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Investigation of Pipeline Failure and Corrosion Rate Prediction Using a Reliability Model for Pipeline Integrity and Safety

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Abstract

Every year, the oil and gas sector spends billions of naira on transmission pipeline corrosion costs, which rise as pipeline networks age and deteriorate. As a result, pipeline operators must reconsider their approaches to corrosion prevention. Companies are being forced to create precise maintenance models based on failure frequency because of corrosion problems. Future line safety, lowering the frequency of failures, and cost-effective pipeline operation all depend on statistical techniques for modeling pipeline failures and making appropriate maintenance decisions. The present study predicted both the reliability and corrosion rate of crude oil pipelines by combining Monte Carlo simulation with degradation models. Corrosion was modeled using linear and power-law formulations that incorporated discrete random samples generated from inline inspection data. The degradation models were used to assess the mean time for failure (MTFF). The average corrosion rate (CRav) has a lower root mean square error (RMSE) than the largest occurrence projected random number (CRfreq), according to the TML shown against the RMSE of the predicted models. The RMSE for the degradation models ranged from 1.89 % to 17.02 %. This chart shows that the deterioration models correctly predicted the pipeline corrosion rate to be between 83.91% and 98.06%. Also, the Linear Model Law had the lowest recorded value of 1.98% and the most of 16.11%, while the Power Law degradation was the lowest at 1.88% and the most at 17.01%. When compared to the Monte Carlo Simulation value, which is 2.11 at the lowest and 1.01 at the highest, all of the findings fall between 1.89 and 17.02 percent. Consequently, the RMSE of the degradation models varied between 1.89 and 17.02 percent. Additionally, R^2 for the Linear Model ranges from 0.925 to 0.990, but it ranges from 0.989 to 0.999 for the Power Model. According to the results, the degradation model has correctly predicted the field corrosion of the pipelines and will be a crucial tool for predicting when the pipelines will break.

Keywords: Corrosion, Pipeline, Prediction, Monte Carlo Simulation, Reliability Model.

INTRODUCTION

The most widely used means of moving natural gas and crude oil are pipeline systems. Nearly 70% of oil and gas products are distributed globally via pipelines [1, 2]. Additionally, pipeline networks are expanding annually as a result of new pipes being built in new locations. Because of safety issues, pipelines need the highest level of dependability. Pipeline systems are getting increasingly complicated and are situated too close to densely inhabited areas, sometimes known as "high-consequence areas" (HCAs). As seen in Figure 1, pipeline breakdown brought on by corrosion of gas and oil infrastructure might happen between scheduled inspection periods.

Thus, to predict failure probabilities, it is crucial to determine the growth rate of corrosion using appropriate models. Pipeline systems are run as continuously as possible and incident-free due to economic and public safety reasons. Achieving this goal is necessary for effective maintenance tactics. Determining the reliability of the system is the first essential step in doing successful maintenance. Mathematical models can be used to formulate pipeline system reliability. The chance of pipeline failures can be estimated, and future failure patterns can be predicted using mathematical models.

Figure 1: Pipeline failure [3]

Corrosion represents a key challenge to pipeline integrity in oil and gas industries, so Pipeline Integrity Management (PIM) programs are vital for preventing failures. To ensure safety and dependability, these programs incorporate mitigation measures like coatings, cathodic protection, and corrosion inhibitors in addition to monitoring and inspection techniques like In-Line Inspection (ILI) using "intelligent pigs" and risk-based assessments [4-6]. Pipeline Integrity Management (PIM) programs are essential for preventing failures [7], and corrosion poses a danger to pipeline integrity in the oil and gas sector [8–10]. In order to guarantee safety and dependability, these programs combine inspection and monitoring methods like In-Line Inspection (ILI) employing "intelligent pigs" and risk-based assessments with mitigation solutions including coatings, cathodic protection, and corrosion inhibitors [11]. Data collection, analysis, and interpretation are essential to applying reliability to pipeline networks. As a result, failure data modelling would greatly aid operators in both anticipating the pattern of these unfortunate events and giving them a detailed understanding of the pipeline system's mishap. [12].

Corrosion could be described as the progressive deterioration of metals and some other similar materials due to chemical reactions in the atmosphere [13-15]. This process transforms the metal into a more stable state, such as an oxide, hydroxide, or sulfide [16]. One common manifestation of iron corrosion is rusting, which occurs when iron reacts with oxygen and water to form a reddish-brown substance that erodes the metal [17]. Corrosion rate, which is the rate at which a metal deteriorates as shown by its weight loss over a given length of time, is managed through a complete plan that involves evaluating the rate, implementing preventative measures, and performing maintenance [18-20]. Management strategies aim to lower the rate in order to minimize damage, costs, and safety risks. These methods include the application of inhibitors or passivators, protective coatings (like paint), and cathodic protection. The corrosion control plan of the oil and gas sector is supported by regular maintenance and monitoring and includes chemical inhibitors, cathodic protection, protective coatings, and material selection [21]. Maintaining asset life, reducing costs, and ensuring safety in difficult situations all depend on this comprehensive approach, which extends from the design phase to operations.

2. MATERIALS AND METHODS

The present study determines the most apt corrosion-growth model to illustrate how pitting depth distributions in underground pipelines evolve by processing and analyzing historical In-Line Inspection (ILI) corrosion data. Three consecutive magnetic flux leaks (MFL) ILIs of an operational pipeline, the design data for which is provided below, provided the data that were employed. While the second and third measurements were taken in 2010 and 2015, respectively, the first pit depths were taken in 2020. This project will determine how different boundary conditions and pipeline corrosion correlate with different pipeline strains. Using a probabilistic failure model for corroded pipelines, the present study systematically assesses how random environmental, operational, and design factors, including fluid pressure, corrosion rate, pipe diameter, defect depth and length, material yield strength, and wall thickness, influence the probability of failure. The present study employed root mean square (RMSE) and coefficient of determination (R^2) to evaluate the predictive performance of the model deployed. RMSE and R^2 are widely accepted statistical metrics for evaluating the predictive performance and goodness-of-fit of regression models, as demonstrated in various studies [22-25].

2.1 Pipeline stresses

Axial stresses are often caused by the restrained thermal strains of the following when the temperature of a pipeline is changed in an axial direction, as given by Equation (1).

$$\varepsilon = \alpha\Delta\sigma \qquad (1)$$

2.2 Estimation of Pipeline Corrosion Wastage

The best estimate of the pipeline corrosion rate will be provided by the annual corrosion rate (ACR), which is used to predict the corrosion waste of the pipeline. This will be accomplished by use root mean square error (RMSE) to compare the field data and the anticipated corrosion rates. Equation (2)[26], where n is the number of years of used corrosion data, CR_p is the Predicted Corrosion rate for ith year, and CR_i is the Measured field corrosion rate for ith year from Inline-inspection data; can be used to compute the RMSE.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(CR_p - CR_i\right)^2} \qquad (2)$$

The pipeline corrosion waste for the years 2000, 2005, and 2010 is predicted using the ACR with the lower RMSE, accordingly. The corrosion waste is a measure of the pipeline's total wall thickness loss over time. Decisions about risk-based inspection (RBI) are aided by knowledge of corrosion waste. In predicting corrosion rates, the best ACR (from Equation 3)[27], where δ_{CR} is the Change in the corrosion rate from one year to year, CR_p is the Previous value of the corrosion rate, μ is the Average value of the corrosion rate in each pipeline, σ is the Annualized volatility or standard deviation of the corrosion rate, δT is the change in time (in years) from one step to another, and ε is the Probability distribution for the period of the years; 1, 2, ..., i. is CR_1, CR_2, ..., CR_i, are used for the corrosion wastage for the nth year (CR_n) given by equation (4) [28].

$$\frac{\delta_{CR}}{CR_p} = e^{\mu\delta T + \sigma\varepsilon(\delta T)^{\frac{1}{2}}} \qquad (3)$$

$$CR_n = CR_1 + CR_2 + \ldots + CR_i = \sum_{i=1}^{n} CR_i \qquad (4)$$

2.3 Degradation Analysis and Reliability Estimation

Degradation refers to the decline in a system's integrity and functionality caused by aging, operational use, and external influences such as environmental conditions and human actions. It is necessary to estimate the rate of degradation, and reliability in order to forecast the pipeline's remaining life. Degradation can be described as a stochastic process since it is an ongoing process of wear and deterioration. The measured degradation for i_{th} tested device (i=1, 2 ……..n) will consist of a vector of m_i measurements made at time points $t_{i1}, \ldots t_{im_i}$. At the m_i time point, the degradation measurement (Y_{ij}) of device i is given by Equation (5)[29], where, tij is the Pipe wall thickness.

$$Y_{ij} = \eta\left(t_{ij}\right) + \epsilon_{ij}, 1 < i \leq n, i \leq j \leq m_i \qquad (5)$$

The process in which a system loses its functionality and integrity as a result of its operation, ageing and other factors like human and environmental effects is called degradation. Forecasting the pipeline's remaining life requires estimating the rate of degradation and reliability. Since wear and deterioration occur continuously during degradation, the phenomenon is best described as a stochastic process, mathematically determined using Equations (6) and (7)[30], where, CR is the degradation of pipeline due to corrosion, T_m is the Time A, and β is the Constants of model parameters.

$$CR = \alpha T_m + \beta \qquad (6)$$

$$CR = \beta(T_m)^{\alpha} \qquad (7)$$

The pipeline failure time was estimated using the degradation model equations mentioned above. When the thickness of the corroded wall is between 45% and 85% of the original wall thickness, the failure time is thought to have arrived. The study of life data was done using the average time of failure (mean time to failure). Using the degradation model and the relationship displayed in Equation (8)[31], [32], [33], where P is the percentage of corroded wall thickness (45%-85%), and CR_{it} is the Measured corrosion rates along the pipeline at years (1, 2,..., n); the mean time to failure (MTTF) for the pipeline was determined.

$$MTFF = \begin{cases} \dfrac{p * ti - CR_{it} - \beta}{\alpha} & for\ \ Linear\ Model \\ \left[\dfrac{p * ti - CR_{it}}{\beta}\right]^{\frac{1}{\alpha}} & for\ \ Powermodel \\ \dfrac{\log\left[\dfrac{p * ti - CR_{it}}{\beta}\right]}{\alpha} & for\ \ Exponential \\ e^{\frac{p * ti - CR_{it} - \beta}{\alpha}} & for\ \ Logarithmic \end{cases} \qquad (8)$$

2.4 Pipeline Data

The pipe is produced in OML 23, Niger Delta, Nigeria, and runs smoothly on three-phase crude. Table 1 displays the pipeline table that was used.

Table 1: Pipeline data

Pipe Material	**API 5L G X-56 Steel**
Length of Pipeline	16Km
Yield Strength	56KSI
Ultimate Tensile Strength	71KSI
Pipe Outer Diameter (OD)	323.90mm
Specified Wall Thickness	12.7mm
Operating Pressure	56.63 Bar
Design Pressure	80.90 Bar
Operating Temperature	40^0C
Design Temperature	100^0C

2.5 Inline Inspection Data

Before analyzing the ILI data, the thickness measurement location (TML) area was defined along the length of the pipeline to enable pairing of corrosion features across inspections. Defects were considered matched only if they occupied the same TML and the measured pit depths in the later inspections were greater than or equal to those in the preceding inspections (i.e., second ≥ first, third ≥ second). The matching procedure took into account the MFL-ILI tools' usual odometer and depth measurement inaccuracies. The studies that followed only included the matched flaws, guaranteeing that only the real evolution of problems over time was considered, excluding any defects that might have arisen in the interim between the three inspections. The ILI data are referred to as "2010-ILI," "2015-ILI," and "2020-ILI," which refer to the matched defect populations measured in 2010, 2015, and 2020, respectively. The depth distribution from the 2010 ILI run was used as the initial depth profile for each CR model under evaluation. An empirical corrosion-rate distribution was then derived from the observed depth changes of the matched defects over the time interval δt and compared to the distributions of corrosion rate predicted using the candidate CR models.

3.0 RESULTS AND DISCUSSION

ACR is modeled using the modeling equations (1) to (8). Using linear and power models, degradation analysis was carried out using inline inspection data. Regression analysis and the identification of model constants used to forecast the best fit equations were conducted using the Microsoft Excel analytical tool. Equation (8) was applied to estimate the MTFF at each measured corrosion rate in the field using these predicted equations of best fit. In this study, the pipeline's wall thickness was 12 mm, and the value of p was supposed to be 55%. The site of the thickness measurement was determined, and the results verified that corrosion existed in the years 2010 2015, and 2020, respectively (Figure 2). Inline-inspection data corrosion rate (mm/year) mean and standard deviation were calculated using the results for 2000, 2015, and 2020. The mean rate of corrosion increased between the study years of 2010, 2015, and 2020. To anticipate the annual corrosion rate and corrosion waste, the annualized corrosion rate (ACR) is calculated using the most common corrosion section of the simulation runs, standard deviation, and the mean corrosion rates. Future pipeline corrosion rate predictions are made using the ACR with the lowest inaccuracy.

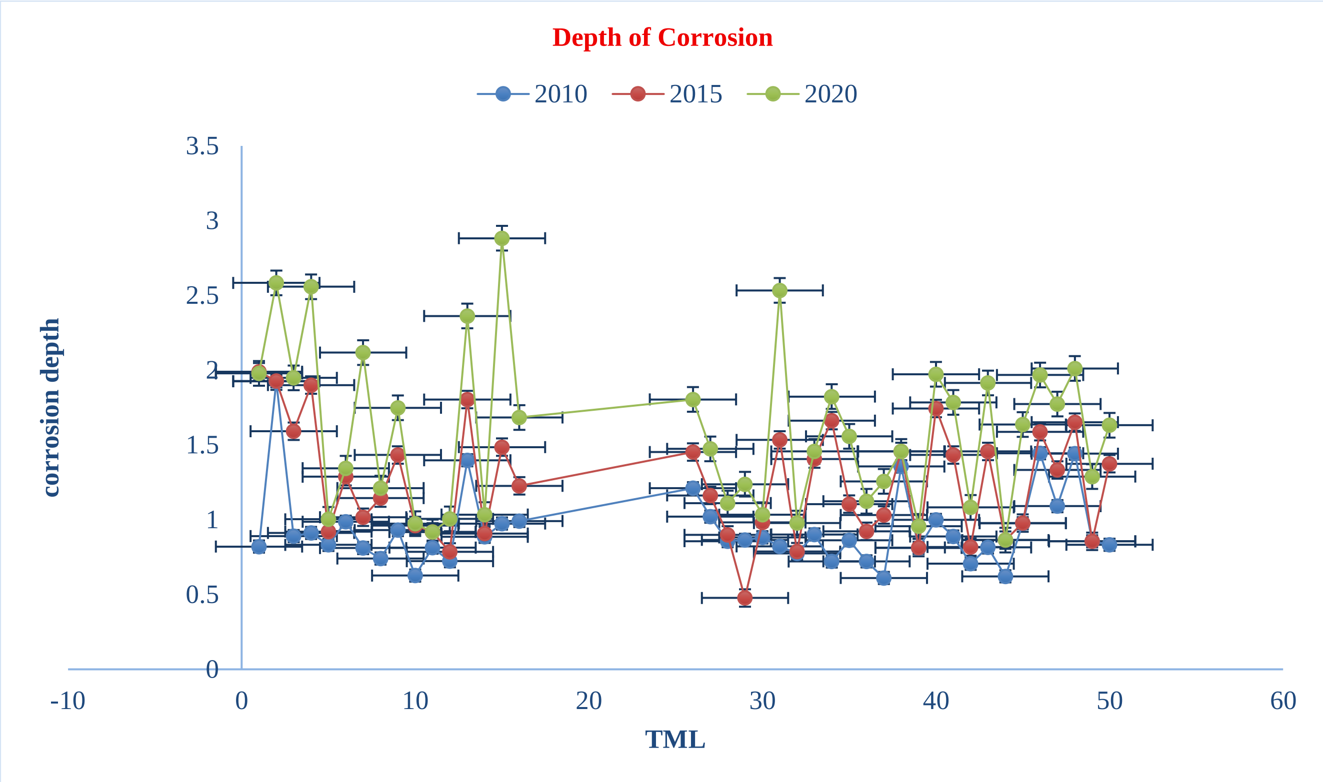

Figure 2: Depth of corrosion

Figure 3 shows the plot of RMSE against TML of the predicted models. Furthermore, as shown in Figure 3, the greatest occurrence projected random number (CRfreq) bigger than the RMSE for the average corrosion rate (CRav). In this study, the RMSE for the deterioration models ranged from 1.89 % to 1EQE.02 %. This figure indicates that the pipeline corrosion rate was accurately anticipated by the degradation models to be between 83.91 % to 98.06%. According to the plot, the Linear Model Law had the lowest recorded value of 1.98% and the maximum of 16.11%, while the Power Law degradation was the lowest at 1.88% and the most at 17.01%. All of the results lie between 1.89 and 17.02 % when compared to the Monte Carlo Simulation value, which is 2.11 at the lowest and 17.01 at the maximum. As a result, the deterioration models' RMSE ranged from 1.89 % to 17.02 %.

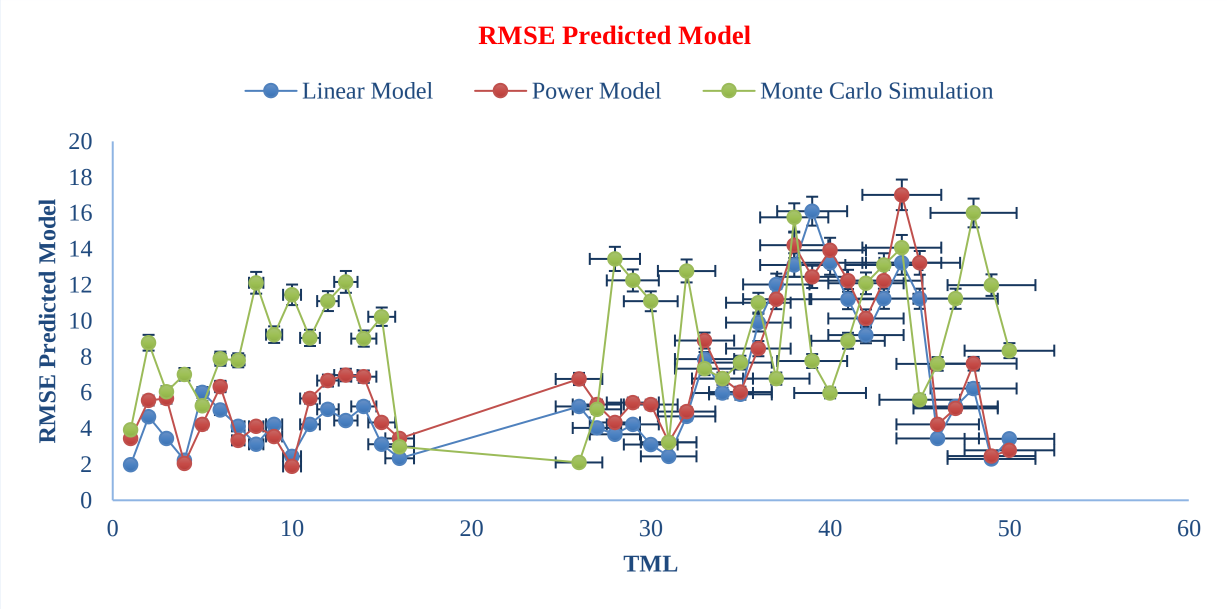

Figure 3: RMSE Predicted Model

Additionally, the pipeline corrosion rate could be predicted with an accuracy of 83.99 % to 98.84% using the average corrosion rate (CRav) derived from Monte Carlo simulation. Experts will therefore have a clear understanding of the pipes' dependability for improved integrity management if they use it to anticipate pipeline corrosion in the future. The variation of the pipelines' corrosion rates as determined by Monte Carlo simulation (CRpred) and the Degradation Model, as well as the inline-inspection data (field data), is displayed in Figure 4. For the Linear Model, R^2 falls between 0.925 and 0.990, while for the Power Model, it falls between 0.989 and 0.999. The findings show the deterioration model reliably predicted in-field pipeline corrosion, and will therefore be an essential tool for forecasting when the pipelines would fail.

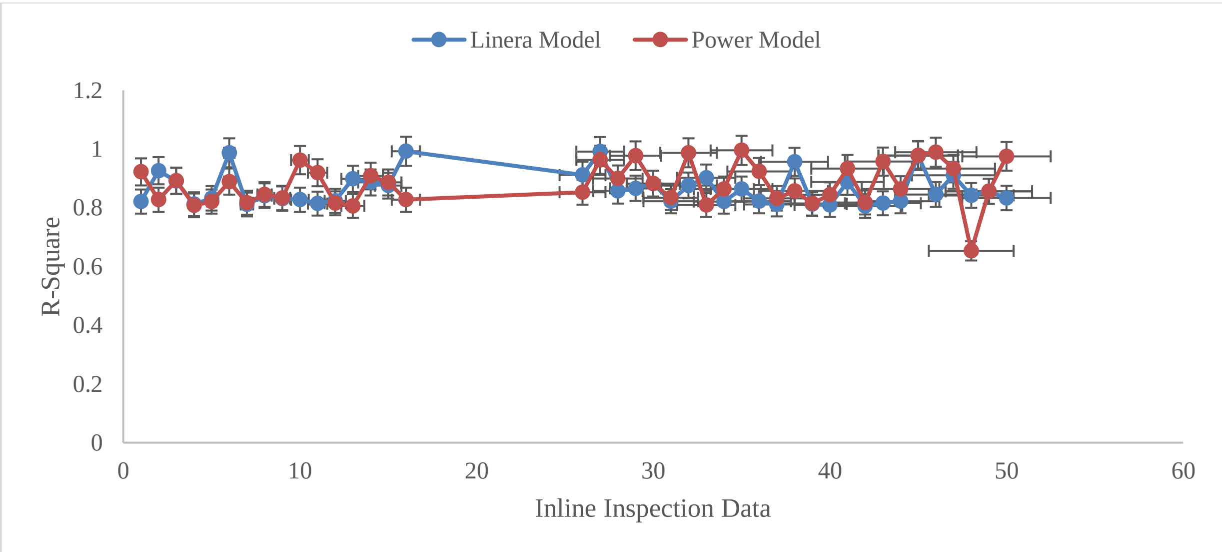

Figure 4: Corrosion Rates for Pipelines

4.0 CONCLUSION

The purpose of this study is to develop a reliability model for pipeline integrity and safety in order to anticipate pipeline failure and corrosion rate. While a large body of research has been done on repairable systems, less has been done on oil pipelines. As a result, this study attempts to create a tiny link between earlier research on repairable systems or other kinds of networks. In this study, pipeline corrosion was predicted and the pipeline's dependability over a specific time period was established using Monte Carlo simulation and degradation models. This research was conducted using field data from inline inspections. The pipelines' MTFF was estimated, and corrosion was predicated using linear and power-law models. The statistical outputs also provide expected failure counts and can be used to support reliability evaluations, risk assessments, and decisions about optimal maintenance. The project's conclusion demonstrated that the pipeline corrosion rate could be more accurately predicted by employing Degradation Models and Monte Carlo Simulation.

REFERENCES

1. Alfon, P., Soedarsono, J. W., Priadi, D., and Sulistijono, S. (2012). Pipeline Material Reliability Analysis Regarding to Probability of Failure Using Corrosion Degradation Model. Advanced Materials Research, 422, 705-715
2. Amirat, A., Mohamed-Chateauneuf, A. and Chaoui, K. (2006). Reliability assessment of underground pipelines under the combined effect of active corrosion and residual stress. International Journal of Pressure Vessels and Piping, 83, 107-117
3. Muhammad, W., Milos B.D. (2022). External corrosion of oil and gas pipelines: A review of failure mechanisms and predictive preventions. Journal of Natural Gas Science and Engineering, 100. https://doi.org/10.1016/j.jngse.2022.104467
4. Beavers, J., Thompson, N. (2006). External corrosion of oil and natural gas pipelines. American Society of Mechanical Engineers Handbook, 13, 1015-1024
5. Caleyo, F. F., Alfonso, L. L., Alcántara, J. J., and Hallen, J. M. (2008). On the estimation of failure rates of multiple pipeline system. Journal of Pressure Vessel Technology, 130(2), 021704
6. Gopika, V., S.K. Bidhar, H.S. Kushwaha, A.K. Verma, A. Srividya (2003). A comprehensive framework for evaluation of piping reliability due to erosion–corrosion for risk- informed in service inspection. Reliability Engineering & System Safety, 82(2), 187-193
7. Hopkins, P. (2004). Pipeline integrity-Some lessons learnt. In: WTIA international pipeline integrity & repairs conference; 2004. Sydney, Australia.
8. Klechka, E.W. (2002). Pipeline integrity management and corrosion control. Materials Performance, (2), 4-7.
9. Manian, L., Hodgdon, A.M. (2005). Pipeline integrity assessment and management. Materials Performance, 18-22.
10. Menno, T., Van, O.O., Mastrigt, P., Francis, A. (2006). An external corrosion direct assessment module for a pipeline integrity management system, 6th International Pipeline Conference, September 25-29, 2006, Calgary, Alberta, Canada.
11. Oyejide, J.O., Orhorhoro, E.K., Ogie, A.O., Idi, U.S. (2017). Investigation of the Effect of Annealing on the Corrosion Resistance of Medium Carbon Steel in Sea Water. Journal of Emerging Trends in Engineering and Applied Sciences, 8(5), 219-224
12. Huang, X., Zhang, L., Zhang, R., Chen, X., Zhao, Y., Yuan, S. (2021). Numerical simulation of gas-liquid two-phase flow in the micro-fracture networks in fractured reservoirs. J. Nat. Gas Sci. Eng., 94, 104101
13. Zhang, C., Gallichan, R., Leung, D.P., Budgett, D.M., McCormick, D. (2023). A high-precision and low-power capacitive pressure sensor interface IC with wireless power and data transfer for a pressure sensor implant. IEEE Sens. J., 23, 7105–7114
14. Rusin, A., Tomala, M., Łukowicz, H., Nowak, G., Kosman, W. (2021). On-line control of stresses in the power unit pressure elements taking account of variable heat transfer conditions. Energies, 14, 4708
15. Okuma S.O., Orhorhoro E.K., Tamuno R.I. (2020). Corrosion evaluation on mild steel in different selected media International Journal of Engineering Applied Sciences and Technology, 5(3), 33-38
16. Shao, C., Bao, N., Wang, S., Zhou, J. (2022). Study on the prediction method and the flow characteristics of gas-liquid two-phase flow patterns in the suction chamber. Int. J. Numer. Methods Heat Fluid Flow, 32, 2700–2718
17. Brodov, Y.M., Aronson, K.E., Ryabchikov, A.Y., Nirenshtein, M.A., Murmanskii, I.B., Zhelonkin, N.V. (2020). State of the art and trends in the design and operation of high- and low-pressure heaters for steam turbines at thermal and nuclear power plants in Russia and abroad: Part 2. Heater design and operation peculiarities. Therm. Eng., 67, 790–799.
18. Omoyi C.O., Orhorhoro E.K. & Ekanemberc B.A. (2024). Investigation of The Inhibition Action of Talinum Triangulare on the Corrosion of Mild Carbon Steel in Seawater. Journal of Materials Engineering, Structures and Computation, 3(3), 45-56
19. Qu, M., Yan, X., Wang, H., Hei, Y., Liu, H., Li, Z. (2022). Energy, exergy, economic and environmental analysis of photovoltaic/thermal integrated water source heat pump water heater. *Renew. Energy*, *194*, 1084–1097
20. Zhang, G., Cai, W., Tong, B., Sun, Y., Hu, E. (2023). Interfacial wave of the gas-liquid two-phase flow in unsaturated reservoir pores. Colloids Surf. A Physicochem. Eng. Asp. 2023, 670, 131597
21. Zahedi, R., Babaee Rad, A. (2022). Numerical and experimental simulation of gas-liquid two-phase flow in 90-degree elbow. Alexandria Eng. J., 61, 2536–2540.
22. Adeleke, T.B., Lawani, A.O., Oyejide, O.J., Osuizugbo, I.C., Enuezie, K.U., Amadhe, F., Anjorin, R.O., Chiejine, C.M., 2025. Firefly-optimized ensemble learning framework for accurate solar PV power forecasting. Next Research 2, 100811. https://doi.org/https://doi.org/10.1016/j.nexres.2025.100811
23. Amaya-Gómez, R., Riascos-Ochoa, J., Muñoz, F., Bastidas-Arteaga, E., Schoefs, F., Sánchez-Silva, M., 2019. Modeling of pipeline corrosion degradation mechanism with a Lévy Process based on ILI (In-Line) inspections. International Journal of Pressure Vessels and Piping 172, 261–271. https://doi.org/10.1016/j.ijpvp.2019.03.001
24. Essang, N.P., 2019. Simulation and Modelling of Pipeline Corrosion and Integrity Management in Oil and Gas Industry. International Journal of Trend in

Scientific Research and Development. https://doi.org/10.31142/ijtsrd21411

25. Khan, F., Yarveisy, R., Abbassi, R., 2021. Cross-country pipeline inspection data analysis and testing of probabilistic degradation models. Journal of Pipeline Science and Engineering 1, 308–320. https://doi.org/10.1016/j.jpse.2021.09.004
26. Li, J., Wang, Z., Zhang, Y., Fu, H., Liu, C., Krishnaswamy, S., 2017. Degradation data analysis based on a generalized Wiener process subject to measurement error. Mechanical Systems and Signal Processing 94, 57–72. https://doi.org/10.1016/j.ymssp.2017.02.031
27. Liu, H., Cai, X., Meng, X., 2025. Fast and Accurate Prediction of Corrosion Rate of Natural Gas Pipeline Using a Hybrid Machine Learning Approach. Applied Sciences (Switzerland) 15. https://doi.org/10.3390/app15042023
28. Okwu, M.O., Otanocha, O.B., Edward, B.A., Oreko, B.U., Oyekale, J., Oyejide, O.J., Osuji, J., Maware, C., Ezekiel, K., Orikpete, O.F., 2024. Investigating the Accuracy of Artificial Neural Network Models in Predicting Surface Roughness in Drilling Processes. Procedia Comput Sci 232, 1982–1990. https://doi.org/https://doi.org/10.1016/j.procs.2024.02.020
29. Olaye, M., Enuzie, K.U., Imala, O.O., Boma, G., Lawani, A.O., 2025. Multivariate Regression Approach in Modelling Catalytic Cracking Variables of Petroleum Refining. Nigerian Journal of Engineering Science Research 8, 164–170. https://doi.org/10.5281/zenodo.17410289
30. Oyejide, O.J., Ahmad, F., Kamaruddin, S. bin, Okwu, M.O., Amadhe, F., Basit, A.T., Anjorin, R., Abdulmalek, M., 2025. Novel stack-model configuration for Merox-treated gasoline yield prediction synergized with EMMS-CFD hydrodynamic analysis. Knowl Based Syst 325. https://doi.org/10.1016/j.knosys.2025.113980
31. Ren, Z., Chen, K., Yang, D., Wang, Z., Qin, W., 2024. Predicting the External Corrosion Rate of Buried Pipelines Using a Novel Soft Modeling Technique. Applied Sciences (Switzerland) 14. https://doi.org/10.3390/app14125120
32. Tian, Q., Liu, S., Meeker, W.Q., 2019. Using degradation models to assess pipeline life. Applied Stochastic Models in Business and Industry 35, 1411–1430. https://doi.org/10.1002/asmb.2489
33. Xu, S., Huang, C., Zhao, H., 2025. Prediction of the corrosion rates of subsea pipelines via KPCA. Scientific Reports 15. https://doi.org/10.1038/s41598-025-09685-6

