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S & M 3254

Design of Backpropagation Neural Network for Aging Estimation of Electric Battery

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(Received October 19, 2022; accepted February 27, 2023; online published February 28, 2023)

Keywords: electric vehicle battery, state of charge, machine learning methods, neural network, backpropagation algorithm

The state of charge (SOC) of an electric vehicle is very important for predicting the remaining battery level and safely protecting the battery from over-discharge and overcharge conditions. In this regard, a neural network (NN) algorithm using backpropagation (BP) has been proposed to accurately estimate the SOC of a battery. Lithium polymer batteries have a nonlinear relationship between their estimated SOC and the current, voltage, and temperature. In this study, a lithium polymer battery with a capacity of 3.7 V/16 Ah was applied. A charge/discharge experiment was performed under constant current and temperature conditions at a discharge rate of 0.5 C. The experimental data were used to train a backpropagation neural network (BPNN) that was used to predict the SOC under charging conditions and the depth of dispatch (DOD) performance under discharge conditions. As a result of the experiment, the error of the proposed BPNN model was found to be 0.22% of the mean absolute error in the discharge DOD and 0.19% of the mean absolute error in the charging SOC at 10, 50, 100, and 150 cycles. Therefore, the high performance of the SOC learning model of the designed BP algorithm was confirmed.

1. Introduction

Owing to the recent increase in global demand for electric mobility and electric vehicles, research on the efficient management and lifespan prediction of battery packs is being actively conducted. Energy efficiency management has a large effect on the cost of running a battery because losses must be made up by buying more energy. To achieve efficiency, various battery management systems (BMSs) and thermal management systems have been developed and manufactured to provide optimal battery life and performance.[1–3] It is also crucial to predict the battery state of charge (SOC) and discharge to determine the battery longevity.

To predict the battery life, the battery model and the importance of the SOC had been estimated by various methods. Estimation using the open-circuit voltage method is simple and highly accurate.[1,4] In this paper, we reveal that the output voltage of a lithium-ion battery under a constant current discharge conforms to a simulated Thevenin equivalent circuit model built of

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https://doi.org/10.18494/SAM4181

ISSN 0914-4935

several RC parts, but it has a hysteresis effect. Other classical methods such as the discharge test method have higher accuracy but require time, specific test conditions, and estimation of the battery SOC in real time. The extended Kalman filter method is also suitable for nonlinear systems with large current fluctuations, but it may have poor performance if the initial settings are poorly assigned with a very short observation time before the observed trajectory converges to the target or reaches the setting tolerance. A particle filter method has few constraints and no Gaussian conditions are needed, but accuracy is unstable. To overcome the shortcomings of the classical method, a learning model for the SOC of the battery based on artificial intelligence (AI) is required. A neural network (NN) with an intelligent algorithm is one of the most powerful tools for estimating the battery SOC and depth of dispatch (DOD).[5–10] This method has the ability of self-learning, and no battery model is required. The three layers in the NN are the input layer, hidden layer, and output layer. Outputs are obtained from the input data layer, then compared with the target output. These outputs contain errors. To avoid these errors in the output layer, weights and biases are added in the hidden layer, and the errors are corrected by updating the weights in the hidden layer. Other machine learning algorithms such as the k-nearest neighbors (KNN) method were described in a previous paper.[11] The KNN regression technique, which is based on the voltage degradation parameter, has also been utilized to estimate the SOC values of a battery.[12–16]

In this paper, a battery NN model using the backpropagation (BP) method (BPNN) was proposed to design the SOC estimation model of a battery cell. In Sect. 2, we analyze the BP of the proposed NN model, in Sect. 3, we train the model, and in Sect. 4, we analyze the experimental results.

2. Design of BPNN Battery Model

Two methods are used in the mathematical model of the battery SOC: one considers the physical model, and the other considers the equivalent circuit model. In this study, we considered the basic Thevenin equivalent circuit model shown in Fig. 1.

The above SOC equivalent circuit consists of resistors and a capacitor. When the input voltage is applied, the output is obtained from point E in the figure. The discharge of the battery

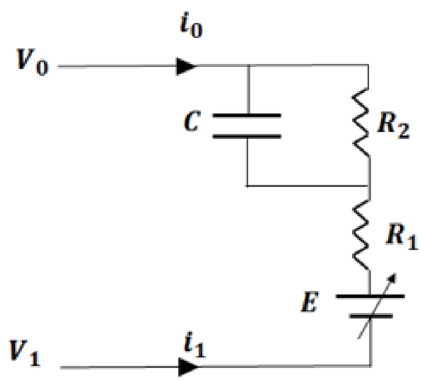

Fig. 1. Basic Thevenin equivalent circuit model.

follows the constant current method.[2] The equations describing the output battery voltage, the potential and terminal voltage, and the degradation of the battery equations are respectively given as

$$E\left[i(t),T(t),t\right]=V\left[i(t),T(t),t\right]-Ri(t), \tag{1}$$

$$V\left[i(t),T(t),t\right]=\sum_{k=0}^{n}C_k DOD^k\left[i(t),T(t),t\right]+E, \tag{2}$$

$$Degradation=\frac{1}{C_q}\int_0^t \alpha[i(t)]\cdot\beta[T(t)]\cdot i(t)dt, \tag{3}$$

where C_k is the coefficient of the kth-order term in the polynomial, E is the equilibrium potential, $\beta(T)$ is the temperature factor, and α is the discharge rate. The capacity of a battery depends on the SOC and DOD parameters. These parameters are also very important for estimating the battery life. SOC and DOD have the same relationship as Eq. (6). If SOC is recorded as 100%, then DOD is 0%; similarly, if SOC is 0%, then DOD is 100%. In other words, if SOC increases, DOD decreases and vice versa. The Coulomb charge count extracted during the charge and discharge of the battery is given in Eq. (4). The SOC based on this Coulomb charge is given in Eq. (5). Also, the relationship between DOD and SOC is given in Eq. (6).

$$Q_T=\int_0^T I(t)dt \tag{4}$$

$$SOC(T)=\frac{Q_T}{C_q} \tag{5}$$

$$DOD(T)=1-SOC(T) \tag{6}$$

Here, Q_T is the Coulomb count and C_q is the total capacity of the battery.

The BPNN consists of a multilayer feedforward NN model. The main principle is that the result after forward propagation is error-prone. BP can then be used to minimize or correct the error. In this algorithm, an s-type function is used as the transfer function between neurons, and the range of output values is (0, 1). The BPNN has a three-layer structure, which consists of an input layer, a hidden layer, and an output layer. The structure is shown in Fig. 2, in which the node cells between layers are connected and interact. If the mean absolute error (MAE) between the output value of the output layer and the predicted output value does not meet the required value, then a reverse process with weights corrected by the gradient descent method is performed so that the output value of the output layer meets the required value. Equations (7) and (8) show the unit of the corresponding NN.

$$K_j=k\left(\sum_{i=1}^{m}(w_{ij}x_i+\theta_i)\right)\left(j=1,2,\ldots,l\right) \tag{7}$$

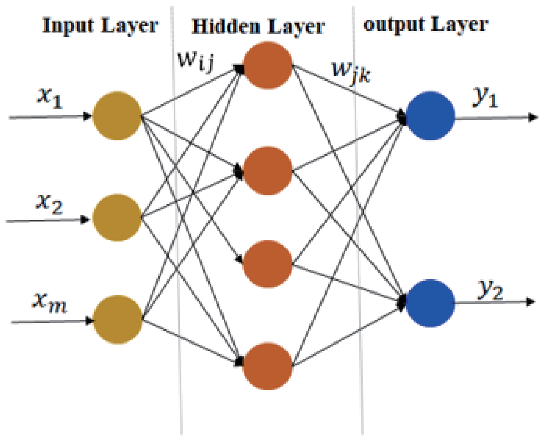

Fig. 2. (Color online) BPNN three-layer model.

$$y_k = q\left(\sum_{j=1}^{l}(w_{jk}\,p_i + \theta_k)\right)\left(k = 1, 2, \ldots, n\right) \tag{8}$$

Here, k_i represents the output of the hidden layer, y_k represents the output of the output layer, w_{ij} represents the connection between the input and hidden layers, w_{jk} is the connection weight between the hidden and output layers, m is the number of inputs, l is the number of hidden layers, n is the number of output layers, $x_i = [x_1, x_2, x_3, \ldots, x_m]^T$ is the input variables, and θ is the threshold value.

The MAE calculated in the preceding feedback process is expressed as

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left(T_i - A_i\right). \tag{9}$$

The error reverse weight of correction value is

$$w_{a+1} = w_a - \eta\frac{\partial E}{\partial w_a}, \tag{10}$$

where T_i is the prediction, A_i is the true value, n is the total number of data points, w_{a+1} is the weight correction, w_a is the current state weight, and η is the learning rate. By continuous training and error adjustment, the NN can obtain the best training model, enabling the MAE to meet the set requirements. By using the BP method, which is a weight estimation process, the accuracy of SOC estimation is increased so that the estimated value does not fall into the local minimum.

To increase the speed with which the BP finds the optimal solution, the following weight and threshold correction equations are employed:

$$\theta_k(h+1) = \theta_k(h) + b\sigma_k, \tag{11}$$

$$\theta_i(h+1) = \theta_i(h) + b\eta_i, \tag{12}$$

$$w_{ij}(h+1) = w_{ij}(h) + \alpha\eta_j w_{ij} x_j, \tag{13}$$

$$w_{jk}(h+1) = w_{jk}(h) + \alpha\sigma_k y_k, \tag{14}$$

where h is the learning number, x_j is the jth input signal, η_j is the BP learning rate in the hidden layer, σ_k is the BP learning rate in the output layer, θ_k is the threshold value in the kth layer, and b is the threshold coefficient.

3. Training of SOC and DOD Models

In this study, experiments were carried out in real time to obtain the battery SOC, which was predicted using the BPNN model algorithms. The error obtained in both algorithms was compared by comparing the experimental and predicted results. SOC and DOD predictions using the BP algorithm are compared with the results of experiments.

When predicting the characteristics of a target battery, the estimation of the battery's SOC is mainly affected by the voltage, current, and environmental temperature. Also, to enable the learning model of the BP algorithm to learn the parameters of the battery, the input layer was set up with three neurons.

The number of nodes in the hidden layer and the number of layers are positively correlated with the complexity of the NN. The number of nodes in the hidden layer is generally determined by

$$l = \log_2 m, \tag{15}$$

$$l = \sqrt{n+m+a}\cdot \tag{16}$$

Here, m is the number of input layer nodes, n is the number of output nodes, and a is the adjustment coefficient, which is between 0 and 10. In the present experiment, the number of hidden layer nodes was set at three, which minimizes the MAE. The only final output variable is the estimated value of the SOC; thus, n = 1. Figure 3 shows the output layer for the training sample.

4. Experimental Results and Discussion

In this study, an artificial NN learning mode was designed using the BP algorithm for three lithium polymer pouch batteries as research objects. The battery cell applied in the experiment had a nominal voltage of 3.2 V and a rated current capacity of 16 Ah. The charge and discharge limit was 3.7 V and the lower voltage limit was 2.5 V. The maximum discharge current was 1 C.

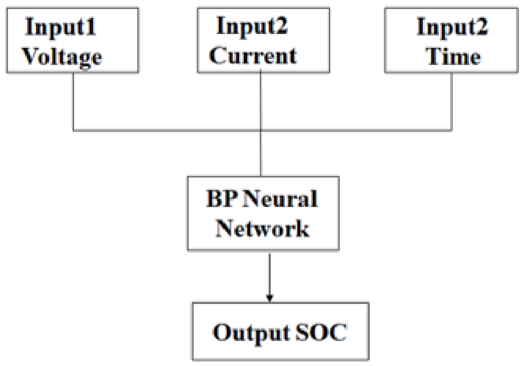

Fig. 3. Output layer for the training sample.

All training data were collected at a discharge rate of 0.5 C. The experimental setup including the power supply for charging, the discharging device, the controller for sensing the voltage and current, the voltmeter for measuring the voltage, the lithium polymer battery, the thermocouple, and the computer are shown in Fig. 4.

The initial temperature of the battery was set to 25 ℃, then the battery was charged and discharged using a load unit. The battery was charged in the constant current charging mode at full power. After 30 min, the battery was discharged at a rate of 0.5 C until the voltage reached 2.5 V, which indicated that the battery had discharged completely. During the test period, the controller recorded the current, voltage, and temperature through sensors every 2 s. A dataset of 1527 samples was obtained, 1221 of which were used as training data and 306 of which were used as testing data.

After training the NN, the next step was to optimize the weights and biases of the learning model to minimize the error. Simultaneously, the theoretical output was compared with the actual output of the network. The key parameters of the network model were determined and are given in Table 1.

The BP structure for this experiment is shown in Fig. 5. The raw data from the experiment were collected with current, voltage, and temperature sensors. Values of voltage V, current I, and temperature T were split into testing and training data.

In this BP process, the error value between the output value of the feedforward process and the target value of the learning model is obtained, and the weights and biases are modified to minimize this error using the BP method. This trained model performs experiments in 200000 iterations and in a way that minimizes errors. The battery specifications used in the experiment are shown in Table 2.

The steps in BP process are as follows.

1. *Initialization*: Collect sensor data through experiments.
2. *Feed forward*: Define the size of the input, hidden, and output layers.
3. *Error calculation*: Consider an example weight for the minimum error to meet the target value.
4. *Derivative of error*: Apply implementation such as sigmoid.
5. *Backpropagate*: Perform BP to minimize errors.

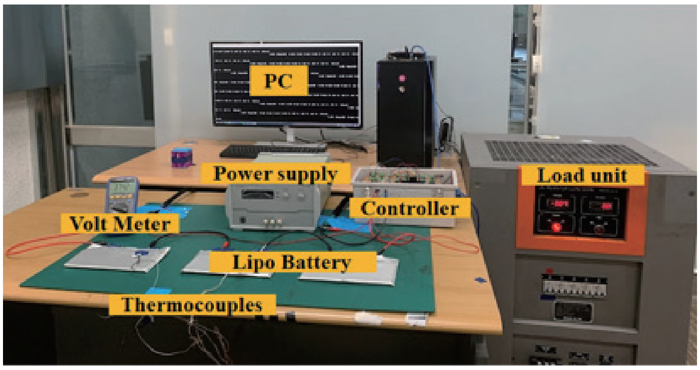

Fig. 4. (Color online) Experimental setup.

Table 1
Parameters of network model.

Parameter	Value
Maximum number of iterations	200000
Learning rate	0.05
Target MAE	5–9

Table 2
Parameters of the lithium polymer battery.

Parameter	Value
Current (A)	16
Rated Voltage (V)	3.7
Voltage (V)	12.0
Power (W)	192
Circuit	3S1P

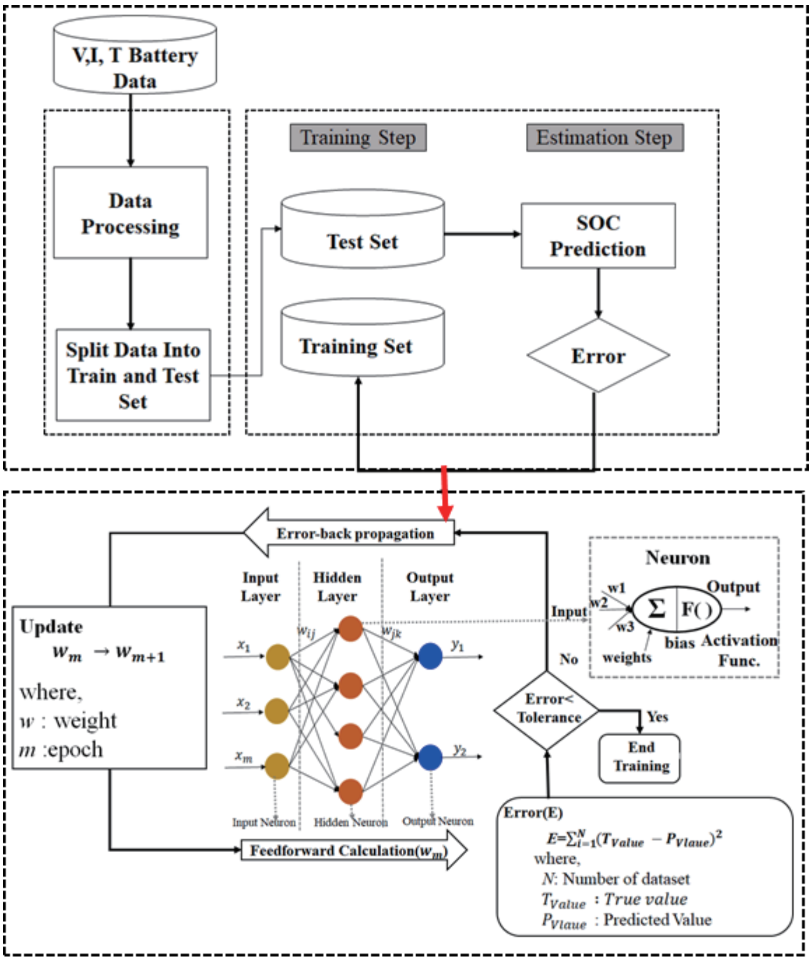

Fig. 5. (Color online) BPNN structure.

6. *Update weights*: Update the weights using gradient descent.
7. *Iterate until convergence*: Iterate until the error is minimized.
8. *Analysis*: Compare experimental results.

The structure of the NN is shown in Fig. 2 and the steps involved in the BP process are shown in Fig. 6. The experimental data are sent to the machine learning algorithm and used for training to obtain the SOC, then the predicted value is compared with the experimental result.

In the DOD experiment, actual experimental data of 10, 50, 100, and 150 cycles were measured under a 0.5 C discharge test condition, and the error was analyzed by applying the battery learning model to which the proposed BP algorithm was applied. This error analysis test is shown in Fig. 7. The MAE of the DOD calculated from the experimental results shows a deviation of 0.22%. Therefore, it is confirmed that the error in the proposed learning model is minimized by using the BP algorithm. In the experiment, we observed a gradual drop in the voltage of the battery with increasing number of successive discharge cycles. During the first 10 cycles, the battery voltage decreased, and it took 90 min for the battery to be fully discharged. However, after 50 cycles, a sharp drop in voltage was observed, and the battery was fully discharged within 80 min. This result shows that the DOD predicted by the BP model is the same as the actual measured experimental value.

The experimental SOC value is compared with the predicted SOC. The SOC experimental values for 10 cycles [Fig. 8(a)], 50 cycles [Fig. 8(b)], 100 cycles [Fig. 8(c)], and 150 cycles [Fig. 8(d)], and the estimates are shown separately.

The SOC experiment was carried out in the same manner as the DOD experiment using the same battery cell and under a charging condition of 0.5 C. The experiment was performed by measuring the actual experimental value of SOC for 10, 50, 100, and 150 cycles and training the proposed BP battery model. The actual and estimated values of the load test have an SOC error of 0.19%, calculated as the MAE of the test result. Therefore, the predicted SOC is very close to the measured or calculated SOC value. The average absolute error and the comparison between the predicted and experimental results are shown in Figs. 8(a) to 8(d).

Lastly, by implementing the BP algorithm to predict the SOC under charging conditions and DOD performance under discharge conditions, we obtained a very small value of error between

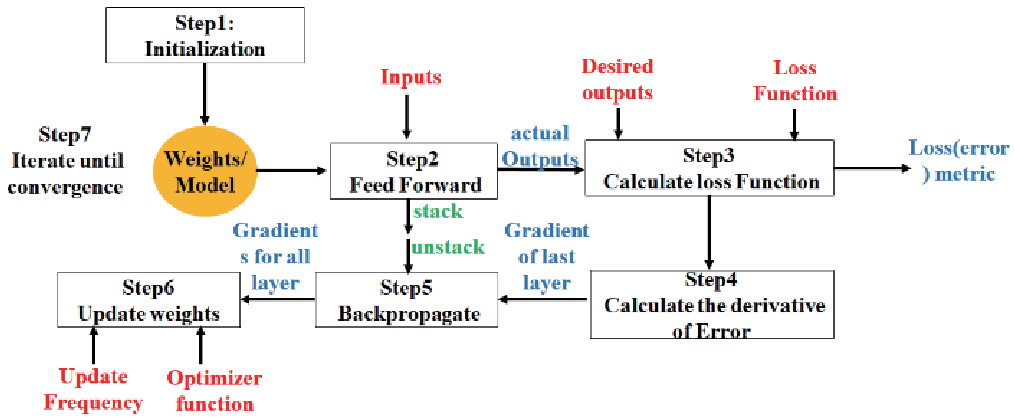

Fig. 6. (Color online) BP evaluation model.

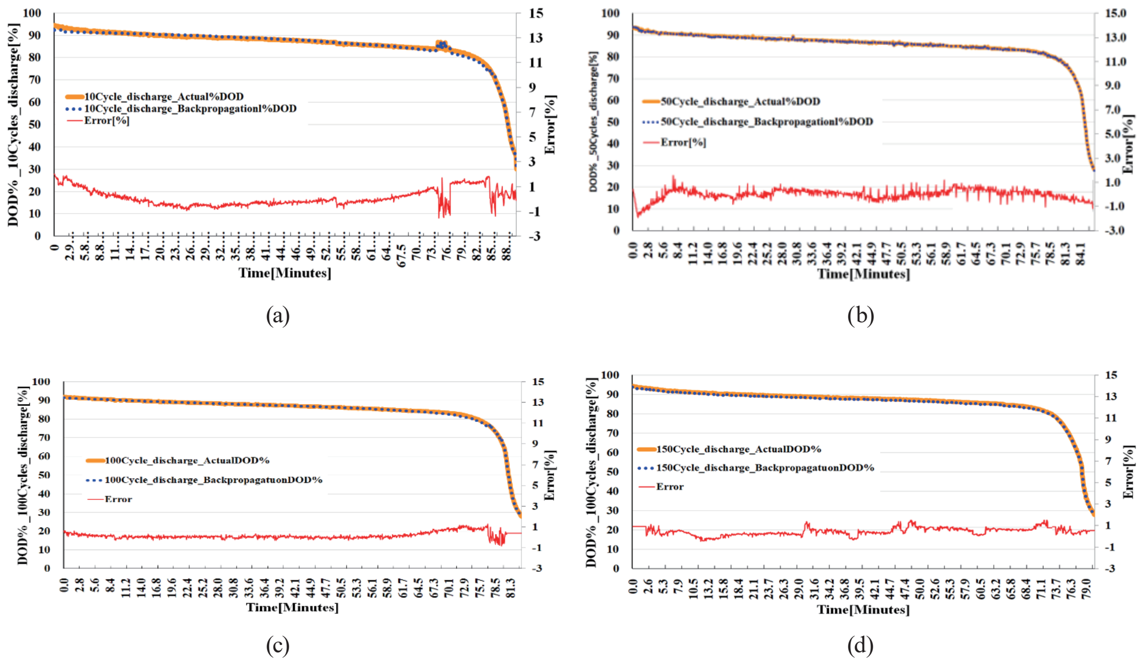

Fig. 7. (Color online) Experimental results during discharge condition of DOD for (a) 10, (b) 50, (c) 100, and (d) 150 cycles.

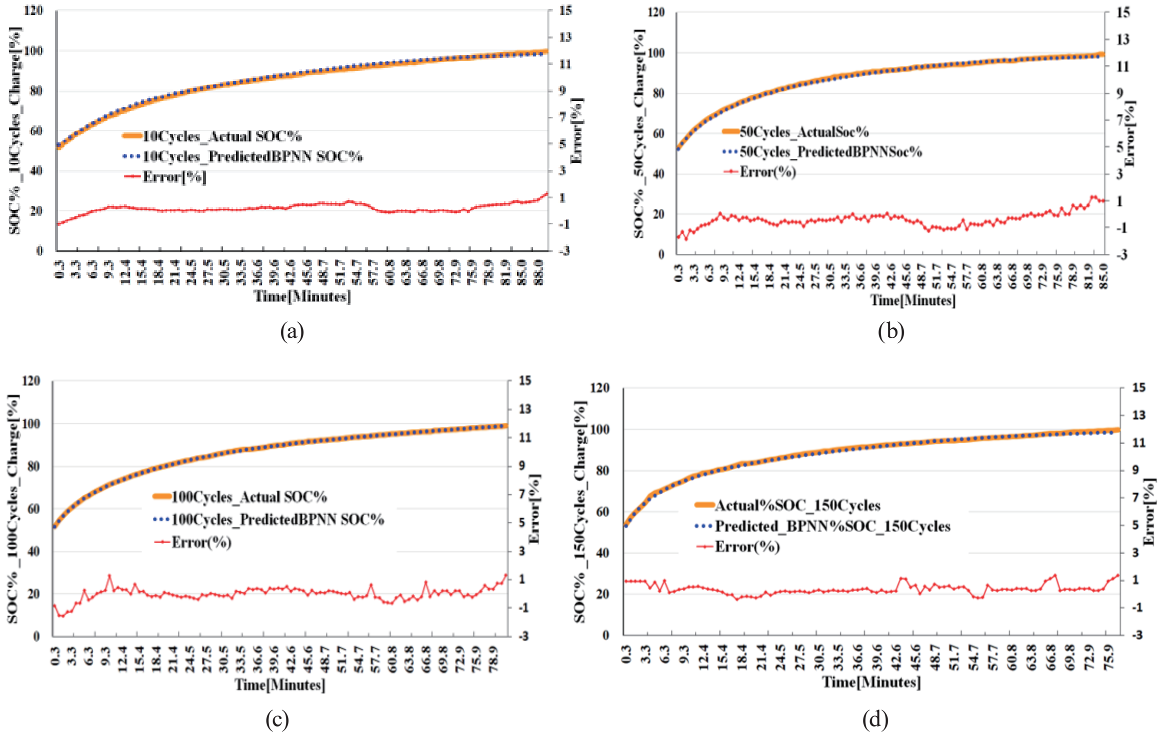

Fig. 8. (Color online) Experimental results during charge condition of SOC for (a) 10, (b) 50, (c) 100, and (d) 150 cycles.

Table 3
Error values of DOD for BPNN and KNN during discharge condition.

Discharging	BPNN	KNN
50 cycles	0.005	0.44
150 cycles	0.006	0.36

Table 4
Error values of SOC for BPNN and KNN during charging condition.

Charging	BPNN	KNN
50 cycles	−0.08	0.58
150 cycles	0.037	0.037

the predicted and actual values. In this experiment, the error value predicted through repeated experiments of 50 cycles and 150 cycles using BPNN and KNN methods is shown in Table 3 for DOD and Table 4 for SOC.(12)

5. Conclusion

In this study, a battery pack design considering aging of the battery during the charge/discharge cycle is being studied. In this paper, we propose a method of estimating the SOC for each battery using the BP algorithm. As the experimental conditions of the applied battery cell, the SOC was estimated in real time using a lithium polymer with a nominal voltage of 4 V and a capacity of 16 A at room temperature. In this experiment, the change in battery voltage was observed after 10, 50, 100, and 150 cycles in a state in which the battery was charged and discharged by a constant current method at discharge and charge rates of 0.5 C. The DOD prediction performance of the battery has an MAE of 0.22%, as shown in Fig. 7, and the SOC prediction rate has an MAE of 0.19%, as shown in Fig. 8. Using this learned battery model, we plan to conduct a study on the predictive analysis of DOD and SOC of batteries using a battery learning model that applies a BP algorithm to a battery package of 80 kW used in electric vehicles in the future.

Acknowledgments

This work was supported by the research grant of the Busan University of Foreign Studies in 2022. This grant was applied to develop this work and also attend the technical seminar. Finally, I would like to express my sincere gratitude to Busan University of Foreign Studies.

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