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A novel method for lithium-ion battery state of energy and state of power estimation based on multi-time-scale filter

Xu Zhang, Yujie Wang, Ji Wu, Zonghai Chen*

Department of Automation, University of Science and Technology of China, Hefei 230027, PR China

HIGHLIGHTS

- The equivalent circuit model is estimated for battery states estimation.
- Battery peak current is analyzed by multi-constrained conditions.
- A novel multi-time-scale observer is used to estimate SOE and SOP concurrently.
- The accuracy of the proposed method is verified under different conditions.

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ABSTRACT

The battery state of energy and state of power are two important parameters in battery usage. The state of energy represents the residual energy storage in battery and the state of power represents the ability of battery discharge/charge. To estimate the two states with high accuracy, the characteristics of battery maximum available capacity and open-circuit voltage are analyzed under different working temperatures. Meanwhile, the equivalent circuit model of the battery is employed to embody the battery dynamic performance. To improve the accuracy of the battery states estimation, the multi-time-scale filter is applied in battery model parameters identification and battery states prediction. Besides, the state of power is analyzed by multi-constrained conditions to ensure battery work with safety. The proposed approach is verified by experiments operated on lithium-ion battery under new European driving cycle profiles and dynamic test profiles. The experimental results indicate the proposed method can estimate the battery states with high accuracy for actual application. In addition, the factors affecting the change of battery states are analyzed.

1. Introduction

Environmental pollution and energy crises make people develop new energy. Lithium-ion batteries, which have the characteristics of long cycle life, low self-discharge rate and environmental friendliness, are widely applied in energy storage system [1]. To ensure the battery work with high efficiency, the accurate estimation of battery state of energy (SOE) and state of power (SOP) is necessary.

SOE is commonly defined as the ratio of the residual energy to the maximum available energy [2], which is the function of battery load current and terminal voltage [3]. There have existed many methods on SOE estimation. The power integral method was the most common method among them, which can directly measure the battery usage energy [4]. However, this method was easily influenced by measurement noise and current drift. Lin et al. [5] proposed a novel multi-model fusion estimation method to estimate the SOE by taking the dynamic load and different temperatures into consideration. However, this method was too complex and cannot be used in real application. Zhang et al. [6] proposed a model based on uncertain working conditions and the degradation of battery internal parameters in SOE estimation. Liu et al. [7] took the discharge current and battery temperature into consideration, and proposed a method of back-propagation neural network (BPNN) to improve the accuracy of SOE estimation. However, this method was an open-loop estimation and its estimation will be poor if the battery initial states were incorrect. Besides, He et al. [8] presented a novel Gaussian model to reflect the battery actions and used the central difference Kalman filter (CDKF) in real-time SOE prediction. In reference [9], Zheng et al. took the ambient temperature, current rate and cell aging level into consideration and built up the quantitative relationship between SOC and SOE. Dong et al. [10] proposed dual filters of extend Kalman filter-particle filter (EKF-PF) in SOE estimation under different working temperatures and discharge/charge

* Corresponding author.
E-mail address: chenzh@ustc.edu.cn (Z. Chen).

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Nomenclature

U_t	terminal voltage (V)
U_{OCV}	open-circuit voltage (V)
R_0	ohmic resistance (Ω)
SOC	state of charge
I_b	battery loading current (A)
$I^{chg,vol}$	cell charge peak current limited by terminal voltage (A)
$I^{chg,SOC}$	cell charge peak current limited by SOC (A)
I_{chge}	cell design charge peak current (A)
p^{chg}	battery charge peak power (W)
$U_{t,\max}$	upper cut-off voltage (V)
$z_{\max}$	upper cut-off SOC
OCV	open-circuit voltage (V)
$\mathbf{x}$	PSO particle position
$fitness(\cdot)$	fitness function
EKF	extend Kalman filter
UKF	unscented Kalman filter
AUKF	adaptive unscented Kalman filter
PF	particle filter
EKF-PF	extend Kalman filter-particle filte
HPPC	hybrid pulse power characterization
MAE	mean absolute error
BMS	battery management system
U_p	polarization voltage (V)
z	SOC
E_{rem}	battery residual energy (Wh)
E_{ava}	battery maximum available energy (Wh)
E_{chge}	battery pack charge energy (Wh)
$I^{dis,vol}$	cell discharge peak current limited by terminal voltage (A)
$I^{dis,SOC}$	cell discharge peak current limited by SOC (A)
I_{dis}	cell design discharge peak current (A)
p^{dis}	battery discharge peak power (W)
$U_{t,\min}$	lower cut-off voltage (V)
$z_{\min}$	lower cut-off SOC
Ca	cell capacity (Ah)
NEDC	New European Driving Cycle
SOP	state of power (W)
$\boldsymbol{v}$	PSO particle velocity
SOE	state of energy
BPNN	back-Propagation Neural Network
PC	personal computer
CDEF	central difference Kalman filter
RELS	recursive extended least squares
RMSE	root-mean square error
PSO	particle swarm optimization

current rate. Wang et al. [11] also proposed a particle filter (PF) based on the data-driven model in SOE estimation. All of above methods can estimate the SOE with their own advantages. However, most of those methods only can be used in single cell SOE estimation.

Unlike SOE, the SOP is employed to reflect the battery power capability, which is a key parameter to ensure the battery work in a safe region. It cannot be measured by measuring equipment directly. The common method of peak power prediction was hybrid pulse power characterization method (HPPC), which can calculate the peak charge/discharge power based on the design maximum and minimum voltage limits [12]. This method was simple and easy to implement. Unfortunately, it can be only used in laboratory and cannot predict SOP on-line. Other methods on SOP prediction use complex algorithms based on dynamic battery models. In reference [13], to ensure the accuracy estimation of battery SOP, the relationship between polarization resistance and SOC was first set up and then the PF was proposed to avoid the influence of measurement noise. Xiong et al. [14] put forward a method of a Kalman filter joint estimator to predict the SOP. A recursive extended least squares (RELS) algorithm [15] was also used to estimate SOP by on-line equivalent-circuit model parameters identification.

All of the above methods have their own advantages and can accurately estimate battery SOE and SOP. However, most of methods are too complex to implement on a microcontroller and not suitable for battery pack SOE and SOP estimation. In general, a battery is made up of a lot of single cells. The differences in cells' parameters and working temperatures lead to the cells' inconsistency and make the method of battery SOE and SOP difficulty. To solve these problems, the equivalent circuit battery model is first applied to reflect dynamic behavior of a battery in this paper. And then, the method of particle swarm optimization (PSO) is applied in battery model parameters identification while the battery SOE and terminal voltage are predicted by unscented Kalman filter (UKF). Besides, the SOP is determined by cells' terminal voltage, SOC and design limit. The proposed method is simple and can be implemented on a microcontroller.

This paper is organized as follows: In Section 2, the definition of SOE, SOP and the battery model are introduced. In Section 3, the algorithm of PSO-UKF is presented. Section 4 describes the test bench and the battery characteristics test method. In Section 5, the New European Driving Cycle (NEDC) and dynamic test profiles are used to verify the proposed method. Section 6 gives the conclusions.

2. Battery model and the definition of SOE and SOP

2.1. Battery model

To reflect the dynamic characteristics of the battery, an accuracy model is necessary [16]. Many models have been proposed [17], the equivalent circuit model [18] is a common used model among them as shown in Fig. 1. It contains n open-circuit voltages (OCV) U_{OCV}, n resistors R_0, n polarization RC networks.

The electrical behavior of the battery model in continuous-time domain can be described as:

$$\begin{cases} \dot{U}_p^i = -\frac{1}{R_p^i C_p^i} U_p^i - \frac{1}{C_p^i} I_b \\ U_t^i = U_{OCV}^i - R_0^i I_b - U_p^i \end{cases} \quad (i = 1,2,\ldots,n) \tag{1}$$

where U_p is the voltage of the polarization RC network, U_t is the terminal cell voltage. The unit of cells' voltage is volt (V). I_b is the battery load current. The number of series cell in the battery pack is n. R_0 is the electrical resistance, U_{OCV} is the OCV which is function of SOC [6] shown as follows:

$$U_{OCV}(z) = K_0 + K_1 z + K_2 z^2 + K_3/z + K_4 \ln(z) + K_5 \ln(1-z) \tag{2}$$

where z denotes SOC, K_i $(i = 0,\ldots,5)$ are six coefficients.

Defining $\alpha_p = \exp(-\Delta t/R_p C_p)$, Eq. (1) in discrete-time domain can be expressed as:

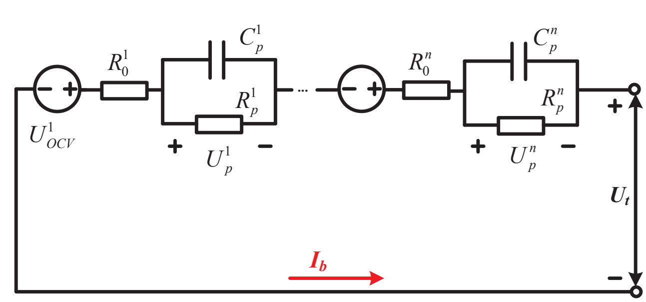

Fig. 1. Schematic diagram of the battery model.