State-of-charge estimation method of lithium-ion batteries based on long-short term memory network

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Abstract. This paper presents a method to estimate the state-of-charge (SOC) of lithium-ion batteries based on long-short term memory network (LSTM). The method is mainly composed of two parts: (1) A linear neural network is used to identify the parameters of second-order equivalent circuit model. (2) A LSTM network is built to estimate the SOC of lithium-ion battery. The linear neural network is trained using the American Dynamic Stress Test Condition (DST) dataset of battery (1st cycle), while the LSTM network is trained using the Chinese Standard Operating Condition (QCT) datasets of battery (1st, 10th and 20th cycle). After that, the trained LSTM network is tested using DST datasets of the batteries and QCT datasets under different temperatures. The results show that the LSTM network can accurately estimate the SOC of lithium battery under different temperatures, different working conditions and lifespan.

Keywords: lithium battery; long-short term memory network; working condition; lifespan; state-of-charge.

1. Introduction

As the most widely used energy storage battery in the electric vehicles, lithium battery has attracted much attention in recent years. In order to ensure battery safety and performance, battery management system (BMS) is developed. An efficient BMS prolongs the battery life and protects the battery from over-charging and over-discharging [1].

The SOC estimation is one of the main tasks of BMS [2, 3]. The function of battery SOC is the same as that of the traditional fuel meter that is showing the percentage of available energy remaining. Usually, accurate SOC estimation enables users to know when the battery is supposed to be recharged [4-6]. However, the charge and discharge process of the batteries, which is accompanied by complex electrochemical reactions, will be affected by the change of the external environment, so it is still a great challenge to study the accurate SOC estimation algorithm [7, 8].

At present, many SOC estimation algorithms have been put forward. The main methods for the SOC estimation include the current integral method, the Kalman filter method, the particle filter method and the neural network model. The current integral method [9] has the advantages of simple operation, but it requires high precision of the sensor. At the same time, it is sensitivity to the initial SOC value and
the battery nominal capacity. The Kalman filter methods [10-13] including unscented Kalman filter method and extended Kalman filter method have good nonlinear ability, but they are not suitable for BMS because of high computing cost and poor robustness. The Particle filter method [14-16] has similar advantages and disadvantages. At present, neural network model [17, 18], which has the advantages of strong adaptability and self-learning ability, is the most popular intelligent algorithm. Due to the changing working conditions of the batteries and insufficient accuracy of test equipment in actual operation, the neural network is more suitable for battery SOC estimation in theory. One of the biggest limitations of neural network in practical application is that it takes massive datasets to train the network. However, with the development of hardware, computing power has been greatly improved. Therefore, it is not a difficult task to train the network.

The SOC estimation method based on the neural network, in which battery voltage and battery temperature are chosen as an input vector and SOC is taken as an output signal, is proposed in Ref. [19]. In order to optimize the structure and parameters of the neural network, the training error value of the BP neural network [20] is used as the fitness of the genetic algorithm to find the optimal weights and thresholds of the neural network. The orthogonal least square method is adopted to determine the optimal node number of the hidden layer [21]. Meanwhile, the gene algorithm is utilized to get the optimal weights and thresholds. The voltage, the current, the temperature and SOC are selected as an input vector and the terminal voltage is an output signal [22]. In order to optimize inputs of the neural network, neuron controller is introduced. The advantage of this method is that it has low requirements for hardware, but the accuracy of estimation is greatly affected by the initial value of input vector. To address this problem, the authors [23] consider the voltage and the current of 10 seconds as inputs to train the neural network. Due to the constantly changing characteristics of battery in the decay process, battery life decay should be taken into account when training neural network. Historical values of current, voltage, temperature and ohmic resistance are taken as a input vector and SOC is chosen as an output signal [24]. However, this method, which calculates the ohmic internal resistance adopting the Ohm’s law, does not take polarization reactions into account. The first-order equivalent circuit model [25] is selected to identify the open circuit voltage, which is used as the input of the neural network. The neural network overcomes the defect that the relationship of OCV-SOC changes with the battery life decay, but this method will put much pressure on hardware. A recurrent neural network with long-short term memory [26] suitable for estimating sequence data is proposed. The voltage, the current and the temperature are selected as the inputs to train the network. However, the current studies do not consider the effects of working conditions, life decay and abnormal inputs on the SOC estimation synthetically.

To overcome the above-mentioned defects, a new LSTM network is put forward to estimate the SOC. In this method, some parameters related to temperature, working conditions and life decay are selected as the part of the inputs, which can represent the effects of temperature, working conditions and life decay on the SOC estimation. Meanwhile, the method selects the battery parameters of the past 3 seconds as an input vector, which enables the LSTM network to learn more information about battery status at current time and avoid the anomaly of the estimated SOC caused by the inputs at single time. The results are verified by aging cycle experiments under QCT condition and DST condition.

2. Experiments

To consider the effects of temperature, working conditions and battery lifespan on the SOC estimation, aging cycle experiment is conducted under working conditions. The maximum capacity of the batteries is 2.4Ah. When the nominal capacity fades to 80% of the maximum capacity, the test is terminated. Current curves of DST condition and QCT condition, which were employed in aging cycle experiments, are shown in Fig. 1. The test workbench (LANHE CT2011B) used in aging cycle experiments consists of a current load module, a data collection module, a charge and discharge module and a security protection module. In this test workbench, the battery’s terminal voltage, current, and capacity are set to record once a second.

One cycle consists of five parts: (1) charge with constant current of 2A until charge voltage reaches 4.2V, (2) charge with constant voltage 4.2V until charge current reaches 0.2A, (3) rest for 30 minutes,
(4) discharge with DST condition or QCT condition until discharge voltage reaches 3.5V, (5) discharge with constant current of 2A until charge voltage reaches 2.8V.

The experiments carried out 175 complete charge and discharge cycles under DST condition and 192 complete charge and discharge cycles under QCT condition. The DST dataset of the battery (1st cycle) is selected to train the model of parameter identification and the QCT datasets of the battery (1st, 10th and 20th cycle) are adopted for training the model of SOC estimation. Besides, the datasets of other aging cycles are employed to test the trained models.

![Image](image_url)

**Fig. 1** Schematic of the battery test loading profiles: (a) DST test. (b) QCT test.

3. Equivalent circuit model and identification of model parameters for lithium battery

3.1. Equivalent circuit model of lithium-ion battery

Currently, the available battery models include equivalent circuit model, electrochemical model and thermal model. The equivalent circuit model is widely applied as the result of its simpler structure and excellent description of battery dynamic performance. The second-order equivalent circuit model utilized in this paper is shown in Fig. 2.

![Image](image_url)

**Fig. 2** Second-order Thevenin model.

As seen in Fig. 2, the load current of the second-order equivalent circuit model is expressed mathematically as:

$$i_i = C_1 \frac{dU_1}{dt} + \frac{U_1}{R_1} = C_2 \frac{dU_2}{dt} + \frac{U_2}{R_2}$$

Where $R_0$ is ohmic resistance, $R_1$ is electrochemical-polarization resistance, $C_1$ is electrochemical-polarization capacitance, $R_2$ is concentration-polarization resistance and $C_2$ is concentration-polarization capacitance. $U_1$ and $U_2$ denote electrochemical-polarization voltage across $R_1$ and concentration-polarization voltage across $R_2$, respectively. $i_i$ stands for load current, which is positive when discharging and negative when charging.

The mathematical expression of the second-order equivalent circuit model is expressed as:
\[ U_{OCV} = U_1 + i_1 R_0 + U_1 + U_2 \]  

Where \( U_{OCV} \) and \( U_t \) denote the open-circuit voltage and terminal voltage, respectively.

### 3.2. Identification algorithm of model parameters

To identify the model parameters, Eq. (3) and Eq. (4) are obtained by Laplace transformation of Eq. (1) and Eq. (2).

\[ i_s(s) = C_s U_1(s) + \frac{1}{R_1} U_1(s) = C_s U_2(s) + \frac{1}{R_2} U_2(s) \]  

\[ U_{ocv}(s) = U_1(s) + i_s(s) R_0 + U_1(s) + U_2(s) \]  

Eq. (4) substituted by Eq. (3) is modified as Eq. (5).

\[ U_{ocv}(s) - U_1(s) = i_s(s) \left( R_0 + \frac{1}{C_s + \frac{1}{R_1}} + \frac{1}{C_s + \frac{1}{R_2}} \right) \]  

A bilinear transformation method shown in Eq. (6) is employed for the discretization calculation of Eq. (5) and the result is shown in Eq. (7).

\[ s = \frac{2}{T} \frac{1 - z^{-1}}{1 + z^{-1}} \]  

\[ U_i(k) = U_{ocv}(k) + k_1[U_i(k-1) - U_{ocv}(k-1)] + k_2[U_i(k-2) - U_{ocv}(k-2)] + k_3 i_1(k) + k_4 i_1(k-1) + k_5 i_1(k-2) \]  

Where \( k_1, k_2, k_3, k_4, k_5 \) are the parameters for the discrete model and \( T \) is the sampling interval. \( R_0, R_1, R_2, C_1, C_2 \) can be calculated as:

\[ R_0 = -k_3 + k_4 - k_5 \]  
\[ R_1 C_1 R_2 C_2 = \frac{1 + k_1 - k_2}{4(1 - k_1 - k_2)} \]  
\[ R_1 C_1 + R_2 C_2 = \frac{1 + k_2}{1 - k_1 - k_2} \]  
\[ R_0 + R_1 + R_2 = \frac{-k_3 - k_4 - k_5}{1 - k_1 - k_2} \]  
\[ R_0 R_1 C_1 + R_0 R_2 C_2 + R_1 R_2 C_2 + R_2 R_1 C_1 = \frac{k_5 - k_3}{1 - k_1 - k_2} \]  

As the sampling interval is short, for example one second, the change of the open-circuit voltage can be ignored in the process of the charging and discharging, namely

\[ \Delta U_{OCV}(k) = U_{OCV}(k) - U_{OCV}(k-1) = U_{OCV}(k-1) - U_{OCV}(k-2) \approx 0 \]  

So Eq. (7) can be simplified as Eq. (14)
\[ U_t(k) = k_0 + k_1 U_t(k-1) + k_2 U_t(k-2) + k_3 i_t(k) + k_4 i_t(k-1) + k_5 i_t(k-2) \]  \hspace{1cm} (14)

where \( k_0 = (1 - k_1 - k_2) U_{\text{acc}}(k) \).

Considering that neural networks have a good fitting effect on nonlinear functions, the linear neural network shown in Fig. 3 is employed to identify the model parameters.

![Neural network](image-url)

**Fig. 3** Neural network for model parameter identification.

The linear neural network consists of the following 4 parts.

1. Input vector \( x = [U_t(k-1), U_t(k-2), i_t(k), i_t(k-1), i_t(k-2)]^T \).
2. The weights \( w = [k_1, k_2, k_3, k_4, k_5] \).
3. The biases \( b = [k_0] \).
4. Output signal \( U_t = wx + b \).

According to the gradient descent method, the iterative algorithm of parameters is shown as:

\[
J(w,b) = (U_t(k) - \bar{U}_t(k))^2
\]  \hspace{1cm} (15)

\[
k_1(k) = k_1(k-1) - \eta \frac{\partial J(w,b)}{\partial w} \frac{\partial w}{\partial k_1}
\]  \hspace{1cm} (16)

\[
k_2(k) = k_2(k-1) - \eta \frac{\partial J(w,b)}{\partial w} \frac{\partial w}{\partial k_2}
\]  \hspace{1cm} (17)

\[
k_3(k) = k_3(k-1) - \eta \frac{\partial J(w,b)}{\partial w} \frac{\partial w}{\partial k_3}
\]  \hspace{1cm} (18)

\[
k_4(k) = k_4(k-1) - \eta \frac{\partial J(w,b)}{\partial w} \frac{\partial w}{\partial k_4}
\]  \hspace{1cm} (19)

\[
k_5(k) = k_5(k-1) - \eta \frac{\partial J(w,b)}{\partial w} \frac{\partial w}{\partial k_5}
\]  \hspace{1cm} (20)

\[
k_0(k) = k_0(k-1) - \eta \frac{\partial J(w,b)}{\partial b} \frac{\partial b}{\partial k_0}
\]  \hspace{1cm} (21)
where $\overline{U}_r(k)$ denotes the estimated value of the terminal voltage, $J(w,b)$ stands for the error of the neural network and $\eta$ is the learning rate of the neural network.

3.3. Identification results

According to the model proposed in Fig. 4, the linear neural network is used to identify the first cycle data of lithium-ion battery under DST condition. The identified parameters (R0, R1, R2, C1, C2 and Uocv) are shown in Fig. 4.

![Graphs showing identified parameters](image)

**Fig. 4** Parameter values of the battery: (a) Ohmic Resistance, (b) Electrochemical-polarization resistance, (c) Concentration-polarization resistance, (d) Electrochemical-polarization capacitance, (e) Concentration- polarization capacitance, (f) Open-circuit voltage.

As the battery was discharged between 3.6V and 4.2V under DST condition, the identified parameters fluctuate with discharge current obviously. In contrast to Fig. 4 (a-c), the magnitude of $R_1$ is larger than that of $R_0$ and $R_2$, which shows that the electrochemical polarization hinders the discharge process seriously, but the values of $R_0$, $R_1$ and $R_2$ decrease initially and increase afterwards with the discharging process. As illustrated in Figs. 4d and 4e, the variation trends of $C_1$ and $C_2$ are opposite to that of $R_1$ and $R_2$.

In order to analyze the changes of battery parameters in the process of battery cycle decay, battery parameters of five cycles are selected for comparison, as described in Fig. 5. As seen in Fig. 5 a, the ohmic resistance ($R_0$) increases significantly as the battery fades. From Fig. 5 (b-e), because the polarization resistance and the polarization capacitance are greatly affected by the internal electrochemical reaction of the battery, it does not increase strictly with the decay of the lithium battery. It can be drawn from the above analysis that ohmic resistance ($R_0$) can reflect the state of battery life decay, so R0 can be used as one of the input parameters of the SOC estimation model.
4. SOC estimation algorithm based on long-short term memory network

As compared with traditional neural network, the recurrent neural network can be interconnected and interacted with each other, so it can be used to predict sequence data. At the same time, recurrent neural network memorizes the results of the previous computation and applies it to the current output, that is, the nodes between the hidden layers are connected and the inputs of hidden layer includes the output of the input layer and the last output of the hidden layer. The structure of recurrent neural network is shown in Fig. 6.

However, as the gradient transferring of traditional RNN is a multiplication process, the gradient will explode or diffuse during backpropagation, which will be difficult to converge to the optimal solution of the problem. For the purpose of overcoming the problems of traditional RNN gradient explosion or
gradient dispersion, the structure of traditional RNN is improved by replacing the hidden layer with memory cell, which introduces a long-short term memory (LSTM) network. The architecture of LSTM network is shown in Fig. 7.

![Fig. 7 Structure of LSTM network.](image)

It can be seen from the figure that the memory cell includes the forget gate, the input gate, the memory cell and the output gate. The forget gate allows the LSTM network to forget or rewrite the information to the memory cell. Because the LSTM network can work by combining parameters of adjacent time, it avoids the abnormal SOC estimation value caused by the exception of the single parameter and makes the estimated value of SOC more stable. Temperature has a great influence on batteries, but it changes little in a specific period of time, and the temperature of each part of the battery is not consistent. Thus, selecting temperature as an input of the model leads to big errors. As shown in Table 1, the effect of temperature on battery performance can be reflected in the change of battery capacity [27], and the discharges capacity shows higher with the increase of the temperature. So the residual capacity of the battery is considered as an input parameter to reflect the effect of temperature on the performance of the battery.

| Temperature(℃) | -15 | -10 | -5  | 0   | 25  | 45  |
|----------------|-----|-----|-----|-----|-----|-----|
| Capacity(Ah)   | 1.128 | 1.461 | 1.747 | 1.941 | 2.318 | 2.375 |

In order to utilize the memory function of the LSTM network and consider the influence of working conditions and battery life decay on the precision of SOC estimation, terminal voltage, residual capacity, current, previous estimated SOC and ohmic resistance of consecutive three seconds are selected as an input vector of the LSTM network. That is, the input vector is defined as $i_t = [V_{t}, R_0[t], A[t], AH[t], SOC[t-1], V_{t+1}, R_0[t+1], A[t+1], AH[t+1], SOC[t], V_{t+2}, R_0[t+2], [t+2], Ah[t+2], SOC[t+1]]$.

The structure of the model estimating SOC is shown in Fig.9. The model includes the following five parts: (1) input layer, (2) the full-connected layer between the input layer and the LSTM network, (3) LSTM network, (4) the full-connected layer between the LSTM network and the output layer, (5) output layer.

![Fig. 8 Structure of SOC estimation algorithm based on long-short term neural network.](image)
Combining Fig. 7 and Fig. 8, the mathematical expressions of SOC estimation algorithm are represented as:

\[ x_t = i_t w_i + b_i \]  
\[ f_t = \sigma(w_f[h_{t-1}, x_t] + b_f) \]  
\[ \phi_t = \sigma(w_i[h_{t-1}, x_t] + b_i) \]  
\[ \tilde{C}_t = \tanh(w_c[h_{t-1}, x_t] + b_c) \]  
\[ C_t = f_t C_{t-1} + \phi_t \tilde{C}_t \]  
\[ O_t = \sigma(w_o[h_{t-1}, x_t] + b_o) \]  
\[ h_t = O_t \tanh(C_t) \]  
\[ y_t = h_t w_k + b_k \]

Where \( i_t \) is the input vector; \( w_i \) and \( b_i \) are values of the weight and bias between the input layer and the LSTM network at time \( t \), respectively. \( h_{t-1} \) is the output value of LSTM network at the previous time; \( w_f, w_i, w_o \) and \( b_f, b_i, b_o \) are weight values of the forget gate, the input gate, the memorize unit and the output gate, respectively; \( b_c \) is bias of the forget gate, the input gate, the memorize unit and the output gate, respectively; \( f_t, \phi_t, \tilde{C}_t \) and \( O_t \) are output values of the forget gate, the input gate, the memorize unit and the output gate, respectively; \( C_t \) is the state of LSTM network at the current time; \( h_t \) is the output value of LSTM network at the current time; \( w_k \) and \( b_k \) are values of the weight and bias between the LSTM network and the output layer; Finally, \( y_t \) is value of the estimated SOC at the time of \( t \).

According to the above-mentioned model, the QCT datasets of the battery (1st, 10th and 20th cycle) are used to train the LSTM network. Meanwhile, the QCT dataset of the battery (170th cycles) is utilized as verification-data to verify the model. The trained LSTM network is used to estimate the cyclic data of batteries under QCT condition (except for the trained data) and the estimated error is shown in Fig. 9a. As illustrated in Fig. 9, the average estimation error of every cycle is less than 1.6\%, so the LSTM network is suitable for the change of whole battery life decay process. To test the adaptability of the trained model to different working conditions, the DST datasets of the battery are estimated by the trained LSTM network and the estimated error is described in Fig. 9b. It can be seen from the figure that the corresponding average estimation error of every cycle is below 1.2\%.

Fig.9. SOC estimation error under working conditions: (a) QCT condition. (b) DST condition.
The data of the QCT datasets of battery at the different temperatures (0°C, 25°C, 45°C) are used to verify the adaptation of LSTM model. The estimated results are shown in Fig. 10. As illustrated in Figs. 10a, 10c and 10e, the curve of estimated value basically coincides with the curve of true value. However, the error is relatively large when the current changes greatly, which can be seen in Figs. 10b, 10d and 10f. It is clear that the estimation error is less than 2%. This indicates that the model can estimate the data at different temperatures accurately, and the capacity can better reflect the effect of the temperature on battery performances.

![SOC estimation curve and SOC estimation error curve of single cycle under DST condition: (a) SOC estimation curve (0°C), (b) SOC estimation error curve (0°C), (c) SOC estimation curve (25°C), (d) SOC estimation error curve (25°C), (e) SOC estimation curve (45°C), (f) SOC estimation error curve (45°C)](image)

**Fig.10.** SOC estimation curve and SOC estimation error curve of single cycle under DST condition:
(a) SOC estimation curve (0°C), (b) SOC estimation error curve (0°C), (c) SOC estimation curve (25°C), (d) SOC estimation error curve (25°C), (e) SOC estimation curve (45°C), (f) SOC estimation error curve (45°C)

5. **Conclusion**
A novel SOC estimation method is proposed in this paper. The main conclusions are summarized as:

1. The linear neural network is employed to identify the parameters of the second-order equivalent circuit model. According to the identified results, the ohmic resistance increases with the battery life decay, therefore, it can be used as one of the input parameters of the model.
(2) Considering the effects of temperature, working conditions and battery life decay on SOC estimation, the LSTM network is established for SOC estimation. Meanwhile, aging cycle experiments are conducted under working conditions to collect the datasets to train and verify the LSTM network.

(3) The SOC estimation algorithm has a good robustness against life decay and working conditions. When the battery fades under QCT condition, the average estimation error of every cycle is less than 1.6% and the maximum estimation error is less than 2.5%.

(4) The SOC estimation algorithm has a good robustness against different temperatures. The maximum estimation error is less than 2% at different temperatures (0°C, 25°C, 45°C).

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