Prediction of Corrosion Rate for Carbon Steel in Soil Environment by Artificial Neural Network and Genetic Algorithm

Amir Akhtari-Goshayeshi [1], M. Ghobadi [2], Ehsan Saebnoori [1,*], Alireza Zarezadeh [3], Mohammad Rostami [4], Mohammad Nematollahi [5]

[1] *Advanced Materials Research Center, Department of Materials Engineering, Najafabad Branch, Islamic Azad University, Najafabad, Iran.*
[2] *Department of Technical Inspection, Abadan Facility of petroleum engineering, Petroleum University of Technology, Abadan, Iran.*
[3] *Department of Safety Engineering, Abadan Facility of petroleum engineering, Petroleum University of Technology, Abadan, Iran.*
[4] *Department of chemical Engineering, Abadan Facility of petroleum engineering, Petroleum University of Technology, Abadan, Iran.*
[5] *Department of Materials Engineering, Isfahan University of Technology, Isfahan, Iran.*

ARTICLE INFO

Article history:

Received 12 January 2020
Accepted 5 April 2020
Available online 15 April 2020

Keywords:

Artificial neural network (ANN)
Genetic algorithm (GA)
Optimum structure
Current efficiency
Corrosion Rate
Weight Loss
Soil Environment

ABSTRACT

In this study, the corrosion rates for St37 carbon steel in some soil types with different conditions were measured. The effects of the parameters of moisture amount, soil particle size, and salt concentration were determined by the mass loss method. An Artificial Neural Network (ANN) model with three inputs and one output was established to simulate the experimental data. It was observed that the Levenberg–Marquardt algorithm with hyperbolic tangent sigmoid transfer function provided the best results in training with the lowest MSE and MAE compared to the other methods in the model. The R values for training, validation, and test were presented, and the value of 0.98684 was achieved for the complete data set, which demonstrates a high level of ANN performance. The Genetic Algorithm (GA) was also used to find optimum inputs for the target of minimum corrosion rate value. The results showed a good agreement between the model prediction and experimental values.

1-Introduction

External corrosion of the buried pipelines for transmission of water, oil, and gas is caused by the exposure of the pipe to the soil. The amount of this corrosion has a direct relationship with soil corrosivity. Therefore, considering the high volume of pipes used in the soil environment, it is essential to investigate the corrosion rate of transmission pipes as a significant economic issue [1]. Many factors are useful in determining soil corrosion rates and investigating these factors and providing solutions to reduce them and prevent the destruction of buried structures. Soil can be considered as a heterogeneous environment of pores where the space of its holes can be filled with water or gas [1]. Alcántara [2] showed that in the comparison between soil and other environments such as the atmosphere or seawater, due to the extreme complexity of the soil environment, it is not possible to classify and determine a set of fixed factors. The presence of any corrosive ions in the

* Corresponding author:
E-mail address: ehsan.saebnoori@gmail.com

soil significantly increases the corrosion rate of the pipes in contact with the soil. Chloride and sulfate ions and soil acidity are the most critical factors affecting the corrosion rate in buried pipelines. These ions increase the corrosion rate by decreasing the electrical resistance of the soil. Finding a reliable method based on soil parameters is very important. This study has been carried out to introduce a methodology for the prediction of essential parameters affecting soil using artificial neural networks and genetic algorithms.

Artificial neural network (ANN)

Nowadays, the Artificial Neural Network (ANN) models are the most capable modeling techniques which have been found in many different applications of various fields, such as civil, IT, Electricity, environmental pollution, and corrosion science [4]. ANN method is now almost a standard modeling skill based on a statistical approach, and it has increased interest for the prediction of different types of corrosion and has helped to diminish numerous experiments, excess finance costs, and waste of time. It is a codified numerical computerized plan that can model complex dependency between promiscuous experimental inputs and their relative outputs; also, it is possible to reduce the error between them [5-8]. The majority of researchers agree that ANN is inspired by the behavior of biological neurons, and it works like a brain, which is composed of small parts called neurons and synapses for transferring signals to the neuron [9, 10-15]. A group of neurons forms a subsystem, and the brain is consisting of subsystems collection. The inputs to the neurons are weighted, and these weights are revised during learning. The fundamental structure of an artificial neural network model is concluded of three layers, i.e., input, hidden, and output layer, these layers work as subsystems and neurons have the same function in two networks [5,16].

ANNs are trained to recognize linear and nonlinear relationships between the inputs and output variables in a required problem for a given data set [17, 12]. As mentioned above, the input layer comprised of a neuron for each input variable is considered, and also some hidden layers may be added, which consist of any number of neurons placed in parallel. The sum of the weighted inputs and the bias forms the input to the so-called transfer function, which transfers input signals into an output. The idea is used to perform the learning process called a learning algorithm that can modify the synaptic weight of the network. When the brain receives a provocation, it goes into the neural network for analysis by an electrical impulse. The effectors convert the electrical signal, which was generated into the feedback as system outputs [18]. The connections between each layer are universally defined in terms of weights and bias [11]. A schematic illustration of the ANN methodology based on the human nervous system is showed in Fig. 1. Usually, one hidden layer is supposed; however, by using two or more hidden layers, the ANN performance may improve significantly. Accordingly, a network with two hidden layers shows suitable performance. As shown in Fig.2 in each neuron, the inputs are linearly combined with a set of previously random-defined weights w and the bias b. After the data was processed by weight and bias, the results are transferred from hidden neurons to the output layer utilizing a transfer function, which is often nonlinear [9, 12, 19-20]. Transfer functions are in the forms of a linear and sigmoidal function. The linear transfers function, such as Purelin, transforms inputs into the neuron in a linear form. Contrary, the sigmoidal function facilitates creating a non-linear connection between neurons and layers, which leads to a nonlinear relation between input and output. The common types of sigmoidal functions are logsig and tansig [6]. It was ready to be trained after the instruction of the network [15]. The network used the information in the training data and then assimilated the resulting output with the desired one. For this aim, the errors were propagated back through the structure. This helps to adapt the weights for application to the next record that will be processed. This promotion occurred over and over as the weights were regularly corrected. First of all, the network starts with random weights and bias values and executes a transfer function that produces a simulated output, and the value of training error is achieved [11]. Choosing the number of neurons in the hidden layers needs excellent attention to prevent the overfitting phenomenon in the network, which can be caused by too many neurons [10].

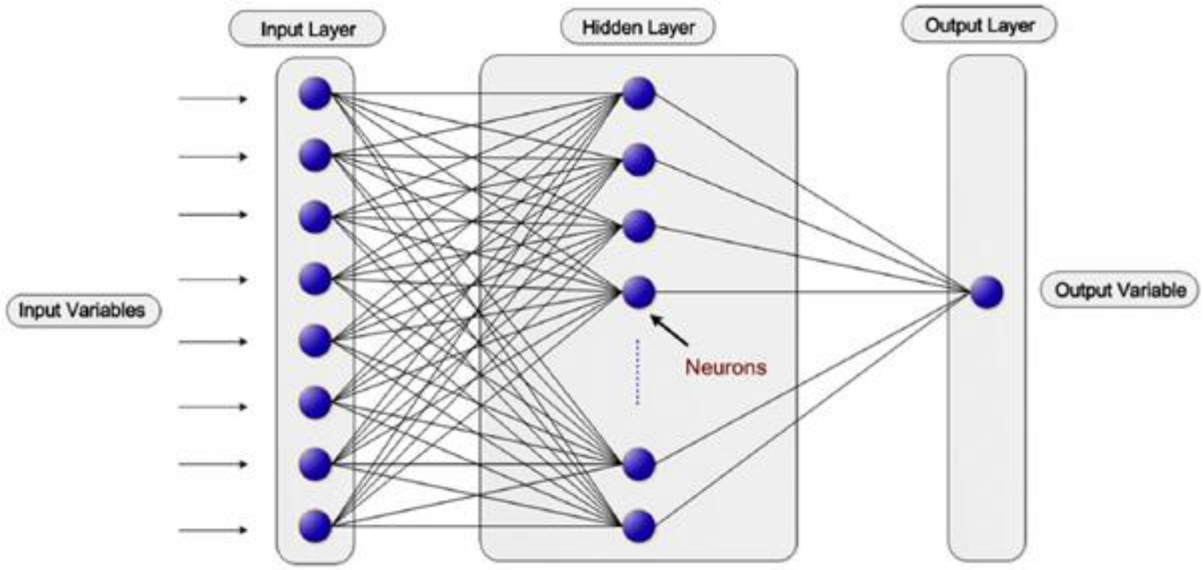

Fig. 1 A schematic of a multi-layer neural network model [19].

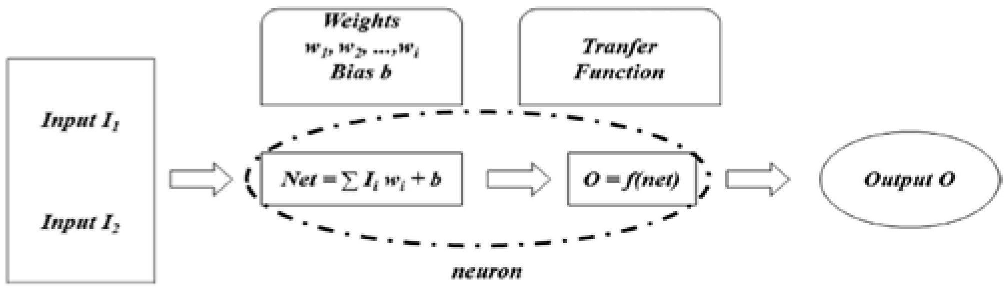

Fig. 2 Single neuron activity [18]

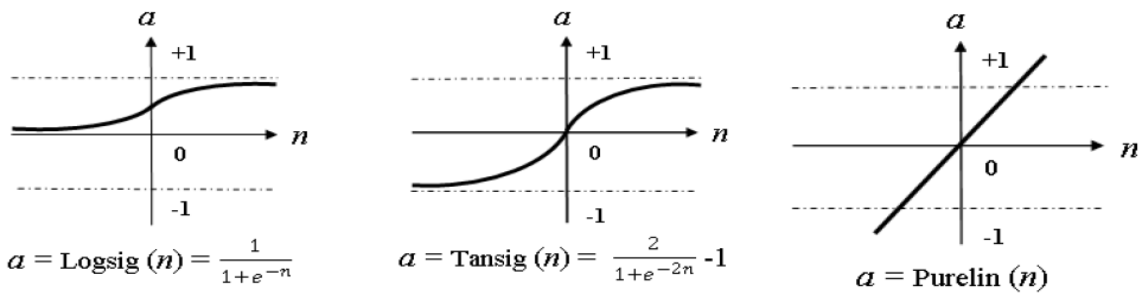

Fig. 3 different types of transfer functions [25]

A variety of formations for ANN structure could be supposed, and many combinations for the number of layers and neurons in each layer may be considered. So, several networks are essential to be inspected to find the best results. Trial-and-error methods are the most appropriate way of finding the best number of hidden layers and number of neurons in each hidden layer. In each trial, the experience and ability of the programmer play an essential role. Stanley [21] demonstrated the operation and performance of the network that affected how the neurons are connected in a network typology. It is common to compose a more accurate network; regarding this, the data were divided into training, validation, and test group. The validation is used to analyze the performances of the ANN, and the test set is useful to confirm the performance of the selected architecture. There are many different training algorithms. The details for different training algorithms are given in [22, 23]. the most usual and conventional models in many practical applications are Feedforward neural networks [24]

There are various ways to investigate the performance of the ANN model, which will discuss in this study. ANNs have been used propitiously by several researchers for corrosion prediction, which successfully analyzed complex systems in all of these studies [25-32]. In the present paper, the experimental and computational analysis was used to investigate the corrosion rate of steel in the soil environment, thereby we use the artificial neural network – genetic algorithm (ANN-GA) approach to optimize each parameter and minimize corrosion. The GA that firstly introduced by professor Holland [33] is an Evolutionary Algorithm (EA), which works on Darwin's theory of natural selection and inspired by the nature of living creatures that can be used to solve linear and nonlinear optimization problems without gradient information [34, 35]. The rest of the paper is providing the experimental dataset in the laboratory.

2. Experimental procedure

The metal specimens used in this study were DIN ST37 carbon steel with dimensions of 30 × 23 × 2 mm for weight loss test in a specified environment for each test. The chemical composition of DIN ST37 steel is measured by Optical Emission Spectrometer and presented in Table 1.

The electrolytes used for corrosion tests were sodium chloride (NaCl) and sodium sulfate (Na_2SO_4) in one molar concentration. These electrolytes are also added to different soil and used to reach the moisture content required in the resistance test. The test electrolyte was an aqueous solution of NaCl and Na_2SO_4, clay with soil, clay with sand, sand, and washed sand, and compositions of an equal portion of each with the moisture content of 10, 20, and 30%. All were tested after sandblasting, washing, and weighing, and the weight loss corrosion tests were done for three months. The various mechanical, electrolytic, and chemical treatments were employed according to ASTM G1[36] after the tests for cleaning the samples.

3. Results and discussion

The corrosion rate for each sample was calculated by applying the equation (1) where W is weight loss in milligrams, ρ is metal density in g/cm^3, A is the area of the sample in cm^2, T is the time of exposure of the metal sample in hours, and K is a constant (here K is 534). It can be seen that the corrosion rates depend on environments and corrosive ions.

$$\text{Corrosion Rate (mpy)} = \frac{(K \times W)}{(A \times T \times \rho)} \quad (1)$$

ANN model

It is tough and somehow impossible to find a mathematical equation between some environmental parameters like moisture for calculation of the corrosion rate; so, ANN is used for this prediction. In the research, the program package MATLAB 2018a with the Neural Network toolbox was used to formulate the artificial neural network and data processing; as a result, corrosion rate prediction is achieved. As it is mentioned before, the ANN structure consists of three layers, input, hidden, and output. First, according to the nature and purpose of the experiments, Neural network inputs and outputs were defined. Having different variables such as types of soil (different particle sizes), two different salts (molecular weight of salt) will affect the corrosion rate; they are used as the input for experimental analysis and corrosion rate prediction.

The structure of the ANN model used in this study is presented in Fig. 4. In this model, four inputs and one output are introduced to build a neural network, and a total of 28 series of experimental attempts were employed. Table 2 shows the selected inputs and output parameters for the ANN developed in this work. The critical point of this study is the use of two types of salt, which the ANN model is valid for two salts.

Table 1. Chemical composition of DIN ST37 carbon steel samples.

C	Si	Mo	S	P	Ni	Cr	Mn	Cu	Fe
0.112	0.125	0.007	0.03	0.004	0.063	0.078	0.295	0.028	99.02

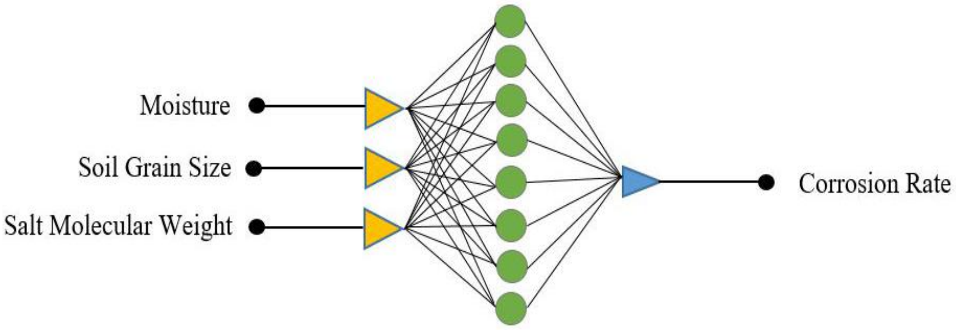

Fig. 4 Typical structure for the ANN model used in this study.

Table2- experimental data for the ANN formation.

	Inputs of ANN			Experimental output
	Moisture (%)	Particle Size (NM)	Salt (g/mole)	Corrosion Rate (mpy)
1	10	93.75	58.44	0.412705
2	20	93.75	58.44	4.476259
3	30	93.75	58.44	3.417195
4	10	93.75	142.04	1.160653
5	20	93.75	142.04	5.653419
6	30	93.75	142.04	5.671198
7	20	2.44	58.44	0.321275
8	30	2.44	58.44	2.481308
9	20	2.44	142.04	0.139685
10	30	2.44	142.04	1.570818
11	10	375	58.44	5.273731
12	20	375	58.44	9.793165
13	30	375	58.44	10.93858
14	10	375	142.04	1.761297
15	20	375	142.04	4.925789
16	30	375	142.04	7.295349
17	10	234.37	58.44	2.82544
18	20	234.37	58.44	5.840089
19	30	234.37	58.44	5.181031
20	10	234.37	142.04	1.615263
21	20	234.37	142.04	4.127047
22	30	234.37	142.04	5.511195
23	10	188.72	58.44	0.535881
24	20	188.72	58.44	1.704153
25	30	188.72	58.44	4.232445
26	10	188.72	142.04	0.114287
27	20	188.72	142.04	1.347322
28	30	188.72	142.04	4.452131

The range of variables would be different from different natures, so, to avoid the one parameter, all of the variables are arranged in the range of 0 to 1, which is usually called the normalization method. These Parameters have a large value and enable the ANN to distinguish the dependence and communal influence of each parameter more efficiently; thus, make a desirable assessment of the output. When the simulation has been completed for enabling better readability and interpretation, it is possible to do post-processing in which the obtained data is scaled backward in the actual range of values.

Table 3. Boundaries of the input and output parameters used for developing the ANN model.

Inputs	Range
Moisture	10-30
Particle Size	2.44-375
Salts Molecular weight	58.44 and 142.04
Corrosion Rate	0.114287-10.93858

Table 3 displays the minimum and maximum values that have been used for the normalization of parameters. The normalization formula is:

$$X_{norm}=\frac{(X-Xmin)}{(Xmax-Xmin)} \quad (2)$$

In which X_{norm} is the normalized value, x is the actual value, Xmax is the maximum value, and Xmin is the minimum value of parameters.

During training, the process was surveyed by evaluating the validation data [37]. As discussed earlier, the data from pre-processing were randomly divided into three parts, so 70% of data were used for training, 15% for validation, and 15% for the testing set, respectively [38].

The performance of the system in each of the training, validation, and testing steps is calculated by various statistical error formulas. In this article, MSE, MAE, and R were used to find the best and suitable network for the prediction of corrosion rate. These errors were determined by:

Mean Square Error (MSE);

$$MSE=\frac{1}{n}\sum_{i=1}^{n} (t-o)^2 \quad (3)$$

Mean Absolute Error (MAE);

$$MAE=\frac{1}{n}\sum_{i=1}^{n} |t-o| \quad (4)$$

Where n is the number of data in training, t is experiment data, and O is predicted data.

Correlation Coefficient (R);

$$R^2=1-\frac{\sum_{i=1}^{n-1} (t-o)^2}{\sum_{i=1}^{n-1} (t-m)^2} \quad (5)$$

In this case, t is the target output value of instance i, o is the predicted output value of instance i, and m is the mean value of the test data set. Thus, the model with the smallest value of MAE MSE is chosen as the best model for prediction. Also, for the case of R, the closer to unity is represented as a suitable model.

Researchers agree that the hidden layer act as feature detectors and only one hidden layer gives the right answer. However, universal principles suggest that a network with a single hidden layer with a large number of neurons cannot interpret any input-output structure accurately. So, more than one hidden layer can be used to reach a trustable answer. Thus, for this purpose, two hidden layers were employed. One of the most crucial factors to reach a better ANN answer is to find the best number of neurons in each hidden layer. If too few numbers of neurons are selected, the ANN is not capable of felicitous input-output mapping; on the contrary, if too many neurons are used, overfitting may occur, and a more extended training period will be expected [19, 10]. Several networks were designed with trial and error strategies to find a suitable number of neurons in the hidden layer. Also, the network was trained for each number of hidden neurons (each network structure), to receive the least error and fill the best network [39].

The essential parameters for finding the optimum structure are the number of hidden layers, the number of neurons in each hidden layer, the transfer function, and the training function. Therefore, to reach the best structure, several models were tested, and the most suitable transfer function was selected for the best training algorithm model. In this work, nine different training algorithms from the commercial application (MATLAB) were utilized to set up the network and three different transfer functions (tansig, logsig, and purelin), which were examined for each training algorithm. The nine training algorithms used in this study are listed in Table 4. During the training and testing processes, the performance of the network for the structures with different types of training algorithms and transfer functions was tested, and the error between the simulated and experimental output is calculated until the best transfer functions, and training algorithms will be understood.

Table4. The nine training algorithm and their symbol.

Training Algorithm	symbol
Levenberg–Marquardt backpropagation	LM
BFGS quasi-Newton backpropagation	BFG
Resilient backpropagation	RP
Scaled Conjugate Gradient	SCG
Conjugate Gradient With Powell/Beale Restarts	CGB
Fletcher- Powell Conjugate Gradient	CGF
Polak- Ribiere Conjugate Gradient	CGP
One-step Secant	OSS
Variable Learning Rate Backpropagation	GDX

There are few studies which focused on a comparison between different training algorithm and transfer functions in corrosion science. Ayegba et al. used different training algorithms such as; Gradient descent with variable step size and momentum term (GDX); Levenberg Marquardt (LM) algorithm and Resilient back-propagation (RP) to build the network and also used three different transfer functions (tansig, logsig, and purelin). ANN model used to predict the effect of a vertical 90 °bend on an air–silicone oil mixture over a wide range of flow rates. Finally, the best structure for ANN was attained, and the prediction was completed [7].

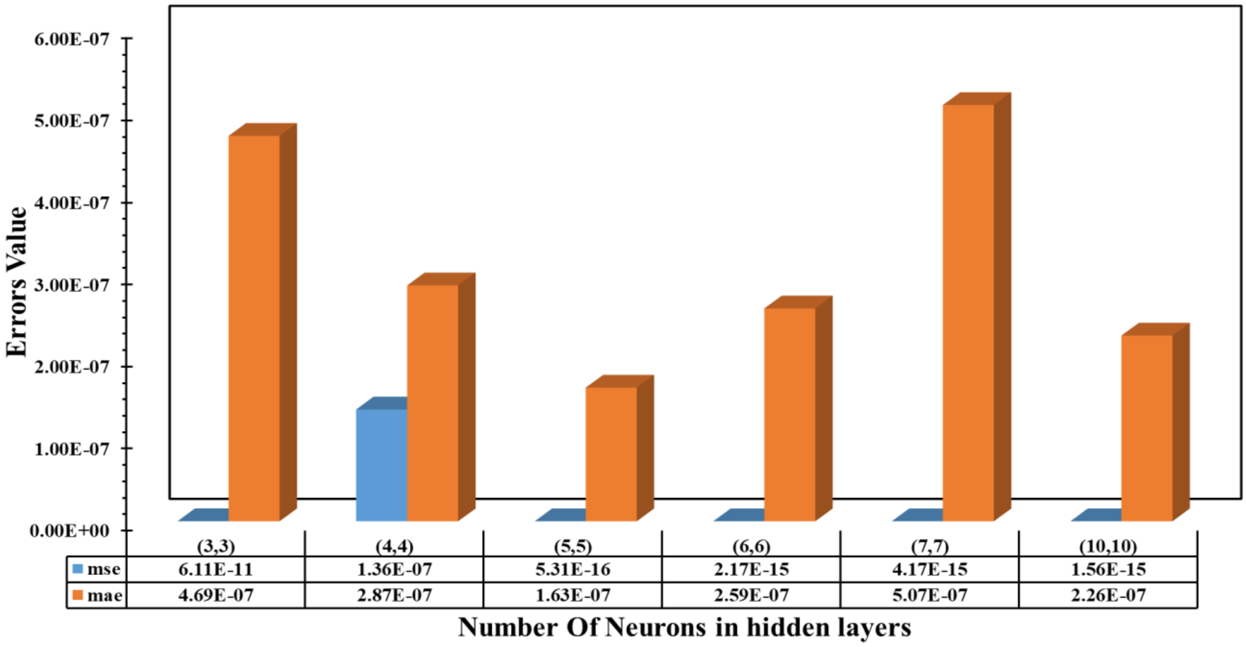

Fig. 5 Comparison of different number of hidden layers

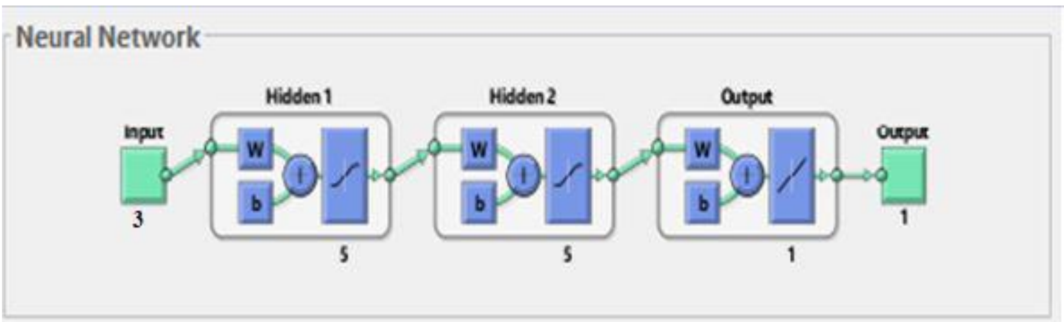

Fig. 6 Number of neurons in each layer used for neural network architecture

Taghavifar et al. tested five prominent training BP methods, Levenberg–Marquardt back-propagation, Gradient descent back-propagation, BFG Squasi-Newton back-propagation, Resilient back-propagation, and Bayesian regulation back-propagation with different transfer function. Finally, the feed-forward Artificial Neural Network (ANN) with backpropagation (BP) learning algorithm is used to estimate the rolling resistance of the wheel [16].

3.2 GA model

A binary GA toolbox developed by the University of Sheffield (“USGA” toolbox for short after this) is widely used in engineering optimization [35]. The GA frequently changes the population of particular solutions. The parents who were selected randomly by GA, at each progression, at the present population and used them for producing next-generation children [14]. The despicable species are eliminated through competition. The GA applies three operators, selection, crossover, and mutation, to transfer superior species to the next generation. The operator that is responsible for choosing the parents to make the next generation is selected [33]. Fitness function plays an essential role in the efficiency of GA for optimization. All the required variables should be added to the fitness function and given proper weightings [37]. In this paper, the corrosion rate is considered as the fitness function. Variables should be converted into the original value and went out to form the normalized mode and used in the GA. The results of GA will be shown in the next step of this paper.

4.1 ANN Results

To find the optimal neurons in every hidden layer, we used the trial and error method. For this purpose, 20 different neurons in each layer were tried, and the error values were investigated. In Fig. 5, the MSE and MAE of training samples for a different number of neurons in hidden layer with tansig transfer function and Levenberg–Marquardt BP algorithm are shown, error values decrease considerably when the number is five in each hidden layer and shows the best performance. Therefore, The ANN model used in this work consists of 3-5-5-1 in each layer, as illustrated in Fig.6.

After finding the best neurons’ number, all the nine algorithms were applied in 3 different transfer functions. Fig. 7a-c demonstrates the performance results for three transfer functions with different algorithms. It is clear that the tansig transfer function shows the least error values and seems to be suitable for the network. The objective function provides the basis for performance evaluation and network algorithm selection. Moreover, finding the best algorithm for the prediction of corrosion rate is intended, so to have a better comparison for this algorithm, the error value for the algorithm is inspected in different transfer functions. Fig 8. Shows a comparison between MSE and MAE values of levenberg – marquardt (lm) in 3 types of the transfer function, the lm algorithm has resulted in the best answer in all the three transfer functions. As can be seen, by the small values of MAE and MSE, it is observed that the ANN model, based on the LM algorithm with tansig transfer function, performs well. It is in agreement with the literature, which indicates the fastest and less memory consumption in levenberg – marquardt training algorithm [23]. Because of its compatibility, lm is the most popular algorithm around the world, and it is frequently used by several researchers [7, 16, 19, 14, 38, 39].

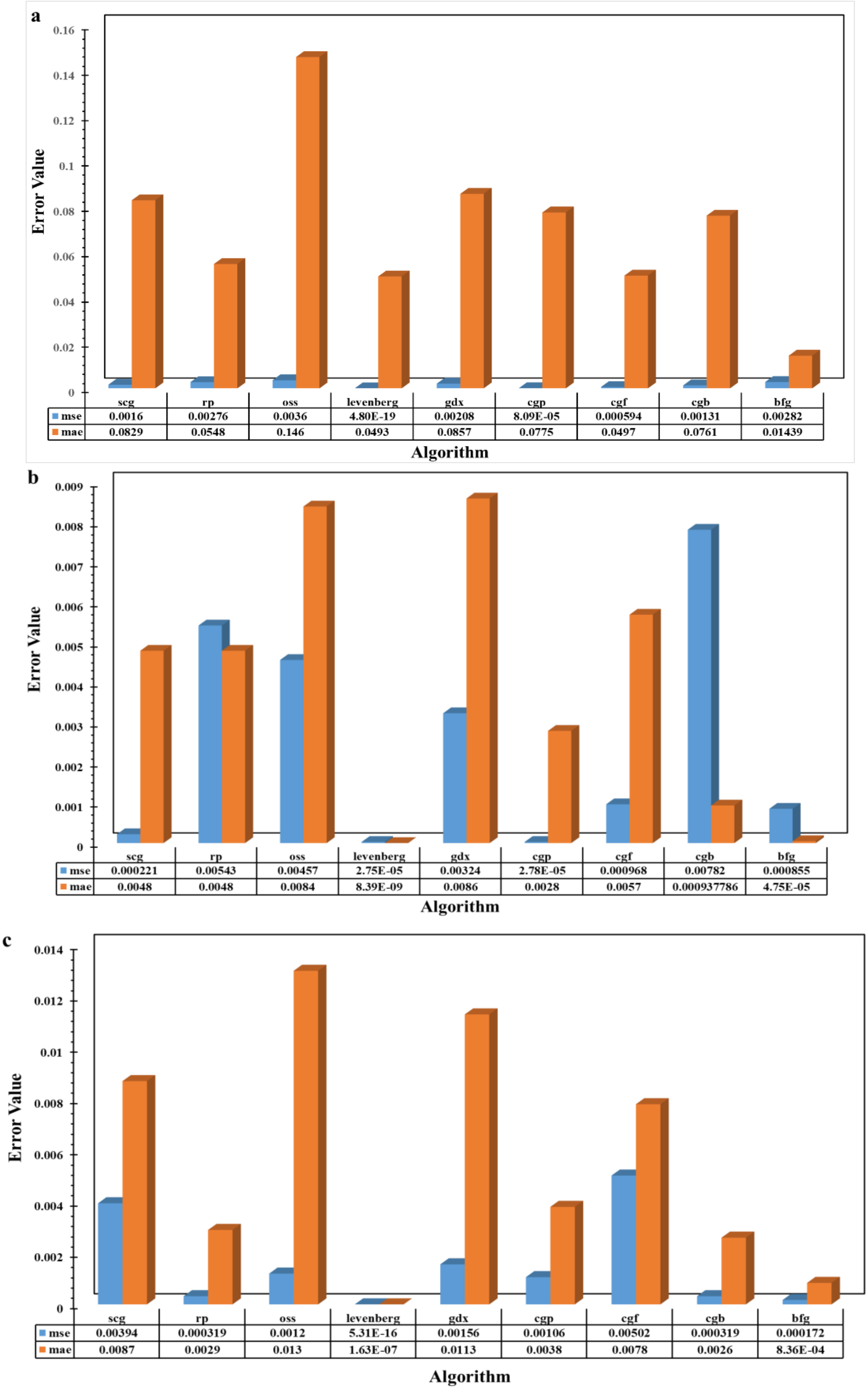

Fig. 7 Performance of ANN models with a different algorithm for a) logsig, b) purelin, c) tansig transform function.

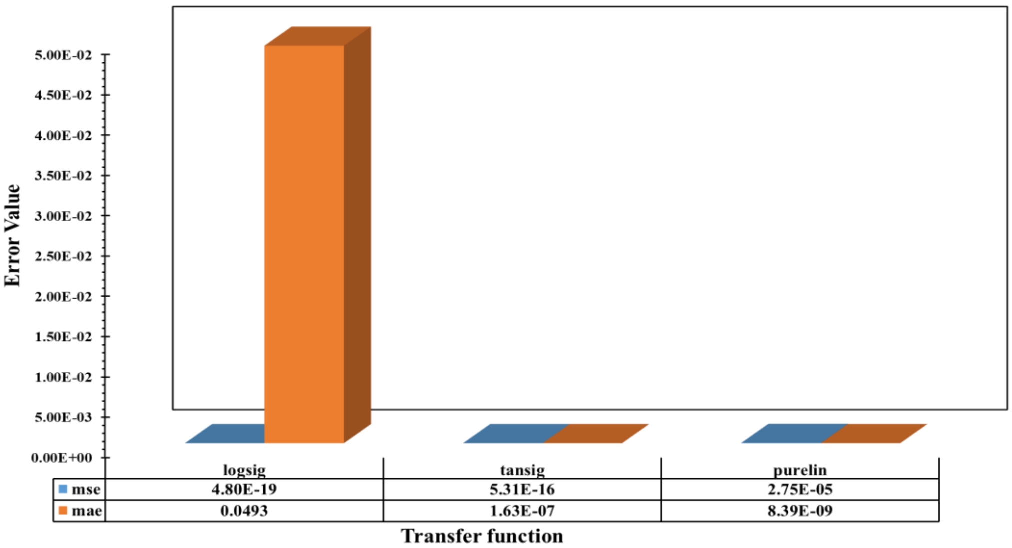

Fig. 8 Performance of ANN models with the different transfer functions for leverberg algorithm.

The training was conducted separately for each group. Being successfully proved in this study, the Levenberg–Marquardt algorithm with Hyperbolic tangent sigmoid transfer function provided the best results in training with the lowest MSE and MAE compared to the other methods. To have a computationally efficient ANN and achieve a better architecture, the MSE of 5.31×10^{-16} was selected as the optimal structure for the prediction. In Fig. 9, the MSE variations are shown for the training, validation, and test the samples during the number of epochs. Fig. 10 shows the measured (input) data and the simulation result of one of the 28 networks. The representation accuracy of neural networks can be implied by the values of R^2 with 1, 0.95685, 0.96134, and 0.98684 for training, validation, and test and for the complete data set, respectively. The target is the corrosion rate, which is determined by coupons exposed to simulating environments with laboratory corrosion chambers, and Output is the value obtained from the prediction model. The Y=T line is where the y-axis value equals the target value. The R values are used to find the relationship between outputs and targets, and it is a useful indicator to check the prediction efficiency of the ANN model. According to the R values in each step, the coefficient of determination values shows the acceptable accuracy.

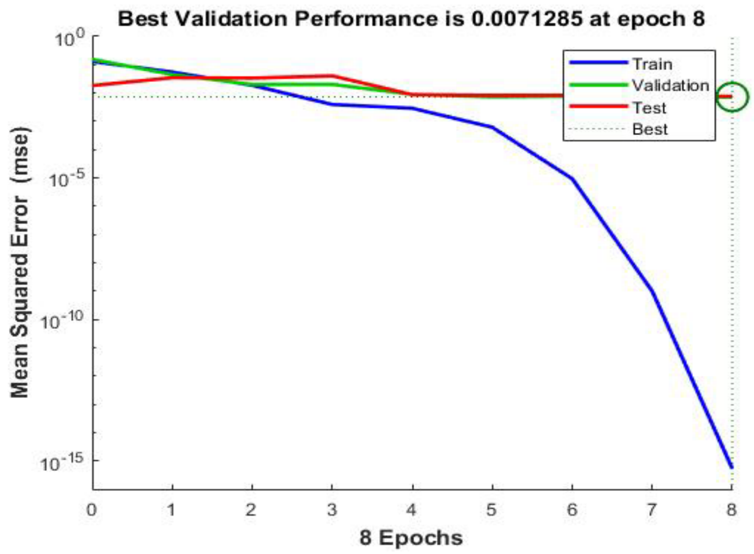

Fig. 9 Regression result of neural network training for MSE of all epochs.

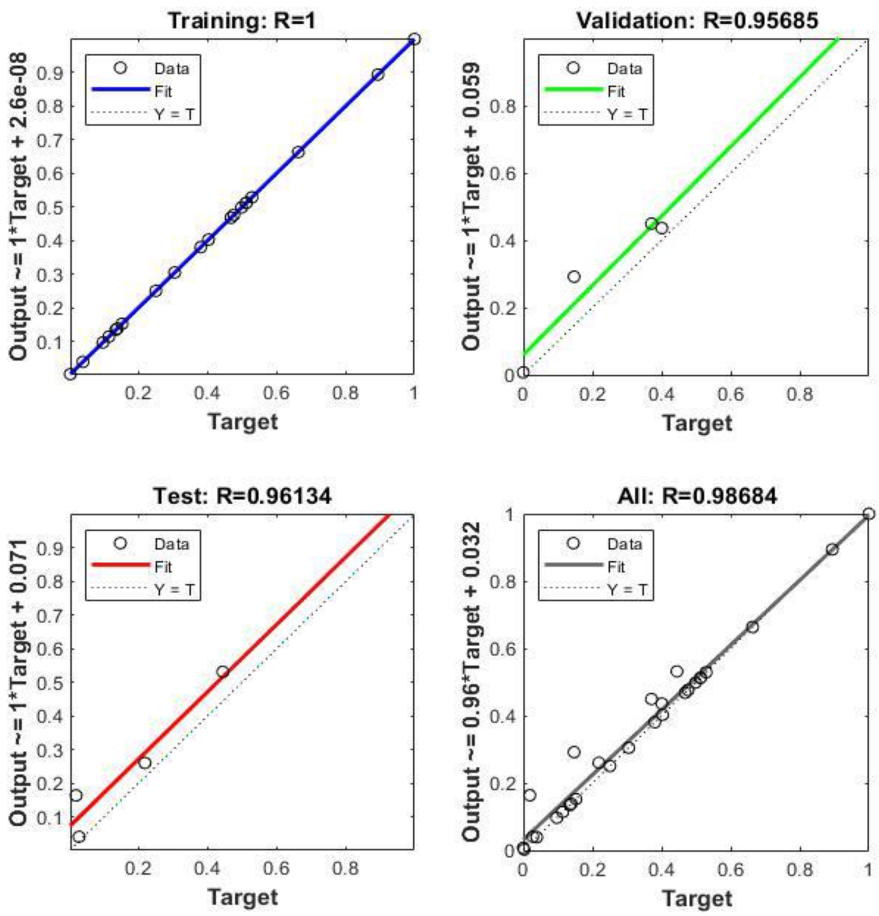

Fig. 10 The outputs of the ANN model and experimental to measured corrosion rate using training, validation, test, and the complete data sets.

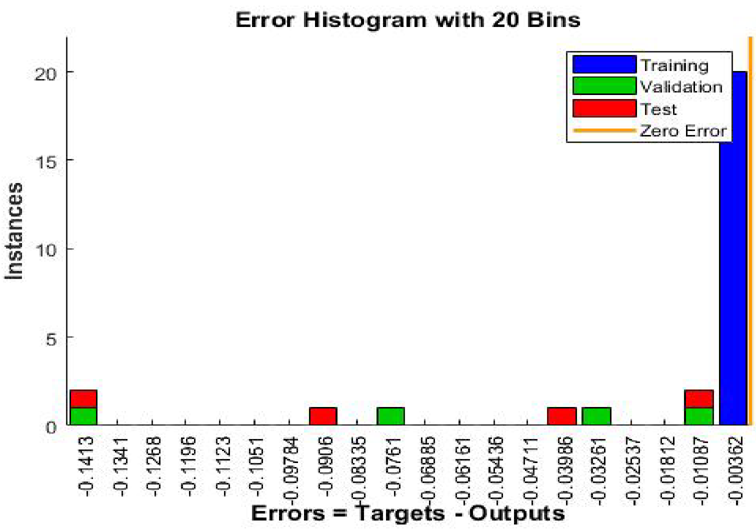

Fig. 11 Error-values for all modeling steps.

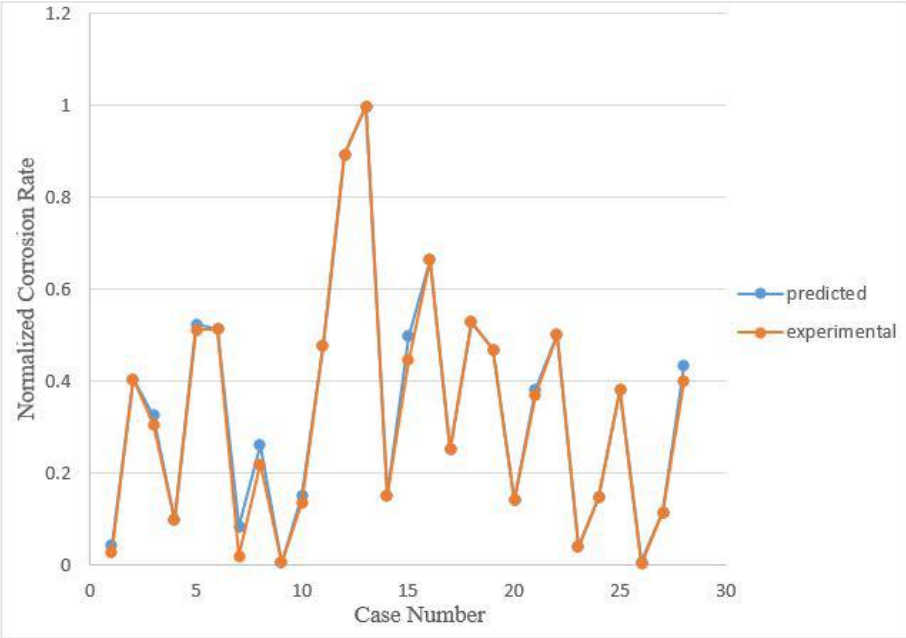

Fig. 12 Experimental and ANN predicted results for 28 case numbers.

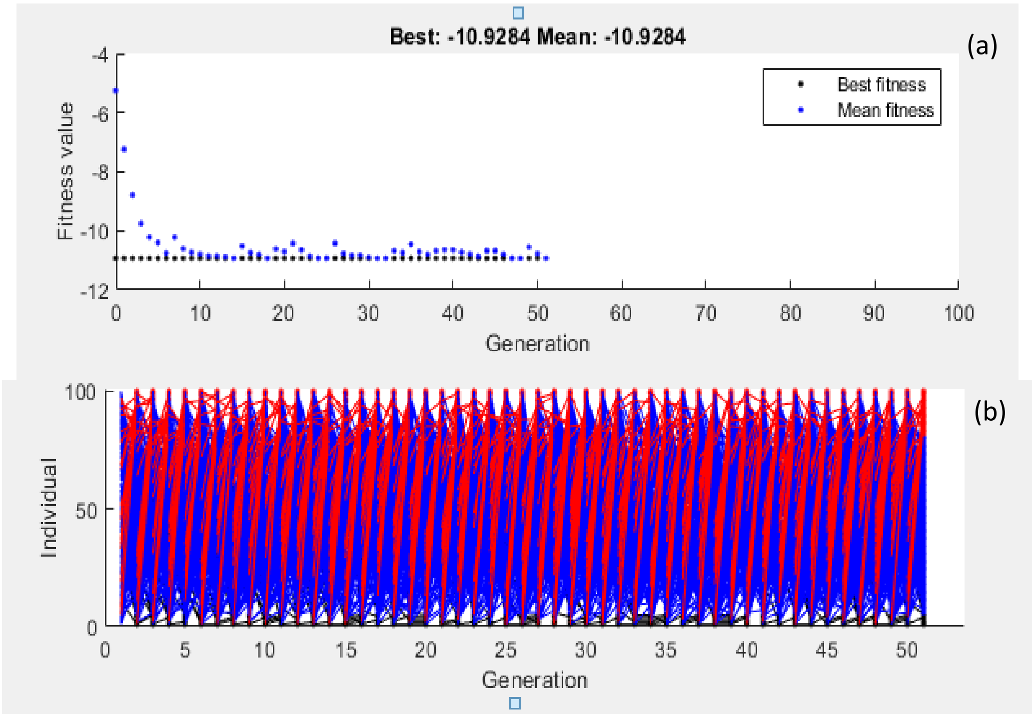

Fig. 13 Best fitness plot for corrosion rate (a) and Genealogy plot of optimization with GA (b).

In Fig.11 the error graph for all modeling steps was presented. The ANN network completely follows the measured values indicating that the network has managed to imitate the corrosion rate fully. For all qualified results, a Root Mean Square Error (RMSE) after the simulation was calculated. To investigate the accuracy of the predicted corrosion rate, we put the predicted and experimental data set in one chart according to 28 tests, as shown in Fig. 12. The prediction model was in perfect agreement with the actual results.

4.2 GA Results

After acquiring the best number of neurons in hidden layers and testing the whole algorithms in three transfer functions to find the lowest error, our optimized ANN model was ready to pair with GA and acted as the fitness function to approach the optimal amount to reduce the corrosion rate of ST37 metal. Optimum inputs for minimum corrosion rate for sodium sulfate salt in the soil are 29.977 (%) and 8.626 (nm) for moisture and Soil particle size, respectively.

Fig 13. Shows the best fitness plot gained from GA and explains the stop in the improvement of future generation and the reproduction in GA after 51 iterations. After optimization, the final optimum corrosion rate based on the plot is 10.9 %. It also showed that GA initially guessed a number and development in the other guesses has been observed. In Fig14. The Genealogy of the individual line from one generation to the other until 50 generations drawn by GA is presented. Red lines indicate mutation children, and blue lines show across over the section, and blackline indicates elite individuals.

5.Conclusion

Corrosion rates for St37 steel in three classes of soil environments with different soil particles size in the presence of NaCl and Na_2SO_4 as salt solutions were measured. Moisture content in the soils was fixed at 10, 20, and 30 %. The ANN model is used to predict the corrosion rate of ST37 metal in some corrosive environments, while the genetic algorithm is being employed to optimize the model. ANN structure was successfully trained, including two hidden layers and five neurons in each layer. The results showed that the predicted model had a good agreement with the actual results. Finally, the error's value for ANN was achieved as follows: the MSE value of 5.31×10^{-16}, the MAE value of $1.63\times10^{-7,}$ and the value of R^2 was 0.98684. Therefore, the corrosion rate, including the effecting parameters, can be anticipated with a high degree of accuracy by knowing the values of the Input data using ANNs. Results from GA indicated the optimum amount of variables for having the lowest corrosion rate after 51 generations.

6.References

[1] A. Saatchi, F. Javid, M. Samadi-Khoshkhoo, *Materials Selection for Minimizing Corrosion in the Chemical Industries*, Arkon Publications, **2008**.

[2] J. Alcántara, B.Chico, J. Simancas, I. Díaz, M. Morcillo, *Marine atmospheric corrosion of carbon steel: A review*. Materials, **2017**, 10(4), 406.

[3] *IEEE Guide for Measuring Earth Resistivity, Ground Impedance, and Earth Surface Potentials of a Ground System, Normal Measurements*, in IEEE Std 81-2012, pp.1-86 28 December **2012**.

[4] Y. Erzin, B. Hanumantha Rao, D.N. Singh, *Int. J. Therm. Sci.*, **2008**, 47, 1347.

[5] Y. Zhang, H. Chen, B. Yang, S. Fu, J. Yu, Z. Wang, *Results Phys*., **2018**, 11, 625.

[6] D. J. Đozić, B. D. Gvozdenac Urošević, *Application of Artificial Neural Networks for Testing Long-Term Energy Policy Targets*, Energy, **2019**.

[7] P. O. Ayegba, M. Abdulkadir, V. Hernandez-Perez, I. S. Lowndes, B. J. Azzopardi., *J. Taiwan Ins. Chem. Eng*., **2017**, 74, 59.

[8] O. Martín, M. López, F. Martín, *J. Mater. Process. Technol.*, **2007**, 183, 226.

[9] Á. Mulero, M. Pierantozzi, I. Cachadiña, G. Di Nicola, *An Artificial Neural Network for the surface tension of alcohols*, Fluid Phase Equilibria, **2017**.

[10] Ó. Martín, P.DeTiedra, M. López, *Corros. Sci.*, **2010**, 52, 2397.

[11] G. Dhanarajan, V. Rangarajan, C. Bandi, A. Dixit, S. Das, K. Ale, R. Sen., *J. Biotechnol.*, **2017**, 256, 46.

[12] X. Wen-Zheng, C. Bao Li, J. Choung, J. Lee. *Adv. Eng. Softw*., **2017**, 112, 255.

[13] S.K. Rana, S. Lata, *Mater. Today Proc.*, **2018**, 5, 5837.

[14] V. Kumar, A. Kumar, D. Chhabra, P. Shukla, *Bioresource Technol.*, **2019**, 271, 274.

[15] Y. Kai, Y. Zhang, L. Yang, Y. Zhao, N. Li, C. Xie., *Appl. Therm. Eng.*, **2019**, 150, 686.

[16] H. Taghavifara, A. Mardania, H. Karim-Maslaka, H. Kalbkhanib, *Appl. Soft Comput.*, **2013**, 13, 354.

[17] M.A. Salam, S.M. Al-Alawi, A.A. Maqrashi, *J. Electrostat.*, **2006**, 64, 338.

[18] A. Cascardi, F. Micelli, M. Antonietta, *Eng. Struct.*, **2017**, 140, 199.

[19] J. Shi, J. Wang, D.D. Macdonald, *Corros. Sci.*, **2015**, 92, 217.

[20] S.D. Kumar, D.K. Verma, Y. Singh, S.H. Hasan. *J. Environ. Chem. Eng.*, **2017**, 5, 1302.

[21] J. Stanley, *Introduction to Neural Networks*, California Scientific Software, Sierra Madre, California, **1990**.
[22] S. Malinov, W. Sha, J. J. McKeown, *Comput. Mater. Sci.*, **2001**, 21, 375.
[23] L.V. Fausett, *Fundamentals of Neural Networks: Architectures, Algorithms and Application*, Prentice-Hall, New York, **1994**.
[24] R.C. Silva, J. Guerreiro, A. Loula, *Adv. Eng. Sofw.*, **2007**;38, 868.
[25] M. Dorofki, A.H. Elshafie, O. Jaafar, O.A. Karim, S. Mastura. *Int. Proc. Chem., Biol. Environ. Eng*. **2012**, 33 39.
[26] D.D. Macdonald, P.C. Lu, M. Urquidi-Macdonald, *Proc. Int'l. Symp. on Plant Aging and Life Prediction of Corrodible Structures*/95, NACE International, Houston, TX, **1995**, pp. 1–7.
[27] P.C. Lu, *Engineering Science, and Mechanics*, Pennsylvania State University, **1994**, pp. 1–274.
[28] J.P. Cai, R.A. Cottis, S.B. Lyon, *Corros. Sci.* **1999**, 41, 2001.
[29] S. Pintos, N.V. Queipo, O.T. de Rincon, A. Rincon, R. Morcillo, *Corros. Sci.*, **2000**, 42, 35.
[30] M. Halama, K. Kreislova, J. Van Lysebettens, *Corros.*, **2011**, 67, 65006.
[31] H.M.G. Smets, W.F.L. Bogaerts, *Corros.*, **1992**, 48, 618.
[32] M. Ben-Haim, D.D. Macdonald, *Corros. Sci.*, **1994**, 36, 385.
[33] J. Wang, Z. Sun, Y. Dai, S. Ma, *Appl. Energy*, **2010**, 87, 1317.
[34] S. Ranjna, A. Singh, A. Tarafdar, N.C. Shahi., *Bioresource Technol.*, **2018**, 270, 751.
[35] Q. Huan, G. Yi, L. Zijian, L. Yu, Z. Haolong, *Adv. Eng. Softw.*, **2018**, 121, 235.
[36] ASTM G1- Standard Practice for Preparing, Cleaning, and Evaluating Corrosion Test Specimens.
[37] S. Malinov, W. Sha, *Mater. Sci. Eng. A*, **2004**, 365, 202.
[38] G. Jiang, J. Keller, P.L. Bond, Z. Yuan, *Water Res.*, **2016**, 92, 52.
[39] Y. Zhang, H. Chen, B. Yang, S. Fu, J. Yu, Z. Wang, *Results Phys.*, **2018**, 11, 625.
K.S. Sangwan, S. Saxena, G. Kant, *The 22nd CIRP Conference on Life Cycle Engineering Procedia CIRP 29*,**2015**, pp. 305–310.