Computers and Chemical Engineering 64 (2014) 114–123

Contents lists available at ScienceDirect

Computers and Chemical Engineering

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

Adaptive gain sliding mode observer for state of charge estimation based on combined battery equivalent circuit model

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ARTICLE INFO

Article history:
Received 3 February 2013
Received in revised form 8 February 2014
Accepted 16 February 2014
Available online 22 February 2014

Keywords:
Adaptive gain sliding mode observer
Battery management system
Combined battery equivalent circuit model
Electric vehicle
Lithium-polymer battery
State of charge

ABSTRACT

An adaptive gain sliding mode observer (AGSMO) for battery state of charge (SOC) estimation based on a combined battery equivalent circuit model (CBECM) is presented. The error convergence of the AGSMO for the SOC estimation is proved by Lyapunov stability theory. Comparing with conventional sliding mode observers for the SOC estimation, the AGSMO can minimise chattering levels and improve the accuracy by adaptively adjusting switching gains to compensate modelling errors. To design the AGSMO for the SOC estimation, the state equations of the CBECM are derived to capture dynamics of a battery. A lithium-polymer battery (LiPB) is used to conduct experiments for extracting parameters of the CBECM and verifying the effectiveness of the proposed AGSMO for the SOC estimation.

1. Introduction

In recent decades, the progressive increase of petrol costs and air pollution of the exhaust fumes from petrol-driven vehicles has stimulated a surge of research and innovation in electric vehicle (EV) technologies. Lithium-ion or lithium-polymer batteries (LiPBs) have been adopted as primary power sources in EVs due to their merits in high power and energy densities, high operating voltages, extremely low self-discharge rate and long cycle life in the comparison with other types of batteries such as lead-acid or nickel-metal hydride batteries. For the application of the batteries in EVs, the state of charge (SOC) is one of the key parameters which corresponds to the amount of residual available capacity, its accurate indication is crucial for optimising battery energy utilisation, informing drivers the reliable EV travelling range, preventing batteries from over-charging or over-discharging and extending battery life cycles. Unfortunately, the SOC cannot be directly measured by a sensor as it involves in complex electrochemical processes of a battery. An advanced algorithm is required to estimate the SOC with the aids of measurable parameters of a battery such as terminal voltage and current.

A variety of the SOC estimation techniques has been reviewed by Piller, Perrin, and Jossen (2001) and each method has its own advantages in certain aspects. The ampere-hour (Ah) counting is the most applicable approach for the SOC indication in many commercial battery management systems (BMSs). It simply integrates the battery charge and discharge currents over time and accumulates errors caused by the embedded noises in current measurements. Furthermore, this non-model and open-loop based method has difficulty in determining the initial SOC value. An improved version of the Ah counting has exhibited better SOC estimation results by on-line evaluating charge and discharge efficiencies with the recalibration of the cell capacity (Ng, Moo, Chen, & Hsieh, 2009).

Battery impedance measurement technique is also used for the SOC estimation through injecting small ac signals with a wide range of frequencies into a battery to detect the variation of battery internal impedances (Rodrigues, Munichandraiah, & Shukla, 2000). However, the measured impedances cannot completely model the dynamics of batteries in the case of large discharge current in EVs. Furthermore, the application of impedance spectroscopy has to be carried out in temperature-controlled environment that requires bulky and costly auxiliary equipment since the temperature significantly affects impedance curves.

Another category of the SOC estimation methods is based on "black-box" established on machine learning strategies, which includes artificial neural networks (ANNs) (Shen, 2007; Shen, Chan, Lo, & Chau, 2002), fuzzy neural networks (Li, Wang, Su, & Lee, 2007), adaptive fuzzy neural networks (Chau, Wu, Chan, & Shen, 2003) and support vector machine (Hansen & Wang, 2005). These data-oriented approaches can accurately estimate the SOC without its

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http://dx.doi.org/10.1016/j.compchemeng.2014.02.015
0098-1354/

Nomenclatures

C_n	nominal capacity of LiPB (Ah)
C_p	polarisation capacitance (F)
e_{Vt}, e_Z, e_{Voc}, e_{Vp}	estimation errors
Δf_1, Δf_2, Δf_3	system uncertainty terms
R_i	ohmic resistance (Ω)
R_p	polarisation resistance (Ω)
Z	state of charge
$\hat{Z}$	estimated state of charge
V_{oc}	open circuit voltage (V)
$V_{oc}(Z)$	open circuit voltage as a function of state of charge
V_p	polarisation voltage (V)
$\hat{V}_p$	estimated polarisation voltage (V)
$\hat{V}_t$	estimated battery terminal voltage (V)
V_t	battery terminal voltage (V)
η	coulomb efficiency
ρ_i	uncertainty bounds
$\hat{\Gamma}_1$, $\hat{\Gamma}_2$, $\hat{\Gamma}_3$	adaptive switching gains
$\dot{\hat{\Gamma}}_1$, $\dot{\hat{\Gamma}}_2$, $\dot{\hat{\Gamma}}_3$	adaptive switching gains updating laws
γ_1, γ_2, γ_3	adaptation speed adjusting values

accurate initial state, but they require a large amount of data to train ANNs, which leads to the large computation burden in the BMS. Moreover, the SOC estimation results would be unpredictable in the presence of the conditions where the current profiles in EVs are different from those represented by the training data.

The Kalman filter (KF), as an optimal recursive estimator which is able to estimate the states of a linear dynamic system (Ristic, Arulampalam, & Gordon, 2004), has been developed to estimate the SOC based on linear state space battery models (Barbarisi, Vasca, & Glielmo, 2006). For nonlinear battery models, the enhanced versions of KF have been intensively investigated to achieve better results for on-line SOC estimation, such as extended KF (EKF) (Dai, Wei, Sun, Wang, & Gu, 2012; Hu, Youn, & Chung, 2012; Hu, Li, & Peng, 2012), adaptive extended KF (AEKF) (Han, Kim, & Sunwoo, 2009), sigma-point KF (SKF) (Plett, 2006a,b) and unscented KF (UKF) (He, Williard, Chen, & Pecht, 2013; Zhang & Xia, 2011). The EKF utilises the first-order Taylor series expansion to linearise the nonlinear function. This local linearisation can give rise to large estimation errors when the degrees of nonlinearity in battery models are significant and the covariance of process and measurement noises is assumed to be constant. Adaptively updating the covariance of process and measurement noises, the AEKF has been developed to improve the online SOC estimation accuracy. Instead of local linearisation, the SKF and the UKF use an unscented transformation to approximate the probability density function of the nonlinear systems with a set of sample points or so-called sigma points. Essentially, all above-mentioned KF-based approaches are based on the assumption that the covariance of measurement and process noises described by a Gaussian probability density function has to be known a priori. Moreover, their complex matrix operations may result in numeric instabilities.

The H_∞ observer based approach has also been proposed to estimate the SOC without the requirement of the exact statistical properties of the battery model (Zhang, Liu, Fang, & Wang, 2012). This approach minimises the errors between the outputs of the battery and its model so that the SOC estimation error is less than a given attenuation level. However, in order to tackle modelling errors and external disturbances, the feedback gain of H_∞ observer must be obtained by solving a linear matrix inequality, which may not provide the optimal solution for ensuring tracking error convergence.

More recently, sliding mode observer (SMO) based SOC estimation methods were adopted to overcome battery model uncertainties, external disturbances and measurement noises with sufficient large switching gains (Kim, 2006; Chen, Shen, Cao, & Kapoor, 2012). This method relies on the exhaustive understanding of battery dynamics for the appropriate selection of the switching gains, which lead to the trade-off between the magnitude of chattering in the SOC estimation and the convergence speed to reach the sliding mode surface and trigger the sliding motion.

In this paper, an adaptive gain slide mode observer (AGSMO) based on a combined battery equivalent circuit model (CBECM) has been proposed for the SOC estimation. The main advantage of the AGSMO is that the robust behaviour of the SOC estimation is guaranteed in the presence of the modelling errors, which are considered as the bounded uncertainties. This is achieved by dynamically adjusting the switching gain of the SMO in response to the tracking error while ensuring the reachability of the sliding mode surface and triggering the sliding mode. Once the sliding mode is activated, the switching gain is self-tuned to an "adequate" level to counteract the modelling errors and reduce the chattering levels, thereby improving the SOC estimation accuracy.

This rest of this paper is organised as follows. In Section 2, a CBECM is presented to model the battery dynamic behaviour. In Section 3, the AGSMO design methodology for estimating the SOC is explained. Section 4 elaborates the procedures to extract battery model parameters. Section 5 validates the proposed AGSMO for the SOC estimation by experimental results and Section 6 concludes.

2. Battery modelling

A suitable battery model is essential to the development of the model-based BMS in real EVs, which requires less computation power and fast response to ever-changing road conditions. Many types of models are developed to capture lithium-ion battey dynamics for various purposes (Ramadesigan et al., 2012). In general, they can be categorised into two main groups, which are electrochemical and equivalent circuit models (He, Xiong, & Fan, 2011; Hussein & Batarseh, 2011; Hu, Youn et al., 2012; Hu, Li et al., 2012). The electrochemical models describe the physical phenomena which occur inside batteries such as the material and charge transfer processes, ionic conduction, solid phase diffusion. They utilise partial differential equations with a large number of unknown parameters and thus a large amount of memory required, which leads to long computation time and slow response. They are usually used for battery design and simulation and hardly suitable for the BMS design in real EVs (Smith, Rahn, & Wang, 2010).

On the other hand, the equivalent circuit models simply consist of resistors, capacitors and voltage sources to form a circuit network, which leads to short computation time and quick response. Furthermore, they are the circuit in nature which is easily integrated into the BMS and power control in real EVs. Various battery equivalent circuit models have been proposed to reflect dynamic characteristics of the battery as a result of the trade-off between modelling accuracy and complexity (Lee, Kim, Lee, & Cho, 2008; Cho et al., 2012; Chen, Gabriel, & Mora, 2006; Abu-Sharkh & Doerffel, 2004).

In this paper, the combined battery equivalent circuit model (CBECM) is used to represent the dynamical behaviors of LiPB, as shown in Fig. 1. A capacitor, C_n represents the nominal capacity of the battery on the left in the model. The current source, I denotes the discharge or charge current of the LiPB and the corresponding battery terminal voltage is expressed by V_t. The voltage across the C_n as the open circuit voltage (OCV), V_{oc} varies in the range of the SOC, Z from 0% to 100% and it represents the SOC of the battery quantitatively. A resistor, R_i and a parallel-connected