

State-of-charge Estimation of Lithium-ion Batteries Based on PSO-BP Neural Network

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Abstract: The state of charge (SOC) of lithium-ion battery is a variable and cannot be measured directly by sensors. Therefore, accurate estimation of battery state of charge is the key to ensure the safe and reliable operation of battery management system (BMS) and reduce the required battery cost. In the research of estimating the state of charge of lithium-ion batteries, the initial setting of the weights and thresholds of the BP neural network easy to falls into the local minimum problem, which makes the SOC estimation insufficiently accurate. Therefore, a method of SOC estimation of lithium-ion battery based on particle swarm optimization (PSO) and BP neural network is proposed in this paper. Taking lithium manganese battery (LiMn_2O_4) as the object, use the multi-physics simulation platform COMSOL to conduct charging and discharging experiments on it, and collect the relevant performance parameters of the battery. Under the condition of constant temperature and constant current, the SOC of the battery is inferred according to the voltage and discharge rate. Building a PSO-BP neural network model with voltage and discharge rate as input and battery SOC as output. The performance of SOC estimation is evaluated from the aspects of overall correlation, training time and robustness. It is compared with the estimation method based on BP neural network. The simulation results show that the absolute error of the estimation method based on PSO-BP neural network is 2.68%, which is 3.18% higher than that of BP neural network, and the accuracy is higher. The proposed method has more advantages.

Keywords: Lithium-ion Batteries, State of Charge Estimation, Particle Swarm Optimization, BP Neural Network

1. Introduction

With the development of society and the advancement of science and technology, the consumption of primary energy and environmental pollution have become increasingly serious. Among them, oil energy is even more scarce, and the world is facing the crisis of oil energy depletion [1]. People are also paying more and more attention to the application of clean energy. Lithium-ion batteries are widely used in new energy electric vehicles and other energy storage fields due to their high energy density, long service life, low discharge rate and no pollution. Lithium-ion batteries have become the most important part of the energy supply for electric vehicles [2]. Battery management system (BMS) is the core technology of lithium batteries. The state of charge (SOC) of the battery is one of the most important indicators of lithium batteries.

How to accurately estimate the SOC of the battery is the focus and difficulty of current research.

Currently, SOC estimation methods mainly include the following categories:

Open circuit voltage method. Calculate the SOC based on the monotonic correspondence between the open circuit voltage (OCV) of the lithium battery and the state of charge (SOC) of the battery.

Ampere integral. It is calculated by measuring the discharge current of the battery and integrating the current over time [3]. Since the current fluctuation of the system is very large, and the current sampling is performed once at a certain interval, so that the sampling value and the average value over a period of time may not be similar, and the accumulation over a long period of time will cause a large error.

Model-based approach. Such as the widely used extended

Kalman filter (EKF), unscented Kalman filter (UKF) and particle filter (PF), etc. By modeling the battery, the battery model is used to simulate the battery behavior. Kalman filtering is to regard a process as an infinite set of states played continuously on the time axis [4]. The dynamic process is described by the state equation, the observation information is described by the measurement equation, and the estimated value of the previous time and the observed value of the current time are iterated with each other to update the estimation of the state variable. Various algorithms extended from this method have been applied in many computing fields.

Data-based estimation methods. By identifying the nonlinear relationship between SOC and measurable battery parameters (current, voltage, temperature, etc.), a large amount of training data can be obtained, and the battery SOC can be predicted by the intelligent algorithm learning network parameters autonomously.

Common methods include back propagation (BP) neural network, radial basis function (RBF) neural network, support vector machine (SVM) and limit learning machine (ELM), etc. Anton et al. [5] proposed a support vector machine method to extract model parameters from the battery charge and discharge test cycle, and build a battery state of charge estimator with battery current, battery voltage and battery temperature as independent variables. There is still room for improvement in the accuracy of SOC estimation. Sahinoglu et al. [6] proposed a method for estimating the state of charge of lithium-ion batteries based on machine learning, using Gaussian Process Regression (GPR) framework to estimate the SOC of lithium-ion batteries. The accuracy of the estimation depends to a large extent on the quality and quantity of the training data, and the training process may take a lot of time. Wei He et al. [7] applied a multilayer feedforward neural network (NN) to estimate the SOC of a lithium-ion battery as a function of battery current, voltage, and temperature. The UKF is applied to the SOC estimation of the neural network, which further improves the estimation accuracy of the method.

In this paper, the method of combining BP neural network and PSO is used to jointly estimate the SOC of battery. Using battery voltage and battery discharge rate as input parameters, and SOC as output parameters, a PSO-BP neural network model is established. PSO is used to update the weights and thresholds of BP neural network to find the optimal value. The simulation experiment results show that the lithium battery SOC estimation based on PSO-BP neural network is better than the estimation method based on BP neural network, and it has good practicability.

2. Simulation Test of Lithium-ion Battery and Acquisition of Sample Data

2.1. Simulation Platform

Taking lithium manganate battery (LiMn_2O_4) as the object, a one-dimensional model of the battery is constructed by using COMSOL, a multi-physics simulation platform, and a complete charge discharge experiment is carried out.

Through the simulation, the discharge voltage, current and SOC of the battery are obtained. Some parameters of the experimental process are shown in Table 1.

Table 1. Some experimental parameters.

Parameters	Value
Temperature	298K
Charging current	-17.5A/m ²
Discharge current	17.5A/m ²
Discharge time	2000s
Charging voltage	4.2V
Discharge cut-off voltage	3.5V

The charging and discharging time of the battery: 2000s for charging—300s for open circuit—2000s for discharging. The voltage changes with time during the charging and discharging process is shown in Figure 1.

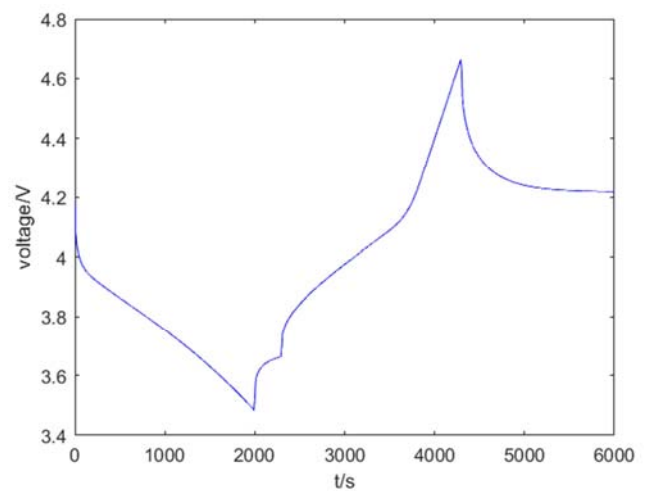


Figure 1. Voltage change with time during charging and discharging.

2.2. Selection of Network Sample Data Sets

Table 2. Part of the sample data.

Discharge rate (/C)	Voltage (V)	SOC
0.1	4.03	0.87
0.1	3.94	0.78
1	3.77	0.66
1	3.73	0.53
2	3.68	0.55
2	3.43	0.58
4	3.75	0.83
4	3.67	0.78

The battery test with different discharge rate modes is carried out on the above simulation platform. Under constant temperature conditions (25°C), the battery is subjected to constant current discharge at four different rates of 0.1C, 1C, 2C and 4C respectively, and the data of the whole process will be automatically saved to the data set. A total of 114 sets of data were selected for this experiment. These data include battery voltage and SOC collected at four different discharge rates (0.1C, 1C, 2C, 4C). Among them, 100 groups are selected as training data, and 14 groups are used as test data. Some experimental data are shown in Table 2.

3. Lithium-ion Battery SOC Estimation Model

The SOC of lithium battery is used to reflect the remaining power of the battery, which is numerically equal to the ratio of the remaining power to the battery capacity [8]. However, SOC cannot be measured directly. It is an estimated value calculated according to battery voltage, current, discharge rate, temperature and other factors.

The SOC of lithium-ion battery is generally defined from the perspective of power and capacity [9]. From the perspective of electricity, it is defined as the ratio of the remaining electricity of the battery to the rated capacity under the same conditions at a certain discharge rate.

Expressed by mathematical formula as:

$$\text{SOC} = \frac{Q_c}{C_i} \quad (1)$$

Q_c : The remaining capacity of the battery.

C_i : The capacity of the battery when discharged at a constant current.

From the perspective of normalization, the initial SOC is considered to be 1, and the ratio of the battery discharge capacity to the battery maximum discharge capacity is subtracted, and the result is the SOC at the current moment.

$$\text{SOC} = 1 - \frac{\eta}{Q_{\max}} \int I_{\text{eff}} dt \quad (2)$$

η : Coulomb efficiency; Q_{\max} : Maximum charge discharge capacity of battery; I_{eff} : Charge discharge current, charge is negative and discharge is positive.

3.1. SOC Estimation of Lithium-ion Battery Based on BP Neural Network Model

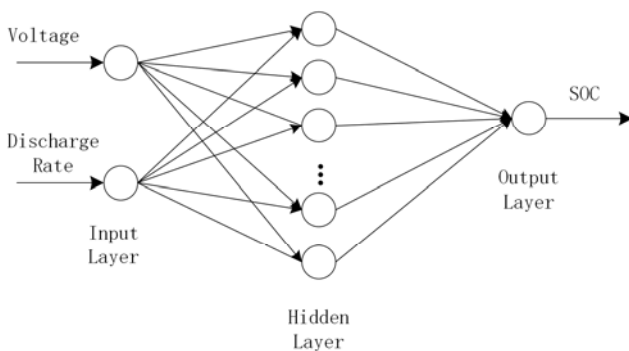


Figure 2. BP neural network topology structure diagram.

BP neural network is a supervised learning model with strong nonlinear mapping ability [10]. It contains input layer, output layer and hidden layer. The structure of BP neural network is shown in Figure 2. There are two inputs: voltage and discharge rate; One output: SOC of lithium-ion battery.

$$X = [V, C] \quad (3)$$

$$Y = [\text{SOC}] \quad (4)$$

X : Input; Y : Output; V : Voltage; C : Discharge rate; SOC : The state of charge.

Determining the number of hidden layer nodes:

$$l < \sqrt{(m+n)} + a \quad (5)$$

l : Number of hidden layer nodes; m : Number of output layer nodes; n : Number of input layer nodes; a : Constant between 0~10.

There are two input nodes: voltage and discharge rate; one output node: the SOC of the lithium battery. Through many experiments, it is determined that the number of hidden layers is 5, and the tansig function is used between the input layer and the hidden layer, the output layer uses the purelin linear activation function [11], and the learning of the BP network uses the LM algorithm function.

Implementation steps of BP algorithm:

Data selection and normalization

Select 100 groups from the input and output data as network training data, 14 groups as network test data, and normalize the training data.

Building a neural network

The input layer node is 2, the hidden layer node is 5, and the output layer node is 1.

Network parameter setting

Set the number of network iterations to 100, the learning rate to 0.1, and the network error to 0.0004.

BP neural network training

Training BP neural network with training data.

BP neural network estimation

The trained BP neural network is used to predict the output of nonlinear function, and the fitting ability of BP neural network is analyzed through the predicted output and expected output of BP neural network.

Although BP neural network has strong adaptive and self-learning ability, the traditional BP neural network is an optimization method of local search. It needs to solve a complex nonlinear problem [12-13]. The weight of the network is gradually adjusted along the direction of local improvement, which will make the algorithm fall into local extremum and the weight converge to local minimum. This leads to the failure of network training. Therefore, in order to improve the prediction effect, PSO is used to optimize the weight and threshold of BP neural network in the fixed neural network topology.

3.2. SOC Estimation of Lithium-ion Battery Based on PSO-BP Neural Network

3.2.1. Theoretical Basis of Particle Swarm Algorithm

The particle swarm optimization algorithm is a random search algorithm based on group collaboration developed by simulating the foraging behavior of bird groups. It belongs to

a heuristic global optimization algorithm [14]. Its basic idea is to seek the optimal solution through collaboration and information sharing between individuals in the group.

Suppose that in a D-dimensional search space, there is a population of n particles $X = [X_1, X_2, \dots, X_n]$, the i-th particle is represented as a D-dimensional vector $X_i = [X_{i1}, X_{i2}, \dots, X_{iD}]^T$, it represents the position of the i-th particle in the D-dimensional search space. According to the objective function, the fitness value corresponding to each particle position can be calculated. The velocity of the i-th particle is $V_i = [V_{i1}, V_{i2}, \dots, V_{iD}]^T$, Its individual extreme value is $P_i = [P_{i1}, P_{i2}, \dots, P_{iD}]^T$, The global extremum of the population is $P_g = [P_{g1}, P_{g2}, \dots, P_{gD}]^T$.

In each iteration, the particle updates its own speed and position through individual extreme values and global extreme values. The update formula is as follows:

$$V_{id}^{k+1} = \omega V_{id}^k + c_1 r_1 (P_{id}^k - X_{id}^k) + c_2 r_2 (P_{gd}^k - X_{id}^k) \quad (6)$$

$$X_{id}^{k+1} = X_{id}^k + V_{id}^{k+1} \quad (7)$$

ω : Inertia weight; $i = 1, 2, \dots, n$; $d = 1, 2, \dots, D$; k : Current iteration number; V_{id} : Particle velocity; c_1, c_2 : Acceleration factor, represents a non-negative integer; r_1, r_2 : Random number distributed between [0, 1].

The fitness value is calculated every time the particle updates its position, and the positions of individual extreme value and group extreme value are updated by comparing the fitness value of new particle with the fitness value of individual extreme value and group extreme value.

3.2.2. Algorithm Flow Based on PSO-BP

Particle swarm algorithm optimization BP neural network is divided into three parts: BP neural network structure determination, particle swarm algorithm optimization, and BP neural network prediction. Among them, particle and velocity initialization gives random values to the initial particle position and particle velocity, and the individual extreme value and group extreme value are determined according to the initial particle fitness value [15]. BP neural network prediction uses the optimal individual obtained by particle swarm optimization algorithm to assign the initial weight and threshold of the network, and the network is trained to predict the output.

The PSO optimized BP neural network algorithm flow is shown in figure 3.

4. Simulation Result Analysis

4.1. SOC Estimation Based on BP Neural Network

The BP neural network is used to predict the SOC of the lithium battery, and the prediction effect is shown in Figure 4. At first, the prediction effect is good, and then the error increases obviously. The prediction curve gradually deviates

from the actual curve, and the overall prediction effect is not ideal.

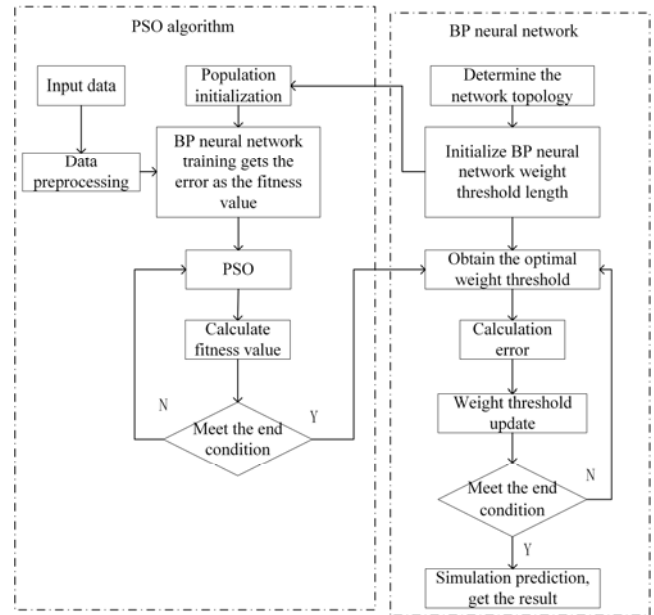


Figure 3. PSO-BP algorithm flow.

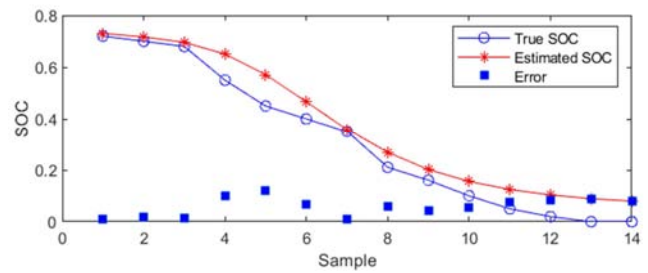


Figure 4. SOC estimation result based on BP neural network.

Reasons for the above situation:

Network overtraining.

The adjustment of network weights and thresholds converges to the local optimum.

By changing the number of training samples and reducing the number of training the network, it is found that the network performance has not been significantly improved. Therefore, it is judged that the reason for the unsatisfactory prediction effect is the setting of the initialization weight and threshold.

4.2. SOC Estimation Based on PSO-BP

The SOC of lithium battery is estimated by the combination of particle swarm optimization algorithm and BP neural network. BP neural network weight threshold optimization based on PSO algorithm, each particle represents the weight and threshold of the neural network, and the optimal initial value and threshold of the network are found through particle optimization [16]. PSO algorithm parameter settings: the population size is 30, and the number of iterations of the algorithm is 100.

Similarly, input the test samples in the table into the

network, and the prediction results are shown in Figure 5.

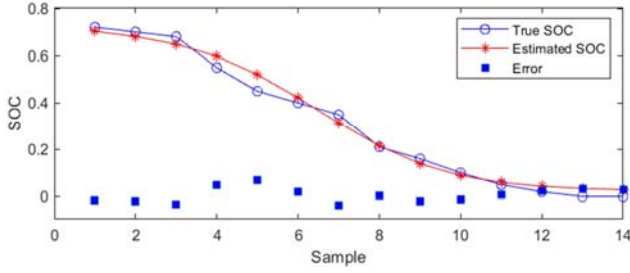


Figure 5. SOC estimation result based on PSO-BP neural network.

It can be seen that the estimated result of battery SOC is in good agreement with the actual value, and the average absolute error is 2.68%.

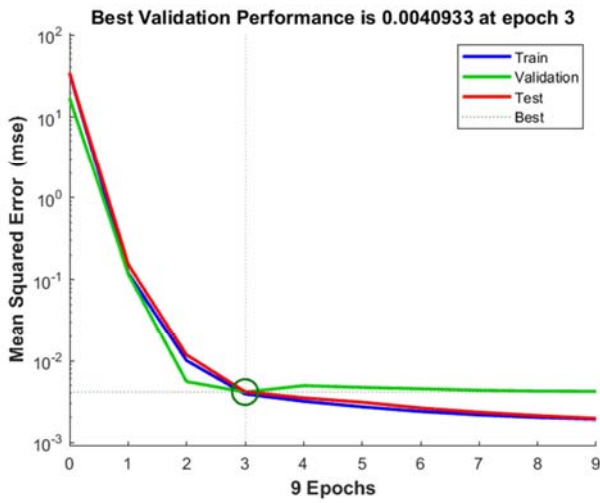


Figure 6. The mean square error changes with the number of training images.

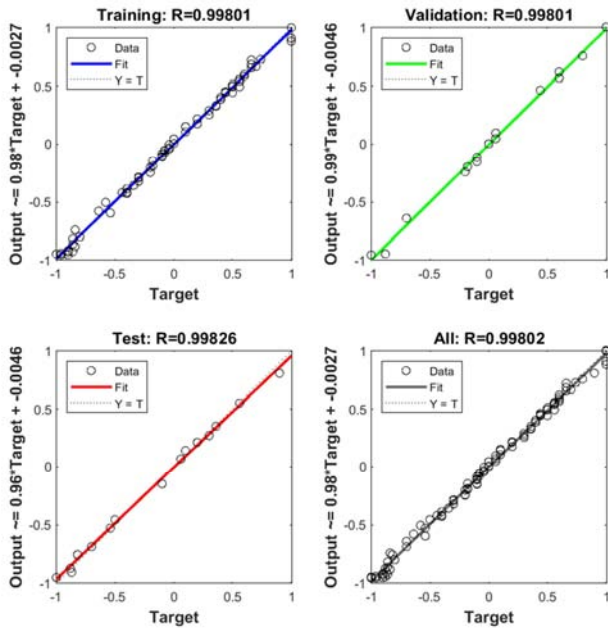


Figure 7. Correlation analysis.

The variation of the mean square error of the training set, the verification set and the test set with the number of iterations is shown in Figure 6, where the best verification performance at the third time is 0.0040933.

Figure 7 shows the correlation analysis between the training set, the validation set, the test set and the overall. It can be seen from the figure that there is a strong correlation between each sample set and the target value.

The following figure (Figure 8) is a comparison diagram of the SOC estimation of lithium batteries based on the BP neural network and the PSO-BP neural network. It can be seen that the prediction curve based on the PSO-BP neural network is more consistent with the actual curve than the BP neural network.

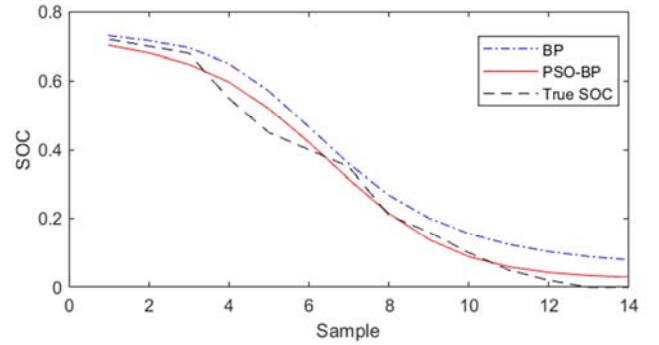


Figure 8. Algorithm comparison diagram.

4.3. Performance Evaluation

The performance of BP neural network and PSO-BP neural network is evaluated using mean absolute error (MAE), mean square error (MSE) and root mean square error (RMSE) criteria:

$$MAE = \frac{1}{K} \sum_{i=1}^K |y_i - \hat{y}_i| \quad (8)$$

$$MSE = \frac{1}{K} \sum_{i=1}^K (y_i - \hat{y}_i)^2 \quad (9)$$

$$RMSE = \sqrt{\frac{1}{K} \sum_{i=1}^K (y_i - \hat{y}_i)^2} \quad (10)$$

Where y_i is the true value while \hat{y}_i is the estimated value. The MAE measures how close estimates are to the corresponding outcomes without considering the sign. The RMSE is more sensitive to large errors than the MAE. It characterizes the variation in errors.

By analyzing the errors of the two algorithms based on BP neural network and PSO-BP, as shown in Table 3, it can be seen that the mean square error of the actual test SOC value and the predicted SOC value based on PSO-BP neural network is 0.00098483, while the SOC estimation error based on BP neural network is 0.0046284. The experiment shows

that the SOC estimation of lithium battery based on PSO-BP neural network has good estimation effect.

Table 3. Error analysis.

Algorithms	MAE	MSE	RMSE
BP	0.058614	0.0046284	0.068033
PSO-BP	0.026829	0.00098483	0. 031382

5. Conclusion

This paper proposes a PSO-BP neural network model for lithium-ion battery SOC estimation. The data are collected through the battery discharge under different conditions (0.1C, 1C, 2C, 4C). These data are used for off-line training and verification of the proposed network. The model uses PSO to deeply optimize the weights and thresholds of the BP neural network. It takes the voltage and discharge rate of the lithium-ion battery as the network input, and the battery state of charge is the network output. On this basis, its SOC estimation performance is evaluated. The results show that the optimized network can better obtain the non-linear relationship between battery parameters (voltage, discharge rate) and SOC, and the average absolute error is within 3%, and the estimation accuracy is improved by 3.18% compared with the BP neural network. The problem of inaccurate SOC estimation of lithium-ion battery by BP neural network is solved. When the SOC prediction is inaccurate, the network quickly converges to the real SOC, and the overall MSE and RMSE are reduced. Therefore, this paper solves the following problems:

The proposed PSO-BP neural network model is a data-driven SOC estimation method. Compared with the model-based SOC estimation method, the quality of the model and the internal structure of the battery are not considered.

The combination of the two algorithms solves the problem that the initial weight and threshold of BP neural network are easy to fall into local minimum.

The accuracy of SOC estimation based on PSO-BP neural network is obviously better than BP neural network, and this method has more advantages.

In conclusion, this method has higher adaptive ability, and has good research prospects and application value for the battery management system of new energy vehicles in the future.

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