

State-of-Charge Estimation of Li-ion Battery using Extended Kalman Filter

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Abstract

The Li-ion battery study is based on its equivalent circuit PNGV model. The parameters of this model are identified by HPPC test. The discrete state space equation is established based on the model. The basic theory of extended Kalman filter algorithm is applied and then the filtering algorithm is set up under the noisy environments. Finally, one kind of electric car is used for testing under the UDDS driving condition. The difference between the theoretical value and the simulation value using extended Kalman filter under the noisy environment is compared. The result indicated that the extended Kalman filter keeps an excellent precision in state of charge estimation of Li-ion battery and performs well when disturbance happens.

Keywords: li-ion battery, PNGV model, SOC, EKF

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1. Introduction

Li-ion battery is the most widespread adoption power source of electric car with the advantages of high voltage, large specific energy, no memory, long cycle life and so forth. Not being overcharged or over-discharged is one of the major concerns of Li-ion battery. So, accurate estimation of state of charge (SOC) is the main task on battery management system (BMS). Not only does it provide the strategy for vehicle control such that damage to the battery can be avoided, but also can it help using the battery energy more reasonably, so that the electric vehicles (EV) can control and predict the driving range more effectively and achieve the ultimate goal of energy saving, environmental protection, and to extend the life of the battery pack [1].

SOC is a state value that can't be measured directly. It should be estimated by certain algorithm using some physical quantities such as voltage, current etc. gathering by EV's BMS in the process of driving. However, due to the interference of environmental factors such as electromagnetic radiation as well as the accuracy of measuring element, the voltage and current value acquired by BMS has large noise which will impact the SOC estimation.

The main method of battery SOC estimation includes Ah counting method, open circuit voltage (OCV) method, the linear model method, neural network method and Kalman filter (KF) method [2]. Ah counting method can't estimate SOC of battery itself. And the algorithm also has some shortcomings such as the variable of Coulombic efficiency is difficult to be accurately measured, the accumulated sampling error etc. It is not suitable for the occasions where the voltage and current change dramatic. The most significant drawback of OCV method is battery needs to stand for a long time to eliminate the battery polarization effects to gain the accurate voltage value before every each measurement. So it doesn't apply to the battery online SOC estimation. The most effective use of OCV method is in initial SOC estimation of EV after long time standing and often used in combination with Ah counting method. The linear model method is suitable for the low-current situation, applies only to the lead-acid battery. The neural network method is a highly nonlinear system, applicable to SOC estimation of all kinds of battery. But, it needs a large number of experiment data for training [11]. Using KF method for optimal estimation to the state value disturbed by environmental noise takes advantage of the temporal transfer relationship of the system to estimate the state

of system with a set of recursive formula. It is applied to the linear, time-varying, multi-input and multi-output system. After linearization, KF method is also used to recursive calculation in nonlinear systems. This method is also known as the extended Kalman filter (EKF) [2]. It is suitable for noise filter in the harsh environment like EV driving process.

In this paper, PNGV is adapted as equivalence circuit model of Li-ion battery. The state space equation is established after the model parameters are identified by Hybrid Pulse Power Characterization (HPPC) test. Then, after examine the basic theory of EKF, the EKF model of battery in noisy environments is proposed for SOC estimated. Finally, the proposed method is tested in UDDS cycles and then the simulation result is compared with the actual value.

2. Battery Model

According to related research, PNGV equivalent circuit model can better describe the external characteristics of the li-ion battery; also it is simple to use. As shown in Figure 1, it consists of two capacitors (C_0 , C_1) and three resistors (R_0 , R_1). The ohm resistance R_0 describes the internal resistance of the battery, the capacitor C_0 characterizes the changes in the electromotive force. The resistive and capacitive link R_1 , C_1 represents the polarization of Battery [2].

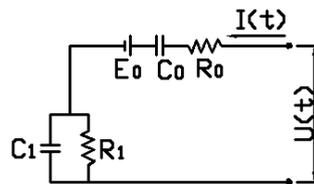


Figure 1. PNGV Model

To identify the model parameters, a HPPC test procedure is conducted on Li-ion battery. The test profile is shown in Figure 2. Through the pulse discharging, model parameters can be identified based on voltage response data using least squares method. First, the time constant of RC circuit can be identified from the zero-input response segment. And then, the parameters C_1 , R_1 are to be gained through zero state response segment. Parameter R_1 is determined by the voltage rise segment at the end of the current pulse. Parameter C_0 is determined by the voltage difference before and after discharge [1, 3].

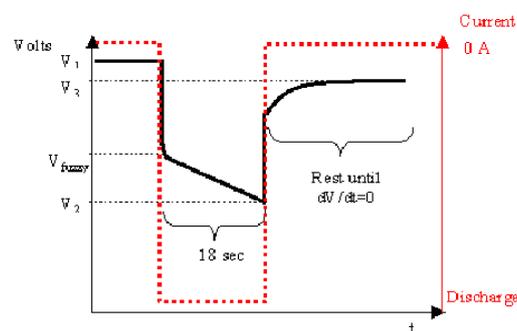


Figure 2. HPPC Test Profile

3. Model Validation

To validate the model and model parameters obtained with the procedure described above, charging and discharging tests are proposed. The profiles of this test is shown in Figure

3. The initial charge session (positive current) is based on step of 5A every 30 seconds, up to 25A. then, a subsequent discharge session includes 5A steps every 15 seconds, starting from -25A. A resting time of one minute between two sessions was introduced. At the beginning of the test, the battery is fully charged [4].

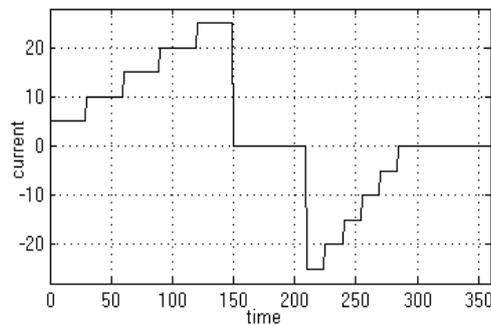


Figure 3. Profile of Charging and Discharging Test

Experiment and simulation proceeds as steps describe above. Figure 4 shows the result of experiment value (solid line) and simulated voltage response (dash line). As we can see in this figure, there is some deviation between voltage response and the actual voltage at the time of late current pulse and after the evacuation of current pulse. The reason is that it is difficult for a single resistance and capacitance link to describe the polarization of the battery. This also shows the highly nonlinear nature of the battery system. However, the maximum deviation is still under 0.7V, therefore, the PNGV model can reflect the actual characteristics of this kinds of Li-ion battery.

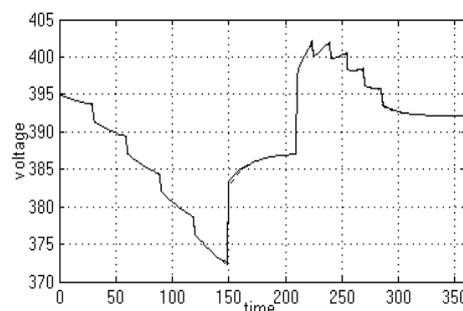


Figure 4. Comparison of Voltage Response in Simulation and Experimentation

4. State-Space Equations Establishment

The state-space description is more than a description of the system on input and output. As the system state is not necessarily the value that can be physically measured or observed, the most important functionality of state-space description is for the consideration of the system state, that is, the input causes the change of state, and the state determines the output. If the battery system is described by state-space, the problem that SOC can't be measured can be solved. Specifically, setting SOC as one of the state vector of system, state-space equation can be established according to the differential equations written by physical law or other aspects of mechanism. So the system state can be deduced by the measurable quantity and observable quantity. That is SOC.

For the convenience of computing, the equivalent circuit model of battery can be expressed as discrete state space equation. State vectors are set as:

$$X = [SOC(k) \ U_{c1}(k)]^T \quad (1)$$

Where $SOC(k)$ is the battery SOC at k times. $U_{c1}(k)$ is the voltage of capacitor C_1 at k times, it reflects the polarization of battery.

According the definition of SOC, it can be expressed as Equation (2) using Ah counting method:

$$SOC(t_k) = SOC(t_0) + \int_{t_0}^{t_k} \frac{\eta i(t)}{C_0} dt \quad (2)$$

Where $i(t)$ is the battery current, η is the efficiency of charge or discharge, C_0 is the battery rated capacity.

The RC circuit of the equivalent circuit model describes the polarization effect of the Li-ion battery. Using Kirchoff's current law and the definition of ideal capacitor, the differential equation to RC circuit is:

$$C_1 \frac{dU_{c1}}{dt} = I(t) - \frac{U_{c1}}{R_1} \quad (3)$$

Discrete state space equation established [2].

$$\begin{bmatrix} SOC(k+1) \\ U_{c1}(k+1) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & \exp(-T/(R_1 C_1)) \end{bmatrix} \begin{bmatrix} SOC(k) \\ U_{c1}(k) \end{bmatrix} + \begin{bmatrix} \frac{\eta T}{C_0} \\ R_1(1 - \exp(-T/(R_1 C_1))) \end{bmatrix} I(k) + w \quad (4)$$

Where, T is the sampling time, I(k) is the current at ktime, w is the input noise.

Output equation is:

$$U(t) = U_{ocv} - U_{c1} - I(t)R_0 \quad (5)$$

Where T is sampling time, v is the measurement noise.

By battery discharge test, the relationship between OCV (open-circuit voltage) and SOC could be identified. The test begins with fully (SOC=100%) charged to 100% DOD (depth of discharge). It is made up of 10 segments. The battery continues discharging at constant current $C_1/1$ rate for 6 minutes at each segment, and followed by a 1 hour rest to allow the battery to return to an electrochemical and thermal equilibrium condition. The voltage value at end of each segments are recorded. Then the relationship between SOC and OCV of battery is established [4]. As shown in Figure 6.

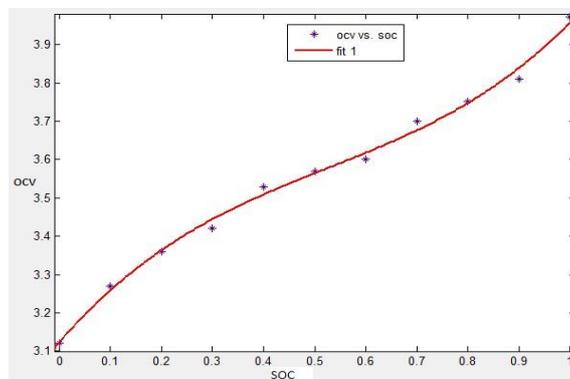


Figure 5. The Relationship between SOC and OCV After Fitting

5. EKF Algorithm Establishment

Using the concept of the state space, Kalman filter (KF) changed the general description of filtering problem. That is, the signal is only the output of a linear system which disturbed by white noise but not the second-order characteristics or spectral density function of signal process which should be known. And this input-output relationship can be described by a state equation. In addition, using a linear recursive filtering method, KF can calculate on the basis of a limited time data and requires less statistics data. So it needn't store the past observational data. When new data is observed, new estimated value can be calculated using a set of recursive formula, which uses the state transition equation by means of process itself according to the new estimated value and the former time estimated value. The calculation process is used iteration method, so it is simple and direct, especially suitable for the online estimation of the computer [7].

The li-ion battery is a complex system. Its' observed value and SOC value to be the estimated have nonlinear relationship. So it can not apply Kalman filter formula directly. But, if the observation equation is to be linearization, that is, the observation equation is carried on the Taylor series expansion and then the quadratic term is omitted. The linearized equation can be used to recursive calculation with KF formula. This method is also known as the extended Kalman filter (EKF) [5].

The observation equation after linearization is shown as below:

$$U(k) = \left[\frac{\partial U_{ocv}[soc(k)]}{\partial soc} \Big|_{soc = \hat{soc}(k|k-1)} \quad -1 \right] \begin{bmatrix} SOC(k) \\ U_{c1}(k) \end{bmatrix} - I(k)R_0 + v \quad (6)$$

The final coefficient matrix of discrete state space equation is:

$$A_k = \begin{bmatrix} 1 & 0 \\ 0 & \exp(-T / (R_1 C_1)) \end{bmatrix}, \quad B_k = \begin{bmatrix} -\frac{\eta T}{C_0} \\ R_1(1 - \exp(-T / (R_1 C_1))) \end{bmatrix}, \quad C_k = \left[\frac{\partial U_{ocv}[soc(k)]}{\partial soc} \Big|_{soc = \hat{soc}(k|k-1)} \quad -1 \right] \quad (7)$$

The EKF algorithm based on state space equation is established as follow [5-6]:

State estimate time update:

$$\hat{X}_{k|k-1} = A_k X_{k-1} + B_k u \quad (8)$$

Error covariance time update:

$$P_{k|k-1} = A_k P_{k-1} A_k^T \quad (9)$$

Kalman gain matrix:

$$K_k = P_{k|k-1} C_k^T (C_k P_{k|k-1} C_k^T + R_k)^{-1} \quad (10)$$

State estimate measurement update:

$$\hat{X}_k = \hat{X}_{k|k-1} + K_k \left[U(k) - \hat{U}(k) \right] \quad (11)$$

Error covariance measurement update:

$$P_k = (I - K_k C_k) P_{k|k-1} \quad (12)$$

Where, $\hat{X}_{k|k-1}$ is the predict value of state variable at k-1 step to k step, $P_{k|k-1}$ is the predict value of error covariance at k-1 step to k step. P_{k-1} is the error covariance. K_k is the gain. R_k is the noise covariance matrix. \hat{X}_k is the estimate value at k step. $U(k)$ is the measurement value. \hat{U}_k is estimate value of measurement.

As we can see from the filtering formula, the optimal linear filter of KF algorithm is formed by constant “feedback and calibration” [7]. As shown in Figure 6. It shows the properties of “feedback and calibration” of EKF and its information channel.

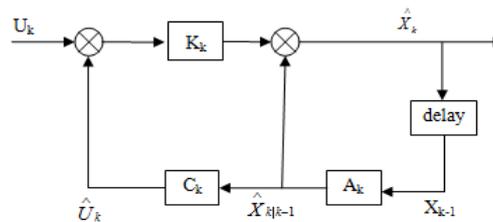


Figure 6. The EKF “feedback and calibration” Chart

6. Test and Simulation Analysis

The automotive profile test is necessary to verify whether or not the proposed PNGV model and EKF algorithm is valid in battery SOC estimation. The batteries used for experiments are 100 strings 6 AhLi-ion battery. Before the start of the test, the battery is fully charged (SOC=100%). Taking the experiment at UDDS conditions for example to illustrate the application of the filtering algorithm. UDDS stands for Urban Dynamometer Driving Schedule, and refers to United States Environmental Protection Agency (EPA) mandated dynamometer test on fuel economy that represents city driving conditions which is used for light duty vehicle testing. Each cycle time is 1369 seconds, 7.45 miles, average speed of 19.59mph. Conditions cycle is shown as below:

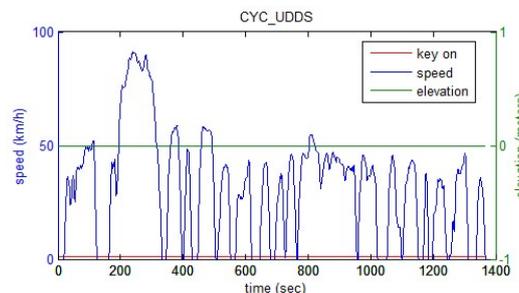


Figure 7. EPA Urban Dynamometer Driving Schedule (UDDS)

In this paper, one period of UDDS is employed to verify the SOC estimation approach. The voltage and current profiles sampled during UDDS cycles are shown in Figure 8 and Figure 9.

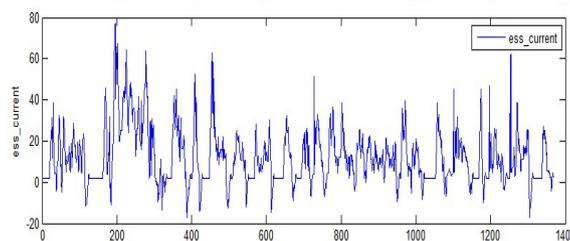


Figure 8. Current Profile Sampled during UDDS Cycles

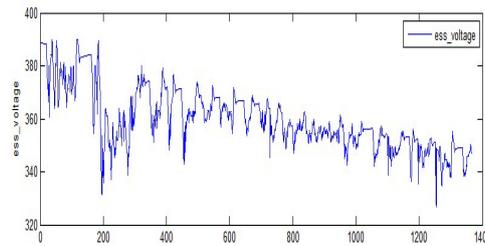


Figure 9. Voltage Profile Sampled during UDDS Cycles

From above figure we can see that the battery is in a rapidly changing dynamic process under the UDDS cycle. The current and voltage change very intensely, which is bound to produce noise in the data collection process and ultimately affect the SOC estimated. Simulation under this working cycle can test the algorithm estimation ability well.

Figure 10 shows the comparison of the SOC curves with EKF estimations and experiment. The black curve is the SOC with experiment in UDDS cycles. The red curve is the SOC with EKF estimation in UDDS cycles under the noise environment. Figure 11 shows the SOC errors between the EKF estimation and experiment. As can be seen, after the initial 300 seconds fluctuation, the SOC estimation can quickly converge to the actual value. After about 400 seconds, the error can be maintained in the range of 5%, which will meet the needs of actual use. This shows that SOC estimation with EKF is helpful in eliminating the environment noise and measurement noise. So it has better accuracy in battery SOC estimation.

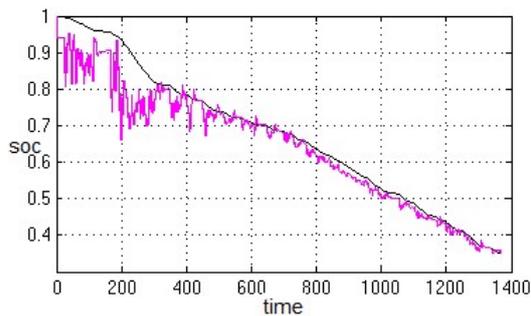


Figure 10. SOC Curves with EKF Estimation and Experiment

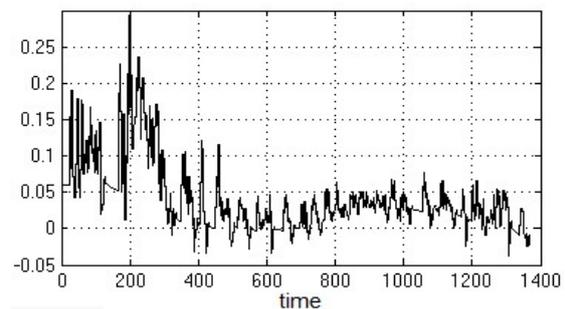


Figure 11. SOC Estimation Error Curves with EKF Algorithm

7. Conclusion

Battery SOC estimation is one of the most important tasks in the EV's BMS. It is not only the basic parameter which decided the vehicle control strategy, but also helping drivers to use battery power more reasonably to control and predict the driving range. In this paper, the equivalent circuit model of Li-ion battery is studied and a discrete state space equation is set up. On this basis, the SOC estimation method with EKF algorithm is proposed. The results of the proposed method are compared with the experiment value. The comparisons show that the EKF algorithm can restrain the noise, has sufficient accuracy under the noise environment. So this method has good practical value in SOC estimation of Li-ion in EV's BMS.

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