SOC Estimation of Li-Ion Battery Based on Unscented Kalman Filter

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***Abstract*—The accurately estimating the battery charging state is a key problem in battery management system. In this paper, an adaptive lithium-ion battery (SOC) estimation method is presented based on the the Unscented Filter(UKF). The common equivalent circuit model is enhanced, which includes the effect of different discharge rate and temperature on SOC. The SOC estimation algorithm is improved and verified in different types of lithium-ion batteries. An adaptive joint estimation of the battery SOC is then presented to enhance system robustness with battery aging. The results show that this method can provide accurate SOC estimation and high computational efficiency, which is suitable for the embedded system applications.**

***Keywords*—li-ion battery model, SOC Online estimation, Unscented Kalman filter**

I. INTRODUCTION

With the energy crisis, environmental degradation and other resource problems, the lithium ion battery has been widely used in a clean and renewable energy system. The SOC (State of Charge) of a single battery is defined as the ratio of residual capacity and the rated capacity of the battery[1,2]. SOC is one of the most important state variables for battery work and aging, and a precise SOC meter is critical for optimal battery management. However, SOC cannot be directly measured and must be calculated by other variables. Therefore, in the practical application, accurate lithium ion Battery model is established and SOC accurately estimated is still one of the core challenges of BMSs (Battery Management Systerm)[3,4].

The current typical methods for SOC estimation include Ah counting method (the coulomb measurement)[5,6], open circuit voltage method[7,8], artificial neural network, Kalman filtering, Kalman Filter, KF) [9], the Extended Kalman filtering (Extended Kalman Filter and EKF)[10-12], Unscented Kalman filtering (Unscented Kalman Filter, UKF)[13,14]. The calculation of Ah counting method is simple, but only for a short is of high accuracy, smooth change of current. The error of it will gradually accumulated even divergence and will be inaccurate for long volatile or in high temperature condition of the current integral. Open circuit voltage method need after a long rest to reach a steady state when the battery system establishs the relationship between the open circuit voltage and SOC, by measuring the open circuit voltage to obtain estimates of the SOC.It cannot used in online measurement. The artificial neural network needs to train a large number of similar battery data to obtain the sample data, but the accuracy of the estimation results particularly depends on the training data and methods[15,16].

Extended kalman filter is an extension of kalman filtering, and the unscented kalman filter is another extension of kalman filtering. In the nonlinear system, kalman filtering is used to predict the state of it. The error will be larger, so the method of extended kalman filter and unscented kalman filter is the most widely used. The unscented kalman filter does not need the error of gaussian type as the extended kalman filter does. And the exact jacobian matrix does not need to be calculated. The unscented kalman filter in this paper is based on the improved equivalent circuit model. In order to adapt to the actual constraints, the characteristics of the battery system interference need to be discussed when using. Using online unscented kalman filtering analysis state of lithium ion battery under different charging and discharging rate and different temperature. Adaptive SOC estimation algorithm can obtain the battery aging status for the battery health status (SOH) estimation or battery diagnosis.

II. IMPROVED EQUIVALENT CIRCUIT MODEL.

With the development of battery research, the researchers have established various models to accurately reflect the charging and discharging characteristics of the battery. It can be seen that the battery is a typical dynamic nonlinear system, and many of its features can be expressed in the state vector. When modeling the battery, the selection of state variables determines the accuracy of the model. Therefore, the SOC that can represent the battery charged state is selected as the element in the state vector. Based on the submodel of the UKF estimation method, it is described that the relationship between the SOC and the measured voltage and the different charging and discharging rates and different temperatures.

A. Mathematical Model

Since SOC is defined as the ratio of the remaining capacity to the rated capacity of the battery, the capacity is calculated through the accumulation of time. The nominal capacity of the lithium ion battery is obtained by 0.5C discharge. Firstly, the battery was charged at standard charging rate of 0.5C and a full charge achieve the rated capacity. Then the battery to discharge at the same rate until the cut-off voltage rating. As a result, the battery was discharged under a constant discharge rate of 0.5C at room temperature (25°C) until nominal cut-off voltage was reached. The total capacity was calculated by the multiplication of the discharge rate and discharge time. The entire process was repeated several times under each temperature, until all of the data were obtained. And the residual capacity battery working condition is highly correlated with the change of temperature, battery discharge rate, cell aging condition and battery self-discharge rate, etc. The influence of temperature on total capacity is shown in Fig. 1.

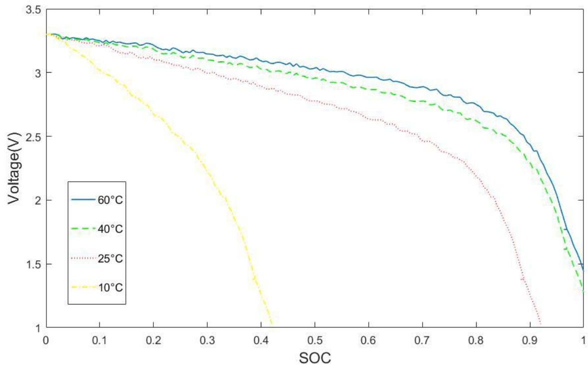

Fig. 1. The relationship between SOC and voltage at different temputeratures

The effect of discharge rate on total battery capacity is shown in Fig. 2. Battery originally is also full of electricity, and then discharge under different discharge rate at room temperature (25°C). The calculation method of total capacity is the same as the above method, and the experiment is repeated several times with different discharge rate until all data are obtained.

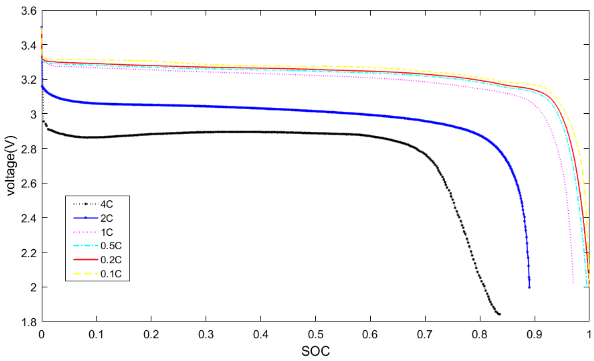

Fig. 2. The curves of SOC and voltage at different discharge rates

As shown in Fig. 1 and 2, when the battery works under certain discharge rate, the temperature increases. And the share of the remaining capacity increases at the end of the discharge. When the discharge ratio is larger, the residual capacity will be smaller in the end of charging. Therefore, two variables qT and qi were taken for modeling analysis. At t moment, qT and qi respectively indicate the capacity of the battery in both cases. Since these two variables have a good characteristic, qT is defined as a trigonometric polynomial, and qi is defined as a exponential polynomial.

$$q_T = k_0 \sin(k_1 T + k_2) + k_3 \sin(k_4 T + k_5) \tag{1}$$

$$q_i = l_0 e^{l_1 i/C} + l_2 e^{l_3 i/C} + l_4 \tag{2}$$

where $K = [k_0, k_1, k_2, k_3, k_4, k_5]$ and $L = [l_0, l_1, l_2, l_3, l_4]$ are coefficients of the two polynomials.

Considering the influence of temperature and charging rate on the battery SOC, the equation of $SOC(t)$ is calculated according to the definition of SOC as follows:

$$soc(t) = soc(0) + \int_0^t (\eta\sigma(i,T) i(\tau)/q_n) d\tau + \varepsilon \tag{3}$$

where $soc(0)$ is the initial SOC; η is the Cell Coulombic efficiency and η = 1 for discharge; $i(\tau)$ is the instantaneous discharging current at time τ ; ε is aging factor; $\sigma(i,T) = \frac{q_n}{q_i} \bullet \frac{q_n}{q_T}$ is the dimensionless proportion coefficient, which is a function of current *i* and temperature *T*.

For discharge, equation (3) can be discretized into the following equation when the KF is utilized for recursion:

$$\begin{aligned} soc_{j+1} = & \frac{1}{(k_0 \sin(k_1 T + k_2) + k_3 \sin(k_4 T + k_5))} \\ & * \frac{q_n i_j \Delta t}{(l_0 e^{l_1 i/C} + l_2 e^{l_3 i/C} + l_4)} + soc_j + \varepsilon \end{aligned} \tag{4}$$

As observed from equation (4), the SOC is highly nonlinear to the discharging current and working temperature.

The relationship between terminal voltage and discharge rate and SOC uses a simplified electrochemical combination model. The electrochemical combination model is obtained by the Shepherd model, Unnewehr model and Nerst model, as shown in equation (5) :

Measurement model:

$$\begin{aligned} U_j = & m_0 - R i_j - m_1 / soc_j - m_2 soc_j + m_3 In soc_j \\ & + m_4 In(1 - soc_j) \end{aligned} \tag{5}$$

In the above model, R is the internal resistance of the battery; and m0 to m4 are empirical constants. As observed from Equation (5), the battery measurement model is also highly nonlinear.

B. Simulink Model

The equivalent circuit model can effectively simulate the dynamic characteristics of the battery, so it is widely used in the modeling of lithium ion battery. Equivalent circuit model can adopt by changing the input current signal to simulate different conditions of lithium ion battery,and not only combine with other methods in simple and convenient calculation.To make the model more accurate,it can be able to join the influence of other factors such as,temperature. RC model has excellent performance in typical equivalent circuit models such as Rint model, Thevenin model and PNGV model. Therefore, the multi-RC structure is used as the main frame of the model. The multi-RC model structure is shown in Fig. 3. The open circuit voltage of the battery is characterized by the voltage source Em. The internal resistance of the battery is characterized by resistance R0; Zq and Eq represent some of the parasitic capacitors produced by internal chemical reactions in batteries.

It can be seen from the transient response curve of the multi-RC model that the more the series RC branches are, the better the response curve will be. But the calculation of the model is also becoming more complicated. To satisfy accuracy and flexibility of the model, this paper select 2RC equivalent circuit as the basic circuit. 2RC circuit can also be seen as not only characterization of transient response, but also the battery internal polarization reaction. At the same time, it requests that the circuit is in constant current and constant voltage charging mode, the current is smooth and not abrupt, the voltage fluctuation is small and the impedance characteristic is better. Therefore, inductance is added on the circuit. The structure of the 2RC model is shown in Fig. 4.

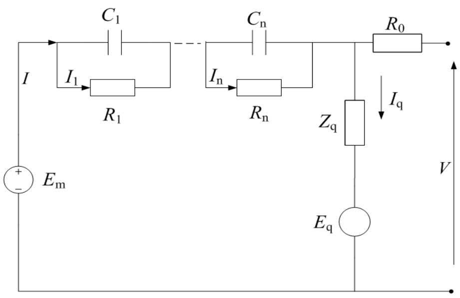

Fig. 3. Multiple RC equivalent mode

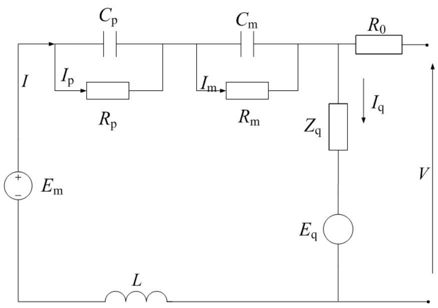

Fig. 4. 2RC equivalent model

After selecting the basic equivalent circuit model frame of lithium ion battery, the basic model of the lithium ion battery structure was built in simulink and the simulation model was shown in Fig. 5. Known from the analysis of 1.1, the influence of battery system for SOC estimation is the most important two factors. The influence of temperature and discharge rate on SOC is highly nonlinear. Among them, the SOC affects the change of open circuit voltage. Therefore, the common mean model does not apply to the selection of model parameters. Using two-dimensional function of simulink, selected state vector in 1.1 will be input to two-dimensional function as the change of parameters. Firstly, using the relations of temperature and the circuit voltage, the superposition of 2RC branch power output to the thermal module. Computing the temperature, thermal module will affect the RC branch and inductance, the parameter of which changes. In addition, the calculation of SOC is affected by the influence of the current change. SOC is an important variable that influences the change of circuit opening voltage, and also affects the RC branch and inductance. The discharge rate is to simulate the input current, through the current transformer having an influence on the circuit model. The parameter data of the experiment is compared with the data determined by the two-dimensional function. And the parameters of the optimized model are obtained.

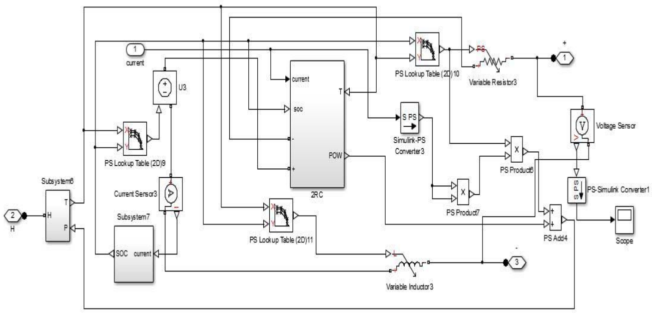

Fig. 5. The structure model of lithium ion battery

The whole lithium-ion battery model is shown in Fig. 6. The model is included the affect of the lithium ion battery cell structure, the SOC model, battery heating effect, the influence of different working conditions, voltage fluctuation, the current sensor module and the oscilloscope module. The equivalent circuit model can display the waveform of current, voltage, SOC and temperature, and change the output waveform of the signal generation module, which can simulate the working condition of different charging and discharging rates.

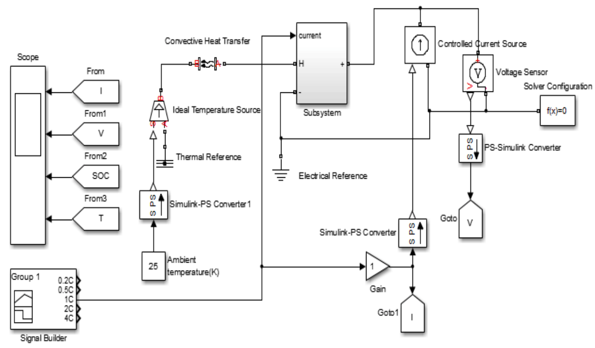

Fig. 6. Lithium ion battery equivalent circuit model

III. SOC ESTIMATION BASED ON UKF

The complex electrochemical reactions in the battery lead to errors in the measurement data when estimating SOC. Therefore, in the discretization formula of SOC and terminal voltage, the error term ζ , the system noise ς and current measurement error of the battery system should be added.And the formula is shown in formula (6) and (7).

$$
\begin{aligned}
soc_{j+1} &= \frac{1}{(k_0 \sin(k_1 T + k_2) + k_3 \sin(k_4 T + k_5))} \\
&\quad * \frac{q_n i_j \Delta t}{(l_0 e^{l_1 i/C} + l_2 e^{l_3 i/C} + l_4)} + soc_j + \zeta + \varepsilon
\end{aligned} \tag{6}
$$

$$
\begin{aligned}
U_j &= m_0 - Ri_j - m_1 / soc_j - m_2 soc_j + m_3 Insoc_j \\
&\quad + m_4 In(1 - soc_j) + \varepsilon + \varsigma
\end{aligned} \tag{7}
$$

The estimation method of kalman filter is used in nonlinear system. The extended estimation method breaks the limitation of kalman filter estimation. Unscented kalman filter is a kind of minimum mean square error (MMSE) estimator. In addition to accurate, it is different from that extended kalman filter that unscented kalman filter can be applied to non-gaussian noise and highly nonlinear system. The unscented kalman filter is more suitable for the high non-linearity of the battery system, and the random system is estimated.

In order to compensate the possible non-gaussian interference, the measurement error and calculation error of SOC and terminal voltage are included in the state vector. The extended state vector x_{k-1} and p_{k-1}^{x} its covariance have the following form in the SOC estimation algorithm based on the UKF method.

$$x_{k-1} = [soc_{k-1} \;\; 0 \;\; 0]^{T} \tag{8}$$

$$p_{k-1}^{x} = \begin{bmatrix} p_{k-1} & 0 & 0 \\ 0 & \zeta & 0 \\ 0 & 0 & \varsigma \end{bmatrix} \tag{9}$$

where k=1,2， …， ∞.

The steps of UKF appling to SOC estimation:

In fact, the initial state and covariance are not important to the UKF algorithm, because it can converge to the truth value quickly. The initial value of this article uses a random value.

$$\hat{x}_0 = E[x_0]\,, \quad p_0^{x} = E[(x_0 - \hat{x}_0)(x_0 - \hat{x}_0)^{T}] \tag{10}$$

(1) Calculate the weighted sigma points:

$$S = \{W_{\mathrm{i}}, X_{\mathrm{i}}; i = 0,1,2...2\mathrm{N}\} \tag{11}$$

$$X_0 = \hat{x}_{k-1} \tag{12}$$

$$X_i = \hat{x}_{k-1} + (\sqrt{(N+\lambda)p_{k-1}^{x}})_i, i = 1,2,\ldots,N \tag{13}$$

$$X_i = \hat{x}_{k-1} - (\sqrt{(N+\lambda)p_{k-1}^{x}})_{i-N} \\ ,i = N+1, N+2,\ldots,2N \tag{14}$$

with the parameters α, β for the unscented transform given, the parameter $\lambda = \alpha^2 N - N$ can be calculated and the weights for the sigma points are:

$$w_m^{(0)} = \lambda/(N+\lambda) \tag{15}$$

$$w_m^{(0)} = \lambda/(N+\lambda) + (1-\alpha^2+\beta) \tag{16}$$

$$w_m^{(i)} = w_c^{(i)} = 1/(2(N+\lambda)), i = 1,\ldots,2N \tag{17}$$

The superscripts m and c here indicate that the weights are used for the estimation of the mean and covariance, respectively. Thus, we have $\sum_{i=0}^{2N} w_m^{(i)} = 1$ and $\sum_{i=0}^{2N} w_c^{(\mathrm{i})} = 2 - \alpha^2 + \beta$ Generally, we can choose $0 \le \alpha \le 1, \beta \ge 0$. Disturbing statistics is available in the sense of maximum likelihood estimation. In the actual system, the noise characteristic is usually unknown, and the adjustment weight is part of the design iteration process. In the case of the gaussian distribution, the optimal value of the product is 2, but the interference of the battery usually does not conform to the gaussian type.. Thus, the often-recommended parameters α=1, β=0 are used instead. $(\sqrt{(N+\lambda)p_{k-1}^{x}})_i$ is the i-th column of the square root matrix of the matrix $\sqrt{(N+\lambda)p_{k-1}^{x}}$

(2) Time update equations:

Sigma points updating $X_{k|k-1}$:

$$X_{k|k-1} = soc(X_{k-1}, \mu_k) \tag{18}$$

State estimation x_k^{-} :

$$x_k^{-} = \sum_{i=0}^{2N} w_m^{(i)} X_{i,k|k-1} \tag{19}$$

Covariance of the estimated state p_k^{x-} :

$$p_k^{x-} = \sum_{i=0}^{2N} w_m^{(i)} (X_{i,k|k-1}^{x} - x_k^{-})(X_{i,k|k-1}^{x} - x_k^{-})^{T} \tag{20}$$

(3) Measurement update equations:

Measurement updating $Y_{k|k-1}$:

$$Y_{k|k-1} = U(Y_{k-1}, \mu_k) \tag{21}$$

Measurement estimation y_k^{-}:

$$y_k^{-} = \sum_{i=0}^{2N} w_m^{(i)} Y_{i,k|k-1} \tag{22}$$

Covariance of the estimated measurement p_k^{y-} :

$$p_k^{y-} = \sum_{i=0}^{2N} w_m^{(i)} (Y_{i,k|k-1} - y_k^{-})(Y_{i,k|k-1} - y_k^{-}) \tag{23}$$

Cross-covariance p_k^{xy-} of $X_{k|k-1}$ X and $Y_{k|k-1}$:

$$p_k^{xy-} = \sum_{i=0}^{2N} w_m^{(i)} (X_{i,k|k-1}^{x} - x_k^{-})(Y_{i,k|k-1} - y_k^{-}) \tag{24}$$

Kalman gain K_k :

$$K_k = p_k^{xy}(p_k^{y-})^{-1} \tag{25}$$

State update $\hat{x}_k$:

$$\hat{x}_k = x_k^{-} + K_k(y_k - y_k^{-}) \tag{26}$$

Covariance p_k^{x} of state update $\hat{x}_k$:

$$p_k^{x} = p_k^{x-} - K_k p_k^{y-} K_k^{T} \tag{27}$$

IV. SIMULATION AND MODEL VALIDATION

The experiment adopts BTS 7.5. X battery detection system of shenzhen xinwei company, using 18650 3.2V/1500 mAh lithium iron phosphate ion battery, and the charging and discharging test of the battery is carried out with different charging and discharging rate. The experiment in this paper was carried out with a discharge rate 0.5C and then an aging diacharge rate 4C. Discharge the battery to the cut-off voltage and fill it with a cycle. Since the voltage of the battery in the simulation model is obtained by induction current, there will be positive and negative points. The horizontal coordinate of the curve is plotted on cycles , the vertical coordinate of which is the capacity at the end of each charge and discharge, as shown in Fig. 10. Then charge and discharge current as the input signal input to the model.,as shown in the simulation curve of Fig.10. The value of SOC in the simulation curve is 1 to 0, so it needs to be multiplied by the nominal capacity to compare with the experimental data. In order to make the graphic observation more clear, Fig.7 shows the voltage,Fig.8 shows the SOC and Fig.9 shows temperature (cycling experiment 10s simulation of the lithium ion battery). In order to verify the accuracy of the established lithium ion battery model, the experimental results are compared with the simulation results,as in Fig. 10. From the results, it can be seen in Fig. 10 that, tiny deviation in the results of contrast diagram of simulation curve and experimental curve is only in part of the location. The actual characteristics of lithium ion battery can be established by the model.

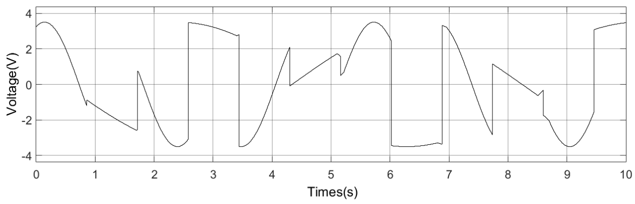

Fig. 7. Voltage waveform

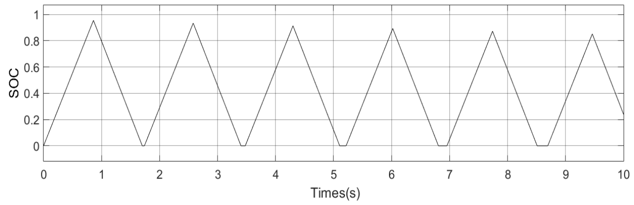

Fig. 8. SOC waveform

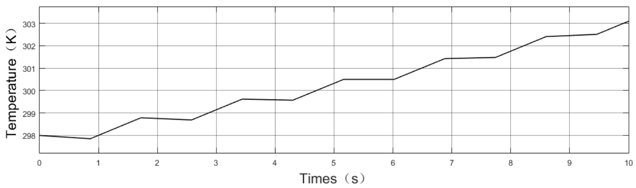

Fig. 9. The temperature wave

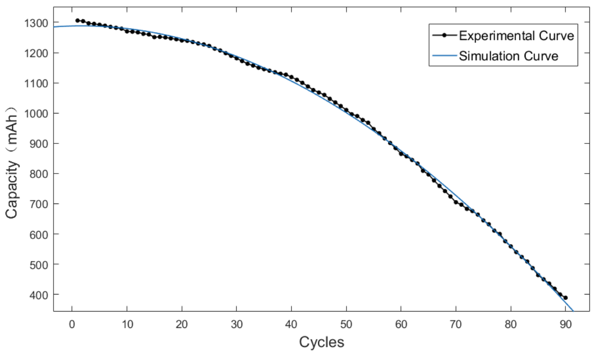

Fig. 10. Cycle times and capacity relation curve

In order to verify the UKF SOC estimation algorithm, the capacity curve obtained by discharging at 1C discharge rate,as in Fig. 11. The total discharge time was 4100s, with three discharging 1000s, the middle interval of 50, and finally the discharge of 1000s.

The SOC estimation algorithm proposing by the model is used to deal with the experimental data. Fig. 11 shows the SOC estimation results based on UKF and EKF. The initial SOC algorithm based on UKF is set to approximate its actual value and the standard covariance of the initial SOC is set to 0.1. The estimation results of UKF and EKF are compared in the SOC estimation maximum error, average SOC estimation error, SOC estimation mean square error (MSE) and estimation speed. As shown in Table 1, the SOC based on UKF is estimated to exceed the performance based on EKF. From the curve shown in Fig. 11, it can be observed that in the first discharge, UKF algorithm has better SOC curve to estimate the true, while the method EKF failes to catch up the real value of the SOC. The algorithm of UKF converges faster, and the algorithm of EKF in the center of discharge is better, but the EKF algorithm can not estimate the SOC value of the battery very well at the end of discharge. The same problem does not exist in the UKF estimation algorithm. The fast convergence speed of UKF indicates that it is more suitable for embedded applications than the kalman filter.

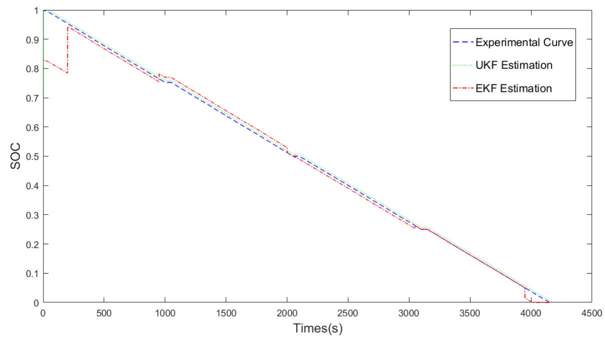

Fig. 11. Test curve and estimated curve

TABLE I. COMPARISON OF TWO ALGORITHMS

Algorithm	*Maximum error*	*Mean error*	*Mean square error*	**Speed**
UKF	4.91%	3.7%	5.1 × 10−4	1.59 ms/sample
EKF	19.6%	5.8%	2.3 × 10−3	2.97 ms/sample

V. CONCLUSIONS

In this paper, an unscented kalman filtering algorithm is proposed for the online SOC estimation of battery discharge. Firstly, set up an improved battery model in different operating conditions to implement this algorithm, especially in battery features such as real-time temperature and different discharge rate. And put forward a online battery SOC estimation and battery aging effect compensation based on SOC estimation method. The proposed adaptive SOC estimation algorithm based on UKF can be used to estimate the lithium ion battery effectively. Experimental results show that the proposed algorithm is effective and suitable for on-line estimation of SOC and embedded applications.

ACKNOWLEDGMENT

This work is supported by the National Natural Science Foundation of China (No. 51577048, 51637001, 51107031), the Natural Science Foundation of Hebei Province of China (No. E2018208155), the Overseas Students Science and Technology Activities Funding Project of Hebei Province (No. C2015003044), the Hebei Industrial Technology Research Institute of Additive Manufacturing (Hebei University of Science and Technology) open projects funding, the National Engineering Laboratory of Energy-saving Motor & Control Technique, Anhui University (No. KFKT201804), Key project of science and technology research in Hebei provincial colleges and universities (ZD2018228).

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