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Modeling and Prediction of Corrosion Penetration Rate in Crude Oil Pipelines Using Back Propagation Artificial Neural Network Approach

[1] GalalH.Senussi&[2] Omar Elmabruk

[1] Mechanical Engineering Department, [1]Faculty of Engineering, Omar Al-Mokhtar University, El-Baida, Libya.

[2]Industrial and Manufacturing Systems Engineering Department, Faculty of Engineering, Benghazi University, Benghazi, Libya

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ABSTRACT

Today in oil and gas fields, one of the most important crucial issue problem for any oil and gas industrial is the corrosion penetration rate (CPR) during crude oil transportation processes by pipeline that made of carbon steel. Many parameters have been known to be effective for corrosion control especially in the pipeline transportation process. These parameters are pH, temperature, pressure and shear stress. Several researches have been done with these issues using different methods. In this study, the main issue is to implement back propagation artificial neural network approach to develop a strong and capable model that is able to give an accurate prediction values for CO2 corrosion penetration rate (CPR) under certain operating parameters. Are liable model is developed to map inputs parameters namely pH, temperature, pressure and shear stress with the outputs (CPR).The results from this prediction model showed that, with small set of examples, the back propagation network (BPN) was able to adjust its weight coefficients. Which means that, the input generated a proper output. Also, the (BPN) model developed was validate by means of calculating the mean absolute errors (MAE). The value of (MAE) was 0.00457 mm/y which indicated the accuracy and reliability of the model.

I INTRODUCTION

The Artificial Neural Networks (ANN) have received an increased attention for solving many real complex world problems. Numbers of research and development works are increasing rapidly in recent years. Compared with traditional methods, ANN have solved many complex problems successfully where traditional methods have failed [1]. Several researches on CO2 corrosion prediction and the effects of species like HAc with several other operating parameters including temperature, pH, and flow rate condition introduced [2-5].

MINITAB software version16 was used to design the experiments (DOE), to mathematically model the effect of the operating parameters on the CPR and to set the optimal operating parameters that produce a minimum value of the response

(CPR). NORSOK M-506 software was used to calculate CPR for each experiment. The best response value was analyzed using the response surface and contour plots. The optimal operating parameters were 126 °F for temperature, 195 psi for pressure, and 5.65 for pH, the corresponding CPR value was 1.4 mm/year. [6]

A mathematical model to predict CO2 corrosion, sweet environment, penetration rate (CPR) of the Libyan Arabian Gulf Oil Company (AGOCO) Sarir-Tobruk steel pipeline was introduced. It was conducted at different values of the most significant operating parameters; temperature (112-126°F), pressure (195-494 psi) and pH (5.51-5.65). The MINITAB software version16 was used to design the experiments (DOE), Fuzzy logic was developed using MATLAB (2013) Toolbox to predict CO2 corrosion penetration rate (CPR) and NORSOK M-506 software was used as a simulation tool to calculate CPR for each experiment. It was found that, the predicted CO2 corrosion penetration rate was very close to that calculated using NORSOK M-506 with a Mean Absolute Error (MAE) of 0.01. Therefore, it was concluded that Fuzzy Logic is a promising technique that could be used confidently in predicting the CPR during transporting the crude oil through the steel pipeline. [7] By applying an artificial neural network technique (ANN), Galal H. Senussi introduced a model to predict a mechanical property of six types of stainless steel based on distance from the ground surface. The emphasis was used on investigating the performance of the neural network using back propagation algorithm. The results of the introduced simulation with small set of examples showed thatANN is able to adjust its weight coefficients and will generates a proper output as a result to input. [8]

II ARTIFICIALNEURAL NETWORK (ANN)

ANNs are computational modeling tools that have been extensively used in many disciplines to model complex real-world problems [9].ANNs are used when data has noisy, unknown distributions, intensive, contains complex relationships between many factors, and other technologies are not adequate to deal with these conditions [10].

Figure 1 shows the ANN basic model. It includes the inputs, weights, threshold, activation function and an output. The ANN components model are the actual activity within the neuron cell, adding and activation function and the adder function sums up all the inputs modified by their respective weights, while the activation function controls the amplitude of the output of the neuron. An acceptable range of output is usually between 0 and 1, or -1 and 1. [11]

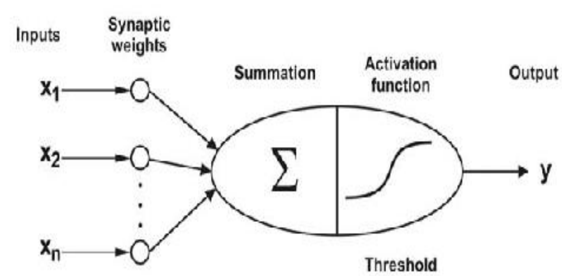

Figure 1. The ANN basic model [11]

Back propagation is one of the most common known methods. It has powerful to teach patterns and adjust its weights using a feedback method [12].Back propagation (BP) is an iterative gradient-descent algorithm designed to minimize the mean squared error (MSE) between the actual output of anode and the desired output as specified in the training set. In the validation phase a neural network tends to optimize the length of network training, the number of hidden neurons and learning parameters (learning rate and momentum). The best network obtained is stored and tested in the next phase. In final phase (testing phase), the network is tested and evaluated by new sample. The network which has the best results will be applied in practice. [13]

III EXPERIMENTAL METHOD ANALYSIS AND RESULTS

There are many parameters affecting the corrosion penetration rate of the Sarir-Tobruk pipeline, in this paper the operating parameters investigated are temperature, pressure, pH and shear stress and their corresponding ranges are given in Table 1.

Table 1 Operating parameters and corresponding ranges

Parameters	Notation	Unit	Range	
			Lower value	Upper value
Temperature	Temp	F°	112	126
Pressure	P	Psi	195	494
pH	pH	-	5.51	5.65
Share stress	SS	Pa	1	30

The back propagation artificial neural network (BAN) approach is used to develop the mathematical model and to study the effect of the selected parameters on the response corrosion penetration rate (CPR).

The main steps to build the ANNs model are the preparation of data and modeling, the training and testing of neural networks and finally the analysis of results and selecting the best model. The following are more details regarding the ANNs building steps.

1- Preparation of data and modeling

Table2 shows the experimental data. Temperature, pressure, PH, shear stress represent input variables and Corrosion Penetration Rate (CPR) represents the response variable (output). Different model structures, different number of hiding layers and/or different numbers of neurons are applied. Architecture of Neural Network (4555 5 1)gave satisfied results. Thefirstlayer containsfour neurons and represents input. The second, third, fourth, and fifth contain five neurons for each and represent the hidden layers. The last layer contain one neuron; it represents the output (CRP)in figure2.

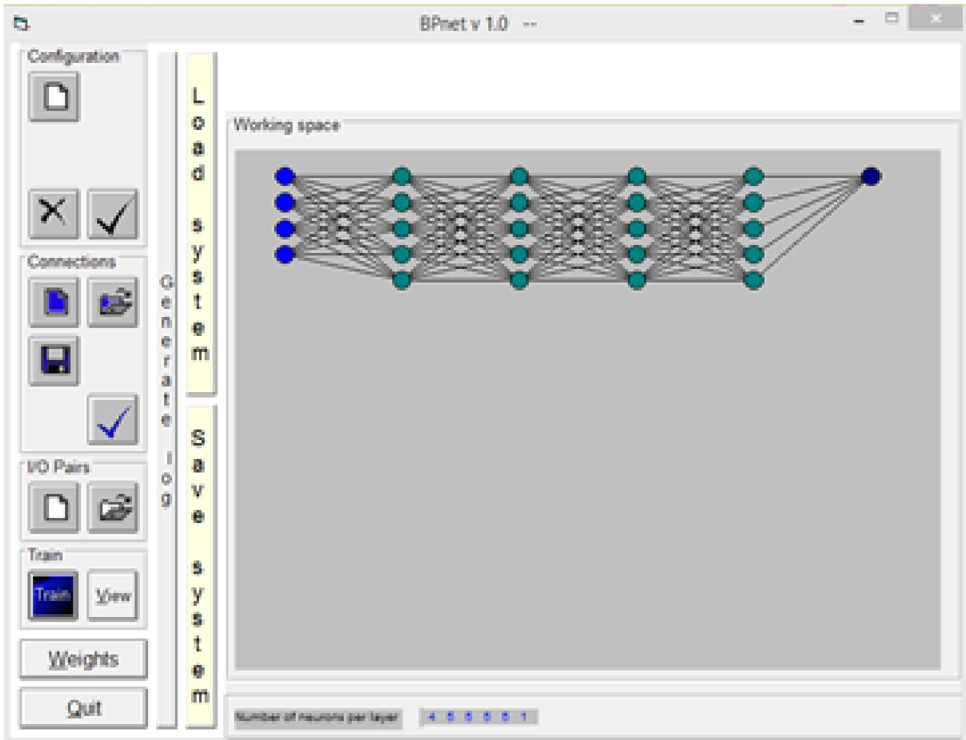

Figure2. Network building stage

Table2. The experimental data

Real Values					Normalizing Values [0, 1], step 0.2				
Temperature X1(C°)	Pressure X2 (bar)	PH X3	Shear Stress X4 (Pa)	CPR Y1(mm/y)	X1 new1	X2 new1	X3 new1	X4 new1	Y1 new1
48.59	23.8	5.58	16.2	2.3	1.5	1.5	1.5	1.524	1.374
48.59	23.8	5.58	15.5	2.3	1.5	1.5	1.5	1.5	1.374
44.4	34.2	5.51	1	3.07	1	2	1	1	1.786
52.78	13.4	5.65	1	1.63	2	1	2	1	1.016
48.59	23.8	5.58	15.5	2.29	1.5	1.5	1.5	1.5	1.368
48.59	23.8	5.57	15.5	2.31	1.5	1.5	1.428	1.5	1.379
44.4	13.4	5.65	30	2.08	1	1	2	2	1.256
44.4	34.2	5.51	30	3.12	1	2	1	2	1.812
48.59	24.32	5.58	15.5	2.33	1.5	1.525	1.5	1.5	1.390
48.59	23.8	5.58	15.5	2.3	1.5	1.5	1.5	1.5	1.374
48.79	23.8	5.58	15.5	2.3	1.526	1.5	1.5	1.5	1.374
52.78	13.4	5.51	1	1.86	2	1	1	1	1.139
48.59	23.8	5.58	14.8	2.3	1.5	1.5	1.5	1.475	1.374

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52.78	34.2	5.65	30	2.2	2	2	2	2	1.320
44.4	34.2	5.65	1	2.72	1	2	2	1	1.598
44.4	13.4	5.51	30	2.3	1	1	1	2	1.374
48.59	23.8	5.58	15.5	2.3	1.5	1.5	1.5	1.5	1.374
52.78	13.4	5.51	30	1.81	2	1	1	2	1.112
44.4	13.4	5.65	1	1.38	1	1	2	1	0.882
52.78	13.4	5.65	30	1.58	2	1	2	2	0.989
48.59	23.8	5.58	15.5	2.3	1.5	1.5	1.5	1.5	1.374
52.78	34.2	5.51	30	2.55	2	2	1	2	1.508
48.59	23.8	5.58	15.5	2.3	1.5	1.5	1.5	1.5	1.374
48.59	23.28	5.58	15.5	2.27	1.5	1.475	1.5	1.5	1.358
52.78	34.2	5.65	1	2.9	2	2	2	1	1.695
44.4	34.2	5.65	30	2.77	1	2	2	2	1.625
48.59	23.8	5.58	15.5	2.3	1.5	1.5	1.5	1.5	1.374
52.78	34.2	5.51	1	3.25	2	2	1	1	1.882
48.59	23.8	5.58	15.5	2.3	1.5	1.5	1.5	1.5	1.374
48.59	23.8	5.58	15.5	2.3	1.5	1.5	1.5	1.5	1.374
44.4	13.4	5.51	1	1.6	1	1	1	1	1

2- Network Training:

The training sets were established in MS Excel from [0, 1] in steps of 0.03 and the data values were normalized, with 32 sample examples, the obtained networks were trained on a training sample was (70% total sample). A model (4 5 5 5 5 1) was applied as an artificial neural network (ANN) model. A sigmoid function was used as an activation function.

The learning rule was the delta rule, with momentum $\lambda = 0.2$ and learning parameter. $\mu = 0.2$. Mean Absolute Error (MSE) was used to calculate the error as a means model validation in the neural network training phase. The value of MSE is 0.005. Figure3 and table 3 show the BPN screen and the final statistical results in training stage respectively.

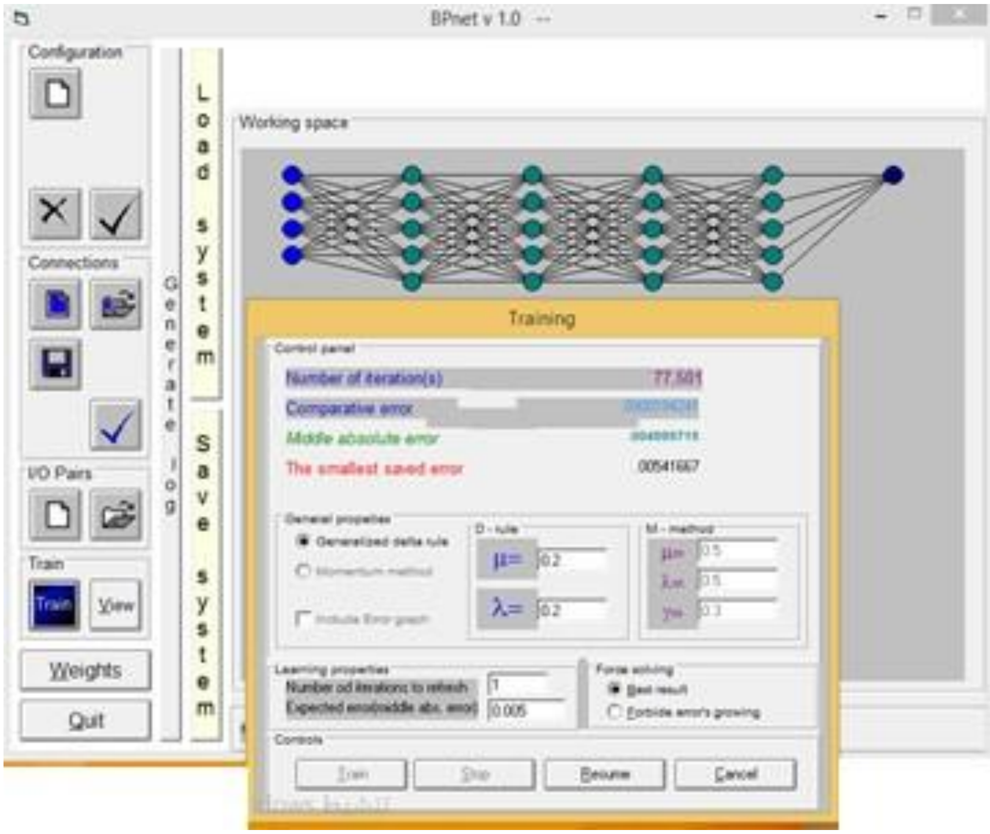

Figure 3. The back propagation neural network

Table3. BPN Final statistical results

Number of Iterations	Comparative Error(mm/y)	Middle absolute Error(mm/y)	The smallest Error(mm/y)
77,501	**1.8E-05**	**4.9E-03**	**5.4E-03**

3- Network Testing

In testing stage, 30% data of total sample were used randomly. Figure 4 represents the forecasted value of one of the BPN output. Table 4 shows BPN outputs forecasted value as compared with the real data. It is clear that MAE is very small (0.00457) and the outputs are very close to the target.

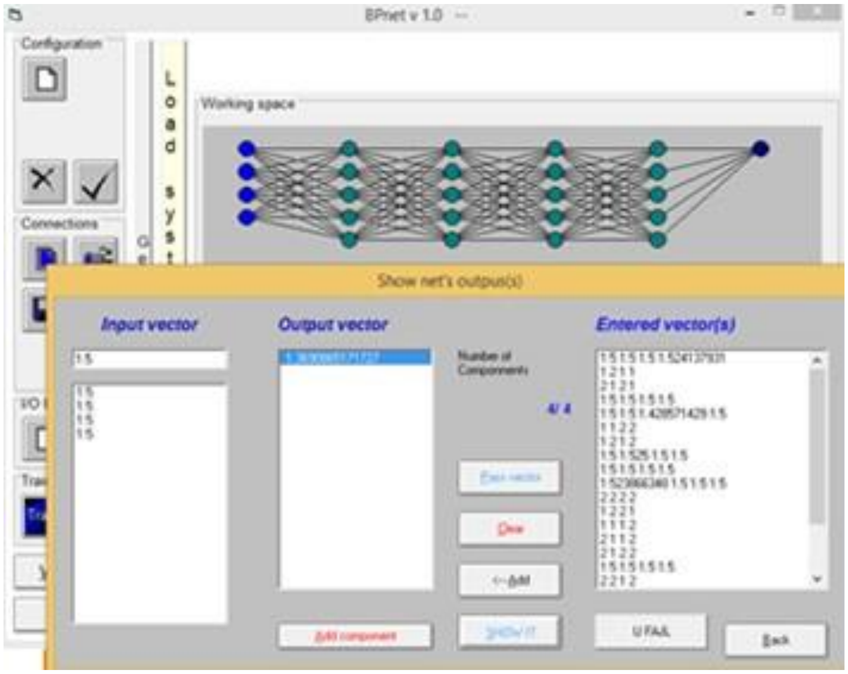

Figure 4. The forecasted value of one of the BPN output.

Table4. The BPN outputs forecasted value as compared with the real data

Corresponding target(mm/y)	Testing BPN output(mm/y)	Error (mm/y)	Square Error	MAE (mm/y)
1.374331551	1.369086517	0.005245	2.75104E-05	
1.139037433	1.08342839	0.055609	0.003092366	
1.374331551	1.367678662	0.006653	4.42609E-05	
1.374331551	1.369086517	0.005245	2.75104E-05	
0.882352941	0.990137917	-0.10778	0.011617601	
1.695187166	1.550596498	0.144591	0.020906461	
1.625668449	1.698889683	-0.07322	0.005361349	
1.374331551	1.369086517	0.005245	2.75104E-05	
1.374331551	1.369086517	0.005245	2.75104E-05	
				0.00457

IV RESULT AND DISCUSSION

The model (4 5 5 5 5 1) with learning parameters μ=0.2 and λ=0.2 and expected error of 0.005 was used in training and testing stages. 70% of the data were used as training and 30% of the data were used for testing and validation. The results showed that the BPN provides good prediction of corrosion rate penetration. From the obtained results it is clear that the model has strong predicting capabilities. Figure 5shows the different magnitude errors between real data and BPN outcomes.

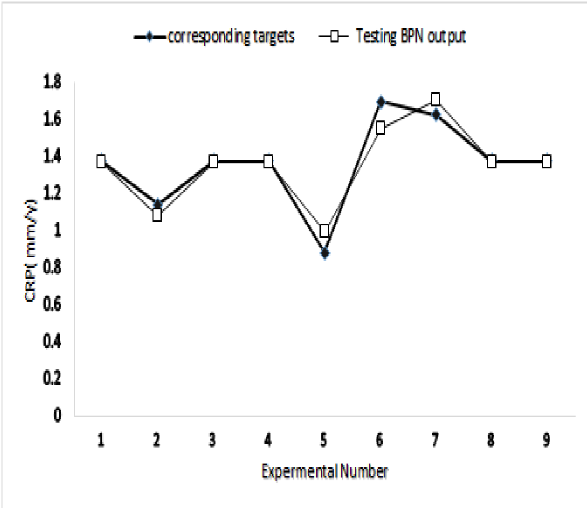

Figure. 5. BPN outcome compared with real data at input 0.13.

It is clear that there is good agreement between the corresponding targets values and testing output values (CPR).

V CONCLUSION

The overriding purpose of this study was to implement the Back Propagation Artificial Neural Network Approach to predict the CO2 corrosion penetration rate of the Sarir-Tobruk pipe line used for crude oil transportation processes. From this study, the following points could:

- A BPN model was successfully introduced and used to predict the CO2corrosion penetration rate (CPR) within the range of the input parameters.
- The result of this analysis indicates the possibility of improving the obtained values by minimizing the cost function. At same value learning parameters (λ and μ), Neural Network consists of six layers (1neuron in the input layer, 5,5,5,5 neurons in the hidden layer and 1 neuron in the output layer) provide a good desired outputs with less processing time compared with others models.

REFERENCES

[1] Galal H. Senussi and others, "Forecasting Optimal Production Program Using Profitability Optimization by Genetic Algorithm and Neural Network" World Academy of Science, Engineering and Technology International Journal of Mechanical, Aerospace, Industrial, Mechatronic and Manufacturing Engineering Vol:8, No:5, 2014.

[2]. Zhang G. "On The Fundamentals of Electrochemical Corrosion of X65 steel in CO2-Containing Formation Water in the Presence of Acetic Acid in Petroleum Production", Corrosion Science 2009; 51: 87–94.

[3]. Amri J, Gulbrandsen E, and Nogueira, "The Effect of Acetic Acid on the Pit Propagation in CO2 Corrosion of Carbon Steel", Electrochemistry Communications 2008; 10: 200–203.

[4]. Martin C.F., "Prediction CO2 Corrosion with the Presence of Low concentration Acetic Acid in Turbulent Flow Conditions", Master Thesis of UTP 2009.

[5]. Mokhtar I. C. "Prediction CO2 corrosion with The Presence of Acetic Acid", PhD theses of UMIST 2005.

[6] Omar M. Elmabrouk et al, "Optimization Of Crude Oil Transportation Process Using Response Surface Method", Benghazi

international conference oil and gas, 24-26 October 2018, Benghazi-Libya. [8] G.H. Senussi "Prediction of Mechanical Properties of Stainless Steel Using an Artificial Neural Network Model" Reference Module in Materials Science and Materials Engineering 2017.

[7] Bushra H. Elmoghrabi et al, "Modelingand Prediction of CO2 Corrosion Penetration Rate of Pipeline using Fuzzy Logic Technique", Journal of Engineering Research (University of Tripoli), Issue (26), September 2018, pp 15-24.

[8] G.H. Senussi "Prediction of Mechanical Properties of Stainless Steel Using an Artificial Neural Network Model" Reference Module in Materials Science and Materials Engineering 2017.

[9] Liao, S.H., Wen, C.H., (2007). Artificial neural networks classification and clustering of methodologies and applications – literature analysis form 1995 to 2005. Expert Systems with Applications, Vol.32, no.1, pp. 1-11.

[10] Hardgrave, B.C., Wilson, R. L., (1994). Predicting graduate student success: a) comparison of neural networks and traditional technique. Computers & Operations Research, Vol.21, no. 3, pp. 249-263.

[11] Zoran Miljković and others, "USING ARTIFICIAL NEURAL NETWORKS TO PREDICT PROFESSIONAL MOVEMENTS OF GRADUATES" Croatian Journal of Education, Vol: 13 (3/2011), pages: 117-141, Paper submitted: 28th June 2011, Paper accepted: 7th December 2011

[12] Rumelhart, D. E., Hinton G. E., Williams, R. J., (1986). Learning internal representations by error propagation in parallel distributed processing, In Parallel distributed processing, ed. D.E. Rumelhart, J.L. McClelland, and the PDP Research Group (pp. 318-362). Cambridge: MIT Press.

[13] G.H.Senussi "Prediction of Mechanical Properties of Stainless Steel Using an Artificial Neural Network Model" Reference Module in Materials Science and Materials Engineering, 18 December 2016 (Cover date: 2017