} \]  

(3)

The transfer function \( G(s) \) can be obtained from (3) as (4).

\[ G(s) = \frac{U_{HPF}(s)}{I_{HPF}(s)} = R_i + \frac{R_{ct}}{(R_{ct}C_{dl})s + 1} = \frac{(R_{ct}C_{dl})s + R_i + R_{ct}}{(R_{ct}C_{dl})s + 1} \]  

(4)

By using the forward transformation method shown in (5) the discrete transfer function of the battery model with the sampling time \( T \) can be obtained as (6).

\[ s = \frac{z-1}{T} = \frac{1-z^{-1}}{Tz^{-1}} \]  

(5)

Where, \( z \) is the discretization operator.

\[ G(z^{-1}) = \frac{R_i + \frac{TR_{ct}}{R_{ct}C_{dl} + T} - \frac{R_{ct}C_{dl}}{T + R_cC_{dl}}z^{-1}}{1 - \frac{R_{ct}C_{dl}}{T + R_cC_{dl}}z^{-1}} \]  

(6)

Where:

\[ a_1 = -\frac{R_{ct}C_{dl}}{T + R_{ct}C_{dl}} \]

\[ b_0 = R_i + \frac{TR_{ct}}{R_{ct}C_{dl} + T} \]

\[ b_1 = -\frac{R_{ct}C_{dl}}{T + R_{ct}C_{dl}} \]

The time domain relationship between different samples of input/output can be expressed as (8).

\[ U_{\text{HPF,k}} = -a_1U_{\text{HPF,k-1}} + b_0I_{\text{HPF,k}} + b_1I_{\text{HPF,k-1}} \]  

(8)

The above function (8) is the specific form of the ARX model in (9) for the equivalent circuit shown in Figure 1 [18].

\[ y_k = -a_1y_{k-1} + b_0u_{k} + b_1u_{k-1} \]  

(9)

### 3 Online parameter identification algorithm

The Recursive Least Square (RLS) algorithm is used to estimate the coefficient factors, \( a_i \), \( b_j \) and \( b_1 [18] \).

The update gain \( L_k \) of the RLS algorithm is as follows.

\[ L_k = \frac{P_{k-1}q_k}{\lambda_k + \phi_k^T P_{k-1} \phi_k} \]  

(10)

The estimated coefficient vector \( \hat{\theta}_k \) can be calculated as (11).

\[ \hat{\theta}_k = \hat{\theta}_{k-1} + L_k[U_{\text{HPF,k}} - \phi_k^T \hat{\theta}_{k-1}] \]  

(11)

The covariance matrix \( P_k \) of the estimated coefficient vector \( \hat{\theta}_k \) can be calculated as (12).

\[ P_k = \frac{1}{\lambda_k} \left[ P_{k-1} - \frac{P_{k-1} \phi_k q_k^T P_{k-1}}{\lambda_k + \phi_k^T P_{k-1} \phi_k} \right] \]  

(12)

Specifically,

\[ \phi(k) = [-U_{\text{HPF,k}}, I_{\text{HPF,k}}, I_{\text{HPF,k-1}}]^T \]  

(13)
\[
\theta(k) = \begin{bmatrix} a_{i,k} & b_{0,k} & b_{1,k} \end{bmatrix}^T \tag{14}
\]

Where, \( \phi(k) \) is the input vector obtained from the input data including the dynamic voltage of the battery \( U_{HPF,k-1} \) at time index \( k-1 \), the high-pass filtered battery current \( I_{HPF,k} \) and \( I_{HPF,k-1} \) at time index \( k \) and \( k-1 \), respectively. \( \theta(k) \) is the coefficient vector which needs to be identified. \( \lambda(k) \) (\( 0 < \lambda < 1 \)) is the forgetting factor which can be used to give more weight to the recent data than the old data [18].

After identifying \( a_i, b_0 \) and \( b_1 \), the parameters of the battery model at each time step can be determined by the inverse parameter transformation as (15).

\[
\begin{align*}
R_i &= \frac{b_1}{a_i} \\
R_{et} &= \frac{(a_i - 1)(b_1 - b_0 a_i)}{(a_i + 1)d_i} \\
C_{dl} &= \frac{-T_a d_i^2}{(a_i^2 - 1)(b_1 - b_0 d_i)}
\end{align*} \tag{15}
\]

4 SOC estimation using a nonlinear state observer

In order to deal with the highly nonlinear relationship of the OCV-SOC, the nonlinear state observer is applied for the battery SOC estimation. Based on the battery model as shown in Figure 1, the state equation of the battery can be expressed as (16).

\[
\dot{x} = \begin{bmatrix} \dot{U}_{Cdl} \\ \dot{SOC} \end{bmatrix} = \begin{bmatrix}
- \frac{1}{R_{et} C_{dl}} & 0 \\
0 & -\frac{\eta}{C_n}
\end{bmatrix} \begin{bmatrix} U_{Cdl} \\ SOC \end{bmatrix} + \begin{bmatrix} \frac{1}{C_{dl}} \\
\eta \end{bmatrix} I_b \tag{16}
\]

\[
= Ax + Bu
\]

Where, \( U_{Cdl} \) is the voltage dropped on the double layer capacitance \( C_{dl} \), \( \eta \) is the coulomb efficiency of the cell, \( I_b \) is the battery current and \( C_n \) is the nominal capacity of the battery.

The observation equation can be expressed as follows.

\[
U = g(x) = OCV(SOC) + U_{Cdl} + R_i I_b \tag{17}
\]

\[
\dot{g}(x) = \begin{bmatrix} \frac{\partial g(x)}{\partial U_{Cdl}} \\ \frac{\partial g(x)}{\partial SOC} \end{bmatrix} = \begin{bmatrix} 1 \\ OCV \end{bmatrix} \tag{18}
\]

The instantaneous OCV is calculated based on the nonlinear OCV-SOC function fitted as (2) and the battery impedance value calculated from (15) is used to reconstruct the dynamic voltage fraction. Therefore, the estimated terminal voltage of the battery can be expressed as (19).

\[
\hat{U} = OCV(SOC) + \hat{U}_{Cdl} + R_i I_b \tag{19}
\]

Here, the Lyapunov stability theory is used to verify the convergence of the nonlinear state observer [17]. \( A \) is allowed to have one eigenvalue with the real part equal to 0 and the real part of all other eigenvalues should be smaller than 0 [17], [19].

The eigenvalue \( \lambda \) of matrix \( A \) is calculated and the results are shown in (20).

\[
\begin{align*}
\lambda &= 0 \\
\dot{\lambda} &= -\frac{1}{R_i C_{dl}} < 0
\end{align*} \tag{20}
\]

Therefore, the nonlinear observer can be suggested as (21) where a difference between the estimated voltage \( \hat{U} \) and the measured voltage of the battery \( U \) causes an update of the battery state.

\[
\dot{x} = A\dot{x} + Bu + K\hat{g}^T(x)(U - \hat{U}) \tag{21}
\]

Where, the gain \( K \) is a symmetric matrix and a positive definite solution to the Lyapunov equation shown in (22).

\[
A^T K^{-1} + K^{-1}A = -D \tag{22}
\]

Where, the rank of matrix \( D \) is equal to that of \( A \). Both matrix \( K \) and its inversion \( K^{-1} \) are positive definite and \( d, k_1 \) and \( k_2 \) are undetermined positive constants.

\[
\begin{align*}
D &= \begin{bmatrix} 2d & 0 \\ 0 & 0 \end{bmatrix} \\
K &= \begin{bmatrix} k_1 & 0 \\ 0 & k_2 \end{bmatrix} \\
K^T &= K
\end{align*} \tag{23}
\]

The observer error can be expressed as (24).

\[
e_\chi = x - \hat{x} \tag{24}
\]

Hence,

\[
\dot{e}_\chi = \dot{x} - \dot{\hat{x}} = (Ax + Bu) - (A\dot{x} + Bu + K\hat{g}^T(x)(U - \hat{U})) = A(x - \hat{x}) - K\hat{g}^T(x)(U - \hat{U}) = A e_\chi - K\hat{g}^T(x)e_\chi = \left[A - K\hat{g}^T(x)\hat{g}(x)\right]e_\chi
\]

The following result states that the observer error is asymptotically stable by using the Lyapunov function which is selected as shown in (26).

\[
V(e_\chi) = e_\chi^T K^{-1} e_\chi \tag{26}
\]
Also its derivative is as follows.

$$\dot{V}(e_x) = e_i^T K^{-1} e_x + e_i^T K^{-1} \dot{e}_x$$

$$= \left[ (A - Kg)^T \hat{g} \right] e_x + e_i^T K^{-1} \left[ (A - Kg)^T \hat{g} \right] \dot{e}_x$$

$$= e_i^T A^{-1} e_x - e_i^T \hat{g} \hat{g} K^{-1} e_x + e_i^T K^{-1} A e_x - e_i^T \hat{g} \hat{g} K^{-1} e_x$$

$$= e_i^T (D + 2Dg) \hat{g} e_x$$

$$= -e_i^T (D + 2Dg) \hat{g} e_x$$

Where,

$$D + 2Dg = \begin{bmatrix} 2d & 0 \\ 0 & 2 \end{bmatrix} + 2 \begin{bmatrix} 1 \\ \hat{O}CV \end{bmatrix}$$

$$= 2 \begin{bmatrix} d + 1 & \hat{O}CV \\ \hat{O}CV & \hat{O}CV^2 \end{bmatrix}$$

$$= 2M$$

Then, $M$ can be proved to be a positive definite matrix using a non-zero column vector $z = [a \ b]^T$ as follows. Where, $a$ and $b$ are real numbers.

$$z^T M = \begin{bmatrix} a & b \end{bmatrix} \begin{bmatrix} d + 1 & \hat{O}CV \\ \hat{O}CV & \hat{O}CV^2 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix}$$

$$= a^2 d + a \hat{O}CV + b \hat{O}CV^2 > 0$$

Thus, $\dot{V}(e_x)$ is negative definite and as a result the error system in (24) is asymptotically stable. The each dynamic system in (19) and (21) can be selected as an observer for the system in (17) and (16), respectively.

The nonlinear state observer in (21) enables the online estimation of the battery SOC by evaluating the sequences of the battery voltage and current, and by considering the information of the battery impedance parameters derived from the dynamic fraction of the battery voltage.

### 5 SOC estimation of the multiple cells in a battery module

To reduce the calculation effort a simplified cell model in combination with a lean algorithm based on the vector computation is presented, enabling to access the individual cell SOC. In the method the deviation of cell individual SOC is estimated by evaluating the OCV as well as the gradient of the OCV-SOC curve at an instantaneous operating point. The calculation steps are performed from (30) to (39) [20].

The dynamic voltage of each cell of the battery module forms the vector $U_k$ as follows.

$$U_{e, k} = [U_{f_{1,k}}, U_{f_{2,k}}, \ldots, U_{f_{m,k}}]^T$$

(30)

The mean cell voltage $\bar{U}$ can be derived by taking an average value of the vector $U_k$ elements as (31).

$$\bar{U}_k = \frac{1}{n} \sum_{i=1}^{n} U_{f_{i,k}}$$

(31)

Under a certain current excitation the voltage drops at each cell in a series connection are different depending on the actual impedance of the battery cell. Higher impedance of the cell presents higher voltage drop. Therefore, the vector of dynamic cell voltage fractions can be expressed by (32).

$$U_{p_{1,k}} = \begin{bmatrix} L_{1, k-1} \\ L_{2, k-1} \\ \vdots \\ L_{n, k-1} \end{bmatrix} = \bar{U}_k$$

(32)

Where, vector $L$ reflects the ratio of each cell’s impedance calculated by considering the dynamic voltage fraction of the cell voltages.

The deviation of $U_p$ from individual cell voltage $U_k$ manipulates $L$ as (33).

$$\begin{bmatrix} U_{f_{1,k}} \\ U_{f_{2,k}} \\ \vdots \\ U_{f_{m,k}} \end{bmatrix} = \begin{bmatrix} L_{1, k-1} \\ L_{2, k-1} \\ \vdots \\ L_{n, k-1} \end{bmatrix} + g A \bar{U}_k$$

(33)

The derivation of the SOC-OCV curves produces an OCV gradient as (34).

$$m = \frac{dOCV}{dSOC}$$

(34)

The OCV variation vector $\Delta$OCV of n cells can be estimated by using (35).

$$\begin{bmatrix} \Delta_{OCV_{1,k}} \\ \Delta_{OCV_{2,k}} \\ \vdots \\ \Delta_{OCV_{n,k}} \end{bmatrix} = m_k \begin{bmatrix} \Delta_{SOC_{1,k}} \\ \Delta_{SOC_{2,k}} \\ \vdots \\ \Delta_{SOC_{n,k}} \end{bmatrix}$$

(35)

The estimated individual OCV values of the cells considering the ratio vector $L$ and the dynamic voltage fraction of the battery $U_{RRC}$ is expressed as (36).
\[
\begin{bmatrix}
OCV_{1,k} \\
OCV_{2,k} \\
\vdots \\
OCV_{n,k}
\end{bmatrix}
= \begin{bmatrix}
U_{1,k} \\
U_{2,k} \\
\vdots \\
U_{n,k}
\end{bmatrix}
- \begin{bmatrix}
L_{1,k} \\
L_{2,k} \\
\vdots \\
L_{n,k}
\end{bmatrix} U_{RBC,k}
\] (36)

The different between the OCV variation from the measurement and the model is then calculated by (37).

\[
\begin{bmatrix}
e_{1,k} \\
e_{2,k} \\
\vdots \\
e_{n,k}
\end{bmatrix}
= \begin{bmatrix}
OCV_{1,k} \\
OCV_{2,k} \\
\vdots \\
OCV_{n,k}
\end{bmatrix}
- \begin{bmatrix}
OCV_{1,k} \\
OCV_{2,k} \\
\vdots \\
OCV_{n,k}
\end{bmatrix} - \begin{bmatrix}
\Delta OCV_{1,k} \\
\Delta OCV_{2,k} \\
\vdots \\
\Delta OCV_{n,k}
\end{bmatrix}
\] (37)

The cell individual SOC variation vector \(\Delta SOC\) can be recursively calculated by (38) considering the impedance data, where \(g_{cell}\) is the feedback gain.

\[
\begin{bmatrix}
\Delta SOC_{1,k} \\
\Delta SOC_{2,k} \\
\vdots \\
\Delta SOC_{n,k}
\end{bmatrix}
= \begin{bmatrix}
\Delta SOC_{1,k-1} \\
\Delta SOC_{2,k-1} \\
\vdots \\
\Delta SOC_{n,k-1}
\end{bmatrix} + g_{cell} \begin{bmatrix}
e_{1,k} \\
e_{2,k} \\
\vdots \\
e_{n,k}
\end{bmatrix}
\] (38)

Finally, the individual cell SOC value which is calculated as (39) is the sum of the cell SOC variation and the mean battery SOC value.

\[
\begin{bmatrix}
SOC_{1,k} \\
SOC_{2,k} \\
\vdots \\
SOC_{n,k}
\end{bmatrix}
= \begin{bmatrix}
\Delta SOC_{1,k} \\
\Delta SOC_{2,k} \\
\vdots \\
\Delta SOC_{n,k}
\end{bmatrix} + \begin{bmatrix}
SOC_{k} \\
SOC_{k} \\
\vdots \\
SOC_{k}
\end{bmatrix}
\] (39)

6 Experimental results

In order to validate the proposed algorithm for the SOC estimation by using the nonlinear state observer, a dynamic charge/discharge current profile as shown in Figure 3(a) is applied to the battery. It is the 1/20 scale-down battery current profile required for the electric vehicle to complete the eight cycles of Urban Dynamometer Driving Schedule (UDDS) started after a 30 minutes relaxation time at the beginning of the test. It can be seen from the Figure 3 that each UDDS cycle lasts for 22 minutes and 15% of the SOC is reduced at each cycle. Therefore, the current direction in the UDDS cycle number 3, 5, and 7 is reversed so as not to fully discharge the battery. This profile was designed to excite the cell in a fashion similar to what would be experienced in an EV application. Moreover, the current profile exhibit dynamic characteristic with stiff change in the magnitude of the current and operates in between the high and mid SOC range, which is typical in EVs applications. The battery cell used for the test is a Lithium-Ion battery from Samsung SDI (3.6V, INR18650-15L 1500mAh). At first, the current profile is applied to a single cell. The cell is connected to the bipolar DC power supply (NF BP4610). A program created in Labview 11.0 automatically controls the output of the bipolar DC supply and records the voltage and current of the battery at every second through an NI PCI-6154 and a sensing circuit. The ambient temperature during the test was 25°C.

In order to compare the performance of the proposed method, another system using linear observer was implemented according to the reference [20] and tested for the SOC estimation for the multiple Lithium-Ion batteries. Figure 3(b) depicts the battery voltages estimated with the nonlinear state observer and the linear state observer and the measured voltage obtained from the experiments. The relative errors between them are shown in Figure 3(c) as a function of time. The results show that the nonlinear state observer method provides more accurate results in the voltage estimation. The average voltage estimation error of the nonlinear state observer is 0.360 % which is less than that of the linear state observer (0.416 %).

Figure 3(d) shows the estimated SOCs with the nonlinear state observer and the linear state observer and their errors with respect to the SOC calculated by the Coulomb counting method. Since the initial true SOC is known and error accumulated during the short period of time is negligible, the coulomb counting method can be used as a reference. In the experiments, 50% of SOC was given as an initial value for the estimation to verify if the proposed algorithm converges to the true SOC value. As shown in the Figure 3(e) the estimated SOC tracks the true SOC value within 30 minutes and the estimation error of the nonlinear state observer is maintained less than 3% thereafter while the estimation error of the linear state observer exceeds 4%. The SOC estimation result of the nonlinear state observer is better in comparison with the linear state observer.
In order to validate the simplified algorithm for the SOC estimation of the individual cell, the same current profile is used with a battery module consisting of six cells connected in series. Same type of the battery used for the single cell test is used for the validation test of the battery module. The battery module is also connected to the bipolar DC power supply (NF BP4610). Another Labview program created in Labview 11.0 controls the output of the bipolar DC supply and records the voltage and current of the battery at every second through an NI 9205, NI cDAQ-9174 and six voltage sensor circuits for the module test. The experimental setup for the battery module test is shown in Figure 4. The current profile is shown in Figure 5(a) and the voltage response of each cell in the battery module is shown in Figure 5(b).

Figure 5(c) shows the estimated SOC values of individual cell in the module by using the proposed method and the Coulomb counting method during the entire module validation test, while the SOC estimation error in percentage is shown in Figure 5(d). In the experiments 30% of SOC value was given as an initial value. As shown in Figure 5(d), estimated SOC of each cell in a module tracks on its true SOC after 1.5 hour and the estimation error of the each cell is less than 3.5% thereafter.

7 Conclusions

In this paper an SOC estimation algorithm for the multiple Lithium-Ion batteries by using a nonlinear state observer with online parameter identification is presented. Since the parameters of the battery are estimated online by the ARX model, time-
consuming and labour-intensive pre-tests are not required and the estimation reliability can be guaranteed under the various operating condition. In addition it has been proven by the comparison that the performance of nonlinear observer is better than that of the linear observer by 1%. The proposed algorithm can be used for the BMS system for the Lithium-Ion battery module to monitor the SOCs of the multiple cells.

References


Authors

Ngoc-Tham Tran: received his B.S. in Electrical Engineering from Danang University of Technology, Danang, Vietnam, in 2010. He is currently working toward his M.S. at Soongsil University, Seoul, Republic of Korea. His current research interests include Battery Management System for Electric Vehicle (battery modelling, SOC/SOH estimation).
**Kim-Hung Nguyen**: received his B.S. degrees in Electrical Engineering from Hanoi University of Science and Technology, Vietnam, in 2014. Currently, he is pursuing M.S. degrees in Electrical Engineering at Soongsil University, Republic of Korea. His research interests are in DC/DC Converter, Soft Switching techniques for PWM converters, Battery Management System for Electric Vehicle.

**Woojin Choi**: received his B.S. and M.S. in Electrical Engineering from Soongsil University, Seoul, Republic of Korea, in 1990 and 1995, respectively. He received his Ph.D. also in Electrical Engineering from Texas A&M University, USA, in 2004. From 1995 to 1998, he was with Daewoo Heavy Industries as a Research Engineer. In 2005 he joined the School of Electrical Engineering, Soongsil University. His current research interests include the modeling and control of electrochemical energy sources such as fuel cells, batteries and supercapacitors, power conditioning technologies used in renewable energy systems, and dc–dc converters for fuel cells and hybrid electric vehicles.