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Original Article

Quantitative estimation of corrosion rate in 3C steels under seawater environment

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ABSTRACT

An artificial neural network method is proposed to correlate the relationship between the corrosion rate of 3C steels with seawater environment factors. The predictions with the unseen test data are in good agreement with experimental values. Further, the developed model used to simulate the combined effect of environmental factors (temperature, dissolved oxygen, salinity, pH values, and oxidation-reduction potential) on the corrosion rate. 3D mappings remarkably reveal the complex interrelationship between the input environmental parameters on the output corrosion rate. The quantitative estimation of corrosion by virtual addition/subtraction of environmental factors individually to a hypothetical system helps to understand the impact of each parameter.

1. Introduction

3C steel is a widely used engineering and structural materials, the tonnage of which is used in chemical processing plants, offshore engineering, petroleum production, pipes, and construction, etc. It has excellent working performance (such as physical, chemical, and mechanical properties) and process characteristics (such as welding performance, toughness, and cutting performance). However, 3C steels suffer due to corrosion in aggressive environmental conditions and have become an essential economic problem [1]. In general, the individual influence of temperature, dissolved oxygen, pH, salinity, and oxidation-reduction potential on the corrosion rate is independently known. However, the combined effect and the interrelationship among these variables on the corrosion rate is multifaceted and not well understood [2]. Therefore, predicting the life of the steel structures in the marine environment has been a challenging task. Corrosion models help in predicting the life of the structure, and also

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helps in understanding the kinetics of the corrosion process and the weight of each involved environmental parameter. Ever since several researchers have formulated models for carbon steels by the empirical formula [3,4], cellular automata methodology [5], linear model [6], numerical simulations [7,8], and support vector regression [9]. The artificial neural networks (ANN) method was applied to express metals corrosion behavior [10–17] and other materials science problems [18,19]. Most of the ANN models used were limited to predict corrosion rate with test data-sets and to study the effect of a single parameter or two parameters on the corrosion rate. So far, hardly there is any report on the modeling of multi-parameters on corrosion. While understanding the capability of ANN, it is believed that such a large number of parameters could be incorporated into a single model. It has been a significant motivation behind the current investigation. The present study aims to employ the ANN model to describe the corrosion rate of 3C steels as a combined effect of temperature, dissolved oxygen, salinity, pH, and Oxidation-reduction potential. Efforts have been made to utilize primary data on various process parameters as a feed and to obtain a quantitative output of combined effect.

2. Materials and methods

2.1. *Experimental database*

In the present investigation, the corrosion rate data of 3C steels reported by Liu et al. [9,12] under different seawater environments, have been used as input. Considered input parameters were temperature (9.5–31.16 °C), dissolved oxygen (0.8–40 mg/L), salinity (2.82–41.34 ppt), pH (5.1–9.32) values, oxidation-reduction potential (171–414 mV) and the considered output was, a corrosion rate (3.61–22.64 μA cm^{-2}).

2.2. *Modeling methodology*

The developed ANN model was trained with the back-propagation algorithm [20–24], and Fig. 1 (a) shows the schematic representation of the present framework. The model architecture consists of an input layer, hidden layers, neurons in hidden layers, learning rate, momentum term, and an output layer. The input and output layers of the model were fixed as five environmental parameters and corrosion rate, respectively. The model training consists of fine-tuning of the weights among the neurons until the calculated output for each set of input data is close to the respective measured output.

The model to correlate the relationships among inputs, and the corrosion rate; the available 46 data sets were divided into 36 training and ten testing datasets. ANN model Hyperparameters were selected based on the root mean sum squared error (RMSE) and the mean inaccuracy in output prediction (E_{tr}) by trial and error method [25,26].

$$RMSE = \frac{1}{p}\sum_{p}\sum_{i}\left(T_{ip} - O_{ip}\right)^2 \qquad \text{eq. (1)}$$

$$E_{tr}(y) = \frac{1}{N}\sum_{i=1}^{N}\left|\left(T_i(y) - O_i(y)\right)\right| \qquad \text{eq. (2)}$$

where, $E_{tr}(y)$ = mean error in prediction of training and testing data set for output parameter y, N = Total data sets, $T_i(y)$ = Targeted output, and $O_i(y)$ = Output calculated.

Seventy-two models were constructed by varying the above parameters and identified the ideal model with 5-2-2-1 (as shown in Fig. 1 (a)) architecture, which consists of 0.85 momentum term and 0.4 learning rate at 60,000 iterations. This ideal model produced RMSE, mean error of training and

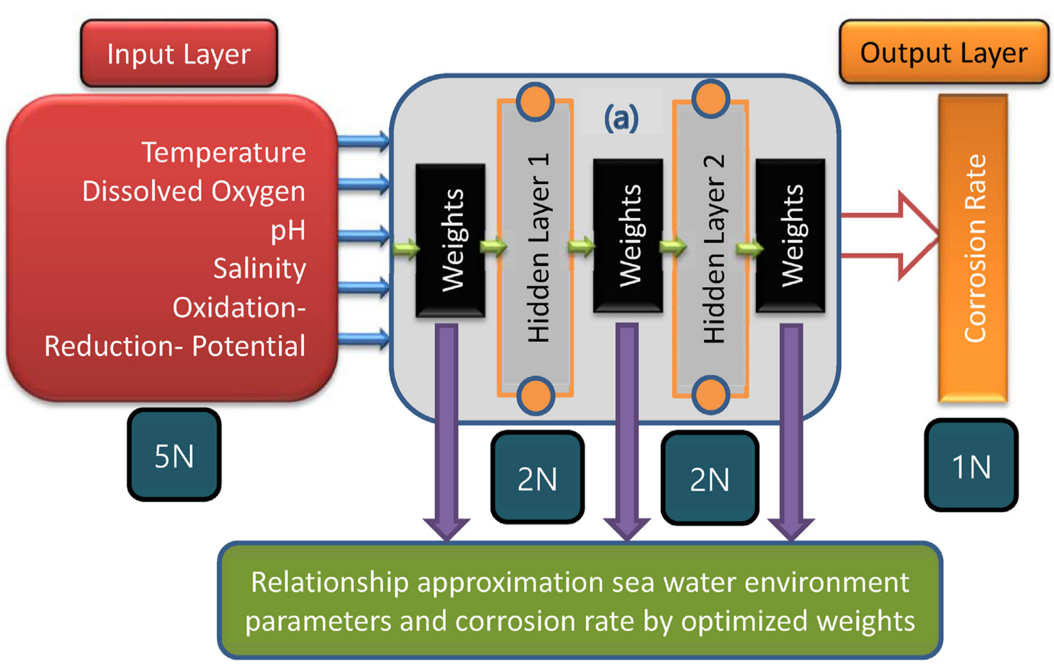

Fig. 1 – Schematic representation of the proposed ANN model (5-2-2-1 Architecture).

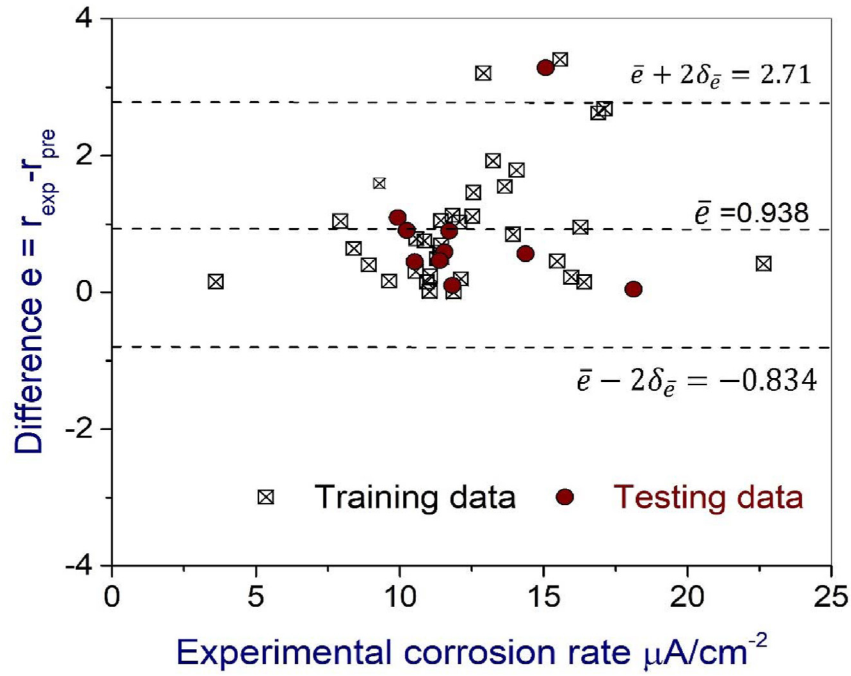

Fig. 2 – Difference between the experimental and the predicted corrosion rate against the experimental value of corrosion rate in 3C steels.

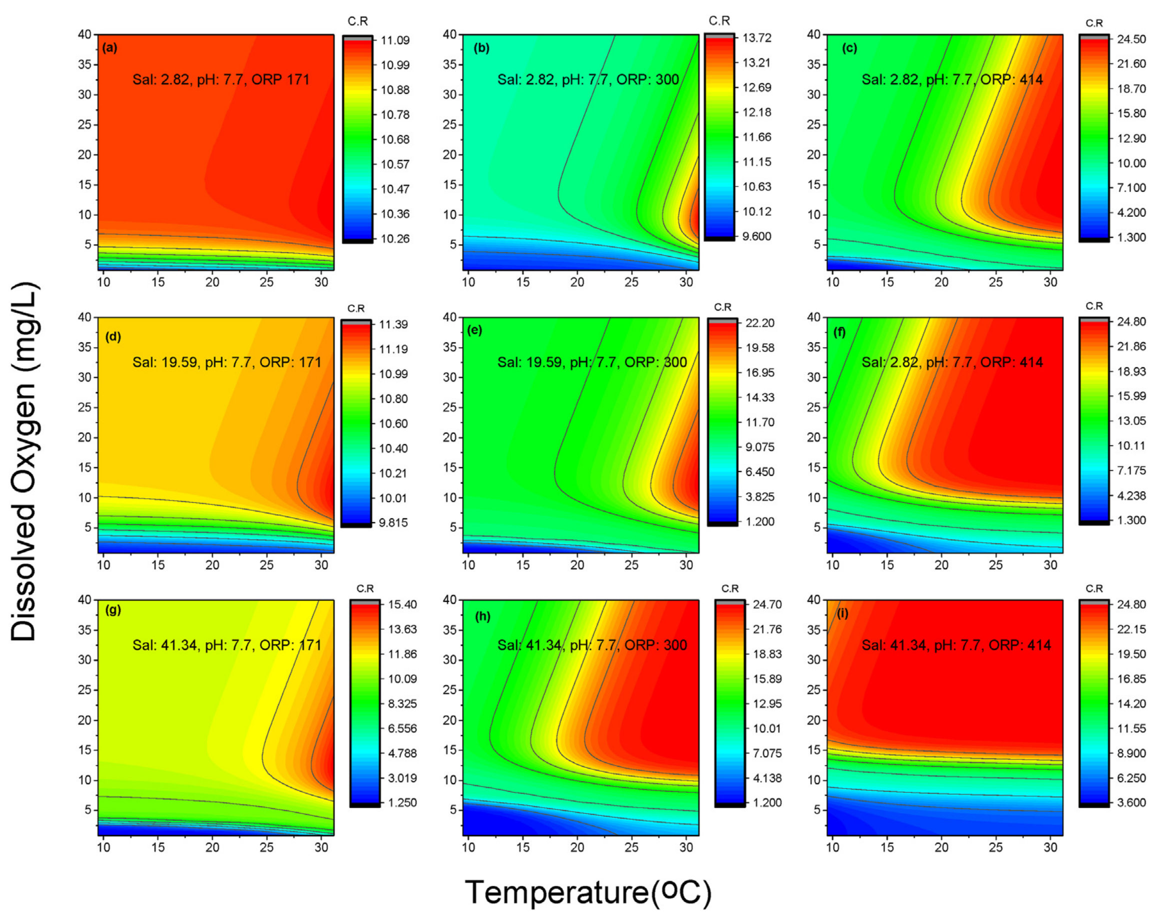

Fig. 3 – 3D mappings of ANN Model predicted corrosion rate as a function of temperature and dissolved oxygen at minimum, mean, and maximum values of salinity and ORP values at the mean value of pH (7.77).

Table 1 – Matrix of simulated maximum corrosion rates as a function of temperature, dissolved oxygen, ORP, and salinity at 7.77 pH value.

		Temperature (9.5–31.16 °C)		
		171 ORP	300 ORP	414 ORP
Dissolved	2.82 Salinity	11.09	13.72	24.50
Oxygen	19.59 Salinity	11.39	22.20	24.80
(0.8–40 mg/L)	41.34 Salinity	15.40	24.70	24.80

testing data as 0.001256, 0.965, and 0.8399, respectively. Initially, the weights were randomly generated between −0.5 and + 0.5, and the weights of the ideal model were varied from −22.11 to 18.75. These weights will be used to simulate the corrosion rate at various combinations of input parameters.

3. Results and discussion

3.1. *Model performance*

Figure 2 shows the variance among the experimental and predicted corrosion rates against the experimental corrosion rate for training and testing data sets. The variable r_{pre} is the predicted value, r_{exp} is the actual value, and thus 'e' is the error in prediction. The degree of agreement between the predicted and experimental corrosion rate is measured by the bias, projected by the mean difference $\bar{e}$ and the standard deviation of the difference $\delta_{\bar{e}}$. The mean difference is 0.938, and the standard deviation is 0.886. The lower limit of the agreement is equal to $(\bar{e} - \delta_{\bar{e}}) = -0.834$, and the upper limit of the agreement is equal to 2.71. Most of the differences to lie between $\bar{e} - 2\delta_{\bar{e}}$ and $\bar{e} + 2\delta_{\bar{e}}$ denoted as the limits of agreements, and if the predictions are typically distributed, 95% of the differences will lie between these limits [9,27]. From Fig. 2, it can be realized that the maximum (43/46 = 93.48%) of the differences lie inside the boundary scope between $\bar{e} - 2\delta_{\bar{e}}$ and $\bar{e} + 2\delta_{\bar{e}}$. Only one sample out of ten unseen testing data and two samples from training data lie outside the scope.

3.2. *Performing sensitivity analysis on developed model*

The impact of environmental variables on the corrosion rate was predicted as a function of temperature (in the ranges of 9.5–31.16 °C) and dissolved oxygen (in the range of 0.8–40 mg/L) at minimum, mean and maximum values of salinity and oxidation-reduction potential by performing sensitivity analysis as shown in Fig. 3 and Table 1. The pH value kept at a mean value of 7.77.

At minimum values of salinity and ORP, the change in corrosion rate is marginal at the entire temperatures and dissolved oxygen range. The maximum corrosion rate (10.99–11.09 μA cm^{-2}) occurs above 7.5 mg/L of dissolved oxygen at all temperatures (Fig. 3(a)). Figure 3(d and e) represents the simulated corrosion rate at mean and maximum values of salinity at minimum ORP. The predicted ranges of corrosion rate at mean value lie moderately between 9.82 and 11.39 μA cm^{-2} and considerable (1.25–15.4 μA cm^{-2}) at the maximum amount. Figure 3 (b & c) shows the predicted ranges of corrosion rate at mean and maximum ORP values keeping minimum salinity. The corrosion rate is moderate at the mean value of ORP (9.6–13.72 μA cm^{-2}) and significant at the maximum amount of ORP (1.3–24.5 μA cm^{-2}). The predictions show that higher ORP values resulted in higher corrosion rates irrespective of other parameters. The combined effect of the mean values of salinity and ORP results enhanced the corrosion rate, ranging from 1.2 to 22.2 μA cm^{-2}. The other screenshots of the standalone ANN model were presented in supplementary materials.

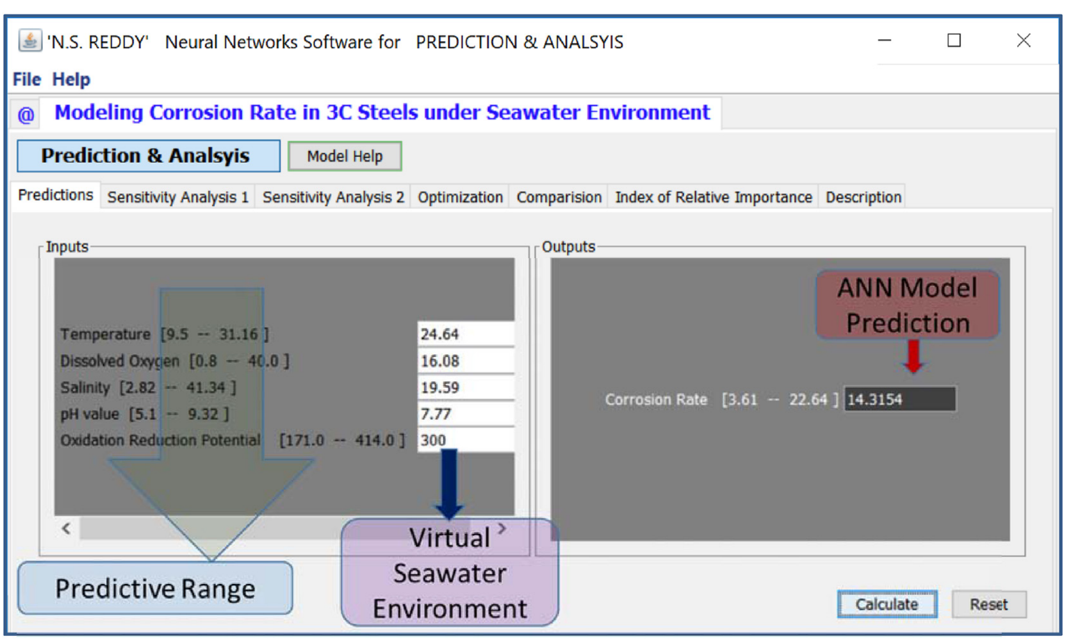

Fig. 4 – ANN model Graphical user interface of predicted corrosion rate in 3C steels at mean values of five seawater environmental factors. (Virtual Seawater Environment System).

3.3. *Creation of a virtual seawater environment to quantitative estimation of the effect of parameters on corrosion rate*

A virtual seawater environment system was created with the mean values of the parameters (24.64T-16.08DO-19.59 Sal-7.77 pH-300 ORP) [28–30]. Initially, the corrosion rate was predicted in the virtual seawater environment by using the weights of the ideal model. The predicted corrosion rate was 14.315 μA cm^{-2} and shown as a snapshot of the graphical user interface of the model in Fig. 4. Two samples with a broad range of settings, i.e., 3.61 μA cm^{-2} (24.27 T-0.8DO-32.56 Sal-8.1 pH-171 ORP) and 16.4 μA cm^{-2} (25.9 T-6.71DO-30.1 Sal-5.1 pH-378 ORP) were selected to validate the proposed method.

Figure 5 (a) shows the decrease in temperature (by 0.37 °C) from the virtual system resulted in a reduction in corrosion rate (to 1.27 μA cm^{-2}), subtraction of DO from 15.28 (mg/L) decreases the corrosion rate (to 7.3 μA cm^{-2}). Further addition of salinity 13.06 ppm and pH (0.04) reduce the corrosion rate. The decrease in ORP from 300 to 171 resulted from a reduction of the corrosion rate to 2.89 μA cm^{-2}. This value is nearer to the experimental value of 3.61 μA cm^{-2}.

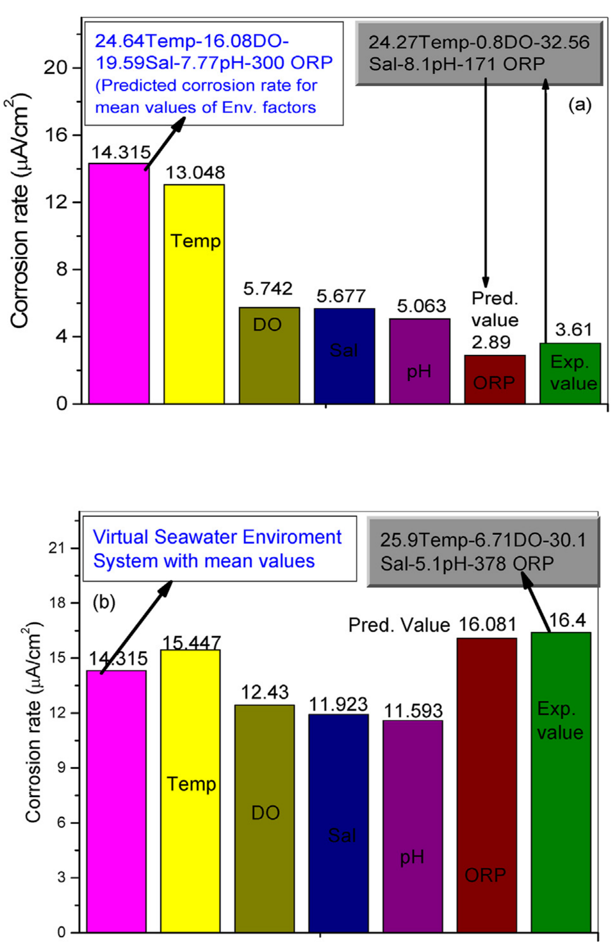

Fig. 5 – (a & b). Quantitative Estimation of corrosion rate in steels by virtual addition/subtraction of environmental parameters to the hypothetically predicted system at mean values of environmental parameters.

Figure 5 (b) shows the rise in temperature from 24.64 to 25.9 resulted in an increase in the corrosion rate to 1.132 μA cm^{-2}. The decrease in DO from 16.08 to 6.71 resulted in a reduction of the corrosion rate by 3.02 μA cm^{-2}. Changes in salinity and pH value effects marginally on the corrosion rate. An increase in ORP from 300 to 378 raises the corrosion rate by 4.488 μA cm^{-2} and reaches to 16.081 μA $cm^{-2,}$ and it coincides with the measured value of 16.4 μA cm^{-2}.

The addition/subtraction of temperature, dissolved oxygen, salinity, and ORP to the virtual seawater environment system, and several predictions were in good agreement with the actual corrosion behavior [2]. However, the decrease in pH resulted in a marginal reduction in the corrosion rate in Fig. 5(b) was not consistent. The difference in quantitative estimation of corrosion rate with measured values is 0.72 and 0.319 μA cm^{-2} only. This unexpected prediction could be attributed to the viability of minimal experimental data. However, this is the first time the combined effect of environmental parameters on the corrosion rate of 3C steels could be predicted quantitatively.

4. Conclusions

An ANN model was used successfully to predict the corrosion rate of 3C steels at new instances, to establish the effect of the interrelationship among environmental parameters. The predictions with unseen test data are in good agreement with measured values. The developed Graphical user interface of the model can predict the corrosion rate of 3C steels at an infinite number of possible combinations of seawater environment parameters within the predictive range. The virtual 3D mappings offer an automatic way to compare the corrosion rate in different environmental conditions. The proposed method can be applied to any nonlinear complex system with multiple inputs and multiple outputs.

Data availability

The raw data required to reproduce these findings are available to download from the reference numbers 9 and 12.

Declaration of Competing Interest

The authors declare that they have no known competing for financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jmrt.2021.01.039.

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