Electrochimica Acta 264 (2018) 400–409

Contents lists available at ScienceDirect

Electrochimica Acta

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

A chaos genetic algorithm based extended Kalman filter for the available capacity evaluation of lithium-ion batteries

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A R T I C L E I N F O

Article history:
Received 2 September 2017
Received in revised form
18 January 2018
Accepted 20 January 2018

Keywords:
Chaos genetic algorithm
State of charge
Extended Kalman filter
Lithium-ion batteries
Adaptive switch mechanism

A B S T R A C T

Lithium-ion batteries are developed rapidly in electric vehicles, whose safety and functional capabilities are influenced greatly by the evaluation of available capacity. Combined with the evolution trend description of state of charge from extended Kalman filter and an adaptive switch mechanism, this paper advances an adaptive chaos genetic algorithm based extended Kalman filter for the state of charge determination of lithium-ion batteries, where a combined state space model is used for simulating their dynamics. It combines the advantage of local linear approximation capability from extended Kalman filter with the global optimal search mechanism from chaos genetic algorithm. The method is applied for the state of charge determination of lithium-ion batteries, and results of lab tests on physical cells, compared with model prediction, are presented. Furthermore, the innovation magnitude bound test and innovation whiteness test are employed for verifying the performance of the proposed method. Results confirm that the advanced method may quickly evaluate state of charge with high accuracy and has great robustness without being affected by the uncertain initial value.

1. Introduction

With the great attention to environment pollution and energy crises, lithium-ion batteries are developed rapidly in electric vehicles (EVs) and hybrid electric vehicles (HEVs) because of their high energy density, long cycle life, low self-discharge rate and environmental compatibility. As an integral part of EV battery management systems [1], the rate capability of lithium-ion batteries is a crucial issue for the commercialization of Lithium batteries in HV and HEV. Accurate estimation of cell available capacity, which directly reflects the behavior of battery pack usage, is essential for the safety and functional capabilities of the whole system.

As a value which is incapable of being detected directly, cell state of charge (SoC) is usually accessed by a method based on the characteristics of the battery, such as gravity, potential of hydrogen (PH), voltage, current and temperature. Many different types of methods have been developed for that. Electrochemical method [2] is very accurate, but complex and requires the outstanding comprehension of cell electrochemical processes, which are usually modeled with a set of equations consisting of time variant spatial partial differential equations. Voltage method [3,4] converts a reading of the battery voltage to the SoC with the known discharge curve (voltage vs. SoC) of the battery. It's complicated to get accurate available capacity because of not considering the influence of battery current and temperature. Coulomb counting method calculates SoC by measuring the battery current and integrating it with time. This method must be re-calibrated on a regular basis since it suffers from long-term drift and lacks of a reference point. Impedance based models [5,6] represent each electrochemical process in the cell by impedance elements in an electrical circuit through impedance spectroscopy measurements, which require additional high frequency equipment. Kalman filter, which operates recursively on streams of noisy input data to produce a statistically optimal estimate of the underlying system state, is a most common selection for accessing cell SoC adaptively. Reference [7] employs one order equivalent circuit model to simulate cell dynamics and proposes an improved extended Kalman filter (EKF) to access cell SoC. Reference [8] uses iterated extended Kalman filter to realize this. Literature source [9] uses discrete wavelet transform (DWM) based denoising technique for discharging/charging voltage signal, inverse DWM of the filtered detailed coefficients for signal reconstruction, and equivalent circuit model (ECM) based SoC estimation algorithm with EKF for SoC estimation. Reference [10] advances a combined method to get available capacity which uses recursive least square (RLS) algorithm to obtain model parameters and UKF

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https://doi.org/10.1016/j.electacta.2018.01.123

to access SoC. However, whether extended Kalman filter (EKF) [7–9] or unscented Kalman filter (UKF) [10–12] based methods, they rely on the given initial value to a certain extent. Endowed a more accurate value, the selected method would converge to the real one more quickly. Otherwise, model prediction accuracy would decline and evaluation results might even diverge from the real value.

Literature source [13] advances an improved particle filter (PF) based method, which restricts solution space based on a simplified output equation and adopts adaptive filter gain to accelerate the convergence process. Reference [14] introduces an integrated SoC estimator, where recursive least square (RLS) method is used for parameter identification and PF is used for on-line SoC estimation based on the prior knowledge given by the adaptive EKF. PF based methods [13–16] use random particles satisfied with specified distribution to represent cell available capacity, which accelerate search process with bigger search region but bring greater computation complexity. PF based methods perform well in the foremost prediction steps, but waste unnecessary computation after the prediction error turns to be low.

In order to overcome the aforementioned downsides, this paper presents an adaptive chaos genetic algorithm (CGA) based extended Kalman filter method for the SoC determination of lithium-ion batteries. A combined state space model, evolved from electrical circuit equations and experience model [17], is employed to simulate battery dynamics based on the measured battery parameters, such as terminal voltage, current and temperature. Combined with the evolution trend description of SoC from extended Kalman filter and adaptive switch mechanism, an adaptive CGA based extended Kalman filter method is advanced for the SoC prediction of lithium-ion batteries. Extensive experimental data is applied to demonstrate the effectiveness of the developed modeling and estimation scheme.

The remainder of this paper proceeds as follows. In section 2, the theory development and parameter identification of combined state space model is presented including the introduction of electrical circuit model, coulomb counting method and experience model. In section 3, an adaptive CGA based extended Kalman filter is proposed for the SoC determination of lithium-ion batteries. Experimental results including innovation magnitude bound test and innovation whiteness test to rectify the proposed algorithm are provided in section 4, followed by the conclusion of this work in section 5.

2. Combined state space model theory development

Lithium-ion battery is a nonlinear dynamic system. It requires a precise model to represent its behavior before using Kalman filter related method to access cell SoC. Besides straightforward for understand, an effective electrical circuit model can simulate the entire dynamic electrical characteristics of cell, so this paper employs an evolved classical one.

2.1. Electrical circuit model

As depicted in Fig. 1, a two-order improved Thevenin circuit model with two RC networks [18] is employed to describe the dynamic characteristics of $LiFePO_4$ battery, such as nonlinear open-circuit voltage, current, temperature, transient response, hysteresis effect and available capacity. In this model, two circuits are connected by controlled sources. One is the controlled current source which is controlled by the battery flowing current (i) and is used to model the cell behavior among SoC, runtime and available capacity. It uses self-discharge resistor (*RselfDis*) to characterize the self-discharge energy loss and full-capacity capacitor (*CCapacity*) to represent the available capacity stored in the battery. The other is a controlled voltage source which is controlled by the open circuit voltage V_{oc}. It is employed to bridge SoC to the open-circuit voltage (V_{oc}). The RC parallel network, composed of *RTransient_S*, *CTransient_S*, *RTransient_L* and *CTransient_L*, is employed to describe the transient response and hysteresis effect of cell.

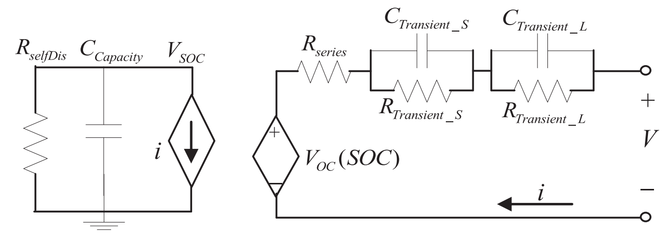

Fig. 1. Electrical circuit model for $LiFePo_4$ batteries.

2.2. State space model for lithium-ion batteries

Based on the coulomb counting method, cell SoC is usually defined as the ratio of standard available capacity to the nominal capacity (*CCapacity*),

$$SOC(t) = SOC_0 - \frac{1}{C_{Capacity}} \int_o^t \eta(i^{\pm}(t), T(t)) i^{\pm}(t) dt \tag{1}$$

where SOC_0 is the initial value, $SOC(t)$ is the cell SoC, and $\eta(i^{\pm}(t), T(t))$ is cell coulombic efficiency which differs with charging/discharging current $i^{\pm}(t)$ and cell temperature $T(t)$ at the time t. Work current $i^{\pm}(t)$ is assumed to be positive as discharge current $i^{+}(t)$ and negative as charge current $i^{-}(t)$.

Experience model [17,19] usually describes cell model as

$$\begin{aligned} V(t) &= V_{oc}(SOC(t)) - i^{\pm}(t) R^{\pm}_{series} \\ &= \left[K_0, K_1, K_2, K_3, K_4\right] [1, SOC(t), 1/SOC(t), \ln(SOC(t), \ln(1 - SOC(t))]^T - i^{\pm}(t) R^{\pm}_{series} \end{aligned} \tag{2}$$

which gives a good description between cell SoC and open circuit voltage $V_{oc}(SOC(t))$, but does not characterize the transient response and hysteresis effect of cell. The vector $V(k)$ is the cell terminal voltage, $K_i (i = 1, 2, 3, 4)$ is the constant chosen to make the model fit for the training data set, and $R^{\pm}_{series}$ is the cell internal resistance which differs with the process of charge or discharge and is expressed as discharge resistance R^{+}_{series} and charge resistance R^{-}_{series} [19].

If adaptive methods like Kalman filter are adopted for the SoC determination, cell model represented with state space equations must be established first. Based on the established SoC definition equation (1), experience equation (2) and equivalent electrical