

# Prediction of Corrosion Rate of Q235 Steel under the Marine Environment

**Liangtao Ma\* and Haifang Dong**

Wuhan second ship design and Research Institute, China

\*Corresponding author e-mail: 330498971@qq.com

**Abstract.** A generalized regression neural network is used to predict the corrosion rate of metals in marine environment. The environmental temperature, oxygen content, pH value, salinity and potential are taken as input, and the corrosion rate is taken as output. A3 steel was selected to test the 25 sets of data, 18 groups of data were selected for training, and 7 sets of data were used as the verification. The results show that the generalized regression neural network prediction, select the default S value, the average prediction error is 5.72%, higher than the BP neural network was used to predict the 6.56%, using cross validation method to select the optimal S value, the optimal value of S under the average prediction error of the forecast is 2.38%. It shows that the prediction of corrosion rate of metal materials in marine environment by generalized regression neural network is feasible in technology, and has high prediction accuracy and application value.

## 1. Introduction

In recent years, with the development of society and science and technology, people pay more attention to the vast ocean. But including marine shipping, offshore oil and marine nuclear power, marine technology cannot do without a variety of materials and metal materials as the main force of marine products and equipment, the corrosion is very serious, marine corrosion loss total corrosion losses 1/3[1]. At the same time, because most of the offshore structures are far away from the land, the maintenance and maintenance of the offshore structures are very inconvenient, and the cost of maintenance and repair is expensive. Therefore, it is of great significance to predict the corrosion of marine structural products so as to take corresponding measures in advance to reduce the loss.

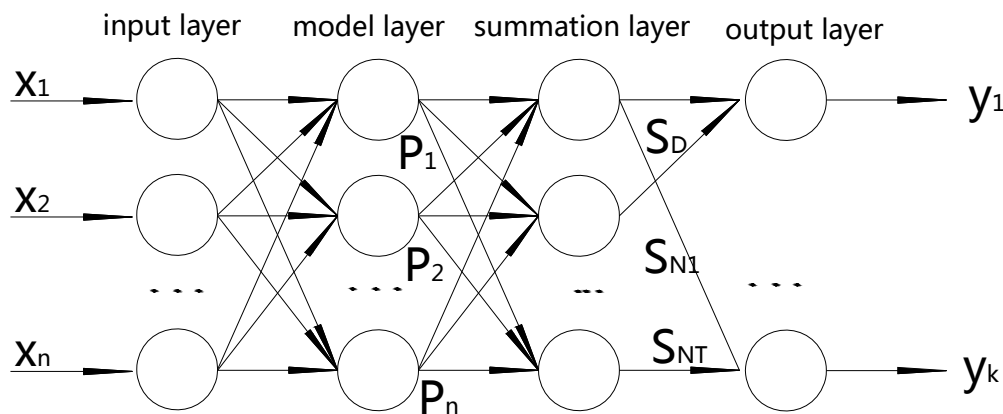
The development of modern mathematical theories and methods provides a strong theoretical foundation and technical support for the quantification and modeling of corrosion science. Cai Jianping and Cohen, Institute of metal research, Chinese Academy of Sciences, predict corrosion of metals in the atmosphere by neural networks [2]. Ren Zhenjia et al. [3-4] measured the influence of different crude oil on pipeline corrosion rate by weightlessness experiment, and established artificial neural network models such as BP, GA and GA-BP algorithm. Liu Wei et al. established a prediction model of corrosion research and a prediction model of corrosion rate in actual seawater environment by using grey neural network, respectively [5-6]. Haque and other [7] neural networks were used to study the corrosion fatigue properties of DP steel. Kamrunnahar [8] et al. Used neural network as a data mining tool to predict the corrosion behavior. But the neural network has some limitations, the BP neural network is a feed-forward neural network, mainly based on the prediction error adjustment of



network weights and thresholds, so that the BP neural network to predict the output approaching the desired output, but if the sample is less cannot guarantee the prediction accuracy. GRNN (generalized regression neural network) on a radial neural network has strong nonlinear mapping capability and flexible network structure and a high degree of fault tolerance and robustness, suitable for solving nonlinear problems, and in a few data, the prediction effect is good, high precision.

## 2. Establishment of generalized regression neural network model

The generalized regression neural network is composed of four layers, which are input layer, model layer, summation layer and output layer corresponding network input  $X=[x_1, x_2, \dots, x_n]$  is  $Y=[y_1, y_2, \dots, y_n]^T$ .



**Figure 1.** The structural diagram of generalized regression neural network

### (1) The input layer

The number of neurons in the input layer is equal to the dimension of the input vectors in the learning samples, and the simple distribution units on each neuron are directly transferred to the model layer.

### (2) The model layer

The number of neurons in the model layer is equal to the number of learning samples  $n$ , and the neurons correspond to different samples:

$$p_i = \exp \left[ -\frac{(X - X_i)^T (X - X_i)}{2\sigma^2} \right] \quad i=1, 2, \dots, n \quad (1)$$

The output of the neuron  $I$  is the exponential form of the square of the  $D_i^2 = (X - X_i)^T (X - X_i)$  Euclid distance between the input variable and its corresponding sample  $X$ . In the formula, the input variables for the network and the learning samples corresponding to the  $I$  neurons are presented.

### (3) The summation layer

The summation layer is calculated with the (1), it is the weighted sum of all model neurons output between the pattern layer in the  $i$  neurons and the sum of the layer of  $j$  molecules for neurons and weights for the  $i$  output sample medium first  $j$  elements, transfer function:

$$S_{nj} = \sum_{i=1}^n y_{ij} P_i \quad j=1, 2, \dots, k \quad (2)$$

## (4) The output layer

The number of neurons in the output layer is equal to the dimension of learning  $k$  output vectors in the sample, each neuron will output division and layer, the corresponding output neuron  $J$   $\hat{Y}(X)$  estimation result of  $J$  elements, and its value is:

$$y_j = \frac{S_{nj}}{S_D} \quad j=1, 2, \dots, k \quad (3)$$

Based on the theory of generalized regression neural network, nonlinear regression analysis, the regression of non independent variable  $Y$  with independent variable  $x$  makes the calculation of  $Y$  with maximum probability value. The joint probability density function of the random variable  $x$  and the random variable  $y$  is  $f(x, y)$ . When the observed value of  $X$  is  $X$ , then the  $Y$  is relative to the  $X$  regression, that is, the conditional mean value is :

$$\hat{Y} = E(y / X) = \frac{\int_{-\infty}^{+\infty} y f(X, y) dy}{\int_{-\infty}^{+\infty} f(X, y) dy} \quad (4)$$

$\hat{Y}$  is the predicted output of  $Y$  under the condition that the input is  $X$ .

Using the Parzen nonparametric estimation, the density function  $\hat{f}(X, y)$  can be estimated from the sample data set  $\{x_i, y_i\}_{i=1}^n$ .

$$\hat{f}(X, y) = \frac{1}{n(2\pi)^{\frac{p+1}{2}} \sigma^{p+1}} \sum_{i=1}^n \exp\left[-\frac{(X - X_i)^T (X - X_i)}{2\sigma^2}\right] \exp\left[-\frac{(Y - Y_i)^2}{2\sigma^2}\right] \quad (5)$$

In the formula,  $X_i$  and  $Y_i$  are the sample values of random variables  $X$  and  $Y$ ;  $n$  is the sample capacity;  $P$  is the dimension of the random variable  $x$ ; the width coefficient of the Gauss function is called the smoothing factor.

Replace the 333 with  $\hat{f}(X, y)$ , and exchange the integral and the order of addition:

$$\hat{Y}(X) = \frac{\sum_{i=1}^n \exp\left[-\frac{(X - X_i)^T (X - X_i)}{2\sigma^2}\right] \int_{-\infty}^{+\infty} y \exp\left[-\frac{(Y - Y_i)^2}{2\sigma^2}\right] dy}{\sum_{i=1}^n \exp\left[-\frac{(X - X_i)^T (X - X_i)}{2\sigma^2}\right] \int_{-\infty}^{+\infty} \exp\left[-\frac{(Y - Y_i)^2}{2\sigma^2}\right] dy} \quad (6)$$

Because of  $\int_{-\infty}^{+\infty} z e^{-z^2} dz = 0$ , the output of the network is  $\hat{Y}(X)$  when the two integral is calculated.

$$\hat{Y}(X) = \frac{\sum_{i=1}^n Y_i \exp\left[-\frac{(X - X_i)^T (X - X_i)}{2\sigma^2}\right]}{\sum_{i=1}^n \exp\left[-\frac{(X - X_i)^T (X - X_i)}{2\sigma^2}\right]} \quad (7)$$

The estimated value of  $\hat{Y}(X)$  is the weighted average of  $Y_i$  of all observed values, and the weight factor of  $Y_i$  is the exponent of the square of the Euclid distance between  $X_i$  and  $X$  of the corresponding sample.

Through the above steps of generalized neural network prediction model is established, we use the measured data to verify the accuracy of the sea test [9] obtained the corrosion rate data of Q235 steel in seawater under different environmental parameters of a total of 25 groups, including 5 kinds of

environmental impact parameters and the parameters of the corrosion rate data in each group specifically, as shown in the following table:

**Table 1.** The Q235 steel corrosion rate in various marine environmental conditions

Serial number	Ocean Temperature/°C	Dissolved Oxygen/mg·L <sup>-1</sup>	Salinity 10 <sup>3</sup> mg/L	PH	Redox Potential/mV	rate $\mu\text{A}\cdot\text{cm}^{-2}$
1	24.27	0.8	32.56	8.1	171	2.55
2	27.45	2.6	35.37	7.96	287	10.96
3	27.23	4.2	31.94	7.89	289	12
4	28.72	6.8	32.21	8	325	13.33
5	28.52	8.4	32.1	8.01	345	17.31
6	28.45	9.9	31.95	7.93	309	22.48
7	23.95	7.61	9.17	8.04	231	8.13
8	24.95	6.8	16.29	7.82	341	9.07
9	24.6	7.52	24.42	7.57	210	10.74
10	27.32	3.12	29.31	8.2	281	13.59
11	24	7.95	30.2	8.1	324	12.89
12	27.78	6.35	31.38	7.2	356	13.61
13	27.97	6.05	31.94	6.6	384	14.6
14	30.7	7.15	31.74	6.5	401	15
15	29.37	6.82	30.12	6.2	414	15.39
16	25.9	6.71	30.1	5.1	378	18.22
17	29.35	6.09	29	6.3	400	16.45
18	27	6.7	30.7	7	350	12.6
19	27.9	5.15	31.5	9.2	264	9.08
20	25.55	6.67	31	8.09	320	12.49
21	24.31	6.42	40.67	7.88	250	8.75
22	24.11	6.38	41	7.98	228	8.99
23	17.45	7.48	34.08	8.1	135	17.05
24	21.95	8.28	34.64	7.95	113	17.34
25	27.19	4.91	33.5	7.99	275	15.48

In the data, choose to train 18 sets of data were predicted and compared with the actual value of 7 sets of data, each data of the environmental temperature, oxygen content, pH, salinity and potential as input, the corrosion rate as the output, to establish the mapping relation between input and output. Because the dimension of each environmental parameter is different from other parameters, and the numerical range is also different, so the data normalization is needed in the prediction system. The above data and calculation process are calculated by importing Matlab to write the calculation code, and the data are as follows:

**Table 2.** The prediction results and relative errors using generalized regression neural network

Serial number	19	20	21	22	23	24	25
Measured values	9.08	12.49	8.75	8.99	17.05	17.34	15.48
Predicted values	9.56	12.01	9.21	9.53	15.51	17.85	14.29
Relative error (%)	5.29	3.84	5.26	6.01	9.03	2.94	7.29

The above data are predicted by generalized regression neural network, and are compared with the predicted values of BP neural network.

### 3. Establishment of BP neural network model

A multilayer feedforward neural network is used in BP neural network. The main feature of the network is that the signal is transmitted forward and the error is transmitted back. In forward transfer, the input signal is processed from the input layer through the hidden layer until the output layer. The state of neurons in each layer only affects the state of the next layer of neurons.

Analysis of measured data, according to the nonlinear function fitting characteristics determine the structure of BP neural network, the environmental temperature, oxygen content, pH, salinity and the potential of the 5 parameters as the input of the training network, the corrosion rate as the output, due to the nonlinear function of 5 input parameters, an output parameter, select the node of hidden layer the number is 10, so the structure of the BP neural network 5-10-1. Also select 25 sets of data in the 1-18 sets of data as training data, select the 19-25 sets of data as the predicted data, in Matlab programming through calculation, the results are as follows:

**Table 3.** The prediction results and relative errors using BP neural network

Serial number	19	20	21	22	23	24	25
Measured values	9.08	12.49	8.75	8.99	17.05	17.34	15.48
Predicted values	8.85	11.22	8.36	9.86	16.32.	18.31	16.83
Relative error (%)	2.53	10.16	4.46	9.68	4.28	5.59	8.72

From the above data we can see that the original data were predicted by GRNN neural network of the original, 7 sets of data and forecast the income compared to the values of the maximum error is 9.03%, the average error is 5.72%; the value predicted by BP neural network, the forecasting results show that the prediction error was 10.16%, the average error is 6.5%; from the above analysis results, the prediction results using GRNN network analysis results of the maximum error and the average error was less than BP neural network, GRNN network in fewer samples can be used to predict the corrosion rate and the prediction accuracy of BP neural network to high.

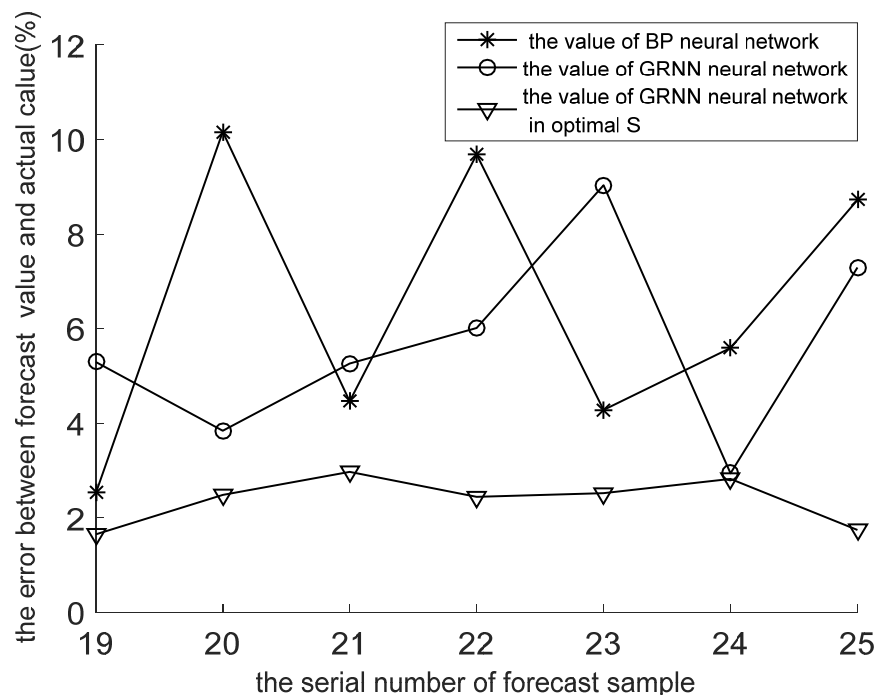
### 4. Choosing the optimal extended velocity value

In the GRNN neural network, which is used to predict the result of the above mentioned methods, the spread value is the default value of 1, but the default value is not the optimal value, this method uses cross validation, write the corresponding calculation program to obtain the best spread value, the optimal spread value on corrosion rate prediction. By calculating the above steps, the optimal spread value is 0.6. Under the optimal spread value, the predicted results are as follows:

**Table 4.** The relative error of generalized regression neural network under the optimal S value

Serial number	19	20	21	22	23	24	25
Measured values	9.08	12.49	8.75	8.99	17.05	17.34	15.48
Predicted values	9.23	12.18	9.01	9.21	16.62.	17.83	15.21
Relative error (%)	1.65	2.48	2.97	2.44	2.52	2.82	1.74

From the above prediction results, the maximum error of the prediction results is 2.97% and the average error is 2.38% under the optimal spread value. Compared with the default spread value, the accuracy of the result is improved greatly. The results of the three predictions are compared with those shown in figure 2:



**Figure 2.** The error of prediction results under different forecasting models

## 5. Conclusion

According to the prediction results in the previous paper, the BP neural network is used to predict the corrosion rate of Q235 steel. The average error between the predicted values of the 7 sets of prediction data is 6.5% compared with the actual value.

The corrosion rate of Q235 steel by generalized regression neural network prediction, choose the default diffusion speed value, by comparing the predicted results and measured results, the average error of 7 prediction data is 5.75%, the precision is higher than that under the same conditions by using BP neural network to predict the results of average error, which has high accuracy.

In the generalized regression neural network, the optimal expansion speed is calculated by the cross operation method. Under the optimal expansion speed, the prediction error of the 7 sets of data is 2.38% compared with the measured value. At the same time, the accuracy of the prediction results is greatly improved compared with the default value.

In the case of less sample data, generalized regression neural network can be used to predict the corrosion rate under ocean conditions, and through cross validation to select the optimal S value can get higher accuracy, through multi prediction of the corrosion rate in advance can take corresponding measures to protect materials and reduce due to corrosion caused the loss.

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