Study the Effect of Seawater Environments and Surface Roughness on Uniform Corrosion Rate of Carbon Steel Using Neural Network Modeling

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Abstract

In this research, the effect of seawater environments and surface roughness on uniform corrosion rate of carbon steel (A516 grade 65) was studied depending on the experimental work and artificial neural network modeling. The experimental work involves chemical composition, samples machining, roughness measurements (for carbon steel specimens), conductivity and salinity measurements (for seawater), and uniform corrosion test. Weight loss technique was employed in determining the uniform corrosion rate in carbon steel material. Also, artificial neural network (ANN) model was built to predict the values of uniform corrosion rate (mpy) at different values of conductivity, salinity for seawater and roughness factor for carbon steel depending on the experimental results which were used train and test the ANN.

The results obtained of uniform corrosion rate by ANN predictions are shown to be agreed well against experimental values. i.e. correlation coefficient, R=0.9974

دراسة تأثير محيط ماء البحر وخشونة السطح على معدل التاكل المنتظم للصلب الكربوني بأستخدام الشبكات العصبية الاصطناعية

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الخلاصة

في هذا البحث ، تم دراسة تأثير محيط ماء البحر وخشونة السطح على معدل التاكل المنتظم في الصلب الكربوني (A516 grade 65) اعتماداً على الاختبارات العملية ونموذج الشبكة العصبية الاصطناعية. تضمنت الاختبارات العملية التحليل الكيميائي لمادة الصلب الكربوني ، تشغيل وتحضير العينات ، قياسات خشونة السطح للعينات ، قياسات موصلية وملوحة ماء البحر ، واختبار التاكل المنتظم. استخدمت طريقة فقدان الوزن في حساب معدل التاكل المنتظم في الصلب الكربوني. كذلك تم بناء نموذج الشبكة العصبية الاصطناعية لتنبؤ قيم معدل التاكل المنتظم (ملغرام/سنة) عند قيم مختلفة لموصلية وملوحة ماء البحر وخشونة سطح العينات وذلك بالاعتماد على نتائج الاختبارات العملية والتي استخدمت لتدريب واختبار الشبكة العصبية الاصطناعية.

أظهرت نتائج البحث بأن هنالك توافق كبير بين قيم معدل التآكل المنتظم التي تم التنبؤ بها بواسطة الشبكات العصبية الاصطناعية وبين قيم معدل التاكل المنتظم العملية ، أي ان قيمة معامل الارتباط = 0.9974

1. Introduction

Corrosion involves the interaction (reaction) between a metal or alloy and its environment. Corrosion is affected by the properties of both the metal or alloy and the environment [1]. Due to aggressive environment prevailing in seawater, the materials of construction are subjected to corrosion of varying degree. There are many factors influencing the initiation of one or several corrosion processes. These factors include nature of material, surface finish, seawater environment ,temperature, etc[2].

Carbon Steel, the most widely used engineering material, accounts for over 64 million tons, or approximately 88%, of the annual steel production in the United States. Despite its relatively limited corrosion resistance, carbon steel is used in large tonnages in marine applications, nuclear power and fossil fuel power plants, transportation, chemical processing, petroleum production and refining, pipelines, mining, construction, and metal-processing equipment. The cost of metallic corrosion to the total economy must be measured in hundreds of millions of dollars per year. Because carbon steels represent the largest single class of alloys in use, both in terms of tonnage and total cost, it is easy to understand that the corrosion of carbon steels is a problem of enormous practical importance. This, of course, is the reason for the existence of entire industries devoted to providing protective systems for irons and steels [3].

The basic properties of ANN are that it is particularly suited to problems whose solution is complex and difficult to specify. Neural networks learn by example, and as long as examples are available and an appropriate design is adopted, effective solutions can be constructed far more quickly than is possible using traditional approaches, which are entirely reliant on experience in a particular field. Training a neural network is computationally intensive, but the computational requirements of a fully trained neural network when it is used on test data can be modest. Many other processing techniques are based on the theory of linear system; in contrast, neural networks can be trained to generate non-linear mappings and this often gives them an advantage for dealing with complex, real-world problems [4].

One of the more important factor used in this study is surface roughness. The terms surface finish and surface roughness are used very widely in industry and are generally used to quantify the smoothness of a surface finish. In 1947, the American Standard B46.1-1947 [5], Surface texture is the pattern of the surface which deviates from a nominal surface. The deviations may be repetitive or random and may result from roughness, waviness, lay, and flaws. Surface finish could be specified in many different parameters. Due to the need for different parameters in a wide variety of machining operations, a large number of newly developed surface roughness parameters were developed. Some of the popular parameters of surface finish specification are described as follows:

• Roughness average (Ra): This parameter is also known as the arithmetic mean roughness value, AA (arithmetic average) or CLA (center line average). Ra is universally recognized and the most used international parameter of roughness. Therefore,

$$Ra = \frac{1}{L}\int_0^L |Y(x)|\,dx \qquad \ldots(1)$$

where Ra = the arithmetic average deviation from the mean line

L = the sampling length

y = the ordinate of the profile curve It is the arithmetic mean of the departure of the roughness profile from the mean line.

• Root-mean-square (rms) roughness (R*q*): This is the root-mean-square parameter corresponding to R*a*:

$$Rq = \sqrt{\frac{1}{L}\int_0^L (Y(x))^2\,dx} \qquad \ldots(2)$$

• Maximum peak-to-valley roughness height (R*y* or R*max*): This is the distance between two lines parallel to the mean line that contacts the extreme upper and lower points on the profile within the roughness sampling length.

Since Ra and Rq are the most widely used surface parameters in industry, Ra was selected to express the surface roughness in this paper.

Several papers have been employed for seawater corrosion such as Corrosion Behavior of Selected Metals in Arabian Gulf Seawater [6], Corrosion Initiation and Propagation of Ni-Base Alloys in Seawater Applications [7], Localized Corrosion Tendencies of Piping Materials used in

Chlorinated Seawater [8], and Understanding and Modeling Galvanic Corrosion in Marine Environments [9], etc.

2. Experimental Work

The experimental work includes: specimens preparations, surface preparation, conductivity/salinity measurements and uniform corrosion test. The results were used in the training and testing of the artificial neural network to predict uniform corrosion rate (mpy) for carbon steel.

2.1 Specimens preparations

Sixty specimen of carbon steel A516 grade 65 were machined from solid bar (length 1m , diameter 12 mm) by sawing Machine to 5 mm depth and 12mm diameter as shown in Fig. (1).

Fig. (1) Specimens of the present work

2.2 Chemical Composition

The chemical composition of the specimens used in the present study was carried out using optical emission spectrometer (PM1-Master PRD model 2008, Germany). The chemical composition was found correspond to Alloy A516 grade 65 according to ASTM standard values [10] given in Table (1).

2.3 Surface preparation

The specimens were subjected to different degrees of surface finish. Polishing of the specimens is carried out by machine (Struers Knuth-Rotor-3) type, using successively different grades of abrasive papers. The preliminary polishing stages were alternately longitudinal and circumferential to ensure that longitudinal scratches made by the coarser grades of abrasive papers are removed, but the direction of the final stage was longitudinal. The finished test section of the specimens became obviously contain no unintentional stress raisers, such as transverse scratches or poorly-blended transition fillets. The measurements of surface roughness were performed using surface roughness tester type *Qualitest TR-110, US* in terms of surface roughness factor *Ra* in (μm) according to ISO 4287:1997 Standard. The prepared specimen surfaces with different surface roughness factor were utilized for precorrosion stage.

2.4 Conductivity/Salinity Measurements

Aqueous chloride solutions of varying chloride concentration and seawater (Shatt Al-Arab, Shatt Al-Basrah seawater) were used during the uniform corrosion tests. Conductivity is a measurement of the conductive material in the liquid sample. Measures the ability of water to carry an electrical current. It is dependent upon the concentration and type (oxidation state and mobility) of ions in the water and the water temperature. While, salinity is a measure of the salt concentration of water; higher salinity means more dissolved salts.

Standard Operating Procedure (SOP) for Field Measurements of Conductivity/Salinity with a Conductivity YSI Meter and Probe. This SOP is to be followed for all field measurements of conductivity or salinity using the YSI 30 meter and probe.

2.5 Uniform corrosion Test

Corrosion behaviour is a combined property of the metal and the environment to which it is exposed. Therefore, there is no universal corrosion test for all purposes. The factors associated with both the metal and the environment should be considered and controlled, when necessary, to establish appropriate exposure conditions during testing. Uniform corrosion is one of

the most common forms of corrosion; therefore, it must be designed for in many situations. The damage appears as the thickness of the metal decreases uniformly until failure occurs. Fortunately, uniform corrosion is usually easy to measure and predict; this facilitates proper design [1].
The freshly prepared specimens of 12mm diameter and 5mm thickness were weighted to the nearest 0.0001 g. The uniform corrosion process involved immersion of specimens in different seawater conductivity/salinity at temperature of 25±2^{o}C, within a specified duration period of 24, 48, 72 and 96 hours in each individual conductivity/salinity. After uniform corrosion test was done, the specimens were weighted again to calculate the loss mass in every specimen.
Uniform corrosion rates are represented as a loss of metal thickness as a function of time. These values were measured from mass loss data. Mass loss is a measure of the difference between the original mass of the specimen and the mass when sampled after exposure. As mass loss was monitored, the reduction of thickness as a function of time was calculated and monitored. Uniform corrosion rates are usually expressed as millimeters per year (mm/yr), mils per year (mils/yr), and/or inches per year (in./yr). A corrosion rate in mils per year was calculated from weight loss data with the following expression:

$$mpy=(534w/dAt) \qquad \ldots(3)$$

where w is weight loss in milligrams, d is metal density in grams per cubic centimetre (g/cm3), A is area of exposure in square inches (in.2), and t is exposure time in hours.

3. Artificial Neural Network Modeling

The artificial neural network modelling was used to predict the uniform corrosion rate in carbon steel under the effect of seawater environments and metal surface roughness. The inputs are conductivity (S/m), salinity (g/kg), and roughness factor (μm) and output was corrosion rate (mpy). The randomly selected data used to train and test neural network are 45 and 12 respectively.
During the training process, the network weights are continuously adjusted till the difference between the predicted output and experimental value is minimized, i.e. the error function defined as the sum of squares of the difference between predicted and experimental value on all the data reaches a set limit or the number of predetermined training operations are completed. A critical factor in developing a robust model is the numerical optimization technique applied for minimizing the error. Neural network functions depend non-linearly on their weights and so the minimization of the corresponding error function requires the use of iterative non-linear optimization algorithms. These algorithms make use of the derivatives of the error function with respect to the weights of the network. Resilient backpropagation algorithm is the optimization technique employed in building of present artificial neural networks. After completing the training process, the model is tested using another batch of data which has not been used in the training set [11].
The following statistical parameters of significance are calculated at the end of the training and testing calculations:
1. *Correlation coefficient* (*R*): is a measure of how the actual and predicted values correlate to each other. The goal is to maximize the value of *R*.
2. *Mean square error* (MSE): is a statistical measure of the differences between the values of the outputs in the training set and the output values the network is predicting. The goal is to minimize the value of MSE.
The statistical parameters used to give a description for good training for the present artificial neural networks modelling are: R= 0.9974, MSE=$1.232*10^{-6}$
Two hidden layers are used in the neural network modelling of the present study

because it performs significantly better than one hidden layer. Although, using a single hidden layer might be sufficient in solving many functional approximation problems, some other problems may be easier to be solved with two hidden layers configuration [12].

The number of nodes in the hidden layer will be selected according to the following rules:

1. The maximum error of the output network parameters should be as small as possible for both training patterns and testing patterns.
2. Mean square error should be small as much as possible.

The optimal configurations in two hidden layers networks with minimum mean square error (MSE) and maximum correlation coefficient for the present neural network are 17:8 (17 nodes in the first hidden layer and 8 in the second hidden layer).

4. Discussion

4.1 Neural Network Architecture

The architecture of neural network for this model is given in Figure (2). It consists of three nodes in the input layer, two hidden layers are chosen which gives minimum mean square error (MSE) and maximum correlation coefficient, the first hidden layer has (17) nodes, and the second hidden layer has (8) nodes. The output layer has single node which was represented by uniform corrosion rate.

The decision function used for both of the first hidden layer and second hidden layer is (*tansig*), and for the output layer is (*purelin*). These functions were chosen for first hidden, second hidden and the output was obtained by trial and error until the best performance was achieved by approaching the minimum values of mean square error and maximum correlation coefficient. The results obtained of uniform corrosion rate by artificial neural network prediction was shown to be agreed well against experimental values. i.e. correlation coefficient, R=0.9974 as shown in Figure (3).

4.2 Surface Roughness

Figure (4) shows the effect of surface roughness factor on uniform corrosion rate at different salinity weight. It was found that uniform corrosion rate increases directly with the increase of both roughness factor and salinity weight. For instance, rough surface corrodes and enhances general corrosion more readily than smooth surface [1].

Also, the low roughness factor with different salinity weight (Figure 4) did not show a remarkable increase in uniform corrosion rate. In general, samples prepared with a smooth surface finish (low roughness factor) are not susceptible to corrosion and exhibit a higher corrosion potential (i.e. decrease uniform corrosion rate) [1].

4.3 Salinity/Conductivity

The effect of salinity weight on uniform corrosion rate of carbon steel A516 grade 65 at different roughness factor was shown in Figure (5). It is clear that increasing of salinity weight will increase the uniform corrosion rate. Increase of salt in seawater increase the corrosion rate of iron. This increase is reported to be proportional to the increase of salt concentration. [13]. A similar effect is reported for chloride ion in HCl. Thus, chloride ion accelerates the corrosion of ion in acidic solutions [14].

The effect of seawater conductivity on uniform corrosion rates of carbon steel A516 grade 65 at 25±2^{o}C as studied by weight loss method indicate that the uniform corrosion rates do not follow a regular pattern at different roughness factor but in general, the uniform corrosion rate increase directly with increasing of seawater conductivity as shown in Figure (6).

Metcalf and Eddy (1991) [15] states that "the electrical conductivity (EC) of water is used as a surrogate measure of total dissolved solids (TDS) concentration.

Conductivity typically has a strong linear relationship to TDS. Therefore, increasing of conductivity will increase of TDS and this means that increasing of TDS leads to increase of uniform corrosion rate in seawater because the passive film of metal will break down [16].

5. Conclusions

The most important conclusions that can be drawn from the present study are as follow:

1. The results of artificial neural network modelling were found to be agreed well with that obtained from experimental work.
2. In general, increasing of salinity weight with extended conductivity resulted in an increase of uniform corrosion rate.
3. There is a large effect of rough surface on increasing of uniform corrosion rate.

6. References

[1] Metals Handbook, “Corrosion: Fundamentals, Testing, and Protection”, Vol.13A, ASM, Metals Park, Ohio, 2003

[2] Anees U. M., Shahreer A. , and Ismaeel A., “Corrosion Behavior of Steels in Gulf Seawater Environment”, WSTA 4th Gulf Conference, Bahrain, 1999

[3] Coburn S.K., “Atmospheric Factors Affecting the Corrosion of Engineering Metals”, ASTM STP 646, Philadelphia, 1978

[4] L Tarassenko, “A guide to neural computing applications”, John Wiley & Sons Inc., New York, 1998

[5] Brosheer, B. C., “How Smooth is Smooth? Part-I, Specification and Evaluation of Machined Finishes”, American Machinist, McGrow-Hill , pp. 97-112., 1948

[6] Al-Ghamdi A. M., Nusair Y. H., and Cocks F. H., “Corrosion Behavior of Selected Metals in Arabian Gulf Seawater”, *Proceeding of the 7th Middle East Corrosion Conference,* Bahrain, pp 475-486. 1996

[7] Oldfield J. W., “Corrosion Initiation and Propagation of Ni-Base Alloys in Seawater Applications”, Corrosion '95 paper 266 NACE, 1995

[8] Boah J. K. and Frazer P., “Localized Corrosion Tendencies of Piping Materials used in Chlorinated Seawater”, *Proceeding of the 7th Middle East Corrosion Conference*, Bahrain, p 409, 1996.

[9] Shifler D. A., “Understanding and Modeling Galvanic Corrosion in Marine Environments”, Corrosion/ 2006, NACE, 2006

[10] ASTM International, “Specification for pressure vessel plates, for moderate and lower temperature service”, ASTM 516, 1995

[11] L Tarassenko, “A guide to neural computing applications”, John Wiley & Sons Inc., New York, 1998

[12] Mathwork Inc., "Preprocessing and postprocessing", NNW tool box, (Mathlab help), 2007

[13] Abd. El Rehim S.S., Shalaby M. Sh., and Abd. El Halum S.M, “Effect of Some Anions on the Anodic Dissolution of Delta-S2 Steel in Sulfuric Acid”, *Surface. Technology.*, Vol 24, p 241, 1985

[14] Chin R. J. and Nobe K., “Electrodissolution Kinetics of Iron in Chloride Solutions”, *J. Electrochem. Soc.*,Vol 119 (No. 11), p 1457, 1972

[15] Metcalf and Eddy, “Wastewater Engineering McGraw-Hill” , New York, 1991.

[16] Kriston A., and Lakatos-Varsa M. “Testing and analyzing metastable corrosion”, Electrochimical Acta. Journal, Vol. 46, pp. 3699– 3703, 2001

Table (1) Results of chemical composition in wt% for carbon steel A516 grade 65 compared to ASTM Standard

Material	**Carbon**	**Manganese**	**Phosphorus**	**Sulphur**	**Silicone**
Chemical Composition	0.20	0.83	0.01	0.035	0.20
ASTM Results [21]	0.24 max.	0.79-1.30	0.035 max.	0.035	0.13-0.45

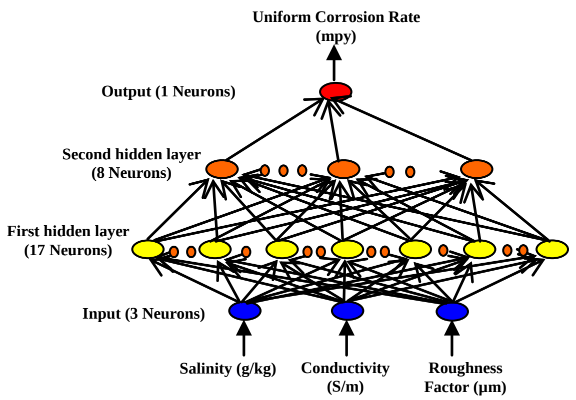

Fig. (2) The Structure of The Proposed ANNs.

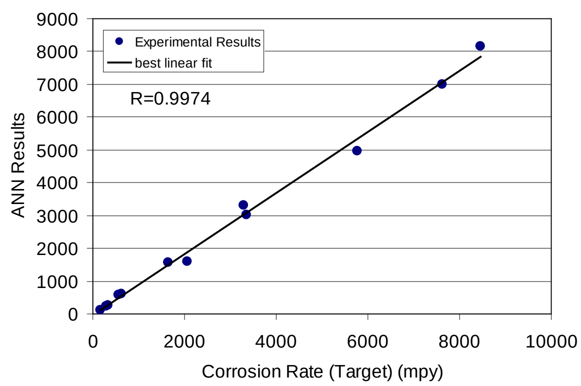

Fig.(3) Comparison between ANN Results and Target Results using Resiliant Backpropagation Algorithm

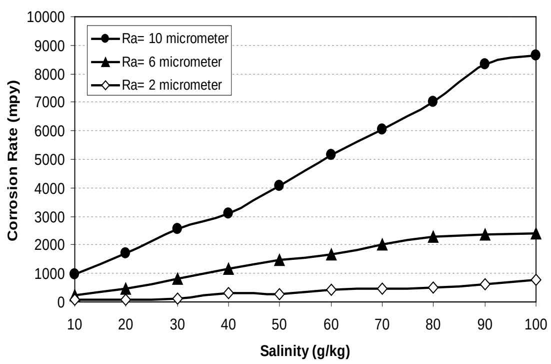

Fig. (5) Effect of salinity on corrosion rate at different roughness factor

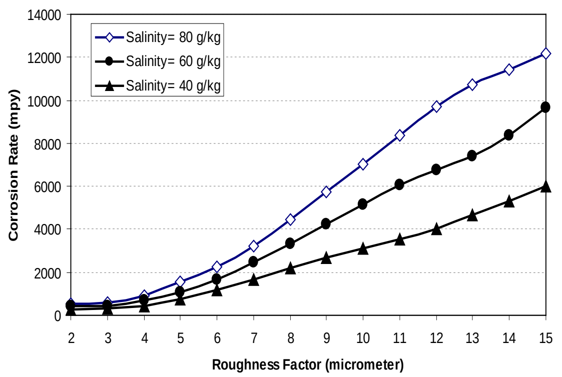

Fig. (4) Effect of roughness factor on corrosion rate at different salinity weight

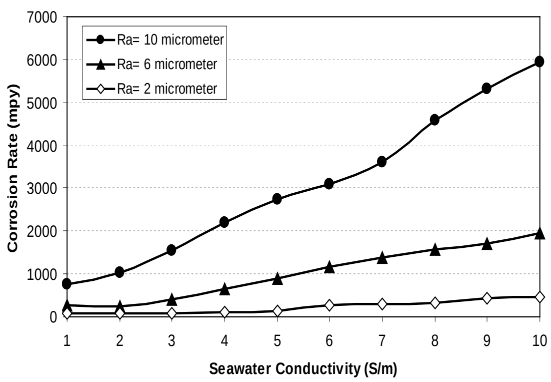

Fig. (6) Effect of Seawater Conductivity on corrosion rate at different roughness factor