Research in Estimation of Temperature for Power Battery Based on Back Propagation Neural Network

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Abstract

In dealing with the increment in environment pollution and source consumption, research has focused on the application of renewable energy source. Batteries, especially power batteries, which has great prospects in the fields, are among the attention. Rechargeable batteries are widely used in many electrical systems to store and deliver energy. However, there is a wide variety of Power Batteries and they have different weak Points. In order to develop and apply battery in a more efficient and appropriate method, their response to various operating conditions must be understood. Knowing the battery temperature variation in electric vehicles (EVs) is very important issue. Temperature depends on ambient temperature, charging current and charging time. Recently neural networks have been successful used for power system applications. In the literature, there are many neural networks for power system applications. However, Back Propagation (BP) has demonstrated better capabilities. This paper presents neural network for temperature estimation of power batteries. The main contribution of this paper is consideration of non-uniform temperature field and the temperature effect in batteries. In addition, the results of estimation and actual measured values are compared, proving the feasibility and accuracy of the method.

Keywords: *Power batteries, Neural Network, BP*

1. Introduction

As the original main energy storage for hybrid electric vehicle, power battery is the most key parts of hybrid electric vehicles [1]. The battery available capacity refers to the quantity of elec-tricity that can be delivered at a certain discharged current and temperature before reaching the specified cutoff voltage [2]. Knowing the temperature in electric vehicles (EVs) is very important issue. The temperature increase depends on the charging temperature and current for different kinds of battery [3-5]. For Ni-MH battery temperature variation directly affect the performance and battery life issues, we study on Ni-MH battery charging temperature distribution of storage. To achieve the level of practicality and industrialization, one of the important issues that must be resolved in the process of charging and discharging battery is non-uniform temperature field.

It has been proved and discussed by experts that the performance of the battery in charging, dis-charging and recycling state may suffer significant degradation with the increasing temperature. So the temperature control may act as a crucial role of the performance of the power battery, which may also affect the economic and applicability of the power battery. Then, the battery thermal effects have gradually become the hot issues in the battery application fields.

The neural network can be widely applied in prediction field in a short time for its great generaliza-tion ability [6]. Neural network toolbox is one of the toolboxes developed in the Matlab environment, which is applied to establish typical transformation function and conduct design, study, test and simulation of network [7] based on artificial neural network principle with using the Matlab language. For a variety of network models, neural network toolbox integrates a variety of learning algorithms to provide users with great convenience. The toolbox can be applied to establish a deep essence of the neural network principle for beginners, as for the users, they can achieve their thoughts by applying abundant functions, even if they do not understand the essence of the algorithm; then for researchers, the powerful extension of toolkit may provide them great convenience which saves them a lot of programming time [8] by applying abundant functions.

Domestic and foreign researchers have achieved a lot of useful exploration in predicting and simu-lating different battery power systems using neural networks. At present, the more common and relatively mature application is of the prediction of the remaining capacity of the batteries, the state of charge (SOC), the state of health (SOH) and cracking extent of the battery [9-11] with Matlab. As is described above, this paper has achieved the prediction of the thermal effects of nickel-hydrogen battery using the BP neural network.

2. Acquisition and Processing of Experimental Data

In order to make accurate prediction of the surface temperature of the battery with BP neural network, a large number of experimental data should be acquired, and tested. The acquisition of experimental data is to conduct thermal measurements for some kind of nickel-metal hydride bat-tery:

Firstly in constant temperature environment, conduct charging and discharging recycling experiment with different magnification and measure the surface temperature of the recorded cell. Secondly with different temperature degrees, conduct charging and discharging recycling experiments with constant magnification and measure the surface temperature of the recorded cell as well [12, 13]. Conclusions can be drawn from the details that the experiment data increased along with the charging time in the charging magnification of 1C/3C/5C, with the environment temperature of -10℃/ 0℃/ 10℃/ 20℃/ 40℃, the surface temperature of the battery is listed below respectively. Part of the results obtained from the measurement of surface temperature with 3C charging magnification, in different environment temperature, and different charging time are shown in Table 1:

Table 1. Sample Values of Battery

Environment(℃) / Time(min)	-10	0	10	20	30	40
10	-10.04	0.09	10.7	20.9	30.72	40.54
20	-9.88	0.12	10.96	21.04	30.84	40.72
30	-9.88	0.12	10.96	21.04	30.84	40.72
40	-9.49	0.32	11.1	21.18	31.03	40.84
50	-8.96	0.78	11.55	21.58	31.47	41.23
60	-8.62	0.78	11.55	21.58	31.47	41.23
70	-8.36	1.27	12.07	21.97	31.81	41.65
80	-8.04	1.49	12.23	22.15	32.02	41.82
90	-7.74	1.8	12.51	22.35	32.16	41.98
100	-7.51	2.05	12.78	22.57	32.34	42.17

Figure 1, 2 and 3 have shown the results of the surface temperature distribution of battery charged with 1C, 3C and 5C under 20℃.

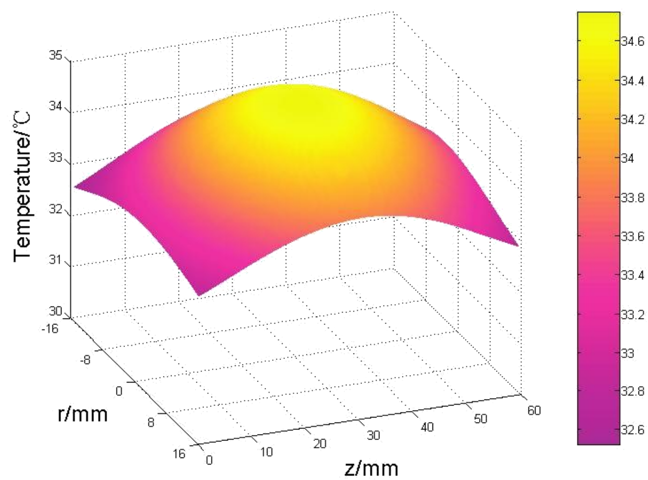

Figure 1. Surface Temperature Distribution Map of (20℃, 1C) Charging

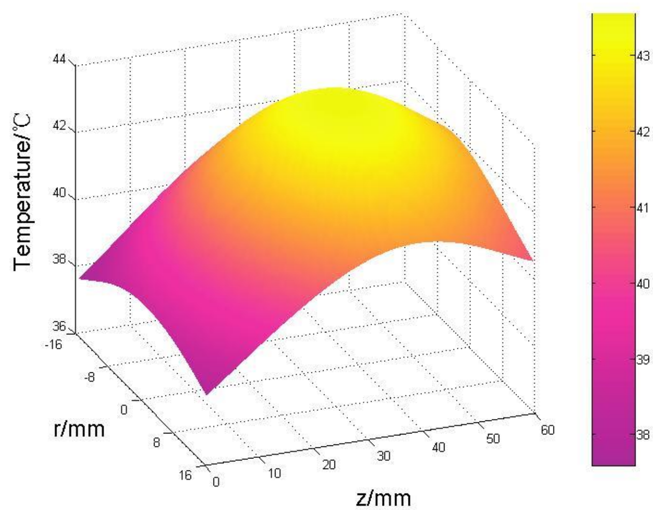

Figure 2. Surface Temperature Distribution Map of (20℃, 3C) Charging

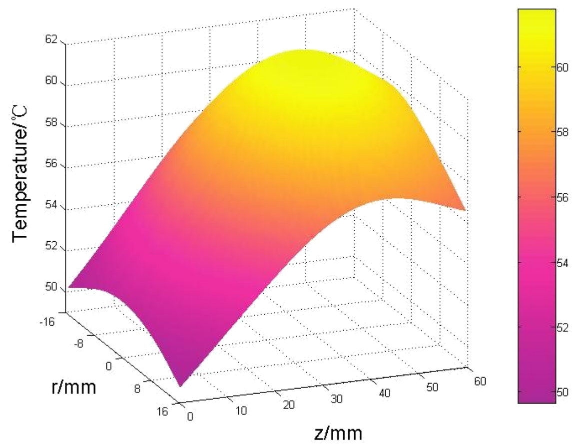

Figure 3. Surface Temperature Distribution Map of (20℃, 5C) Charging

3. Establish, Test and Examine the Neural Network

The surface temperature is a function of ambient temperature, charging current and charging time when charging. Relationships are represented as:

$$T = f\,(T\,amt;\, I;\, t) \qquad (1)$$

There must be correspond surface temperature values after given a set of values of environmental temperature, charging current and charging time.

The structure principle of establishing a neural network is shown in Figure 4.

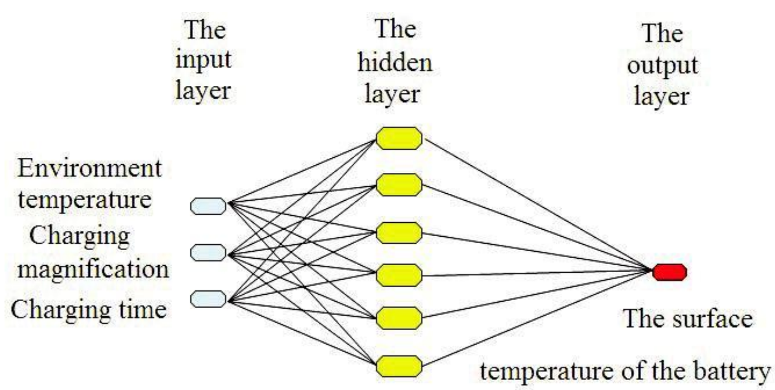

Figure 4. Structure Principle of Establishing the Neural Network

The neural network toolbox of Matlab is applied to establish, test and examine the neural net-work; and the establishment of the neural network consists of three layers: the input layer with three nodes, the hidden layer with s nodes and an output layer with one node. The input vector of input layer of is P=[P1, P2, P3], where P1 is the environment temperature of the battery, P2 is charging magnification of the battery, and P3 for the charging time; then the output vector of the output layer is the surface temperature of the battery [14].

Currently, several fast algorithms such as flexible algorithm, variable learning magnification algorithm and variable gradient algorithm with a variety of improvements are

proposed based on the standard BP test algorithm. The author applied the variable learning magnification algorithm out of the considerations of network convergence.
Concrete realization process consists of the following steps:

1) Import the training samples (P,T) and the checking samples(P_{new}, T_{new}) from data file and con-duct normalization: To prevent the neurons getting into saturation, the output amplitude of which it connected with other neurons must be limited; to enhance the generalization ability of prediction network, speed up learning, the input samples should be normalized when using the BP algorithm. Combine the experiment charge data of 1C, 3C, and 5C, and conduct normalization of the input data, which ensures the data is distributed in (-1, 1). The standard formula is described as follows:

$$P_{max} = max(P; P_{new}) \quad (2)$$

$$T_{max} = max(T; T_{new}) \quad (3)$$

$$P = P=P_{max} \quad (4)$$

$$T = T=T_{max} \quad (5)$$

2) Generate initial BP network, set the number of neurons of layers separately, and active functions, training algorithm, the weights and thresholds. As for the determination of the number of the neurons in the hidden layer of BP neural network, the common method is to check and compare with a BP network of different numbers of hidden layer, and select the ideal S. Then 3, 5, 7, 9, and 11 is selected as the value of S respectively to conduct comparison with the experimental results.

Compare the largest relative error, the mean relative error, training times to generate Table 2.

Table 2. Results of comparison under the Different Numbers of Hidden

Number of the neurons	Train results	The goal	Training times	The epochs
3	0.00166	0.001	495	1000
5	9.77e-04	0.001	474	1000
7	9.99e-04	0.001	433	1000
9	9.85e-04	0.001	458	1000
11	9.81e-04	0.001	460	1000

Finally select 7 is the best hidden nodes. The activation functions in the hidden layer are taken as symmetric Sigmoid function with the expression:

$$S(x) = [1 - \exp(-x)] / [1 + \exp(-x)] \quad (6)$$

The activation functions in the output layer are taken as linear function with the expression:

$$g(x) = x \quad (7)$$

The BP network generated is shown in Figure 5.

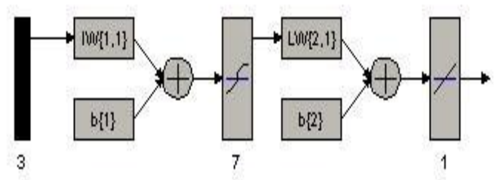

Figure 5. BP Network

3) Set the number of the training, target value, learning speed and train the BP network. SCG algorithm is more widely applied when considering the occasions of large scale network. So the SCG algorithm is selected in the comparing process of network learning. The training program and process are shown in Figure 6.

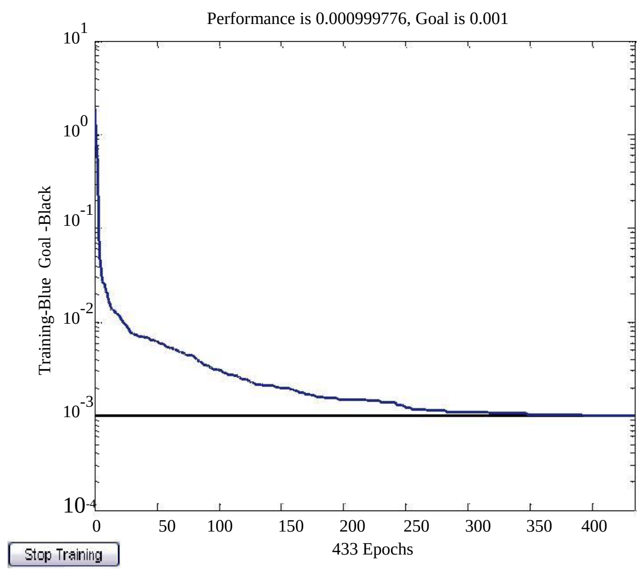

Figure 6. Training the BP Network with SCG algorithm

4. Analyze the Testing Result and Predict the Temperature

4.1. Matlab provides function used for further analysis on the results of network training

The function postreg has analyzed the relationship between the network output and target value using linear regression which also the changing rate of network output to that of target output relatively, which evaluates the results of network training as well.

$$[m; b; r] = postreg(zongyuce\ outputs; T_{new}) \quad (8)$$

We can get the parameters below:

$$m = 0{:}9962;\ b = 0{:}0011;\ r = 0{:}9982$$

Postreg function may return three values, where m and b represents the optimal slope of the regres-sion line and intercept on y-axis, when m=1, b=0 is set up, the network output and target output are exactly the same, the performance of which is optimal. While, r is the correlation coefficient of the network output and target output, the closer it approaches to 1, which indicating that the network output is closer to the target output, and the better the network performance. At the same time, the performance of the network is shown in Figure 7.

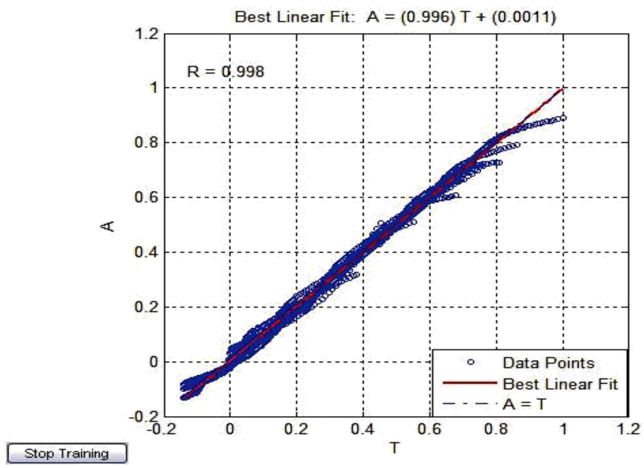

Figure 7. Analysis on the results of network training

In Figure 6, the abscissa represents the target output, while the ordinate represents the network output, the "O" represents the data, and the ideal regression line (which means linear network output equals to the target output) with the dashed line, while the optimal regression is shown with the solid line. The dashed line and straight lines are in good agreement which indicates that the network has very good performance.

4.2. Simulate the output of the network with function

The command of which is $a = Sim(Net; P)$. Conduct comparison with target value to test the performance of the network. The comparison is shown in Fig 8.In addition the output of the network is very close to the target value, which proves that BP network is feasible after training.

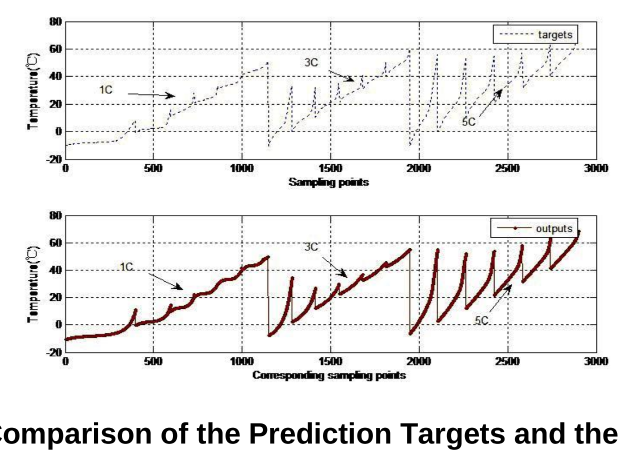

Figure 8. Comparison of the Prediction Targets and the Practical Output

4.3. Analysis of the results

Conduct prediction of testing samples and normalization of the output values using BP network and make analysis on the performance of the network by comparison. Then restore the network output as the surface temperature of the battery with the analysis of the error, the results are shown in Table 3.

Table 3. Results of comparison under the different numbers of hidden

Test conditions(C/℃/s)	Measured temperature values(℃)	Estimated temperature values(℃)	Relative error
1 / -10 /1500	-7.98	-8.94	0.12
1 / 10 /2010	15.31	13.32	0.13
1 / 20 /2520	24.18	26.43	0.0933
1 / 30 /3000	35.17	40.44	0.15
3 / 0 /1000	12.24	11.06	0.096
3 / 20 /1100	30.95	28.47	0.08
3 / 40 /1300	58.19	63.36	0.089
5 / -10 /700	39.96	36.32	0.091
5 / 10 /800	54.77	48.75	0.11
5 / 30 /750	57.29	62.78	0.096

As is shown that the maximum error is 0.13, minimum error is 0.08, in addition the output of the network is very close to the target value.

5. Conclusions

Many aspects should be taken into consideration when predicting the temperature of the battery, such as the difference in charging environment, charging magnification which may reduce human interference, and thus more objective indeed. However, as for difference of the heat production mechanism of different types of power battery, there may be some impact caused by material factors in the design of neural network structure, which determines the fact that the impact factors suitable for nonlinear problems should be taken into consideration. In addition, a variety of practical problems in the application should also be seriously considered, and increase the capacity of training samples, improve the network structure can be conducted to improve the accuracy of the prediction which ensures the satisfactory prediction results.

Acknowledgements

The work was supported by the State Key Development Program for Basic Research of China (2009CB220107).

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