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Multi-parameter battery state estimator based on the adaptive and direct solution of the governing differential equations

Shuoqin Wang[a,*], Mark Verbrugge[b], John S. Wang[a], Ping Liu[a]

[a] HRL Laboratories, LLC, Malibu, CA, United States
[b] Chemical Sciences and Materials Systems Lab, General Motors R&D, Warren, MI, United States

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ABSTRACT

We report the development of an adaptive, multi-parameter battery state estimator based on the direct solution of the differential equations that govern an equivalent circuit representation of the battery. The core of the estimator includes two sets of inter-related equations corresponding to discharge and charge events respectively. Simulation results indicate that the estimator gives accurate prediction and numerically stable performance in the regression of model parameters. The estimator is implemented in a vehicle-simulated environment to predict the state of charge (SOC) and the charge and discharge power capabilities (state of power, SOP) of a lithium ion battery. Predictions for the SOC and SOP agree well with experimental measurements, demonstrating the estimator's application in battery management systems. In particular, this new approach appears to be very stable for high-frequency data streams.

1. Introduction

Lithium ion batteries have attracted great interest for automotive applications due to their high energy and power density, wide temperature range, and long cycle life [1–7]. In order to realize the full benefit of these traction batteries, efficient energy management is essential. In many battery-powered systems such as electric vehicles (EV) and hybrid electric vehicles (HEV), energy efficiency is enhanced by intelligent management of the electrochemical energy storage system [8]. These applications require a battery state estimator (BSE) to ensure accurate and timely estimation of the state of charge (SOC), the charge and the discharge power capabilities (SOP), and the state of health (SOH).

Various battery models have been studied within the framework of a BSE [9–24]. A physics based electrochemical model may be able to capture the temporally evolved and spatially distributed behavior of the essential states of a battery [9,10,23]. It is built upon fundamental laws of transport, kinetics and thermodynamics, and requires inputs of many physical parameters [24]. Because of its complexity, relative long-simulation time, and difficult control of the output, this kind of model may be more suitable for battery design and analysis rather than a BSE. A (zero dimensional) lumped parameter approach based on an equivalent circuit model may be more suitable for a practical BSE due to ease of implementation. The single RC circuit model discussed in this paper is a simple and apparently robust approach that has been studied for the aforementioned purposes of a BSE [14,21,22,25,26]. It should be noted that this approach is fundamentally correct only when the battery is exposed to small signal perturbations around equilibrium. Highly non-equilibrium behavior of the battery is difficult to address. For such behavior, more physical effects need to be included along with a more detailed model, at the expense of the simplicity and robustness [11–13,20].

Many state estimators employ a superposition integration (SI) scheme [25,27–30] to predict in real-time the SOC, SOP, and SOH. This approach has been applied to Li-ion (lithium ion), lead acid, and NiMH batteries wherein the SI algorithm is based on a simple one-RC-circuit model of the battery as shown in Fig. 1. Inputs to the algorithm include the battery current, voltage, and temperature; the algorithm is used to regress the model parameters such as the open circuit voltage (V_{oc}), the high-frequency resistance (R), the charge-transfer resistance (R_{ct}) and capacitance (C). SOC, SOP and SOH can then be determined using the model parameters. Due to limited memory storage and computing speed of embedded controllers employed in many applications, the algorithm has been implemented with recursive relations using circuit parameters from previous time steps and experimental measurements acquired in the current-time step to regress new circuit parameters. The method of weighted recursive least squares (WRLS) is employed in the SI algorithm, wherein input

* Corresponding author. Tel.: +1 310 317 5183; fax: +1 310 317 5840.
E-mail address: swang@hrl.com (S. Wang).

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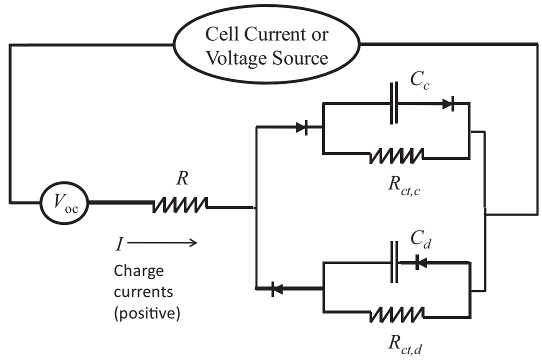

Fig. 1. Equivalent circuit employed in this work for the battery. Positive current corresponds to charging.

data is damped exponentially over time. As a result, newer information has a preferential impact on the value of regressed parameters.

We have found that the aforementioned SI algorithm becomes unstable at high sampling rates (e.g., for date-sampling frequencies above 10 Hz). As part of this work, the SI algorithm was applied to amorphous carbon/NMC (nickel, manganese, cobalt oxide) batteries (Hitachi cells intended for GM's high-voltage Belt/Alternator/Starter application, termed BAS+) and tested in a simulated HEV environment [31]. We also found that the numerical stability of the regression of the model parameters was sensitive to initial (seed) values. This sensitivity often led to numerical anomalies in the parameter regression. Both of above mentioned instabilities might be due to the fact that the SI algorithm is intrinsically a nonlinear model. Inside the model a "measured" term is the function of the parameter to be determined [25]. In addition, the current SI algorithm uses only one set of model parameters to describe both the charge and discharge events for the battery. In order to accommodate the possibility of different electrode kinetics processes for charge and discharge [32,33], the SI algorithm employed a fixed parameter $r = R_{ct,\,\mathrm{charge}}/R_{ct,\,\mathrm{discharge}}$, which represented the ratio between the values of R_{ct} for cell charge relative to discharge. Similarly, the charge-transfer time-constant, which is the multiplication of the R_{ct} and C, was assumed to be the same for both events.

In order to address these shortcomings, we have developed an improved battery state estimator, which we refer to as the direct differential (DD) algorithm. Similar to the SI algorithm, the DD algorithm employs the one RC-circuit model shown in Fig. 1 and the WRLS method to regress model parameters in real-time. Hence, the DD algorithm outputs the SOC, SOP, and SOH (deduced from changes in the regressed impedance parameters relative to those of a new, healthy battery) with the inputs of the voltage, current and temperature. Unlike SI, the DD algorithm is a strict linear model. Consequently, we have observed much more stable parameter regression upon application to simulated data. The algorithm treats the charge and discharge events separately; therefore there is no need for the fixed parameter r. Overall, implementation of the DD algorithm showed superior performance compared with the SI algorithm, including less sensitivity to initial (seed) parameter values and better stability at high sampling rates.

This report is organized as follows. Section 2 details the derivation of the DD algorithm; Section 3 overviews the algorithm's regression capability through the use of simulated data; Section 4 describes the experimental setup including essential hardware and software elements; and experimental results are presented and discussed in Section 5. These include parameter regression in real-time, SOC prediction via Coulomb titration results, and 2 s and 10 s power projections. Finally, summary and open questions are provided in Section 6.

2. The direct differential algorithm

The application of Kirchhoff's circuit laws using the one RC-circuit model in Fig. 1 produces the following differential equation:

$$V = (R + R_{ct})I + RR_{ct}C\frac{dI}{dt} - R_{ct}C\frac{dV}{dt} + V_{oc} \tag{1}$$

All of the symbols in the equation are defined in Fig. 1; V and I are measured inputs (their time derivatives being derived directly from measurements) and R, R_{ct}, C, and V_{oc} are model parameters regressed at each time step. Therefore, the formalism corresponds to a parameter identification problem in the control theory [34]. Positive currents correspond to charge (cf. Fig. 1). In order to address the differences between the charge and discharge kinetic processes, Eq. (1) is expanded into the following:

$$\begin{aligned} V = {} & \left[(R + R_{ct})I + RR_{ct}C\frac{dI}{dt} - R_{ct}C\frac{dV}{dt} + V_{oc}\right]_c \\ & + \left[(R + R_{ct})I + RR_{ct}C\frac{dI}{dt} - R_{ct}C\frac{dV}{dt} + V_{oc}\right]_d \\ & = (R_c + R_{ct\_c})I_c + R_cR_{ct\_c}C_c\left(\frac{dI}{dt}\right)_c - R_{ct\_c}C_c\left(\frac{dV}{dt}\right)_c + V_{oc\_c} \\ & + (R_d + R_{ct\_d})I_d + R_dR_{ct\_d}C_d\left(\frac{dI}{dt}\right)_d - R_{ct\_d}C_d\left(\frac{dV}{dt}\right)_d + V_{oc\_d} \end{aligned} \tag{2}$$

In this equation, all model parameters and variables with the subscript "d" are associated with the discharge process, while those with the subscript "c" are with the charge process. Unlike the aforementioned SI algorithm, the DD algorithm explicitly treats the discharge and charge cases separately. The parameters are regressed by applying the measured values of the current I and voltage V of the battery in real-time. The derivatives of the current and voltage over time are approximated with the difference equations; i.e., $dI/dt = (I(t) - I(t - \Delta t))/\Delta t$ and $dV/dt = (V(t) - V(t - \Delta t))/\Delta t$. (A central difference formulation can be employed to achieve higher numerical accuracy.) If the current I is positive (charging), $I_c = I$, $(dI/dt)_c = dI/dt$, $(dV/dt)_c = dV/dt$, and all variables associated with discharge are set to zero. The same convention holds for discharge currents. In the application to the Li-ion batteries of this work, we simplify Eq. (2) by assuming $R_d = R_c = R$ since the observed difference between the high-frequency-impedance for charging and discharging events is small. Fig. 2 depicts the cell potential of the Li-ion battery as a function of SOC. Since there is only slight hysteresis at the C/3 rate, it is reasonable to assume that the hysteresis is minimal for the V_{oc} vs. SOC relationship; hence, $V_{oc\_c} = V_{oc\_d} = V_{oc}$. The final equation of the DD algorithm for the Li-Ion battery estimator becomes:

$$\begin{aligned} V = {} & (R + R_{ct\_c})I_c + RR_{ct\_c}C_c\left(\frac{dI}{dt}\right)_c - R_{ct\_c}C_c\left(\frac{dV}{dt}\right)_c \\ & + (R + R_{ct\_d})I_d + RR_{ct\_d}C_d\left(\frac{dI}{dt}\right)_d - R_{ct\_d}C_d\left(\frac{dV}{dt}\right)_d + V_{oc} \end{aligned} \tag{3}$$

The WRLS method is applied to regress the model parameters. The method is briefly described as follows. Consider a linear dynamical model with input variables $\{x_l(t),\ l = 1,\ 2,\ \ldots,\ L\}$ and output variable $y(t)$ and assume these variables are sampled at discrete