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Review

Deep Learning in State of Charge Estimation for Li-ion Battery: A Review

Chen Zhong [1], Dawei Zhang [1,3]*, Peijuan XU [2] and Yiyang Tian [1]

[1] School of Automobile, Chang'an University;
[2] School of Transport Engineering, Chang'an University;
[3] State Key Laboratory of Traction Power, Southwest Jiaotong University;
* Correspondence: dwzhang@chd.edu.cn;

Abstract: As one of the critical state parameters of the battery management system, lithium battery state of charge (SOC) can provide an essential reference for battery safety management, charge/discharge control, and energy management of electric vehicles. To analyze the application of deep learning in electric vehicle power battery SOC estimation, this study reviewed the technical process, common public datasets, and the neural networks used, structural characteristics, advantages and disadvantages of lithium battery SOC estimation in deep learning method. First, the specific technical processes of the deep learning method for SOC estimation were analyzed, including data collection, data preprocessing, feature engineering, model training, and model evaluation. Secondly, the current commonly and publicly used lithium battery dataset was summarized. Then, the input variables, data sets, errors, and advantages and disadvantages of four types of deep learning methods, were concluded using the structure of neural network used for training as the classification criterion. Finally, the challenges and future development directions of lithium battery SOC estimation in deep learning method were explained.

Keywords: Electric Vehicles; Review; SOC Estimation; Deep Learning; Lithium-ion Battery

1. Introduction

With the intensification of global warming and climate anomalies caused by carbon dioxide emissions [1], it has become a worldwide consensus to reduce and control the production of fossil fuel-based fuel vehicles. Therefore, the accelerated transformation of vehicle electrification is an important trend in the current development, but a major obstacle to its wide application is the range limitation [2]. Lithium batteries, as the power source of most electric vehicles nowadays [3], have the advantages of high stability, high energy density, and long cycle life [4]. Nowadays, due to the increased demand for electric vehicles, the requirements for battery performance and energy management have increased; and the battery status, an important parameter of the battery management system [5], its accuracy is related to the rationality of energy distribution, length of the range, and safety of the battery.

State of Charge (SOC) is a more important parameter in the battery state parameters, indicating the remaining power of the battery, which is equivalent to the amount of fuel in a fuel car. However, the electrochemical reflection in lithium batteries is complex and very sensitive to temperature and material fatigue [6], and SOC is not a physical parameter that can be measured directly by instruments; currently, the value of SOC is usually estimated by measuring parameters with strong correlation (e.g. voltage, current, temperature, capacity, charge, etc.). The specific mathematical expression (1) for the ratio of the battery capacity in the current state to the battery capacity at full charge is as follows,

$$\mathrm{SOC} = \frac{C_{\mathrm{curr}}}{C_{\mathrm{full}}} \times 100\% \tag{1}$$

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where C_{curr} is the real-time battery capacity, and C_{full} is the battery state of its fully charged state. When the battery is fully charged, the SOC is 100%; and SOC is 0% when the battery discharge is completed [2].

Currently, there are two main types of approaches for lithium battery SOC estimation: model-driven and data-driven. The main idea of model-driven is to build models to estimate SOC values through scientific knowledge of lithium batteries, which are divided into the following three categories: electrochemical model [7-9], equivalent circuit model [10-13], and statistical mathematical models [14]. The data-driven method is to measure the data related to lithium batteries and then use the data to generate a model. There are two common types of filtering algorithms [13, 15-20]and machine learning, which is mainly divided into traditional machine learning and deep learning; fuzzy logic [21, 22], support vector machines [23], and neural networks [24, 25] are the current traditional machine learning methods commonly used for lithium battery SOC estimation. The advantage of model-driven is that it uses known scientific knowledge as the basis, which is reliable and explanatory; the disadvantage is that it needs to understand the knowledge of multiple disciplines, which takes a long time. The advantage of data-driven is that it does not require much multidisciplinary knowledge compared with model-driven and takes a short time; the disadvantage is that the accuracy of the model depends on the quality and quantity of the data, and many models are in the state of a black box, which is less interpretable than model-driven.

The main research themes of the lithium battery SOC estimation review are model-driven [26-29], data-driven [30, 31], model and data driven [32, 33], and machine learning [2, 34], but few reviews are focused on deep learning. In recent years, deep learning has been applied in computer vision, natural language processing, life science [35], and some important research results have been achieved [36]. In 2017, some scholars tried to apply deep learning to the lithium battery SOC estimation problem, which has some advantages over the previous methods in terms of time and accuracy.

This study reviewed the application of deep learning methods in lithium battery SOC estimation from four aspects. The first part is the technical process of deep learning method to estimate lithium battery SOC, the second part is about some high-quality public lithium battery data sets, and the third part is about different neural networks structure of deep learning in lithium battery SOC estimation problem application, the fourth part is to analyze and evaluate the characteristics of different neural networks as well as the future development of SOC estimation in deep learning method.

2. Process of SOC Estimation using Deep learning Method

The flow chart of the SOC estimation technology of lithium battery based on deep learning is shown in Figure1. The main process includes five processes: data collection, data preprocessing, feature engineering, model training, and model prediction.

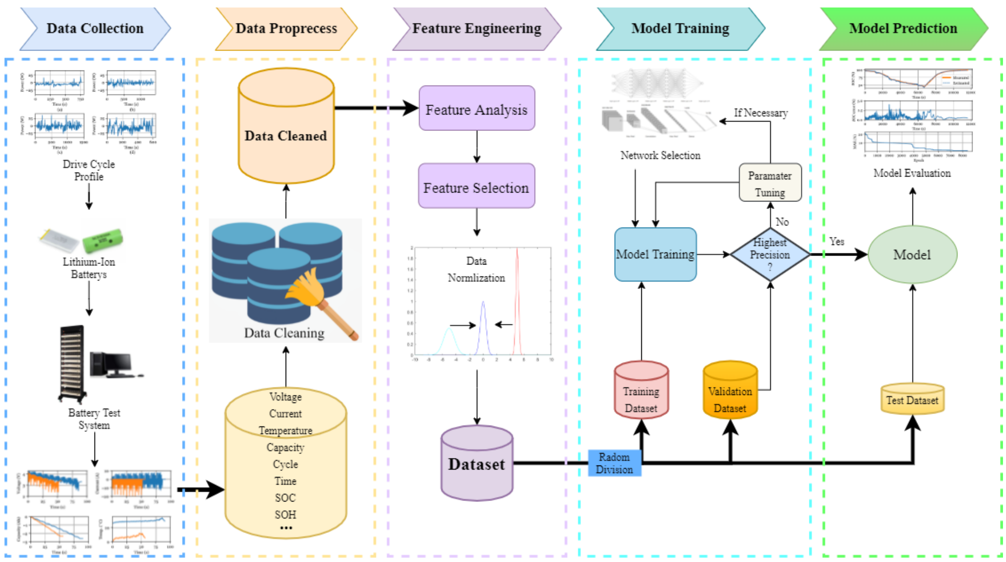

Figure 1. Flowchart of deep learning method for estimating SOC of li-ion battery

Data collection is a time-consuming part of the whole process. To simulate the state changes of lithium batteries in real driving conditions, the parameter changes caused by the load of lithium battery in driving conditions are generally recorded to form driving cycles, which are loaded on the tested lithium battery. Common drive cycles include DST (Dynamic Stress Test), US06, FUDS (Federal Urban Driving Schedule) [37], and BJDST (Bei Jing Dynamic Stress Test) [38]. Since the ambient temperature has a significant impact on the lithium battery, in order to simulate the state of the lithium battery at different temperatures, a thermal chamber is generally used as the temperature variable in the simulated lithium battery test. The original data measured by the instrument generally needs to be pre-processed, that is, data cleaning, which is because the test process has a certain probability of random conditions leading to missing data or the introduction of noise signals and other situations.

Feature engineering refers to analyzing or designing features that are strongly correlated with the SOC of lithium batteries based on the measured data, to reduce the difficulty in the next step of model training. Due to the different units of different units, the size of the value may be different or even very greatly; in model training, the neural network cannot recognize the change of the unit, and can only perform numerical operations. But variables with too large values will reduce the weight of variables with small values, which is not conducive to finding the relationship between the measured variable and the SOC of the lithium battery during model training, so the data is generally standardized, that is, a unified standard is selected to perform the numerical transformation on the data. The commonly used data normalization is the maximum-minimum normalization process, as shown in equation (2),

$$x_i^{'} = \frac{x_i - X_{Min}}{X_{Max} - X_{Min}} \qquad (2)$$

where, $x_i^{'}$ is the value of a variable after normalization, X_{Min} and X_{Max} is the minimum and maximum value of the variable. After the maximum-minimum normalization, the values of different unit variables are transformed between 0 and 1. Then the standardized feature data is randomly divided into the training set, validation set, and test set. The training set is used to train a model related to the lithium battery SOC with the feature data, the validation set is used to verify whether the parameters of the training set are reasonable to adjust the model parameters, and the test set is used to test the generalization ability of the trained model and can only be used once. The trained model is trained in the selected neural network with the training set, and the model trained by the training set is verified in the validation set to see if the accuracy reaches the highest accuracy, If the desired accuracy is not achieved, you can choose to adjust the parameters of the neural network, and then Model training; if necessary, the neural network can also be re-selected for training. If a satisfactory accuracy is achieved, the trained model is tested in the test set to derive the predicted SOC values. The final step is model evaluation, the predicted SOC values are compared with the actual SOC values in the test set using the root mean square error equation (RMSE), the mean error equation (MAE), or the mean square error (MSE) to evaluate the model accuracy, and the root mean square error, mean error, and mean square error are shown in equation (3),

$$\begin{cases} \mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(\mathrm{SOC}_{\mathrm{pre}} - \mathrm{SOC}_{\mathrm{act}}\right)^2} \\ \mathrm{MAE} = \frac{1}{N}\sum_{k=1}^{N}\left|\mathrm{SOC}_{\mathrm{pre}} - \mathrm{SOC}_{\mathrm{act}}\right| \\ \mathrm{MSE} = \frac{1}{N}\sum_{k=1}^{N}\left(\mathrm{SOC}_{\mathrm{pre}} - \mathrm{SOC}_{\mathrm{act}}\right)^2 \end{cases} \tag{3}$$

where N is the number of variables, $\mathrm{SOC}_{\mathrm{pre}}$ is the predicted SOC value through the model in deep learning method, and $\mathrm{SOC}_{\mathrm{act}}$ is the actual SOC values in the test set. The smaller the error obtained from the above formula, the higher the model accuracy.

3. Li-ion Battery Dataset

Li-ion battery data is the most important part of the process of SOC estimation, because high-quality lithium battery data can better understand the relationship between lithium battery electrochemistry, use conditions, design, etc. Since different types of lithium batteries have different state attributes, and the life cycle of lithium batteries is getting longer and longer, For the failure of lithium batteries, the complexity of failure, and life cycle testing for lithium batteries is also getting higher and longer, Therefore, some research institutions have disclosed the test data of lithium batteries obtained by testing.

NASA was the first organization to make the lithium battery dataset publicly available [39]. The dataset [40] is about lithium battery state parameters by performing charging and discharging tests at three different temperatures, including 4°C, 24°C, and 43°C, and recording the impedance as a damage criterion.

The CALCE battery research team at the University of Maryland [41] tested several common types of lithium batteries with different materials and capacities, which were measured separately at 10 different temperatures ranging from -40°C to 50°C. The A123 lithium iron phosphate battery dataset, which is often used in the lithium battery SOC estimation problem, was tested at eight different temperatures ranging from -10°C to 50°C by DST and FUDS drive cycles.

Aiming to optimize the fast charging of lithium batteries, the Toyota Research Center (TOYOTA) cooperated with the Massachusetts Institute of Technology (MIT) and Stanford University tested 124 and 224 phosphoric acids of 1.1Ah and 3.3V in a temperature-controlled convection box at 30℃. The tested batteries were to rapidly charge lithium batteries at a rate of 4C, then discharge at the same rate, and cycle until failure [42, 43].

The Panasonic 18650PF Li-ion battery dataset [44] was tested on a brand new 2.9Ah Panasonic 18650PF cell by Phillip Kollmeyer at Wisconsin-Madison University using a 25-amp, 18-volt digatron firing circuits universal battery tester channel in an 8-cubic-foot thermal chamber. The battery, charged after each test at a 1C rate to 4.2V, 50mA cut off, with battery temperature 12degC or greater, was performed at five different temperatures and a series of tests.

Then, a brand new turnigy graphene 5000mAh 65C cell [45] and 3Ah LG HG2 li-ion battery [46] was performed at McMaster University by Phillip Kollmeye; both of which were tested in n 8 cu.ft. thermal chamber with a 75amp, 5 volt digatron firing circuits universal battery tester channel with a voltage and current accuracy of 0.1% of full scale.

Zhang et al [47] from the China University of Science and Technology, conducted charge and discharge tests on three lithium iron phosphate batteries under constant current and DST conditions at room temperature. This dataset can be used for lithium battery SOC estimation, lithium battery performance measurement, and dynamic characteristics analysis of the pack operation. Wang et al [48] used the BTS-8000 to perform discharge tests on four LiFePO4 battery packs and supercapacitors under DST and UDDS conditions at room temperature, and the data can be used not only for Li-ion battery SOC estimation but also for Li-ion battery and supercapacitor performance measurement, model parameter calibration, and dynamic characterization.

Each dataset comes with a full test process that is not reproduced here. The dataset is often in ".mat", ".xlsx", or ".csv" format, and each dataset includes a "Readme" file that describes the test parameters, naming principles, notes, and other details about the dataset. Table 1 provides a review of the publicly accessible higher-quality lithium battery datasets.

Table 1. Publicly Available Lithium Battery Datasets

Dataset	Battery	Data	Ambient Temperature	Number of Battery	Refs
NASA-PCoE	2 Ah 18650	Voltage, Current, Temperature	43 °C, 4 °C, 4 °C	34	[40]
CALCE	1.1Ah, $LiCoO_2$ 1.5Ah, $LiCoO_2$ 1.35Ah, $LiCoO_2$ 2.4Ah, $LiFePO_4$ 2.23Ah, $LiFePO_4$ 2.3Ah, LNMC	Current, Voltage Charge Capacity, Discharge Capacity, Charge Energy, Discharge Energy, dV/dt	50 °C,45°C,40℃,30℃, 25 ° C, 20℃,0° C, -5° C, -10℃,-40° C	144(1.5Ah, $LiCoO_2$)	[41]
Toyota - MIT - Stanford	1.1 Ah, $LiFePO_4$	Temperature, Current, Voltage, Charge, Discharge Capacity, Per-cycle Measurements of Capacity, Internal Resistance and Charge Time	30 °C	124 224	[42] [43]
Panasonic 18650PF	2.9 Ah, NCA Panasonic 18650PF	Voltage, Current, Capacity, Energy, Temperature	25 °C,10 °C, 0 °C, -10°C, -20 °C	1	[44]
Turnigy Graphene	5 Ah, Turnigy Graphene	Voltage, Current, Time, Power	40°C, 25 °C,10 °C, 0 °C, -10°C, -20 °C	1	[45]
LG 18650HG2	3Ah, LG HG2	Voltage, Current, Power, Battery Case Temperature		1	[46]
IFP-1865140	10Ah, $LiFePO_4$	Voltage, Current, Capacity	25 °C	3	[47]
IFP-1665130		Voltage, Current, Time		4	[48]

4. Deep Learning Neural Network Structure in SOC Estimation

The SOC estimation of li-ion battery in deep learning method is to use deep learning theory of computer science to build a model that builds the approximate relationship between input data (voltage, current, temperature, power, capacity, etc.) and output data (SOC) by available data. According to different neural network structures, it can be classified into single, hybrid, and trans structure. Figure2 depicts a summary of the major neural network structure that utilized in deep learning for lithium battery SOC estimation.

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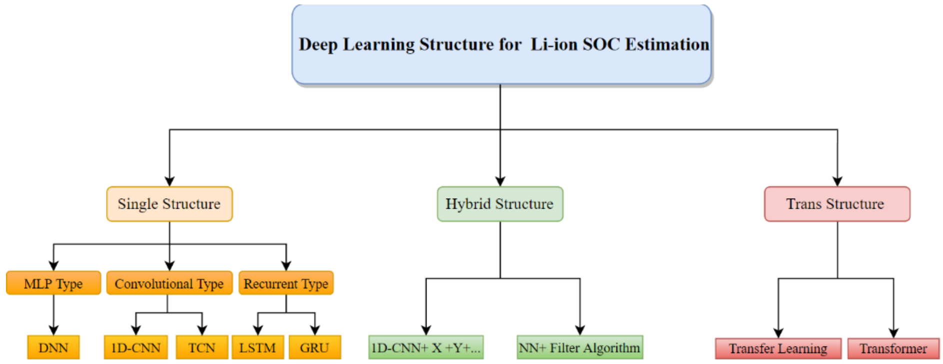


Figure 2. Deep learning neural network structure for li-ion Battery SOC estimation

4.1. Single Structure

The single structure is only used a deep learning structure to estimate SOC, in this chapter, it includes Multi-layer perceptron (MLP) type, convolutional type, and recurrent type.

4.1.1. MLP type – DNN

Multi-layer perceptron, also known as artificial neural network, is derived from Deep Neural Network (DNN) after the arithmetic power is improved and the training parameters are increased, its advantage is that it does not limit the dimensionality of the input, it is highly adaptable to the data, and theoretically, 3-layer perceptron can fit any function nonlinearly, the disadvantage is easy to over-fit [49] when the network has massive parameters. Figure 3 shows the structure of a deep neural network with four hidden layers, each containing 8 neurons.

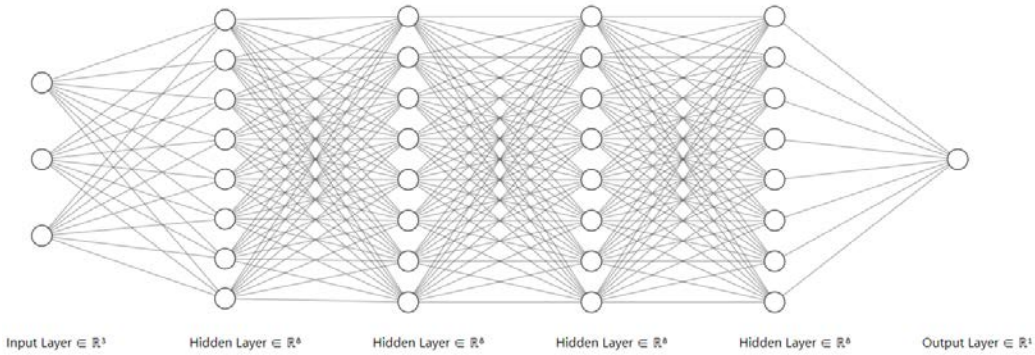


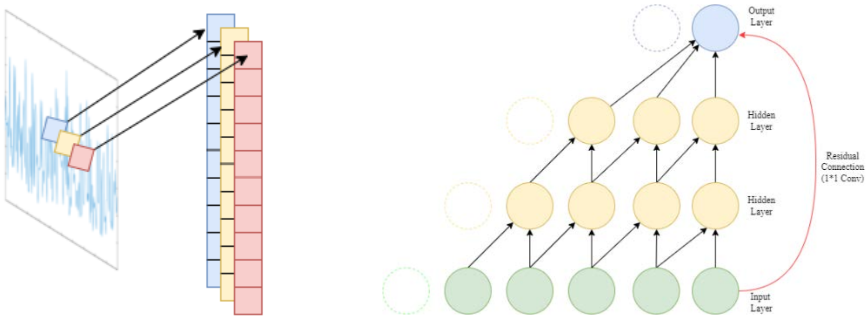
Figure 3. Deep neural network with 4 hidden layers

Ephrem et al. [50] used the DNN to train a model for SOC estimation, and tested Panasonic 18650 lithium battery under different temperatures and driving cycles[44], in which 7 fully discharged datasets were selected as training dataset,"US06" and "HWFET" as the validation dataset, the test set is the data set under the changing temperature of 10 ℃-25℃, the input is current, voltage, average voltage, and average current, and it is verified separately at each temperature; after the test set test and compared with the other 4 methods, the lowest RMS error obtained was 0.78%. SHRIVASTAVA et al. [51] tested the Panasonic 18650 lithium battery, using "DST, FUDS, US06" as the training dataset and validation dataset, "WLTP" as the test set; the input was voltage, current, and temperature; then the model was compared with SVR (Supper Vector Regression) method, the RMS of using DNN method is significantly smaller than SVR. HOW et al. [52] used the INR lithium battery dataset from the CALCE dataset [41] to train its lithium battery SOC model, "DST" as the training dataset, and "FUDS, BJDST, and US06" as the test dataset, with current, temperature, and voltage as inputs, after training, the model was tested in the "DST" test dataset and compared with five methods, and the RMS was 3.68%. Kashkooli et al.

[53] tested eight commercial 15 Ah lithium battery cells, which is cycled at various constant rates of charge/discharge and conducted at one-mouth interval for a period of 10 mouths; the measurement data was divided randomly in three groups, in which of 70% is used for training, 15% for cross-validation, and 15% for testing; the test performance in MSE using DNN is 0.0247%.

4.1.2. Convolutional type - TCN

Convolutional type neural networks in Li-ion battery SOC estimation applications are mainly variants of convolution neural networks (CNN [54]) in time series data, which are one-dimensional convolutional neural networks [55] (1D-CNN) and temporal convolution network [56] (TCN). The primary benefit of a one-dimensional convolutional neural network is that it can extract and categorize one-dimensional signal data while using less computer capacity. It has been frequently employed in real-time monitoring tasks such as defect prediction and categorization in recent years. Li-ion battery SOC estimation is a regression problem, but models in 1D-CNN are not as accurate in regression prediction problems as in classification problems, so they are typically employed as a feature extraction layer in conjunction with other networks. The main benefits of time-domain convolutional networks are the expansion of the feature extraction range by increasing the perceptual field by expanding the causal convolution and the mitigation of the gradient explosion problem by residual connection [57], which allows for the training of models with more parameters and higher accuracy. The schematic diagram of the convolutional neural network is shown in Figure 4.



(a) (b)

Figure 4. Convolutional Type: (a) 1D-CNN schematic; (b) Dilated causal convolution and residual connection in TCN

HANNAN et al. [58] constructed a multi-layer time-domain convolutional layer with feedforward direction and optimized the learning rate using an optimization algorithm, using "Cycle 1- Cycle 4, Cycle NN, UDDS, LA92" from the dataset [44] as the training set and "US06, HWFT" as the test set; and the MSE of the test is 0.85% when compared with four models.

4.1.3. Recurrent type - LSTM

As shown in Figure 5, recurrent types mainly include Recurrent Neural Network (RNN), Long Short-Term Memory [59] (LSTM), and Gated Recurrent Unit [60] (GRU). Gradient explosion or disappearance occurs in recurrent neural networks as parameters are increased, then, the creation of LSTM alleviates the problem of gradient explosion in the recurrent neural network, followed by GRU with fewer parameters than LSTM. At present, the LSTM is the most used network of recurrent neural network in the lithium battery SOC estimation problem, followed by the GRU, and not many recurrent neural network is used directly [61]. The benefit of a recurrent neural network is that it can utilize the previous output as the next input, thus exploiting the relationship of the input variables; but, owing to its one-way operation and historical data calculation, it takes longer to train than neural networks that can run in parallel.

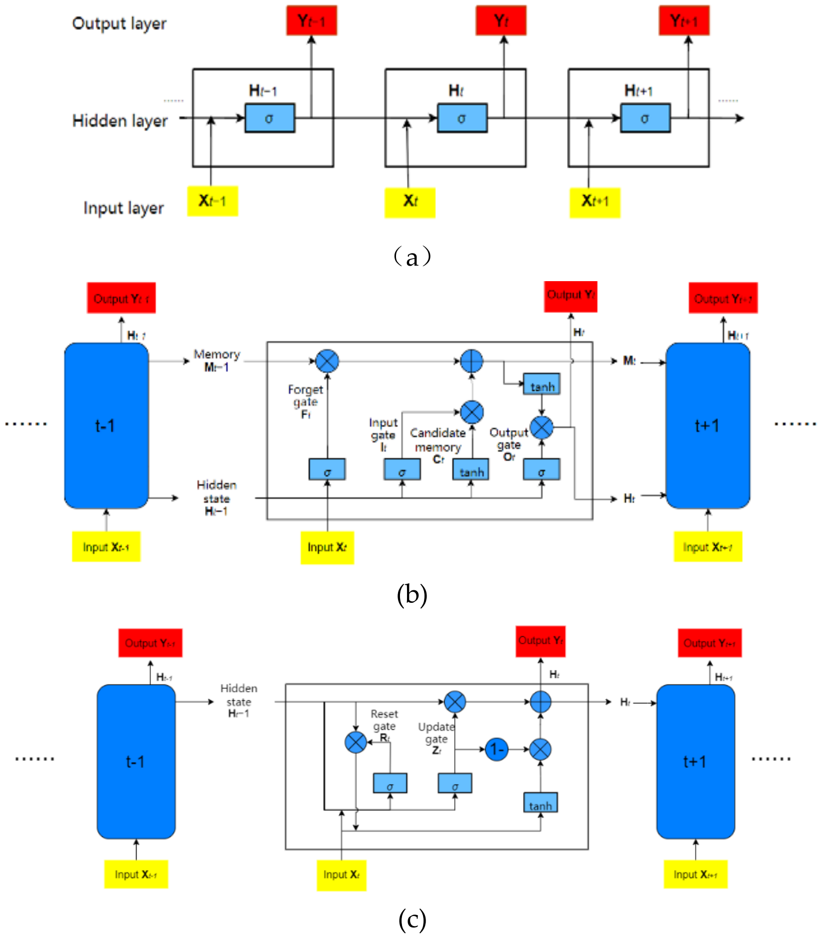


Figure 5. Recurrent Type: (a) Recurrent neural network; (b) Long short-term memory neural network; (c) Gated recurrent unit

Ephrem et al. [62] adopted LSTM to train the lithium battery SOC model under fixed and varying ambient temperatures in the dataset [44]. In the fixed ambient temperature SOC model, the training dataset is the data under eight mixed drive cycles, and the two discharge test cases are used as validation dataset; the test dataset is the charging test case; in the varying ambient temperature SOC model, the training dataset is 27 drive cycles include three sets of nine drive cycles recorded at 0℃, 10℃, and 25℃. The test dataset is the data of another mixed drive cycle. Both models' input variables are voltage, current, and temperature. After evaluation, the model achieved the lowest MAE of 0.573% at 10℃ , and an MAE of 1.606% with ambient temperature from 10 to 25℃. Cui et al. [63] used LSTM with encoder-decoder [64] structure in the dataset [41], the input is I_t, V_t, I_{avg}, V_{avg}, and the test result of it is the RMSE of 0.56% and MAE of 0.46% in US06, which is higher than that of only using LSTM and GRU in that paper. Wong et al. [65] used the undisclosed dataset of 'UNIBO Powertools Dataset' as a training dataset and dataset [46] as a test dataset in LSTM structure, the input variable is current, voltage and temperature, the result of MAE is 1.17% in 25 ℃. Du et al. [66] tested two LR1865SK Li-ion battery cells at room temperature, and used the dataset [40] as the comparative case to test the model trained by LSTM, the input variable is current, voltage, temperature, cycles, energy, power, and time; the result of MAE is 0.872% at an average level. YANG et al. [67] used the LSTM to build a model for lithium battery SOC estimation, the data was obtained from the A123 18560 lithium battery under three drive cycles including DST, US06, and FUDS; the input vector is current, voltage, and temperature. In addition, the model robustness was tested in the unknown initial state of the lithium battery, with the Unscented Kalman Filter [68] (UKF) method for comparison; the test results the RMS of LSTM was significantly smaller than that of UKF.

4.1.4. Recurrent type – GRU

YANG et al. [69] trained the model by using GRU, the dataset was tested from three LiNiMnCoO2 batteries with DST and FUDS drive cycles; the input vector is current, voltage and temperature. Then, the trained model was tested in a dataset of another different material; it obtained 3.5% of max RMS. The authors of studies [70-72] all used GRU as the neural network for model training; the dataset is the INR 18650-20R and A123 18650 lithium battery from the CALCE dataset [41] with inputs of voltage, current, and temperature, respectively; and the RMS error obtained from the test dataset was not significantly different. Kuo et al. [73] tested a 18650 Li-ion battery cell and used GRU with an encoder-decoder structure, in which the input vector is current, voltage, and temperature; further, they compared with LSTM, GRU, and sequence-to-sequence structure, the result shows that the MAE of their proposed neural network is lower than other methods at three different drive cycles and temperatures.

4.2. Hybrid Structure

The main idea of the hybrid neural network in the estimation of lithium battery SOC is to improve the prediction accuracy of the model by combining the advantages of various types of neural networks. The current common architecture in the lithium battery SOC estimation problem is 1D-CNN as a feature extraction layer to extract deeper features of the input data, and a recurrent neural network (LSTM or GRU is used more often) as a model building layer to construct a model between the SOC and the input variables. Some scholars also added the fully connected layer (FC) before the final output layer to improve the accuracy of the model. The architecture of 1D-CNN +X+Y in lithium battery SOC estimation is depicted in Figure 6.

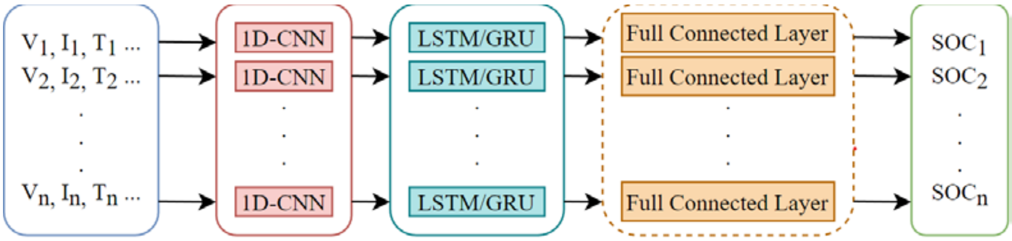


Figure 6. 1D-CNN+X+Y architecture diagram

4.2.1. 1D-CNN+LSTM

SONG et al. [74] used a neural network combination of "1D-CNN + LSTM" to build the model with input of voltage, current, temperature, average voltage, and average current, for the dataset, the 1.1 Ah A123 18650 lithium battery was tested at seven different temperatures with drive cycles of US06, FUDS. The results showed that the error of the "1D-CNN+LSTM" method was significantly smaller than the method that only used one neural network when tested in the test dataset and compared with the 1D-CNN and LSTM methods.

4.2.2. 1D-CNN+GRU+FC

HUANG et al. [75] used a "1D-CNN+GRU+FC" neural network architecture with the input of voltage, current, and temperature; the dataset was obtained from the BAK 18650 lithium battery at seven different temperatures with drive cycles of DST and FUDS. Compared with the method of one neural network such as RNN, GRU, and support vector machine, it achieved the lowest RMS.

4.2.3. NN + Filter Algorithm

NN + Filter Algorithm type is to use neural network and filter algorithm for improving li-ion SOC estimation performance, Figure 7 is a case of that structure which is the combination of LSTM and Adaptive H-infinity Filter that can be found in [76] with more detail.

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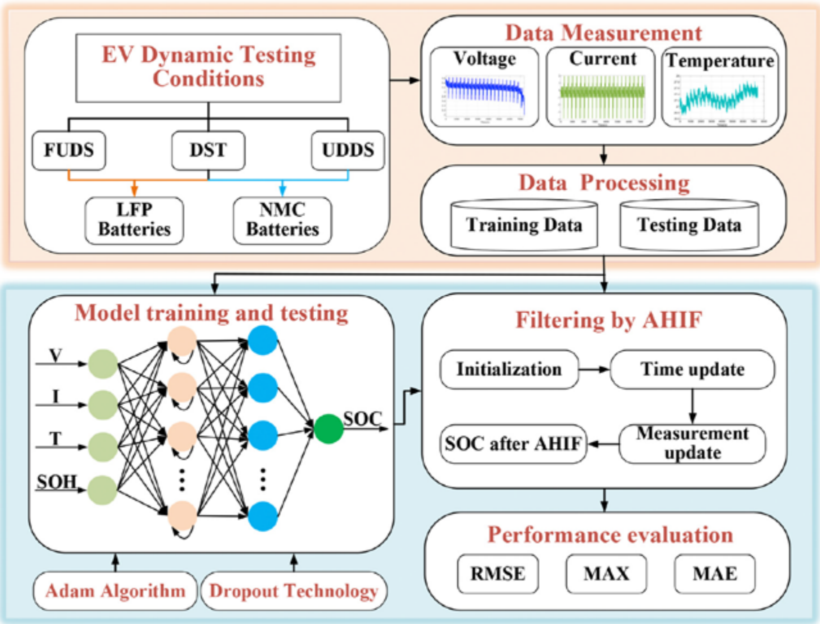

Figure 7. A case of NN + Filter Algorithm architecture diagram (LSTM+AHIF [76])

YANG et al. [77] tried to combine the advantage of both LSTM and UKF. They used LSTM and offline training neural network to get a pre-trained model with the data obtained; then, the real-time data obtained was inputted into UKF and pre-trained model, whose data inputted was after normalization. And, the UKF in it is to filter out the noise and improve the model performance. After this, combinations of LSTM and filtering class algorithms appear as "LSTM+CKF (Cubature Kalman Filter)" [78], "LSTM+EKF (Extended Kalman Filter)" [79], and "LSTM+AHIF (Adaptive H-infinity Filter) [76], through the test dataset, their model performance is better than the models only trained by LSTM.

4.3. Trans Structure

Trans structure is mainly used to transfer the knowledge of source data to target data, in this chapter, it includes the section of transfer learning and transformer.

4.3.1. Transfer Learning

As depicted in Figure 8, the knowledge is utilized from learning task trained by source data to that of target data, it can improve the robustness of the model to achieve higher performance. And some researchers applied transfer learning to enhance the performance of SOC estimation.

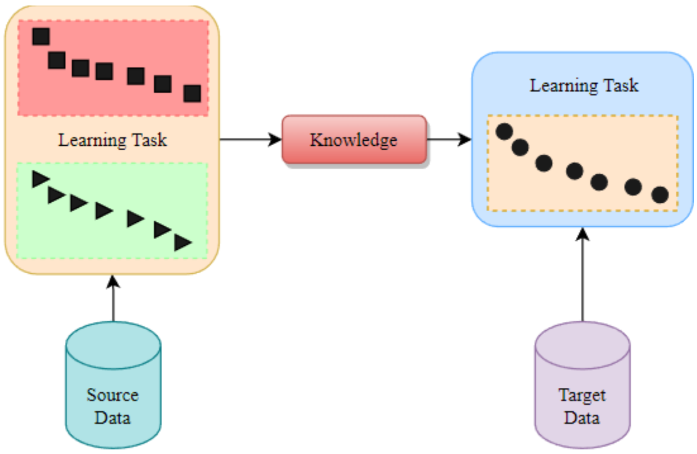

Figure 8. Schematic of transfer learning

Bian et al. [80] added a fully connected layer after bidirectional LSTM on this basis with inputs of voltage, current, and temperature; and the datasets were three different lithium battery datasets, A123 18650, INR 18650-20R from CALCE dataset [41] as the target dataset, and Panasonic lithium battery dataset [44] as the pre-trained dataset, then, they used transfer learning to transfer feature in model trained with the pre-trained dataset to the model trained with target dataset. Compared with the method of one neural network such as RNN, LSTM, and GRU; the model of transfer learning method achieved the lowest RMS.

Liu et al. [81] applied TCN to two different types of lithium battery data and migrated the trained model for lithium battery SOC estimation as a pre-trained model to another battery dataset by transfer learning [82]. The training dataset of the pre-trained model is "US06, HWFET, UDDS, LA92, Cycle NN" corresponding to 25°C, 10°C, and 0°C in the dataset [44], and the test set is "Cycle 1- Cycle 4"; the input vector is current, voltage, and temperature. The model trained under 25°C was migrated to the new lithium battery SOC model as a pre-trained model by transfer learning, the training dataset of the new lithium battery SOC model is the data measured under two mixed driving cycles in the dataset [45], the test dataset is "US06, HWFET, UDDS, LA92" in the dataset [45], and its RMS range is obtained: 0.36% - 1.02%.

4.3.2. Transformer

Transformer [83] is based on encoder-decoder structure and attention mechanism which is multi-head attention, it can enhance the connection and relation of data, hence the transformer is applied in natural language process, image detection, and segmentation, etc. In recent years, some scholars tried to use structure based on the transformer for SOC estimation. The diagram of transformer is shown in Figure 9.

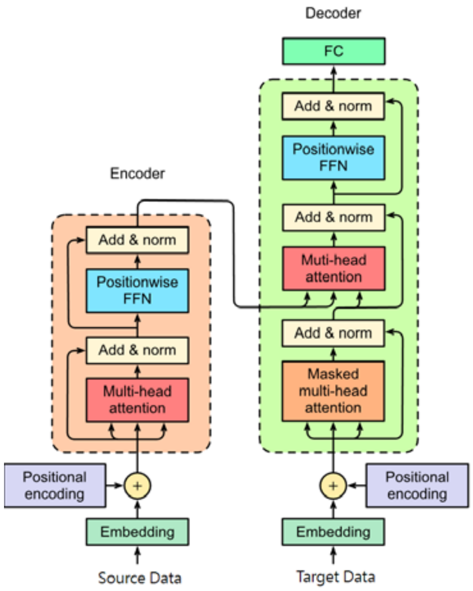

Figure 9. Structure of transformer

Hannan et al. [84] used the structure which is based on the encoder of transformer [83] to estimate SOC, the dataset was used in [46]; the input variable is current, voltage, and temperature, and compared with different methods include DNN, LSTM, GRU and other deep learning methods, their test performance is 1.19% of RMSE and 0.65% of MAE.

Shen et al. [85] used two encoders and one decoder of the transformer, in which its input variable is current-temperature and voltage-temperature sequence; the dataset is [41], in which the 'DST' and 'FUDS' are used as training dataset, the 'US06' is used as test dataset; further, they added a close loop to improve the performance of SOC estimation, then, compared with LSTM and LSTM+UKF, the test results show that the RMSE of their proposed method is lower than that of others.

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5. Evaluation and future development

For further analysis and evaluation, Table 2 summarized the literature, lithium battery datasets, input variables, and errors using various neural network models of deep learning to solve the problem of lithium battery SOC estimation. (I: current, V: voltage, T: temperature, t: time, Iavg: average current, Vavg: average voltage, MAX: maximum error)

Table 2. Summary table of lithium battery SOC in deep learning methods

Neural Network		Refs	Dataset	Input Variables	Error
Single Structure	DNN	[50]	[44]	$V(t), T(t), I_{avg}(t), V_{avg}(t)$	MAE: 0.61%, RMSE: 0.78%, MAX (25 °C):2.38%
		[51]	Undisclosed	$V(t), I(t), T(t)$	RMSE: 2.0527, MAE: 0.00421
		[52]	[41]	$V(t), I(t), T(t)$	RMSE: 3.68%, MAE: 0.13%
		[53]	Undisclosed	$V(t), I(t), T(t), Time, Condition$	MSE: 0.0247%
	TCN	[58]	[44]	$V(k), I(k), T(k)$	(25°C) RMSE: 0.85, MAE: 0.70, MAX (25 °C): 2.96 (-20 ~ 25°C) RMSE: 2.00, MAE: 1.55, MAX (25 °C): 7.63
	LSTM	[61]	Undisclosed	$V(t), V(t-1), V(t-2),$ $I(t), I(t-1), I(t-2),$ $SOC(t), SOC(t-1), SOC(t-2)$	RMSE: 0.4127~0.7012 RMSE: 0.4127~0.5476
		[62]	[44]	$V(k), I(k), T(k)$	RMSE: 0.7%, MAE: 0.6%, MAX (25 °C): 2.6%
		[63]	[41]	V, T, I_{avg}, V_{avg}	RMSE: 0.45% ~ 1.89%, MAE: 0.37% ~ 1.48%
		[65]	[46], Undisclosed	$V(k), I(k), T(k)$	RMSE: 1.57% ~ 2.89%, MAE: 1.17% ~ 2.22%
		[66]	[40], Undisclosed	$V(t), I(t), T(t),$ $Cycles, Energy, Power, Time$	RMSE: 0.731% ~ 1.860%, MAE: 0.608% ~ 1.165%
		[67]	Undisclosed	$V(t), I(t), T(t)$	RMSE: 1.07%~1.39%, MAE: 0.94%~2.45%
	GRU	[69]	Undisclosed	$V(k), I(k), T(k)$	RMSE < 3.5%, MAE < 2.5%
		[70]	[41]	$V(k), I(k), T(k)$	RMSE: 0.65%, MAE: 0.46%; RMSE: 0.75%, MAE: 0.52%
		[71]	[41]	$V(t), I(t), T(t)$	RMSE: 0.84% ~ 1.08%
		[72]	[41]	$V(k), I(k), T(k)$	RMSE: 0.55% ~ 2.45%, MAE: 0.42% ~ 1.77%
		[73]	Undisclosed	$V(t), I(t), T(t)$	RMSE < 1.5%, MAE < 0.6%
Hybrid Structure	1D-CNN+ LSTM	[74]	Undisclosed	$V(t), I(t), T(t), I_{avg}(t), V_{avg}(t)$	RMSE: 0.54% ~ 1.38%, MAE: 0.33% ~ 0.87%
	1D-CNN+ GRU+FC	[75]	Undisclosed	$V(t), I(t), T(t)$	RMSE: 0.0098 ~ 0.0211, MAE: 0.0078 ~ 0.0168
	LSTM+ UKF	[77]	Undisclosed	$V(t), I(t), T(t)$	RMSE: 0.93%, MAE: 0.82%
	LSTM+ CKF	[78]	Undisclosed	$V(k-1), I(k), T(k), SOC(k)$	MAE < 2%
	LSTM+ EKF	[79]	[41, 44]	V, I, T, dV	RMSE: 0.48%
	LSTM+ AHIF	[76]	Undisclosed	$V(k), I(k), T(k), SOH$	RMSE: 0.22% ~ 1.09%, MAX: 0.89% ~ 2%, MAE: 0.21% ~ 1.18%
Trans Structure	Transfer learning	[80]	[41, 44]	$V(t), I(t), T(t)$	RMSE: 0.49% ~ 1.57%, MAE: 0.39% ~ 1.32% RMSE: 0.49% ~ 1.57%, MAE: 0.39% ~ 1.32%
		[81]	[44, 45]	$V(k), I(k), T(k)$	(25°C) RMSE: 0.36% ~ 1.02%, MAE: 0.26% ~ 0.61%
	Transformer	[84]	[46]	$V(k), I(k), T(k)$	RMSE: 0.9056%, MAE: 0.4459%
		[85]	[41]	$I(t)-T(t), V(t)-T(t)$	(50°C) RMSE: 0.54%, MAE: 0.49%

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As a data-driven method to solve the SOC estimation problem of lithium batteries, deep learning methods have the advantages of high accuracy, short modeling time, and do not require a lot of complex interdisciplinary knowledge. Specific to each network, due to different characteristics, various advantages and disadvantages in practical applications are also different. Therefore, Table 3 summarizes the advantages and disadvantages of various neural networks for deep learning methods to solve the problem of lithium battery SOC estimation. DNN is able to handle the li-ion battery data without thinking,

Table 3. Evaluation of SOC estimation for lithium batteries in deep learning methods

Neural Network		Advantage	Disadvantage
Single	DNN	Unlimited data input dimensions	Prone to overfitting and local optimum problems
	1D-CNN	Extraction of time series data features	Lower precision when it is only used
	TCN	Handling time-series data	Lower robustness
	LSTM	Longer historical time series data can be linked, alleviating the problem of gradient disappearance and gradient explosion	Many calculation parameters, large capacity storage, and long training time
	GRU	Fewer computing parameters	Long training time
Hybrid	1D-CNN+X+Y+…	Combining the advantages of multiple neural networks	Relatively complex model
	NN + Filter Algorithm	Merge the advantages of neural network and filter algorithm	Large capacity storage, long process time, and complex structure
Trans	Transfer learning	Transfer feature of source data to target data	It is not easy to decide which part can be as knowledge to transfer for the target learning task.
	Transformer	It can achieve the data feature connection	Higher calculation complexity, computing power requirements, and data demand

it is easy to raise the problem of overfitting and local optimum in SOC estimation when it uses several MLP layers. 1D-CNN can extract effectively the data features of li-ion battery data, but it has lower precision of SOC estimation than other neural network structures when it is only used by the 1D-CNN structure. TCN is designed for time series data by using the convolutional neural network structure, but its robustness of SOC estimation is lower than others. LSTM can process long-term li-ion battery data for SOC estimation and it alleviates the problem of gradient disappearance and explosion, but it has several calculation parameters for SOC estimation and it needs large capacity storage to process li-ion battery data, therefore, it costs long training time. GRU has fewer calculation parameters of SOC estimation than LSTM and it also can alleviate the gradient disappearance and explosion problem, but it still needs a long training time. 1D-CNN+X+Y combines the advantage of different neural networks to estimate SOC and it can further improve the precision of SOC estimation with appropriate parameters of neural network, but it has a relatively complex model structure compared with the single structure of neural network. NN + Filter Algorithm can merge the benefit of neural network and filter algorithm to improve SOC estimation performance, but it needs a large capacity to store li-ion battery data, a long time to further process parameters, which spends more time than only using neural network structure to estimate SOC. Transfer learning for SOC estimation can transfer knowledge about different types of li-ion battery data to target data, but it is difficult to determine which part of knowledge to transfer to the target data. The transformer can provide the connection between li-ion battery feature, but it needs a large amount of data and computing power due to its high calculation complexity.

It is a multi-factors determined problem that chooses an appropriate deep learning structure for SOC estimation, which is depending on the data, results in precision, consuming time, etc. The amount and quality of available data is the first factor to be considered, in other words, SOC estimation using a deep learning method that is data-driven

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will get good performance in data system with large quantity and high quality. The training time and precision of SOC estimation need to be jointly considered for the selection of deep learning structure because in most cases indicated that training time is positively correlated with SOC estimation accuracy, but its precision will not increase significantly with the training time when it beyond a certain threshold. From the perspective of data, without thinking about the factor of training time, if the amount of data is not rich, the recurrent structure and transfer learning can be firstly preferred, the reason is that li-ion battery data is the time series sequence and recurrent structure can effectively process the history input data; when the amount of data is rich, hybrid structure and transformer can be well applied in the SOC estimation problem. From the perspective of training time and SOC estimation performance, in the condition of the same amount of data, the hybrid structure can be adopted into SOC estimation because its precision is higher than that of the single structure but its training time is more than it. Therefore, the selection of a deep learning structure is based on the quality and quantity of available data as well as the desired result in the reality of SOC estimation.

Although deep learning can handle a large amount of data and the effect is good, objectively speaking, three main problems need to be solved before using deep learning methods to solve the problem of lithium battery SOC estimation before it can be widely used in practice:

1. **Data**: Due to the different battery types, battery parameters, and battery manufacturers that may be used for different electric vehicles, the SOC of the lithium battery that provides power cannot be generalized by one or one type of model. Failure and life cycle testing of lithium batteries take a long time and have a significant time cost. Generally, scientific research institutions or colleges and universities conduct battery parameter tests, so the quantity and quality of data obtained are limited. At present, models trained by deep learning can only achieve high accuracy under certain operating conditions or certain temperatures. For a general model, the amount of data is far from enough, and to maximize the utilization ratio of li-ion cell data, there are some methods can be used: (1) time series data augmentation, the li-ion data can be further augmented because it is the time series data, there are several methods can be found in the paper [86]; and in the state of charge for li-ion battery estimation problem, adding noise is the simple and effective method, this can be found in the paper [84]. (2) creating new variable based on original data, it can be created by some variable such as the derivation of voltage, current, and temperature based on voltage, current, and temperature; in addition, it should be created according to the science of li-ion. (3) transfer the model from the different li-ion datasets, to improve the precision of SOC estimation, the model can be frozen or fine-tuned in some neural network layer to accomplish the target learning tasks, furthermore, when the amount of data is enough, the pre-trained model like GPT-3 and BERT can be applied into li-ion SOC estimation problem.

2. **Computing power**: Most electric vehicles generally choose an in-vehicle computing platform with high-cost performance and low computing power and power consumption as the "brain" of electronic and electrical equipment due to cost or power consumption reasons. To speed up the training, most of the deep learning is currently based on special processing units, such as graphics processing units, and tensor processing units. For accelerated operations; however, these special computing units are designed without considering power consumption and cannot be directly used for onboard computing power platforms for electric vehicles. In addition, at present, all lithium battery SOC estimation based on deep learning is to test the battery separately under simulated driving conditions and conduct offline training according to the obtained data. On-board training is carried out on the data measured by the sensors in the environment.

3. **Interpretability**: Previously, there is no recognized scientific explanation for machine learning in computer science, but it is only used as a black box. This feature results in a lack of stability and interpretability compared with traditional methods. There is no

fixed solution to the situation that does not meet expectations, so it sometimes takes a long time.

6. Conclusions

We reviewed the lithium battery SOC estimation methods based on the deep learning method and the commonly used lithium battery SOC datasets in recent years, studied four types of neural networks include single, hybrid, and trans structure, then, analyzed the advantages and disadvantages of various neural networks, further listed some methods to improve the data utilization rate and future development.

Lithium battery SOC estimation in deep learning method belongs to the intersection of computer science, data science and battery chemistry. At present, both deep learning and battery fields still have many complex problems that are difficult to solve or understand. From the perspective of efficiency, deep learning methods are higher than methods such as mathematical models, but they do not have a deeper understanding of the changes in battery state parameters. From the question itself, there are two aspects worth paying attention to:

1. **High-quality data**: Some public lithium battery data sets may not meet the actual needs due to reasons such as models or unexpected situations. From the actual needs, it may be necessary to re-test the lithium battery. In the next step, the SOC test of the lithium battery may be considered. Establishing a set of accepted testing methods or standards, which may be an efficient way to generate high-quality data at scale, can avoid duplication of testing, reduce testing time and improve data quality.

2. **Computer science**: Most of the existing deep learning-based lithium battery SOC estimation researches use neural networks that have made breakthroughs in the field of computer science as a method to migrate to this problem. In the future, we can focus on breakthrough research results in the field of computer science, which can be studied by referring to relevant theories and algorithms; the relevant science of battery chemistry can be used as a priori knowledge to construct the characteristics related to the state parameters of lithium batteries.

With the expansion of computer science, together with the advanced devices for data storage (like cloud storage) and high-quality data, we envision deep learning to be a promising technique to model the real-time battery in the future.

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