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# Electro-thermal battery model identification for automotive applications

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ABSTRACT

This paper describes a model identification procedure for identifying an electro-thermal model of lithium ion batteries used in automotive applications. The dynamic model structure adopted is based on an equivalent circuit model whose parameters are scheduled on the state-of-charge, temperature, and current direction. Linear spline functions are used as the functional form for the parametric dependence. The model identified in this way is valid inside a large range of temperatures and state-of-charge, so that the resulting model can be used for automotive applications such as on-board estimation of the state-of-charge and state-of-health. The model coefficients are identified using a multiple step genetic algorithm based optimization procedure designed for large scale optimization problems. The validity of the procedure is demonstrated experimentally for an A123 lithium ion iron-phosphate battery.



## 1. Introduction

In recent years, the use of hybrid powertrain technology has become a very effective method of improving fuel economy for automobiles. Vehicles with hybrid powertrains contain two or more separate power sources that are selected to complement each other as well as to provide added capabilities (such as regenerative braking) to improve the efficiency of the overall operation. Almost all commercial form of hybrid powertrain involves some combination of an internal combustion engine (ICE) and one or more electric machines (EM) (often referred to as hybrid electric vehicles, or HEV). While the ICE derives its power from fossil fuel, the EM obtains its energy from a battery pack. In order to minimize weight and size and still meet the energy and power demand while driving, typical battery cells have high power and high energy density. In older generations of HEVs (such as the Toyota Prius), nickel-metal hydride (NiMH) cells have been the battery choice due to their lower prices and good energy density. This choice is appropriate for HEVs that operate exclusively in a charge-sustaining mode, where the battery pack is maintained in a narrow range around a selected state-of-charge (SoC). Plug-in hybrid vehicles (PHEV) that require electric traction for extended periods, in a charge depleting mode, demand much more from the battery pack. In addition, their need for an all-electric range (AER) requires significantly more energy on-board. With the emergence of PHEVs, the vehicle electrification industry has opted to use the higher energy/power density lithium ion batteries.

Managing the battery pack for P/HEVs is a challenging problem. The objective of decreasing fossil fuel consumption while increasing drivability is in conflict with the objective of prolonging the life of the battery pack. If the full energy content of the battery pack is used, then clearly more gains are possible. However, the life of a rechargeable battery is significantly shortened when the battery is fully discharged or overcharged. In addition, overcharging (especially in the case of the lithium ion battery) can lead to catastrophic failure in the form of thermal runaway. Therefore, combining the objectives of improving fuel economy and drivability with battery life maximization dictates the requirement for careful SoC management of the battery. Furthermore, as batteries age, they become less able to store and supply energy. Consequently, the battery management system must be aware of the state-of-health (SoH) of the battery pack so that the vehicle control strategies can be adjusted accordingly. Having accurate models for use in estimating these critical characteristics, particularly for on-board vehicle application, therefore becomes an important requirement.

State-of-charge is commonly defined as the ratio between the amount of charge stored in the battery to the amount of charge that can be stored when the battery is fully charged. As such, SoC can be estimated by integrating the current going in and out of the battery pack. However, system noise and sensor calibration can render the electrical current measurement inaccurate, resulting in potentially large errors over time when that measurement is integrated. Another way to estimate the SoC is via the open circuit voltage

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(OCV), taking advantage of the fact that a one-to-one mapping exists between the SoC and the OCV at a given temperature. However, the sensitivity of SoC to errors in OCV is very high due to the flatness of the OCV dependence on SoC for lithium ion batteries (see [1–3]). Because of various dynamics that characterize the battery behavior, a sufficiently accurate OCV can only be obtained after a long rest period (often several hours). This method for SoC estimation is therefore not realistic in real-time operation when the battery is constantly being used. Consequently, sole dependence on direct measurements typically does not produce accurate or useful estimates for SoC. SoH estimation is very similar to SoC estimation in terms of measurement difficulties. For example, a common way to quantify the SoH is via the capacity of the battery. However, as P/HEV batteries are never fully discharged, the capacity cannot be measured directly. In addition, any solution used to solve these estimation problems must be implementable on-board in real time, requiring only standard on-board measurements. This effectively rules out indirect frequency domain based ideas such as proposed in [4].

Of the many algorithms proposed in the literature to solve the SoC and SoH estimation problems (see [5] for a summary of basic algorithms used), model-based algorithms (such as extended Kalman filter [6,7] and sliding mode observers [8]) are attractive because they are efficient, robust, and do not require significant tuning, which is typical for numerically based methods such as artificial neural networks [9]. In order for model-based algorithms to be widely applicable, a control-oriented dynamic model is needed. The two types of models that are commonly used to describe the input-to-output behavior of a battery are electrochemical models [10] and equivalent circuit models [11]. Complexities of electrochemical models generally prohibit them from being used effectively in solving on-board estimation problems. Equivalent circuit models represent a simplification of electrochemical models by using electrical circuit elements to describe the battery behavior. For example, charge transfer across a boundary can be represented by a resistor in parallel with a capacitor, wherein ion diffusion can be represented by wave propagation on a transmission line. The appropriate construction of the equivalent circuit can be obtained via electrochemical impedance spectroscopy. Equivalent circuit models obtained this way are capable of exhibiting accuracy over a wide frequency range. However, very accurate equivalent circuit models tend to require distributed or nonlinear elements such as transmission line elements and Warburg impedances, which make on-board real-time application problematic. As seen in [12] however, battery responses at room temperature to typical current inputs seen in automotive applications can be approximated using an equivalent circuit that only contains resistors and capacitors. In such a model, circuit elements are scheduled on SoC and current direction. Models of this type are well suited for model-based algorithms. The primary shortcoming of the model presented in [12] is the fact that isothermal conditions were assumed. Because temperature can significantly affect battery behavior (such as increasing or decreasing the internal resistance), models that do not account for temperature change must themselves be scheduled or otherwise have limited use as part of a realistic on-board battery management system.

In this paper, the model in [12] is extended to include temperature dependence. The model is based on an equivalent circuit consisting of a voltage source and parallel resistor and capacitor circuits. Temperature dependence is addressed by allowing the model parameters to be dependent on temperature as well as SoC and current direction, resulting in a structure with a non-trivial number of unknown coefficients to be identified. These coefficients are identified in a multiple step genetic algorithm (GA) based optimization procedure, designed for large scale optimization problems. The identification procedure is discussed in detail for a modeling process with validation on an A123 lithium ion iron–phosphate battery.

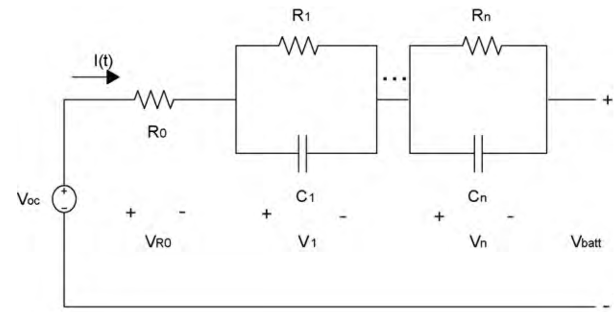


**Fig. 1.** Equivalent circuit used for battery model.

## 2. Battery model

Because the intended application for this model is for use in on-board estimation problems, the equivalent circuit structure employed herein will contain no distributed elements (such as transmission line) and nonlinear or pure frequency domain quantities such as the Warburg impedance. The resulting model structure may therefore be characterized using ordinary differential equations, where the specific structure selected is the Randle equivalent circuit shown in Fig. 1. The circuit is comprised of an ideal OCV, an internal resistance $R_0$, and $n$ parallel $RC$ circuits to approximate the battery dynamics. While not the most sophisticated model structure possible, this structure is selected because of its simplicity and universality. As reported in the earlier work [12], this structure provided a very good approximation for lithium ion battery dynamics at room temperature. Therefore, a natural next step is an extension to the case of multiple temperatures.

The dynamic equation that describes the voltage across the $i^{th}$ $RC$ circuit is given by

$$\frac{dV_i}{dt} = \frac{1}{R_iC_i}V_i + \frac{1}{C}I. \tag{1}$$

For convenience in identification, this equation can be viewed as a first order dynamic system in the form

$$\frac{dV_i}{dt} = -A_iV_i + A_iB_iI, \tag{2}$$

where $A_i = 1/(R_iC_i)$ and $B_i = R_i$ are the inverse of time constant and input coefficients, respectively. For now, $R_i$ and $C_i$ (consequently $A_i$ and $B_i$) are assumed to be dependent in some fashion on operating conditions. The precise nature of this dependence, and its justification, are discussed later.

The OCV in this equivalent circuit model is a function of the SoC. Technically, the OCV can have small variation with respect to the temperature. However, in experimental data collected, this difference is inconsistent and very small, so in this work the OCV is not parameterized as a function of the temperature. The SoC variation for a fixed temperature has a particular form. That is, the battery terminal voltage drops quickly as the SoC approaches 0% and rises as SoC reaches around 100% [13]. In a relatively large transitional portion of the SoC, the relation is nearly linear, and throughout the region the OCV is a strictly increasing function of the SoC. Given these characteristics, the OCV is modeled herein by a double exponential function as

$$V_{oc}(z) = V_0 + \alpha(1-\exp(-\beta z)) + \gamma z + \zeta\left(1-\exp\left(-\frac{\varepsilon}{1-z}\right)\right), \tag{3}$$