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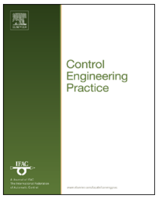

State of charge estimation for lithium-ion batteries: An adaptive approach

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ABSTRACT

State of charge (SoC) estimation is of key importance in the design of battery management systems. An adaptive SoC estimator, which is named `AdaptSoC`, is developed in this paper. It is able to estimate the SoC in real time when the model parameters are unknown, via joint state (SoC) and parameter estimation. The `AdaptSoC` algorithm is designed on the basis of three procedures. First, a reduced-complexity battery model in state-space form is developed from the well-known single particle model (SPM). Then a joint local observability/identifiability analysis of the SoC and the unknown model parameters is performed. Finally, the SoC is estimated simultaneously with the parameters using the iterated extended Kalman filter (IEKF). Simulation and experimental results exhibit the effectiveness of the `AdaptSoC`.

1. Introduction

Lithium-ion (Li^+) batteries have gained widespread use in numerous applications from consumer electronics to power tools soon after their first commercialization in 1991, thanks to their higher capacity but reduced size, superior power performance with longer cycle life (Nishi, 2001). Recent advances in electric vehicles and smart grids further strengthen the leading role of Li^+ batteries as electrical energy storage devices. Nowadays battery management systems (BMSs) are used in almost all Li^+ battery powered applications to monitor the battery status and regulate the charging and discharging processes for real-time battery protection and performance enhancement (Chaturvedi, Klein, Christensen, Ahmed, & Kojic, 2010; Pop, Bergveld, Notten, & Regtien, 2005). A fundamental component in a BMS is the module for estimation of the state of charge (SoC), the design of which has been a long-standing challenge and will be the focus of this paper.

Literature review: SoC can be defined as the percentage ratio of the present battery capacity to the maximum capacity. Two straightforward yet typical *non-model-based* SoC estimation methods are voltage translation and Coulomb counting. The former infers the SoC from the predetermined open circuit voltage (OCV)–SoC lookup table using the OCV measurement. Despite reliability, it requires the battery to rest for a long period with cutting off from the external circuit to measure the OCV, thus restricting its practical implementation without interrupting system operation. Coulomb counting, which is based on numerical integration of the current over time, may suffer from a 'drift' of SoC estimates from the true values due to cumulative integration errors and noise corruption. For a survey of both methods, refer to Pop et al. (2005), Piller, Perrin, and Jossen (2001) and the references therein.

In recent years, considerable attention has been directed toward *model-based* approaches for real-time SoC estimation with improved accuracy. Equivalent circuit models (ECMs), which include virtual voltage source, internal resistance and RC network to simulate battery dynamics, have been used extensively. The state observability of a ECM is studied in Chiasson and Vairamohan (2006), by which a SoC estimation algorithm is designed. In Plett (2004), the extended Kalman filter (EKF) is applied to ECMs to estimate the SoC with approximate dynamic error bounds. The estimation results are enhanced in Plett (2006) using the sigma-point Kalman filter (SPKF) that is known to have better accuracy and numerical stability. Other nonlinear observer-based design approaches have also been used to construct ECM based SoC estimators. Among them, sliding mode observer (Kim, 2006), adaptive model reference observer (Verbrugge & Tate, 2004) and Lyapunov-based observer (Hu & Yurkovich, 2012) are highlighted here.

Another important type of battery models is built upon electrochemical principles that describe intercalation and deintercalation of Li^+ ions and conservation of charge within a battery. Such electrochemical models have the merit of ensuring each

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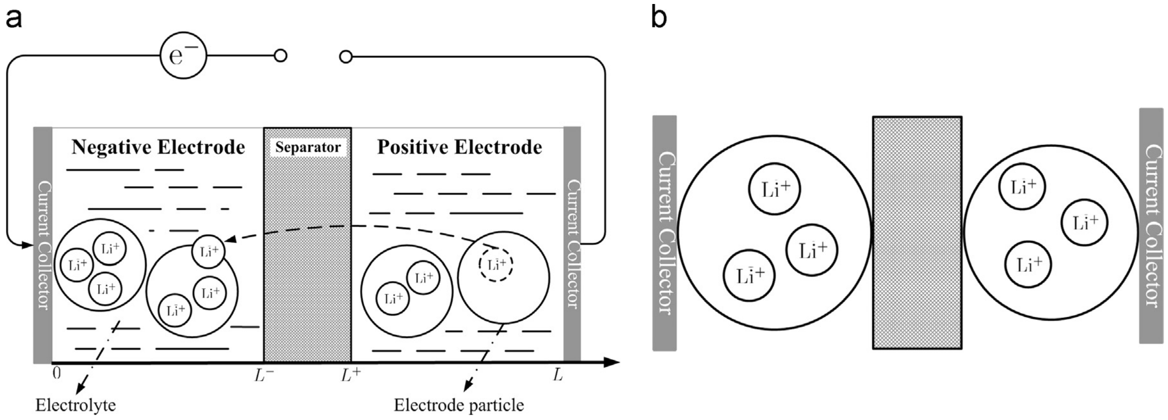

Fig. 1. (a) Schematic characterization of a Li$^+$ battery; (b) the single-particle model.

model parameter to retain a proper physical meaning. However, they have a complex structure based on partial differential equations (PDEs), often necessitating model simplification or reduction. A linear reduced-order electrochemical model is established in Smith, Rahn, and Wang (2008), to which the classical KF is employed for SoC estimation. In Domenico, Di Fiengo, and Stefanopoulou (2008), the EKF is implemented to estimate SoC using an ordinary differential equation (ODE) model obtained from PDEs by finite-difference discretization. The unscented Kalman filter (UKF) is used in Santhanagopalan and White (2010) to avoid model linearization in SoC estimation. Rather than using the ODE model after simplification, nonlinear SoC estimators are also developed in Klein et al. (2013), Moura, Chaturvedi, and Krstic (2012) through direct manipulation of PDEs.

Adaptive SoC estimation, which enables the SoC to be estimated when the model parameters are unavailable, has been discussed for some ECMs and electrochemical models, e.g., Plett (2006), Barbarisi, Vasca, and Glielmo (2006), and McIntyre, Burg, Dawson, and Xian (2006). This paper makes new contributions to study of this topic, with the aim of developing an adaptive SoC estimator that is easy to implement and sound both theoretically and practically.

Statement of contributions: An electrochemical battery model with reduced complexity in structure is derived from the single particle model (SPM) first. For this model, a detailed analysis of joint local observability/identifiability of the SoC variable and the model parameters is performed, which indicates that the SoC variable can be locally identified for admissible input. This result shows that adaptive estimation of SoC is achievable. On the basis of the analysis, an adaptive SoC estimator, `AdaptSoC`, is built using the iterated extended Kalman filter (IEKF), where the SoC and model parameters are estimated concurrently but only SoC estimates are reliable. Through both simulation and experimental study, the `AdaptSoC` algorithm is shown to have excellent SoC estimation performance in the presence of unknown parameters. Meanwhile, its efficient implementation lends itself to practical application. The analysis and results presented in this paper can also be readily extended to other types of battery models.

2. A reduced-complexity model

In this section, the working mechanism of Li$^+$ batteries is briefly introduced first, followed by a review of the single particle model (SPM). Then a reduction of the SPM is developed for the purpose of SoC estimation.

Table 1
Definitions and nomenclature.

Variables	
Φ_s	Electric potential in the solid electrode
Φ_e	Electric potential in the electrolyte
c_s	Concentration of Li$^+$ in the solid electrode
c_{ss}	Concentration of Li$^+$ at a particle's spherical surface
J	Molar flux of Li$^+$ at the particle's surface
J_0	Exchange current density
η	Overpotential of reaction in the cell
U	Open-circuit potential
I	External circuit current
V	Terminal voltage
r	Radial dimension of the particle
Physical parameters	
D_s	Diffusion coefficient of Li$^+$ in the solid electrode
$\overline{r}$	Radius of the spherical particle
F	Farady's constant
S	Specific interfacial area
T	Temperature of the cell
α^a	Anodic charge transport coefficient
α^c	Cathodic charge transport coefficient
R	Universal gas constant
R_c	Phase resistance
R_f	Film resistance of the solid electrolyte interphase
ρ	Coulombic efficiency of the cell
C_n	Nominal capacity of the cell
Subscripts	
s	Solid electrode phase
e	Electrolyte phase
n	Negative electrode
p	Positive electrode
j	n or p

2.1. The working mechanism of Li$^+$ batteries

A schematic description of a Li$^+$ battery is shown in Fig. 1(a). The positive electrode is typically made from Li compounds, e.g., $Li_xMn_2O_4$ and Li_xCoO_2. Small solid particles of the compounds are compressed together, giving birth to a porous structure. The negative electrode is also porous, which usually contains graphite particles. The interstitial pores at both electrodes provide intercalation space, where the Li$^+$ ions can be moved in and out and stored. The electrolyte contains free ions and is electrically conductive, where the Li$^+$ ions can be transported easily. The separator physically separates the electrodes apart. It allows the migration of Li$^+$ ions from one side to the other, but prevents electrons from passing through. The electrons are thus forced to flow through the external circuit.

During the charging process, Li$^+$ ions are extracted from the particles at the positive electrode into the electrolyte, and