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Original Article

Predictive Model for Corrosion Rate of Mild Steel using Artificial Neural Network

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Abstract - *The potential of using an Artificial Neural Network (ANN) in predicting the corrosion rate of mild steel exposed to five corrosive environments has been studied in the present work. The corrosion rate of mild steel exposed to five different environments, namely, hydrochloric acid, alkaline solution, natural seawater, freshwater, and pasty soil, using the laboratory immersion test method, has been investigated. Three sets of samples were prepared and exposed, each for corrosion rate tests across the five (5) prepared polyethylene-sealed environments. At an interval of four weeks, samples were collected, observed, cleaned, and subjected to corrosion rate tests for twenty weeks. The experimental results of the corrosion rate data obtained by the weight loss method were used to create a database for training and testing the feedforward backpropagation NN model. The result shows the training R-value of 0.99983, validation R-value of 0.99956, test R-value of 0.99562, and the overall R-value of 0.99981. This indicates that the experimental data agrees with the simulated data with minimum difference. Moreover, the result proves that the developed model and the network training, testing, and validation procedure are significantly acceptable. Hence, the validation of the proposed ANN agrees with the actual experimental results. This shows that the ANN model could be attractive as a corrosion rate estimator.*

Keywords - *ANN, Corrosion, Mild steel, Model, Predictive model.*

1. Introduction

Mild steel is an important and affordable engineering material and has drawn attention due to its properties such as strength, toughness, malleability, machinability, ductility, weldability, and minimal cost compared to other materials [1]. They find application in various industries, such as automobile body components, structural shapes and sheets, etc. [2]. However, mild steel, like other materials experience some type of interaction when used under different conditions in chemical and allied industries handling alkaline, acid, and salt solution. Chloride, sulfate, and nitrate ions in aqueous media are particularly aggressive and accelerate the corrosion of these mild steels [3][4].

Often, such interactions impair the material's usefulness as a result of the deterioration of its mechanical properties (e.g., ductility and strength), other physical properties, or appearance. Corrosion is the degradation or destruction of metal by chemical or electrochemical reaction with its surroundings (environment). In other words, corrosion is an electrochemical process involving metals; electricity and chemical reactions are involved, and the material is lost.

The corrosion of steel has received a considerable amount of attention as a result of industrial concern [5]. Therefore, these materials must be thoroughly characterized concerning the ease with which they react to a specific environment to control these interactions. Implementing this control requires conducting certain tests by exposing the metals to the corrosive environment to which their utility is needed for a specified time and carefully studying the effect on the material by observing the changes between the corroded and un-corroded metal [6].

The weight loss method is the most direct way of measuring the corrosion rate of metal/alloys. However, the problem associated with the method is the longer time required to measure the corrosion loss for the material. Some other methods commonly used to measure corrosion are polarization behavior, impedance study, and pitting evolution [7].

Osarolube et al. [8] studied the corrosion behavior of mild and high-carbon steels in various acidic media. They reported that the corrosion rate of mild and high carbon steel is significant in varying concentrations of the acidic media. Also, Al-Amiery et al. [4] examined the corrosion performance of mild steel in 1m HCL by weight loss method and other techniques. They concluded that physical and chemical interactions between a metal and its environment cause changes in its characteristics, which might alter its functions. Similarly, Chuka & Sinebe [9] studied the effects and rate of corrosion of mild steel in five different environments by conducting corrosion tests and reported that the rate of corrosion observed was proportional to the time of exposure, where the corrosion rate in the acidic medium is faster than the other mediums. Similarly, Mamoon et al. [10] studied the effect of corrosion on the mechanical properties of mild steel exposed to five stagnant environments. Mechanical properties tests (tensile, hardness, and impact) were conducted on the exposed mild steel. The results obtained were compared with that of unexposed samples. The finding reveals that the acidic environment greatly affects the hardness and universal tensile strength of the mild steel material at a faster rate, even in air-restricted environments.

Prevention of corrosion of metals often requires the ability to predict the material's performance in a particular environment to determine the inherent corrosiveness of the system [11]. An effort to predict corrosion damage can be achieved by creating a corrosion rate prediction model, which is often difficult. Input data such as chemical, physical, mechanical, and metallurgical aspects are needed in developing the prediction model [12]. An ANN is a highly connected array of elementary processors called neurons. The multi-layered perceptron (MLP) ANN is the most widely used model and consists of one input layer, one or more hidden layers, and one output layer [13].

In this study, ANN is used in predicting the corrosion rate of mild steel exposed to five corrosive environments using the result of our earlier publication [10]. From the literature, the result of the findings reveals that ANN has been successfully used in performance analysis, notably in the prediction of the corrosion rate and mechanical, tribological, and other properties of a variety of materials, which is a promising field of research in predicting experimental trends and has become increasingly popular due to its ability to solve problems much faster as well as learn from small experimental data [14].

Research by Lin et al. [13] employed ANN to develop a regional forecasting model for predicting atmospheric corrosion rates of carbon steel within general and coastal industrial zones. Similarly, Kamrunnahar and Urquidi-Macdonald [15] and Prudhvi et al. [16] predicted the corrosion behavior of metal alloys and friction stir-processed AA5083, respectively, using a supervised neural network. Another research by Kamrunnahar & Urquidi-Macdonald, [7] developed an algorithm for predicting the behavior of corrosion-resistant metal alloys using supervised neural network methods. Again, Rocabruno-Valdés et al. [11] developed a direct ANN model for predicting the corrosion rate of metals in biodiesel using the experimental values obtained using the electrochemical noise technique. Akhtari et al. [6] also predicted the corrosion rate for carbon steel in a soil environment by ANN and genetic algorithm (GA).

Xia et al. [17] correctly predicted the hardness and corrosion rate of magnesium alloys, concluding that ANN can be exploited in predicting the corrosion resistance of existing and future magnesium alloys. Kenny et al. [18] modeled to predict the corrosion rates of low-carbon steel, copper, and aluminum metals according to environmental parameters in an equatorial climate. Ji & Ye [19] used machine learning to predict the corrosion rate of steel in carbonated cementitious mortars and concluded from the results that machine learning is a promising tool for predicting the corrosion rate of steel embedded in cementitious mortars.

Supriyatman et al. [12] predicted the corrosion behavior of metals based on some laboratory experimental data using a feedforward neural network and corrosion rate prediction of gas pipelines using ANN, respectively. Finally, Li et al. [20] modelled the corrosion rate data of carbon steel in carbonated mixtures of Methyl Diethanolamine (MDEA) based solution using ANN. They studied the effect of neuron quantity in the hidden layer on the ANN model performance and found that increasing the neuron quantity enhances the training accuracy and reduces the testing accuracy.

From the literature reviewed above, it is evident that corrosion is an inevitable phenomenon, and its behavior has been studied for decades to learn the trends that govern its long-term behavior. Environmental effects on the behavior of most metals, especially mild steel, are poorly understood. Some parameters that play a role in these metal's potential response are difficult to directly quantify or evaluate experimentally.

It has become paramount to conduct controlled experimentation in well-chemically defined environments and subsequently use the results obtained to develop a predictive corrosion model that aids design engineers in selecting the best material for use in various environments. In this work, a prediction model of the corrosion behavior of mild steel exposed to different controlled chemical environments, which is not reported, is presented and proposed.

2. Material and Methods

2.1. Model Development

The present research is an elaboration of the author's previous research on the investigation of the effect of corrosion on the mechanical properties of mild steel exposed to five different environments [10]. The experimental data from the authors' previous research are taken as input by the network. The network is trained by iterative adjustment of the weights until the mean-square error is minimized. MATLAB was used to develop the ANN model with a feedforward configuration with one input layer (two neurons), one hidden layer, and one output (one neuron) layer of neurons. The Levenberg Marquardt (LM) algorithm was used to train the developed ANN model.

2.2. Data Processing

Experimental corrosion rate results from our previous research were noted for the five different environments (Acid, Alkaline, Seawater, Freshwater, and soil). Three samples were exposed to each environment every 4 weeks, and a total of 75 sets of corrosion rate data were obtained. The present study used 55 corrosion rate experiment results (73%) for training and 20 (27%) for testing. After creating the network, the test dataset was used to test the network. The accuracy of the network was identified by the Root Mean Square Error (RMSE) produced after training the test data. A lower value of RMSE gives higher prediction accuracy. To test the trained network, 20 datasets were used.

2.3. Predictions Using Tested Network

The trained network predicted the corrosion rate from a new dataset. New input parameters were selected, and conformation experiments were performed to simulate the network.

3. Results and Discussions

3.1. ANN Prediction Results

A backpropagation neural network with 3 layers of one input, one hidden, and one output layer is created, as shown in Figure 1. From the figure, it can be seen that the input, hidden, and output layer has two (2), ten (10), and one (1) neurons, respectively.

A coefficient of determination (R) of 0.99981 was obtained from the created. This signifies that the network will give a good prediction result since the value of R obtained is nearer to 1. From the literature, it is reported that the closer the value of R is to 1, the network gives a better prediction result—the regression plot of the created network where the overall coefficient of determination is shown in Figure 2.

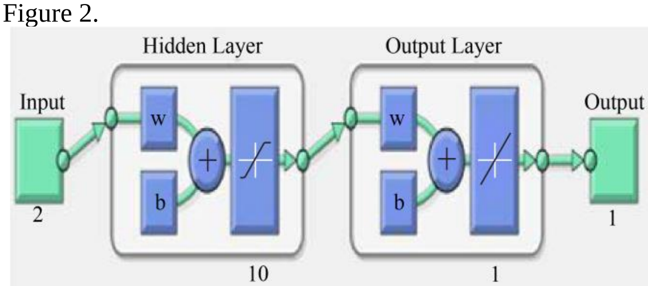

Fig. 1 Created neural network

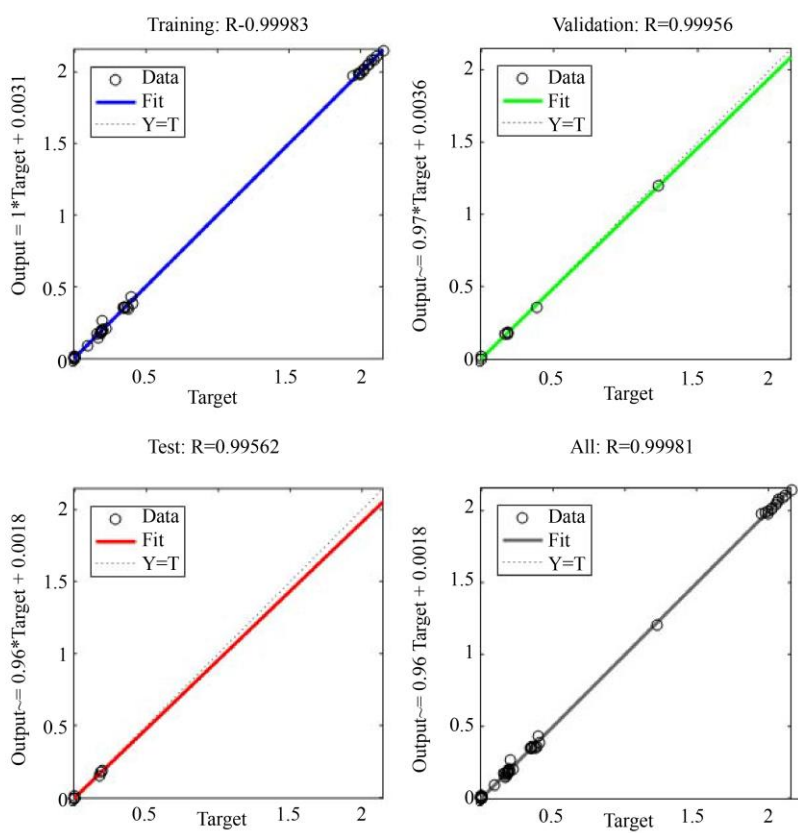

Fig. 2 Regression plot of the network

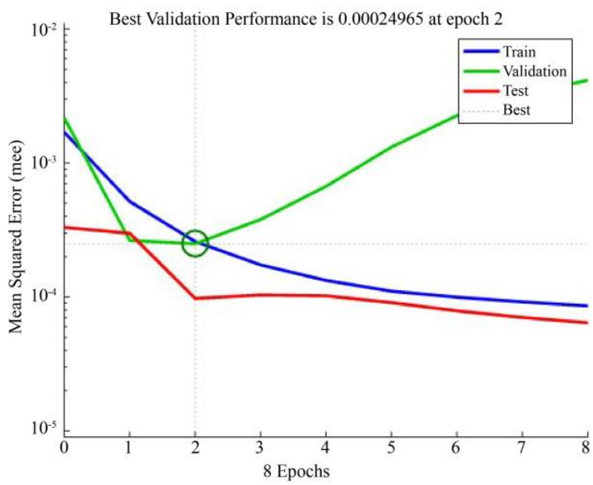

Fig. 3 Network training performance plot

The created network was trained and validated before being tested. The test dataset was used to make predictions using the trained network. The predicted corrosion rate obtained from the network was juxtaposed with the experiment corrosion rate obtained, as shown in Table 1.

Table 1. Experimental and predicted comparison

Exp No.	Actual Corrosion Rate	Predicted Corrosion Rate	Exp No.	Actual Corrosion Rate	Predicted Corrosion Rate
1	0.179	0.172	11	0	-0.00575
2	0.167	0.143	12	0.194	0.216
3	0	0.0383	13	0.363	0.355
4	0	0.475	14	0.365	0.354
5	0	0.00925	15	0.551	0.452
6	2.144	2.139	16	0.188	0.183
7	0.352	0.354	17	0.181	0.177
8	2.858	2.455	18	0	0.356
9	0	0.00364	19	0	0.0141
10	0	0.0576	20	0	0.0154

3.2. Discussions

The experimental dataset obtained from the corrosion rate test of mild steel exposed to different chemically controlled environments was used to create the backpropagation neural network. The training of the network stops on reaching maximum validation checks of 6. This is indicated in the overall progress of the network, as shown in Figure 4. Again, it can be seen from the Figure that the number of epochs with 8 iterations and the performance (MSE) with 8.58 x 10^{-5}, gradient decent of 4.89 x $10^{-4,}$ and mu value of 1.0 x 10^{-5} was obtained.

Similarly, a three (3) layer neural network training stat plot for a network with 2 input nodes, 10 hidden nodes, and one output node with a combination structure as (2-10-1) is shown in Figure 5. The training stops when the validation parameter max_fail reaches a maximum of 6 validation checks at epoch 8 with the gradient decent value 0.00048874 with a reasonable Mu value of 1.0 e^{-5}.

The network training performance is shown in Figure 3. The value of training, validation, and test performance returned by the function train of the network was plotted. It can be seen that even though the training continues until 8 epochs, the best validation performance is reached at epoch 2 with the value of 0.00024965.

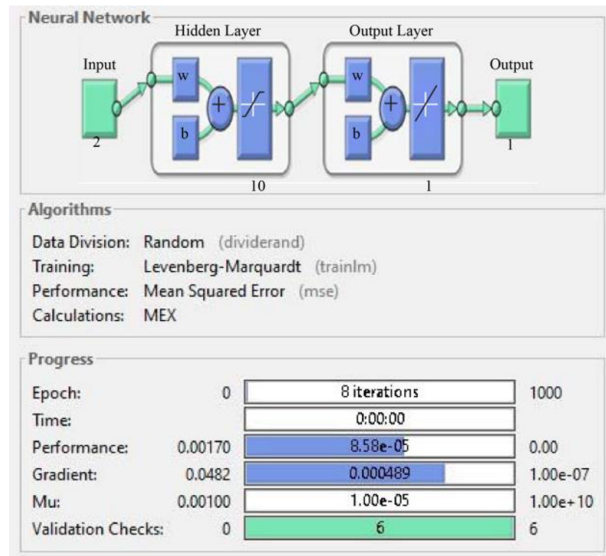

Fig. 4 Overall progress of the network

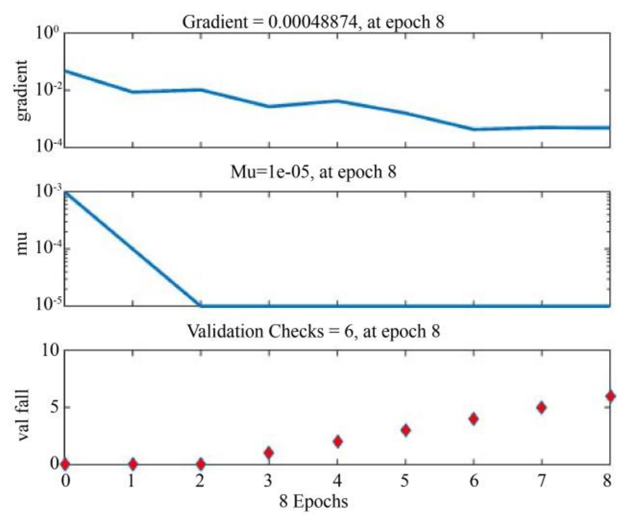

Fig. 5 ANN training state plot

Furthermore, the regression analysis was performed in the ANN model after the network concluded training, testing, and validation. It is the statistical process for estimating the relationships between the output and target of the network. The plot regression function takes two parameters (targets, outputs) values and plots the linear regression of targets relative to the outputs. Figure 2 shows the regression plot of training, test, validation, and overall regression. The small circle shows the data representation in the model. After the regression plot has been constructed, the diagnosis of the model is important to confirm the goodness of fit. In our model, the network shows significantly acceptable R values near one.

The Training R-value was 0.99983, the validation R-value 0.99956, the test R-value 0.99562, and the overall R-value equal to 0.99981. This proves that the developed model, network training procedure, testing and validation are significantly acceptable.

4. Conclusion

It can be concluded that an artificial neural network model has been selected and trained with the corrosion rate data collected from the author's reported experimental examination where the best fitting training data were acquired with architecture of three layers, type 2:10:1 considering a Levenberg Marquardt learning algorithm, a tangent hyperbolic and linear transfer functions in the hidden and output layer respectively. Experimental and simulated data were compared satisfactorily through a linear regression model with an overall correlation coefficient of 0.99981 and a mean square error, MSE, of 8.58 x 10-5 in the validation stage. The ANN approach is useful for developing a neural network model to estimate the corrosion rate of low-carbon steels. Validation of the proposed ANN shows a fair agreement with the actual experimental results.

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