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AN ARTIFICIAL NEURAL NETWORK MODEL FOR THE CORROSION CURRENT DENSITY OF STEEL IN MORTAR MIXED WITH SEAWATER

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ABSTRACT: Corrosion is a very complicated phenomenon in the field of science and engineering. Over the years, several numerical models have been developed to predict the damage caused by the corrosion process. The use of the artificial neural network in modeling corrosion has gained popularity in recent years. Many of the factors affecting corrosion are difficult to control. Thus, the artificial neural network may be a better technique to consider due to its ability to tolerate relatively imprecise, noisy or incomplete data, less vulnerability to outliers, filtering capacity and adaptability. This study aims to generate a corrosion current density prediction model using the artificial neural network approach. Microcell corrosion current density is defined as the rate of corrosion expressed in electric current per unit area of cross-section. Several variables were considered as input variables namely: age, water to cement ratio, cement content, compressive strength, type of mixing water, corrosion potential, solution resistance, and polarization resistance. These variables were entered into the neural network architecture and simulated in MATLAB. The feedforward backpropagation technique was used to generate the best model for the corrosion current density. The best neural network architecture consists of 8 input variable, 8 neurons in the hidden layer and one output variable. The resulting neural network model satisfactorily predicted the corrosion current density with a coefficient of correlation values of 0.96536, 0.80817, and 0.7662 for training, validation and testing phases, respectively.

Keywords: Neural network, Corrosion current density, Seawater, Mortar

1. INTRODUCTION

Concrete is probably the most widely used building material in the world. It is a composite material made of cement, aggregates, water, and some admixtures. The durability of concrete may be compromised through processes like alkali-aggregate reaction, sulfate attacks, freeze-thaw cycles, and corrosion, among others. Among all these, corrosion of the reinforcing steel in concrete has become a great concern as this may result in sudden failure of structures. Thus, developments in the design, construction, and maintenance of concrete structures are encouraged to mitigate huge economic, social, health, safety, and environmental impacts.

Corrosion of steel is one of the main causes of failure in concrete structures. Theoretical and empirical models help determine its behavior over time and therefore engineers can decide on maintenance and repairs needed to prolong the service life of a structure. Moreover, it is a very complicated phenomenon in the field of science and engineering. Over the years, several numerical models have been developed to predict the damage caused by the corrosion process. Numerical methods can be classified as deterministic and probabilistic. Deterministic models helped to understand the mechanisms of localized corrosion but were not really practical for actual prediction [1]. On the other hand, probabilistic (stochastic) approaches presented high-level statistics and other mathematical methods in processing field data and were found to predict local corrosion phenomena successfully [1]. Examples of modeling techniques are the multiple linear regression, finite element method (FEM), Bayesian updating and artificial neural network (ANN).

FEM has been applied in previous studies [2], [3] [4], [5] and [6]; while a Bayesian updating approach of an existing steel loss model based on monitored data was proposed in [7].

The use of ANN in modeling corrosion has gained popularity in recent years. The technique can be applied to complex problems and is independent of the physical processes involved but rather the relationships present in a set of data [8]. Many of the factors affecting corrosion are difficult to control. Thus, ANN may be a better technique to consider due to its ability to tolerate relatively imprecise, noisy or incomplete data, less vulnerability to outliers, filtering capacity and adaptability.

Therefore, a model that can predict such corrosion behavior of steel reinforcement will help design engineers in developing better design practices for corrosion management, i.e., repair and rehabilitation procedures, thus extending the service life of structures and saving costs. Modeling is a useful tool in the quantitative understanding of key elements in concrete and their interactions. This can be accomplished by considering time-dependency of transport properties of concrete, repair or replacement of concrete cover, corrosion propagation, chloride penetration mechanisms other than diffusion, structure geometry, environmental humidity and temperature fluctuations and decay of structures under combined physical, chemical and mechanical deterioration processes as summarized by [9]. Therefore, improvements on existing models can be made to better simulate the corrosion behavior of reinforced concrete structures, especially those mixed with non-conventional materials like seawater and fly ash. Additionally, their performance in the chloride-laden environment through time can be assessed.

Corrosion may occur as either microcell or macrocell. Microcell corrosion is characterized by continuous and uniform corrosion along the steel bar while macrocell is often local, particularly for chloride-induced corrosion [10]. Microcell corrosion of reinforcements must normally co-exist with that of macrocell [11, 12]. In microcell corrosion, the anode and cathode are located adjacent to each other resulting to a uniform iron dissolution over the whole surface [13]. This type of corrosion produces uniform removal of steel and contains anodic and cathodic sites that are microscopic in size [14]. Microcell corrosion is the major corrosion mechanism for steel in concrete after more than 3 years of testing [15]. This type of corrosion is normally present in laboratory tests on small samples of reinforced concrete [11]. This type of corrosion produces accumulated rust in a relatively small region on the bar surface [2].

This study aims to generate a microcell corrosion current density prediction model using the ANN approach. Corrosion current density is defined as the rate of corrosion expressed in electric current per unit area of cross-section. It can be obtained from polarization resistance measurements of a steel bar. Referring to Fig. 1, the microcell corrosion current density for steel element is given by Eq. (1).

$$b_i = \frac{K}{Rp_i} \tag{1}$$

Where: bi = microcell corrosion current density of steel element i (A/cm^2); Rpi = polarization resistance of steel component i (ohm·cm^2), and K = 0.0209 (V).

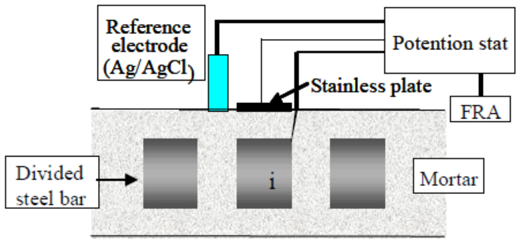

Fig. 1 Microcell corrosion measurement [16]

Several factors such as age, concrete cover, surface chloride content, water to cement ratio, carbonation depth, moisture content, cement content, compressive strength, and solution pH were considered as input variables in previous research. In this study, the factors used as input variables were: age, water to cement ratio, cement content, compressive strength, type of mixing water, corrosion potential, solution resistance, and polarization resistance.

This paper is organized as follows: The introduction is followed by some literature on ANN modeling of corrosion; followed by the methodology highlighting the data collection, identification of the input and output variables, and building the ANN models; and then results and discussion; finally, conclusions of the research are presented.

2. ANN MODELLING FOR CORROSION

With the development of new technology and computer software, mathematical modeling and computation became easier and faster. In this proposed study, regression and artificial neural network (ANN) modeling are the initial modeling techniques being considered.

ANNs mimic the learning process of the human brain. They generalize mathematical models by processing information at elements called neurons. Signals are passed between neurons over connections links. A weight is assigned to each link which multiplies the signal transmitted. The output is obtained by applying an activation function to the net input. A neural network is characterized by its architecture, training or learning algorithm and activation function. Network architecture is the arrangement of neurons into layers and the connection patterns within and between layers. Neural networks are further classified as single or multilayer and are therefore feedforward networks. Training is the method for setting the values of the weights. An activation function is applied to the sum of the weighted input signal. Typical activation functions are a unit step, linear, sigmoid and hyperbolic tangent. Neural networks are used to find the solutions to constrained optimization problems and can be applied for storing, recalling classifying and mapping data or patterns [16].

Some ANN models related to measuring steel corrosion in concrete are found in [8], [17], [18], [19], [20] and [21].

3. METHODOLOGY

3.1 Data Collection and Identification of Input Variables

Input data were obtained from the experimental quantities and equipment test results in [22]. Rectangular mortar prism specimens (40 mm x 40 mm x 160 mm) with steel reinforcements of 10 mm in diameter and 100 mm length were cast. Ordinary Portland cement (OPC) was the main binder used and replaced with fly ash. The fly ash content in the specimens was varied from 0% to 50% at 10% interval, while the water to cement (w/c) ratios were held at 0.35, 0.40, 0.45, 0.55, 0.65.

A 5 mm cover was applied from the top surface of the prism specimen. Insulated copper wires were soldered at both ends of the steel and then covered with epoxy. These wires were necessary for the corrosion monitoring equipment (CT-7) in measuring the potential and polarization resistance.

In this study, several input variables as used in the previous literature were considered in determining the best ANN model. A total of eight (8) input variables were entered namely: age (days), w/c, cement content (%), compressive strength (MPa), type of mixing water (freshwater or seawater), corrosion potential (mV), solution resistance (Ω) and polarization resistance (Ω). The corrosion potential, solution resistance, and polarization resistance were measured from the corrosion monitoring equipment. On the other hand, the output variable is the microcell corrosion current density defined as the rate of corrosion expressed in electric current per unit area of cross-section.

3.2 Structuring the ANN Models

The Neural Network Toolbox in MATLAB R2018a was used in constructing the ANN corrosion current density model estimation. Data were divided into three sets: 60% for training the neural network, 20% for validation and 20% for testing. These sets were randomly selected in MATLAB. The feedforward backpropagation technique was used to generate the best model. This algorithm gradually reduces the error between the model output and the target output by minimizing the mean square error (MSE) over a set of training set [23]. The MSE is a good overall measure of the success of the training process [24], [25]. The weights and a bias value, on the other hand, were updated according to the Levenberg-Marquardt network training function. This is often the fastest backpropagation algorithm and highly recommended, though it requires more memory that other algorithms [26]. A two-layer feed-forward network with sigmoid hidden neurons and linear output neurons was used. This can fit multi-dimensional mapping problems arbitrarily well, given consistent data and enough neurons in its hidden layer [26].

3.3 Trial ANN Model Architectures

The best ANN model to estimate the microcell corrosion current density was determined by defining the number of neurons (nodes) in the input and output layers, a number of hidden layers and the number of neurons in each hidden layer. The model generated utilized the 8 input variables. There is no specific rule in determining the number of hidden layers and the number of neurons in each hidden layer [27]. In this study, one hidden layer was used and the following rules were employed to determine the optimum number of neurons: (a) a network with n-input and m-output units requires a hidden layer with at most 2n+1 units, (b) should be between the average and the sum of nodes on the input and output layers; (c) seventy-five percent (75%) of the input nodes [28]. Thus, the simulation was done in the range of 5-17 neurons in the hidden layer.

4. RESULTS AND DISCUSSION

After several simulations, ANN Structure 8-8-1 (8-input variables, 8-nodes in the hidden layer, 1-output) was found to be the best model to estimate the microcell corrosion current density. Figure 2 shows the ANN Structure 8-8-1. ANN Structure 8-8-8 obtained a satisfactorily acceptable correlation coefficient, R, values of 0.96536, 0.80817, and 0.7662 for training, validation and testing phases, respectively. A correlation coefficient of 0.85983 was achieved considering all data points. Figure 3 presents the regression line while Fig. 4 shows the training performance for ANN Structure 8-8-1.

The resulting MSEs for each phase are seen in Table 1.

Table 1 MSE for different training phases

Phase	Samples	MSE
Training	85	0.0062789
Validation	28	0.0471508
Testing	28	0.1299260

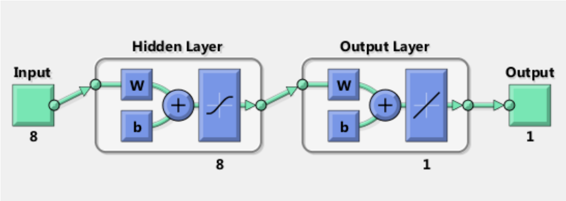

Fig. 2 ANN structure 8-8-1

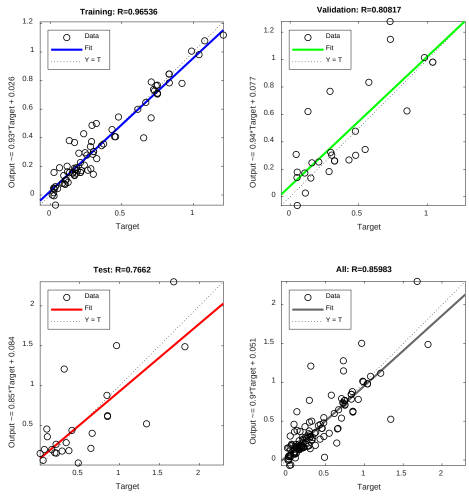

Fig. 3 Regression lines for ANN structure 8-8-1

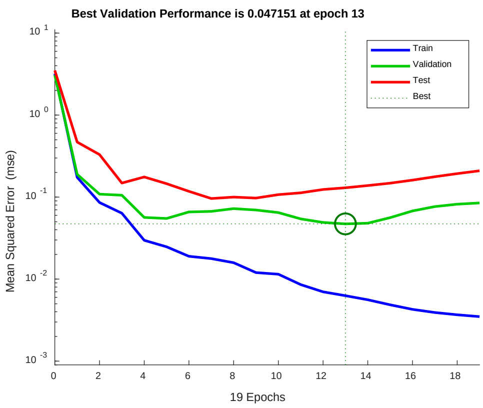

Fig. 4 Training performance of ANN structure 8-8-1

5. CONCLUSION

This paper presents an artificial neural network model for estimating the microcell current density of steel in mortar mixed with seawater. This value is necessary for computing the corrosion rate of steel, which is one of the main causes of failure in structures. Several input variables were considered in constructing the ANN model namely: age, water to cement ratio, cement content, compressive strength, type of mixing water, corrosion potential, solution resistance, and polarization resistance.

From several trials, ANN Structure 8-8-1 was chosen as the best architecture having the highest correlation coefficient values of 0.96536, 0.80817, and 0.7662 for training, validation and testing phases, respectively, in a range of 5-17 neurons in the hidden layer. The resulting MSE in the training phase is 0.0062789. The best validation performance is 0.047151 and occurred at epoch 13. The test set and validation set errors to have relatively similar characteristics.

Finally, it can be concluded that the neural network technique provided good predicting ability despite the non-uniform distribution and incompleteness of the data set. Expanded data set may improve the results. Sensitivity analysis and relative importance of the input variables can be conducted to enhance the reliability and validity of the results.

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