SOC Estimation of Lithium Battery Based on IPSO-BP Neural Network

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Abstract—Based on the analysis of the accurate estimation method of the state of charge (SOC) of lithium battery for electric vehicles, aiming at the shortcomings of back propagation (BP) neural network model, an algorithm based on Improved Particle Swarm Optimization (IPSO) is proposed to optimize the parameters of BP neural network. In this algorithm, the particle swarm optimization algorithm is optimized by introducing shrinkage factor to limit the particle speed, so as to determine the initial parameters of BP neural network. Finally, the battery estimation model is established by using the data set of lithium battery published by NASA PCoE, and the simulation test is carried out by using MATLAB platform. The results show that the method can effectively reduce the SOC error and control the error within 2%. It has practical significance for SOC estimation in battery management system.

1. INTRODUCTION

With the decrease of exploitable energy in the world, more and more countries attach importance to the development of new energy in recent years. The application of lithium battery has been fully utilized in many industries. Electric vehicle can not only save energy, but also reduce the air pollution of traditional automobile, which is a double excellent choice.

SOC is one of the important indicators of lithium battery. Other parameters used to evaluate battery performance indicators are calculated based on it, such as battery health status (SOH), power state (SOP), battery safety state (SOS), battery functional state (SOF), because the accuracy of SOC estimation directly affects the reliability of the whole battery management system. This indicator can not only prevent the battery from overcharge and over discharge, but also accurately inform the user of the battery power and remaining mileage, and make an accurate arrangement for the user's next journey. Accurate SOC can not only give full play to the capacity of the battery, but also improve the safety of the battery [1]. However, because SOC belongs to the internal characteristics of the battery, it cannot be directly measured in the process of use. It can only be estimated by the known parameters of the battery, such as battery temperature, voltage, charge discharge rate, internal resistance. [2-6].
SOC is the ratio of the remaining capacity of the battery to the actual total capacity of the battery [7]. At present, SOC research mainly includes ampere hour integration method, open circuit voltage method, battery internal resistance method, Kalman filter method, neural network method [8-10]. Because lithium ion battery is a highly nonlinear system, it is difficult to fit a model to accurately estimate the future state of lithium battery. Neural network has excellent performance in solving nonlinear system problems by applying artificial intelligence theory. It has the characteristics of high nonlinearity, high fault tolerance and robustness, self-learning and real-time processing. Neural network can obtain the internal law of nonlinear system by training the known data samples, without considering the internal details of the battery, which can solve battery SOC estimation [11]. At present, the estimation accuracy based on neural network is not high, and the prediction network is easy to fall into local minimum. Particle swarm optimization (PSO) has good robustness and global search ability in solving population theory [12]. PSO is used to optimize the weights and thresholds of neural network, and then input into neural network to get better results. But in the process of flight, the particle is easy to cross the boundary frequently because of its high speed, which reduces the search ability and increases the operation time of the algorithm. Therefore, this paper proposes a neural network based on IPSO to estimate battery SOC. The accuracy of SOC estimation is further improved by improving PSO, which is verified by NASA PCoE battery data.

2. SOC PREDICTION MODEL OF LITHIUM BATTERY BASED ON BP NEURAL NETWORK

BP neural network is a multilayer feedforward neural network trained according to the error reverse propagation algorithm, and is the most widely used neural network [13]. BP neural network calculates the output value according to the input layer data, initial weight and threshold, compares the current output value with the sample value, and then adjusts the connection weights and thresholds in reverse. A three-layer neural network can approach the continuous function with arbitrary precision, so three-layer BP neural network is used to estimate SOC, which are input layer, hidden layer and output layer. The results show that the voltage, current and temperature of lithium battery are the main factors affecting the SOC state. Therefore, the voltage, current and temperature of lithium battery are taken as three input layers and SOC as one network output layer, that is, SOC = f (U, I, T). As shown in Figure 1, the three-layer BP neural network structure model.

![Figure 1. Structure of BP neural network](image)

The number of hidden layers can be initially set according to the general empirical formula, and a more reasonable result can be obtained after many simulation tests. The common empirical formula is as follows:

\[ L = \sqrt{(m + n)} + a \]  

(1)

Where L is the number of hidden layer nodes, n is the number of input nodes, M is the number of output nodes, and a is an integer between 1 and 10.
3. IPSO-BP NEURAL NETWORK MODEL

3.1 PSO algorithm
PSO algorithm originates from the research on the predation behavior of birds [14]. Each possible solution is assumed to be a particle, and the optimal solution is obtained by adjusting its position and velocity according to mutual information and fitness value in an n-dimensional space. If M particles form a population, \( Z(z_1, z_2, \cdots, z_m) \). Each particle searches iteratively in the solution space according to certain rules and produces two extremum each time. One is the optimal solution \( p_{id} \) searched by the particle itself, and the other is the current optimal solution \( p_{gd} \) of the whole population. Update your position according to these two extremes. Let the velocity of the \( i \) particle be \( v_i(t) = (v_{i1}(t), v_{i2}(t), \cdots, v_{im}(t)) \), and the position is expressed as \( z_i = (z_{i1}, z_{i2}, \cdots, z_{im}) \). The position update is shown in equation (3), and the updating formula of particles is as follows:

\[
v_{id}(t + 1) = \omega v_{id}(t) + c_1 r\text{rand}() [p_{id} - z_{id}(t)] + c_2 r\text{rand}() [p_{gd} - z_{id}(t)]
\]

(2)

Where \( t \) is the number of iterations, \( D \) is the dimension of population space, and \( \omega \) is the inertia weight. Rand() is a random number distributed on \((0,1)\). \( c_1 \) and \( c_2 \) are learning factors and \( c_1 \) are cognitive learning factors, which represent the coefficients adjusting to their optimal position. \( c_2 \) is a social learning factor, which represents the coefficient moving towards the optimal position of the whole population.

3.2 Improved PSO algorithm
Particle swarm optimization algorithm is easy to enter the local optimal solution in the optimization process, and premature convergence will result in large error [15]. The empirical information of particles and other particles is determined by the learning factors \( c_1 \) and \( c_2 \), indicating the mutual exchange of information between particles. Therefore, if the learning factor \( c_1 \) is given a larger value, the particles can only fly in the vicinity of themselves, which will affect the subsequent search results. If the learning factor \( c_2 \) is given a larger value, it will lead to premature convergence to the local minimum value. In order to achieve an effective balance between global search and local search, shrinkage factor is introduced here. The introduction of contraction factor can not only ensure the convergence of PSO, but also eliminate the limitation of velocity boundary. The speed update is shown in equation (4), and the formula of contraction factor is shown in equation (5).

\[
v_{id}(t + 1) = \varphi \{ \omega v_{id}(t) + c_1 r\text{rand}() [p_{id} - z_{id}(t)] + c_2 r\text{rand}() [p_{gd} - z_{id}(t)] \}
\]

(4)

\[
\varphi = \frac{2}{[2-c-\sqrt{c^2-4c}]} \quad c = c_1 + c_2
\]

(5)

Where: \( \varphi \) is the contraction factor and \( c \) is the learning factor.

3.3 Specific steps of IPSO-BP neural network model
a) The number of neurons in the input layer, hidden layer and output layer of BP neural network is determined by the input and output data sets, and the network topology is determined;

b) The particle swarm is initialized, and the dimension of particles is calculated from the ownership value and threshold value of BP. In this design, three input layers, eight hidden layers and one output layer are set, and the particle dimension is 41. \( c_1 \) and \( c_2 \) are set to 2.05, and the maximum number of iterations is 100;

c) The fitness value is calculated from the randomly generated weights and thresholds to determine the individual and all optimal of each particle;

d) According to the formula (3) (4) (5), the velocity and position of particles are updated, and the individual optimum and all optimal are updated. The initial weights and thresholds of BP neural network are determined;

e) The neural network is trained and predicted.
4. Simulation Experiment and Analysis

4.1 Sample data selection

In order to test the accuracy of the improved PSO BP neural network algorithm, this paper uses the battery data from NASA research center, which is widely used in this field [16]. In the experiment, the rated capacity of the battery is 2A/H. The voltage, current and surface temperature of the battery are included as the input samples of the model, and the SOC of the battery is taken as the output sample. No. 17 battery was selected for constant current discharge test at 0.5C discharge rate at room temperature. After screening, 205 groups of data were selected as the training samples of the model, and another 44 groups were selected as the test data to verify the accuracy of the model.

4.2 Result analysis

In order to compare the advantages of the algorithm, Matlab is used to verify the improved PSO BP neural network and BP neural network. In order to facilitate observation, the same samples are used for network training and prediction. Fig. 2 shows that the prediction output of the two algorithms is compared with the actual SOC, and the results show that ipso algorithm is closer to the real value. In Figure 3, the error between the predicted value and the actual value can reach about 8%. Figure 4 shows the relative error between the predicted value and the real value of ipso algorithm, which is basically stable at about 1.5%, with high accuracy, which is obviously better than that of BP neural network prediction.

![Figure 2. Comparison of BP predicted value, IPSO-BP predicted value and measured value](image1)

![Figure 3. Relative error between predicted value and measured value of BP neural network](image2)
5. CONCLUSION
In this paper, through theoretical analysis, we know that the improved BP neural network model has strong global search ability, and solves the problems of BP neural network easily falling into local optimum and uncertain initial weights and thresholds. Based on the standard PSO-BP neural network model, shrinkage factor is introduced to prevent premature convergence. The accuracy of the results is verified by using NASA battery data. The feasibility of BP neural network model based on improved particle swarm optimization is proved.

ACKNOWLEDGMENT
The research was supported by Shanghai Polytechnic University-Key Discipline Construction (XXKZD1605) and Graduate program fund of Shanghai Polytechnic University (EGD19YJ0041).

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