Indian Journal of Science and Technology, Vol 8(26), DOI: 10.17485/ijst/2015/v8i26/81677, October 2015
ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645

Comparative Study on the Battery State-of-Charge Estimation Method

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Abstract

Accurate SOC (State-of-Charge) estimation has been an important part for all applications including energy storage systems. The accurate SOC estimation protects a battery to be deeply discharged and over-charged. Many studies on SOC estimation methods have been developed for evaluating more accurate SOC value. The battery SOC can be influenced by the battery temperature, the type of battery and the external conditions. Because of these reasons, SOC estimation methods differ from battery applications such as energy storage system, hybrid electrical vehicle or electrical vehicle. This paper analyzes and compares the strengths and weaknesses of typical estimation methods which have been studied by researchers. By comparing these advantages and disadvantages of various methods, this paper presents proper estimation methods suitable for energy storage applications.

Keywords: Ampere Hour Counting, Electrochemical Impedance Spectroscopy, Open Circuit Voltage, Kalman Filter, SOC (State of Charge)

1. Introduction

According to the depletion of fossil fuels and the energy and environmental problems, the needs for using high efficient electrical energy have increased. In order to cope with these needs, a battery or ESS (Energy Storage System) which can store electrical energy is widely used in the various fields such as EV (Electrical Vehicle), HEV (Hybrid Electrical Vehicle) and grid frequency regulation equipment[1]. In these systems, it is necessary to check the SOC (State of Charge) of a battery when the battery is operated. In the case of an EV, a vehicle should inform the accurate battery SOC information to a user because he or she should know when the vehicle should be charged and how long he or she can derive the vehicle. This paper reviews previous studies on the battery SOC estimation in the literature. Based on the reviews of the previous studies on the battery SOC estimation, this paper also analyzes the strengths and weaknesses of estimation techniques which have been used.

2. State-of-Charge Estimation Methods

2.1 Ampere Hour Counting (Coulomb Counting Method)

An ampere hour counting method is the most common technique for estimating a battery SOC by integrating the current from a battery. This estimation method is good for tracking the rapid changes of SOC[1]. If an initial value (SOC_0) at time t_0 is already known, the battery SOC at the specific time t can be obtained from the result of the following equation:

$$SOC = SOC_o + \frac{1}{C_N}\int_{t_0}^{t}(I_{batt} - I_{loss})dt \quad (1)$$

Where C_N is the rated capacity of battery, I_{batt} is the battery current and I_{loss} is the battery current by the loss reactions. This coulomb counting SOC estimation method is used for laptop batteries and other professional por-

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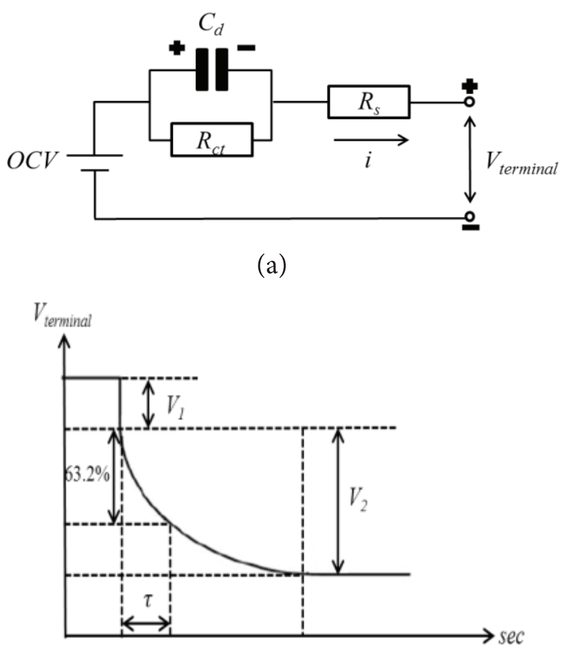

Figure1. Randles battery model and its terminal voltage[7]. (a) Randles battery equivalent circuit model. (b) Change in the battery terminal voltage.

table devices. One disadvantage of this SOC estimation method is that incorrect initial I_{batt} and I_{loss} may produce a large estimation error[2]. Thus, it should use accurate initial I_{batt} and I_{loss} to reduce the estimation error. Another disadvantage of this method is that it may take long time to estimate the SOC. Although there may exist irregularities among batteries, this method is the most common method for most battery applications[2]. In addition, if the battery currents are accurately measured, this method can estimate the accurate SOC of the target battery.

2.1 Open Citcuit Voltage

An Open Circuit Voltage (OCV) SOC estimation especially works for a lead-acid battery[3,4]. This battery SOC estimation technique withan open circuit voltage is the easiest method although it can be incorrect. The open circuit voltage of a battery depends on the ambient temperature of cells. In addition, each cell in batteries has different chemical characteristics so that each cell has different voltage profiles[4,5]. In other words, an open circuit voltage in the low temperature is lower than that in the high temperature. All kinds of batteries show this temperature dependent characteristic which may distort battery voltage measurement[6]. Because of this temperature dependent characteristic, the open circuit voltage estimation during the battery operating state usually produces a SOC estimation error. Therefore, to obtain accurate SOC estimation results, the battery should rest for reaching the equilibrium state of cells before measuring the open circuit voltage of a battery. When the SOC of a battery is estimated by this method, the state of a battery should be truly in the floating state without the load of battery.

As shown in Figure 1, the open circuit voltage method may use the Randles battery model[7] that consists of the cell internal resistance (R_s), the polarization resistance (R_{ct}) and the double layer capacitance (C_d) by the effect of the double layer charge transfer. A battery OCV in Figure 1a is a battery terminal voltage when a battery is in the no load steady state condition. Based on the Randles equivalent circuit shown in Figure 1a, the battery terminal voltage($V_{terminal}$) can be expressed as[7]

$$V_{terminal} = OCV(SOC) - i(R_S + R_{ct}(1 - e^{-t/\tau})), \quad (2)$$

where the parameters in (2) can be calculated by τ

$$R_S = \frac{V_1}{i}, R_{ct} = \frac{V_2}{i}, C_d = \frac{\tau}{R_{ct}}, \quad (3)$$

where V_1, V_2, and τ can be obtained by the time varying battery terminal voltage shown in Figure 1(b). As depicted in Figure 1(b), the time constant in the RC parallel circuit ($\tau = R_{ct}C_d$) is defined as the time in which the battery terminal voltage decreases up to 63.2% from the normal voltage value. A battery charge can be expressed as a function of SOC. Therefore, the open circuit voltage method is to estimate the battery SOC by measuring the OCV and data collected by (2).

2.1 Kalman Filter

A battery SOC estimation method with a Kalman filter is based on an algorithm which uses in accurate measured state variables due to time-varying noises. The Kalman filter estimates the SOC value by modeling the battery system including the unspecific parameters required for the SOC measurement. An advantage of the Kalman filter estimation method is that it can automatically provide an estimation value in the dynamic state. Therefore, this method is suitable for dynamic model applications such as HEV and EV. To use this Kalman filter method for these dynamic applications, the secondary battery model is required as shown in Figure 2[8].

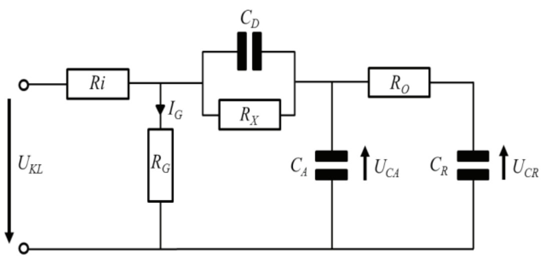

Figure 2. Battery model for dynamic applications[8].

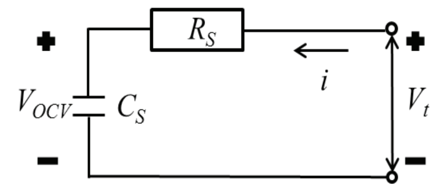

Figure 3. Battery model for the EKF[11].

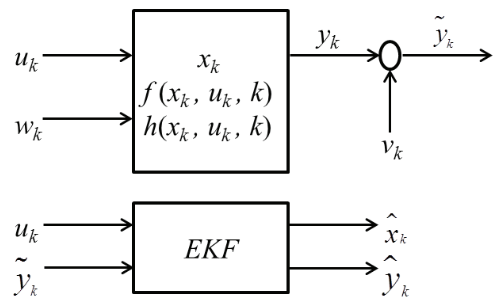

Figure 4. Nonlinear discrete-time process[11].

However, an extended Kalman filter (EKF) method is mainly used because of the non-linear characteristics of the battery. This EKF SOC estimation method requires the battery model that can exactly represent the dynamic state[9]. Although this method can measure the SOC of the battery in the operating conditions, it has the disadvantage that the SOC estimation time increases in accordance with increasing the state variables[10]. The EKF model that has open circuit voltage (V_{OCV}), battery current (i), internal resistance (R_S) and terminal voltage (V_t) as shown in Figure 3[11] is a batter estimation method than the Kalman filter. The non-linear process including process noise (w) and sensor noise (v) can be represented as shown in Figure 4[11]. In this process, state variables (x), output (y) and input data (u) are derived as follows:

$$x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} V_{OCV} \\ C_S \\ R_S \end{bmatrix}; \quad y = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} V_t \\ i \end{bmatrix}; \quad u = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} = \begin{bmatrix} V_t \\ i \end{bmatrix} \tag{4}$$

$$\begin{cases} \dot{x} = \begin{bmatrix} -1/R_S C_S & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} 1/R_S C_S & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} + w \\ y = \begin{bmatrix} 1 & 0 & 0 \\ -1/R_S & 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} 0 & R_S \\ 1/R_S & 0 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} + v \end{cases} \tag{5}$$

$$x_k = f(x_{k\text{-}1}, u_k, k) + w_{k\text{-}1} \tag{6}$$

$$y_k = h(x_k, u_k, k) \tag{7}$$

$$\tilde{y}_k = y_k + v_k \tag{8}$$

As shown in equation (4), the input and output vectors of EKF method are equal (i.e., V_t and i_b). The standard state form is derived as equation (5). The non-linear discrete-time process equations (6) ~ (8) can be derived from Figure 4. In equation (6), equation (7) and equation (8), k means a discrete time point, the vector input value (V_t and i) represents u_k, and the actual state vector value represents x_k which includes open circuit voltage (V_{OCV}), battery current (i), internal resistance (R_S). The output vector (V_t and i) represents y_k. The can be derived from the sum of x_k and y_k. $f(x_{k\text{-}1}, u_k, k)$ and $h(x_k, u, k)$ are

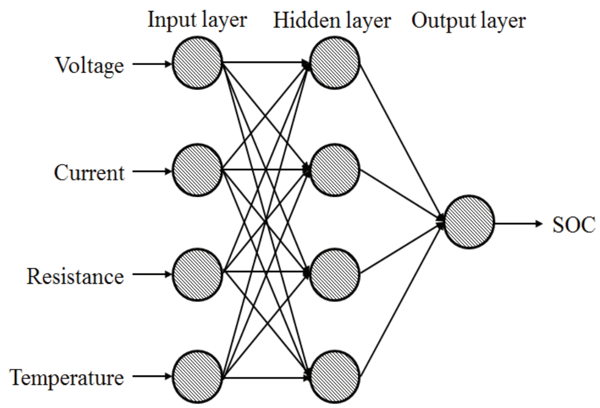

Figure 5. BP neural network for a battery model[17].

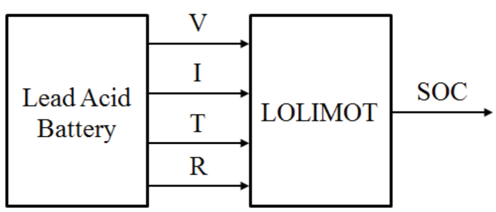

Figure 6. SOC estimation logic using the LOLIMOT[20].

respectively the general functions of past and next state that include the process of noises (w_k and v_k)[11]. The state variables including V_{OCV}, C_S and R_S can be derived from the OCV state of battery model using the input, actual output and process noise of the EKF.

2.4 Electrochemical Impedance Spectroscopy

An Electrochemical Impedance Spectroscopy (EIS) SOC estimation method uses the impedance spectra of the measurement object. This method can estimate State-of-Health (SOH) as well as SOC in all energy storage systems because SOC and SOH affect battery impedance[12]. This EIS method is suitable for a lead-acid battery and SOH estimation is more accurate than SOC estimation[13]. For a Li-ion battery, this SOC estimation method can only be used for an initial stage[14]. Although many researchers have attempted to estimate SOC with the EIS, this method is seldom used for practical SOC estimation because it still has problems to solve. Ambient temperature may affect the battery impedance particularly at the electrochemical processes at low frequency. Therefore, estimating SOC and SOH with this method requires to be implemented at high frequency. In addition, this EIS estimation can use a fuzzy logic methodology[15]. For a lithium-sulpuric dioxide system, this fuzzy model can be used to a battery SOC by parameters resulting from impedance spectroscopy. The accuracy of this battery SOC estimation is ±5%[15].

2.5 Neural Network

A Neural Network uses a mathematical algorithm model for Complex Neural Network characteristics or parallel process. The Neural Network can achieve processing data and solve relations between various initial complex factors[16]. A BP Neural Network which is one of Neural Network algorithms solves a non-linear system and has a simple topology structure compared with the typical Neural Network methods[17]. This BP Neural Network can estimate battery SOC as shown in Figure 5[17]. The structure of the BP Neural Network is composed of three layers including input layer, hidden layer and output layer. The input layer includes battery voltage, current, resistance and ambient temperature. The number of the hidden layer depends on the system accuracy. The output layer of this system produces an estimated SOC value.

The goal of this method is to reduce the minimum error value. However, the system error depends on the number of training data and experiment methods. The training data that are used to estimate SOC can be obtained from the experiments of charging and discharging batteries. This training method typically minimizes error functions. Thus, these errors increase if the BP Neural Network method uses not enough trained information from SOC values[18]. Therefore, training data from a large amount of batteries should be used for obtaining an accurate SOC value. This is because a battery discharge characteristics may differ from the amount of the electrolyte in batteries although their type and manufacturer are same.

2.6 Locally Linear Model Tree

A Locally Linear Model Tree (LOLIMOT) SOC estimation method uses a Nero-fuzzy network system. This method estimates the SOC of a non-linear battery system with a local linear model which is based on an assumed non-linear function and polynomial linear models[19]. The LOLIMOT is based on the normalized Gaussian weighting functions. In the case of a lead acid battery for an HEV,

Table 1. Summary of SOC estimation methods

Method	Applications	Advantages	Disadvantages
Ampere hour counting	all energy storage	online, easy, simple, accurate	sensitive to parasitic reaction, cost for accurate current estimation, need a loss model
Open circuit voltage	Lead Acid, Li-ion, Zn/Br	online, simple	low dynamic, need long rest time, sensitive to temperature
Kalman filter	dynamic application, HEV, EV	online, dynamic	need a suitable battery model, initial parameterproblem
EIS	all energy storage	SOH estimation, online	sensitive to temperature, sensitive to frequency (high frequency required)
Neural network	all energy storage	online, simple	need many training data for accuracy
Linear model	Lead Acid, HEV	online, simple	need reference data for fitting parameters

some errors may occur by this method because training data are bigger than the test information. As shown in Figure 6, the training data input of this method consist of battery terminal voltage (V), load current (I), ambient temperature (T), battery internal resistance (R) and its output data which are SOC values[20].

3. Conclusion

This paper presented an overview of battery SOC estimating methods. Table 1 compared these battery estimation methods. Based on the comparison of these estimation methods, it can be concluded that the ampere hour counting method is the most suitable technique for all energy storage systems because it can directly and easily transfer SOC information from a battery to a system[21]. If the battery currents are accurately measured, this method can also estimate the accurate SOC of the target battery.

4. Acknowledgments

This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Science, ICT and Future Planning (NRF-2014R1A1A1036384).

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