SOC Estimation of Mine Power Supply Based on Improved BP Neural Network Algorithm

Gaojian Ren¹, Yin Lin², Zhongguang Sun³, Yan Shao⁴

¹State Key Laboratory of The Gas Disaster Detecting, Preventing and Emergency Controlling, China Coal Technology and Engineering Group Chongqing Research Institute, Chongqing, 400039, China;
²State Key Laboratory for the Coal Mine Disaster Dynamics and Controls, Chongqing University, Chongqing 400044, China
³Author Email: fjcdnf@qq.com

Abstract: Ni-MH, with high electric energy density and high stability, is the main backup battery of mine power supply. To improve the estimation accuracy of battery SOC (state of charge) and prolong its service life, this paper takes the single Ni-MH battery as the experimental object, and adopts an improved BP neural network that adds an adaptive rate momentum term to increase the discharged amount of electricity. The input characteristics of the network are the same as temperature, current and terminal voltage. According to the variance of the error between the expected output and the actual output of the training sample, the momentum term is adjusted; The adaptive learning rate is increased according to the change direction of the back propagation error. By comparing the standard BP neural network algorithm, the convergence speed is increased by 70%, and the generalization error is within 4%.

1. Introduction
Ni-MH battery has good safety performance, which is the current main backup battery of mine power supply. SOC estimation methods mainly include ampere-hour method, internal resistance, Kalman filtering, linear model and neural network algorithm. Currently, mine backup power supply mainly adopts ampere-hour method combined with certain front and rear end correction, but the overall accuracy and reliability are not high.

Based on the charging and discharging characteristics of Ni-MH battery, the input characteristics are added. The input characteristics of the network are terminal voltage, temperature, charging and discharging rate and discharged quantity. The BP neural network algorithm with adaptive rate and momentum term is adopted to estimate the SOC of the battery in real time, and the standard BP neural network algorithm is compared.

2. Principle and Improvement of BP Neural Network Algorithm

2.1. BP Neural Network Algorithm
BP neural network includes input layer, hidden layer and output layer. It is a feedforward neural network with error back propagation, which consists of input forward propagation and error back propagation. Three-layer BP network can fit any nonlinear system and is suitable for SOC estimation.
modeling of nickel hydrogen battery.

Set the input vector as a, the output vector as b, \( w_{ij} \) as the weight between the input and hidden layers, and \( w_{jk} \) as the weight between the hidden layer and the output layer.

The first is feedforward calculation. Under the action of input sample \( b \), the input of No. \( i \) neuron in the hidden layer is as follow:

\[
\text{net}_i^b = \sum_{j=1}^{M} w_{ij} x_j^b - \theta = \sum_{j=1}^{M} w_{ij} x_j^b - \theta \quad (i=1, 2, 3, \ldots, b)
\]

The output is as follow:

\[
o_i^b = g(\text{net}_i^b)
\]

Thereinto, \( g \) is the activation function of the hidden layer; \( w_{ij} \) is the weight between hidden layers of the input layer; \( X_j \) is the output of the No. \( j \) input layer neuron; and \( \theta \) is the threshold.

The output of the No. \( i \) neuron in the output layer is also obtained as follows:

\[
\text{net}_k^b = \sum_{i=1}^{q} w_{ki} o_i^b - \theta_k = \sum_{i=1}^{q} w_{ki} o_i^b - \theta_k \quad o_k^b = g(\text{net}_k^b)
\]

In the process of forward propagation, after the output result \( o_k^b \) of the output layer has the same error as the result given in this paper, the network feeds back this output forward from the output layer, and constantly corrects the weights between the layers in the feedback process.

The cost function at the output is as follow:

\[
J_b = \frac{1}{2} \sum_{k=1}^{L} (t_k^b - o_k^b)^2
\]

Thereinto, \( o_k^b \) is the estimated value of the network and \( t_k^b \) is the actual value given by the sample.

The traditional BP neural network takes the gradient descent algorithm as its core, and the weights are adjusted along the opposite direction of the gradient change of the cost function function to reduce the overall error. After various iterations, the estimation network model within the allowable range of design error is achieved. The weight and the new formula are as follows:

\[
w(k+1) = w(k) + \Delta w(k)
\]

\[
\Delta w(k) = -Lr * \frac{\partial J(k)}{\partial w(k)}
\]

In the formula: \( Lr \) is the learning rate; \( \Delta w(k) \) is the partial derivative of the quadratic error function to the weight \( w \).

Traditional BP neural network will bring training time over learning rate, but it will increase learning time. Meantime, the solution directly obtained by the gradient descent method is not necessarily the global optimal solution, it is likely to be the local extreme value, and it is difficult to jump out after entering the extreme value, resulting in the decrease of the accuracy of the algorithm.

2.2. BP Neural Network Algorithm for Increasing Momentum Term

To avoid that the solution obtained by gradient descent method is a local extreme value, consider adding momentum term, similar to a low-pass filter, to slip over the minimum value on the error surface.

\[
\Delta w'(k) = -Lr * \frac{\partial J(k)}{\partial w(k)}
\]

After the momentum term is added, the weight adjustment formula becomes:

\[
w(k+1) = w(k) + mc^* \Delta w(k - 1) + \Delta w'(k)
\]
The BP neural network after adding momentum term adds the influence factor of the weight modification direction at time K-1, and the modification amount of the connection weight at time K+1 is the sum of time K-1 and time K. If the direction of the weight adjustment vector at time K-1 and K is the same, the weight modifier at this time will be strengthened to accelerate the convergence speed of the algorithm. On the other hand, it will slow down the change speed of the weight value, which is conducive to the convergence of the algorithm.

2.3. Momentum Term BP Neural Network Algorithm for Increasing Adaptive Rate

After the introduction of momentum term into BP neural network algorithm, when the error value gradually stabilizes, a larger momentum term may cause an over-adjustment of a certain weight value, which may cause the whole network to jump out of the convergence interval and enter the continuous oscillation stage, thus prolonging the learning time and even causing non-convergence. Meantime, a smaller momentum term is needed. When the error continues to decrease, it shows that the change direction of this weight is the same as the change direction of the last weight. In order to speed up convergence, a larger momentum term is needed.

To adaptively adjust the momentum term coefficient mc, the value of mc is dynamically adjusted by estimating the mean square error MSE of the output value of the network. MSE is defined as follows:

\[ \text{MSE}(k) = \mathbb{E}[(t_k - o_k)^2] \]  

Thereinto, \( t_k \) is the actual output of the estimation network, and \( o_k \) is the actual output given by the sample. The coefficient of adaptive adjustment momentum term is defined as:

\[ mc(k) = \gamma [1 - e^{\text{MSE}(k)}] \]  

To avoid the contradiction between the adjustment speed of a certain weight and the learning duration, the adaptive speed is increased.

3. Establishment of Experimental Sample Collection and Estimation Network

3.1. Characteristics of Ni-MH battery

Taking a single Ni-MH battery with a rated voltage of 1.2V and a rated capacity of 0.8AH as the experimental object, the voltage, current, temperature and discharge capacity of the battery during the charging and discharging process of 0.1C, 0.2C, 0.3C and 0.4C were measured at 25°C. The corresponding relationship between battery state of charge (SOC) and voltage under different charge and discharge rates is shown in Fig. 1.
3.2. BP Neural Network Establishment and Parameter Setting

BP neural network can use a plurality of characteristic quantities as inputs, and the discharged quantity of the battery has strong correlation with the SOC value. To improve the accuracy and reliability of estimation, the discharged quantity is added as the input characteristic quantity, and the temperature, voltage and charge-discharge ratio are used as the inputs of the neural network together, and the state of charge (SOC) of the battery is used as the output of the estimation network.

Since the SOC change of Ni-MH battery is nonlinear, the nonlinear excitation function of neural network mainly includes asymmetric S-type function and hyperbolic tangent symmetric S-type function. This paper adopts hyperbolic tangent function.

The algorithm adopts gradient descent method to increase adaptive learning rate and momentum term, and the number of neurons in hidden layer of network is calculated according to empirical formula as below:

\[ L = b + \sqrt{x + y} \]  

Thereinto, \( L \) is the number of neurons in the hidden layer; \( x \) is the number of input feature quantities; \( y \) is the number of output feature quantities; \( b \) is a constant of 0–10.

4. Verification of Network Generalization Ability

Using the experimental platform, the voltage, discharged power, temperature and SOC values at different charging and discharging rates are collected. After the data are normalized, a sample set is formed. The total number of samples is 2,500, of which 2,000 are training samples and 500 are testing samples. BP neural network, improved BP neural network and BP neural network with increased input characteristic quantity are trained respectively. The change of MSE (mean square error) of the model with the number of iterations in the training process of the three algorithms is shown in Fig. 2.
The state of charge is estimated through the trained three networks, and the error comparison of the three estimated networks is shown in Fig. 3.

As can be seen from the chart, under the same training set, the number of iterations after increasing the input feature quantity is 420, the convergence speed is 26.7% higher than that of BP neural network algorithm, and the estimation accuracy is 54.3%. The improved BP estimation network with increased input features has completed 130 iterations of convergence, the absolute value of estimation error is less than 2%, and the convergence speed is 70% higher than that before the improvement. In addition, the stability is very good during the whole estimation process, which fully shows that the improved BP neural network estimation network with increased features has better accuracy and stability.

5. Conclusion
To solve the problem of poor accuracy and stability of SOC estimation for mine backup power supply, this paper increases the characteristic quantity of discharged electricity and adopts an improved BP neural network with an increased adaptive rate momentum term, which greatly improves the accuracy and reliability of the estimation network. Experiments show that by adding input features and using improved BP neural network to estimate the SOC of nickel-hydrogen battery, the iterative convergence speed is increased by 70%, and the error is within the range of 4%, which can stably and accurately estimate the SOC value.
Acknowledgements

I gratefully acknowledge the financial support of Special Project of Science and Technology Innovation Venture Capital of Tiandi Co., Ltd. and CSTC, and my gratitude also extends to the cooperation of the colleagues from the research institute.

Special Project of Science and Technology Innovation Venture Capital of Tiandi Co., Ltd. (Project No.: 2019-TD-MS016); CSTC (cstc2019jcyj-msxmX0633)

References

[1] Chen Zhijun, Li Yangying. (2017) Neural Network BP Algorithm Improvement and Performance Analysis [J]. Software Guide, 16 (10) 39 – 41.
[2] L. Xu, J. Wang, and Q. Chen. (2012) “Kalman filtering state of charge estimation for battery management system based on a stochastic fuzzy neural network battery model.” [J]. Energy Conversion and Management, 53:33–39
[3] Y. Zhang, X. M. Cheng, Y. Q. Fang, et al. (2013) On SOC estimation of lithium-ion battery packs based EKF[C]. Proceedings of the 32nd Chinese Control Conference. Xi'an, China, July26-28, 7668–7673
[4] Hu X, Sun F, Zou Y. (2013) Comparison between Two Model-Based Algorithms for Li-ion Battery SOC Estimation in Electric Vehicles[J]. Simulation Modelling Practice & Theory, 34(4): 1–11.
[5] Li B, Zhao Y. (2014) Estimation of Power Battery SOC Based on Peukert Equation and Extended Kalman Filtering[J]. China Mechanical Engineering, 25(6): 848-851.
[6] Huang Shangqing, Zhao Zhiyong, Sun Libo. (2017) Improvement of BP neural network algorithm [J]. Science and Technology Innovation Guide, (20) 146 –147.