Research on On-line Identification of Equivalent Circuit Model Parameters and SOC Estimation for Lithium-ion Batteries

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Abstract. The online identification model parameters can reflect the real terminal voltage state of the battery in real time and provide accurate observation data for battery SOC estimation. BMS is an important part of new energy vehicles, which supervises and controls the working process of the battery. The core of BMS is SOC estimation, and the accuracy of its estimation is related to whether the battery works efficiently and safely. Based on Thevenin model, FFRLS-EKF and KF-EKF were used to estimate the SOC of ternary lithium battery under DST condition. The estimation results show that FFRLS-EKF has a maximum error of 0.0079, which can estimate the SOC of the battery well.

1. Introduction

With the continuous development of science and technology of society, People’s living needs are constantly improving, and the demand for travel is also more eager. During the new round of oil price rise, the use cost of automobile fuel also rises, and some new energy vehicles show a comparative cost advantage. In order to avoid the excessive burden of fuel costs, some consumers give up the traditional fuel vehicles and choose the relatively low consumption of new energy vehicles. However, the research of power battery is very important in the development process of new energy vehicles.

Lithium-ion battery [1] as a commonly used power battery of new energy vehicles, restricts the development of electric vehicles due to its power density, safety performance, cost and other factors, which requires Battery Management System(BMS) to effectively control and manage the battery. State of Charge (SOC) is an important part of BMS [2], which is closely related to the service life and usable mileage of the vehicle. Accurate estimation of SOC values can prevent the over charge or over discharge of the battery and ensure the safe and reliable use of the power battery. Conventional SOC estimation process consists of three parts: equivalent model, model parameter identification and SOC estimation. Commonly used SOC estimation methods [3] includes Ampere-hour integration method, Kalman Filter (KF) [4], particle swarm optimization, neural network, etc. Many scholars at home and abroad have carried out a series of studies on SOC estimation. Liu [5], based on the dynamic Thevenin
model and the principles of Unscented Kalman Filter (UKF) algorithm and Particle Filter (PF) algorithm, proposed the Unscented Kalman Particle Filter (UPF) algorithm. The simulation results show that the UPF based on dynamic Thevenin model can predict the SOC in real time and has strong anti-noise robustness. Tian [6] proposed a method based on Deep Neural Network (DNN) to estimate SOC with 10 mins charging voltage and current data as input. This method can estimate the SOC quickly and accurately, and can play a calibration role as the estimation of SOC by ampere-hour integration method. Zhang [7] proposed an improved AUKF to solve the problem that traditional UKF could not estimate SOC when the error covariance matrix was not positive definite. Firstly, the Forgetting Factor Recursive Least Square (FFRLS) method is used to identify the parameters of the battery model. Using these identified parameters, the Cholesky decomposition of the traditional AUKF error covariance matrix is replaced by the singular value decomposition. In order to improve the SOC estimation accuracy of the Extended Kalman Filter (EKF) method of lithium batteries, Li W [8] proposed a Multi-Innovation Extended Kalman Filter (MI-EKF) algorithm. By expanding the single information about the current moment to multiple information of the current moment and the previous moment to estimate the battery SOC, the information is increased and a more accurate estimate of the SOC is obtained.

2. Battery model analysis
For the method of on-line parameter identification based on model, the accuracy of the fitting degree of the terminal voltage of the lithium-ion battery model is directly proportional to the accuracy of model parameter identification. To paper the follow-up work, need to select a reasonable structure of battery equivalent circuit model, in addition to the number of identification parameters is moderate and has higher fitting precision, and it won't cause too much computation burden, so before analysis model of battery, need the battery related experiments, analysis of the external characteristic parameters and obtain certain curve.

2.1 External characteristics of lithium batteries
Lithium-ion battery refers to a chargeable and discharging high-energy battery in which lithium-ion are embedded and detached from anode and cathode materials. During the charging process, the lithium ions go back and forth between the positive and negative electrodes, also known as the "rocking chair battery". The chemical equation of lithium-ion battery is:

\[
LiM_m\text{O}_n + nC_{\text{charge}} \rightarrow Li_{\alpha M_m\text{O}_n} + Li_{\beta C_n}
\]

The advantages of lithium-ion batteries are large capacity and high operating voltage. The capacity is twice that of the same nickel metal hydride battery, which is more suitable for long time work. It has strong charge keeping ability, wide allowable working temperature range, long cycle service life, small size, light weight and high specific energy.

2.2 equivalent circuit model
Battery model is an important part of SOC estimation process. At present, there are many kinds of anode and cathode materials for batteries, which lead to great differences in the chemical mechanism of batteries. For different batteries, different models are required, and researchers at home and abroad have proposed a variety of models [9]. Such as Electrical Property Model, Aging Model, Electro-thermal Coupling Model, and Thermal Model. The research object of the paper is Thevenin equivalent circuit model in electrical model [10]. The model is shown in Figure 1:
In the schematic diagram of Thevenin model, UL represents the terminal voltage of the battery; UOC represents the voltage source, which is equivalent to the open-circuit voltage of the battery. Ro is the internal ohmic resistance of the battery, representing the transient polarization reaction of the battery. R1 and C1 are the polarization resistance and polarization capacitance of the battery, respectively. RC parallel network is composed to represent the steady-state polarization reaction of the battery. The mathematical expression of Thevenin model is as follows:

\[ U_L = U_{oc} - I*R_0 - U_1 \]
\[ U_1 = -\frac{U_1}{R_1C_1} + \frac{I}{C_1} \]  

3. On-line identification method

3.1 Model parameter identification method

The accuracy of model parameters has a strong direct proportional relationship with SOC estimation. The commonly used model parameter identification methods include RLS, FFRLS, KF and PF, etc. The paper mainly introduces and analyses FFRLS and KF algorithm.

3.1.1 FFRLS algorithm

FFRLS is an improved algorithm of RLS. When using RLS for parameter identification, with the increase of data volume, data saturation will inevitably occur. For linear systems, this phenomenon is particularly obvious, and the parameter estimation will be biased. For this reason, forgetting factor \( \lambda \) should be added on the basis of RLS to gradually weaken the influence of past data and strengthen the role of new data. The algorithm recursive formula is as follows:

\[
\begin{align*}
\dot{\theta}(k+1) &= \dot{\theta}(k) + K(k+1)[y(k+1) - \phi^T(k+1)\dot{\theta}(k)] \\
K(k+1) &= P(k)\phi(k+1)[\lambda + \phi^T(k+1)P(k)\phi(k+1)]^{-1} \\
P(k+1) &= \frac{1}{\lambda}[E - K(k+1)\phi^T(k+1)]P(k)
\end{align*}
\]

According to Equation (1), the discrete transformation of the battery model expression is shown as follows:

| Table 1. Lithium battery model conversion process |
|-----------------------------------------------|
| Equivalent Circuit Model                      |
| The Continuous System Transfer Function       |
| \( \frac{dU_c}{dt} = -\frac{R_0 + R_1}{C_0R_0S + 1}U_c \) |
| Difference Equation Model                     |
| \( U_d(k) = -aU_d(k-1) + a_1I(k) + a_2I(k-1) \) |
### RLS Model Initial Condition

| \[ \phi(k) = \begin{bmatrix} \begin{bmatrix} a_1, a_2, a_3 \end{bmatrix} \end{bmatrix} \] | \[ \theta(k) = \begin{bmatrix} \begin{bmatrix} a_1, a_2, a_3 \end{bmatrix} \end{bmatrix} \] |
|---|---|

### Model Parameter

\[
\begin{align*}
R_0 &= \frac{a_2-a_0}{2a_0} \\
\tau &= \frac{1-a_1}{2a_0} \\
R &= (1+2\tau)(a_1-R_0) \\
C_1 &= \frac{\tau}{R}
\end{align*}
\]

### 3.1.2 KF algorithm

KF identification algorithm is a linear system equation of state, through the system input and output observation data, the optimal estimation of the system state algorithm. KF algorithm mainly includes two main equations: measurement equation and observation equation. Equation of state and measurement equation are shown in Equation 3:

\[
\begin{align*}
X(k) &= A(k)X(k-1) + T(k)\omega_k \\
Y(k) &= H(k)X(k) + \nu_k
\end{align*}
\]

In both formulations, \( k \) represents the value of the present moment, \( k-1 \) represents the value of the previous moment, \( X \) is the state vector, \( A \) is the state transition matrix, \( \omega \) is the process noise of the state equation, which is assumed to be Gaussian white noise in this paper, variance is defined as \( Q \), and \( T \) is the noise driven matrix. \( H \) is the observation matrix, \( Y \) is the observed value, \( \nu \) is the measurement noise of the measurement equation, which is assumed to be Gaussian white noise in this paper, and the variance is defined as \( R \). The recursive process of KF algorithm is shown in the figure below:

State one-step prediction:

\[
\hat{X}(k+1|k) = \phi \hat{X}(k|k)
\]

Update the state:

\[
\begin{align*}
\hat{X}(k+1|k+1) &= \hat{X}(k+1|k) + K(k+1) + \epsilon(k+1) \\
\epsilon(k+1) &= Y(k+1) - H \hat{X}(k+1|k)
\end{align*}
\]

Filter gain matrix:

\[
K(k+1) = P(k+1|k)H^T[H \hat{P}(k+1|k)H^T + R]^T
\]

One-step prediction covariance matrix:

\[
P(k+1|k) = \phi P(k|k) \phi^T + \Gamma Q \Gamma^{-1}
\]

Covariance matrix update:

\[
\begin{align*}
P(k+1|k+1) &= [I_p - K(k+1|k)H]P(k+1|k) \\
\hat{X}(0|0) &= \mu_0, P(0|0) = P_0
\end{align*}
\]

### 3.2 Model parameter identification method

As one of the most widely used filtering algorithms, KF algorithm has high accuracy in the optimization estimation of linear systems, but its filtering effect is not ideal in nonlinear systems. To solve this problem, KF derived a variety of filtering methods for nonlinear systems, such as UKF, AUKF and EKF, among which EKF has a small amount of computation and ideal filtering effect, and has been recognized by the academic community and widely used.

Battery SOC estimation is a typical nonlinear problem, and EKF is the first choice of optimal estimation method for SOC estimation. The iterative algorithm of EKF is,

\[
\begin{align*}
\hat{A}_v &= \left. \frac{\delta \hat{g}(x, u)}{\delta x_v} \right|_{x = x_i, u = u_i} \\
\hat{C}_v &= \left. \frac{\delta \hat{g}(x, u)}{\delta x_v} \right|_{x = x_i, u = u_i}
\end{align*}
\]

Definition:

Initial conditions of filtering:

\[
\begin{align*}
\hat{x}(0|0) &= E(x_0), P(0|0) = \text{var}(x_0)
\end{align*}
\]
Status estimation time update:
$$x_{k|k-1} = f(x_{k-1|k-1}, u_{k-1})$$
(11)

Error covariance time update:
$$P_{k|k-1} = A_{k-1} P_{k-1|k-1} A_{k-1}^T + \Gamma_{k-1} Q_{k-1} \Gamma_{k-1}^{-1}$$
(12)

Filter gain matrix:
$$K_k = P_{k|k-1} C_k^T [C_k P_{k|k-1} C_k^T + R_k]^{-1}$$
(13)

Status estimation measurement update:
$$x_{k|k} = x_{k|k-1} + K_k [y_k - g(x_{k|k-1}, u_k)]$$
(14)

Covariance matrix update:
$$P_{k|k} = (I - K_k C_k) P_{k|k-1}$$
(15)

4. Experimental analysis
To verify the effect of FFRLS-EKF and FFRLS-EKF algorithms in estimating SOC under typical dynamic conditions. In the paper, a dynamic pressure test is designed to verify the advantages and disadvantages of the two algorithms based on the custom dynamic DST test data. The DST working condition includes battery charging, discharging and shelving states. The specific test steps are as follows:
(1) Constant discharge of 0.5C current for 60S;
(2) Constant discharge for 20s with 0.2C current;
(3) Lay up 10s;
(4) 0.5C current constant charge for 20s;
(5) Lay up 10s,
(6) With 1C current constant exile 120s;
(7) Cycle step (1) until the end of discharge.

Some of the current and voltage waveforms are shown in Figure 2.

![Fig.2. DST test current and voltage curve](image)

After the test is completed, the test data is imported into the simulation model, and the FFRLS-EKF algorithm and KF-EKF algorithm are respectively applied to conduct SOC estimation. The SOC estimation effect is shown in Figure 3, and the error diagram is shown in Figure 4. Since there are charging, discharging and shelving processes of the battery in the DST condition, the SOC in the obtained SOC waveform has both a decrease and an increase. The initial SOC value set by the two algorithms is 0.9. As can be seen from Figure 3, the following effect of the two algorithms is good. As
can be seen from Figure 4, the convergence degree of KF-EKF is relatively stable, while FFRLS-EKF converges much faster than KF-EKF at the beginning of discharge. When SOC is between 0.9 and 0.3, FFRLS-EKF adds forgetting factor in the recursion process, so the initial error of operation has little influence on the subsequent operation, and the maximum error is only 0.0079, while the maximum error of KF-EKF is 0.012, which is 51.89% higher than that of the latter. Based on the above analysis, the convergence speed and degree of FFRLS-EKF are significantly improved compared with KF-EKF.

5. Conclusions
In order to accurately estimate the model parameters of the battery, the traditional off-line estimation is abandoned and the current hot discussion of online identification is studied. Firstly, the background of this study and the current research situation at home and abroad are introduced. Secondly, the experiments of capacity and open-circuit voltage are done, and the commonly used models are analysed. Then several common identification algorithms and SOC estimation algorithms are introduced in detail. Finally, based on Thevenin model, FFRLS-EKF and KF-EKF were used to estimate the battery SOC, and the battery parameters identified by FFRLS were closer to the real value.

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