



Battery state of health monitoring by estimation of the number of cyclable Li-ions



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ABSTRACT

This paper introduces a method to monitor battery state of health (SOH) by estimating the number of cyclable Li-ions, a health-relevant electrochemical variable. SOH monitoring is critical to battery management in balancing the trade-off between maximizing system performance and minimizing battery degradation. The decrease of cyclable Li-ions indicates the effect on the SOH of degradation mechanisms that consume cyclable Li-ions. The unavailability of the number of cyclable Li-ions through non-invasive measurements makes its estimation necessary for in-situ SOH monitoring. In this paper, the extended Kalman filter (EKF) is used to estimate the number of cyclable Li-ions as an unknown battery parameter. The single particle model (SPM), a simplified battery electrochemical model, is used as the model in the EKF to achieve a computational complexity suitable for on-line estimation. Simulations are performed under typical electric vehicle current trajectories using an example parameter set for a hybrid-electric-vehicle battery. In the simulations, the battery is represented by the Doyle–Fuller–Newman (DFN) model, an electrochemical model with higher fidelity than the SPM. To comply with the practice, instead of using the same parameters as the DFN model in the SPM, parameterization of the SPM is performed before estimation of the number of cyclable Li-ions. The simulations show high estimation accuracy of the number of cyclable Li-ions using the EKF, even with the structural and parametric differences between the DFN model and the SPM, under both the ideal conditions and various non-ideal conditions (i.e., SOC estimation error, additional modeling error, and measurement noise).

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1. Introduction

Battery state of health (SOH) monitoring is critical to battery management in particular for balancing the trade-off between maximizing system performance and minimizing battery degradation. However, SOH is an abstract concept that needs to be deduced from other quantities that are correlated with battery health. This paper refers to these quantities as SOH indicators.

Based on the choice of the SOH indicators, the SOH monitoring literature can be divided into two categories. Most of the literature uses battery degradation effects, such as capacity fade and power fade, as the SOH indicators. Capacity fade can be identified as a parameter in empirical battery models using the extended Kalman filter (EKF) (Plett, 2004a,b,c). Power fade can be estimated from battery internal resistance, e.g. using the central difference Kalman filter as a parameter in a linear time-varying model (Remmlinger, Buchholz, Soczka-Guth, & Dietmayer, 2013). Equivalent circuit models or other empirical models

are often sufficient for these applications as the mapping between the SOH indicator and the battery voltage, current and temperature. The simplicity of these models is the key advantage to these techniques. However, degradation effects can be inaccurate in representing the SOH, because they are not only related to the battery SOH, but are also influenced by environmental conditions and use patterns (A123 Systems, 2012).

The second category uses health-relevant electrochemical variables as the SOH indicators. The benefit of using these variables is that they can uniquely indicate the level of battery health independent of environmental conditions and use patterns. Some example electrochemical variables used as SOH indicators are the number of cyclable Li-ions, the solid-electrolyte-interphase (SEI) film resistance, and the side reaction current density. In Moura, Chaturvedi, & Krstić (2014), the number of cyclable Li-ions, the SEI film resistance, and the battery state of charge (SOC) are estimated using an adaptive PDE observer and nonlinear least squares. The SEI film resistance can also be estimated using

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Nomenclature for Electrochemical Variables

This nomenclature contains only electrochemical variables for readers' convenience. The variables for the control and estimation purposes either follow the common standard in the control literature or are explained within the context.

0_r	the coordinate at the center of particles along r direction, m
$0_j/L_j$	the coordinate at the starting/ending point of an electrode along the x direction, m
A	total area of sections, m^2
$a_{s,j}$	specific surface area of porous electrodes, m^{-3}
$c_{h,j}$	Li-ion concentration, $mol \cdot m^{-3}$
$c_{s,max,j}$	maximum concentration in the solid phase, $mol \cdot m^{-3}$
$D_{h,j}$	diffusion coefficient, $m^2 \cdot s^{-1}$
F	Faraday constant, $96487 C \cdot mol^{-1}$
f_j	activity coefficient
I	current, A
$i_{0,j}$	intercalation reaction exchange-current density, $A \cdot m^{-2}$
$i_{h/total}$	phasic/total superficial current density, $A \cdot m^{-2}$
J_j	intercalation current density, $A \cdot m^{-3}$
k_j	reaction rate, $A \cdot m^4 \cdot mol^{-2}$
R	universal gas constant, $8.314 J \cdot mol^{-1}$
r	coordinate along the radius of particles, m
R_{film}	solid-electrolyte-interphase film resistance, $\Omega \cdot m^2$
R_j	radius of electrode particles, m
T	temperature, K
t	time, s
t^+	transference number
$U_{ref,j}$	equilibrium potential, V
V	voltage, V
x	coordinate along the thickness of the anode-separator-cathode sandwich, m

Greek Symbols

$\alpha_{a/c,j}$	anodic/cathodic transfer coefficients of electrochemical reaction
η_j	overpotential for intercalation reaction, V
$\kappa_j^{eff}/\sigma_j^{eff}$	conductivity of electrolyte/solid phase, $S \cdot m^{-1}$
$\phi_{h,j}$	potential, V
θ_j	solid phase stoichiometry
$\epsilon_{h,j}$	volume fraction

Subscripts

h	Phase name, where s and e stand for solid phase and electrolyte phase, respectively.
j	Section name, where p, n and sep stand for cathode, anode and separator, respectively.

retrospective-cost subsystem identification (RCSI) (D'Amato, Forman, Ersal, Ali, Stein, Peng, & Bernstein, 2012; Zhou, Ersal, Stein, & Bernstein, 2013) or an adaptive nonlinear observer (Dey, Ayalew, & Pisu, 2015). The side reaction current density can be estimated using RCSI (Zhou, Bernstein, Stein, & Ersal, 2017; Zhou, Ersal, Stein, & Bernstein, 2014) or a two-step filter (Zhou, Ersal, Stein, & Bernstein, 2015).

This paper belongs to the second category. In this work, the number of cyclable Li-ions is estimated using the EKF. In a Li-ion battery, the number of cyclable Li-ions is a measure of the charge that moves between the electrodes during charge and discharge of the battery. Therefore, the number of cyclable Li-ions is a measure of the capacity of Li-ion batteries from the first principles (Christensen & Newman, 2005; Ramadass, Haran, Gomadam, & White, 2004). During the process

of Li-ion-consuming electrochemical degradation, cyclable Li-ions are consumed through side reactions, which results in capacity fade (Arora, White, & Doyle, 1998; Christensen & Newman, 2005). Therefore, the number of cyclable Li-ions at a particular moment in the battery life reflects the remaining capacity after degradation. The EKF-based estimation algorithm developed in this paper estimates the number of cyclable Li-ions from charge and discharge data of current and voltage. By estimating the number of cyclable Li-ions repeatedly through the life of the battery, the changes in the remaining cyclable Li-ions can be tracked, and thus the battery SOH observed.

The number of cyclable Li-ions has the following advantages compared with other electrochemical SOH indicators. (i) Compared with the SEI film resistance that can be applied only to the SEI-film-formation mechanism, the number of cyclable Li-ions is a general SOH indicator for all electrochemical-based mechanisms that consume Li-ions. (ii) Compared with the side reaction current density, the number of cyclable Li-ions is expected to be more robust to uncertainties, because it results from the integration of the side reaction current density over time and space.

In this paper, SOH monitoring is investigated for Li-ion batteries whose cathode material is $LiMn_2O_4$ (LMO) mixed with other Li-compounds, a widely used battery material in the hybrid electric vehicle (HEV) and electric vehicle (EV) industry today. In this paper, this group of materials that mix LMO with other Li-ion compounds is referred to as LMO-mixture materials. LMO-mixture battery material is favored by the HEV/EV industry because of its high specific energy and power, low cost, and high thermal stability (Nagpure, Bhushan, & Babu, 2013; Tarascon & Armand, 2001). A battery with LMO alone as the cathode material is not suitable for HEV/EV applications because of its short life span (Nagpure et al., 2013), which is mainly a result of dissolution of Mn (Amine, Liu, Kang, Belharouak, Hyung, Vissers & Henriksen, 2004; Wohlfahrt-Mehrens, Vogler, & Garche, 2004). Adding other Li-ion compounds, such as $LiCoO_2$ (LCO), $LiNiO_2$ (LNO), and $LiNiMnCoO_2$ (NMC), to LMO-cathode can increase the battery life by reducing Mn dissolution (Albertus, Christensen, & Newman, 2009). Some examples of LMO-mixture materials in the HEV/EV industry include the Nissan Leaf and the Renault Kangoo that use LMO mixed with LNO as the cathode material, as well as the Chevrolet Volt that uses LMO mixed with NMC as the cathode material. Furthermore, with Mn dissolution reduced by adding other Li-compounds, Li-ion consumption dominates Mn dissolution and becomes the main aging mechanism for batteries with LMO-mixture cathode materials (Han, Ouyang, Lu, Li, Zheng, & Li, 2014; Wang, Purewal, Liu, Hicks-Garner, Soukazian, Sherman, Sorenson, Vu, Tataria, & Verbrugge, 2014). Therefore, the number of cyclable Li-ions is a suitable SOH indicator for these batteries.

Compared with (Moura et al., 2014), which also estimates the number of cyclable Li-ions as the SOH indicator, albeit for a battery with different cathode material, this paper proposes three novel approaches to take practical conditions into account in simulations. (i) In this paper, the system model used in the algorithm is the single particle model (SPM) (Di Domenico, Stefanopoulou, & Fiengo, 2010; Santhanagopalan, Guo, Ramadass, & White, 2006), a simplified battery electrochemical model that contains only two states, which yields a computational complexity suitable for on-line estimation. To verify the sufficiency of using the SPM in the algorithm, the true system (the battery) is represented in the simulations with the Doyle-Fuller-Newman (DFN) model (Doyle, Fuller, & Newman, 1993), an electrochemical model with higher fidelity than the SPM. In contrast, the simulations in (Moura et al., 2014) are based on the SPM only. (ii) In practice, parameters of the battery are not directly available, and are typically estimated from the input-output signal pairs of the battery, which is referred to as parameterization. Therefore, unlike (Moura et al., 2014) that assumes the parameters other than the ones subject to on-line estimation are known, in this paper the process of parameterization is also simulated as a preparation stage for estimation of the number of cyclable Li-ions. This preparation stage brings the simulation study closer to practice

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