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Estimation of the SOC of Energy-Storage Lithium Batteries Based on the Voltage Increment

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ABSTRACT State of charge (SOC) estimations are an important part of lithium-ion battery management systems. Aiming at existing SOC estimation algorithms based on neural networks, the voltage increment is proposed in this paper as a new input feature for estimation of the SOC of lithium-ion batteries. In this method, the port voltage, current and voltage increment are taken as inputs and the current SOC is used as output to train a neural network. Different from the adaptive filtering algorithm, which requires complex equivalent circuit parameter identification, this algorithm uses the voltage increment instead of the open circuit voltage (OCV); hence, the complexity of the SOC estimation algorithm is reduced, and the problem of inaccurate estimation caused by neural network algorithms without considering the internal structure of the battery is avoided. The experimental results show that compared with the traditional neural network algorithm, the neural network SOC estimation algorithm based on the voltage increment could improve the accuracy of SOC estimation.

INDEX TERMS Lithium battery, state of charge, neural network, mind evolutionary algorithm, voltage increment.

I. INTRODUCTION

Lithium batteries are one of the hotspots in the research field of energy storage, given their high specific energy and power. As an energy unit, the estimation of the state of charge (SOC) is critical, as improvement of its accuracy will lead to better efficiency.

SOC estimation approaches can be divided into four methods, including the ampere-hour integration method, the open circuit voltage (OCV) method, the adaptive filtering method and machine learning algorithms.

The ampere-hour integration method, also known as the charge accumulation method, is one of the most common SOC prediction methods. This method obtains the change in the state of charge or discharge over a period of time after integrating the current over the battery capacity and then calculates the present SOC from the known initial value. Luo *et al.* [1] obtained the initial SOC value by the OCV method, obtained a correction factor for different rates, coulombic efficiencies and temperatures from a battery pack charge and discharge test, corrected for the battery capacity, and then estimated SOC by the ampere integral method.

The OCV method, which is used to calculate the current SOC [2], is based on the relationship between the OCV and the battery SOC. However, measurement of the OCV requires the battery to stand for a long time, which brings great difficulties to the real-time measurement of SOC. Therefore, this method is often combined with the ampere-hour integration method to calculate the initial SOC value [1], [3].

For the estimation of SOC in a battery system, adaptive filtering uses the SOC value as a state variable to obtain an optimal estimation. The adaptive filtering methods mainly include Kalman filtering and H∞ filtering [4]. These methods further include adaptive Kalman filtering [5], adaptive regression extended Kalman filtering [6], the data-driven extended Kalman filtering algorithm [7] and so on. In addition to single algorithms, unscented Kalman filtering can be combined with the ampere-hour integration method [8].

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These methods are very sensitive to the selection of initial values. Inaccurate initial values will seriously affect the estimation of SOC, and the accuracy of Kalman filter estimation depends on the accuracy of the model. Nevertheless, these algorithms are suitable for variable current conditions.

Compared with the adaptive filtering method, which is sensitive to the initial value, machine learning algorithms have wider applicability with a simpler model training procedure, broader choice of training data, and smaller computational cost [9]. Machine learning algorithms usually take the lithium-ion battery port voltage, charge and discharge current and temperature as the inputs of the model and the SOC as the output of the model. There is no need to know the exact relationship between the input/output data, and calculations can be directly based on the input/output data. The network topology is automatically adjusted to achieve SOC estimation. For the real-time prediction of the battery state of charge in hybrid electric vehicles, Chemali *et al.* [10] used the Bayesian extreme learning machine (BELM) method. Regarding the problems of the low accuracy of SOC and its poor online adaptability, Song *et al.* [11] used a fast sparse bayesian algorithm for training and then combined this algorithm with an incremental learning method to establish an incremental learning correlation vector machine model, which improved SOC estimation.

Artificial neural network algorithms, a kind of machine learning algorithms have always been concerned. RNN (recurrent neural network), which is composed of many massively connected simple neurons that can operate concurrently, is widely used in recent years [12]. Therefore, a lot of related methods on soc estimation have been presented, such as dynamically driven recurrent networks (DDRNs) [13], the combination of long short-term memory networks and recurrent neural networks [14], the combination of convolutional neural networks and long short-term arithmetic memory networks [15], convolutional gating recurrent neural networks [16], improved BP neural networks [17], MEA-BP neural networks, recurrent neural networks (RNNs) based on a gated recurrent unit (GRU) [18], improved nonlinear autoregressive with exogenous input (NARX)-based neural network (NARXNN) algorithms [19], a hybrid of the vector autoregressive moving average (VARMA) approach and long short-term memory (LSTM) [20], and improved back-propagation neural networks (BPNNs) using the backtracking search algorithm (BSA) method [21]. Chaoui and Ibe-Ekeocha [13] proposed an accurate estimation method for SOC based on the combination of long-short-term memory (LSTM) and a recurrent neural network. This method can be used in systems without using any battery model, filter or Kalman filter. Wang *et al.* [15] proposed a combined convolutional neural network (CNN) and long short-term memory (LSTM) network, inferring battery SOC from measurable data such as current, voltage, temperature, etc., which can be more accurately estimated at different temperatures than those appropriate for SOC measurement. Hu and Wang [16] proposed a convolution recursive unit (CNN-GRU) network for the estimation of the state of charge of lithium-ion batteries. This method compared two deep learning models (recursive neural network and gated recursive unit models) and two traditional machine learning methods (support vector machines and extreme learning machines) with respect to their SOC estimation accuracy for lithium-ion batteries. To improve the GA-BP algorithm, Guo *et al.* [17] proposed an SOC estimation model based on the fuzzy weighting algorithm and combined a GA-BP neural network with the ampere-hour integration method to achieve more accurate SOC estimation. The adaptive filtering algorithm requires battery modeling, making the calculation process more complicated. It is not necessary to model the battery to estimate SOC by neural network, but it is not accurate to estimate SOC by using only the port voltage, current and temperature. Computationally efficient algorithms were proposed in [22] to approximate each cell's SOC at any time of the equalization process and to calculate the system equalization time. Han *et al.* [23] proposed a computationally efficient algorithm for estimating the battery cell state evolution throughout the charge equalization process.

Different from the idea of re-extracting features of convolutional neural networks, a novel idea is proposed in this paper; that is, based on the voltage and current of the port, the voltage increment is introduced as a new feature, and an MEA-BP (mind evolutionary algorithm-back propagation) neural network is used to estimate the SOC to achieve increased estimation accuracy. When using 0.2C charging data from an energy-storage lithium battery for simulation, the mean square error estimated by the MEA-BP network is 4.079e-05, while that of the voltage increment MEA-BP algorithm is reduced to 1.765e-05.

II. SOC ESTIMATION BASED ON MEA-BP NETWORK

To reflect the superiority of the incremental neural network in terms of SOC estimation, an MEA-BP neural network is proposed in this paper. The algorithm block diagram is shown in Fig. 1.

To optimize the initial threshold and weight of the BP algorithm and enhance its robustness, the mind evolutionary algorithm (MEA) is chosen to optimize the BP algorithm. The main idea of MEA-BP is to map the solution space to the code space by BP topology, where each code corresponds to a value of the problem. In this paper, the 2-5-1 BP topology is selected, and the reciprocal of the mean square error of the training set is used as the scoring function of each individual and population. By using MEA, continuous iterations are repeated to output the optimal individual, and the results serve as the initial BP weights and thresholds used to train the network.

Step 1: Process data, manage and analyze the experimental data, and calculate the incremental voltage.

Step 2: Generate the training set and the test set by extracting the odd columns as the training data set and the even columns as the test data set.

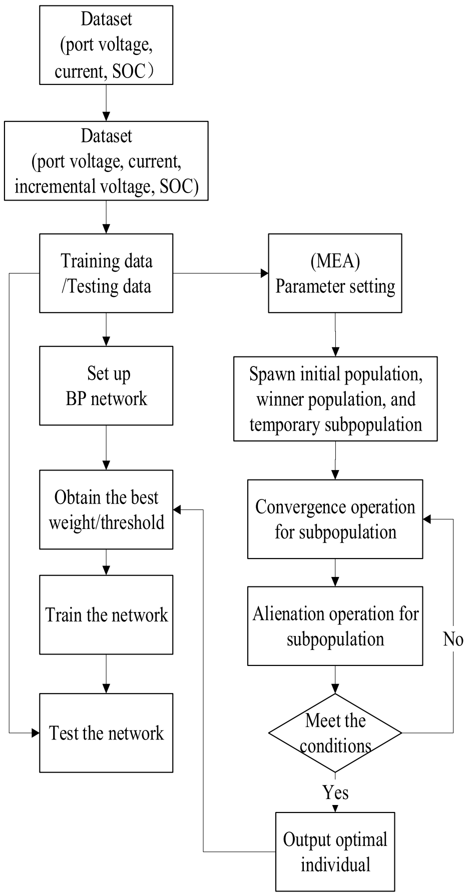

FIGURE 1. **SOC estimation process based on the MEA-BP algorithm.**

Step 3: Generate the initial population, winning subpopulation and temporary subpopulation by using the MATLAB initial population generation function and subpopulation generation function.

Step 4: Perform a convergence operation on all subpopulations and then determine whether the subpopulations are mature. If true, the convergence operation will end. If false, a subpopulation is generated with a new center, and then the convergence operation is performed again until the subpopulation matures. Subsequently, the individual with the highest score in each subpopulation is regarded as the individual of that subpopulation.

Step 5: After the convergence operation is completed, perform the alienation operation and release or replace the winning subgroup and temporary subgroup according to the score.

Step 6: When the condition for stopping iteration is satisfied, the optimization process is ended. According to the coding rules, obtain the best individual for analysis and obtain the initial weight and threshold of the BP network.

Step 7: Train the BP network algorithm.

Step 8: Calculate the hidden layer output, H_{j}, output layer output, Y_k, and error, e_k;

$$H_j = f(\sum_{i=1}^{n} W_{ij}X_i - a_j) \tag{1}$$

where $j = 1, 2, \ldots, l$, X is the input parameter, and H_{j} is the hidden layer output.

$$Y_k = \sum_{j=1}^{l} H_j W_{jk} - b_k \tag{2}$$

$$e_k = O_k - Y_k \tag{3}$$

where the weight is W, the threshold is b, the real result is O, and the values of k are $1, 2, \ldots, m$.

Step 9: Update weights and thresholds. If the error meets the conditions, the training is completed; if not, the weights and thresholds are updated. Then, repeat step 8 until the conditions (the training mean square error is less than 10^(-4) or the number of training times is more than 100) are met.

$$W_{ij} = W_{ij} + \eta H_j(1 - H_j)X(i) \sum_{k=1}^{m} W_{ij}e_k \tag{4}$$

Note: i take $1, 2, \ldots, n$; j take $1, 2, \ldots, l$.

$$W_{jk} = W_{jk} + \eta H_j e_k \tag{5}$$

Note: j take $1, 2, \ldots, l$; k take $1, 2, \ldots, m$.

$$a_j = a_j + \eta H_j(1 - H_j) \sum_{k=1}^{m} W_{jk} e_k \tag{6}$$

Note: k take $1, 2, \ldots, m$; j take $1, 2, \ldots, l$.

$$b_k = b_k + e_k \tag{7}$$

Note: k take $1, 2, \ldots, m$; a_j, b_k are constantly updated thresholds.

III. SOC ESTIMATION INPUT FEATURE SELECTION BASED ON THE MEA-BP NETWORK

Different from SOC estimation algorithms based on a physical model, a neural network can directly estimate SOC. Only the parameters voltage, current, and temperature during battery charging and discharging are used, and the change in the equivalent circuit parameters of the battery is not considered. The estimation results are not accurate enough. If the adaptive filtering algorithm is used for complex equivalent circuit parameter identification, the calculation time for SOC estimation is greatly increased. Based on the research on SOC estimation algorithms and neural networks, this paper introduces the incremental voltage as an input feature quantity to improve the estimation accuracy of SOC in a neural network algorithm.

A. FACTORS INFLUENCING THE SOC OF ENERGY-STORAGE LITHIUM BATTERIES

Energy-storage lithium batteries are a nonlinear system; the SOC depends on many factors, such as the ambient temperature, the charge and discharge rate, the working state of the battery, and the internal structure of the battery.

1) AMBIENT TEMPERATURE

Lithium ion energy-storage batteries work normally at a certain temperature. If the ambient temperature changes, the available capacity of the battery will change. When the temperature is low, the battery activity is low, and the available capacity of the battery will decrease. When the temperature is too high, the battery activity increases, and the available capacity will also increase. Therefore, when estimating the battery SOC, it is necessary to consider the influence of the battery temperature.

2) BATTERY CHARGE/DISCHARGE RATE

The charge and discharge current of the battery will affect the capacity of the battery. When only considering the charge and discharge rate, the discharge capacity is negatively related to the discharge rate, and the charge capacity is negatively related to the charge rate.

3) WORKING STATE OF THE BATTERY

Charging and discharging are not directly opposite processes with respect to the battery SOC, but have a hysteresis-like curve.

4) THE INTERNAL STRUCTURE OF THE BATTERY

The internal structure of different batteries is reflected in different battery parameters; that is, the equivalent circuit parameters of the battery are different. In the case of the Thevenin equivalent circuit in Fig. 2, different batteries have different resistances and capacitances.

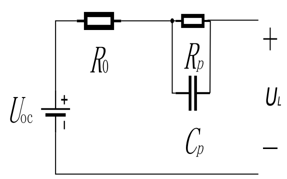

FIGURE 2. Thevenin equivalent circuit of the battery.

Although the neural network algorithm is relatively simple to use, it only uses the port voltage, current and temperature as the parameters for SOC estimation and does not take into account the internal structure of the battery, which leads to insufficient accuracy of the estimated results. Though the OCV method and the adaptive filtering method take into account the internal structure of the battery, parameter identification is required, which results in overly cumbersome calculations. Based on experience, it is decided to introduce a new input feature quantity that takes into account the internal structure of the battery into the neural network algorithm.

B. SOC ESTIMATION ALGORITHM WITH THE VOLTAGE INCREMENT AS AN INPUT CHARACTERISTIC QUANTITY

Based on the input and output characteristics of the battery, the introduction of the OCV into the neural network can improve the SOC estimation effect. The OCV can be measured or calculated. The measurement of the OCV can only be carried out after the battery is unloaded and has been standing for a long time. OCV calculation requires equivalent circuit parameters after parameter identification. The measurement of OCV and its calculation is too complicated to be a new feature of the neural network.

Based on the above analysis, the incremental voltage is introduced as a new feature quantity because the incremental voltage includes not only the port voltage increment but also the OCV increment, which takes into account the influence of the internal structure of the battery on the SOC, and the calculation is very simple.

The incremental voltage is defined as the increment of voltage within one minute after cross-flow charging and discharging, and its calculation formula is:

$$\Delta u = u(t+1) - u(t) \tag{8}$$

where t represents time, and u is the measured voltage across the battery terminals, Δu.

IV. EXPERIMENT

Three new lithium-ion batteries are connected in parallel in this paper. Constant current charge and discharge experiments are conducted at 25°C. All the devices are listed in TABLE 1.

TABLE 1. Information on the experimental device.

	Index	Product Standard
Battery	Nominal voltage	3.65V
	Capacity	60Ah
	State of health	100%
HV-PACKS TESTER	Voltage range	0-150V
	Accuracy of output voltage	< ±0.1% fs
	Accuracy of output current	< ± 0.1%fs

A. DATA ACQUISITION AND PREPARATION

To obtain the data required for simulation, battery charging and discharging experiments are carried out. HV-PACKS TESTER produced by Digatron, a test system device for battery, is shown in the Fig.3 and several indexes are exhibited in Tab.1. During the whole experiment, the port voltage and current are recorded every 0.1 s for SOC estimation.

The steps of the experiment are as follows:

Step 1: Discharge the parallel battery pack at 0.2C until it cannot be discharged; that is, the SOC at this moment is 0;

Step 2: After that, charge at 0.2C until the voltage does not increase, recording the port voltage and current during the charging process;

Step 3: Discharge at 0.2C until the battery cannot be discharged, that is, the SOC at that moment is 0, and record the voltage and current values of the port during the process;

Step 4: After that, charge at 0.3C until the voltage does not increase, recording the relevant data in the process;

Step 5: Finally, discharge at 0.3C to obtain the port voltage data during discharge.

(a) Internal structure

(b) External structure

FIGURE 3. Internal structure and external structure of the HV-PACKS TESTER.

The current and voltage data obtained during the experiment are used to verify the algorithm. First, the SOC value at each moment is acquired using the ampere-hour integration method. The SOC value at the current moment is calculated from the initial charge amount and the change in the charge amount. SOC(t_1) at time $t_1$is given, and SOC(t_2) at time t_2 is calculated by the ampere-hour integration method, and the calculation formula is as follows.

$$\mathrm{SOC}(t_2) = \mathrm{SOC}(t_1) + \frac{\int_{t_1}^{t_2} i(t)dt}{Q_c} \tag{9}$$

where Q_c is the rated capacity of the battery, $i(t)$ is the current during charging and discharging, charging is positive, and discharging is negative.

Using SOC values from 0.1 to 0.9, an SOC estimation simulation experiment based on the incremental voltage of an energy-storage lithium battery is carried out.

B. EXPERIMENTAL AND RESULTS

Considering that batteries mainly work in the range of SOC values of 0.2 to 0.8, SOC values in the range of 0.1 to 0.9 are selected. The port voltage, current, and voltage increment are input parameters, and the SOC is the output data. In this paper, 0.2C and 0.3C charging and discharging data are selected; odd-numbered columns are extracted as training data, and even-numbered columns are regarded as test data.

With increasing epochs, the mean squared error decreases. Hence, we can achieve proper convergence. At fewer than 20 epochs, the mean square error decreases rapidly. At greater than 20 epochs, the error reduction rate decreases, and at 75 epochs, the error reaches the limit conditions. If we set a smaller error limitation, the training time would be greatly increased. Hence, the convergence of the present estimation error we set is effective. The mean squared error during training is shown in Fig. 4.

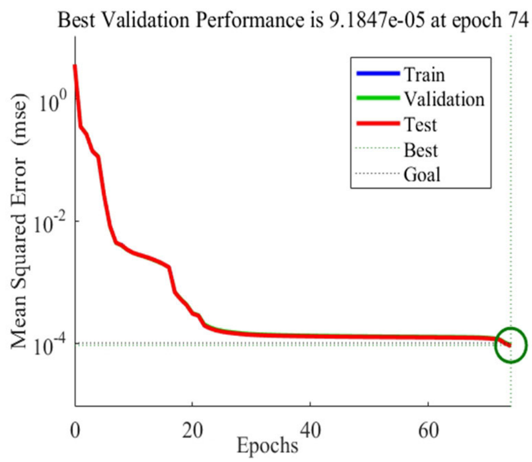

FIGURE 4. Mean Squared Error during training.

In this paper, the GA-BP algorithm, PSO-BP algorithm and MEA-BP (Mind Evolutionary Algorithm- Back Propagation) algorithm are screened. On the one hand, MEA-BP is essentially the same as GA-BP. On the other hand, compared with the GA-BP and MEA-BP algorithms, the calculation of the PSO-BP algorithm is too slow, which is not conducive to application. Therefore, the MEA-BP algorithm is selected in this paper, and a mind evolutionary BP neural network algorithm is constructed to perform nonlinear data fitting to realize the estimation of SOC. The simulation results for charging SOC estimation and discharging SOC estimation are shown in Fig. 5 and Fig. 6, respectively.

C. COMPARISON

To reflect the advantages of the improved MEA-BP algorithm with the voltage increment, SOC estimation by the MEA-BP algorithm is carried out in this paper. The soc estimation and real soc in the charging process is shown in Fig. 7. The SOC estimation and real SOC in the discharging process is shown in Fig. 8.

To measure the improvement of the algorithm obtained by introducing the voltage increment, mean absolute percentage error and relative error are selected for evaluation. The mean absolute percentage error (MAPE), an evaluation of

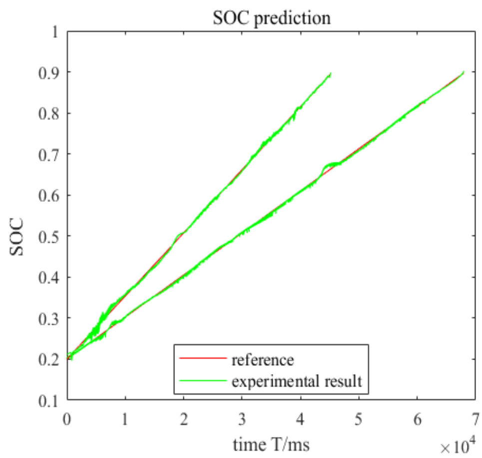

FIGURE 5. **SOC estimation when charging by the MEA-BP algorithm based on voltage increment.**

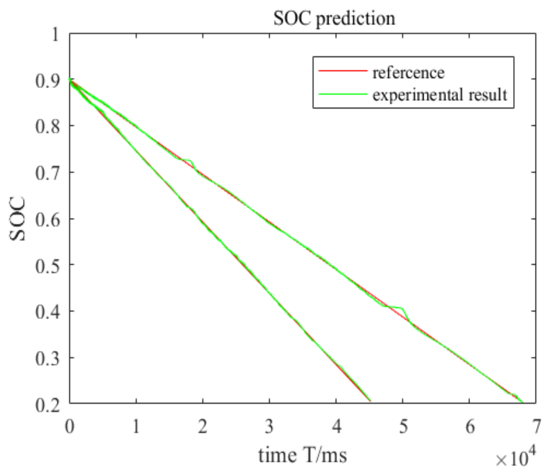

FIGURE 6. **SOC estimation when discharging by the MEA-BP algorithm based on voltage increment.**

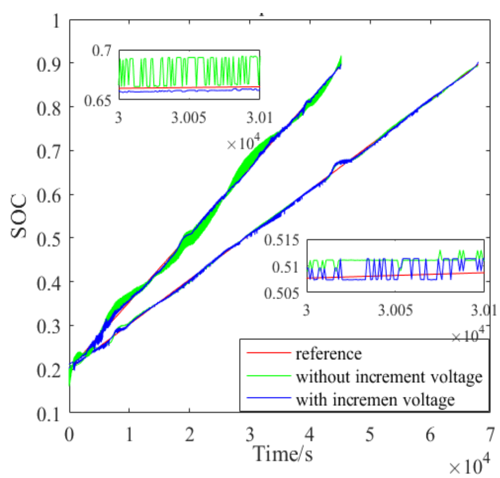

FIGURE 7. **SOC estimation and real SOC in the charging process.**

prediction results, is defined as:

$$MAPE = \frac{1}{N}\sum_{l=1}^{N}\left|\frac{y_i - y_i}{y_i}\right| \times 100\% \tag{10}$$

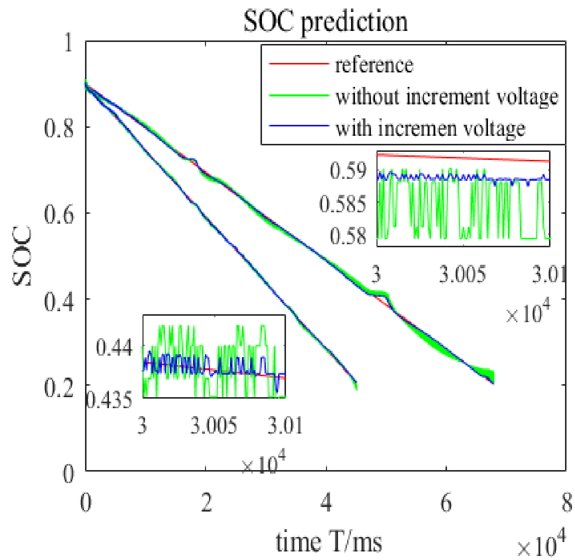

FIGURE 8. **SOC estimation and real SOC in the discharging process.**

TABLE 2. **Mean absolute percentage error of SOC estimation based on MEA-BP with voltage increment and without voltage increment.**

		MAPE (WITH ΔU)	MAPE (without Δu)
Charging	0.2C	0.5150%	1.008%
	0.3C	0.6717%	1.1148%
Discharging	0.2C	0.6308%	1.1148%
	0.3C	0.3934%	0.7334%

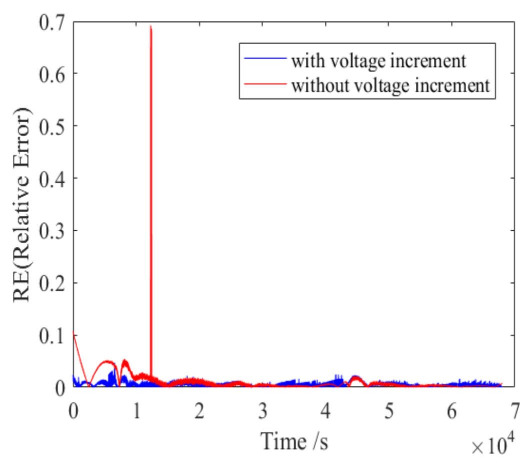

FIGURE 9. **SOC relative error of the MEA-BP algorithm during 0.2C charging.**

The definition of relative error (RE) is:

$$RE = \left|\frac{y_i - y_i}{y_i}\right| \times 100\% \tag{11}$$

According to equations (10) and (11), the mean square error (see TABLE 2) and the relative error graph (as shown below) for the voltage increment-based MEA-BP algorithm and the non-increment-based MEA-BP algorithm are shown in Fig. 9-12.

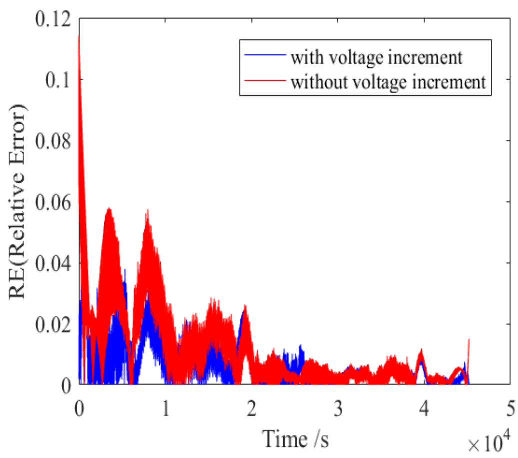

FIGURE 10. SOC relative error of the MEA-BP algorithm during 0.3C charging.

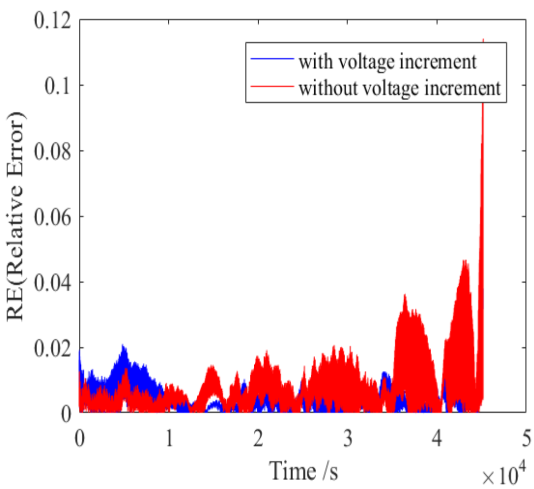

FIGURE 11. SOC relative error of the MEA-BP algorithm during 0.2C discharging.

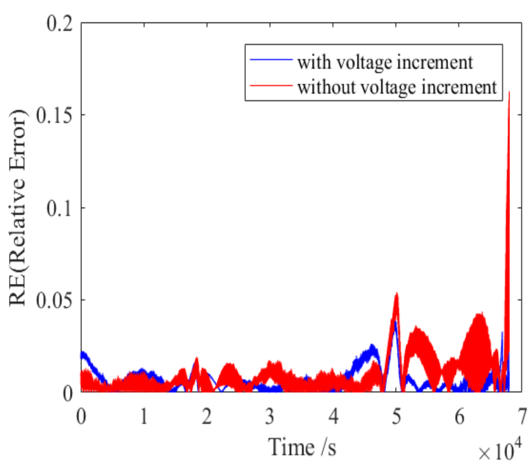

FIGURE 12. SOC relative error of the MEA-BP algorithm during 0.3C discharging.

It can be seen from the relative error graph that the incremental voltage not only reduces the relative error but also reduces the absolute error, that is, it improves the accuracy of battery SOC estimation. In addition, using the incremental voltage can maintain the relative error less than 5%, and the mean absolute percentage error is less than 1%. This result represents substantial progress in the estimation of SOC.

V. CONCLUSION

In this paper, a voltage increment-based neural network algorithm is proposed to estimate the SOC of lithium-ion batteries in real time. This method takes the port voltage, current and voltage increment as inputs and the current SOC as output to train the neural network. The benefit of this method is that it not only has the simple input and output characteristics of the neural network algorithm but also takes into account the internal structure of the battery as the voltage increment is used as the input.

To verify the effectiveness of the method, data from 0.2C and 0.3C charging and discharging experiments are selected. A total of four groups of data and the MEA-BP neural network are used for simulation experiments. The experimental results show that compared with the MEA-BP algorithm, using the voltage increment as input results in better performance and a smaller estimation error.

In the future, we will do research about time-varying charging and discharging current to improve the universality and applicability.

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