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# Evaluation of electrochemical models based battery state-of-charge estimation approaches for electric vehicles

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#### HIGHLIGHTS

• Two order-reduced electrochemical models of lithium-ion batteries are derived.

• The reduced models are verified and evaluated experimentally.

• A SPM-based SoC estimation approach combined with EKF is proposed.

• The performances of five model-based approaches are compared under a UDDS test.

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#### ABSTRACT

Real-time and accurate state-of-charge (SoC) estimation of lithium-ion batteries is a critical issue for efficient monitoring, control and utilization of advanced battery management systems (BMS) in electric vehicles (EVs). The electrochemical mechanism model can accurately describe the spatially distributed behavior of the internal states of the battery, but the model is complex and computationally huge, which is difficult to simulation in vehicle BMS. To solve these problems, it is necessary to simplify the battery mechanism model and study the model-based SoC estimation approaches. In this paper, two orderreduced models including an average-electrode model (AEM) and a single particle model (SPM) are first proposed. Additionally, the reduced-models combined with algorithms, including an extended Kalman filter (EKF), a sliding-mode observer (SMO) with a uniform reaching law (URL) and an SMO with an exponential reaching law (ERL), are employed to design battery SoC observers. To achieve an optimal trade-off between the tracking accuracy and convergence ability, the performances of these approaches are compared under an Urban Dynamometer Driving Schedule (UDDS) test. The comparison results indicate that the SPM-EKF approach can obtain a reliable battery voltage response and a more accurate SoC estimation than other approaches.

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#### 1. Introduction

To date, incentives for environment-friendly society have played an important role in promoting transportation electrification. Electric vehicles (EVs) have received increasing attention due to their low emissions and high efficiency compared with other vehicles [1–3]. For automotive industry lithium-ion (Li-ion) batteries have been among the most attractive candidates for electric vehicles (EVs) applications because of their beneficial features,

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http://dx.doi.org/10.1016/j.apenergy.2017.05.109 0306-2619/© 2017 Elsevier Ltd. All rights reserved. such as a high-power density and high-energy density, and a long service life [4,5]. To guarantee safe and efficient operation of Li-ion batteries, a battery management system (BMS) is required to monitor and control the batteries so as to ensure a longer life-span [6]. Thus, a real-time, precise state estimation of Li-ion is essential for BMS. However, some of these states cannot be directly obtained by the sensors and they are estimated by using some measurable variables such as voltage and current. State-of-charge (SoC) is one of these states with a particular concern in the BMS. The SoC represents the remaining battery capacity that is available from the battery. Based on the accurate SoC estimation, the BMS can determine the end of battery charge and discharge, optimize energy efficiency and protect the battery from being over-charged or over-discharged [6]. In this study, we aim to derive order-

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2

C. Lin et al./Applied Energy xxx (2017) xxx-xxx

#### Nomenclature

$A \\ c_e \\ \kappa^+ \\ c_s^i \\ c_{s,e}^i \\ C_{s,max}^i \\ D_s^i $	current collector area (cm <sup>2</sup> ) electrolyte phase Li-ion concentration (mol/L) reaction rate [A·mol <sup>1.5</sup> /m <sup>5.5</sup> ] solid phase Li-ion concentration (mol/m <sup>3</sup> ) solid phase Li-ion concentration at surface (mol/m <sup>3</sup> ) solid phase Li-ion saturation concentration (mol/m <sup>3</sup> ) effective diffusion coefficient in solid phase (m <sup>2</sup> /s)	$F$ $I$ $L^{i}$ $r$ $R^{i}$ $i = p, n$	Faraday's number (C/mol) battery current (A) length of the electrodes (m) radial coordinate (m) radius of solid active particle (nm) positive/negative electrode
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reduced electrochemical mechanism models and evaluated the performances of model-based battery SoC estimation approaches for EVs. We summarize the related literature and introduce our contributions as follows.

Extensive efforts have been made to explore the task of SoC estimation over the past two decades. These approaches can be roughly divided into three types: (1) non-model based approaches, (2) machine learning algorithms, and (4) model-based approaches [6,7]. In the following paragraphs, each category is reviewed, and our contributions are presented.

The non-model based approaches mainly include the Coulomb counting and the open-circuit voltage (OCV) based techniques [8]. The Coulomb counting approach can be used to easily calculate the SoC by directly integrating battery current over time [9]. However, it suffers from problems such as inaccuracy of the initial SoC value and accumulated calculation errors [10]. To reduce the initial SoC errors, an OCV-based approach is often applied to calculate the initial SoC value from the monotonic relationship between OCV and SoC. Although this is an effective way to recalibrate accumulated errors, it is difficult to perform real-time measurements of the OCV because of the long resting periods required in this approach [11]. Machine learning algorithms including artificial neural networks [12], fuzzy logic [13] and support vector regression (SVR) [14] treat a battery as a kind of "black box". These algorithms can establish the corresponding nonlinear relationship between the battery inputs and outputs based on a large set of training data [6]. A limited robustness and a significant decrease in SoC estimation accuracy may result from the use of a limited training data set because these algorithms strongly rely on the quantity and quality of the training data set. In addition, these algorithms are unacceptably time-consuming.

To solve these problems, many model-based SoC estimation approaches have been presented by researchers recently. Modelbased estimation approaches can obtain high SoC accuracy in a closed-loop system by self-correcting and tackling disturbance uncertainty. Dynamic characteristics of the batteries can be described by an Equivalent circuit models (ECMs) or an electrochemical mechanism models. The model-based SoC estimation approaches can be developed by employing Kalman filter, voltage inversion techniques, linear parameter varying system techniques, sliding-mode observer (SMO), multi-rate particle filtering (PF) and back-stepping PDE, etc. Among all the proposed algorithms, a Kalman filter family accounts for a large proportion because of its advantage in finding an optimal solution for a linear Gaussian system. A variety of the Kalman filter appears in non-linear batteries. For instance, Plett et al. [15] used an ECM to simultaneously estimate the battery SoC and the model parameters. Xiong and colleagues successively used ECMs with an Kalman filter (EKF) and an unscented Kalman filter (UKF) in [11,16] to identify the battery SoC and model parameters for a BMS in a real environment. Verbrugge and colleagues used ECMs combined with voltage inversion techniques, such as ampere-hour integration and adaptive parameter identification approaches [17]. Recently, a linear parameter varying system techniques was proposed in [18]. Although these ECM-based estimation approaches have the advantage of simplicity, fewer calculations and acceptable precision, they require large amounts of experimental data for parameterization. Moreover, it is difficult to obtain the internal dynamic characteristics of the batteries, and the parameters identified in these models lack clear physical meanings.

In light of these shortcomings, electrochemical mechanism models that rely on a set of coupled nonlinear partial differential equations (PDEs) that describe the battery dynamics, such as Liion diffusion and electrochemical kinetics, have recently attracted considerable attention for the SoC observer designs of Li-ion batteries. To mitigate the potential issues related to the model complexity and computation burden, full order electrochemical mechanism model (known as pseudo two-dimensional model (P2D)) is required to be reasonably order-reduced. Some estimation algorithms based on order-reduced electrochemical mechanism models have been developed for battery SoC and parameter estimation. A common type of order-reduced model, called a single-particle mode (SPM), is based on the hypothesis that the solid-phase of each electrode can be idealized as a unique spherical particle and that the Li concentration gradients in space and time in the electrolyte can be neglected. A number of SPM-based SoC estimation approaches, including a SMO with a uniform reaching law (URL) (hereafter denoted as SMO-URL) [19], Unscented Kalman filtering [20], multi-rate particle filtering (PF) [21] and a PDE state estimator, have been represented in the literature. Santhanagopalan and White used an SPM-based EKF to estimate the SoC of Li-ion batteries [22]. In [23,24], SMO observer and Luenberger type PDE nonlinear observer are adopted on SPM and P2D model to estimate battery SoC. An adaptive PDE observer framework was proposed in [25], where a back-stepping PDE observer is applied on a SPM for battery SoC estimation and parameter identification [26]. Soon after the development of the SPM, electrolyte effects were considered by several researchers in a type of orderreduced model, known as an average-electrode model (AEM) [27]. Domenico and colleagues used an AEM in combination with a low order EKF to design an observer for battery SoC estimation [28], and the results were compared with those of a full order model simulation [29-31]. From the above review on orderreduced model-based SoC estimation approaches, the most of existing work has one or more of the issues, which can be concluded as follows: (1) utilization of a fully linearized model; (2) computational complex in real-time applications; (3) lack of theory verification for the convergence of the estimation algorithms.

To address the above issues, we employ finite difference methods to derive two order-reduced models including AEM and SPM in a state space form. In this paper, we analyze the state space and observability properties of the reduced models and provide an analytical proof of stability properties for the estimation algorithms. In this study, we also proposed order-reduced electrochemical mechanism models based SoC estimation approaches by using EKF. To further explore the potential application of SoC estimation approaches in EVs, a comparison of the performances of the reduced-model based approaches, including EKF, SMO-URL and Download English Version:

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