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Domain applications

State-of-charge estimation for lithium-ion batteries under various operating conditions using an equivalent circuit model

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ABSTRACT

This paper describes a state-of-charge estimation methodology for lithium-ion batteries in hybrid electric vehicles. The proposed methodology is intended for SOC estimation under various operating conditions including changes in temperature, driving mode or power duty. The suggested methodology consists of a recursive estimator and employs an equivalent circuit as the electrochemical cell model. Model parameters are estimated by parameter map on experimental cell data with various temperatures and current conditions. The parameter map is developed by a least sum square error estimation method based on nonlinear programming. An adaptive estimator is employed and is based on the combination of current integration and battery model based estimation. The proposed SOC estimation methodology is demonstrated with experimental LiB pack data under various driving schedules with low and ambient temperature and sensor failure cases. Our results show that the proposed methodology is appropriate for estimating SOC under various conditions.

1. Introduction

In recent years, energy storage systems such as lithium-ion batteries have been highlighted in portable electronics, hybrid electric vehicles and plug-in hybrid electric vehicle applications. In particular, lithium-ion batteries have higher power, high energy density, and higher open circuit voltage than other types of batteries. Thus, lithium-ion batteries are used as principal or auxiliary power supply devices for electric vehicles, hybrid electric vehicles and plug-in hybrid electric vehicles (Park, Kim, Kim, Moon, & Lee, 2007). The state-of-charge (SOC) is equivalent to a fuel level for the battery pack in a battery electric vehicle and is the key to controlling the battery system and estimating the maximum available power and state-of-health of the battery (Kim, Sohn, Lee, & Kim, 2008; Lukic, Cao, Bansal, Rodriguez, & Emadi, 2008). Therefore, the SOC estimation is an important aspect of hybrid electric vehicles and plug-in hybrid electric vehicle applications. The principal power supply device for hybrid electric vehicles is an internal combustion engine and battery serves as the auxiliary power supply device. On the other hand, battery serves as the principal power supply device for plug-in hybrid electric vehicles. For both types of the vehicles battery holds an important role as the motive force, thus many studies regarding the secondary battery have been carried out for a past decade (Bradley & Frank, 2009).

Coulomb counting has been the most common method of measuring the SOC. This method is easy for calculation but accumulates errors due to incorrect measurements. The open circuit voltage based method with a dynamic battery model has been suggested as an alternative. However, this method is only accurate during rest periods on low current and not during moderate or high current periods. Therefore, adaptive estimation methods such as neural networks, fuzzy logic, and extended Kalman filters have been used based on Coulomb counting and open circuit voltage based methods (Han, Kim, & Sunwoo, 2009; Hansen & Wang, 2005; Kim, Lee, & Cho, 2011; Lee, Kim, Lee, & Cho, 2008; Plett, 2006; Singh, Vinjamuri, Wang, & Reisner, 2006; Wang, Cao, Chen, & Wang, 2007; Weigert, Tian, & Lian, 2011).

The estimation methods described above are accurate under moderate operation conditions due to the adaptive nature of the estimator. However, these methods cannot be applied to various operating conditions. Battery operating conditions include several variables, for example, various power duty conditions occurring during current fluctuation, low and high temperatures, and varying SOC ranges. The power duty conditions change due to power demand from the power train of the vehicle. The power duty is low for urban driving schedules but high for highway driving schedules. Power duty is extremely high in high acceleration aggressive schedules identified as the "Supplemental Federal Test Procedure" driving schedule (Tatur, Tyrer, Tomazic, Thornton, &

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Nomenclature

a	absolute current value (A)
a_{ii}	ith element of the diagonal of the covariance matrix
A	covariance matrix for the parameter estimation
b_i	the estimated value of the parameter β_i
C	electric double layer capacitor (F)
D	duration of the low current (s)
I	current (A)
J	Jacobian matrix used for parameter estimation
k	discrete-time increment
$Q_{\max}$	battery capacity (Ah)
R	lumped interfacial resistances (Ω)
R_0	lumped series resistances (Ω)
s	the standard deviation of the model error
SOC_c	final estimated value of state-of-charge (SOC) by SOC estimation methodology
SOC_i	state-of-charge (SOC) estimated by current integration
SOC_v	state-of-charge (SOC) estimated by battery model
SSE	sum square error
t	time (s)
$t_{(1-\alpha/2)}$	the statistic for a confidence level of $(1-\alpha)$ given by Student's t-distribution
T	temperature (K)
V	experimentally measured battery voltage (V)
$\widehat{V}_k$	model-estimated battery voltage (V)
V_0	open circuit voltage (V)
β_i	unknown model parameter

McDonald, 2005). Existing SOC estimation methods have been applied to and demonstrated in high duty cycles, but are not sufficient to be applied to real systems. Temperature is one of the major variables determining battery operating conditions since hybrid electric vehicles are operated under extremely hot or cold conditions. However, existing SOC estimation methods rarely take into consideration the power duty and temperature; therefore, they are not sufficient for application to real systems (Gomez, Nelson, Kalu, Weatherspoon, & Zheng, 2011). Battery sensor failure is another possible obstacle for battery operation. Since the SOC needs to be estimated on-line in real time, the necessity for a robust estimation method should be emphasized for practical operations.

For SOC estimations in various operating conditions, a combination of Coulomb counting and the open circuit voltage based method is often used to overcome their individual shortcomings. The open circuit voltage based method is especially important for a dynamic battery model, which describes the battery cell in various conditions and is necessary for the SOC estimation. Dynamic battery models have been developed based on the electrochemical cell model. However, the battery models for various conditions are complicated, making them unsuitable for on-line SOC estimations. Therefore, identifying reduced complexity but rigorous models for various current and temperature conditions are important issues for the SOC estimation. A battery model employing a parameter estimation method based on sum square error minimization from experimental data is adequate for such a purpose.

In this study, a dynamic battery model and SOC estimation methodology were proposed for the estimation of the SOC under various battery system operating conditions. This paper is organized as follows. The dynamic battery model with the parameter estimation method based on sum square error minimization is described in Section 2, followed by the development of the equivalent circuit model and parameter analysis. A SOC estimation method for various operating conditions is suggested in Section 3. A combination of current integration and model based estimation is proposed. Demonstrations of the model and methodology are described under various operating conditions in Section 4. Finally, the paper closes with conclusions.

2. Dynamic battery model

2.1. Equivalent circuit model

The electrochemical cell dynamic voltage model for Li-ion batteries is a function of current, temperature, and voltage according to Eq. (1).

$$f(V, I, T) = 0 \tag{1}$$

The model is classified as follows: first principle model, equivalent circuit model, and black box model. The first principle model is a rigorous model based on electrochemistry, thermodynamics, and transport phenomena (Catti & Montero-Campillo, 2011; Garcıa, Chiang, Carter, Limthongkul, & Bishop, 2005; Martínez-Rosas, Vasquez-Medrano, & Flores-Tlacuahuac, 2011; Methekar, Ramadesigan, Pirkle, & Subramanian, 2011; Sikha, White, & Popov, 2005). It consists of several partial differential equations and ordinary differential equations. However, the computational load is high and the computational time required is longer than each SOC estimation interval. From some studies about computational algorithm optimization with model reformulation, the computational time was obtained equal or less than the interval of the SOC estimation – 10 ms (Dao, Vyasarayani, & McPhee, 2012; Subramanian, Boovaragavan, Ramadesigan, & Arabandi, 2009). However, this result has difficulties for direct application to real battery management system. The above computation of the first principle modeling was performed at a personal computer environment. On the other hand, an embedded system such as a micro control unit is used as the computation device instead of the personal computer in the battery management system environment. Therefore, the computational time is increased at the practical application. Furthermore, the battery management system takes various roles – data acquisition and storage from the system, the SOC estimation, capacity and power fade estimation, available maximum power calculation, cooling and heating of the system with on-line control and diagnosis of the system (Jung, Lee, & Kim, 2002). Accordingly, the SOC estimation algorithm is more beneficial when the algorithm is simple and light. Therefore, it is not adequate for SOC estimations.

The black box model is based on measured data and statistical approaches (Snihir, Rey, Verbitskiy, Belfadhel-Ayeb, & Notten, 2006; Wang, Cao, & Chen, 2006). It is suitable for cases in which theoretical or very complex models are difficult to solve using only existing modeling methods. It cannot be applied to interpolation and extrapolation; thus, it is not appropriate for SOC estimations. The equivalent circuit model is a reduced model based on electrochemistry (Dubarry & Liaw, 2007; Verbrugge, Liu, & Soukiazian, 2005). The model is described as a set of resistances and capacitances (Verbrugge & Conell, 2002). This model is simpler than the first principle model, and the computational runtime is extremely short. In addition, this model is based on a theoretical background. The equivalent circuit model also has disadvantages. The only monitored variables from the model are current and voltage. The behavior in the cell for the specific point could not be estimated by the model. Therefore, the equivalent circuit model is not adequate for the study of the ion transport behavior or electric potential estimation. However, the purpose of this study is estimation of the SOC and the required variables are current and voltage, fortunately. Therefore, the equivalent circuit model is reasonable for SOC estimations in spite of the disadvantages.