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Brief Papers

Stochastic dynamic modeling of lithium battery via expectation maximization algorithm ☆

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ABSTRACT

Lithium battery is a reliable source for mobile, computers and electric vehicles. However, the internal chemical reaction of lithium battery is complex and susceptible to external influences, such that the traditional model-driven approach cannot model it accurately. In this paper, based on the data-driven approach, an expectation maximization algorithm is proposed to model a class of lithium battery. By using the expectation maximization algorithm, the model parameters and actual values of test, as well as the noise intensity can be identified simultaneously. The NASA battery data sets are employed to demonstrate the effectiveness of the proposed algorithm. Several indices are presented to evaluate the inferred lithium battery models.

1. Introduction

Lithium battery is a rechargeable battery with high energy density, low temperature performance, low self-discharge rate and long lifetime. It has been widely used in portable power products, hybrid electric vehicles and mobile communication [1–4]. Note that, the lithium battery failure can lead to the performance degradation, operating error or even catastrophic failure of the whole complex system [5]. In order to overcome battery failure, achieve effective lithium battery energy management, make full use of the power, extend the life of lithium battery and improve the safety and reliability of the system, it is necessary to model the lithium battery, analyze the characteristics, and estimate parameters. However, due to the time-varying and strong nonlinear characteristics, as well as influences by random factors as driving loads and operating environment in its application, it is difficult to obtain a precise battery model. Recently, there has been an increasing research interest to model lithium battery [6–9].

On the one hand, in order to optimize battery's physical parameters, some physical models have been greatly utilized for battery model design based on traditional model-driven approaches, such as electrochemical model and equivalent circuit model. Unfortunately, the speed of producing predictions as well as the configuration are unideal, hence, only limited analytical insight is provided to system designers [10]. In addition, in order to describe a new parameter estimation algorithm for the lithium battery model, the sequential quadratic programming method is used in [11] to estimate the model parameters in accordance with the application bandwidth of the battery. Due to the frequency response characteristics of the battery, standard identification algorithms cannot perform such an identification successfully. In [12], the authors proposed a time-scaled battery model parameter identification method to identify the slower and faster battery dynamics separately. However, it is worth noting that the existing work ignored the nonlinear capacity effects, hence the lithium battery cannot be modeled accurately. In [13], an accurate and simple electrical battery model is proposed, where the nonlinear capacity effects are considered to reduce the modeling error.

On the other hand, the internal chemical reaction of lithium battery is complex and susceptible to external influences. There exists a strong non-linear characteristic and noise. Thus, the internal chemical reaction cannot be expressed directly, and traditional model-driven approach cannot model accurately. Compared with the traditional model-based modeling, data-driven approach only requires online or offline experimental data, and can only rely on experimental data to establish the appropriate model. For example, in [14], a data-driven battery State of Health (SOH) estimation approach is realized based on the Gaussian process model algorithm. In [15], an online support vector regression algorithm is applied to realize battery remaining useful life (RUL). An online dynamic RUL

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estimation framework is proposed to achieve the online application and precise prediction.

Obviously, the stochastic dynamic model can be used to describe the complexity and non-linear characteristic of lithium battery, which consists of the first-order autoregressive stochastic dynamic process and the noisy measurement. The rational for choosing a stochastic dynamic model for the lithium battery is justified from the following three aspects. First, the model should be describe the internal relationship of battery. Second, the model is convenient for digital computation since the time series data of battery are actually obtained as a series of discrete-time points. Third, the observations of the model should be regarded as noisy due to our inability to perfectly and accurately measure the signals. As such, the modeling method should be capable of tackling available time series with acceptable accuracy.

After specifying the model structure, we need to find a way to jointly estimate the model parameters and the actual signal intensities simultaneously. The expectation maximization (EM) algorithm can be considered as an appropriate candidate because of its capability of handing the estimation problem via time series data. It is a general iterative method to compute maximum likelihood estimates of a set of parameters. The EM algorithm has been widely applied to various areas including classification, function approximation, clustering analysis, density estimation and construction of hidden Markov models in the field of statistics and machine learning [16–19]. In particular, two new EM Boolean factor analysis algorithms were introduced to maximize the likelihood of a Boolean factor analysis in [20]. In [21], an annealed EM algorithm was presented, and showed its effectiveness for extraction of fetal electrocardiograms.

In this paper, the EM algorithm is used to model the lithium battery for the first time. The EM algorithm is an iterative parameter estimation algorithm, and can identify both the model parameters and actual signal intensities of test simultaneously. Experimental results with the NASA battery data sets show that the approach can be effectively applied to model the battery. The main contribution of this paper is mainly threefold. (1) The lithium battery model is viewed as a stochastic dynamic model so as to describe the internal relationship of battery. (2) The EM algorithm is applied to jointly estimate the model parameters and the actual signal intensity. (3) The algorithm is validated in a comprehensive way through NASA battery data sets in terms of some well-defined criteria.

The remainder of this paper is organized as follows. In Section 2, the lithium battery is described as a stochastic dynamic model. The EM algorithm is introduced in Section 3 for handling the sparse parameter identification problem and noisy data analysis. In Section 4, our developed algorithm is applied to the NASA battery sets. We also make the model quality evaluation in Section 5 to verify the almost stability and robustness of the model. Some concluding remarks are provided in Section 6.

2. Stochastic dynamic model for the lithium battery

From the electrochemical model and equivalent circuit model, although the equation of model can represent lithium battery interior structure, but the lithium battery is a very complex electrochemical system with physical/chemical processes and some extra side reactions, such as aging, diffusion and self-discharge effects. As a result, the above two models cannot satisfy universal model of lithium battery. In this section, the lithium battery should be regarded as universal state-space model, and the model parameter can be obtained via the EM algorithm. Besides, the measured data from lithium batteries are often contaminated by noises. The dynamic of lithium battery can be modeled as

$$y_i(k) = x_i(k) + v_i(k) \tag{1}$$

where $y_i(k)$ is the measured value of the ith state variable at time k. $x_i(k)$ is the actual value of the ith state variable at time k. $v_i(k)$ is a zero mean Gaussian white noise sequence with covariance $V_i > 0$, $i = 1, 2, \ldots, n$, $k = 1, 2, \ldots, m$, n is the number of states, and m is the sampling time points.

Then, we model the lithium battery containing n states by the following stochastic discrete-time dynamic system:

$$x(k+1) = a_i x(k) + w_i(k) \tag{2}$$

where a_i represents the relationship between the states at time k and the states at time $k+1$. $w_i(k)$ is a zero mean Gaussian white noise sequence with covariance $W_i > 0$, $w_i(k)$ and $v_i(k)$ are mutually independent. Now, denote

$$x(k) \triangleq \begin{bmatrix} x_1(k) & x_2(k) & \cdots & x_n(k) \end{bmatrix}^T \tag{3}$$

In this paper, our aim is to establish the model (1) and (2) from the measurement data

$$y(k) \triangleq \begin{bmatrix} y_1(k) & y_2(k) & \cdots & y_n(k) \end{bmatrix}^T \tag{4}$$

To handle such a system identification problem, we introduce the EM algorithm to identify the model (1) and model (2). Before introducing our algorithm, we define the vector

$$\theta \triangleq \begin{bmatrix} a_1 & a_2 & \cdots & a_n & W_1 & W_2 & \cdots & W_n & V_1 & V_2 & \cdots & V_n \end{bmatrix} \tag{5}$$

which consists of all parameters to be estimated in (1) and (2).

3. Em algorithm for parameter identification

In this section, the main idea of the EM algorithm was introduced in [22–28]. Then we make use of the Kalman filtering and Kalman smoothing approaches to derive the iterative computation procedure for the proposed model (1) and (2). Each iteration is decomposed into an Expectation step (E-step) and a Maximization step (M-step). The E-step is using the current parameter estimation and observed data to estimate the logarithm likehood of the complete data. The M-step updates the new parameter by maximizing the logarithm likehood function of the estimation. Hence, given the observations Y and the current parameter estimation, the natural logarithm of the conditional expectation of probability density function for the completed data was defined as:

$$J(\theta, \theta^{(l)}) \triangleq \mathbb{E}_{\theta^{(l)}}[L(X, Y, \theta) | Y] \tag{6}$$

where

$$\begin{aligned} L(X, Y, \theta) \triangleq & -\sum_{i=1}^{n} \left\{ \frac{m}{2} \ln|W_i| + \frac{1}{2} \sum_{k=1}^{m} [x_i(k) - a_i x(k-1)]^T \right. \\ & \times W_i^{-1} [x_i(k) - a_i x(k-1)] + \frac{m+1}{2} ln|V_i| \\ & \left. + \frac{1}{2} \sum_{k=0}^{m} [y_i(k) - x_i(k)]^T V_i^{-1} [y_i(k) - x_i(k)] \right\} + C. \end{aligned} \tag{7}$$

with the constant C being independent of θ.

The new parameter to be estimated can be obtained by

$$\theta^{(l+1)} \triangleq \underset{\theta}{\operatorname{argmax}} J(\theta, \theta^{(l)}) \tag{8}$$

which leads to

$$a_i^{(l+1)} = \left\{ \sum_{k=1}^{m} \mathbb{E}_{\theta^{(l)}}[x_i(k) x^T(k-1) | Y] \right\}$$