Electrical Power and Energy Systems 62 (2014) 783–791

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

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

State of charge estimation for Li-ion batteries using neural network modeling and unscented Kalman filter-based error cancellation

Wei He, Nicholas Williard, Chaochao Chen, Michael Pecht *

Center for Advanced Life Cycle Engineering (CALCE), University of Maryland, College Park, MD 20742, USA

A R T I C L E   I N F O

Article history:
Received 3 July 2013
Received in revised form 15 April 2014
Accepted 30 April 2014
Available online 18 June 2014

Keywords:
Neural networks
Unscented Kalman filter
State of charge estimation
Lithium ion batteries
Electric vehicles
Battery management systems

A B S T R A C T

Lithium-ion batteries have been widely used as the energy storage systems in personal portable electronics (e.g. cell phones, laptop computers), telecommunication systems, electric vehicles and in various aerospace applications. To prevent the sudden loss of power of battery-powered systems, there are various approaches to estimate and manage the battery's state of charge (SOC). In this paper, an artificial neural network–based battery model is developed to estimate the SOC, based on the measured current and voltage. An unscented Kalman filter is used to reduce the errors in the neural network-based SOC estimation. The method is validated using LiFePO4 battery data collected from the Federal Driving Schedule and dynamical stress testing.

1. Introduction

Lithium-ion (Li-ion) batteries have attracted attention due to their high energy density and long cycle life compared with other battery chemistries. State of charge (SOC) estimation provides information about when a battery needs to be recharged and allows battery management systems (BMSs) to prolong the battery life by preventing batteries from over-charging or over-discharging.

SOC is defined as the percentage of remaining capacity relative to the maximum capacity of the battery. Many SOC estimation approaches have been developed, among which Coulomb counting [1,2] is the most popular one. In Coulomb counting, the current is integrated over time to estimate SOC. Although Coulomb counting is easy to implement, the measurement and calculation errors can be accumulated by the integration function, and thus the estimation of SOC tends to drift from the actual values. The voltage-based method [3] estimates the SOC based on a voltage–SOC lookup table. However, voltage-based methods do not work well for Li-ion batteries because of their flat plateau of discharge characteristics. To provide more robust estimates, equivalent circuit models (ECMs) have been proposed for SOC estimation using extended Kalman filters (EKFs) [4–9] and unscented Kalman filters (UKFs) [10,11]. Plett [4,8,9] developed an enhanced self-correcting model that takes hysteresis effects into consideration to estimate SOC using EKFs. He et al. [7] proposed an improved Thevenin model wherein SOC is estimated using EKFs.

Studies have been conducted to establish data-driven models for battery modeling and SOC estimation that do not require detailed physical knowledge of Li-ion batteries. The commonly used data-driven models include support vector machines [12–14] and neural networks [15–18]. For example, Hansen and Wang [12] developed a support vector machine (SVM) based method for SOC estimation. The estimator was validated using US06 dynamical operation data with a root mean square (RMS) error of less than 6%. Anton et al. [13], proposed a state-of-charge estimator using support vector machine. The inputs to SVM were voltage, current and temperature, and output was SOC, with training data and testing data under the same loading condition. Therefore, the generalization ability of the proposed SVM was unknown. Lee et al. [15] developed an SOC estimation approach based on a fuzzy neural network with B-spline membership functions. But this method was only tested using data obtained by constant current discharge, which is different from the real-life loading condition of many battery powered systems like EVs and UAVs. Cheng et al. [16] proposed a SOC estimation method for Ni–MH batteries using a three-layer feed-forward neural network; where the inputs to the neural network (NN) were battery current, temperature, voltage and its first and second derivatives. Though Cheng's method is promising, the estimation results show high estimation variance, probably due to over-fitting or under-fitting, which is a common

* Corresponding author. Tel.: +1 301 405 5323; fax: +1 3013149269.
E-mail address: pecht@calce.umd.edu (M. Pecht).

http://dx.doi.org/10.1016/j.ijepes.2014.04.059
0142-0615/

problem for data-driven methods. Therefore, researchers have been developing hybrid methods to improve the accuracy of data-driven SOC models. Charkhgard and Farrokhi [19] used an extended Kalman filter (EKF) to infer the SOC based on a radial basis function neural network battery model. However, EKF is only accurate to first order or second order of a nonlinear system in the sense of Taylor expansion. Furthermore, only three inputs were used in Charkhgard and Farrokhi's model to train the NN, namely, the voltage from the previous sample and the current and SOC of the present sample, which is not sufficient to capture the capacitive effects in the Li-ion battery system dynamics.

In this paper, we develop a SOC estimation method based on neural network and unscented Kalman filter (UKF). To capture the time constant of the battery dynamics, multiple current, voltage, and temperature measurements are used as inputs to the neural network, and the SOC is used as the neural network output. The number of inputs in a neural network and the neural network structure are determined by a constructive method, where the generalization capability and the accuracy of the neural network are optimized. In order to reduce the estimation error of the neural network, a UKF is developed to filter out the outliers in the neural network estimation. UKF has been proven to be better than EKF [20,21] because it is accurate to 3 orders for any non-linear system. We train our SOC model using dynamical stress testing data and validate it using data from the Federal Urban Driving Schedule (FUDS) and US06 Highway Driving Schedule. This paper is organized as follows: Section 2 reviews the basic principles of NN, illustrates the generation of the training data and testing data, and discusses the methodology to select the optimal neural network structure. Section 3 develops a UKF algorithm to reduce SOC estimation error and Section 4 gives the SOC estimation results of our approach. Section 5 presents our conclusions.

2. Neural network SOC model

Neural networks (NNs) are computational intelligence tools that have been widely used for system modeling [22,23], anomaly detection [24], prognostics [25], and classification [26]. An NN comprises a set of interconnected simple processing elements called neurons that mimic the information processing and knowledge acquisition capabilities of the human brain. There are several characteristics of NNs that make them an attractive choice for system modeling. NNs can fit any nonlinear function with sufficient neurons and layers to make them suitable for complex system modeling. NNs can learn and update their internal structure to adapt to a changing environment. NNs are efficient in data processing because of their parallelism in computation. NNs are data-driven in nature and able to build a system model without detailed physical knowledge of a system [27].

2.1. Theory of neural network

A neural network consists of an input layer with nodes to represent the input variables, one or more hidden layers with nodes to mimic the nonlinearity between the system input and output, and an output layer to represent the system output variable. Fig. 1 shows the structure of a feed-forward neural network for SOC estimation. The inputs to the neural network are current (I), voltage (V), and temperature (T), and the output is the battery SOC. The nodes between two adjacent layers are interconnected. The input layer passes on the inputs with weights; no processing takes places in this layer. The hidden layers and output layers are processing layers with the activation function at each node. The hyperbolic tangent sigmoid function is often used in the hidden layer as an activation function. It is defined as:

$$\mathcal{F}_{tansig}(u) = \frac{2}{1+e^{-2u}} - 1 \tag{1}$$

In the output layer, the linear transfer function is used as an activation function for regression and fitting problems, as:

$$\mathcal{F}_{lin}(u) = u \tag{2}$$

The output of a processing node j in the hidden or output layer is given by:

$$y_j = \mathcal{F}(u_j) = \mathcal{F}\left(\sum_i \omega_{ij} x_i + b_j\right) \tag{3}$$

where x_i is the output from the ith node at the previous layer, ω_{ij} is the weight of the interconnection from the ith node of the previous

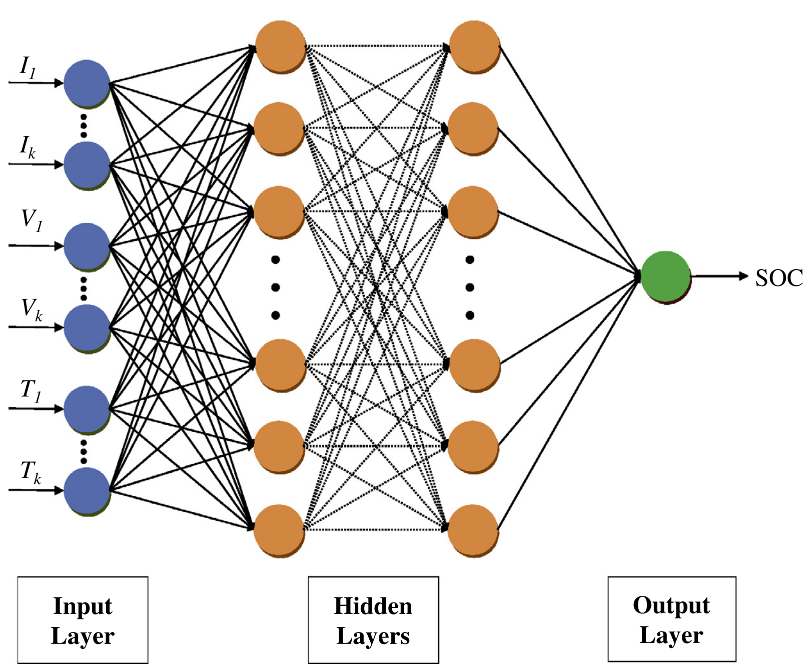

Fig. 1. The structure of a multilayer feed-forward neural network.