Estimation of state of charge of lithium battery based on parameter identification of fractional order model

H X Shen¹, X Li¹, L Chen¹, H H Xun¹, W X Chen²

¹School of Opto-Electronic and Communications Engineering, Xiamen University of Technology, Xiamen, China
²School of Aerospace Engineering, Xiamen University, Xiamen 361102, China

Abstract. Accurate estimation of state of charge of lithium battery is one of the important performance parameters for safe and reliable operation of lithium battery. A fractional order second-order Thevenin equivalent circuit model was proposed by based on the improvement of the traditional Thevenin equivalent circuit model for accurately estimating the state of charge of lithium-ion battery. In order to overcome the shortcomings of the least square method easily enter into local convergence or even unable to converge, an adaptive genetic algorithm is proposed to identify the parameters of lithium battery model, and global parameter identification is carried out to improve the convergence of the algorithm. Matlab simulation shows that the parameters of fractional order model of the second-order Thevenin equivalent circuit identified by adaptive genetic algorithm are better than those of integer order model identified by least square method. Combined with extended Kalman filter, the estimation of state of charge accuracy control is realized, with the accuracy error being within 1.61%.

1. Introduction
The state of charge (SOC) of the battery is one of the core contents of the lithium battery management system, which is usually expressed as the percentage of the actual remaining capacity of the battery to the rated capacity [1]. Due to the poor accuracy of integer-order models, the study suggested that nonlinear systems have fractional properties [2]. Fractional calculus is an extension of integer calculus, describing non-integer order integrals and derivatives. Ortigueira and Machado pointed out that the fractional model can describe the system's dynamic behavior and has a better ability to fit experimental data [3]. Therefore, fractional calculus is widely used in nonlinear systems, including signal processing [4] and SOC estimation.

Literature [5] estimates SOC based on a dual-scale adaptive particle filter algorithm. The algorithm estimates lithium battery parameter identification and SOC, respectively. It is suitable for any type of lithium battery. However, this method requires massive data. Insufficiency or inaccuracy will affect the accuracy of the estimation, which takes a long time and requires a lot of preparatory work.

Literature [6] considered the temperature in the resting state, the size of the charge and discharge current, etc. and proposed three algorithms based on the ampere-hour integration method-open circuit
voltage method-load voltage method to jointly estimate the SOC of the lithium battery; the estimation accuracy of the algorithm can be controlled within 0.3% and it takes a long time to estimate the SOC.

Literature [7] proposed the parameter identification of the lithium battery model based on the least square method, using the extended Kalman filter algorithm to estimate the SOC of the lithium battery online, but the least square method is a partial algorithm.

Therefore, this paper proposes to construct a fractional-order model based on the integer second-order Thevenin equivalent circuit model, and uses an adaptive genetic algorithm to identify model parameters, which solves the convergence in the parameter identification process. Improve the accuracy of the model, and estimate the SOC of the lithium battery through the extended Kalman filter.

2. Fractional equivalent circuit model

2.1. Second equivalent circuit model

Compared with experimental verification, battery modeling can effectively reduce the verification cycle and many algorithms rely on lithium battery models. For example, the extended Kalman filter in this article relies on the model when estimating SOC; theoretically, the more RC links, the more the lithium battery model Accurate, but the amount of calculation will increase exponentially, and the practicality will be lower. Therefore, after weighing the contradiction between the accuracy and practicability of the model, this article adopts the second-order Thevenin equivalent circuit model. The lithium battery model is shown in Figure 1.

Establish the relationship between lithium battery SOC and capacity, as shown below:

\[ SOC(k+1) = SOC(k) + \frac{I\Delta t}{Q_n} \]  
(1)

Where \( I \) is the charge and discharge current of the lithium battery at \( k+1 \), \( Q_n \) is the maximum rated capacity of the lithium battery, \( \Delta t \) is the sampling period of the system, \( SOC_{k+1} \) and \( SOC_k \) are the SOC values at \( k+1 \) and \( k \).

According to Kirchhoff's current law and Kirchhoff's voltage law, the time-domain calculus equation of the second-order RC network lithium battery model can be obtained as follows:

\[
\begin{align*}
    C_1 \frac{dU_1}{dt} &= I - \frac{U_1}{R_0} \\
    C_2 \frac{dU_2}{dt} &= I - \frac{U_2}{R_2} \\
    U_b &= U_{oc}(SOC) - IR_0 - U_1 - U_2
\end{align*}
\]  
(2)

2.2. Fractional model
Most of the things in nature are not integers, and more are expressed as fractions. Among them, the performance of lithium batteries also exhibits the characteristics of fractions, mainly due to the presence of capacitance in the second-order RC equivalent circuit. According to the research of Westerlund and Ekstam, most of the capacitors have a fractional order characteristic [8].

Constructing a fractional-order lithium battery model has the following advantages over an integer-order model:

(1) It can better express the complex changes inside the lithium battery.
(2) Better reflect the static and dynamic characteristics of lithium batteries.
(3) The fractional order includes the integer order. When the fractional order is an integer, the lithium battery behaves as an integer order.

In the frequency domain, the component capacitance is used to represent the fractional characteristics of the lithium battery model. The frequency domain expression of the capacitance \( C_f \) is:

\[
Z(j\omega) = \frac{1}{C_f(j\omega)^n}
\]  

(3)

Where \( n \) is the order of the fractional order, \( C_f \) is the size of the capacitor, \( \omega \) is the sampling frequency, and \( j \) is the imaginary unit.

The definition of Grunwald-Letnicov’s fractional calculus [8] and formulas (1), (2) and (3) get the following formula:

\[
\begin{bmatrix}
\frac{\Delta t^m}{\tau_1} & 0 & 0 \\
0 & \frac{\Delta t^n}{\tau_2} & 0 \\
0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
U_{1,k} \\
U_{2,k} \\
SOC_k
\end{bmatrix}
+ 
\begin{bmatrix}
-\frac{\Delta t^m}{C_1} \\
-\frac{\Delta t^n}{C_2} \\
\Delta t/Q_n
\end{bmatrix}
I_k - 
\sum_{i=1}^{k+1} x_i^n U_1(k+1-i)
\]  

(4)

Where \( U_{1,k} \) and \( U_{2,k} \) represent the voltages across the fractional model capacitors \( C_1 \) and \( C_2 \) at time \( k \), \( U_{1,k+1} \) and \( U_{2,k+1} \) are the voltages across the fractional model capacitors \( C_1 \) and \( C_2 \) at time \( k+1 \), respectively. \( \tau_1 = R_1C_1, \tau_2 = R_2C_2 \).

Suppose vector,

\[
x_k = \begin{bmatrix}
U_{1,k} \\
U_{2,k} \\
SOC_k
\end{bmatrix}
\]

\[
A = \begin{bmatrix}
\frac{\Delta t^m}{\tau_1} & 0 & 0 \\
0 & \frac{\Delta t^n}{\tau_2} & 0 \\
0 & 0 & 1
\end{bmatrix},
B = \begin{bmatrix}
-\frac{\Delta t^m}{C_1} \\
-\frac{\Delta t^n}{C_2} \\
\Delta t/Q_n
\end{bmatrix}
K_i = \begin{bmatrix}
x_i^n & 0 & 0 \\
0 & x_i^n & 0 \\
0 & 0 & 0
\end{bmatrix}, u_k = I_k.
\]

Where \( m \) and \( n \) are the order of the lithium battery model, therefore, the space state equation at \( k+1 \) is simplified to:

\[
x_{k+1} = Ax_k + Bu_k - \sum_{i=1}^{k+1} K_i x_{k+1-i}
\]  

(5)

In the same way, let \( h_k = U_{SOC_{SOC}} \), \( \lambda = (-1 \ -1 \ 0) \), \( y = U_b \), so the output equation (the terminal voltage of the lithium battery) at \( k+1 \) is:

\[
y_{k+1} = \lambda x_{k+1} + h_k - u_{k+1} R_0
\]  

(6)
2.3. Genetics algorithms and adaptive genetic algorithms for parameter identification

The identification of lithium battery parameters can be transformed into an optimal solution problem with constraints and parameters [9]. Compared with the least squares identification method, the advantage of genetic algorithm is that it only needs to determine the value of the objective function to obtain the optimal solution. Therefore, genetic algorithm is feasible and efficient for finding the optimal parameter matrix of the lithium battery model [9]. No matter how many parameters are identified, the genetic algorithm can be identified, and there is no problem of imbalance between the input and output of the least square method.

The optimization goal of parameter identification is to minimize the sum of squares of the difference between the measured terminal voltage $U_b$ and the voltage $U_T$ predicted by the fractional model. Therefore, the objective function is defined as:

$$Obj\left(\hat{b}_{ik}^{(i)}\right) = \frac{1}{L} \sum_{i=1}^{L} (U_b(i) - U_T(i))^2$$

In the formula, $L$ represents the number of selected populations. The larger the $L$, the wider the search range, and vice versa, the smaller. $\hat{b}_{ik}^{(i)}$ represents the identification value of the k-th element in the i-th individual when inherited to the first generation, and $b_{ik}^{(max)}$ is inherited Total algebra. The adaptability condition is to compare the difference between the measured terminal voltage $U_b$ and the voltage $U_T$ predicted by the fractional model. The objective function calculates the fitness of each individual. According to the proportional selection method, the fitness can be expressed as:

$$K(i) = \frac{\sqrt{Obj\left(\hat{b}_{ik}^{(i)}\right)}}{\sqrt{\sum_{i=1}^{L} (U_T(i) - \overline{U_T}(i))^2}}$$

Among them, $\overline{U_T}(i)$ represents the average value of the predicted voltage $U_T$ of the fractional model in the past i time period. The individuals who have reached the fitness level are regarded as the remaining individuals who survive the fittest (as the parent), and then directly inherited to the next generation [10]. Equation (7) can be seen that when the value of $K(i)$ is 0, it means that the terminal voltage $U_R$ and the voltage $U_T$ predicted by the fractional model are equal when the fitness is maximum, but due to the influence of errors such as measurement noise, $K$ is never possible to take 0.

Adaptive Genetic Algorithm (AGA) is an improvement of the basic genetic algorithm. The core idea of adaptive genetic algorithm is: in a certain generation of population, the crossover probability and mutation probability corresponding to each individual are different [11]. Keep the excellent individuals as much as possible, the crossover probability and mutation probability are small; the poor individuals cross and mutate as much as possible to generate new individuals, the crossover probability and mutation probability are larger. Through the adaptive adjustment of genetic parameters, the convergence accuracy of the genetic algorithm is greatly improved, and the convergence speed is accelerated. Adaptive genetic algorithm ensures the convergence of genetic algorithm while maintaining group diversity.

The crossover probability $CrossOverRat(i)$ and mutation probability $MutationRat(i)$ can be expressed as:

$$CrossOverRat(i) = k_i \frac{K_{max} - K(i)}{K_{max} - K_{ave}}$$

$$MutationRat(i) = k_i$$
It can be seen from the above formula that the crossover probability and the mutation probability of the individual with the greatest fitness are 0, so at this time $K_1 < K_{max}$, the crossover probability and the mutation probability are greater than 1, so the crossover probability (9) and the mutation probability should be (10) Assign the value:

\[ \text{CrossOverRate}(i) = k_3 \]  
\[ \text{MutationRate}(i) = k_4 \]  

Among them, $k_1, k_2, k_3, k_4$ are all less than 1, $k_1, k_3$ are the initial and maximum values of crossover probability, $k_2, k_4$ are the initial and maximum values of mutation probability, and $K_{max}$ is the maximum value of fitness.

3. Extended Kalman Filter

According to the description in literature [12], extended Kalman can solve nonlinear problems. Combining formula (5) and formula (6), the state equation and output equation of the fractional extended Kalman filter are as follows:

\[
\begin{align*}
    x_{k+1} &= Ax_k + Bu_k + w_k - \sum_{j=1}^{k+1} K_j x_{k+1-j} \\
    y_{k+1} &= Cx_{k+1} - R_0 u_{k+1} + h(x) + v(k)
\end{align*}
\]  

(13)

Among them, $u_k$ is the value of system noise at k time, $v_k$ is the value of measurement noise at k time, system noise and measurement noise are both white noises, the variance of system noise is $Q_k$, and the variance of measurement noise is $R_k$.

The process of extended Kalman filtering can be expressed as follows:

1. Initialization parameters: $x_0, P_0, Q_0, R_0$

2. According to the posterior state estimation value $\hat{x}_k$ at the previous moment, the prior state estimation value at k+1 can be obtained as:

\[
\hat{x}_{k+1} = A\hat{x}_k + B I_k - \sum_{j=1}^{k+1} K_j \hat{x}_{k+1-j}
\]  

(14)

The predicted output value is:

\[
\hat{y}_{k+1} = C\hat{x}_{k+1} - I_{k+1} R_0 + h(\hat{x}_{k+1})
\]  

(15)

3. Update the last parameter value.

The prior state error covariance $\tilde{P}_{k+1}$ can be expressed as:

\[
\tilde{P}_k = (A - K_1) P_k (A - K_1)^T + Q_k + \sum_{j=2}^{k+1} K_j (x_k - \hat{x}_k) K_j^T
\]  

(16)

The Kalman gain $L_{k}$ can be expressed as:
The posterior state estimate can be expressed as:

\[ \hat{x}_{k+1} = \bar{x}_{k+1} + L_k (y_{k+1} - \hat{y}_{k+1}) \quad (18) \]

(5) Update the posterior state error covariance.

The difference between the actual state value and the posterior state estimate is:

\[ x_{k+1} - \hat{x}_{k+1} = (I - L_k H_{k+1}) (x_{k+1} - \bar{x}_{k+1}) - L_k v_k \quad (19) \]

Among them, \( I \) represent the identity matrix.

The posterior state error covariance \( P \) can be expressed as:

\[ P_{k+1} = (I - L_k H_{k+1}) \bar{P}_k (I - L_k H_{k+1})^T + L_k R_k L_k^T \quad (20) \]

When the time reaches the next moment \( k+2 \), the steps (2) ~ (5) are looped until the end of the sampling time.

4. Simulation and analysis

This paper uses INR18650 cylindrical ternary lithium battery as the test object of the model. The nominal value of the lithium battery is 3.7V, and the maximum cut-off voltage is 4.2V. The case of room temperature is taken as an example for the pulse discharge experiment. According to the steps in Literature [13], the characteristic curve of the pulse voltage response is obtained by MATLAB simulation as shown in Figure 2. This paper adopts 1C discharge rate to discharge the battery. When the battery voltage drops to a discharge cut-off voltage of 2.75V, the battery SOC is 0. Literature [14,15] describe the experimental procedures in detail. MATLAB is used to linearly fit the obtained OCV-SOC data. In general, the 5th and 6th orders are used for fitting, but the fitting accuracy are relatively poor. Because the paper uses the OCV-SOC charging curve to expand Kalman performs the calibration, it requires accurate ground fitting. The more the fitting order, the larger the corresponding calculation amount. Considering the computer performance and fitting accuracy, this paper adopts 8th order to fit the data. The charging fitting curve of OCV-SOC is shown in Figure 3.

![Figure 2. Characteristic curve of pulse voltage response.](image)

![Figure 3. OCV-SOC fitting curve.](image)

This paper uses MATLAB for simulation. When using the adaptive genetic algorithm, for the relevant parameter settings, the population number in this paper is set as 140, and the evolution of the genetic algorithm in this article is 22 generations (fewer evolution times could easily cause non-convergence, while too many times is likely to cause a waste of time and resources). Since the adaptive genetic algorithm can reduce the evolutionary algebra, the evolution algebra is set as 11
generations, and the convergence is adjusted by adjusting the initial and maximum values of the mutation probability and the crossover probability. The adaptive mutation probability is generally 0.005. The mutation probability is too large if it is selected within 0.1, where it is easy to lose the optimal solution; if the mutation probability is too small, it will affect the diversity of the population, and it is not easy to produce excellent individuals; The empirical value of crossover probability ranges from 0.25 to 0.99. If the crossover probability is too small, it is not conducive to the development of population diversity. If it is too large, excellent individuals could be missed. This paper adjusts the convergence by adjusting the sizes of $k_1, k_2, k_3, k_4$ to obtain the most suitable crossover and mutation probability. The following are the values of four groups of $k_1, k_2, k_3, k_4$, and the corresponding waveforms of the difference between the maximum fitness and the minimum fitness and the variance of the fitness are obtained.

The first group: the values of $k_1, k_3$ are set to 0.5, and the values of $k_2, k_4$ are set to 0.03. The resulting simulation diagram is as follows:

![Figure 4](image1.png) **Figure 4.** The difference between the maximum fitness and the minimum fitness.

![Figure 5](image2.png) **Figure 5.** Fitness variance.

The second group: the values of $k_1, k_3$ are set to 0.5, and the values of $k_2, k_4$ are set to 0.05. The resulting simulation diagram is as follows:

![Figure 6](image3.png) **Figure 6.** The difference between the maximum fitness and the minimum fitness.

![Figure 7](image4.png) **Figure 7.** Fitness variance.

The third group: the value of $k_1, k_3$ are set to 0.7, the value of $k_2, k_4$ are set to 0.05, and the resulting simulation diagram is as follows:

![Figure 8](image5.png) **Figure 8.** The difference between the maximum fitness and the minimum fitness.

![Figure 9](image6.png) **Figure 9.** Fitness variance.

The fourth group: the value of $k_1, k_3$ are set to 0.8, the value of $k_2, k_4$ are set to 0.08, and the resulting simulation diagram is as follows:
From the above four sets of waveforms, it can be seen that only the second and fourth group present fixed difference between the maximum and minimum fitness values of the second and fourth groups and the fitness variance when the algebra after eleven generations of evolution ends, so the corresponding waveform is convergent. When the difference between the maximum and minimum fitness values is smaller and the fitness variance is smaller, the adaptive genetic algorithm converges. Therefore, through comparison, this paper chooses the second group as the crossover and mutation probability of the adaptive genetic algorithm.

Figure 12 and Figure 13 show the variation of mutation probability and crossover probability of each individual in the last generation. It can be seen from formula (9) to (12) that the crossover and mutation of adaptive genetic algorithm are limited and finite. When $K_i < K_{\text{max}}$, the crossover probability and mutation probability are greater than one, so it is necessary to re-initialize the crossover and mutation probability. From the comparison of Figure 4 and Figure 11, it can be seen that the crossover and mutation probability is 0.5 and 0.05; therefore, the upper limit of the mutation probability in Figure 12 is taken as 0.05, and the upper limit of the crossover probability in Figure 13 is taken as 0.5. The crossover probability and mutation probability of genetic algorithm are fixed, while the crossover probability and adaptive probability of adaptive genetic algorithm are variables. Also, the crossover and mutation probability of different individuals are different, which is the essential difference between adaptive genetic algorithm and genetic algorithm.

Figure 14 is the comparison of the maximum fitness and average fitness difference between adaptive genetic algorithm and genetic algorithm. Figure 15 is the comparison of fitness variance. The crossover and mutation probabilities of genetic algorithm are set to 0.75 and 0.03 respectively.
Figure 14. Compare the difference between maximum fitness and average fitness in adaptive genetic algorithm and genetic algorithm.

Figure 15. Comparison of fitness variance.

In nature, the probability of crossover and mutation of each individual is different and can be easily affected by the state of the individual. On the one hand, the genetic algorithm does not consider the changes of individual states and the differences of individuals; on the other hand, genetic algorithms need to do a lot of experiments to derive the probability of crossover and mutation. This crossover probability and mutation probability are conducted among the whole population, while the crossover and mutation probability of a certain individual in a certain generation. And that lead to the fundamental reason for the poor convergence of genetic algorithms. The adaptive genetic algorithm changes the probability of crossover and mutation as the individual changes. It is more adaptable to individuals, and will not do some useless crossover and mutation, which greatly improves the convergence. Comparing Figure 14 with Figure 15, it can be seen that the curve of adaptive genetic algorithm is smoother than genetic algorithm, and it has converged in the 11th generation, which proves that the convergence of adaptive genetic algorithm is higher than genetic algorithm.

Therefore, the adaptive genetic algorithm is used to change the probability of crossover and mutation with individual changes, which improves the convergence of genetic algorithm. Adaptive genetic algorithm is a parameter of global identification. The optimal solution of the identification parameter is shown in Table 1:

Table 1. Parameter identification of adaptive genetic algorithm.

| R0/Ω  | R1/Ω  | R2/Ω  | C1/F  | C2/F  | m    | n    |
|-------|-------|-------|-------|-------|------|------|
| 0.003721 | 0.0026 | 0.003156 | 12632.48 | 610476.2 | 0.989524 | 0.983206 |

The adaptive genetic algorithm parameter identifies the second-order fractional model of the lithium battery and obtains the error of the terminal voltage in Figure 16. It can be seen from the figure that the error of the terminal voltage reaches maximum at the beginning and the end. It can be seen from the charge fitting curve in Figure 3 that when the SOC is less than 0.1 or the SOC is greater than 0.95, the internal resistance of the battery changes greatly. The voltages of these two sections drop rapidly. This is because the interior of the battery changes drastically, so the SOC of the lithium battery is difficult to estimate. However, the adaptive genetic algorithm has global characteristics that can reduce the impact of lithium batteries when estimating the SOC in these two stages, and the terminal voltage error accuracy of the final estimated SOC model is about 3%. Figure 17 shows the model error of the least square method when identifying the model parameters. It can be seen from the figure that the model error exceeds 5% at the end. The comparison of the simulation waveforms proves that the global parameter identification of the adaptive genetic algorithm solves the issues at
final charge and discharge stage. The accuracy of the model is improved by solving the problem of difficult to estimate the SOC.

![Figure 16. Adaptive genetic algorithm parameter identification model error.](image)

![Figure 17. Least square method parameter identification model error.](image)

The parameter identification of fractional-order model that adopts Adaptive genetic algorithm is integrated with the extended Kalman filter to estimate SOC (denoted as FOEKF); while the least square method is used to identify integer-order model, in combination with extended Kalman filter to estimate SOC (denoted as EKF).

Figure 18 and Figure 19 are the fractional-order model of adaptive genetic algorithm parameter identification and the integer-order model of least squares parameter identification. The comparison between the real value of SOC is predicted by extended Kalman filter and the comparison of their SOC error; Table 3-2 is the comparison of their maximum error and average error. It can be seen intuitively from Figure. 18 and Table. 2 that when the adaptive genetic algorithm parameter identifies the fractional model, the extended Kalman filter used to estimate the SOC is with the highest accuracy. It can be seen from Figure. 19 that for both adopting the least square method or the adaptive genetic algorithm in the parameter identification model, as long as the extended Kalman filter algorithm is used to estimate the SOC, the value jumps around the true value, only with different fluctuation error. Therefore, when using the extended Kalman filter algorithm to estimate the SOC, no matter what parameter identification algorithm is used, the change trend of overall SOC can always be predicted.
5. Conclusions
In this paper, an adaptive genetic algorithm is proposed to identify the fractional order model of the second order Thevenin equivalent circuit of lithium battery, and the SOC is estimated by extended Kalman filter. First of all, the fractional order model contains both integer order model, differential model and integral model, which is more in line with the complex working state of lithium battery, to be able to describe the lithium battery model more comprehensively compared with the integer order model; secondly, the adaptive genetic algorithm is an improved algorithm of genetic algorithm. It is a global algorithm that can overcome the shortcomings of leading local convergence and even divergence of the least square method; Finally, the extended Kalman filter is used to estimate the SOC of lithium battery. The extended Kalman filter, as a closed-loop control algorithm, has its working mode be summarized as “one-step prediction, one-step correction”. Compared with the results of integer order model identified by least square method, it is proved that AGA-FOEKF has higher SOC accuracy and the maximum SOC estimation error is less than 1.61%, indicating the AGA-FOEKF has high engineering application value.

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