Application of RBF Radial Basis Network in Specific Capacity Attenuation of Battery

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***Abstract*— the physical structure parameters and testing conditions of porous carbon in anode materials are closely related to the electrochemical properties of batteries. Exploring the physical structure and testing conditions of porous carbon can improve the electrochemical properties of the battery. In this paper, 220 sets of relevant experimental data were collected, and the relationship model of pore size and distribution, carrying capacity, specific surface area of porous carbon material, pore capacity and battery test conditions and specific capacity attenuation rate of the battery was established by using the principle of radial basis network (RBF). The average error is 15.58%. It provides a theoretical basis for the design of porous carbon anode materials.**

***Index Terms*— porous carbon/sulfur composites; Initial discharge specific capacity; Radial basis network;**

I. INTRODUCTION

With the rapid development of the global economy, the demand for energy is growing rapidly, and the main source of energy is still non-renewable fossil energy. The continuous consumption of fossil energy not only makes it face the danger of exhaustion, but also has a serious impact on the environment [1]. Therefore, it is very important to find clean and renewable new energy sources to replace the traditional fossil energy sources. Meanwhile, the utilization of new energy resources needs to find a matching energy storage device. Secondary batteries, with high conversion efficiency through the conversion between chemical energy and electric energy, have become an important energy storage device in the field of new energy [2].

In recent years, great progress has been made in the study of lithium-sulfur batteries, but there is still a big gap between the current level and the theoretical value. Many scholars have done a lot of research on related issues. For example, Chen et al. established a mathematical analysis model of lithium-sulfur battery, which mainly explored the relationship between current density, ion diffusion coefficient, anode material thickness and discharge specific capacity [6]. Ding et al. analyzed the influence of factors such as the ratio of carbon and sulfur and the current carrying capacity of battery anode materials on the charging and discharging performance of the battery, which will provide certain guidance for the design of anode materials [7]. Dunnan made equal use of spearman rank correlation coefficient and canonical correlation coefficient analysis method to explore the relationship between physical structure parameters of porous carbon in positive electrode materials, test conditions and battery electrochemical properties, which provided certain guidance for exploring the mathematical model of positive electrode material structure, test conditions and electrochemical properties [8].

The physical structure parameters and testing conditions of porous carbon in anode materials are closely related to the electrochemical properties of batteries. Based on the analysis of 220 groups of experimental data in porous carbon of lithium-sulfur battery reported in the literature, the relationship model of pore size and distribution, carrying capacity, specific surface area of porous carbon material, pore capacity and battery test conditions and specific capacity attenuation rate of battery was established by using the principle of radial basis network (RBF). The prediction of the last 10 groups of experimental data is carried out to verify the fitting effect of the model, which provides a certain theoretical basis for the design of porous carbon anode materials.

II. ESTABLISHMENT OF RBF NETWORK MODEL

In this paper, RBF network is mainly used to establish the mathematical model of pore size and distribution, carrying capacity, specific surface area of porous carbon material, pore volume, battery test conditions and initial specific capacity of battery.. The initial discharge specific capacity of battery is selected as the dependent variable, denoted as y. And 8 factors that have significant influence on it are taken as independent variables. It is assumed as follows: the percentage of micropores (less than 2*nm*), mesopores (between 2*nm* and 50*nm*) and macropores (more than 50*nm*) in the porous carbon material: the micropores are denoted as x_1; The mesopore is denoted as x_2; The big hole is x_3; The sulfur load is denoted as x_4; The specific surface area ($m^2\ g^{-1}$) is denoted as x_5; The pore volume ($cm^3\ g^{-1}$) is denoted as x_6; And the test conditions of the assembled battery: the test multiplier power (C) is denoted as x_7 and the number of cycles performed by the battery is x_8.

2.1 experimental data preprocessing

Firstly, the data collected in the literature were processed in this paper. In order to facilitate the calculation, the percentages of micropore x_1, mesoporous x_2, macropore x_3 and sulfur load x_4 were calculated. For example: 30%, 50% directly into: 30, 50. Outliers were removed and 211 groups of effective data were selected for research and analysis. Some data are shown in the following table:

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Table 1 relevant experimental data

The serial number	microporous	mesoporous	Sulfur loads	Specific surface area	Pore volume	Test rate	Number of cycles	Specific capacity decay rate
1	100	0	53.4	1231	0.91	0.5	200	0.34
2	100	0	52.5	1133	0.86	0.5	200	0.34
3	100	0	50.3	991	0.82	0.5	200	0.38
4	100	0	50	1438	1.12	0.5	200	0.34
5	0	100	60	3164	1.88	0.5	800	0.06
				...				
210	0	100	57.4	1036	0.806	0.5	300	0.17
211	20	80	72	1013	1.26	0.5	200	0.1

2.2 model establishment and experimental data prediction

The most common radial basis function in RBF network is gaussian function. The connection weight between its output and the network is linear, which has the characteristics of simpler network structure, faster learning convergence, ability to approximate nonlinear functions and strong anti-interference ability [10-12].

2.2.1 radial basis network model of electrochemical properties:

$$y=\sum_{i=1}^{m}\omega_{ik}R_i(X),\qquad R_i(X)=\exp(-\frac{1}{2\sigma_i^2}\|X-c_i\|^2)$$

$X=[x_1,x_2,x_3\cdots x_8]$ corresponding independent variables are respectively: micropore, mesopore, macropore, sulfur load, specific surface area, pore volume, test ratio, and cycle number, namely input vector. y represents the dependent variable: the initial discharge capacity of the battery, namely the output vector. $R_i(X)$ is the activation function of the ith neuron in the hidden layer. ω_{ik} is the connection weight between the ith neuron in the hidden layer and the kth neuron in the output layer. c_i is the center of the ith radial basis function. σ_i is the spread coefficient of the ith radial basis function. m is the number of neurons in the hidden layer. $\|X-c_i\|$ is the norm of the vector, that is the distance between x and c_i.

RBF network learning algorithm is as follows:

Step1: find the base function center

Initialize the network and randomly select n samples as the clustering center c_i, $i=1,2,\cdots,n$. The training samples x_k, $k=1,2,\cdots,201$ are clustered according to the latest rules to obtain the set U_i, $i=1,2,\cdots,n$. Adjust the clustering center, calculate the mean value of training samples in each set, obtain the new center $c_i^{'}$, and determine it as the final base function center when $c_i^{'}$ fixed.

Step2: find the variance $\sigma_i=\frac{c_{\max}}{\sqrt{2n}}$, $i=1,2,\cdots n$, where $c_{\max}$ represents the maximum distance of each center.

Step3: calculate the weight from hidden layer to output layer .

$W=e^{\frac{n}{2}\|x_k-c_i\|^2}$, $i=1,2,\cdots,n$

The spread is an important parameter in the RBF network. The larger the spread is, the smoother the radial basis network fitting will be, and the approximation error will also become larger. The smaller the spread is, the more accurate the approximation of the function will be. However, the approximation process is not smooth and the performance of the network is poor, which will lead to excessive stress [13-14].

2.2.2 Prediction of experimental data

In this paper, 211 groups of experimental data were brought into RBF network for model test. The last 10 groups of data in table 1 were predicted. First, 200 tests were conducted for different expansion coefficients. Spread value is taken from 1 to 200, and the optimal spread value is found according to the principle of minimum standard error. The corresponding standard error is shown in figure 1 below:

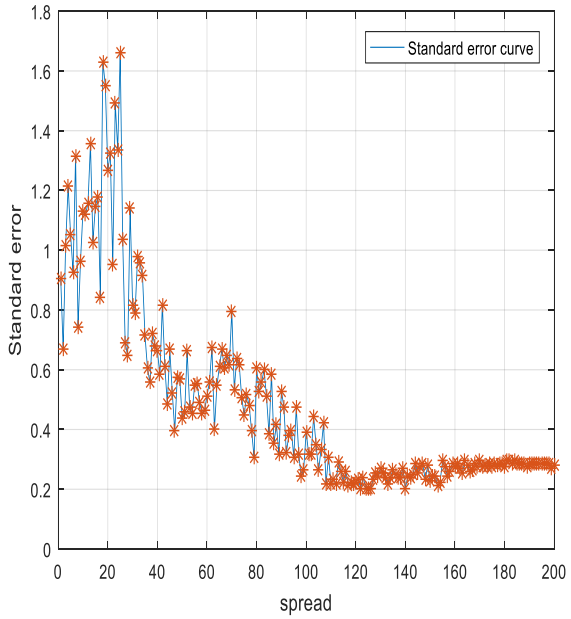

Figure 1 standard error corresponding to different spread values

It can be seen from figure 1 that, with the difference of spread value, the standard error of the predicted initial discharge specific capacity of the battery varies greatly. When spread value is 1-100, the standard error is large and the variation range is large. When the value is 100-140, the minimum standard error appears and there is a small fluctuation. After 140, the standard error is basically stable.

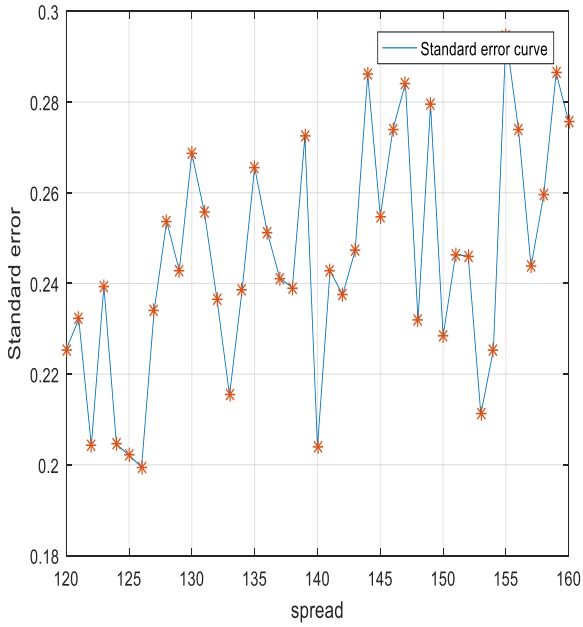

Figure 2 standard error corresponding to different spread values

In order to judge the value of the minimum spread standard error more accurately, the value range of spread is reduced to 120-160. According to the figure above, it can be clearly obtained that when spread value is 126, the minimum standard error reaches 0.249, that is, the optimal spread value is 126.

The RBF network model was used to predict the last ten groups of experimental data, and the table and line chart were compared. As follows:

Table 2 actual and predicted initial discharge specific capacity

serial number	Actual specific capacity attenuation	RBF network predicts specific capacity decay rate	relative error
1	0. 7	0. 542	22. 61%
2	0. 45	0. 472	4. 91%
3	0. 67	0. 750	11. 93%
4	1. 15	1. 246	8. 30%
5	0. 98	0. 796	18. 77%
6	1. 47	1. 603	9. 05%
7	1. 36	0. 952	29. 97%
8	1. 21	0. 837	30. 80%
9	0. 17	0. 189	11%
10	0. 1	0. 092	8. 5%

It can be concluded from table 2 that the group with the largest relative error is the eighth group, the actual value is 1.21, the predicted value is 0.837, and the relative error rate is 30.80%. The second group had the smallest relative error, the actual value was 0.45, the predicted value was 0.472, and the relative error rate was 4.91%. And the average relative error is 15.58%, the fitting effect is good.

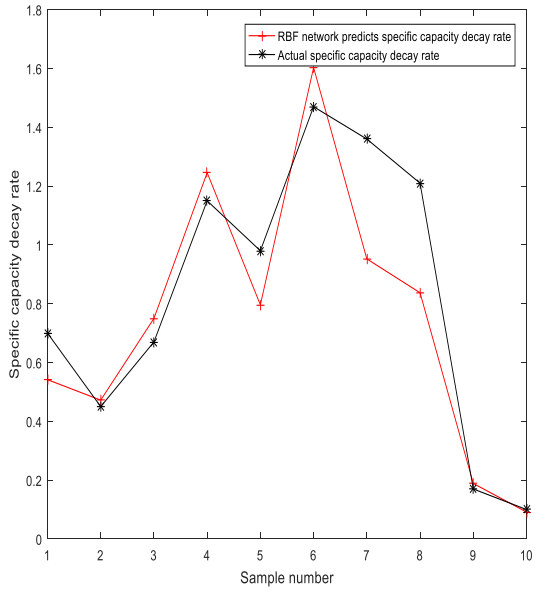

Figure 3 RBF network specific capacity attenuation ratio comparison diagram

CONCLUSION

RBF network model was used to simulate the relationship between physical structure parameters of porous carbon in anode materials, testing conditions and specific capacity attenuation rate of battery. The obtained simulation results have a small error with the actual test data, with an average relative error of 15.58%. This shows that RBF network can well fit the relationship between dependent variables and independent variables, and provides certain theoretical model guidance for the design of physical structure parameters and test conditions of porous carbon in the anode material of lithium-sulfur battery.

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