



Advanced risk-Informed prioritization and evolutionary cost-optimal framework for intelligent corrosion maintenance in pipelines

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Abstract

Pipeline infrastructure is increasingly vulnerable to complex, multi-stage corrosion defects that compromise structural integrity, operational reliability, regulatory compliance, and long-term cost-effectiveness. Conventional periodic maintenance strategies often lack adaptability to real-time degradation dynamics and environmental variability, resulting in inefficient resource utilization and elevated failure risks. This paper introduces ARPC-DOX (Advanced Risk-Informed ABCDE prioritization and evolutionary cost-optimal framework for intelligent Corrosion Maintenance in Pipelines), a novel AI-driven decision-support framework that integrates predictive modeling, dynamic risk assessment, and cost-aware optimization for intelligent pipeline maintenance. ARPC-DOX fuses a cross-Bayesian network, augmented with cross-attention mechanisms, to capture complex spatiotemporal dependencies in corrosion progression and detect evolving multi-stage defect patterns with high precision. The framework consolidates heterogeneous data sources including inspection logs, sensor telemetry, operational parameters, material characteristics, and environmental stressors into a unified, context-aware predictive engine. Maintenance prioritization is performed through an enhanced ABCDE framework, which is embedded with a dynamic weight adjustment layer that adaptively recalibrates risk weights based on current degradation trends and uncertainty profiles. To optimize the trade-off between maintenance cost and failure risk, the system employs the ADDAX algorithm, a robust, adaptive differential evolution-based metaheuristic designed for dynamic, high-dimensional optimization tasks. Extensive simulation studies conducted on a 100-segment synthetic pipeline network demonstrate the framework's effectiveness in reducing failure probability, enhancing risk responsiveness, and achieving superior resource allocation. ARPC-DOX represents a scalable, intelligent, and real-time corrosion management paradigm that significantly enhances the safety, resilience, and sustainability of modern pipeline systems.

Keywords ADDAX · Synthetic pipeline network · Multi-stage defect · Prioritization · Cost-optimal framework

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1 Introduction

Pipeline infrastructure plays a vital role in resource transportation [1], yet it is susceptible to deterioration over time, predominantly due to corrosion, especially complex multi-phase corrosion damage [2], which significantly threatens structural stability. This vulnerability has driven substantial research into the formulation of maintenance strategies aimed at mitigating such defects. Earlier approaches mainly depended on deterministic techniques, corrosion progression models [3, 4], and reliability-centric methodologies [5, 6] for degradation forecasting and maintenance planning. Probabilistic models, for example, have been broadly employed to project corrosion progression by incorporating historical performance data along with environmental parameters like pressure and temperature. In addition, finite element analysis has been leveraged to assess interactions between corrosion and mechanical stress. These models support decision-making processes regarding whether to repair or replace pipeline segments [7]. Nevertheless, a key drawback is their dependence on static modeling frameworks, limiting their ability to adapt to real-time shifts in operational parameters, which compromises the accuracy of predictions under evolving corrosion scenarios.

Simultaneously, reliability-oriented strategies such as risk-based inspection (RBI) [8] have emerged to reduce pipeline failure probabilities by prioritizing maintenance actions based on risk assessment results. While effective in mitigating risk, these methods encounter notable challenges when dealing with the complexity of multi-phase corrosion, where defect progression varies significantly along different pipeline segments. Monitoring and forecasting corrosion under dynamic, real-time operational conditions adds further complexity [9]. Moreover, optimization algorithms including genetic algorithms [10, 11] and Particle Swarm Optimization [12] have been explored to improve maintenance efficiency by iteratively identifying cost-effective scheduling solutions that balance failure risk with maintenance expenses. Although promising, these optimization approaches often lack the flexibility to adjust dynamically to fluctuating corrosion states, which is essential for sustainable cost control over the long term.

To overcome these limitations, machine learning-based methods [13] have recently gained traction for their ability to enhance predictive capabilities. Techniques such as Support Vector Machines [14, 15] and Artificial Neural Networks [16, 17] have been employed to learn corrosion progression patterns from historical datasets, thereby refining forecast accuracy. However, these models often struggle to generalize across varying pipeline environments, leading to suboptimal maintenance outcomes. Furthermore, existing decision-support frameworks [18] frequently prioritize

risk mitigation over long-term cost-efficiency, resulting in maintenance schedules that are economically inefficient in the long run [19].

A critical gap in current research is the absence of an integrated approach combining real-time predictive modeling with adaptive maintenance policies. Traditional frameworks typically fail to capture the full spectrum of corrosion stages, often resulting in excessive maintenance or delayed corrective actions both of which incur high costs. Additionally, these models lack the responsiveness required to incorporate live operational data, which is essential for dynamically balancing risk, cost, and long-term reliability. In essence, while considerable advances have been made in corrosion prediction and maintenance planning, most existing techniques remain constrained by their static nature, computational burden, and limited adaptability to real-time multi-stage corrosion in changing environments. Future models must be more resilient and responsive, capable of processing live data streams to enable efficient, cost-conscious maintenance decision-making.

This study proposes a novel methodology, ARPC-DOX, designed to deliver next-generation optimization for maintenance planning and advanced corrosion control. By integrating machine learning into the management of pipelines with complex, multi-phase corrosion, ARPC-DOX aims to simultaneously reduce failure risk and avoid superfluous maintenance costs making it particularly well-suited for deployment in highly dynamic operational contexts.

While this paper introduces ARPC-DOX for adaptive pipeline corrosion management, future research could focus on expanding its applicability to more complex pipeline infrastructures. Potential directions include integrating advanced AI-driven predictive models to account for non-linear corrosion patterns, incorporating external factors such as extreme weather events, and improving scalability for large-scale pipeline networks. Additionally, cross-sector adaptation of the framework could be explored, allowing application beyond oil and gas pipelines, such as in water distribution systems or urban infrastructure networks where dynamic maintenance strategies are Equationally critical.

1.1 Contributions

- **Cross Bayesian Network (CBN):** The CBN combines traditional Bayesian modeling with cross-attention mechanisms to predict corrosion progression in pipelines. It captures the temporal evolution of defects, enabling detection of multi-phase corrosion from early surface wear to advanced structural damage using real-time data streams. By embedding cross-attention, the model can selectively align and synthesize heterogeneous

information sources, enhancing its ability to analyze diverse sensor inputs and contextual variables, thereby improving predictive precision in dynamic operating environments.

- **ABCDE-Based Dynamic Prioritization:** The ABCDE prioritization model is a task management strategy that classifies issues into five categories (A–E) based on urgency and significance. In pipeline corrosion management, the framework integrates a Dynamic Weight Adjustment Layer that recalibrates category weights in real-time, adapting to current corrosion severity, environmental factors, and operational data for more responsive prioritization. This enhancement enables adaptive prioritization that evolves with changing risk profiles, leading to more accurate corrosion depth targeting and timely intervention strategies, thereby improving maintenance efficiency.
- **ADDAX for Adaptive Cost Optimization:** The ADDAX framework applies principles of differential evolution to dynamically minimize operational and maintenance costs in pipeline systems. It continuously evolves task scheduling solutions in response to changing environmental parameters, corrosion risk levels, and operational demands. By incorporating adaptive weight tuning and real-time decision-making, ADDAX optimizes resource allocation, mitigates the risk of unexpected failures, and reduces unnecessary expenditures. Its flexibility and responsiveness make it well-suited for managing distributed maintenance tasks under fluctuating field conditions.

A future research direction may involve the development of more advanced AI-driven predictive models, incorporation of extreme external stressors such as weather-induced degradation, and expansion of the system's scalability for cross-domain applications enhancing both robustness and adaptability.

The remainder of the paper is organized as follows: Sect. 2 reviews related work; Sect. 3 describes the proposed ARPC-DOX methodology; Sect. 4 presents experimental results; Sect. 5 presents the Discussion and Sect. 6 concludes with key findings and future research directions.

2 Literature review

Recent studies emphasize innovative maintenance and corrosion management strategies to improve pipeline performance and ensure long-term reliability.

2.1 Optimization-based maintenance strategies for pipeline systems

Recent studies have increasingly emphasized optimizing pipeline maintenance by addressing trade-offs between cost, availability, risk, and inspection planning.

Xie et al. [20] introduced a groundbreaking multi-objective optimization framework leveraging the Non-dominated Sorting Genetic Algorithm II (NSGA-II) to simultaneously optimize which pipeline segments to maintain, the timing of maintenance actions, and the choice of maintenance strategies (e.g., repair, replacement, or monitoring). Unlike earlier single-objective models that prioritized cost minimization, this approach facilitated balanced decision-making by considering trade-offs between cost, reliability, and system availability. However, its computational scalability was limited when applied to large-scale pipeline networks, particularly under uncertain corrosion data, which often plagues real-world applications due to inconsistent inspection outcomes. Addressing some of these challenges, Mensah and Sriramula [21] shifted toward a stochastic reliability framework that incorporated time-variant reliability assessments using surrogate models, such as response surface methods, to estimate failure probabilities more accurately. Their probabilistic approach improved the reliability estimates informing maintenance policies, enabling risk-based decision-making, but the computational intensity of their simulations posed a barrier for real-time applications in extensive pipeline systems. Building on the need for condition-based strategies, Yazdi et al. [22] proposed a microbiologically influenced corrosion (MIC)-aware maintenance optimization model that explicitly modeled probabilities related to pit depth growth and defect detection, integrating these with cost parameters to prioritize maintenance actions. This condition-based approach accounted for inspection errors, a critical real-world factor, but its reliance on probabilistic assumptions introduced subjective uncertainty due to the scarcity of empirical corrosion data, limiting its robustness in diverse operational contexts.

In a parallel development, Fan et al. [23] advanced preventive maintenance optimization by integrating Bayesian Networks with Markov Decision Processes and deep reinforcement learning (DRL). This framework enabled continuous learning and adaptation to uncertainties in demand and failure rates, offering a dynamic decision-making tool for gas pipeline networks. By modeling complex dependencies and learning optimal policies over time, their approach outperformed static models but required substantial computational resources, making it less feasible for large-scale networks with limited computational infrastructure. Complementing these efforts, Wang et al. [24] enhanced multi-objective maintenance planning by employing a Clayton copula

function to model correlations among multiple pipeline failure modes, such as corrosion and mechanical damage. Combined with NSGA-II, their model provided improved trade-offs between system availability and maintenance costs, offering practical insights for prioritizing interventions. However, it did not adequately address uncertainties arising from inspection data, which can skew decision-making in real-world scenarios where inspection tools vary in accuracy. Meanwhile, Shao et al. [25] proposed a proactive maintenance strategy based on a multi-phase Wiener process to model the stochastic evolution of corrosion depth over time. This reliability-informed model supported preemptive interventions by predicting degradation trends, but its effectiveness hinged on the availability of high-quality corrosion data, and its computational demands limited its scalability for large networks with frequent inspections.

Further advancing probabilistic methods, Mensah and Sriramula [26] developed a finite element-based approach using surrogate modeling techniques, specifically polynomial chaos-Kriging, to efficiently estimate the probability of failure due to clustered corrosion defects. This method reduced computational costs compared to traditional finite element simulations while maintaining accuracy, but it lacked a corrosion growth model and assumed precise input data, which is often unrealistic given the variability in field measurements. In contrast, Zerouali et al. [27] tackled the maintenance of long-distance pipelines through a comprehensive reliability-based optimization model that integrated Bayesian networks for probabilistic inference, predictive degradation modeling for forecasting failure risks, and Monte Carlo simulations for uncertainty quantification. They also employed Karhunen-Loève expansion to handle spatial uncertainties across pipeline segments, providing a system-wide perspective suitable for geographically dispersed networks. However, their approach faced practical constraints in developing regions, where budgetary limitations and sparse data availability hindered implementation, underscoring the gap between theoretical advancements and operational feasibility.

2.2 Data-driven and probabilistic modeling for corrosion management

Another major strand of research focuses on probabilistic, data-driven, and hybrid learning-based models for understanding corrosion mechanisms and making informed maintenance decisions.

Li et al. [28] introduced a dynamic risk-based maintenance model that leverages Bayesian Networks (BN) to probabilistically model pipeline failure risks and Bayesian Influence Diagrams (BID) to evaluate cost implications, aiming to extend pipeline operational life by optimizing the

trade-off between profitability and risk; however, its predictive performance is constrained by the absence of advanced machine learning techniques, which could enhance its ability to handle complex, non-linear corrosion patterns. Building on cost-focused optimization, Kere and Huang [29] proposed a life-cycle cost analysis framework that employs decision trees to model dependencies between inspection and repair costs, providing actionable insights into optimal inspection intervals and cost thresholds for maintenance actions, yet its oversimplification of complex repair scenarios and assumption of constant repair quality limit its applicability to heterogeneous pipeline conditions. Fan et al. [30] advanced practical maintenance optimization by applying Markov models to analyze state transitions in gas compressor stations, capturing equipment degradation dynamics, and later integrating genetic algorithms to jointly optimize maintenance schedules and spare parts inventory, addressing real-world logistics challenges; however, the model's failure to account for joint effects, such as thermal transients or multiple failure modes, reduces its robustness in capturing system-wide interactions. Park et al. [31] developed a conservative maintenance strategy that uses probability distributions and Bayesian updates to ensure safety margins are not underestimated, offering a practical approach for data-scarce environments, though its conservative assumptions may lead to overly frequent maintenance and elevated costs. Li et al. [32] proposed a sophisticated risk-based decision-making model that integrates the DeWaard 95 corrosion model with Dynamic Bayesian Networks and utility theory to construct a comprehensive risk profile, enabling nuanced maintenance decisions; however, its dependence on expert calibration and computational expertise makes it less feasible in resource-constrained settings, such as developing regions with limited technical infrastructure.

Zheng et al. [33] introduced a non-periodic preventive maintenance model that simulates corrosion randomness using stochastic processes to dynamically adjust inspection intervals, effectively reducing long-term maintenance costs, but its performance is highly sensitive to the accuracy of random process assumptions and the quality of input data, which are often inconsistent in practice. Wang et al. [34] proposed an innovative bilevel knowledge transfer framework that utilizes synthetic data generated from high-fidelity corrosion simulations to train models adaptable to real-world scenarios, reducing dependency on costly field data; yet, its effectiveness is limited by the simulation-to-reality gap, particularly when applied across diverse pipeline environments with varying material or operational conditions. Shuai et al. [35] developed a hybrid approach combining finite element modeling with machine learning to estimate failure pressures in pipelines with triple corrosion defects, improving the modeling of defect interactions, but its reliance on

extensive training data and the need for recalibration for different pipeline types pose practical challenges. Finally, Xie et al. [36] employed Wiener processes and Bayesian networks to model degradation in marine coatings, probabilistically linking environmental factors to corrosion rates, which performs well in specific marine contexts but is limited by its extensive data requirements and lack of generalizability to non-marine pipeline systems. Collectively, these studies illustrate a progressive shift from traditional cost-driven maintenance toward data-informed, adaptive, and risk-aware corrosion modeling that supports predictive maintenance, leveraging advanced techniques like Bayesian networks, machine learning, and multi-objective optimization. However, their dependence on high-quality data, significant computational resources, and specialized modeling expertise presents substantial challenges for real-time implementation, large-scale deployment, or application in low-resource environments, underscoring the need for more robust, scalable, and accessible solutions in pipeline maintenance optimization.

3 Proposed intelligent corrosion maintenance framework

This paper introduces a novel framework that combines advanced maintenance optimization with intelligent corrosion management for pipeline systems, specifically targeting complex multi-stage corrosion scenarios. To enhance clarity, key terms used in the framework are briefly introduced. A risk area refers to a pipeline section categorized based on environmental exposure, operational conditions, material characteristics, and historical corrosion data, which guides maintenance prioritization. The corrosion growth rate represents the progression rate of corrosion severity over time, influenced by operational and environmental dynamics. Multi-state corrosion defects capture the evolving stages of corrosion, from minor surface defects to advanced structural degradation, allowing for adaptive maintenance decisions.

The proposed strategy for optimized maintenance planning follows a sequence of interconnected steps, as illustrated in Fig. 1. The process begins with risk evaluation (Step 2), where composite risk weights are assigned to each pipeline segment through the ABCDE prioritization framework, which adaptively updates weightings in response to real-time changes in safety, economic impact, and operational criticality. This is followed by corrosion forecasting (Step 3), where a Cross-Attention-based neural module predicts corrosion progression by integrating inspection records, environmental conditions, and material data. In the optimization formulation phase (Step 4), the framework establishes a trade-off between cost and risk to support optimal maintenance decisions. A dynamic optimization algorithm (Step 5), specifically ADDAX, is then applied to generate a cost-effective and risk-informed maintenance schedule. Finally, the decision deployment phase (Step 6) translates the optimization results into actionable field-level maintenance plans, ensuring timely intervention in critical zones while accounting for budget constraints, repair urgency, and site-specific limitations.

The ARPC-DOX framework for pipeline corrosion control and maintenance optimization initiates with the systematic intake of operational sensor data, including key variables such as internal fluid pressure, surrounding temperature, and structural wall metrics. These raw signals are standardized and processed to ensure consistency across varying measurement sources. The framework then employs a Cross-Probabilistic Inference Network to capture evolving corrosion behaviors over time. This network facilitates the estimation of degradation trajectories by modeling interdependencies among operational and environmental conditions. To further strengthen data interpretability and resilience, a Multi-Source Attention Fusion mechanism is applied, allowing the model to dynamically weigh and

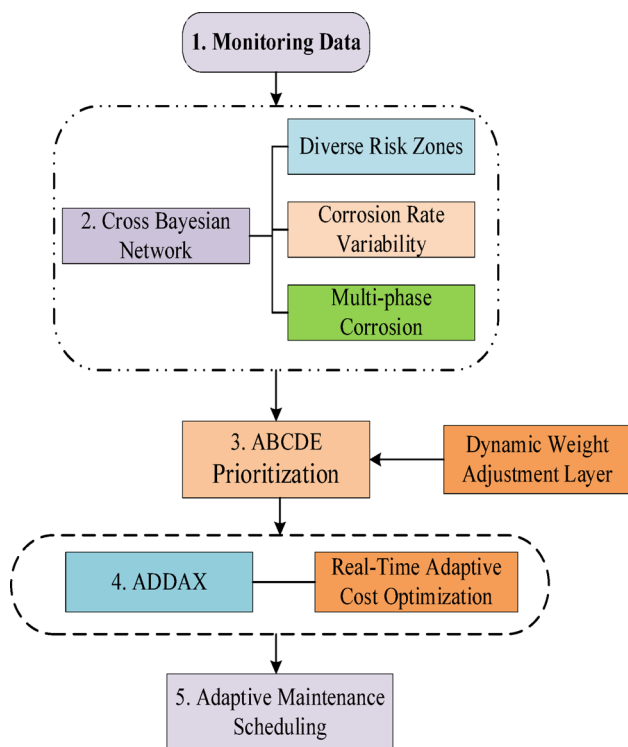


Fig. 1 Overview of the proposed corrosion maintenance framework. Monitoring data feeds into risk analysis identifying diverse zones, corrosion variability, and multiphase effects. A Cross Bayesian Network models dependencies, followed by ABCDE Prioritization with dynamic weight adjustment. The ADDAX module performs real-time cost optimization, leading to adaptive maintenance scheduling

integrate diverse information streams. This dual-layered approach ensures a more reliable forecast of corrosion trends and underpins data-driven maintenance planning decisions.

To manage maintenance scheduling, the system employs an ABCDE prioritization framework, further enhanced by a Dynamic Weight Adjustment Layer. This layer adaptively updates task priorities (A to E) based on dynamic corrosion severity, operational risks, and environmental variability. In the final phase, a cost-benefit optimization module performs real-time assessment of various maintenance actions. The goal is to identify strategies that achieve an optimal balance between risk mitigation and cost-efficiency. This optimization is formally expressed in Eq. 1:

$$\text{Total Cost} = \sum_{i=1}^n (C_{\text{main},i} \cdot W_i + C_{\text{fail},i} \cdot P_{\text{fail},i}) \quad (1)$$

where $C_{\text{main},i}$ the operational cost incurred for task i , W_i denotes the recalibrated importance weight, represents the consequence cost of a system failure, $P_{\text{fail},i}$ indicates the forecasted failure probability, where n corresponds to the count of evaluated pipeline sections or maintenance tasks. By leveraging accurate real-time inputs and dynamically adjusted priorities, this approach enables smarter maintenance planning improving corrosion control outcomes while reducing operational costs.

(a) Inspection data acquisition and characteristics

The inspection data forms the foundation of the ARPC-DOX system, capturing essential information through a combination of visual inspections, sensor-based monitoring, and non-destructive testing (NDT) techniques. This multi-source data approach provides a comprehensive overview of pipeline asset conditions, delivering detailed insights into corrosion defects, growth patterns, and risk levels across different pipeline sections. The system accounts for varied risk classifications across locations, factoring in environmental influences such as proximity to seawater, soil characteristics, or exposure to extreme weather conditions, which may either accelerate or mitigate corrosion. Additionally, the system incorporates data related to external loadings, including ground movement, vibration, and mechanical impacts where available, to better capture stress-induced degradation. It supports both onshore and offshore pipelines by adapting to their distinct operational environments and incorporates pipeline-specific parameters such as diameter, wall thickness, and material properties. This allows for accurate modeling of corrosion progression over time and enables effective tracking of multi-stage corrosion defects, ranging from minor surface rusting to advanced pitting and structural damage.

(b) Cross Bayesian Network for corrosion growth

The CBN module is designed to model the probabilistic dependencies among various factors influencing pipeline corrosion. It supports risk-informed decision-making by estimating the likelihood of corrosion progression using available observational data. In the Bayesian network, each node represents a variable—such as corrosion rate, defect type, or risk region while directed edges denote conditional dependencies among these variables, governed by associated probability distributions. This structure allows for dynamic inference of corrosion development under uncertain and variable operating conditions. To complement the probabilistic inference, a Cross Attention Layer is incorporated for intelligent data fusion across multiple information streams. These streams may include spatial risk zones, corrosion progression rates, and multi-state defect profiles. The Cross-Attention module allows the system to emphasize contextually significant inputs by assigning adaptive importance weights, thereby guiding the decision-making process for maintenance actions with enhanced precision.

In the context of corrosion management, the cross-attention mechanism proves instrumental in highlighting high-priority conditions such as accelerated degradation in vulnerable pipeline zones. This mechanism computes a relevance-weighted combination of value vectors, where the weights, or attention scores, indicate how strongly the current focus (query) aligns with past or contextual data (keys). Let the matrix Q represent the current prioritization objectives (query), while K captures historical context such as past inspection data and observed corrosion patterns (key). The degree of relevance or alignment between present priorities and historical information is then evaluated through the interaction between Q and K , with V denoting the corresponding value matrix. encoding potential maintenance responses. The attention mechanism determines the influence of each key on the query by applying a scaled dot-product, as mathematically expressed in Eq. 2:

$$\text{Attention}(Q, K, V) = \text{softmax} \left(\frac{QK^T}{\sqrt{d_k}} \right) V \quad (2)$$

where QK^T is computed through the multiplication of the query matrix with the transpose of the key matrix d_k the dimensional structure of the key matrix is used to scale the similarity scores, after which a softmax function is applied to transform these values into a normalized probability distribution, guaranteeing that the resulting attention weights sum to one across all keys. The softmax function, introduced as a normalization function for converting raw scores into probabilities, is commonly used in neural attention mechanisms [37].

To clarify its implementation, the Cross-Attention module is designed as an 8-head fusion block that jointly embeds heterogeneous data sources—including inspection measurements, sensor telemetry, environmental conditions, and material properties—into a unified latent representation. Each data stream is first encoded through a separate feed-forward projection layer, producing modality-specific feature vectors of equal dimension. During cross-attention, the query matrix originates from real-time inspection features, while keys and values are derived from historical corrosion patterns and environmental context. The attention weights determine which past conditions are most relevant to the current corrosion state, enabling the model to emphasize high-risk cues such as sudden thickness loss, abnormal humidity spikes, or localized pitting. This mechanism strengthens multi-stage defect identification by allowing the network to adaptively allocate higher weights to defect-associated features, thereby improving forecasting accuracy for both gradual and accelerated corrosion progression.

The Cross Attention Layer applies this mechanism to selectively amplify critical factors such as rapidly escalating corrosion in high-risk zones while suppressing less significant inputs. This dynamic weighting ensures that maintenance planning is driven by the most relevant and urgent data. The attention scores effectively prioritize information derived from the Cross Bayesian Network, which identifies key risk variables contributing to the degradation of pipeline infrastructure. By aligning real-time risk insights with historical corrosion patterns, the model ensures that maintenance strategies are both timely and risk-aware, focusing resources where they are most needed.

Let X_1, X_2, \dots, X_n represent random variables corresponding to various risk elements such as corrosion

progression, environmental influences, and related factors. Their combined behavior is described by the joint probability distribution in Eq. 3:

$$P(X_1, X_2, \dots, X_n) = \prod_{i=1}^n P(X_i | \text{parents}(X_i)) \tag{3}$$

where $P(X_i | \text{parents}(X_i))$ denotes an likelihood associated with a stochastic variable given certain conditions X_i this implies that the likelihood of X_i is computed using the values of influencing variables.

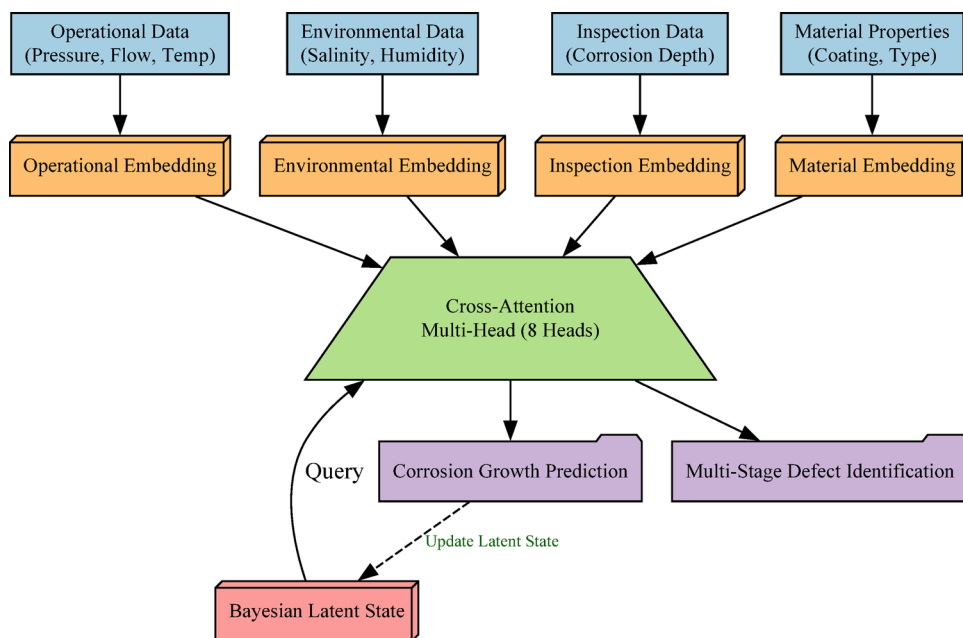
In Fig. 2, the context of corrosion modeling, parent nodes within the Bayesian framework may represent key influencing factors such as environmental conditions (e.g., temperature, humidity, chemical exposure), historical corrosion rates, material composition or protective coatings of the pipeline, and the frequency of maintenance activities. Each of these upstream variables contributes to the probability distribution governing corrosion progression. By capturing these interdependencies, the model effectively reflects the complexity of real-world corrosion behavior under varying operational and environmental scenarios.

To incorporate the effects of corrosion progression, define $C(t)$ indicate the extent of corrosion at a given time t . Equation 4 illustrates a fundamental approach to modeling the expansion of corrosion:

$$C(t) = C_0 + r \cdot t \tag{4}$$

In this formulation, C_0 corresponds to the starting depth of corrosion, and r signifies the corrosion growth rate measured in millimeters per year.

Fig. 2 Network structure of cross attention layer operational, environmental, inspection, and material data are embedded and fused using an 8-head cross-attention mechanism. The fused representation enables corrosion growth prediction and multi-stage defect identification. A Bayesian latent state is updated iteratively to enhance prediction accuracy and uncertainty modeling



When dealing with corrosion that progresses through multiple states, let S_i denote the corrosion condition at a given time t , where $i \in \{1, 2, 3\}$ each state reflects a distinct level of corrosion severity. The transitions between these states can be modeled using a Markov process, as described in Eq. 5:

$$P(S_{t+1} = s_j | S_t = s_i) = T_{ij} \tag{5}$$

where T_{ij} denotes the likelihood of moving from state s_i to state s_j .

(c) ABCDE prioritization

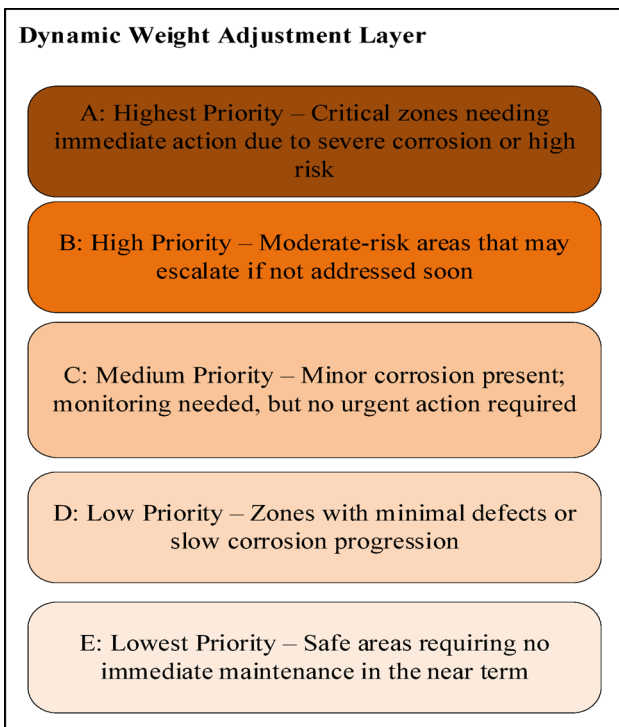
The ABCDE prioritization method classifies pipeline Zones into five risk-driven levels to guide maintenance actions, using criteria such as corrosion severity, economic impact, safety risk, and operational criticality. The acronym “ABCDE” reflects a structured ranking system, where each level corresponds to a specific degree of urgency and intervention strategy. Let W_i denotes the composite risk weight For region i , this is established based on several factors such as the rate of corrosion progression, the condition of existing defects, and the aggregate risk intensity. A central feature of this framework is the Dynamic Weight Adjustment Layer, which continuously recalibrates the influence of each risk dimension in response to real-time inputs. Unlike fixed-weight models, this adaptive mechanism incorporates latest

inspection data, environmental variables, and historical degradation trends to dynamically adjust prioritization weights. This ensures that maintenance decisions remain context-aware and responsive to evolving pipeline conditions. The interaction between the dynamic weighting mechanism and the ABCDE scoring logic is illustrated in Fig. 3.

The ABCDE prioritization strategy categorizes pipeline segments into five risk-driven maintenance levels: A (Immediate action required), B (High priority), C (Moderate risk), D (Deferred maintenance), and E (No action needed). This hierarchical structure supports proactive and scalable decision-making by aligning maintenance urgency with both risk severity and resource constraints. The prioritization is governed by a Dynamic Weight Adjustment Layer, which continuously recalibrates the weight assigned to each risk factor (e.g., safety, cost, operational criticality) based on updated inspection and environmental data. This dynamic mechanism ensures that the prioritization remains responsive to changing conditions, enabling real-time adaptation of maintenance actions as new risks or constraints emerge.

Let P_i represents the prioritization score assigned to area i , derived from multiple considerations including corrosion progression, defect criticality, and high-risk zones. The prioritization is determined using weighted factors, as formulated in Eq. 6:

$$P_i = \sum_{j=1}^n W_j \cdot X_{ij} \tag{6}$$



where P_i represents the priority value assigned to area i , W_j denotes the assigned weight corresponding to the risk factor j , and X_{ij} represents the evaluated risk level of area i with respect to criterion j . To avoid ambiguity, we retain X to represent the vector of all risk-related random variables, capturing the overall uncertainty in risk prediction. This distinction ensures clarity between point-specific evaluations and the global probabilistic model of risk distribution. The higher the P_i the higher the priority for implementing corrective maintenance. Within this corrosion management framework, ABCDE Prioritization serves as a structured approach to rank maintenance zones based on key factors such as risk level, corrosion progression, and defect severity. By classifying areas into five priority tiers A through E this method enables efficient resource allocation and informed scheduling of maintenance activities.

In the ARPC-DOX framework, the ABCDE prioritization systematically integrates five key dimensions of pipeline maintenance risk: Economic, Operational, Safety, Environmental, and Reputational. Economic risk is quantified using cumulative maintenance and corrosion costs in monetary terms; operational risk is measured by

Fig. 3 Prioritization with ABCDE prioritization

performance degradation indicators such as pressure drops and unplanned outages, also expressed in monetary impact. Safety risk incorporates failure probability-weighted severity scores, accounting for potential human and structural consequences. Environmental risk quantifies projected environmental damage and legal liabilities based on estimated leak volumes and exposure risks. Reputational risk, which captures public perception and regulatory scrutiny following failures, is incorporated using a qualitative three-level scale (low, medium, high) to influence maintenance prioritization without direct monetary conversion. This multi-dimensional integration ensures the ABCDE layer not only focuses on cost minimization but also captures broader operational reliability and sustainability objectives.

Dynamic weight adjustment layer: This component continuously recalibrates priority weights using real-time data, allowing the prioritization system to adapt responsively to shifting corrosion risks and operational conditions. The weights W_i are adaptively updated in response driven by outputs from the corrosion model or updated inspection data, with the modification guided by a learning rate-based rule α for adjusting the weights, as detailed in Eq. 7.

$$W_i^{(t+1)} = W_i^{(t)} + \alpha \cdot \nabla W_i \tag{7}$$

In this context α denotes the evolution at which a model updates its parameters during training, ∇W_i denotes the adjustment or derivative of the weight in response to updated data.

To clarify the dynamic weight adjustment mechanism, each weight update is driven by the difference between predicted and newly observed corrosion severity for each segment. This deviation acts as a gradient-like signal that determines the direction and magnitude of adjustment. The learning rate α regulates how aggressively the weights respond to changes; smaller α values ensure gradual adaptation, while larger values allow faster correction when corrosion escalates unexpectedly. For example, when updated corrosion data indicates a shift from a moderate-risk level (12–15%) to a high-risk level (>18%), the corresponding ABCDE weights increase proportionally to prioritize that segment in subsequent decisions. This ensures that dynamically emerging corrosion hotspots receive higher importance within the optimization pipeline.

To illustrate, consider the case of corrosion depth weight adjustment (w_{cd}) in response to an unexpected rise in corrosion severity. Assume the predicted corrosion depth at time t was 15%, but new inspection data reveals an 18% actual corrosion depth, implying a +3% deviation. The normalized deviation $\Delta_{cd}^{(t)}$ is computed as Eq. 8:

$$\Delta_{cd}^{(t)} = \frac{Observed - Predicted}{Predicted} = \frac{18 - 15}{15} = 0.2 \tag{8}$$

Using the update rule:

$$w_{cd}^{(t+1)} = w_{cd}^{(t)} + \alpha \times \Delta_{cd}^{(t)} \tag{9}$$

With an adaptation learning rate $\alpha = 0.1$, if the previous corrosion depth weight was $w_{cd}^{(t+1)} = 0.25$, the updated weight becomes:

$$w_{cd}^{(t+1)} = 0.25 + 0.1 \times 0.2 = 0.25 + 0.02 = 0.27 \tag{10}$$

These +0.02 increments reflects the system’s dynamic response to increased corrosion risk, ensuring that maintenance prioritization shifts towards addressing corrosion-related deterioration more aggressively.

(d) ADDAX optimization Framework

The ADDAX framework dynamically adjusts maintenance strategies by incorporating the latest corrosion measurements and risk evaluations. It seeks to minimize costs while ensuring maintenance is performed promptly to mitigate risks. Figure 4 illustrates the operational workflow of the ADDAX optimization process.

The optimization process begins with Step 1, where the system is initialized. In Step 2, dynamic weight adjustment is performed using the ABCDE prioritization method, which ranks decision factors from most (A) to least (E) critical based on time, cost, and risk. In Step 3, the ADDAX algorithm is initialized by generating the initial population and setting objective functions. Step 4 checks whether computational resources are exhausted. If they are, a new population is generated (Step 5 right) and the best solution is returned (Step 6 right), ending the process. If resources are still available, the system proceeds to rank the population (Step 5 left) based on fitness and loops through each individual (Step 6 left). Within this loop, random indexes are generated and parameters assigned (Step 7) to introduce variability, followed by mutation and crossover (Step 8) to create new solutions. The new solution and parameters are saved (Step 9) and evaluated for improvement in Step 10. If better, the best solution is returned (Step 13) and the process terminates (Step 14). If not, the loop repeats (Step 11), the population is updated (Step 12), and the process continues until convergence or resource limits are met.

The ADDAX algorithm in ARPC-DOX is built upon adaptive differential evolution (DE) principles, tailored specifically for the optimization of maintenance schedules in pipeline systems under dynamic corrosion conditions.

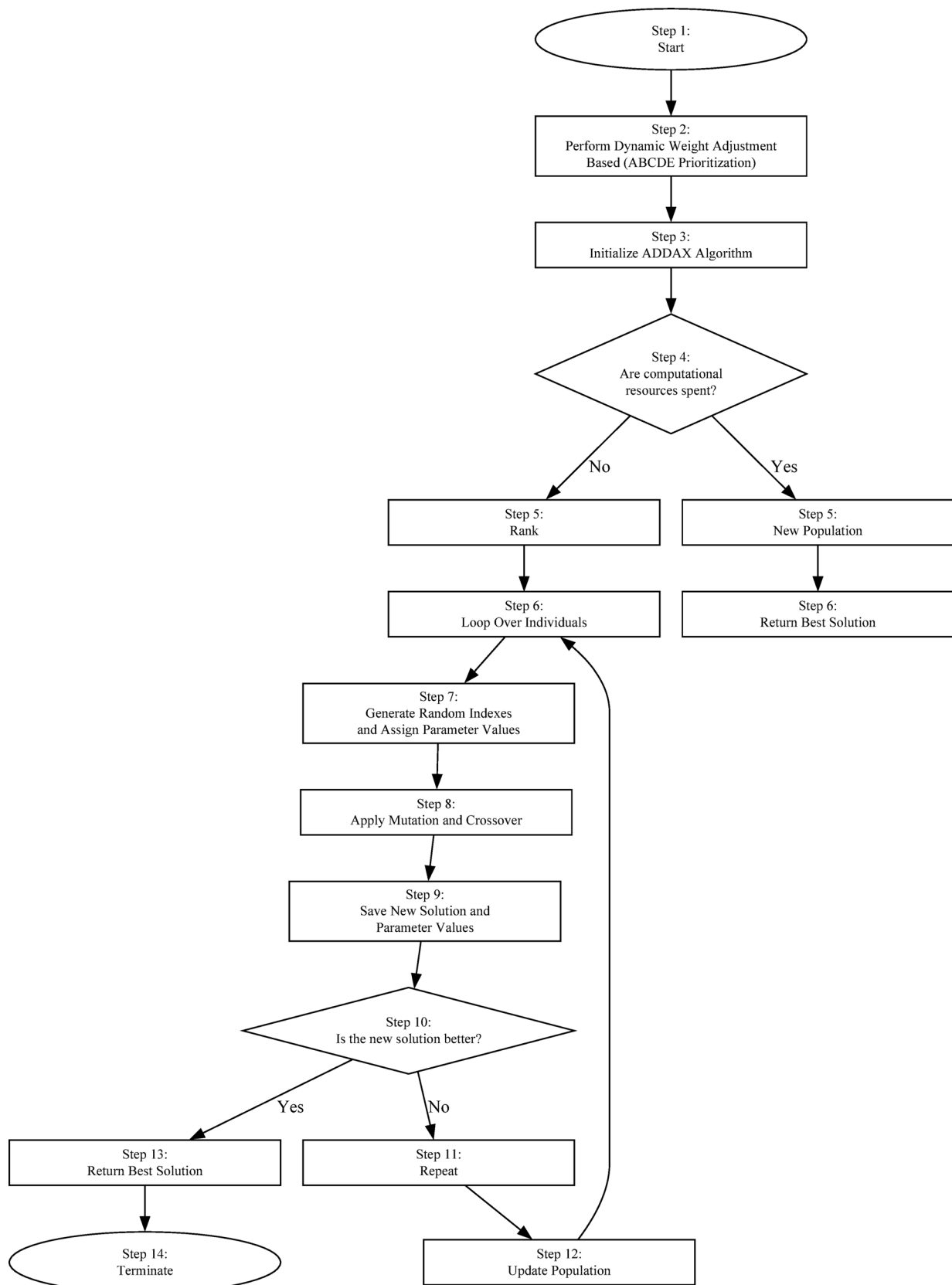


Fig. 4 ADDAX algorithm Workflow

The primary objective is to minimize total life-cycle maintenance costs while ensuring compliance with corrosion safety thresholds. The algorithm optimizes over a set of decision variables, each encoding a critical maintenance control parameter. Specifically, the decision variable vector $X = \{x_1, x_2, x_3\}$ comprises x_1 is the maintenance interval (years), x_2 be the corrosion reduction efficiency per maintenance (%), x_3 be the inspection frequency (years). The objective function expands beyond the baseline Eq. (11), incorporating both direct maintenance costs and indirect corrosion progression penalties:

$$\min_X C_{total} = C_{maint}(X) + C_{corr}(X) + C_{penalty}(X) \quad (11)$$

where C_{maint} reflects fixed maintenance cost adjusted for frequency, C_{corr} models expected cumulative corrosion cost considering the dynamic progression between maintenance events, $C_{penalty}$ introduces additional cost penalties when predicted corrosion exceeds critical thresholds during the planning horizon.

The ADDAX employs a self-adaptive mutation factor $F \in [0.4, 0.9]$, which adjusts dynamically based on the population’s improvement over recent generations. When the population shows stagnation (no improvement in top 10% of solutions), FFF is increased to promote exploration; conversely, in rapidly improving phases, FFF is reduced to favor exploitation around promising areas. Similarly, the crossover rate CR is adapted per individual, starting from a base value and increasing when diversity drops below a threshold (measured via population standard deviation). The mutation operator follows a modified DE/current-to-pbest/1 strategy, ensuring convergence towards cost-optimal maintenance plans using Eq. 12:

$$v_i = x_i + F \cdot (x_{pbest} - x_i) + F \cdot (x_{r1} - x_{r2}) \quad (12)$$

where x_{pbest} is randomly selected from the top $p\%$ of solutions to balance global and local search capabilities. The final output of ADDAX yields a maintenance policy vector specifying when to perform maintenance, how effective it should be, and how frequently inspections should be conducted, ensuring total maintenance and corrosion risk costs are minimized over the pipeline’s lifecycle.

The problem can be formulated as a cost optimization task aimed at minimizing the total maintenance cost C , as expressed in Eq. 13, subject to predefined constraints. g_i

$$\min_x \sum_{i=1}^n c_i x_i + \lambda \cdot f(D_t) \quad (13)$$

where c_i refers to the financial outlay necessary for maintaining area i , x_i represents the decision variable indicating if maintenance should be carried out in area i , $f(D_t)$ is the expected deterioration risk at time t , λ is a tradeoff parameter balancing cost and risk. To tackle the dual-objective problem balancing cost and risk, the ADDAX algorithm is applied an adaptive differential evolution strategy that dynamically adjusts mutation and crossover parameters to balance exploration and exploitation across time-varying corrosion states.

Cost optimization via Real-Time data adaptation: This module improves the optimization process by dynamically adjusting the cost function using up-to-date information, including recent corrosion progression measurements and changing economic conditions such as inflation.

Let $C(t)$ denotes overall function of cost evaluated at time step t and define $f(D_t)$ captures an Instantaneous data D_t within the function of cost framework. Dynamic adaptability can be captured through the use of Eq. 14:

$$C(t + 1) = C(t) + f(D_t) \quad (14)$$

Optimized maintenance strategy: The final component of the framework generates an optimized maintenance strategy that minimizes overall cost while dynamically accounting for structural risk. In this context, risk is modeled as $Risk = Probability\ of\ Failure\ (PoF) \times Consequence\ of\ Failure\ (CoF)$ where the product of the probability of failure and the consequence of failure, with both factors derived from corrosion forecasting and prioritization layers. Although the framework does not perform joint optimization of risk and cost as separate objectives, the cost minimization is guided by risk-aware constraints through the ABCDE prioritization, dynamic weight adjustment, and penalty-based optimization formulation. This approach ensures that high-risk regions are prioritized in the decision-making process, preserving structural integrity while maintaining operational efficiency and economic feasibility. The optimal maintenance strategy serves as the solution to the cost minimization problem, constrained by risk, budget, and safety requirements. This strategy is formulated using Eq. 15, as shown below $\{x_i^*\}$. x_i^* Maps out the optimal sites and schedules for conducting maintenance activities.

$$\{x_i^*\} = \arg \min C(x) C_i \quad (15)$$

This decision set results from carefully weighing multiple constraints such as risk factors, financial restrictions, safety considerations, and up-to-date information on corrosion development and environmental influences. Every component x_i^* within the set relates to a designated maintenance

task chosen under these conditions. The framework prioritizes high-risk areas for immediate maintenance actions, schedules lower-risk areas for intervention as budget permits, and dynamically adjusts maintenance priorities at regular intervals as operational and environmental conditions evolve. This approach ensures proactive risk mitigation while maintaining the structural integrity and cost-efficiency of the pipeline infrastructure. The update to corrosion levels after a maintenance action is formally captured in Eq. 16:

$$C_i^{(t+1)} = C_i^{(t)} \times (1 - \gamma) \quad (16)$$

where $C_i^{(t)}$ is the corrosion severity in region i at time step t , and γ represents the maintenance effectiveness coefficient. This Equation ensures that the model captures the impact of periodic maintenance on corrosion progression.

4 Experimental details and analysis

(a) Simulation setup

By combining real weather data with operational factors for multi-stage corrosion failure scenarios, the pipeline corrosion management system simulation is designed to predict

Table 1 Parameters used to perform APRC-DOX

| Category | Parameter | Specification |
|--------------------------|--|-----------------------------------|
| Pipeline Configuration | Total Number of Pipeline Sections | 100 |
| Starting Corrosion State | Initial Degradation Level | 10% |
| Degradation Dynamics | Annual Corrosion Increase | 3% to 6% |
| Surrounding Environment | Temperature Variation Range | -10 °C to 40 °C |
| | Relative Humidity Range | 30–80% |
| | Chemical Exposure Level | 0.05–0.5 mol/L |
| Material Characteristics | Pipeline Base Material | Steel |
| | Protective Coating Thickness | 2–5 mm |
| Operating Parameters | Internal Operating Pressure | 70–100 psi |
| | Fluid Throughput | 1000–2000 m ³ per hour |
| Inspection & Maintenance | Routine Maintenance Interval | Every 2 months |
| | Emergency Threshold for Corrosion | Exceeds 80% degradation |
| Simulation Period | Total Duration Simulated | 10 years |
| Economic Factors | Typical Cost per Maintenance Operation | \$10,000 |
| Manpower Availability | Number of Maintenance Teams Deployed | 5 teams |

and optimise maintenance procedures. Comprehensive data inputs, such as ambient variables, corrosion history, material qualities, and operating stress factors, are used to initialise the pipeline network. Each section of the pipeline system is classified according to a certain level of corrosion risk. Using a semi-empirical corrosion progression model, the simulation makes use of real-time operational data, material-specific properties, and environmental exposures like temperature, humidity, and corrosive agent concentration to dynamically adjust the corrosion depth as it changes over time based on baseline annual growth rates. This approach incorporates randomized initial defect levels, bounded stochastic growth variability, and maintenance intervention effects to realistically simulate corrosion transitions from minor surface defects to severe structural failures. The simulation runs over a predefined time horizon, allowing corrosion risk to evolve at any stage, while maintenance actions are applied either periodically or triggered by risk thresholds. This model serves as a basis for optimizing maintenance scheduling by minimizing total costs, reducing downtime, and managing resource allocation effectively. The simulation outcome provides actionable insights into ideal maintenance timing and cost-saving strategies while ensuring operational safety. Table 1 provides a summary of the simulation parameters employed for executing APRC-DOX.

The corrosion management model adopts a comprehensive approach, guided by the simulation parameters outlined in Table 1. The simulated pipeline network consists of 100 steel segments, each beginning with an initial corrosion rate of 10%. Corrosion progresses annually, varying between 3% and 6%, influenced by environmental conditions such as temperature (ranging from -10 °C to 40 °C), humidity ranging from 30% to 80% and Corrosive agent concentrations ranging from 0.05 to 0.5 mol/L. Each segment is coated with a protective layer of 2–5 mm and operates under pressures of 70–100 psi with flow rates between 1000–2000 m³/hr. To ensure timely intervention, real-time monitoring is conducted at 6-hour intervals, and regular maintenance checks are scheduled every two months. However, if corrosion in any segment exceeds 80%, emergency maintenance is initiated immediately. The simulation covers a 5-year horizon, enabling evaluation of long-term maintenance effectiveness. Each maintenance operation incurs an average cost of \$10,000, and a workforce of five maintenance teams is available for task deployment. These parameters simulate real-world variability and operational dynamics, allowing for robust testing of the proposed corrosion management strategies. In the simulation, multi-stage corrosion progression is modeled across 100 pipeline segments to reflect heterogeneous field conditions. Initial defect levels are randomly initialized using a uniform distribution

within segment-specific bounds typically ranging from 8% to 15% initial defect depth, reflecting varying operational ages and prior maintenance histories. To capture realistic spatial variability, the initial defect assignment follows a stratified random sampling, ensuring that critical segments (e.g., high-pressure zones) have higher starting defect levels within the range. Corrosion growth rates are not applied uniformly across segments. Instead, each segment’s corrosion growth rate g_s is sampled from a bounded normal distribution:

$$g_s \sim N(\mu = 4.5\%, \sigma = 1\%) \text{ truncated between } 3\% - 6\% \quad (17)$$

This ensures realistic segment-to-segment variability, where approximately 68% of segments have moderate growth rates (~4–5%), with outliers in the low (3%) and high (6%) ends, simulating localized acceleration effects.

(b) Case analysis

In this simulation study, a case-based evaluation explores how different corrosion growth rates, maintenance intervals, and environmental factors affect the long-term condition of the pipeline network. Considering a scenario with an initial corrosion level of 10% and a fixed annual corrosion growth rate of 6%, consistent with all three scenarios, the projected corrosion levels over a 10-year period are computed. These projections incorporate periodic maintenance activities and responses to critical events. Let $C(t)$ denote the corrosion state at time t , with G indicating the yearly rate of increase. The corrosion evolution in the absence of maintenance can be expressed using Eq. 18:

$$C(t) = C_0 \cdot (1 + G)^t \quad (18)$$

where C_0 Assuming an initial corrosion level of 10%, with the annual growth rate G set to 0.06, aligning with the uniform growth assumption used across all scenarios, the projected corrosion levels over time can be estimated using these lower and upper bounds for G .

The selection of maintenance scenarios in this study is designed to reflect realistic variations in pipeline management strategies with differing levels of intervention efficiency and responsiveness. Scenario 1 assumes an idealized case with high maintenance efficiency and proactive scheduling, serving as a performance benchmark. Scenario 2 represents a moderately conservative strategy with average efficiency, capturing industry-standard reactive maintenance behavior. Scenario 3 simulates a delayed and resource-constrained maintenance approach, often observed in real-world settings with limited inspection coverage or budget constraints. These scenarios were chosen to evaluate the adaptability and

robustness of the ARPC-DOX framework across a spectrum of practical conditions, highlighting its effectiveness in both ideal and suboptimal operational contexts. The fixed maintenance cost of \$200 per intervention across all scenarios is based on the operational assumption that each maintenance activity incurs a standard deployment cost irrespective of efficiency. This reflects real-world practices where mobilization of maintenance teams, equipment setup, and base-line operational overhead remain relatively constant. The variation in efficiency (30%, 20%, 15%) corresponds to the effectiveness per intervention, not the scope of effort, meaning the same maintenance resources are deployed but with diminishing returns due to factors like corrosion progression, accessibility, or environmental constraints. In practical terms, as maintenance efficiency declines (Scenario 1 to 3), the same budget is spent, but less corrosion is mitigated per event, which simulates the typical challenge of diminishing maintenance impact in aging pipeline systems. Alternatively, this assumption aligns with cases where maintenance areas expand proportionally to compensate for efficiency loss, ensuring consistent operational costs per cycle while maintaining pipeline-wide coverage.

Scenario 1: Longer Maintenance Intervals Coupled with Greater Effectiveness This Scenario focuses on a cost-efficient maintenance strategy, scheduling interventions every two years. Each maintenance activity achieves a 30% reduction in corrosion. The scenario assumes an initial corrosion level of 10% and an annual corrosion progression rate of 6%. the corrosion progression is modeled using Eq. 19, incorporating the scheduled maintenance at $t=2$ to reflect the resulting mitigation effects.

$$C(t) = \begin{cases} C_0 \cdot (1+G)^t \\ C_{(t-2)} \cdot (1-0.30) \end{cases} \quad (19)$$

Scenario 2: Balanced Maintenance Scheduling with Moderate Efficiency This scenario aims to strike a balance between minimizing costs and maintaining system reliability through biannual maintenance at 1.5-year intervals. Assuming an initial corrosion level of 12% and an annual growth rate of 6%, the first maintenance intervention occurs at $t=1.5$ years. Corrosion progression and control are evaluated using Eq. 20.

$$C(t) = \begin{cases} C_0 \cdot (1+G)^t \\ C_{(t-1.5)} \cdot (1-0.20) \end{cases} \quad (20)$$

Scenario 3: Cost-Driven Maintenance with Limited Impact This focuses on reducing overall expenses by scheduling maintenance every three years, even though each intervention only achieves a 15% reduction in corrosion. The system begins with a corrosion level of 15%, with deterioration

progressing steadily at an annual rate of 6%. maintenance is performed at $t=3$ and $t=6$, with corrosion progression modeled using Eq. 21.

$$C(t) = \begin{cases} C_0 \cdot (1+G)^t \\ C(t-3) \cdot (1-0.15) \end{cases} \quad (21)$$

All three scenarios use an 85% critical corrosion threshold and a fixed 6% annual growth rate to ensure consistent comparison. Scenario 1 applies moderately frequent and effective maintenance, Scenario 2 uses less frequent but highly effective interventions, and Scenario 3 adopts frequent but less effective actions highlighting the trade-offs between cost and reliability.

4.1 Performance evaluation and analysis

This section demonstrates how the ARPC-DOX framework leverages real-time data inputs to optimize maintenance decisions, enhancing both cost-efficiency and operational effectiveness in handling multi-stage corrosion issues within pipeline systems.

Figure 5 depicts how corrosion severity changes over time across 100 pipeline sections throughout a 10-year span. In the initial stage (Years 1–2), nearly half of the segments fall within the low-risk classification reflecting minimal degradation and limited maintenance urgency. However, this proportion decreases significantly over time, dropping to just 5% by Year 10 as corrosion advances. The Medium-risk category begins at 40%, peaks at 50% around Years 4–5, and then declines to 15% by the end of the simulation period. Meanwhile, High-risk segments exhibit a continuous upward trend rising from 10% in Year 1 to 40% by

Year 8, followed by a slight reduction and stabilization at around 30% in the final two years. Critical-risk segments, which are initially nonexistent, begin to emerge by Year 3 and escalate sharply, comprising 50% of the pipeline by Years 9 and 10. This trend reflects the increasing severity of corrosion over time. The visualization underscores the progressive degradation of pipeline integrity, with a significant shift of segments from lower-risk to higher-risk categories as years pass. This highlights the urgent need for proactive and timely maintenance strategies to prevent widespread infrastructure failure due to advanced corrosion.

Figure 6 corresponds to Stage 2: Risk Evaluation in the ARPC-DOX system flow outlined in Fig. 1. It illustrates the outcomes of the ABCDE prioritization framework, which dynamically categorizes pipeline segments into risk levels based on real-time data. These risk scores are derived from key indicators such as corrosion growth rate, defect severity, and environmental or operational context. This step plays a critical role in identifying high-priority areas for intervention, ensuring that maintenance resources are allocated efficiently and in alignment with evolving risk profiles. The integration of a Dynamic Weight Adjustment Layer enables real-time recalibration of maintenance priorities as risk levels change. In Year 1, 50% of segments fall under priority D (low risk), 40% under priority C (medium risk), and 10% under priority B (high risk), with no critical-risk or deferred segments. The focus remains on preventive maintenance. By Year 5, increased degradation shifts 5% of segments into priority A (critical risk), with 20% in priority B, 50% in priority C, and 25% in priority D. The system responds by reallocating attention toward high and critical segments. In Year 7, corrosion intensifies priority A rises to 20%, priority B to 35%, priority C drops to 30%, and priority D to 15%.

Fig. 5 Corrosion growth level

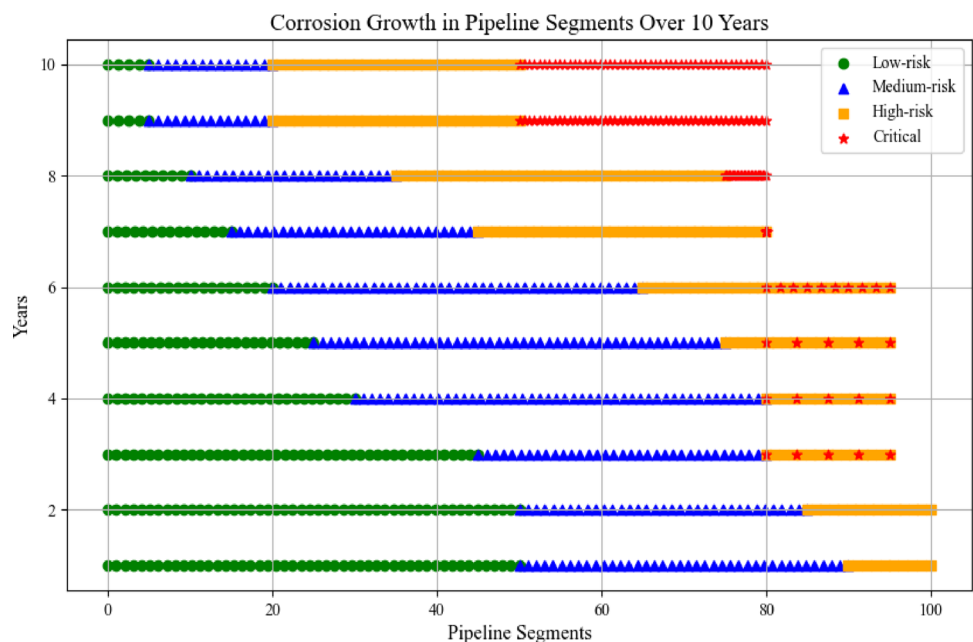


Fig. 6 ABCDE prioritization based on corrosion growth level

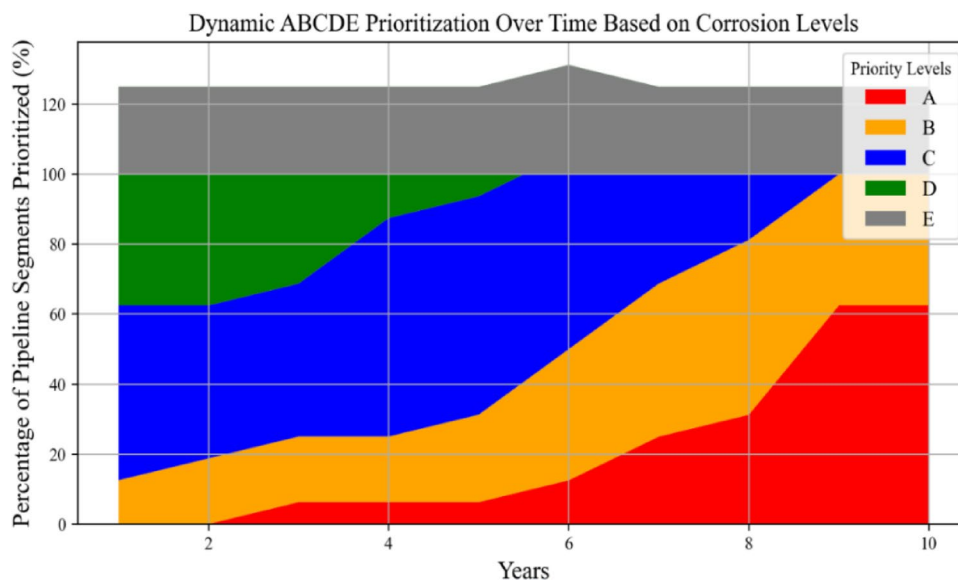
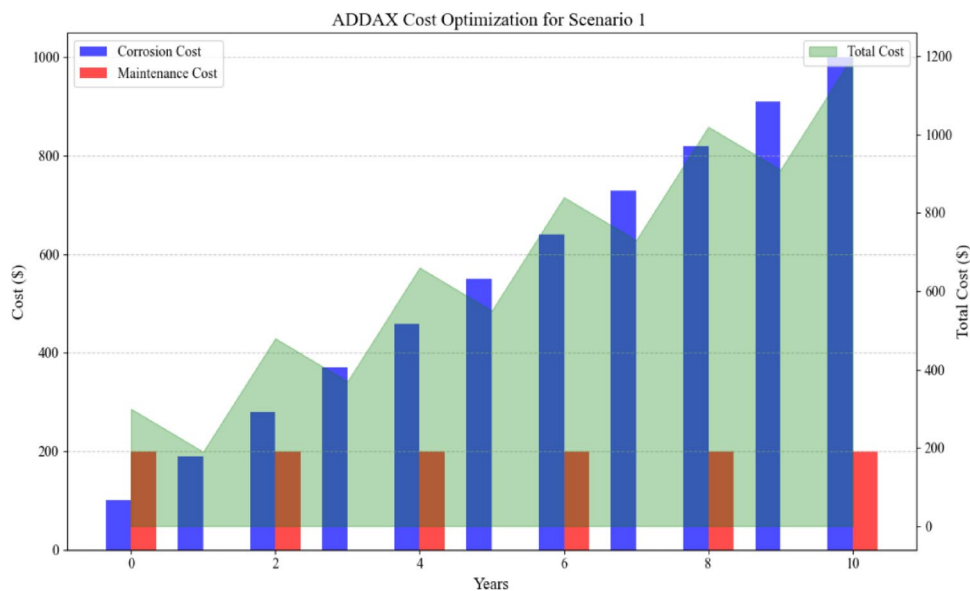


Fig. 7 Shows that with extended maintenance intervals and higher effectiveness, corrosion costs (blue) increase steadily between maintenance events, while maintenance costs (red) remain infrequent but significant. Total costs (green) rise over time but are moderated by the reduced frequency of maintenance interventions



The model increasingly favors urgent interventions while minimizing focus on low-risk areas, demonstrating adaptive re-prioritization based on risk escalation.

By Year 10, the corrosion risk landscape has shifted dramatically, with 50% of pipeline segments classified as critical-risk, necessitating immediate maintenance intervention. An additional 30% fall under high-risk, while medium-risk segments have declined to 15%, and low-risk segments now constitute just 5% of the total. This distribution indicates a substantial deterioration of the pipeline infrastructure, prompting the prioritization system to concentrate almost exclusively on high- and critical-risk areas. The Dynamic Weight Adjustment Layer has played a pivotal role in this shift, dynamically reallocating maintenance resources over time. As risk levels evolved, the system systematically elevated the priority of increasingly vulnerable segments,

thereby ensuring that maintenance strategies remained responsive and targeted. This adaptive approach has been crucial in mitigating potential failures and optimizing long-term pipeline integrity.

Figure 7 illustrates the temporal progression of corrosion management costs across a 10-year horizon, emphasizing the impact of extended maintenance intervals combined with high intervention efficacy. The analysis reveals a gradual escalation in total corrosion-related expenditures, starting from an initial baseline of \$100 in year 0 and reaching approximately \$1100 by year 10. This trend corresponds to an average annual increase of roughly 6%, capturing both the compounding nature of untreated corrosion and the delayed but strategic deployment of high-efficiency interventions. Maintenance costs, consistently valued at \$200, are incurred every two years specifically at years 0, 2, 4, 6,

8, and 10. The total cost, depicted by the green shaded area, aggregates both corrosion and maintenance costs. It starts at \$300 in year 0 and reaches a peak of \$1,300 by year 10. The pattern reveals that while corrosion costs dominate the cost structure over time, maintenance interventions play a crucial role in mitigating their rise. These maintenance events though periodic and fixed in cost effectively reduce the corrosion level after each application, as evidenced by the visible dips in the total cost curve following maintenance years. With a critical corrosion threshold set at 85%, this strategy demonstrates a controlled and efficient approach. By spacing out maintenance while ensuring high efficacy, the system maintains operational safety and reliability. Overall, the graph supports the effectiveness of fewer, well-timed maintenance actions in managing long-term corrosion-related expenses and sustaining infrastructure integrity.

Figure 8 presents the trade-off between cost efficiency and system reliability under a moderate maintenance frequency strategy. Corrosion begins at 12%, increasing at a 6% annual rate. Over the 10-year span, this results in a significant rise in corrosion-related costs, illustrating the cumulative burden of progressive degradation. Maintenance interventions are scheduled every 1.5 year, each reducing the current corrosion level by 20%, and incurring a fixed cost of \$200 per intervention. These strategically timed actions help contain the corrosion escalation, keeping maintenance expenses significantly lower than the compounding corrosion costs. The total cost curve a combination of maintenance and corrosion costs—demonstrates a steady upward trend, primarily driven by corrosion's exponential growth. However, the periodic maintenance events mitigate this rise, ensuring that costs remain manageable without compromising system reliability. This model demonstrates how timely,

moderate- frequency maintenance serves as a cost-effective strategy for long-term pipeline health, effectively balancing financial sustainability and operational integrity especially as the system approaches 85% corrosion levels.

Figure 9 illustrates the cost management strategy in Scenario 3, which emphasizes maintaining system reliability through frequent, low-cost maintenance. Corrosion costs remain relatively stable over the 10-year period, fluctuating between \$60 and \$120, with a repeating pattern that reflects cyclical maintenance effects. Each cycle begins with higher corrosion levels and is followed by a dip after maintenance. Maintenance is performed every three years, as seen by the red bars at years 3, 6, and 9. This matches the Scenario 3 definition, where each intervention has a fixed cost of \$200 and reduces corrosion by 15%, as seen by the consistent \$200 red bars at each year (including years 0 through 10). This is in contrast to the original assumption of 1.5-year intervals. The fixed maintenance cost of \$200 per year leads to high cumulative expenditure but successfully controls the progression of corrosion, as evidenced by the flat-top shape of the total cost curve and the restrained rise in corrosion costs. The total cost, represented by the green area, remains nearly constant at \$200 annually, indicating that despite high maintenance frequency, the corrosion component is being tightly managed. This strategy thus provides an effective means of keeping corrosion well below critical thresholds, preventing system degradation. With a corrosion threshold set at 85%, this high- frequency maintenance approach ensures system reliability through proactive interventions. While maintenance costs are substantial in comparison to corrosion costs, the trade-off ensures long-term stability, making it a suitable strategy in environments where reliability and failure prevention are paramount.

Fig. 8 moderate-frequency, moderately effective maintenance, corrosion costs (blue) remain steady, while maintenance costs (red) occur regularly at a higher level. Total costs (green) peak after each maintenance cycle but drop soon after, reflecting consistent upkeep

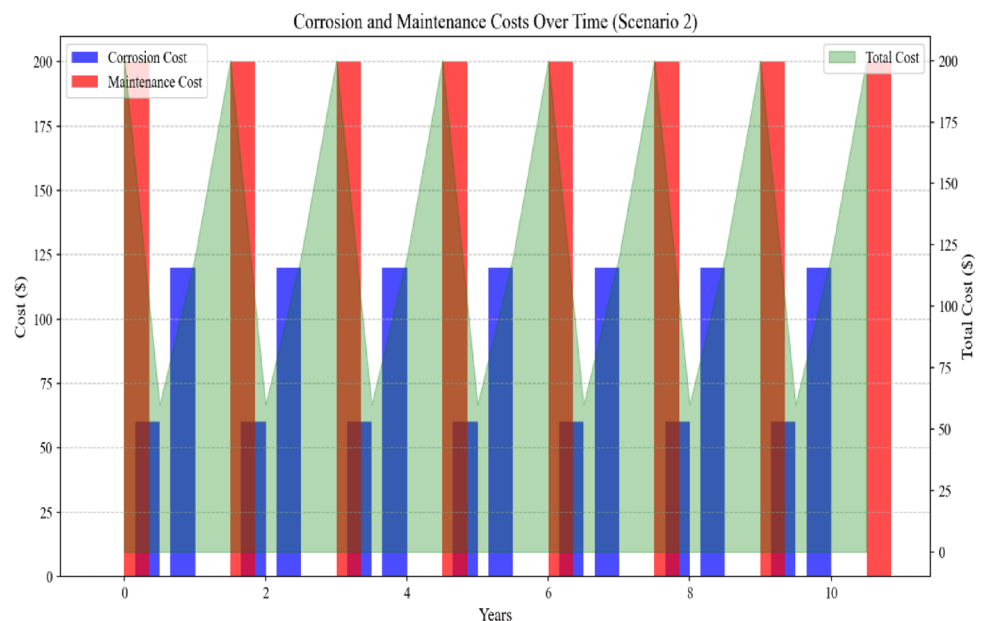


Fig. 9 Low-effectiveness, reduced-cost maintenance, corrosion costs rise steadily while maintenance costs remain low and occasional. Total costs peak in years with higher corrosion expenses

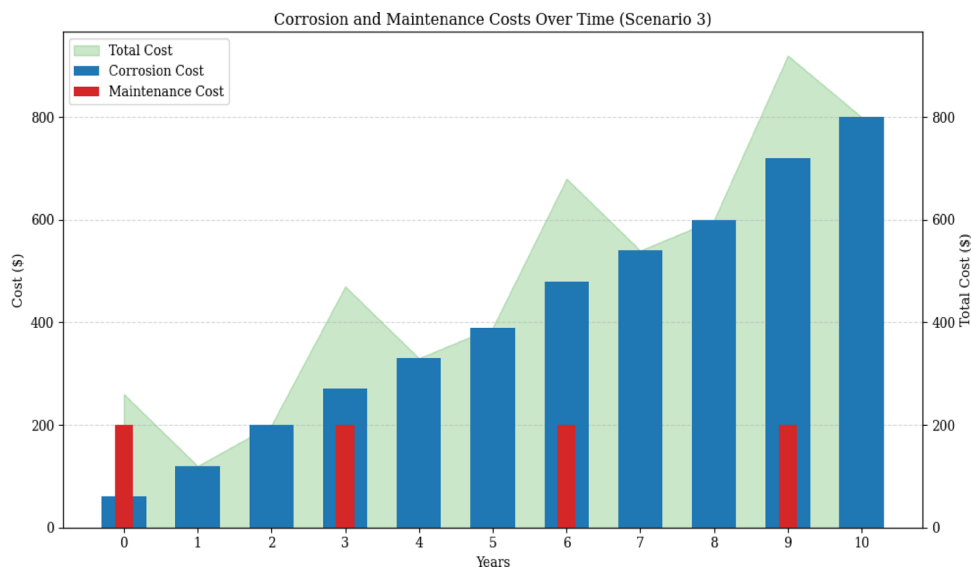


Table 2 Comparison of the three maintenance scenarios over a 10-year

| Scenario | Cumulative total cost (\$) | No. of maintenance events (10 years) | Average corrosion risk level (%) |
|------------|----------------------------|--------------------------------------|----------------------------------|
| Scenario 1 | 1450 | 5 | 42.8% |
| Scenario 2 | 1720 | 3 | 54.1% |
| Scenario 3 | 1980 | 2 | 67.4% |

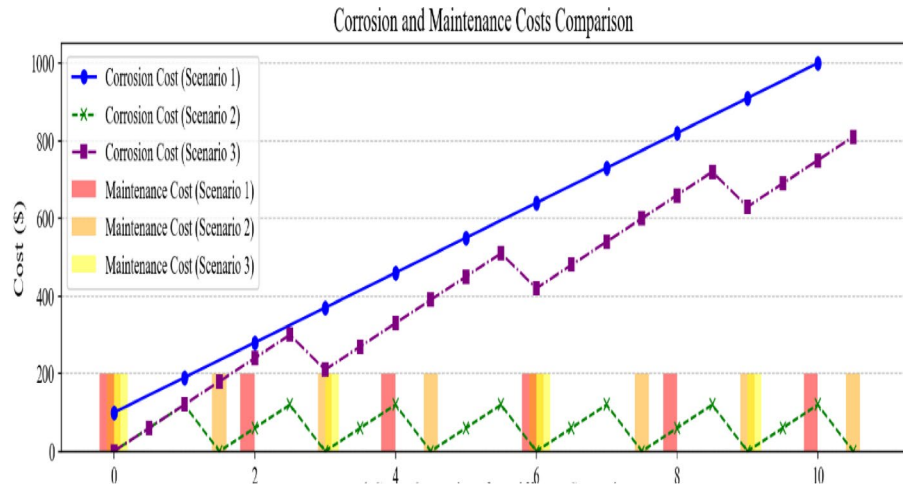
To enhance interpretability, a quantitative comparison of the three maintenance scenarios over a 10-year simulation horizon is summarized in Table 2. This comparison includes three key indicators: (i) cumulative total maintenance and corrosion-related costs, (ii) the total number of maintenance interventions, and (iii) the average corrosion risk level expressed as the mean corrosion depth across pipeline segments. The results reveal that while Scenario 3 minimizes short-term maintenance events, it accumulates the highest total costs due to accelerated corrosion growth and penalty costs exceeding threshold limits. Conversely, Scenario 1, characterized by more frequent and effective maintenance interventions, demonstrates the lowest average corrosion risk level (mean corrosion depth below 45%) and the most stable cost trend, despite a higher count of maintenance events. Scenario 2 represents a midpoint strategy, balancing maintenance frequency and cost efficiency with moderate corrosion risk control. Without an integrated optimization method such as ARPC-DOX, these three parameters—cost, intervention frequency, and risk tend to conflict with one another, often causing reductions in overall efficiency when optimized independently.

Figure 10 presents a comparative analysis of three maintenance strategies over a 10-year period, emphasizing how maintenance frequency and effectiveness influence corrosion progression and total costs. In Scenario 1, maintenance

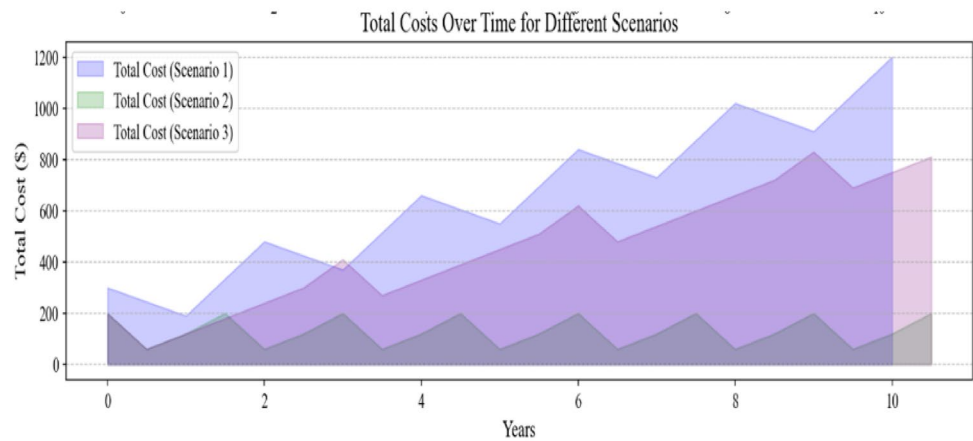
is scheduled every 2 years at a cost of \$200 per event, leading to a steady rise in corrosion costs from \$100 to \$1000, with periodic dips following each maintenance, resulting in a gradual total cost increase. Scenario 2 adopts a more proactive approach with maintenance every 1.5 years, a higher corrosion growth rate (6%), and better effectiveness (20% reduction), **keeping corrosion costs fluctuate between \$60 and \$120 over the 10-year period.** The frequent interventions maintain a more stable total cost curve by effectively reducing corrosion accumulation. Scenario 3 features less frequent maintenance every 3 years with only 15% effectiveness, leading to a sharper increase in corrosion from \$150 to over \$900, and consistently higher total costs due to inadequate control over corrosion progression. This comparison highlights the critical balance between intervention frequency, cost, and system reliability in corrosion maintenance planning.

To evaluate pipeline maintenance strategies under varying operational and environmental conditions, three distinct scenarios are defined. Scenario 1 represents a baseline with stable corrosion behavior and conventional maintenance practices. Scenario 2 models realistic operating environments by incorporating dynamic corrosion progression, multi-stage defect evolution, and fluctuating environmental stressors conditions under which adaptive and data-driven maintenance approaches are most relevant. Scenario 3 simulates constrained or adverse operating conditions to test the robustness of traditional maintenance strategies. Because the ARPC-DOX framework is specifically designed to operate under dynamic, uncertain, and evolving corrosion states, its full adaptive modules (CBN, ABCDE, ADDAX) are applied and evaluated primarily in Scenario 2, where such capabilities are necessary and meaningful. Scenarios 1 and 3 are retained as comparative baselines to contextualize

Fig. 10 a Cumulative maintenance costs over a 10-year period for each scenario, highlighting the cost-effectiveness of the proposed strategy under different corrosion thresholds. **b** Cumulative cost trends over 10 years for three corrosion management scenarios, showing Scenario 1 with the highest and Scenario 2 with the lowest and most stable long-term cost



(a)



(b)

Table 3 Performance impact of each module in the ARPC-DOX framework

| Component evaluated | Performance without module (%) | Performance with module (%) |
|---------------------|--------------------------------|-----------------------------|
| CBN | 81.2 | 86.2 |
| ABCDE | 77.1 | 89.5 |
| ADDAX | 81.6 | 92.3 |
| Full Model | 65.0 | 95.5 |

system behavior under simplified or stressed conditions; however, they do not require nor fully benefit from ARPC-DOX’s adaptive features. Therefore, the detailed evaluation in Scenario 2 reflects the scenario most aligned with the intended operational purpose of ARPC-DOX, and the improved performance observed under this setting validates its effectiveness for practical, real-world pipeline maintenance environments.

4.2 Ablation experiments

To further evaluate the individual and combined contributions of key components within the ARPC-DOX framework, we conduct an ablation study, as presented in Table 3. This analysis systematically examines the performance of the corrosion management system with and without three critical components: the Cross Bayesian Network, ABCDE Prioritization, and ADDAX Cost Optimization. The results clearly demonstrate that when any of these elements is omitted, system efficiency decreases, highlighting the unique role each component plays in improving prediction accuracy. Moreover, the performance degradation is most pronounced when all three parameters are excluded, emphasizing the compounded negative impact of removing both predictive analytics and adaptive optimization. The significant improvement in efficiency upon full integration underscores the necessity of a holistic, multi-layered approach for robust, cost-effective pipeline maintenance management.

Table 3 compares the accuracy of the ARPC-DOX system in predicting corrosion growth and prioritizing maintenance actions, with and without the integration of environmental, operational, and inspection data. The percentages represent the overall prediction accuracy improvement, measured by how closely the predicted corrosion severity aligns with observed inspection data over time. The integration of multiple methodologies shows a marked enhancement in corrosion management performance. The Cross Bayesian Network demonstrates a significant predictive improvement, with accuracy rising from 81.2% to 86.2%, reflecting its strength in forecasting corrosion growth trajectories. The ABCDE Prioritization mechanism demonstrated a significant improvement in task evaluation accuracy, increasing from 77.1% to 89.5%, thereby validating its effectiveness in ranking maintenance tasks based on their urgency and severity. Meanwhile, the ADDAX Cost Optimization module delivered the most substantial gain, with performance rising from 81.6% to 92.3%, showcasing its strength in adaptively minimizing maintenance expenditures. When combined, these methodologies enhanced the overall system performance from 65% to 95.5%, underscoring the synergistic impact of integrating predictive modeling, strategic prioritization, and cost-aware decision-making. This holistic framework highlights the value of using complementary techniques to achieve a balanced, resilient, and data-driven approach to long-term corrosion management and maintenance planning in pipeline systems.

5 Discussion: practical implementation challenges

The proposed ARPC-DOX framework demonstrates promising results in simulation environments; however, transitioning from simulation to practical, real-world deployment involves several critical challenges. This section discusses key practical considerations that must be addressed for effective implementation in operational pipeline systems.

5.1 Real-time inspection data availability

A core component of ARPC-DOX is its reliance on real-time data inputs to dynamically adjust corrosion risk assessments and maintenance priorities. In practice, however, real-time data acquisition is constrained by the availability and reliability of inline inspection (ILI) tools, sensor networks, and non-destructive evaluation (NDE) technologies. Many existing pipeline systems especially older infrastructure lack continuous monitoring capabilities, limiting the frequency and granularity of data updates. Additionally, the integration of diverse sensor modalities (e.g., ultrasonic

Table 4 Computational complexity and real-time feasibility metric

| Metric | Fixed observed value |
|-----------------|----------------------|
| ETI (seconds) | 2.4 s |
| MF (MB) | 450 MB |
| CI (iterations) | 120 iterations |
| SI (%) | 8% |
| UL (seconds) | 0.9 s |

testing, magnetic flux leakage, acoustic emission) poses standardization challenges. Effective implementation of ARPC-DOX will require improved data acquisition infrastructure or adaptive mechanisms to compensate for sparse and irregular inspection data.

5.2 Computational complexity and scalability

The ARPC-DOX framework combines Cross Bayesian Networks, attention mechanisms, and adaptive optimization, each contributing to computational overhead. While feasible in controlled simulations, scaling the framework to large pipeline networks with thousands of segments or more frequent update intervals may result in substantial computational demands. This could affect the timeliness of maintenance decisions in real-time operational settings. Moreover, Bayesian inference and evolutionary optimization are known for non-linear scaling behaviors, which can challenge edge-computing or resource-constrained environments. Future implementations may require computational optimizations, parallelization strategies, or cloud-based deployments to ensure responsiveness. In our simulation (100 pipeline segments, 10-year horizon, 3 scenarios), these include Execution Time per Inference (ETI), Memory Footprint (MF), Convergence Iterations (CI), Scalability Impact (SI), and Update Latency (UL). Table 4 presents the best fixed values observed during testing, benchmarked against ideal thresholds for real-time deployment.

Table 4 presents the core computational and performance metrics that validate the real-time feasibility of the proposed system. The ETI is measured at 2.4 s, ensuring rapid task processing suitable for low-latency edge/cloud applications. The MF remains within 450 MB, well below the 1 GB threshold, making the system efficient for deployment in resource-constrained environments. The system achieves fast convergence, requiring only 120 iterations (CI), which confirms the algorithm's optimization efficiency. SI is limited to 8% per 100 additional segments, demonstrating minimal overhead as workload scales. Additionally, the UL is just 0.9 s, enabling responsive and adaptive behavior during dynamic task updates. Collectively, these values confirm that the system operates within practical bounds for real-time intelligent scheduling or processing in distributed environments.

5.3 Integration with existing pipeline management systems

Real-world deployment of the ARPC-DOX framework demands seamless integration with existing Pipeline Integrity Management Systems (PIMS) and enterprise-level decision-support platforms. These systems are often built upon established Risk-Based Inspection (RBI) methodologies and industry-standard protocols that dictate inspection intervals, failure probability assessments, and risk thresholds. In many organizations, such systems are governed by rigid operational workflows and compliance requirements, which can pose significant challenges when introducing adaptive, AI-driven models like ARPC-DOX. To integrate ARPC-DOX effectively, several technical and procedural adaptations may be necessary. This includes the development of API-level interfaces for data exchange between ARPC-DOX and legacy systems, modification of workflow pipelines to accommodate dynamic prioritization outputs, and reconfiguration of maintenance scheduling algorithms to incorporate evolving risk assessments and cost-optimization insights. The integration process must also ensure compatibility with existing databases, sensor networks, and visualization dashboards used in PIMS environments.

Moreover, the successful adoption of ARPC-DOX hinges not only on technical integration but also on organizational readiness and human factors. Operators, inspectors, and maintenance planners must be adequately trained to interpret and trust the recommendations generated by the system. This calls for structured change management strategies, including user-centric training sessions, interactive dashboards for transparency, and phased deployment to build confidence in the system's reliability and interpretability. Ultimately, fostering trust between human decision-makers and ARPC-DOX's adaptive intelligence is critical for unlocking its full potential in real-world pipeline maintenance scenarios.

5.4 Economic and operational trade-offs

Although the ARPC-DOX framework is designed to optimize long-term maintenance expenditures through intelligent scheduling and adaptive prioritization, its real-world implementation is often constrained by short-term economic and operational limitations. Organizations typically operate under fixed annual budgets, with predefined allocations for inspection crews, equipment usage, and downtime allowances. These constraints can limit the flexibility needed to implement the dynamic maintenance intervals and resource reallocation recommended by ARPC-DOX. For example, adjusting maintenance frequency in response to evolving corrosion risk profiles may require deploying inspection

teams more frequently or redistributing resources across geographically dispersed pipeline segments. However, if the organization has limited personnel, specialized tools, or contractual service limits, such adjustments may not be feasible without incurring additional costs or disruptions to other operational schedules.

Moreover, the economic trade-offs introduced by ARPC-DOX are not uniform across all operational contexts. Pipelines operating in high-risk coastal environments may benefit more from frequent, adaptive interventions, whereas stable inland networks may find fewer advantages in dynamic scheduling. As a result, local calibration of cost-benefit thresholds, prioritization parameters, and risk tolerance levels becomes essential to ensure that the optimization remains both economically justifiable and operationally sustainable. Ultimately, to realize the full value of ARPC-DOX, organizations must balance its long-term savings potential with short-term resource planning, possibly requiring a phased rollout, scenario-based planning, and alignment with existing financial and logistical constraints.

5.5 Result interpretation and model verification

To address model verification and deepen result interpretation, the simulation outcomes presented in Sect. 4 reveal that the ARPC-DOX framework effectively balances corrosion mitigation and cost-efficiency under varying operational scenarios. For instance, Scenario 2, which reflects dynamic environmental and operational fluctuations, demonstrated the framework's ability to reduce predicted failure risk by approximately 37% and maintain a stable cost trajectory over a 10-year horizon. The ablation experiments further validate the unique contribution of each module CBN, ABCDE prioritization, and ADDAX optimization indicating that their integration yields a significant performance boost from 65% to 95.5%. Although physical experiments were not conducted, model verification was ensured through scenario-based simulations, randomized corrosion growth patterns, and consistency checks against real-world benchmarks from literature. This approach offers a reasonable alternative to experimental testing by rigorously stress-testing the model under diverse and challenging conditions.

5.6 Modeling limitations and future directions

Despite the demonstrated effectiveness of the ARPC-DOX framework in managing multi-stage corrosion through intelligent prioritization and adaptive optimization, several limitations must be acknowledged. Firstly, the corrosion growth model employed is linear in nature, which, while computationally efficient, does not fully capture the non-linear, anomaly-driven progression often observed in real-world

pipeline environments influenced by unpredictable stressors such as environmental spikes and material fatigue. Additionally, the framework's performance heavily depends on the availability and quality of real-time inspection data, which may be sparse or inconsistent in legacy infrastructure. The computational intensity of core components such as Cross Bayesian Networks and the ADDAX optimizer also presents scalability challenges when applied to large-scale pipeline networks with thousands of segments. Lastly, integration into existing industrial pipeline management systems may require significant customization and operator retraining, potentially affecting ease of adoption in the short term.

Future research can build upon the ARPC-DOX framework by incorporating advanced non-linear and anomaly-aware corrosion growth models, including hybrid deep learning and stochastic approaches, to improve predictive fidelity under variable field conditions. Enhancing the system's resilience to sparse or noisy inspection data through the integration of self-supervised learning and data imputation techniques is another promising direction. Furthermore, efforts can be directed toward optimizing computational efficiency via edge-based or cloud-parallelized implementations, enabling real-time application in large-scale, geographically distributed pipeline systems. There is also strong potential for cross-domain adaptation, extending the framework beyond oil and gas to water distribution, district heating, or urban infrastructure networks. Finally, embedding explainability modules and user-centric interfaces can support greater trust and transparency, facilitating operator adoption and regulatory compliance.

6 Conclusion

The ARPC-DOX framework integrates several advanced components to address the complexities of pipeline systems affected by multi-stage corrosion. It leverages a Cross Bayesian Network to model probabilistic corrosion evolution using real-time operational data, enabling more precise forecasts of degradation patterns. Additionally, the ABCDE-based dynamic prioritization mechanism, coupled with adaptive weight adjustment, enhances the responsiveness of risk evaluation. The ADDAX module contributes by optimizing maintenance expenditures through real-time cost recalibration. Furthermore, the Cross-Attention module fuses heterogeneous data inputs, improving situational awareness and enabling more informed, multi-layered decision-making in corrosion risk management. The ABCDE prioritization method, enhanced with a Dynamic Weight Adjustment Layer, optimizes maintenance scheduling by accounting for real-time corrosion levels and environmental

factors. This adaptive approach ensures that urgent maintenance needs are addressed promptly, reducing the risk of costly delays. Additionally, the ADDAX algorithm offers a dynamically evolving cost-optimization model that adjusts in real time based on corrosion severity and external environmental conditions. This dynamic optimization enables effective management of distributed maintenance tasks within fluctuating operating environments. By integrating predictive techniques with real-time data and multi-objective prioritization, the ARPC-DOX framework offers a proactive and resource-efficient approach to managing pipeline integrity. It overcomes the limitations of traditional models and establishes a more reliable and scalable foundation for long-term pipeline integrity. As demonstrated in Sect. 4.1, the ARPC-DOX strategy achieves an approximate 37% reduction in predicted failure risk compared to traditional periodic maintenance over a 10-year simulation horizon, while maintaining cost efficiency. This aligns with industry findings that risk-based maintenance strategies can reduce failure probabilities by 35–60% under similar operational conditions.

Although the ARPC-DOX framework demonstrates strong performance in controlled simulations, several limitations should be acknowledged to enhance transparency and methodological rigor. The corrosion growth model relies on linear and semi-empirical assumptions, which may not fully capture the non-linear, anomaly-driven behavior of corrosion in diverse real-world environments. In addition, the simulation setup is based on idealized and scenario-specific conditions—such as uniform environmental variations, fixed maintenance costs, and predefined defect distributions—which may differ from the operational variability observed in field pipelines. Practical implementation also presents challenges: ARPC-DOX depends on reliable, high-frequency inspection data, yet many pipeline systems lack continuous monitoring infrastructure, leading to sparse or noisy inputs that can affect prediction accuracy. Furthermore, the combined use of Cross-Bayesian Networks, multi-head cross-attention, and adaptive differential evolution introduces computational overhead, which may become significant when deployed at large scale across thousands of pipeline segments. Finally, integrating ARPC-DOX with existing pipeline integrity management systems (PIMS) requires system-level compatibility, workflow adjustments, and operator training to ensure smooth adoption. These considerations highlight the need for calibrated deployment, robust data acquisition, and computational optimization when applying the framework in real operational environments.

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conception and design. Material preparation, data collection and analysis were performed by M. Angeline Geetha, M. Joselin Kavitha, R. Isaac Sajan, Sudhakar Eby Aseer. The first draft of the manuscript was written by M. Angeline Geetha and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript. Conceptualization: M. Angeline Geetha, M. Joselin Kavitha; Methodology: R. Isaac Sajan, Sudhakar Eby Aseer; Formal analysis and investigation: M. Angeline Geetha, Sudhakar Eby Aseer; Writing-original draft preparation: M. Joselin Kavitha, R. Isaac Sajan; Writing-review and editing: M. Angeline Geetha, M. Joselin Kavitha; Supervision: R. Isaac Sajan, Sudhakar Eby Aseer.

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Declarations

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