

SOC Prediction for Lithium Battery Via LSTM-Attention-R Algorithm

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Abstract: New energy vehicles are developing rapidly in the world, China and Europe are vigorously promoting new energy vehicles. The State of Charge (SOC) is circumscribed as the remaining charge of the lithium battery (Li-ion), that indicates the driving range of a pure electric vehicle. Additionally, it is the basis for SOH and fault state prediction. Nevertheless, the SOC is incapable of measuring directly. In this paper, an LSTM-Attention-R network framework is proposed. The LSTM algorithm is accustomed to present the timing information and past state information of the lithium battery data. The Attention algorithm is used to extract the global information of features and solve the problem of long-term dependency. To ensure the diversity of feature extraction, the Attention algorithm in this paper uses multi-headed self-attentiveness. The CACLE dataset from the University of Maryland is used in this paper. Through the training of the model and the comparison, it is concluded that the LSTM-Attention-R algorithm networks proposed in this article can predict the value of SOC well. Meanwhile, this paper compares the LSTM-Attention-R algorithm with the LSTM algorithm, and also compares the LSTM-Attention-R algorithm with the Attention algorithm. Finally, it is concluded that the accomplishment of the network framework contrived is superior to the performance of these two algorithms alone. Finally, the algorithm has good engineering practice implications. The algorithm proposed provides a better research direction for future parameter prediction in the field of lithium batteries. It has a better theoretical significance.

Keywords: Attention Mechanisms; Long Short-Term Memory; Lithium Battery; State of Charge; Deep Learning.

1. Introduction

New energy vehicles are developing rapidly in the world [1, 2], China and Europe are vigorously promoting new energy vehicles. The main reasons are the shortage of fossil fuels and worsening air pollution [3]. What's more, the carbon dioxide emitted by cars has caused the global temperature to rise and extreme weather to occur frequently. New energy vehicles, especially pure electric vehicles [4]. It can run entirely on electricity. Its main advantages are no use of fossil energy and no polluting automobile exhaust [5]. This is of great significance for environmental protection and reducing the consumption of oil resources [6].

The most important cost of an electric vehicle is the lithium-ion battery, which accounts for almost a third of the cost of a pure electric vehicle. Therefore, lithium-ion battery is the core component of pure electric vehicle Battery management system is the core unit of lithium-ion battery pack management. Lithium-ion batteries are the power source for electric cars. The SOC of lithium-ion battery is the most important indicator to measure the remaining charge. The value of SOC directly determines the driving range of electric vehicles. The value of SOC also reflects the overall performance of lithium-ion batteries. Its performance directly determines the performance of electric vehicles. Its safety directly determines the safety of electric vehicles. More importantly, SOC is the main parameter of SOH estimation. The inaccurate SOC estimation determines that many parameters of lithium-ion battery cannot be calculated. To sum up, accurate prediction of SOC is a very critical and meaningful research direction [7].

The estimation of SOC [9, 10], which is the most important in Li-ion batteries. Because the SOC indicates how much power is left in the lithium battery, it determines how much power the lithium battery can continue to discharge. Inaccurate estimation of SOC can lead to miscalculation of electric vehicle driving range. Furthermore, SOC is the basis for other performance indicators, such as SOH estimation [6, 11], fault diagnosis [12], thermal management, etc., which are all based on SOC. Therefore, the estimation of SOC is a very momentous research topic for Li-ion battery. In contrast, the composition of Li-ion battery [13] itself is complex. In the charging process, Li-ion battery is converted from electrical energy to chemical energy. In the procedure of discharge, the lithium battery is converted Conversion from chemical to electrical energy [14]. And in the resting process, the lithium battery itself has a self-discharge effect. All these characteristics make the estimation of SOC of LiBs very difficult.

Currently, the research for SOC estimation of LIBs (Li-ion batteries) is a very hot direction. Researchers in various countries around the world have conducted relatively in-depth research in this area [15]. There are three main directions to study the estimation of Li-ion battery SOC. The first direction is on account of the simple measurement method. The main basis of this tactic is that the SOC of Li-ion battery and the open circuit voltage have a very large positive correlation. And with the discharging process during the driving of the vehicle, the current will continue to discharge, and the integration of current discharge over time is the amount of power discharged. However, the disadvantages of this method are also very obvious. First, the measurement of the open

circuit voltage itself is very difficult. Only very specialized research institutions can measure it. Secondly, The process of measuring the open-circuit voltage itself is time-consuming [16]. Each short time discharge requires 2 hours of resting before the open circuit voltage value can be measured. Third, there is a cumulative error in the ampere-time integration. As time goes by, the cumulative error of ATS integration will become larger and larger, which will lead to less and less exactitude of SOC estimation. Fourth, the battery will age with the increase in service life. The process of battery aging is not accounted for by the simple measurement method. The second direction is the model-based estimation method. This method is by modeling the LiBs. The SOC is capable of better estimated by accurate modeling. the goodness of the model directly determines the goodness of the estimation. The value estimated by the model is used as the estimated value of SOC of Li-ion battery. There are generally the following commonly used models. Electrochemical Model (EM). The P2D [17] model utilizes a group of coupled prejudiced differential equations to portray the lithium-ion concentration and possibility in the solid phase of the LiBs (Li-ion battery), and is the most widely used EM for appraisal the SOC of LiBs. The electrochemical model mainly reflects the internal chemical reaction mechanism of the battery and has high accuracy, but it is difficult to determine all the parameters and has great computational complexity and time-consuming. EIM [1].and EIS are a cell measurement technique proposed by Heaviside in 1894 and is commonly used to model electrochemical impedance circuits. The EIM can accurately describe the battery characteristics, but the matching process is difficult, complex, and unintuitive in practice. ECM [18] be accustomed to expound and imitate the dynamic peculiarity of the LiB, that treats the battery as a two-port network and exploits voltage, resistors, capacitors as well as other devices to form a circuit to resemble the internal peculiarities of the LiB. Various ECM models have been manipulated for the SoC computation of LiBs, such as Rint [19] model, Thevenin model, 2nd order resistor-capacitor parallel equivalence model, and PNGV model. The third direction is a data-driven approach. The term "data-driven impression method" refers to the process of directly estimating SOC from LiB data by measuring IR, voltage, current, as well as temperature. Data-driven SOC impression approaches frequently employ machine learning rostrums to spontaneously learn the network parameters and determine the relationship between battery parameters and SOC using intelligent algorithms due to the recent rapid growth of machine learning. Artificially intelligent artificial neural networks, SVM [20], and Extreme Learning Machine (ELM) [21] are all common machine learning techniques for SOC estimate.

In this paper, it proposes a new LSTM-Attention-R network framework. It is able to extract the temporal information of lithium battery features using Stacked LSTM networks. Meanwhile, adding Stacked Attention network can avoid the problem of long-term dependency of LSTM network. The added Stacked Attention network can better focus on the global information. The LSTM-Attention-R network architecture designed in this paper can well combine the advantages of the two networks and avoid their disadvantages. Through the performance comparison, the new network framework proposed in this paper is better than the LSTM network and Attention network, and the training error and testing error of are smaller.

2. Related Works

There are three methods to approximate the SOC to LiB [22]. The first method is the direct measurement method. The OCV [23] measurement method is more accurate, but requires specialized equipment for measurement, and the process of OCV measurement requires resting. Therefore, it is not too much used in practice, and is usually measured by manufacturers after special instruments. In addition, OCV measurement can be inaccurate with the avail of LiBs. This is because the increase in polarization internal resistance causes the previously measured OCV values to no longer be accurate. Wei Zhongbao [24] suggests that OCV values can be better measured by using a low-current method. Movassagh [25] presents a scheme for estimating SOC through the coulomb counting method. Wang Zuolu[26] has a practice for appraising the value of SOC by ECM model. The model-based SOC estimation method focuses on the lithium-ion battery as an equivalent circuit or electrochemical model. Choi Woosung [27] uses the EIS method to model the lithium-ion battery. Yang Fangfang [28] presents a new idea of mixing LSTM and UKF. Liu Xiangsi [29] uses the EM method to model the solid-state batteries. The SOC is then estimated by the model. The third method is based on a data-driven approach [30]. Data-driven approaches are a popular direction in LiBs SOC approximation at this stage. Zou Runmin [31] proposes a convolutional informer network-based procedure to estimate the SOC of lithium-ion batteries. Wu Lifeng [32] proposed an algorithm based on Attention-based encoder-decoder networks. By further modifying the Attention-based encoder-decoder networks algorithm, it can be applicable to the dataset of lithium-ion batteries. Tian Yong [33] proposes a method based on attentional sequence-to-sequence architecture. This method originates from the field of natural language processing. Li Jiarui [34] proposes a CNN+LSTM algorithm. By combining CNN and LSTM algorithms to extract features of lithium-ion battery data, SOC estimation is performed by CNN+LSTM. El Fallah, Saad [35] uses a very deep GRU network approach. Almaita, Eyad [8] proposed a technique to judge the SOC of a group of lithium-ion batteries using LSTM algorithm. Liu Yuefeng [36] proposed a method based on TCN along with Transfer Learning. This allows fine-tuning under the model trained by other researchers. The SOC can be reckoned by fine-tuning the parameters.

3. Methodology

3.1. Selection of Hyperparameters

The loss function is selected, and this article be associated with the regression problem, for that reason the two loss evaluation functions, MSE [10] and MAE, are generally used.

$$J_{mse}(w) = \frac{1}{NN} \sum_{nn=1}^{NN} (Y_{nn}(w, x) - O_{nn}(w, x))^2 \quad (1)$$

$$J_{rmse}(w) = \sqrt{\frac{1}{NN} \sum_{nn=1}^{NN} (Y_{nn}(w, x) - O_{nn}(w, x))^2} \quad (2)$$

$$J_{mae}(w) = \frac{1}{NN} \sum_{nn=1}^{NN} |Y_{nn}(w, x) - O_{nn}(w, x)| \quad (3)$$

Selection of the activation function.

$$f_{\sigma}(x) = \frac{1}{1+e^{-x}} \quad (4)$$

$$f_{tanh}(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (5)$$

$$f_{relu}(x) = MAX(0, x) \quad (6)$$

$$f_{mish}(x) = x * \tanh(1 + e^x) \quad (7)$$

The gradient descent algorithm chooses stochastic gradient descent. The weight update w formula is as follows.

$$w_{t+1} = w_t + \gamma \nabla_t J(w) \quad (8)$$

3.2. Attention Mechanisms

With the birth of Attention is all your need paper. Attention mechanism algorithms have gained further attention. The attention mechanism is an imitation that replicates human attention by taking into consideration the fact that the brain concentrates on one area at a time while reducing or even ignoring the attention of other areas. By varying the weights of the model's input features and emphasizing the more important influencing elements, attention enables the model to generate more accurate decisions. Figure 1 is a diagram of the attention mechanism. Neither LSTM nor GRU has completely solved the long dependency problem. The state of the present moment probably has a lot to do with the state of the n - m moment. Recurrent neural networks are all transmitted step by step through the state of the previous moment. The attentional mechanism is the ability to directly relate values of distant moments to the present moment. Mainly through Q, K, V these three characteristic matrices to calculate the attention score

$$Attention(Q, Source) = \sum_{i=1}^{L_x} Similarity(Q, K_i) * V_i \quad (9)$$

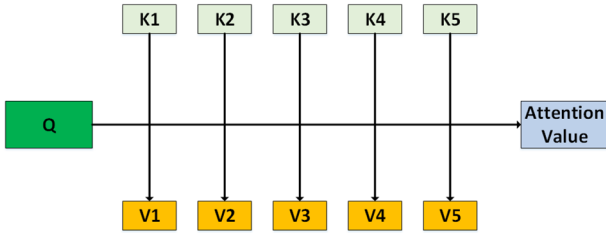


Figure 1. Diagram of attention mechanism

L_x presents the length of the Source. That is, the length of the data input to the attention mechanism. In the field of natural language processing, Source generally invites over the Embedding process. There are many ways to measure the similarity of Q and K. There are additive models, dot product models, and Cosine models. In addition, their similarity can also be learned by a multi-layer perceptron model. In this paper, we mainly use Scaled Dot-Product Attention.

$$Similarity(Q, K) = Softmax\left(\frac{QK^T}{\sqrt{d_n}}\right) \quad (10)$$

$$Attention(Q, K, V) = Similarity * V \quad (11)$$

d_n Stand for Scaled factor. This paper uses Multi-Head Attention mechanism. Multi-Head Attention is to use different W^Q, W^K, W^V to get different Attention, and finally stitch these Attentions together as output.

$$Head_h = Attention(QW_h^Q, KW_h^K, VW_h^V) \quad (12)$$

$$MHA(Q, K, V) = Concat(head_1, head_2 \dots head_h) \quad (13)$$

3.3. LSTM-Attention-R

LSTM-Attention network is a hybrid structure. It is a hybrid of Stacked LSTM network and Stacked Attention network. LSTM+ Attention network is used to extract temporal information by Stacked LSTM. Stacked Attention network is used to extract global information. When the layers

of Stacked LSTM network or Stacked Attention network are deeper, their performance should be superior. However, when the number of layers of Stacked LSTM network and Stacked Attention network is too many, the performance of the network not only does not become more superior, but also the gradient disappears. In order to better the number of stacked layers. In this paper, we design to fuse the LSTM-Attention network with the residual module in ResNet to form the LSTM-Attention-R network. The LSTM-Attention-R network improves the number of stacked layers of the Stacked LSTM network by adding the residual module to the Stacked LSTM network. The number of network layers stacked can be better extracted to the information features of the lithium battery. And with the stacked network depth can better extract and learn the high-dimensional features in the lithium battery features. This is more helpful to improve the estimation and prediction of the SOC of lithium battery. Secondly, in order to better stack the Stacked Attention network, this paper also fuses and stacks the Stacked Attention network and the residual module in ResNet. This can better stack the layers of Stacked Attention network.

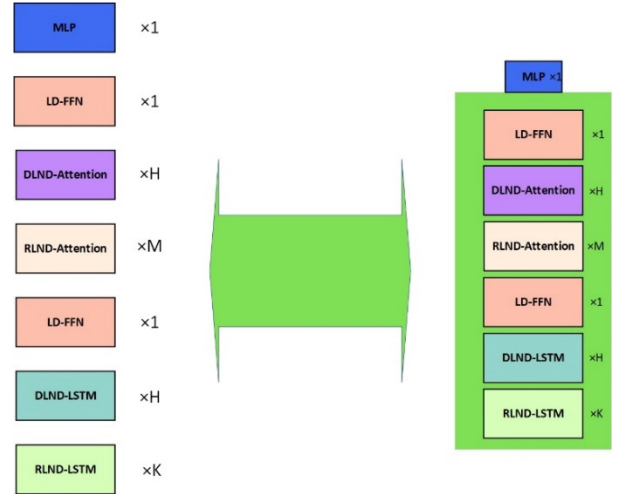


Figure 2. LSTM-Attention-R networks

4. Experiment

The data selected for this paper is the CACLE dataset from the University of Maryland. The CACLE dataset is a public dataset. Table 1 shows the basic parameters of lithium batteries. The battery model used in this paper is 18650-20R. The calculation of SOC of Li-ion battery is highly dependent on temperature and initial capacity. Therefore, in-depth testing is needed specifically for the initial capacity. In order to simulate the real situation of Li-ion battery in normal operation, each country has different standards to test Li-ion battery. The main ones are as follows: DST, FUDS, US06, BJDST. The main one used in this paper is BJDST. and since temperature also has a great influence on lithium batteries. So, the dataset used in this paper is at normal operating temperature of 25 degrees

Table 1. Parameters of lithium batteries

Battery Parameters	Specifications Value
Battery Type	INR 18650-20R
Capacity Rating	2000mAh
Cell Chemistry	LNMC/Graphite
Weight	45.0g
Dimensions(mm)	18.33±0.07mm
Length	64.85±0.15mm

These battery models also determine the maximum capacity of this lithium battery, as well as the platform voltage, the number of soul rings and other information. However, the SOC calculation is required to use the maximum initial capacity of the lithium battery. The test of the lithium battery is used by ArBin battery test platform. The initial capacity of the test, as well as current, voltage and other parameters are stored in an Excel table.

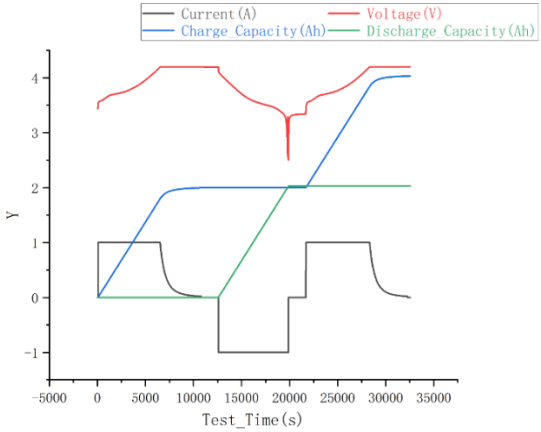


Figure 3. Test data of initial capacity of LiBs.

The process of charging and discharging the battery can be seen from the data. Figure 3 represents the test chart of the initial capacity. First, constant current limiting charging (CCCV) is performed. That is, constant current charging is performed at a current of 1A, and then trickle charging is performed during the voltage achieves the rated voltage. Until the current is less than a certain minimum value, then charging stops. Then it is left for a period of time, and then a constant current discharge of 1A is performed. When the voltage attains the minimum voltage required, the charging ends. After another resting period. The battery test platform continues to charge the battery until it reaches the rated voltage and then trickle charge is performed. The main purpose of trickle charging is to ensure the increase of charging capacity. During the charging process, the charging capacity is continuously increasing and the discharging capacity is kept constant. During discharging, the discharging capacity is continuously increasing and the charging capacity is kept constant. During the resting process, both charging capacity and discharging capacity are kept constant. The main purpose of resting is to achieve OCV stability. As can be seen from the graph, the voltage of the LIBs declines during the resting process.

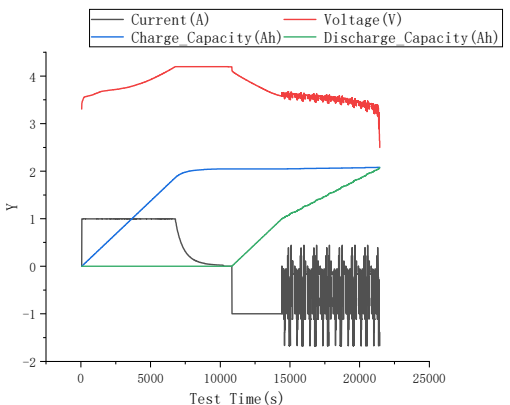


Figure 4. SOC test data at 50 percent under BJDST conditions

The BJDST working condition test was continued at a room temperature of 25 degrees Celsius for the battery. In the process of working condition test, there are divided into 50% SOC test case and 80% SOC test case.

As can be seen in Figure 4, the current is first charged at 1A. When the voltage reaches the rated value, then trickle charging is performed. When the trickle charge current is less than a certain value, the charging is stopped. After sitting for a period of time, Arbin's charge/discharge testbed then performs a 1A current discharge. When the discharged capacity reaches 50% of SOC. Stop discharging. Then conduct frequent charging and discharging. Finally, the capacity is discharged until it is finished.

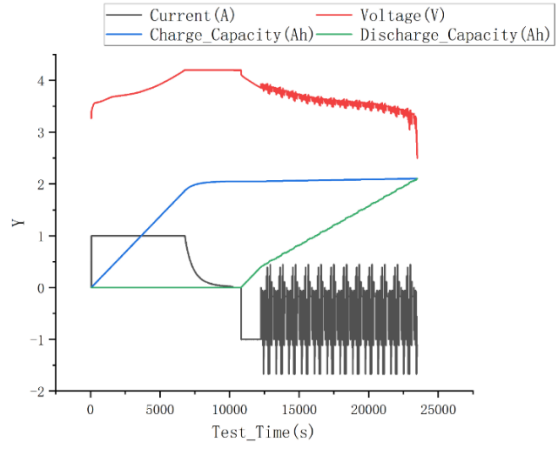


Figure 5. SOC test data at 80 percent under BJDST conditions

This can be seen in Figure 5. The current is first charged at 1A. Then, when charged to the rated voltage, trickle charging is performed to guarantee that the LIBs preserve be fully charged. The lithium battery is left to sit for a period of time. Then, Arbin's battery test rig then discharges at a current of 1A. When the discharge is 20%, which means the SOC is equal to 80, frequent charging and discharging is performed. When SOC is equal to 0, the discharge stops.

5. Results and Discussion

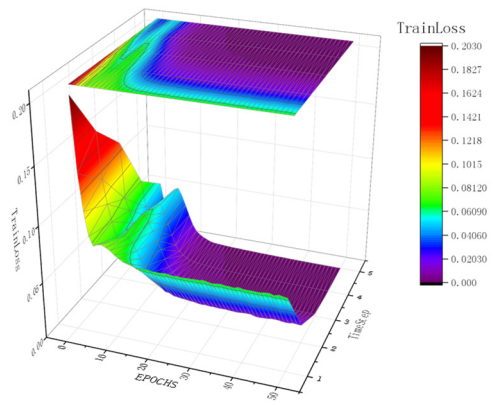


Figure 6. Train error at different values of TimeStep and different values of EPOCH

The testing of LiBs is itself a time series model. Therefore, the previous values have a strong influence on the values of the later values. This is equivalent to an autoregressive model, so it is more sensitive to TimeStep, and the number of EPOCHs. The thickness of the LSTM is chosen to be 64. The

depth of the LSTM is 2, and the depth of the Attention network is 2. There are 2 heads of Attention. In this paper, the values of TimeStep are set to 1,2,3,4,5 and the number of EPOCHs is also up to 50.

As can be seen from the figure 6, the training error is further decreasing as the number of EPOCHs continues to increase. This does not vary with the TimeStep. However, the results for the number of TimeStep are very interesting. When TimeStep is greater than or equal to 3, it puts up be seen that the results of the training error have started to flatten out. This indicates that the reduction of training error has flattened out as TimeStep increases. When TimeStep is 1, the utmost number of times of EPOCH corresponds to 50. the minimum training error is 0.06534. When TimeStep is 2 and the greatest number of EPOCHs amounts to 50, the minimum training error is 0.01581. When TimeStep is 3 and the supreme number of EPOCH remains 50, the minimum training error is 0.001799. When TimeStep is 4 and the paramount number of EPOCH is 50, the minimum training error is 0.001799. The minimum training error is 0.00033. When the value of TimeStep is 5 and the uttermost number of EPOCH endures 50, the minimum training error is 0.00014. However, it is often not the training error but the testing error that measures the performance of the algorithm. In this paper, the test error is still measured by setting the greatest number of EPOCH to 50. The values of TimeStep are from 1 to 5 at a time. This paper wants to select the most suitable model by different values of EPOCH and different values of TimeStep.

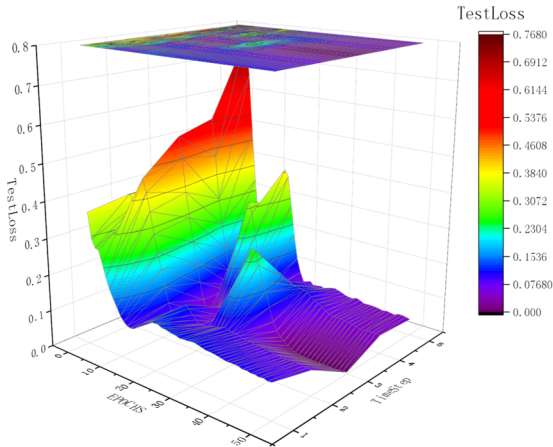


Figure 7. Test error at different values of TimeStep and different values of EPOCH

The figure 7 represents the test error values corresponding to different EPOCHs and different TimeStep. When TimeStep is 1, the test error of the model is relatively large compared to the other TimeStep values. However, the overall error fluctuation is not too large. When the value of TimeStep is 1, the minimum value of test error is 0.09081 when the maximum value of EPOCH is 50. It can also be seen from the figure that when TimeStep is 3, the test error has the smallest value compared to the other TimeStep. The minimum test error value is 0.001372. When the value of TimeStep is 5, it can be seen that the maximum error is the largest among the other TimeSteps. Moreover, the value of the test error is increasing sharply around EPOCH of 20, which indicates that the model is not very adaptable as well as generalized to lithium battery data. In contrast, this paper concludes that a TimeStep of 3 is the most suitable training model. The model with TimeStep of 3 is used

to predict the data of the test set, and the prediction results are shown as follows.

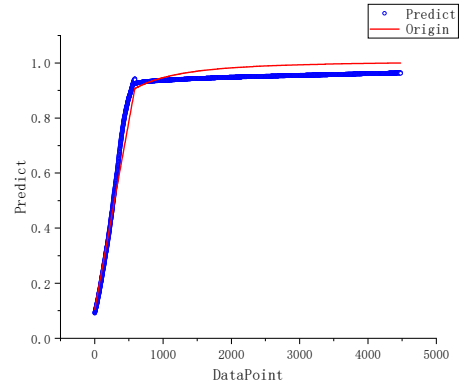


Figure 8. Predictions of the model when TimeStep is equals to 3

In the prediction of the results, it can be seen that the predicted trend of the model algorithm is the same as the trend of the true value, however, the average mean square error is used in the error calculation process. Figure 8 represents the model's predictions. This shows that this algorithm has great engineering practice significance. It can meet the requirements of engineering practice. The algorithm conceived in this article can be used in practical industrial sessions. It has the practical value of promotion. Over and above that, the algorithm designed in this paper is a combination of traditional RNN and attention model mechanism. The innovation by combining the algorithms. It shows that the direction has great research value. Therefore, the algorithm sketched has a relatively good theoretical value. This provides a more instructive idea for SOC prediction and SOH of LiB and fault state prediction. The combination of LSTM and Attention module in this paper further shows that the combined use of LSTM and Attention module is better than using LSTM alone. The use of LSTM algorithm can ensure that the model has certain temporal information extraction and temporal feature extraction. Using the Attention module can better solve the long-term dependency problem.

Table 2. Accomplishment comparison of different algorithms.

Id	Algorithm	TrainError (%)	TestError (%)
1	LSTM	2.4%	5.2%
2	Attention	4.6%	5.8%
3	LSTM-Attention-R	0.011%	0.98%

The LSTM-Attention-R algorithm has the best performance. Table 2 represents the performance comparison under different algorithms. This is because the LSTM algorithm can provide temporal information and features very well. The hidden variables of the previous states are guaranteed. However, LSTM cannot decipher the problem of long-term dependency, Attention module can puzzle out the complication of long-term dependency, Attention module can pay attention to both local information and global information. This can better ensure the flexibility of information feature acquisition. It naturally elucidates the conundrum of long-term dependency of LSTM. However, the Attention algorithm itself does not encode and acquire temporal information. The natural language processing domain ensures the inclusion of temporal information features only by further embedding the location coding. Therefore, it is theoretically

concluded that the LSTM-Attention-R algorithm is superior to either of these two algorithms. This provides a new research direction to straighten out the SOC prediction of lithium batteries. From the experimental consequences achieved, it can be seen that the results are indeed as hypothesized, and the advantages of both can be better combined and optimized. The proposed algorithm in this paper has great practical engineering significance.

6. Conclusion

This paper knuckles down to the appreciation and prediction of the SOC of a LiBs. the SOC itself is incapable of been measured directly. In this paper, an algorithm model combining LSTM and Attention is proposed. The algorithmic model proposed is able to predict the value of SOC relatively well. This shows that the LSTM-Attention-R algorithm model can avoid the long-term dependency problem well, and also ensure the embedding and extraction of temporal information features. For the LSTM-Attention-R algorithm, this paper also designs the effect of different TimeStep on this algorithm. The better value of TimeStep is obtained. Also, the predicted and estimated values of LSTM algorithm are compared in this paper. In addition, the estimation and prediction of the SOC of the power lithium battery using the simple Attention algorithm. The final results are derived. The LSTM-Attention-R algorithm has better performance than LSTM or Attention algorithm alone.

With the LSTM-Attention-R algorithm designed, the SOC estimation and prediction problem can be well solved. It can be seen from the test error. It has better engineering practice significance. By applying the algorithm in this paper to engineering practice, the problem of inaccurate SOC estimation can be better solved. the value of SOC characterizes the driving range of this pure electric vehicle. Simultaneously, the value of SOC is also the basis of SOH and fault state judgment. Therefore. The algorithm designed in this paper can better predict the driving range of pure electric vehicles. Also, the safety of the lithium battery PACK can be better ensured. This also ensures the safety of the pure electric vehicle. Most significantly, the algorithm is a combination of two different algorithmic models, which means that the Attention algorithm can be better applied to the field of Li-ion battery parameter prediction by combining with RNN algorithm. This has a relatively large theoretical significance. Also, the algorithm designed in this paper provides a new way of thinking and direction for future researchers in this fields.

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