

Development and Evaluation of an Integrated AI-Based Technology for Pipelines Integrity Assessment

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Abstract

This research examines the monitoring of the integrity of pipeline infrastructure in the Oil and Gas Industry. It emphasizes the importance of proactive monitoring, robust predictive maintenance practices, and cutting-edge innovative technologies to ensure the safety and reliability of both piggable and non-piggable pipelines. The study examines factors such as pressure fluctuations to develop an applicable strategy for implementation of AI-Driven Digital Twin Framework for Pipeline Maintenance, ROW Surveillance, and Corrosion Control Optimization, identifying vulnerabilities in pipeline systems. It stresses the significance of maintenance practices in the right-of-way (ROW) conditions and addresses the risks posed by poor asset integrity among major Oil and Gas Producers in meeting global energy demands as varying levels of infrastructure integrity can threaten supply stability to OPEC quotas, the nation economic drives and environmental health. The 300 pipeline segments studied resulted in a classification of 157 pipeline segments as Low Risk, 137 segments as Medium Risk, and 6 pipeline segments as High Risk indicating that most of the evaluated pipelines still retain acceptable levels of structural integrity. This is also supported by an average Digital Twin Integrity Index (DTII) of 69.12 demonstrating that the integrity state of the pipelines was stable, and an average Remaining Useful Life (RUL) of 22.11 years was indicative of moderate long-term sustainable operational capacity of the pipelines. However, the evaluation provided identification of 6 critical condition pipelines that require immediate maintenance, and 24 anomalous pipelines were identified using an anomaly detection system. The research advocates for improved transparency, better oil and gas infrastructure management, and increased investment in pipeline safety measures to secure the future of global energy supply. Given the extensive pipeline network, it's crucial to have effective and predictive maintenance systems to identify leaks quickly. The report found that the use of AI-powered digital twin systems, predictive analytics, fiber optic surveillance, anomaly detection models, anomaly detection algorithms, predictive AI-models, AI-based corrosion prediction models to cushion pipeline cathodic protection systems, smart PIG inspections and robotic crawler ultrasonic testing can greatly enhance pipeline reliability, predictive maintenance planning, structural integrity monitoring and environmental sustainability in complex oil and gas operating environments.

Keywords: Innovation, Strategies, Inspection, Real-time, Integrity.

1.0 Introduction

Worldwide, millions of kilometers of pipelines are in use to transport oil and gas products as the nation's become more industrialized and so the demands for energy have been growing (Henry et al.). Nigeria has one of the largest pipeline networks in Africa with an estimated 5,001km pipeline, including multi-product pipelines of about 4,315km and crude oil pipelines of 666km from the major storage depots to refineries, export terminals and distribution points (Francis et al). These pipelines are inter-lined pipelines between the Port Harcourt refinery, the Warri refinery, Kaduna refinery, the Dangote refinery, and the offshore terminals like Bonny and Escravos within environments of swamp, land terrain, shallow water and deep offshore environments typical of the Niger Delta region were carried out. Nigeria also has more than 206 trillion cubic feet of proven gas reserves, which makes it one of the largest gas reserve holders in the world (Adewale et al.). Therefore, safe and reliable pipeline transportation of crude oil and gas is vital to economic sustainability, export revenue generation, power generation, and industrial feedstock supply in the era of the global energy transition.

The Nigerian oil and gas industry is plagued with serious integrity management issues despite the critical need for pipeline infrastructure (Bright F. et al.). Pipelines are subjected to severe operating conditions in the shallow water environment, deep offshore, Niger Delta swamp and land terrain environments, including internal or external corrosion, microbiologically influenced corrosion (MIC), degradation of coatings, hydrodynamic loading, erosion, soil instability, illegal bunkering, sabotage, and vandalism, and third-party interference (Joseph et. al.). Such degradation processes can substantially diminish structural reliability, leading to the potential for leaks, ruptures, environmental pollution, fire outbreaks, and operational shutdowns. Adequate management and comprehensive preventive measures of the oil and gas pipeline infrastructure from running into failure phases plays a crucial role in the energy market as they are the primary fuel source across board and a significant annual revenue generation in trillions of dollars globally (Omorogiuwa et al.). The smart oil and gas pipeline industry is witnessing the emergence of new capabilities with the advent of Artificial Intelligence (AI), Digital Twin technology, Internet of Things (IoT), machine learning, fiber optic sensing systems, robotics and predictive analytics. Operational and corrosion data can be fed to AI-driven predictive models to predict future corrosion trends, estimate remaining useful life (RUL), categorize risk level and facilitate predictive maintenance planning (Zachariah Mayer et al.). In the same way, Digital Twin systems enable the development of virtual copies of physical pipeline assets, which continuously feed operational data, environmental conditions, outputs from sensors, and information on structural integrity to allow for real-time monitoring and decision making (Victor N. O. et al.).

Thus, the amalgamation of AI-based corrosion prediction, Digital Twin systems, anomaly detection algorithms, robotic inspection systems, fiber optic sensing technologies, and environmental risk analysis seem to hold promise in enhancing predictive maintenance, operational reliability, corrosion monitoring, and environmental sustainability in pipeline systems (Eyinda et al.). These smart technologies assist with the shift from reactive maintenance approaches to proactive and condition-based integrity management approaches with a view of reducing operational disruptions and environmental impacts.

The focus of this study is therefore on development and implementation of an integrated digital twin framework for predictive integrity assessment, corrosion monitoring, maintenance optimization, right-of-way surveillance and operational risk management of piggable and unpiggable pipelines under operating conditions of Nigeria. The research aims to achieve higher reliability for pipelines, better decision making for predictive maintenance, less environmental risk, and better sustainable management for oil and gas pipelines based on the application of advanced artificial intelligence and intelligent monitoring technologies.

The objectives of the study are to: evaluate the performance of multi-modal inspection and monitoring technologies (AI-based corrosion prediction, fiber optic sensing, and robotic UT crawlers) for assessing the structural integrity and environmental risks of piggable and unpiggable pipelines. To develop and validate an AI-driven Digital Twin framework that integrates multi-source sensor data, anomaly detection, and physics-informed corrosion kinetics to predict Remaining Useful Life (RUL), calculate a composite Digital Twin Integrity Index (DTII), and generate risk-based maintenance decisions. To develop and validate an integrated framework for optimizing maintenance practices, right-of-way (ROW) surveillance, and corrosion control procedures for piggable and unpiggable pipeline systems using AI-driven digital twin technology. To evaluate the effectiveness of proactive and reactive pipeline integrity management strategies in minimizing operational disruptions and environmental impacts.

2.0 Methodology

2.1 Research Design

The study adopted a simulation-based quantitative research method for investigating pipeline integrity conditions and evaluating strategies for minimizing operational disruptions and environmental impacts using literature-derived operational parameters and probabilistic modeling techniques. The methodology integrated risk classification, digital twin integrity assessment, cathodic protection evaluation, fiber optic surveillance analysis, anomaly detection simulation, and environmental impact assessment within a unified analytical framework developed using Python programming tools including NumPy, Pandas, Matplotlib, and Seaborn.

A total of 300 pipeline segments were generated and used to represent statistically distributed pipeline infrastructure conditions data within different operational environments commonly reported in Niger Delta pipeline systems. The generated pipeline dataset incorporated environmental conditions, risk categories, integrity indices, maintenance requirements, cathodic protection status, fiber optic surveillance alerts, and anomaly detection indicators derived from literature-based industrial standards and failure distributions.

2.2 Simulation Algorithm

The study adopted a simulation-based quantitative research method for investigating pipeline integrity conditions and evaluating strategies for minimizing operational disruptions and environmental impacts using literature-derived operational parameters and probabilistic modeling techniques. The methodology integrated risk classification, digital twin integrity assessment, cathodic protection evaluation, fiber optic surveillance analysis, anomaly detection simulation, and environmental impact assessment within a unified analytical framework developed using Python programming tools including NumPy, Pandas, Matplotlib, and Seaborn. The visualization tools that were used across the studies were scatter plots, box plots, histograms, pie charts, heat maps, DTII distribution plots, environmental impact comparison charts, maintenance prioritization charts and risk concentration matrices. The overall research materials helped to simulate, predict, monitor, visualize, optimize the integrity assessment of piggable and unpiggable pipeline systems under typical operational conditions reported in the Niger Delta area of Nigeria. Asset integrity reflects the condition, safety, reliability, and maintenance effectiveness of oil and gas infrastructure as a lack of accessible or transparent information about asset integrity, suggesting regulatory gaps or limited disclosure. Various maintenance practices for pipelines within the right-of-way (ROW) are also suggested.

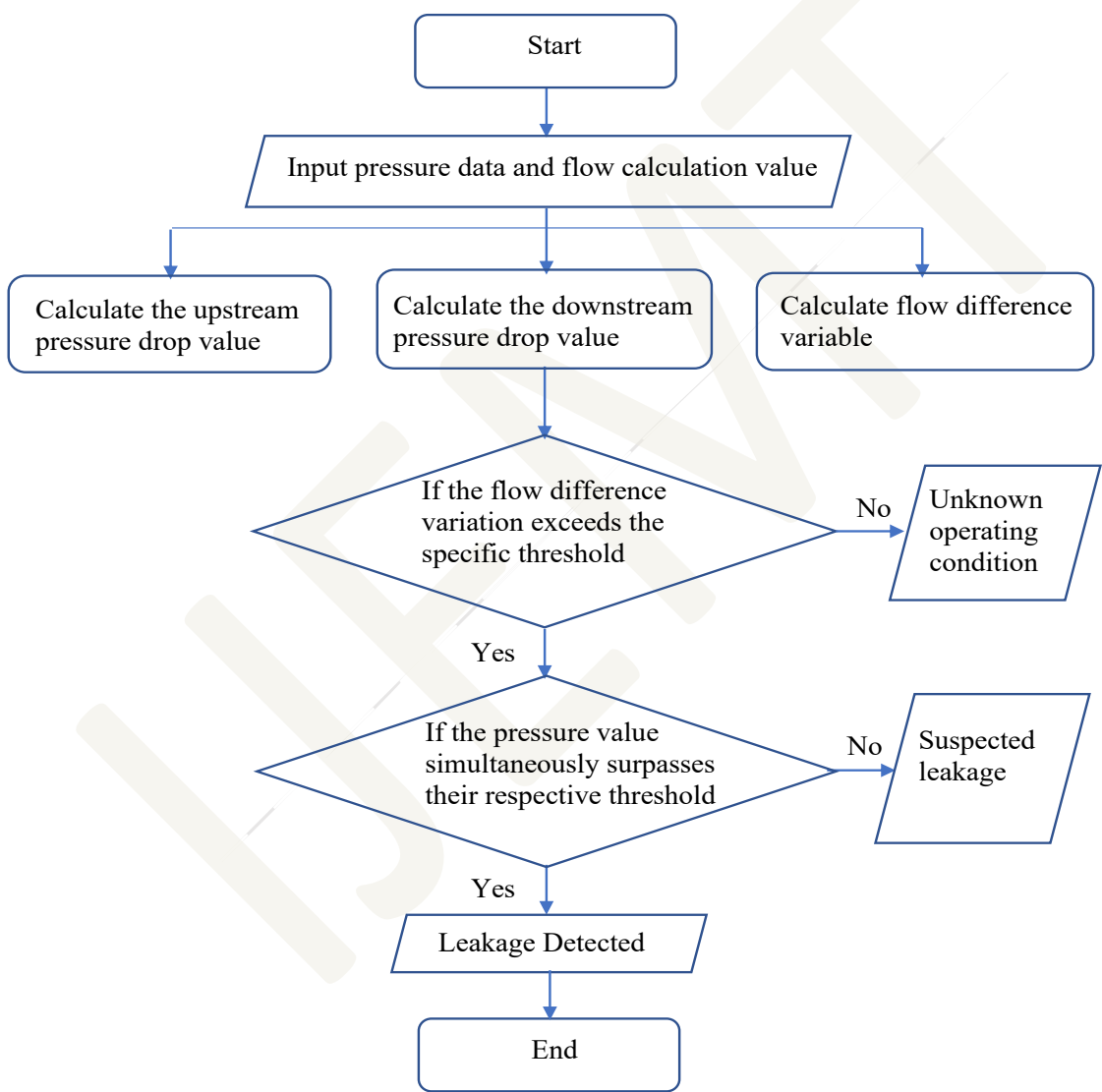


Figure 1: Algorithm for leak detection in pipelines

2.3 Materials

The research materials used for this study include Pipeline data lake Digital twin integrity index (DTII), Smart Pig magnetic flux leakage (MFL) simulation models, ultrasonic testing (UT) defect assessment systems, fiber optic Distributed Acoustic Sensing (DAS), Distributed Temperature Sensing (DTS), SCADA operational monitoring variables, robotic crawler wall thickness measurements, drone and satellite surveillance indicators, and AI-based corrosion prediction models. In the investigation of maintenance, surveillance and corrosion control measures plus that of the evaluation strategies for minimizing distributions and environmental impacts, the research materials also included API 580 risk classification distributions; NACE cathodic protection failure

probability models; environmental sensitivity coefficients; fiber optic surveillance alert distributions; probabilistic disruption assessment models; proactive and reactive mitigation simulation frameworks; environmental impact scoring systems; threats indicator and statistical risk visualization frameworks.

3.0 Pipelines Integrity Assessment Schemes And Strategies

The research materials utilized in the Studies involved computational simulation tools, artificial intelligence models, probabilistic integrity assessment frameworks, literature-derived operational datasets, digital twin algorithms and visualization systems which were used to assess the integrity condition of piggable and unpiggable pipeline system operations within representative of Niger Delta that includes shallow water, deep offshore, Niger Delta swamp and land terrain environments.

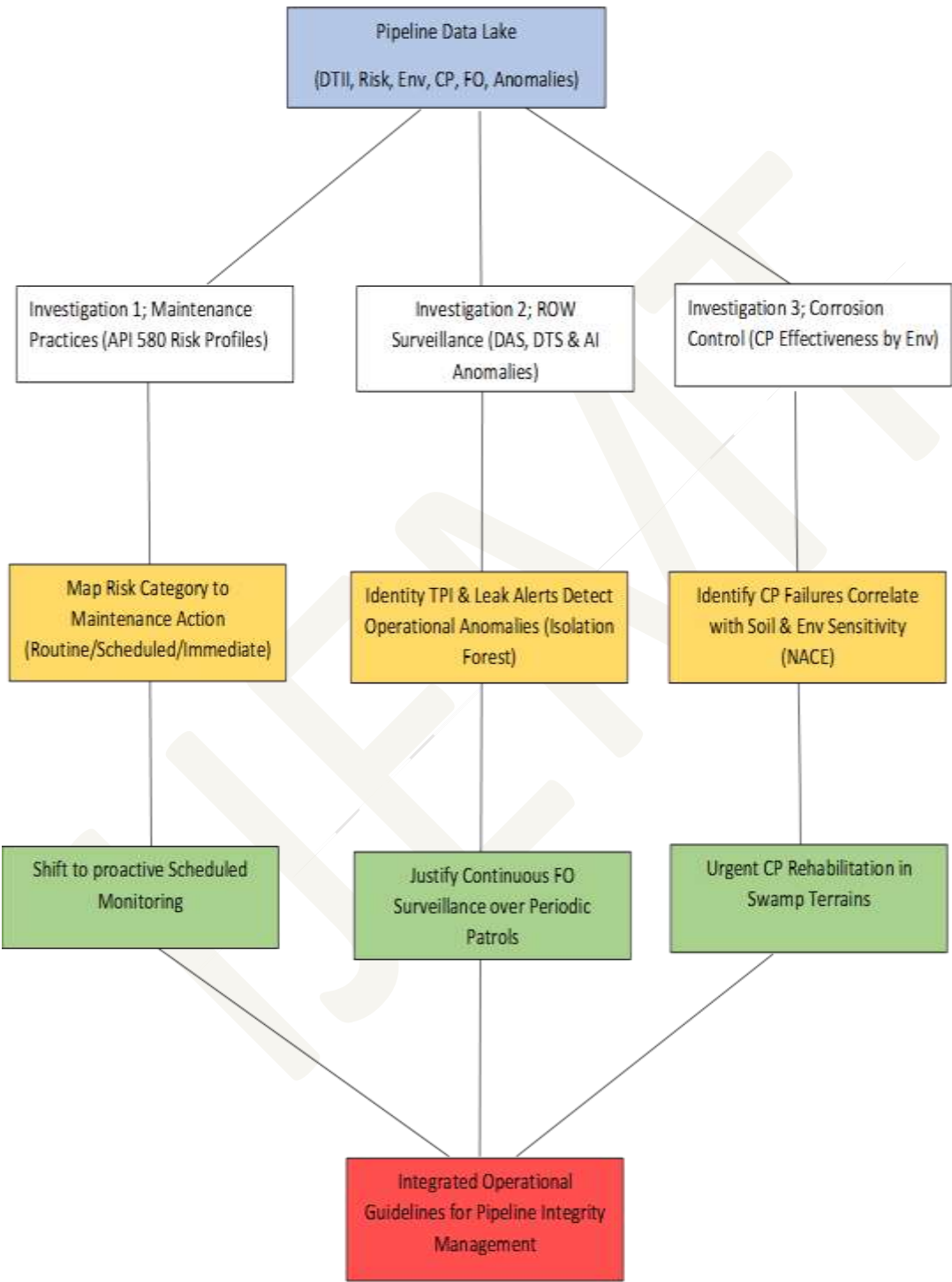


Figure 2: Investigation of pipeline maintenance, surveillance and corrosion control

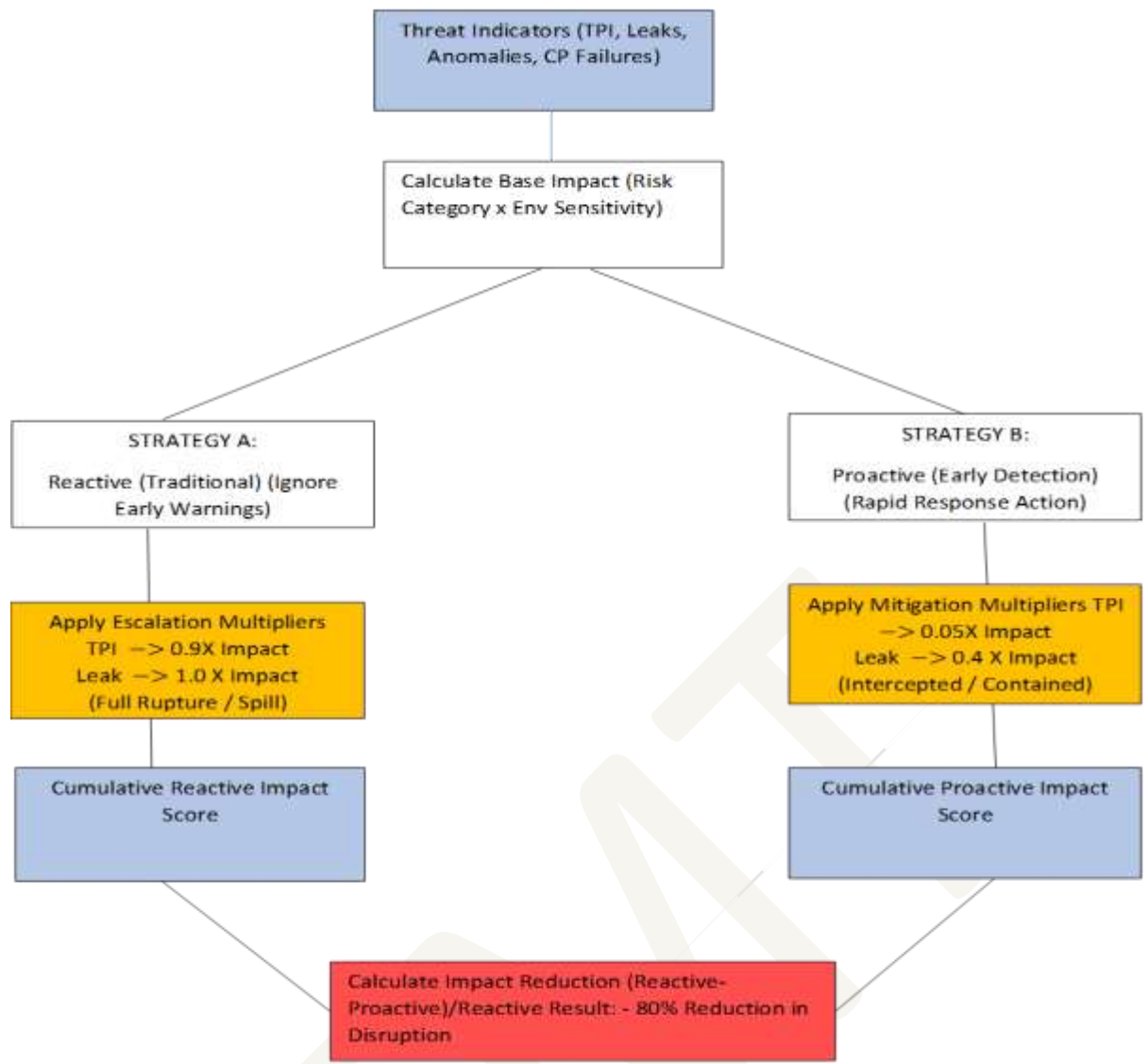


Figure 3: Evaluating strategies for minimizing pipeline disturbances and impacts

3.1 Risk Classification Model

Pipeline risk conditions were modeled using probabilistic risk distributions based on API 580 Risk-Based Inspection (RBI) guidelines for aging infrastructure systems. The probability distribution adopted for the risk classification is expressed as:

$$P(R_i) = \{P_L, P_M, P_H\} \tag{1}$$

where:

- $P(R_i)$ = probability distribution of risk category for pipeline i
- P_L = probability of low-risk pipelines
- P_M = probability of medium-risk pipelines
- P_H = probability of high-risk pipelines

The maintenance action associated with each risk category was assigned using:

$$M_i = \begin{cases} M_R, & R_i = R_L \\ M_S, & R_i = R_M \\ M_I, & R_i = R_H \end{cases} \tag{2}$$

where:

- M_i = maintenance action assigned to pipeline i
- R_L = low-risk category
- R_M = medium-risk category
- R_H = high-risk category
- M_R = routine maintenance
- M_S = scheduled monitoring
- M_I = immediate intervention

3.2 Digital Twin Integrity Index (DTII)

The Digital Twin Integrity Index (DTII) was used to evaluate the structural and operational integrity condition of each pipeline segment. The DTII values were generated using a normal probability distribution expressed as:

$$DTII_i \sim N(\mu_d, \sigma_d^2) \quad (3)$$

where:

$DTII_i$ = integrity index for pipeline i

μ_d = mean integrity index

σ_d = standard deviation of integrity index

For degraded high-risk pipelines, the DTII distribution was represented as:

$$DTII_{HR} \sim N(\mu_h, \sigma_h^2) \quad (4)$$

where:

$DTII_{HR}$ = integrity index for high-risk pipelines

μ_h = degraded mean integrity index

σ_h = degraded standard deviation

The DTII values were constrained within operational bounds using:

$$DTII_b = \min[\max(DTII_i, DTII_{min}), DTII_{max}] \quad (5)$$

where:

$DTII_b$ = bounded integrity index

$DTII_{min}$ = minimum allowable DTII

$DTII_{max}$ = maximum allowable DTII

3.3 Environmental Distribution Model

The operational environments were simulated using literature-derived environmental distributions representative of Niger Delta pipeline systems. The environmental probability distribution is expressed as:

$$P(E_i) = \{P_D, P_{LT}, P_S, P_{SW}\} \quad (6)$$

where:

P_D = probability of deep offshore environment

P_{LT} = probability of land terrain environment

P_S = probability of Niger Delta swamp environment

P_{SW} = probability of shallow water environment

The environmental classification is represented as:

$$E_i \in \{E_D, E_{LT}, E_S, E_{SW}\} \quad (7)$$

where:

E_i = operational environment of pipeline i

3.4 Cathodic Protection Failure Model

Cathodic protection effectiveness was modelled using environment-dependent failure probabilities derived from NACE corrosion control standards. The failure probability model is expressed as:

$$P(CP_f) = \begin{cases} \alpha_1, & E_i = E_S \\ \alpha_2, & E_i = E_{LT} \\ \alpha_3, & E_i = E_{SW} \\ \alpha_4, & E_i = E_D \end{cases} \quad (8)$$

where:

$P(CP_f)$ = probability of cathodic protection failure

$\alpha_1, \alpha_2, \alpha_3, \alpha_4$ = environmental CP failure probabilities

The cathodic protection status was generated using:

$$CP_i = \begin{cases} 0, & r < P(CP_f) \\ 1, & r \geq P(CP_f) \end{cases} \quad (9)$$

where:

CP_i = cathodic protection status of pipeline i

r = randomly generated probability value

$CP_i = 1$ indicates effective cathodic protection

$CP_i = 0$ indicates ineffective cathodic protection

3.5 Fiber Optic DAS/DTS Surveillance Model

Fiber optic Distributed Acoustic Sensing (DAS) and Distributed Temperature Sensing (DTS) alert conditions were modelled using literature-based surveillance distributions:

$$P(F_i) = \{P_N, P_T, P_L\} \quad (10)$$

where:

P_N = probability of normal operational condition
 P_T = probability of third-party interference alert
 P_L = probability of suspected leak alert

The surveillance classification was represented as:

$$F_i \in \{F_N, F_T, F_L\} \quad (11)$$

where:

F_i = fiber optic surveillance status of pipeline i

3.6 AI-Based Anomaly Detection Model

Operational anomalies were modeled using a probabilistic anomaly detection framework represented as:

$$P(A_i) = P_A \quad (12)$$

where:

$P(A_i)$ = probability of anomaly occurrence
 P_A = anomaly detection probability

The anomaly classification is expressed as:

$$A_i = \begin{cases} 1, & \text{Anomaly detected} \\ 0, & \text{Normal operation} \end{cases} \quad (13)$$

where:

A_i = anomaly detection state

3.7 Environmental Impact and Disruption Assessment

The environmental impact assessment model was developed using a cumulative disruption scoring framework based on pipeline risk severity and environmental sensitivity.

The base impact score was assigned as:

$$B_i = \begin{cases} \beta_1, & R_i = R_L \\ \beta_2, & R_i = R_M \\ \beta_3, & R_i = R_H \end{cases} \quad (14)$$

where:

B_i = base impact score
 $\beta_1, \beta_2, \beta_3$ = risk-dependent impact coefficients

Environmental sensitivity coefficients were assigned using:

$$S_i = \begin{cases} \gamma_1, & E_i = E_D \\ \gamma_2, & E_i = E_{LT} \\ \gamma_3, & E_i = E_S \\ \gamma_4, & E_i = E_{SW} \end{cases} \quad (15)$$

where:

S_i = environmental sensitivity coefficient
 $\gamma_1, \gamma_2, \gamma_3, \gamma_4$ = environmental weighting factors

The potential maximum impact was calculated using:

$$PMI_i = B_i \times S_i \quad (16)$$

where:

PMI_i = potential maximum impact score for pipeline i

3.8 Reactive Strategy Model

The reactive integrity management strategy assumed that operational threats escalated into severe incidents before intervention. The reactive impact model is expressed as:

$$RI_i = \begin{cases} PMI_i \times \delta_1, & F_i = F_L \\ PMI_i \times \delta_2, & F_i = F_T \\ PMI_i \times \delta_3, & A_i = 1 \\ PMI_i \times \delta_4, & CP_i = 0 \end{cases} \quad (17)$$

where:

RI_i = reactive impact score
 $\delta_1, \delta_2, \delta_3, \delta_4$ = reactive escalation coefficients

3.9 Proactive Strategy Model

The proactive integrity management strategy incorporated early fault detection and rapid response mechanisms. The proactive impact model is expressed as:

$$PI_i = \begin{cases} PMI_i \times \theta_1, & F_i = F_L \\ PMI_i \times \theta_2, & F_i = F_T \\ PMI_i \times \theta_3, & A_i = 1 \\ PMI_i \times \theta_4, & CP_i = 0 \end{cases} \quad (18)$$

where:

PI_i = proactive impact score
 $\theta_1, \theta_2, \theta_3, \theta_4$ = proactive mitigation coefficients

3.10 Impact Reduction Analysis

The percentage reduction achieved by the proactive strategy was calculated using:

$$Reduction(\%) = \frac{RI_T - PI_T}{RI_T} \times 100 \quad (19)$$

where:

RI_T = total cumulative reactive impact
 PI_T = total cumulative proactive impact

4.0 Results and Discussions

The integrity assessment for piggable and unpiggable pipelines has been carried out using Smart Pig inspection data, artificial intelligence (AI)-based corrosion predictions, robotic crawler ultrasonic thickness measurements, fiber optic distributed acoustic sensing/distributed temperature sensing (DAS/DTS) monitoring, and environmental risk analysis for shallow water, deep offshore, Niger Delta swamp and land installations (see Figure 2 and 3). The Figures also presents the current versus AI predicted defect depths for piggable pipelines, pressure margin distributions for piggable pipelines in shallow water, deep offshore, Niger Delta swamp and land configurations, and the distributions of ultrasonic thickness for unpiggable pipelines located in shallow water, deep offshore, Niger Delta swamp and land locations; and the leak and intrusion alert status of fiber optic systems for unpiggable pipelines; and the relative concentration of high-risk and low-risk pipeline segments within the classified assessment area (by environment). In addition, the results indicate that there were 7 unpiggable pipeline segments identified as being at risk for leaks and 38 unpiggable pipeline segments that were classified as having ineffective cathodic protection systems.

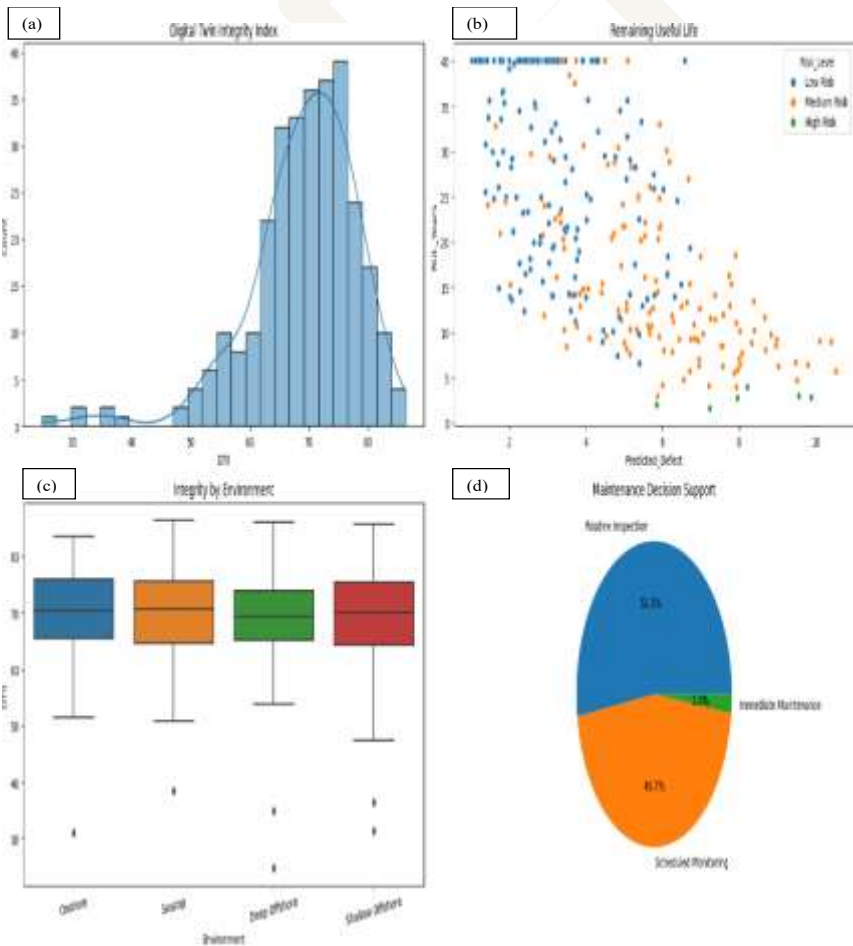


Figure 4: Graphical results of the AI-driven digital twin framework

4.1 Discussion of Findings

The first result plot named (a) is the overall average Digital Twin Integrity Index that is calculated to be 69.12, which suggests that the pipeline network simulated is in relatively good condition, though not at peak performance. DTII is a new integrated integrity indicator that was developed to integrate pressure loading, the severity of corrosion, and the risk indicators from the environment sensors. This means the integrity index is a more useful measure of pipeline condition than traditional single-parameter pipeline assessment techniques. A value near 70 will indicate that the safety margins are still good for most pipelines, but there are also network sections that are structurally less reliable. The DTII values ranged between 0 and 100; pipelines that were near 100 were very stable and pipelines that were near 0 were highly degraded and had a high risk of failure. The Digital Twin Integrity Index' histogram offers further understanding of the integrity distribution of the pipeline network. The histogram shows that most of the pipeline segments were grouped together within the range of about 60 to 80 DTII, with the maximum concentration in the range of 70–75 DTII. Most of the pipelines had acceptable levels of structural integrity, as seen in this distribution. A small number of pipeline segments, however, had lower tail outliers with a DTII value below 40, meaning that there were some severe degradation conditions. These low-integrity outliers may be due to pipelines experiencing higher corrosion growth rates, higher operational stress ratios, adverse environmental exposure, or higher levels of threat that were detected by the sensors. The second result plot, named (b) is the Remaining Useful Life scatter plot that is one of the most significant visualizations of pipeline degradation behavior. The scatter plot is used to show the relationship between the corrosion defect depth prediction and the estimated remaining useful life of the pipelines, as well as the pipeline's risk classification. The remaining useful life is found to have a strong inverse correlation with the extent of corrosion defect. Pipelines with small, predicted defect depths had high remaining useful life values, typically near the maximum of 40 years. On the other hand, the pipelines which had high corrosion defects prediction value showed lower RUL values, and some of the pipelines had RUL values less than 5 years. The inverse relationship is completely in accordance with the corrosion engineering principles. The thickness of the remaining metal that can resist the loading during operation gradually decreases as the corrosion defect gets deeper. This, therefore, leads to reduced structural safety margins and reduced service life. The scatter plot shows that the clustering of high-risk pipelines in the lower right of the plot is consistent with the pipelines having both severe corrosion degradation and critically low remaining life, consistent with the effectiveness of the framework in indicating this. These pipelines are the weakest link in the network and engineering intervention in them is necessary since now. The scatter plot also shows that most pipelines in the medium-risk group have moderate levels of corrosion and RUL between about 8 and 25 years. This type of pipeline is not yet structurally critical, but it needs to be monitored and maintained to preempt problems. The scatter plot shows that the transitions from low risk to medium risk and eventually to high-risk conditions are gradual, which is a good reflection of progressive degradation, as opposed to abrupt or unrealistic classification boundaries.

The average RUL calculated from the framework is significantly more realistic than the previous unrealistic value of around 58 years and is taken prior to introducing the RUL correction model. The new RUL model featured several degradation accelerations factors such as aging effect, soil corrosivity, environment severity, cathodic protection performance, and third-party interference.

The third result plot, named (c) is the integrity by environment which gives the marked decrease in the estimated service life and is therefore, more representative of the more severe corrosion environment and exposure conditions in Nigeria, particularly in swamp environments and onshore environments, where exposure and corrosion are often more severe.

The integrity variations measured from the boxplot under various environmental conditions provide further insights into the effect of operating environment on structural integrity. Onshore, Swamp, Deep Offshore and Shallow Offshore were the environments considered in the study. The data are quite similar in respect to the median DTII values across the various environments; however, one can see some interesting differences in the spread and lower-bound distributions of the data. The integrity variations measured by the DTII across operating environments highlight the framework's ability to capture geographic degradation disparities. Pipelines within swamp areas exhibit higher structural uncertainty, reflected by greater variability and lower DTII outliers in the framework's calculations. Onshore pipelines also show relatively high variation in integrity scores, which the digital twin attributes to higher exposure metrics for vandalism and third-party interference. On quantifying these environmental impacts systematically, the framework translates physical threats into measurable shifts in structural integrity indices.

Offshore pipelines in deep water are typically characterized by uniform integrity distributions, with fewer data points that may be considered extreme. Offshore systems may have better

monitoring systems, less third-party interference and better controlled operating conditions to be beneficial. However, the presence of some low integrity offshore outliers clearly indicates that there are degradation mechanisms that can occur in offshore pipelines, including CO₂ corrosion, erosion-corrosion, fatigue loading and failure of cathodic protection.

The fourth result plot, named (d) is the maintenance decision support pie chart that is an integrated summary of the operational recommendations generated by the framework in the maintenance decision. Some 52.3% of pipelines were given routine requirements, and 45.7% were given requirements for scheduled monitoring. Immediate maintenance intervention was needed for only 2%. The maintenance decision support module within the digital twin translates the integrated integrity assessments into prioritized operational workflows. By categorizing the network into routine requirements (52.3%), scheduled monitoring (45.7%), and immediate intervention (2%), the framework shifts integrity management from reactive repair to predictive asset allocation and efficient resource distribution.

The framework's risk distribution output indicates that only 2% of the network requires immediate intervention, confirming that system-wide catastrophic failure is highly unlikely under current operating scenarios.

However, the significant proportion of pipelines classified as medium risk (45.7%) suggests that a large portion of the network is undergoing gradual degradation. If proactive predictive monitoring is not implemented, these segments are at risk of transitioning into critical condition categories. Thus, pipeline companies should focus on medium-risk pipeline assets on predictive maintenance, improved inspection planning, and corrosion control treatments.

5.0 Conclusions

The executive summary of the simulation results concludes that out of the 300 pipelines analyzed, 157 were deemed to be at low risk, 137 were deemed to be medium risk and only 6 were deemed to be at high risk. With this distribution, most of the pipeline network is structurally stable in the present operating conditions. Some 52.3% of pipelines were determined to be low risk, and 45.7% were deemed to be medium risk. Approximately 2% of the pipeline population needed immediate maintenance intervention. This distribution is representative of a moderately managed pipeline system in which integrity management programs and corrosion protection efforts are partially successful, but aging pipeline systems and environmental conditions cause localized risks to continue. The number of medium risk pipelines is also noteworthy under engineering considerations as it shows that, while most pipelines remain in service, a significant share of the infrastructure is slowly transitioning into higher levels of degradation. Medium-risk pipelines are usually those that have lower structural margins, a higher corrosion potential, lower remaining wall thickness, or higher exposure to the environment. This type of pipeline currently does not require emergency repair actions, but they should be monitored constantly, maintenance scheduled based on predictive methods and inspected more often so as not to pass into a high-risk zone. Therefore, the results indicate that pipeline companies should not only target only the critical pipelines but need to target proactive management of medium risk assets to prevent a quicker deterioration in the future. The optimization of maintenance part of the framework successfully demonstrated the transition from a reactive maintenance approach to a predictive and risk-informed maintenance approach in pipeline integrity management. Results indicated that a limited number of pipelines needing immediate attention and a larger number needing routine maintenance or scheduled monitoring. All of this indicates that AI-based predictive maintenance solutions can be a great asset to maintenance prioritization, resource allocation, minimizing emergency repair, and maximizing service life of pipelines. The corrosion control evaluation also showed that poor cathodic protection systems are still one of the biggest factors in increased corrosion and loss of structural integrity in pipeline systems in Nigeria. The most critical number of ineffective cathodic protection segments was found in the Niger Delta swamp where the environment is very aggressive, which shows the detrimental effect of aggressive environmental factors on the performance of the cathodic protection system. It is important to have an ongoing corrosion monitoring program and system-specific cathodic protection methods, as low DTII scores have been correlated with ineffective cathodic protection.

The advantages of proactive and reactive integrity management strategies were clearly demonstrated in the comparative evaluation, with proactive monitoring systems being the superior approach in terms of reducing operational disruption and environmental impacts. The proactive strategy resulted in about 79.7% reduction in cumulative disruption and environment impact when compared with the conventional reactive strategy. The significant decrease underscores the critical need for early detection, ongoing monitoring, predictive analytics, and swift response measures to avert integrity threats from becoming catastrophic pipeline failures.

Recommendations

Regulatory bodies and pipeline operators should invest in the development of advanced predictive analytics, AI-driven surveillance systems and risk-based maintenance frameworks that will give priority to medium and high-risk segments of pipeline for early intervention, helping to enhance long-term structural integrity, operational sustainability, and environmental safety within the Nigerian oil and gas industry.

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