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A data-driven multi-scale extended Kalman filtering based parameter and state estimation approach of lithium-ion polymer battery in electric vehicles

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HIGHLIGHTS

- A data-driven multi-scale extended Kalman filtering is developed for battery system.
- A lumped parameter battery model against different aging levels has been proposed.
- The proposed approach has less computation efficiency but higher estimation accuracy.
- The proposed approach can estimate battery parameter, capacity and SoC concurrently.
- The robustness of the proposed approach against different aging levels is evaluated.

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ABSTRACT

Accurate estimations of battery parameter and state play an important role in promoting the commercialization of electric vehicles. This paper tries to make three contributions to the existing literatures through advanced time scale separation algorithm. (1) A lumped parameter battery model was improved for achieving accurate voltage estimate against different battery aging levels through an electrochemical equation, which has enhanced the relationship of battery voltage to its State-of-Charge (SoC) and capacity. (2) A multi-scale extended Kalman filtering was proposed and employed to execute the online measured data driven-based battery parameter and SoC estimation with dual time scales in regarding that the slow-varying characteristic on battery parameter and fast-varying characteristic on battery SoC, thus the battery parameter was estimated with macro scale and battery SoC was estimated with micro scale. (3) The accurate estimate of battery capacity and SoC were obtained in real-time through a data-driven multi-scale extended Kalman filtering algorithm. Experimental results on various degradation states of lithium-ion polymer battery cells further verified the feasibility of the proposed approach.

1. Introduction

To address the two urgent goals nowadays of protecting the environment and achieving energy sustainability, it is of strategic significance on a global scale to replace oil-dependent vehicles with electric vehicles. Battery, as an important on-board electric energy storage, has been widely used in various electric vehicles. However, to satisfy the operation voltage and traction power requirements of electric vehicles, battery packs have to be made up of hundreds of cells connected in series or parallel to overcome the limitations of low energy density, low cell capacity and low cell voltage. But how to avoid the adverse effect of cell inconsistency on battery pack performance and prolong the service life of both the pack and the cells are posing tremendous technological challenges to battery State-of-Charge (SoC) and capacity estimation techniques. Its accurate estimation is not only beneficial for the efficient vehicular energy management, but also for the diagnosis and prognosis of the battery behavior.

A wide variety of SoC estimation methods have been put forward to improve battery SoC determination [1–16], each one has its own advantage. The most commonly used methods fall into two major categories: the lumped parameter battery model including equivalent circuit models [1–9] and electrochemical model [10] based SoC estimation method and the "black box" based methods, such as artificial neural networks based methods [11–13], fuzzy logic based methods [14,15] and support vector regression (SVR) based

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method [16]. The authors in [1] presented a comparative study of the equivalent circuit model-based SoC estimation approaches algorithms including Luenberger observer, extended Kalman filtering (EKF) and sigma point Kalman filtering (SPKF) to monitor the SoC of a $LiFePO_4$ lithium-ion battery (LiB) cell, and the results showed that the SPKF was an optimal choice to estimate dynamic SoC behavior. The authors in [2–4] presented an equivalent circuit battery model-based method for real time battery cell SoC estimation using linear parameter varying (LPV) system and reduced order EKF techniques. Xiong et al. [5,6] proposed an equivalent circuit model based SoC estimation method using adaptive Extended Kalman Filter (AEKF) to estimate battery SoC through the measurements of battery current and voltage. The authors in [10] proposed a reduced order electrochemical model to estimate internal battery potentials, concentration gradients, and SoC from external current and voltage measurements. The authors in [11] presented a novel approach using adaptive artificial neural network and neuron-controller for online cell SoC determination. The authors in [16] presented v-Support Vector Regression algorithm based method to estimate the SoC.

A common drawback of the above SoC estimation methods is that the model parameters are identified with offline data or the training data for "black-box" models is built by previously measurement; as a result, the battery model parameters variances following with its degradation and varied operation conditions are ignored. Thus, the reliability and applicable of these SoC estimators were not sufficiently discussed. In order to overcome these drawbacks, online parameter identification methods were proposed to track the real-time behavior of the battery. The authors in [17,18] used the method of recursive least square with an optimal forgetting factor to carry out the online battery parameters identification and state estimation. However, both the model parameters and capacity are important battery parameters, while the above method fails to estimate the battery capacity and model parameters concurrently. The reliable capacity estimate is indispensable for an accurate SoC estimate, and which is of paramount importance for battery State-of-Health (SoH) indication.

A number of research methods have been proposed for estimating the cell capacity and then to calculate the SoH with the estimated capacity taking the SoH is the ratio of estimated capacity over its nominal value, most of them are carried out with lumped parameter models [5,19–26]. The authors in [19] presented a neural-network model online estimation method for SoH of valve-regulated lead acid batteries on the basis of the relationship between the estimated SoC and the battery open circuit voltage. The authors in [20] presented a probabilistic neural network (PNN) based SoH estimation method for LiB, where the PNN was trained using 100 pieces of batteries. The authors in [21] presented an experiment data based SoC and SoH estimation method with fuzzy logic system, while the experiment data were provided from electrochemical impedance spectroscopy (EIS) measurements on new and aged cells. However, for electric vehicles application, it is not easy to obtain the overall data for training, which leads to the inaccuracy prediction in complex variable practical application. On the contrary, the dynamic battery model-based method can provide a cheap alternative in estimation or it can be used along with a sensor-based data-driven scheme to provide some redundancy. The authors in [22–26] presented battery model-based dual/joint Kalman filters method to estimate the battery SoC and capacity concurrently. However, their model parameters were identified by offline data and the influence of the battery degradation or operation conditions over model parameters are not discussed, as a result, their performance are not verified adequately. Furthermore, the authors in [22–25] used dual EKF or dual SPKF to execute the capacity and SoC joint estimation with one time scale. However, in considering the system parameter inclines to change slowly over time while system state is prone to fast variation over time, it is not an optimal choice to use the same calculated time scale for battery parameter and state calculation; on the contrary, it will largely increase the computational burden of battery management system (BMS). Thus the time scale separation based method, which uses macro scale to calculate the battery parameter and uses micro scale to calculate the battery state, will lower the computation cost of BMS. The authors in [26] used the two time scales to estimate the battery capacity and SoC concurrently, and the difference of estimated SoC with dual scales was used as an innovation to update the Kalman gain to correct the capacity. But it is very hard to obtain the "true" SoC, thus it is not easy and reliable to obtain accurate capacity by the estimated SoC especially when the estimated SoC is not stable.

The purpose of this paper is to establish general battery parameter and state dual estimation method using data-driven multi-scale EKF algorithm, which is a key technique to safeguard the optimal and safe use of battery – energy source in various electric vehicles and promote the commercialization of electric vehicles. The description of the research system and the data-driven multi-scale EKF algorithm are presented in Section 2. Section 3 describes the implementation flowchart of the proposed approach. To evaluate the proposed approach, four different health status of lithium-ion polymer battery (LiPB) cells are used to carry out the verification are shown in Section 4. The experiment, simulation results and evaluation of the proposed method are reported in Section 5 before conclusions are drawn in Section 6.

2. Data-driven multi-scale extended Kalman filtering

To make the discussion more convenient, firstly the section constructs a very general framework for discrete-time lumped dynamic system with dual scales. Afterwards, based on the review of dual EKF, the implementation process of online measured data driven based multi-scale EKF is built.

2.1. System description

In regarding that the slow-varying characteristic on battery parameter and fast-varying characteristic on battery state, we use multi-scale method to construct the discrete time state-space equation, where the system parameter and system state are predicted with the macro and micro scale separately. To be more specific, we consider the problem of learning both the hidden states χ and parameters θ of a very general framework for discrete-time nonlinear dynamical system as:

$$\begin{cases} \boldsymbol{\chi}_{k,l+1} = \mathbf{F}(\boldsymbol{\chi}_{k,l}, \boldsymbol{\theta}_k, \mathbf{u}_{k,l}) + \omega_{k,l}, \boldsymbol{\theta}_{k+1} = \boldsymbol{\theta}_k + \rho_k \\ \mathbf{Y}_{k,l} = \mathbf{G}(\boldsymbol{\chi}_{k,l}, \boldsymbol{\theta}_k, \mathbf{u}_{k,l}) + \upsilon_{k,l} \end{cases} \tag{1}$$

where $\boldsymbol{\chi}_{k,l}$ is the system state matrix at the time $t_{k,l} = t_{k,0} + l \times T$ $(1 \leqslant l \leqslant L)$, herein the T is a fixed sampling interval between two adjacent measurement points, k and l being the two time-scales indices for system parameter with macro scale and system state with micro scale respectively; $u_{k,l}$ is the exogenous input matrix at time $t_{k,l}$; $\mathbf{y}_{k,l}$ is the system observation (or measurement) matrix at time $t_{k,l}$; $\omega_{k,l}$ and ρ_k are the process noise matrix for state and model parameter respectively, $\upsilon_{k,l}$ is the measurement noise matrix. Note that L represents the level of time-scale separation and that $\boldsymbol{\chi}_{k,0} = \boldsymbol{\chi}_{k-1,L}$. θ_k is the parameters matrix under the kth macro scale, and $\boldsymbol{\theta}_k = \boldsymbol{\theta}_{k,0:L-1}$. With the defined system, we aim at estimating both the system state χ and model parameter θ from the noisy observations $\mathbf{Y}$.

2.2. Review of dual EKF method

The EKF provides an efficient approach for generating approximate maximum-likelihood estimates of the state of a discrete-time nonlinear dynamical system. However, the prediction precision of