State of Charge Estimation of Lithium-ion Battery Based on Improved Recurrent Neural Network

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Abstract. Aiming at the problem of gradient disappearance and gradient explosion in the recurrent neural network (RNN) algorithm in the battery estimation model, this paper proposes a state of charge (SOC) estimation model developed using an independent recurrent neural network (IndRNN). Firstly, the Thevenin equivalent model of the battery is established, and the parameters of the equivalent model are identified through experiments. Then, the Relu activation function is introduced into the RNN to separate the neurons in each layer. Finally, the model was trained on various experimental data sets collected from the lithium iron phosphate battery experimental platform under different discharge conditions. Without any prior knowledge about the battery interior, the proposed battery model successfully characterizes the non-linear behavior of the battery. The results show that under different discharge conditions, IndRNN is better than RNN in terms of maximum error, the mean error, and the root mean square error (RMSE), which greatly improves the accuracy of SOC estimation.

1. Introduction
With the development of the times, people's attention to new energy is gradually getting people's attention. Among them, the development of new energy vehicles is particularly rapid, especially the power battery pack plays an important role in new energy vehicles, and its health and use status directly affect the service life and performance of new energy vehicles. Among the common battery pack models, lithium-ion batteries have the characteristics of high electric energy density and fast charging and discharging speeds. Therefore, most new energy vehicles on the market use lithium-ion battery packs as their energy source. Common lithium-ion battery cell voltage and current cannot meet the requirements of loads, and they are mostly used in series and parallel in actual applications. This also brings about the imbalance between the battery cells, usually by establishing a battery management system[1] (BMS) to monitor the state of the battery so that the entire battery pack can work more safely and effectively. An important indicator based on BMS is the SOC of the battery. SOC directly determines the number of cycles of the battery and the efficiency of the entire battery pack.

It is important to obtain an accurate battery pack SOC, but the SOC cannot be directly measured. Obtaining the SOC of a battery pack is mostly an estimation method[2]. The most commonly used measurement data-driven techniques are artificial neural network (ANN), genetic algorithm (GA), fuzzy logic (FL) and support vector machine (SVM). In this model, genetic algorithm identifies the battery model parameters online, and provides the obtained parameters to the Coulomb counting method to improve the accuracy of SOC estimation. In the FL-based SOC prediction, the data set obtained by the Coulomb counting method is used for SOC prediction[3] SVM uses various kernel functions and regression algorithms to convert a nonlinear system model into a linear system model[4]. Neural network
is a biologically-inspired calculation method that has been successfully used to solve many problems related to battery\textsuperscript{[5]}, such as battery model parameter identification, SOC estimation, and state of health (SOH) estimation. Traditional neural network architectures, include feedforward neural network (FNN) and backpropagation neural network (BPNN).

In neural networks, SOC estimation is achieved by offline training of the network using experimental data under different ambient temperature conditions. A single-layer neural network is used to estimate SOC with battery parameters, voltage and current, and experimental data collected from the laboratory are used to obtain high accuracy after training. Although many successful research results of FNN and BPNN based on SOC estimation methods have been proposed, they cannot solve many problems. In recent years, data-driven SOC estimation based on deep learning has attracted the attention of researchers\textsuperscript{[6]}. Different from other neural networks, this article introduces a robust and accurate battery model for SOC estimation developed using IndRNN. To achieve the purpose of improving the estimation accuracy.

2. System modeling and parameter identification

2.1. Establishment of battery model

There are many battery models, including Rint equivalent model, Thevenin equivalent model, and second-order RC equivalent model. The main way is to use capacitors, resistors and other components to form a model describing the battery. The Rint equivalent model mainly simulates the internal resistance of the battery, which is quite different from the actual situation. The Thevenin equivalent model adds a set of RC circuits on the basis of the Rint equivalent model to better simulate the polarization phenomenon of the battery. The structure of the model design is simple, and the parameters involved in the algorithm are few. Compared with the Thevenin equivalent model, the second-order RC equivalent model adds a set of RC loops to represent electro-chemical polarization and other phenomena, with higher accuracy, but the design model involves more parameters, higher algorithm complexity, and structure. It is complicated and often takes up more resources of the control system. Based on this, this paper chooses Thevenin equivalent model to simulate battery characteristics. The Thevenin equivalent model is shown in Figure 1. \( V_b \) is the open circuit voltage of the battery, \( C_1 \) is the battery polarized capacitor, \( V_{c1} \) is the terminal voltage of the polarized capacitor, \( R_i \) is the internal ohmic resistance of the battery, and \( V_\text{oc} \) is the terminal voltage across the internal resistance. \( R_i \) is the battery polarization resistance, \( V_0 \) is the load Port voltage of the battery, and \( I_o \) is the battery load Current.

![Figure 1. Thevenin equivalent model of the battery](image)

According to Kirchhoff's law, the equation of state of Thevenin equivalent model can be obtained, as shown in the following equation (1-4).

\[
V_0(t) = V_b(t) - V_{c1}(t) - V_{oc}(t)
\]

\[
\frac{dV_{c1}}{dt} = \frac{V_{c1}}{C_1} + \frac{I_o}{C_1R_i}
\]

\[
V_b = f[soc(0) - \int_0^t \frac{i_o dt}{C_n}]
\]
Where $C_n$ is the rated capacity of the battery.

$$V_n = R_i I_o$$  \hspace{1cm} (4)

Comprehensive analysis of the above equation and discretization operations on them, equation (5) and (6) can be obtained.

$$\begin{bmatrix} V_{c1,k+1} \\ S_{oc,k+1} \end{bmatrix} = \begin{bmatrix} 1 - \frac{T}{R_i C_1} & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} V_{c1,k} \\ S_{oc,k} \end{bmatrix} + \begin{bmatrix} \frac{T}{C_1} \\ \frac{T}{C_n} \end{bmatrix} I_{o,k}$$ \hspace{1cm} (5)

Where $T$ represents the system sampling period.

$$V_{a,k} = \begin{bmatrix} 1 & 1 \\ 1 & V_{c1,k} \end{bmatrix} - R_i I_{o,k}$$ \hspace{1cm} (6)

2.2. Parameter identification

In the laboratory, set up a battery experiment platform. The battery used is a lithium iron phosphate battery with a capacity of 20Ah and a rated voltage of 3.2V. The battery is charged and discharged at the load end. The battery test experiment platform is shown in Figure 2. The specific operation method is as follows. Charge and discharge the battery at a current of 1/20C at a room temperature of 25℃. The charge cut-off voltage is 3.65V and the discharge cut-off voltage is 2.8V. The average value of the two sets of data obtained is used as a relationship diagram, as shown in Figure 3.

![Battery test experiment platform](image1.png)

![SOC-OCV fitting curve diagram](image2.png)

3. Introduction of algorithm

In recent years, data-driven SOC estimation based on deep learning has attracted the attention of researchers. Unlike other neural networks, RNN use an internal cell to predict output by analyzing the time dependence of previous input data and current input features. Therefore, the output of a particular neuron depends not only on the current input, but also on the output of the previously hidden state. Based on the time step, RNN can effectively retain the history of previous information to predict future output. Their current output values are predicted based on the history of past output and their current input over time.

Most of the existing data-driven technologies cannot provide good SOC estimation accuracy. This is because the current battery parameters are only considered to estimate the SOC, however, the past battery parameter values must be considered for estimation. Therefore, SOC estimation must be regarded as a time series problem, rather than increasing the complexity of a non-ordered series problem that increases the sequence dependence between input variables. The resulting gradient attenuation makes it difficult to capture the long-term dependent function of a single neuron, which leads to the problem of gradient disappearance and gradient explosion. Therefore, in order to achieve a robust and
accurate estimation of SOC. This article proposes a method using IndRNN technology to connect neurons in a specific layer to different layers, but they are independent of each other. Therefore, each neuron in a particular hidden layer only receives its past information, rather than receiving information from all hidden layer neurons. The main reason for choosing IndRNN for SOC estimation is to enable the network to obtain knowledge of long-term dependence and correct the gradient problem. A basic IndRNN unit structure is shown in Figure 4.

By introducing the Relu activation function, the neurons in each layer are separated. Make certain modifications on the basis of RNN to get the algorithm of IndRNN, as shown in equation (7).

\[ h_t = \sigma(W_{x_t} + u \odot h_{t-1} + b) \]  

Among them is the ReLU activation function, \( W_{x_t} \) is the weight matrix between the input layer and the hidden layer, \( u \) is the cyclic weight vector, and \( b \) is the bias vector of the hidden layer. The activation function ReLU can be defined as in equation (8).

\[ \sigma = f(x) = \begin{cases} x, x \geq 0 \\ 0, x < 0 \end{cases} \]  

The loss function \( L_s \) after each forward conduction is shown in equation (9).

\[ L_s = \frac{1}{m} \sum_{t=1}^{m} |s_t - s_t'| \]  

At time \( t \), each neuron will take the input at this moment and its own state at time \( t-1 \) as the total input. Therefore, IndRNN can make each neuron process a space independently, which makes it easier to meet the requirements of visualization. The equation for the gradient is shown in equation (10).

\[ \frac{\partial J_n}{\partial h_{n,t}} = \frac{\partial J_n}{\partial h_{n,T}} \frac{\partial h_{n,T}}{\partial h_{n,t}} = \frac{\partial J_n}{\partial s} \prod_{k=t}^{T-1} \sigma_{n,h_{k+1}} u_n = \frac{\partial J_n}{\partial h_{n,T}} \prod_{k=t}^{T-1} \sigma_{n,h_{k+1}}. \]  

Compared with the traditional RNN, the continuous product operation is no longer an operation on the matrix, but an activation function is used to separate the cyclic weight coefficients. Through the above equation (7-10), the training of the IndRNN network can be completed, and an IndRNN system framework can be established, as shown in Figure 5.
4. Experimental verification
In this experiment, 10,000 sets of data were measured in the laboratory, of which 5,000 were used as the training data set for training, and the remaining 5,000 were used as the test data set to test the neural network training results, and then the error rates of the two were compared. Each data set is composed of important battery parameters, such as current, voltage, battery capacity, temperature and power recorded every 1s interval. The parameters of the input layer include battery voltage ($V_i$), current ($I_i$) and temperature ($T_i$) at time step $t$. Each neuron in the cyclic hidden layer represents that there are several neurons $(k)$ from $h(t)$ to $h(k)$. The final output of IndRNN is the estimated battery SOC at time step $t$. The overall process involved in battery SOC estimation based on IndRNN is shown in Figure 6, and the flowchart for designing battery SOC estimation based on IndRNN is shown in Figure 7.

![IndRNN architecture for estimating SOC](image)

![Flow chart of SOC estimation with IndRNN](image)

During the experiment, the proposed SOC estimation model is realized using Tensorflow machine learning framework with python and keras in Intel Core i7-6700HQ CPU at 2.60GHz as a clock speed and 16GB RAM. In the training phase, experimental data obtained through drive cycles into the IndRNN network to analyze the association among different battery parameters. After the constructive IndRNN network training process, SOC can be estimated by providing laboratory data acquisition as inputs to the network. The input layer includes time step battery voltage ($V_i$), current ($I_i$) and temperature ($T_i$).

The SOC state generated by the network is used as an output, and the hidden layer is updated using equation (7). It can be seen from Figure 6 that the input layer of the IndRNN neural network selected in this paper has 3 neurons, the hidden layer is set to 1500 neurons, and the output layer has 1 neuron. We configured the appropriate hyper parameters and trained by Adam optimizer for the network, so as to reduce the error rate of SOC estimation.

This article uses three evaluation indicators, namely maximum error, the mean error, and the root mean square error (RMSE). As shown in equation (11-13).

$$\text{Max} = \max \left| s_i - s'_i \right|$$ (11)

$$\text{Mean} = \frac{1}{m} \sum_{i=1}^{m} \left| s_i - s'_i \right|$$ (12)

$$\text{RMSE} = \left( \frac{1}{m} \sum_{i=1}^{m} (s_i - s'_i)^2 \right)^{\frac{1}{2}}$$ (13)

where $m$ represents data point length, $s_i$ indicates actual SOC value and $s'_i$ is the estimated SOC at time step $t$.

5. Results and analysis
This article will list the two results produced by the two experiments performed under different discharge
methods, and then compare and analyze the two different neural network SOC estimation results, and use the RNN algorithm and this algorithm to estimate the lithium battery SOC. The comparison of the SOC estimation results between the algorithm and the algorithm in this paper is shown in Figure 8, and the SOC estimation error curve is shown in Figure 9.

![Figure 8. Comparison of SOC estimation results under constant current discharge](image)

![Figure 9. Comparison of SOC estimation error under constant current discharge](image)

The estimation result of battery SOC under variable working conditions is shown in Figure 10, and the comparison of SOC estimation error is shown in Figure 11. The laboratory changed the conditions of discharge current and temperature to produce variable working conditions for experiments.

![Figure 10. Battery SOC estimation results under variable operating conditions](image)

![Figure 11. Comparison of battery SOC estimation error under variable working conditions](image)

In the case of different discharge rates, the three evaluation indicators of the two algorithms are shown in Table 1.

| Condition          | Model   | Maximum(%) | Mean(%)  | RMSE(%) |
|--------------------|---------|------------|----------|---------|
| constant current   | RNN     | 1.3225     | 0.9824   | 1.8542  |
| discharge          | IndRNN  | 0.7356     | 0.3895   | 0.8625  |
| variable duty      | RNN     | 2.8965     | 1.9654   | 3.7589  |
| discharge          | IndRNN  | 1.1257     | 0.7245   | 1.8256  |

In Figure 8 and Figure 9, in the constant current discharge process, in the early stage of discharge, the SOC estimation curve and the ideal value coincide relatively high, and the error rate of IndRNN is slightly lower than that of RNN. In the later stage of discharge, the RNN's estimated deviation value of SOC accumulates over time, and the error becomes larger and larger. The accuracy of the IndRNN algorithm is obvious. The error will slowly converge to less than 1% in the later stage. The battery is close to the discharge limit in the later stage, and the internal chemical environment is more complicated. The error rate at this time is also within a reasonable range.

In Figure 10 and Figure 11, the SOC state will fluctuate during the variable working condition discharge process. The two algorithms in the early stage have good follow-up performance, and the
RNN will be more and more affected by the cumulative error in the later stage.

In Table 1, it can be seen that under different discharge rates, the maximum error, the mean error, and the RMSE of the IndRNN algorithm are controlled within a smaller range. And it has good adaptability and correction function, which can converge the error rate.

6. Conclusion

This paper proposes a data-driven deep learning method using IndRNN architecture to estimate the SOC of lithium iron phosphate batteries. The experimental data collected from the laboratory is used for training and testing. Two experimental analyses were carried out to prove the effectiveness and advantages of the proposed battery model for SOC estimation and to verify the accuracy of the model under different discharge conditions. The results show that under the two test conditions, the average RMSE is 1.3441%, and the average maximum absolute error is 0.5570%, which proves the effectiveness of the proposed SOC estimation method. In addition, the maximum error produced during the entire test is only 0.9306%, which is far below the acceptable SOC error range of the project. Due to its high accuracy, the proposed SOC estimation model using IndRNN can be applied to the BMS of modern electric vehicles. In the future, by building a larger data set, the SOC estimation accuracy can be further improved.

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