SoC Estimation for Lithium-Ion Batteries in Automotive Systems: Sliding Mode Observation

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***Abstract*—In this study, Thévenin-equivalent circuit-based lithium-ion battery is modeled for State of Charge (SoC) estimation via sliding mode technique. Internal resistance and open-circuit potentials for different charge and discharge rates are included as look-up tables for precise energy based modeling of the lithium-ion battery. A solution for SoC estimation is proposed under two assumptions which simplifies battery model and estimates the states with sliding mode observation techniques. The method gives a chance for general usage of various battery chemistries. Successful simulations have been performed to illustrate the effectiveness of the proposed solution technique.**

Keywords— Li-Ion Battery, SoC Observer, Sliding Mode;

I. Introduction

State of Charge (SoC) estimation in electrically driven automotive systems is one of the most important parameter which determines stored energy in the high voltage battery and thereby available range of the vehicle. Currently universal Battery Management Systems (BMS) count capacity, $C_{k+1} = C_k + i\Delta t$ (Ah), to determine the storage. This seems to be the easiest and the best method to predict a SoC value. However, things work different in real life. Stored energy in the battery can be calculated by integration of capacity-potential curve. Since it is nonlinear, counting of capacity causes some errors. The operating temperatures and discharge/charge cycles also determines the shape of the curve. Under these conditions instead of counting capacity, evaluation of stored energy is the most accurate procedure.

Sliding mode based observation is widely used in automotive, aviation, chemical, oil, etc. industries. The sliding mode techniques give a challenge for robust stabilization for uncertain systems and presence of bounded disturbances and unmodeled dynamics. In literature, sliding mode observation is widely studied for linear, nonlinear, uncertain systems with and without time delays [1-5]. Lithium-ion battery equivalent circuit models and measurements of some parameters are evaluated in [6-9]. An iterative method for SoC estimation is studied in [10]. Sliding mode observation for SoC estimation for lithium-ion batteries are considered in [11-14]. Adaptive observer methods for SoC and State of Health (SoH) estimation are evaluated in [15-17].

In this study, Thévenin-equivalent circuit-based lithium-ion model is build to simulate dynamic behavior of lithium-ion cell. Open-circuit potential U_{OC} and internal resistance R_O parameters of mathematical model are defined as look-up tables from measurement experiments. Therefore mathematical model coincides with experiment results. Implementation of such a method for general purpose in automotive applications is not possible. U_{OC} and R_O have to be determined for each different cell before usage and have to be updated periodically with SoH changes. This is very tough procedure in commercial automotive industry. On the other hand, some BMS in market count capacity (Ah) instead of counting energy (Wh) to estimate SoC. Counting capacity gives a rough estimation and there exists approximately up to 10% of SoC errors. These BMS eliminate the SoC errors by reset to full value (100%) at every full charge. This is not valuable and reliable technique and stored energy cannot be calculated correctly. This will affect cell health; performances of electrical vehicle, and maintance of high voltage source. These disadvantages are motivations of this study which puts forward a simple but valuable solution for some lithium-ion battery types with various chemistry properties. A solution is developed under two assumptions which simplifies battery model and estimates the states with sliding mode observation technique. The technique gives a chance for general usage of various battery chemistries such as Lithium Cobalt Oxide (LCO, $LiCoO_2$); Lithium Manganese Oxide (LMO, $LiMn_2O_4$); Lithium Nickel Manganese Cobalt Oxide (NMC, $LiNiMnCoO_2$); Lithium Nickel Cobalt Aluminum Oxide (NCA, $LiNiCoAlO_2$); Lithium Polymer (Li-Po); etc. Developed solution can be easily installed in real-time embedded vehicle control units without any periodic maintances, and can be tuned for various cell chemistries by setting up initial parameters for considered cell in battery pack at the end of line of vehicle production.

The benefits of developed approach versus proposed methods in literature [11-17] are smooth and continuous estimation of terminal voltage and SoC value; easy installation on real-time embedded vehicle control units; no adaptation is required; and capability to be used with wide range on lithium-ion battery chemistries by simple initial setup. A disadvantage of this study is neglecting State of Health monitoring and calculation of battery cells. When SoH is considered a general solution to BMS could be developed.

This study is organized as follow. In second section full nonlinear lithium-ion battery model is evaluated. Then a simplified model is built for sliding mode observer design. In third section sliding mode observation techniques is evaluated for SoC estimation of the battery. Fourth section is a comparison of results. And section five concludes this study.

II. Lithium-Ion Battery Model

A. *Typical Lithium-Ion Battery Model*

Consider Thévenin-equivalent circuit-based lithium-ion battery model [7-8] as shown in Fig. 1. U_L is terminal voltage, I_L is load current with positive value at discharge and negative value at charging, U_{OC} is open-circuit voltage, R_O is internal resistance, R_{TH} is polarization resistance, C_{TH} is equivalent capacitance to describe transient responses on loading, U_{TH} is voltage and I_{TH} is current across the capacitance.

The dynamics of electrical behavior of the Thévenin-equivalent circuit-based lithium-ion battery model can be written as [7-8] below. Note that, current is positive in sign during discharge ($i_L < 0$) and negative in sign while charging ($i_L > 0$).

$$\dot{U}_{TH}(t) = \frac{-1}{R_{TH}C_{TH}}U_{TH}(t) + \frac{1}{C_{TH}}i_L(t)$$
$$U_L(t) = U_{OC} - i_L(t)R_O - U_{TH}(t) \tag{1}$$

where open-circuit potential $U_{OC} = U_{OC}(E)$ is a function of energy. In this study for an accurate battery model, $U_{OC}(E)$ curve is implemented from charge-discharge tests as a look-up table in association of Fig. 6 for Samsung INR18650-20R 2000mAh (Green) Li-Polymer cell. R_O is a function of internal resistance which depends on current demand, state of charge and cell temperature because of chemical process properties inside. From charge-discharge test at room temperature internal resistance is assumed to vary with current demand, $R_O = R_O(i_L)$. In the mathematical model $R_O(i_L)$ is implemented as look-up table (see Fig. 7).

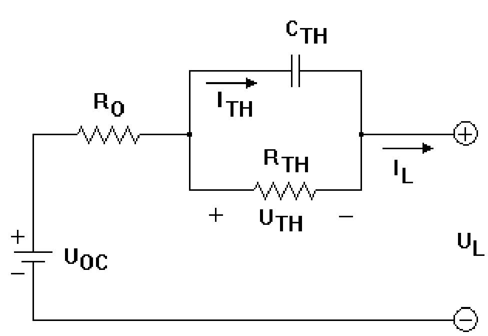

Fig. 1. Thévenin-equivalent circuit-based lithium-ion battery model diagram

Since calculation of open-circuit potential depends on energy of the cell, energy equation is evaluated as:

$$E(t) = E(t - \Delta t) - \frac{\Delta t}{3600}i_L(t)U(t - \Delta t) \tag{2}$$

where Δt is the time step (ex.: $\Delta t = 0.01s$), and $E(t - \Delta t)$ is prior energy value at a time t. For discharging, initial conditions are $E(t_0) = E_{MAX}$, $U = U_L(t - \Delta t)$, and $U_L(t_0) = V_{MAX}$. For charging, initial conditions are $E(t_0) = 0$ and $U = 4.2\,V$.

TABLE I. Lithium Ion Cell Properties

Cell Name	Samsung SDI, INR18650-20R 2000mAh (Green)								
Size	Weight: 42.4gr, Length: 64.9mm, Diameter:18.2mm								
Potential	V_{MAX} = 4.2V, V_{MIN} = 2.8V, $V_{NOMINAL}$ = 3.6V								
Test Condition	Charge Potential: 4.2V, Terminating current: 0.1A								
Test current, A	**0.2**	**0.5**	**1**	**2**	**3**	**5**	**10**	**20**	**30**
Capacity[a], Ah	2.061	2.045	2.012	1.976	1.965	1.959	1.958	1.934	1.724
Energy[a], Wh (E_{MAX})	7.610	7.542	7.400	7.210	7.101	6.995	6.868	6.341	5.401

a. Measured during tests

Fig. 2. Samsung SDI, INR18650-20R 2000mAh (Green) cells

Therefore, SoC percentage can be calculated from the following simple relation:

$$SoC = E(t)\frac{100}{E_{MAX}} \tag{3}$$

Note that, another important parameter for lithium ion cells is SoH. In this study SoH is assumed to be 100% for a brand new cell. SoH is not considered and evaluated at this time in the study.

B. *Reduced Battery Model*

The reduced battery model is exactly as same as typical lithium-ion battery model's energy equation (3) and SoC (3) relation. But the difference is in dynamics of electrical behavior. The assumptions stated below simplify and differentiate the batter model.

Assumption 1, Suppose that a lithium-ion cell has an open-circuit potential U_{OC} discharge curve as shown Fig. 3 with blue dots. To simplify the model assume open-circuit potential U_{OC} as line (shown in red) which closely describe the nonlinear measurement curve as shown in the figure. This line can be described as:

$$U_{OC\,MODEL} = -\frac{V_{MAX} - V_{MIN}}{E_{MAX}}E(t) + V_{MAX} \tag{4}$$

In general, internal resistance R_O, as described above, depends on current demand, SoC, and cell temperatures due to chemical properties inside the cell. During the tests, we have taken measurements only of internal resistance versus current demand and plot it in Fig. 7. Moreover, the resistance around V_{MIN} and V_{MAX} (see Fig. 3) is greater than the resistance around nominal voltage. As a result, internal resistance should be determined experimentally or modeled by knowledge of chemistry. It is a tough to implement internal resistance with these characteristics in real-time embedded vehicle control units. At this stage, a second assumption is accounted to simplify the model.

Assumption 2, Consider that internal resistance R_O slightly changes for current demand variations and let r_O be an average value of measured curve in Fig. 7. So assume,

$$R_O(i_L) = r_O \tag{5}$$

Therefore dynamic behavior of the equivalent circuit based lithium-ion battery model can simplified as:

$$\begin{aligned} \dot{U}_{TH}(t) &= \frac{-1}{R_{TH}C_{TH}}U_{TH}(t) + \frac{1}{C_{TH}}i_L(t) \\ U_L(t) &= -U_{TH}(t) - r_O i_L(t) + U_{OC_{MODEL}} \end{aligned} \tag{6}$$

The set of above equations are the base of observer design procedure in following section.

III. Sliding Mode Observer for SoC Estimation

Sliding mode based observation tutorial is given in [1]. In this study sliding mode observation is considered to estimate instantly electrical/hybrid road vehicle battery SoC value under discharge and charge conditions at real-time in an embedded vehicle control unit.

Consider sliding mode observer with following structure [2]:

$$\begin{aligned} \dot{\hat{U}}_{TH}(t) &= \frac{-\hat{U}_{TH}(t)}{R_{TH}C_{TH}} + \frac{i_L(t)}{C_{TH}} + L\left(U_L - \hat{U}_L\right) + S_o\left(U_L, \hat{U}_L\right) \\ \hat{U}_L(t) &= -\hat{U}_{TH}(t) + U_{OC_{MODEL}} - r_O i_L(t) = \hat{U}_{OC} - r_O i_L \end{aligned} \tag{7}$$

where L is a constant gain matrix, and

$$S_o\left(U_L, \hat{U}_L\right) = \begin{cases} \dfrac{P^{-1}C^T\left(U_L - \hat{U}_L\right)}{\left\|U_L - \hat{U}_{TH}\right\|}, & \left\|U_L - \hat{U}_L\right\| > \epsilon \\ \dfrac{P^{-1}C^T\left(U_L - \hat{U}_L\right)}{\epsilon}, & \left\|U_L - \hat{U}_L\right\| \le \epsilon \end{cases} \tag{8}$$

where P is solution to the algebraic Riccati equation.

The convergence of sliding mode observer according to a theorem in [2] is established as follows: Consider observable dynamic system (6) where rank of $(-1/R_{TH}C_{TH}, -1)$ is 1.

Estimated error dynamics of sliding mode observer (7) are exponentially stable for a positive P defined in (9):

$$2P\left(\frac{-1}{R_{TH}C_{TH}} + L\right) + \lambda_f^2 PP + 1 = -Q \tag{9}$$

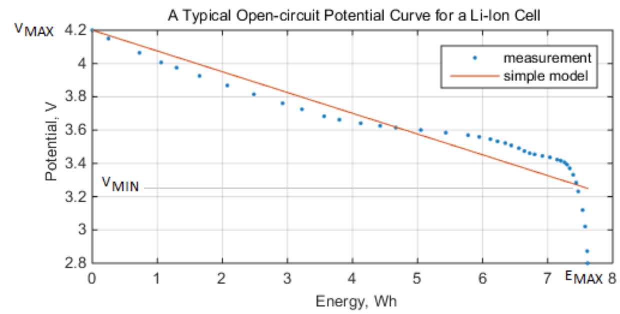

Fig. 3. A typical open-circuit potential curve for considered Li-Ion cell and suggested reduced battery model.

where λ_f is Lipschitz constant for $f(i) = i_L/C_{TH}$, and Q is a positive number, and $-1/R_{TH}C_{TH} + L < 0$.

IV. Comparison of Results

A battery pack defined by Eqs. (1-3), that has capacity of 60Ah and nominal potential of 345V, has been built up from tested Samsung SDI-INR18650-20R 2000mAh lithium-ion cells for simulation.

The parameters of the battery dynamic model which describes considered cell are as follows: polarization resistance $R_{TH} = 0.010$, equivalent capacitance $C_{TH} = 550F$, and constant internal resistance $r_0 = 0.030\Omega$.

It is suitable to select sliding mode observer parameters as $L = -1$ and $Q = 1.0$. Then Lipschitz constant can be determined from condition below:

$$\|f(i_1) - f(i_2)\| < \lambda_f \|i_1 - i_2\| \tag{10}$$

as $\lambda_f = 1$. Then a solution for algebraic Riccati equation can be obtained as $P = 0.9538$. The neighborhood in control law is selected to be $\epsilon = 0.10$.

No consider that, the battery pack first is discharge at constant current with 20A, and then is charged with 10A. Note that, discharging current is positive in sign and charging current is negative in sign. The time responses of charging and discharging process are shown in Fig. 4. As seen from the figures, the most important thing is that SoC is estimated smoothly and continuously which best fits for commercial automotive industry. Sliding mode observer successfully tracks battery terminal potential and observes open-circuit potential form full charge to empty case and vise versa with approximately 0.5V of errors without any chattering. Another important point is that sliding mode observer includes neglected unmodeled dynamics for the reduced (simple) battery model.

Another simulation test with repeated pulse discharges with period of 100 seconds is performed for 1000 seconds. The time responses of the battery model and sliding mode observer are shown in Fig. 5. The measured variable, that is terminal potential, is tracked successfully. On the other hand, open-circuit potential with reduced (simple) battery model is calculated in a small vicinity of nonlinear battery model value. The observed SoC value is continuous and has maximum 0.05% estimation errors again without any chattering.

As a results, developed technique estimates continuously SoC of a battery in a small vicinity of measured value. The developed technique can be applied in BMS in commercial automotive industry in pure electric or hybrid vehicles.

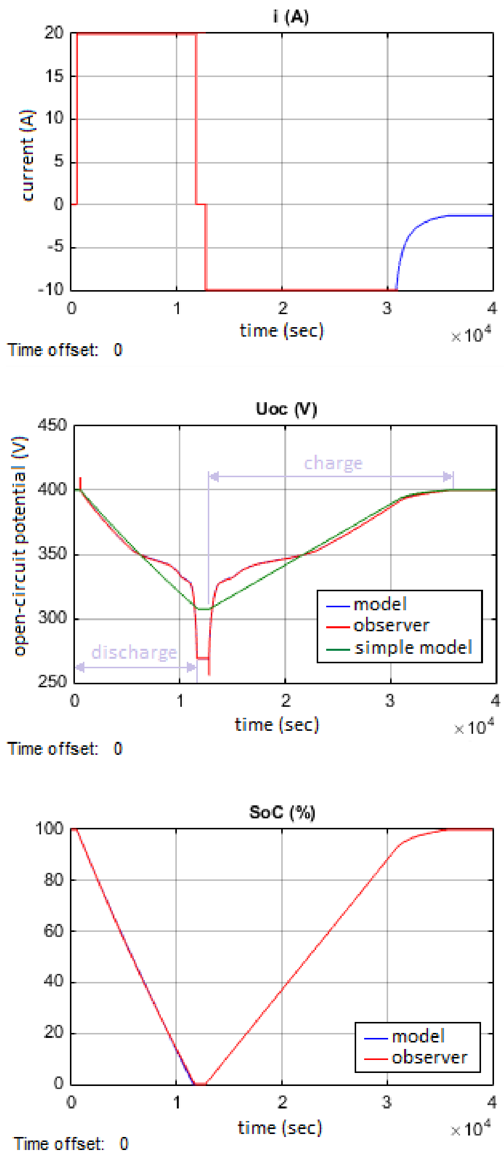

Fig. 4. Full discharge and charge behavior of the modeled battery

V. Conclusions

Nonlinear look-up tables based Thévenin-equivalent circuit-based lithium-ion model is build for precise simulation of an electrical vehicle battery behavior for charge and discharge regimes. A technique is developed to estimate smooth and continuous values of SoC for various lithium-ion battery chemistries. Successful simulations have been performed to illustrate the effectiveness of the proposed solution technique. Developed solution can be easily installed in real-time embedded vehicle control units without any periodic maintances. The algorithm can be tuned for various cell chemistries by setting up initial parameters for considered cell in battery pack at the end of line of vehicle production.

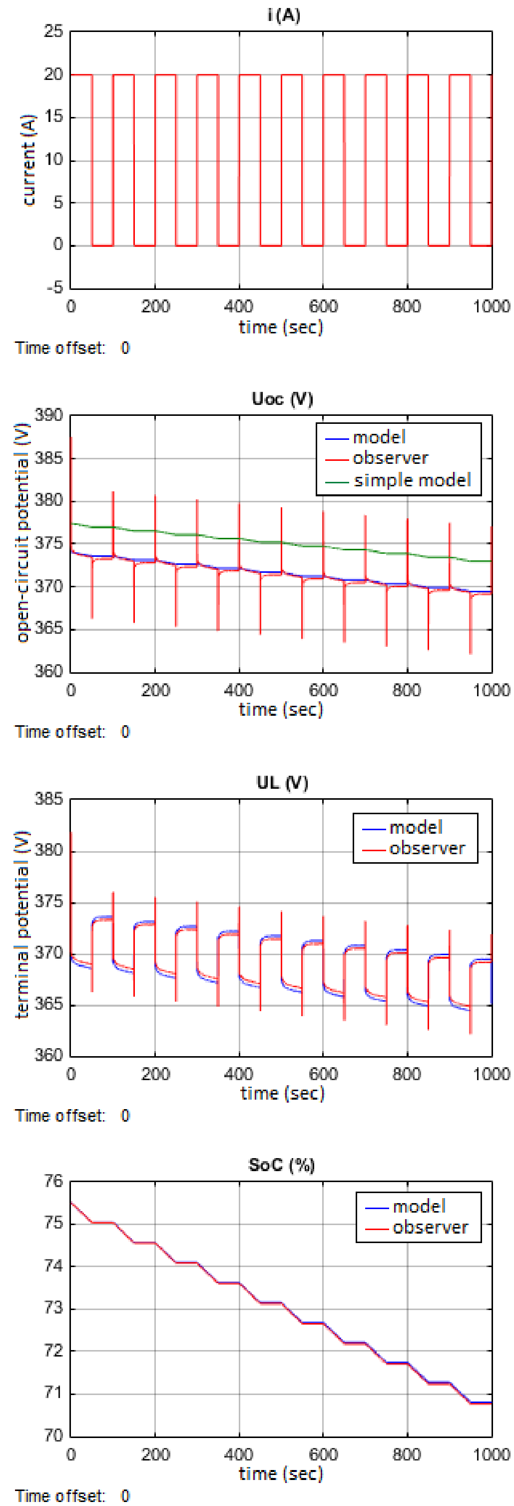

Fig. 5. A close look to performances of sliding mode observer

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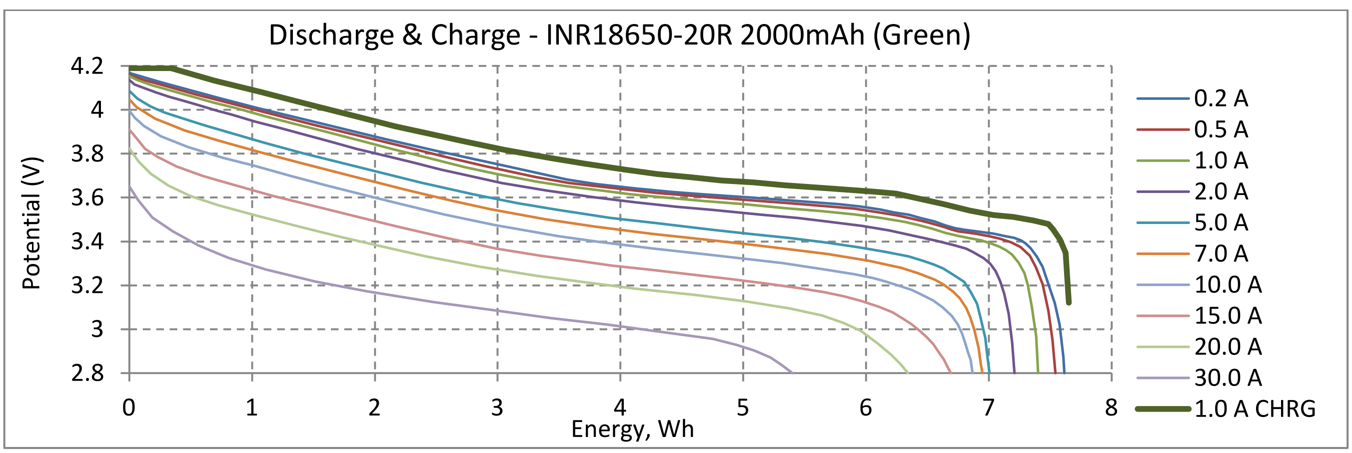

Fig. 6. Cell discharge/charge curves with energy (Wh) range.

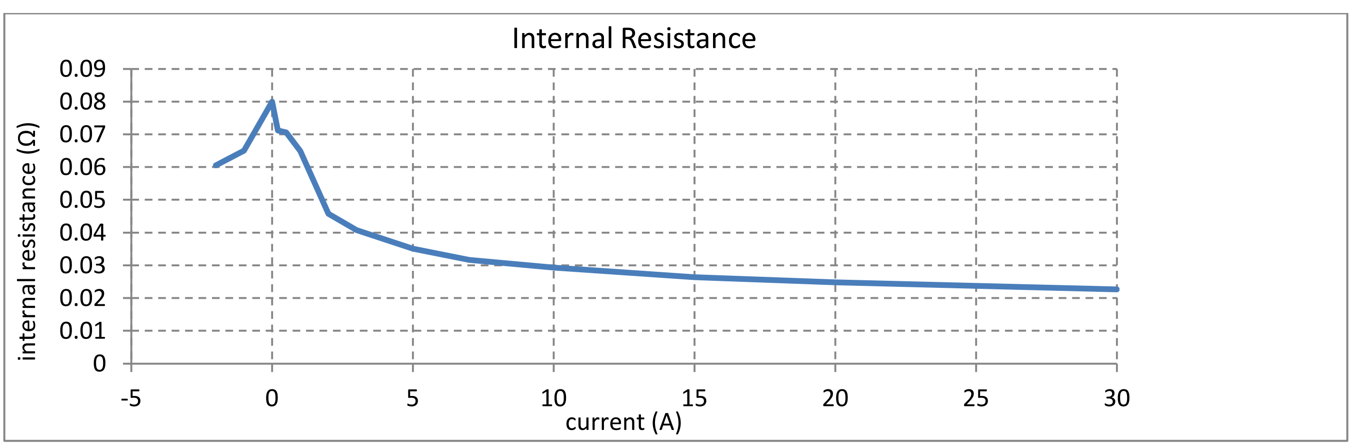

Fig. 7. Internal resistance versus current.