

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

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Abstract

In this study, an integrated framework of Artificial Intelligence (AI) based Digital Twin for predictive integrity assessment, corrosion monitoring, pipeline maintenance optimization and disruption reduction was developed and evaluated for both piggable and unpiggable pipeline system under Nigeria environmental conditions. The challenges faced with pipeline corrosion, poor operational condition, vandalism, inadequate cathodic protection system and environmental hazards in shallow water, deep offshore, Niger Delta swamp and land terrain environment were the focus of the study. The methodology was based on the adoption of a unified digital twin architecture that combines the Smart Pig inspection data, AI-based corrosion prediction, robotic crawler ultrasonic thickness measurement, Distributed Acoustic Sensing/Distributed Temperature Sensing (DAS/DTS) fiber optic monitoring system, anomaly detection algorithms, environmental risk analysis and predictive maintenance decision support models. The study involved 300 pipeline segments. The results of the integrity assessment revealed that many pipelines had operating pressure margins that were safe, and that no pipeline segment was forecast to experience greater than 80% pipeline wall loss over the next 12 months. The Mean Absolute Error (MAE) value for the AI-based corrosion prediction model was 1.520 mm, indicating that the model has a good predictive capability. Out of the 300 pipeline segments assessed, 157 were determined to be low risk, 137 medium risks, and 6 were high risk, and the average Digital Twin Integrity Index (DTII) was 69.12, and the average Remaining Useful Life (RUL) was 22.11 years. The study also identified 24 pipeline sections that were considered anomalous, 7 pipeline sections that were suspected to have a leak, and 38 locations where cathodic protection was not working. In addition, proactive integrity management strategies resulted in cumulative disruption and environmental impact scores that were reduced from 4844.0 in reactive management to 983.8, which is about 79.7% less than reactive management. The report found that the use of AI-powered digital twin systems, predictive analytics, fiber optic surveillance, and anomaly detection can greatly enhance pipeline reliability, predictive maintenance planning, structural integrity assessment, and environmental sustainability in complex oil and gas operating environments.

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

1.0 Introduction

In the global energy industry, pipelines are the safest, most cost effective and efficient way to transport crude oil, natural gas and refined petroleum products over long distances (Belvederesi et al.). The security and reliability of pipeline infrastructure is, therefore, essential to the security and sustainability of energy supplies, industrial development, economic growth and environmental protection. Nevertheless, pipeline incidents due to corrosion, third party interference, maintenance problems, equipment failure, coating degradation, operational fatigue, vandalism and others are still serious environmental, social, economic and safety concerns globally. Therefore, pipeline integrity has become a prerequisite concern in the oil and gas industry (Palmer-Jones et al.), especially for countries with long pipeline transportation networks (LPWN), like Nigeria. The typical pipeline integrity management practices mainly focus on the periodic integrity inspection methods involving Smart Pigging, Ultrasonic testing, Visual integrity inspection, and Pressure testing (Kishawy and Gabber). Smart Pig inspection systems give reliable information about the internal corrosion defects and loss of wall thickness but are only suitable for pipelines that can be pigged. Some percentage of pipeline systems, particularly old pipelines and geometrically complex systems, have restrictions in the form of diameter changes and bends, operational limits or inaccessible configurations and are considered Unpiggingable pipelines. Therefore, the application of traditional inspection technologies is not enough to meet the requirement of obtaining a comprehensive integrity assessment of the whole pipeline infrastructure (Varela et al.). In addition, the inspection process is often time-consuming, costly, infrequent and usually a reactive approach. Often, defects are only discovered when there has been substantial structural damage. This restriction can impact operators' ability to conduct predictive maintenance and raise risks of catastrophic pipeline failure. Difficult environmental conditions in Nigeria are characterized by swamp terrain, flooding, vandalism, illegal tapping and slow response to emergencies that have make the pipelines vulnerable and thereby further compounding the challenges. This study fulfilled the gaps on corrosion monitoring in the oil and gas industry through the deployment of one of the best solutions for corrosion monitoring in the industry that rely on an integrated framework that combines real-time electronic probes, non-intrusive ultrasonic sensors, physical weight-loss coupons and advanced pipeline integrity software, because a single technique leaves dangerous blind spots undiscover, while leading asset operators maximize safety and optimize chemical injection via multi-layered matrix of internal and external monitoring techniques, and equally proffered solutions to treat many people found leaving withing the ROW of Nigerian Pipelines through the deployment of Artificial Intelligence (AI) solutions to offer the pipeline asset with powerful frameworks and security architecture that would help to analyze, detect and mitigate the complex causes and devastating impacts of pipeline disasters in Nigeria on criminal activities (vandalism plus oil theft) and environmental degradation (corrosion plus structural wear of the pipelines) that will help Nigeria oil and gas pipeline asset.

2.0 Methodology

2.1 Research Design

A typical research design for this topic integrates computational simulation tools, artificial intelligence models, and a probabilistic integrity assessment framework by following a structured four-stage methodology: data collection and preprocessing, AI model training, numerical simulation, and reliability analysis for an integrated pipeline integrity framework which equally combines multimodal data collection, physics-informed digital twin synchronization, and

probabilistic risk modeling. This approach merges internal high-resolution inspection data, continuous external sensing, and contextual environmental factors into a unified predictive system.

Stage 1: Data Collection, Preprocessing and Multimodal Ingestion that involved pipelines historical data gathering, environmental factor logging, smart PIG Inspection, fiber optic sensing, environmental risk metrics and data cleaning.

Stage 2: Artificial Intelligence Model Development / Data Preprocessing and Fusion that considered algorithm selection, predictive mapping, data validation, signal alignment and feature extraction.

Stage 3: Computational Simulation / Digital Twin Architecture / Synchronization that considered Finite Element Analysis (FEA) and Computational Fluid Dynamics (CFD) involving failure boundary generation, pipelines virtual mapping, state updates and simulations.

Stage 4: Probabilistic Integrity Assessment Framework / Environmental Risk and Integrity Assessment that considered Monte Carlo simulation, Limit state function definition, reliability updating, probabilistic failure analysis and risk ranking.

Then, further focused on a specific part of the pipeline integrity assessment, such as

- i. The **mathematical formulation** of the limit state function
- ii. Specific **AI algorithms** for remaining useful life prediction
- iii. **Software tools** best suited for the finite element analysis

The computing platform used was Python programming language with the different analytical libraries such as Pandas for data processing, NumPy for numerical computations, Matplotlib and Seaborn for visualization, and Scikit-Learn for artificial intelligence and machine learning implementation. The machine learning models used in the studies were linear regression models, random forest regressors, and isolation forest anomaly detection model. The simulated datasets generated were a set of pipeline systems in swamp environment characteristic of Niger Delta, land terrain environment, shallow offshore and deep offshore environments. The datasets included operational and structural parameters like pipeline diameter, wall thickness, pipe grade, specified minimum yield strength (SMYS), operating pressure, operating temperature, flow rate, corrosion rate, defect length, defect depth, cathodic protection potential, acoustic monitoring signals, fiber optic vibration data, drone intrusion indicators, vegetation stress indicators, soil corrosivity indices, humidity condition, remaining useful life estimate, Digital Twin Integrity Index (DTII), anomaly classification and maintenance priority classification and environmental risk conditions.

2.2 Materials

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 the representative of Niger Delta environments. The studies were performed in a python based analytical environment for generation, processing, simulation, prediction, assessment and visualization of pipeline operational and structural integrity conditions. The results obtained for this research were secondary, derived from literature-based engineering parameters that were reported in pipeline integrity studies or API 580 Risk Based Inspection (RBI) standards, NACE corrosion control guidelines, ASME B31G defect assessment procedures, digital twin integrity management framework and reported operational characteristics of Nigerian oil and gas pipeline systems. With these literature derived parameters, realistic pipeline operating conditions, corrosion degradation

behavior, cathodic protection performance, anomaly detection conditions, fiber optic surveillance alerts, environmental risk exposure and maintenance decision-support scenarios were simulated. The research materials used for the Multi-model integrity assessment system covers AI-Based Corrosion Prediction, Fiber Optic Monitoring, and Structural Integrity Assessment of Pipeline Systems that integrates that of 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.

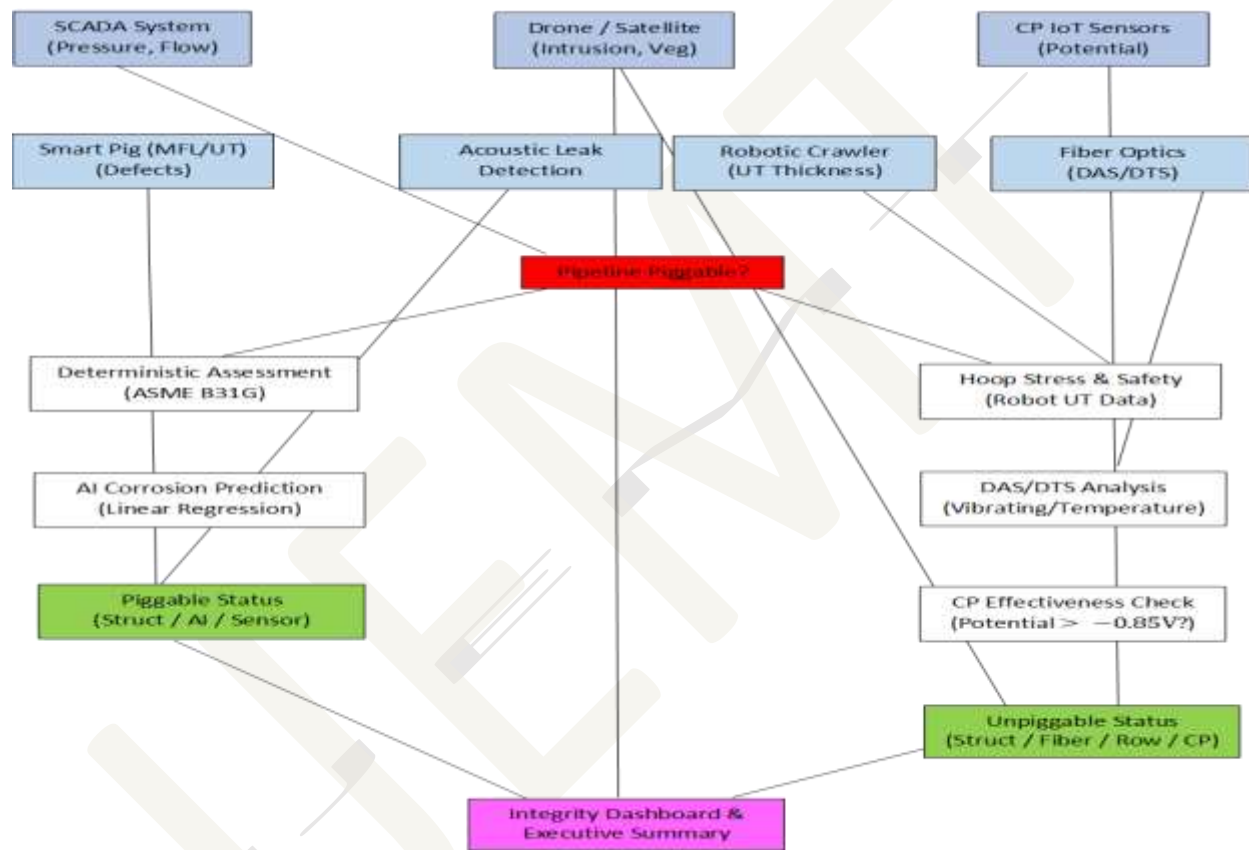


Figure 1: Multi-model integrity assessment system

The research materials on the part of Novel AI-driven digital twin framework for integrity assessment of piggable and unpiggable pipelines,” comprised a Digital Twin Integrity Index framework, physics-informed AI corrosion prediction models, Random Forest machine learning algorithms, and Isolation Forest anomaly detection systems, multi-source sensor fusion models, predictive maintenance prioritization engines, and remaining useful life (RUL) prediction frameworks, as well as probabilistic environmental risk assessment systems. The integrity assessment for piggable and unpiggable pipelines using different ideal and innovative methods for the Nigerian oil and gas pipelines terrain was carried out. The study employed a hybrid deterministic–probabilistic framework that uses the concept of artificial intelligence based digital

twin to assess the structural integrity of piggable pipeline systems under different environment and operation conditions in Nigeria.

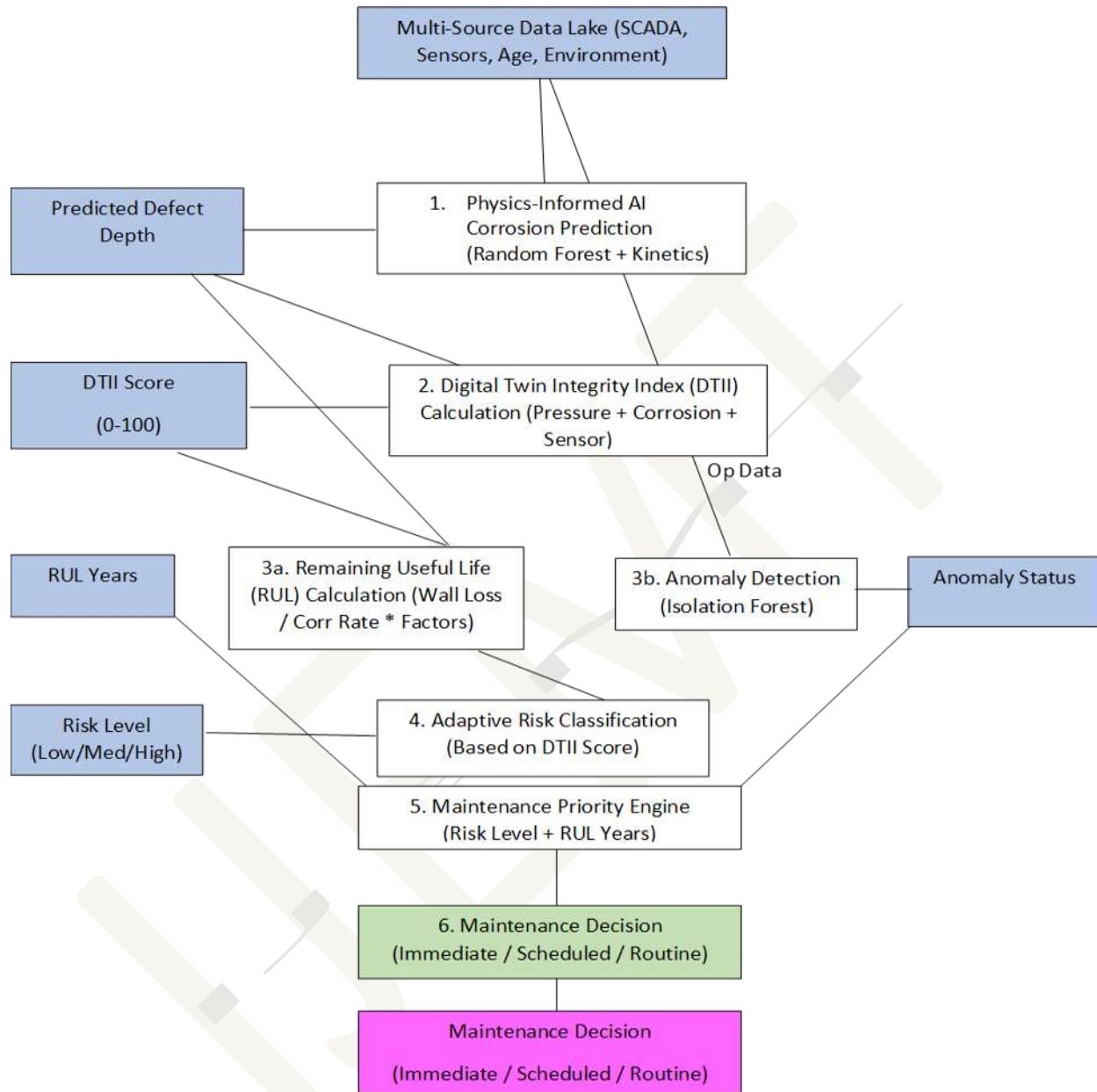


Figure 2: Novel AI-driven digital twin framework

The methodology included the development of an integrated pipeline integrity assessment framework that could integrate deterministic corrosion assessment models, physics-informed machine learning techniques, anomaly detection algorithms, real-time monitoring technologies study and risk-based decision analysis for pipeline integrity assessment and predictive maintenance planning. The created framework merged several sources of operational data, structural data, environmental data and monitoring data of pipeline systems in the Niger Delta

region. Incorporated datasets and monitoring systems that comprised of Smart Pig magnetic flux leakage (MFL) inspection data, Supervisory Control and Data Acquisition (SCADA) operational data, fiber optic Distributed Acoustic Sensing (DAS) and Distributed Temperature Sensing (DTS) systems, robotic crawler ultrasonic thickness measurements, drone-based right of way surveillance systems, satellite vegetation stress monitoring, cathodic protection measurements and artificial intelligence-based predictive analytics for structural integrity assessment and risk prediction. Integrated digital twin-based methodological framework for structural integrity assessment and predictive maintenance of piggable and unpiggable pipelines. The data collation, generation and simulation of pipeline data for both piggable and unpiggable pipeline systems within environments of swamp, land terrain, shallow water and deep offshore environments typical of the Niger Delta region were carried out. Several pipeline sections were simulated to capture realistic operational and environmental conditions in pipelines in Nigeria. These datasets generated include pipeline diameter, wall thickness, operating pressure, flow rate, temperature, corrosion rate, corrosion defect depth, corrosion defect length, pipeline age, soil corrosivity index, relative humidity, cathodic protection condition, fiber optic vibration signals, acoustic monitoring signals, drone intrusion indicators and vegetation stress indicators.

2.3 Synthetic Data Used

The data collected for the purpose of this work include: (1) pipe diameter; (2) pipe wall thickness; (3) pipe operating pressure and/or flow rate; (4) pipe operating/ambient temperature; (5) pipe age; (6) corrosion rate; (7) depth of defects; (8) length of defects; (9) cathodic protection (CP) potential; (10) relative humidity; (11) soil corrosivity index; (12) fiber vibration response; (13) acoustical noise; (14) evidence of drone intrusion; and (15) stress/health parameters of vegetation. The following material grades were included as part of this study based upon the use of API 5L X52, X60 and X70 material specification, which are commonly used by the Nigerian pipeline industry. The sources of the pipeline synthetic data include NORSOK M-506 Simulations on Mendeley Data, Conditional Tubular Generative Adversarial Networks, COMSOL Multiphysics / ANSYS and Empirical Standards Coding (ASME B31G and DNV-RP-F101).

3.0 Results and Discussions

The results in Figure 3.1 shows the outcome of the integrity assessment of piggable and unpiggable pipeline systems in Nigeria under various operating conditions such as shallow water, deep offshore, Niger Delta swamp and land terrain regions. The findings include a combination of Smart Pig inspection analysis, artificial intelligence (AI) corrosion prediction, robotic crawler ultrasonic thickness measurement, fiber optic sensing system analysis, and environmental risk evaluation techniques to evaluate the condition of the pipeline infrastructure, corrosion severity, pressure safety margins, susceptibility to leaking and operational reliability.

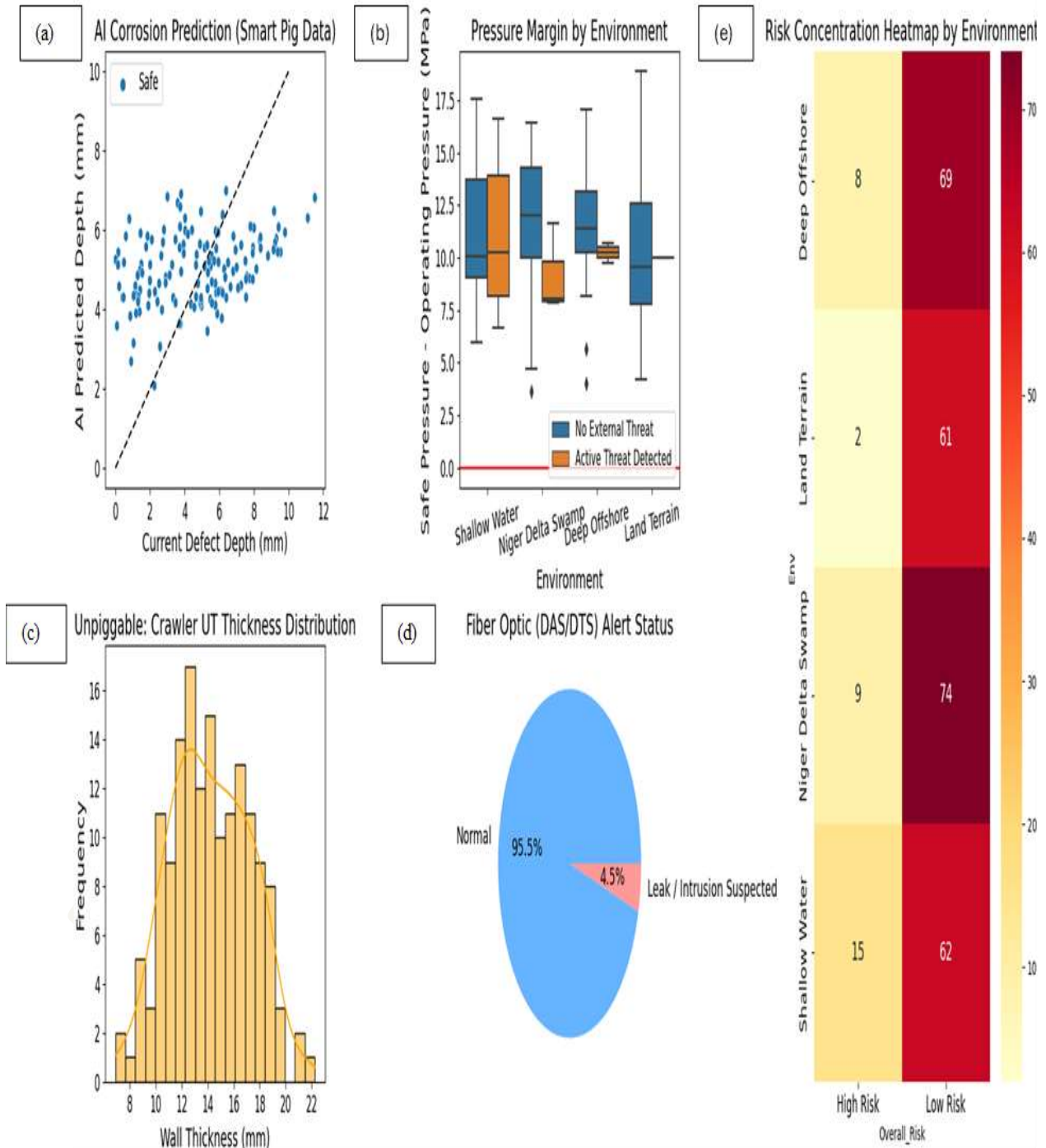


Figure 3: AI-based corrosion prediction, fiber optic monitoring, and structural integrity assessment results of pipeline systems

The first result plot, named (a) is the Smart Pig vs. AI-Assisted Defect Depth that compares the current measured defect depth from smart pigging with the corresponding defect depth projected by the AI diagnostic module for piggable pipelines. The x-axis shows the current defect depths between about 0 mm and 12 mm, and the y-axis displays the AI-projected depths between about 0

mm and 10 mm. The dashed diagonal line from the origin to the upper right corner represents the ideal alignment, where the projected corrosion depth equals the measured depth. The scatter distribution shows that most pipeline sections inspected have current defect depths ranging from around 1 mm to 8 mm. Most of the predicted corruptions are clustered in the range of around 4 mm to 6.5 mm, while the current defect depths are concentrated around 3 mm to 6 mm with their corresponding predicted depths ranging between 4.5 mm and 5.8 mm. The defect depths measured are approaching ~11.5 mm and the defect depths predicted by the AI are less than ~7 mm.

The narrow spread of the predicted defect depths within a relatively narrow range suggest that the AI model predicts a gradual and stable corrosion rate, rather than rapid or accelerated corrosion. If corrosion is severe, predicted defect depths would usually be considerably greater than the current wall loss situation. The outcome of the analysis indicates however, that most of the piggable pipelines will still operate within controlled corrosion environments in the future.

A significant finding in the scatter plot is that a few data points for high defect depths in the current plot fall below the reference line for a diagonal scatter plot. For instance, pipeline sections that have current defect depth of about 9 mm to 11 mm are projected to have defect depth of about 5.5 mm to 6.8 mm in future evaluations. This indicates that the AI model is predicting lower corrosion rates in highly corroded areas, which may be due to corrosion control programs, maintenance efforts, cathodic protection systems, or the rehabilitation of the coatings. On the other hand, sections of pipeline that have smaller current defect depths (1 mm to 3 mm) are expected to grow in the future and reach defect depths of 4 mm to 5.5 mm, which means that these sections are likely to become more prone to corrosion activity.

The importance of this finding is that AI-assisted analysis converts traditional inspection information into predictive integrity data. While traditional smart pigging focuses on detecting existing corrosion faults, this diagnostic AI projects future corrosion trends. This capability is vital for identifying specific physical anomalies, such as the 7 leak suspects and 38 ineffective CP segments identified in this assessment that require targeted physical intervention and inspection scheduling. Also, the concentration of most data points in the “Safe” structural classification is indicative of the fact that none of the evaluated pipeline segments are currently at critical failure conditions. This is consistent with the summary interpretation where 0% of pipeline segments are expected to have wall loss above 80% over the next 12 months. Instructively, this means that there is a structural integrity limit on both the remaining wall thickness and the residual burst strength of the pipelines being assessed which will keep them in safe service operation.

The second result plot (b) is the Pressure Margin by Environment which shows the pressure margins for pipelines under different environments. The pressure margin is the difference between the allowable pressure and the operating pressure, in terms of MPa. Positive values of the pressure margins represent safe operating conditions of the structure, while values that are close to zero represent high failure risk.

In the shallow water conditions for “No External Threat”, the pressure margins are found to be approximately between 6 MPa and 17.5 MPa, with a median pressure margin around 10 MPa. The range of interquartile values lies roughly between 9 MPa and 13.5 MPa. The shallow water pressure ranges under “Active Threat Detected” conditions approximately from 6.7 MPa to 16.8 MPa and have a median slightly higher than 10 MPa. Based on these results, it can be concluded that shallow water pipelines remain structurally strong with significant residual strength even under hydrodynamic loading, marine corrosion and external mechanical disturbance.

The pressure margins for the Niger Delta swamp environment range from approximately 4.8 MPa to 16.5 MPa, with a median value of around 12 MPa, and a low outlier of 3.7 MPa. Under “Active Threat Detected” conditions, these margins drop considerably, ranging from about 7.8 MPa to 11.7 MPa with a median around 8 MPa. This physical reduction in pressure margin directly correlates with the harsh realities of swamp terrains, including high moisture levels, microbiologically influenced corrosion (MIC), unstable soil conditions, and continuous third-party interference.

Pressure margins in the deep offshore environment under “No External Threat” are approximately between 8 and 17 MPa with a median of approximately 11.5 MPa. A relatively lower structural safety margin is observed with two lower outliers around 5.7 MPa and 4 MPa, representing isolated offshore sections. When the pressure margin is “Active Threat Detected”, the pressure range is compressed to between 9.8MPa and 10.8MPa, with a median value of 10.2MPa. The narrow spread reflects an improvement in the conditions of the offshore operations, mainly because of the more stringent design requirements, improved material selection and better corrosion control systems.

The land terrain pipelines have the most pressure margin variations of all the assessed terrains. The pressure margins are from 4.2 MPa to 18.8 MPa with a median value around 9.5 MPa under “No External Threat” condition. When the primary threat is active, the pressure margin is in the range of around 10 MPa. There is a wide range of variability in the land terrain pipelines, which may be related to the inconsistent operational conditions or exposure to excavation damage, vandalism and illegal tapping activities, mechanical impacts or coating degradation.

An important result from the evaluation of the pressure margin is that none of the pressure margins fall below the zero-pressure threshold. This confirms that none of the assessed pipelines currently operate at pressure levels exceeding their safe allowable operating pressure. Physically, this implies that all evaluated segments possess positive residual strength margins against immediate burst failure.

The third result plot (c) is Unpiggable: Crawler UT Thickness Distribution” which shows the wall thickness distribution from robotic crawler ultrasonic testing inspection of unpiggable pipelines. Because of the geometric restrictions and/or operational requirements, conventional inline inspection tools cannot be used on unpiggable pipelines, so robotic crawler systems with ultrasonic sensors offer an alternative approach to direct wall thickness assessment.

The histogram is between 7.5mm and 22.5 mm approximately. Most measurements are made in the range of 11 mm to 18 mm. The peak thickness is around 12 mm to 13 mm with a total of about 17 observations. There are further peaks between 15 mm and 17 mm with observation counts around 10 to 13. The fitted density distribution indicates that the wall thickness distribution is approximately normal with the median around 14 mm to 15 mm. This means that most pipeline segments not yet piggable have moderate to high wall thickness (WT) values and continue to have good structural integrity conditions. The skew-side of the distribution towards 7.5 mm and 8 mm, however, is structurally significant. If such localized thinning occurs, the burst pressure capacity may be significantly reduced, and a higher risk of initiating a leak or failure by fatigue may exist. These thinner sections are probably corrosion hot spots or areas of pipeline where coatings have deteriorated or where there is ineffective cathodic protection.

The value of this finding is that the robotic crawler inspection system can directly inspect inaccessible sections of the pipeline. Unpiggable pipelines have traditionally been an integrity management challenge, as traditional in-line inspection techniques are ineffective. The crawler-based ultrasonic inspection system thus significantly helps to mitigate integrity uncertainty by providing direct wall thickness measurement in areas that are difficult to access in pipelines.

The fourth result graph (d) is “Fiber Optic (DAS/DTS) Alert Status” which shows the state of operational condition of unpiggable pipelines monitored by Distributed Acoustic Sensing and Distributed Temperature Sensing. As seen in the pie chart, the percentage of pipeline segments monitored that are “Normal” is about 95.5 percent and the percentage of “Leak / Intrusion Suspected” is about 4.5 percent. The assessment summary also shows seven sections of the pipeline that were not piggable were identified for possible leakage using the fiber optic sensing system. Although the quantity of suspicious segments in the monitored network only accounts for 4.5% of the network, the result is very significant because even a few leaks can lead to serious environmental pollution, fire hazard, production losses and economic damage.

The high proportion of 95.5% normal suggests that most of the monitored pipeline sections are in a normal state with no abnormality being detected. Meanwhile, when suspicious segments are found, it means that DAS/DTS systems are effective in continuous real-time monitoring. The leak-proof, intrusion-proof, anti-sabotage fiber optic sensing technologies look for any abnormal vibrations, acoustic anomalies, thermal disturbances or intrusion signatures caused by leaks, sabotage or unauthorized digging. This is especially crucial in the Nigerian operating conditions as pipeline vandalism and illegal bunkering activities are significant integrity threats. Fiber optic systems can then monitor these leaks continuously and can reduce the time required for leak detection response times to conventional inspection methods.

The result plot titled (e) is the Risk Concentration Heatmap by Environment which shows the concentration of high-risk and low-risk sections of pipelines by operating environment. The values of the heatmap are significant characteristics of an environmental risk. There are 8 segments in the Deep Offshore environment that have been identified as being at high risk and 69 at low risk. This means that while the pipeline system offshore is generally stable, some isolated sections need attention to integrity and some monitoring. The Land Terrain environment has 2 high-risk segments and 61 low-risk segments recorded. This is the lowest level of high-risk observations across all environments, indicating comparatively low levels of integrity conditions and exposure to vandalism and mechanical interference.

In the Niger Delta Swamp environment, 9 hazard segments are recorded and 74 low hazard segments. This environment, therefore, has the greatest low-risk concentration and a high concentration of high-risk. This is indicative of the complicated nature of swamp operations and how a combination of aggressive degradation mechanisms exists alongside large-scale monitoring and maintenance. There are 15 high-risk observations and 62 low-risk observations in the Shallow Water environment. This means that shallow water pipelines have a higher probability of failure because of marine corrosion, hydrodynamic loading, deterioration of pipeline coatings, anchor encounters, and mechanical disturbance by fishing.

The heatmap can thus be used to identify the most structurally vulnerable operational area of the assessed pipeline systems as shallow water, while land terrain pipelines show the lowest number of high-risk observations. Additionally, another assessment result shows that 38 sections of pipelines have ineffective cathodic protection systems that need repair. This discovery is very important because cathodic protection is one of the most important ways to prevent pipelines from corrosion when they are buried or in water. Cathodic protection with poor results contributes to faster electrochemical corrosion processes, faster coating degradation and wall thinning. Therefore, the results plotted in the Figure 3-a, b, c, d and e demonstrates how effective it is to use multiple technologies for inspection and monitoring to improve predictive maintenance capabilities, reduce uncertainties and enhance the ability to assess structural reliability; support

risk-based maintenance decisions; minimize the probability of failure; and promote sustainable pipeline integrity management in Nigeria's oil and gas industry which involves very challenging operational conditions.

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.

4.0 Conclusions

An integrated Artificial Intelligence (AI)-driven Digital Twin framework for predictive integrity assessment, maintenance optimization, corrosion control, surveillance of the right-of-way and environmental risk reduction for both piggable and unpiggable pipeline systems under Nigerian environmental conditions was successfully developed and evaluated in this study. The research tackled key challenges to pipeline degradation, growth of corrosion, pipeline vandalism, anomalies during operation, ineffective cathodic protection systems, environmental disruption, and the integration of Smart Pig Temperature inspection data, robotic crawler ultrasonic testing, fiber optic Distributed Acoustic Sensing (DAS), Distributed Sensing (DTS), anomaly detection algorithms, environmental risk analysis, and predictive AI models. The study demonstrated that the pressure margin is still a viable test to assess structural reliability and structural residual burst strength in all the study terrain environments, namely shallow water, deep offshore, Niger Delta swamp and land. The outcomes indicated that environmental conditions had a significant effect on the behaviours of pipeline degradation; although all pipelines were found to have positive safety margins maintained. 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. Pipeline operators should utilize integrated AI-driven digital twin systems in combination with Smart Pig inspections, robotic crawler ultrasonic testing, DAS/DTS fiber optic monitoring and anomaly detection models to provide continuous monitoring, real-time integrity assessments and predictive maintenance of pipelines that are either piggable or unpiggable in keeping these critical asset reliable for their economical values, human and environmental security.

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