Prediction of Corrosion for Austenitic Stainless Steel Aged Using Artificial Neural Network

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Abstract

Artificial Neural Networks (ANNs) is one of the most popular techniques for exploration of complex phenomena. Artificial neural network can be employed to predict corrosion behavior on austenitic stainless steel.

Austenitic stainless steel is using in the field of nuclear science. It is used as a manufacturing material for nuclear fuel clad tubes and fuel sub assembly wrappers in fast breeder reactors flowing to its superior mechanical properties at elevated temperatures. Hence, these austenitic stainless steel are particularly useful in nuclear reactors. The reactor's temperatures are usually very high thus their corrosion properties must be assessment for integrated weld of nuclear reactors.

In this research, Artificial neural network with the ability to learn from experimental values is used as an intelligent information processing system to get the corrosion rate with aging. Corrosion determined by potentiodynamic technique of as-weld, and after heat treatment for 50 hr, 500 hr and 1000 hr at 550 $^{\circ}$C at room temperature, which is immersed in the test solution 3% NaCl.

A new ANN model is developed as an intelligent information processing system to get the corrosion rate with aging using Experimental data. The developed ANN model is trained to predict the current density I_{corr} and corrosion potential E_{corr} of 316L, 308L and 310 austenitic stainless steel. The trained developed ANN model gives an excellent correlation coefficient and the error range (less 10%) for this application, which represents a good accuracy of the model since results of this model showed good agreement with the experimental results and no significant differences between them. Moreover, the developed ANN model could be a useful tool in predicted the corrosion for long time that cannot be achieved experimentally for the three Austenitic stainless steel martials

Keywords*: austenitic stainless steel, aging, corrosion and artificial neural network.*

1. Introduction

Corrosion is caused by synergetic interaction of material, mechanics and environment [1,2], and is an important aging degradation mechanism for structural alloys which can affect the integrity of nuclear power plants [3,4].

The assessment of corrosion within an engineering system often forms an important aspect of condition monitoring but it is a parameter that is inherently difficult to measure and predict. Corrosion is usually characterized by a very long incubation time [5,6]. Austenitic stainless steels are widely used in nuclear power plants because their high resistance to corrosion. However, several cases of corrosion have been discovered in the stainless-steel components in pressurized water reactors, which raises the concerns of life extension and safe operation of the plants [7–9].

Corrosion protection is among the most important economic and safety concerns of the industrial world. To control corrosion effectively, the accurate prediction of corrosion behavior is a fundamental requirement. At first sight this may seem relatively easy, but complex nature does not work as simple as we expect. Artificial neural network is one of the most popular techniques for exploration of complex phenomena (ANN). ANN is employed to predict most of corrosion behavior of metals [10-13] The artificial neural network analysis application of corrosion data is of key interest.

In most instances data needs to be used with conventional theory to obtain meaningful information and relies on expert interpretation.
Recently work has been carried out using artificial neural networks to investigate various types of corrosion data in attempts to predict corrosion behavior with some success. Different works about corrosion modelling can be found in the literature [14-18]. Among all the modelling techniques, artificial neural networks have been applied as an efficient tool in material science, characterization and testing.

2. Materials and Procedures Preparation

Stainless steels (SS) Electrodes with diameter 4 mm weld deposit on carbon steel (CS) plate using fusion welding process. A manual shielded metal arc welding (SMAW) process was used for one layer. Three different commercial, rutile coated shielded arc electrodes of class American Welding Society (AWS), welding current was 120 A, welding voltage was 60 V and DC Positive electrode. The chemical composition of the electrodes and plate are shown in Table (1).

Table (1): The chemical composition (wt.%)

Types	C	Si	Mn	Cr	Ni	Mo	P	S	Fe
Carbon Steel (CS)	0.2	0.23	1.37	0.01	0.01	0.005	0.02	0.008	Basis
E316 L	<0.003	0.8	0.8	18.5	12	2.6	-	-	Basis
E308L	<0.003	0.8	0.8	19	10	-	-	-	Basis
E310	0.15	0.2	2	25	20	-	-	-	Basis

Some of specimens were subjected to an aging temperature of 550 ºC for various holding times 50, 500 and 1000 hr followed by air-cooling. The specimens were ground under water on rotating disc, using abrasive paper with grades ranging from 180 to 2000. Then polished to mirrored surface by using diamond paste with grades 3 and 1micron.

3. Experimental of Corrosion

Potentiodynamic polarization technique using a potentiostat (Electrochemical Impedance Analyzer, Model 6310) user to determinate the electrochemical corrosion behavior of as-weld, and after heat treatment for 50 hr, 500 hr and 1000 hr at 550 °C at room temperature.

The surface area of (SS) is equal to (CS) area which is immersed in the test solution 3% NaCl prepared from duple distilled water and reagent grade salt. From previous work [19-21] potentiodynamic technique are shown in Table (2).

Table (2): Corrosion potential E_{corr} and corrosion current density I_{corr} for 316L,308Land310

Aging condition (hr)	316L		308L		310	
	E_{corr} (mV)	I_{corr} (A/cm^2)	E_{corr} (mV)	I_{corr} (A/cm^2)	E_{corr} (mV)	I_{corr} (mA/cm2)
0 (as weld)	-514	1.35E-03	-504	2.10 E-03	-514	4.3 E-03
50	-583.7	5.20E-03	-566	2.40 E-03	-480	5.3 E-06
500	-462.1	6.44E-06	-453	1.72 E-05	-421	300.1 E-06
1000	-785.3	5.60E-04	-550	1.42 E-06	-522	1.6 E-03

4. Artificial Neural Networks

Artificial neural networks (ANNs) are flexible model for non-linear statistical analysis that can be used for data classification and regression calculation. They appearances like a box that links input and output data together via a set of non-linear functions [22]. Moreover, ANNs are the collections of mathematical models that emulate some of the properties of the human biological nervous system and learning process. ANNs are formed by several neurons located in different layers. The hidden layers represent the interaction between the input and output layers.

In ANNs, a neuron can be defined as the unit that provides the map between the input and the output according to the activation function defined for each layer in the network. The activation function can be linear or non-linear function. The transfer function provides an output corresponding to the weight summation of the inputs for each neuron. The weighted sum is defined as a function of weight and bias values. These parameters define the connections between the neurons of the different layers and their values are adjusted in the training stage. The principal objective of the iterative training process is to minimize the error between the output provided by the model and the target [23].

The backpropagation algorithm is the most popular technique used in the training stage. This process involves two steps: Forward Computing and Backward Computing. In the first step, the signal from the input nodes is propagated forward through the hidden layer to compute the output signal in the output layer but in the second step, the difference between the computed output and the desired target is calculated then based on this measurement, the connections between neurons are modified in the backward step adjusting the weight values as in figure (1) [23].

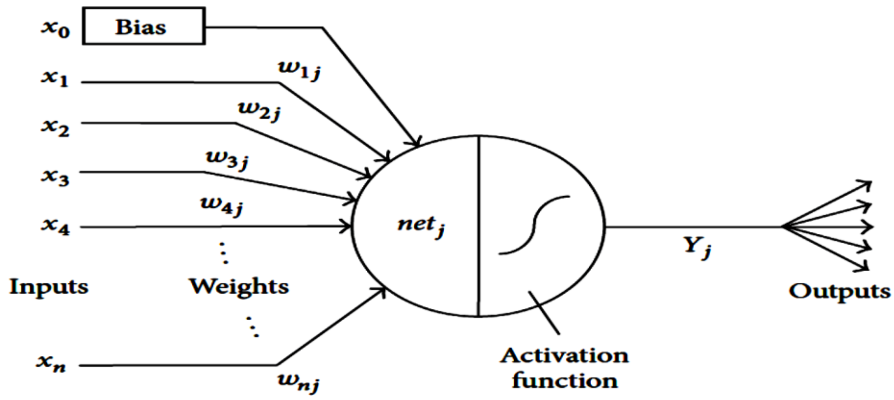

Figure (1): Architecture of an individual neuron for backpropagation neural network. [23]

5. The developed ANN model

Three feed-forward artificial neural network model with the back-propagation algorithm is developed to predict the corrosion potential and corrosion current density for 316L, 308L and 310 austenitic stainless steel materials. The flow chart of developed ANN model procedure which used backpropagation as neural network is shown in Figure (2). They are two phases on the developed ANN modeling one is phase to train the network model, while the other phase is to validate the network model with data, which were not used for training.

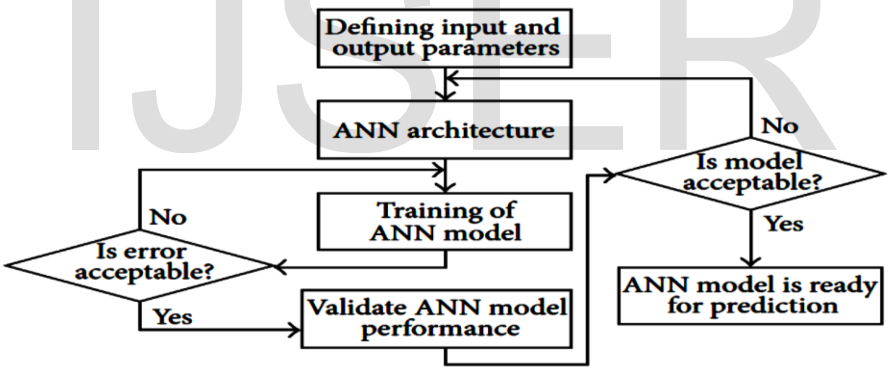

Figure (2): Flow chart of developed ANN modeling procedure.

5.1. The developed model Neural Network Architecture

Choosing the optimum network architecture is one of the challenging steps in neural network modeling. In this study architecture of the developed ANN model using backpropagation neural network (BPNN) with three layers: input layer, hidden layer, and output layer. As there are four inputs and four outputs, the numbers of neurons in the input and output layer had to be set to 4 and 4, respectively. In the many applications, the backpropagation architecture with one hidden layer is enough [14]. Therefore, only one hidden layer has been used in this study with 50 neurons. Initial connection weights are randomly selected in the range -1 to 1. All the calculations are performed using the developed model. During the simulation the total squared error was used as the criterion of the learning efficiency of the network in the training process. Sigmiod function is chosen as the transfer function. Several trainings with changing the number of hidden units, iterations, learning rate, momentum and transfer function were performed to find the best structure that shown in table (3).

Table (3): The Neural network configuration for the training

Parameter	Specification
No. of neurons in input layer	4
No. of neurons in hidden layer	50
No. of neurons in output layer	4
Training function	purelin, trainscg
Performance function	Mean squared error (MSE)
Activation function	Logsig
Maximum epoch (training time)	3000
Performance goal	1.0×10^{-6}
Learning rate	0.05
Normalized range	-1 to 1

5.2. The training of the Neural Network

In the developed ANN model forward learning using the ANN parameters in table 3, the net input data which contains the data of Corrosion potential E_{corr} and corrosion current density I_{corr} for 316L,308Land310 is calculated by summing the input values multiplied by their corresponding weight. Once the net input is calculated, it is converted to an activation value. The weight on the connection from the i^{th} neuron in the forward layer to the j^{th} neuron is indicated as w_{ij}. The output value Y_j of neuron j is computed by the following equations:

$$net_j = \sum_{i=0}^{n} w_{ij} x_j + x_0 \qquad (1)$$

$$Y_j = f_{act}(net_j) \qquad (2)$$

where net_j is the linear combination of each of the x_j values multiplied by w_{ij}, x_0 is a constant known as the bias, n is the number of inputs to the j^{th} neuron, and $f$act is the activation of neuron j.
In the developed ANN model network, the hidden layer with log-sigmoid (S-shaped curves) activation function is used for the prediction. The log-sigmoid activation function is given in:

$$Y_j = \frac{1}{1+\exp(-net_j)} \qquad (3)$$

In backward learning, the generated output of the network is compared to the desired output, and an error is computed for each output neuron. The error vector E between desired values and the output value of the network is defined as:

$$E = \sum_j E_j = \sum_j (T_j - Y_j)^2 \qquad (4)$$

where Y_j is the output value of the j^{th} output neuron and T_j is the desired value of the j^{th} output neuron. Errors are then transmitted backward from the output layer to each neuron in the forward layer. The process is repeated layer

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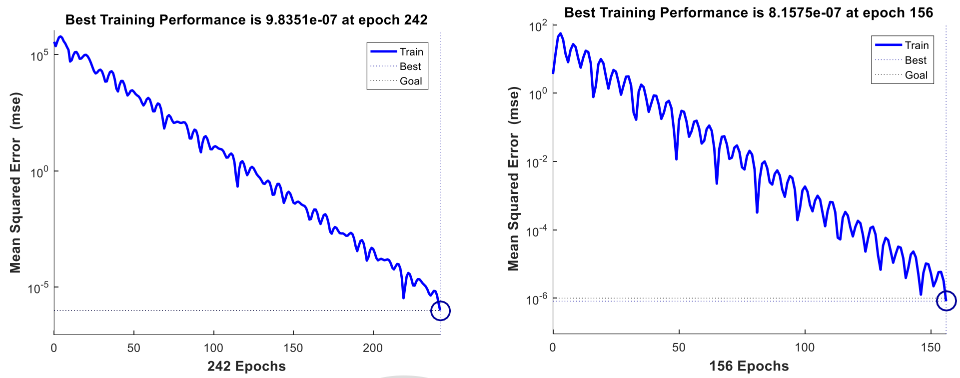
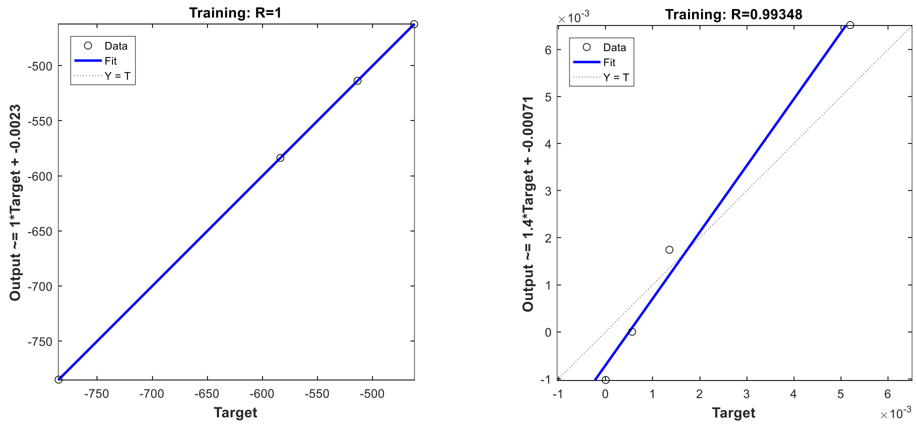
6. Results and Discussion

From Figure (3) to Figure (8) represent the performance of developed ANN model (4-50-4) network at the end of training for the three martials 316L, 308L and 310 and the simulation. The predicted Corrosion potential E_{corr} and corrosion current density I_{corr} for 316L, 308L and310. In the training of 4-50-4 network is confirmed by the correlation with the experimental data. From the figures it seen that, as the number of epochs is increased, the error decreased and converged to very small values. In addition, it can be seen that there is high correlation between the predicted and measured Experimental values of Corrosion potential E_{corr} and corrosion current density I_{corr} for 316L, 308L and310.



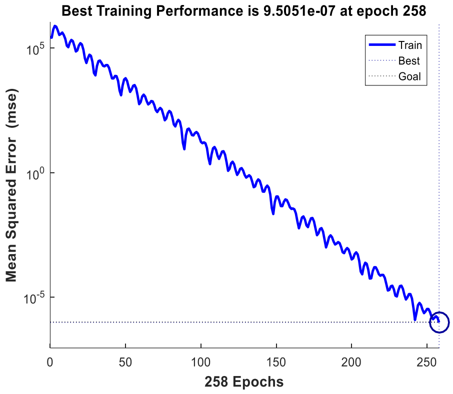
(a) E_{corr} (b) I_{corr}

Figure (3): The Performance of the developed ANN architecture during training Corrosion potential E_{corr} and corrosion current density I_{corr} for 316L.

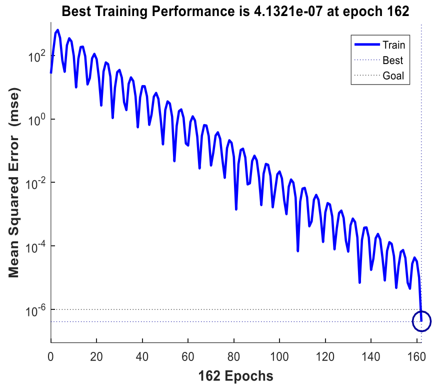


(a) E_{corr} (b) I_{corr}

Figure (4): The regression of the developed ANN architecture during training of Corrosion potential E_{corr} and corrosion current density I_{corr} for 316L.

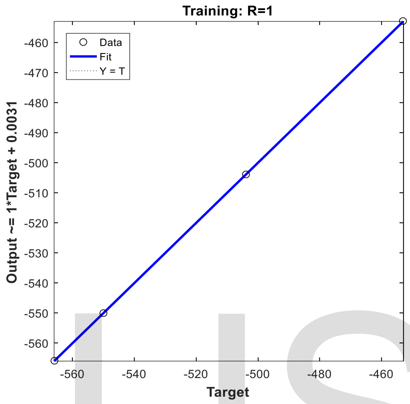


(a) E_{corr}

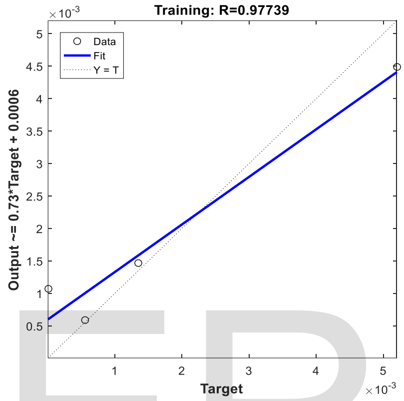


(b) I_{corr}

Figure (5): The Performance of the developed ANN architecture during training Corrosion potential E_{corr} and corrosion current density I_{corr} for 308L.

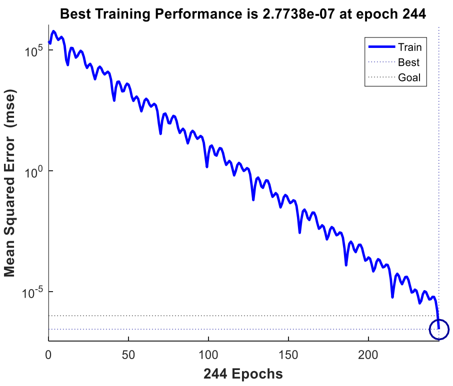


(a) E_{corr}

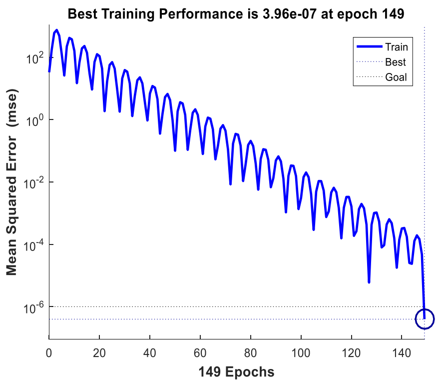


(b) I_{corr}

Figure (6): The Performance of the developed ANN architecture during training Corrosion potential E_{corr} and corrosion current density I_{corr} for 308L.

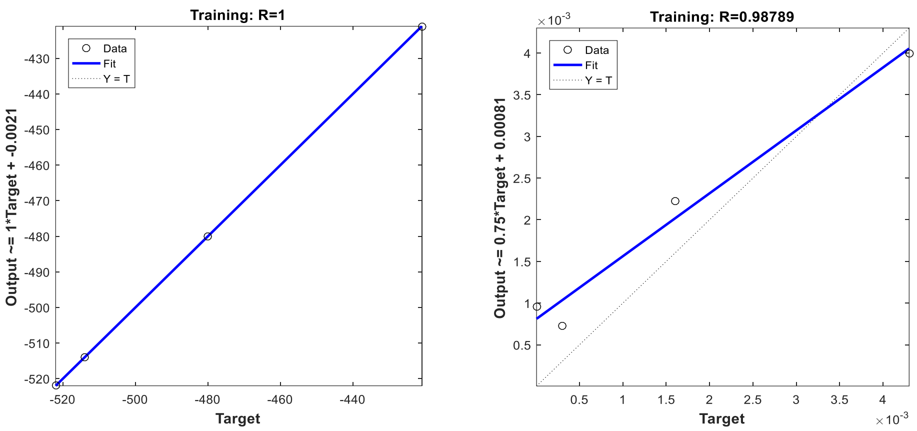


(a) E_{corr}



(b) I_{corr}

Figure (7): The Performance of the developed ANN architecture during training Corrosion potential E_{corr} and corrosion current density I_{corr} for 310.



(a) E_{corr} (b) I_{corr}

Figure (8): The Performance of the developed ANN architecture during simulation of Corrosion potential E_{corr} and corrosion current density I_{corr} for 310.

From previous figures it found that, in the neutral network training with the experimental input data of 316L, the performance plot of E_{corr} & I_{corr} in figure (3) (a,b). It shows the best training performance for E_{corr} happened at the epoch of 242 and for I_{corr} happened at the epoch of 156. The regression results of E_{corr} & I_{corr} are plotted in Figure (4) (a,b) The solid blue line represented the best fit linear regression line between predicted outputs and actual targets. The relationship between outputs and targets is indicated by the R value of one for E_{corr} and near one (0.99348) for I_{corr} . There is a perfect linear relationship between outputs and targets as shown in Figure (4). It is apparent that the developed ANN model was well-trained and predictive.

Moreover, in the neutral network training with the experimental input data of 308L, the performance plot of E_{corr} & I_{corr} in figure (5) (a,b). It shows the best training performance for E_{corr} happened at the epoch of 258 and for I_{corr} for happened at the epoch of 162. The regression results of E_{corr} & I_{corr} are plotted in Figure (6) (a,b) The solid blue line represented the best fit linear regression line between predicted outputs and actual targets. The relationship between outputs and targets is indicated by the R value of one for E_{corr} and near one (0.97739) for I_{corr}. There is a perfect linear relationship between outputs and targets as shown in figure (6). It is apparent that the developed ANN model was well-trained and predictive.

Furthermore, in the neutral network training with the experimental input data of 310, the performance plot of E_{corr} & I_{corr} in figure (7) (a,b). It shows the best training performance for E_{corr} happened at the epoch of 244 and for I_{corr} for happened at the epoch of 149 The regression results of E_{corr} & I_{corr} are plotted in Fig. 8 (a,b) The solid blue line represented the best fit linear regression line between predicted outputs and actual targets. The relationship between outputs and targets is indicated by the R value of one for E_{corr} and near one (0.98789) for I_{corr}. There is a perfect linear relationship between outputs and targets as shown in Fig. 8. It is apparent that the developed ANN model was well-trained and predictive.

According to the ANN simulation results for of Austenitic stainless steel 316L, 308L and 310. in the training stage, as shown in figures (4, 6 and 8), it is found that the correlation coefficient R between ANN predicted retardances and the experimental measured data as high as one for E_{corr} and 0.99345, 0.97735 and 0.98789 for I_{corr} while it is achieved. However, the predicted errors are in acceptable error range (less 10%)

for this application. Thus, the developed ANN model can be used for predict the E_{corr} & I_{corr} for the three Austenitic stainless steel martials.

7. Validation of the developed ANN model

For validation, the computational method used to predict the E_{corr} & I_{corr} in the developed ANN model, the network is trained using the as weld condition and the after aging time for 50hr, 500 hr and 1000hr as input data and its corresponding values for three 316L, 308L and 310 as austenitic stainless steel martials. Also, the output value is predicted for the aging time for 10hr, 75hr, 750hr and 1500hr. The results are illustrated in tables (4-6) they show that the training and the predicted data is nearly to the measuring data of E_{corr} & I_{corr}.

Percentage Error for as weld and aging time condition at as weld condition and the after aging time for 50hr, 500 hr and 1000hr as input data and its corresponding values for three 316L, 308L and 310 as austenitic stainless steel martials. Also, Percentage Error the output value is predicted for the aging time for 10hr, 75hr, 750hr and 1500hr. The results are illustrated in tables (7) they show that the minimum percentage error is 0% and the maximum is 2.7%.

Table (4): The implemental and perdition E_{corr} & I_{corr} for 316L

Aging condition (hr)	**Exp. data**		**Prediction**		**Aging condition (hr)**	**Prediction**	
	E_{corr} (mV)	**I_{corr} (A/cm^2)**	**E_{corr} (mV)**	**I_{corr} (A/cm^2)**		**E_{corr} (mV)**	**I_{corr} (A/cm^2)**
0 (as weld)	-514	1.35E-03	-513.9997	2E-03	**10**	-583.6987	1.5346
50	-583.7	5.20E-03	-583.6987	5.10E-03	**75**	-583.6987	0.0058
500	-462.1	6.44E-06	-462.1008	6.44E-06	**750**	-609.1787	2.4468
1000	-785.3	5.60E-04	-785.2994	5E-04	**1500**	-785.2994	0.0005

Table (5): The implemental and perdition E_{corr} & I_{corr} for 308L

Aging Condition (hr)	**Exp. data**		**Prediction**		**`Aging Condition (hr)**	**Prediction**	
	E_{corr} (mV)	**I_{corr} (A/cm^2)**	**E_{corr} (mV)**	**I_{corr} (A/cm^2)**		**E_{corr} (mV)**	**I_{corr} (A/cm^2)**
0 (as weld)	-504	2.10 E-03	-503.9995	0.0027	**10**	-904.7185	0.6670
50	-566	2.40 E-03	-565.9990	0.0028	**75**	-565.9991	0.2616
500	-453	1.72 E-05	-453.0003	0.0005	**750**	-502.6643	2.3528
1000	-550	1.42 E-06	-549.9989	0.0011	**1500**	-549.9989	0.0011

Table (6): The implemental and prediction of E_{corr} & I_{corr} for 310

Aging Condition (hr)	**Exp. data**		**Prediction**		**Aging Condition (hr)**	**Prediction**	
	E_{corr} (mV)	**I_{corr} (A/cm^2)**	**E_{corr} (mV)**	**I_{corr} (A/cm^2)**		**E_{corr} (mV)**	**I_{corr} (A/cm^2)**
0 (as weld)	-514	4.3 E-03	-513.9986	0.0036	**10**	-374.0075	1.4617
50	-480	5.3 E-06	-479.9995	0.0006	**75**	-350.2016	0.1934
500	-421	3.001E-04	-421.0002	0.0007	**750**	-471.5807	3.8348
1000	-522	1.6 E-03	-521.9994	0.0026	**1500**	-521.9994	0.0026

Table (7): E_{corr} & I_{corr} % percentage Error between experimental and predication data after aging time at 0, 50, 500 & 1000

Aging condition (hr)	E_{corr} % 316L	I_{corr}% 316L	E_{corr} % 308L	I_{corr} % 308L	E_{corr} % 310	I_{corr} % 310
0 as weld	0.03	1.35E-01	0.05	5.346E-03	0.15	0.057140
50	0.13	5.20E-01	0.10	0.090	0.05	0.065616
500	0. 08	6.44E-04	0.03	5.389E-03	0.02	0. 25967322
1000	06	5.60E-02	0.11	0. 0560	0.06	0. 3642

8. Conclusions

In this work, a comparison is made between experimental results of corrosion current density I_{corr} and corrosion potential E_{corr} and computational prediction using artificial neural network (ANN) for calculating the corrosion current density I_{corr} and corrosion potential E_{corr}. Corrosion determined by potentiodynamic technique of as-weld, and after heat treatment for 50 hr, 500 hr and 1000 hr at 550 °C at room temperature. The surface area of (SS) is equal to (CS) area,

From the training and testing of the ANN simulation results, an ANN model was developed successfully and had high ability for the prediction of E_{corr} & I_{corr} for the three Austenitic stainless steel martials. In The trained (ANN) model gives an excellent correlation coefficient and the error values are also significantly low, which represents a good accuracy of the model. Since, the developed ANN model training/learning is very fast and the networks are very good at interpolation, (ANN) thus, it is particularly useful for the as weld condition and after aging and it is applicable to all conditions. Moreover, the simulation results in the training stage show a high correlation coefficient between experimental data and predicted data. Furthermore, the developed ANN model could be a useful tool in predicted the corrosion for tie between time learning and for long time that complex to achieve experimentally but with some errors thus, more well-trained for the developed ANN model for further used to predict of E_{corr} & I_{corr} with more data will be more excellent to predicted for long time with more accuracy. The predicted errors are in acceptable error range (less 10%) for this application. Thus, the developed ANN model can be used for predict the E_{corr} & I_{corr} for the three Austenitic stainless steel martials

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