A Novel Online Adaptive Fast Simple State of Charge Estimation for Lithium Ion Batteries

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***Abstract*—this paper proposes a novel simple adaptive and on-line approach to estimate the state of charge (SOC) in Lithium Ion (Li-Ion) batteries based on a new model parameter identification method. First, a novel discrete model for the Li-ion battery is developed. This model is the key step in the development of the proposed parameter estimation algorithm. The estimated parameters are used for on-line calculation of the battery's open circuit voltage (VOC) that is required for SOC estimation with no prior knowledge of battery parameters. The paper then proposes a moving window lease mean square approach to adaptively update the estimated parameters in a very fast and accurate manner. The SOC estimation will be updated at the end of every window cycle. The proposed method for SOC estimation provides a simple, fast, comprehensive, and precise estimation capable to track the changes of the model/battery parameters. Unlike other estimation strategies, only battery terminal voltage and current measurements are required.**

Keywords—State of Charge(SOC); Li-ion battery; Estimation; Discrete Model.

I. INTRODUCTION

Lithium Ion (Li-Ion) battery due to its beneficial characteristics is the premium choice in smart grids and electric vehicles. Accurate information on the State of Charge (SOC) is very important since safety, life time, and performance of the battery is influenced by this factor. [1-6].

State of charge (SOC) estimation is the most important issue in the battery management systems. By an accurate SOC estimation, not only the available battery capacity can be determined, but it also leads to more control over the charge and discharge processes which results in longer battery life. In recent decades, several techniques for SOC estimation have been developed and presented in literature. These techniques can be classified in four main categories; Open circuit voltage method, Coulomb Counting method, intelligent method, and Filter/Observer-based methods. Among these techniques, accurate estimation of Li-ion battery states and effective battery modeling are vigorous to improve the performance of the energy systems employing Li-ion batteries. There should be an algorithm to manage the battery cells which can estimate the remaining energy of the lithium battery cell. On one hand, an accurate estimation of battery charge will result in more safety, reliability, and efficiency in batteries in use. On the other hand, the algorithm for estimation the battery charge or SOC should be simple enough to decrease the processing capacity [7-12].

The simplest method for determining the state of charge of a battery is open circuit voltage test. For different kinds of batteries, different relationship exists between SOC and open circuit voltage of the battery. In this method, the open circuit voltage of the battery is determined by measuring the terminal voltage after a long time rest; at least after two hours, and then based on the relationship, SOC is estimated. This method is useful for applications in which the battery can rest for periods of long time, so it is not applicable for dynamic SOC estimation and not very accurate. There is no need an algorithm to implement but battery needs to be in resting mode for a long time [13].

The most common method for estimating SOC in which the discharge current of the battery over time is integrated and used, is Coulomb counting technique.

In general, the coulomb counting method estimates the battery remaining capacity by accumulating the charge or discharge current of the battery. The accuracy of this method depends on the initial SOC estimation and whether the discharge current measurement is accurate or not.

In this method, the SOC is estimated by integrating the discharge or charge current over the battery's operating time. The losses during charging and discharging processes result in accumulative errors. This method is easy to implement but dependent on the initial SOC, and not suitable for PEV's with frequent charge/discharge profiles due to the need of accurate initial conditions.

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The nonlinearity and the complexity involved in battery characteristics, require a powerful tool to model these devices.

The nonlinearity and the complexity involved in battery characteristics, require a powerful tool to model these devices. Intelligent methods such as fuzzy logic, Back Propagation (BP) neural network, artificial neural network ANN, Radial Basis Function (RBF) network, Fuzzy Neural Networks (FNN) are among appropriate tools that can successfully address these issues. There is a main limitation for using all these methods that is a need for a large amount of data to train the network and get an algorithm applicable for all operating conditions.

The Kalman filter algorithm, a good method for state estimation in dynamic systems such as battery field, holds acceptable accuracy and is dealing with noise. Large computational time and memory, complicated algorithm, difficult determination of feedback gain of Kalman filter are some important disadvantages of this technology and not also proper feedback gain results in the divergence of the estimated states [14-15].

Filter/ Observer-based methodology for SOC estimation is one of the popular methods which apply the measured input of the battery to the model, then use this signal and the present/past states of the model to calculate the output. The difference between the measured and calculated output, which is called error signal, is fed to the feedback method to update the states estimation of the model. The Feedback/Observer-based method applied for the algorithm, could be Luenberger observer, sliding mode observer, Proportional-Integral observer (PI), etc. Luenberger observer, used for SOC estimation of the batteries in feedback/observer-based methods results in acceptable estimation provided that an accurate battery model is used, which is hard to achieve. In addition, even if we apply an accurate enough battery model for SOC estimation, the calculation process of this method is very complicated and not useful for online applications. Sliding-mode observer has been applied in [16-20] to estimate SOC in a Li ion battery. Robustness against parameter uncertainties and disturbances is a positive property of this observer. However, there is a chattering problem which is not negligible.

This paper proposes a novel simple adaptive and on-line approach to estimate the state of charge (SOC) in Lithium Ion (Li-Ion) batteries based on a new model parameter identification method.

II. PROPOSED DISCRETE TIME MODEL FOR BATTERY

Based on the battery model shown in Fig.1, a new discrete linear four parameters model for Voc estimation is proposed in this paper. The SOC then can be calculated from the estimated Voc since there is a relationship between Voc and SOC defined by a Voc-SOC curve. A valid assumption is that we have access to the terminal voltage and terminal current of the battery at any time. The goal is to estimate Voc by means of terminal voltage and terminal current.

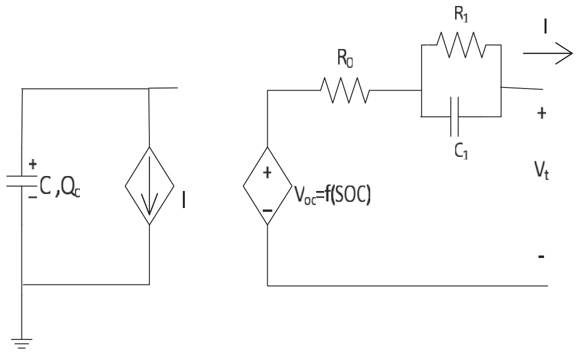

Fig. 1. Li-ion battery model

The equation (1) for this battery model during charging and discharging can be written as:

$$V_t(t) = V_{oc}(t) - V_{c_1}(t) - R_0 I(t) \tag{1}$$

$$\frac{dV_{c_1}(t)}{dt} = \frac{I(t)}{C_1} - \frac{V_{c_1}(t)}{C_1 R_1} \tag{2}$$

Where $I(t)$ and $V_t(t)$ represent the charging/discharging current and terminal voltage of the battery, respectively. Assume $I(t)$ is within in a small time; Δt, so, by discretizing (2) we have

$$\frac{V_{C_1}(t+\Delta t) - V_{C_1}(t)}{\Delta t} = \frac{1}{C_1} I(t) - \frac{1}{C_1 R_1} V_{C_1}(t) \tag{3}$$

During Δt due to the large ratio between the battery's capacitor, C, and the transient capacitor ;C_1, $V_{oc}(t+\Delta t) - V_{oc}(t) \to 0$, and we can have:

$$V_t(t+\Delta t) - V_t(t) = -V_{C_1}(t+\Delta t) + V_{C_1}(t) \\ -R_0 I(t+\Delta t) + R_0 I(t) \tag{4}$$

$$e(t) = -\frac{\Delta t}{C_1} I(t) + \frac{\Delta t}{C_1 R_1} V_{C_1}(t) \\ -R_0 I(t+\Delta t) + R_0 I(t) \tag{5}$$

Where $e(t)$ is defined as

$$e(t) = V_t(t) - V_t(t+\Delta t)\,, \\ t_k = t_{k-1} + \Delta t \quad k = 2, .., n \tag{6}$$

We rewrite equation (5) by replacing V_{C_1} from equation (1) and we have equation (7) as

$$e(t) = R_0 I(t+\Delta t) + I(t)\left[\frac{\Delta t}{C_1} + \frac{\Delta t}{C_1 R_1} R_0 - R_0\right] + \frac{\Delta t}{C_1 R_1} V_t(t) - \frac{\Delta t}{C_1 R_1} V_{OC}(t) \quad (7)$$

Based on equation (7), terminal voltage difference between two sequential sampling times depends on $V_{oc}(t)$, $V_t(t)$, $I(t+\Delta t)$, $I(t)$. Although (as explained before), $V_{oc}(t)$ is a time changing variable, it can be considered constant within small time intervals.

III. PARAMETERS ESTIMATION FOR THE PROPOSED MODEL

Based on new parameters defined in (8), we can reach to the key equations (9).

$$e(t) = \alpha_1 I(t+\Delta t) + \alpha_2 I(t) + \alpha_3 V_t(t) + \alpha_4 \quad (8)$$

$$V_{OC} = -\frac{\alpha_4}{\alpha_3}\ ,\ R_1 = \frac{\alpha_2 - \alpha_3\alpha_1 + \alpha_1}{\alpha_3}$$
$$C_1 = \frac{\Delta t}{\alpha_2 - \alpha_3\alpha_1 + \alpha_1}\ ,R_0 = \alpha_1 \quad (9)$$

Equations (9) are quite important in estimating battery's model parameters in our proposed technique. We have a discrete and linear model of battery parameters and our goal is to estimate the parameters. It is considerable that V_{OC} equation in equations (9), is the most important equation that can be applied to estimate V_{oc} with no knowledge of parameters.

Considering the measuring error can be modeled by a white noise, a least square regression can be a solution for this problem. The measured variables are the battery's terminal voltage and the current in/out of the battery.

Equation (8) in a discrete form can be rewritten as:

$$E = A\alpha \quad (10)$$

In which each of the matrix E, A, α are defined as equation (11) and n is the nth discrete-time data sample with a time period of Δt and Supposed we have N+1 data samples in one-time interval , Δt. Now the goal is to find the best fit for elements of vector α such that it minimizes the Euclidean norm, also called norm 2th, of the error vector.

$$A = \begin{bmatrix} I(n+1) & I(n) & V_t(n) & 1 \\ \vdots & \vdots & \vdots & \vdots \\ I(N+n+1) & I(n+N) & V_t(n+N) & 1 \end{bmatrix}$$

$$\alpha = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \end{bmatrix}\quad , \quad E = \begin{bmatrix} e(n) \\ e(n+1) \\ e(n+2) \\ \vdots \\ e(n+N) \end{bmatrix} \quad (11)$$

The best solution is the optimum parameter set that minimizes the equation $\|E - A\alpha\|_2$.
The solution of this minimization scheme is [21]:

$$\alpha = (A^T A)^{-1} A^T E \quad (12)$$

IV. SIMULATION AND EXPERIMENTAL RESULTS

The simulation results show that our proposed estimator converges to real values, even by fast changes in the parameters. For this simulation, battery's current and its terminal voltage are sampled for period of 2 seconds with a sampling frequency of 500 Hz, to fill in the E vector and the A matrix in (10). Sample simulation results are shown in figures 2,3,4,and 5. These figures depict that with very fast changes in the model parameters, our algorithm converges very fast.

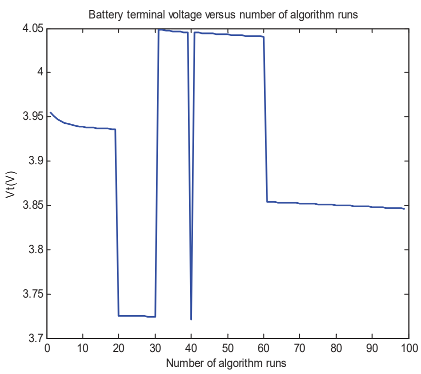

Fig. 2. V_t vs. number of algorithm runs for R_0 changes

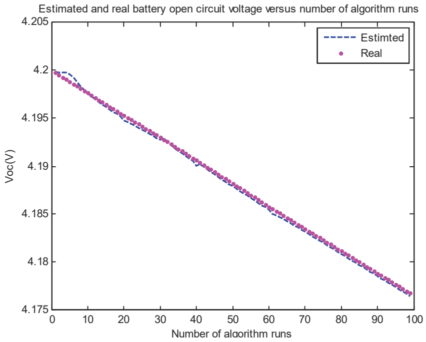

Fig. 3. V_{oc} vs. number of algorithm runs for R_0 changing

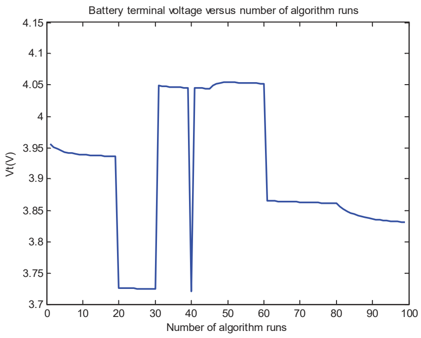

Fig. 4. V_t vs. number of algorithm runs for R_0 & R_1 changes

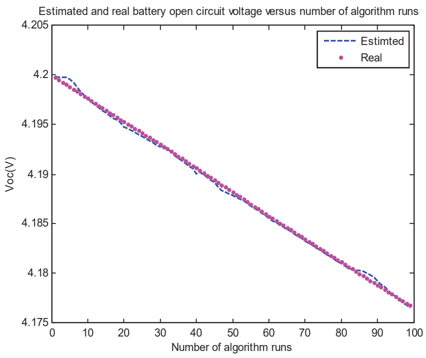

Fig. 5. V_{oc} vs. number of algorithm runs for R_0 & R_1 changes

We used Li-ion battery cell (CGR18650CG) with the characteristics of 2200 mAh nominal capacity, 4.2 V maximum voltage, some resistances with parallel and series connection to provide different loads for discharging battery. A National Instruments USB-6001 data acquisition (DAQ) device (NI USB-6001) as interface with the Li-ion battery is used to control the hardware switches and also for measurement. Two analog inputs with the resolution of 14-bit are applied for terminal voltage and current acquisition. NI USB-6001 is compatible with ANSI C, C# .NET, LabVIEW, and Measurement Studio. The battery should be as close as possible to the NI USB-6001 to prevent ohmic voltage drops.

Based on the datasheet information for our Li-ion battery cell, the nominal capacity of the cell is 2200 mAh which can be explained as 2.2 A ×60min = 132 Amin. The maximum current rate for the cell is 1C-rate or 2.2A. So, we can discharge the battery with 2C-rate or 1.1A. The obtained result for $V_{oc} - SOC$ curve is shown in Fig. 6.

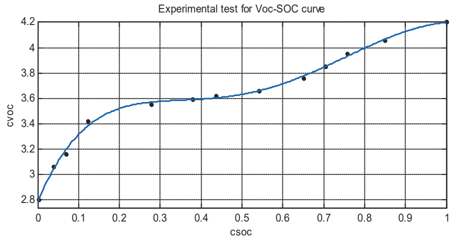

Fig. 6. Experimental result for $V_{oc} - SOC$ curve

The data sampled from terminal voltage and current by NI USB-6001 are saved and applied for SOC estimation algorithm by computer. Measurement Studio software in computer is used for collecting and saving data via NI USB-6001 and Matlab is used for control the relay switches and SOC estimation algorithm. The experimental set-up is shown in Fig. 7.

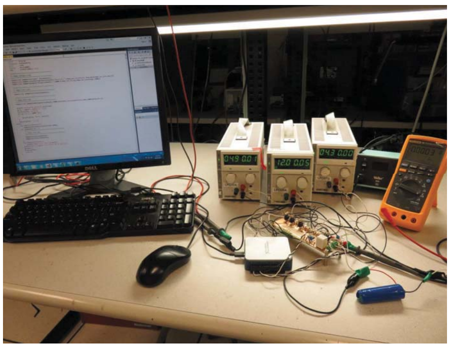

Fig. 7. Experimental set up

The experimental results for Voc estimation and SOC estimation are are shown in Figures 8 and 9.

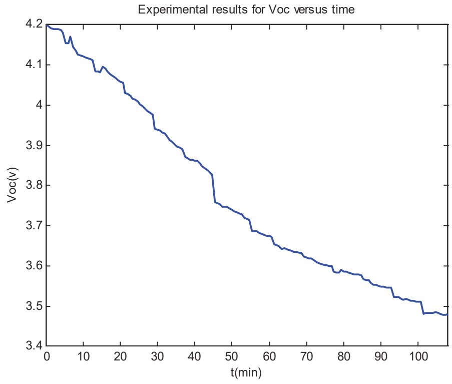

Fig. 8. Experimental result for V_{OC} estimation

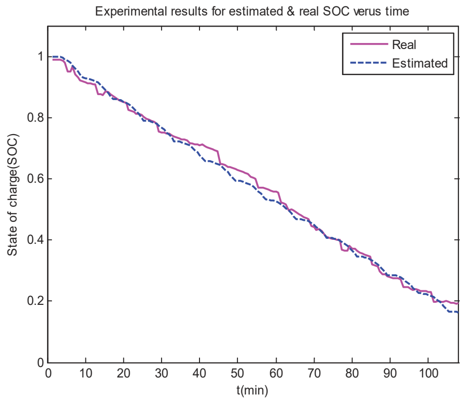

Fig. 9. Experimental results for estimated and real SOC vs. time

V. CONCLUSION

An ideal SOC estimation method should be accurate, adaptive, simple, fast, and easy to implement. All SOC estimation methods developed so far sacrifice one or two of the aforementioned factors; mainly accuracy, simplicity, and quickness for the sake of others, however our proposed online adaptive estimation algorithm preserves all the simplicity, quickness, and accuracy factors together, and needs just the battery terminal voltage and current. The proposed powerful method can fallow all changes in the battery parameters due to various factors.

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