Multilayer Perceptron Model for the prediction of corrosion rate of Aluminium Alloy 5083 in seawater via different training algorithms

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Abstract. Corrosion inhibitor is often opted as a corrosion protection method for various industries worldwide. The development of eco-friendly corrosion inhibitor has become a trending concern due to the various environmental regulations impose by several countries. However, a laboratory testing would be such a tedious, costly and time-consuming process. Therefore, artificial neural network (ANN) has been used extensively to predict the verdict based on the experimental values. In this study, 3-layered Multilayer Perceptron (MLP) models were developed with 3 inputs (Electrochemical Impedance Spectroscopy, Ω.cm²), (Potentiodynamic polarization, A/cm²), (weight loss, %), and one output (corrosion rate, mm.yr⁻¹). The data were divided into three parts; 70%, 15%, and 15% for model development, model validation and model testing, respectively. Three training algorithms were tested during the model development, including the Levenberg-Marquadt (LM), Bayesian Regularization (BR), and Scale Conjugate Gradient (SCG). Results revealed that the best MLP models during the development were using neuron number 4 (r = 0.99272), 6 (r = 0.99155), and 2 (r = 0.98624) for LM, BR and SCG, respectively. Among the three training algorithms, LM is opted as the best training algorithm for the corrosion rate prediction which executed high correlation coefficient (R) values during development (R = 0.99272), validation (R = 0.99905), and testing (R = 0.97908). These findings will be an essential tool for the model development with the sole purposes of predicting the corrosion rate in line to ensure the exact time for repair and maintenance schedule.

1. Introduction
Corrosion has become a serious problem to marine industry due to its detrimental effect either for the structure, environment, or human beings. Brutal damage of marine infrastructure by seawater has caused a reduction in the lifespan of the materials. The problem could be combatted by using various corrosion prevention methods such as coatings, inhibitors, material selections and to name a few. For industrial batch operations and closed-loop systems, inhibitor has been the most practical solution to reduce corrosion rate [1]. However, many available organic inhibitors were known to be toxic and costly. There is a growing interest in the search for plant extracts as green corrosion inhibitors [2]. Corrosion inhibitors extracted from seed and plant extracts were studied by numerous researchers [3-6]. These researcher findings stated that the tested sustainable corrosion inhibitor exhibits an inhibition efficiency in the range of 67 – 98.8%.

Aluminium alloy is widely used in marine industry especially for shipbuilding industry due to its lightweight and better corrosion resistance in comparison to the carbon steel. With respect to the usage
of aluminium alloy in the marine industry, it is very crucial to determine the corrosion rate of aluminium alloy. The conventional method to determine the corrosion rate of aluminium alloy via experimental technique is time consuming and costly. Therefore, an alternative technique is required to obtain a simple, fast and accurate data for corrosion rate prediction [7].

Artificial neural network (ANN) would be one of the best alternative methods to determine the corrosion rate of inhibited metal in corrosive media. Crushed leaves of *Sida Acuta* (Malvaceae) was tested as a corrosion inhibitor for mild steel in hydrochloric acid [8]. The authors have used time (h), concentration of acid (M) and quantity of crushed leaves (g) as an input in ANN to predict the corrosion rate of the inhibited metal. The mean squared error (MSE) generated by ANN was found to be <0.1. The behavior of corrosion inhibitor on bronze was evaluated via ANN by Millán et al 2018 [9]. The metal was exposed to 3.5% sodium chloride (NaCl) + 0.1 M Na₂SO₄ at 25, 40 and 60°C. The inputs were frequency, temperature, and inhibitor concentration while the predicted output was $Z_{re}$, $Z_{im}$, and $Z_{mod}$. The value of MSE were 0.00659, 0.00475 and 0.00686 for $Z_{re}$, $Z_{im}$, and $Z_{mod}$ respectively.

We have conducted an experimental procedure to evaluate the corrosion inhibition of *Lawsonia inermis* as a corrosion inhibitor for aluminium alloy 5083 (AA5083) in seawater. The experimental results were reported elsewhere [11]. Here, the extension of the study was conducted to predict the corrosion rate of the inhibited metal. ANN was utilized in this study where three types of training algorithm were applied known as Levenberg-Marquadt (LM), Bayesian Regularization (BR), and Scale Conjugate Gradient (SCG).

2. Methodology

2.1. Experimental work

Potentiostat/galvanostat (Autolab PGSTAT 302N) was used for the experimental work to determine the inhibition behavior of *Lawsonia inermis* for aluminium alloy in seawater. Two methods were used namely as electrochemical impedance spectroscopy (EIS) and potentiodynamic polarization (PP). The details of the procedure were reported in our previous work [11]. The output from the experimental work were used to determine the corrosion rate via ANN.

Gravimetric method via weight loss analysis was conducted to determine the percentage of weight loss upon addition of *Lawsonia inermis* as a corrosion inhibitor in mild steel. The results were reported in our previous work [12]. The percentage of weight loss of inhibited samples were used as the input in ANN section.

2.2. Artificial neural network

36 data patterns (input and output data) were retrieved from the experimental analysis and categorized into training (70% of dataset), validation (15% of dataset), and testing (15% of dataset). It is important to mention that both the input and output data were normalized owing to the different ranges of the dataset. Min-max data normalization is essential for proper execution of the sigmoid transfer function and prevention of abrupt ending of the learning process as shown in equation (1). Then the data are display in Matlab as inputs and output in matrices. Based on data, inputs and output are arranging in form of 3 times 36 and 1 times 36, respectively in form of matrices.

$$x_{\text{normalized}} = \frac{(x - x_{\text{minimum}})}{x_{\text{maximum}} - x_{\text{minimum}}} + 0.1$$ (1)
Multilayer feed forward neural network (MFNN) trained by Levenberg-Marquadt (LM), Bayesian Regularization (BR), and Scale Conjugate Gradient (SCG) back propagation algorithm was supervised and adopted in the current study to develop the predictive model. An ANN model with three input parameters (Electrochemical impedance spectroscopy (EIS), potentiodynamic polarization (PP) and weight loss, one output parameter of corrosion rate, and one hidden layer was developed using the neural network toolbox of Matlab® software (R2019b, Mathworks®, Natick, MA, USA) as depicted in figure 1. Since there are no standard procedures for the determination of the required hidden neurons, trial and error method is adopted in this study. Hence, while investigating the optimum number of neurons required to build the ANN model, the number of hidden layers is fixed at one. Moreover, after several iterations, the best ANN was selected based on correlation coefficient ($R$) (equation (2)).

![Artificial Neural Network (ANN) structure for corrosion rate prediction.](image)

$$R = \frac{\sum_{i=1}^{n} (P_i - \bar{P})(O_i - \bar{O})}{n.Spred.sobs}$$

Where $n =$ total number measurements at a particular site $P_i =$ predicted values, $O_i =$ observed values, $\bar{P} =$ mean of predicted values, $\bar{O} =$ mean of observed values, $Spred =$ standard deviation of predicted values and $Sobs =$ standard deviation of the observed values.

3. Results and discussions

3.1. Pearson correlation determination

Table 1 shows the Pearson correlation of EIS with corrosion rate of inhibited aluminium alloy in seawater. The negative sign as shown by EIS indicates the input is inversely proportional to the output [13]. This is due to nature of EIS data where polarization resistance ($R_p$) was selected as input data. Polarization resistance is a measure of electrical resistance on metal substrate where the higher the resistance is, the lower of corrosion rate will be. $R_p$ in this study is presented by adsorption of studied inhibitor molecule together with formation of oxide layer in aluminium surface. The correlation coefficient ($R$) shows that experimental data is accurate with predicted data hence it is justified with exhibited trend with the relationship of $R_p$ and corrosion rate.

Meanwhile, the Pearson correlation shows that PP and WL are proportional to the corrosion rate [14]. This is obviously true as the value of PP increases, corrosion rate will increase as the metal surface gained more ionic conductivity. Ionic conductivity enhances the current flow from the electrolyte to the electrode and finally initiate the corrosion process on the metal surface. The trend was found to be similar
with WL where the Pearson correlation shows a positive correlation with the corrosion rate. As the corrosion process started to increase, the weight loss percentage will also increase due to the anodic dissolution occurs on the metal surface. Consequently, the corrosion rate will increase as well.

### Table 1. The Pearson correlation of the input parameters.

| Parameter | Pearson Correlation |
|-----------|---------------------|
| EIS (Ω.cm$^2$) | 1                  |
| PP (A.cm$^2$)   | -0.598294723        |
| WL (%)        | -0.5211999150.928802545 |
| CR (Average) (mm/year) | -0.5658690410.9881478040.920397340.92039734 | 1 |

#### 3.2 Model performance evaluation

The accuracy of the developed ANN model with different training algorithms relies on the R values. Higher R values show a good agreement between observed and predicted data. As seen in figure 2-4, $r$ was used as an indicator to evaluate the correlation between the predicted and actual corrosion rate. The R for training and testing phases was 0.99272 and 0.97908 respectively. This is an indication of the desirable results of the LM as seen in figure 2. The predicted data was found to fall within the 1:1 slope line. Figure 3 shows the correlation plot of predicted and actual corrosion rate using BR algorithm. The $r$ for training and testing phases was 0.99155 and 0.99178 respectively. It was found that BR algorithm exhibits slightly lower precision in comparison to LM. For SCG algorithm, the $r$ for training and testing phases was 0.98264 and 0.98093. SCG shows the lowest precision among all tested algorithm as depicted in figure 4.

**Figure 2.** Correlation of a) training, b) validation, c) test and d) overall between the actual and predicted corrosion rate for Levenberg-Marquadt (LM) algorithm.
Figure 3. Correlation of a) training, b) validation, c) overall and d) overall between the actual and predicted corrosion rate for Bayesian Regularization (BR) algorithm.

Figure 4. Correlation of a) training, b) validation, c) test and d) overall between the actual and predicted corrosion rate for Scale Conjugate Gradient (SCG) algorithm.
Based on the considered performance criteria, LM was found to be the best algorithm to be used for corrosion rate prediction. This is aligned with the result of predicted corrosion rate as reported elsewhere [15] while [16] has reported that LM algorithm shows R value of 0.8471 for the prediction of corrosion rate in oil and gas well. This could be due to the Levenberg–Marquardt backpropagation training algorithm is a modified version of Newton’s method. It presents the best performance in the search for the weights of neuron connectors. Besides, this algorithm is the fastest method for training moderate-sized feed forward neural networks, very efficient implementation. The Levenberg-Marquardt algorithm also designed to approach second-order training speed without having to compute the Hessian matrix [17, 18].

Figure 5 shows the overlapping plot of actual and predicted corrosion rate for 36 tested sample numbers. LM algorithm shows the most significant correlation where the corrosion rate prediction shows a lower deviation from the actual corrosion rate. Meanwhile, BR algorithm has lower prediction precision with larger deviation of the predicted output in comparison to LM algorithm. SCG algorithm shows the lowest precision of predicted output contrast to the other two algorithms.

![Figure 5](image.png)

**Figure 5.** Comparison of actual and predicted corrosion using LM, BR and SCG algorithm.

4. Conclusion

Artificial neural network (ANN) was utilized in this study to predict the corrosion rate of aluminium alloy (AA5083) inhibited by *Lawsonia inermis*. ANN provide a fast, accurate and cost-efficient method to determine corrosion rate in comparison to the experimental method. Selection of hidden layers and neurons are important because it will eventually affect the overall results. Using too few neurons in the hidden layers will result under fitting while using too many neurons in the hidden layers can result in several problems. The objective of this study, which is to correlate the influence of EIS, PP and WL towards corrosion rate. Three different algorithms namely as Levenberg-Marquardt (LM), Bayesian Regularization (BR), and Scale Conjugate Gradient (SCG) were used to predict the corrosion rate of the inhibited aluminium alloy. It was found that LM gives the best prediction value of corrosion rate due to the high correlation coefficient (R) values during development (R = 0.99272), validation (R = 0.99905),
and testing ($R = 0.97908$). Hence, machine learning techniques have successfully been shown to predict corrosion rate with a good correlation coefficient value and consequently reduces time, cost and effort in determining corrosion rate for metals.

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