Automatica 50 (2014) 896–902

Contents lists available at ScienceDirect

Automatica

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

Brief paper

A high-gain adaptive observer for detecting Li-ion battery terminal voltage collapse☆

Shayok Mukhopadhyay, Fumin Zhang [1]

School of Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, GA 30332, USA

ARTICLE INFO

Article history:
Received 3 January 2013
Received in revised form
27 June 2013
Accepted 19 November 2013
Available online 19 December 2013

Keywords:
Adaptive systems
Adaptive filters
Detection algorithms
High-gain
Trend

ABSTRACT

We use a high-gain adaptive observer and a trend filtering algorithm to detect early stages that lead to terminal voltage collapses in Li-ion batteries. This approach allows accurate detection without having sophisticated battery models. Theoretical analysis proves that the physical Li-ion battery becomes unstable when the estimated states of the observer enter instability. The trend filtering algorithm is able to detect such instability under large perturbations from the discharge current. Extensive simulation and experimental results demonstrate the effectiveness of the algorithms and its robustness under realistic perturbations.

1. Introduction

Low self-discharge rate, no memory effect, and high energy density are some of the characteristics (Linden & Reddy, 2002) that make Li-ion batteries viable as power sources for a broad range of applications. The terminal voltage of a battery drops sharply from its operating value when it is in a low state of charge (SoC) (Hatzell, Sharma, & Fathy, 2012). Hence early detection is crucial to avoid system failure.

A constant threshold voltage can be used to determine that a particular battery is discharged (Kim & Shin, 2009). This method is inaccurate since the terminal voltage of a battery depends on the discharge current it supplies. Using a constant voltage threshold can lead to false alarms in the presence of noise or large spikes in the discharge current. Another strategy is to use a threshold on the SoC. This strategy is affected by load demand, number of charge–discharge cycles and temperature. Determining the SoC involves a method named "coulomb counting", which introduces errors as the measured input current is integrated in the presence of measurement errors (Pop, Bergveld, Danilov, & Regtien, 2008).

Incorporating battery models improves the accuracy of detecting an impending terminal voltage collapse. Various types of battery models (Chen & Mora, 2006; Knauff, Dafis, Niebur, Kwatny, & Nwankpa, 2007; Rao, Vrudhula, & Rakhmatov, 2003) and associated identification techniques exist (Abu-Sharkh & Doerffel, 2004; Liu, 2011; Schweighofer, Raab, & Brasseur, 2003; Wang et al., 2012). Dynamic battery models along with adaptive thresholds (Zhang, Shi, & Mukhopadhyay, 2013) can overcome some problems with constant thresholds. Filtering algorithms (Plett, 2004; Wang & Cassandras, 2012) for state estimation and fault detection strategies like residual generation can also be used. All the above methods require detailed battery models. Substantial time and effort (Coleman, Hurley, & Lee, 2008; Sitterly, Wang, Yin, & Wang, 2011) is needed to obtain such models. Battery characteristics may differ from the model used; resulting in voltage collapse before a particular algorithm detects it. Existing results are either dependent on a particular testing methodology or on a particular type of model (Coleman et al., 2008; Plett, 2004). This paper presents an approach that aims at reducing such dependence without sacrificing the ability to detect voltage collapses.

The contributions of this paper are as follows. We present a general method for detecting Li-ion battery voltage collapses without the requirement of a detailed model. Inspired by universal adaptive stabilization (UAS) (Ilchmann, 1993; Mukhopadhyay, Li, & Chen, 2008) we develop a high-gain adaptive observer which allows us to detect changes in the trend of the transient states of a Li-ion battery. The change in trend helps us decide whether

☆ This research was partially supported by the ONR grants N00014-09-1-1074 and N00014-10-10712 (YIP), and NSF grants ECCS-0841195 (CAREER), CNS-0931576, OCE-1032285, and IIS-1319874. The material in this paper was partially presented at the 51st IEEE International Conference on Decision and Control (CDC), December 10–13, 2012, Maui, Hawaii, USA. This paper was recommended for publication in revised form by Associate Editor Kyung-Soo Kim under the direction of Editor Toshiharu Sugie.

E-mail addresses: shayok@gatech.edu (S. Mukhopadhyay), fumin@gatech.edu (F. Zhang).

[1] Tel.: +1 404 385 2751; fax: +1 4048944641.

0005-1098/$ – see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.automatica.2013.12.011

the terminal voltage of a battery is about to collapse. To the best of our knowledge, we are not aware of previous results in the literature that follow a similar approach. This method only requires the measurement of the terminal voltage of a battery and works in the presence of measurement noise or voltage spikes due to non-smooth current discharges. It is not necessary to measure the discharge current nor to use coulomb counting techniques. Thus the cost of accurate current measurement and associated errors are eliminated. This method does not estimate the SoC of a battery and does not set a static threshold on the SoC or terminal voltage, hence it is considerably robust to variations in the SoC and the terminal voltage.

This paper is organized as follows. Section 2 introduces battery models and earlier stability results. Section 3 presents the formulation of the voltage collapse detection problem. The high-gain adaptive observer and a proof of convergence is provided in Section 4. A trend detection algorithm is introduced in Section 5 for detecting terminal voltage collapse. Simulations and experimental results are presented in Sections 6 and 7 respectively. A few preliminary results have appeared in our previous paper (Mukhopadhyay & Zhang, 2012). This paper contains improved proofs and experimental results.

2. Battery model and stability

Chen and Mora's (CM) model (Chen & Mora, 2006), shown in Fig. 1, is an equivalent circuit representation of a Li-ion battery showing two coupled circuits. The left half models the variation of the SoC ρ (commonly known as the capacity remaining) and the right half models the variation of battery output voltage y as a function of the charge/discharge current $i(t)$. Knauff et al. (2007) derived the following state space realization for the CM model

$$\dot{\rho} = -\frac{1}{C_c} i \tag{1}$$

$$\dot{x}_1 = -\frac{x_1}{R_{ts}C_{ts}} + \frac{i}{C_{ts}} \tag{2}$$

$$\dot{x}_2 = -\frac{x_2}{R_{tl}C_{tl}} + \frac{i}{C_{tl}} \tag{3}$$

$$y = E_o - x_1 - x_2 - iR_s, \tag{4}$$

where y represents the voltage output from the battery, x_1 represents the voltage drop across $R_{ts} \parallel C_{ts}$ and x_2 represents the voltage drop across $R_{tl} \parallel C_{tl}$. The state $\rho \in [0, 1]$ represents the SoC. It has an initial value of 1. The states $x_1, x_2 \in [0, \infty)$ have initial values set to 0. The circuit components $C_{ts}, C_{tl}, R_s, R_{ts}, R_{tl}, E_o$ are nonlinear functions of the SoC ρ given as follows:

$$C_{ts} = -k_4 e^{-k_1\rho} + k_3 \tag{5}$$

$$C_{tl} = -k_6 e^{-k_2\rho} + k_5 \tag{6}$$

$$R_s = k_7 e^{-k_8\rho} + k_9 \tag{7}$$

$$R_{ts} = k_{10} e^{-k_{11}\rho} + k_{12} \tag{8}$$

$$R_{tl} = k_{13} e^{-k_{14}\rho} + k_{15} \tag{9}$$

$$E_o = -k_{16} e^{-k_{17}\rho} + k_{18} + k_{19}\rho - k_{20}\rho^2 + k_{21}\rho^3 \tag{10}$$

$$C_c = 3600 C f_1 f_2 \tag{11}$$

where $k_i > 0$ for $i = 1, 2, \ldots, 21$ are constants satisfying $k_1 < k_2 < k_3 < k_4 < k_5 < k_6$. In Eq. (11) $f_1, f_2 \in [0, 1]$ are factors accounting for the effects of temperature and charge–discharge cycles respectively. By default, $f_1 = f_2 = 1$, but their values will decrease after each charge–discharge cycle. C is the Ampere-hour capacity and E_o is the open-circuit voltage of a battery. The process of determining the constants $k_1 - k_{21}$ in Eqs. (5)–(10) takes considerable experimental effort (Abu-Sharkh & Doerffel, 2004; Chen & Mora, 2006; Coleman et al., 2008; Schweighofer et al., 2003) and the constants may be different for each battery.

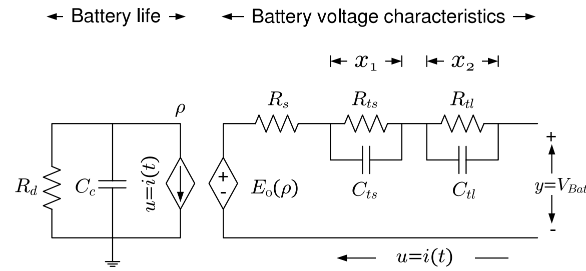

Fig. 1. Chen and Mora's battery model.

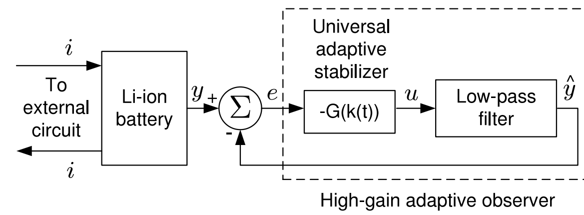

Fig. 2. Battery output voltage tracking with UAS.

The following facts regarding the stability of the CM model are known from Zhang et al. (2013). There exist two thresholds δ_2 and δ_1, $\delta_2 > \delta_1 > 0$ such that if the SoC satisfies $\delta_2 < \rho \le 1$ then the subsystem (2), (3) is asymptotically stable. If $\delta_1 \le \rho \le \delta_2$ then the subsystem is not asymptotically stable, and if $0 < \rho < \delta_1$, then the subsystem is unstable. Then we see from (4) that the terminal voltage y drops very fast to 0, i.e. collapses as the subsystem loses stability and $x_1, x_2 \to \infty$ exponentially fast.

3. Problem formulation

As a battery is gradually discharged, the value of its SoC ρ will decrease until the terminal voltage collapses. Our goal is to detect when a Li-ion battery makes a transition from its stable region of operation (i.e. $\rho \in (\delta_2, 1]$) to the unstable region (i.e. $\rho \in (0, \delta_1)$) based on the measurements of its terminal voltage y. On the other hand a temporary drop in terminal voltage does not imply that the battery is unstable. And therefore such temporary drops in terminal voltage make it difficult to detect when a battery is about to die (i.e., that the terminal voltage is about to collapse soon). Any algorithm for detecting battery failure needs to avoid false alarms caused by temporary voltage drops, yet still be sensitive enough to detect when ρ moves out of the stability region.

An observer (or filter) can be designed to estimate the SoC ρ, and then one can use the thresholds δ_1 and δ_2 to determine whether the battery is stable or not. This approach has been taken by many in the literature (Liu, 2011; Plett, 2004). The challenge with this approach is that it requires the measurement of the input current i. In addition, it relies on the use of an accurate model such as the CM model for the observer, which may not always be feasible in applications.

In this paper we propose an approach that does not require measuring the discharge current i. Therefore, we will not produce an estimate for the SoC. Instead, we aim to estimate the states x_1 and x_2 and detect battery voltage collapse based on the trend of these two states. We will also show that this approach does not require an accurate battery model for the observer.

4. The high-gain adaptive observer

Fig. 2 shows the high-gain adaptive observer we propose for detecting the terminal voltage collapse of a Li-ion battery. It consists