State-of-Charge Estimation of the Lithium-Ion Battery Using Neural Network Based on an Improved Thevenin Circuit Model

Haoliang Zhang[1], Woonki Na[2], and Jonghoon Kim[3]
1:mars_zhang@mail.fresnostate.edu, 2:wkna@csufresno.edu, and 3: whdgns0422@cnu.ac.kr

[1]Department of Electrical and Computer Engineering, California State University, Fresno, CA, USA
[2]Department of Electrical and Computer Engineering, California State University, Fresno, CA, USA
[3]Department of Electrical Engineering, Chungnam National University, Daejon, Korea

Abstract— **This paper focuses on real-time estimation of State of Charge (SOC) in Lithium-Ion battery. Because of the highly complex electrochemical reaction inside the battery the conventional first order battery model is not accurate and cannot respond to the battery's conditions correctly because of the simplicity of the model. So, the neural network (NN) is selected to estimate the SOC dynamically due to its strong nonlinear fitting ability. The NN strategy also was used to implement the parameter identification for the battery model.**

KEYWORDS— NEURAL NETWORK, SOC, AND LITHIUM-ION BATTERY

I. INTRODUCTION

In recent years, under the background of global energy shortage, the pure electric vehicle becomes a popular study filed because of its high economic efficiency and lower environmental pollution. Considering battery is the best power source for the next generation vehicle, and the accurate estimation of the battery performance is critical technic for the electronic vehicle operation [2]. Lithium-ion batteries have been widely used in many industrial fields. In order to use the Lithium-ion battery safely and efficiently, the internal states of the battery must be monitored appropriately promptly [3]. For a Lithium-ion battery, migration of the electrolyte and the activity of electrode materials is affected by temperature, hysteresis, cells age and self-discharge rate [4]. Furthermore, the battery is not charge/discharge with the constant current. Usually, the battery used under complex conditions, temperatures, and even extreme environments.

The safety of electric vehicle highly depends on Battery Management System (BMS). There are several factors evaluating the batteries states. Especially, the accurate state-of-charge (SOC) is one of the most important factors of BMS [5]. Different from the common vehicle that can measure reaming gasoline by the float ball, the SOC of the electric vehicle cannot be measured directly but only be measured by external information of the battery [6]. The SOC is affected by the complicated internal nonlinear characteristics of the battery such as mobility of a charged particle, discharge current, battery age, etc. Furthermore, the working temperature and external environment also make the real-time SOC measurement difficult.

Among all estimation methods, equivalent circuit models are widely selected, which includes the Rint model [7], the Thevenin model [8], the RC model, and the partnership for a new generation of vehicle (PNGV) model [9]. The first order Thevenin model was widely used in the past because of its reliability, when the battery is discharged with stable current and voltage. But considering highly complex electrochemical reactions inside of the battery, the first order of battery cannot reflect the battery's condition accurately during the charge or discharge process. Because of above reason, the improved Thevenin model was proposed which is second order Thevenin model, comparing with the first order, second order Thevenin model add extra RC circuit to first order due to polarization characteristics of battery [10]. But the improved Thevenin model need a lot of calculation, which is time-consuming, at the flat period, it has almost same accuracy as first order.

In order to use equivalent circuit model, the accurate parameter identification is needed. The neural network is the powerful algorithm used to identify system because of its strong nonlinear mapping ability. The SOC and the present terminal voltage are the output signals. In the parameter identification process, the activation function of the neural network is a linear function. In the battery modeling process, backward or forward difference method is used to solve the mathematical express of the Thevenin model. In this way, the relationship between the weights of the networks and the circuit parameters can be found. The experiment data will be used to train the initial weights of the neural network.

In this project, open circuit voltage (OCV), terminal cell voltage, and impedance at certain frequencies are all used to estimate the SOC of the battery. This project used a linear neural network to identify the battery model parameters. When the parameters of battery model are decided, it is necessary to use a neural network to estimate SOC based on the OCV. This new method can reduce the amount of calculation and give the best SOC estimation of Lithium-Ion battery during charge and discharge.

II. SYSTEM MODEL AND PARAMETER IDENTIFICATION

The section will briefly introduce the concept of the overall system and control for ease understanding of this work.

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A. Overall System

The overall system diagram is shown in Fig 1. There are four main steps in this paper : (1) battery parameters identification, (2) select the suitable battery model based on MSE, (3) calculating the OCV by the decided battery model, (4) using the OCV-SOC function to estimate the SOC.

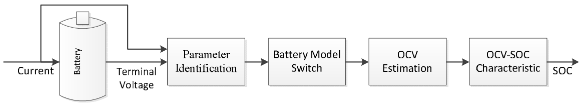

Fig. 1 Overall system schematic

B. Battery model

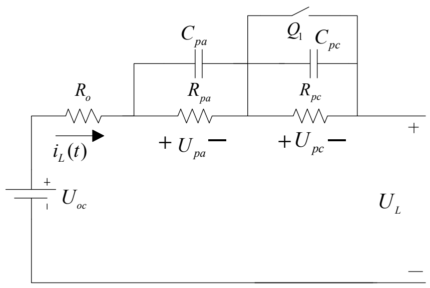

Fig. 2 Variable-order RC Equivalent Circuit Model

The accurate SOC estimation depends on reliable and practicable battery model. But the real-time order of the battery model is unknown, so it is hard to determine the real-time battery's SOC. In this paper, the SOC estimation is based on either first or second order battery equivalent model, use MSE to determines the battery model in real-time.

In Fig.2, R_0 , R_{pa} , C_{pa} are the Ohmic resistance, polarization resistance, and the capacitance. C_{pc} and R_{pc} are concentration polarization capacitance and concentration polarization resistance, Q_1 is a switch that determines the model could be first order or second order. Fig. 3 shows the first order structure [11]. The first order model considers polarization resistance R_p and polarization capacitor C_p. U_p is the voltage across the capacitance C_p, $i(t)$ is charge/discharge current.

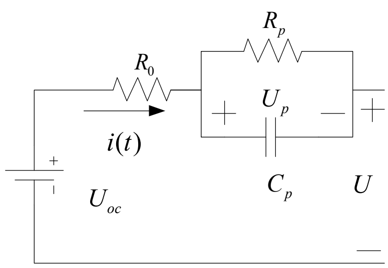

Fig. 3 Thevenin circuit model

The electrical behavior of Thevenin model can be expressed as follows,

$$\frac{dU_p(t)}{dt} = -\frac{U_p(t)}{R_pC_p} + \frac{i(t)}{C_p} \quad (1)$$

$$U(t) = U_{oc}(t) - R_o i(t) - U_p(t) \quad (2)$$

There are many discrete methods for the Thevenin model, such as backward difference method [12], forward difference method and bilinear transform method [13]. On the assumption that

$$\frac{\mathrm{d}U_{oc}(t)}{\mathrm{dt}} = (U_{oc}(t) - U_{oc}(t-\Delta t))/\Delta t \approx 0 \quad (3)$$

When the battery undergoes slow charge/discharge process, the open circuit voltage $U_{oc}(t)$ only has a slight change at a short sample period, then taking derivative of $U(t)$

$$U(k) = \frac{R_pC_p}{T+R_pC_p}U_L(k-1)\frac{R_oR_pC_p + R_o\mathrm{T} + \mathrm{T}R_p}{R_pC_p+T}i_L(k) + \frac{R_oR_pC_p}{T+R_pC_p}i_L(k-1) + \frac{T}{T+R_pC_p}U_{oc}(k) \quad (4)$$

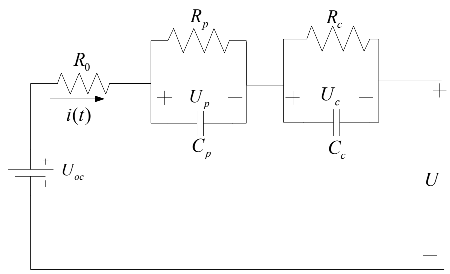

Fig. 4 Improved Thevenin model structure

Fig. 4 shows the second order Thevenin model that adds another RC branch to the Thevenin model. In Fig. 4, $C_c$and R_c are concentration polarization capacitance and concentration polarization resistance respectively. U_c is the voltage across the concentration polarization capacitance [14].

Similar to the improved Thevenin model, the mathematic expressions of the second order model are represented as follows.

$$\frac{\mathrm{d}U_p(t)}{\mathrm{dt}} = -\frac{U_p(t)}{R_pC_p} + i_L(t)/C_p \quad (5)$$

$$\frac{\mathrm{d}U_c(t)}{\mathrm{dt}} = -\frac{U_c(t)}{R_cC_c} + i_L(t)/C_c \quad (6)$$

$$\mathrm{U}(t) = U_{oc}(t) - R_o i_L(t) - U_p(t) - U_c(t) \quad (7)$$

Assuming $\frac{\mathrm{d}U_{oc}(t)}{\mathrm{dt}} \approx 0$, taking the time the derivative of $U_L(t)$ gives

$$\frac{\mathrm{d}U_L(t)}{\mathrm{dt}} = -\frac{1}{R_cC_c}U_L(t) + \left[\frac{1}{R_pC_p} - \frac{1}{R_cC_c}\right]U_p(t) - \left[\frac{R_o}{R_cC_c} + \frac{1}{C_c} + \frac{1}{C_p}\right]i_L(t) + \frac{1}{R_cC_c}U_{oc} - R_o\frac{\mathrm{d}i_L(t)}{\mathrm{dt}} \quad (8)$$

C. Experimental battery characteristic

The high-power cell 18650-HE4 lithium-ion batteries are utilized in the charge/discharge experiments. Fig. 5 shows battery discharge experimental equipment. The lithium-ion battery has a nominal capacity 2.5Ah. The nominal voltage is 3.7V, setting the maximum charging voltage to 4.2 V and the cutoff voltage to 2.5V. Fig. 4 shows the thermal chamber and the measurement equipment, the test is carried out under

25.3°C in a constant thermal regulated chamber to reduce the influence of temperature. Thus, the battery's temperature varies within a very small range during the charge-discharge cycles. In this experiment, the temperature variation is not considered, and record the battery's terminal voltage, current, and the SOC states every five seconds.

Fig. 4 Thermal chamber and measurement equipment

Fig.5 Battery discharging bench

In order to eliminate the measurement errors and environmental noise, run the identical experiments with several lithium-ion batteries. Fig. 6 shows the example of five cells terminal voltage curves.

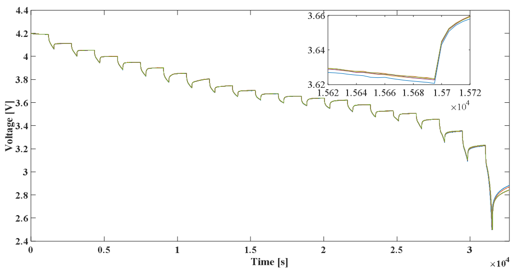

Fig. 6 Experimental voltage variety of five batteries

III. SIMSCAPE VERIFICATION

Fig. 7 and 8 show the Simscape simulation structure for both Thevenin model and improved Thevenin model. Considering the existing components in Simscape cannot satisfy the requirement to build the real battery, using Simcape language create the battery, resistance, and capacitor

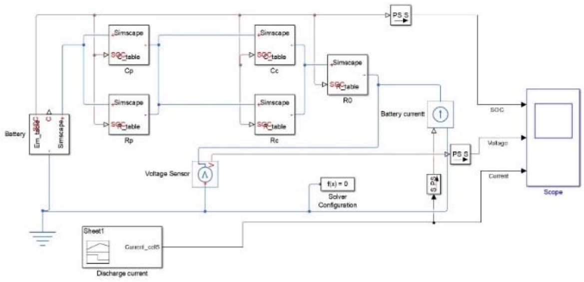

Fig. 7 Simscape circuit of improved Thevenin model

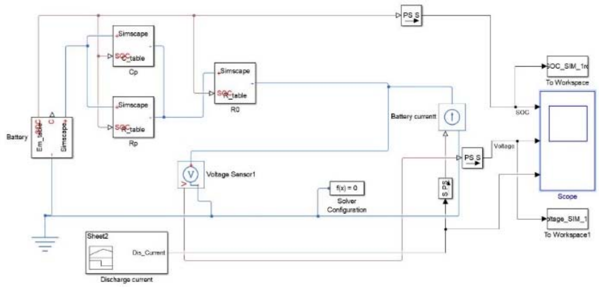

Fig. 8 Simscape circuit of Thevenin model

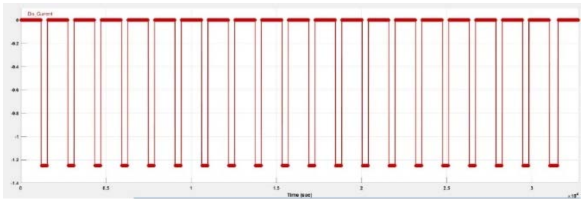

Fig. 9 Signal builder of current

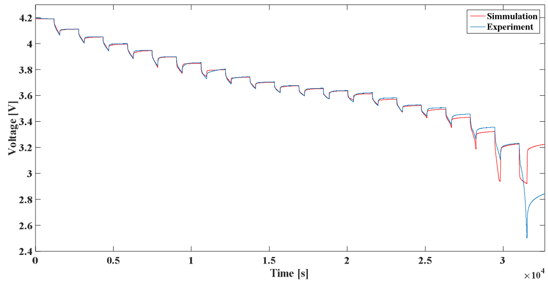

Fig. 10 Simulation results of the Thevenin model and experiment data

Fig. 10 and 11 show the simulation results of Thevenin model and estimation error, it is observed that the model has the accurate estimation result at the most period but the error is increased at the end of discharge due to polarization effect.

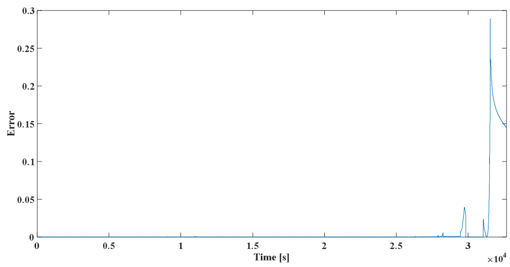

Fig. 11 Estimation error of Thevenin model

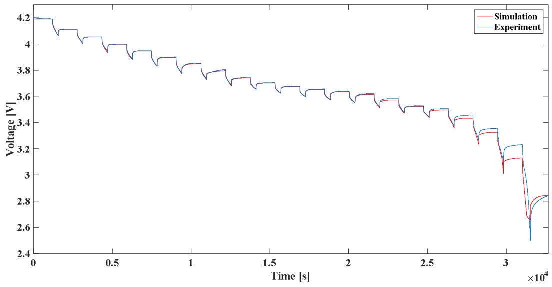

Fig. 12 Simulation results of improved Thevenin model and experiment data

Fig. 12 and 13 show the simulation results of the improved Thevenin model and the estimation error. It is observed that the model has a better estimation result compared to the Thevenin model but still a deviation at some period exist.

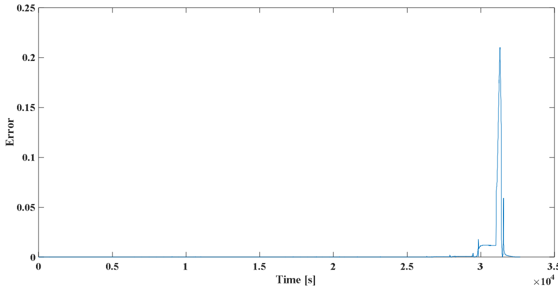

Fig. 13 Estimation error of improved Thevenin model

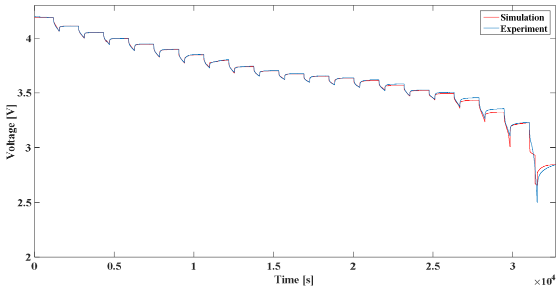

Fig. 14 Simulation results of variable Thevenin model and experiment data

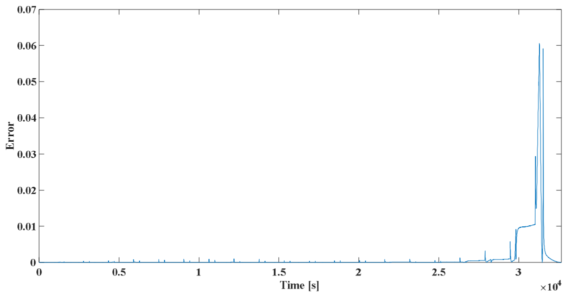

Fig. 15 Estimation error of variable Thevenin model

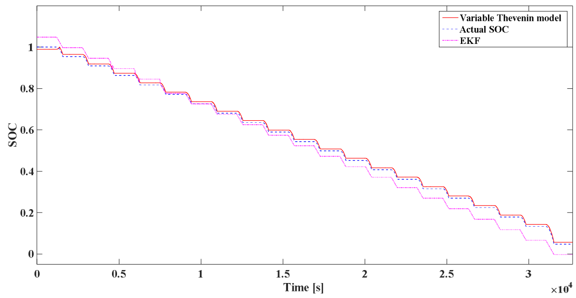

Fig. 16 Comparison of the actual SOC, the SOC estimation by EKF, and the SOC estimation by variable Thevenin model

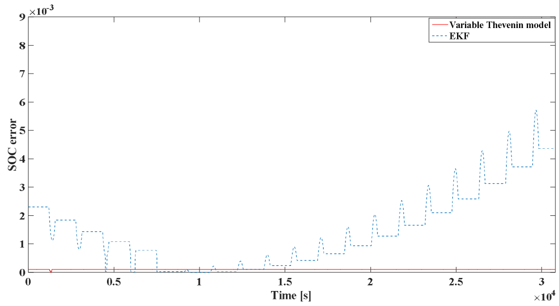

Fig. 17 Comparison of SOC estimation error by proposed algorithm and EKF

The SOC estimation results and error are shown in Fig. 14 and Fig. 15, the Fig. 16 compares the actual SOC with the estimation SOC by EKF and SOC estimation SOC by the proposed algorithm. Moreover, Fig.17 shows the comparison of SOC estimation error between the proposed algorithm and EKF. It demonstrated the satisfactory SOC estimation performance with the proposed algorithm.

IV. Conclusion

Overall, the system performed as expected. A variable order battery model has been proposed, and use NN to identify the model parameters, then the identified parameters are provided to both Thevenin model and Improved Thevenin model. The better estimation results were used to determine the SOC based on estimation error. The K-means algorithm is used to process the experimental data to eliminate the individual difference. The variable order Thevenin model has good estimation results during discharge periods. The proposed methods give the best SOC estimation results as well as the two advantages : (i)Having high accuracy, (ii)Low computation. The proposed battery model was successful in the charge/discharge operation.

Acknowledgment

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