Identification of Battery Models for Enhanced Battery Management

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ABSTRACT

Circuit models of batteries are investigated for their utility in real-time identification. Typical models of resistance-capacitance types for Lithium Ion batteries are employed to show that identifiability and sensitivity are essential issues in such models when real-time system identification is attempted. With certain structural modifications of the models to facilitate algorithm implementation, recursive identification algorithms are shown to provide fast convergence.

Keywords: state of charge, battery model, system identification, model parameters, battery management

1 Introduction

A large-scale battery system consists of hundreds even thousands battery cells, which have different characteristics even when they are new, and change with time and operating conditions due to aging, operational conditions, and chemical property variations. SOC (state of charge), battery health, remaining life, charge and discharge resistance and capacitance demonstrate nonlinear and time-varying dynamics [2]–[4], [6], [8], [10]. Consequently, for enhanced battery management, system diagnosis, and optimal power efficiency, it is necessary to capture battery cell models in real time [8]. This paper studies circuit models of batteries for their utility in real-time identification [7].

For evaluation, we employ the resistance-capacitance battery model which is part of ADVISOR developed at National Renewable Energy Laboratory (NREL) [1], [6], see Figure 1. The parameters of the components are functions of the SOC (state of charge) and cell temperature (T). In addition, the resistance values differ when the battery is in "charge" mode or "discharge" mode. In [6], the parameters of the model and their dependence on the SOC and temperatures are experimentally established. The battery model contains two capacitors (C_b and C_c) and three resistors (R_e, R_c, and R_t). C_b models the main storage capacity of the battery. Cc captures the fast charge-discharge aspect of the battery and is much smaller than C_b. These are expressed as $R_b(S,T,\eta)$, $R_c(S,T,\eta)$, $R(S,T,\eta)$, $C_b(S,T), C_c(S,T)$ when needed. In this work, we will use system identification methods to identify them in real time, without lab testing facilities. The issues of system identifiability and model structures will be investigated.

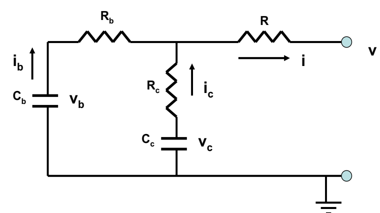

Figure 1: Battery models

2 Battery Models

To describe the model details, we define the following symbols.

$$
\begin{aligned}
v &= \text{terminal voltage (V)}\\
i &= \text{terminal current (A)}\\
v_b &= \text{voltage of the capacitor } C_b \text{ (V)}\\
i_b &= \text{current through the capacitor } C_b \text{ (A)}\\
v_c &= \text{voltage of the capacitor } C_c\\
i_c &= \text{current through the capacitor } C_c \text{ (A)}\\
T_a &= \text{air temperature (deg C)}\\
T &= \text{cell temperature (deg C)}\\
q &= \text{heat transfer rate}\\
q_b &= \text{heat transfer rate generated by the battery cell}\\
q_{ac} &= \text{air conditioning forced heat transfer rate}\\
S &= \text{SOC}\\
S_b &= \text{SOC}_{C_b}\\
S_c &= \text{SOC}_{C_c}\\
\eta &= \begin{cases} 1, & \text{charge;}\\ 0, & \text{discharge} \end{cases}
\end{aligned}
$$

It was given in [6] that the overall state of charge is a weighted combination of the state of charges of C_b and C_c. $\text{SOC} = \alpha_b \text{SOC}_{C_b} + \alpha_c \text{SOC}_{C_c}$, where $\alpha_b + \alpha_c = 1$. In the NREL/Saft model, $\alpha_b = 20/21$ and $\alpha_c = 1/21$. SOC_{C_b} and SOC_{C_c} will be related to the voltages on C_b and C_c later. The thermal model is a lumped first order linear dynamics, $q = \frac{T-T_a}{R_T}$, $C_T\dot{T} = q_b - q - q_{ac}$.

In [1], [6], the parameters of the model and their dependence on the SOC and temperatures are experimentally established. The states of charge for C_b and C_c are closely related to the voltages $S_b = g_b(v_b)$ and $S_c = g_c(v_c)$, and can be experimentally established. In the normal operating ranges of S and T, they can be well approximated by linear functions [6].

From $S = \alpha_b g_b(v_b) + \alpha_c g_c(v_c)$, model parameters become functions of the state variables v_b, v_c, T and the mode β

$$\begin{aligned}&R_b = f_{R_b}(v_b, v_c, T, \eta), R_c = f_{R_c}(v_b, v_c, T, \eta),\\&R = f_R(v_b, v_c, T, \eta), C_b = f_{C_b}(v_b, v_c, T),\\&C_c = f_{C_c}(v_b, v_c, T).\end{aligned} \tag{1}$$

The battery model is derived from the following basic equations. from

$$\begin{aligned}C_b\dot{v}_b &= i_b\\C_c\dot{v}_c &= i_c\\v_b - i_bR_b &= v_c - i_cR_c\\i &= i_b + i_c\\v &= v_c - i_cR_c - iR\\q &= \frac{T-T_a}{R_T}\\C_T\dot{T} &= q_b - q - q_{ac}\end{aligned}$$

These lead to $i_c = \frac{v_c-v_b}{R_c+R_b} + \frac{R_b}{R_c+R_b}i$. With state variables v_b, v_c, T; inputs i (current load), T_a (air temperature), q_b (battery cell generated heat flow rate), and q_{ac} (cooling air flow rate); operating mode η; and outputs v (terminal voltage), S (state of charge), and T; the state space model is

$$\begin{aligned}\dot{v}_b &= \frac{v_b-v_c}{(R_c+R_b)C_b} + \frac{R_c}{(R_c+R_b)C_b}i\\&= f_1(v_b, v_c, T, \eta) + g_1(v_b, v_c, T, \eta)i\\\dot{v}_c &= \frac{v_c-v_b}{(R_c+R_b)C_c} + \frac{R_b}{(R_c+R_b)C_c}i\\&= f_2(v_b, v_c, T, \eta) + g_2(v_b, v_c, T, \eta)i\\\dot{T} &= \frac{1}{C_T}q_b - \frac{T}{C_TR_T} + \frac{T_a}{C_TR_T} - \frac{1}{C_T}q_{ac}\\v &= \frac{R_bv_c+R_cv_b}{R_c+R_b} - (\frac{R_bR_c}{R_c+R_b} + R)i\\&= h_1(v_b, v_c, T, \eta) + m_1(v_b, v_c, T, \eta)i\\S &= \alpha_b g_b(v_b) + \alpha_c g_c(v_c) = h_2(v_b, v_c, T)\\T &= [0,0,1]\begin{bmatrix}v_b\\v_c\\T\end{bmatrix}\end{aligned} \tag{2}$$

Remark 1 By (1), the model parameters depend on the state and the system is highly nonlinear. Within the inputs, i is controlled (by power electronics and load) as discharge ($i > 0$) and charge ($i < 0$). T_a is a disturbance but is measured with some measurement noise. Since q_b is not modeled in detail, it will be considered as an unmeasured disturbance to the battery system. q_{ac} is controlled (by the cooling system). The cooling system dynamics is not considered in this model. As a result, we will view q_{ac} as a control input. The outputs v and T are measured with measurement noise. S is not measured.

Denote the state vector by $x = [v_b, v_c, T]'$, input vector $u = [i, T_a, q_b, q_{ac}]'$, output vector $y = [v, S, T]'$. The state space model (2) may be written in an abstract form, for methodology and algorithm development, as

$$\begin{cases}\dot{x} &= f(x,\eta) + g(x,\eta)u\\y &= h(x,\eta) + m(x,\eta)u\end{cases} \tag{3}$$

This is a nonlinear system in an affine form. Since η is a control variable taking only two possible values, the system (3) is a hybrid system.

For simulation studies, we use the NREL/Saft model [5], [6]. The model structure is given in Figure 1. Nominal values of the parameters at temperature 20 (deg C) are $C_b = 82\ kF$, $C_c = 4.074\ kF$, $R_b = 1.1\ m\Omega$, $R_c = 0.4\ m\Omega$, $R = 1.2\ m\Omega$. Dependence of these parameters on S and T is derived from experimental data. The data was extracted from the NREL/Saft model graphs [5] graphs using using ScanIt$^{\text{TM}}$software [9].[1]

Using the Least Squares (LS) method, polynomial models were derived from these data sets. For example, a third order polynomial model $y = a_1 + a_2x + a_3x^2 + a_4x^4$ is derived from the data set $\{(x_k, y_k), k = 1, \ldots, n\}$ as follows. From $y_k = \phi_k^T\theta + e_k$ where $\phi_k^T = [1, x_k, x_k^2, x_k^3]$ and $\theta^T = [a_1, a_2, a_3, a_4]$, define

$$Y = \begin{bmatrix}y_1\\y_2\\\vdots\\y_n\end{bmatrix}; \quad \Phi = \begin{bmatrix}\phi_1^T\\\phi_2^T\\\vdots\\\phi_n^T\end{bmatrix}$$

This leads to the observation equation $Y = \Phi\theta + E$ where E represents observation errors from the data. The LS method selects the estimate of θ by minimizing $J = (Y - \Phi\theta)^T(Y - \Phi\theta)$. If Φ is full rank, the optimal estimate is given by $\widehat{\theta} = (\Phi^T\Phi)^{-1}\Phi^TY$. By using the data sets derived from the graphs [5], the following functions are derived.

$$\begin{aligned}C &= \text{capacitance (F)}\\T &= \text{cell temperature (degree Celsius)}\\P &= \text{capacity (Ah)}\\i &= \text{current (A)}\\V &= \text{terminal voltage (V)}\\V_{oc} &= \text{open circuit voltage (V)}\\S &= \text{state of charge (\%)}\\R_{dis} &= \text{resistance in discharging mode } (\Omega)\\R_{cha} &= \text{resistance in charging mode } (\Omega)\end{aligned}$$

- For Capacitance versus temperature:

  $C = 7.77 * 10^4 + 0.043 * 10^4T - 0.0004 * 10^4T^2$
- For battery capacity versus temperature under a constant discharging current:

  $P = 6.00 + 0.048 * T - 0.0003 * T^2$

[1]We thank Dr. A. Pesaran for permission to use the graphs.

- For capacity versus temperature and discharge current:
  $P = 5.66 * 10 - 6.65 * 10^{-2} i + 1.11 * 10^{-3} i^2 -$
  $6.32 * 10^{-6} i^3 + 7.79 * 10^{-2} T - 9.15 * 10^{-4} T^2 +$
  $5.63 * 10^{-5} * i * T$
- For open circuit voltage versus temperature and SOC:
  $V_{oc} = 3.34 + 1.14 * 10^{-2} S - 1.63 * 10^{-4} S^2 +$
  $1.05 * 10^{-6} S^3 - 6.98 * 10^{-3} T + 8.10 * 10^{-5} T^2 +$
  $5.07 * 10^{-} * S * T$
- For internal resistance (during discharge) versus temperature and terminal voltage:
  $R_{dis} = 1.37 * 10 - 1.08 * 10 V + 2.83 * 10 V^2 -$
  $2.49 * 10^{-3} V^3 - 5.55 * 10^{-3} T + 1.31 * 10^{-5} T^2 +$
  $1.28 * 10^{-3} * V * T$
- For internal resistance during charging mode versus temperature and terminal voltage:
  $R_{cha} = -4.01 * 10^{-1} + 4.56 * 10^{-1} V -$
  $1.54 * 10^{-1} V^2 + 1.64 * 10^{-2} V^3 - 1.59 * 10^{-3} T +$
  $1.45 * 10^{-5} T^2 + 2.12 * 10^{-4} * V * T$

3 System Identification

Although system parameters in the battery model (2) can be established by using experimental data from lab testings, for real-time operating under a battery management system (BMS), the parameters must be derived using real-time operational data. This is due to several factors: (1) New batteries have different characteristics even for the same model, due to manufacturing variations. (2) Battery features depend on many factors that cannot be totally captured in model details. (3) Batteries experience significant aging effects. Consequently, it is not only desirable, but in fact imperative that model parameters be obtained individually in real time.

3.1 Identifiability

We first derived the transfer function for the battery model shown in Figure 1. Using $1/Cs$ for the capacitors and deriving the transfer function in the s-domain, this leads to

$$\frac{V(s)}{I(s)} = \frac{d_1 s^2 + d_2 s + 1}{c_1 s^2 + c_2 s} \tag{4}$$

where

$$\begin{aligned} d_1 &= C_b C_c (R R_b + R R_c + R_b R_c) \\ d_2 &= (R C_c + R C_b + R_c C_c + R_b C_b) \\ c_1 &= C_b C_c (R_b + R_c) \\ c_2 &= (C_b + C_c) \end{aligned}$$

The input-output model (4) contains 4 coefficients. However, the internal circuit model in Figure 1 contains 5 parameters. As a result, it cannot be identified. When the load current is a step function of magnitude I_0, the initial voltage jump V_0 allows us to calculate R_0 which provides an equation $R = R_0 - R_b || R_c$, reducing the number to 4 parameters.

Define $\eta = [d_1, d_2, c_1, c_2]'$ and $\beta = [R_b, R_c, C_b, C_c]'$. Then the above equations define a function $\mu = H_1(\beta)$. The circuit model (4) is identifiable if the Jacobian matrix is invertible

$$J(\beta) = \frac{\partial H_1(\beta)}{\partial \beta} = \tag{5}$$

$$\begin{bmatrix} C_b C_c (R + R_c) & C_b C_c (R + R_b) & C_c (R R_b + R_c + R_b R_c) & C_b (R R_b + R R_c + R_b R_c) \\ C_b & C_c & (R + R_b) & (R + R_c) \\ C_b C_c & C_b C_c & C_c (R_b + R_c) & C_b (R_b + R_c) \\ 0 & 0 & 1 & 1 \end{bmatrix}$$

Assumption 1 Let the true parameter of the battery circuit model be β_0. The circuit model (4) is assumed to be identifiable, namely $J(\beta_0)$ is invertible.

3.2 Identification

We shall start with a off-line modeling method. Recursive algorithms for tracking time-varying parameters will be covered in the next section.

Suppose that the signal sampling interval in a BMS is τ. Let the sampled values be $v_k = v(k\tau)$, $i_k = i(k\tau)$, etc. To derive a sampled expression to identify parameters in (4), we note that

$$\frac{\frac{1}{s} I(s)}{V(s)} = \frac{Y(s)}{V(s)} = \frac{c_1 s + c_2}{d_1 s^2 + d_2 s + 1} = \frac{\frac{c_1}{d_1} s + \frac{c_2}{d_1}}{s^2 + \frac{d_2}{d_1} s + \frac{1}{d_1}} \tag{6}$$

where $Y(s) = \frac{1}{s} I(s)$. Using the forward approximation, we have $y_k = y_{k-1} + \tau i_{k-1}$. (6) is mapped to

$$G(z) = \frac{\frac{c_1}{d_1} \frac{z-1}{\tau} + \frac{c_2}{d_1}}{\frac{(z-1)^2}{\tau^2} + \frac{d_2}{d_1} \frac{z-1}{\tau} + \frac{1}{d_1}} = \frac{b_1 z + b_2}{z^2 + a_1 z + a_2} \tag{7}$$

where

$$\begin{aligned} b_1 &= \tfrac{c_1}{d_1} \tau \\ b_2 &= \tfrac{c_2}{d_1} \tau^2 - \tfrac{c_1}{d_1} \tau \\ a_1 &= \tfrac{d_2}{d_1} \tau - 2 \\ a_2 &= 1 - \tfrac{d_2}{d_1} \tau + \tfrac{1}{d_1} \tau^2 \end{aligned}$$

Define $\theta = [a_1, a_2, b_1, b_2]'$. The above relationship defines a mapping to the circuit parameters

$$\theta = H_2(\mu) = H_2(H_1(\beta)) = H(\beta). \tag{8}$$

For small τ, the mapping $H_2(\cdot)$ is invertible. As a result, under Assumption 1, $H(\cdot)$ is invertible.

The discrete-time system (7) leads to the recursive equation

$$y_k = -a_1 y_{k-1} - a_2 y_{k-2} + b_1 v_{k-1} + b_2 v_{k-2} = \phi_k' \theta \qquad (9)$$

where the regressor is $\phi_k' = [-y_{k-1}, -y_{k-2}, v_{k-1}, v_{k-2}]$.

Utilizing the recursive least-squares algorithm [7] with a sampling interval $T = 0.001$ second

$$\begin{aligned}
&\widehat{\theta}(t) = \widehat{\theta}(t-1) + K(t)(y(t) - \varphi^T(t)\widehat{\theta}(t-1))\\
&K(t) = P(t)\varphi(t)\\
&= P(t-1)\varphi(t)(\lambda + \varphi^T(t)P(t-1)\varphi(t))^{-1}\\
&P(t) = (P_{(t-1)}^{-1} + \varphi^T(t)\varphi(t))^{-1}\\
&P(t_0) = (\varphi^T(t_0)\varphi(t_0))^{-1}
\end{aligned}$$

we generates a model

$$G(z) = \frac{0.7177z - 0.7177}{z^2 - 1.9999z + 0.9999} \qquad (10)$$

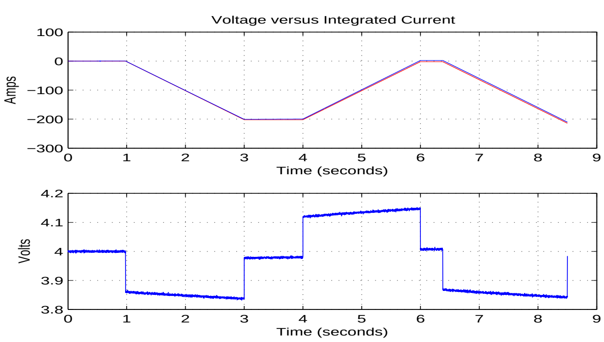

Figure 2: Comparison of difference equation utilizing recursive least squares method and Simulink model data

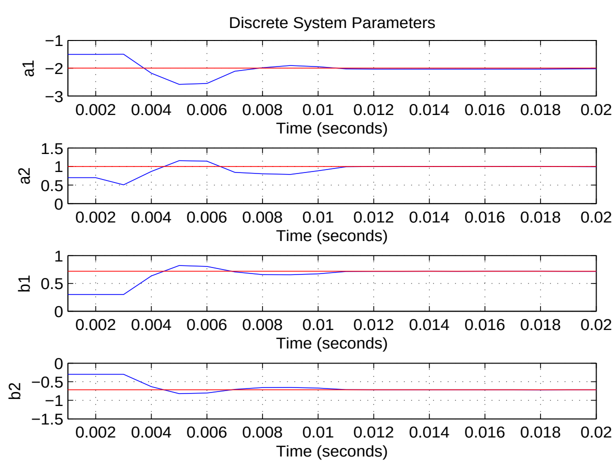

Figure 3: Convergence to true parameters

4 Conclusion

For system identification of circuit models of battery systems, identifiability and parameter sensitivity need to be carefully considered. In this paper, initial jump of the output measurements under a step load change is used to ensure identifiability. Recursive identification algorithms are shown to provide fast convergence when measurement noises are relatively low. The problem of large measurement noise and bias correction will be presented somewhere else.

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