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Extreme learning machine based spatiotemporal modeling of lithium-ion battery thermal dynamics

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HIGHLIGHTS

- A data based thermal model is developed for lithium ion batteries
- The model is efficient enough for online control oriented applications.
- The temperature distribution of the whole battery can be estimated in real-time with the developed model.
- The training of the nonlinear model only contains a linear process.

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ABSTRACT

Due to the overwhelming complexity of the electrochemical related behaviors and internal structure of lithium ion batteries, it is difficult to obtain an accurate mathematical expression of their thermal dynamics based on the physical principal. In this paper, a data based thermal model which is suitable for online temperature distribution estimation is proposed for lithium-ion batteries. Based on the physics based model, a simple but effective low order model is obtained using the Karhunen–Loeve decomposition method. The corresponding uncertain chemical related heat generation term in the low order model is approximated using extreme learning machine. All uncertain parameters in the low order model can be determined analytically in a linear way. Finally, the temperature distribution of the whole battery can be estimated in real time based on the identified low order model. Simulation results demonstrate the effectiveness of the proposed model. The simple training process of the model makes it superior for onboard application.

1. Introduction

Electrical vehicles (EVs) and hybrid electrical vehicles (HEVs) have attracted great attention in both industry and academic field in recent years. Lithium-ion batteries are becoming increasingly popular for energy sources of EVs and HEVs due to their high specific energy and energy density [1]. The safety, life, and performance of lithium ion batteries are all related to its thermal behavior [2]. A battery thermal management system that keeps the battery to work within an optimal temperature range is crucial in EV/HEV application.

The thermal process of lithium ion batteries is a typical distributed parameter system (DPS), which can vary both temporally and spatially. However, only limited sensors can be used for online temperature measurement in practical battery management systems (BMS). An accurate mathematical model is needed for online monitoring of the temperature distribution especially that cannot be measured. A lot of effects have been done in developing detailed mathematical model of lithium ion battery thermal process based on the physical principal. Usually, these models contain a heat transfer model combined with a heat generation model that describes the electrochemical reactions related behaviors. Lumped thermal models combined with equivalent-circuit electrical model [3,4] or electrochemical model [5–7] have been proposed. These models are simple enough for online application. However, only one or two temperature values can be estimated with these lumped models. This may leads to oversimplification for the larger batteries

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used in EVs and HEVs since their temperature may vary significantly in space. The distributed thermal models coupled with electrochemical model [8–11] can describe the detailed temperature distribution of batteries. While these models described in complex partial differential equations provide important information for battery design improvement, they cannot be used directly for online estimation and control due to the extensive computation needed.

To make it more compatible for online control related application, some physics based reduced order distributed electro-thermal models [12–14] have also been proposed for lithium ion batteries. For the purpose of real time estimation, a lot of work has also been done to develop efficient reduced order battery electrochemical models [15–18]. However, the temperature distribution was not seriously considered in most of these models. Due to the overwhelming complexity of the electrochemical related behaviors and internal structure, it is difficult to obtain an accurate mathematical expression of thermal dynamics inside lithium ion batteries based on the physical principal. Data based approach can be used to identify the thermal model from measured current, voltage and temperature distribution data. Artificial neural networks (ANN) have been widely used to model complex nonlinear systems due to their general approximation abilities. However, large computation burden involved in training ANN using traditional methods and the training algorithm may be trapped into local optimal. Extreme learning machine (ELM) [19] is a recently proposed algorithm to train single layer feedforward neural networks. Compared with other traditional ANN modeling methodology, the training algorithm of the ELM is much faster since only the weights of the output layer is needed to be trained. Therefore, it is more suitable for online application. Motivated by these advantages, ELM has successfully implemented in many fields [20–22]. However, few works can be found in ELM based modeling of DPS.

In this paper, an ELM based approach is proposed to learn an equivalent low order thermal model for lithium ion batteries. First, the Karhunen–Loeve decomposition is used to obtain the spatial basis functions for model reduction. Then, a low order form of the physics based model can be obtained using Galerkin's method. An ELM is established to represent unknown electrochemical related behaviors in the low order model. The output weights of the ELM and other uncertain parameters in the low order model can be simultaneously determined analytically in a linear way. Finally, the temperature distribution of the whole battery can be estimated in real time based on the identified low order model.

2. Battery electrochemical–thermal model

2.1. Physics based modeling

Consider a flat plate prismatic lithium ion battery and neglect the temperature variation in the thickness direction of battery cell, a two dimensional thermal model is considered in this paper. Based on the energy conservation law for lithium ion batteries, the heat transfer function can be described as follows:

$$\rho C_p \frac{\partial T}{\partial t} = \frac{\partial}{\partial x}\left(\lambda_x \frac{\partial T}{\partial x}\right) + \frac{\partial}{\partial y}\left(\lambda_y \frac{\partial T}{\partial y}\right) + Q(x,y,t) \tag{1}$$

where $T(x,y,t)$ is the spatiotemporal distributed temperature of the battery, x and y is the spatial coordinates, ρ is the battery density, C_p is the cell heat capacity, λ_x and λ_y is the thermal conductivity in the x and y direction respectively, and $Q(x,y,t)$ is the heat generation term.

The convective heat transfer is considered at the boundary, as:

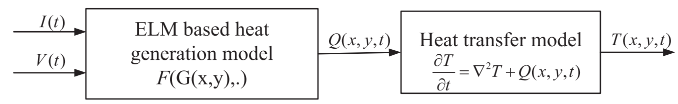

Fig. 1. ELM based spatiotemporal thermal model of lithium ion batteries.

$$-\lambda_X \frac{\partial T}{\partial X} = h(T - T_{\mathrm{air}})$$

where X can be the coordinates x, or y; h is the convective heat transfer coefficient on the surfaces of the battery, T_{air} is the environment temperature.

The electrochemical related heat generation term $Q(x,y,t)$ is a complex process composed of activation, concentration, and ohmic losses etc. Various expressions of Q have been proposed based on different assumptions of the physical principal [1]. Generally, Q can be expressed as a complex nonlinear function of the solid phase potential, the liquid phase potential, the current density, the temperature etc [9,28]. However, most of these variables are not measurable in practical battery management systems. All these variables are related to the applied current I and voltage V of battery. To build a computational efficient model for online temperature distribution estimation, a data based approach is proposed here to learn an equivalent form of Q with respect to I and V, which is assumed to be the following form:

$$Q(x,y,t) = F(G(x,y), I(t), V(t)) \tag{2}$$

where $G(x,y)$ denoted the effects of current distribution, electrode configuration, and other effects that cannot be modeled accurately. In this paper, ELM is used to identify the heat generation term Q from the measured current I, voltage V and temperature distribution data $T(x,y,t)$. The model structure is shown in Fig. 1.

2.2. Time/space separation based low order modeling

The model Eqs. (1) and (2) described in PDE is infinite dimensional in space, it cannot be directly used in battery management systems for online estimation and control due to the extensive computation needed. Furthermore, the direct identification of ELM based heat generation model from the measured current, voltage, and temperature data is also not easy due to the infinite dimensional nature of the process. The time/space separation based methods using spatial bases functions (BFs), which have been widely used for model reduction of DPS [23], can be used to learn an efficient low order form of Eq. (1).

As shown in Fig. 2, the modeling methodology includes two stages. In the first stage, Karhunen–Loeve decomposition is used to find a set of orthogonal spatial bases function (BFs) $\{\varphi_i(x,y)\}_{i=1}^{\infty}$ for

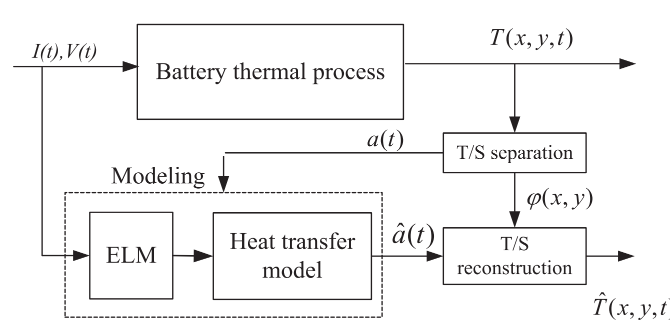

Fig. 2. ELM based low order modeling for lithium ion battery thermal process.