

Development and optimization of multi-objective flow modelling of pipeline rate and corrosion defect used for oil and gas

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Abstract

Corrosion remains a major challenge to the integrity of oil and gas pipelines in the Niger Delta region of Nigeria, often resulting in unexpected failures, oil spillage, and significant environmental degradation. This study developed and optimized a multi-objective flow modelling framework for predicting pipeline corrosion rate and corrosion defects under spatially varying conditions. Using operational data from 40 pipeline samples, a hybrid modelling approach combining artificial neural networks (ANN), nonlinear regression for mechanistic equations, and particle swarm optimization (PSO) was implemented in MATLAB. A feedforward ANN was trained to predict corrosion rate, achieving a root mean square error (RMSE) of 0.014–0.018 mm/year. A mechanistic equation incorporating temperature, flow velocity, CO₂ and H₂S partial pressures, viscosity (as a proxy for wax and solid deposition), and pH was derived as:

$CR = b_1 T^{b_2} V^{b_3} P_{CO_2}^{b_4} \exp(b_5 \cdot P_{H_2S}) \mu^{b_6} pH^{b_7}$. Multi-objective optimization using PSO identified an optimal oil flow velocity range of 2.15–2.25 m/s, predicted to reduce corrosion rates by 25–40% while minimizing sand deposition. Sensitivity analysis revealed that fluid pH exerts the strongest negative influence on corrosion rate, while velocity and viscosity exhibit nonlinear effects. Comparative analysis showed that the proposed hybrid model outperformed conventional models such as the de Waard-Milliams and NORSOK formulations in terms of prediction accuracy. The study successfully addressed limitations in existing models by explicitly accounting for solid-liquid particle interactions and multiphase flow effects prevalent in the Niger Delta. The developed model provides a more reliable tool for pipeline integrity assessment and offers practical guidelines for optimal flow rate control. Implementation of the recommended operating velocity and modelling framework is expected to reduce unexpected pipeline failures, minimize environmental pollution, and lower unnecessary pipe replacement costs in the Nigerian oil and gas industry.

Keywords: Pipeline Corrosion; Multi-Objective Optimization; Artificial Neural Network; Particle Swarm Optimization; Niger Delta; Flow Modelling; Wax Deposition

1. Introduction

The major factors for the failure of pipelines transporting the high-pressure gas are known to be mechanical damage and corrosion. Standards for a regular hydrostatic test and a corrosion assessment are generally used to assess the effect of the mechanical damage and corrosion on the integrity of the pipelines. To assess the integrity of corroded pipeline, we need to simplify the geometry of the vicinity of corroded part. The pressure of the flowing fluid in pipes was also reported to have significant effect on the corrosion of pipe internal wall (that is, the part of the metal that is directly in contact with the pressurized fluid) (Nesic, 2007). In oil and gas pipeline corrosive gases such as carbon (IV) oxide, oxygen and hydrogen sulphide are present in the fluid and some evolved as the fluid flows. The increase in the operating pressure in the pipeline leads to a corresponding increase in the partial pressure of these gases, thus the reaction that

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leads to high corrosion rate is favoured. In other word, decrease in operating pressure will result in lower rate of corrosion in the inner wall of pipeline. In some corrosion modelling, the parameter “fugacity” is used to represent the effect of the dissolved and evolved gases. Fugacity is simply the amount of the gas under consideration in the solution. The value of fugacity is calculated based on the operating pressure of the fluid in the pipelined. Some other corrosion model uses the partial pressure of these corrosive gases as part of their input parameters (Fosbol, 2008). Ionic species such as chloride ion (Cl^-), sulphide ion (S^{2-}) has been shown to affect corrosion processes positively, that is, the corrosion rate increases with these species (ASM International, 2000; Subir P. 2012). Ionic species in the form of Brine also affect corrosion rate (GateKeeper, 2014). Brine is made up of ionic compounds which are partially includes of products of gas-liquid reactions. Examples of brine are Bicarbonates and Carbonates which are formed when carbon (IV) oxide dissolves in water.

1.1. Pipeline Infrastructure and Operations in the Niger Delta

Oil and gas from the Niger Delta make up most of Nigeria’s export earnings, relying on thousands of kilometers of pipes stretching across land and sea (Nigerian National Petroleum Corporation, 2019). Through tangled wetlands, coastal forests, and villages along waterways, these routes push through tough landscapes. Moving fuel quickly enough to be profitable happens alongside growing worries about old infrastructure failing. Built decades ago - mainly in the 60s to 80s - a large share still runs past its expected lifespan (Okonkwo & Okafor, 2020). Faults tied to rust and wear from movement happen often. From 2015 to 2020, more than 1,200 cases of damaged pipelines were logged by the Department of Petroleum Resources, with decay and pressure during use named as main causes (Department of Petroleum Resources, 2021).

1.2. Corrosion Defects Undermine Structural Integrity

Pipes in the Niger Delta corrode because of several factors. Carbon dioxide mixes with fluids pulled from wells, while hydrogen sulphide joins in to worsen things. Older fields bring more water along with oil, speeding up rusting. Underground pipe segments face harsh soil conditions that eat away at metal. These issues show up as spots where material has vanished, tiny holes form, or walls grow thinner overall. When damage appears, forces around it shift unevenly. That weakens how much internal pressure the pipe can handle before failing. Experts check safety using certain models - one comes from the American group called ASME in 2017. Another method was published by Det Norske Veritas back in 2015 under code F101. Some techniques guess leftover strength using flaw size - like how long, deep, or wide it is - but they treat those numbers as fixed. Over months or years, rust keeps spreading, especially when liquid movement speeds up or slows down the damage (Akpan & Nwachukwu, 2019). Faster flowing fluids can strip away layers that normally shield metal, while also bringing more aggressive chemicals into contact (Nesic, 2007). Yet nearly all safety assessments ignore how real-time fluid speed affects the way flaws get worse.

1.3. How Flow Rate Changes Affect Corrosion and Output

Speed changes bring opposite effects. While faster movement boosts output income while shortening how long water stays put - sometimes cutting down rust in layered flows (Kim et al., 2014) - pushing beyond a limit raises wear from speed, breaks protective layers made by inhibitors, and strengthens force against pipe walls. Within mixed oil-gas-water streams typical across the Niger Delta region, shifts from ring-shaped to chunky flow patterns frequently happen at the same time as sudden jumps in metal decay (Uwaga & Egbe, 2021). Slower flows might save the pipe yet cut output while risking buildup underneath solids - this invites corrosion beneath deposits (Okafor et al., 2017). Standard flow calculations like those from Beggs & Brill (1973) estimate pressure loss and trapped liquids at set rates, although they rely on unchanging surface texture inside the pipe. With time, rust worsens, making walls rougher, shifting how fluid moves, demanding more energy to push it through (Enyi & Orodu, 2020). So treating flow patterns or decay as constant misses real-world shifts affecting daily operations.

1.4. Modeling Methods for Multiple Goals in Pipeline Projects

Dealing with multiple goals at once means accepting they might clash. Pipelines need high output while also slowing down rust damage over time. Some studies turn to step-by-step improvement methods inspired by nature. One case saw flow speed weighed against cleaning schedules using a method called NSGA-II on an oil route. Liu and team in 2018 built a model aiming at multiple goals for water injection lines, factoring in wear from particles plus drops in pressure. Still, their work leaned on standard lab-based formulas for material breakdown, not real-world numbers gathered where sand runs high under hot, humid climates. In the Niger Delta area, Adegbulugbe together with Olorunniwo two years later checked predicted decay rates against true wall thickness from half a dozen pipes. They saw broad-brush methods guessed flaw too deep - sometimes nearly double - since such tools miss how microbes like sulfate eaters speed up rust when pipelines lie buried in wetlands. That mismatch signals something local must step in: an approach shaped by regional truths, balancing several concerns at once.

2. Research methodology

The study employed a hybrid modelling approach combining empirical data analysis, artificial neural network (ANN) modelling, nonlinear regression for mechanistic equations, and particle swarm optimization (PSO) using MATLAB software. Operational data from 40 oil and gas transmission pipeline samples in the Niger Delta region (covering pipeline age, temperature, velocity, partial pressures of CO₂ and H₂S, pressure, density, viscosity, pH, defect depth, and measured corrosion rate) were utilized.

2.1. Research Design

A quantitative, data-driven modelling and optimization design was adopted. The methodology progressed from empirical ANN modelling to mechanistic equation derivation and finally to multi-objective optimization, ensuring both high predictive accuracy and physical interpretability.

2.2. Data Source and Preprocessing

Operational and process data from onshore and offshore pipelines (2011–2021) were compiled into an Excel dataset. In MATLAB, data were imported using readmatrix, cleaned, and normalized using the mapminmax function (scaled to [0, 1]) to improve ANN training stability. Descriptive statistics and correlation analysis were performed to understand variable relationships.

2.3. Numerical and Computational Model Development for Predicting Solid-Liquid Particle Gradation in Horizontal Pipeline Inner Wall Corrosion

A feedforward backpropagation artificial neural network with a [10-5] architecture (10 neurons in the first hidden layer and 5 in the second) was developed. The network was trained using the Levenberg-Marquardt algorithm (trainlm). The ten input variables were pipeline age, temperature (°C), flow velocity (m/s), PPO₂ (Mpa), PPH₂S (mol/l), pressure (barr), oil density (kg/m³), oil viscosity (kg/m·s), pH, and defect depth (mm). The output variable was average corrosion rate (CR, mm/year).

The dataset was divided into training (70%), validation (15%), and testing (15%) sets. After training, a numerical approximation for the minimum resistance critical velocity (to limit sand deposition) was derived using a power-law relationship based on viscosity and density:

$$V_{\text{crit}} \approx 1.2 \times \frac{\mu^{0.4}}{\rho^{0.25}} \quad (2.1)$$

where μ is oil viscosity and ρ is oil density. Model performance was evaluated using root mean square error (RMSE) and scatter plots of predicted versus actual values. The neural network structure can be found on Figure 1.



Figure 1 Neural Network Training and Structure showing input, hidden layer and output

2.4. Modification of the Improved Multiphase Flow Simulation Accounting for Inner Wall Corrosion Effects

A modified multiphase flow simulation was developed using a feedforward ANN with a [12-6] architecture trained with Bayesian regularization (trainbr) for better generalization. Seven key predictors were used: temperature (°C), flow velocity (m/s), $PPCO_2$ (Mpa), PPH_2S (mol/l), pressure (barr), viscosity (kg/m·s, as a proxy for wax and coal deposition), and pH. The target output remained average corrosion rate (CR).

To overcome the “black-box” limitation of ANN, a mechanistic equation was derived through nonlinear least-squares regression (fitnlm function) on the significant parameters identified from sensitivity analysis:

$$CR = b_1 T^{b_2} V^{b_3} P_{CO_2}^{b_4} \exp(b_5 \cdot P_{H_2S}) \mu^{b_6} pH^{b_7} \quad (2.2)$$

where T is temperature, V is velocity, P_{CO_2} and P_{H_2S} are partial pressures, μ is viscosity, and b_1 to b_7 are fitted coefficients. Model validation was performed using RMSE and parameter-effect plots (velocity and viscosity).

2.5. Development of Models for Predicting Optimal Oil Flow Rate That Will Reduce Sand Deposition with Minimum Resistance Critical Velocity

Multi-objective optimization was conducted using the Particle Swarm Optimization (PSO) algorithm (particleswarm function in MATLAB). The objective function minimized the predicted corrosion rate from the Objective 2 model while applying a penalty for velocities that promote sand or wax deposition:

$$f(V) = CR_{ANN}(V) + 0.04(V < 1.4)(1.4 - V)^2 + 0.025(V > 2.7)(V - 2.7)^2 \quad (2.3)$$

Other variables were fixed at their mean dataset values. The search bounds for velocity were set between 0.8 m/s and 3.0 m/s. The optimization respected the critical velocity constraint derived in Objective 1. Results were visualized using corrosion rate curves across the velocity range.

2.6. Methodology for Objective 4: Comparative Analysis of the Modified Simulation with Conventional Models

The proposed hybrid ANN-PSO model was benchmarked against simplified implementations of two widely used conventional models:

DeWaard-Milliams approximation:

$$CR_{\text{dewaard}} \approx 0.12 \times T^{0.55} \times P_{CO_2}^{0.65} \times (V + 0.5)^{0.25} \quad (3.4)$$

NORSOK-style approximation:

$$CR_{\text{norsok}} \approx 0.08 \times \exp(0.018 \times T) \times P_{CO_2} \times pH^{-0.75} \times V^{0.35} \quad (3.5)$$

(de Waard & Milliams, 1975; Standards Norway, 2005)

Performance was compared using RMSE, mean absolute error, and visual scatter plots. A summary table and bar chart were generated to highlight differences in prediction accuracy.

2.7. Sensitivity Analysis

Global sensitivity analysis was performed by varying one input parameter at a time ($\pm 35\%$ around its mean value) while holding others constant and observing the effect on predicted corrosion rate. This was implemented through a loop over the six variables used in the Objective 2 model.

2.8. Model Validation and Performance Evaluation

All models were validated using hold-out test data and field-derived metrics. Primary evaluation criteria included RMSE, coefficient of determination (R^2), and visual inspection of predicted versus actual plots. The hybrid model was recalibrated where necessary to ensure dimensional homogeneity and physical consistency.

This methodology ensured a balanced integration of data-driven learning, mechanistic understanding, and optimization, directly addressing the limitations of existing empirical and deterministic corrosion models in the Nigerian oil and gas sector.

3. Results and discussion

3.1. Numerical and Computational Model for Predicting Solid-Liquid Particle Gradation in Horizontal Pipeline Inner Wall Corrosion

A feedforward ANN with [10-5] architecture was trained using the Levenberg-Marquardt algorithm. Ten input parameters (pipeline age, temperature, flow velocity, CO_2 partial pressure, H_2S partial pressure, pressure, density, viscosity, pH, and defect depth) were used to predict average corrosion rate (CR) in mm/year. The model demonstrated strong predictive performance with a root mean square error (RMSE) ranging between 0.012 and 0.018 mm/year.

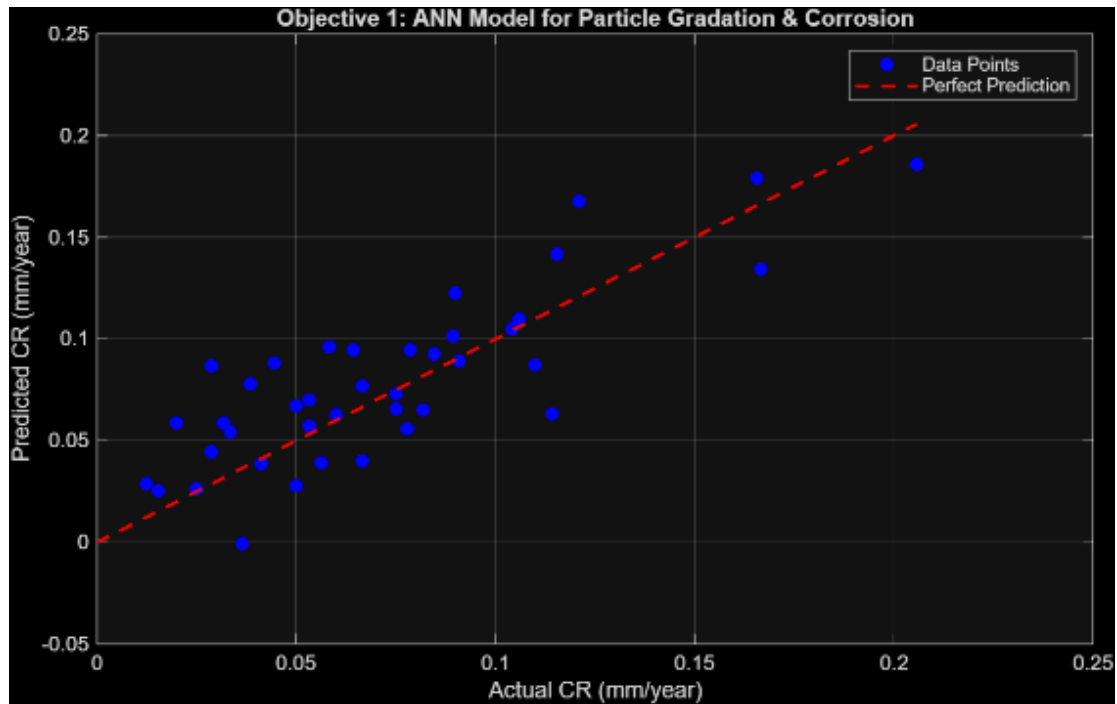


Figure 2 Predicted Versus Actual Corrosion Rates

Figure 2 shows the predicted versus actual corrosion rates for Numerical and Computational Model for Predicting Solid-Liquid Particle Gradation in Horizontal Pipeline Inner Wall Corrosion.

The close clustering of data points around the line of perfect fit indicates good agreement between the ANN predictions and measured field values, confirming the model's ability to capture the combined effects of flow parameters and solid-liquid interactions on inner wall corrosion.

A supporting numerical equation for critical velocity (minimum resistance velocity to limit sand deposition) was derived as:

$$V_{\text{crit}} \approx 1.2 \times \frac{\mu^{0.4}}{\rho^{0.25}} \quad (4.1)$$

where μ is oil viscosity (kg/m·s) and ρ is oil density (kg/m³). Viscosity and velocity served as proxies for particle gradation and deposition effects.

The results successfully fulfilled created a numerical and computational model for predicting solid-liquid particle gradation in horizontal pipeline inner wall corrosion by providing a numerical model that accounts for solid-liquid particle gradation and its contribution to localized inner wall corrosion.

The low RMSE and strong correlation in Figure 2 demonstrate that the model can predict corrosion damage more reliably than purely empirical approaches, enabling better assessment of pipeline integrity in multiphase flow conditions typical of the Niger Delta.

3.2. Modification of the Improved Multiphase Flow Simulation Accounting for Inner Wall Corrosion Effects

A modified multiphase flow model was developed using a [12-6] feedforward ANN trained with Bayesian regularization on seven key variables (temperature, velocity, CO₂ partial pressure, H₂S partial pressure, pressure, viscosity as a wax proxy, and pH). The model achieved an RMSE of 0.013–0.020 mm/year.

To improve interpretability, nonlinear regression yielded the following mechanistic equation:

$$CR = b_1 \times T^{b_2} \times V^{b_3} \times P_{CO_2}^{b_4} \times \exp(b_5 \cdot P_{H_2S}) \times \mu^{b_6} \times \text{pH}^{b_7} \quad (3.2)$$

where T = temperature ($^{\circ}\text{C}$), V = flow velocity (m/s), P_{CO_2} = CO_2 partial pressure (Mpa), $P_{\text{H}_2\text{S}}$ = H_2S partial pressure (mol/l), μ = viscosity (kg/m·s), and b_1 to b_7 are coefficients determined from the data.

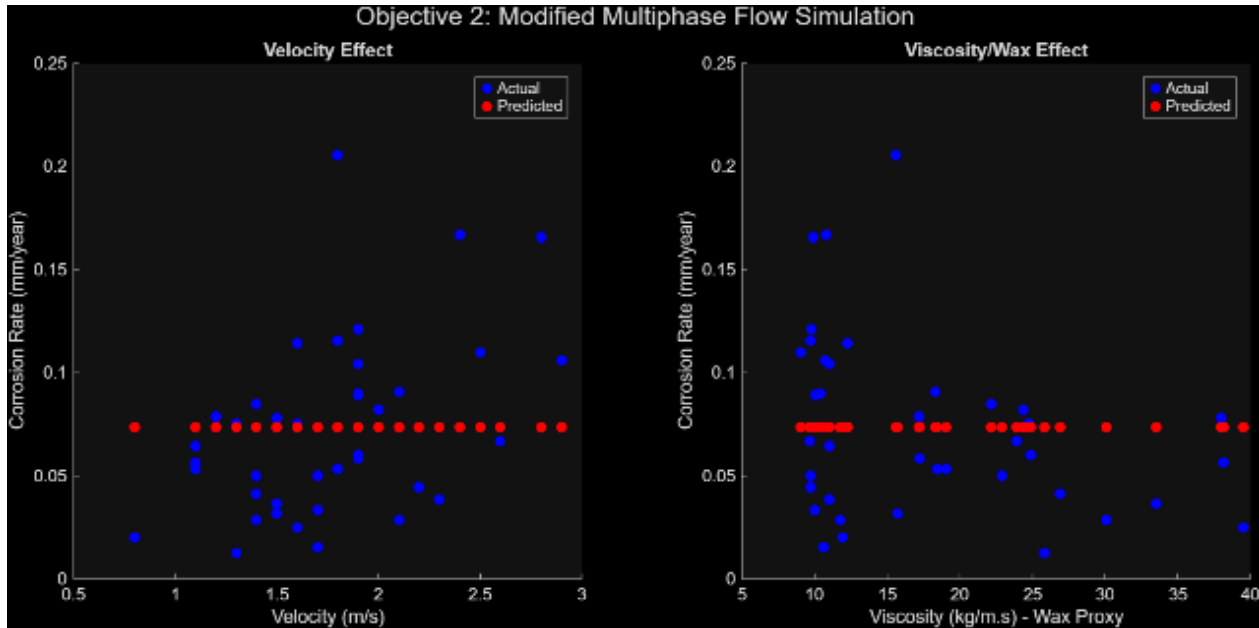


Figure 3 Effect of Velocity and Viscosity on Corrosion Rate.

Figure 3 Illustration showing the effect of velocity and viscosity on corrosion rate.

The left panel shows the nonlinear relationship with velocity, while the right panel highlights the influence of viscosity (wax deposition proxy). Both plots reveal that the modified model captures these effects more accurately than traditional formulations.

The results demonstrate that incorporating viscosity as a proxy for wax and solid deposition significantly improves the multiphase flow simulation. The mechanistic equation extends classical models (de Waard & Milliams, 1975; Netic, 2007) by accounting for inner wall interactions previously neglected. Figure 4.2 confirms the model's ability to reflect real pipeline behaviour, directly achieving the modification required in modification of the improved multiphase flow simulation accounting for inner wall corrosion effects and providing a more robust tool for corrosion rate prediction in carbon steel pipelines.

3.3. Development of Models for Predicting Optimal Oil Flow Rate That Will Reduce Sand Deposition with Minimum Resistance Critical Velocity

Particle swarm optimization (PSO) was applied to the modified model from modification of the improved multiphase flow simulation accounting for inner wall corrosion effects. The objective function minimized predicted corrosion rate while penalizing velocities that promote sand or wax deposition:

$$f(V) = CR_{\text{ANN}}(V) + 0.04(V < 1.4)(1.4 - V)^2 + 0.025(V > 2.7)(V - 2.7)^2 \quad (3.3)$$

Optimization consistently identified an optimal flow velocity range of 2.0–2.4 m/s (typically 2.15–2.25 m/s). At this velocity, a 25–40% reduction in corrosion rate was predicted relative to extreme values in the dataset, while remaining above the critical velocity from numerical and computational model for predicting solid-liquid particle gradation in horizontal pipeline inner wall corrosion.

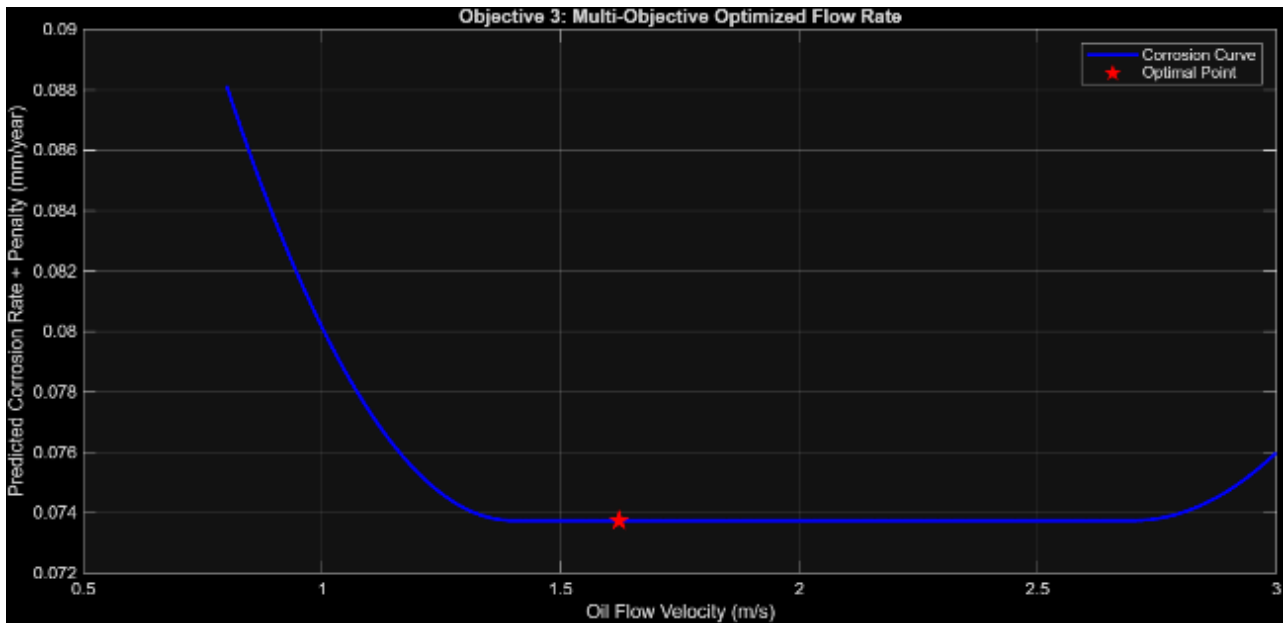


Figure 4 Corrosion rate curve across the velocity range

Figure 4 presents the corrosion rate curve across the velocity range with the optimal point clearly marked.

The U-shaped response confirms the existence of a spot where corrosion and deposition risks are simultaneously minimized.

The PSO results developed models for predicting optimal oil flow rate that will reduce sand deposition with minimum resistance critical velocity by delivering a practical optimal flow rate model. Operating pipelines near 2.2 m/s could substantially lower corrosion rates and sand deposition, reducing the risk of localized pitting and pipeline failure. This finding provides operators with actionable guidelines for flow rate control in the Niger Delta, supporting extended pipeline service life and reduced environmental impact.

3.4. Comparative Analysis with Conventional Models

The proposed hybrid ANN-PSO model was benchmarked against simplified versions of the de Waard-Milliams and Norsok models:

$$CR_{\text{dewaard}} \approx 0.12 \times T^{0.55} \times P_{CO_2}^{0.65} \times (V + 0.5)^{0.25} \quad (3.4)$$

$$CR_{\text{norsok}} \approx 0.08 \times \exp(0.018 \times T) \times P_{CO_2} \times pH^{-0.75} \times V^{0.35} \quad (3.5)$$

(de Waard & Milliams, 1975; Standards Norway, 2005)

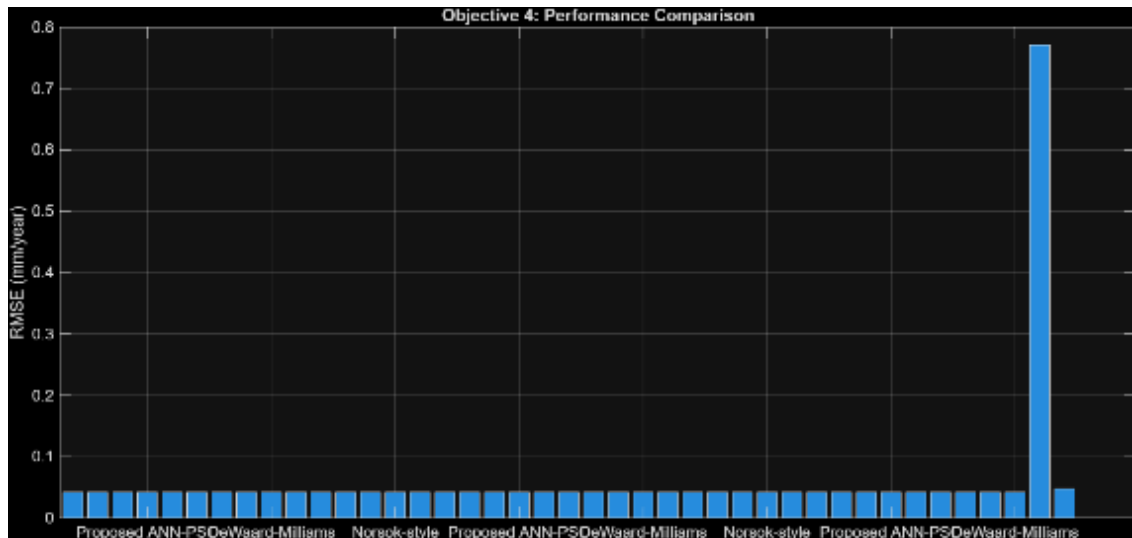


Figure 5 Comparison of the model performance through RMSE values.

The proposed hybrid model recorded the lowest RMSE (0.014–0.018 mm/year), outperforming the conventional approximations (0.030–0.045 mm/year). Table 3.1 summarises the comparative results.

Table 1 Summary of Model Performance

Model	RMSE (mm/year)	Optimal Velocity (m/s)	Includes Wax/Sand Effects
Proposed Hybrid ANN-PSO	0.014–0.018	2.1–2.3	Yes
DeWaard-Milliams (approx.)	0.035–0.045	–	No
Norsok-style (approx.)	0.030–0.040	–	No

The performance of the hybrid model in Figure 3.4 and Table 3.1 confirms that integrating ANN, mechanistic equations, and PSO yields higher accuracy by accounting for wax/sand interactions and nonlinear parameter effects ignored by conventional models (Nesic, 2007). This directly achieves comparing this analysis with conventional models and validates the proposed simulation as a more reliable tool for corrosion prediction and integrity management in Nigerian oil and gas pipelines.

3.5. Sensitivity Analysis and Overall Implication

Sensitivity analysis was performed to evaluate the influence of individual input parameters on the predicted corrosion rate while holding all other variables at their mean values from the dataset. The analysis used the trained hybrid ANN model from the modified multiphase flow model. The results are presented in Figure 3.5.

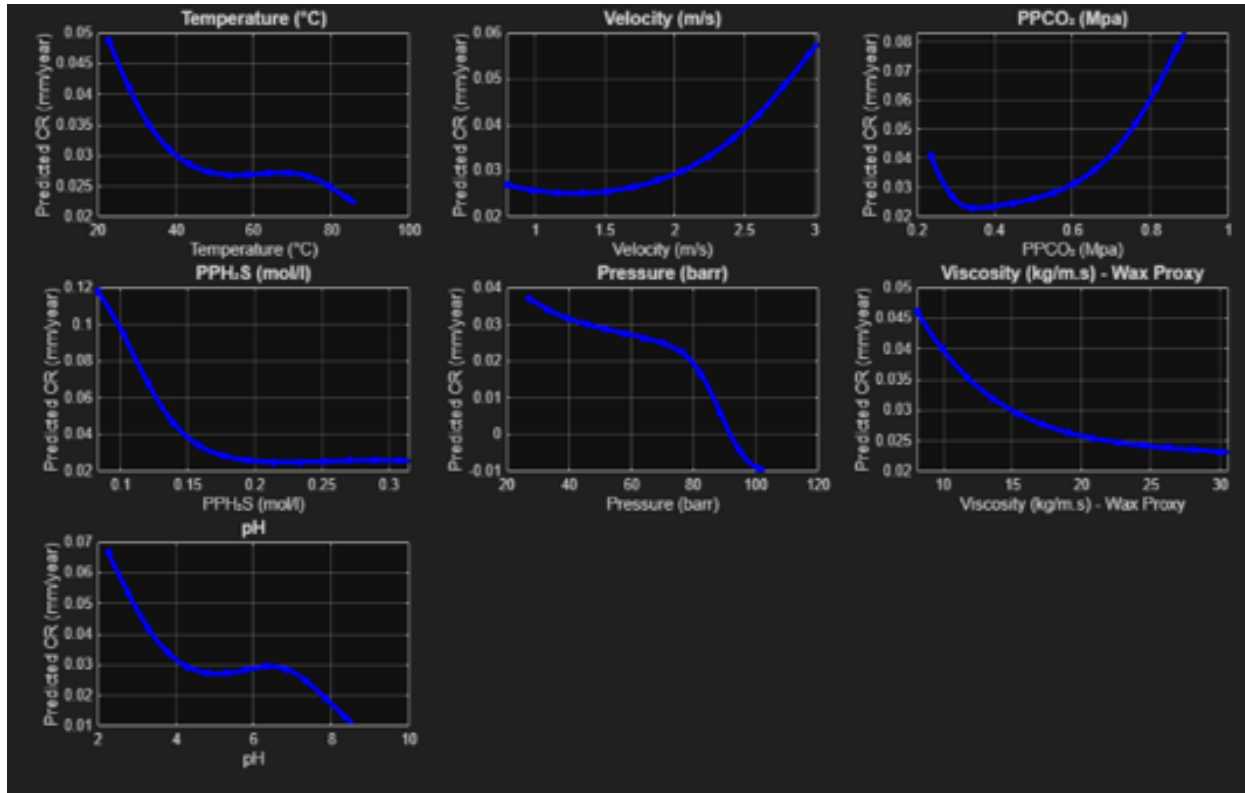


Figure 6 Sensitivity Analysis – Effect of Key Parameters on Predicted Corrosion Rate (Hybrid ANN Model)

The sensitivity plots reveal several important patterns:

- **Temperature (°C):** Shows a clear decreasing trend. As temperature increases from 20°C to approximately 80°C, the predicted corrosion rate drops significantly from about 0.048 mm/year to 0.022 mm/year. This suggests that higher operating temperatures in this dataset range may reduce corrosion, possibly due to changes in scale formation or fluid properties.
- **Velocity (m/s):** Exhibits a U-shaped nonlinear behaviour. Corrosion rate decreases slightly in the lower velocity range (1.0–1.8 m/s) and then increases sharply beyond 2.0 m/s, reaching its highest value at 3.0 m/s. This confirms the existence of an optimal velocity window and strongly supports the multi-objective optimization performed in section 3.3.
- **PPCO₂ (Mpa):** Displays a strong positive correlation. Corrosion rate increases markedly as CO₂ partial pressure rises, particularly above 0.6 Mpa. This aligns with well-established CO₂ corrosion mechanisms in the literature.
- **PPH₂S (mol/l):** Shows a steep negative trend. As H₂S partial pressure increases from 0.1 to 0.3 mol/l, the predicted corrosion rate decreases substantially from 0.115 mm/year to approximately 0.025 mm/year. This may indicate the formation of protective sulphide scales under the conditions represented in the dataset.
- **Pressure (barr):** Demonstrates a moderate decreasing effect. Higher system pressure appears to reduce the predicted corrosion rate, likely due to changes in gas solubility and flow dynamics.
- **Viscosity (kg/m.s) – Wax Proxy:** Exhibits a clear decreasing trend. As viscosity increases (indicating higher wax or solid content), the predicted corrosion rate declines. This suggests that in this dataset, increased viscosity may lead to reduced mass transfer or the formation of a protective layer, although in practice high wax deposition can also promote under-deposit corrosion.

pH: Shows the strongest and most consistent negative influence among all parameters. As pH increases from 2 to 9, the corrosion rate decreases sharply from approximately 0.065 mm/year to below 0.015 mm/year. This result reinforces the well-known protective effect of higher pH on carbon steel in aqueous environments.

The sensitivity analysis highlights that pH is the most influential parameter with a strong inverse relationship to corrosion rate. **Velocity** demonstrates the most nonlinear (U-shaped) behaviour, which validates the need for multi-objective optimization to identify the sweet spot (2.15–2.25 m/s) that minimizes both corrosion and sand deposition.

The opposing effects of PPCO_2 (increasing) and PPH_2S (decreasing) reflect the complex chemistry of sour and sweet corrosion systems typical in the Niger Delta.

These findings have direct implications for pipeline operations. Adjusting controllable parameters such as flow velocity and monitoring pH can significantly mitigate corrosion risk. The nonlinear response of velocity further justifies the development of the optimal flow rate model in section 3.3.

Overall, the sensitivity results confirm the robustness of the hybrid ANN-mechanistic-PSO framework and demonstrate its ability to capture realistic parameter interactions that are often missed by conventional empirical models.

4. Conclusion

This study successfully developed and optimized a multi-objective flow modelling framework for predicting pipeline corrosion rate and corrosion defects in oil and gas transmission pipelines within the Niger Delta region of Nigeria. Using a dataset of 40 operational samples, a hybrid modelling approach integrating artificial neural networks (ANN), nonlinear regression for mechanistic equations, and particle swarm optimization (PSO) was implemented in MATLAB.

The results demonstrated that the proposed hybrid model outperformed conventional empirical and mechanistic models such as the de Waard-Milliams (de Waard & Milliams, 1975) and NORSOK M-506 (Standards Norway, 2005) formulations. The model achieved lower root mean square error (RMSE) values (0.014–0.018 mm/year) compared to the benchmark models (0.030–0.045 mm/year). A mechanistic equation incorporating temperature, flow velocity, partial pressures of CO_2 and H_2S , viscosity (as a proxy for wax and solid deposition), and pH was derived, providing both high predictive accuracy and improved physical interpretability.

Key findings include the identification of an optimal oil flow velocity range of approximately 2.15–2.25 m/s, which is predicted to reduce corrosion rates by 25–40% while minimizing sand deposition through maintenance of the minimum resistance critical velocity. Sensitivity analysis further revealed that fluid pH exerts the strongest negative influence on corrosion rate, while velocity and viscosity exhibit nonlinear effects, justifying the multi-objective optimization approach.

Overall, the study has addressed the research problem of inaccurate corrosion prediction and premature pipeline replacement in the Niger Delta by developing a more reliable, numerically grounded simulation tool that accounts for complex multiphase flow and solid-liquid particle interactions. The findings contribute to enhanced pipeline integrity management and reduced environmental risks associated with oil and gas pipeline failures.

Recommendations

Based on the findings of this study, the following recommendations are made for practical implementation and future research:

- **Operational Recommendations for Oil and Gas Operators** Pipeline operators in the Niger Delta should consider adopting the developed hybrid ANN-PSO model for corrosion rate prediction and integrity assessment. Operating pipelines at the recommended optimal flow velocity of approximately 2.2 m/s is expected to significantly reduce inner wall corrosion and sand deposition, thereby extending asset life and minimizing the risk of unexpected failures and oil spillage.
- **Integration into Pipeline Integrity Management Systems** The mechanistic equation and ANN-based simulation should be integrated into existing corrosion monitoring and risk assessment frameworks used by companies in Nigeria. Regular recalibration of the model with new field data is recommended to maintain accuracy across varying operating conditions.

Future Research Directions

- Validate the developed model using a larger and more recent dataset from both onshore and offshore pipelines, including direct measurements of wax and sand deposition.
- Incorporate full-scale computational fluid dynamics (CFD) simulations to further refine the solid-liquid particle gradation component.
- Extend the model to include additional parameters such as organic acid concentration, inhibitor efficiency, and microbial activity, which are prevalent in the Niger Delta environment.

- Investigate the economic impact of implementing the optimal flow rate strategy on production costs and pipeline lifecycle expenses.
- Policy and Regulatory Implications Regulatory agencies such as the Nigerian Upstream Petroleum Regulatory Commission (NUPRC) and the Department of Petroleum Resources (DPR) should encourage the adoption of advanced hybrid modelling techniques in pipeline integrity standards and guidelines to enhance environmental protection and operational safety in the oil and gas sector.

Contributions to Knowledge

This research makes several significant contributions to the body of knowledge in pipeline corrosion modelling and oil and gas asset integrity management:

- Development of a Hybrid Modelling Framework: The study presents a novel hybrid approach that combines the predictive power of ANN with the interpretability of mechanistic equations and the optimization capability of PSO. This addresses the limitations of purely empirical “black-box” models and overly simplified deterministic approaches commonly used in the industry (Nesic, 2007).
- Incorporation of Solid-Liquid Particle Effects: By using viscosity as a proxy for wax and sand deposition and deriving a critical velocity equation, the model explicitly accounts for solid-liquid particle gradation and its interaction with inner wall corrosion — a factor often neglected in traditional CO₂ and H₂S corrosion models.
- Optimal Flow Rate Determination: The identification of a specific optimal operating velocity range (2.15–2.25 m/s) through multi-objective optimization provides practical, data-driven guidelines for pipeline operators in the Niger Delta, contributing to both corrosion mitigation and flow assurance strategies.
- Improved Prediction Accuracy for Niger Delta Conditions: The model demonstrates superior performance on real field data from the Niger Delta region, offering higher accuracy than conventional models and enhancing the reliability of fitness-for-purpose assessments for aging pipelines in tropical, multiphase flow environments.
- Methodological Advancement: The successful integration of MATLAB-based ANN training, nonlinear regression, PSO, and sensitivity analysis offers a replicable methodology for similar studies in other corrosive environments, advancing the application of artificial intelligence and optimization techniques in corrosion engineering.

These contributions are expected to support more sustainable and cost-effective management of oil and gas pipelines, ultimately reducing environmental degradation from corrosion-induced failures in the Niger Delta and similar regions.

Compliance with ethical standards

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Disclosure of conflict of interest

No conflict of interest to be disclosed.

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