Control Engineering Practice 54 (2016) 81–90

Contents lists available at ScienceDirect

Control Engineering Practice

journal homepage: www.elsevier.com/locate/conengprac

An adaptive sliding mode observer for lithium-ion battery state of charge and state of health estimation in electric vehicles

Jiani Du [a], Zhitao Liu [b,*], Youyi Wang [a], Changyun Wen [a]

[a] The School of Electrical and Electronic Engineering, Nanyang Technological University, 50 Nanyang Avenue, 639798 Singapore
[b] State Key Laboratory of Industrial Control Technology, Institute of Cyber-Systems and Control, Zhejiang University, Hangzhou 310027, China

ARTICLE INFO

Article history:
Received 16 February 2015
Received in revised form
18 May 2016
Accepted 21 May 2016
Available online 4 June 2016

Keywords:
Adaptive sliding mode observer
State of charge (SOC) estimation
State of health (SOH) estimation

ABSTRACT

As the demand for electric vehicle (EV)'s remaining operation range and power supply life, Lithium-ion (Li-ion) battery state of charge (SOC) and state of health (SOH) estimation are important in battery management system (BMS). In this paper, a proposed adaptive observer based on sliding mode method is used to estimate SOC and SOH of the Li-ion battery. An equivalent circuit model with two resistor and capacitor (RC) networks is established, and the model equations in specific structure with uncertainties are given and analyzed. The proposed adaptive sliding mode observer is applied to estimate SOC and SOH based on the established battery model with uncertainties, and it can avoid the chattering effects and improve the estimation performance. The experiment and simulation estimation results show that the proposed adaptive sliding mode observer has good performance and robustness on battery SOC and SOH estimation.

1. Introduction

As the environmental-friendly vehicle with better energy efficiency, electric vehicles (EVs) have achieved rapid development currently (Ahmed, El Sayed, Arasaratnam, Jimi & Habibi, 2014; Xi, Li & Xu, 2014). However, there are still some limitations in EVs, such as the driving range, the charging time and the lifetime of the battery.

Since lithium-ion (Li-ion) battery has the advantages of high power and energy density, weak memory effect, low self-discharging rate and long cycle life (Wang, Zhang & Chen, 2014), it has been widely used in EVs. Li-ion battery meets the specific operational and environmental demands for EV's power devices. As the power supply, the Li-ion battery pack consists of series and parallel-connected batteries that should be controlled and supervised for reliable and safe operations (Sitterly, Wang, Yin & Wang, 2011). Thus, EV operation problems have resulted in the development of a battery management system (BMS) that understands the battery behavior, including the key functions of state of charge (SOC) and state of health (SOH) estimation (Fang, Wang, Sahinoglu, Wada & Hara, 2014).

SOC reveals the battery's available capacity. It is an important parameter which could be used to monitor the battery's charge and discharge process and predict the operation range of EVs (Jossen, Späth, Döring & Garche, 1999). SOC can be predicted online directly via Coulomb counting technique. However, this method is open-loop and its accuracy is influenced by the accumulated error and initial SOC error. Using open circuit voltage (OCV) to obtain SOC is also a commonly used method. In Petzl and Danzer (2013), an increment OCV measurement method is proposed and the OCV behavior is described accurately.

For any closed-loop online estimation algorithm, it is necessary to establish the battery model at first. The equivalent circuit model for Li-ion battery is commonly used in BMS for design and prediction (Plett, 2004; Hu, Li & Peng, 2012). Represented by mathematical equations derived from electric circuit theory, this kind of model can reduce the computation and need simple estimation algorithm compared with the electrochemical model. In Seaman, Dao and McPhee (2014), a survey of equivalent circuit model and electrochemical battery models is given, and it showed the differences between the two different models.

Based on the existing battery models, Kalman filter is widely applied for SOC estimation. In Fang et al. (2014); He, Xiong, Zhang, Sun and Fan (2011); Plett (2006); Di Domenico, Prada and Creff (2013), some improved nonlinear Kalman filter versions are used to provide SOC estimation with accuracy and robustness. However, the Kalman filter variants' statistical property demand for system noises may be in conflict with practical EV driving condition, as the statistical characteristics could not be known in advance. Moreover, the estimation performance is dependent on the model's accuracy, which it is difficult to obtain accurately because of Li-ion battery's complex inner electrochemical reactions. In order to

* Corresponding author.
E-mail address: ztliu@iipc.zju.edu.cn (Z. Liu).

http://dx.doi.org/10.1016/j.conengprac.2016.05.014
0967-0661/

solve the problem, some other methods are used to estimate SOC of Li-ion batteries. In Sheng and Xiao (2015), the fuzzy least square machine learning strategy is used to calculate SOC and the noise effect is reduced. In Gao, Liu and He (2011); Jiani, Youyi and Changyun (2013), the algorithm of particle filter is used on the nonlinear battery model with the statistical properties of non-Gaussian distributions. An H_∞ observer is applied to estimate Li-ion battery SOC despite the system noise statistical property in Zhang, Liu, Fang and Wang (2012), and it is used under practical conditions with unknown errors.

SOH is another important factor for Li-ion batteries. The accurate prediction of SOH can help avoid inconveniences of fatal accidents for the sudden malfunction of the battery. Li-ion battery's operation conditions are relevant to its SOH. SOH is defined as the battery's performance relative to its fresh condition, and could be used to predict the battery aging process (Chiang, Sean & Ke, 2011). SOH can be shown from battery parameter variation, such as the capacity reduction or inner resistance increase. Dual Kalman filter method is commonly used to estimate SOC and SOH simultaneously during battery operations. In Plett (2004); Kim, Lee and Cho (2012); Hu, Youn and Chung (2012); Lee, Kim, Lee and Cho (2008), two nonlinear Kalman filters are used to estimate battery SOC and SOH. An enhanced method based on Coulomb counting is proposed to estimate the Li-ion battery SOC and SOH in Ng, Moo, Chen and Hsieh (2009). The charging and discharging efficiency is considered and SOH is determined by the maximum releasable capacity. Fuzzy logic and neural networks are also used to estimate SOH (Lin, Liang & Chen, 2013; Landi and Gross, 2014), whereas these intelligent techniques inevitably depend on large data training sets and plenty of experiments.

Recently, the sliding mode technique is also applied for the battery SOC and SOH estimation. In Gholizadeh and Salmasi (2014); Kim (2008); Chen, Shen, Cao and Kapoor (2014), sliding mode observer is used as a reliable and robust tool for SOC estimation. In Kim (2010), a dual sliding mode observer method is applied on a simple circuit model to estimate battery SOC and SOH. The sliding mode observer is proposed and developed in Utkin (1992). This kind of observer deals with system uncertainty and noise efficiently during the estimation. When the sliding surface is reached, the equivalent control method can be applied to obtain some unknown system quantities (Utkin, 1992; Drakunov, 1992). In Chen and Kano (2004), an adaptive gain observer combined with sliding mode method is proposed. This kind of observer is simple to implement and robust to the *a priori* knowledge of the system noise.

In this paper, the equivalent circuit model with two resistor and capacitor (RC) networks for Li-ion battery is established. The values of the RC parameters are obtained from experiments. There may be some modeling errors for the parameters, so model uncertainties are given in the model. Based on our battery model, a sliding mode observer with adaptive gain is used to estimate battery SOC, and a different definition form with the one in Lin et al. (2013) is used for the observer gain. Comparing with the sliding mode observer in Kim (2008), the proposed observer can avoid the chattering effects and improve the estimation performance. Then, based on the proposed observer, another adaptive observer is designed to estimate SOC and SOH. Here, SOH is defined to be related to the parameter of the battery model, the proposed adaptive observer is used to estimate the states (SOC) and the unknown time-varying parameter (SOH) in the model at the same time. The experimental results and simulations show good accuracy and robustness of the proposed method.

2. Li-ion battery modeling

2.1. The equivalent circuit model

By considering the appropriate tradeoff between accuracy and complexity, the equivalent circuit model with two RC networks (Chen & Rincon-Mora, 2006) for Li-ion battery is selected as the battery model in the paper and investigated in this section. The equivalent circuit of the Li-ion battery is shown in Fig. 1. Here, V_t represents the terminal voltage. The battery's OCV is represented by a voltage source and the dynamic behavior is described by resistors and capacitors in the circuit. The function $g(SOC)$ represents the relationship between OCV and SOC. The series resistance R_s describes the battery's instant dynamics when the current changes. The RC network parameters, R_1, C_1, R_2, C_2, describe the dynamic property of the battery. The voltages across the two RC networks are represented by V_1, V_2. Series resistor R_s is responsible for the instantaneous voltage drop of the step response. R_1, C_1, R_2, C_2 are responsible for the short and long time constants of the step response. Using two RC time constants, instead of one or three, is the best tradeoff between accuracy and complexity (Chen & Rincon-Mora, 2006).

2.2. Model equations

The model equations describing the model circuit are given as follows:

$$\dot{Z} = \frac{1}{C_n} I \tag{1}$$

$$\dot{V}_1 = -\frac{1}{R_1 C_1} V_1 + \frac{1}{C_1} I \tag{2}$$

$$\dot{V}_2 = -\frac{1}{R_2 C_2} V_2 + \frac{1}{C_2} I \tag{3}$$

$$V_t = g(Z) + V_1 + V_2 + R_s I \tag{4}$$

where Z represents SOC, C_n represents the battery nominal capacity. Assume that $g(Z)$ is approximated by a series of piecewise linear functions (Kim, 2008):

$$g(Z) = k_i \cdot Z + d_i, \quad i = 1, 2\ldots\ . \tag{5}$$

Neglecting the current time derivative in one sampling interval, the time derivative of (4) is obtained as:

$$\dot{V}_t = -V_d + b_1 I, \tag{6}$$

where $V_d = \frac{V_1}{R_1 C_1} + \frac{V_2}{R_2 C_2}$, $b_1 = k_i \frac{1}{C_n} + \frac{1}{C_1} + \frac{1}{C_2}$.

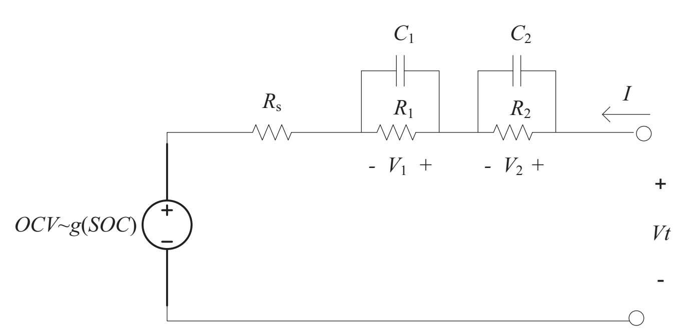

Fig. 1. The equivalent circuit model for Li-ion battery.