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A technique for dynamic battery model identification in automotive applications using linear parameter varying structures

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ABSTRACT

In this paper, a rapid calibration procedure for identifying the parameters of a dynamic model of batteries for use in automotive applications is described. The dynamic model is a phenomenological model based on an equivalent circuit model with varying parameters that are linear spline functions of the state of charge (SoC). The model identification process is done in a layered fashion: a two step optimization process using a genetic algorithm (GA) is used to optimize the parameters of the model over an experimental data set that encompasses the operating conditions of interest for the batteries. The level of accuracy obtained with this procedure is comparable to other black/gray box techniques, while requiring very little calibration effort. The process has been applied to both lithium ion and NiMH chemistries with good results. An extension of this technique to identify a model with both SoC and temperature dependence is discussed.

1. Introduction

One of the most attractive technologies for improving fuel economy in the automotive industry is the use of hybrid powertrain technology, where a vehicle is driven by two power sources. Currently, the dominant form of this technology is charge-sustaining hybrid electric vehicles (HEV), where the two power sources are an internal combustion engine (ICE) and an electrical machine (EM). Under strong consideration, and likely to emerge in the market over the next couple of years are the Plug-in Hybrids (PHEV) which are hybrids capable of operating in both charge-depleting modes and charge-sustaining modes. Central to these hybrid implementation forms is the battery pack. Due to cost, weight and packaging constraints, current production battery packs are made with nickel-metal hydride (NiMH) cells. But the automotive industry is fast evolving to lithium ion or lithium ion polymer chemistries, which has more favorable power and energy densities.

The central challenge to any P/HEV development is the design of the vehicle energy management system (EMS). A properly designed EMS allows the EM to supplement the ICE or the ICE to charge the battery to improve ICE efficiency, allows regenerative braking whenever possible, allows the EM to assist in drivability under load demand, and more. To do so, the EMS must have a well designed battery management system (BMS) that tracks the state of charge (SoC) and state of health (SoH) of the battery pack as feedback variables to the EMS as well as perform maintenance actions such as cell balancing and cooling to provide maximum lifetime for the pack. The SoC estimation problem is particularly challenging because of the length of time these vehicles are in service under the charge-sustaining mode where the battery pack operates with high efficiency and slow aging. However, when operated in this mode for an extended time, noisy current integration deviates from the true power consumption making direct measurement of SoC unreliable (see Pang, Farrell, Du, & Barth, 2001; Serrao, Chehab, Guezennec, & Rizzoni, 2005; Verbrugge & Tate, 2004 for more on the SoC estimation problem). Moreover, with regard to state of health, the battery undergoes an aging process, which depends on many factors (temperatures, severity of use in terms of both current magnitude and depth of discharge, and so on), rendering the relationship to battery health difficult to characterize. Furthermore, whatever solution one uses to solve these problems must be readily implementable onboard, typically limited to standard onboard measurements.

Many physically based and *ad hoc* algorithms have been proposed in the literature (and some are implemented in production) for general modeling, SoC estimation, and other related problems (see Piller, Perrin, & Jossen, 2001 for a summary of basic algorithms used for SoC estimation). Examples of these algorithms include the standard current integration and open circuit voltage measurement to more advanced techniques such as sliding mode observers (Kim, 2006), fuzzy logic (Malkhandi, 2006), and Kalman filters (Plett, 2004). When the SoC problem is solved, the SoH problem becomes more tractable because SoC

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trajectory plays a role in determining the battery's SoH. For example the dual-Kalman filter idea used in Plett (2004) is very promising. Many of these algorithms are model-based techniques that require a control-oriented model that is simple enough but can also describe the input to output (I–V) dynamic characteristics of the battery with sufficient accuracy. Therefore being able to find a control-oriented model of a battery is an important problem in P/HEV development. Furthermore, these models are also used for vehicle simulation for design and optimization studies and, very importantly, for developing and calibrating energy management strategies and controllers.

Several types of models are often used to capture input to output behaviors. Electrochemical models are based on the battery physical construction and chemistry. These models can be extremely accurate in predicting the output behavior of the battery because they characterize the fundamental mechanism of battery power generation. Such models typically contain systems of coupled partial differential equations that can be cumbersome to simulate/solve and are generally not suitable for control design (see Gomadam, Weidner, Dougal, & White, 2002; Ledovskikh, Verbitskiy, Ayeb, & Notten, 2003; Newman, Thomas, Hafezi, & Wheeler, 2003 for example models). Furthermore, due to the proprietary nature of most readily available batteries, the parameters needed to fit the model are often unavailable. The other approach that is often adopted as a compromise between accuracy and usability is the equivalent circuit-based model. Such models use a combination of SoC dependent voltage source, resistors, capacitors, and possibly nonlinear elements such as the Warburg impedance to approximate the underlying dynamics. While not as accurate as the electrochemical models, these models are often much simpler in structure thus making them suitable for onboard implementation. When operating conditions are restricted (i.e. operating in a certain range of temperature and SoC), the inaccuracy in these models can be less than 5%, which when treated properly can produce usable results for vehicle energy management. Because a physical analogy exists between the components used for the equivalent circuit model and the actual battery, this class of model is often called gray box. Some black box type models (i.e. those that simply fit input to output behavior without any physical analogy) have also been tried with success as well (for example neural networks models as seen in Chan, Lo, & Shen, 2000).

This paper focuses on the identification of an equivalent circuit-based model. Because the battery dynamics are complex, the challenge for such a model is that it must adequately describe the battery dynamic behavior for a range of operating conditions. As previous research has noted (Barsoukov & Macdonald, 2005), the static and dynamic behavior of typical batteries for these applications vary with current direction, SoC and temperature. Therefore a single equivalent circuit model cannot describe the battery operation over a large range of SoC and temperature. A solution to this problem is to schedule the model parameters based on the operating condition. Typically, the battery will be exercised in a restricted region of operating condition, leading to the identification of a constant model based on the resulting data set. By repeating the process over the operating region of interest, one can compose a model that can emulate the battery behavior in a boarder context while still retaining the basic equivalent circuit structure. If no nonlinear elements are used in the dynamic part of the model, the composite model is a linear parameter varying (LPV) model (for references on LPV systems see Lim, 1999; Shamma & Athans, 1992) whose coefficients are piecewise constant functions of SoC and temperature. The difficulty with such a model is that because the coefficient functions are inherently discontinuous at the zone boundaries, care must be taken to prevent undesirable transition effects when simulating with noisy current measurements. Furthermore, the experiments (and subsequent parameter identification) required to calibrate the model parameters are typically extensive and tedious to perform.

In this paper, it will be shown that an LPV model based on an *RC* circuit network structure whose coefficients are linear splines (continuous piecewise linear functions) can also model batteries with good accuracy for use in automotive applications. The inherent continuity property in the coefficients of the model makes it a desirable alternative to the zone-based models. The other properties of the linear spline functions make the model flexible and the identification process systematic. Specifically, with a properly designed input and identification procedure, the entire LPV model can be identified quickly and accurately. To validate the process, model identification is performed for a lithium ion battery and a NiMH battery, with the lithium ion battery intended for use in a future PHEV application and the NiMH currently used in a commercial HEV vehicle. The identified LPV model is validated in different ways to show the success of the identification. Because the focus of this study is to show a proof of concept of the overall identification and model structure, temperature variation is not considered (i.e. all data are collected under isothermal conditions). Extension to include temperature is discussed briefly.

2. Battery model

As noted, typical battery current-to-voltage behavior exhibits significant dynamical behavior. While the physical sources of the dynamical behavior are linked to electrochemistry, ion diffusion, and so forth, requiring partial differential equations to describe the net electrical dynamical behavior can be, and is often approximated, by equivalent electrical circuits of reduced order. The equivalent electrical circuit usually consists of a low-order linear system (an *RC* circuit network, for example), an ideal voltage source whose output is referred to as the open circuit voltage (OCV), and sometimes includes nonlinear elements such as Warburg impedances. This electrical-circuit equivalent framework is very popular in the vehicle literature as it is very amenable to models suitable for vehicle simulation, optimization and control. Furthermore, the automotive industry is favoring a model-based approach for vehicle control development, which inherently requires suitably simplified models, easily identified and calibrated with physical experiments. These models, while only approximating the physical behavior of the systems (batteries in this case) are very tractable for control applications. Therefore the structure selected for the modeling identification procedure in this paper is an equivalent circuit model.

2.1. Equivalent circuit model

The equivalent electrical-circuit model selected to model the battery is shown in Fig. 1. The model consists of an internal resistance, n series connected parallel *RC* circuits, and an ideal voltage source. The order of the model is equal to n, since the voltage to current behavior of each *RC* circuit can be described by an independent first-order linear differential equation. To compensate for the effect of SoC, temperature and current direction have on the battery behavior, the resistors and capacitors in this equivalent circuit model are functions of the current flow direction, SoC and temperature. The OCV is parameterized as a monotonic function of the SoC and temperature. Because temperature effect is excluded in this paper, the parameters do not depend on temperature (all experiments are conducted at 25 °C).