State of Charge Estimation for Li-ion Batteries based on double Extended Kalman Filtering Method

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Abstract. Lithium-ion batteries have been widely used in daily life, and their state of charge (SOC) has received considerable attention and investigation. This paper presented a model based on double extended Kalman filtering (DEKF) method, which combines the advantages of Ampere-hour method and extended Kalman filtering error cancellation. A series of charge-discharge experiments on LiFeCOPO4 batteries have been carried out with different configurations of constant currents and temperature. Experiment results show that the proposed DKEF method effectively improves the precision of SOC estimation, and can be used in large-scale industrial production.

Introduction

Due to their high energy density and long cycle life compared with other battery chemistries, lithium ion batteries have been adopted in automotive manufacturing, especially for hybrid and electric vehicles [1]. Meanwhile, state of charge (SOC) estimation, is one of the key issues in battery management system (BMS) of those automobile, and has received considerable attention and investigation [2].

Typically, SOC is defined as the percentage of remaining capacity relative to the maximum capacity of the battery, which reflects the remaining power of battery. SOC is an important indicator of battery status, since it provides information when a battery needs to be recharged and allows BMSs to prolong the battery life by preventing from over-charging or over-recharging. Thus, it is of great concern to acquire the current value of SOC which is however hard to measure directly. Since SOC is closely relative to battery's other characters, such as the voltage, current, temperature and degree of aging. We thus often take advantage of these measurable parameters to estimate the value of SOC [3].

For the importance and yet difficulty of estimation in SOC, extensive works have been done in this area. There are various methods for SOC estimation depending on the battery information, type, and application environment. Nowadays there are three major estimation approaches: Ampere-hour integral method, open circuit voltage method and Kalman filtering method. In Ampere-hour integral method, the current is integrated over time to measure the consumption of electricity. Although Ampere-hour method is easy to implement, the measurement and calculation errors can be accumulated by the integration function [4]. The open circuit voltage method estimates the SOC based on the voltage of battery after a long time of still standing, and achieves the SOC close to its real value, however, which is hard to meet the requirement of dynamic estimation [5]. And Kalman filtering method regards battery as a power system, and makes the optimal estimation for this power system in minimum range, which can filter the fixed noise and get the optimal estimation of SOC [6-8].

In this paper, a method based on double extended Kalman filtering (DEKF) is developed for the estimation of SOC, which combines the advantages of Ampere-hour method and extended Kalman filtering error cancellation. The experiment results show that the proposed method provides a relatively more accurate estimation of SOC and reduces the impact of measurement error from the current sensor.

The battery mode

The battery model types. The battery system models can be divided into three major types: electrochemical model, mathematical model and electrical model. Electrochemical model, which can reflect the battery internal reaction mechanism and the related design parameters, is used to optimize the battery structure design. However, this kind of battery model is not suitable for control design since it has a relatively complex structure in which the parameters of battery structure influenced by the specific factors such as material and size are difficult to calculate and determine. Currently used in battery, the mathematical model based on empirical formula and several theoretical methods are currently used to predict battery runtime, efficiency, capacity and etc. in system design. However, due to the over simplification, it is only applicable to certain situations in which the results suffer from large errors and cannot reflect battery performance of charging and discharging voltage and current. Therefore this method cannot be used in circuit design and simulation analysis of the key features. The electrical model mostly takes advantage of the voltage source, resistance and capacitance circuit, simulates the dynamic characteristics of battery, which is more intuitively easy to use and suitable for combining with circuit simulation experiment. The electrical model has precision between electrochemical and mathematical models and typically can be divided into the equivalent circuit model, AC impedance model and running time model.

In order to simulate the battery dynamic characteristics, we adopt double Resistance-Capacitance (RC) rings model which is one of the electrical models to the simulation in this paper. Details of the double RC rings model are provided in the next subsection.

The double RC rings model. As Fig. 1 shows, the double RC rings model connects one more capacitor in parallel on the basis of Partnership for a New Generation of Vehicles (PNGV) model, which constitutes a new RC ring with previous resistance. Compared to the PNGV model, as one more shunt capacitance, the capacitor has the function of preventing voltage mutation and stable voltage, thus it can better simulate the steady state performance of the battery relative to a single resistor RC ring model.

Prior works have shown that battery model can be equivalent to a resistance with multiple RC rings [9], therefore, the equivalent circuit with more RC rings can better represent dynamic characteristics of a battery. However, more RC rings will introduce more complexity. We choose two RC rings in this paper based on the consideration of the actual application and calculation.

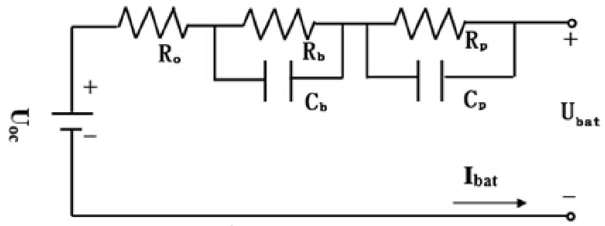

Fig. 1: The equivalent circuit model of double RC rings

In figure 1, Rb and Cb are double layer capacitance resistances of the battery. When two phases of high conductivity contact, it will charge for redistribution. This process can be simulated by the electric double layer capacitance resistances. Rp and Cp are capacitance resistance for the characterization of the battery internal diffusion phenomenon. Uoc is the open circuit voltage. Ro is battery internal resistance, including the resistance produced by various membrane electrode surface layer resistance, etc. Ubat is the voltage of the battery.

Then the state function (1) and output function (2) are carried out by the Kirchhoff Laws for voltage and current as follows.

$$\begin{bmatrix} U_b \\ U_p \\ SOC \end{bmatrix}_{k+1} = \begin{bmatrix} 1-\frac{T_s}{\tau_b} & 0 & 0 \\ 0 & 1-\frac{T_s}{\tau_p} & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} U_b \\ U_p \\ SOC \end{bmatrix}_{k} + \begin{bmatrix} \frac{T_s}{C_b} \\ \frac{T_s}{C_p} \\ -\frac{\eta T_s}{C_n} \end{bmatrix}_{k} i_k + W_k \quad (1)$$

$$U_{bat,k+1} = -U_b - U_p + [-R_o] i_k + U_{oc} + V_k \quad (2)$$

$$U_{oc} = f_{uoc}(SOC(k)) \quad (3)$$

Where W_k is the noise of system process, V_k is the noise of system measurement. And T_s is the time of system sampling, τ_s is the time constant of RC ring, which is combined by capacitance C_b, resistance R_b. τ_p is the time constant of RC ring, which is combined by capacitance C_p, resistance R_p. C_n is the capacity of battery, i_k is the current through the battery, which is positive in charge and negative in discharge. Compared to the PNGV model, double RC rings model has one more RC ring, which can reflect the dynamic characteristics of battery. And in the operation process of electric vehicle, working condition of the battery is complex and the fluctuation of current is also high.

Double extended Kalman filtering algorithm

The core idea of Kalman filtering algorithm is to make the optimal estimates of the minimum variance sense for the state of the dynamic system. Kalman filtering algorithm is a recursive, convergence, and anti-jamming algorithm, and can filter out interference and get the estimate closer to the true value. So the estimate will become more and more close to the real value as the round of KF algorithm increases.

In this paper, double extended Kalman filtering algorithm is applied for the estimation of SOC. DEKF algorithm is mainly based on the extended Kalman filtering algorithm with the advantage of Ampere-hour method.

Extended Kalman filtering algorithm. Kalman filtering algorithm is generally applied to linear systems. While EKF algorithm adopts the same core idea of KF and transforms some linear items of KF algorithm into nonlinear forms, it therefore can be better applicable to nonlinear systems.

The state functions for a general nonlinear system are given by

$$X(k+1) = f(X(k), I, W(k)) \quad (4)$$

$$Y(k) = h(X(k), I, V(k)) \quad (5)$$

The corresponding EKF arithmetic program contains five steps as follows.

Step1: Set the initial system state estimation and initial state error covariance;

Step2: The current moment function of the system state and covariance and relationship;

$$A = \frac{\partial f}{\partial X}(X_{old}, I, 0) \quad (6)$$

$$X_{ud} = f(X_{old}, I, 0) \quad (7)$$

$$P_{ud} = A * P_{old} * A^T + Q \quad (8)$$

Step3: Get the Kalman gain matrix K of the current moment, in which matrix C is the Jacobi matrix of the open circuit voltage under status partial derivatives;

Step4: Get the system output calculated by state equation, and calibrate it with a priori estimates with the value obtained by measurement calibration, then update the current status value and covariance.

Step5: Update the system state value and covariance.

Then turn back to the first step for iteratively calculation. Through these five iteratively steps, the optimal estimation of the current system can be acquired. The definitions of parameters above are summarized in Table 1.

Table 1: The definitions of parameters

Parameter	Definition	Parameter	Definition
$W(k)$	System process noise	Q	System process noise covariance matrix
$V(k)$	System output noise	R	System output noise covariance matrix
$X(k)$	State value when t=K	A, B, C, D	System state function matrix
$Y(k)$	Output when t=K	Y_{new}	System update output value
I	Input when t=K	$Y_{measure}$	System output measurement
K	Kalman gain matrix	Δ_Y	Difference of output and its update
X_{new}	State update value	P_{new}	Covariance matrix update value
X_{ud}	State estimate value	P_{ud}	Covariance matrix estimate value
X_{old}	State original value	P_{old}	Covariance matrix original value

The principle of DEKF. In practice, the battery is a high non-linear system, which may cause deviation in batter modeling. The accuracy of batter modeling will affect the SOC estimation based on EKF algorithm since the SOC value of EKF algorithm is obtained mainly through the adjustment of internal SOC parameters by the battery voltage. In addition, when using Ampere-hour method for SOC estimation alone, current sampling error (including zero resource) can cause cumulative error of estimated results.

In order to reduce the dependence of the SOC estimation algorithm on system model, we present double extended Kalman filtering algorithm which combines the advantages of EKF and Ampere-hour method and can overcome a certain extent of zero drift. DEKF based on KF is a secondary structure algorithm with a two-layer Kalman filter, in which the SOC estimation is acquired by two Kalman filters. DEKF algorithm firstly uses the Kalman filtering algorithm to modify the SOC by the battery voltage. Then the revised SOC is used as an output to the second Kalman filter, which can modify the SOC estimate by Ampere-hour integral method, finally get the final SOC estimate. Combining with the advantages of EKF and Ampere-hour method, DEKF can achieve more stable and accurate estimation of SOC.

The principle diagram of the proposed double extended Kalman filtering algorithm is shown in Fig. 2 and has three steps as follows.

i) The first step is to get the current voltage parameters of battery, and input them into EKF algorithm for the estimation SOCEKF;

ii) Then this SOCEKF is regarded as the output, along with the battery current parameters, for the next KF filter. In this KF filter, this state function is Ampere-hour integral function;

iii) In the KF algorithm, the new value of SOC estimation is acquired by the comparison and process of the SOCAH (step ii) and SOCEKF (step i).

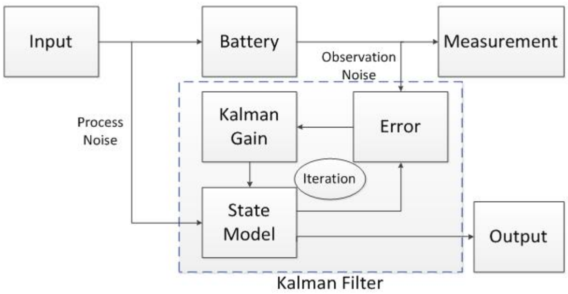

Fig. 2: The principle diagram of double extended Kalman filtering

Numerical Results

In this section, we present numerical results from experiments for various conditions. During the experiments, we record the SOC estimation of DEKF algorithm and compare it with the reference value referred to as the final standard SOC.

There are six groups of experiments under different temperature condition as -10℃, 0℃, 20℃, 30℃, 40 ℃ and 55 ℃ and each group has ten circulating charge and discharge tests. The experimental results of DEKF SOC estimation are summarized in Table 2. Note that the estimation error is the difference between the estimated SOC and the reference value.

Table 2: Experimental results of DEKF SOC estimation

Group No.	Temperature (℃)	Current zero drift (A)	Final standard SOC	Estimated SOC	Estimation error
1	-10	0.037	54.82%	50.35%	-4.47%
2	0	0.032	54.82%	51.89%	-2.93%
3	20	0.007	54.82%	52.37%	-2.45%
4	30	-0.009	54.82%	52.86%	-1.96%
5	40	-0.012	54.82%	53.65%	-1.17%
6	55	-0.025	54.82%	54.52%	-0.31%

As the national standard Technical specification of battery management system for electric vehicles (QC/T 897-2011) defines, the condition 4 of charging and discharging is chosen as the test condition. There are ten steps in test process as follows:

Step1: **(Adjust SOC)** Adjust the battery pack SOC to 100% in a standard charging way;

Step2: **(Discharge battery pack)** Discharge battery pack out 40% power at 0.3 C (4.5 A) current, for 80 minutes, then SOC should be 60%;

Step3: 10 minutes standing;

Step4: Discharge the battery pack at 1C current for 23s. Discharge battery pack out 0.639% power at 1 C (15 A) current, for 23 second, then SOC should be 59.361%;

Step5: Discharge the battery pack at 1/3 C current for 8s discharge battery pack out 0.074% power at 1/3 C (5 A) current, for 8 second, then SOC should be 59.287%;

Step6: Charge the battery pack at 1/3 C current for 23s;
Charge battery pack out 0.213% power at 1/3 C (5 A) current, for 23 second, then SOC should be 59.500%;

Step7: Discharge the battery pack at 1/30 C current for 16s;
Discharge battery pack out 0.024% power at 1/30 C (0.5 A) current, for 16 second, then SOC should be 59.485%;

Step8: Repeat 3-6 steps, cycle for ten times until the final SOC is 54.823%;

Step9: 10 minutes standing;

Step10: End.

The experiment results have shown that the precision of battery SOC estimation increases with the rising temperature, meanwhile the current zero drift value shrinks from positive to zero, then become negative.

From Table 2, the best working temperature of Hall current sensor is 20 ℃to 30℃, in which battery DEKF SOC estimation error can be within 2.5%. From -10 ℃ to -20℃, the current zero drift is positive and gradually decreases, while the DEKF SOC estimation error is reduced. From 30 ℃ to 55℃, current zero drift is negative, and its absolute value tends to increase gradually, however the DEKF SOC estimation error still constantly decreases and is close to zero

Due to the DEKF SOC estimation algorithm is weighted by Ampere-hour method and EKF algorithm, so the precision of DEKF SOC estimation algorithm has much to do with the accuracy of EKF algorithm and Ampere-hour method. From -10 ℃ to 20℃, the SOC estimations of the Ampere-Hour method and EKF algorithm are more accurate. From 30 ℃ to 55℃, however, the SOC estimation errors are positive and tend to rise for the Ampere-hour method and are negative for EKF algorithm. By counteracting those two trends, the proposed DEKF algorithm for SOC estimation can be much more accurate.

Conclusion

In this paper, we adopted double RC rings to represent batteries and proposed a double extended Kalman filtering algorithm for the estimation of battery SOC. The experiments results have validated the proposed DKEF algorithm and further shown that DKEF can effectively improve the precision of SOC estimation. Since the SOC estimation still has more or less error due to the current zero drift, more accurate current detection and modelling will be our future work.

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