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Analysis in atmospheric corrosion behavior of bainite steel exposed in offshore platform based on the artificial neural network

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Abstract. Back propagation (BP) neural network model was established, using the corrosion data of five kinds of recently developed bainite weathering steel and the commercial weathering steel 09CuPCrNi exposed in the offshore platform in Wanning. The influences of elements P, Cu, C and Cr on the corrosion behavior of weathering steel were studied according to the model. The experimental results indicate that the corrosion depth of bainite weathering steel corroded for 1 year could decline owing to the increasing contents of P, Cu and Cr in steel while C has little effect on the variation of the corrosion depth.

Introduction

The corrosion resistance ability of steel structure exposed in littoral is affected by alloy elements and coastal atmospheric environment prominently. This effect can be enhanced gradually with the decrease in the distance between the exposure position and the coastline [1]. The offshore platform built in Wanning has the shortest distance as well as the high temperature and humidity circumstance. In addition, it possesses the atmospheric environment with extremely high concentration of sea salt particles, which is caused by the splashed seawater derived from the collision between sea waves and the platform. This terrible environment makes revealing the impact of metallurgical and environmental factors on the corrosion depth and predicting the corrosion degree more difficult.

BP neural network has been exploited to analyze the non-line relationship between various factors and material corrosion behavior for many years [2]. The structures of the network based on different exposure regions or types of steel are quite different [3]. Some previous network models focused on the corrosion properties of conventional steels exposed to inshore atmospheric environment [4-6], but little attention was paid to the recently developed bainite steels corroded in the offshore platform circumstance. In this investigation, five types of bainite steel and 09CuPCrNi were exposed and corroded in the offshore platform in Wanning for 1 year. The corrosion data were collected and employed to build BP neural network model. The influences of alloy elements such as P, Cu, Cr, and C on the corrosion properties of steel were imitated and studied according to the model, aiming at offering references for corrosion behavior prediction of bainite weathering steel applied in this environment.

Materials and corrosion methods

Commercial weathering steel 09CuPCrNi and five sorts of bainite steel were prepared by Wuhan Iron and Steel (Group) Corporation. Chemical compositions and mechanical properties of these steels are listed in Tab. 1 and Tab. 2. Samples with size of 100mm×50mm×5mm were ground with 400–1000 grit silicon carbide papers, cleaned ultrasonically with acetone and then rinsed with distilled water. After dried and weighed, the samples were exposed for 1 year in the offshore platform built in Wanning, in accord with GB/T 6464-1997.

Tab. 1 Chemical compositions of test steels (mass %)

Steel	C	Mo	Nb	Cu	Ni	Cr	P	Si	Mn	S	B
bainite 1#	0.026	0.21	0.096	1	1.01	1	0.02	0.27	1.39	0.0075	0.0005
bainite 2#	0.04	0.41	0.1	0.6	0.64	0.63	0.019	0.35	1.47	0.0077	0.0012
bainite 3#	0.04	0.2	0.19	0.6	0.59	0.62	0.016	0.4	1.53	0.0082	0.0006
bainite 4#	0.038	0.21	0.11	0.6	0.61	0.63	0.017	0.33	1.53	0.0089	0.0005
bainite 5#	0.151	0.22	0.083	0.61	0.63	0.63	0.019	0.44	1.51	0.0086	0.0008
09CuPCrNi	0.088	-	-	0.31	0.31	0.42	0.086	0.26	0.51	0.0058	-

Tab. 2 Mechanical properties of test steels

Steel	Yield strength (MPa)	Tensile strength (MPa)	Elongation (%)
bainite 1#	785	830	16
bainite 2#	795	835	16.5
bainite 3#	795	845	13
bainite 4#	700	745	19
bainite 5#	760	840	12.5
09CuPCrNi	380	510	22

Establishment of BP neural network model

The BP neural network was developed, which was composed of input layer, hidden layer and output layer. The environmental factors (including average concentration of sea salt particles, corrosion cycle, average temperature and humidity) as well as the metallurgic factors (including the contents of C, Mo, Cu, Cr, P, Nb and Ni) were chosen as input parameters. The output parameter was corrosion depth. Totally, 30 samples were selected as training data to train the neural network and another 6 samples were used as testing data to examine the prediction ability of it. The transfer functions for hidden layer and output layer were the Tansig function and the Logsig function, respectively. To simplify the calculation and improve the efficiency of the system [2, 7], all samples were normalized into the [0, 1] interval by employing Eq. 1:

$$X_i' = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \quad (1)$$

where X_i' is ith pattern after primary processing; X_i is ith pattern prior to primary processing; $X_{\max}$ is the maximum among all patterns prior to primary processing and $X_{\min}$ is the minimum among all patterns prior to primary processing.

However, it is not ease to choose the appropriate number of parameters in hidden layer because there is no definite rule to determine it [8]. Considering the present neural network model, which was composed of 11 input parameters and 1 output parameter, the number of parameters in hidden layer was selected from 4 to 13 and adopted tentatively in the establishment of neural network model, according to Kolmogorov formula. After training 10000 epochs, the relationship between the number of parameters in hidden layer and the prediction standard error is depicted in Fig. 1, which reveals the fact that the minimum standard error emerges when the number of parameters in hidden layer is 8. At this situation, the imitational precision of the model can reach 10^{-4} (shown in Fig. 2). As a result, the topological structure of the BP neural network model can be determined as 11-8-1.

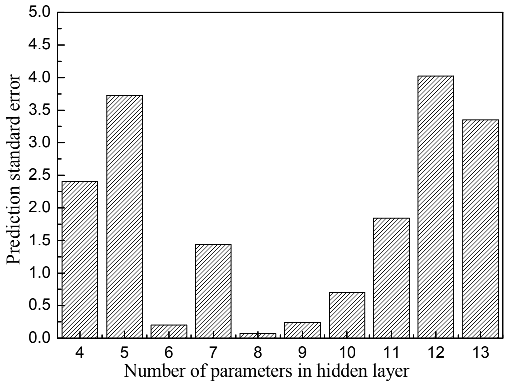


Fig. 1 Prediction standard error versus number of parameters in hidden layer

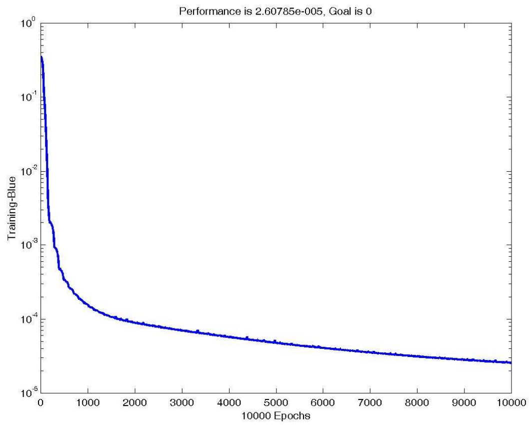


Fig. 2 Imitational precision of the model

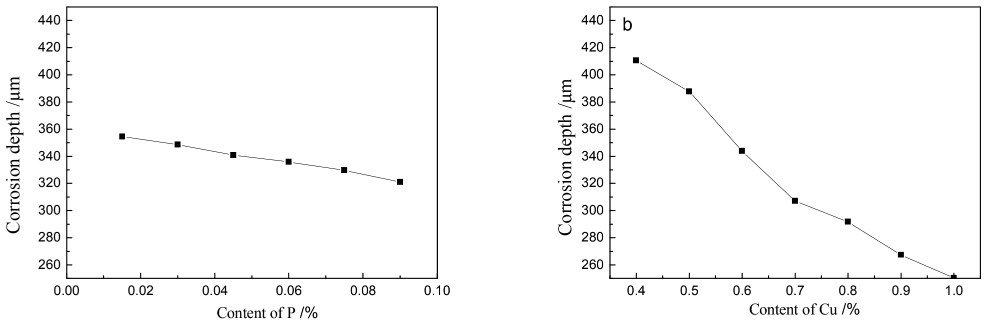
Tab. 3 shows the measured results and predicted results by using the built model. The two results agree with each other with reasonable experimental accuracy, indicating that the model is practical [2].

Tab. 3 Results of measured and predicted

No.	Imitated corrosion depth (μm)	Measured corrosion depth (μm)	Relative error (%)
1	16.05	16.20	0.92
2	316.95	298.30	6.25
3	155.10	165.00	6.00
4	24.80	27.70	10.54
5	15.76	17.20	8.38
6	362.04	386.60	6.35

Single sensitivity analysis prediction

The established model could be applied to explore the impacts of the contents of some key alloy elements (such as P, Cu, Cr and C) on the corrosion behavior of weathering steel [9, 10]. Changing the content of a certain element based on bainite steel 4# and holding the other factors fixed, the relationships between corrosion depth and the contents of the elements were detected and are described as shown in Fig. 3 and Fig. 4.

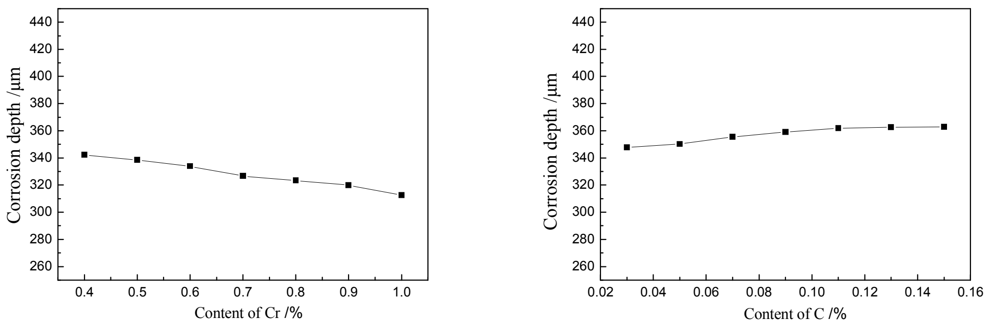


(a) (b)

Fig. 3 Corrosion depth versus element content: (a) P; (b) Cu.

From Fig. 3, it can be obviously seen that the both increments in the contents of P and Cu make the corrosion depth of bainite steel exposed in offshore platform for 1 year decrease steadily. The improved corrosion resistance ability may be due to the formation of protective rust provoked by element P and the compact rust layers produced by Cu compounds, which aggregate around and fill the cracks and holes in rust layers [11-13].

Some former investigations have illuminated the point that Cr plays a basic role in alleviating the short-term corrosion tendency of weathering steel corroded in terrible atmospheric environment whereas takes little effect on the long-term corrosion behavior of it [14, 15]. In the present imitation, the increase in the Cr content diminishes the corrosion depth of bainite steel corroded for 1 year in the offshore platform (Fig. 4a), indicating that the phenomenon corresponds to the verified views well.



(a) (b)

Fig. 4 Corrosion depth versus element content: (a) Cr; (b) C.

Element C alloyed in bainite steels trends to form C-rich-phase. This phase on the one hand can accelerate the corrosion process due to the appearance of galvanic corrosion, but on the other hand promote the formation of rust layers to protect the steel [16]. According to what is shown in Fig. 4b, it is evident that the variation of corrosion depth of the bainite steel is unconspicuous with the C content increasing, testifying the view that the two opposite effects caused by element C may counteract each other in the terrible atmospheric environment.

Conclusions

The prediction of testing samples was carried out by the established BP neural network model, which took the metallurgical and environmental factors for input parameters and corrosion depth for output parameter. The predicted results are consistent with the measured results satisfactorily, proving the model applicable to the terrible atmospheric environment.

The contents of P, Cu, Cr and C as alloy elements in steel may impact the corrosion resistance ability of the steel corroded in the terrible atmospheric environment such as the offshore platform in

Wanning. These influences have been simulated by the built model, pointing out that the increasing contents of P, Cu and Cr in steel decrease the 1-year-corrosion-depth while C has little effect on the variation of this characteristic.

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