Applied Energy 151 (2015) 41–48

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

A novel Gaussian model based battery state estimation approach: State-of-Energy

HongWen He [a,b,*], YongZhi Zhang [a], Rui Xiong [a,b,*], Chun Wang [b,c]

[a] National Engineering Laboratory for Electric Vehicles, School of Mechanical Engineering, Beijing Institute of Technology, Beijing 100081, China
[b] Collaborative Innovation Center of Electric Vehicles in Beijing, Beijing Institute of Technology, Beijing 100081, China
[c] School of Mechanical Engineering, Sichuan University of Science and Engineering, Zigong, Sichuan 643000, China

HIGHLIGHTS

- The Gaussian model is employed to construct a novel battery model.
- The genetic algorithm is used to implement model parameter identification.
- The AIC is used to decide the best hysteresis order of the battery model.
- A novel battery SoE estimator is proposed and verified by two kinds of batteries.

ARTICLE INFO

Article history:
Received 9 February 2015
Received in revised form 13 April 2015
Accepted 15 April 2015
Available online 29 April 2015

Keywords:
Electric vehicles
Lithium-ion battery
State of energy
Gaussian model
Akaike information criterion
Central difference Kalman filter

ABSTRACT

State-of-energy (SoE) is a very important index for battery management system (BMS) used in electric vehicles (EVs), it is indispensable for ensuring safety and reliable operation of batteries. For achieving battery SoE accurately, the main work can be summarized in three aspects. (1) In considering that different kinds of batteries show different open circuit voltage behaviors, the Gaussian model is employed to construct the battery model. What is more, the genetic algorithm is employed to locate the optimal parameter for the selecting battery model. (2) To determine an optimal tradeoff between battery model complexity and prediction precision, the Akaike information criterion (AIC) is used to determine the best hysteresis order of the combined battery model. Results from a comparative analysis show that the first-order hysteresis battery model is thought of being the best based on the AIC values. (3) The central difference Kalman filter (CDKF) is used to estimate the real-time SoE and an erroneous initial SoE is considered to evaluate the robustness of the SoE estimator. Lastly, two kinds of lithium-ion batteries are used to verify the proposed SoE estimation approach. The results show that the maximum SoE estimation error is within 1% for both $LiFePO_4$ and $LiMn_2O_4$ battery datasets.

1. Introduction

Nowadays the lithium-ion battery (LiB) is drawing a vast amount of attention as the most important onboard energy storage for electrified vehicle. To guarantee safe, efficient, and durable operations, an effective battery management system (BMS) is necessary [1–3]. However, due to the strong time-variable and nonlinear characteristics, accurate estimation of state-of-charge (SoC) is still remaining a challenge [4].

In terms of battery SoC estimation methods, large numbers of research approaches have previously been proposed, each one having its relative advantage, as reviewed by Ref. [5]. Due to the closed-loop estimation ability and strong inhibiting effect on noises, the Kalman filter (KF)-based SoC estimator is widely studied. Generally, researches are conducted through systems formed by the Ampere–Hour integral method and other battery models [6]. In considering that battery shows strong nonlinear characteristic during its working process, the extended Kalman filter (EKF) is usually adopted [7–16]. Ref. [17] studied the adaptive extended Kalman filter and Ampere–Hour merging method, pointing out that the meaning of AEKF as a state observer lies in: the AEKF can precisely estimate the voltage and adjust the Kalman gain according to the terminal voltage error between the measured values and the estimated values timely. The erroneous SoC estimation brings bigger terminal voltage errors, which will in turn causes a

* Corresponding authors at: National Engineering Laboratory for Electric Vehicles, School of Mechanical Engineering, Beijing Institute of Technology, Beijing 100081, China. Tel./fax: +86 (10) 6891 4842.

E-mail addresses: hwhebit@bit.edu.cn (H. He), zhangyz0130@163.com (Y. Zhang), rxiong@bit.edu.cn (R. Xiong), ono77@qq.com (C. Wang).

http://dx.doi.org/10.1016/j.apenergy.2015.04.062
0306-2619/

strong Kalman gain and then compensates the SoC estimation in an efficient closed loop feedback. However, the core content of the EKF used for SoC estimation is to establish a reasonable battery equivalent model and build a group of state equations. Accordingly, this method is highly dependent on the prediction precision of battery model and inaccurate battery model may cause unreliable SoC estimation. To avoid the linearization error of battery model and improve the model precision for SoC estimation, the central difference Kalman filter (CDKF) is adopted and which has the potential to estimate battery SoC with its nonlinear behavior [18,19].

Nevertheless, the SoC defines the ratio of the residual active material to the total original active material inside a battery. In this way, the SoC indicates only the capacity state rather than the energy state on which the battery application conditions are dependent. Therefore, the state of energy (SoE) of the battery, which provides the essential basis of energy deployment, load balancing, and security of electricity for the complex energy systems, is a key parameter in the battery system. For pure EVs, the SoE is a more critical index for the remaining driving range estimation, energy optimization and management. Refs. [20–22] have done a series work in battery SoE estimation. Their simulation results agree well with the experimental results. However, these SoE estimation approaches fail to achieve reliable predictions against different kinds of LiB cells. The trajectory of the battery model parameter cannot be fully described with a limited number of experiments. What is more, it needs to be validated under all of its possible working conditions. It is evident that it is not practical for EV, which has large number of battery cells in it. Thus, a data-driven SoE prediction approach is a good choice to achieve desirable SoE estimates.

1.1. Contribution of the paper

A key contribution of this study is that a data-driven estimator for battery state of energy is developed, thus the prone-error and time consuming periodic calibration experiments could be avoided. What is more, the performance of the estimator has been verified and evaluated by different kinds of lithium-ion batteries ($LiFePO_4$ and $LiMn_2O_4$). In the proposed estimator, the Gaussian model is employed to construct the battery model and the genetic algorithm is used to implement model parameter identification. To determine an optimal tradeoff between battery model complexity and prediction precision, the Akaike information criterion (AIC) is used to decide the best hysteresis order of the combined battery model. It is noted that compared to EKF, the CDKF avoids the linearization error of the battery model and improves the model precision for SoE estimation. Furthermore, results show that the CDKF-based SoE estimator has a good robustness against erroneous initial SoE values.

1.2. Organization of the paper

The remainder of the paper is organized as follows: In Section 2, the battery model is built and the genetic algorithm is used to identify the model parameters. Section 3 describes the SoE definition, the CDKF-based SoE estimation model and the calculation process for estimating SoE. The experiment setup and battery test are introduced in section 4. Section 5 verifies the proposed data-driven estimator with different kinds of batteries. In the final section, some conclusions and final remarks are given.

2. Battery modeling and parameter identification

The batteries, with strong time-variable, nonlinear characteristics in it, are further influenced by such random factors as driving loads, operation environment, et al., in the application in EVs. The real-time, accurate estimation of their state is challenging. Herein, certain more advanced battery model should be constructed for better simulating the complex working characteristics of different kinds of batteries.

In this paper we propose the n-order hysteresis combined battery model, which can be expressed as following.

$$U_{t,k} = \sum_{i=1}^{m} a_i e^{-\left(\frac{z_k - b_i}{c_i}\right)^2} + \sum_{j=0}^{n} (d_j i_{L,k-j} + e_j U_{t,k-j}) \tag{1}$$

where z represents battery SoE; the subscript k indices the sampling moment. U_t represents the terminal voltage, i_L represents the current which is negative at charge and positive at discharge. $a_{1,\dots,m}$, $b_{1,\dots,m}$, $c_{1,\dots,m}$, $d_{1,\dots,n}$ and $e_{1,\dots,n}$ represent the fitting coefficients which are related to battery parameters.

It is noted that the first term on the right side of Eq. (1) is Gaussian model. The statistics performance oriented Gaussian model is used to simulate different open circuit voltage behaviors for different kinds of batteries, where m is usually less than 8 and we use $m = 3$ in this paper. The second term on the right side simulates the hysteresis effect of battery, where n represents the hysteresis order. Note that $e_0 = 0$ here.

The genetic algorithm is used to locate an optimal parameter group for fitting coefficients and the objective function of the genetic algorithm is built as follows [23]:

$$\begin{cases} \min\{f(\hat{\chi}_g)\} \\ \chi = [a_{1,\dots,m}, b_{1,\dots,m}, c_{1,\dots,m}, d_{1,\dots,n}, e_{1,\dots,n}] \\ f(\hat{\chi}_g) = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (U_{t,i} - \hat{U}_{t,i}(\hat{\chi}_g))^2} \end{cases} \tag{2}$$

where $\hat{\chi}_g$ is the estimation value of the current population χ at generation g. $\hat{U}_{t,i}$ is the estimation value of $U_{t,i}$ at the data point i; N is the experimental data length.

3. CDKF-based SoE estimator

3.1. State of energy definition

The SoE reflects the residual energy of a battery, and is defined as the ratio of the remaining energy to the total available energy [20,21]. In this study, SoE has been expressed by the following equation [24,25].

$$z_k = z_{k-1} - \frac{\eta \Delta E_a}{E_a} = z_{k-1} - \frac{\eta U_{t,k-1} i_{L,k} \Delta t}{E_a} \tag{3}$$

where Δt represents the sampling time, ΔE_a represents the variation of battery energy during each sampling time, E_a represents the available energy of battery, η denotes the energy efficiency of battery.

Usually the calculation of battery SoC only considers the charges flow into or out of the batteries, which has completely neglected the energy losses of the electrochemical reactions and internal resistances inside. These energy losses directly cause changes of the terminal voltage and which will decrease faster when battery is in discharge and increase slower when battery is in charge. In fact, the terminal voltage is a very important index of battery energy state. Herein, compared to the SoC of a battery, the SoE is able to indicate the actual available energy when the EV is running and more meaningful to manage the battery energy system and predict the remaining driving range of the pure EVs. In this case, the SoE is more practical than the SoC from the engineering point.