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Application of Artificial Neural Network Model to Predict Corrosion Rates on Pipeline

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ABSTRACT
This study aims at determining corrosion rates in oil and gas pipelines by application of artificial neural network model to predict corrosion rates on pipeline*; and to compare the achieved numerical outcomes with the existing work as special cases. An artificial neural network model capable of predicting the rate of corrosion was developed. The model was able to successfully predict corrosion rate between 0.02mm/yr-0.17mm/yr. The study had a root mean square error of 0.0130; mean absolute error of 0.007, scattered index of 0.1708, and above 91.5% confidence level at training, testing and validation, with coefficient of determination above 95% prediction accuracy, with a relative error of 0.013%-0.047%. Graphs are plotted to show the impact of various physical parameters on pipeline age, environmental pH and temperature. It is detected from the obtained graphical data that multi-factors interactions significantly affect corrosion rates. Furthermore, the contour and surface plots indicate the ascending severity order of the localized attack on the pipes due to factor pairs. The results obtained by ANN predictions are consistent with that of experimental and the validity of the achieved numerical outcomes is ensured by making a comparison with the existing work of special cases. With this concept, the present ANN model reflects the mainstreams understanding of corrosion in acidic environments, and can be easily used to predict the corrosion rates in industrial applications.*

KEYWORDS: Artificial neural network, oil and gas pipelines, rate of corrosion, severity level.

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1. INTRODUCTION
Carbon dioxide gas (CO_2), hydrogen sulfide (H_2S), and organic acidic dissolves in water and their corrosion impact on oil and gas facilities have recently increased dramatically. Corrosion is a key issue of the world industry which gravely destroys industrial and natural environments related to internal and external pipeline corrosion. Corrosive activities cause major impediment to many production materials, due to carbon dioxide gas that dissolves in water and weakens the pH content of water to form a weak carbonic acid (Drazic, 1989; Obaseki *et al*.,2021). Thus, corrosion is a key process playing an important function in economics and safety particularly for oil-gas facilities and potential alloys. Of late, studies on steel corrosion show that it has become an industrial and academic interest, particularly in acid media because of the increasing industrial applications (Bentiss *et al*., 2000; Pandian *et al*., 2013).

Thus pipelines as a medium of transporting oil and gas in the petroleum industry, affect daily lives in most parts of the world like Niger Delta of Nigeria. Modern lives are based on an environment in which energy plays a significant role. Meanwhile, oil and gas are major participants in the supply of energy, electrical power generation, cooking and heating supply; and the primary means by which they are transported are pipelines (Mohitpour *et al*., 2007). Pipeline as an engineering facility do fail in-service owing to deterioration term corrosion (Ahammed, 1998; Revie and Uhlig, 2008). The rate of corrosive destruction depends on acidic nature of the environmental and metallurgical factors such as moisture, chemical composition of steel, environment and fluids, change of temperature and pressure etc. (Ahammed, 1998; Mohitpour *et al*., 2007; Rajput, 2010).

Corrosion is a major problem in oil and gas production and materials transportation as it may

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result to high maintenance cost, and in some cases huge financial and economic loses. Many scientist and engineers have come up with different techniques to predict, reduce and prevent corrosion rates in pipelines exposed to different environmental conditions (EL-Abbasy *et al*., 2014a; EL-Abbasy *et al*., 2014c; EL-Abbasy *et al*., 2015). Therefore, corrosion monitoring and measurement techniques became necessary in the assessment of corrosion rate in order to know when maintenance is to be carried out and repair actions taken. Corrosion assessment and measurement methods include visual examination, weight loss, electrochemical techniques, coupon testing and linear polarization resistance method (Rajput, 2010).
Since the development of a theoretical model capable of explaining the relationship that exists between these factors and the associated corrosion rate is a hectic task. Empirical observations came up with the idea that in a case of complex nonlinear relationships in data sets, neural network model is a more suitable model fit than the regular regression technique (Guidelines, 2009).

Caruana and Niuculescu-Mizil, (2006) carried out a comparison between ten supervised learning algorithms applied on eleven binary classification problems using eight performance metrics. Ren et al. (2012) applied back propagation neural network to predict the corrosion rate of natural gas pipelines. Liao et al. (2012) used particle swarm optimization (PSO) technique to develop a model that predicts internal corrosion rate for wet gas gathering pipelines. Obaseki *et al*. (2021) investigated a mechanistic model for corrosion rate prediction of multiphase oil and gas pipelines in order to know the root cause as well as to ascertain the rate of corrosion in the oil and gas industries. Inner wall corrosion and sand trapping model for oil and gas facilities was investigated by Obaseki *et al*. (2020b). Results show that tiny/sand particles causes wax deposition in oil and gas facilities.
Therefore, adequate information/knowledge of the best variables will impede negative corrosion effect thereby reducing economic loses, enhancing safety, and promoting clean environment. This study aims to determine corrosion rates in oil and gas pipelines by examining multi-factors interactions affecting oil and gas pipelines corrosion and compare the achieved numerical outcomes with the existing work as special cases. An artificial neural network model capable of predicting the rate of corrosion are applied to the study that allow for pipe age, sand flow deposition and chloride concentration. The novelty is that the present ANN model reflects the mainstreams of corrosion in acidic environments, and can be easily used to predict the corrosion rates in industrial applications.

2. MATERIALS AND METHODS

2.1 Data Collection

The data used in this study were obtained from oil and gas field records in the Niger Delta area of Nigeria (Egua-1-company). Field data for forty pipelines were collected from the oil and gas fields and were used as input data to predict corrosion rate along the oil and gas industries and to analyze the effects of several parameters. The forty pipelines were located offshore and were of different sizes and different steel grades. The main characteristics of the forty pipelines are shown in Table 1.

2.2 Model Implementation Process

Normally, implementation of the predictive model by the ANN requires the following steps: data collection, data processing, building the network, training the network, test performance of model, creating the network function and/or building the network.

Thus, figure 1 shows the neural network architecture after the network building. Hidden layer neurons (20) were selected because that is the optimal point that accurate results was obtained during training stage, testing and validation.
The network determined the output corrosion rate by the relation (Mathworks, 2014) as:

$$[Corrosion\ rate\ ] = f\{[weights][inputs] + [bias]\} \quad (1)$$

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Where, f = transfer or activation function which is determined by Levenberg Marquardt (LM) algorithm.

$$\log(CR) = \beta[K\bar{P} + \alpha] + M \quad (2)$$

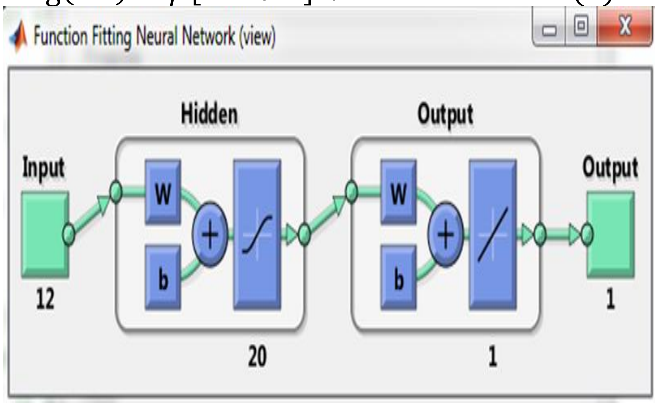

Fig. 1. Neural network architecture

where; CR = corrosion rate in [mm/year]

$$\bar{P} = \log(inputs\ matrix) \quad (3)$$

$$inputs\ matrix = \begin{bmatrix} L \\ D \\ A \\ T \\ P \\ V \\ P_{CO_2} \\ pH \\ Cl \\ SF \\ \rho \\ \mu \end{bmatrix} \quad (4)$$

Where L = pipe length(mm), D = diameter of pipe [mm], A = age of pipe [years], T = Temperature of fluid [^{0}C], P = Flow Pressure [bar], V = Flow velocity [m/s], P_{CO_2} = Partial Pressure of CO_2 [bar]

Table 1. Input data for the model

Pipe	Pipe length (mm)	Diameter(mm)	Pipe age (yr)	Fluid Temp (˚c)	Pressure(bar)	Velocity (m/s)	CO2 partial pressure(bar)	Environmental pH[-]	Chloride(mg/kg)	Sand Flow(m/s)	Density(kg/m^3)	Viscosity(cP)
1	211	305	6	44	55	2.7	4.5	5.6	34.6	1.67	832.60	24.81
2	45	508	37	67	70	1.2	2.5	3.9	36.5	1.04	818.80	10.73
3	121	609	19	69	52	1.02	3.8	3.5	35.9	0.98	817.54	10.00
4	300	400	16	35	64	1.81	6.0	6.4	30.7	0.92	838.18	37.18
5	700	610	29	70	36	1.01	4.6	5.2	36.1	0.58	816.88	9.650
6	500	600	32	69	62	0.92	5.4	3.8	35.3	0.45	817.59	10.03
7	60	609	25	55	70	0.82	2.2	5.6	34.7	0.43	825.98	16.28
8	500	193	8	35	39	2.85	2.2	5.8	32.9	1.83	838.07	36.95
9	242	406	26	67	56	1.85	5.8	3.4	37.1	0.98	818.74	10.70
10	119	914	28	45	59	0.98	4.9	5.1	34.8	0.67	831.69	23.36
11	55	305	40	70	60	2.71	5.3	6.4	35.2	2.01	816.98	9.70
12	100	508	30	48	64	1.56	2.5	4.3	36.9	1.02	830.19	21.17
13	1000	225	13	55	40	2.2	2.0	5.2	33.8	1.97	825.85	16.17
14	45	508	41	67	30	1.95	3.4	5.8	37.9	1.04	818.63	10.63
15	60	609	15	53	45	1.08	2.9	5.3	34.3	0.69	827.08	17.42
16	500	193	11	45	37	2.92	2.2	5.2	31.7	1.56	831.91	23.71
17	121	609	6	70	67	0.76	2.6	3.6	38.7	0.41	817.01	9.71
18	211	305	31	45	45	2.62	5.4	5.7	34.5	1.78	831.94	23.76
19	210	305	27	66	69	1.75	4.3	5.4	34.7	1.08	819.09	10.91
20	250	406	8	63	49	2.85	3.4	5.6	30.1	1.12	821.09	12.22
21	600	610	18	56	55	1.04	3.2	6.5	35.6	0.63	825.31	15.64
22	400	600	14	69	60	1.68	4.9	5.3	35.9	1.02	817.57	10.02
23	145	609	16	67	67	2.32	5.1	5.6	36.8	1.02	818.79	10.72
24	145	406	22	70	65	2.85	2	5.2	37.9	1.78	817.01	9.71
25	60	406	27	46	53	1.9	2.5	5.1	34.9	1.4	831.36	22.86
26	121	609	36	68	70	1.28	3.4	5.2	33.6	1.95	818.21	10.38
27	215	305	10	70	54	2.95	2.31	6.2	36.9	1.35	816.96	9.69

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28	215	305	12	56	46	1.82	2.6	3.5	33.3	1.56	825.27	15.61
29	60	508	40	55	60	1.92	2	5.34	35.9	1.08	825.93	16.24
30	1000	225	11	70	43	3.28	5.4	3.54	38.9	1.98	816.91	9.66
31	45	508	39	69	54	2.24	5.2	4.1	36.8	1.22	817.5	10.00
32	45	508	40	30	56	3.5	4.2	3.5	37.7	1.07	841.3	48.30
33	100	508	23	34	70	1.92	3.5	6.45	31.6	1.23	838.8	39.10
34	100	508	26	28	43	3.38	6 .0	3.4	34.9	1.93	842.4	54.30
35	500	193	9	70	59	3.4	5.1	4.43	38.5	1.91	817.0	9.7 0
36	242	406	21	45	68	2.8	2.5	5.5	35.12	1.77	832.0	23.90
37	242	406	24	43	67	2.58	3.4	5.65	32.76	1.45	833.3	25.90
38	242	406	26	38	69	2.34	3.7	5.64	33.6	1.24	836.3	32.30
39	242	406	28	46	49	1.84	6	4.34	32.9	1.05	831.3	22.80
40	300	400	11	69	53	1.96	5.3	5.34	34.8	0.98	817.5	10.00

pH = environmental pH [-], Cl = Chloride content [mg/kg], SF = Sand flow [m/s], ρ = Oil density [Kg/m^3] and μ = Oil viscosity [cP].

K, α, β and M are constants matrices given as follows;

$$K = \begin{bmatrix} K_{1,1}K_{1,2}K_{1,3}K_{1,4}K_{1,5}K_{1,6}K_{1,7}K_{1,8}K_{1,9}K_{1,10}K_{1,11}K_{1,12} \\ K_{2,1}K_{2,2}\ K_{2,3}K_{2,4}K_{2,5}\ K_{2,6}\ K_{2,7}\ K_{2,8}\ K_{2,9}\ K_{2,10}\ K_{2,11}\ K_{2,12} \end{bmatrix} \quad (5)$$

$$\alpha = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} \quad (6)$$

$$\beta = [\ \beta_{11}\ \beta_{12}] \quad (7)$$

The constant K[-] represent the input parameters exponent factors,α[-] represent the correlation factors and β[-] represent the transformed parameter coefficients. M is the error correction constant. This constant reduces the error in the calculation of the corrosion rate. M is a matrix of a single constant defined as;

$$M = [M] \quad (8)$$

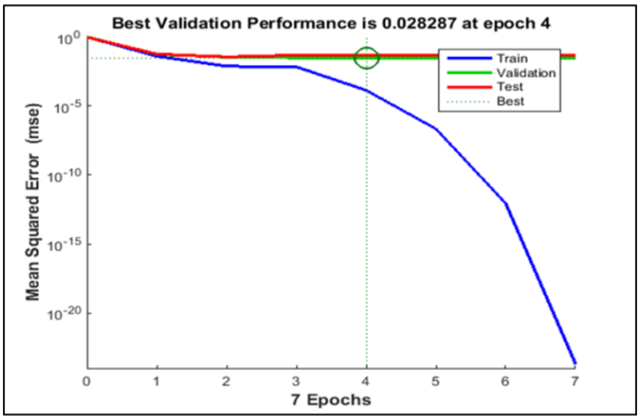

Fig.2: Neural network training performance (MSE) plot

2.3 Back Propagation Neural Network Modeling Detail

In this study, single layer feed forward network with back propagation learning algorithm is applied. The input layer consists of twelve neural cells corresponding to temperature, flow velocity, CO_2 partial pressure, sand flow particle, age of pipe, chloride content, pipe length, pipe diameter, pressure, environmental pH, density, and viscosity. The response (output/target) layer consists of one neural cell corresponding to corrosion rate. The program code was generated using MATLAB 2014b modeling software. The number of neurons in the hidden layer was chosen to be 20. The number of datasets used for training, testing, and validation were taken to be 70%, 15%, 15%, respectively. Figure 2 depicts a diagram of validation performance. Therefore this trained network was used to predict the corrosion rate of the entire network.

Network architecture, the inputs (predictors) and outputs where identified and selected. The input attributes represent the factors influencing the pipeline corrosion (Table 1), while the output indicates the corrosion rate. A supervised ANN, using back propagation algorithm, is applied to implement the corrosion rate prediction model. The network architecture has a total of 33 layers of neurons with 12 predictors' one hidden layer (20 neurons) and one output (response) layer depicted in figure 1.

In model design structure and training process, each variable is represented by one neural cell in the network input and output layers. Twelve neurons make up the layer that represents the

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factors affecting pipeline corrosion, while the output layer contains one neural cell that represents the pipeline corrosion rate. Thus, the number of neurons in the hidden layers proves how well a problem can be learned. During training process the hidden layers rely on the available model building data set and the corresponding outputs. Hence, getting the required number of hidden neurons is a state of trial and error. Hidden layer neurons (20) were selected because that is the optimal point where accurate results were obtained during training and testing stage in this study. Activation function that gave efficient corrosion rate after trial of various functions is the Levenberg Marquardt (LM).

3. RESULTS AND DISCUSSION

3.1. Effect of Temperature

In corrosion processes, temperature speeds up kinetic reaction (chemical, electrochemical and transport fluid), that is to say corrosion rate increases significantly with temperature as seen in fig. 3. As temperature increased from 45°C to 70°C, corrosion factor increased from 0.06 to 0.11 mm/yr. Nesic (2007), thinks that the height in the rate of corrosion is mostly seen within 60°C and 80°C based on water chemistry and flow regime.

Figure 4 shows the contour-surface plot of corrosion rate versus temperature and flow velocity. It is observed that with the increase in temperature and flow velocity, the corrosion rate increases. The reason may be attributed to heat build-up in the physicochemical reaction taking place.

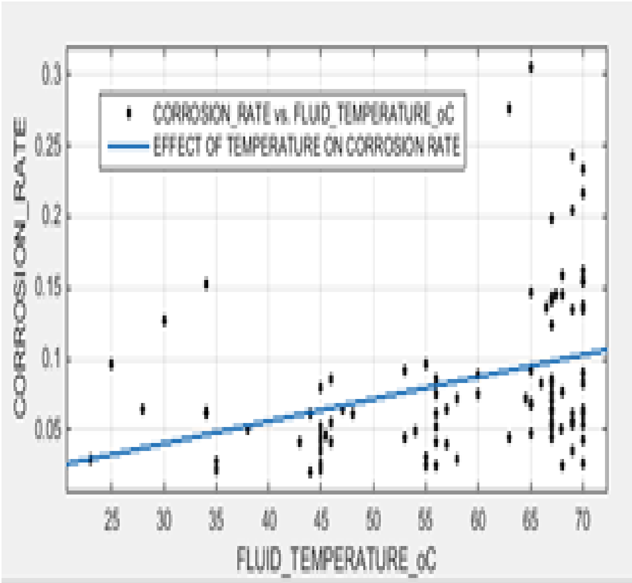

Fig. 3: Effect of temperature on corrosion

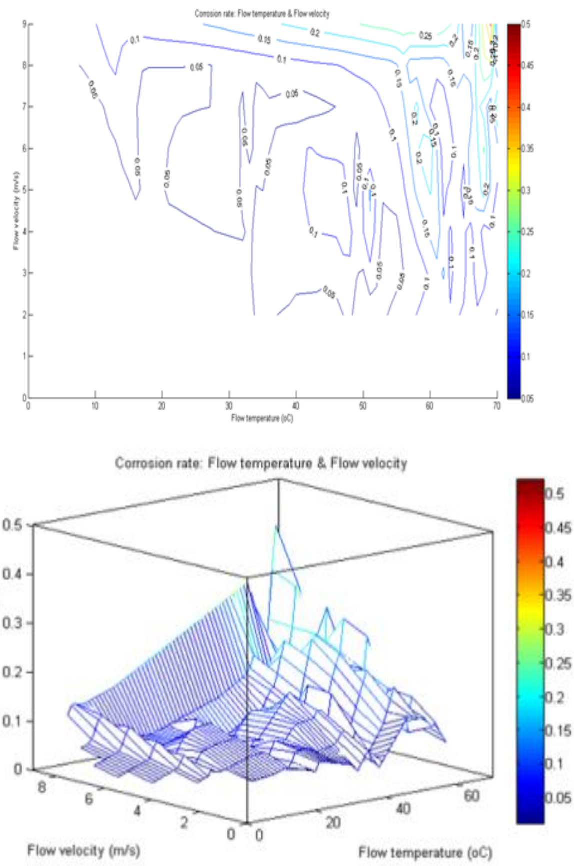

Fig.4: Contour and surface plot of fluid temperature and flow velocity on corrosion rate

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3.2. Effect of Pipeline Age

In fig. 5 the corrosion rate increased significantly. As age of pipeline increased from 5yrs to 40yrs, it was observed that the corrosion rate maintained smooth corrosion within 0.06mm/yr to 0.08mm/yr. An increment of 25yrs to 45yrs however, caused an increase in the corrosion rate from 0.08mm/yr to 0.21mm/yr, respectively this is in line with the work of Natto *et al*. (2005). The localized corrosion effects of dual-phase multiphase interaction of pipeline corrosion process parameters are obvious in figure 6. The yellow-pink–red region of these contour and surface plots indicate the ascending severity order and dominance of the localized attack on the pipes due to factor pairs involved.

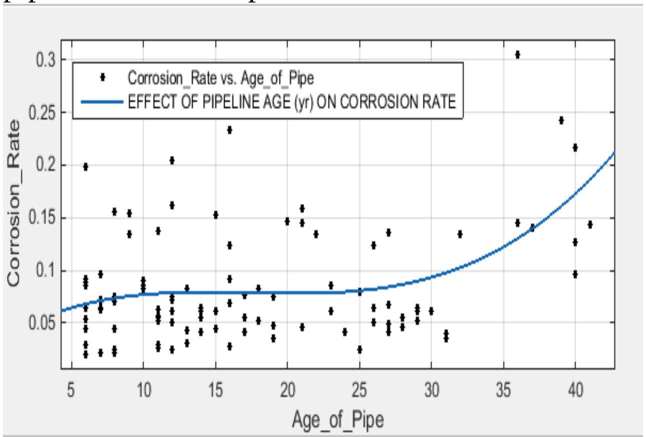
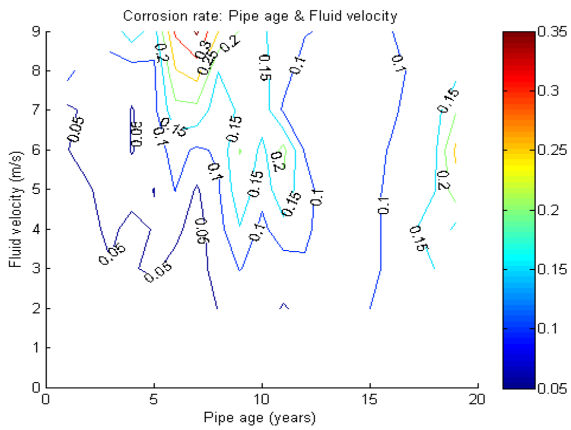


Fig.5: Effect of pipeline age on corrosion



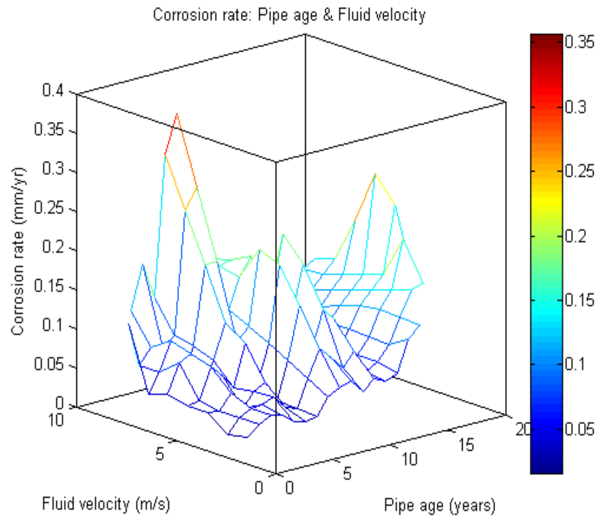


Fig. 6: Contour and surface plots of fluid velocity and pipe age on corrosion rate

3.3. Effect of Environmental pH

Fig.7 shows that an increase in pH reduces corrosion rate of pipelines. The corrosion rate increases with decrease in these parameters. This is in line with the experimental results by Chokshi *et al*. (2005). Sun and Nesic, (2004) stated that “localized corrosion is of large concern, and that pH stabilization technique should be practiced”. On a general view, it is clear that the corrosion rate increased with temperature and reduced with pH. The 3-D plot in figure 8 shows the contour-surface plot of corrosion rate versus fluid temperature and environmental pH. It is observed that the corrosion rate increased with higher temperature and lower environmental pH.

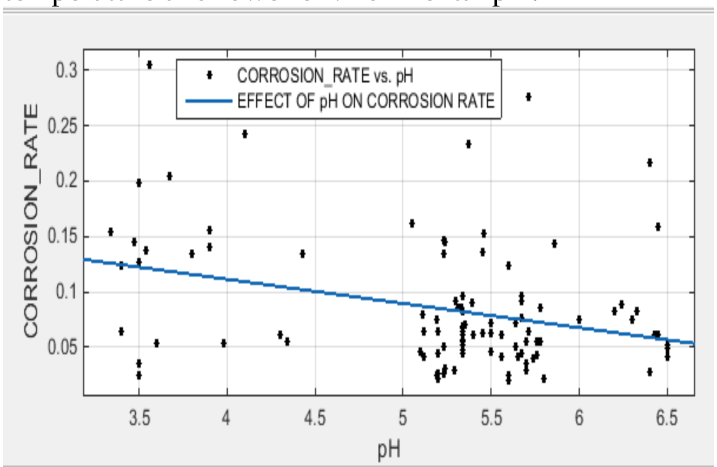


Fig.7: Effect of environmental pH on corrosion

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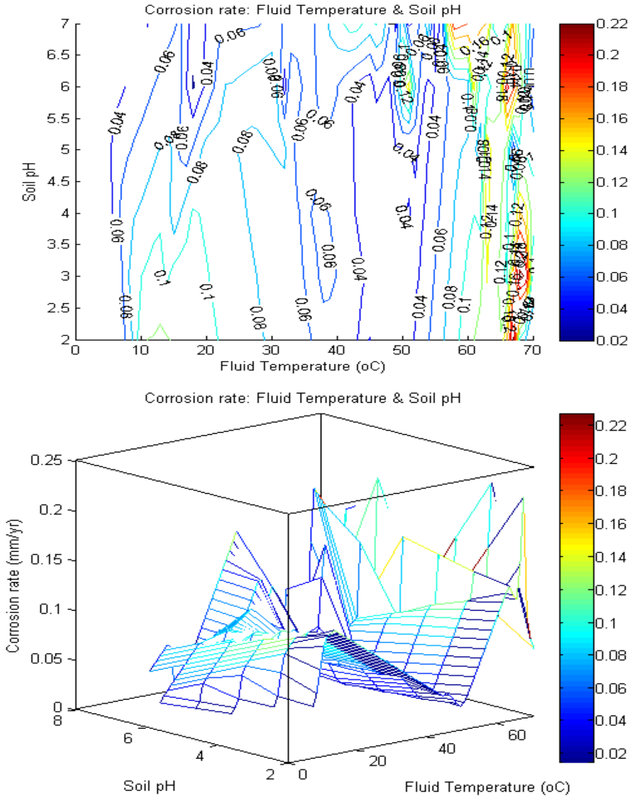

Fig.8: Contour and surface plots of fluid temperature and environmental pH on corrosion rate

3.4 Effect of flow rate

The flow velocity effect is shown in Fig.9. It is obvious that the corrosion rate increases along the pipeline with increase in velocity. This is because at high velocity more heat is generated which compensates for the part of the heat gain due to heat transfers between the transported fluid and surrounding environment. The turbulent flow of fluid increases the velocity near the pipe surface, wiping the passive protective film, which accelerates the corrosion mechanism (Nesic, 2007). However, in figure 10 when flow velocity increases from 1 m/s to 3 m/s, the corrosion rate remains relatively constant (about 0.1 mm/year), but when velocity flows between 3m/s and 3.5m/s, corrosion rate increases to about 0.15 mm/year. The interaction of flow velocity and pressure spikes reaction in the system, increasing corrosion rate to 0.45mm/yr. As a result of this reaction, there is a tendency of an erosional effect on the surface film growth and thickness, washing away the film and exposing the metal area to corrosive medium, thereby leading to an increase in corrosion rate.

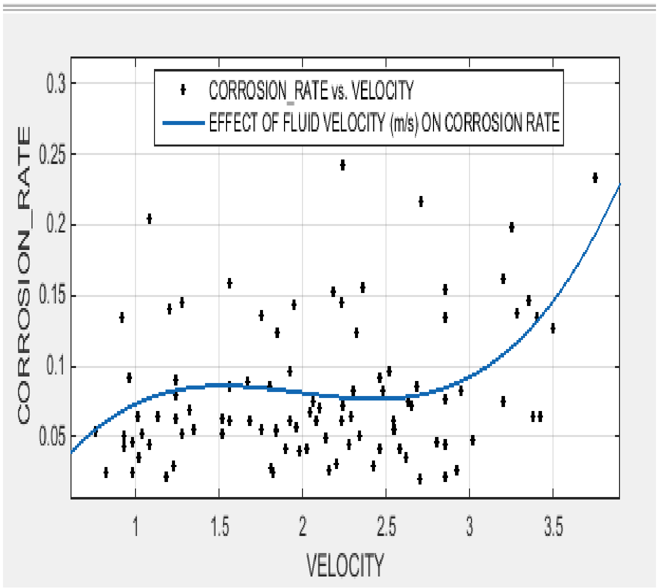

Fig. 9: Effect of flow velocity on corrosion

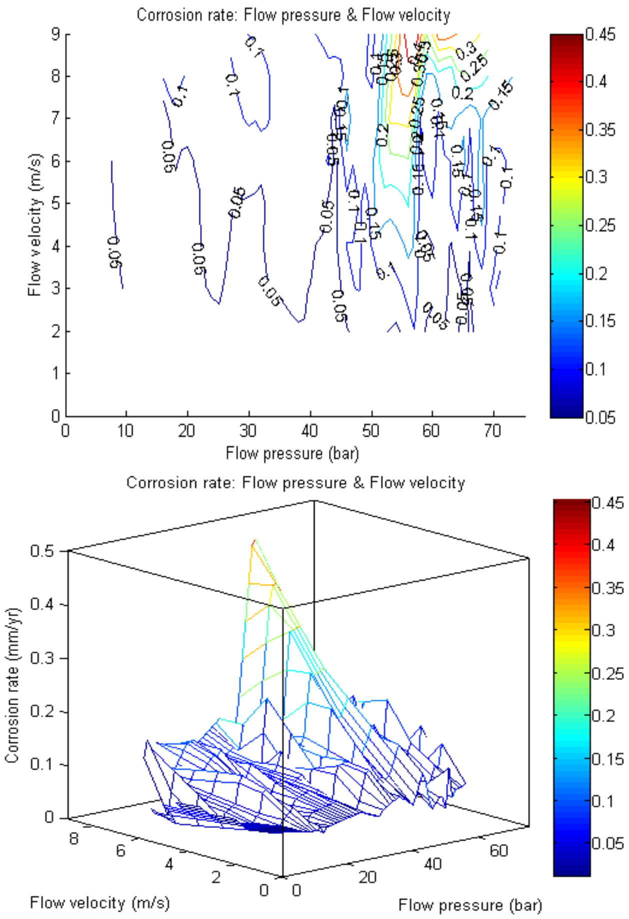

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Fig.10: Contour and surface plot of flow pressure and flow velocity on corrosion rate

3.5. Effect of Sand Flow

A stream of sand outside the pipeline causes erosion, and inside, usually accelerates corrosion by erosive abrasion of a layer of corrosion products deposited on the pipe walls. This is the basic knowledge of corrosion and wear. You will not see the graph rising but the sedimentation destroyed the coating which causes sag and expose the metal to the medium leading to wear. Fig 9, causes localized corrosion. At this point (figure 10) interactions of sand and fluid temperature destroys the protective films of the oil and gas pipeline leading to disbandment where the coating system sags and gives room to water/fluid entrainment that causes corrosion on pipeline surface (Ahammed, 1998). "This causes pitting density, which leads to pipeline failure" (Sun and Nesic, 2004).

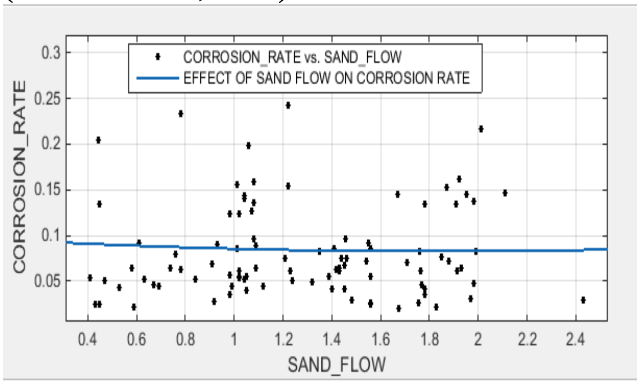
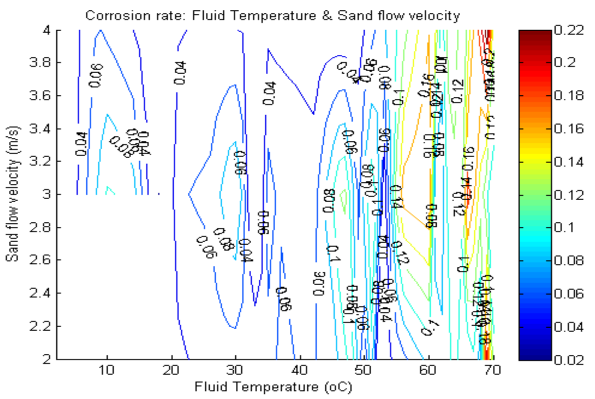


Fig.11: Effect of sand flow on corrosion



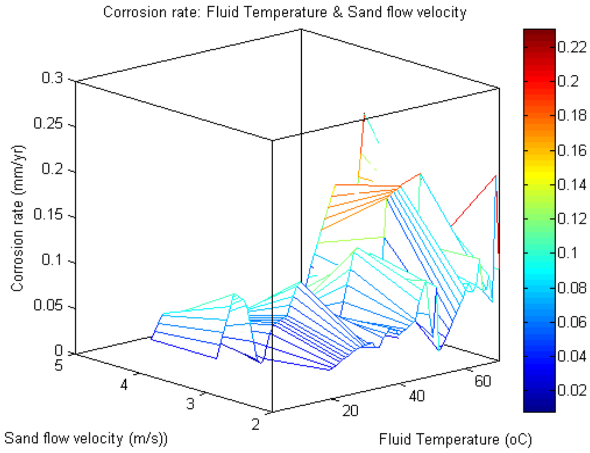


Fig.12: Contour and surface plots of sand flow and fluid temperature on corrosion rate

3.6 Further results verification analysis and validation

A model was developed for the prediction of corrosion rate, using ANN and was compared with experimental value and DeWaard models. Comparatively, results of this study show good indicators to the impressive performance of the model in predicting accurately, the rate of corrosion. Finally, the corrosion model developed in this study was compared with actual value (experimental) and it shows a satisfactory agreement in figure 13.

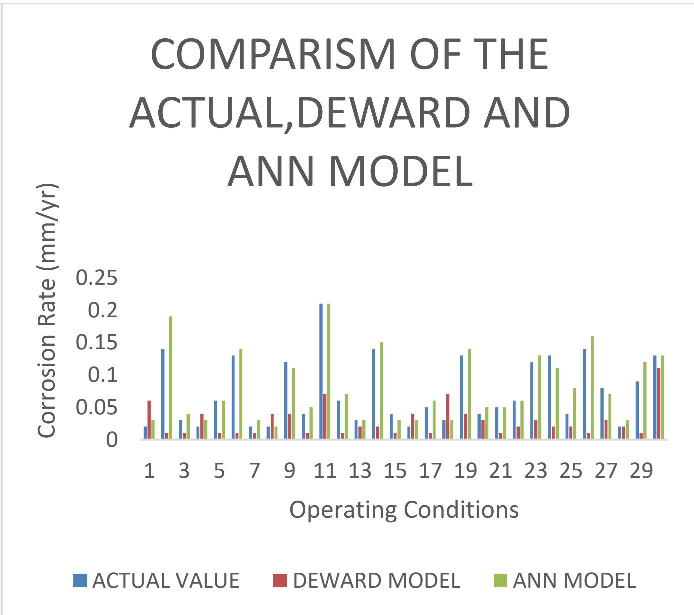


Fig.13: A comparison of the Actual value, developed ANN model with DeWaard at different operating condition

On validation these results were compared with those obtained using the DeWaard model. As shown in Table 2 and figure 13, both techniques provided corresponding models with an R^2 close to 1. Therefore, the model and the validation test results are satisfactory. Also, figure 9 results gotten from the validation confirmed the generalizations and robustness of the compared model.

Table 2: Validation/Comparison of the ANN model

Measurement	DeWaard Lotz	DeWaard Milliams	ANN Model
RMSE	0.0681	0.0526	0.0130
MAE	0.0530	0.0427	0.0079
SI	2.1603	0.4952	0.1708
R^2	0.0233	0.5336	0.9521

4. CONCLUSION

The intent of the present paper was to develop an ANN model and to provide a mainstream understanding of corrosion rate in oil and gas pipelines. Furthermore, the multi-factors interactions were examined to know the impact leading to corrosion in the oil and gas facilities, using MATHLAB 2014 software. The main findings can be listed as follows:

i. The study model was able to successfully predict corrosion rate between 0.02mm/yr-0.17mm/yr. Also prove that increase in temperature, flow rate, sand deposition and pipe age consistently increase in corrosion rates.
ii. The contour and surface plots indicate the ascending severity order of the localized attack on the pipes due to factor pairs.
iii. The results obtained by ANN predictions are consistent with the results of the experimental, and the validity of the achieved numerical outcomes is ensured by making a comparison with the existing work.
iv. The present ANN model reflects the mainstream understanding of corrosion rate in acidic environments, and can be easily used to predict the corrosion rates in industrial applications when coupled with other applications such as computational fluid dynamics (CFD) codes, multiphase flow simulators etc.

5. ACKNOWLEDGEMENTS

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