Energy storage battery SOC estimate based on improved BP neural network

Xiaojing Liu1, Yawen Dai1*
1 Department of Electronic Information Engineering, Wuhan, Hubei, China Wuhan University of Technology, 430070
*Corresponding author’s e-mail: 15071322265@163.com

Abstract The SOC estimation of the battery is the most significant functions of batteries’ management system, and it is a quantitative evaluation of electric vehicle mileage. Due to complex battery dynamics and environmental conditions, the existing data-driven battery status estimation technology is not able to accurately estimate battery status. Aiming at this problem, the multi-implicit BP neural network model and the error elimination due to genetic algorithm are combined to appraise the battery’s state of charge. Firstly, a multi-hidden layer BP neural network is applied to learn about the nonlinear connection between the battery SOC and the measurable variables of lithium-ion batteries, for instance, current, voltage, and temperature. Secondly, the prediction error of the neural network type is denoised by the genetic method to smooth the prediction results. The method proposed in this paper captures long-term dependencies between measurable variables and battery state. Finally, the improvement effect of the method proposed in this paper is verified by comparison with the traditional neural network method.

1. Introduction
As one of the important indicators to measure battery performance, SOC reflects the ratio of the current remaining battery to the rated charge, and the accuracy of SOC estimation directly determines the remaining mileage of the battery, while avoiding overcharging and discharging the battery.

However, in practical applications SOC measurement is very difficult, because SOC cannot be directly measured, and the battery itself is a particularly complex chemical reactor, that is to say, a highly nonlinear, making the accurate measurement of power battery SOC difficult, because SOC cannot be directly measured, only indirectly through the other parameters of the battery to establish a certain relationship, and then reasonable to establish a mapping relationship between them.[7]

In this paper, the method of optimizing the neural network’ original threshold and weight is applied to improve the method of the original threshold and weight of the BP neural network to estimate the battery SOC. As the input variable of neural network training, the real SOC value of the battery can be used as output, the BP neural network is used to resolve the problem that cannot be modeled accurately, and use genetic algorithm to obtain the threshold and the original weight of the neural network, so as to obtain a more efficient and accurate improved BP neural network arithmetic to estimate the SOC, so as to reduce the estimation error. Experimentally verify that the SOC estimation accuracy can be satisfied in multi-input situations.
2. Related work

2.1. BP Neural Network Overview
BP neural network, as a multi-level neural network with feedforward function, is mainly characterized by signal forward propagation and error back propagation. Error back propagation means that transposed back propagation will adjust the network weights and thresholds according to the prognostication error.

2.2. Genetic algorithm
Genetic algorithms use genetic mechanisms that mimic natural and biological evolution. According to the picked adaptability function and by genetic selection, cross and changes of the individual screening. Loop back and forth until the condition is met. The basic operating process of the algorithm is as:

1. Select the action
   The selection operation is to select individuals from the original group with a affirmative probability to the new group. The probability of an individual being picked is positively concerned to the fitness value, that is, the higher the individual fitness value, the greater the probability of being picked.

2. Cross-operation
   Cross-operation is the choice of two individuals, by the exchange of two chromosomes combination, to produce new excellent individuals. The crossover process is to randomly pick one or more chromosomal positions for exchange. The chromosomes come from any two of the population. The operations are shown in Figure 1.

   Figure 1. Cross-operation

3. Variation operation
   The mutation operation is to pick an individual from the group, and then select a certain pot in the chromosome to mutate, thereby producing a better one. This operation is shown in Figure 2.

   Figure 2. Variation operation

3. Model building

3.1 Algorithmic process
Genetic algorithm majorization BP neural network consists of three parts: neural network structure definition, algorithm majorization and network expectation. In them, the BP neural network structure determines the length of the individual genetic algorithm according to the number of the fitting function’s input and output parameters. The algorithm used to optimize the neural network’s weights and thresholds is a genetic algorithm. Network prediction is to train the network by using the weight and threshold of the optimal individual obtained by the optimization algorithm, and then predict the output of the function.

3.2 Genetic algorithm implementation
1. Population initialization
   The individual encoding way is real coding, and every individual is a real str. When the network composition is gotten, the composition, weights and thresholds would be token shape.

2. Adaptability function
   The fitness functions apply the weight and the threshold of the network to contain the output of the expectation system through the exercising data. The absolute error value of the expected output and the expected output is taken as the individual fitness value F, the formula is calculated as:
\[ F = k \left( \sum_{i=1}^{m} \text{abs}(y_i - o_i) \right) \]  

\[ n \text{ is the number of network output nodes; } y_i \text{ is the desired output of the } i\text{th node of the BP neural network; } k \text{ is the coefficient.} \]

3. Select the action

The selection strategy of genetic algorithm includes the roulette selection method, random traversal sampling method and tournament selection method. This article chooses the roulette method, which is to calculate the probability of each individual appearing in the offspring according to the fitness value of the individual, and the picked probability \( p_i \) of every individual is:

\[ p_i = \frac{f_i}{\sum_{j=1}^{N} f_j} \]

\[ F \text{ is the fitness value of individual } i. \text{ Since the value of } F \text{ should be as small as possible, the value of } F \text{ should be reciprocated before individual selection.} \]

4. Cross-operation

Since individuals apply real number coding, the cross-operation method apply real cross-cutting method y k chromosomes a and lth chromosome a, and the cross-operation methods in j-bit are as:

\[ a_{kj} = a_{kj}(1 - b) + a_{ij}b \]

\[ a_{ij} = a_{ij}(1 - b) + a_{kj}b \]

\[ B \text{ is a arbitrary num between } [0,1]. \]

5. Variation operation

Select the j-th gene a of the i-th individual and perform mutation. The operation method is as:

\[ a_{ij} = \begin{cases} a_{ij} + (a_{ij} - a_{\text{max}}) \times f(g) & r > 0.5 \\ a_{ij} + (a_{\text{min}} - a_{ij}) \times f(g) & r \leq 0.5 \end{cases} \]

\[ a_{\text{max}} \text{ is the upper boundary of } a; a_{\text{min}} \text{ is the lower boundary of } a; g \text{ is the current NUM of iterations; } g_{\text{max}} \text{ is the maximum number of iterations; } r \text{ is a random number between } [0,1]. \]

4. Experiment

4.1. Multi-implicit comparison experiment

Comparing the performance of single-hidden BP neural network and double-hidden layer BP neural network from the aspects of running time and prediction accuracy, the network construction is the same, the training iterations are 100 times, the average of 10 prediction results is compared, and the comparison results are as table 1 listed.

| Network category                      | Percentage of prediction error | Run time /s |
|--------------------------------------|-------------------------------|-------------|
| Single-implicit layer BP neural network | 2.456%                       | 4.005       |
| Double implicit layer BP neural network | 2.221%                       | 5.142       |

From the table, it can be known that the expectation error of the double implicit layer neural network has increased, but the running time has increased accordingly.

4.2. Genetic algorithm comparison experiment

The data used in this experiment is from the real problem data of 2021 digital automobile competition, and the voltage and current in the two processes of charging and discharging are selected as input parameters, and the actual measurement SOC is used as the output parameter, and the BP neural network
construction is put to 2-5-2, i.e. 2 points in the input layer, 5 points in the implicit layer, 1 point in the output layer, a total of 2×5 plus 5×1 plus 15 weights, and 5 plus 1 plus 6 threshold, the genetic algorithm encoding length is 15 plus 6 x 21. Each group selects 2,000 input and output data, from which 1,900 are randomly selected as training data and 100 as test data. The prediction is shown in Figure 3.

![Figure 3. BP Neural Network Prediction Results Graph](image)

The threshold and weight results improved by the genetic algorithm are shown in Table 2

| Input layer | The interlayer weight of the implicit layer | The implicit layer node threshold |
|-------------|-------------------------------------------|---------------------------------|
|             | 0.3316                                    | 1.5894                          |
|             | -2.5487                                   | -1.4103                         |
|             | 0.5346                                    | 1.5724                          |
|             | 1.9223                                    | -2.1923                         |
|             | -2.7868                                   | 1.0626                          |
|             | -1.3341                                   | 2.9783                          |

![Figure 4. The improved algorithm tests the Mean Squared Error graph](image)
Analysis of the test results and simulation results data processing to draw the algorithm in the operation of the error curve convergence graph, that is, the algorithm test Mean Squared Error graph, as shown in Figure 4.2, you can see that the overall training error curve is on a downward trend, that is, the training error or training error is rapidly reduced and quickly converge, convergence point is $10^{-6}$ below, the best convergence point is the number of iterations for 8 generations. The convergence value of the traditional BP neural network algorithm before the unoptimized is more accurate at $10^{-0.4}$ and the error is smaller, which shows the advantages of the optimized algorithm in precision. From Figure 4.3, the learning rate of the optimized algorithm can also be obtained, and the efficiency of algorithm estimation is improved.

![Figure 5. The improved algorithm tests the fitting performance evaluation curve](image)

![Figure 6. The improved algorithm tests the lr, valfail, and gradient graphs](image)

Analysis of Regession Illustration 4.4 You can see the overall performance of the trained test data, R value average reached 0.99, closer to 1, indicating that the fitting effect of the algorithm has been greatly improved, in which the training curve, the validation curve and test curve are highly parallel to the simulation curve, compared to the algorithm before the optimization of the large angle deviation has a considerable advantage, far higher than the pre-optimization comprehensive fit performance evaluation index, in the fitting accuracy has been significantly improved.

The optimized 45 sample errors are shown in Table 4

| Table 3. The optimized 45 sample errors |
|----------------------------------------|
| GA-BP neural network prediction error   |
|----------------------------------------|
| -0.0000      0.0015      0.0004      -0.0001     0.0009      -0.0003     0.0003      0.0001      0.0007     |
| -0.0002      0.0000      0.0004      -0.0001     -0.0011     -0.0003     0.0010      0.0011      -0.0004    |
| 0.0003       -0.0002     0.0006      -0.0007     -0.0013     -0.0011     0.0005      0.0007      -0.0004    |
| 0.0015       0.0003      0.0000      0.0007      -0.0008     0.0009      0.0006      -0.0010     0.0001     |
| 0.0015       -0.0012     0.0009      0.0005      -0.0000     -0.0006     -0.0003     0.0010      0.0007     |

5. Conclusions
To improve the robustness and accuracy of the prediction of traditional BP neural network algorithms, genetic algorithms are introduced to majorize the original weight and threshold, and it can be found through comparative experiments that the optimal BP can be found through selection, crossover and variation operations. The neural network weight threshold greatly improves the accuracy of the
prediction results. However, the algorithm also has limitations, it can only improve the prediction accuracy in a limited way, for some sample size is small, uneven sample distribution caused by the neural network prediction error hit the problem, the optimized prediction ability cannot be significantly improved.

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