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Research on corrosion rate prediction of aluminum alloys in typical domestic areas based on BP artificial neural network

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Abstract. By analyzing the climatic factors and aluminum alloys corrosion data in 10 atmospheric corrosion sites, the aluminum alloy atmospheric corrosion prediction model was built. The reasonableness of the corrosion model was verified by using the BP artificial neural network to learn, train, simulate, and compare with the corrosion test results of aluminum alloy samples in 10 typical atmospheric corrosion test stations. The results show that a stable forecasting model can be built based on the BP artificial neural network, which well predicted the corrosion rates of aluminum alloys in 10 typical atmospheric corrosion test stations.

Introduction

Aluminum alloys with low density, excellent mechanical properties, and good processability, have been widely used in aerospace and other fields. As the most widely used aircraft structural materials, aluminum alloys consumption is increasing, but also more and more aluminum alloys are exposed to the atmosphere in recent years. Therefore, the atmospheric corrosion behavior of aluminum alloy has become an important subject of study. However there are too much atmospheric corrosion data, which makes the data processing methods generally complex. The artificial neural network is an abstract mathematical model to reflect the human brain structure and function [1]. The artificial neuron nodes connect to each other to constitute a complex network, which can establish a nonlinear mapping relationship from network input to network output [2]. Accordingly, using BP artificial neural network can contain the nonlinear relationship between corrosion influence factors and corrosion results in neural network topological structure, and learn and train for a certain amount of test sample data, which also reflects its unique superiority in dealing with the complex interaction model. The metal corrosion rate on various states of atmospheric factors can be output, and the reliability of corrosion prediction is relatively good [3-5].

In this paper the atmospheric corrosion prediction model of aluminum alloy was built by analyzing the climatic factors and aluminum alloys corrosion data in 10 atmospheric corrosion sites with the BP neural network method, and using the BP artificial neural network to learn, train, simulate, and compare with the corrosion test results of aluminum alloy samples in 10 typical atmospheric corrosion test stations.

BP artificial neural network

Artificial neurons are simple, but a large number of artificial neurons constitute the neural network， and information processing and storage can be achieved through the interaction between the artificial neurons.The most widely used neural network is the Error Back-Prop-agation Network, aslo called BP artificial neural network, which has the characteristics as simple structure, stable working state, and easy use in hardware. Typical BP artificial neural network has three layers[6], namely input layer, hidden layer and output layer, as shown in Figure 1.The input data $X=(x_1, x_2, \ldots, x_n)$ go form the input layer, in turn through each hidden layer, and finally arrive the output layer. Thus output data $Y=(y_1, y, \ldots, y_m)$ are obtained. The BP artificial neural network with nonlinear characteristics makes the establishment of metal atmospheric corrosion model and predictition possible [7-9].

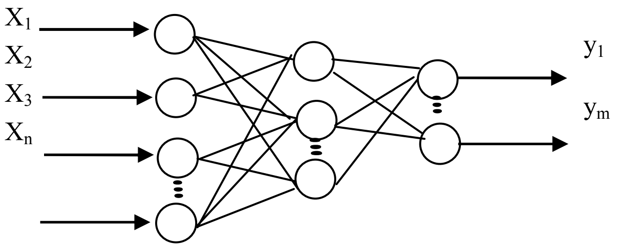

Fig.1 BP Neural Networks

Results and discussion

Statistics of the atmospheric factors. Five environmental parameters of the 10 atmospheric corrosion sites are selected as the evaluation index. They are altitude, annual average temperature, annual average humidity, annual average sunshine time and annual rainfall. The original data are given in Table 1.

Table 1 Weathering data of the 10 atmospheric corrosion sites

station	altitude/m	annural average Temperature[℃]	annual average Humidity[%]	annual Sunshine time[h]	annural Rainfall[mm]
Beijing	73.4	11.9	57	2559.3	586
Wanning	12.3	24.2	86	2026.5	1515
Jiangjin	208	17.9	81	1317	1202.9
Lhasa	3648.7	9	46	3053.1	580.9
Wuhan	23.3	16.8	75	1621.6	1146.8
Guangzhou	6.3	22.7	77	1607	1562.7
Qingdao	12.3	12.3	71	1944	561.7
Xishuangbanna	626	21.6	83	1716	1713
Shenyang	41.6	9.4	66	2279.3	408.5
Dunhuang	1139	9.4	41	3269.5	32.9

Construction of the BP artificial neural network prediction model. The forecast mold for the atmospheric corrosion rate of aluminum alloy is constructed with 3-layer BP artificial network. The first layer is input layer, the second is intermediate hidden layer, and the third is the output layer. The total number of input layer neurons in the neural network is the number of atmospheric factors influencing the corrosion of alumimum alloy, namely the input layer has five neurons nodes which are altitude, annual average temperature, average humidity, annual average sunshine and annual rainfall respectively. The output layer has one neurons nodes. For the intermediate hidden layer, we select four, five, six, seven and eight neurons nodes for network training respectively, and by comparing the convergence speed it is determined the the optimal hidden node number is five. At the same time, in order to prevent network training into local minimum, the additional momentum method is used to train neural network. The momentum coefficient of this BP artificial neural network is 0.7, the minimum training speed is 0.1, the allowable error is 0.0001, and the maximum number of iterations is 5000.

BP neural network prediction model predictions. Fig. 2 shows the error curve of aluminum alloys atmospheric corrosion. It is training to 4734 steps when convergence, and the error curve present a smooth, no obvious fluctuant characteristics.

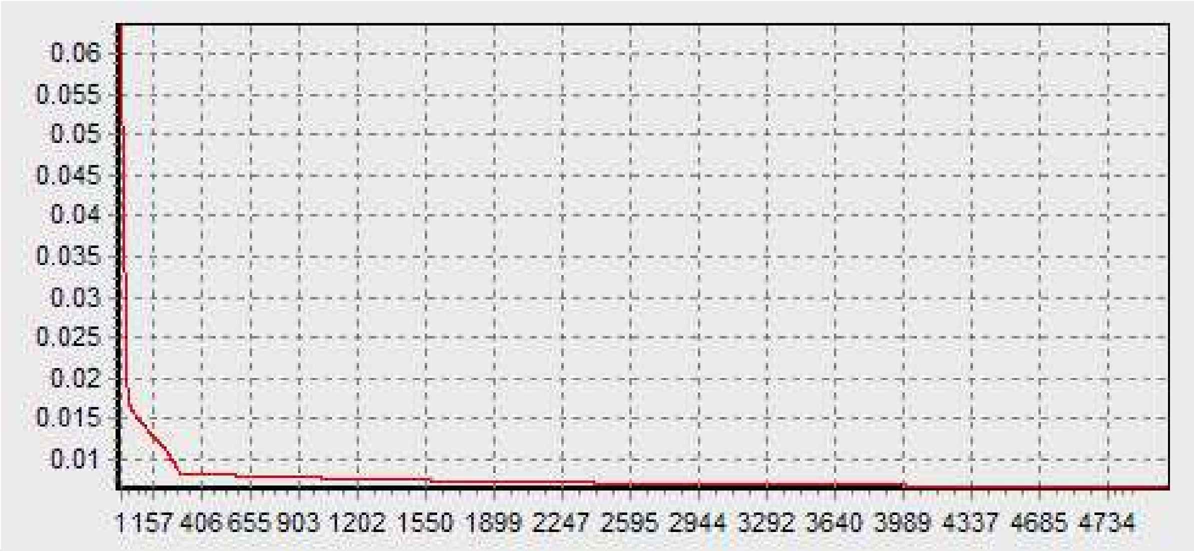

Fig.2 Error curve in 5000-time training(Fitting residual = 0.006815433023)

The prediction results are shown in Table 2. Comparing the prediction results with the measured corrosion data of the 10 atmospheric corrosion test stations it can be found the results are more consistent, and the prediction error of the corrosion rate after the 5000 training are mostly controlled within 10%.

Table 2 Predictive results after 5 000 epochs

station	corrosion rate measured[um/a]	corrosion rate predicted[um/a]	Error [%]
Beijing	0.87	0.7903	9.16
Wanning	0.42	0.4316	2.76
Jiangjin	0.38	0.3715	2.23
Lhasa	0.24	0.2293	4.45
Wuhan	0.82	0.8321	1.56
Guangzhou	0.75	0.7403	1.29
Qingdao	0.096	0.0958	0.20
Xishuangbanna	0.17	0.1694	0.35
Shenyang	0.46	0.4381	4.76
Dunhuang	0.28	0.2537	9.39

Conclusions

The atmoshperic corrosion behavior of aluminum alloys in 10 typical atmospheric corrosion test sites is predicted based on BP artificial neural network. Through continuous accumulation of aluminum alloy atmospheric corrosion data and a large number of training it can establish the aluminum alloy atmospheric corrosion prediction model with good stability and strong ability of generalization. By using this mold, the corrosion rate can be well predicted, and the prediction error is mostly contolled with 10%. This study can be provide a meaningful reference and basis for the corrosion prevention of aluminum alloys in the domestic typical regions, and ay the foundation for further comprehensive research on metal corrosion in typical regions. l

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