Li-ion Battery Modeling and SOC Estimation Using Extended Kalman Filter

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Abstract

Lithium ion batteries are preffered especially in electric car applications over other types of batteries thanks to their intrinsic safety, capacity for fast charging and long cycle life. In order to get an accurate battery model, it is important to be able to determine a couple of state parameters such as state of charge and state of health. In this work, battery management system agorithms were improved for generic Lithium ion battery state of charge estimation using Matlab Simulink. First, an equivalent circuit battery mathematical model was developed with the aim of simulating the behaviour of a lithium-ion battery as accurately as possible. The Thevenin model is achieved by adding an extra RC branch and the model parameters are identified employing the Extended Kalman Filter (EKF). In this work, it is aimed to catch the battery characterization and provide the correct parameters to the Kalman Filter code in order to accurately estimate the SOC.

1. Introduction

While the demand on energy increases day by day, the amount of available fossil fuel reserves deplete. Relying on the fosil fuel consumption caused damages to the environment and incremented greenhouse gas emissions as well. Consequently, the renewable energy technologies have gained more attention and drived the use of more electric vehicles.

Lithium-ion batteries are getting popular in both renewable energy systems and electric vehicles thanks to their high power and energy density. Therefore, accurate battery models are vital to the design and simulation of hybrid/electric vehicle propulsion systems. Modelling and batteries is a toilsome task because of their complex electrochemical structure and nonlinear characteristics. Accurate real-time SOC estimation reporting to drivers is also difficult.

This work addressed these challenges using extended Kalman filter (EKF) algorithm and a two-RC-block equivalent circuit. This battery equivalent circuit model was designed in Matlab Simulink using the Simscape Language. Some charging and discharging cycles including the Federal Urban Driving Schecule (FUDS) experiments were conducted to test the model. Then, an algorithm with the EKF approach was developed to enhance the SOC estimation. This improves SOC estimation using conventional integral based methods such as Coulmb counting especially in high current charges/drains close to impulses. The EKF algorithm not only can be used to implement the parameter identification of the battery model but also can be employed for online SOC estimation and track the battery state of charge parameter [1]–[4].

In summary, to obtain a more accurate and robust SOC estimation, an improved Thevenin battery model was submitted, which is based on the analysis of the nonlinear characteristics of a lithium-ion battery module by experimental results and its parameters were identified by the EKF algorithm.

2. Li-Ion Battery Modeling

The Thevenin model is widely used to model the Lithium ion battery, but it is not accurate enough as all of its elements can change, depending on the state of the battery and its conditions. To improve the model reliability, unlike the general equivalent Thevenin model, extra RC branch is added as shown in Fig. 1. These blocks shown in the figure were created in Simulink Simscape Language to define the custom components as text files. The texts include complete parameterization, physical connections, and equations represented as a couple of causal implicit differential algebraic equations.

The Simscape language makes modeling physical systems easier and more intuitive. The blocks utilize look up tables with variable values for each of battery circuit element employed. These values are obtained by a minimization problem to fit the actual voltage current relation of the battery. This relation is obtained as a result from experimental work as explained in [1] .

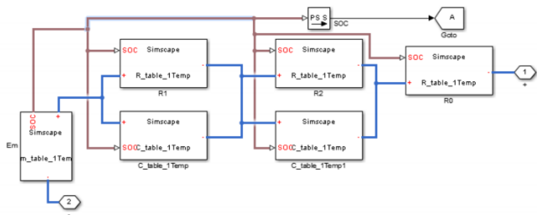

Fig. 1. 2RC Li-ion battery improved physical model design and its Simscape library elements.

The Thevenin model includes three parts as open circuit voltage U_{oc}, internal resistances, and equivalent capacitances. The internal resistances include ohmic resistance R_o, electrochemical polarization resistance R_{pa}, and concentration polarization resistance R_{pc}. The equivalent capacitances which include electrochemical polarization capacitance C_{pa} and concentration polarization capacitance C_{pc}, i_L and U_L are the charging/discharging current and the terminal voltage respectively.

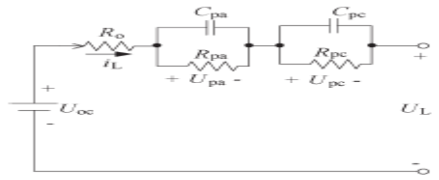

Fig. 2. Generic shematic of the imroved Thevenin model [1].

3. Extended Kalman Filter

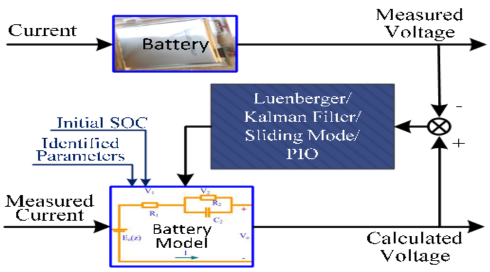

Fig. 3. Equivalent battery model based SOC Kalman filter method [6] .

The Extended Kalman filter is a method for predicting the future state of a system based on the previous ones and convenient form for online real time processing. It consists of two equations. The equations include A,B,C and D matrices that can be constituted using R_o, R_{pa}, R_{pc}, C_{pa} and C_{pc}. The expressions of matrices and vectors are the same as [1]. xk is the system state matrix and one of the matrix value represents SoC. Therefore xk captures the system dynamics. Input of the system is uk which is a control variable matrix and known or can be measured. However, the measurement could result in errors, assumed to be stochastic process noise, wk, which cannot be measured and affects the state of the system [7].

$$xk + 1 = A \times xk + B \times uk + wk$$
$$yk = C \times xk + D \times uk + vk$$

The second equation is the measurement equation and models the output voltage of the system yk, in terms of the input, the state vector and the noise in the measurement of the output, vk which is called measurement noise. The following update equations and computations made in [7].
For the Lithium ion battery module, some parameters for the Extended Kalman Filter code are specified as follows:

$$Q= \begin{bmatrix} 0.1 & 0 & 0 \\ 0.000001 & 0 & 0 \\ 0 & 0 & 10 \end{bmatrix}$$

$$R= \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0.1 \end{bmatrix}$$

$$P= \quad [10]$$

3.1 State of Charge Estimation

Using the Matlab Optimization Tool Box, parameters of the battery such as C_{pa}, C_{pc}, R_0, R_{pa}, R_{pc}, U_{oc} were determined to be used in the Extended Kalman Filter algorithm. The Charge and discharge input current signals as well as the real and estimated SOC curves are shown in Fig. 4. The maximum SOC error calculated as 1% proves the successful implementation of this technique.

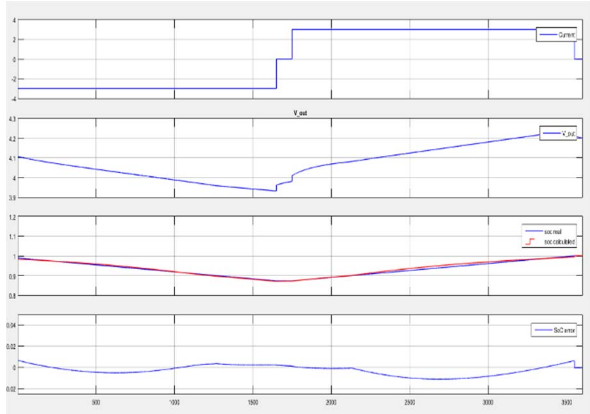

Fig. 4. A comparison of the experimental data versus theoretical results.

4. Experiment

To identify the parameters of the improved Thevenin model, a charge/discharge cycler (Digatron) was used to identify the volatge current relationship of the battery. First, charging and discharging experiments are carried out on one home made li-ion battery pouch cell with nominal voltage of 3.7 V and nominal capacity of 11.8 Ah. Then the battery is discharged at a constant current of 0.3C A from the fully charged state to 90% of the nominal capacity at 20 °C in the thermal chamber. After that, the battery is continuously discharged by a further 10% of the nominal capacity at the same current. The equilibrium potential of the discharge curve is given in Fig. 3.

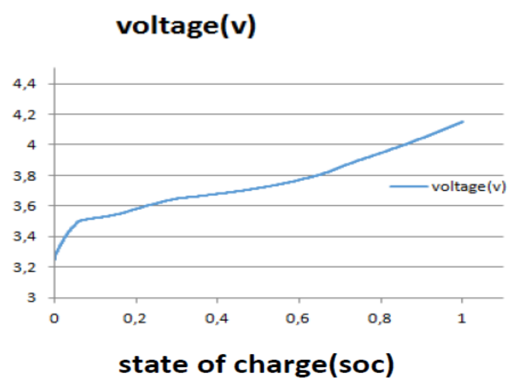

Fig. 5. Open circuit voltage curve versus SOC.

The open-circuit voltage U_{oc} measured as a function of the SOC was curve fitted by a 9[th] order polynomial. A quadratic fitting method was not enough for a correct curve for the EKF.

4.1 HPPC Test

The improved battery model is suitable for all kinds of Li-ion batteries**.** The Hybrid Pulse Power Characterization (HPPC) test was implemented in another Li-ion battery pack with nominal voltage of 57.6 V and nominal capacity of 100 Ah to figure out its accuracy. Charging and discharging input current signals are as follows for the HPPC test :

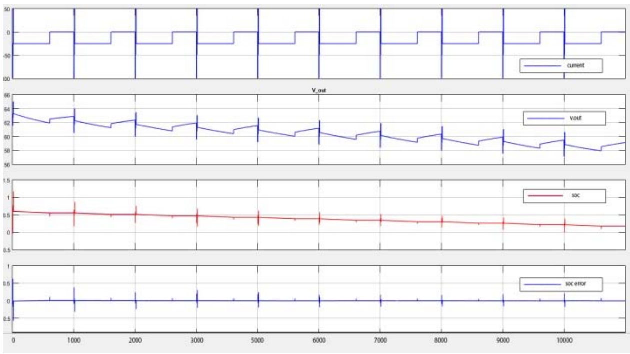

Fig. 6. HPPC test cycle of the battery module model and outputs of the model experiment. (a) curent profile (b) terminal voltage profile (c) calculated SOC (d) SOC error versus time in s.

The initial SOC was set to 0.6. The SOC range in the experiment ranged from 0.6 to 0.1. The Parameters of the battery module model as a function of SOC are updated via linear lookup table and extrapolation. Fig.4 presents the comparison of the experimental data with the model simulation data, which clearly shows a good match of the real and calculated data. The figure shows ripples at the SOC when pulses ocur in the current profile. However, these errors are not accumulated diminishes rapidly as shown in the SOC error curve. This test was performed over 11000 seconds.

4.2 FUDS Test

The current profiles sampled during eight consecutive FUDS cycles are shown below.

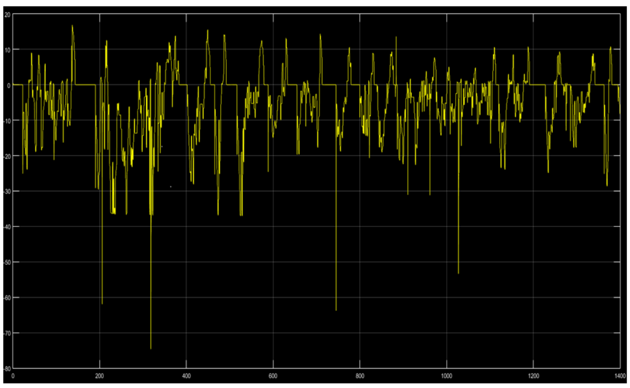

Fig. 7. Current profile during eight FUDS cycles.

The Federal Urban Driving Schedule (FUDS) is a typical driving cycle that is often used to evaluate various SOC estimation algorithms. FUDS test, which is normally terminated by a certain amount of ampere hours removed from the battery in the battery reaches a certain voltage level. In this paper, eight periods of FUDS are employed to verify the SOC estimation approach. Figure 7 depicts the calculated and real SOC associated with an FUDS cycle. As shown in Fig.8 the error associated with the calculated EKF SOC estimator is again aprroved to instantly and diminishes abruptly after the pulses. No error accumulation is shown here and high instant errors can easily be filtered out. This can be compared with the implementation of the EKF of [2]. In our case while the correction takes a few milliseconds to decrease the error below 5%, this is not possible before 2000 s in their case (see fig. 14 in [2]).

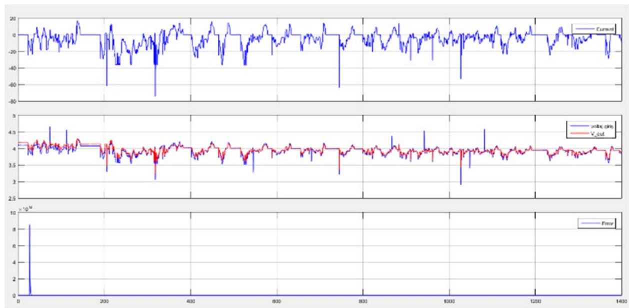

Fig. 8. EKF SOC estimation applied to FUDS cycle. (a) FUDS current profile (b) real (blue) and calculated (red) SOC profiles (c) error of the calculated SOC profile versus time.

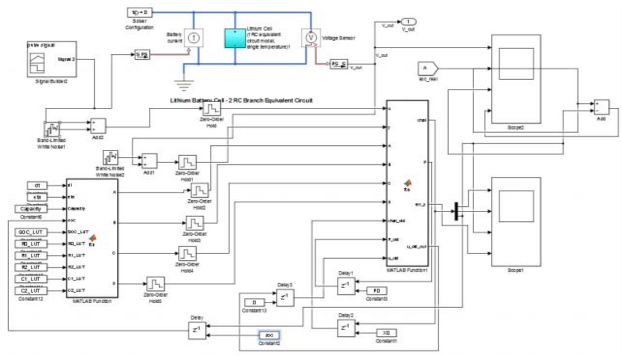

Fig. 9. Matlab Simulink simulation.

Two RC branches equivalent model, Matlab Simulink code blocks and the current signal builder were indicated in Fig.9.To make the estimation difficult, band limited white noise was added to the current signal.2×4 decoder and 9×4 mux include the all codes for estimation. Decoder gets the initial parameters from a matlab file to create A,B,C and D adaptation or state matrices the use of interpolation.Calculated matrices values were use by mux block which keeps The Extended Kalman Filter code.The Extended Kalman filter is a estimator that can use nonlinear state space prediction.With the help of zero-order hold blocks, the continuous time was sampled to discreate signal.The filter equations were discreate time equations.Using experimetal lookup table values,The open circuit voltage of the battery model(Voc) was estimated and compared with the real battery terminal voltage (Vt).The difference between Vt and Voc was multiplied with the Kalman gain.When the difference was zero,the estimation process was terminated.

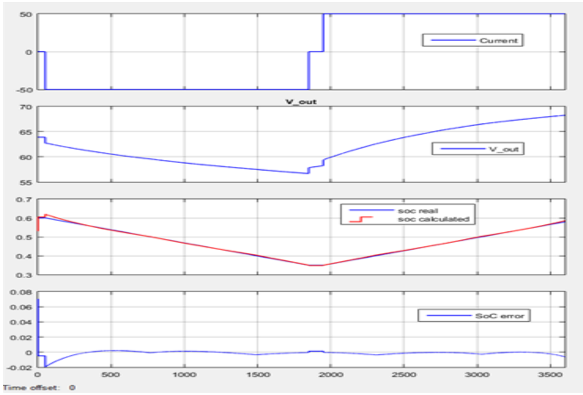

Fig. 10. The EKF SOC estimation applied to current profile. (a)Input current profile (b) output voltage (c) real (blue) and calculated (red) SOC profiles (d) error of the calculated SOC profile.

Unlike the HPPC pulse, this current pulse is simple. Simulation time took 3800 seconds and shows the voltage error curves between the simulation data and the experimental data. It verifies that the parameter identification algorithm and the improved Thevenin model are mathcing accurately.

5. Conclusions

For a Lithium ion battery module, The proposed improved Thevenin model has been implemented, and its parameter identification is performed using the EKF algorithm. To improve the accuracy, reliability, and robustness of the SOC estimation, a couple of experiments put forward based on the improved Thevenin model. The experimental and simulation results show that the error is about 0.01 and the proposed approach of the SOC estimation algorithm is suitable for a lithium-ion power battery module. The response of the EKF is the order of a few milliseconds and competes other reported implementations of the this technique.

6. References

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