OPEN ACCESS
Saudi Journal of Engineering and Technology
Abbreviated Key Title: Saudi J Eng Technol
ISSN 2415-6272 (Print) |ISSN 2415-6264 (Online)
Scholars Middle East Publishers, Dubai, United Arab Emirates
Journal homepage: https://saudijournals.com

Original Research Article

Forecasting Corrosion Rates and Pipeline Reliability in the Oil and Gas Sector Using Monte Carlo Simulation Models

Akusu Onomine Murray[1*], Kingsley Udoka Enuezie[2], Rilwan Omogbolahan Anjorin[3]

[1]Department of Welding and Offshore Technology, Petroleum Training Institute, Effurun, Nigeria
[2]Department of Mechanical Engineering, Bells University of Technology, Ota, Nigeria
[3]Institute of Engineering, Technology and Innovation Management (METI), University of Port Harcourt, Choba, Nigeria

DOI: https://doi.org/10.36348/sjet.2025.v10i11.005 | **Received:** 13.09.2025 | **Accepted:** 08.11.2025 | **Published:** 12.11.2025

***Corresponding author:** Akusu Onomine Murray
Department of Welding and Offshore Technology, Petroleum Training Institute, Effurun, Nigeria

Abstract

The cost of corrosion-related transmission pipeline maintenance, which escalates as pipeline networks age and deteriorates, costs the oil and gas sector billions of naira every year. As a result, pipeline operators should reconsider their approaches to corrosion control. The present study employed the Monte Carlo Simulation model to forecast the rate of corrosion and dependability of pipelines carrying crude oil. The corrosion rate was predicted using a Linear and Power Law Model and discrete random numbers that were simulated from Inline Inspection Data. The study's conclusion demonstrates that the Monte Carlo simulation can forecast the pipelines' corrosion rate with an accuracy of 84.24–97.94%. From Monte Carlo Simulation results, a 2.01 lowest and 15.76 highest were obtained. Every value is within the range of 1.67% to 16.95%. The predicted number of failures is thus provided by the statistical models. Optimal maintenance decisions, risk analysis, and reliability analysis can all benefit from the statistical models' output.

Keywords: Monte Carlo Simulation, Failure, Pipeline, Reliability, Corrosion Rate.

INTRODUCTION

Energy is necessary for modern economies to produce goods and services, encourage the provision of heating, other utilities, and transportation to communities. For the efficient distribution and transportation of liquid and gas goods, pipelines are essential. One of the most common ways to move gas and crude oil from upstream to downstream locations is via pipelines. Pipelines are the favored option, while the oil and gas sector also use alternative modes of transportation such oil-gas tankers, tank trucks, and railroad tank cars. Pipelines are a crucial means of transportation for gas and oil products for two main reasons. First off, massive volumes of gas and liquid may be transported over vast distances using pipelines [1, 2]. For instance, 750 trucks and 225 carloads per day would be needed to replace a modest-sized oil pipeline that can move 150,000 barrels per day with tanker trucks and railroad cars, respectively [3]. Second, in comparison to other modes of transportation, the pipelines' design makes it possible for them to convey oil and gas products to end-use markets swiftly, safely, and affordably [4–10].

Pipeline Corrosion is major threat to both indigenous and international oil and gas companies in Nigeria. The pipeline's integrity is reduced by corrosion, which makes it fail before its intended service life. In 2011, internal corrosion in pipes accounted for 16% of pipeline failures in Canada and 25% of pipeline failures in the United States [11]. Making an approximation of pipeline corrosion rate is crucial to the analysis of pipeline reliability. One way to characterize pipeline corrosion is as a deliberate deterioration of the pipeline wall brought on by the material of the pipeline being affected by operational factors. Since corrosion is a major factor in pipeline failures in the oil and gas sectors [12], minimizing it will unavoidably boost output. Understanding the effects of a component failure on a system is necessary in order to prioritize inspection based on the allowable risk level [13]. To estimate the remaining life, the system must be analyzed in accordance with predetermined standards. Furthermore, the most widely used means of moving natural gas and crude oil are pipeline systems. Almost 70% of the world's oil and gas products are distributed via pipelines [14 – 16]. Additionally, when new pipes are built in new locations, pipeline networks expand annually. Because of safety reasons, pipelines demand the highest level of reliability. As a matter of fact, pipeline systems are getting increasingly intricate and situated in close proximity to densely populated areas known as 'high-consequence areas' (HCAs). Oil and gas facilities' corrosion can lead to pipeline failure between scheduled inspection intervals. It is therefore necessary to know the corrosion growth rate using models to predict the likelihood of failures. Because of worries about the economy and public safety, pipeline systems are run as continuously as feasible without any incidents. Achieving this goal is a prerequisite for effective maintenance measures. Determining the reliability of the system is the first essential step in doing successful maintenance. It is possible to formulate the reliability of pipeline systems using mathematical models. The likelihood of pipeline failures can be estimated, and future failure patterns can be predicted using mathematical models. Data collection, analysis, and interpretation are essential for applying reliability to pipeline networks. As a result, modeling failure data would be very helpful in giving operators a thorough understanding of what went wrong in the pipeline systems, in addition to helping them predict the pattern of these unfortunate accidents.

A kind of simulation called Monte Carlo simulation uses statistical analysis and iterative random sampling to calculate the outcomes. This simulation approach bears a strong resemblance to random experiments, in which the precise outcome is unknown beforehand. These models usually rely on several input parameters that, after being run through the model's mathematical procedures, provide one or more outputs. The models' input parameters are determined by a number of outside variables. These considerations make realistic models vulnerable to systematic variations in the input parameters. Given that the values of this input parameters represent their most likely values, deterministic models that ignore these variances are frequently referred to as base cases. An efficient model should account for the hazards related to different input parameters. Most of the time, scientists create multiple iterations of a model, including the base case, the best-case scenario, and the worst-case scenario depending on the input variable values.

2 METHODOLOGIES

2.1 Inline Inspection Data

Before the ILI data was used, a thickness measurement location (TML) area was established along the length of the pipeline. This allowed the corrosion defects from the two inspections to be matched, provided that the depths of the defects in the second and third inspections were either larger or equal to those of the first and second inspections, respectively. The MFL-ILI tools' normal odometer and depth measurement inaccuracies were taken into account throughout the matching process. In order to ensure that only genuine flaw development over time was taken into account and that defects that may have arisen in the interim between the three inspections were excluded, only the matched defects were included in the ensuing analyses. The designations "2000-ILI", "2005-ILI", and "2010-ILI" in ILI data pertain to the corresponding defect populations that were measured in 2000, 2005, and 2010, respectively. The initial depth distribution for each of the CR growth models under evaluation was the depth distribution of the flaws in the 2000-ILI. The observed pit-depth progression across the 5-year period between the two is best described by comparing this distribution to that of defects observed in 2005-ILI. A comparable evaluation was conducted for the second set of ILI data. A comparison was made between the corrosion rate distributions predicted by the CR models under assessment and an empirical CR distribution that was derived using data from both inspections based on the actual change in depth of the matched defects throughout the interval, δt. Consistent with established modeling practices, the predictive accuracy and reliability of the CR models were quantitatively assessed using the root mean square error (RMSE) and the coefficient of determination (R^2), as previously reported in related works [17 – 20].

In OML 23, Niger Delta, Nigeria, seamless, three-phase crude is produced for the pipe. The pipeline, which has coal tar coating, was put into service in 1995. The pipeline table used are show in Table 1 and 2.

Table 1: Inline-inspection data

TML	d-2013	TML	d-2018	TML	d-2023
1	0.721	1	0.922	1	1.379
2	0.926	2	1.027	2	1.584
3	0.291	3	0.592	3	0.949
4	0.812	4	1.101	4	1.358
5	0.232	5	0.521	5	1.003
6	0.987	6	1.288	6	1.345
7	0.511	7	0.817	7	1.118
8	0.741	8	1.145	8	1.212
9	0.331	9	0.433	9	0.549

TML	d-2013	TML	d-2018	TML	d-2023
10	0.627	10	0.962	10	0.974
11	0.814	11	0.919	11	0.919
12	0.723	12	0.785	12	1.006
13	0.398	13	0.404	13	0.763
14	0.886	14	0.908	14	1.035
15	0.775	15	0.786	15	0.883
16	0.992	16	1.227	16	1.684
17	0.782	17	0.884	17	0.884
18	0.844	18	0.849	18	0.962
19	1.062	19	1.063	19	1.619
20	0.688	20	0.688	20	1.345
21	0.988	21	0.993	21	1.547
22	0.534	22	1.335	22	1.592
23	0.215	23	0.716	23	0.716
24	0.772	24	0.922	24	1.079
25	0.589	25	0.891	25	1.105
26	1.211	26	1.453	26	1.805
27	1.021	27	1.163	27	1.474
28	0.857	28	0.809	28	1.112
29	0.266	29	0.477	29	1.238
30	0.882	30	0.882	30	1.034
31	0.422	31	0.534	31	0.534
32	0.776	32	0.787	32	0.978
33	0.902	33	1.406	33	1.457
34	0.421	34	0.663	34	0.824
35	0.863	35	1.105	35	1.558
36	0.722	36	0.923	36	1.124
37	0.611	37	1.032	37	1.257
38	1.356	38	1.457	38	1.457
39	0.812	39	0.814	39	0.956
40	0.299	40	0.744	40	0.973
41	0.288	41	0.433	41	0.785
42	0.706	42	0.818	42	1.083
43	0.215	43	0.457	43	0.615
44	0.622	44	0.864	44	0.864
45	0.977	45	0.978	45	1.637
46	0.445	46	0.589	46	0.968
47	1.091	47	1.333	47	1.774
48	0.442	48	0.653	48	1.012
49	0.856	49	0.856	49	1.289
50	0.833	50	1.375	50	1.632

(*TML= Thickness Measurement Location)

The pipeline corrosion growth can be analysed with any two set of ILI data. For the purpose of this project work, the 2000-ILI and 2005-ILI data will be used.

Table 2: Pipeline data

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

2.2 MODELING FAILURES

A statistical model for reliability of systems that are repairable will be develop. The definition of the natural gas and oil pipeline system's failure characteristics comes first. Because the rate of corrosion failures is not constant, corrosion failures are taken into consideration in this analysis. Stated differently, corrosion failures either get worse or get better with time. As a result, failure modes during the wear-out phase of corrosion must be described in statistical models. The most crucial stage in making accurate forecasts is characterizing failure, which is dependent on the probability distribution of the number of failures. Compute the failure rate for a given time interval as the first stage in the characterization process. In essence, a nonparametric estimate of the failure rate equation can be used to calculate failure rate. The distributions of each statistical data set vary, as evidenced by the pipeline's failures. Appropriate distribution fitting techniques should be chosen to fit the probability distribution after the failure rate has been determined. Over time, the pipeline systems can become less reliable or get more reliable. The pipeline will be simulated using Monte Carlo simulation. A stochastic method for estimating the likelihood of an event occurring is Monte Carlo Simulation, which generates random numbers between 0 and 1. This simulation tool aids in the development of a mathematical understanding of intricate real-world systems with the goal of utilizing probability of occurrence to describe the system's behavior. Using the mixed congruential method (MCM), randomly distributed random numbers between 0 and 1 must be generated in order to set up the simulation process. The MCM generates a sequence of U (0,1) random numbers denoted by $r_0, r_1, r_2 \ldots r_n$ according to the equation (1).

$$r_i = \frac{[(m \times a \times r_{i-1})(modulo_m)]}{m} \quad (1)$$

where, m is the pre – specified positive integer known as modulus, a is the pre – specified positive integer less than m known as the multiplier, c is the non – negative integer less than m known as the increment.

The pipeline's corrosion rates will be regarded as a random variable that travels along the Brownian Walk, an erratic time series path.

2.3 Estimation of Pipeline Corrosion Wastage

The best estimate of the pipeline corrosion rate will be provided by the annual corrosion rate (ACR), which will be used to predict the corrosion waste of the pipeline. This will be accomplished by utilizing RMSE to compare the expected corrosion rates with the field data. Equation (2) can be used to compute the RMSE.

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

Where n is the number of years of used corrosion data, CR_p is the predicted corrosion rate for ith year using equation (2), CR_i is the Measured field corrosion rate for ith year from Inline – inspection data.

In this study, corrosion waste of the pipelines for the years 2000, 2005, and 2010 is predicted using the ACR with the smallest RMSE. The total wall thickness loss of the pipeline over any given period is represented by corrosion waste. Knowledge of corrosion waste aids in making judgments on risk-based inspection (RBI). The best ACR (from equation 3) for years 1, 2,, i.e., CR_1, CR_2,..., CR_i, is used for the corrosion waste for the nth year (CR_n) provided by equation (4) in order to anticipate the corrosion rates;

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

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

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, ε is the probability distribution.

3. RESULTS AND DISCUSSION

The pipelines' RMSE is described in Table 3.

Table 3. Root Mean Square Error (RMSE) of Predicted Models

TML	MODEL					
	Linear		Power law		Monte Carlo Simulation	
	R^2	%	R^2	%	$CR_{freq.}$ (%)	$CR_{ave.}$ (%)
1	0.821	2.11	0.922	3.45	3.18	3.93
2	0.926	4.65	0.827	5.56	9.23	8.78
3	0.891	3.45	0.892	5.67	7.25	6.05
4	0.812	2.23	0.808	2.06	8.67	7.02
5	0.832	6.01	0.821	4.23	6.23	5.27
6	0.987	5.03	0.889	6.34	8.56	7.89
7	0.811	4.12	0.817	3.34	7.89	7.80
8	0.841	3.12	0.845	4.12	23.45	12.12

TML	MODEL					
	Linear		Power law		Monte Carlo Simulation	
	R^2	%	R^2	%	$CR_{freq.}$ (%)	$CR_{ave.}$ (%)
9	0.831	4.23	0.833	3.56	9.98	9.23
10	0.827	2.45	0.962	1.67	22.12	11.45
11	0.814	4.23	0.919	5.67	9.45	9.05
12	0.823	5.07	0.815	6.67	11.34	11.10
13	0.898	4.45	0.806	6.98	12.23	12.17
14	0.886	5.23	0.908	6.89	10.23	9.01
15	0.875	3.12	0.886	4.34	12.67	10.23
16	0.992	2.34	0.827	3.45	3.05	2.99
26	0.911	5.23	0.853	6.76	2.11	2.06
27	0.991	4.03	0.963	5.34	5.09	5.07
28	0.857	3.67	0.899	4.34	44.23	13.45
29	0.866	4.23	0.977	5.45	12.65	12.25
30	0.882	3.11	0.882	5.34	11.23	11.09
31	0.822	2.45	0.834	3.23	3.47	3.23
32	0.876	4.67	0.987	4.95	17.23	12.78
33	0.902	7.87	0.809	8.90	5.78	7.34
34	0.821	5.98	0.863	6.78	7.78	6.78
35	0.863	5.90	0.995	6.03	7.78	7.67
36	0.822	9.90	0.923	8.45	23.89	11.01
37	0.811	12.03	0.832	11.21	7.76	6.78
38	0.956	13.11	0.857	14.21	16.21	15.76
39	0.812	15.23	0.814	12.45	8.78	7.76
40	0.809	13.23	0.844	13.93	6.09	5.98
41	0.888	11.21	0.933	12.23	9.96	8.89
42	0.806	9.21	0.818	10.13	12.78	12.09
43	0.815	11.23	0.957	12.23	13.24	13.11
44	0.822	13.23	0.864	16.95	21.78	14.08
45	0.977	11.23	0.978	13.23	5.67	5.60
46	0.845	3.45	0.989	4.23	7.78	7.60
47	0.910	5.23	0.933	5.12	11.23	11.23
48	0.842	6.23	0.653	7.61	15.67	15.45
49	0.856	2.31	0.856	2.46	18.23	11.99
50	0.833	3.42	0.975	2.78	12.34	8.34

The results obtained from Table 3 demonstrate that the maximum occurrence projected random number (CRfreq.) has a higher RMSE than the average corrosion rate (CRave). This study found that the deterioration models had an RMSE ranging from 1.67% to 16.95%. This figure demonstrates that the pipeline corrosion rate was predicted by the degrading models with an accuracy ranging from 83.05% to 98.33% (Table 4.2). The plot of TML against the predicted models' RMSE is displayed in Figure 1. According to the plot, the linear model law had a lowest value of 2.11% and a maximum value of 15.23%; the lowest degradation was 1.67% for Power Law and the highest was 16.95 for Power Law. All of the results range from 1.67% to 16.95% when compared to the value found using Monte Carlo simulation, which is 2.01 at the lowest and 15.76 at the highest. Therefore, RMSE of between 1.67%-16.95% was recorded for the degradation models.

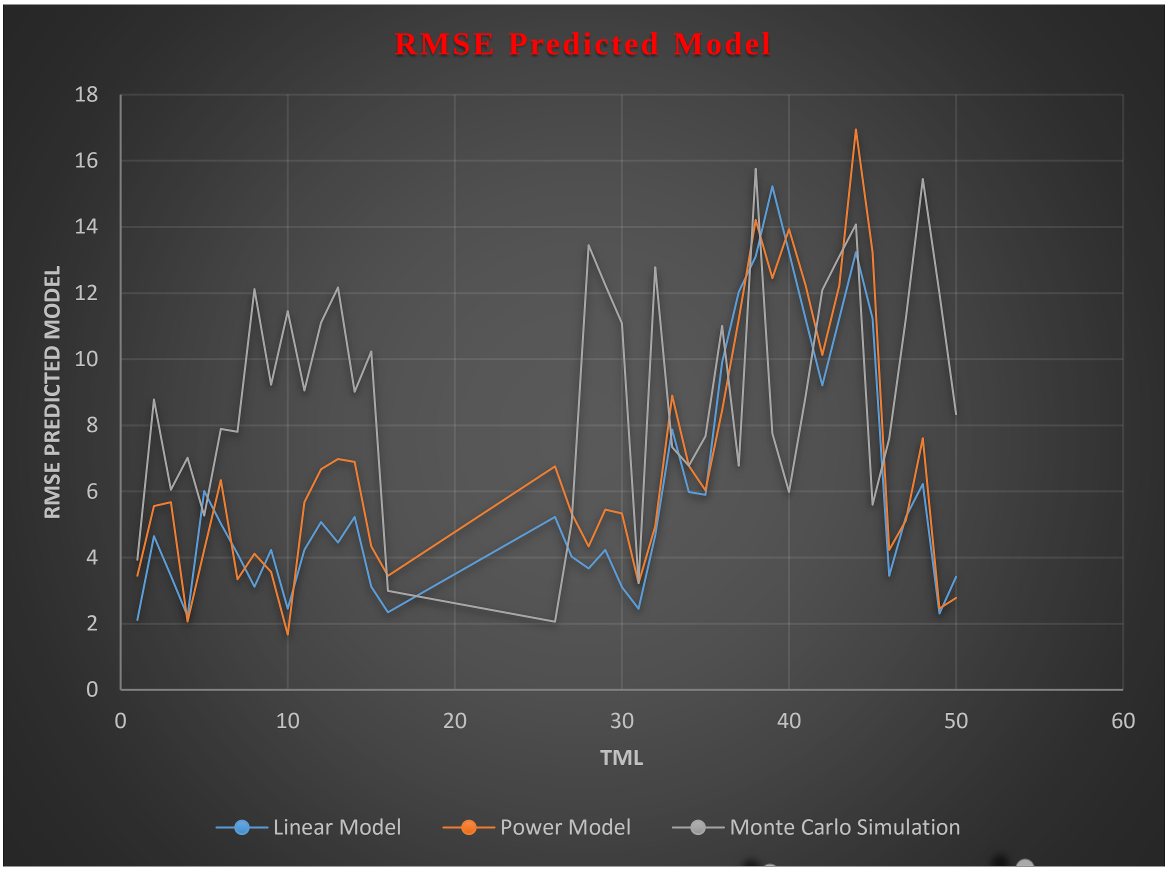

Figure 1: RMSE Predicted Model

Furthermore, Table 4.2 shows that the pipeline corrosion rate could be predicted with an accuracy of 84.24%–97.94% using the average corrosion rate (CRave.) derived from Monte Carlo simulation. Therefore, applying it to forecast pipeline corrosion in the future will provide specialists with a clear understanding of the pipelines' dependability for improved integrity management.

4. CONCLUSION

The purpose of this study is to develop a reliability model for pipeline integrity and safety in order to anticipate corrosion rates and pipeline failures. In this research, the reliability of the pipeline over a specific time was established and pipeline corrosion was predicted using Monte Carlo simulation. For this investigation, inline inspection data, also known as field data, was employed. The project's conclusion demonstrated that the pipeline corrosion rate may be more accurately predicted using both degradation models and Monte Carlo simulation.

REFERENCES

1. Seghier, M. E. A. B., Mustaffa, Z., and Zayed, T. (2022). Reliability assessment of subsea pipelines under the effect of spanning load and corrosion degradation. *Journal of Natural Gas Science and Engineering*, *102*, 104569.
2. Zakikhani, K., Nasiri, F., and Zayed, T. (2020). A review of failure prediction models for oil and gas pipelines. *Journal of Pipeline Systems Engineering and Practice*, *11*(1), 03119001.
3. AOPL. (2014). About Pipelines. www.aopl.org/aboutPipelines
4. BM Ali, M. N., BM Tuselim, A. S., B. Abu Bakar, M. H., Kalam Azad, M. F. A. B. A., M. Fuzi, N. B., and BM Suhot, M. A. (2022, October). Pipeline Integrty Management and the Invent of Analytics for Corrosion Threats. In *Abu Dhabi International Petroleum Exhibition and Conference* (p. D031S110R002). SPE.
5. He, T., Liu, Y., Liao, K., Xia, G., Ye, N., Lyu, X., Chen, S. and Tang, X. (2024). A novel liquid pipeline internal corrosion direct evaluation technology and the application on the water pipeline. *Engineering Failure Analysis*, *158*, p.108053.
6. Bhardwaj, U., Teixeira, A. P., and Soares, C. G. (2020). Uncertainty in reliability of thick high strength pipelines with corrosion defects subjected to internal pressure. *International Journal of Pressure Vessels and Piping*, *188*, 104170.
7. Chalgham, W., Wu, K. Y., and Mosleh, A. (2020). System-level prognosis and health monitoring modeling framework and software implementation for gas pipeline system integrity management. *Journal of Natural Gas Science and Engineering*, *84*, 103671.
8. Liu, Y., and Bao, Y. (2022). Review on automated condition assessment of pipelines with machine

learning. *Advanced Engineering Informatics*, *53*, 101687.
9. Qin, G., and Cheng, Y. F. (2021). A review on defect assessment of pipelines: principles, numerical solutions, and applications. *International journal of pressure vessels and piping*, *191*, 104329.
10. Ma, Q., Tian, G., Zeng, Y., Li, R., Song, H., Wang, Z., Gao, B. and Zeng, K. (2021). Pipeline in-line inspection method, instrumentation and data management. *Sensors*, *21*(11), p.3862.
11. Alamri, A. H. (2020). Localized corrosion and mitigation approach of steel materials used in oil and gas pipelines–An overview. *Engineering failure analysis*, *116*, 104735.
12. Jena, H., Satpathy, S., Sahoo, S., Sahu, S., & Nayak, B. B. (2023). Corrosion Protection Practices and Integrity Management Challenges in Oil and Gas Pipeline. In *Transportation Systems Technology and Integrated Management* (pp. 141-162). Singapore: Springer Nature Singapore.
13. Amaechi, C. V., Hosie, G., & Reda, A. (2022). Review on subsea pipeline integrity management: An operator's perspective. *Energies*, *16*(1), 98.
14. Huang, Z., & Shuai, J. (2023). Performance evaluation method of oil and gas pipeline integrity management. *Journal of Loss Prevention in the Process Industries*, *84*, 105099.
15. Amaya-Gómez, R., Bastidas-Arteaga, E., Sánchez-Silva, M., Schoefs, F., & Muñoz, F. (2023). *Corrosion and Reliability Assessment of Inspected Pipelines*. Springer.
16. Oswell, J., & Dewar, D. (2023). International perspective of pipeline geotechnical advances and current challenges (We Are More Fallible Than We Think We Are). In *Sixth international pipeline geotechnical conference. ACIEM, Bogota*.
17. 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*(4), 100811. https://doi.org/https://doi.org/10.1016/j.nexres.2025.100811
18. 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 Computer Science*, 232, 1982–1990. https://doi.org/https://doi.org/10.1016/j.procs.2024.02.020
19. 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*(1), 164–170. https://doi.org/10.5281/zenodo.17410289
20. 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. *Knowledge-Based Systems*, 325. https://doi.org/10.1016/j.knosys.2025.113980

