SOC estimation algorithm of power lithium battery based on AFSA-BP neural network

Qiuxia Wang1,2, Peizhou Wu2, Jialing Lian1
1Mechanical Engineering Department, Fujian Chuanzheng Communications College, Fuzhou, Fujian, People’s Republic of China
2South East (Fujian) Motor Corporation Ltd., Purchasing Department, Fuzhou, Fujian, People’s Republic of China
E-mail: 869344990@qq.com

Abstract: The non-linear characteristic of power lithium battery restricts the establishment of accurate battery models. To overcome this problem and estimate the battery state of charge (SOC) more accurately, the artificial fish swarm algorithm-back propagation (AFSA-BP) neural network structure was designed based on AFSA and BP neural network theory. According to the test parameters of power lithium battery, the related mathematical model was established. The flow charts of optimising BP neural network with AFSA algorithm and estimating SOC value by AFSA-BP algorithm are given. The specific implementation steps are elaborated. Using the 48 V, 50 Ah lithium iron phosphate (LiFePO4) power battery as experimental object, through the periodic charging and discharging experiments and software simulation, the correctness, validity and accuracy of the application of AFSA-BP neural network in estimating SOC value of the power lithium battery are verified.

1 Introduction

State of charge (SOC) is a core test item of the battery management system (BMS) on electric vehicle. It is used to reflect the dump energy of battery and to predict the endurance mileage of electric vehicle. [1] So the accuracy and precision of SOC estimation have a direct impact on operation status, service life and economic cost of BMS. At present, most of the electric vehicle enterprises adopt fusion algorithm which combines the ampere-hour integral (AHI) method with the open-circuit voltage method. Then, the algorithm is matched with a certain correction method, whereas it requires an accurate battery model. Limited by the complex non-linearity in battery, there are so many problems in the algorithm that the SOC estimation error is too large. Extended Kalman filter (EKF) algorithm can achieve better SOC estimation result. EKF algorithm still needs to build accurate battery models. Moreover, a large number of mathematical operations also impose strict requirements on the hardware of BMS. [2] Artificial neural network (ANN) can avoid the internal complexity of battery [3] and simulate the dynamic characteristics of battery. [4] So it has the ability of generalisation and fault-tolerance. [5] It is suitable for all types of batteries and is becoming more and more popular.

BP neural network is the most widely used ANN at present. [6] It has many advantages, such as simple structure, more adjustable parameters, good operability and high reliability. [7, 8] The learning rate of BP neural network is fixed and small. It leads to long training time and slow convergence speed. [8] In addition, BP neural network is sensitive to initial value and easy to fall into local minimum when optimising weights and thresholds. [5, 9] AFSA algorithm has the advantages of low initial value requirement, fast jumping out of local extreme point to achieve global optimisation, and fast convergence speed. So optimisation of BP neural network by AFSA algorithm can overcome the shortcomings of BP neural network. Finally, the validity and feasibility of using AFSA-BP neural network for SOC estimation are verified by simulation experiments.

2 Structure and modelling of BP neural network

2.1 Network structure

BP neural network is one of multi-layer feed-forward neural network. Each neuron in the network only receives the output of the neuron in anterior layer. Then the neuron passes its output to the neuron in posterior layer. There is no feedback between layers in the network. Errors are transmitted in opposite direction. So BP neural network has strong ability of non-linear processing and learning. When applied to SOC estimation of power lithium battery, the output of BP neural network has only one quantity. Its structure is shown in Fig. 1.

![BP neural network structure for SOC estimation](image)

The first layer, that is the input layer, consists of n neurons. The n neurons in input layer receive n external inputs (x1, x2,...xn). The input layer is only responsible for introducing information from the outside world and forwarding it to the first hidden layer. [6, 10] The hidden layer which consists of m neurons can be multi-layered or single-layered. Single hidden layer structure is used for SOC estimation. The output layer uses only one neuron to output z, which is the SOC, to the outside world. The input layer only serves for information transport. Both the hidden layer and the output layer have the ability of information processing. [6] The connection lines between the neurons represent the connection weights which are the two vectors to be determined after learning the BP neural network. \( v_j \) refers to the connection weight between the jth neuron in the input layer and the jth neuron in the hidden layer. \( w_k \) refers to the connection weight between the kth neuron in the hidden layer and the neuron in the output layer.

2.2 Mathematical modelling

According to the structure of the above BP neural network, each layer of the BP neural network can be expressed by mathematical expressions as follows:
The outputs of the input layer is its inputs \((v_1, x_2, \ldots x_n)\);

② The inputs of the hidden layer is the difference between the dot product, which is between the input layer outputs and the connection weights and the thresholds. The input of the \(i\)th neuron in the hidden layer is set to \(y_i\), then

\[
y_i = \sum_{j=1}^{n} v_{ij}x_j + v_{i0} = \sum_{j=0}^{n} v_{ij}x_j = V_i^T \cdot X \quad (i = 1, 2, \ldots, m)
\]

In the formula, \(V_j\) is the connection weights column vector between input layer neurons and hidden layer neurons, \(V_j = [v_{i1}, v_{i2}, \ldots, v_{in}]^T\), \(X\) is the input column vector, \(X = [x_0, x_1, \ldots, x_n]^T\), \(v_{i0}\) is the threshold of the \(i\)th neuron in hidden layer. \(x_0\) takes \(-1\) and makes the threshold of the neurons in hidden layer negative.

In the SOC estimation of the power lithium battery, the transfer function (i.e. the inspirit function) of the hidden layer is a unipolar Sigmoid differentiable function: \([11]\]

\[
f(y) = \frac{1}{1 + e^{-y}}
\]

So, let the output of the \(i\)th neuron in hidden layer be \(o_i\), then

\[
o_i = f(y_i) = \frac{1}{1 + e^{-\sum_{j=0}^{n} w_{ij}x_j}} \quad (i = 0, 1, \ldots, m)
\]

③ The output layer has the same processing power as the hidden layer. So the output value of the output layer is within \([0, 1]\). Assuming that the input of the neuron in output layer is \(p\), then

\[
p = \sum_{j=1}^{m} w_{j0} + \sum_{j=0}^{m} w_{ij}y_j = W^T O
\]

In the formula, \(W\) is the column vector of the output layer weight, \(W = [w_{11}, w_{12}, \ldots, w_{1n}]^T\), \(O\) is the input column vector, \(O = [o_1, o_2, \ldots, o_m]^T\), \(w_{j0}\) is the threshold of the neuron in output layer. \(o_0\) takes \(-1\) and makes the threshold \(w_{j0}\) negative. The threshold column vector \(V_0 = [v_{01}, v_{02}, \ldots, v_{0m}]^T\) and \(W_0 = [w_{01}]^T\) is the other two vectors to be determined after the learning of BP neural network.

The output of the neuron in output layer is

\[
z = f(p) = \frac{1}{1 + e^{-W^TO}}
\]

Let the expected output of the neuron in output layer be \(z^*\). For M-dimensional training sample set, the output of the \(i\)th training sample is \(z_i\) and the expected output is \(z_i^*\). Then, the output error corresponding to the training sample set can be expressed as the mean square error between the actual output and the expected output. That is to say

\[
E = \frac{1}{M} \sum_{i=1}^{M} (z_i - z_i^*)^2
\]

3 Description and modelling of AFSA algorithm

AFSA algorithm is a stochastic search optimisation algorithm which is based on simulating the behaviour of fish foraging, clustering and tailing. [9] AFSA algorithm has the advantages of distributed processing, robust performance of parameters and initial values, simple implementation and flexible use. [12, 13] The combination of AFSA algorithm and BP neural network can overcome many shortcomings of BP neural network and achieve the goal of optimising the structure of BP neural network.

Suppose there is a fish swarm living in water with uneven distribution of food concentration. When a fish finds that its current food concentration is lower than that of a certain point in its perception range, it will swim to the high food concentration position, which is the foraging behaviour. Usually, the place with the most fish is the place with the highest food concentration in waters. [14] If a fish perceives that the fish swarm is not crowded, it will swim to the fish swarm. If a fish finds a shoal, it will swim to the shoal. This is called clustering behaviour. When a fish finds food, the nearby fish will follow it. This led to fish coming along from further afield [15]. This is called tailing behaviour. By simulating these behaviours of natural fish, each artificial fish can explore its current environment and then choose behaviour to perform. By performing these behaviours, artificial fishes constantly adjust their position and gather around areas of high food concentration ultimately. The global optimal solution is obtained. [16] This is the optimisation idea of AFSA algorithm.

Each artificial fish represents a BP neural network. [11] The state values of each artificial fish are the variables of BP neural network to be optimised, i.e. the weight vectors \(V_i\) and \(W_k\), and the threshold vectors \(v_0\) and \(w_0\). If the state of the \(k\)th artificial fish is \(X(k)\), then

\[
X(k) = \{[v_{j0}(k), w_{j0}(k), v_{0j}(k), w_{0j}(k)]\} \quad i = 1, 2, \ldots, m; j = 1, 2, \ldots, n
\]

In the formula, \(i\) is the number of the neurons in hidden layer and \(j\) is the number of the neurons in input layer. So the state of each artificial fish is \((i \times j + i + 1)\) dimensional variable. Define an artificial fish swarm, in which there are \(N\) artificial fish. Then, \(k = 1, 2 \ldots N\).

The food concentration of an artificial fish in the water is also called the fitness of the artificial fish. The fitness takes the reciprocal of the output error which corresponds to the training sample of BP neural network. For the training samples of group 1, the food concentration of the \(k\)th artificial fish \(F_k(k)\) can be expressed as follows:

\[
F_k(k) = \frac{1}{E_k(k)}
\]

By the iterative learning of training samples, artificial fishes look for the maximum food concentration point (i.e. the maximum fitness) in the water. Finding the maximum fitness means finding the minimum error. Thus, the state variables of artificial fish, i.e. the weights and thresholds of BP neural network, are determined.

Let \(D\) be the maximum perception range of artificial fish and \(S\) is the maximum step length of artificial fish. When the food concentration of position \(t\) is higher than the current position, i.e. \(F_k(k) > F_k(k)\) in the perception range \(D\), the \(k\)th artificial fish moves to position \(t\) in the direction of position \(t\). The state of the artificial fish in the position \(t\) is

\[
X_{New}(k) = X(k) + S \cdot \text{Random} \cdot \frac{X(k) - X(k)}{\|X(k) - X(k)\|}
\]

In the formula, \(\text{Random}\) is a random number within \([0, 1]\). \(\|X(k) - X(k)\|\) represents the distance from the current position of the artificial fish to position \(t\). Obviously, \(\|X(k) - X(k)\| < D\).

If the artificial fish did not perceive higher food concentration position, it moved randomly to the position Next. Here, the state of artificial fish is as follows:

\[
X_{New}(k) = X(k) + S \cdot \text{Random}
\]

Finally, the artificial fish are clustered around several local optimal solutions. The random movement and the random step length increase the possibility of jumping out of the local optimal solution. The crowding restriction of fish swarm in clustering behaviour makes the artificial fish tend to global optimal solution. So the local optimal solution can be avoided.
4 Estimate SOC by AFSA-BP neural network

According to the above analysis, the steps of estimating SOC by AFSA-BP algorithm are described as follows:

Step 1: Set up the structure of BP neural network.

Three-layer of BP neural network structure is selected, i.e. input layer, hidden layer and output layer have only one layer, respectively. The parameters of power lithium battery that can be directly detected are voltage \( U \), current \( I \) and temperature \( T \). Take these three parameters as the BP neural network input. Therefore, the number of the neurons in input layer is \( n = 3 \), and the input amount \( x_1 = U \), \( x_2 = I \), \( x_3 = T \). There is only one final result estimated by BP neural network, which is the SOC of power lithium battery. So the number of the neurons in output layer is 1 and the output \( z = \text{SOC} \). The number of the neurons in hidden layer is determined according to \( m = \sqrt{n + 1 + \alpha} \). In the formula, \( \alpha \in [1, 10] \) [17]. The experimental results show that the output error is the smallest when \( \alpha = 5 \), so the number of neurons in the hidden layer \( m = 7 \) is taken.

Step 2: Generate artificial fish swarm randomly and initialise it.

The initialised parameters include the scale of the artificial fish swarm, i.e. the number of the artificial fishes, the initial weights and thresholds of BP neural network, the perception range of the artificial fish, the maximum moving step, the crowding factor, the maximum number of iterations and probes etc.

Step 3: Calculate the fitness of each artificial fish. Set up bulletin board. Assign the artificial fish with maximum fitness to the bulletin board.

Step 4: Artificial fish searches for companions in its perception range. If a companion is found, it is judged whether the number of companions \( \text{CompNum} \) is equal to 1. If \( \text{CompNum} = 1 \), test whether the companion's fitness \( F(c) \) is greater than the current fitness \( F(k) \).

If \( F(c) > F(k) \), the tailing behaviour is performed. If \( \text{CompNum}>1 \), test whether the fitness \( F(h) \) of the fish swarm centre is greater than the current fitness \( F(k) \). If \( F(h) > F(k) \), continue to judge whether the fish swarm is crowded, that is, whether \( F(h) / \text{CompNum} \leq \alpha F(k) \) is true. It means the fish swarm is too crowded if the formula \( F(h) / \text{CompNum} \leq \alpha F(k) \) is true and the foraging behaviour is performed. Otherwise, it means the fish swarm is not too crowded and the clustering behaviour is performed. If no companions are found in the perception range, the artificial fish performs the foraging behaviour directly.

Step 5: Update the bulletin board and the iteration times plus 1.

Step 6: Judge whether the fitness on the bulletin board meets the expected value \( F(\text{Obj}) \). If the expected value is reached, the optimal solution on the bulletin board is outputted and the optimisation is ended. If the expected value is not reached, continue to judge whether the iteration number reaches the maximum. If the maximum number of iteration has been reached, the optimal solution on the bulletin board is outputted and the optimisation is ended. Otherwise, the next iteration cycle will be started.

Step 7: Assign the optimal weights and thresholds obtained by AFSA algorithm to BP neural network. The BP neural network is trained with training samples to obtain the ability of estimating SOC.

The flow chart of estimating SOC by AFSA-BP algorithm is shown in Fig. 2.

The flow chart of optimising BP neural network with AFSA algorithm is shown in Fig. 3.

5 Experimental verification

5.1 Acquisition of experimental data

In order to verify the feasibility and validity of AFSA-BP neural network in estimating SOC, a pack of 48 V, 50 Ah LiFePO4 power battery was selected as the experimental object. Periodic charging and discharging experiments of the battery pack were carried out at room temperature. The 48 V, 50 Ah LiFePO4 power battery pack is composed of 15 battery cells with rated voltage of 3.2 V in series.
In the formula, $X$ is the measured data before data normalisation. $X$ is the measured data after data normalisation. $X_{\text{max}}$ and $X_{\text{min}}$ are the maximum and minimum values in the measured data sequence, respectively. Some measured data and normalised sample data are shown in Table 1.

### 5.2 Parameter settings

The method of parameter selection in this study is: Find the values range by refers to the reference [19] first. Second, take different values for each parameter in this range. Third, the set of value which is convergent to the target fitness fastest is found by the test.

Set the target fitness $f(OB)=10$. When there are <20 fishes, the iteration number decreases significantly as the fish number increases. When there are >20 fishes, the iteration number does not significantly decreases as the fish number increases. Therefore, generate 20 artificial fishes randomly, i.e. $N=20$, and take the maximum iteration number to 50, i.e. $\text{IterNum}=50$. Based on random distribution, the initial weights and thresholds are usually small random numbers. [17] The larger the perception range and the maximum moving step, the easier the artificial fish jumps out of the local optimum. [11] Set the perception range $D=1$ and the maximum moving step $\Delta =0.1$. In the question of finding the maximum, the formula for the crowding factor is $\sigma = \frac{1}{\beta_{\text{max}}}$. The $\beta$ indicates the closeness of the artificial fish to the extreme value. The $\beta_{\text{max}}$ refers to the maximum number of artificial fish that are expected to accumulate in the field. The larger $\sigma$, the smaller the allowed artificial fish swarm. Although the ability of artificial fish to jump out of local optimum will be stronger, the artificial fish will walk away randomly to avoid overcrowding. Then it is impossible to accurately approximate the extreme point. So take the crowding factor $\sigma = 0.618$. The more the maximum number of probe, the stronger the foraging behaviour and the higher the efficiency of convergence. It will reduce the probability of random movement of artificial fish. Then, it is not easy to overcome the local optimum. So take the maximum probe number $\text{TryNum}=100$.

### 5.3 Data analysis

According to the structure of BP neural network mentioned above, it can be seen that 36 optimal weights and thresholds can be obtained by optimising BP neural network with AFSA algorithm. After assigning them to BP neural network, train the BP neural network with training samples, so that the BP neural network has the ability of SOC estimation. Then, the test samples are substituted into the BP neural network to get SOC test values.

In a strict sense, the true value of SOC is not available. So the error can only be calculated using the agreed true value. Usually, the value obtained by theoretical calculation or the value measured within the maximum and minimum values in the measured data sequence, respectively. Some measured data and normalised sample data are shown in Table 1.

| Table 1 Some measured data and sample data |
|---------------------------------|-----------|-----------|
| group 1 voltage                | 43.71 V   | 0.173515  |
| current                        | 10.01 A   | 0.732758  |
| temperature                    | 27.8°C    | 0.134000  |
| group 2 voltage                | 48.32 V   | 0.520711  |
| current                        | 9.99 A    | 0.670690  |
| temperature                    | 29.1°C    | 0.290000  |
| group 3 voltage                | 50.90 V   | 0.715021  |
| current                        | 10.02 A   | 0.763793  |
| temperature                    | 30.8°C    | 0.494000  |

![Fig. 4](http://example.com/fig4.png)

Fig. 4 Comparison curves of SOC actual values, AFSA-BP test values and AHI test values

indicates that the relative errors are <0.5% even at low SOC values. Therefore, the experimental results fully meet the BMS requirements for SOC estimation accuracy of power lithium battery. The validity and accuracy of the application of AFSA-BP algorithm in SOC estimation of power lithium battery are verified.

In the AFSA-BP algorithm, the biggest time frequency is the update of bulletin board. In each iteration calculation, the bulletin board needs to be updated for each trial of each artificial fish. So the time complexity of this algorithm is about cubic order, expressed as $O(n^3)$. It can be seen that, in terms of time complexity, the AFSA-BP algorithm is not necessarily faster than the EKF algorithm when the parameters are taken appropriately. However, the model of the AFSA-BP algorithm is much simpler than the model of the EKF algorithm. When the optimal weight and threshold of the AFSA-BP algorithm are found offline, the model of the AFSA-BP algorithm is determined. After the model is transplanted to BMS, the BMS only computes a fixed model for each run rather than repeatedly looking for optimal weights and thresholds. To obtain higher estimation accuracy, the EKF algorithm must take a higher order. It also puts higher requirements on the hardware of the BMS. This is extremely unfavourable for the cost control of BMS. In this respect, the AFSA-BP algorithm is more realistic than the EKF algorithm.

### 6 Conclusions

The AFSA algorithm was used to optimise the BP neural network. The optimal weights and thresholds of neurons were obtained through finite iterations. Then, through the data training with a large number of training samples, the BP neural network has the ability of SOC estimation. Higher accuracy of SOC estimation can be obtained. [10, 13] In this research, a BP neural network structure for battery SOC estimation was designed and the mathematical models of each layer of the BP neural network were established. The optimisation process and mathematical model of AFSA algorithm were analysed. The steps and procedures of estimating SOC by AFSA-BP neural network were proposed. For the 48 V/50 Ah LiFePO4 power battery, test samples were obtained by charging and discharging experiments and software simulation methods. The SOC actual values were obtained by performing the EKF theoretical calculation on these test samples. The SOC AFSA-BP test values were compared with the SOC actual values and the SOC AHI test values. Finally, the correctness, validity and accuracy of the design were verified.
Acknowledgments

This work was financially supported by the Science and Technology Development Plan Project of Fujian Transportation Department (No. 201322) and the Education and Scientific Research Projects for Young and Middle-aged Teachers of Fujian Education Department (No. JAT170956).

References

[1] Wang, Q.: ‘The master control software for power lithium battery management system based on MCS D2P development platform’, J. Shenzhen Univ. Sci. Eng., 2018, 35 (5), pp. 473–479
[2] Di Domenico, D., Croft, Y., Prada, E., et al.: ‘A review of approaches for the design of li-ion BMS estimation functions’, Oil Gas Sci. Technol.-Rev. IFP Energies Nouvelles, 2013, 68 (1), pp. 127–135
[3] Ji, Y., Du, H., Sun, H.: ‘A survey of state of charge estimation methods’, Electr. Meas. Instrum., 2014, 51 (4), pp. 18–22
[4] Li, G., Dong, D., Chen, S.: ‘Estimation for SOC of LiFePO4 li-ion battery’, Comput. Simul., 2015, 32 (3), pp. 163–168
[5] Xue, P., Song, Y.: ‘The prediction of lead-acid battery remaining capacity based on improved ant colony algorithm and BP network’, J. Harbin Univ. Sci. Technol., 2016, 21 (6), pp. 95–99
[6] Han, L.: ‘Artificial neural network course’ (Beijing University of Posts and Telecommunications Press, China, 2006, 1st edn. 2006)
[7] Zhou, M., Wang, J., Li, Y.: ‘Optimized BP neural network in the prediction of electric vehicles SOC’, J. Natural Sci. Heilongjiang Univ., 2015, 32 (1), pp. 129–134
[8] Li, J., Feng, L.: ‘The improved BP neural network in SOC prediction research of the lithium battery of the electric car’, Automob. Appl. Technol., 2018, 43 (21), pp. 19–21
[9] Liu, S.: ‘Research on BP neural networks based on improved artificial fish-swarm algorithm’, Comput. Eng. Design, 2009, 30 (20), pp. 4719–4765
[10] Chen, Q., Liu, Y., He, Z.-J.: ‘SOC estimation method of lithium battery based on improved EKF’, J. Fujian J. Univ. Nat. Sci. Ed., 2018, 34 (6), pp. 34–46
[11] Hu, X., Li, Q.: ‘WSN data fusion based on neural network optimized by artificial fish swarm algorithm’, J. Chongqing Univ. Posts Telecommun. (Natural Sci. Ed.), 2018, 30 (5), pp. 614–619
[12] Feng, Z., Tian, L.: ‘SOC prediction for electric vehicle battery based on AFSA-RBF neural network’, J. Chongqing Technol. Business Univ. (Natural Sci. Ed.), 2016, 33 (5), pp. 6–10
[13] Gao, Y., Gui, L., Wang, T., et al.: ‘A novel artificial fish swarm algorithm for recalibration of fiber optic gyroscope error parameters’, Sensors, 2015, 15 (5), pp. 10547–10568
[14] Guo, M., Xing, H., Zhang, D., et al.: ‘Temperature compensation for humidity sensor based on the AFSA-BP neural network’, Instrum. Techn. Sensor, 2017, 54 (8), pp. 6–10
[15] Nie, L.: ‘Artificial fish swarm algorithm and its application’. Master thesis, Guangxi University for Nationalities, 2009
[16] Cheng, C.: ‘Research on swarm intelligence algorithm and its implementation in MATLAB’ (Inner Mongolia Science and Technology Press, China, 2015, 1st edn. 2015)
[17] Yang, S., Han, Q., Xu, L., et al.: ‘Comprehensive effect evaluation of energy saving and emission reduction based on fish-swarm algorithm optimizing neural network’, J. Central South Univ. Technol. Sci. Technol., 2012, 43 (4), pp. 1538–1544
[18] Chen, Q., Zuo, F., Lu, W.: ‘Study on pressure sensor temperature compensation based on IAFSA-BP neural network algorithm’, Microcomput. 2016, 35 (9), pp. 27–33
[19] Wang, L., Shi, Q.: ‘Parameters analysis of artificial fish swarm algorithm’, Comput. Eng., 2010, 36 (24), pp. 169–171

Fig. 5 Absolute error curve of SOC AFSA-BP test values

Fig. 6 Relative error curve of SOC AFSA-BP test values

Acknowledgments

This work was financially supported by the Science and Technology Development Plan Project of Fujian Transportation Department (No. 201322) and the Education and Scientific Research Projects for Young and Middle-aged Teachers of Fujian Education Department (No. JAT170956).

References

[1] Wang, Q.: ‘The master control software for power lithium battery management system based on MCS D2P development platform’, J. Shenzhen Univ. Sci. Eng., 2018, 35 (5), pp. 473–479
[2] Di Domenico, D., Croft, Y., Prada, E., et al.: ‘A review of approaches for the design of li-ion BMS estimation functions’, Oil Gas Sci. Technol.-Rev. IFP Energies Nouvelles, 2013, 68 (1), pp. 127–135
[3] Ji, Y., Du, H., Sun, H.: ‘A survey of state of charge estimation methods’, Electr. Meas. Instrum., 2014, 51 (4), pp. 18–22
[4] Li, G., Dong, D., Chen, S.: ‘Estimation for SOC of LiFePO4 li-ion battery’, Comput. Simul., 2015, 32 (3), pp. 163–168
[5] Xue, P., Song, Y.: ‘The prediction of lead-acid battery remaining capacity based on improved ant colony algorithm and BP network’, J. Harbin Univ. Sci. Technol., 2016, 21 (6), pp. 95–99
[6] Han, L.: ‘Artificial neural network course’ (Beijing University of Posts and Telecommunications Press, China, 2006, 1st edn. 2006)
[7] Zhou, M., Wang, J., Li, Y.: ‘Optimized BP neural network in the prediction of electric vehicles SOC’, J. Natural Sci. Heilongjiang Univ., 2015, 32 (1), pp. 129–134
[8] Li, J., Feng, L.: ‘The improved BP neural network in SOC prediction research of the lithium battery of the electric car’, Automob. Appl. Technol., 2018, 43 (21), pp. 19–21
[9] Liu, S.: ‘Research on BP neural networks based on improved artificial fish-swarm algorithm’, Comput. Eng. Design, 2009, 30 (20), pp. 4719–4765
[10] Chen, Q., Liu, Y., He, Z.-J.: ‘SOC estimation method of lithium battery based on improved EKF’, J. Fujian J. Univ. Nat. Sci. Ed., 2018, 34 (6), pp. 34–46
[11] Hu, X., Li, Q.: ‘WSN data fusion based on neural network optimized by artificial fish swarm algorithm’, J. Chongqing Univ. Posts Telecommun. (Natural Sci. Ed.), 2018, 30 (5), pp. 614–619
[12] Feng, Z., Tian, L.: ‘SOC prediction for electric vehicle battery based on AFSA-RBF neural network’, J. Chongqing Technol. Business Univ. (Natural Sci. Ed.), 2016, 33 (5), pp. 6–10
[13] Gao, Y., Gui, L., Wang, T., et al.: ‘A novel artificial fish swarm algorithm for recalibration of fiber optic gyroscope error parameters’, Sensors, 2015, 15 (5), pp. 10547–10568
[14] Guo, M., Xing, H., Zhang, D., et al.: ‘Temperature compensation for humidity sensor based on the AFSA-BP neural network’, Instrum. Techn. Sensor, 2017, 54 (8), pp. 6–10
[15] Nie, L.: ‘Artificial fish swarm algorithm and its application’. Master thesis, Guangxi University for Nationalities, 2009
[16] Cheng, C.: ‘Research on swarm intelligence algorithm and its implementation in MATLAB’ (Inner Mongolia Science and Technology Press, China, 2015, 1st edn. 2015)
[17] Yang, S., Han, Q., Xu, L., et al.: ‘Comprehensive effect evaluation of energy saving and emission reduction based on fish-swarm algorithm optimizing neural network’, J. Central South Univ. Technol. Sci. Technol., 2012, 43 (4), pp. 1538–1544
[18] Chen, Q., Zuo, F., Lu, W.: ‘Study on pressure sensor temperature compensation based on IAFSA-BP neural network algorithm’, Microcomput. Appl., 2016, 35 (9), pp. 27–33
[19] Wang, L., Shi, Q.: ‘Parameters analysis of artificial fish swarm algorithm’, Comput. Eng., 2010, 36 (24), pp. 169–171

Fig. 5 Absolute error curve of SOC AFSA-BP test values

Fig. 6 Relative error curve of SOC AFSA-BP test values