Novel Estimation Technique for the State-of-Charge of the Lead-Acid Battery by using EKF Considering Diffusion and Hysteresis Phenomenon

Van-Huan Duong¹, Ngoc-Tham Tran¹, Yong-Jin Park¹, and Woojin Choi†

Abstract - State-of-charge (SOC) is one of the significant indicators to estimate the driving range of the electric vehicle and to control the alternator of the conventional engine vehicles as well. Therefore its precise estimation is crucial not only for utilizing the energy effectively but also preventing critical situations happening to the power train and lengthening the lifetime of the battery. However, lead-acid battery is time-variant, highly nonlinear, and the hysteresis phenomenon causes large errors in estimation SOC of the battery especially under the frequent discharge/charge. This paper proposes a novel estimation technique for the SOC of the Lead-Acid battery by using a well-known Extended Kalman Filter (EKF) and an electrical equivalent circuit model of the Lead-Acid battery considering diffusion and hysteresis characteristics. The diffusion is considered by the reconstruction of the open circuit voltage decay depending on the rest time and the hysteresis effect is modeled by calculating the normalized integration of the charge throughput during the partial cycle. The validity of the proposed algorithm is verified through the experiments.

Keywords: extended Kalman filter, state-of-charge estimation, hysteresis effect, diffusion effect, idle start-stop

1. Introduction

Until recently, decreasing greenhouse gas emissions, particularly carbon dioxide (CO₂) is crucial in protecting the earth from the global warming. Meanwhile, the steady increase of traffic volume and frequent traffic congestion in road transportation not only cause a great demand in fuel consumption but also generate a significant portion of the CO₂ emissions and a huge energy waste. For example, in the year of 2011, 56 billion of pounds of CO₂ was produced and 2.9 billion gallons of fuel was wasted during congestion in the US[1]. Given these circumstances, automotive companies and vehicles owners must make changes in their operating strategies such as alternative fuel use, eco-friendly, engine retrofits or upgrades, and engine idle reduction. Idle Start-Stop (ISS) system is a low-cost, fast-growing engine idle reduction technology in the automotive industry, and promising to become a standard feature of the vehicles in the near future.

The ISS system is one way to solve the issue by automatically shutting down the engine when vehicles are at the standstill and in neutral, then restarting back when the vehicles begin to move, which ensures the optimum use of fuel and the energy of the fuel is utilized to its best. Therefore, it can solve the problem of the gas emissions and energy waste during the traffic congestion. The ISS system can also improve fuel efficiency and significantly increase the gasoline mileage and eventually reduce fuel
expense in terms of economy. To safely and efficiently apply the system, the Lead-Acid battery, which generally plays a storage role of the ISS system, needs to be managed carefully. The precise information of the State-of-Charge and State-of-Health (SOH) of the battery is crucial for the ISS system in order to avoid failures of restarting the engine after being shut down. Thus, there is a necessity to develop a Battery Management System (BMS) which ensures the status of the battery such as SOC and SOH. The BMS also has to have a capability to accurately monitoring the SOC to utilize battery reliably and efficiently, thereby ultimately lengthening the lifetime and preventing the permanent damage to the battery.

Various kinds of the SOC estimation algorithm have been reviewed in the literature[2–3]. Among the conventional estimation techniques so far, the Coulomb Counting is the most common method since it utilizes a simple current integration. However, it is disadvantageous that a periodic recalibration is required since the measurement errors will be accumulated over a long period of time, resulting in large estimation error. To improve the Coulomb Counting method, an open circuit voltage (OCV) measurement is regularly applied to reset the integrator depending on OCV–SOC relationship. Unfortunately, OCV of the battery can only be measured after a several hours of rest, thus this method is not desirable for the ISS system, in which the SOC of the batteries need to be continuously estimated online[3–4]. In addition, the SOC of the battery is affected by many simultaneous factors due to the various driving conditions. The Extended Kalman Filter (EKF) has been used in enormous researches to deal with the difficulties of SOC estimation. The EKF computes the best estimate by using the current, voltage, and temperature measurements and the battery model where the SOC is a variable of the model state vector. Whereas the accuracy of the battery model plays a major role for the precise estimation of the SOC, the Lead-Acid battery modeling is difficult and complex because it is highly non-linear and its parameters change sensitively depending on factors such as SOC, aging, history usage, Peukert effect, charge/discharge current level, and especially the hysteresis and diffusion phenomenon which have negative impacts on the estimation. Therefore, it is not feasible to achieve highly precise estimation with the simple model and thus the heavy computation is hardly avoidable. Since one of the main requirements for the BMS is the light computation, a good compromise between them has to be made[5].

This paper proposed a model of Lead-Acid battery which is simple and light in computation. The model takes into account charge/discharge state, the variation of the parameters depending on the SOC, the diffusion and hysteresis phenomenon. The hysteresis effect is modeled by the calculation of the normalized integration of the charge throughput during the partial cycle and the diffusion phenomenon [5, 7, 8, 9] is considered by the reconstruction of the open circuit voltage decay depending on the rest time. Eventually, the simple model consisted of three impedance components is applied to the EKF algorithm to estimate the SOC of the Lead-Acid battery.

2. Battery modeling

2.1 Battery Modelling Discussion

A wide variety of modeling approaches with different levels of complexity have been proposed and developed to present precisely the performance of the automotive batteries. In general, those techniques can likely be divided into four categories: electrochemical models, analytical models, stochastic model, and electrical circuit models. As discusses in[6], the electrochemical models are the most precise but highly complex and difficult to configure and apply to real-time application. The analytical models, the simplified form of electrochemical ones, have a drawback of describing important current-voltage characteristics. One of the other approaches is the stochastic model and it has a good qualitative description of the behavior of the battery under discharge pulses. Unfortunately, this model does not work well for the arbitrary load profiles and also was not developed for Lead-Acid batteries. In conclusion, aforementioned techniques are not good candidates to be selected. In the field of electrical circuit models, impedance–based approaches always not only provide the highly accurate model but also help researchers to comprehend and describe the phenomenon happening inside the Lead-Acid battery in the frequency domain. With the development of the unique technique, Electrical Impedance Spectroscopy (EIS), the analysis
of dynamic behaviors of battery becomes very convenient [9-11].

Fig. 1 shows a model of the Lead–Acid battery which can be used to describe the main static and dynamic phenomena. Here, $E_{eq}$ stands for the equilibrium potential [12] of the battery which depends on the state of battery such as the temperature and the SOC. This potential $E_{eq}$ is measured at standard condition, it depends on the used electrolyte, which determines how many electrons will be released during the metal dissolution. The total potential of the battery is then the difference between the potentials of the two electrodes [9]. The internal resistor $R_i$, representing the resistance of the contacts, the inter-cell connections and the electrolyte, is connected in series with the $R_x$–$C_d$ parallel circuit, consisting of a charge-transfer resistor $R_x$ and a double-layer capacitor $C_d$ which represents the charge-transfer phenomena. The Warburg impedance $Z_W$ represents the diffusion phenomenon caused by the grade of concentration of the electrolyte near the electrode, which draws on the electrode potential a second overvoltage called “diffusion overvoltage”. The precise equivalent circuit of Warburg impedance is shown in Fig. 2 [9-13].

The diffusion overvoltage plays a relatively small role compared to the other components; however it has a relatively long time constant in the voltage transient perspective. It can be also noticed that the diffusion overvoltage of the battery is mostly caused by the first RC components in the equivalent circuit of the Warburg impedance shown in Fig. 2. Therefore, in the vehicle application, the Warburg impedance can be modeled by the $R_W$–$C_W$ parallel circuit. Then the model of the battery becomes a combination of equilibrium voltage, an ohmic resistor, an $R_x$–$C_d$ parallel circuit and an $R_W$–$C_W$ parallel circuit which is a popular model of Lead–Acid battery in terms of Thevenin-based electrical circuit [6], [8]. The model can be further optimized by combining the equilibrium voltage and diffusion $R_W$–$C_W$ parallel circuit to become an OCV component which consists of diffusion factor $\zeta$, hence the complexity of the model is reduced. The proposed model for the Lead–Acid battery is eventually expressed in Fig. 3.

### 2.2 Hysteresis modeling of the OCV

The OCV of the proposed model consists of not only the diffusion effect but also the hysteresis effect. As discussed in literatures, the hysteresis effect is an important factor that needs to be carefully analyzed [13,14]. In case of Lithium-ion battery, since the hysteresis effect is relatively small, a simple method using single average OCV–SOC relationship can be employed. The SOC estimation can be achieved with high accuracy with the method, thus the sliding between OCV for charging and discharging state is not required [15-17]. However, it is not suitable to apply...
that technique to the Lead–Acid battery due to the strong hysteresis phenomenon of the battery. In addition, the hysteresis effect causes significant difficulties in estimating SOC especially when the state of battery turns over from partial charge or discharge, and thus, the OCV curve slides in between the charge and discharge OCV curve. In this scenario, without the effective sliding model between the two curves, the error of SOC value could be higher than 13% as shown in Fig. 4. It can be noticed that due to the hysteresis effect, the initial value and the calibration point will be inaccurate without having knowledge of previous battery status except the case when the battery is fully charged or discharged.

There are several approaches to model the hysteresis effect of the battery [2], [4], [34], [36], [18–19]. However, these approaches are complex thereby causing a low speed of computation and impractical in frequent charge/discharge application such as the battery for the vehicle. Among the many of the proposed techniques, one simple and interesting technique to model the hysteresis phenomena of Lithium-ion battery by taking into account the charge-transfer throughout the battery can be found in [7]. In this research the technique is utilized to examine the strong hysteresis phenomena of the Lead–Acid battery. All the detail procedures for the battery modeling are described in the following Section.

2.3 Parameters Extraction of the Lead–Acid Battery

A 12V, 70Ah Solite AGM70L-DIN battery, a product of Sungwoo Company, is selected for the tests. All the experimental tests are conducted with the battery kept in a chamber at 25°C connecting to the bipolar dc power supply NF BP4610. Host–computer software created in Labview is used to automatically carry out the tests to measure and store voltage and current through a sensing circuit and a NI PCI DAQ 6154 as shown in Fig. 6. As the parameters of the Lead–Acid battery model are affected by the factors such as SOC and charge/discharge state, thus the current pulses at different values of the SOC are applied to the completely discharged battery until it is fully charged and vice versa. The relaxation time after each pulse is set to 3 hours and the current and the voltage of the battery are recorded. After the data is collected, the curve fitting technique is used to extract the OCV, R1, R2, and C0. The process of the parameters extraction for the battery is described in Fig. 5.

The relationships between the parameters and the SOC and the charge/discharge state are then obtained. On the other hand, the tests also help to determine the two factors of the battery model, the hysteresis factor and the diffusion factor.

![Flow chart of the parameter extraction for the battery](image)

![Experimental setup for the parameter extraction](image)
An example of the fitted curve for the extracted parameters can be seen in Fig. 8. The variation of the parameter can be modeled by the fifth order polynomial function with respect to the SOC with high accuracy, in which Chi-square error is less than 1%. The terminal voltage of the Lead-Acid battery is assumed to reach to the stable condition after 3 hours of relaxation and the voltage drops on R-RC connection is eliminated in 3 minutes. The increase/decrease in voltage from 3 minutes to 3 hours is defined as the diffusion overvoltage. With the experimental data, the four fundamental OCV–SOC curves depicted in Fig. 9 can be modeled by the fifth order polynomial function. For instance, the following equation is the polynomial function of OCV discharge with 3-hour relaxation, where $z$ stands for SOC.

\[
OCV_{d3h}(z) = 18.6 z^5 - 41.9 z^4 + 34.7 z^3 - 13.4 z^2 + 4.0 z + 11.3
\]  

(1)

The following equations shows the general forms of the fifth order polynomial function for the charge OCV with 3-hour relaxation $OCV_{c3h}(z)$, charge OCV with 3-min relaxation $OCV_{c3m}(z)$, the discharge OCV with 3-hour $OCV_{d3h}(z)$ and the discharge OCV with 3-min $OCV_{d3m}(z)$.

\[
\begin{align*}
OCV_{c3h}(z) &= \sum_{i=0}^{5} a_{c3hi} \times z^i \\
OCV_{c3m}(z) &= \sum_{i=0}^{5} a_{c3mi} \times z^i \\
OCV_{d3h}(z) &= \sum_{i=0}^{5} a_{d3hi} \times z^i \\
OCV_{d3m}(z) &= \sum_{i=0}^{5} a_{d3mi} \times z^i
\end{align*}
\]  

(2)

Where, $a_{c3hi}$, $a_{c3mi}$, $a_{d3hi}$, and $a_{d3mi}$ are the coefficient of fifth order polynomial function $OCV_{c3h}(z)$, $OCV_{c3m}(z)$, $OCV_{d3h}(z)$ and $OCV_{d3m}(z)$, respectively.

In order to take account the diffusion effect into the OCV component, the relationship between OCV and SOC during the charge depending on the diffusion factor $\zeta$ is obtained by the following equations.

\[
\begin{align*}
OCV'(z, \zeta) &= OCV_{c3h}(z) + \zeta V_d(z) \\
V_d(z) &= OCV_{d3m}(z) - OCV_{d3h}(z)
\end{align*}
\]  

(3)

Thus the OCV during charge dischage according to the rest time can be expressed as (4) and (5), respectively.

\[
\begin{align*}
OCV_c'(z, \zeta) &= (1 - \zeta) OCV_{c3h}(z) + \zeta OCV_{c3m}(z) \\
OCV_d'(z, \zeta) &= (1 - \zeta) OCV_{d3h}(z) + \zeta OCV_{d3m}(z)
\end{align*}
\]  

(4)\hspace{1cm}(5)

![Fig. 8 Variation of the charge transfer resistance on SOC variation and its curve fitting](image1)

![Fig. 7 An example of discharge current pulses of the 12V, 70Ah Solite AGM70L - DIN battery](image2)

![Fig. 9 OCV - SOC relationships of the 12V, 70Ah Solite AGM70L - DIN battery](image3)
Where, the diffusion factor can be calculated by a first order exponential equation with respect to the time as shown in (6). The $\tau$ is the time constant of the diffusion which is lumped into the equilibrium voltage $E_{eq}$. It can be extracted from the OCV–SOC curves with 3-min and 3-hour relaxation tests.

$$\zeta(t_w) = \exp\left(-\frac{t_w}{\tau}\right)$$

(6)

Where, $t_w$ (sec) is the relaxation time of the battery after charge or discharge.

In order to investigate the hysteresis effect, the fully charged battery is discharged continuously to 38 % of SOC then charged back to 78 % by 10 pulses of 4 % of SOC each, then the battery is discharged back to 38 % of SOC with the same method. Fig. 10 shows the OCV curve for the partial charge/discharge cycle. At the 38% of SOC, the OCV is moved to the 3h relaxation charge curve from the 3h relaxation discharge curve and kept moving on the 3h relaxation charge curve from the 64 % of SOC. Similarly at the 78% of SOC, the OCV is moved to the 3h relaxation discharge curve from the 3h relaxation charge curve and kept moving on the 3h relaxation discharge curve from the 52 % of SOC. Thus it can be easily deduced from the experiments that the actual OCV during charge and discharge lies somewhere in between the 3h relaxation charge and discharge curve depending on the charge throughput. Also the transition of the OCV can be empirically reconstructed by introducing a hysteresis model. The hysteresis factor $\alpha$ is used to model the movement of the OCV between the lower (3h relaxation discharge curve, $OCV_{dlh}$) and upper boundary (3h relaxation charge curve, $OCV_{alk}$) curve due to the partial cycles. The function of the OCV–SOC at 3-hour relaxation depending on the hysteresis factor can be obtained by the following equations.

$$OCV(z, \alpha) = (1 - \alpha) OCV_{dlh}(z) + \alpha OCV_{alk}(z)$$

(7)

Thus the OCV during charge/discharge according to the charge throughput of the partial cycle can be expressed as (8).

$$OCV(z, \alpha) = (1 - \alpha) OCV_{dlh}(z) + \alpha OCV_{alk}(z)$$

(8)

The empirical equation of the hysteresis factor corresponding to the charge throughput is expressed as follows [13].

$$\alpha = v\alpha_1 + (1 - v)\alpha_2$$

(9)

For the charge,

$$\alpha_1 = \int h_1 \frac{I}{C_0} dt \quad 0 \leq \alpha_1 \leq 1 \quad (10)$$

For the discharge,

$$\alpha_2 = \int h_2 \frac{I}{C_0} dt \quad 0 \leq \alpha_2 \leq 1 \quad (11)$$

The parameters of the hysteresis model, $v$, $h_1$, and $h_2$, can be extracted by using a parallelogram and the least square estimation. Fig. 10 shows the variation of hysteresis factor and its modeling calculated from the partial cycle test shown in Fig. 11.

By taking account the diffusion factor $\zeta$ into (8), a comprehensive equation for the OCV–SOC relationship can be established as follows.

$$OCV(z, \alpha, \zeta) = (1 - \alpha) OCV_{dlh}(z, \zeta) + \alpha OCV_{alk}(z, \zeta)$$

(12)
Table 1  Battery modeling parameters and factors of a 12V, 70Ah Solite AGM70L - DIN battery

| Name/Unit | Value       |
|-----------|-------------|
| Rm, Rsc, Cdl (Ω, Ω, F) | Function of SOC |
| Capacity, Cυ/Ah | 70          |
| Time constant for ξ, v/s | 2000         |
| Hysteresis vertical factor, v | 0.5         |
| Hysteresis horizontal factor, h1 | 25          |
| Hysteresis horizontal factor, h2 | 4.5         |

The factors ξ and a are updated at every cycle of Kalman filter estimation and the battery modeling parameters and factors are shown in Table 1.

3. SOC Estimation algorithm by using EKF

3.1 Computation Procedure for the Extended Kalman Filter

The basic Kalman filter provides a recursive solution to the linear optimal filtering problem and suitable for real-time applications as it only requires previous and new input data. In case of the nonlinear model, a linearization procedure is required and it is called as extended Kalman filter [2]. In the nonlinear discrete-time system described by the difference equation, the measurement model with additive noise can be represented as (13).

\[
\begin{align*}
\mathbf{x}_{k+1} &= f(\mathbf{x}_k, \mathbf{u}_k) + \mathbf{w}_k \\
\mathbf{y}_k &= g(\mathbf{x}_k, \mathbf{u}_k) + \mathbf{v}_k
\end{align*}
\]  

(13)

Where, \( \mathbf{x}_k \) is the system state vector, \( \mathbf{y}_k \) (V) is the battery measurement voltage, \( \mathbf{w}_k \) is the process noise, \( \mathbf{v}_k \) is the measurement noise, \( \mathbf{Q}_k \) is the process noise covariance matrix, \( \mathbf{R}_k \) the measurement noise covariance matrix at the time index \( k \). Both \( \mathbf{w}_k \) and \( \mathbf{v}_k \) are independent, zero mean, Gaussian noise processes of covariance matrices \( \mathbf{Q}_k \) and \( \mathbf{R}_k \) respectively [20]. The function \( f(\cdot, \cdot) \) represents a nonlinear transition matrix function and the function \( g(\cdot, \cdot) \) represents nonlinear measurement matrix.

The computing procedure for the extended Kalman filter can be summarized as follows.

Step 1: Initialization, for \( k=0 \)

\[
\begin{align*}
\hat{\mathbf{x}}_0 &= \mathbf{E}(\mathbf{x}_0) \\
\mathbf{P}_0 &= \mathbf{E}((\mathbf{x}_0 - \hat{\mathbf{x}}_0)(\mathbf{x}_0 - \hat{\mathbf{x}}_0)^T)
\end{align*}
\]  

(14)

Step 2: Approximation of the nonlinear functions

\[
\begin{align*}
\mathbf{F}_{k-1} &= \frac{\partial f(\mathbf{x}, \mathbf{u}_{k-1})}{\partial \mathbf{x}} \bigg|_{\mathbf{x} = \hat{\mathbf{x}}_{k-1}} \\
\mathbf{G}_k &= \frac{\partial g(\mathbf{x}, \mathbf{u}_k)}{\partial \mathbf{x}} \bigg|_{\mathbf{x} = \hat{\mathbf{x}}_k}
\end{align*}
\]  

(15)

Step 3: Time update

State estimation propagation

\[
\hat{\mathbf{x}}_k \approx f(\hat{\mathbf{x}}_{k-1}, \mathbf{u}_k)
\]  

(16)

Error covariance propagation

\[
\mathbf{P}_k^- = \mathbf{F}_{k-1} \mathbf{P}_{k-1}^- \mathbf{F}_{k-1}^T + \mathbf{Q}_k
\]  

(17)

Step 4: Measurement update

Kalman gain matrix

\[
\mathbf{K}_k = \mathbf{P}_k^- \mathbf{G}_k^T [\mathbf{G}_k \mathbf{P}_k^- \mathbf{G}_k^T + \mathbf{R}_k]^{-1}
\]  

(18)

State estimate measurement update

\[
\hat{\mathbf{x}}_k^+ = \hat{\mathbf{x}}_k^- + \mathbf{K}_k [\mathbf{y}_k - g(\hat{\mathbf{x}}_k^-, \mathbf{u}_k)]
\]  

(19)

Error covariance measurement update

\[
\mathbf{P}_k^+ = (I - \mathbf{K}_k \mathbf{G}_k) \mathbf{P}_k^-
\]  

(20)

3.2 SOC Estimation with EKF

Regarding the selected model, the state space derivation is mentioned in [21] and the state space equations in the discrete form are shown in (21).

\[
\begin{align*}
\begin{bmatrix}
\mathbf{z}_{k+1} \\
V_{\text{G}}_{k+1}
\end{bmatrix} &= \begin{bmatrix} 1 & 0 \\ 0 & 1 - \frac{\Delta t}{R_s C_{dl}} \end{bmatrix} \begin{bmatrix}
\mathbf{z}_k \\
V_{\text{G}}_{k}
\end{bmatrix} + \begin{bmatrix} 0 \\ \frac{\Delta t}{C_d} \end{bmatrix} I_k + \mathbf{w}_k \\
\mathbf{y}_k &= OCV(\mathbf{z}_k, \mathbf{\zeta}_k, \alpha_k) - V_{\text{G}}_{k} - R_k I_k + \mathbf{v}_k
\end{align*}
\]  

(21)

Where, \( C_b \) (As) is the battery nominal capacity, \( I_k \) (A) is the measured current of the battery and \( V_{\text{G}} \) (V) is the voltage drop on \( R_k - C_{dl} \) parallel circuit at the time index \( k \).
Combining and discretizing four equations for the charge/discharge OCV–SOC curves in (2) with the two factors \( \xi \) and \( \alpha \) in (4), (5), and (12), the discrete model of the OCV can be expressed as (22).

\[
OCV(z_k, \xi_k, \alpha_k) = (1 - \alpha_k) \left[ (1 - \xi_k) OCV_{\text{ch}}(z_k) \right] + \xi_k OCV_{\text{dch}}(z_k) + \alpha_k \left[ (1 - \xi_k) OCV_{\text{ch}}(z_k) \right] + \xi_k OCV_{\text{dch}}(z_k)
\]

(22)

In a form of fifth order polynomial,

\[
OCV(z_k, \xi_k, \alpha_k) = \sum_{i=0}^{5} a_{i,k} z_k^i
\]

(23)

where,

\[
a_{i,k} = (1 - \alpha_k) \left[ \xi_k a_{\text{ch},i} + (1 - \xi_k) a_{\text{dch},i} \right] + \alpha_k \left[ \xi_k a_{\text{ch},i} + (1 - \xi_k) a_{\text{dch},i} \right]
\]

(24)

As can be seen in (21), while the approximation is not required for the state equation, the measurement equation requires it because the OCV–SOC relationship is nonlinear. Thus the Taylor series approximation described (15) is required for the nonlinear measurement equation \( g(\cdot, \cdot) \).

\[
F_{k-1} = \begin{pmatrix} 1 & 0 \\ 0 & 1 - \frac{\Delta t}{R_{\text{eq}} C_{\text{eff}}} \end{pmatrix}
\]

(25)

\[
G_k = \frac{\partial g(x_k, u_k)}{\partial x} \bigg|_{x = x_k} = \begin{bmatrix} \frac{\partial OCV}{\partial z_k} - \frac{\partial V_{\text{cell}}}{\partial z_k} \\ \frac{4}{\sum_{i=0}^{5} (i+1) a_{i,k} (z_k)^i} - 1 \end{bmatrix}
\]

(26)

4. Results and discussion

In order to verify the validity of the proposed estimation algorithm by the Kalman filter, the experiment is performed. Fig. 12 shows the result of the cycle tests. The battery, 12V, 70Ah Solite AGM70L - DIN, is again used to verify the developed method. The experimental setup is already shown in the section 2.3. The battery is fully charged to get the precise initial value of the SOC and the coulomb counting is considered as the reference value of the system. The battery is then discharged and charged repeatedly with different amount of charge, and eventually stopped at 75% of SOC.

The advantage of the proposed estimation system in this research is exploited through the comparison of two estimation systems. One is the system taking into account the hysteresis effect, and the other is the system with no hysteresis effect included. The two systems are operated simultaneously to observe the difference. As shown in Fig. 12, the critical errors occur with the system without taking into account the hysteresis effect. When the battery is charged after discharge and discharged after the charge, the error reaches up to 16% as expected in Fig. 4. However, with the proposed estimation method the error is reduced to less than 5%.

5. Conclusion

A novel estimation technique for the State-of-Charge of the lead-acid battery by using EKF considering hysteresis and diffusion effect has been proposed and applied to the AGM Lead-Acid battery.
The hysteresis phenomenon has been successfully modeled by the calculation of the normalized integration of the charge throughput during the partial cycle and the estimation error was reduced significantly. The parameter variation of the equivalent circuit model depending on the SOC and the charge/discharge state also has been modeled by the fifth order polynomial equation and applied to the estimation of the SOC by the Kalman filter. The observed error during the charge/discharge cycle was within 5%, thereby validating the proposed method.

**References**

[1] D. Schrank, B. Eiselle, and T. Lomax, “TTI’s 2012 Urban Mobility Report,” Texas A&M Transportation Institute, Annual Report, 2012.

[2] G. L. Plett, “Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs: Part 2. Modeling and identification,” *Journal of Power Sources*, Vol. 134, pp. 262–276, 2004.

[3] V. Pop, H. J. Bergveld, P. H. L. Notten, and P. P. L. Regtien, “State-of-the-art of battery state-of-charge determination,” *Measurement Science and Technology*, Vol. 16, pp. R93, 2005.

[4] H. Yiran and S. Yurkovich, “Battery state of charge estimation in automotive applications using LPV techniques,” *American Control Conference (ACC)*, pp. 5043–5049, 2010.

[5] M. Thele, J. Schiffer, E. Karden, E. Surewaard, and D. U. Sauer, “Modeling of the charge acceptance of lead–acid batteries,” *Journal of Power Sources*, Vol. 168, pp. 31–39, 2007.

[6] K. Taesic and Q. Wei, “A Hybrid Battery Model Capable of Capturing Dynamic Circuit Characteristics and Nonlinear Capacity Effects,” *Energy Conversion, IEEE Transactions on*, Vol. 26, pp. 1172–1180, 2011.

[7] M. A. Roscher and D. U. Sauer, “Dynamic electric behavior and open-circuit–voltage modeling of LiFePO4–based lithium ion secondary batteries,” *Journal of Power Sources*, Vol. 196, pp. 331–336, 2011.

[8] C. Min and G. A. Rincon-Mora, “Accurate electrical battery model capable of predicting runtime and I–V performance,” *Energy Conversion, IEEE Transactions on*, Vol. 21, pp. 504–511, 2006.

[9] K. Brik and F. ben Ammar, “Causal tree analysis of depth degradation of the lead acid battery,” *Journal of Power Sources*, Vol. 228, pp. 39–46, 2013.

[10] S. Buller, M. Thele, E. Karden, and R. W. De Doncker, “Impedance–based non-linear dynamic battery modeling for automotive applications,” *Journal of Power Sources*, Vol. 113, pp. 422–430, 2003.

[11] M. Thele, S. Buller, D. U. Sauer, R. W. De Doncker, and E. Karden, “Hybrid modeling of lead–acid batteries in frequency and time domain,” *Journal of Power Sources*, Vol. 144, pp. 461–466, 2005.

[12] W. Guoliang, L. Rengu, Z. Chunbo, C.C.Chan, “State of Charge Estimation for NiMH Battery Based on Electromotive Force Method,” Electric Information and Control Engineering (ICEICE), 2011 International Conference.

[13] P. Mauracher and E. Karden, “Dynamic modelling of lead/acid batteries using impedance spectroscopy for parameter identification,” *Journal of Power Sources*, Vol. 67, pp. 69–84, 1997.

[14] T. Xidong, Z. Xiaodong, B. Koch, and D. Frisch, “Modeling and estimation of Nickel Metal Hydride battery hysteresis for SOC estimation,” Prognostics and Health Management, 2008. PHM 2008. International Conference on, 1-12, 2008.

[15] H. Hongwen, X. Rui, Z. Xiaowei, S. Pengchun, and F. JinXin, “State–of–Charge Estimation of the Lithium–Ion Battery Using an Adaptive Extended Kalman Filter Based on an Improved Thevenin Model,” *Vehicular Technology, IEEE Transactions on*, Vol. 66, pp. 1461–1469, 2011.

[16] S. Lee, J. Kim, J. Lee, and B. H. Cho, “State–of–charge and capacity estimation of lithium–ion battery using a new open–circuit voltage versus state–of–charge,” *Journal of Power Sources*, Vol. 185, pp. 1367–1373, 2008.

[17] H. Dai, X. Wei, Z. Sun, J. Wang, and W. Gu, “Online cell SOC estimation of Li-ion battery packs using a dual time-scale Kalman filtering for EV applications,” *Applied Energy*, Vol. 95, pp. 227–237, 2012.

[18] K. W. E. Cheng, B. P. Divalkar, W. Hongjie, D. Kai, and H. Ho Fai, “Battery–Management System (BMS) and SOC Development for Electrical Vehicles,” *Vehicular Technology, IEEE Transactions on*, Vol. 60, pp. 76–88, 2011.

[19] N. A. Windrakko and J. Choi, “Hysteresis modeling for estimation of State–of–Charge in NiMH battery based on improved Takacs model,” Telecommunications Energy Conference, 2009. INTELEC 2009. 31st International, 1–6, 2009.

[20] G. L. Plett, “Extended Kalman filtering for battery management systems of LiPB–based HEV battery packs: Part 1. Background,” *Journal of Power Sources*, Vol. 134, pp. 252–261, 2004.

[21] J. Lee, O. Nam and B.H. Cho, “Li-ion battery SOC estimation method based on the reduced order extended Kalman filtering,” *Journal of Power Sources*, Vol. 174, pp. 9–15, 2007.
Van-Huan Duong

was born in Vietnam in 1985. He received his B.S. in Electrical Engineering from Hanoi University of Science and Technology, in 2008. He received his M.S. in Electrical Engineering from Soongsil University, Seoul, Republic of Korea, in 2013. His current research interests include energy storage management system, MCU/DSP applications, and electric vehicles.

Ngoc-Tham Tran

was born in Quang Nam, Vietnam, in 1987. He 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 modeling, SOC/SOH estimation).

Yong-Jin Park

was born in Seoul, Republic of Korea, in 1988. He received his B.S in Electrical Engineering from Soongsil University, Seoul, Republic of Korea. He is currently working toward his M.S at Soongsil University. His current research interests include dc–dc converter and battery chargers.

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. 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.