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Lithium Battery SOC Estimation Based on EKF-DEKF Composite Model

Shaohua Chen (0009-0009-6418-8077), Wei Kan *(0000-0002-6596-8325), Yichen Yang (0009-0007-1071-6204), Shuyang Liu (0009-0002-0351-9468), Miaomiao Wang (0009-0009-3057-4252)
Automation and Electrical Engineering College, Dalian Jiaotong University, Dalian 116028, China, *Corresponding author's E-mail: 1034967995@qq.com

According to the application requirements of SOC in lithium batteries of Unmanned Aerial Vehicle (UAV), an Extended Kalman filter-Double Kalman filter (EKF-DKF) composite model was proposed to optimize the accuracy of the last 20% stage of State of Charge(SOC) estimation. Based on the equivalent model of second-order resistance-capacitance (RC) circuit improvement, the developed method optimized the identification accuracy of parameters, and set up a MATLAB simulation platform to jointly estimate SOC online with EKF and DKF. The data obtained in laboratory test environment were used for simulation.

Keywords: Lithium battery, SOC estimation method, Unmanned aerial vehicle, EKF-DKF composite model

1 Introduction

With continuous development of emerging energy sources, artificial intelligence, new materials and other fields, unmanned air vehicles (UAVs) integrated these three new technologies to introduce the advantages and strengths of these fields in military, people's livelihood, transportation and other sectors [1]. As the main energy supplying device for all kinds of electric equipment, lithium batteries play an indispensable role in supplying energy for UAVs. Considering their long life and low self-discharge ability, lithium batteries can even replace oil-electric hybrid power supply in the future and become the only power supply mode for UAVs. However, at this stage, it is not uncommon for different dangerous situations to occur due to insufficient battery power or delayed feedback during the operation or task execution of UAVs [2]. Therefore, accurate prediction of state of charge (SOC) value of UAV batteries (battery charge condition for reflecting the remaining ability of the battery) is a vital step to ensure the normal performance of UAVs and promote their working efficiency and range [3].

In the current research, SOC estimation methods including five main approaches of ampere-hour integration method (AH) and Kalman filter methods. The estimation deviation of amp-time integration method accumulates continuously resulting in high overall errors [4]. The open-circuit voltage method requires the supply voltage to be in a stable state and is not the best method for direct application on the UAV [5]. Neural network method has complex calculation steps and requires large data training; The particle filter method has high precision and is suitable for nonlinear non-Gaussian systems.But the particle filter has the problem of particle weight degradation and sample dilution [6]. For battery parameter estimation, extended Kalman filter (EKF) algorithm method is the best choice. EKF evaluates linearization principle of nonlinear functions using partial derivatives and first-order Taylor series expansion.

For an accurate SOC estimation, calculation of Jacobian matrix by EKF algorithm is essential. One limitation of EKF algorithm is that only first-order Taylor expansion can be applied to achieve high accuracy, which depends on well-known battery model parameters and system noise signals, and incorrect background knowledge in estimation process may lead to divergence [7]. Previous studies have used experimental data to build battery models to reduce the impact of measurement and processing of noisy signals. However, due to the data errors in parameter online identification, the estimation results also have errors. Adaptive forgetting factor recursive least squares method for first-order RC model-extended Kalman filter (AFFRLS-EKF) was also proposed for battery SOC estimation. Recursive Least Square (RLS) model had the capacity on reducing the system and parameter fluctuations through repeated updating and realizes real-time acquisition of system characteristics, thereby reducing the negative influence of using only EKF algorithm. This method improves SOC estimation accuracy in steady state, but it is too ideal for parameters to maintain constant during the flight of UAV. Therefore, it was necessary to develop a real-time online parameter identification method to improve EKF. In reference [8], the combination of improved particle swarm optimization (IPSO) and EKF was proposed to achieve noise suppression and parameter identification accuracy improvement. A repeated calculation by EKF form a double Kalman filter (DKF),which in turn updates model parameters in each cycle in a timely manner. However, the problem that SOC estimation accuracy decline in the latter 20% stage of the actual battery discharge process has not been considered, which is also the focus of the UAV lithium battery SOC. Previously, we proposed the estimation of lithium battery SOC based on LSTM while using Adam algorithm to optimize fine-tuning parameters, because adaptive moment estimation (Adam) is a type of learning rate adaptive optimization. This algorithm can replace classical stochastic gradient descent method to more effectively update network weight to further improve the calculation accuracy of SOC [9].

In this work, we tried to modify low accuracy of the above methods by changing real-time parameters when discharge mutation occurred throughout the whole estimation process during UAV flight. At the same time, in the actual flight of UAVs, it is necessary to decrease cost and increase data calculation and transmission rates of SOC estimation [10], and then decrease the corresponding complexity of the algorithm. Therefore, this paper proposed a combination of EKF-DKF. In the first 80% of the whole estimating process, EKF model could ensure the efficiency and quality of estimation, thereby reducing computational difficulty and data volume. In the last 20% of the same process, the application of DKF algorithm could timely update the parameters and achieve immediate estimations.

The remaining of the paper is organized as follows: In Second 2, an improved second-order RC circuit is constructed and HPPC experiment is described. OCV-SOC eight-order fitting simulation is performed based on the obtained test data and the parameter identification of SOC algorithm construction is completed. In Section 3, EKF and DKF algorithms are introduced and the accuracy and complexity of these algorithms are horizontally compared. Through comparison and simulation, it was determined that the SOC estimation of lithium batteries was generally insufficient in the last 20% stage. On this basis, EKF-DKF SOC estimation method for lithium batteries was developed and simulation verification was carried out. Finally, it was concluded that The EKF-DKF algorithm proposed in this paper can improve the dynamic change of battery model. The compensation problem caused by the decrease of parameter estimation accuracy in the late discharge period can be improved. At the same time, it guarantees the accuracy, reduces the complexity of practical application, and finally improves the efficiency.

2 Materials and Methods

2.1 Model of lithium battery

The newly constructed model was applied for SOC estimation of lithium battery pack. Accurate simulation and low complexity of identifying model parameters in SOC estimation is essential. In combination with previous report [11], under the same interference conditions, the complexity of reaction inside the battery was changed under different states of charging or discharging. At discharged status, ions could easily embed into cathode material to form different compounds and intra-cell resistance was smaller. At charged status, ions were removed from the positive electrode material and combined with external circuit, resulting in relatively larger intra-cell resistance. Therefore, we proposed an improved equivalent circuit model
(Fig. 1).

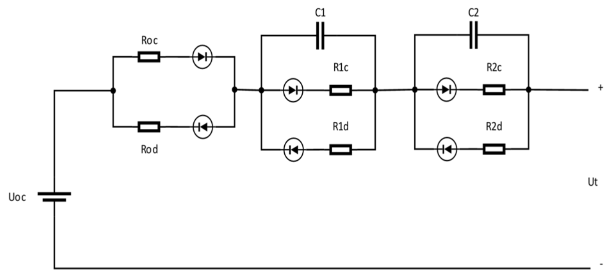

Fig. 1 *Improved model for RC equivalent circuit*

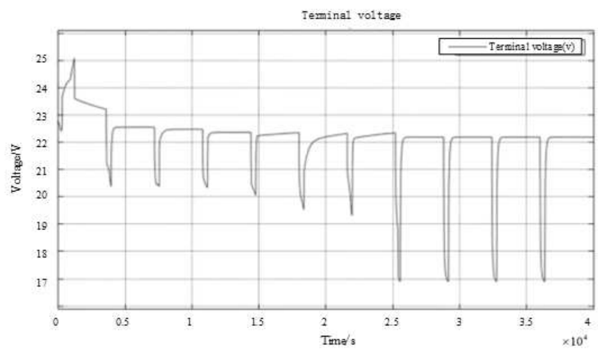

Fig. 2 *Relationship between voltage and time in HPPC experiment*

Base on the traditional model of second-order RC equivalent circuit, one loop was added to show battery status and a diode module was added to control current at each branch of ohmic and polarization internal resistance. Therefore, this model could simulate the parameters of battery at both charge and discharge states.

Assuming U_{0c} as source voltage and R_0 as equivalent ohm intra-cell resistance, R_{0c} and R_{0d} present battery at discharged and charged state, respectively. Due to charge diffusion and polarization capacitance, C_1 and R_1 were generated, which were identified as the R_{1c} and R_{1d} of discharged and charged states, respectively. Due to charge transfer, the concentration difference of polarization capacitance C_2 and polarization resistance R_2 were generated, which were R_{2c} and R_{2d} at the discharged and charged state respectively. When there was current flowing through the circuit, the circuit equation of battery was derived according to Thevenin's theorem, as shown in Equations 1 to 4.

$$\dot{U}_1 = \frac{i}{C_1} - \frac{U_1}{R_1 C_1} \tag{1}$$

$$\dot{U}_2 = \frac{i}{C_2} - \frac{U_2}{R_2 C_2} \tag{2}$$

$$U_t = U_{oc} - U_1 - U_2 - iR_0 = U_{oc} - iR_1(1 - e^{-\frac{t}{\tau_1}}) - iR_2\left(1 - e^{-\frac{t}{\tau_2}}\right) - iR_0 \tag{3}$$

$$U_t = U_{oc} - U_C - U_d = U_{oc} - U_1 e^{-\frac{t}{\tau_1}} - U_2 e^{-\frac{t}{\tau_2}} \tag{4}$$

2.2 Identification of battery OCV-SOC parameter relationship

This paper mainly took battery discharge process as research object for parameter identification. Before parameter identification, it should be understood that battery parameters do not remain constant throughout the SOC cycle. For example, there was a big difference between higher and lower SOC periods [12]. To accurately identify battery model parameters, it was necessary to adopt phased identification to ensure accurate identification of battery model parameters within the whole SOC cycle [13].

(1) Experiment of the discharge process of lithium ion battery under hybrid pulse power characteristic (HPPC) condition with constant current and observation noise

- Step 1: At room temperature, the ternary lithium battery pack was charged, SOC was 100%, and 1h time was given;
- Step 2: 6 min discharge at 0.1C rate was performed for 30min;
- Step 3: The above operations were continued until SOC=0%. (Fig. 2)

(2) Battery open circuit voltage-SOC (OCV-SOC) parameter relationship identification experiment

The discharge experiment of ternary lithium battery (18650) was carried out at room temperature. The voltage data obtained during the discharge process were recorded to associate OCV and SOC. The capacity of test battery pack was 5000mAh, open-circuit and cut-off voltages were 25V and 18V, respectively, and discharge performance was 15A. Therefore, in discharge process, it was considered that when the voltage was 25V, battery was in full charge state and when it was discharged to 18V, the battery was in zero charge state. Experimental procedure was as follows: starting from the battery voltage of 25V, the lithium battery pack was discharged at the rate of 0.1C to 18V, 500 sets of data were recorded at 2 minute-intervals, and the voltage value corresponding to each 10% of power loss was extracted from the 500 sets of data for subsequent relationship fitting (Tab. 1).

Tab. 1 *OCV-SOC test data*

SOC	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
Open circuit voltage (V)	25.0	24.2	23.5	22.9	22.1	21.7	21.4	21.1	20.8	20.4	18.0

As the battery voltage cannot be precisely obtained, this paper proposed OCV curve (integrated primary open-circuit voltage into it) to obtain initial SOC value. Fitted accuracy of OCV curve directly affected the precision of the algorithm. Impedance characteristics, self-discharge and polarization inside the battery resulted in a terminal voltage difference from open-circuit voltage and corresponding equivalent model was originating from ohmic intra-cell resistance and parallel circuit voltage drop. Therefore, we applied small current charge and discharge.

At this moment, the sum of the voltage drop across the internal resistance and the voltage drop across each RC parallel circuit is less than 0.5% of the operating voltage. Therefore, with small currents during charging and discharging, terminal voltage was similar to open circuit voltage; At this time, the charge and discharge curve obtained can be regarded as the open circuit voltage curve of the battery, and the OCV-SOC relationship diagram of the battery can be obtained consequently, OCV-SOC relationship curve could provide a reference for final estimation [14] (Tab. 2).

Tab. 2 *Parameters of the polynomial fitting function*

P1	P2	P3	P4	P5	P6	P7	P8	P9
-2049.0	8985.0	-16270.0	15720.0	-8782.0	2882.0	-542.1	56.8	18.0

According to the data and fitting steps, the expression of OCV-SOC eighth-order fitting curve in battery discharge process was derived, as shown in Equation (5):

$$\mathbf{f(SOC)} = -\mathbf{2049soc^8} + \mathbf{8985soc^7} - \mathbf{16270soc^6} + \mathbf{15270soc^5} - \mathbf{8782soc^4} + \mathbf{2882soc^3} - \mathbf{542.1soc^2} + \mathbf{56.8soc^1} + \mathbf{18soc^0} \quad (5)$$

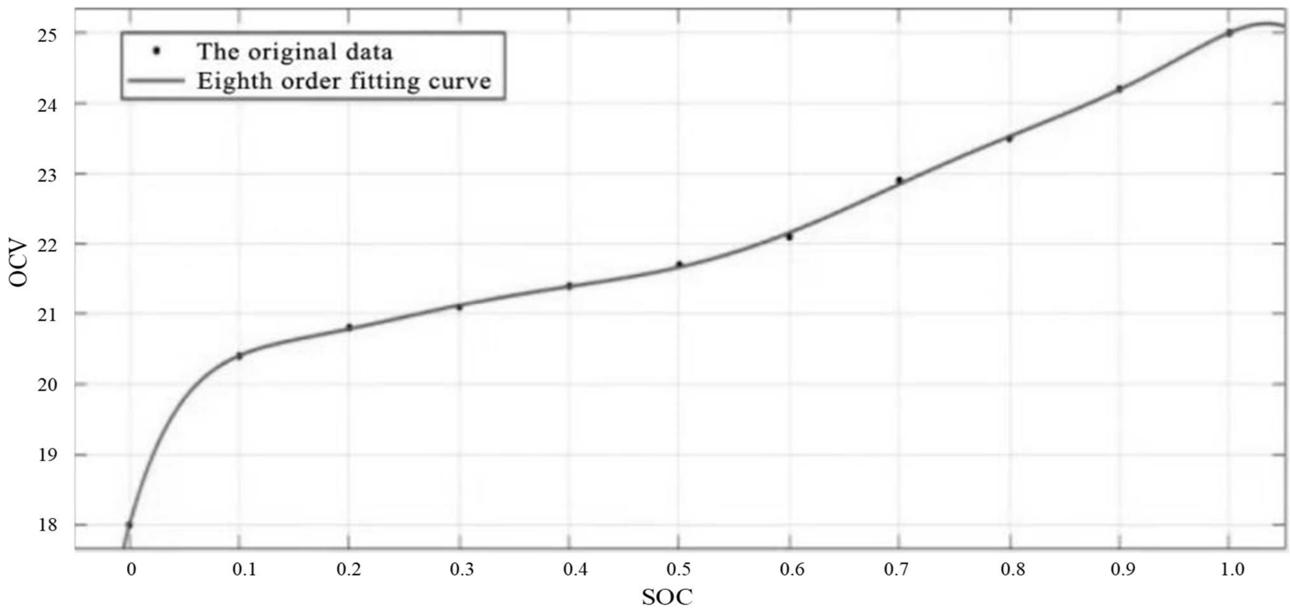

Fig. 3 *OCV-SOC eighth-order fitting curve*

3 Discussion of results

3.1 SOC estimation based on EKF-DKF composite model method

We wrote a special program in Matlab software for SOC estimation through EKF-DKF composite model algorithm, which could verify the convergence, accuracy and estimation efficiency of ternary lithium batteries. In this paper, the current, voltage and charge states collected in actual laboratory test conditions were applied to verify the calculated SOC value.

3.2 Accuracy problems in the comparison of AH, EKF and real SOC

In this paper, we used the methods of AH and EKF as well as the real value of SOC to perform simulation comparison tests and found that when lithium battery was discharged about 20% of remaining power, its discharge characteristics changed from a more gentle discharge trend to a non-linear and substantial power decay, at this stage continued to use AH, EKF algorithm to estimate SOC value will have errors. (Figs. 4 and 5)

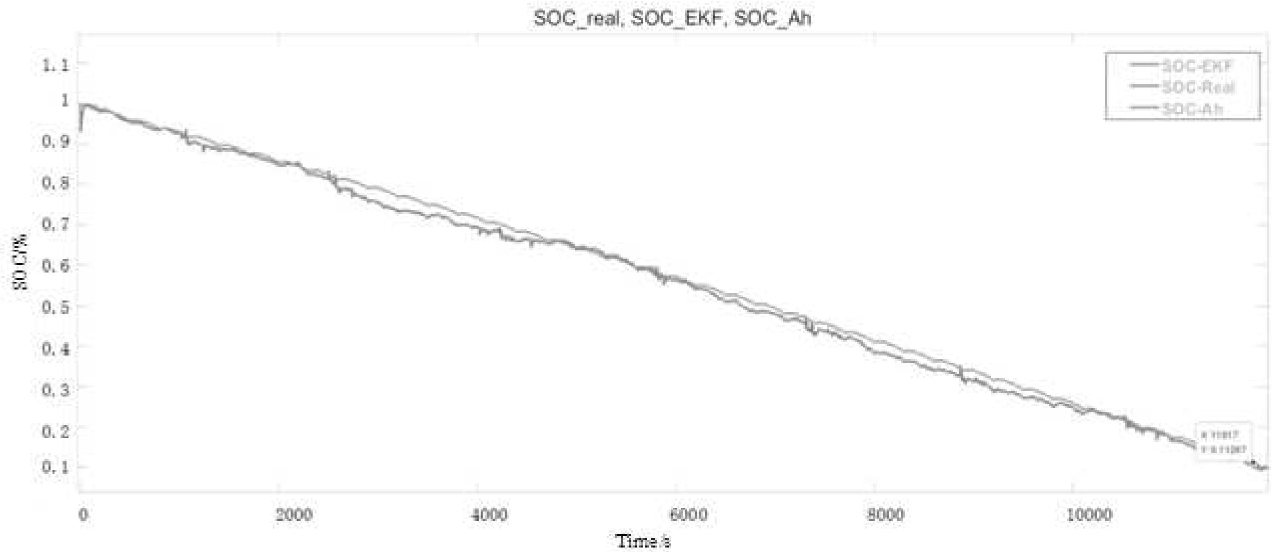

Fig. 4 *The estimation simulation comparison of AH, EKF and SOC real values in the process of battery discharge of 20%-0%*

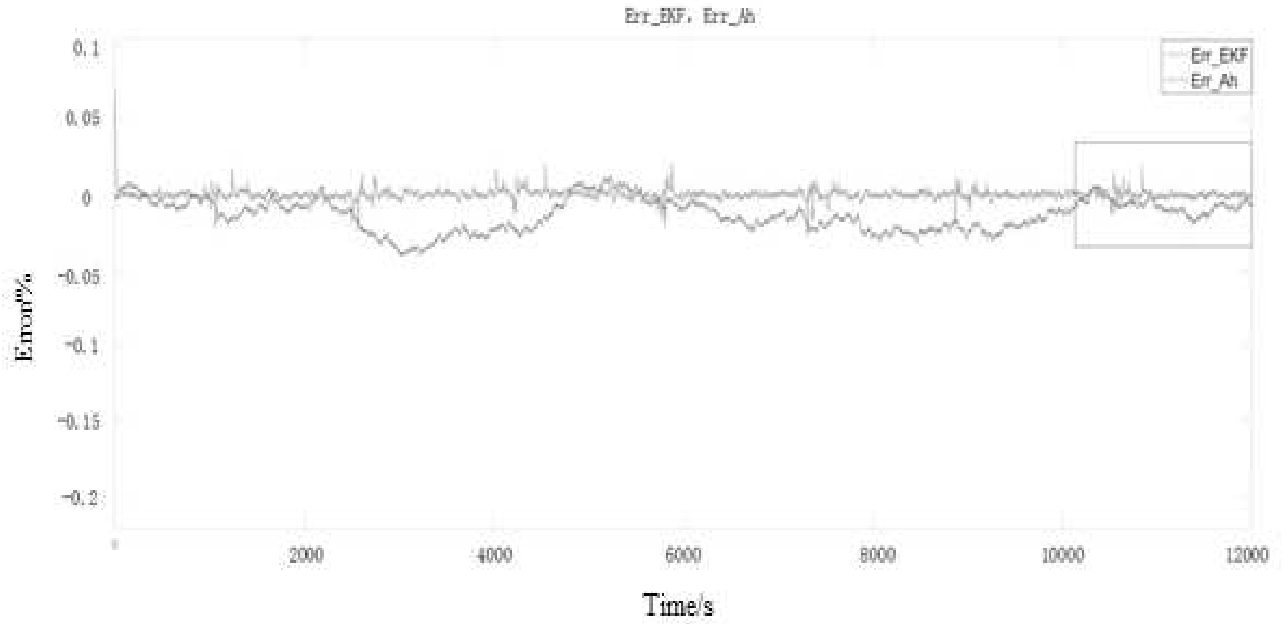

Fig. 5 *Error comparison of AH, EKF and SOC true values during 20%-0% battery discharge*

3.3 Estimation of Li-ion battery SOC by EKF algorithm

In order to accurately estimate the SOC value of a battery, and considering that the battery model is a nonlinear system, the EKF algorithm is commonly used in practical environments. The EKF algorithm extends the original Kalman Filter algorithm by adding a linearization step in the filtering equation derivation process. Specifically, during the state estimation, a real-time linear Taylor approximation is performed on the system equation at the previous estimated state value. Similarly, during the prediction stage, a linearized Taylor approximation is applied to the measurement equation at the corresponding predicted position. EKF was applied to test SOC value, then the minimum variance estimation of SOC was performed by a recursive algorithm. This method was able to maintain good accuracy during the implementation of the algorithm and had a strong correction performance on the initial value as well as the noise [15]. Therefore, EKF algorithm was adopted to estimate SOC at 80% stage before the discharge of the ternary lithium battery to ensure its estimation accuracy while reducing its computational complexity compared to DKF algorithm, thus improving its computational efficiency in practical application.

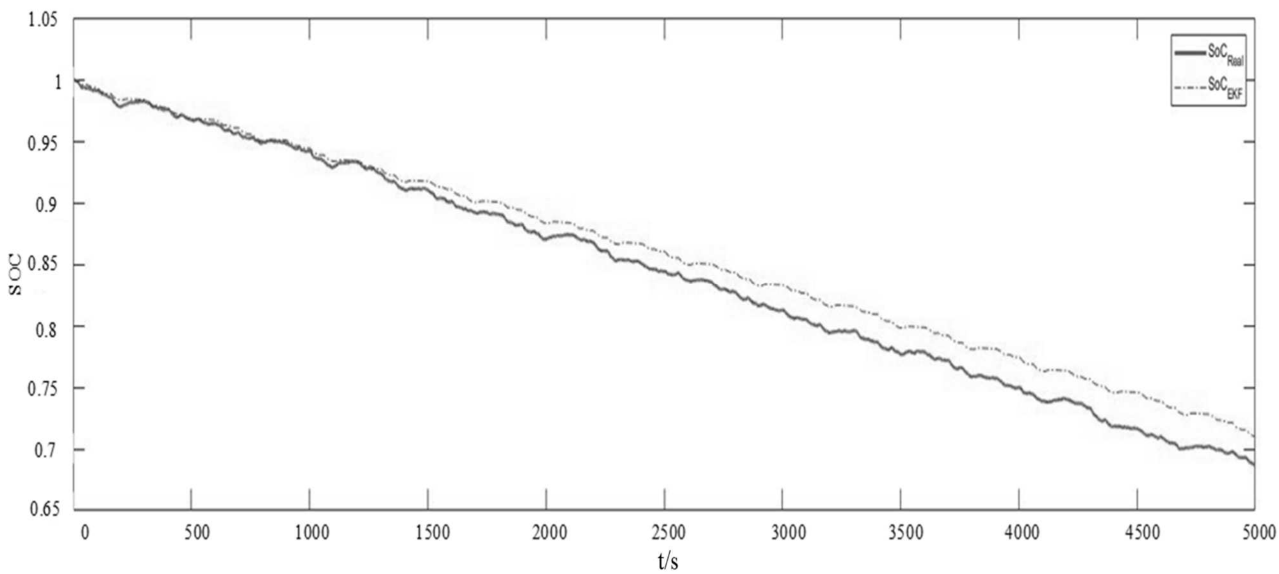

Fig. 6 *EKF algorithm estimation in SOC process simulation*

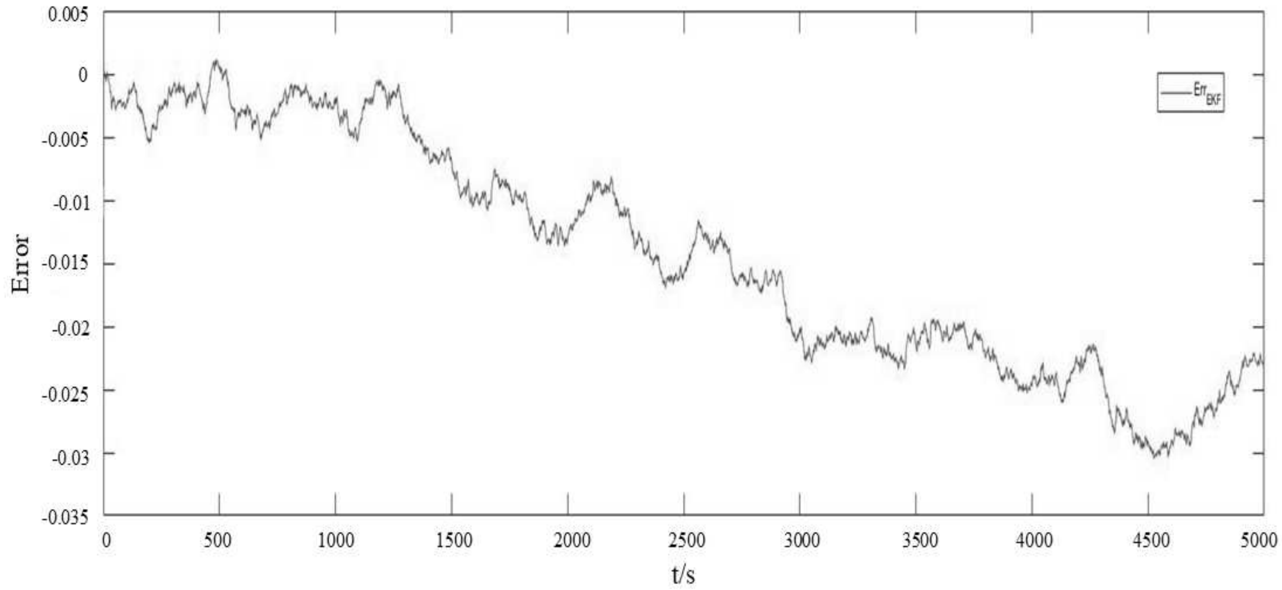

Fig. 7 *EKF algorithm estimation in SOC process error simulation*

The accuracy of EKF was verified by performing a 0.1C per second constant current discharge at room temperature. Fig. 6 illustrates SOC estimation using EKF algorithm method with simulation parameters set as $R_s = 0.024\Omega$, $R_1 = 0.015\Omega$, $R_2 = 0.0015\Omega$, $C_1 = 1000F$, and $C_2 = 2500F$, where the blue curve presents reference SOC estimation and red curve expresses SOC result obtained by EKF filtering. EKF model was relatively converged around the reference value in the whole discharge cycle. It was found that EKF estimation error stayed below 3.1%, but at the middle and late discharge stages, it was obviously deviated (Fig. 7).

3.4 SOC estimation by dual Kalman filter (DKF) algorithm

3.4.1 SOC value under DKF algorithm

EKF performs dynamic identification with a large error when battery model parameters are dramatically changed. However, when battery model parameters were dramatically changed during late discharge, EKF estimation accuracy was decreased and the optimal estimation was not achieved. In the previous discussion on parameter identification, it was mentioned that there are discrepancies in SOC estimation during its operation. However, segmented parameter identification alone cannot fully address the parameter variations caused by model changes during the operation of unmanned aerial vehicles (UAVs) and their impact on EKF. In order to solve the two major problems that EKF algorithm cannot precisely reflect the ongoing changes of battery model and when the SOC of a lithium battery undergoes rapid and dynamic changes, the estimation accuracy is affected due to the fixed estimation model, this paper introduced a simultaneous estimation of battery state and parameters by DKF model. The developed DKF had good adaptability and ultimately improved estimation accuracy. [16]

The overall idea of DKF was to estimate and re-estimate the state and parameters of the system accordingly. Two independent DKF models were applied for this performance. This paper investigated battery SOC estimation using DKF in for new energy vehicles and used the following calculation equations. DKF was used in a nonlinear system estimation, which was expressed as:

$$\begin{cases} x_k = f(x_{k-1}, u_{k-1}, \theta_{k-1}) + w_{k-1} \\ y_k = g(x_k, u_k, \theta_k) + v_k \end{cases} \tag{6}$$

$$\begin{cases} \theta_k = \theta_{k-1} + r_{k-1} \\ d_{k=}g(x_k, u_k, \theta_k) + e_k \end{cases} \tag{7}$$

Where x is the state vector of moment k, u is output vector, θ is parameter vector, and y and d are measurement vectors. It was also expressed that:

$$A_k = \frac{\partial f(x_k,u_k,\theta_k^-)}{\partial x_k}\bigg|_{x_k=x_k^+}, \quad C_k^x = \frac{\partial g(x_k,u_k,\theta_k^-)}{\partial x_k}\bigg|_{x_k=x_k^-}, \quad C_k^\theta = \frac{dg(x_k^-,u_k,\theta)}{d\theta}\bigg|_{\theta_k=\theta_k^-} \tag{8}$$

Parameter initialization: The initialization of the system state and its error covariance was stated as:

$$x_0^+ = E[x_0] \tag{9}$$

$$P_0^{x,+} = E[(x_0 - x_0^+)(x_0 - x_0^+)^T] \tag{10}$$

Also, the initialization of system parameters and their error covariance were derived as:

$$\theta_0^+ = E[\theta_0] \tag{11}$$

$$P_0^{\theta,+} = E[(\theta_0 - \theta_0^+)(\theta_0 - \theta_0^+)^T] \tag{12}$$

Time update of status and parameters:

Status time update:

$$x_k^- = f(x_{k-1}^+, u_{k-1}, \theta_{k-1}^-) \tag{13}$$

$$P_0^{\theta,+} = A_{k-1}P_{k-1}^{x,+}A_{k-1}^T + Q^x \tag{14}$$

The parameter time was updated as:

$$\theta_k^- = \theta_{k-1}^+ \tag{15}$$

$$P_k^{\theta,-} = P_{k-1}^{\theta,+} + Q^\theta \tag{16}$$

SOC estimation based on DKF algorithm:

Discrete state space form RC model was stated as:

$$\begin{cases} x_k = A_{k-1}x_{k-1} + B_{k-1}u_{k-1} + w_{k-1} \\ u_{t,k} = g(x_k, u_k, \theta_k) + v_k \end{cases} \tag{17}$$

$$\begin{cases} \theta_k = \theta_{k-1} + r_{k-1} \\ u_{t,k} = g(x_k, u_k, \theta_k) + e_k \end{cases} \tag{18}$$

Where:

$$A_{k-1} = \begin{bmatrix} \left(1 - \frac{\Delta t}{\tau_{1,k-1}}\right) & 0 & 0 \\ 0 & \left(1 - \frac{\Delta t}{\tau_{2,k-1}}\right) & 0 \\ 0 & 0 & 1 \end{bmatrix},\ B_{k-1} = \begin{bmatrix} \frac{\Delta t}{C_{1,k-1}} \\ \frac{\Delta t}{C_{2,k-1}} \\ \frac{\Delta t}{Q_r} \end{bmatrix},\ C_k^x = \frac{\partial g(x_k, u_k, \theta_k^-)}{\partial x_k}\bigg|_{x_k = x_k^-} \tag{19}$$

Partial principles of DKF filtering for SOC estimation were described above which were applied for calculations in the subsequent simulation modeling and theoretically served for subsequent EKF-DKF combined filtering algorithm for SOC estimation [17].

3.4.2 Verification of SOC estimation by DKF

Constant current discharge with 0.1C per second rate at room temperature was adopted to analyze the final effect of SOC value estimation of lithium batteries by DKF model (Fig. 8). Current and voltage changes under laboratory conditions were applied to DKF algorithm and initial model parameters were introduced. When the battery was only discharged, open-circuit voltage was 25V and SOC was 100%. SOC change occurred in a nonlinear downward trend during the whole constant discharge cycle. A real SOC value within 1% error was obtained which was comparable to that of DKF model. DKF model could solve the last 20% SOC in EKF-DKF filtering combined model proposed in this research.

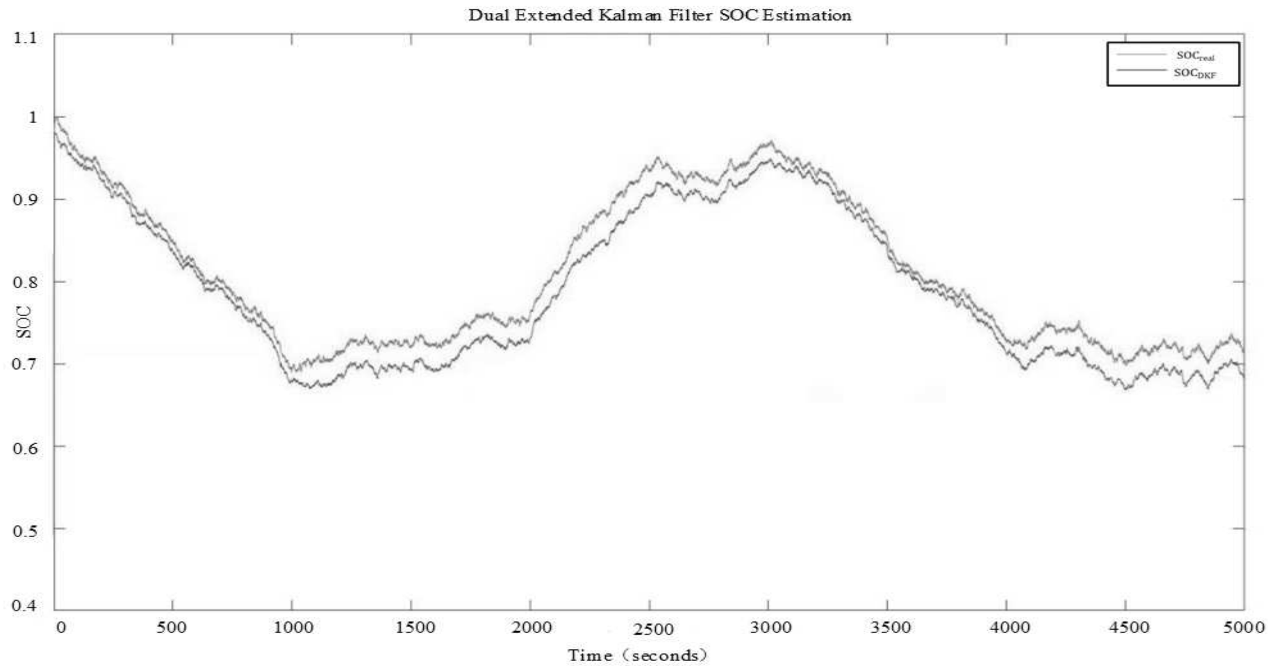

Fig. 8 *DKF algorithm estimation in SOC process simulation*

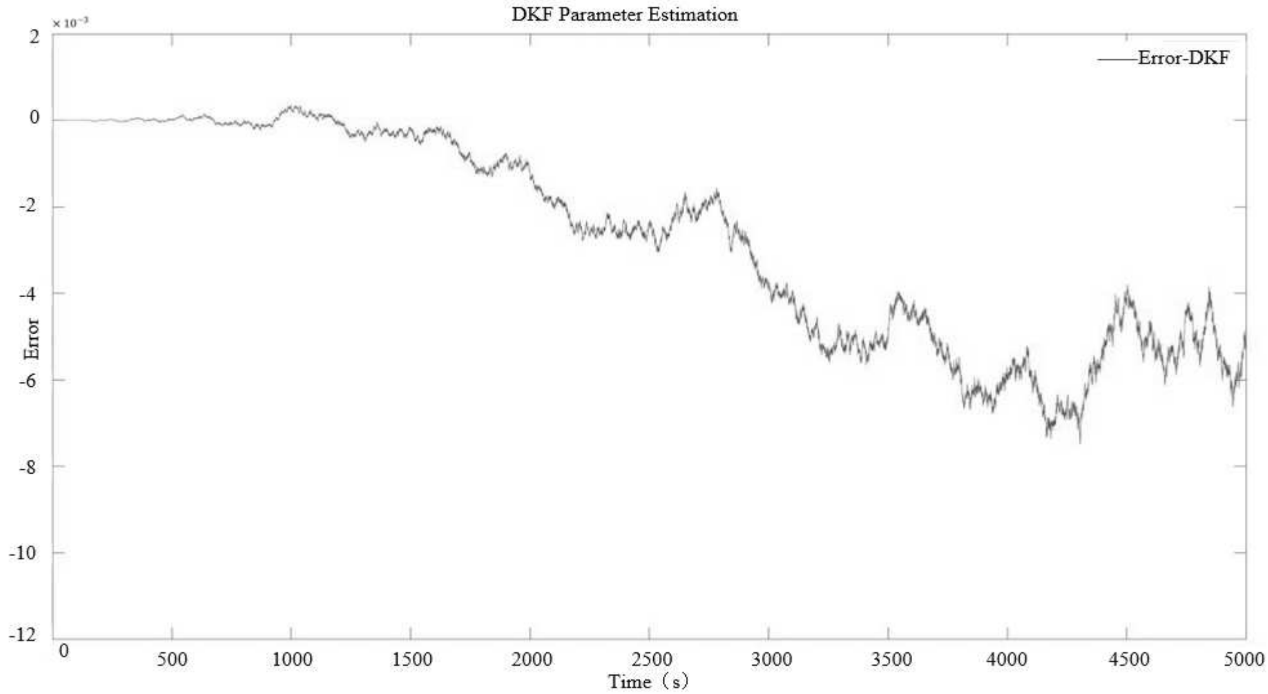

Fig. 9 *DKF algorithm estimation in SOC process error simulation*

3.5 SOC estimation by EKF-DKF combined model algorithm

To solve the shortcomings of EKF and DKF algorithms, this paper proposed an algorithm based on EKF - DKF combined model for SOC solution estimation. Compared to both DKF and EKF algorithms alone, This solution effectively addresses the problem of increasing battery SOC estimation errors caused by severe current fluctuations and low battery levels. This method also solved the problems of complex computation and low efficiency in the whole process of DKF in practical applications. EKF-DKF combined estimation model enabled the estimation results of lithium batteries to maintain high and efficient in the whole SOC cycle.

3.5.1 A scheme of SOC estimation by EKF-DKF combined model algorithm

Composite principle was as follows: The accuracy of Extended Kalman EKF estimation of battery SOC is closely tied to the accuracy of the constructed battery model, which in turn is influenced by the battery's state of charge. And in low battery period, the operation environment of UAV lithium batteries is very complex and changeable and battery model accuracy cannot be guaranteed. Assuming single use of EKF model, at low power state, it is inevitable that model changes introduce errors in parameter identification, leading to a decrease in the accuracy of estimated data and other related issues. To ensure better SOC estimation accuracy in the whole working period, some other SOC estimation algorithms are usually required. While estimating battery SOC and system state due to its good properties, DKF algorithm could fix battery model precision. Also, combining EKF and DKF filter algorithms could make up for the insufficiency of EKF model under the condition of current volatile estimation error increase. Control strategy of EKF-DKF model is illustrated in Fig. 10.

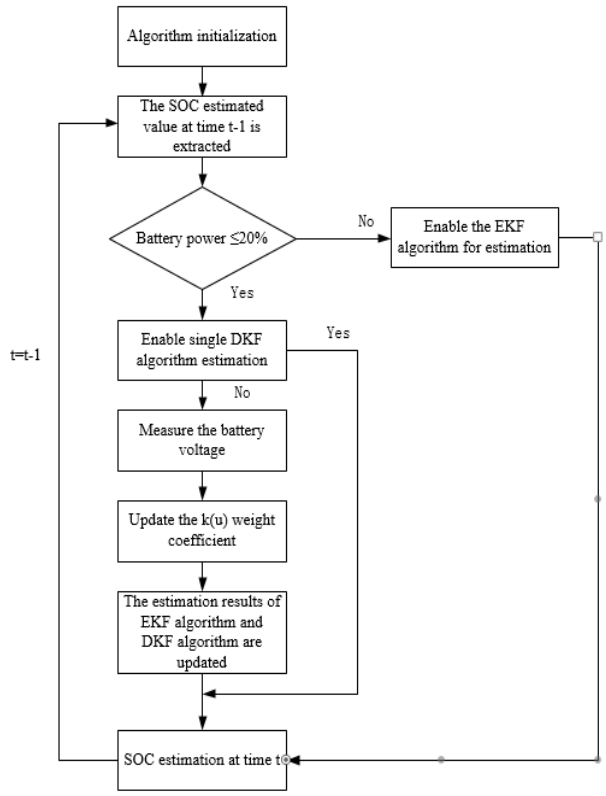

Fig. 10 *EKF-DKF combined algorithm flow*

3.5.2 SOC estimation verification analysis by EKF-DKF combined model

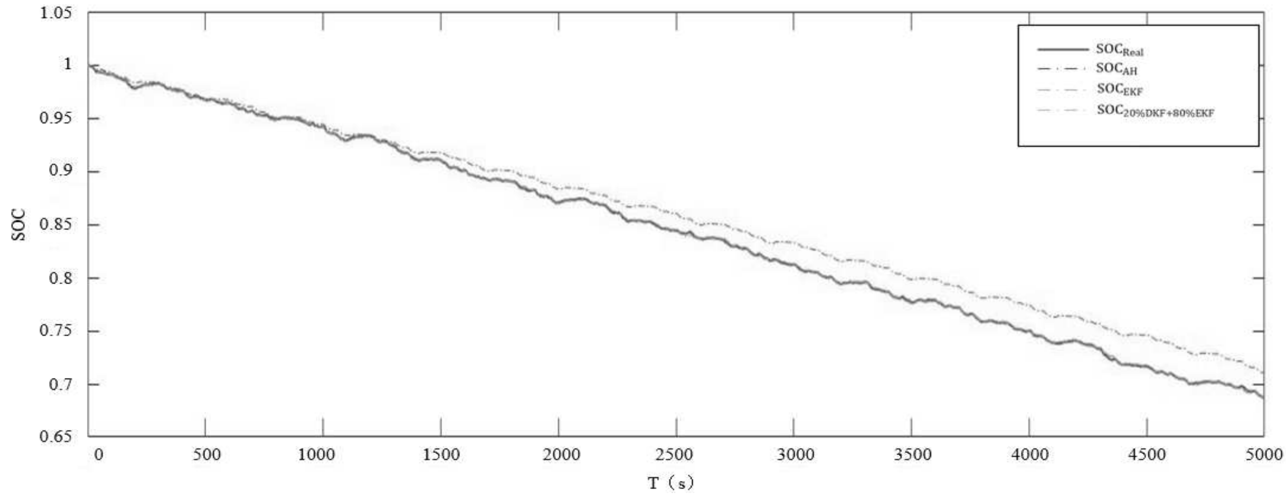

Fig. 11 *EKF-DKF algorithm in estimation SOC process simulation*

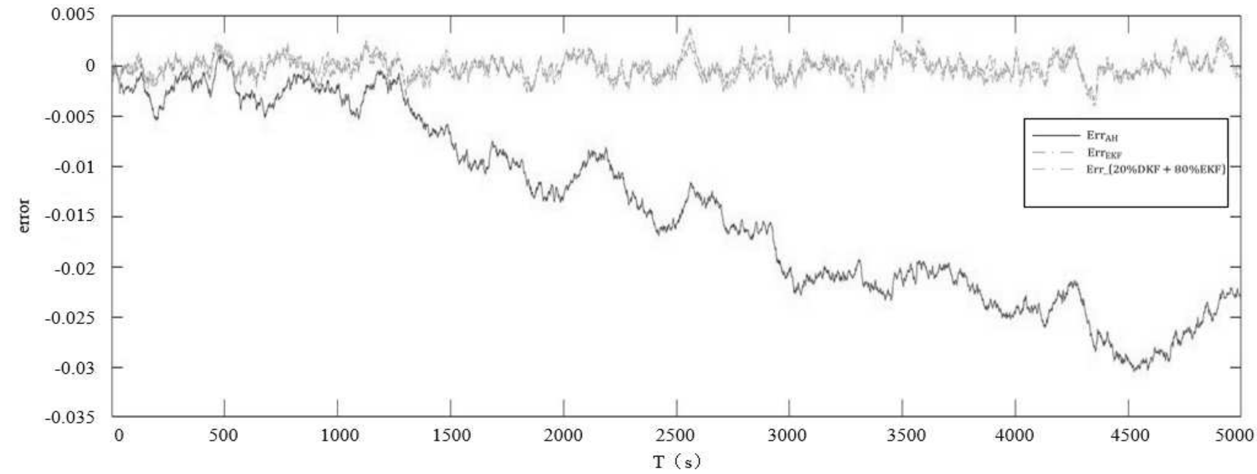

Fig. 12 *EKF-DKF algorithm estimation in SOC process error simulation*

In this research, we applied EKF-DKF composite model to analyze final SOC scheme at room temperature. From Fig. 11, it was seen that in the whole constant exile working condition, EKF-DKF combined model method converged well to the reference value. In the early and middle 80% stage of the working condition, the estimated results were close to those of EKF filtering method. In the last 20% of the working condition, results were similar to those obtained from DKF filtering algorithm. Simulation results showed that EKF-DKF combined model algorithm retained the strengths and avoided the weaknesses. It cleverly solved the phenomenon that estimation error was increased due to the excessive dependence of EKF filtering method on battery model at low battery power as well as the efficiency problem of DKF in SOC estimation. Fig. 12 shows that the estimation error of lithium battery SOC by EKF-DKF composite model method maintained within 0.32%, while those of DKF and EKF alone were within 0.78% and 3.1%, respectively. Especially at later discharge stage, EKF error did not converge in time. It was verified that EKF-DEKF combined model method had higher estimation accuracy.

4 Conclusion

This paper proposed a combined algorithm of EKF-DKF, estimated the SOC of 18650 terpolymer lithium batteries used in UAVs, improved battery modeling, and identified related lithium battery parameters under HPPC condition. On this basis, the actual data measured in laboratory environment were applied for the modeling and simulation of EKF-DKF combined model method. In comparison to the ampere-hour integration method and EKF, this process demonstrates that the EKF-DKF hybrid model estimation approach effectively solves the problem of significant decrease in estimation accuracy at 20% remaining battery capacity due to the severe dynamic changes in battery model and parameter offsets. Moreover, it improves estimation accuracy while reducing the computational complexity in practical applications, thereby increasing the efficiency of practical usage.

Acknowledgement

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