Modeling of Corrosion Rate Under Two Phase Flow in Horizontal Pipe Using Neural Network

Fadhil Sarhan Kadhim
University of Technology
Petroleum Technology Department

Yousif Khalaf Yousif
Ministry of Higher Education and Scientific Research
Research and Development Department

Abstract

The present study develops an artificial neural network (ANN) to model an analysis and a simulation of the correlation between the average corrosion rate carbon steel and the effective parameter Reynolds number (Re), water concentration (Wc) % temperature (T ^{o}) with constant of PH 7 . The water, produced fom oil in Kirkuk oil field in Iraq from well no. k184-Depth2200ft., has been used as a corrosive media and specimen area (400 mm^2) for the materials that were used as low carbon steel pipe. The pipes are supplied by Doura Refinery . The used flow system is all made of Q.V.F glass, and the circulation of the two –phase (liquid – liquid) is affected using a Q.V.F pump .The input parameters of the model consists of Reynolds number , water concentration and temperature. The output is average corrosion rate .The performance of the two training algorithms, gradient descent with momentum and Levenberg-Marquardt, are compared to select the most suitable training algorithm for corrosion rate model. The model can be used to calculate the average corrosion rate properties of carbon steel alloy as functions of Reynolds number, water concentration and temperature. Accordingly, the combined influence of these effective parameters and the average corrosion rate is simulated. The results show that the corrosion rate increases with the increase of temperature, Reynolds number and the increase of water concentration.

الخلاصة

في الدراسة المقدمة، قد تم تطوير نموذج شبكة عصبية اصطناعية(ANN) لتحليل ومحاكاة للعلاقة ما بين متوسط معدل تآكل الكربون الصلب والعوامل المؤثرة وهي (عدد رينولد وتركيز المياه ودرجة الحرارة) بثبات PH . الماء المستخدم بالدراسة هو الماء المنتج مع النفط في حقل النفط في كركوك في العراق برقم .k184-Depth2200ft و قد تم استخدام وسط للتآكل ومنطقة العينة (400 mm^2) على المواد التي تستخدم الانابيب الفولاذية ذات الواطئ والتي توفرها مصفاة الدورة وقد تم استخدام نظام التدفق بواسطة Q.V.F الزجاجي وتدوير ثنائي الطور (سائل – سائل) باستخدام مضخة Q.V.F ، عوامل الادخال للنموذج المقترح كانت رقم رينولدز و تركيز الماء ودرجة الحرارة والناتج الخارج من النموذج هو معدل التأكل . الاداء لطريقتي تدريب الشبكة الاصطناعية وهما (هبوط الانحدار مع الزخم و ليفن بيرك ماركورت) قورن لاختيار طريقة التدريب الاكثر ملائمة للنموذج معدل التأكل ويمكن استخدام هذا النموذج لحساب خواص معدل التأكل لسبيكة الفولاذ كاربون كمعادلة مع معامل رينولد وتركيز المياه ودرجة الحرارة . التأثير المتراكب لهذه العوامل المؤثرة مع معدل التأكل تم تمثيله حيث بينت النتائج ان معدل التأكل يزيد بزيادة هذه العوامل المذكورة انفا .

Keywords: Corrosion rate, Two phase flow, ANN, Modeling

Introduction

The applications of two phase flow are found in petroleum exploration ,transport chemical engineering, nuclear reactors and thermal systems [Wenyin Zhang 2010]. In oil field water is often produced in large quantities with crude and the characteristics of two phase flow are of interest both in well itself where the flow is vertical in the production tubing and in horizontal pipe lines transporting crude oil to filed treating facilities [F. Sarhan 1996]. Many studies have investigated two-phase capillary flow in the last 50 years. Some of them have used mathematical approaches based on numerical simulations to generate a theoretical model of capillary flow. Most of these models have considered two thermodynamic equilibrium regions of sub-cooled liquid and a two-phase vapor–liquid mixture [P.K. Bansal 1998 - S.M. Sami1998 - P. Kritsadathikarn 2002 - M. Fatouh 2007]

The corrosion can be defined as the distractive attach of metal by a chemical or electrochemical reaction with its environment [Uhlig H.H 1977]. Generally the produced water with crude oil leads to corrosion problem because these contents are impurities or dissolved substances such as salt, acid, hydrogen sulfide, carbon dioxide and oxygen which increase the corrosivity of the produced water.

The experimental work

The present study uses low carbon steel pipe which is supplied by Daura Refinery. The pipe is about 2m in length , and 2.54 cm in diameter. It consists of the following chemical composition :

C=0.084% ,Si= 0.225% , Mn=0.787% , P=0.022%,S=0.015% , Cr=0.163%, Mo=0.043% ,Ni=0.13% , Cu=0.232%, V=0.004% , Fe= remains.

The cylindrical specimens, which have a length of 0.5 cm and diameter of 2.54cm and are cut from a carbon steel pipe, are annealed in vacuum at 600C° for an hour (to remove the effect of cold working). Then the furnace is cooled under vacuum to room temperature. Specimens are abraded in sequence under running tap water by using 240,320,420 and 600 emery paper grades. After that, the specimens are washed with running tap water and instantly followed by distilled water. Then they are dried with clean tissue paper ,immersed in ethanol ,dried with clean tissue paper ,immersed in acetone and dried with clean tissue paper respectively. Finally, they are left to dry for an hour over silica gel before use. The water ,which is produced along with oil in Kirkuk oil field from well No. K184, depth of 2200ft , has the following composition:

$CaHCO_3$ =5670ppm, $CaSO_4$ =3451ppm,$CaCl_2$ = 513ppm , $MgCl_2$ =3789ppm,NaCl=13538ppm.

It is worth mentioning that this water was used as corrosive media.

The flow system that has been used, as shown in (figure 1), is made of Q.V.F glass . The circulation of the two-phase liquid (Gas oil-water) was affected using Q.V.F pump and the total flow rate is measured by two calibrated rotary meter with range (0-1400L/hr.).

Different total flow rates, different Reynolds number; (5000, 75000 ,10000, 125000),different phase concentrations (15%, 25%, 35% and 45%) and different temperatures (30 C° and 50 C°) have been tested to calculate the corrosion rate by using weight loss method . Three specimens have been used in each run . The average corrosion rate (A.C.R) was equal to the arithmetical average of three specimens ,The equation of calculation of corrosion rate is as follows:

$$C\,.\,R = \frac{\Delta W}{A * T} \tag{1}$$

where :

A=area of specimens exposed to the environment A=πdl

d=inside diameter of specimen , l=length of specimen .

Δw=weight loss .

The experimental data set were calculated as shown in table(1) and plotted in figure (2). They refer to inputs parameter (Reynolds number, temperature and water concentration) to propose a model and an output (corrosion rate). As shown in table (1), the

highest corrosion rate was found at the temperature (50 o) ,Reynolds number (12500) and a (45%) water concentration, because the increase of temperature leads to the increase of the reaction rate between corrosive media and metal surface. Accordingly, the increase of the flow rate leads to the removal of oxidation results at metal surface . Hence, the corrosive media becomes closely related to metal surface. Finally, it is believed that the increase of water concentration increases the corrosion rate, because the corrosive media covers a large area of metal surface.

Proposed Model and Artificial Neural Network (ANN)

Artificial intelligence (AI) predictions have been widely used in the domain of model systems which are rarely modeled by the use of traditional methods. They have been referred to as having the ability to be trained like humans, by accumulating knowledge throw recurring learning activities[8].

A feed-forward neural network with nine inputs neuron, one with a hidden layer and one with an output neuron, were used. The architecture of the model is depicted in fig (3). The activation function in the hidden layer is Log-Sigmoid transfer function which normalizes the data and, hence, the transformed data which lie between -1 and 1 . In the output layer the linear transfer function is used.

Training a network involves presenting it with examples, and representing the relationship between inputs of process (Reynolds number, temperature and water concentration) and output (average corrosion rate) as well. These examples are called "training data set patterns". Table (1) shows the training data set. There is a large number of training algorithms for feed forward neural network, as discussed in a previous section.

It is very hard to decide which Algorithm performs better for a specific application. Thus the neural network model has been trained using two different training algorithms:

1- Gradient Descent with Momentum Algorithm.

2- Levenberg - Marquardt Algorithm.

The performances of these two training algorithms are compared to decide which algorithm performs better than the other. The neural network may converge to a local minimum rather than a global one. Therefore, some sort of simulated annealing technique is used to find the best solution among many local minima [9]. The annealing technique is clarified as follows: once the network converges to a local minimum, the network state is perturbed in a random direction and by a random magnitude. Then the network dynamics are reactivated. Herby, another local minimum is found. During this process, the algorithm keeps track of the best solution. After finding a predetermined number of local minima, the algorithm terminates and the solution with the lowest error is accepted as the best solution.

After examining the performance of different architectures, a network with one hidden layer (include 9 neurons) trained by Levenberg-Marquardt algorithm has showed good performance indication. Figure (5) shows the training session as the training error decrease versus number of iterations (epochs) until goal error meeting

Where:

W1: weights among Ren and hidden layer.

W2: weights among Temp. and hidden layer.

W3: weights among WC % and hidden layer.

W3: weights among hidden layer and Output layer (corrosion rate).

b1: bias to hidden layer b2:bias to output layer.

Post Training Analysis

The data set obtained from experiments are divided randomly into three subsets, namely training and testing sets in 50% to 10% of the total data, respectively. The training set is used to calculate the gradient and to form the weight factors and bias. The remaining 10% testing data set is used to calculate the prediction error to estimate the accuracy of the models on the unseen data set, but it is often useful to investigate the network response in more details. One option is to perform a regression analysis between the network response (predicted outputs) and the corresponding targets. Figure(6) illustrate a straight line representing the

best linear regression relating targets (actual of average corrosion rate) to network response.
When perfect fit had been found (predicted outputs exactly the same the actual values), the slope of this straight R line would be one .From figure (7) and figure (8) it can be shown that these values are very close, which indicate a good response to training sets.

Neural Network Simulation

Testing of neural network model requirs new independent (test sets) to validate the generalization capability of network. Table (4.8) shows testing data sets for the network and the response of the network to these data sets.
The prediction accuracy for the testing patterns based on mean absolute percent error (APE) criteria in eq. (2) :

$$APE= \{ \left| Predicted - Actual \right| /Actual\}*100\% \quad (2)$$

Conclusions

The main conclusions obtained from the present research are :

1. Corrosion rate increases with increasing Reynolds number, water concentration and temperature.
2. The multilayer feed-forward neural network is successfully mapping the relationship among inputs parameters corrosion rate under two phase flow in horizontal pipe.
3. For the proposed NN model the Levenberg – Marquardt algorithm shows better performance than gradient descent with momentum because it uses 2nd order Taylor series approximation of performance index rather than 1St order approximation as with gradient descent algorithm.

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Table (1) Experimental Data Sets

Set No	water concentration %	Temp C	Re	ACR mmd	Set No	water concentration %	Temp C	Re	ACR mmd
1	15	30	5000	200.7	17	35	30	5000	279.4
2	15	30	7500	250.68	18	35	30	7500	385.2
3	15	30	10000	400.37	19	35	30	10000	540.7
4	15	30	12500	449.22	20	35	30	12500	630.2
5	15	50	5000	260.17	21	35	50	5000	330.15
6	15	50	7500	279.64	22	35	50	7500	416.51
7	15	50	10000	47206	23	35	50	10000	630.85
8	15	50	12500	485.5	24	35	50	12500	649.71
9	25	30	5000	270.53	25	45	30	5000	309.27
10	25	30	7500	306.8	26	45	30	7500	416.79
11	25	30	10000	504.3	27	45	30	10000	618.68
12	25	30	12500	512.6	28	45	30	12500	628.26
13	25	50	5000	301.19	29	45	50	5000	339.16
14	25	50	7500	340.9	30	45	50	7500	360.7
15	25	50	10000	539.1	31	45	50	10000	674.7
16	25	50	12500	619.43	32	45	50	12500	696.8

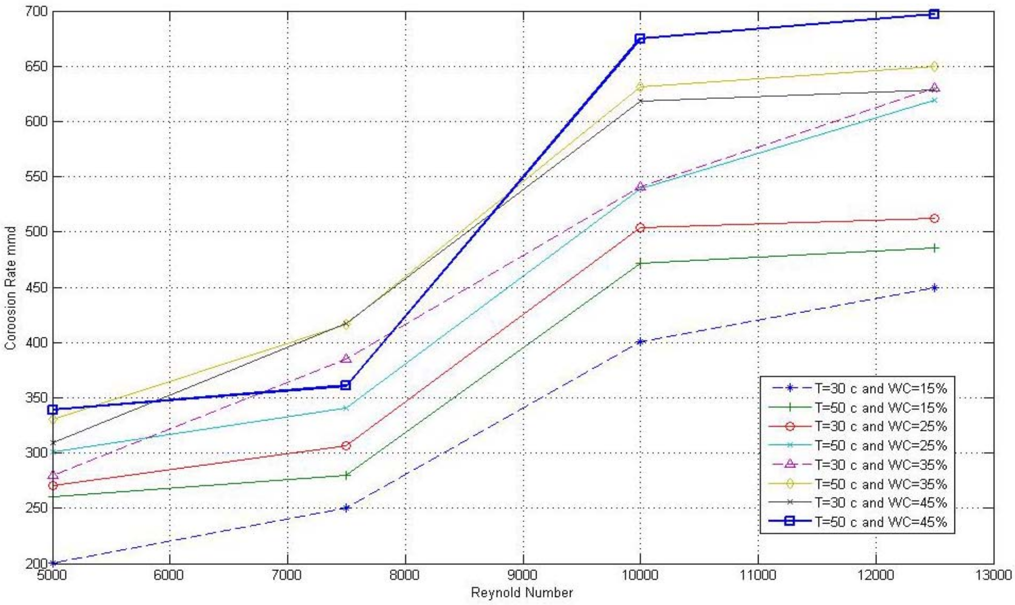

Fig.(2) Corrosion rate Vs Reynolds number

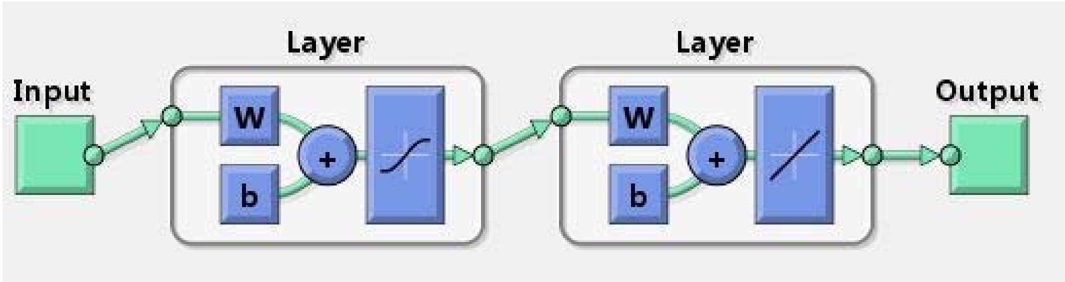

Fig. (3) Artificial Neural Network

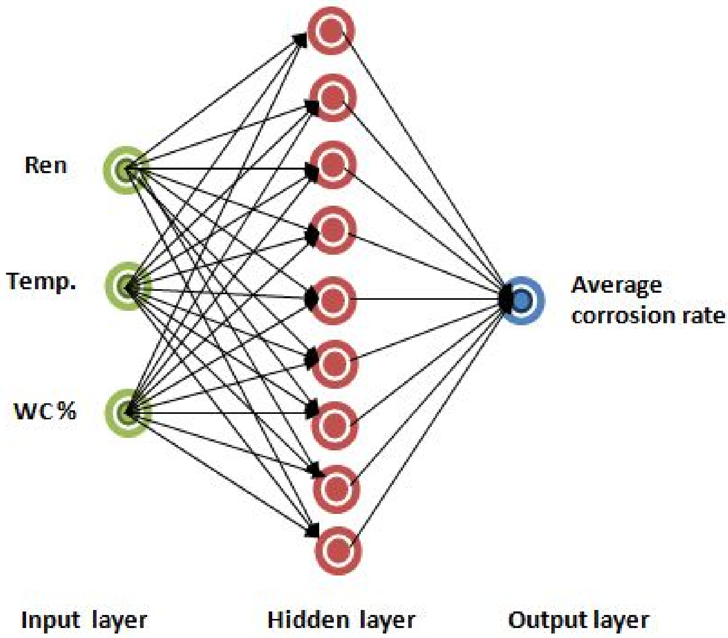

Fig. (4) Neural network architecture

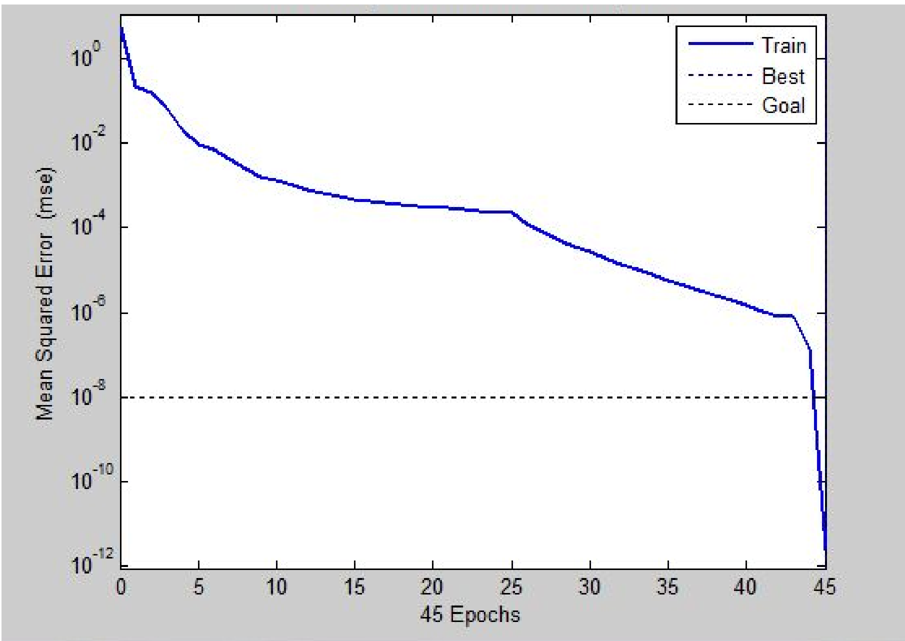

Fig. (5) Training Session

Table (2) The weights and bias between inputs and hidden layer

W1	W2	W3	W4	b1	b2
0.718647	-5.85696	-8.88151	-0.61732	-7.47805	0.049794566
-3.44112	4.323622	2.556928	-1.12072	5.986354	
9.025448	2.243282	1.143872	-0.40574	-2.92597	
11.76387	2.028157	2.87373	2.027852	2.785801	
2.645666	-1.11169	-8.79878	-0.68903	-0.71903	
1.830581	6.81657	-1.17294	-0.69285	-0.14563	
-8.0053	4.26784	3.474221	-1.54134	-3.74571	
-4.17033	8.68734	-3.04253	1.296458	-1.39753	
-11.7345	-0.28785	-1.477	1.566467	-3.95063	

Where:
W1: weights among Ren and hidden layer.
W2: weights among Temp. and hidden layer.
W3: weights among WC % and hidden layer.
W3: weights among hidden layer and Output layer (corrosion rate).
b1: bias to hidden layer b2:bias to output layer.

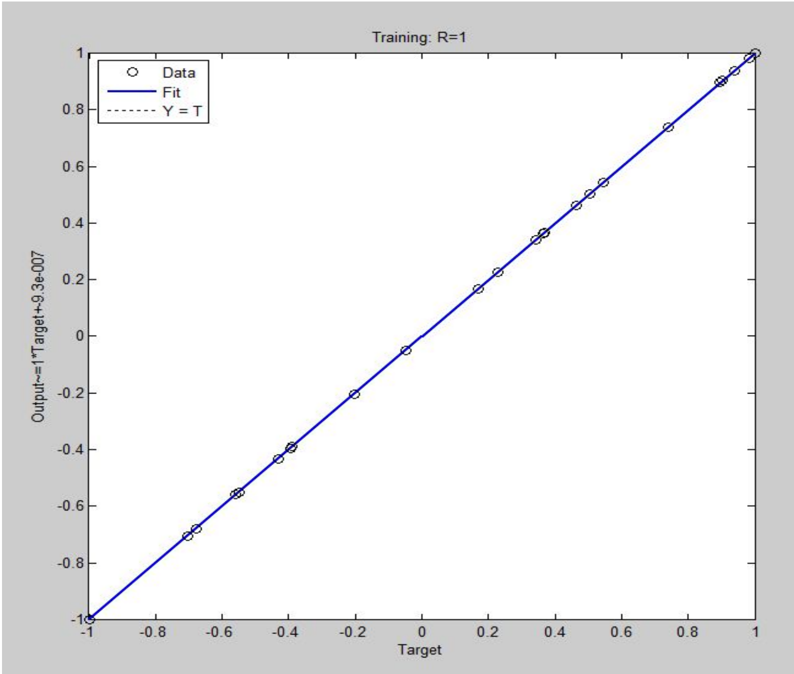

Fig. (6) Best linear fit of average corrosion rate in training set

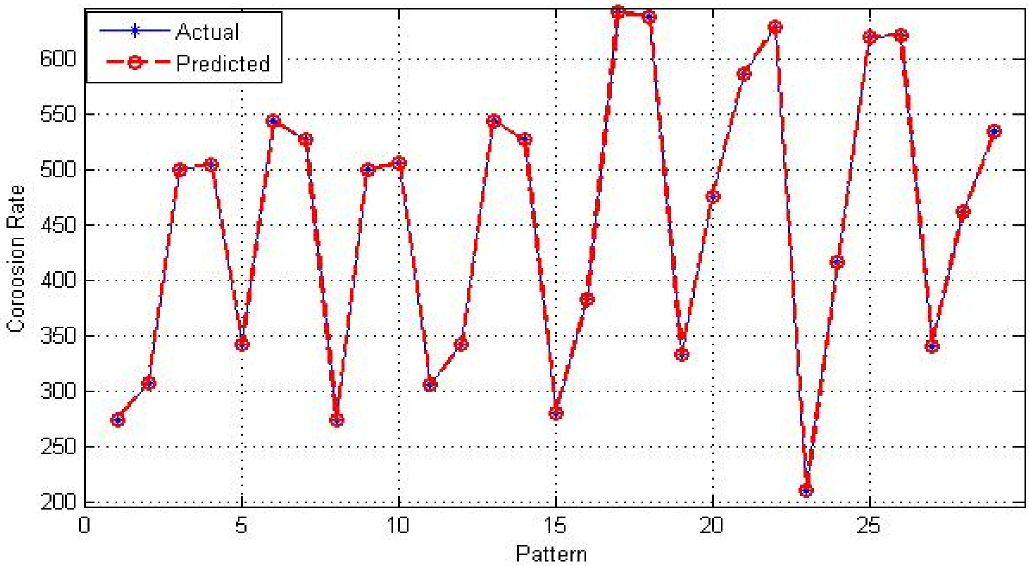

Fig.(7)Predicted and actual corrosion rate for training

Table (3) Test data sets and network response

Set No	ACR mmd	NN Response	APE %
5	306.91	287.9431	6.1799
10	303.99	320.7760	5.5219
31	584.8	578.7600	1.0328

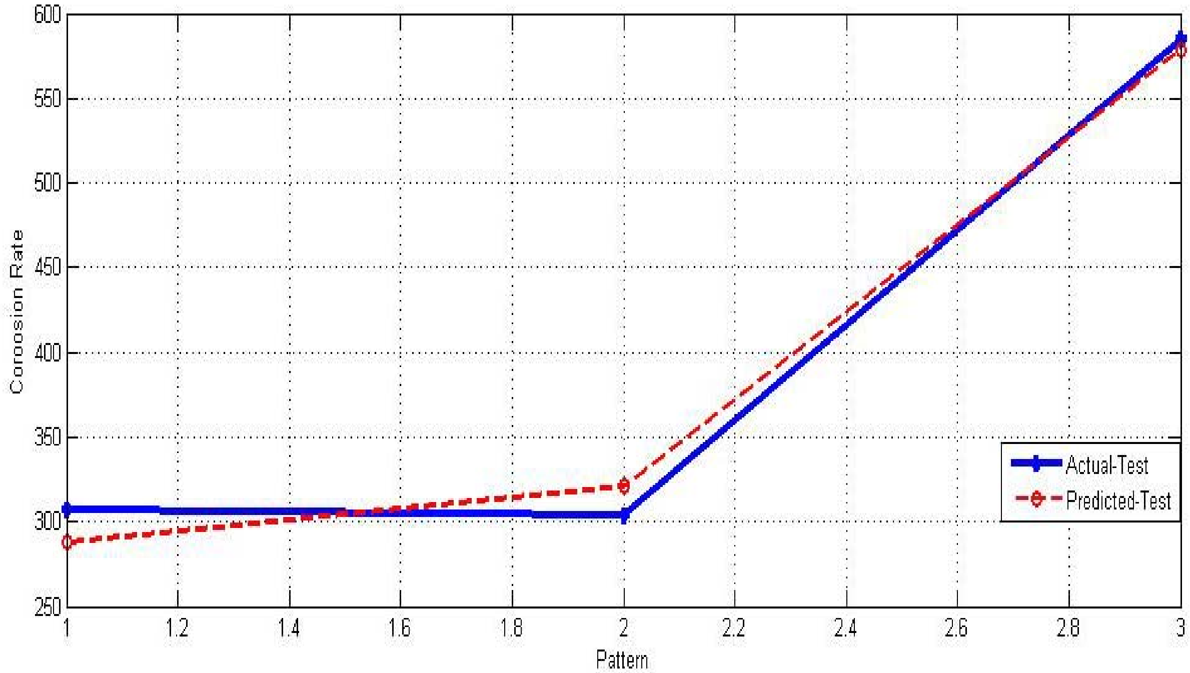

Fig. (8) predicted and actual corrosion rate for testing data sets (unseen in the training)