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Multi-time-scale observer design for state-of-charge and state-of-health of a lithium-ion battery

Changfu Zou [a, *], Chris Manzie [a], Dragan Nešić [b], Abhijit G. Kallapur [a]

[a] Department of Mechanical Engineering, University of Melbourne, VIC 3010, Australia
[b] Department of Electrical and Electronic Engineering, University of Melbourne, VIC 3010, Australia

HIGHLIGHTS

- A multi-time-scale estimation algorithm for singularly perturbed systems is proposed.
- Stability property of estimation errors is rigorously characterized.
- This proposed algorithm is pertinently applied to estimate battery states.
- Reduction techniques are systematically applied to develop appropriate battery model.
- Both the SOC and SOH are demonstrated to be effectively estimated.

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ABSTRACT

The accurate online state estimation for some types of nonlinear singularly perturbed systems is challenging due to extensive computational requirements, ill-conditioned gains and/or convergence issues. This paper proposes a multi-time-scale estimation algorithm for a class of nonlinear systems with coupled fast and slow dynamics. Based on a boundary-layer model and a reduced model, a multi-time-scale estimator is proposed in which the design parameter sets can be tuned in different time-scales. Stability property of the estimation errors is analytically characterized by adopting a deterministic version of extended Kalman filter (EKF). This proposed algorithm is applied to estimator design for the state-of-charge (SOC) and state-of-health (SOH) in a lithium-ion battery using the developed reduced order battery models. Simulation results on a high fidelity lithium-ion battery model demonstrate that the observer is effective in estimating SOC and SOH despite a range of common errors due to model order reductions, linearisation, initialisation and noisy measurement.

1. Introduction

There is an ever-growing trend towards electrifying the powertrain in automotive industry to address the increasingly stringent standards on tailpipe emission and fuel economy. However electric vehicles typically suffer from high relative costs, range anxiety and long charging time [1], which are all related to the battery system. Although lithium-ion batteries have been recognized as a suitable cell chemistry technology for vehicle applications, the properties such as energy/power density, ability to sustain fast “refueling”, longevity, and safety are still clearly inferior to their counterpart, the internal combustion engines [2]. Accordingly, advanced management enabling safe and optimal utilization of the battery becomes sought.

For battery management, accurate knowledge of the state-of-charge (SOC) and state-of-health (SOH) is crucial. SOC represents the available capacity remaining in the battery and is often used in the prediction of vehicle's driving range and terminal conditions for battery operations. SOH quantifies the degree of battery degradation and is useful for prediction of life time. SOC and SOH are separately functions of unmeasurable battery internal states, particularly the ion concentrations and capacity fade [3]. This motivates the development of state estimation algorithms for battery systems that monitor the internal states in real-time. However, this is a very challenging task for at least two reasons. First, the underlying dynamics of a lithium-ion battery describing distributed concentration diffusion and local current and potential changes are governed by coupled nonlinear partial differential

* Corresponding author.
E-mail address: cezou@student.unimelb.edu.au (C. Zou).

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equations (PDE) [4,5]. This system model is very computationally expensive so that its use for online estimator design can be impractical. Second, battery dynamics including electrochemical, thermal, electrical, and aging phenomena, exhibit multiple time-scales [6]. Conventional observer design techniques for this singularly perturbed system may lead to ill-conditioned observer gains and potentially undermine the convergence properties [7].

To alleviate potential issues due to model complexity, various estimation algorithms have been proposed based on reduced-order models. Equivalent circuit models (ECMs) are extensively used for battery state estimation because of their relatively simple mathematical structure. For instance, by designing Kalman filter (KF) or its variations, ECMs have been used for battery parameters and/or SOC estimation, e.g. Refs. [8–10] Meanwhile, ECM-based sliding mode observer (SMO) and particle filter (PF) were proposed for estimation of battery states [11,12]. Recently, attempts at the estimation of SOC and SOH have been made by using similar models, where the SOH was represented by some parameters [13]. However, in ECMs, battery internal dynamics including concentration diffusion and electrochemical kinetics are essentially ignored. This leads to limited accuracy of these models particularly at an extended operating range. Furthermore, without insights into the system physical limitations [4,14], the resulting model-based algorithms may be necessarily conservative.

In light of this, reductions for the physics-based battery model are attracting considerable attention. A semi-rigorous approach for systematic simplification of the full PDE models has been previously proposed in Ref. [5]. The simplified PDE models have been shown a high-fidelity and can be used as a starting point for control-oriented modelling. Using numerical order reduction approaches, partial simplifications have been widely conducted on the temperature model and the electrochemical model, e.g. in Refs. [15,16,17].

Based on the reduced electrochemistry-based models, a number of papers emerged recently for SOC estimation. Specifically, the single particle model (SPM), where each electrode is assumed to be one lumped particle with only two states representing the system dynamics, were used for state estimation and showed efficient under some operating conditions [18,19]. However, few papers have been observed in literature to estimate both SOC and SOH using physics-based models. A simplified SPM that neglects the cathode dynamics for SOC and SOH estimation was considered in Ref. [20]. This is useful only for the specific batteries where the dynamics in the cathode are much faster than that in the anode and at low and moderate charging rates. Additionally, the aging dynamics have not been explicitly considered. Whilst previous attempts at using physics-based models have been proposed, e.g. Ref. [3], they do not directly address the multiple time scales in the problem.

Multi-time-scale estimation theory was studied for a class of linear systems in Ref. [21], and was later extended for some nonlinear systems by Ref. [7]. In those papers, observer design was realised through restriction of the process dynamics on the slow manifold and thus taking analytical and computational advantages that the lower-dimensional systems bring [22]. Whereas, for the battery case, both the fast and slow states are required for SOC and SOH estimation. Another difficulty is that the battery operates over multiple charge and discharge cycles leading to oscillating states in the electrochemical dynamics.

To address the existing issues in battery state estimation, this article proposes a new algorithm for multi-time-scale observer design. The singularly perturbed systems are decomposed into a boundary-layer (fast) model and a reduced (slow) model using a singular perturbation approach and the averaging theory. Based on these simplified models, a nonlinear observer with fast and slow gains is designed for state estimation of the fast and slow dynamics. This theoretical result is applied to a battery system for estimation of the SOC and SOH. Starting from an initial PDE-based high-fidelity battery model, order reduction techniques are systematically used by gradually introducing relevant assumptions. The obtained models are justified to satisfy the requirements of the proposed multi-time-scale estimation algorithm. The performance of the designed estimator for SOC and SOH is demonstrated via simulations.

The rest of this paper is organized as follows. In Section 2, the theory development for multi-time-scale observer design is presented including clearly stated assumptions and rigorous analysis for stability of the error dynamic systems. This theoretical result is applied to a lithium-ion battery for the estimation of SOC and SOH in Section 3. Simulation results to evaluate the proposed algorithm are provided in Section 4, followed by conclusion of this work in Section 5.

2. Multi-time-scale observer theory development

This section describes the development of multi-time-scale estimation algorithm. We consider nonlinear singularly perturbed systems with fast and slow states, $\mathbf{x}_f \in \mathbb{X}_f \subset \mathbb{R}^{n_f}$ and $\mathbf{x}_s \in \mathbb{X}_s \subset \mathbb{R}^{n_s}$, where $\mathbb{X}_f$ and $\mathbb{X}_s$ are bounded sets. u is the system input and $u \in \mathbb{U}$. Particularly in this system, $\mathbf{y}_f$ and $\mathbf{y}_s$ represent the fast and slow measurable system outputs; $\mathbf{z}_f$ and $\mathbf{z}_s$ are the unmeasurable system outputs separately in the fast and slow time-scales and belong to the sets of $\mathbb{R}^{m_f}$ and $\mathbb{R}^{m_s}$. ϵ is a perturbation parameter and is small and positive. The system governing equations can be formulated as

$$\dot{\mathbf{x}}_f = F_f\left(\mathbf{x}_f, \mathbf{x}_s, u, \epsilon\right) \tag{1a}$$

$$\dot{\mathbf{x}}_s = \epsilon \mathcal{F}_s\left(\mathbf{x}_f, \mathbf{x}_s, u, \epsilon\right) \tag{1b}$$

$$\mathbf{y}_f = H_f\left(\mathbf{x}_f, \mathbf{x}_s, u, \epsilon\right) \tag{1c}$$

$$\mathbf{z}_f = W_f\left(\mathbf{x}_f, \mathbf{x}_s, \epsilon\right) \tag{1d}$$

$$\mathbf{y}_s = \mathcal{H}_s\left(\mathbf{x}_f, \mathbf{x}_s, \epsilon\right) \tag{1e}$$

$$\mathbf{z}_s = \mathcal{W}_s\left(\mathbf{x}_f, \mathbf{x}_s, \epsilon\right) \tag{1f}$$

Assumption 1. $\epsilon \ll 1$

If Assumption 1 holds, from Ref. [26] the slow state can be replaced with an equilibrium state $\overline{\mathbf{x}}_s$ and a boundary layer system approximates the fast dynamics, i.e.:

$$\dot{\mathbf{x}}_f(t) = F_f\left(\mathbf{x}_f(t), \overline{\mathbf{x}}_s, u(t), 0\right) \tag{2a}$$

$$\mathbf{y}_f(t) = H_f\left(\mathbf{x}_f(t), \overline{\mathbf{x}}_s, u(t), 0\right) \tag{2b}$$

$$\mathbf{z}_f(t) = W_f\left(\mathbf{x}_f(t), \overline{\mathbf{x}}_s\right) \tag{2c}$$

In the following, an assumption on the stability property of the system (2) is imposed. In the statement, a class-$\mathcal{K}$ function means that a function, $\gamma(\cdot)$, from $\mathbb{R}_{\geq 0}$ to $\mathbb{R}_{\geq 0}$ is continuous, strictly