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State of charge estimation for Li-ion battery based on model from extreme learning machine ☆

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ABSTRACT

Lithium-ion (Li-ion) battery state of charge (SOC) estimation is important for electric vehicles (EVs). The model-based state estimation method using the Kalman filter (KF) variants is studied and improved in this paper. To establish an accurate discrete model for Li-ion battery, the extreme learning machine (ELM) algorithm is proposed to train the model using experimental data. The estimation of SOC is then compared using four algorithms: extended Kalman filter (EKF), unscented Kalman filter (UKF), adaptive extended Kalman filter (AEKF) and adaptive unscented Kalman filter (AUKF). The comparison of the experimental results shows that AEKF and AUKF have better convergence rate, and AUKF has the best accuracy. The comparison from the radial basis function neural network (RBF NN) model also verifies that the ELM model has lighter computation load and smaller estimation error in SOC estimation process. In general, the performance of Li-ion battery SOC estimation is improved by the AUKF algorithm applied on the ELM model.

1. Introduction

Electric vehicles (EVs) have the advantages of no pollution, high efficiency and comfortable driving environment compared with traditional fossil-fuel vehicles (Ehsani, Gao, & Emadi, 2009). Lithium-ion (Li-ion) batteries are commonly used as the power source for EVs since a Li-ion battery has high efficiency, high charging and discharging rate, low self-discharge, and no memory effect (Faa-Jeng, Ming-Shi, Po-Yi, Han-Chang, & Chi-Hsuan, 2012; Chaturvedi, Klein, Christensen, Ahmed, & AKojic, 2010). However to increase battery life and to ensure safe operation (Jossen, Späth, Döring, & Garche, 1999), a battery management system (BMS) is required to supervise the battery's status and control the battery's energy flow.

State of charge (SOC) is an important variable describing the status of a Li-ion battery. SOC is defined as the ratio of the battery's remaining capacity to the nominal capacity (Plett, 2004a). Since over-charging and over-discharging bring inevitable damage to a Li-ion battery, accurate SOC estimation should be provided by the BMS (Plett, 2004b). Piller, Perrin, and Jossen (2001) summarizes different SOC estimation methods.

The most widely used technique for SOC estimation is Coulomb counting (Lee, Nam, & Cho, 2007). The principle of Coulomb counting is to take the battery as a capacitor and obtain its storage energy by current integration. Nevertheless, estimation error may be accumulated for this open-loop algorithm, resulting in the estimate drifting away from the true value. Any initial SOC error also causes a bias in the estimation. Another commonly used technique is the open-circuit-voltage (OCV) method. This method obtains SOC from the battery's OCV-SOC relationship (Coleman, Chi Kwan, Chunbo, & Hurley, 2007). However, accurate OCV measurement requires the battery to be in equilibrium state, while the batteries in EVs are at work during driving. Therefore, the OCV method is not suitable for real-time SOC estimation (Piller et al., 2001).

The impedance spectroscopy technique measures the battery's impedance by testing the voltage response with a small AC current applied to the battery (Ehsani et al. 2009). A spectroscopy is composed of the impedance data extracted from different frequency currents. In (Zenati, Desprez, & Razik, 2010), the intelligent method of fuzzy logic is combined with impedance spectroscopy to achieve better SOC estimation result. This method provides accurate SOC, but it needs specific experiments (Plett, 2004a) so it is not suitable for applications in EVs.

Kalman filter (KF) is a mathematical technique that provides an efficient recursive means for estimating the states of a process by minimizing the mean of the squared error (Simon, 2006; Lerro & Bar-Shalom, 1993). Li-ion battery SOC has a nonlinear relationship with other variables (He, Xiong, & Guo, 2012). Therefore, the nonlinear version of KF, extended Kalman filter (EKF), is widely applied to estimate SOC online (Barbarisi, Vasca, & Glielmo, 2006). The essence of EKF is to linearize the system at each time step to

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approximate the nonlinear system with a linear time varying system. In Plett (2004c), Zhiwei, Mingyu, and Jie (2009), Hu, Youn, and Chung (2012) and Chen et al. (2013), EKF is utilized to do Li-ion battery SOC estimation. However, EKF is only applicable when the model is accurate or has a suitable form. For nonlinear models, the unscented Kalman filter (UKF) is suitable to do state estimation. UKF does not linearize the system and the estimation accuracy can be improved (Simon, 2006). Based on EKF and UKF, adaptive Kalman filters have been developed to achieve much better estimation performance for nonlinear systems by adjusting the noise covariance matrices during estimation (Mohamed & Schwarz, 1999).

In BMS, the techniques to supervise Li-ion batteries are mostly based on existing battery models. The issue of obtaining accurate battery SOC can be divided into battery modeling and state estimation. Battery modeling is used to establish the model describing the battery characteristic accurately. Various models for Li-ion battery have been proposed. There are mainly three kinds of models: the equivalent circuit model, the electrochemical model and the neural network (NN) model.

In He, Xiong, and Fan (2011), several kinds of Li-ion battery equivalent circuit models are analyzed. The equivalent circuit model represents the battery dynamic characteristics by establishing a circuit composed of voltage source, resistors and capacitors. This kind of model is easy to comprehend. However, in practice, the circuit parameters are a non-linear function of SOC. Therefore, they need to be calculated at several SOC points (Lee, Kim, Lee, &Cho, 2008; Hu, Sun, & Zou, 2010). In Chen and Rincon-Mora (2006), the parameters are functions of SOC determined by curve fitting, which results in model with complex form and strong nonlinearity. In addition, since the SOC cannot be measured directly, inaccurately estimated SOC causes the model to be inaccurate.

The electrochemical model (Smith, Rahn, & Wang, 2010) focuses on the battery's inner chemical reaction and predicts the spatially distributed behavior of the essential states of the battery (Chaturvedi et al., 2010). This kind of model is the most accurate for Li-ion batteries. However, the electrochemical model is described by partial differential equations, making the state estimation process difficult.

Recently, modeling batteries by neural networks (NNs) has also been widely applied. NNs can approximate nonlinear mappings directly from existing input–output samples. The NN battery model provides a black-box model with no need to know the battery's inner structure and reaction. The application of NNs brings significance convenience to the modeling process. There is no need to calculate the model parameters separately at different SOC points. The error caused by curve fitting for each parameter is also avoided. In Du, Liu, Chen, and Wang (2012) and Liu, Wang, Du, and Chen (2012), the NN model for Li-ion battery is established with high accuracy in simulation. The established model describes the relationship between SOC and its influential factors with mathematical equations. In this paper, the NN model for Li-ion battery is established.

Although NNs are suitable for Li-ion battery modeling, traditional NNs have the flaws of heavy computation and long training time. The model parameters need to be tuned iteratively during training. The iteration steps need large amounts of computation and make the mapping learning process inefficient (Huang, Zhu, & Siew, 2006; Liang, Huang, Saratchandran, & Sundararajan, 2006). On the other hand, to represent Li-ion battery's dynamic characteristics entirely and achieve the desired model accuracy, the training data sampling time must be short enough. Thus, the amount of training data may be large. Hence, a faster mapping learning algorithm is needed.

In this paper, the extreme learning machine (ELM) algorithm, introduced in (Huang, Zhu, & Siew, 2006), is applied to establish the Li-ion battery model. For ELM, there is no need to tune the model parameters during training. The input weights connecting the input neurons and hidden neurons and the hidden layer biases are chosen randomly (Huang, Zhu, & Siew, 2006; Liang et al., 2006; Huang, Chen, & Siew, 2006; Huang, 2003; Huang, Zhu, Mao, Siew, Saratchandran, & Sundararajan, 2006). The output weights connecting the hidden neurons and output neurons are determined analytically. ELM trains data fast and provides smaller training error with smaller norm of weights (Huang, Zhu, & Siew, 2006).

The application of ELM makes the modeling process simpler and provides a more accurate representation of the battery model's input–output relationship. In this paper, a discrete Li-ion battery model is trained by ELM using the sampled data from experiments. Compared with radial basis function (RBF) NN, the ELM algorithm has simpler modeling process and higher training accuracy, and spends much less time on training. Then, the estimation algorithms of EKF, UKF, adaptive EKF (AEKF) and adaptive UKF (AUKF) are applied to estimate the battery SOC during the whole discharging period. Experimental results show that the SOC estimated by AUKF with the ELM model improves the estimation performance.

The paper is organized as follows. Section 2 describes the battery model trained by the ELM algorithm. A comparison with RBF NN is also shown in this section. In Section 3, the algorithms of EKF, UKF, AEKF and AUKF are described and applied to estimate SOC. The comparisons of the SOC estimation results with the above algorithms and the two established NN models are analyzed in Section 4. Finally, the conclusions are given in Section 5.

2. Li-ion battery modeling

In this section, a discrete model for Li-ion battery cell is established.

2.1. The proposed model

Firstly, the proposed model's inputs and output are determined.

According to the NN theory, the SOC sampled at step k, $SOC(k)$, is taken as the model input since it represents the battery's present status. SOC has a nonlinear relationship with its influential factors, including battery voltage and current. The proposed model should be able to describe this relationship accurately. As the directly measured variable, the current $I(k)$ is taken as an input, and the battery terminal voltage $V(k)$ is defined as the output. Moreover, the terminal voltage at sampling step $k-1$, $V(k-1)$, is also chosen as the third input for the proposed model. $V(k-1)$ represents the battery's status at last step and implies the previous working status. The theoretical ground for the selection of $V(k-1)$ is the form of the equivalent circuit model (Schweighofer, Raab, & Brasseur, 2003) for Li-ion battery. The terminal voltage at step k is expressed as

$$V(k) = OCV(SOC(k)) + R_s I(k) + U_{RC}(k) \tag{1}$$

where R_s represents the battery internal resistance, $U_{RC}(k)$ represents the RC circuit voltage relating to $U_{RC}(k-1)$ via a first order differential equation. To make the model inputs directly measured variables, $U_{RC}(k-1)$ is considered being included in $V(k-1)$. Hence, $V(k-1)$ has a direct relationship with $V(k)$. A function is obtained by synthesizing the unknown parameters

$$V(k) = f(V(k-1), I(k), SOC(k)), \tag{2}$$

which is to be approximated by learning algorithms.

The input vector and output for the proposed battery model are represented by $p(k) = [\,V(k-1) \quad I(k) \quad SOC(k)\,]^T$ and $V(k)$. The proposed model's mathematical equation is expressed by

$$F(p(k)) = V(k) \tag{3}$$