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State of Health Estimation for Lithium-ion Battery Based on D-UKF

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Abstract

This paper considers an accurate estimation method of State of Health (SOH) for lithium battery. An improved battery model is proposed which is based on equivalent circuit model and battery internal electrochemical characteristics. In our study, Double Unscented Kalman Filtering (D-UKF) algorithm is designed to calculate State of Charge (SOC) and SOH of lithium battery at the same time. The feature of our new method is SOH estimation model is derived based on battery internal resistances. The Ohmic resistance (one of internal resistances) can be identified online based on D-UKF algorithm. Two filters defined as UKF1 and UKF2 are working together to calculate the real-value of SOC and Ohmic resistance to obtain final SOH value. The experimental results indicate that our new battery model considers different value of battery internal resistances on different working condition (as different voltages, different currents). Besides, our study verifies the performance and feasibility of new estimation method based on D-UKF. This new algorithm has the practical value to further study for other types of lithium battery.

Keywords: *SOH; lithium battery; D-UKF; SOC; Ohmic resistance*

1. Introduction

Battery State of Health (SOH) describes the battery performance at the present time compared with the performance at ideal conditions (when the battery was new) [1, 2]. It is a measurement that reflects the battery performance and health status. In automotive applications, the lithium-ion battery is one of the frequently-used battery types and the estimation of the battery actual SOH is rather crucial to predict the availability of power and energy in hybrid electric vehicles (HEV) and electric vehicles (EV) [3]. During working periods, the resistance as well as the capacity and in consequence the State of Charge (SOC) of every single cell changes through electrochemical degradation processes like electrolyte decomposition. In theory, by measuring the battery capacity through charge and discharge working periods with the referenced method at certain temperature, the battery SOH can be calculated [4]. Because of this necessity of a reliable SOH estimation method, many algorithms were presented to derive the battery SOH [5, 6]. The researchers in company SAFT proposed a battery lifetime-decay model which is used for qualitative analysis of battery lifetime decay [7]. Ning et al. designed an empirical model defining the battery life-cycle, based on the large amount of experimental results. This model is not appropriate for all types of lithium battery because of their different physical characteristics [8]. Ramadass et al. put forward a mathematical model defining the capacity attenuation of the lithium battery [9]. In paper [10], Alvin et al. proposed a new battery SOH estimation algorithm based on the fuzzy logic theory. The advantage of this method is the battery SOH can be estimated using battery Alternating Current (AC) impedance. Recently, this method has been used in the

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battery management system (BMS). However, it is not applicable for the electrical vehicle system in which the working conditions are more complicate. Plett presented a new estimation method for the change-role of the internal resistances and the real-time capacity of the battery [11, 12]. This method is based on the Extended Kalman Filtering (EKF) algorithm and indicates a new and more validate method to estimate battery SOH. However, standard EKF can not solve the un-linear problem of battery model, so that Double Extended Kalman Filtering (D-EKF) was presented to obtain a better estimation result when system error is significant [13]. According to SOH estimation methods analyzed above, the definition of the battery SOH is usually limited to the cell-aging category. The main parameters used to characterize the degree of cell-aging are the value of battery capacity and the value of battery internal resistances.

In our study, Unscented Kalman Filtering (UKF) algorithm and Double UKF (D-UKF) are used in battery SOH estimation. An improved online parameter identification method is put forward. The battery internal resistances and SOC can be calculated meantime based on D-UKF. The function indicating the relationship between battery internal resistance and SOH (battery life-cycle performance) was established. The battery SOH estimation model is built based on the experiments results of charge and discharge processes and computer simulation results. Lastly, the SOH estimation method for 18650-type lithium battery is improved based on D-UKF algorithm. In the case of using the above method for the battery SOH estimation, some difficulties will arise: Firstly, the battery needs to be fully charged and discharged to determine its present capacity, which is not realistic especially when the battery is already installed in an HEV. Secondly, the battery capacity will change with temperature and with different charge/discharge current profiles. These problems will be solved and future experimental results and simulation results will be presented in my later paper.

2. Principle of UKF Algorithm

The main advantages of the UKF algorithm are: Firstly, the calculation accuracy of nonlinear Gaussian distribution statistics can reach at least three bands and one of non-Gaussian distribution statistics can reach two bands. Secondly, no specific form of nonlinear equation is needed in UKF algorithm, no demand for guidance and Jacobian matrix calculation. Last but not least, the calculation accuracy of UKF is not influenced by the higher-order truncation error, which is caused by the linearization of state and observation equations. Currently, UKF has been successfully used in radar tracking, spacecraft attitude positioning, image tracking, voice processing and other occasions. The flowchart standard UKF algorithm is shown in Figure 1 [14]. The performance of the UKF is better than the traditional Kalman Filtering algorithm and other improvements

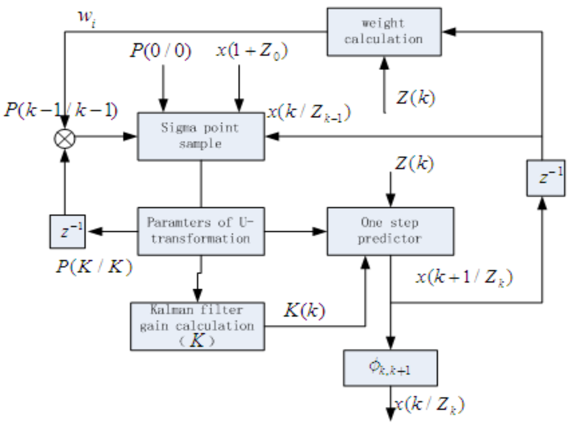


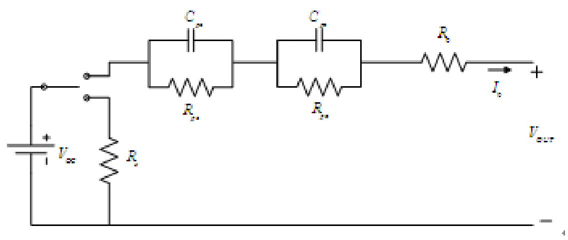
Figure 1. The Flowchart of UKF Algorithm

3. Comprehensive Battery Model

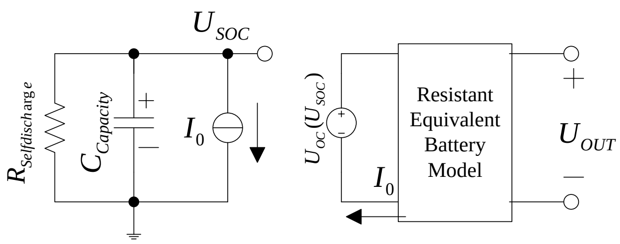
In this section, an improved circuit equivalent model for 18650-type lithium battery is designed based on the electrochemical dynamic characteristics. Later, using the principle of the battery SOH and the theory of the UKF algorithm, the online estimation method of the battery Ohmic resistance value is proposed.

3.1. New Type of Circuit Model for Lithium Battery

Circuit-based models for lithium battery have been built in terms of electric-circuit parameters, such as capacitances, resistances, voltage sources, etc. Two order circuit-based models are a commonly used method for battery controllers because it is possible to represent in terms of mathematical formulas. The RC electrical modeling including uncertainties is shown in Figure 2 (a). The advantage of this model is that the inconsistent factor on charge and discharge conditions should be considered [15]. The parameters of the equivalent circuit model are as follows. V_{OUT} defines the open circuit voltage (OCV) of the lithium battery and is respected to battery SOC. Two RC series networks are denoted by R_{pc} / C_{pc} and R_{pe} / C_{pe} , respectively. The series R_{pc} and C_{pc} defines the concentration resistance of lithium battery model, the series R_{pe} and C_{pe} defines the polarization resistance. The battery Ohmic resistance is represented by R_0 . The discharge load of the circuit model is denoted by R_S .



(A) Two Order Equivalent Circuit Model Based On Simple Theory



(b) Two order equivalent circuit model base on electrochemical dynamic characteristics

Figure 2. Two Order Equivalent Circuit Model for Lithium Battery

When the lithium battery is on discharge condition with the current defined as I_0, the functional relationship of those parameters can be obtained based on circuit principle.

$$\frac{dU_{C_{pc}}}{dt} = \frac{1}{C_{pc}} I_0 - \frac{1}{R_{pc}C_{pc}} U_{C_{pc}} \tag{1}$$

$$\frac{dU_{C_{pe}}}{dt} = \frac{1}{C_{pe}} I_0 - \frac{1}{R_{pe}C_{pe}} U_{C_{pe}} \tag{2}$$

Where, $U_{C_{pc}}$ and $U_{C_{pe}}$ denote the voltage of the series RC networks R_{pc}/C_{pc} and R_{pe}/C_{pe}, respectively. The formula defined as $\frac{dU_{(\cdot)}}{dt}$ givesthe quantity of electricity of the whole circuit loop.

The parameters of the equivalent circuit are related to the working conditions, the direction of current (charge or discharge) and battery SOH. The further effort of our study is that the electrochemical characteristics are introduced into battery model. The advantages of this improved circuit model are its better calculated performance and comprehensive characteristic considering. On the other hand, the equations of this model are still second order differential equations based on electrochemical dynamic characteristics. According to the functions (1) and (2), the specific battery model in dynamic process is shown in Figure 2 (b). The parameters on the left side are $R_{selfdischarge}$, $C_{Capacity}$ and U_{SOC}, denoting the self-discharge resistance, battery available capacity, and battery OCV. The charge or discharge current is presented as I_0, which is positive or negative respectively. The parameters on the right side are $U_{OC}(U_{SOC})$ and U_{OUT}, denoting the electromotive force and terminal voltage of circuit model.

3.2. Online Estimation Model for Battery Ohmic Resistance

An accurate estimated results of the battery internal resistances is important for battery SOH calculation problem. The Ohmic resistance defined as R_0 is studied to validate the online estimation method based on UKF algorithm. The state vector of the battery model is chosen as $x_k = [S_k, U_{1,k}, U_{2,k}]^T$, where S_k, $U_{1,k}$ and $U_{2,k}$ denote the battery SOC, the voltage of the series RC networks R_{pc}/C_{pc} and R_{pe}/C_{pe}, respectively. Based on the definition of the initial Ohmic resistance defined as $q_k = R_{0,k}$, the state equation leads to the following inequality:

$$f(x_k, u_k, q_k) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & e^{-T/t_{pc}} & 0 \\ 0 & 0 & e^{-T/t_{pe}} \end{bmatrix} x_k + \begin{bmatrix} -ht/Q_0 \\ R_{pc}(1-e^{-T/t_{pc}}) \\ R_{pe}(1-e^{-T/t_{pe}}) \end{bmatrix} i_k \tag{3}$$

where, t_{pc} and t_{pe} denote the time constant of the polarization resistances , t is the sampling time, h represents the Kulun coefficient which can be obtained based on the charging and discharging experimental results. Generally, $h = 1$ when the battery is working on the charging condition and $h < 1$ when the battery is working on the discharging condition. Q_0 Stands for the rated capacity of the battery, i_k denotes the charge/discharge current at the moment defining as k .

It noted that the state vector has three parameters and the measurement equation is given by

$$g(x_k, u_k, q_k) = U_0(S_k) - U_{1,k} - U_{2,k} - i_k q_k \tag{4}$$

Where, $g(x_k, u_k, q_k)$ defines the observation vector of battery system, $U_0(S_k)$ denotes the nonlinear function of OCV versus SOC. Moreover,

$$A_k = \frac{\partial f}{\partial x}\Big|_{x=\hat{x}_k} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & e^{-T/t_1} & 0 \\ 0 & 0 & e^{-T/t_2} \end{bmatrix} \tag{5}$$

$$C_k^x = \frac{\partial g}{\partial x}\Big|_{x=\hat{x}_k} = \left[\frac{dU_0(S)}{dS}\Big|_{S=S_k^-}, -1, -1\right] \tag{6}$$

Where, $\frac{\partial f}{\partial x}\big|_{x=\hat{x}_k}$ and $\frac{\partial g}{\partial x}\big|_{x=\hat{x}_k}$ indicating the derivation process of (3) and (4). The main calculation equation for battery Ohmic resistance can be decomposed from parameter C_k^x.

4. SOH Estimation Method for Lithium Battery

In this section a description of the mathematical methods applied in this study is given. Namely this is an Unscented Kalman filter and the support vector regression.

The available capacity of high-capacity lithium battery will be expensed when it loses function or is suddenly fail during the working periods. Recently, three methods of SOH estimation for lithium battery single cell or battery pack are used in practical conditions. One of the methods is based on the internal characteristics of the lithium battery [16]. Based on the internal characteristics during the aging process, the corresponding equation of the battery life-cycle with respect to its parameters can be derived. Another method is based on the Data Mining theory [17]. Practically, the artificial neural network model and the analysis model based on the Data Mining theory are two methods used for the battery SOH estimation purpose. Kim presented a new technique for estimating SOH based on Dual-Sliding-Mode Observer [18]. However, the proposed methods are based on a mathematical model to derive a unified solution for the SOC and SOH.

4.1. Double UKF Algorithm for SOH Estimation

In our study, an improved SOH estimation method based on UKF is proposed. Double Kalman Filtering (D-KF) algorithm proposed by [19] is introduced to build double KF estimators for battery SOH estimation purpose. The structure of D-UKF is presented in Figure 3, which could be used to calculate SOC and internal resistances at the same time. The input parameters of UKF1 are terminal voltage of battery model U_{out}, SOC, current value I, time value t, and two internal resistances. The output parameters of UKF1 are Ohmic resistance R_0 and terminal voltage of two internal resistances. The input/output parameters of UKF2 are exactly opposite to UKF1 and two estimators are used alternately to calculate battery R_0.

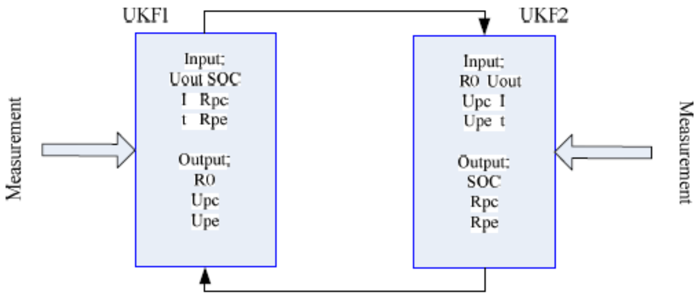


Figure 3. The structure of Double-UKF algorithm

4.2. Online Estimation Method for SOH

Our new estimation method for battery SOH is based on the equivalent circuit model and the internal resistance value [20]. Figure 4 shows the profile of the online SOH estimation method for 18650-type lithium battery. First procedure of the method is building the two order equivalent circuit model for lithium battery. The Ohmic resistance of the circuit model can be identified online based on UKF algorithm. Second part is the experimental results used to derive the equations of battery SOH versus battery Ohmic resistance, Based on the theory in [21] and [22], the estimation model for battery SOH can be decomposed based on battery characteristic parameters and data mining principle.

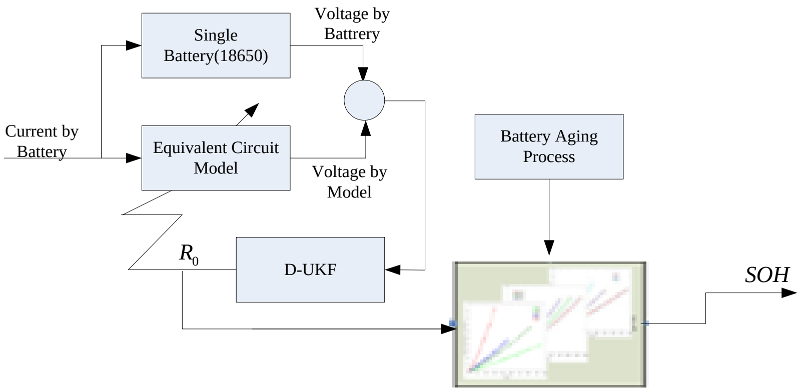


Figure 4. The Structure of Online SOH Estimation Method

5. Battery SOH Estimation Based On D-UKF Algorithm

There are several definitions for battery SOH such as the battery cell's capacity of storing energy and preserving charge for long periods or the ratio of the amount of charge that can be drawn from a new battery to the aged battery [23]. The increase and decrease of series resistance and capacity are reported as the indications of reduced SOH by Kim in [20]. In the following, schemes for the identification of R_0 and estimation of SOH based on D-UKF are explained.

5.1 R_0 Estimation

To estimate the battery Ohmic resistance shown in Figure 4, we use the discharge test data and (4) in linear form. Figure 5 shows that I_0 stands for the input parameter of circuit model, the output parameters are the different value of the open-circuit voltage defined as $U_{OC}(U_{SOC})$ and the terminal voltage defined as U_{OUT}. Based on Kirchhoff and

Laplace Transform theory, the equation of circuit parameters in frequency domain can be obtained as follows:

$$U_0(s) = I_0(s)(R_0 + \frac{R_{pc}}{1+R_{pc}C_{pc}s} + \frac{R_{pe}}{1+R_{pe}C_{pe}s}) \tag{7}$$

Where, $U_0(s)$ stands for the different value of $U_{OC}(U_{SOC})$ and U_{OUT} in Laplace domain, the parameter s denotes the symbol of Laplace Transform.

The differential form of (7) can be expressed as:

$$U(k) = -\alpha_1 U(k-1) - \alpha_2 U(k-2) + \beta_0 I(k) + \beta_1 I(k-1) + \beta_2 I(k-2) \tag{8}$$

Where, α_1 , α_2 , α_3 and β_1 , β_2 are the coefficients of differential equation (8). Defining $\theta=[\alpha_1\ \alpha_2\ \beta_0\ \beta_1\ \beta_2]$ and $h^T(k)=[-U(k-1)\ \ -U(k-2)\ I(k)\ \ I(k-2)]$, then the discrete observation equation based on UKF1 is determined to be,

$$U(k) = h^T(k)\theta + e(k) \tag{9}$$

From (8) and (9), the equation indicating the relationship of internal parameters of the battery model can be decomposed based on the recurrence method.

The coefficients $\theta=[\alpha_1\ \alpha_2\ \beta_0\ \beta_1\ \beta_2]$ can be obtained using UKF algorithm with the state equation and measurement equation of (3) and (9). The proposed R_0 estimator using UKF1 has the following structure:

$$\begin{cases} R_0 = \dfrac{\beta_0 - \beta_1 + \beta_2}{1-\alpha_1+\alpha_2} \\ \tau_{pc}\tau_{pe} = \dfrac{T^2(1-\alpha_1+\alpha_2)}{4(1+\alpha_1+\alpha_2)} \\ \tau_{pc} + \tau_{pe} = \dfrac{T(1-\alpha_2)}{1+\alpha_1+\alpha_2} \\ R_0 + R_{pc} + R_{pe} = \dfrac{\beta_0+\beta_1+\beta_2}{1+\alpha_1+\alpha_2} \\ R_0\tau_{pc} + R_0\tau_{pe} + R_{pc}\tau_{pc} + R_{pe}\tau_{pe} = \dfrac{T(\beta_0-\beta_2)}{1+\alpha_1+\alpha_2} \end{cases} \tag{10}$$

5.2 SOH Estimation Model

Based on the principle and model identification scheme proposed by Hajizadeh et al. [23], the maximum charge and discharge current is defined as follows:

$$\begin{cases} I_{\max} = \dfrac{OCV - V_{\min}}{R_{\Omega}} & disch\arg ing \\ I_{\max} = \dfrac{V_{\max} - OCV}{R_{\Omega}} & ch\arg ing \end{cases} \tag{11}$$

Where, $V_{\min}$ and $V_{\max}$ stand for the maximum and minimum of terminal voltage of battery circuit model, R_{W} stands for the mean value of battery internal resistances (in this paper, the Ohmic resistance is considered only). In the above equation, the maximum current of single cell is mainly determined by resistance R_W, Therefore, the charge and discharge performance on the condition of End of Life (EOF) is very important. The mean value of Ohmic resistance when battery is in EOF defined as R_Ω^{aged}, the value when battery is absolutely new defined as R_Ω^{new}. According to our experiments, the value of two resistances are $R_\Omega^{aged} = 0.048840\Omega$ and $R_\Omega^{new} = 0.02660\Omega$. The battery SOH estimation model based on internal resistance can be defined as follows:

$$SOH_{arbitary} = \left| \frac{R_\Omega^{selected} - R_\Omega^{aged}}{R_\Omega^{new} - R_\Omega^{aged}} \right| \tag{12}$$

Where, $R_\Omega^{selected}$ denotes the resistance value of arbitrary battery and it is noted that the battery SOH is within 0 to 100%.

5.3 SOH Estimation Algorithm Based on D-UKF

Based on the definition of the battery SOH, the increase/decrease of Ohmic resistance value could be used to indicate the degree of battery capacity decay namely battery age. The parameter r_k represents the different increase/decrease value of R_0 at one sample time defining as k and the next sample time defining as (k+1). The value of r_k can be calculated by following equation,

$$R_0^{k+1} = R_0^k + r_k \tag{13}$$

Derived from (4), the measurement equation of UKF is rewritten as follows:

$$U_k = F[SOC_k] - U_k^{R_{pc}C_{pc}} - U_k^{R_{pe}C_{pe}} - R_0 I_k + \Delta E(t) + v_k \tag{14}$$

Practically, the affect caused by the charge current could be omitted because the battery characteristics are fixed. However, the affect caused by the discharge current and the temperature is significant when the working condition of lithium battery changes. In this paper, the experiments were operated under the same temperature, and the function of the battery SOH respected to the battery Ohmic resistance is substituted without the temperature factor. The measured current and voltage during the discharge test are shown in Figure 5.

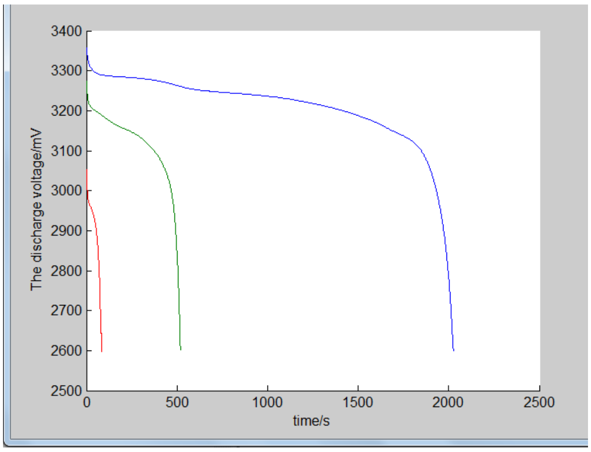


Figure 5. Current And Voltage Profile versus Time

In the previous section, the real-time R_0 has been obtained by UKF1, as it appears in Figure 2. Defining $\eta(r_k, I)$ as the function stands for the capacity decay, then, the empirical model of $\eta(r_k, I)$ can be formulated based on fitting analysis and regression analysis methods as shown in (15),

$$\eta(r_k, I) = R_0(T, I)I^C \tag{15}$$

Where, r_k can be get with (13), T is the absolute temperature, I denotes the discharge current. The constant vector C can be derived from the experimental results.

The calculation model in (15) is not thoroughly identified, thus the subtracted form of R_0 is decomposed based on the simulation results. The equation is given by

$$R_0(T, I) = ae^l + bI^m + c \tag{16}$$

Where, a, b and c denoted the coefficient of the exponential function, *l* and *m* denoted the exponent of the exponential function, *c* denoted the constant term of the exponential function. The value of these parameters will be shown in following sections. The experimental results have shown that the performance of the lithium battery is significantly degreed related to the value of the discharge current. The greater the discharge current is the shorter the battery life cycle is.

6. The Experimental Results and Its Analysis

6.1 Test Setup

Our study mainly focuses on the estimated value of battery SOH under different charge and discharge current and same temperature. To identify and validate the equivalent circuit model for 18650-type lithium battery and to verify the proposed SOH estimation method, a test system was designed. The lithium battery studied were the battery cells with a nominal capacity of 1500 mAh. The nominal, maximum, and cutoff voltages of the battery under study are 3.2V, 3.6V, and 2.9V. According to the characteristics of the internal resistances during the charge and discharge process, the Union-Identification Model for the battery SOH estimation problem is established. The features of our improved identification model were analyzed and the Double-UKF algorithm used for SOC/SOH joint estimation problem is verified. Besides, the change value of charge/discharge current and the difference of the battery Ohmic resistance were calculated. In general, it believes that the temperature and the charge/discharge current are two important factors to change the available capacity of the lithium battery.

6.2 Experimental Results

Three different curves of voltage versus current were shown in Figure 5. The discharge currents of these experiments were 450mA, 1500mA and 3000mA (in some references, these values of current is correspondent to discharge ratio of 0.3C, 1C and 2C), respectively. As proposed in many references, the greater the discharge current is the less time it needs to get to the cut-off voltage. The 18650-type lithium battery with high capacity is selected in our study for its better charge and discharge performance. In our experiments, the battery is connected to the programmable resistive load and discharged from a fully charge condition by 450mA. The measured OCV and battery capacity during the discharge test are show in Table1. We chose 5 seconds as our sample time and the discharge capacity is 12.5 mAh at a time. The OCV takes around a couple of hours to attain steady-state condition.

Table 1. Partly Results of Measured OCV Versus SOC

Sample Time	OCV (V)	Discharge Capacity (mAh)	SOC	Remaining Capacity (mAh)	Discharge Capacity (mAh)
1	3.359	12.5	1	1500	12.5
2	3.3395	12.5	1	1487.5	25
3	3.3339	12.5	0.99166666	1475	37.5
4	3.333	12.5	0.98333333	1462.5	50
5	3.3327	12.5	0.975	1450	62.5
6	3.332	12.5	0.96666666	1437.5	75
7	3.3317	12.5	0.95833333	1425	87.5
8	3.3314	12.5	0.95	1412.5	100
9	3.3311	12.5	0.94166666	1400	112.5
10	3.3308	12.5	0.93333333	1387.5	125
11	3.3305	12.5	0.925	1375	137.5
12	3.3302	12.5	0.91666666	1362.5	150
13	3.3299	12.5	0.90833333	1350	162.5
14	3.3299	12.5	0.9	1337.5	175
15	3.3299	12.5	0.89166666	1325	187.5

The main purposes of our study are researching the factors affect the life cycle of 18650-type lithium battery, building the function of battery OCV, battery SOC and battery SOH. Based on enough experiments and analysis results, Least-Squares algorithm is adopted and two-order equation is chosen to obtain the fitted functions. The measured and fitted curve of SOC versus OCV with both charge and discharge current are shown in Figure 6, when the discharge current is 450mA. The calculated results of the fitted equations are as follows:

Discharge condition,

$$OCV=36.1425-198.472SOC+263.2273SOC^2 \tag{17}$$

Charge condition,

$$OCV=929.6-5579.7SOC+8347.1SOC^2 \tag{18}$$

where, the value of parameter SOC is within 0 to 1, the unit of parameter OCV is mV.

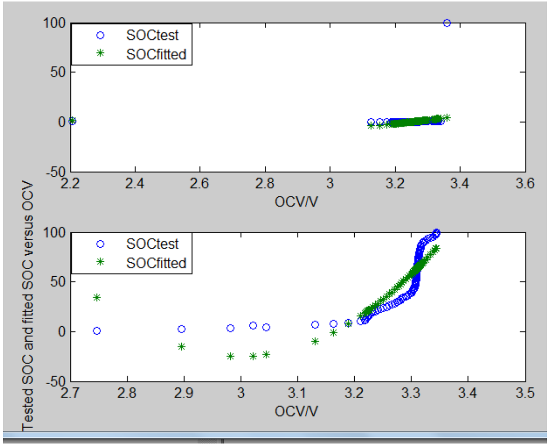


Figure 6. Measured and Fitted SOC versus OCV with Charge and Discharge Current

6.3 Experimental Verification of D-UKF

6.3.1. R_0 Online Identification and Analysis: The measured battery Ohmic resistance R_0 and its fitted value versus life-cycles are shown in Figure 7. The blue line expresses tested value of R_0 and the green spots expresses fitted value using MATLAB software. The results in Figure 7 indicate that the more the life cycle is, the greater the resistance value is. After 180 test cycles, the Ohmic resistance value is over 82 milli-Ohmic and it grows faster than before. The resistance value can reach to 95 milli-Ohmic during last 20 test cycles.

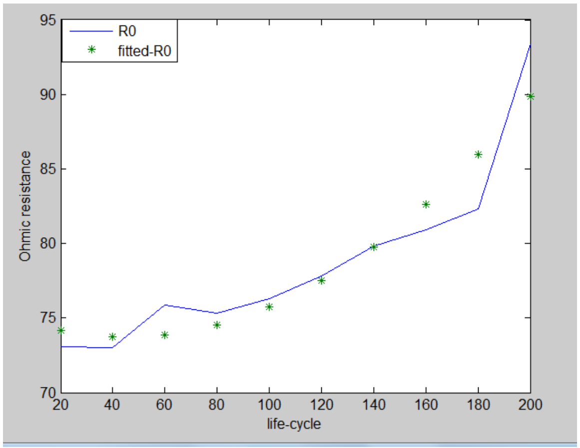
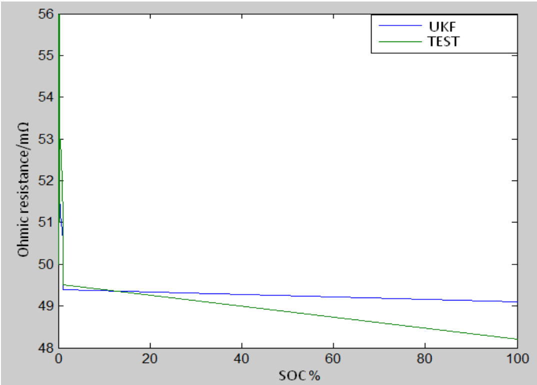


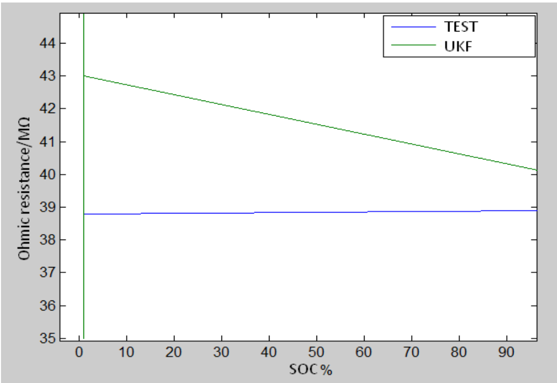
Figure 7. Measured Battery R0 and Fitted R0 versus Life-Cycle

The Ohmic resistance of the battery is determined based on equations (8) and (10). All the experiments have been operated at room temperature (here, we set the temperature factor as 1). Figure 8 indicates the estimation results using UKF algorithm and tested data using battery tester. The blue line and green line express the estimated result and tested result in Figure 8, respectively. Figure 8 (a) shows the value of R_0 with the discharge current of 450mAh. Figure 8 (b) shows the value of R_0 with the discharge current of 3000mAh. The horizontal coordinates of the figures indicate the SOC value of the lithium battery. The two longitude coordinates indicate the value of R_0 using UKF algorithm and the measured value using the resistance tester.

Figure 8 (a) indicates that the measured value of is within 48 $m\mathrm{W}$ to 56 $m\mathrm{W}$ when the discharge current is 450mA (discharge with small current). The estimated value of R_0 based on UKF is between 49 $m\mathrm{W}$ and 50 $m\mathrm{W}$. From Figure 8, the estimated value converged to the true value during the discharge period. The less the value of SOC is, the less the different value is. Figure 8 (b) shows that the measured value of the Ohmic resistance is within 40 mW to 44 mW when the discharge current is 3000mA (the large current). The estimated value of the Ohmic resistance based on UKF is between 38 $m\mathrm{W}$ and 39 $m\mathrm{W}$, and it is smaller than the first experiment with 450mA discharge current. However, the estimated value deviated from tested value during the discharge period. Finally, although the estimated error of the Ohmic resistance is large at the initial moment, the estimated results can converge to the true value using UKF algorithm. Therefore, the experimental results shown in Figure 8 confirm that the estimated error of the Ohmic resistance is within 5% using our new online-identification method.



(A) Estimation Value and Experimental Value Of R_0 With 450mah Current



(b) Estimation and experimental value of R_0 with 3000mAh current

Figure 8. Estimation and Experimental Value of Battery Ohmic Resistance with 450mah Current and 3000mah Current

6.3.2. Verification of SOH Model and Estimation Method: The experiments were operated under two different discharge currents of 450mA small one and 3000mA great one. The results were obtained to calculate and justify the parameters of battery SOH estimation model. From the experimental results shown in Figure 5 to Figure 8, 1000 cycles of charge and discharge experiments were operated in our study. We chose 10 specific points to record and calculate the parameters of the SOC, the Ohmic resistance, the estimated SOH and the SOH estimated error. Table 2 shows the detail information. The calculated SOH value based on real-time capacity were chosen as the true value, in order to calculate the SOH estimated error. From Table 2, it noted that the Ohmic resistance 0 R increased greatly during the charge and discharge cycles. The battery SOH estimated error reaches to the greatest value when 100 charge and discharge cycles were operated. However, the error can converge nearly to zero using our new algorithm based on UKF. Figure 12 shows the battery SOH estimated error during 1000 working cycles.

Table 2. The SOH Estimation Results and Its Errors

Life-cycle	Remained capacity（Ah）	Ohmic Resistance（R_Ω / mW）	SOH estimated (%)（based on resistance）	SOH tested (%)（based on capacity）	SOH estimati-on error
10	1.498	72.8	99.98	98.06	0.0192
20	1.469	73.1	99.02	97.93	0.0109
50	1.398	75.9	96.52	93.2	0.0332
80	1.352	75.3	93.85	90.13	0.0372
100	1.307	76.3	92.76	87.13	0.0563
150	1.258	80.9	88.65	83.87	0.0478
200	1.212	93.4	78.55	80.8	-0.0235
500	1.127	187.6	74.19	75.13	-0.0094
800	1.106	304.2	74	73.73	0.0036
1000	1.100	588.4	73.86	73.33	0.0072

Based on the experimental results shown in Table 2, the coefficients of (14) and (15) can be conducted. Furthermore, Table 3 shows the calculated value of the parameters of battery SOH model using UKF algorithm. To be noted, the value of constant parameter C is calculated after enough experiments and we chose the value as C=2.

Table 3. The Parameters of The SOH Estimation Model For 18650-Type Liuthium Battery

Battery	Battery	Coefficient			Power	
Temperature	Current	a	b	c	α	β
T=318K	0.3C	25468.588	0.122	2641.913	0.002448	1
	2C	26794.652	0.253	1569.254	0.003762	1

The main factors affect the internal resistances of high-capacity lithium battery are as follows: Firstly, the internal resistances of 18650-type lithium battery include the Ohmic polarization resistance, the electrochemical polarization resistance and the concentration polarization resistance. The value of these internal resistances will change during the charge and discharge working condition. It will be smaller and smaller during the charge period and is greater and greater during the discharge period. Secondly, the value of battery internal resistances is correspondent to the value of the working current. The internal resistances will increase when the working current is large at a moment. Theoretically, it is because more than 90% of the sulfuric acid molecular on the battery plate can not spread to the electrode gap dilute. After discharge working period, the internal resistances will be decreased more or less. Meanwhile, the battery terminal voltage will rise to its normal value because the sulfuric acid molecular will diffuse to the electrode gap.

7. Conclusion and Future Work

Figure and table captions should be 11-point Helvetica boldface (or a similar sans-serif font). Callouts should be 10-point Helvetica, non-boldface. Initially capitalize only the first word of each figure caption and table title. Figures and tables must be numbered separately. For example: "Figure 1. Database contexts", "Table 1. Input data". Figure captions are to be below the figures. Table titles are to be centered above the tables. A new SOH estimation method for high-capacity lithium battery based on D-UKF algorithm is proposed. Our main efforts are as follows:

- Firstly, the characteristics, the physical structure of and the internal electrochemical principle of high-capacity lithium battery were studied. The main factors causing the battery capacity attenuation were analyzed systematically and comprehensively. The experimental and simulated results can be used to provide a theoretical principle for SOH estimation method.
- Secondly, the different voltage curves with the different charge/discharge working conditions were obtained. These experiments were operated under different battery initial SOH value, the different charge and discharge current. After analyzing the traditional methods of SOH estimation problem for lithium battery, the online estimation method of Ohmic resistance based on UKF algorithm is studied. Then the battery SOH estimated model is presented based on the calculated value of the Ohmic resistance.
- Last but not least, SOH estimation algorithm for lithium battery is improved based on D-UKF algorithm. The main advantage of our new method is the SOH estimated results can be adjusted using the iteration algorithm. Besides, the performance of our new adaptive battery model is verified and proved to be better than before.

The working performance of lithium battery will decline when the decay rate of battery capacity increases. Some defects still exist as the discharge experiments are operated only with the working current of 450mA and 3000mA. Besides, the estimated errors can not be eliminated because the temperature factor was not considered. Therefore, the parameters of our equivalent circuit model for 18650-typelithium battery need be verified and corrected in the future.

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References

[1] S. G. Li and S. M. Sharkh. Energy and Battery Management of a Plug-In Series Hybrid Electric Vehicle Using Fuzzy Logic, IEEE Transactions on Vehicular Technology, 60, 8 **(2011).**

[2] M. Coleman, W.G. Hurley and L. Chin. Accurate Prediction of Magnetic Field and Magnetic Forces in Permanent Magnet Motors Using an Analytical Solution, IEEE Transactions on Energy Conversion, 23, 3 **(2008).**

[3] J.L. Tucker. The right tools for the right measurement, IEEE Instrumentation and Measurement Magazine, 14, 1 **(2011).**

[4] Lingrong Lu, Fushuan Wen, Gerard Ledwich and Jiansheng Huang. Unit commitment in power systems with plug-in hybrid electric vehicles, International Transactions on Electrical Energy Systems, , 23, 7 **(2013).**

[5] B. Saha, K. Goebel, S. Poll and J. Christophersen. Prognostics Methods for Battery Health Monitoring Using a Bayesian Framework, IEEE Transactions on Instrumentation and Measurement, , 58, 2 (2009).

[6] J. Remmlinger, M. Buchholz, M. Meile, P. Bernreuter and K. Dietmaye. State-of-health monitoring of lithium-ion batteries in electric vehicles by on-board internal resistance estimation, Journal of Power Sources**.**, 196, 12 **(2011)**.

[7] C. Jordy, J. L. Liska and M. Saft. Life duration of saft Ni-MH batteries for EV Application, EVS-16, Beijing, China **(1999)**, pp.10-18.

[8] G. Ning, B. Haran and B. N. Popov. Capacity fade study of lithium-ion batteries cycled at high discharge rates, Journal of Power Source, 11, 7 **(2003)**.

[9] Mathematical modeling of the capacity fade of Li-ion cells, Journal of Power Sources, 12, 3 **(2003)**.
[10] J. Alvin, F. Craig and P. Singh. Determination of state-of-charge and state-of-health of batteries by fuzzy logic methodology, Journal of Power Sources, 80 **(1999)**.
[11] G. Plett. Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs. Part 3, state and parameter estimation, Journal of Power Sources, 134, 2 **(2004).**
[12] G. Plett. Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs Part 1., Journal of Power Sources, 134, 2 **(2004)**.
[13] K. Jonghoon, L. Seongjun and B.H. Cho. Complementary Cooperation Algorithm Based on DEKF Combined With Pattern Recognition for SOC/Capacity Estimation and SOH Prediction, IEEE Transactions on Power Electronics, 27, 1 **(2012)**.
[14] Gao Fei and Li Jianling. Research progress on lithium-ion power battery life prediction, Electronic Components And Materials, 28, 6 **(2009)**.
[15] B. Rosca and B.A. Kessels. On-line Parameter, State-of-Charge and Aging Estimation of Li-ion Batteries, IEEE Vehicle Power and Propulsion Conference, **(2012)** 9.
[16] Noshin Omar (to be published). Optimization of an advanced battery model parameter minimization tool and development of a novel electrical model for lithium-ion batteries, International Transactions on Electrical Energy Systems .
[17] N. Watrin, B. Blunier and A. Miraoui. Review of adaptive systems for lithium batteries state-of-charge and state-of-health estimation, in Proc. IEEE Trans. Electrificat. Conf. **(2012)** 2, 6.
[18] S. Kim, The novel state of charge estimation method for lithium battery using sliding mode observer, J. Power Sourc., 163, 1 **(2006)**.
[19] Wei Xuezhe, Xu Wei and Sheng Dan. Internal resistance identification of Li-ion battery and its application in battery life estimation, Power Technology, 33, 3 **(2009).**
[20] M. Shahriari and M. Farrokhi. Online state-of-health estimation of VRLA batteries using state of charge, IEEE Trans. Ind. Electron, 60, 1 **(2013)**.
[21] Christian Huth, Kai Wittek and S. Thomas. OEM strategies for vertical integration in the battery value chain, Int. J. of Automotive Technology and Management, 13, 1 **(2013)**.
[22] Cao, Jianhua and Gao, Dawei. An Experimental Study on the Service Life of $LiMn^2O^4$ Battery for Vehicles, Automotive Engineering, 34, 8 **(2012)**.
[23] I.Hajizadeh, M. A. Golkar and L. Norum. Robust control of hybrid fuel cell/energy storage distributed power generation system in weak grid under balanced and unbalanced voltage sag, European Transactions on Electrical Power, 21, 2 **(2011).**

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